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ΠΡΟΓΡΑΜΜΑ ΜΕΤΑΠΤΥΧΙΑΚΩΝ ΣΠΟΥΔΩΝ

ΔΙΔΑΚΤΟΡΙΚΗ ΔΙΑΤΡΙΒΗ

Διάδοση και χρήση πληροφορίας σε ανταγωνιστικά δικτυακά αστικά περιβάλλοντα

Ευαγγελία Α. Κοκολάκη

ΑΘΗΝΑ

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PhD DISSERTATION

Information dissemination and consumption in competitive networking urban environments

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ΠΕΡΙΛΗΨΗ

Η συνεισφορά αυτής της διδακτορικής διατριβής έγκειται στην ανάδειξη, μελέτη και κατανόηση φαινομένων και συμπεριφορών σχετικών με τη διάδοση και τη χρήση πληροφορίας μέσα σε δικτυακά κατανεμημένα αστικά περιβάλλοντα και ανταγωνιστικά πλαίσια λειτουργίας. Η μελέτη αφορά σε σύγχρονα περιβάλλοντα δικτύωσης εντός του αστικού ιστού στα οποία η εμφάνιση ευφυών τεχνολογιών αισθητήρων και συστημάτων επικοινωνίας ευνοεί την παραγωγή και τη διάχυση τεράστιων ποσοτήτων πληροφορίας. Αυτή η πληροφορία παρέχει ενημέρωση για το περιβάλλον και τους πόρους του (εν γένει, ασύρματα κανάλια επικοινωνίας, οδικά τμήματα, θέσεις στάθμευσης). Παράλληλα δημιουργεί πολύτιμη γνώση για τους διάφορους, ποικίλης φύσεως, δικτυακούς κόμβους, οι οποίοι καλούνται να αποφασίσουν με ποιον τρόπο να χρησιμοποιήσουν αυτούς τους πόρους για την καλύτερη εξυπηρέτησή τους. Συγκεκριμένα, εξετάζονται περιπτώσεις στις οποίες οι κόμβοι επιδιώκουν να εξυπηρετηθούν χρησιμοποιώντας κάποιο κοινό για όλους, πεπερασμένο σύνολο πόρων. Μέσα σε ένα τέτοιο πλαίσιο, διερευνάται εάν και σε ποιο βαθμό η εμφάνιση του ανταγωνισμού μπορεί να επηρεάσει το βαθμό συνεισφοράς των κατανεμημένων κόμβων στη συλλογική προσπάθεια πληροφόρησης/ενημέρωσης αλλά και τις αποφάσεις των κόμβων που λαμβάνονται βάσει της παρεχόμενης πληροφορίας/ενημέρωσης. Συνεργατικές ή μη συμπεριφορές αλλά και πρακτικές πλήρους ή περιορισμένης λογικής αναλύονται και προσομοιώνονται αξιοποιώντας αποτελέσματα και μελέτες μέσα από ένα μεγάλο εύρος επιστημονικών πεδίων που ξεκινούν από Δίκτυα Επικοινωνιών και Θεωρία Αποφάσεων και φτάνουν σε Γνωσιακή Ψυχολογία και Συμπεριφορική Χρηματοοικονομική. Συνολικά, παρέχονται κατευθύνσεις για την αποτελεσματική διαχείριση του ανταγωνισμού μέσα σε δικτυακά περιβάλλοντα, οι οποίες από τη μία αμφισβητούν την ανάγκη για εξεζητημένα συστήματα πληροφόρησης και από την άλλη αναδεικνύουν την αποτελεσματικότητα των φυσικών μηχανισμών διαχείρισης πληροφορίας και λήψης αποφάσεων που παρατηρούνται στον άνθρωπο, στην επίλυση καταστάσεων συμφόρησης γνωστών μέσα από τον όρο «τραγωδία των κοινών».

ΘΕΜΑΤΙΚΗ ΠΕΡΙΟΧΗ: Δίκτυα Επικοινωνιών

ΛΕΞΕΙΣ ΚΛΕΙΔΙΑ: δικτύωση, Ευφυή Συστήματα Μεταφορών, παίγνια επιλογής πόρων, τραγωδία των κοινών, συμπεριφορική λήψη αποφάσεων

ABSTRACT

The focus of this thesis lies on demonstrating, investigating and understanding decision-making in human-driven information and communication systems within autonomous networking urban environments and competitive contexts. Indeed, the thesis examines modern networks that integrate mobile communication devices with online social applications and different types of pervasive sensor platforms and hence, foster unprecedented amounts of information. When shared, this information can enrich people's awareness about and enable more efficient management of a broad range of resources, ranging from natural goods such as water and electricity, to human artefacts such as urban space and transportation networks. Especially in environments where users' welfare is better satisfied by the same finite set of resources, it is important to understand how the presence of competition shapes decisions and behaviors regarding the information dissemination and building of collective awareness, on the one hand, and the way collective awareness is exploited under different assumptions about the rationality levels of decision-makers, on the other hand. The first of these very general and fundamental questions amounts to deciding whether a networked entity will deviate from the expected behavior (misbehavior) by hiding or falsifying resource or service availability information, to reduce the competition to its advantage. The second amounts to deciding whether a networked entity will compete or not compete for some limited resources. We investigate these two questions by exploiting insights and results from different disciplines ranging from Communication Networks and Decision Theory to Behavioral Economics and Cognitive Science. Our results provide theoretical support for the practical management of limited-capacity resources since they challenge the need for more elaborate information mechanisms. They also reveal useful insights to the dynamics and benefits emerging from human behavior in situations that expose "tragedy of commons" effects.

SUBJECT AREA: Communication Networks

KEYWORDS: networking, Intelligent Transportation Systems, resource selection games, tragedy of the commons, behavioral decision-making

To all those who have prayed for me to have

wisdom, strength and patience

during challenging times.

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Evangelia A. Kokolaki

Athens, June 2014

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Chapter 1

Introduction

1.1 Fundamental aspects of decision-making in collective awareness environments

The tremendous increase of urbanization necessitates the efficient and environmentally sustainable management of various urban processes and operations. Recent advances in wireless networking and sensing technologies can address this need by enabling efficient monitoring mechanisms for these processes and higher flexibility to control them, thus paving the way for the so-called *Smart Cities*.

With the dawn of Smart Cities, the emerging networking environment is centered around powerful entities that (a) can produce services and content to be consumed by others; (b) can act as networking elements transporting information; and (c) can act as classical users or consumers of services or content. These nodes are typically self-owned and managed, thus their behavior can be uncontrollable, unpredictable and driven by self-oriented objectives that may well be in conflict with those of other elements.

This trend is further accentuated by the strong emergence of what is referred to as a *socio-tech* dimension, concerning to the bi-directional coupling and dependencies between the social dimension present in the human associated with a user-node and the networking technologies and capabilities in and around the user-node. As a result basic operations of the networked environment are strongly affected by human behaviors and characteristics. In the opposite direction, human activities and behaviors are also affected by the offerings of the networked environment.

Indeed, Information and Communication Technologies (ICT) increasingly penetrate a broad range of human activities, transforming the way these activities are carried out, altering the human perception about the network and its services, but also shaping human experiences and lifestyles. Intelligent networked sensor nodes (*i.e.*, smart dust), placed on buildings' surfaces or mounted on vehicles, constitute pervasive monitoring platforms that can measure environmental parameters such as pollution concentration, radiation level, road traffic congestion or public transport and parking utilization. The integration of sensing devices of various sizes, scope and capabilities with mobile communication devices, on the one hand, and the wide proliferation of online social applications, on the other, leverage the heterogeneity of users in terms of interests, preferences, and mobility, and enable the collection of huge amounts of information with very different spatial and temporal context. These amounts of information can enrich dramatically people's awareness (and foster more efficient management) of their environment, whether this is the natural environment or the physical space they move in while working, driving, or entertaining themselves. In parallel, this knowledge provides them, at least potentially, with the opportunity to make more informed/intelligent decisions about the way they access and use the resources of their environment, which can range from natural goods such as water and electricity, to human artefacts such as urban space and transportation infrastructure.

If the disseminated information concerns the availability of some limited resource or service, it is important to understand how the presence of competition shapes users' decisions for information discovery, generation, replication and consumption processes. With end-users having an active and increasing role in these operations, it gets compelling to motivate their cooperation/participation and make these operations robust to attempts to manipulate them for the individual benefit as well as steer individuals' decision-making towards more socially efficient actions.

In this thesis, we study scenarios where some finite resource is of interest to a population of distributed users with variable perceptions about the resource supply and demand for it. The high-level question we address is *how efficiently the competition about the resources is resolved under different assumptions about the way the users make their* *decisions*. We devise analytical and simulation models that describe the decision-making process of users concerning the dissemination and consumption of information, when faced with multiple choices. We instantiate this context in a concrete case that we can study systematically, namely an urban environment in which parking space is the resource of interest to the users-drivers and whose availability is disseminated or becomes accessible to the users to some extent. With this information, drivers can make more informed search for parking, while municipal authorities can address more efficiently the challenge to manage the available parking space and reduce the vehicle volumes that cruise in search of it, in order to alleviate not only traffic congestion but also the related environmental burden.

1.2 Outline of the thesis

The thesis is structured around eight chapters, separated into three parts. In the sequel, we present a short summary and the main objectives of each chapter.

In Part I and Chapters 2, 3, 4 in particular, we introduce and describe fundamental concepts and principles in networking solutions for the upcoming smart city environments and present socio-tech issues, trends and challenges that arise in various application paradigms that have been developed through these networks and serve as case-studies in the investigation presented in the following chapters.

Part II explores the effectiveness and side-issues of information within competitive settings. The emergence of intelligent sensing and communication technologies fosters the generation and dissemination of huge amounts of information that collectively enriches people's awareness about their environment and its resources. With this information at hand, users then decide how to access these resources to best serve their interests. However, situations repeatedly emerge where the users' welfare is better satisfied by the same finite set of resources and the uncoordinated access to them gives rise to tragedy of commons effects and serious congestion problems. Part II is structured around two chapters with the first one (Chapter 5) addressing the impact of information dissemination and the second one (Chapter 6) addressing the impact of information consumption on the competition and, ultimately, users' welfare.

In Chapter 5, in particular, we explore how the discovery of service can be facilitated or not by utilizing service location information that is opportunistically disseminated primarily by the consumers of the service themselves. We apply our study to the real-world case of parking service in busy city areas which has attracted the interest of the research community and the private sector in the context of the so-called "Smart City" initiative. As the vehicles drive around the area, they opportunistically collect and share with each other information on the location and status of each parking spot they encounter. The parking space scenario serves as an example of opportunistic networking environments where the user-nodes can collectively gain from the sincere exchange of (parking availability) information (*i.e.*, cooperation), yet each one of them can only gain if certain information is hidden from others (potential competitors); thus, an environment, where the processes of information dissemination (benefiting service discovery) and competition (reducing the service delivery prospects) are coupled and counter-acting. This opportunistically-assisted search is compared against the "blind" non-assisted search and a centralized approach, where the allocation of parking spots is managed by a central server availing global knowledge about the parking space availability. This comparative study concludes with the observation that the availability of information is not always better than the lack of it in competitive environments, as the sharing of information assists nodes by increasing their knowledge about parking space availability but, at the same time, synchronizes nodes' parking choices. This synchronization in turn increases the effective competition and, ultimately, the congestion penalties experienced (*e.g.*, long car cruising when searching for cheap on-street parking spots in busy urban environments). Being aware of the competition, the nodes are motivated to defer from sharing information or deliberately falsify information to divert others away from a particular area of their own interest. The results show that as long as the portion of misbehaving nodes is not very high, the overall performance does not deteriorate significantly, nor does the misbehaving node enjoy any notable performance improvement. This observation suggests that the spatial-temporal-interest diversity in large-scale distributed settings and the dynamicity of the environment, which may render falsified data correct or lack of outdated data advantageous, might confer robustness against misbehaviors.

In Chapter 6 it is investigated how the competition awareness affects the decision to compete or not for some limited-capacity resource set. In essence, we are concerned with the comparison of the decision-making under full against bounded rationality conditions. Fully rational users avail all the information they need to reach decisions and, most importantly, are capable of exploiting all information they have at hand. The impact of perfect rationality is investigated by considering an environment in which the parking space is the resource of interest to the users-drivers and whose availability is disseminated or becomes accessible to some extent. Drivers decide whether to go for the inexpensive but limited on-street public parking spots or the expensive yet over-dimensioned parking lots, incurring an additional cruising cost when they decide for on-street parking spots but fail to actually acquire one. The drivers are viewed as strategic agents who make rational decisions while attempting to minimize the cost of the acquired parking spots. We take a game-theoretic approach and analyze the uncoordinated parking space allocation process as *resource selection game* instances. We derive their equilibria and compute the related *Price of Anarchy* values. It is shown that, under typical pricing policies on the two instances of parking facilities, drivers tend to over-compete for the on-street parking space, giving rise to redundant cruising cost. To alleviate the congestion phenomena, we propose auction-based systems for realizing centralized parking allocation schemes, whereby drivers bid for public parking space and a central authority coordinates the parking assignments and payments. These are compared against the conventional uncoordinated parking search practice under fixed parking service cost, formulated as a resource selection game instance. In line with intuition, the auctioning system increases the revenue of the public parking operator exploiting the drivers' differentiated interest in parking. Less intuitively, the auction-based mechanism does not necessarily induce higher cost for the drivers: by avoiding the uncoordinated search and thus, eliminating the cruising cost, it turns out to be a preferable option for both the operator and the drivers under various combinations of parking demand and pricing policies.

The assumption of perfect information can be relaxed by modeling the uncoordinated users' interaction in terms of Bayesian games where users have only probabilistic information or are totally uncertain about the resource demand. Interestingly, counterintuitive less-is-more effects emerge where more information does not necessarily improve the efficiency of service delivery but, even worse, may hamstring users' efforts to maximize their benefit. Essentially, Game Theory and the Nash equilibrium concept capture users' best responses in terms of expected utility maximization. Nevertheless, several experimental data have shown over time the limitations of the Expected Utility Theory framework to consistently explain the way human decisions are made. At the same time, they have revealed cognitive biases in the way people assess the alternatives they are presented with. Thus, we exploit insights from Bayesian games, Behavioral Economics and Cognitive Psychology (Prospect Theory, Quantal Response and Rosenthal equilibria, heuristic reasoning) to model agents of bounded rationality who cannot exploit all the available information due to time restrictions and computational limitations. We derive the operational states in which the competing influences are balanced (*i.e.*, equilibria) and compare them against the Nash equilibria that emerge under full rationality and the optimum resource assignment that could be determined by a centralized entity. From the comparison between the equilibria under full versus bounded rationality conditions are derived under which very simple heuristic reasoning yields near-optimal results. Overall, our study provides useful insights to the dynamics emerging from the users' behavior as well as theoretical support for the better understanding of effective information dissemination mechanisms in emerging smart city environments.

Although these decision-making models are shown to predict and accommodate people's answers in various experimental data sets, they cannot describe the processes (cognitive, neural, or hormonal) underlying people's decisions. Yet, the efficient and environmentally sustainable management of various urban processes calls for novel solutions that account for behavioral decision-making in a transparent way that reflects the internal reasoning mechanisms. Indeed, transportation engineers need to be able to understand how drivers decide their route to effectively address the plethora of challenges for alleviating the congestion phenomena in city areas. In Chapter 6, we model drivers' decision-making with respect to the parking space search, which has been regarded as one of the major causes of traffic congestion. We view the parking search as an instance of *sequential search problems* and present a game-theoretic investigation of the efficiency of heuristic parking search strategies to locate available parking spot at minimum walking and driving overhead. The analytical study concludes by drawing similarities between the parking game and well-known archetypal games that Game Theory examines.

In the last part, that is Part III (Chapter 7), we seek to experimentally study some fundamental properties of vehicular social applications that have been deployed to assist in the parking search process. The awareness and incentive mechanisms that are commonly incorporated in different instances of social parking applications are modeled and simulation scenarios are considered to explore particular aspects of these applications. It is shown that application users experience improved performance due to the increased efficiency they generate in the parking search process, without (substantially) degrading the performance of non-users. This is extremely important since applications managing common (public) goods should not provide benefits to their users by penalizing or almost excluding non-users. The incentive mechanisms are effective in the sense that they do provide preferential treatment to those fully cooperating but they induce rich-club phenomena and difficulties to newcomers. Interestingly, those problems, that may be a concern for all applications managing common (public) goods, seem to be alleviated by free-riding phenomena and dynamic behaviors.

Finally, Chapter 8 presents collectively the major conclusions of the thesis and suggests possible directions for future research.

This thesis is based on material from the following papers:

Journal articles

1. E. Kokolaki, M. Karaliopoulos, G. Kollias, M. Papadaki, I. Stavrakakis, "Vulnerability of opportunistic parking assistance systems to vehicular node selfishness", Computer Communications, Elsevier, vol. 48, pp. 159-170, July 2014

2. E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, "Leveraging information in parking assistance systems", IEEE Transactions on Vehicular Technology, vol. 62(9), pp. 4309-4317, November 2013

3. E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, "Opportunistically-assisted parking service discovery: now it helps, now it does not", Pervasive and Mobile Computing, Elsevier, vol. 8(2), pp. 210-227, April 2012

Magazine

1. E. Kokolaki, I. Stavrakakis, "Competition Awareness", Awareness Magazine, December 2013 (invited paper)

Conference/workshop proceedings

1. E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, “Trading public parking space”, IEEE WoWMoM workshop on Smart Vehicles, Sydney, Australia, June 16-19, 2014

2. E. Kokolaki, I. Stavrakakis, “Equilibrium analysis in the parking search game with heuristic strategies”, Second International Workshop on Vehicular Traffic Management for Smart Cities (colocated with the IEEE Vehicular Technology Conference), Seoul, Korea, May 18, 2014

3. E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, “Parking assisting applications: effectiveness and side-issues in managing public goods”, Third IEEE SASO workshop on Challenges for Achieving Self-Awareness in Autonomic Systems, Philadelphia, USA, September. 2013

4. E. Kokolaki, M. Karaliopoulos, I Stavrakakis, “On the efficiency of information-assisted search for parking space: a game-theoretic approach”, Seventh International Workshop on Self-Organizing Systems (IFIP IWSOS’13), Palma de Mallorca, May 9-10, 2013

5. E. Kokolaki, M. Karaliopoulos, I Stavrakakis, “On the human-driven decision-making process in competitive environments”, Internet Science Conference, Brussels, April 10-11, 2013, *Best student paper award - Special mention*

6. E. Kokolaki, G. Kollias, M. Papadaki, M. Karaliopoulos, I. Stavrakakis, “Opportunistically-assisted parking search: a story of free riders, selfish liars and bona fide mules”, International Conference on Wireless On-demand Network Systems and Services (IFIP/IEEE WONS), Banff, Canada, March 18-20, 2013

7. E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, “Value of information exposed: wireless networking solutions to the parking search problem”, International Conference on Wireless On-demand Network Systems and Services (IFIP/IEEE WONS), Bardonecchia, Italy, January 26-28, 2011

Part I

Background and Preliminary concepts

Chapter 2

From Digital to Smart Cities

The rapid urbanization of world's population over the twentieth century predominantly imposes significant changes in city forms and urban operations. According to the United Nations "State of the World Population" 2007 report[1], the number of people living in cities has overtook the number of people living in the rural areas and this event was recorded in the history as the "tipping point". The urbanization of society continues to increase: in 2009, the fraction of world population living in urban areas was above 50% (more than 75% in developed countries). It is forecasted that another 10% of the world population will move to metropolitan regions within the next 15 years, leading us into the so-called "Urban Millennium".

The scale and the pace that characterize the phenomenon of urbanization raise evident questions on sustainable management of urban processes and operations, calling for urgent solutions to the growing problems. The recent advances, the pilot implementation of solutions and the pioneering ideas from the area of Information and Communication Technologies (ICT) present a response towards the urbanization problems, giving birth to the so-called' "Digital Cities". This term refers to a connected community that combines flexible, service-oriented computing infrastructure, broadband communication and innovative services to meet the needs of governments and their employees, citizens and businesses[2].

However, urban performance currently depends not only on the city's endowment of

[1] "UN State of the World Population", United Nations Population Fund (UNFPA), 2007.
[2] *http://en.wikipedia.org/wiki/Digital_city*

hard infrastructure ("physical capital"), but also on the availability and quality of knowledge communication and social infrastructure ("intellectual capital and social capital"). The significance of the social and environmental asset and the need to integrating the physical, social and digital dimensions of urban space pave the way to distinguish Digital Cities from their socio-tech counterparts, namely "Smart Cities" which represent a next-generation advancement from Digital Cities [Caragliu *et al.*, 2009]. As it will be clear in the sequel, the critical difference is in the problem solving capability of Smart Cities, while the ability of Digital Cities is in the provision of services via digital communication. In a general rule, in services provision by local administrations, Digital Cities are placed downstream between the public authority and the citizen as recipient of services (as digital marketplaces); while Smart Cities are placed upstream between the citizens and the public authority, enabling co-creation and co-design of services (as Living lab).

Smart Cities bring together cities, industry and citizens to improve urban life through more sustainable integrated solutions. In particular, Smart Cities can be identified along six main dimensions: people, living, governance, environment, mobility, economy. These six dimensions are integrated and connected with traditional regional and neoclassical theories of urban growth and development in order to increase the efficiency, effectiveness and resilience of the overall system, thus utilizing potentials for making social and ecological improvements and positively impacting all aspects of metropolitan life [Giffinger *et al.*, 2007]. This includes the following objectives: improve the quality of life of all citizens and their ability to take active part in society, allow citizens to participate through transparent decision-making processes in the governance of their city, reduce the use of finite resources and support the use of renewable resources, ensure and optimize the long-term provision of public services, enhance the fitness for survival, ability to adapt and general resilience of the settlement area, maintain or increase the competitive strength of the local economy.

All the aforementioned issues are addressed by incorporating new technologies in the area of mobile communications, multimedia services, data storage and ubiquitous computing, and integrating all dimensions of human, collective, and artificial intelligence available within a city [Komninos, 2006] [Komninos, 2008]. Leveraging advances in sensor technologies, urban experiments and data analysis, new insights into creating a data-driven approach to urban design and planning can be provided so that more reliable statistics can be built or rapid reactions can be triggered. For example, “urban sensing” will enable a fine-grained yet pervasive monitoring of critical factors in large urban areas such as the pollution level, road traffic status, public transport utilization, sudden danger situations in buildings or on streets, and resource (*e.g.*, energy, water, gas) usage. Smart grids are envisioned to enhance the reliability, efficiency and safety of energy distribution as well as its conservation, through integrated metering and data communication. 4G cellular systems in urban areas will heavily rely on opportunistic offloading to deliver high quality audio, video and data. Collective awareness platforms will combine online social media, distributed knowledge creation and data from real environments (“Internet of Things”) in order to create awareness of problems and possible solutions requesting collective efforts and foster new forms of social innovation and participatory democratic processes. Finally, Intelligent Transportation Systems (ITS) will revolutionize our experience in transportation, by reducing travel times, improving road safety and unleashing a new generation of infotainment applications through networked vehicles.

Chapter 3

Smart mobility: Intelligent Transportation Systems and Applications

The development of smart vehicles and transportation systems has emerged as one of the most fundamental societal challenges of the next decade. Vehicles have turned from mechanical systems into embedded software platforms on wheels, sometimes with a supporting infrastructure. At the same time, automotive manufacturers are striving to integrate mobile devices, vehicular communication networks, and information and communication systems in order to provide innovative services relating to different modes of transport and traffic management and enable various users to be better informed and make safer, more coordinated, and smarter use of transport networks. This includes developing innovative cooperative systems that enable road users and infrastructures to exchange information in real time and in an autonomous manner, pervasive sensing to monitor the vehicles' operation and the status of surroundings, big middleware platforms for information management and sharing, data analytics for the processing of the monitored data, and appropriate interaction interfaces between drivers and vehicles. Current market estimates suggest that vehicles equipped with these new technological capabilities will top 1.5 billion worldwide by 2020.

To upgrade human mobility in urban areas towards a more sustainable and connected future it is of paramount importance to address the technical, economical and regulatory challenges that arise from the integration of different socio-tech dimensions. On the technical front, the various types of ITS rely on radio services for communication and use specialized technologies encompassing vehicular networks, electrical engineering (sensors, instrumentation, wireless communications, *etc.*), mutlimedia and Internet services to support road, rail, water and air transport (including navigation systems).

As a prospective ITS technology, vehicular networking have recently been attracting an increasing attention from both research and industry communities. The Vehicular Ad-hoc NETworks (VANETs) are a form of Mobile Ad-hoc NETworks (MANETs) that provide means for communication among vehicles (*e.g.*, normal and dedicated) featuring the vehicle to vehicle communication mode (V2V) and between vehicles and fixed road-side infrastructure (*e.g.*, traffic lights, bus stations or toll stations) being referred to as vehicle to infrastructure communication mode (V2I).

The V2V communication infrastructure assumes the presence of high bandwidth and thus, provides low latency data dissemination among vehicles. The radios typically operate on unlicensed band making the spectrum free[1]. In particular, VANETs are expected to implement wireless technologies such as dedicated short-range communications (DSRC) which is a type of Wi-Fi, specifically designed for automotive use and road use measurements, that works in $5.9GHz$ band with bandwidth of $75MHz$ allocated by FCC, or $30MHz$ allocated be ETSI and approximate range of $1000m$. Intelligent vehicular ad-hoc networks (InVANETs), which is another term for promoting vehicular networking, integrates multiple networking technologies such as Wi-Fi IEEE 802.11p, WAVE IEEE 1609, WiMAX IEEE 802.16, Bluetooth, IRA and ZigBee. In April 2014 it was reported that U.S. regulators were close to approving V2V standards for the U.S. market, and that officials were planning for the technology to become mandatory by 2017[2].

On the other hand, Infostations and 3G/4G mobile standards primarily support the V2I communication mode [Frenkiel *et al.*, 2000]. Infostations consist of wireless access points deployed at specific locations in the road network. Infostations' technology envisions intermittent connectivity and can sustain high bandwidth (ultra-high-speed radios of Mbps or even Gbps rates) with low latency. The use of wireless technologies

[1] $http://en.wikipedia.org/wiki/Vehicular\_ad\_hoc\_network$

[2] $http://www.voanews.com/content/vehicles-may-soon-be-talking-to-each-other-/1886895.html$

that utilize unlicensed band makes Internet accesses through Infostation extremely low-cost. For example, current generations of hardware use variants of the 802.11 standard. Finally, the future cellular communication technology promises high data-rates with high mobility support and smooth handoff across heterogeneous networks. Since the spectrum under use in this case is a licensed band, there is an increased cost per bit and thus, Internet access is more expensive than with Infostations.

In many ways VANETs are similar to MANETs. On the one hand, both networks are multi-hop mobile networks having dynamic topology. On the other hand, unlike MANETS the mobility pattern of VANET nodes is predictable, that is, vehicular nodes move on specific paths (roads) and not in random direction. They also differ on the storage capacity, battery and processing power. Sufficient storage capacity and high processing power can be easily made available in vehicles. Moreover vehicles also have enough battery power to allow for long range communication. Another difference is the highly dynamic topology of VANETs due to vehicles' high velocities which makes the lifetime of communication links between nodes quite short. Node density is also unpredictable; during rush hours the roads are crowded with vehicles, whereas at other times lesser vehicles are there, or similarly, some roads have more traffic than other roads. As a last difference from typical MANETs, in VANETs the wired Internet infrastructure is omnipresent and readily accessible via WiFi, DSRC, WiMAX, 3G, LTE, *etc.* [Gerla & Kleinrock, 2011].

The specific characteristics of vehicular networks favor the development and implementation of a myriad of attractive and challenging services and applications related to vehicles, vehicle traffic, drivers, passengers and pedestrians. In fact BMW, Fiat, Renault and other organizations have united to develop a vehicular communication consortium, dedicated precisely to impose Vehicle to Vehicle (V2V) and Vehicle to infrastructure (V2I) communication and develop safety related information and access location-based services. In general, vehicular networking applications can be classified as (a) safety, (b) traffic efficiency/assistance and (c) infotainment applications [Karagiannis *et al.*, 2011] [Gerla & Kleinrock, 2011] [Saira Gillani & Qayyum, 2008].

Safety applications

Providing safety is the primary objective of vehicular communication networks. Safety applications provide information and assistance to drivers to avoid accidents. This can be accomplished by sharing information between vehicles and road-side units which is then used to predict collisions. Such information can represent vehicle position, intersection position, speed and distance heading. For example, electronic sensors in each car can detect abrupt changes in path or speed and send appropriate warnings. Moreover, information exchange between the vehicles and the road-side units is used to detect hazardous locations on roads, such as slippery sections or potholes. In more advanced systems, vehicles involved in a junction merging maneuver negotiate and cooperate with each other and with road-side units to realize this maneuver and avoid collisions or notify close vehicles about lane changes so that others can make better decisions. Likewise, at intersections the system can decide which vehicle has the right to pass first and alert all the drivers. Safety applications demand strict time delay bounds requiring messages to be propagated to the target vehicles with very low latency (a few nano-seconds). Due to intermittent connectivity in infrastructure-based communication, V2I cannot provide delay guarantees in latency critical applications, while the widespread 3G based cellular data access networks can provide continuous connectivity at low bandwidths which could induce a delay up to a few seconds. On the other hand, V2V communication constitutes one pivotal tool in improving the monitoring, distribution, and processing of traffic information for safety and efficiency since it can sustain the latency requirements for data dissemination in such applications.

Traffic efficiency/assistance applications

Traffic efficiency and assistance applications focus on improving the vehicle traffic flow, traffic coordination and traffic assistance and provide information of relevance bounded in space and/or time. This class of applications includes (a) speed management and (b) cooperative navigation. The first one aims at assisting the driver to avoid unnecessary stopping and manage the speed of his vehicle for smooth driving. With the second one, the navigation of vehicles is managed through cooperation among vehicles and through cooperation between vehicles and road-side units. For example authorities may change traffic rules according to a specific situation (*e.g.*, bad weather) or for accommodating ambulances, fire trucks, and police cars. Also information about the road congestions can be provided/displayed to reducing the congestion and improving the capacity of roads. In a more advanced approach, congestion at road intersections can be handled using intelligent traffic signals that can adjust themselves in response to the traffic conditions. Some other applications can also be envisioned like automated call to emergency services, en-route and pre-trip traffic assistance. These applications require either intermittent or continuous Internet connectivity and hence, a tight integration of V2V and V2I functionalities may respond to the emerging requirements.

Infotainment applications

As with many other communication networks, vehicular networks can be used to obtain various content and services (not directly related to travelling). In this respect there are two typical groups of infotainment applications: (a) cooperative local services and (b) global Internet services. The first type focuses on infotainment that can be obtained from locally based services such as point of interest notification, local electronic commerce and media downloading, while the second type includes virtually every application that is currently used in the Internet including peer-to-peer gaming, chatting, content sharing, *etc.*. Commuters can enjoy the facility of Internet connectivity where other traditional wireless Internet connectivity options (*e.g.*, Wi-Fi, Wi-MAX *etc.*) are not available. With VANETs, this possibility may be realized if a vehicular node connected to Internet share its connectivity with others. In principle, delay-tolerant Internet-connectivity-based applications as well as the privacy and security concerns that are present in many of them can be addressed through the V2I communication. Yet, as in traffic efficiency/assistance applications, pure V2I-based solutions will not be sufficient to address the challenges concerning latency and connectivity arisen for every case.

In this thesis we primarily interested in competitive networking contexts and hence, apply our study in instances of parking assistance applications that expose features of such environments. These applications lie at the intersection of traffic management and infotainment applications. In the following chapter we outline research on the development and modeling of parking assistance systems.

Chapter 4

Parking assistance systems

The efficient use of urban space has always been both a requirement and a challenge in the process of city planning. It calls for several interventions in the way cities are organized, including the efficient management of the car volumes that daily visit the city centre and other popular in-city destinations. Part of this task is the effective operation of the sometimes minimal parking space. The reduction of time that vehicles spend searching for parking places alleviates not only the traffic congestion problems but also the environmental burden.

The real dimensions of the parking place search problem depend on several factors. The existence of popular destinations, personal parking preferences, and the drivers' unwillingness to park but only in close proximity to the destination, aggravate the problem. The general problem of parking space search has seen contributions from different scientific disciplines such as economics, transportation, operations research, and computer science. Academic research but also public and/or private initiatives have made a remarkable effort in the past years to solve the problem through parking assistance systems. Common feature of these systems is the exploitation of wireless communications and information sensing technologies to collect and share information about the availability of parking space in the search area. This information can be then used to steer the parking choices of drivers with the aim to reduce the effective competition over the parking space and make the overall search process efficient.

4.1 Centralized parking systems

On the assisted parking search front, initial work focused on *centralized* parking (reservation) systems. The system in [Boehle *et al.*, 2008] consists of four components: an on-board device located in the vehicle, intelligent network enabled lampposts, a sensor network that monitors the availability of parking places and a centralized parking spot scheduling/reservation server. Likewise, in the architecture in [Wang & He, 2011], every parking lot runs a reservation authority that collects parking requests via the Internet, extracts real-time statistics about its parking availability and routes them to a centralized management system that dynamically determines and broadcasts the parking fees, drawing on the relationship between parking demand and supply. Both systems are shown to better distribute the car traffic volume. Along the same line, Lu *et al.* in [Lu *et al.*, 2009] propose SPARK for reducing the parking search delay. SPARK consists of three distinct services, *i.e.*, real-time parking navigation, intelligent antitheft protection and friendly parking information dissemination, all making use of roadside network infrastructure. Finally, the authors in [Mathur *et al.*, 2010] design, implement, and evaluate a system that generates a real-time map of parking space availability. The map is constructed at a central server out of aggregate data about parking space occupancy, collected by vehicles circulating in the considered area. In a similar approach, the Parkomotivo system[1] has been launched to monitor through a dedicated wireless sensor network and analyze using a data mining engine, on-street parking patterns in the city of Lugano (Switzerland). Drivers' can be informed by the Parkomotivo's tweet stream about the collected real-time parking availability data.

4.2 Opportunistic parking systems

Work on opportunistic parking search assistance, where information about the location and vacancy of parking spots is opportunistically disseminated among vehicles, is rarer and more recent. In [Verroios *et al.*, 2011] the vehicular nodes solve a variant of the Time-Varying Travelling Salesman problem while dynamically planning the best feasible

[1] Parkomotivo: parking application for the city of Lugano, available online in $http://www.bmob-park.com$

trip along all (reported to be) vacant parking spots. The solution attempts to minimize the total transit cost of the travelled path taking account of the time needed to reach a parking spot, the walking time from the spot to the actual destination and the probability to find the spot available. Despite the interesting treatment of the parking problem, it makes in advance the rather debatable assumption that vehicles' trips follow necessarily all reported spots. Moreover, the applied cost function may paradoxically prioritize a parking spot of lower over another of higher availability, when they tie in all other criteria (time to park, walking time). In [Caliskan *et al.*, 2006], vehicles are allowed to exchange aggregate parking information of variable - low - accuracy in order to limit the volume of disseminated information for the sake of scalability. Simulation measurements and conclusions are derived for the profile of nodes' cache entities (*i.e.*, information dissemination rates, freshness and spatial distribution of information in nodes' cache) under full or selective dissemination. On the other hand, the way the opportunistic exchange of information among vehicles may sharpen competition for parking space is treated in [Delot *et al.*, 2009]. The authors propose a distributed virtual parking space reservation mechanism, whereby vehicles vacating a parking spot selectively distribute this information to their proximity. Hence, they mitigate the competition for the scarce parking spots by opportunistically controlling the diffusion of the parking information among drivers.

4.3 Parking systems through vehicular social networks

The more recent approaches to the assisted parking search add a social media layer over the vehicular network. These have a strong distributed flavor in that the mobile applications run on drivers' smartphones (or could run on-board vehicles) and information is collected opportunistically as these move around in the city. Yet, they are coupled by a social networking front end that lets the information spread (and reservations happen) almost instantaneously, in ways that resemble a centralized system. Almost all proposed applications feature an incentive mechanism that rewards application users with points each time they handover a parking spot to another application user. Under "ParkingDefenders" (Athens, Greece)[2], high-score users enjoy higher chances to be chosen by

[2] ParkingDefenders: parking application for Athens (Greece), available online in *http://www.parkingd.com*

a parking spot defender, whereas with “ParkShark” (New York)[3] such users get informed prior to others about vacant spots. On the other hand, in “PlaceLib” (Paris)[4] and “Kurb” (San Francisco)[5] the subscribers announce when they leave a spot and hand their spot to another driver who announced that he is looking for one. The offer is rewarded by an amount of non-monetary credits that can be consumed to send a request for an offered spot.

4.4 Modeling the parking spot selection problem

4.4.1 Operations research

The first formulations of the parking search problem appeared in the context of the broader family of stopping problems. In [MacQueen & Miller, 1960] parking spots are spread randomly with density λ over equal-size blocks that are adjacent to the driver's travel destination. The driver circles through them, crossing the destination every time such a circle is over, and upon encountering a vacant spot he has to decide whether to take it or skip it and seek for a better one. Ferguson in *http : //www.math.ucla.edu/ tom/Stopping/* considers a simpler variant of the problem, whereby the driver's destination lies in the middle of an infinite-length straight line with parking spots that are occupied with probability *p*. In either case, the optimal policy for the drivers is shown to be of the threshold type: they should occupy an available vacant parking spot whenever this lies within some distance $r = f(\lambda)$, resp. $f(p)$, from their destination and continue searching otherwise.

4.4.2 Economics

Pricing and the more general economic dimensions of the parking allocation problem are analyzed from a microeconomical point of view in [Anderson & de Palma, 2004]. Anderson and de Palma view the parking spots as common property resource and question whether free access or some pricing structure result in more efficient use of the parking capacity. Working on a simple model of city and parking spot distribution, they show

[3]ParkShark: parking application for New York City, available online in *http : //www.parkshark.mobi/www/*

[4]PlaceLib: parking application for Paris, available online in *http : //www.placelib.com*

[5]Kurb: parking application for San Francisco, available online in *http : //www.kurbkarma.com*

that this use is more efficient (in fact, optimal) when the spots are charged with the fee chosen in the monopolistically competitive equilibrium under private ownership; whereas drivers are better off when access to the parking spots is free of charge. The degree of importance of the parking pricing policy in resolving drivers' quesswork of choosing parking space, has inspired the developers of SFpark[6] to establish and operate an advanced parking assistance system that not only collects and distributes real-time information about meter and garage parking space in San Francisco but, most importantly, it uses a demand-responsive pricing mechanism to match the parking availability to the emergent demand.

4.4.3 Game Theory

Subsequent research contributions have explicitly catered for strategic behavior and the related game-theoretic dimensions of general parking applications. In [Arnott, 2006], the games are played among parking facility providers and concern the location and capacity of their parking facility as well as which pricing structure to adopt. Whereas, in the two other works, the strategic players are the drivers. In [Arbatskaya *et al.*, 2007], which seeks to provide cues for optimal parking lot size dimensioning, the drivers decide on the arriving time at the lot, accounting for their preferred time as well as their desire to secure a space. In a work more relevant to ours, Ayala *et al.* in [Ayala *et al.*, 2011] define a game setting where drivers exploit (or not) information on the location of others to occupy an available parking spot at the minimum possible travelled distance, irrespective of the distance between the spot and driver's actual travel destination. The authors present distributed parking spot assignment algorithms to realize or approximate the Nash equilibrium states.

[6] SFpark: parking application for San Francisco, available online in $http://sfpark.org/$

Part II

Effectiveness and side-issues of competition awareness

Advances in information and communication technologies (ICT) have dramatically changed the role of users and resulted in unprecedented rates of information generation and diffusion. On the one hand, many different types of sensors are being integrated with mobile communication devices. On the other hand, online social applications are proliferating. Together, these developments add to the heterogeneity of users in terms of interests, preferences and mobility, and enable the collection and dissemination of huge amounts of information with very different spatial and temporal contexts. This information can be intelligently controlled by platforms that collectively enrich people's awareness about their environment and its resources and promote new forms of participatory processes and approaches to managing them.

Aside from contributing to building collective awareness, users may actually exploit awareness of their environment to meet their own needs or achieve certain individual objectives. Overall, users are actively involved in both the dissemination and consumption of the information.

However, situations repeatedly emerge where the users' welfare is better satisfied by the same finite set of resources, ranging from natural goods such as water and electricity, to human artefacts such as urban space and transportation networks. In these environments, competition naturally emerges among entities (both people and networked nodes) desiring to use those resources. If the disseminated information concerns the availability of some limited resource or service, it is important to understand how the presence of competition shapes decisions taken by these entities regarding the specific way these entities participate in disseminating information and creating collective awareness and the way collective awareness is exploited if at all. The first of these very general and fundamental questions amounts to deciding whether a networked entity will deviate from the expected behavior (*misbehave*) by hiding or falsifying resource or service availability information, to reduce the competition to its advantage. The second amounts to deciding whether a networked entity will *compete or not compete* for some limited resources.

Chapter 5

Information dissemination

In competitive autonomic networking environments, user nodes face a strategic dilemma: on the one hand, they need to cooperate to support the networking infrastructure and information flow; on the other hand they are tempted not to do so, *e.g.*, in order to conserve own system resources or create an advantage for themselves. In various mobile applications involving competition for scarce resources, networked entities (user nodes) have to autonomously decide whether to dispose private information about the resources. Information is essentially a kind of asset; sharing it, user nodes assist their potential competitors, in anticipation of their support in due course.

Another feature of emerging network paradigms is the strong spatiotemporal dimension associated with both the demand and supply of the overwhelming (in volume) content and services. The spatial dimension has emerged mainly due to the localized nature of most sensing devices, the mobility of the user-nodes that inherently contains the notion of location, the (limited-range) wireless communication medium, the need to contain (locally) most of the low demand services/content to address scalability issues, *etc.*. The temporal dimension has emerged mostly due to the spontaneous nature of the services/content and the high dynamicity of the emerging networking environments due to - among others - the user-node mobility.

Recent trends such as the smart city initiative [Caragliu *et al.*, 2009] expose all these dimensions and give rise to further settings, where truthful altruistic information sharing is required but not guaranteed. We investigate a realistic scenario of city-level parking assistance service that instantiates such emerging environments.

5.1 Impact of perfect cooperation

5.1.1 Introduction

In this section we draw on a concrete parking space search application to explore fundamental tradeoffs of wireless networking solutions to the provision of real-life services. In particular, we consider a city area, wherein each vehicle (mobile user) moves towards a chosen destination and seeks vacant parking space in its vicinity. Three main approaches to the parking space search problem are investigated, each representing a distinct paradigm of how wireless networking communications can assist the information management process. In the first approach, the vehicles execute the currently common "blind" sequential search for parking space by wandering around the destination. In the second distributed approach, the vehicles, while moving around the area, opportunistically collect and share with each other information on the location and status of each parking spot they encounter. Finally, with the third approach, the allocation of parking spots is managed by a central server availing global knowledge about the parking space availability.

We use both simulation and analysis to systematically compare the three radically different paradigms for collection, sharing, and exploitation of service-related information. Two scenarios drive our discussion. The first one involves vehicles seeking parking space all over the city area (uniformly distributed destinations). The second scenario features a single area that acts as an attraction pole for vehicles (hotspot). We assess the effectiveness of the parking search process through user-oriented performance metrics, such as the parking search time and route length, and the proximity of the found/assigned parking spot to the user travel destination, but also through system-oriented performance metrics, such as the average utilization of parking spots.

5.1.2 Approaches to parking space search

We summarize three basic approaches to the parking space search problem. Each one represents a distinct *paradigm* for localizing and occupying vacant parking spots[1].

[1]Note that current navigation systems can locate parking lots, yet they cannot provide information about the availability of parking places therein.

In the same time, they reflect existing or under development systems; some of them are indicatively presented in Chapter 4. In all three cases, there is a fixed set of parking spots $\mathcal{P}$, with $|\mathcal{P}| = P$, distributed across a city area $\mathcal{A}$, and a finite population of vehicles $\mathcal{V}$, with $|\mathcal{V}| = V$, moving therein. Vehicles drive towards their travel destinations and enter the parking search process as soon as they approach them, *i.e.*, enter the initial parking search area (Ref. Figure 5.1). The *main differentiation factor* among the three approaches is *the way users (i.e., vehicles) exploit, or do not exploit, information about the availability of parking space within the search area.* Each parking spot is equipped with a sensor providing information about its occupancy status. Vehicles, properly equipped with short-range wireless interfaces and adequate storage and processing capacity, may collect information on the status of each parking spot they encounter. Moreover, they may acquire and store additional global or partial, accurate or imprecise, knowledge about the distribution of the free parking space throughout the area $\mathcal{A}$ via communicating with other vehicles or a central server.

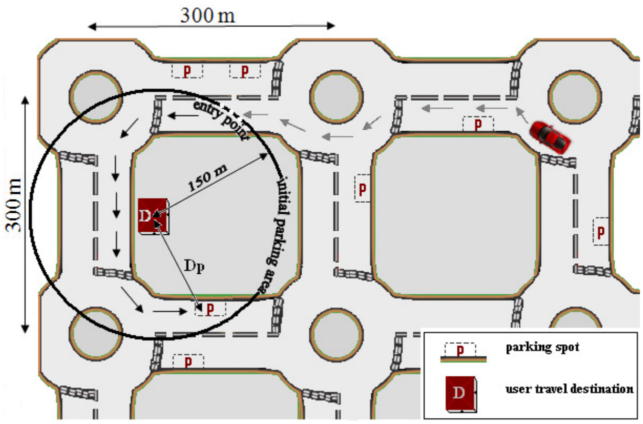


Figure 5.1: Section of city area $\mathcal{A}$ showing the vehicle's path towards a parking spot close to its travel destination.

Non-assisted parking search (NAPS)

According to the current common practice in search for parking space, drivers wander around their travel destination and sequentially check the availability of encountered parking spots. Typically, the search is initially carried out within an area around the drivers' travel destination (*initial parking search area*), whose size depends on the drivers' attitude and sense of traffic load and parking demand thereby. The radius of the search area then grows progressively as parking search time increases until drivers find a vacant parking spot and occupy it. This, essentially *blind*, search practice gives often rise to congestion problems and results in fuel/time wastage, especially around popular travel destinations such as shopping areas and business districts in big cities.

Opportunistically-assisted parking search (OAPS)

Information about the location and status of parking spots may become available to vehicles with the opportunistically-assisted parking search (OAPS) scheme. Indeed, recent advances in wireless communication, sensing and navigation technologies promise to make the parking search process smarter and more efficient. One way to do this is by equipping parking spots with sensors providing information about their occupancy status (*e.g.*, [Caliskan *et al.*, 2006]) and vehicles with devices (*e.g.*, PDAs supporting ad-hoc communication mode) able to collect and share information about parking spots' location and status as they circulate around. Alternatively, sensors can be mounted onboard the vehicles and actively monitor road-side parking availability (*e.g.*, via ultrasonic rangefinders, [Mathur *et al.*, 2010]). However it is collected, this information can be further filtered across time (*aging*) and space through use of timestamps and knowledge of the parking spot coordinates (*e.g.*, via GPS) and help vehicles make more informed decisions. Rather than wandering randomly in the parking search area, a vehicle can now direct its search towards selected parking spots that are listed in its cache as the closest vacant ones to its travel destination. If the spot is actually vacant when it arrives at it, it occupies it; otherwise, it repeats the spot selection process, being also prompt to occupy any vacant spot it may find on its way to the candidate spot.

The opportunistic information dissemination mechanism of OAPS does not enforce global common knowledge about the availability of parking space. As the status of parking spots changes in time, stored data are potentially outdated after some time interval. Therefore, the frequency of information updates is critical for the effective operation of the scheme. The faster information circulates across the wireless networking environment, the more accurate data will be stored in the caches of vehicles.

On the other hand, depending on the travel destinations of the users, the fast dissemination of information may synchronize the caches and, consequently, the movement patterns of individual vehicles and aggravate the effective competition for given parking spots. As we show in Section 5.1.5, how this tradeoff is resolved for OAPS depends on several factors such as the number of vehicles moving in the area $\mathcal{A}$, their speed, travel preferences (destinations), and the road grid structure.

Mobile storage node opportunistically-assisted parking search (msnOAPS)

The inflow of information to each vehicle may increase further through the use of dedicated or normal vehicles *Mobile Storage Nodes* (*MSNs*), *i.e.*, city taxicabs. The MSNs are equipped with wireless interfaces that allow them to collect parking information and share it with other mobile nodes, *i.e.*, user-vehicles and MSNs. These nodes act as relays, creating additional contact opportunities between vehicles and hence, space-time paths for the flow of parking information.

Regarding the storage capability of these nodes, it is assumed that the MSNs can handle data about all considered parking places. As the occupancy status of parking places changes with time, the accuracy of their stored information tends to drop. Therefore, the information they disseminate is not always useful.

Centrally assisted parking search (CAPS)

With CAPS, the full information processing and decision-making tasks lie with a central processor (server). Vehicles and parking spot sensors are only responsible for transmitting to the server parking requests and spot vacancy information, respectively. The semi-real-time two-way communication of the server with the vehicles and the parking spot sensors calls for heavier network infrastructure, both wired and wireless.

When submitting its parking request, each vehicle specifies its destination to the centralized server. In a First-Come-First-Served (FCFS) manner[2] the server queues the requests and satisfies them, reserving for the vehicle that parking spot amongst the vacant ones, which lies closest to its destination. The user is then notified about the reservation, *i.e.*, parking spot he should drive to. Therefore, and contrary to NAPS and OAPS, the vehicle is directed towards a guaranteed vacant parking spot. While waiting

[2] Different scheduling disciplines are generally applicable when processing the parking requests. Herein, we focus on the FCFS policy for exploring the relative performance of the centralized paradigm for sharing and processing information and demonstrating the related tradeoffs.

for the system assignment, the user keeps on moving towards random directions within the area.

Two more remarks are worth making about the parking search approaches and the way we investigate them in this work. Firstly, the structural difference between distributed and centralized systems also differentiates their installation, operational and maintenance costs. A fixed centralized infrastructure requires not only a large amount of investment upfront but also an elaborated architectural design for maintenance purposes. Furthermore, additional concerns are related to the system scalability with the number of monitored parking places and the burden of potentially re-dimensioning of the sensing web. On the contrary, vehicular networks emerge as a cost-effective networking platform that exploits the powerful, in terms of energy and computational might, vehicular nodes in favour of a wide range of applications. Ref. [Mathur *et al.*, 2010] reports installation and operating costs for fixed infrastructure, whereas [Carreras *et al.*, 2005] [Mathur *et al.*, 2010] [Caliskan *et al.*, 2006] highlight the savings of an infrastructure-free system.

Secondly, throughout Section 5.1 we assume that vehicular nodes are fully cooperative. Partial or no cooperation of vehicles/drivers is a concern for both the CAPS and OAPS approaches. Although the OAPS scheme has inherent diversity, selfish and/or malicious behaviors can undermine its performance significantly. Thereby, the detection and penalization of misbehaviors is really challenging. We extend this study to accommodate misbehavior instances in Section 5.2. On the other hand, considering that practical implementation of the CAPS approach avail V2I communication infrastructure, supervisory mechanisms can consist a separate level in the overall system architecture. For instance, these mechanisms could vouch for system robustness through either implementing barrier-controlled metered parking spaces or enforcing penalties in a pervasive sensing road platform. In the same notion, the established fixed sensor network need to function not only to monitor the parking space availability but also confirm the parking events (and thus support billing).

5.1.3 Performance evaluation methodology

Simulation environment

We have developed a simulation environment in the C programming language that reproduces in adequate detail the three parking search approaches. We briefly summarize it below:

Road grid: The simulator implements a grid of two-lane roads (one lane in each direction) in a city environment; each road traverses the grid from the one side to the other, as shown in Figure 5.2. Additionally, there are roundabouts in every intersection, connecting up to four converging roads. Parking spots are uniformly distributed across roads' lanes of the grid.

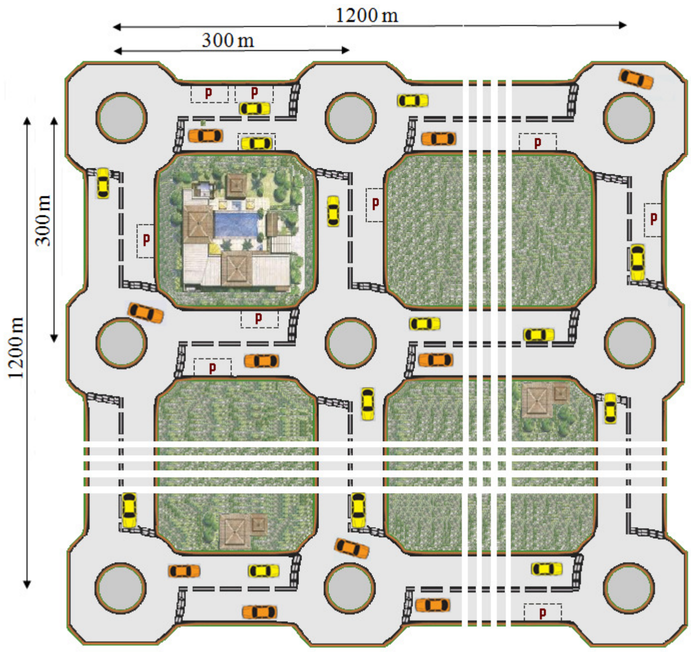


Figure 5.2: Simulation environment: $1200 \times 1200m^2$ road grid with randomly distributed parking places.

Vehicle movement: The vehicle mobility model comes under the broad category of behavioral mobility models. Two levels of behavior can be identified: the *global*, determining how destinations are selected and the way the vehicles choose the route towards them; and the *local*, addressing how the vehicles move within the roads comprising the route.

At the *global* level, every time a vehicle frees a parking spot, it chooses a new destination and drives towards it. Once it reaches adequately close to the destination (*initial parking search area*), the parking search process is initiated. The initial parking search area is circular; it is centered at the travel destination with radius equal to half the distance between two adjacent road intersections. Where the vehicle drives next depends on the employed search strategy.

- Under the NAPS strategy, the vehicle will circulate randomly within its initial parking search area. This random movement has been modelled by the selection of random geographical coordinates that correspond to a point inside the cyclic parking area.

- Under the OAPS strategy, the vehicle will consult with the information stored in its memory. In particular, the stored records (parking spot, status, timestamp) are filtered both temporally, to exclude information that is outdated (*i.e.*, coupled with a timestamp that is beyond a threshold value), and spatially, to retain as candidates only spots in the current search area. Out of the remaining spots, the nearest-to-destination available one is selected (*Full use of Memory, FM*). If no record survives the spatiotemporal filtering step, the driver chooses randomly one spot within the parking search area and moves towards it (*Random use of Memory, RM*). In the absence of *any* information about parking spots within the current area of interest, the vehicle circulates blindly/randomly within the area (*No Memory, NoM*). In all cases, vehicles move along shortest routes to their destinations (in Manhattan distance terms) and occupy the first available parking spot on their way to them rather than pursing closer-to-destination, yet non-guaranteed, parking options.

- Under CAPS, the user moves randomly within the parking search area till he is directed by the system to drive to the reserved parking spot. The centralized server queues the requests and processes them in a First-Come-First-Served order.

The above procedure defines where the user should drive next. Upon arrival to this location, the user faces two possibilities: (a) the location corresponds to a vacant parking spot. The user then occupies it for some time interval that may follow different probability distributions. By the end of this interval, the vehicle vacates the spot and selects another destination; (b) the location does not correspond to a parking spot or, if it does, it is occupied - both count as failed attempts. Upon a failed attempt, under NAPS/OAPS, it will check anew its memory (if available), and repeat the search, whereas under CAPS, it continues the random movement within the bounds of this city environment along the horizontal and vertical roads (notice that the centralized system quarantees the reservations and hence, no vehicle is driven towards occupied spot). If the failed attempts in the current parking search area exceed a threshold value, the range of the search area is increased.

At the *local* level, the position of each vehicle by the next simulation time step depends on its current position and velocity. More specifically, the vehicles adapt their speed according to their distance from: (a) the front vehicles (they are not allowed to overtake one another); (b) the next intersection; and (c) the nearest parking spot, assuming that they decelerate when encountering parking spots to check their status. Their speed is zeroed when they get stuck in traffic jam, enter a roundabout intersection, or park. Finally, the vehicles are not allowed to stop or move in the reverse direction of the traffic flow.

Simulation set-up

For the simulations we consider a two-lane road grid with dimensions $1200 \times 1200m^2$, as shown in Figure 5.2. The distance between two adjacent intersections in the grid is $300m$ and parking places are uniformly distributed alongside road lanes. The numbers of vehicles and parking spots vary to generate different vehicle and parking spot densities. Guidance for the selection of the vehicle densities are provided by relevant research efforts reported in literature. For instance, in [Caliskan *et al.*, 2006] the authors study a networking environment, where the vehicular nodes' (not stable) density is drawn near $33veh/km^2$. Similarly, [Carreras *et al.*, 2005] explores the performance of a V2V communication platform, assuming $50veh/km^2$ moving according to the Manhattan Model. Motivated by these values, we end up with vehicle densities ranging from 3.5 to $45veh/km^2$.

The parking time of all vehicles are i.i.d. exponential RVs with means ranging from 300 to $3600s$. We assume an exponentially increasing rate for the search area and an increment step fixed to the half of the distance between two adjacent intersections. The duration of simulations is $10^5 s$, which is enough time to generate a significant number of parking events in all runs. The maximum vehicle speed is set to $v_{max} = 50km/h$; note that the actual instantaneous vehicle velocity may range anywhere in $[0, v_{max}]$, as explained in paragraph "Simulation environment" in this section. The vehicle-parking spot sensor communication range is set to $15m$, whereas the intra-vehicle communication range is $70m$. In all graphs reported in Sections 5.1.5 and 5.1.6, we plot the averages of ten simulation runs together with their 95% confidence intervals.

Performance metrics

1. *Driver-level metrics:* When someone moves towards a specific destination, he aims for the shortest route and minimum travel time (these may not be necessarily compatible objectives). When he needs to park, on top of that, he prefers the nearest to the destination-parking place (best parking place). In the ideal case, someone will reach it travelling the shortest possible route from his initial location to that parking place (best way). Therefore, the metrics we consider for comparing the three approaches to parking search are:

   (a) *Parking search time, T_{ps}:* Once the driver enters the initial parking search area (Ref. Figure 5.1), he will start seeking for a parking place. This time is highly dependent on the parking space density in the considered area, traffic congestion level, and competition for parking space around the destination.

   (b) *Parking search route length, R_{ps}:* It refers to the distance a driver travels till he parks his vehicle, measured from the moment he enters the initial parking search area. The parking space density and the demand for parking are the two factors that primarily affect R_{ps} for given city area and vehicle speeds. Besides expressing user satisfaction, R_{ps} and T_{ps} also reflect social objectives in that more travelling results in additional fuel consumption and environmental burden.

   (c) *Destination-parking spot distance, D_p:* It expresses the geographical distance of the two points and, contrary to T_{ps} and R_{ps}, it is exclusively a measure of user satisfaction: the closest the parking spot lies to the destination, the more attractive it is.

2. *System-level metric:* In order to capture the actual exploitation of the road parking capacity, we employ the metric *Availability time*, T_a which measures the average time each parking spot remains vacant.

5.1.4 Modeling the centralized approach

In this section, we present an analytical model for the centralized approach to parking space search (CAPS) and use it to analytically derive its main performance measures. The model is later validated in Section 5.1.5 against simulation results.

Anytime, the C vehicles may find themselves in one of three *states*: (a) travelling towards their destination without yet having issued a parking request to the system; (b) driving within the parking search area having issued a parking request and waiting for a parking assignment; and (c) parked (or on the way to the parking spot that is reserved for them by the system). The system can be modelled by a finite-source $G/G/r$ queue with $r = P$ servers (parking spots).

G/G/r model input process. A vehicle enters the queueing system when it submits a parking request, *i.e.*, when it crosses the border of the initial parking search area. Under uniform distribution of travel destinations and parking spots in the area $\mathcal{A}$, the time T_t that vehicles spend travelling, from the moment they release a parking spot till the time they issue a new parking request, is a random variable (RV) written as

$$T_t = D_t/v \tag{5.1}$$

In equation (5.1), v is the vehicle speed and D_t the random variable denoting the line picking distance, whose probability distribution is known for various known geometries such as circular, square, rectangular areas [Mathai, 1999]. For example, for square areas of unit side length, $f_{D_t}(x)$ is given by

$$f_{D_t}(x) = \begin{cases} 2x(x^2 - 4x + \pi) & \text{for } \ 0 \leq x \leq 1 \\ 2x[4\sqrt{x^2-1} - (x^2 + 2 - \pi) - 4\tan^{-1}\sqrt{(x^2-1)}] & \text{for } 1 \leq x \leq \sqrt{2} \end{cases}$$

so that the probability distribution function of the travelling time within a square area of side length l can be written

$$f_{T_t}(t) = v \cdot f_{D_t}(vt/l)/l \tag{5.2}$$

and its expected value and variance are

$$\begin{aligned} \overline{T_t} &= \int_0^{\sqrt{2}l} t f_{T_t}(t)dt \approx 0.52l/v = 1/\lambda \\ \sigma_t^2 &= \int_0^{\sqrt{2}l} (t^2 - \overline{T_t}) f_{T_t}(t)dt \approx 0.06l^2/v^2 \end{aligned} \tag{5.3}$$

where λ denotes the rate at which each vehicle submits parking requests to the system.

G/G/r model service time. The vehicle (requests) may stay in the queue for variable time T_q, before they are processed, depending on the request backlog and the order in which requests are treated. The service time, T_s, starts when the vehicle is assigned with a parking spot and directed to drive there, and consists of two components: the parking time spent in the reserved parking spot, T_p, plus the travel time, T_f, spent on driving towards the reserved parking spot, starting from its position at the moment the assignment was communicated to it (*final leg travel time*).

Generally, the distribution of T_f depends on the proximity of the assigned parking spot to the vehicle travel destination. Different policies may constrain this distance; for instance, there may be an upper bound on how far from the travel destination a car may park, beyond which vacant parking spots are not considered eligible for a vehicle. The mean ($1/\mu$) and variance of T_s are given by $\overline{T_p} + \overline{T_f},\ \sigma_p^2 + \sigma_f^2 - 2\overline{T_p} \cdot \overline{T_f}$, respectively.

G/G/r performance measures. In assigning parking spots to vehicles, the server effectively solves an instance of the machine interference problem (MIP), also referred to as the machine repairman problem [Haque & Armstrong, 2007] [Iravani & Krishnamurthy, 2007], with partially cross-trained repairmen. In our problem, in particular, machines correspond to vehicles and parking spots to cross-trained repairmen, who can serve more than one machine but with variable efficiency, *i.e.*, user satisfaction according to the proximity of the spot to its travel destination. In the general case, the server has to take two decisions: in what order will the requests be processed (*sequencing decision*) and which parking spot should be assigned to which vehicle (*loading decision*).

For the most common scheduling policy, *i.e.*, First-Come-First-Served, the derivation of the main performance measures can draw on the diffusion approximations of Wang and Sivazlian in [Wang & Sivazlian, 1990]. The probability distribution function of the number of vehicles, C_{is} that are "in-system", *i.e.*, either parked or travelling towards the reserved parking space or having submitted a parking request to the system, is approximated by:

$$f_{C_{is}}(x) = \begin{cases} K_1 \cdot g_1(x) & \text{for } 0 \leq x \leq P \\ K_2 \cdot g_2(x) & \text{for } P \leq x \leq C \end{cases}$$

where $g_1(x)$ and $g_2(x)$ are functions of the means and variances of the variables T_t (λ, σ_t), and T_s (μ, σ_s), respectively, and the ratio $\rho = \lambda \setminus \mu$:

$$\begin{aligned} g_1(x) &= \frac{\left[\frac{(C-x)\rho\lambda^2\sigma_t^2 + x\mu^2\sigma_s^2}{C\rho\lambda^2\sigma_t^2}\right]^{\beta_1}}{(C-x)\rho\lambda^2\sigma_t^2 + x\mu^2\sigma_s^2} e^{-\frac{2(\rho+1)x}{\rho\lambda^2\sigma_t^2 - \mu^2\sigma_s^2}}, \ \beta_1 = \frac{2C\rho\left[1 + \frac{(\rho+1)\lambda^2\sigma_t^2}{\mu^2\sigma_s^2 - \rho\lambda^2\sigma_t^2}\right]}{\mu^2\sigma_s^2 - \rho\lambda^2\sigma_t^2} \\ g_2(x) &= \frac{\left[\frac{(C-x)\rho\lambda^2\sigma_t^2 + P\mu^2\sigma_s^2}{(C-P)\rho\lambda^2\sigma_t^2 + P\mu^2\sigma_s^2}\right]^{\beta_2}}{(C-x)\rho\lambda^2\sigma_t^2 + P\mu^2\sigma_s^2} e^{\frac{2(x-P)}{\lambda^2\sigma_t^2}}, \ \beta_2 = \frac{2P(1 + \frac{\lambda^2\sigma_t^2}{\mu^2\sigma_s^2})}{\rho\lambda^2\sigma_t^2} \end{aligned} \tag{5.4}$$

and K_1, K_2, constants given by the solution of the 2×2 system of equations

$$\begin{aligned} K_1 \cdot g_1(P) - K_2 \cdot g_2(P) = 0 \\ K_1 \int_0^P g_1(x)dx + K_2 \int_P^C g_2(x)dx = 1 \end{aligned} \tag{5.5}$$

It is then possible to estimate the expected number $\overline{C_{is}}$ of vehicles that are being served or wait for their parking requests to be served, and the expected number $\overline{C_t}$ of travelling vehicles, respectively, as

$$\overline{C_{is}} = \int_0^C x f_{C_{is}}(x)dx, \ \ \overline{C_t} = C - \overline{C_{is}} \tag{5.6}$$

whereas, the expected number of vehicles already parked or on their final leg to a reserved parking spot, C_s, is

$$\overline{C_s} = P - \int_0^P (P-x)K_1 g_1(x)dx \tag{5.7}$$

The utilization of each parking spot, *i.e.*, the percentage of time it is occupied (or *reserved*) by a vehicle, is

$$\overline{U_s} = \overline{C_s}/P \tag{5.8}$$

Finally, the mean time vehicles spend on parking search, $\overline{T_{ps}}$, is the sum of the expected time they wait for a parking assignment, $\overline{T_q}$, and the expected final leg travel time, $\overline{T_f}$; or, equivalently, the difference of the mean total time they spend in the system, $\overline{T_{is}}$ minus the mean parking time (Figure 5.3), the former being given by Little's result [Agnihothri, 1989].

$$\overline{T_{ps}} = \overline{T_q} + \overline{T_f} = \overline{T_{is}} - \overline{T_p} = \overline{C_{is}}/\lambda(C - \overline{C_{is}}) - \overline{T_p}. \tag{5.9}$$

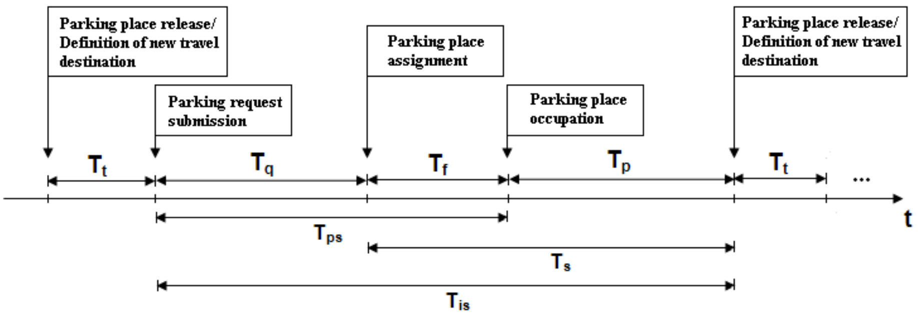


Figure 5.3: The set of RVs relevant to the parking search process and their time dependence.

G/M/r model approximation. The analysis simplifies considerably when the final leg travel time is negligible compared to the vehicle parking time ($T_f \ll T_p$). In particular, when T_p is exponentially distributed, the main performance measures of the centralized parking space assignment system can be given by the detailed analysis of Sztrik for the $G/M/r$ system, and resemble those of the $M/M/r$ system [Sztrik, 1985]. The (discrete) probability distribution for the in-system number of vehicles is given by

$$p_n = \begin{cases} \binom{C}{n}\rho^n p_0 & \text{for } 1 \leq n < P \\ \binom{C}{n}\frac{n!}{P!P^{n-P}}\rho^n p_0 & \text{for } P \leq n \leq C \end{cases}$$

with $p_0 = (1 + a_1 + ... + a_C)^{-1}$ where a_i are coefficients multiplying p_0 in p_n expression. The expected number of in-system vehicles and queued parking requests are

$$\overline{C_{is}} = \sum_{i=1}^{C} i \cdot p_i, \ \overline{C_q} = \sum_{i=1}^{C-P} i \cdot p_{i+P} \tag{5.10}$$

respectively, the time the parking requests are queued is

$$\overline{T_q} = \frac{\overline{C_q}}{\lambda(C - \overline{C_{is}})} \tag{5.11}$$

and the expected parking search time is still given by equation (5.9).

5.1.5 Simulation results and analytical model validation

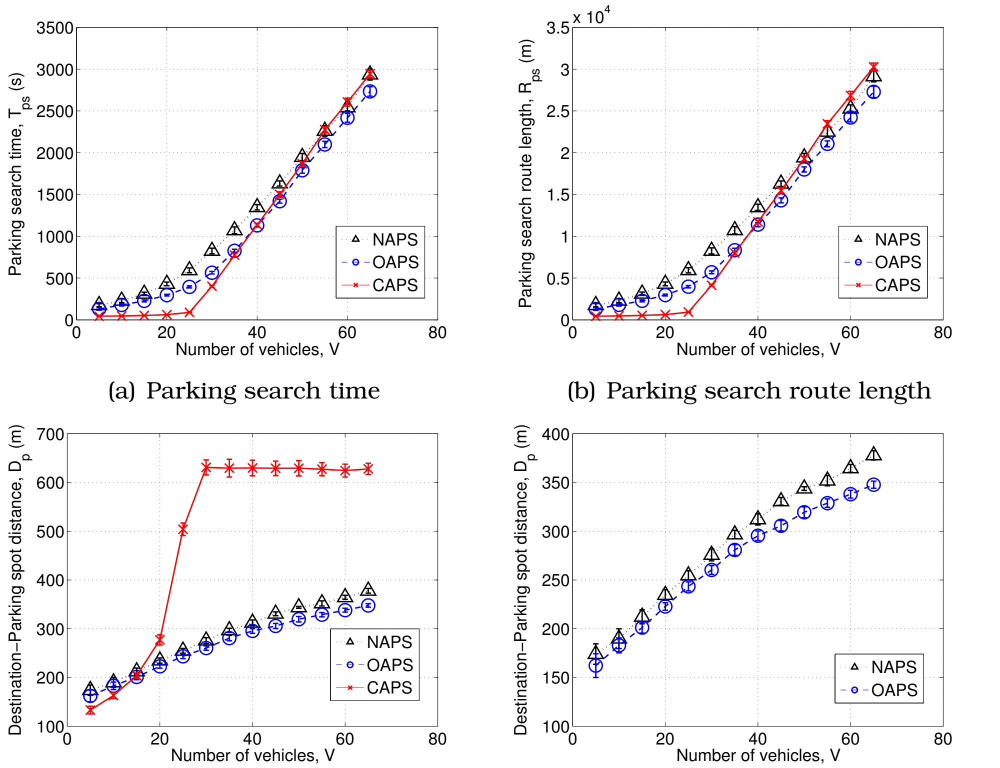
We show simulation results for all four metrics presented in Section 5.1.3; we also use them to validate our analytical model. In all cases, the metric values are averaged over all parking events and plotted against the number of vehicles, for fixed number of parking spots.

Uniformly distributed destinations

General trends: Figure 5.4 compares the three approaches with respect to all three metrics for a fixed number of parking spots, $P = 25$. Intuitively, and for all three approaches, the performance deteriorates with the number of vehicles moving in the city area $\mathcal{A}$. Even when the travel destinations of the vehicles are uniformly spread over this area, their increase results in higher competition for individual parking spots. For NAPS and OAPS, this means that the probability to encounter a vacant spot decreases. Table 5.1 lists the average number of unsuccessful decisions per vehicle, *i.e.*, how many times on average each vehicle encounters an occupied parking spot while wandering (NAPS) or driving towards a parking spot he became aware of from other vehicles (OAPS). For CAPS, there are no unsuccessful decisions; what increases is the average waiting time for the assignment of a parking spot by the central server. Moreover, the higher competition does not only increase the search/waiting time and the distances that vehicles travel till they eventually park (Ref. Figure 5.4(a) and Figure 5.4(b)); it also results in the assignment of "worse" parking spots, located further away from the actual user travel destinations.

NAPS vs. OAPS: The benefits from information sharing and exploitation become obvious when comparing NAPS with OAPS: the opportunistic system consistently outperforms the non-assisted one for all three metrics, irrespective of the number of vehicles. With NAPS, vehicles spend much of their time wandering "blindly" without even encountering a parking spot, whether vacant or occupied. Whereas with the opportunistic system, the search is more directed and the parking spot encounters more frequent than with NAPS. Increase of the vehicle population leads to: (a) higher dissemination rates of information about parking spots amongst the vehicles. The vehicles can therefore make more informed choices as to where they should seek for (vacant) parking spots; (b) more competition for the parking spots. Chances are now higher that not only the travel destinations of two or more vehicles are in close proximity but also that vehicles share the *same* information and, depending on their destinations, target the same parking spots. Many of the travels towards these spots prove, in the end, to be useless due to belated arrivals and only add to the total parking search time.

Looking at Figure 5.4(a) and Table 5.1, one can see that the tradeoff faster information dissemination versus increased competition is resolved in favour of the opportunistic scheme. With OAPS, the vehicles make much better use of time than with NAPS. Within a given time window, they will discover more parking spots. Some of them will be occupied and on average, as Table 5.1 suggests, they will end up failing more times than in NAPS. Nevertheless, their persistent directed movement is compensated in that they manage to find vacant parking spots faster than with NAPS.



(a) Parking search time

(b) Parking search route length

(c) Destination-parking spot distance

(d) Destination-parking spot distance (zoom-in)

Figure 5.4: Comparison of the NAPS, OAPS and CAPS approaches: uniformly distributed user destinations, $\overline{T_p} = 1800$, $P = 25$.

CAPS: With the centralized approach, two distinct components comprise the overall parking search time: (i) the waiting time, T_q, and (ii) the final leg travel time, T_f (Ref. Figure 5.3). When the vehicles are fewer than or in the order of the parking spots (~ 30), T_f dominates the overall parking search time since there are always one or more vacant spots, where the user can be directed to. As the cars tend to outnumber parking spots, the parking requests in the server's queue start piling up and T_q dominates the overall parking search time (Ref. Figure 5.7).

The second noteworthy remark about the CAPS approach is the tradeoff between the achieved parking search time (route length) and attractiveness of the assigned parking spots (Ref. Figure 5.4(c)). Leaving aside very small vehicle populations, the centralized system consistently assigns parking spots that lie further away from the actual travel destinations, when compared to NAPS and OAPS. For $V > 35$, all 25 parking spots are constantly reserved. Each vehicle is assigned the first place that becomes vacant, which may be located anywhere within the parking area $\mathcal{A}$. Therefore, the average destination-parking spot distance D_p eventually converges to the expected distance of two randomly selected points within a square area; namely, the expected value of the square line picking problem, which is known to equal $0.52 \times l = 624m$, where l denotes the length of the square sides [Mathai, 1999].

Table 5.1: Average unsuccessful parking attempts per vehicle for NAPS and OAPS, $\overline{T_p} = 1800$, $P = 25$.

Parking search approach	Scenario	Vehicle number					
		5	15	25	35	45	55
NAPS	Unif.Dis.Dest.	0.27	1.55	4.33	9.19	15.18	21.92
NAPS	Hotspot	1.9	8.38	14.26	21.65	28.03	34.4
OAPS	Unif.Dis.Dest.	0.39	2.39	6.04	15.03	26.85	40.22
OAPS	Hotspot	5.6	18.74	31.71	42.46	51.51	63.4

CAPS vs. OAPS and NAPS: More interesting is the way the performance ranking of the three schemes evolves. As Figure 5.4(a) and Figure 5.4(b) suggest, their relative performance with respect to parking search time and route length changes twice. CAPS outperforms the two for $V < 40$, then gets worse than the opportunistic scheme and for even higher number of vehicles $V > 55$ loses to NAPS as well. The reason for this behavior is the combination of the reservation mechanism of CAPS and the more random mobility patterns of the vehicles in NAPS and OAPS.

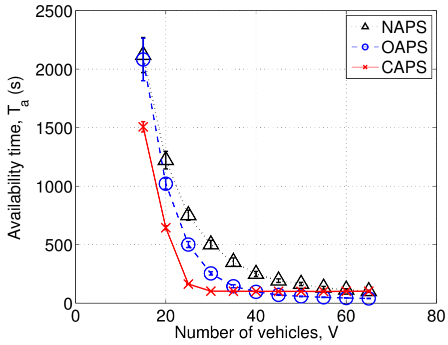


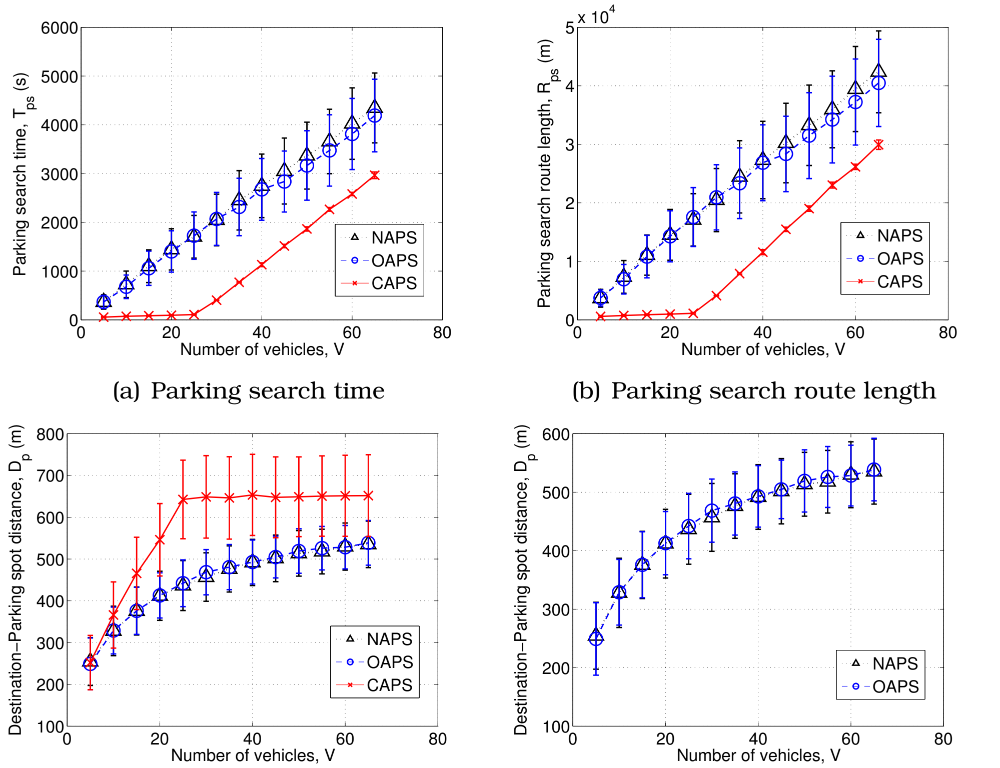
Figure 5.5: Average time each parking spot remains vacant: uniform distributed travel destinations, $\overline{T_p} = 1800$, $P = 25$.

More specifically, the better (more intensively) the systems manage to use the availability of parking spots, the better they score with respect to T_{ps} and R_{ps}. For the centralized system, Figure 5.5 suggests that there is a hard bound as to how efficiently this can be done in the light of the reservation system. As the number of vehicles grows, the parking space availability drops. Eventually, they are being reserved immediately after they are released. However, a reserved spot does not necessarily accommodate a stationary vehicle. The final leg travel time, during which the vehicle drives towards the reserved parking spots, is effectively “wasted" for the system. Even worse, this time grows together with the final leg length which converges to $0.52 \times l$ for $V > 35$, as discussed earlier. On the contrary, both the opportunistic and, for a higher number of vehicles, the NAPS approach manage to benefit from their movement in the area and utilize almost fully the parking space availability. In fact, the comparative performance of the systems in this scenario is an argument in favour of self-organization, and rather cooperative self-organization (OAPS).

Hotspot scenario

We consider exactly the same setting with paragraph “Uniformly distributed destinations” in this section, only now the user travel destinations are concentrated within a particular (hotspot) road rather than being distributed uniformly over the area $\mathcal{A}$. In other words, we impose higher correlation in the mobility patterns of individual vehicles and dramatically increase the competition for certain parking spots (those located in the proximity of the hotspot).

General trends: Two are the general remarks that can directly be made when comparing the curves in Figure 5.6 with those in Figure 5.4. Firstly, the performance of the non-assisted and opportunistic schemes deteriorates dramatically, whereas the centralized system experiences minimal degradation. Secondly, and closely related to the first remark, the relative ranking of the schemes changes: contrary to what we had when user travel destinations were uniformly distributed, CAPS outperforms NAPS and OAPS throughout the vehicle population range. Moreover, the opportunistic scheme only marginally outperforms the "blind" non-assisted scheme.



(a) Parking search time

(b) Parking search route length

(c) Destination-parking spot distance

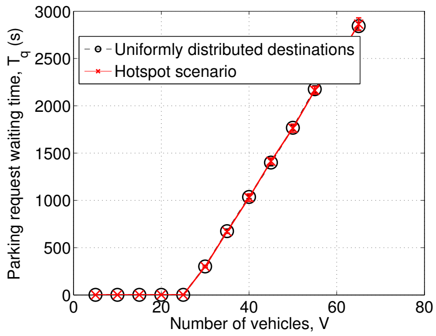
(d) Destination-parking spot distance (zoom-in)

Figure 5.6: Comparison of the NAPS, OAPS and CAPS approaches: spatially concentrated user destinations (hotspot scenario), $\overline{T_p} = 1800$, $P = 25$.

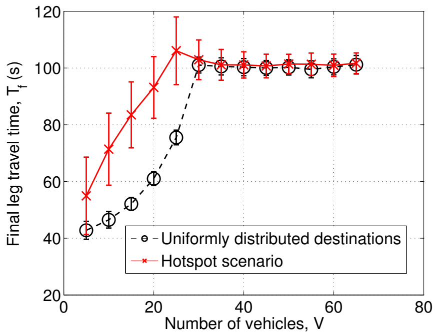
NAPS and OAPS: The correlation in the location of user travel destinations does not affect all parking approaches in the same way. With NAPS, vehicles still wander "blindly", only now this wandering is bounded within a given radius around the popular road. Since the competition for a parking spot is much higher, they encounter more occupied parking spots, as can be seen from the Table 5.1. Overall, the search time and the route length increase and the vehicles need to compromise with more remote parking spots.

The synchronization artefacts are worse for the opportunistic system. With all vehicles moving in the same area, information about parking spots disseminates even faster and all vehicles end up sharing similar information. And since practically they are all interested in the same set of parking spots, the ranking of parking spots is common for all of them. Therefore, they end up following similar trajectories within the search area and often encounter occupied spots. Even worse, the information they now share is of less "value". Consider one of those vehicles competing for a vacant parking spot in the area around the popular road. The moment it finds one, it occupies it without communicating this to another vehicle. In other words, vehicles share information about *where* relevant parking spots are but less frequently do they become aware of vacant parking spots through information exchanges with other vehicles. Eventually, they may find a parking spot without real help from the system.

The vehicle concentration around the hotspot under NAPS and OAPS also induces congestion. As can be seen in Figure 5.6(a) and Figure 5.6(b),[3] when the vehicles grow more, the relationship between the parking search time and route length is no longer linear; vehicles break more often since they encounter more cars ahead of them (Ref. Section 5.1.3). Note that this is different than with uniformly distributed travel destinations, as Figures 5.4(a) and 5.4(b) suggest.



(a) Parking request waiting time



(b) Final leg travel time

Figure 5.7: Components of the overall parking search time under CAPS: $\overline{T_p} = 1800$, $P = 25$.

CAPS: The centralized approach emerges as the winning approach in the hotspot scenario. The existence of popular destinations has a different impact on the two com-

[3]These findings for T_{ps} and R_{ps} are confirmed by the measurement of the average vehicle velocity under both the first ($\overline{v} = 10m/s$) and the second scenario ($\overline{v} = 9.5m/s$).

ponents of the overall parking search time (Ref. discussion in paragraph “Uniformly distributed destinations” in this section). The waiting time in the system queue T_q for the parking spot assignment remains practically the same. The central server sees a similar load of parking requests, irrespective of their destinations. Contrary to the other two approaches, having global view over the status of parking spots over the whole area $\mathcal{A}$, it can better resolve competition amongst vehicles and make faster parking space assignments to them. Only this comes at a penalty: the assigned parking spots lie further away from the popular road. This is why the final leg travel time, T_f, significantly exceeds its counterpart under uniformly distributed travel destinations (Ref. Figure 5.7). Even if for high vehicle numbers, the destination-parking spot distance converges to the same value, *i.e.*, the expected value of the square line picking problem. Higher destination-parking spot distances emerge also for NAPS and OAPS, but the penalty is higher for the CAPS system.

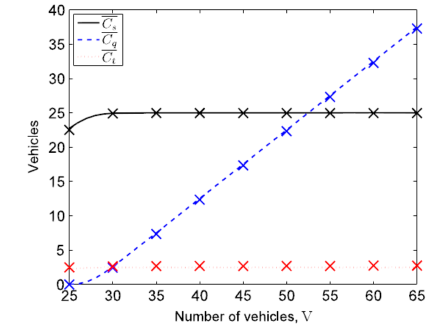
Validation of the analytical model for the CAPS scheme

In this paragraph, we compare the simulation results with the predictions of the analytical model for the performance of the CAPS approach in Section 5.1.4. We do this for various numbers of vehicles and different values of the expected parking time T_p, for both scenarios for the parking space distribution-uniformly distributed and hotspot. Figures 5.8(a)-5.8(d) plot the results for $\overline{C_t}$, $\overline{C_q}$, $\overline{C_s}$, *i.e.*, the expected numbers of vehicles travelling towards their destination, waiting for a parking assignment and parked or about-to-park (on their way to occupy a reserved parking spot), respectively; whereas, Figures 5.8(e)-5.8(f) depict the expected parking search $\overline{T_{ps}}$. Lines correspond to the model predictions in equations (5.3) and (5.9)-(5.11), and “x” marks stand for the simulation results. Confidence intervals are also plotted, but in most cases they are too tight to be visible in the plots.

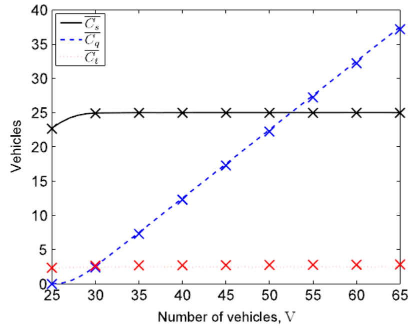
In all cases, the simulation results are in excellent agreement with the model predictions suggesting that the model can give a much faster yet accurate estimation of the centralized system performance. Since the existence of a popular road does not practically affect these performance measures for $V > P$ (Ref. paragraph “Hotspot scenario" in this section), the model can also predict the performance of CAPS for a broad range of parameters in the hotspot scenario.

5.1.6 Sensitivity Analysis

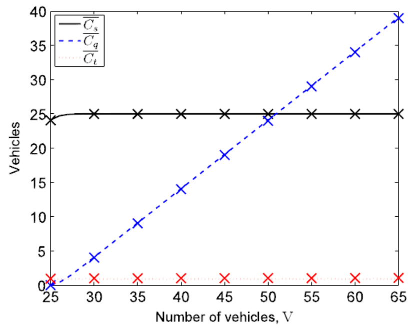
The additional simulation runs in this section let us study the impact of two parameters upon the performance of the parking search approaches, the mean parking time and number of parking spots. Moreover, for the OAPS scheme only, we assess the possible performance benefits due to the introduction of additional Mobile Storage Nodes that



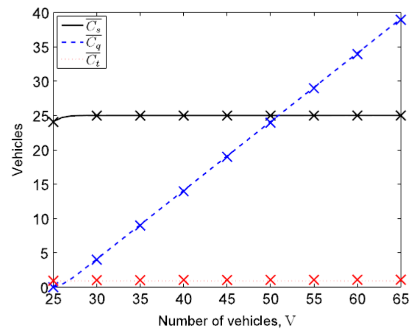
(a) Expected vs. average number of vehicles in different states, $\overline{T_p}$=600s



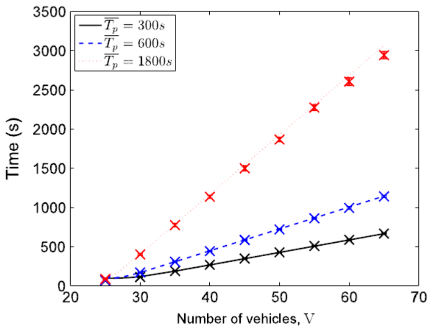
(b) Expected vs. average number of vehicles in different states, $\overline{T_p}$=600s



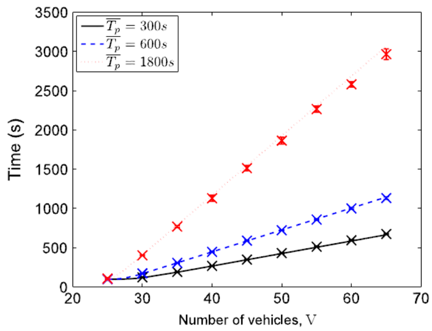
(c) Expected vs. average number of vehicles in different states, $\overline{T_p}$=1800s



(d) Expected vs. average number of vehicles in different states, $\overline{T_p}$=1800s



(e) Parking search time, T_{ps}



(f) Parking search time, T_{ps}

Figure 5.8: Comparison of the model predictions with the simulation results for CAPS: uniformly distributed user destinations (left) and hotspot scenario (right), $P = 25$.

further leverage the information exchange among vehicles.

The impact of the average parking time on NAPS, OAPS and CAPS

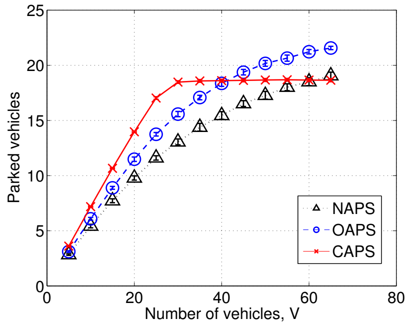
As Figures 5.9(a), 5.9(c) and 5.9(e) suggest, the higher the average parking time interval is, the more vehicles are found parked at each time instance. Vehicles spend more time in search of a parking spot, since they encounter occupied parking spots within their parking area of interest, more frequently.

In particular, the increase rate of the parking search time depends on the redundancy of the available parking choices. For $V < 25$, there is always at least one vacant parking spot so that the increase of the average parking time affects only the location of the respective best parking spot (Ref. Section 5.1.3), for given destination coordinates. On the contrary, when vehicles outnumber parking spots, any additional increase in the average parking time decreases the parking capacity levels at any time instance; and for high parking time values, the first encounter of an empty parking place will delay significantly. Table 5.2 bears out the aforementioned assertion as it reveals the analogical relation between average parking time and average unsuccessful attempts until parking.

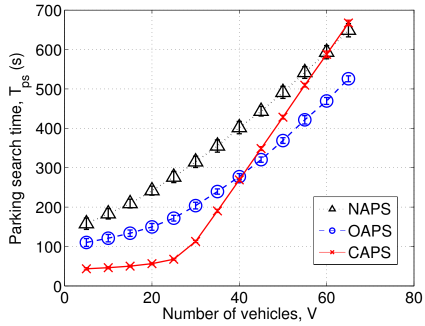
Another noteworthy remark is the invariability of the performance ranking of all three approaches (Ref. Figures 5.9(b), 5.9(d) and 5.9(f)). In particular, OAPS outperforms NAPS irrespective of $\overline{T_p}$. Indeed, the improvement factor gradually grows as the $\overline{T_p}$ decreases. However, the intersection point of the three corresponding curves shifts to the left, since the centralized system deteriorates faster with the parking time. Specifically, the increased parking time results in further increase of the first component of the overall

Table 5.2: Average unsuccessful parking attempts per vehicle for NAPS and OAPS: uniformly distributed travel destinations, $P = 25$.

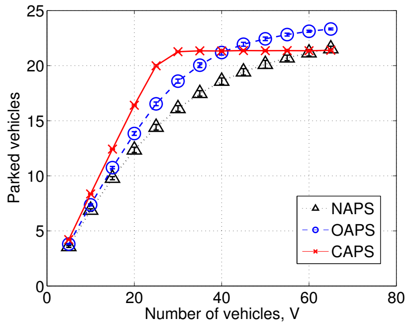
Parking search approach	Average parking time	Vehicle number					
		5	15	25	35	45	55
NAPS	300	0.16	0.63	1.22	1.95	2.81	3.73
OAPS	300	0.21	0.84	1.78	3.10	4.73	6.71
NAPS	600	0.19	0.94	2.04	3.58	5.35	7.42
OAPS	600	0.28	1.30	2.89	5.67	9.32	13.53
NAPS	3600	0.30	1.96	6.77	16.85	29.79	43.76
OAPS	3600	0.40	3.68	9.55	28.37	52.76	78.21



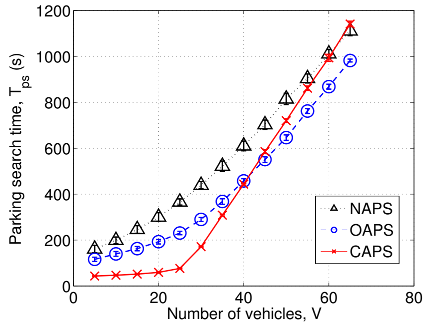
(a) $\overline{T_p}$=300s: Average number of parked vehicles



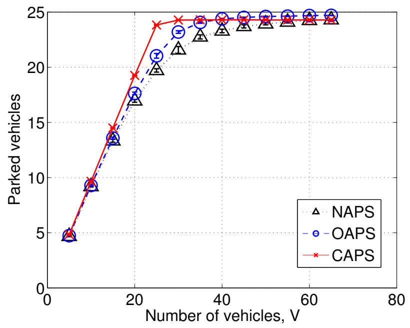
(b) $\overline{T_p}$=300s: Parking search time



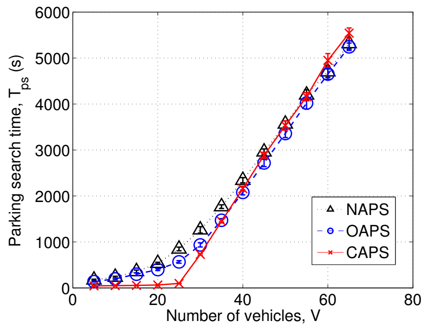
(c) $\overline{T_p}$=600s: Average number of parked vehicles



(d) $\overline{T_p}$=600s: Parking search time



(e) $\overline{T_p}$=3600s: Average number of parked vehicles



(f) $\overline{T_p}$=3600s: Parking search time

Figure 5.9: Comparison of the NAPS, OAPS and CAPS approaches on different average parking time values: uniformly distributed user destinations, $P = 25$.

parking search time in CAPS, *i.e.*, the waiting time, T_q which presides over CAPS's dramatic parking search time deterioration. Specifically, any increase in the average parking time, further delays the vacancy of the occupied parking spots and consequently the serving of the parking requests in the server's queue.

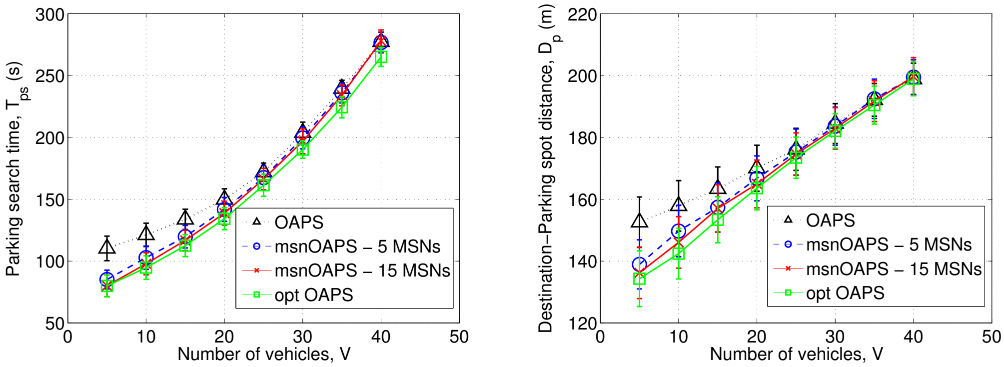
Finally, it is worth stressing that these results assume exhaustive parking search attempts, *i.e.*, attempts that are only terminated upon the detection of an empty parking spot. Nevertheless, there is some evidence that the duration of the parking search process is upper bounded by some time limit T_{up}. For example, Ref. [le Fauconnier & Gantelet, 2006] reports a T_{up} value equal to $15min$; otherwise, the drivers resign from their effort to park, *e.g.*, they might stop looking for a (cheaper or free-of-cost) public parking spot and decide to visit a much more expensive private parking lot. This would practically correspond to a “parking failure event”. In our case, as Figure 5.9 suggests, the T_{up}-min threshold would introduce several parking search failure events while reducing the search delays for those users that are successfully “served”. More generally, T_{up} introduces a tradeoff between number of parking search failures and average search delays of successful parking searches.

The impact of Mobile Storage Nodes

Uniformly distributed destinations The introduction of MSNs increases the contact opportunities between vehicles and thus the speed of information spread. These nodes act as vehicles that travel constantly within the area $\mathcal{A}$ and are not interested in parking. Consequently, the MSNs foster the information diffusion process without introducing additional competition burden.

According to the plots in Figures 5.10(a)-5.10(b), even 5 MSNs improve the overall performance, as long as there is some flexibility in the parking assignment process (*e.g.*, low competition). In particular, for $V < 25$, the MSNs indicate potentially unknown to the users alternative parking choices or update the already stored parking information. Indeed, Figure 5.10(b) suggests that the exploitation of the data collected and transferred by MSNs directs users to more attractive parking spots.

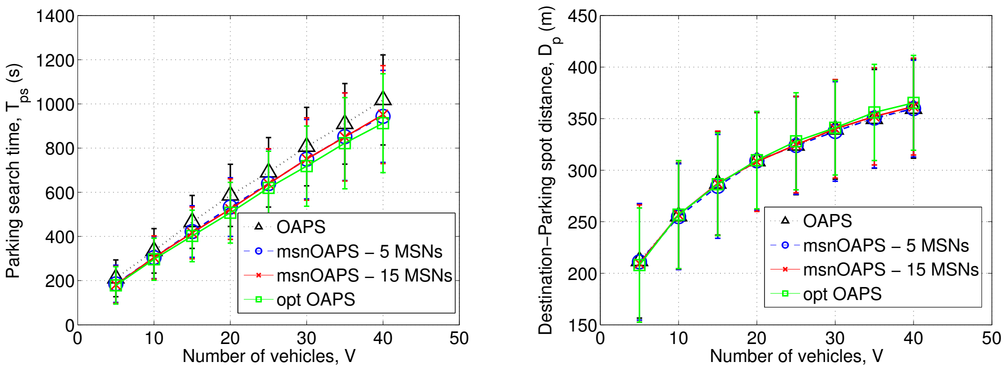
The growth of the MSNs’ population results in further increase of the frequency of the user memory updates. However, the gain obtained from the increased MSN number proves to be important only when the contact/communication probability between vehicles is low. In particular, starting from an improvement rate in the order of 20%, the parking search time improvement is gradually minimized. Furthermore, the Figure 5.10 includes, additionally, a plot regarding an ideal real-time information scheme (plot opt OAPS) that maximizes the speed of information spread and thus the memory update frequency. It emerges that even a few service cars result in time and distance gain comparable to that achieved in the optimal approach.



(a) Parking search time (b) Destination-parking spot distance

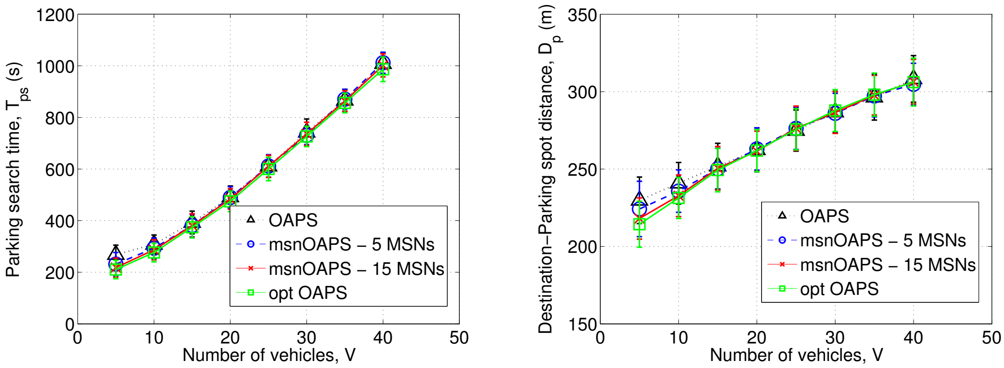
Figure 5.10: Study of the impact of the implementation of MSNs on the efficiency of OAPS: uniformly distributed user destinations, $\overline{T_p} = 300s$, $P = 25$.

Hotspot scenario As MSNs circulate constantly, monitoring all parking places within the area considered, they feed users new information that they usually ignore due to their persistent movement along specific roads. Unlike the uniformly distributed destination case, the improvement factor of the MSN activity over the parking search time varies around a particular ratio ($\sim 8\%$) irrespective of the vehicle volume (Figure 5.11(a)). For $V < P$, the intensive competition among users for a particular set of parking spots as well as the different movement patterns of vehicles and MSNs diminish the value of the enhanced information diffusion, against the previous scenario. However, for $V > P$, the need for information is higher now, since vehicles recycle information about only a limited subset of the parking spots, upon their encounters with each other. Finally, as Figure 5.11(b) suggests, any further increase in the update frequency of drivers' memory does not change the place they park.



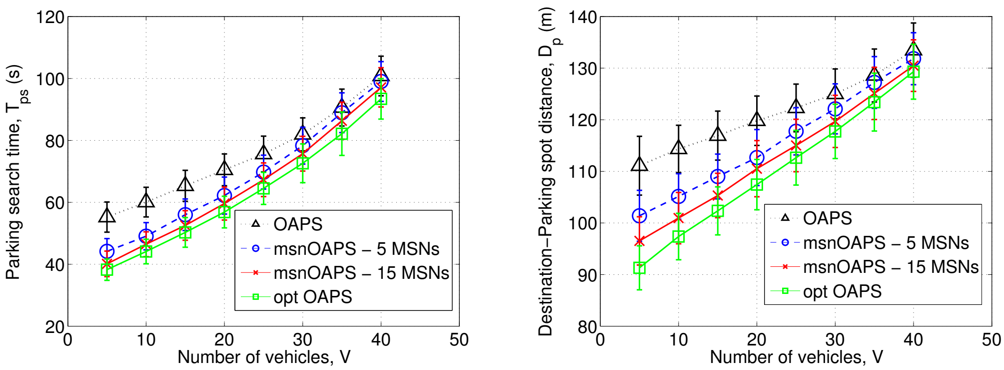
(a) Parking search time (b) Destination-parking spot distance

Figure 5.11: Study of the impact of the implementation of MSNs on the efficiency of OAPS: spatially concentrated user destinations (hotspot scenario), $\overline{T_p} = 300s$, $P = 25$.



(a) Parking search time (b) Destination-parking spot distance

Figure 5.12: Adding Mobile Storage Nodes to the OAPS scheme: uniformly distributed user destinations, $\overline{T_p} = 300s$, $P = 10$.



(a) Parking search time (b) Destination-parking spot distance

Figure 5.13: Adding Mobile Storage Nodes to the OAPS scheme: uniformly distributed user destinations, $\overline{T_p} = 300s$, $P = 50$.

Mobile Storage Nodes and number of parking places In general, the higher the parking density is, the more alternatives exist for parking space assignment. Since users can occupy an empty parking spot they encounter on their way, the increment in parking places increases the encounter possibility of an empty one, and thus decreases the search time needed (Figures 5.10(a), 5.12(a) and 5.13(a)). Moreover, since parking places and user destinations follow the same uniform spatial distribution, it stands to reason that the increase in the number of the alternative parking choices results in decrease of the average destination-parking spot distance D_p (Figures 5.10(b), 5.12(b) and 5.13(b)). Finally, concerning the msnOAPS approach, the implementation of MSNs is justified when many parking places are offered and the induced competition is less (due to either lower number of parking seekers or less overlapping preferences of parking space).

5.2 Impact of misbehaviors

5.2.1 Introduction

As introduced and described in Section 5.1, advanced parking assistance systems fostered by recent advances in wireless networking, sensing and car navigation technologies, aim at helping drivers find vacant parking spots easier and faster by collecting and sharing information about the location and status (occupied/vacant) of parking spots. In *centralized* systems, a central server communicating with sensors at the parking spots coordinates the parking spot assignment process: it receives the drivers' requests for parking space, reserves parking spots for them, and directs them thereto (*e.g.*, [Wang & He, 2011]). Whereas, in *opportunistic* systems, vehicles themselves serve as mobile sensing platforms that collect and store information about the location and status of parking spots and share it with each other through vehicle-to-vehicle (V2V) communication technologies (*e.g.*, [Caliskan *et al.*, 2006]). Opportunistic systems do not incur the upfront infrastructure cost of centralized systems, thus presenting a lighter and more scalable solution that leverages to-be-built-in vehicle equipment. On the other hand, opportunistic systems lack central coordination and rely on the vehicular nodes' willingness to share collected information. This cannot be taken for granted since the sharing of information assists nodes by increasing their knowledge about parking space availability but, at the same time, *synchronizes* nodes' parking choices. This synchronization in turn increases the competition for the vacant parking spots, in particular when drivers' travel destinations overlap [Kokolaki *et al.*, 2012].

The following sections present a study that questions the robustness of opportunistic parking assistance systems to non-cooperative vehicular node behaviors, which deviate from the purely *altruistic* norm of *always* and *truthfully* sharing the cached information with encountered vehicles. Hence, we let nodes *misbehave* and study how this affects fundamental performance indices such as the parking search time and the distance of the acquired parking spots from the drivers' travel destinations. The dual question from the individual nodes' viewpoint is whether they *do* have incentives to misbehave in that misbehaving allows them to achieve better search times and/or parking spot-destination distances. Two intuitive misbehavior instances are considered. In the first one, nodes defer from sharing parking information with other vehicles essentially acting as *free riders*. In the second one, they deliberately falsify information about the parking spots' status (*selfish liars*), *i.e.*, spots close to the misbehaving vehicle's destination are advertised as occupied whereas all others as vacant. The two misbehaviors essentially impair in different manner the *amount* and *accuracy* of information that is disseminated across the network.

5.2.2 Opportunistically-assisted parking search and imperfect cooperation

In Section 5.1.2 we describe the *opportunistically-assisted* parking search (OAPS) scheme under which vehicles equipped with standard wireless interfaces such as 802.11x in ad-hoc mode, share with each other information they acquire in the course of their search about the location and status of parking spots they encounter.

Critical for the efficiency of this opportunistically-assisted parking search are the *amount* and *accuracy/timeliness* of the information that is stored at the vehicles' caches and shared among them. Both are subject to strong spatiotemporal effects: vehicles generally possess partial rather than global information about parking space availability and as the status of parking spots changes over time stored data are potentially outdated after some time interval. Moreover, vehicular nodes have good reasons to hide information from other, potentially competitor, vehicles. Overall, the processes of information dissemination (benefiting discovery of parking spots and their availability) and competition growth (reducing the chances to acquire a spot) are coupled and counter-acting. Indeed, the faster information circulates across the wireless opportunistic networking environment, the more similar (accurate or not) data are stored in the caches of vehicles. Thus, depending on the travel destinations of users, the movement patterns of individual vehicles get synchronized and sharpen the effective competition for given parking spots. This additional level of competition, this time for information at the "service discovery" level, motivates various deviations from the perfectly cooperative (altruistic) behavior.

In the following sections, we consider in detail two such deviations, hereafter called misbehaviors for the sake of brevity. In the first one, misbehaving nodes defer from sharing their own information with other vehicles, while readily accepting such information from other vehicles that make it available. These free riders reduce the amount of disseminated information but also its accuracy since vehicles' caches are less frequently updated with fresh information about the spots' occupancy status. On the contrary, the second misbehavior instance involves the dissemination of falsified information about the status of parking spots. Nodes do so in order to create zones free of competition around their travel destinations by diverting encountered vehicles away from them. Compared to the first misbehavior instance, this one affects only the accuracy of the disseminated information.

Implementation-wise, the exchange and dissemination of parking information will be managed by software agents onboard the vehicles and the described misbehaviors can emerge in at least two ways, each one being better suited to one of the two misbehavior instances described in Section 5.2. First, the software onboard the vehicles may allow configuration/personalization features, the deferral from forwarding information being one of them. Secondly, the software itself may be misbehaving (*e.g.*, forge information) as a default option to increase its competitiveness against commercial competitor software products. The deliberate violation of normative behavior is anything but unusual in commercial hardware/software products. For example, Bianchi *et al.* in [Bianchi *et al.*, 2007] report on such symptoms for various popular 802.11b wireless adapters.

Inferring *a priori* the impact of these rather common misbehaviors is not straightforward for two main reasons. The first one is the aforementioned spatiotemporal effect. For example, misbehaving nodes that forge information may inadvertently correct outdated information (*i.e.*, turn the availability status of the advertised parking spots to their real up-to-date value) and, thus, end up assisting the process. The second reason relates to the cache synchronization effects that emerge as the frequency of information updates rises. It may be argued that the two types of misbehaviors can serve as regulators for the synchronization phenomena and the resulting competition. We explore these aspects in detail in Section 5.2.4.

Table 5.3: Simulation parameters

Parameters	Values
Simulation grid	$1200 \times 1200m^2$
Simulation time duration	10^5 sec
Number of uniformly distributed spots, P	25
Number of vehicles, V	$5 - 70$
User maximum speed, u_{max}	$14m/s \sim 50km/h$
Vehicle - spot sensor commun. range	$15m$
Vehicle - Vehicle commun. range	$70m$
Exponential parking time with mean, $1/\mu$	$1800sec$
Distance between adjacent roundabouts	$300m$
Linear increase step of parking search area	$150m$
Radius of Interest, RoI	$150, 350, 500m$
Ratio of misbehaving nodes, p	$0, 0.3, 0.5, 0.8, 1$

5.2.3 Performance evaluation methodology

The simulation environment used for our study is described in Section 5.1.3 (Ref. paragraph "Simulation environment"). In what follows, we outline those features that are critical to this investigation.

Information exchange process: Upon an encounter between two vehicles, each part merges its own list with the received information and deletes duplicate parking spot records keeping only the latest one. The information that needs to be exchanged involves a status vector with one bit per spot together with the related coordinates and timestamps, and its transmission is assumed to be error-free. Hence, contact times between vehicles suffice for exchange of this information (no partial transfer instances).

Cooperative *vs.* misbehaving vehicles: All vehicles inform their memory cache every time they hit a parking spot sensor. Well-behaving (cooperative) vehicles *share truthfully* stored information about the location and status of parking spots each time they encounter other vehicles. On the other hand, misbehaving vehicles realize the two misbehavior instances described in Section 5.2.2:

Information Denial: Upon encounters with other nodes, they suppress information they store about the location and availability of parking space, whereas they update their cached information with all the new knowledge offered. During their search, they use the cached information the same way as cooperative nodes.

Information Forgery: They advertise all parking spots within a specific distance from their destinations (*Radius of Interest, RoI*) as occupied, and all others as vacant, while setting the relevant timestamps to fresh values. Being more suspicious about falsified information, they persist more when searching around their destinations; namely, they run additional random trips (in the RM or NoM mode) over the initial parking search area before they decide to increase the range of their search.

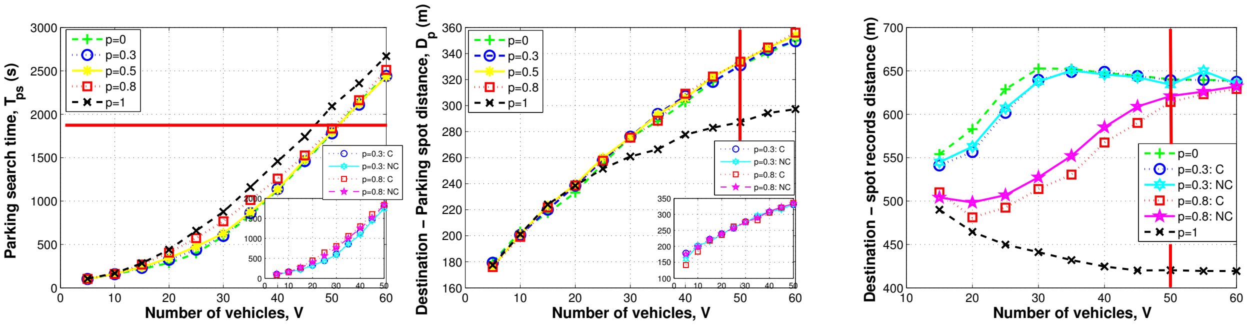
Simulation set-up and performance metrics

Unless otherwise stated, the simulations are run with the parameter values (value ranges) shown in Table 5.3. Following the methodology for the investigation of the impact of perfect cooperation on information dissemination (Ref. Section 5.1), two scenarios drive the study on the impact of misbehaviors as well: the first one involves vehicles seeking parking space all over the city area (uniformly distributed destinations); the second scenario features a single area that acts as an attraction pole for vehicles (hotspot).

The effectiveness of the parking search process is assessed through two main performance metrics throughout our study: the average time spent for searching available parking place (*Parking search time,* T_{ps}) and the average geographical distance between the vehicles' travel destinations and the selected parking spots (*Destination - Parking spot distance,* D_p). In addition, at a more microscopic level, we extract results for the amount and the profile of the information that is stored in vehicles' caches as well as the way vehicles use it and benefit from it, by plotting statistics about the percentage of time (*i.e.*, total search attempts) the vehicles search in *FM* and *RM* mode.

5.2.4 Simulation results - analytical insights

All our plots compare the metric values under perfect vehicular nodes' cooperation against those under different misbehavior intensities for various levels of parking demand. Each point in the plot results from averaging parking events over either the full set of nodes, or, separately, cooperative (denoted by 'C') and non-cooperative (denoted by 'NC') ones. Drivers are assumed to be persistent in their search. Alternatively, they could abandon their search for on-street parking space and head for a more expensive parking



(a) Average parking search time (b) Average destination-spot distance (c) Average distance from destination of spot records in vehicles' caches

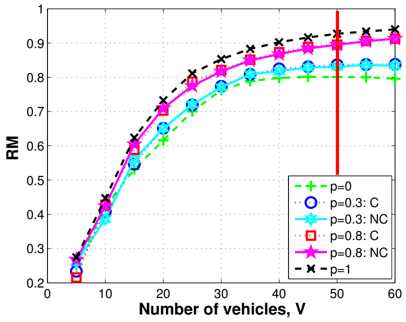
Figure 5.14: Robustness of the opportunistically-assisted parking search to *Information Denial*: uniformly distributed destinations.

lot, once the search time exceeds some deadline (maximum parking search time, T_{ps}^{max}). In this case, the delays experienced by the successful parking attempts would be lower than those shown in the respective figures of this section, and definitely upper bounded by T_{ps}^{max}. A red line in the plots corresponds to T_{ps}^{max}=1800 seconds. For a recent survey on the distribution of T_{ps}^{max}, interested readers are referred to [IBM, 2011].

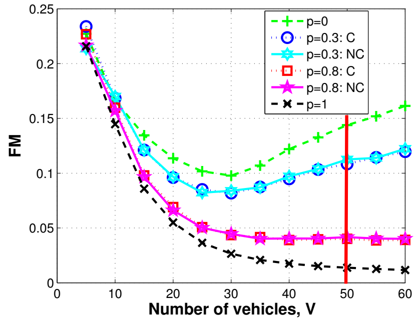
Uniformly distributed travel destinations

Information Denial The first remark out of Figure 5.14 is that the system exhibits remarkable robustness to this misbehavior instance. Neither the average parking search time (Figure 5.14(a)) nor the destination-spot distance (Figure 5.14(b)) are penalized even when half the vehicular nodes defer from sharing information. An increase in parking search time becomes visible when 80% of the nodes misbehave and evolves to a tradeoff when all nodes misbehave; namely, if all vehicles defer from information sharing, they end up acquiring spots closer to their destinations at the expense of higher search times[4]. The reason for this can be traced in the combination of Figures 5.14(c) and 5.15(a). Without information sharing, the caches of nodes are primarily populated with records of spots around their destination (initial parking search area), encountered during their

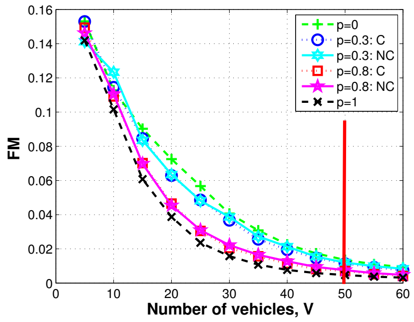
[4]It is important to notice that Figures 5.14(a) and 5.14(b) point to a tradeoff, depending on what each one values more. In fact, if all vehicles defer from information sharing, the gain in distance is less that $60m$ and the respective decrease in search time is in the order of $250s$, *i.e.*, $4min$. If one would like to weigh the two metrics towards an aggregate one, the outcome would favor the - cooperative - opportunistic system: walking $60m$ for an average driver takes less than $1min$, which is clearly less than $4min$. It would be different though if someone wanted to minimize the walking distance due to some injury that renders walking uneasy.



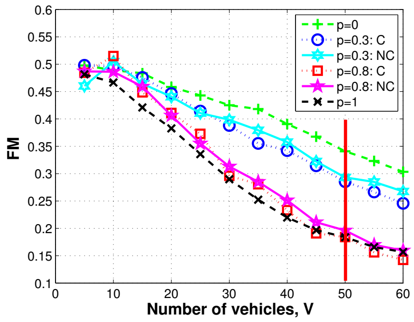
(a) Ratio of parking attempts in RM mode



(b) Ratio of parking attempts in FM mode



(c) Ratio of successful parking attempts in FM mode



(d) Ratio of successful parking attempts in FM mode over all successful attempts

Figure 5.15: Search mode and parking attempt success rates under *Information Denial*: uniformly distributed destinations.

first search attempts. As these spots are occupied (for medium-to high demand), and although vehicles gradually increase the range of their search, they still end up randomly selecting one of these spots (RM mode) with high probability. Contrary to when even a few nodes share information, their caches are not refreshed with records of more distant spots communicated by other vehicles[5] (Figure 5.14(c)). Instead they are only occasionally enriched with some randomly encountered spot in the destination proximity, where their search ends up being restricted. Reading the system robustness the other way round, equally remarkable is the failure of selfishly misbehaving nodes to attain better performance, when compared to what cooperative nodes achieve (Ref. to ingraphs in Figures 5.14(a), 5.14(b)).

On the other hand, Figure5.15 gives clear insights into the fundamental inefficiency

[5]As the demand increases and larger amounts of information are circulated, the vehicles' caches store information about more spots. Eventually, for high inter-vehicle communication rates, caches store information about all spots and the average distance between drivers' destinations and stored parking spots approximates the expected distance of two randomly selected points within the square area (*square line picking problem*, [Mathai, 1999]), known to equal $0.52 \times l$, where l denotes the square side length.

of opportunistically-assisted search, the coupling of information sharing (*about* parking spots) with the generated competition (*for* parking spots). The ratio of search attempts in FM mode (Figure 5.15(b)) starts from low levels at small demand, where anyway it is easier for a vehicle to find a spot, and decreases as the number of competing vehicles grows, where more spots are occupied, more vehicles are parked, and the flow of information is yet too slow to fill the vehicles' caches with adequately fresh information about vacant spots. When the demand grows even further and more vehicles end up cruising around, the information flow (at least for low or moderate intensity of misbehavior) is strengthened. Vehicles find fresh records about vacant spots in their caches, yet these are only a few and the competition for them so sharp that this information rarely results in a successful attempt (Figures 5.15(c), 5.15(d)). For higher intensity of misbehaviors, both the frequency and success rate of search in FM mode decrease.

Analytical insights: To better anticipate the way the system operates, let $\overline{Q}$ be the average number of parked vehicles and $\overline{M}$ the average number of spot records at their caches. The information about these spots is either collected when the vehicles run across them, primarily during their first random attempts, or obtained upon their communication with other cooperative vehicles. With uniform distributed interests and parking opportunities and with even a small population of cooperative vehicles, all vehicles have the potential to learn about any parking spot in the area.

After a vehicle populates its cache with the first entries, it visits them repeatedly either in FM or RM mode and parks only when two conditions are met: (a) one of the on-average $\overline{M}$ spots it is aware of is vacated; (b) it is the first among all other vehicles to randomly choose to move to it among all vehicles also storing a record for this spot. More formally, with $\overline{M}$ spots stored, events of type (a) are presented to the vehicle with Poisson rate $\mu\overline{M}$, if $\overline{M} < \overline{Q}$ and $\mu\overline{Q}$, otherwise. Upon each such epoch, the vehicle "succeeds" (event of type (b)), with a probability that depends on how many of the $V - \overline{Q}$ vehicles searching for parking space are aware of this particular spot. When $\overline{M} < \overline{Q}$, the expected value of this probability, p_s can be written as the sum of the probabilities of k other vehicles also storing a record for this spot, times the probability of winning the competition among the $k + 1$ informed vehicles, that is,

$$p_{s,1} = \sum_{k=0}^{V-\overline{Q}-1} \frac{1}{k+1} B\left(k; V-\overline{Q}-1, \frac{\overline{M}}{\overline{Q}}\right) \tag{5.12}$$

where $B(k; V-\overline{Q}-1, \frac{\overline{M}}{\overline{Q}})$ is the Binomial distribution with parameters $(V-\overline{Q}-1)$ and $\overline{M}/\overline{Q}$ for k vehicles being aware of the spot. When $\overline{M} \geq \overline{Q}$, the probability p_s can be written as the probability of winning the competition among the other non-parked vehicles, that is,

$$p_{s,1} = \frac{1}{V-\overline{Q}} \tag{5.13}$$

Hence, the number of attempts each vehicle makes before eventually parking points to a Geometrical distribution $Geom(p_s)$ so that the mean parking search time can be approximated as

$$T_{ps}^{an,1} = \frac{1}{p_{s,1}\mu \cdot min(\overline{M},\overline{Q})} \approx \left[(V-\overline{Q}-1)min\left(\frac{\overline{M}}{\overline{Q}},1\right)+1\right] \frac{1}{\mu \cdot min(\overline{M},\overline{Q})} \tag{5.14}$$

In addition, and most commonly under low parking demand, many vehicles park in vacant spots (known or not to them) that they encounter while travelling to other places. Any vehicle can park at a randomly met vacant spot provided that it is the first one that detects it within its parking search area. In fact, since every spot constitutes a potential candidate parking place for all vehicles in search for parking, a tagged vehicle competes for a particular spot against all other non-parked vehicles. In this case, the effective probability of success and the resulting average parking search time can be approximated by

$$p_{s,2} \approx \frac{1}{(V-\overline{Q}-1)/P+1} \tag{5.15}$$

$$T_{ps}^{an,2} = \frac{t}{p_{s,2}} \approx \left[\frac{(V-\overline{Q}-1)}{P}+1\right] t \tag{5.16}$$

where, $t = 0.52 \times l/u$ is the travel time at $u = u_{max}/2$ average speed, between two randomly selected points within the square area with $l = 1200m$ size length (square line picking problem, [Mathai, 1999]).

The total parking search time, T_{ps}^{an}, is a function of both $T_{ps}^{an,1}$ and $T_{ps}^{an,2}$. Since

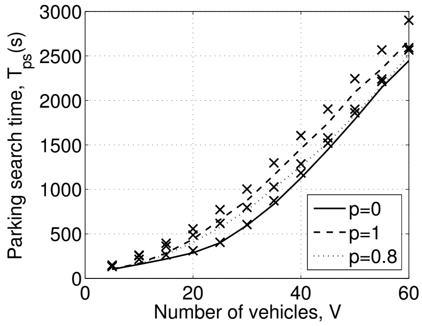


Figure 5.16: Information Denial, uniformly distributed destinations: Average parking search time, lines correspond to simulation results, and "×" marks stand for the predictions from Eq. (5.17).

parking events in randomly met spots occur with probability $(P - \overline{Q})/P$, the two values are weighed as

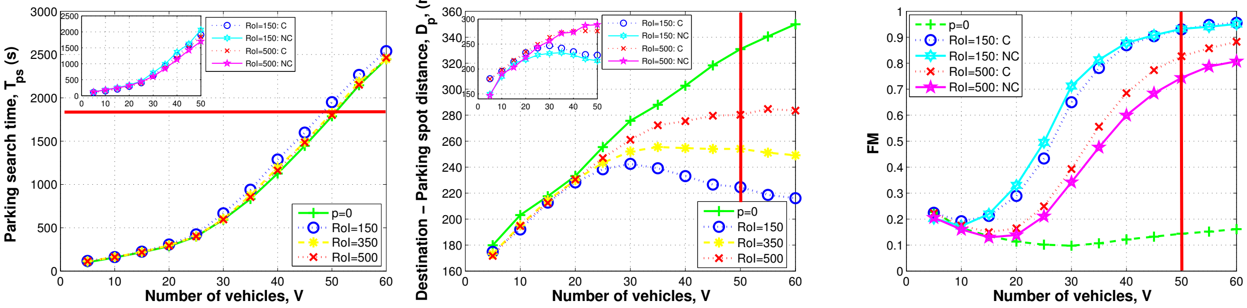
$$T_{ps}^{an} = (\overline{Q}/P)T_{ps}^{an,1} + (1 - \overline{Q}/P)T_{ps}^{an,2} \tag{5.17}$$

In Figure 5.16, we plot the simulation results against what equation (5.17) predicts. The values of the input variables for equation (5.17) are drawn from Table 5.4.

Information Forgery Under Information Forgery, the vehicular nodes try to spontaneously generate competition-free zones around their travel destinations. For small RoI values, these zones are narrow and disjoint. Since misbehaving nodes advertise parking spots outside these zones as vacant and the drivers' destinations are uniformly distributed, the (cooperative) nodes end up (incorrectly) listing spots around their own travel destinations as vacant for most of the time. These spots emerge as top choices out of the spatiotemporal filtering step (FM mode) and attract repeated parking attempts (Figure

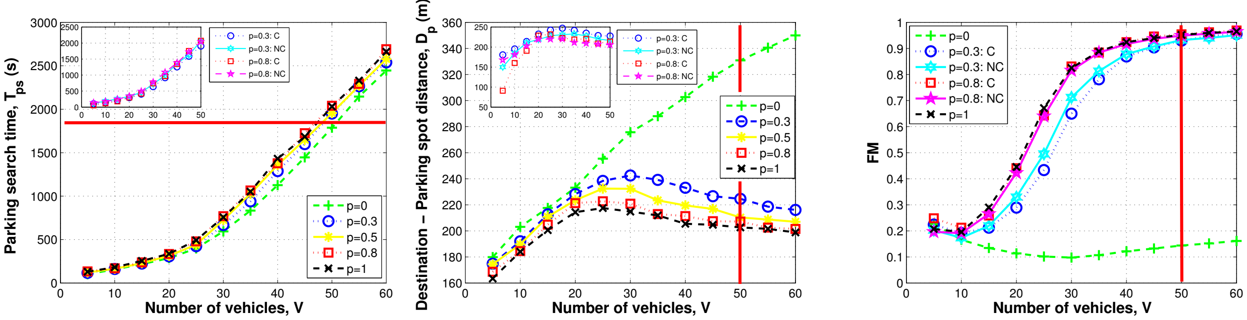
Table 5.4: Average number of parked vehicles and stored records under *Information Denial*: uniformly distributed destinations.

		Number of vehicles, V					
		10	20	30	40	50	60
$p = 0$	$\overline{M}$	4.4	11.2	23.1	24.5	24.8	24.9
	$\overline{Q}$	8.9	16.6	21.8	23.7	24.2	24.4
$p = 1$	$\overline{M}$	3.5	4.1	4.8	5.1	5.4	5.7
	$\overline{Q}$	8.8	15.6	19.5	21.2	22.2	23
$p = 0.8$	$\overline{M}$	3.3	5.2	9.7	16.6	21.8	23.5
	$\overline{Q}$	8.8	15.8	20.3	22.7	23.8	24.1



(a) Average parking search time (b) Average destination-spot distance (c) Ratio of parking attempts in FM mode

Figure 5.17: Robustness of the opportunistically-assisted parking search to *Information Forgery*: uniformly distributed destinations, $p = 0.3$.



(a) Average parking search time (b) Average destination-spot distance (c) Ratio of parking attempts in FM mode

Figure 5.18: Robustness of the opportunistically-assisted parking search to *Information Forgery*: uniformly distributed destinations, $RoI = 150m$.

5.17(c)). As a result, the vehicles park closer to the destination at the expense of higher search times. As misbehaving nodes become more aggressive and the zones they try to induce start to overlap ($RoI = \{350, 500\}$), most spots in the vehicles' caches are reported as occupied, the vehicles exercise more the RM mode, and a tradeoff emerges between destination-spot distances and parking search times, as shown in Figures 5.17(a) and 5.17(b).

Contrary to the Information Denial misbehavior, under Information Forgery the misbehavior intensity and its impact do not only depend on the number of misbehaving nodes but also on the population of cooperative nodes. The latter inadvertently propagate forged information across the network once they get infected with it upon encounter with a misbehaving node. This has two direct consequences. First, the destination-spot distance *vs.* parking search time tradeoff is now milder[6], as shown in Figures 5.18(a) and 5.18(b);

[6] As in Figures 5.14(a) and 5.14(b), it should be noted that under Information Forgery the gain in distance

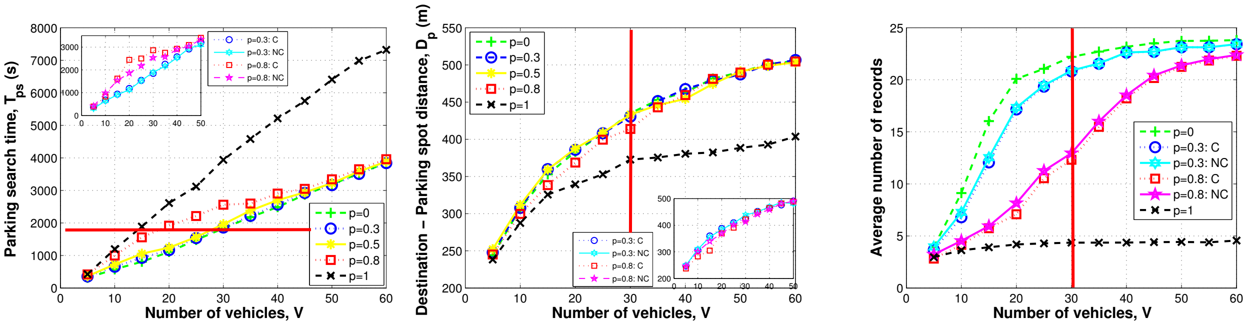
for given RoI even a small ratio of misbehaving nodes suffices to populate the vehicles' caches with supposedly vacant spots and steer their attempts to spots around their travel destinations (Figure 5.18(c)). Secondly, with a small exception for low parking demand levels ($V < P$), misbehaving nodes cannot gain any substantial performance advantage over cooperative nodes (Ref. to ingraphs in Figures 5.17(a), 5.17(b), 5.18(a), 5.18(b)) since the manipulated information they generate, bounces back to them after one or more hops over cooperative nodes.

Hotspot scenario

As we may recall from Section 5.1.5, under a fully cooperative setting, the spatial concentration of vehicles' travel destinations within a particular road segment, which is called hotspot, has two direct consequences on the information stored in their caches. First, as all vehicles cruise along the hotspot area and encounter each other more frequently, they tend to synchronize their caches with records about the same set of spots. Secondly, and most importantly, they rank these spots identically. Hence, at least as long as drivers let the system direct their attempts, their trips get synchronized, competition sharpens and parking search times increase substantially.

Information Denial In the hotspot setting, the Information Denial has a double-edged effect. On the positive side, the system is shown to be resilient to the free rider behavior; even when half the nodes defer from sharing information, the average parking search times and spot-destination distances are almost intact, as shown in Figures 5.19(a) and 5.19(b), respectively. Furthermore, misbehaving nodes do not gain in both performance indices by hiding information (Ref. to ingraphs in Figures 5.19(a) and 5.19(b)). On the other hand, this misbehavior does not manage to break the inherent synchronization effects and drive the system to a better-than-nominal performance level. When eventually, with most nodes in the network misbehaving, differentiation is achieved at the vehicles' caches, it is outweighed by a substantial decrease of disseminated information. Vehicles do not get informed about and do not take advantage of vacant parking spots further

ranges between $20m$ to $130m$ for all values of number of vehicles that retain parking search time below $30min$ (red line). The respective decrease in search time is in the order of $250s$, *i.e.*, $4min$. Again, far more than the time an average driver needs to traverse $130m$.



(a) Average parking search time (b) Average destination-spot distance (c) Average number of records in memory

Figure 5.19: Robustness of the opportunistically-assisted parking search to *Information Denial*: hotspot road.

away from their common destinations (Figure 5.19(c)). They rather end up parking closer to them, yet at the expense of unacceptable cruising times, even under moderate parking demand levels.

Analytical insights: Consider a random (tagged) vehicle searching for a parking spot under three different cases:

p=1: The vehicles do not exchange any information with each other. The stored records at the vehicles' caches are what vehicles discover by cruising in the parking search area. In fact, these spots are those encountered by the vehicle during its first attempts, while still not having any information at its cache for spots within its parking search area and moving randomly. After the vehicle populates its cache with some entries, and as long as no parking spot is recorded as vacant, it will be repeatedly making use of its memory in RM mode (Figure 5.20), *i.e.*, it will be randomly choosing one of the stored spots and move towards it in the hope of finding it vacant. Therefore, since its cache is

Table 5.5: Average number of parked vehicles and stored records under *Information Denial*: hotspot road.

		Number of vehicles, V					
		10	20	30	40	50	60
$p=0$	$\overline{M}$	9.1	20.1	22.2	23.2	23.7	23.8
	$\overline{Q}$	7.3	12	14.6	16.3	17.7	18.4
$p=1$	$\overline{M}$	3.6	4.2	4.4	4.4	4.4	4.6
	$\overline{Q}$	6.2	8.1	9.2	9.7	10	10.5
$p=0.8$	$\overline{M}$	4.3	7.6	12.6	18.4	21.3	22.3
	$\overline{Q}$	6.4	9.5	11.9	15	17.3	18.3

not refreshed with up-to-date information by other nodes, the vehicle will park only when it is the first to randomly choose to move to a particular spot that is vacated, among all vehicles also storing a record for this spot.

Thus, as in the scenario with uniformly distributed destinations, the expected value of this probability, p_s can be written

$$p_s = \sum_{k=0}^{V-\overline{Q}-1} \frac{1}{k+1} B\left(k; V-\overline{Q}-1, \frac{\overline{M}}{\overline{Q}}\right) \tag{5.18}$$

and the mean parking search time can be approximated as

$$T_{ps}^{an} = \frac{1}{p_s \mu \overline{M}} \approx \left(\frac{\overline{M}(V-\overline{Q}-1)}{\overline{Q}} + 1\right) \frac{1}{\mu \overline{M}} \tag{5.19}$$

p=0: This is the other extreme, whereby all vehicles exchange information with each other, ending up knowing about more spots, on average, than there are occupied. Now, the vacation of *any* currently occupied spot constitutes an opportunity for the tagged vehicle, yet it competes for it with all $V - \overline{Q} - 1$ vehicles searching for a vacant spot. Hence,

$$p_s = \frac{1}{V-\overline{Q}} \tag{5.20}$$

$$T_{ps}^{an} = \frac{1}{p_s \mu \overline{Q}} = \frac{(V-\overline{Q})}{\mu \overline{Q}} \tag{5.21}$$

0<p<1: In the intermediate cases, where cooperative and misbehaving nodes coexist, the vehicles exchange information, albeit less aggressively than when $p = 0$. Depending on the number of cooperative vehicles, we can distinguish two cases:

$\overline{M} \geq \overline{Q}$: The vehicle releasing a spot may be a cooperative or misbehaving one with probabilities 1-p and p, respectively. In the first case, all nodes are eventually informed about the event and do compete for it. In the second case, no vehicle is informed about the spot vacation and they continue using their memory in RM mode (Figure 5.20). In either case, the probability of success for the tagged vehicle and the resulting average parking search time are as in (5.20) and (5.21).

$\overline{M} < \overline{Q}$: If the vehicle releasing the spot is a cooperative one, the effective probability of success p_s is still given by (5.20). However, if it is a misbehaving one, then the vehicles

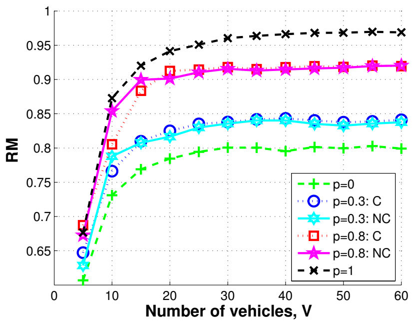


Figure 5.20: Ratio of parking attempts in RM mode under *Information Denial*: hotspot road.

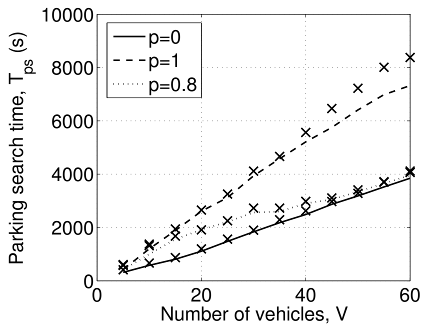


Figure 5.21: Information Denial, hotspot road: Average parking search time, lines correspond to simulation results, and "×" marks stand for the predictions from Eqs. (5.19), (5.21) and (5.23).

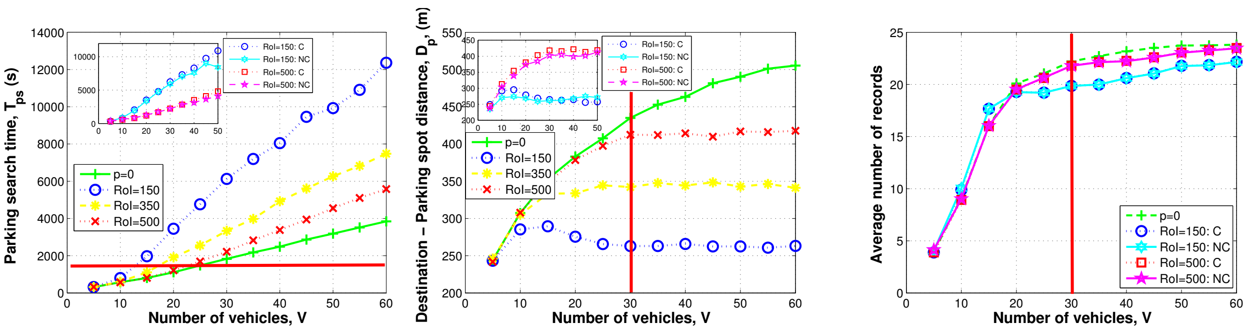
find themselves in a race similar to the one for $p = 1$, provided that, with probability $\overline{M}/\overline{Q}$, they are aware of the particular spot's location. Hence, the resulting average parking search time can now be approximated by

$$p_s = \frac{1-p}{V-\overline{Q}} + \frac{\overline{M}}{\overline{Q}} \sum_{k=0}^{V-\overline{Q}-1} \frac{p}{k+1} B\left(k; V-\overline{Q}-1, \frac{\overline{M}}{\overline{Q}}\right) \tag{5.22}$$

$$T_{ps}^{an} = \frac{1}{p_s \mu \overline{Q}} \tag{5.23}$$

The search times derived from simulation and the ones computed analytically, using Table 5.5 for the average number of parked vehicles and stored records, are compared in Figure 5.21.

Information Forgery In the hotspot scenario, the zones that misbehaving vehicles try to clear from competition overlap and all spots beyond a distance equal to RoI are advertised as vacant by misbehaving nodes. For small RoI, vehicles persistently direct their attempts



(a) Average parking search time (b) Average destination-spot distance (c) Average number of records in memory

Figure 5.22: Robustness of the opportunistically-assisted parking search to *Information Forgery*: hotspot road, $p = 0.3$.

towards the few spots lying close to their common destinations so that their caches are not enriched with information about vacant spots further away, as shown in Figure 5.22(c). The synchronization/competition effect is stronger and vehicles waste even more time in myopically searching for a parking spot around the hotspot road (Figure 5.22(a)). However, as a result of this search mode, the vehicles park closer to their destination (Figure 5.22(b)). Interestingly and rather counter to intuition, as misbehaving nodes become more aggressive and try to clear from competition larger areas (*i.e.*, $RoI = \{350, 500\}$), the parking search times improve for all vehicles. The reason is that vehicles are steered by the content of their caches to expand their search further away from the hotspot area and have the chance to encounter and, potentially occupy, spots they were not aware of. Essentially, the movement of vehicles in a broader area helps alleviate, though not resolve, the synchronization effect. Again, as with uniformly distributed travel destinations, misbehaving nodes cannot attain some performance advantage since the falsified information returns back to them, this time even faster due to more frequent encounters between vehicles (Ref. to ingraphs in Figures 5.22(a), 5.22(b)).

Mobile Storage Nodes for the hotspot scenario

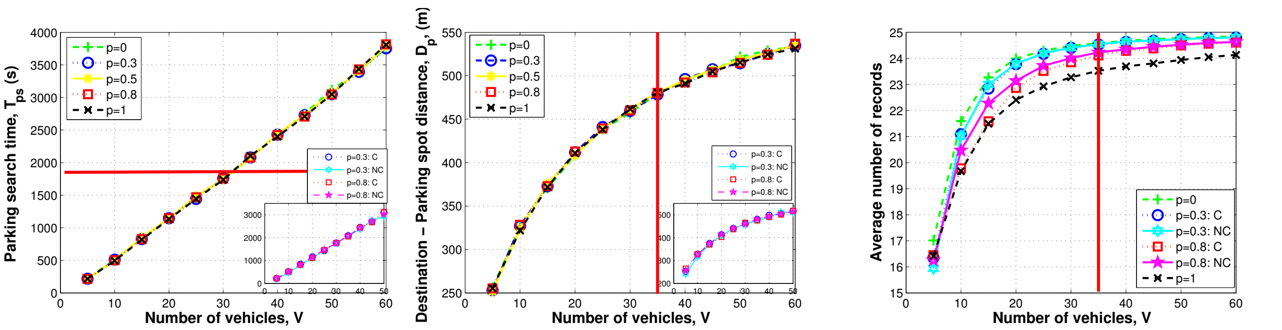
As explained in Section 5.1.2, the Mobile Storage Nodes (MSNs) can be either dedicated or normal vehicles, *e.g.*, city cabs, equipped with wireless interfaces that allow them to collect parking information from the entire area and share it with other vehicles and MSNs. By relaying information, MSNs accelerate the spread of information across the networks. Yet, their efficiency as countermeasures for the two misbehavior instances is very different.

Information Denial In this case, even a very small number of MSNs restore the information flows at the level (and even better) of the fully-cooperative system. The use of MSNs renders both the average parking time and the spot-destination distance independent of the number of free rider vehicles, as can be clearly seen in Figure 5.23. Even when vehicles do not exchange information with each other at all, the achieved parking search times are better than those under the fully cooperative system. The addition of more MSNs (we experimented with up to 15 MSNs) does not bear visible changes to the performance metrics; on the other hand, similar results are obtained with even one MSN. In fact, a single encounter with MSN informs nodes about the location of *all* parking spots in the area, helping them expand their search in a broader area around the hotspot road and partly randomize their driving patterns. Yet, the synchronization phenomena due to the vehicles' overlapping travel destinations are not fully eliminated and retain the parking search times at significantly higher levels than when the destinations are uniformly distributed.

Analytical insights: Since the mobile non-competing storage nodes fill the nodes' caches with almost all the available information, irrespective of the ratio of misbehaving nodes, the resulting system comes under the pure Information Denial case in the hotspot scenario when $\overline{M} \geq \overline{Q}$. Thus, both the probability of success and the average parking search time follow the expressions in (5.20) and (5.21), respectively. In Figure 5.24, we plot the average parking search time as derived with simulations against the outcome of equation (5.21), using Table 5.6 for the average number of parked vehicles in the particular scenario.

Table 5.6: Average number of parked vehicles under *Information Denial*: hotspot road with Mobile Storage Nodes.

	Number of vehicles, V					
	10	20	30	40	50	60
$p = 0$	7.7	12.4	15.1	17	18.2	19
$p = 1$	7.7	12.3	15.1	16.9	18.2	19
$p = 0.8$	7.7	12.4	15.1	16.9	18.2	19.1



(a) Average parking search time (b) Average dest-spot distance (c) Average number of records in memory

Figure 5.23: Mobile Storage Nodes and *Information Denial*: hotspot road.

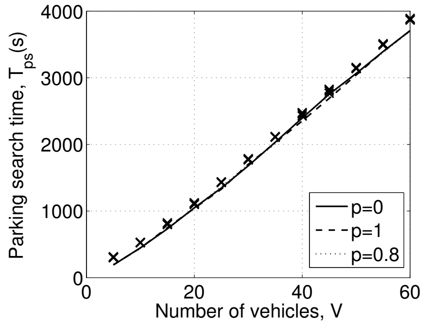


Figure 5.24: Mobile Storage Nodes and Information Denial, hotspot road: Average parking search time, lines correspond to simulation results, and “×” marks stand for the predictions from Eq. (5.21).

Information Forgery When nodes misbehave this way, the MSNs are a far less efficient solution. Although they collect and store up-to-date information about the actual status of parking spots as they move randomly within the grid, this information is *rewritten* upon encounters with misbehaving nodes but also cooperative nodes that have been polluted with falsified information. Thus, the MSNs end up further fostering the diffusion of falsified information. The synchronization effects at the vehicles' caches get even stronger and the the eventual decrease of search times thanks to additional fresh information is marginal (Figure 5.25).

Analytical insights: The counter-efficiency of MSNs in coping with selfish liars can be interpreted through a simple model of interacting objects. The model does not intend to capture the exact interaction of vehicles in the hotspot scenario but rather the essence of the emerging synchronization effects. Let S and C be the populations of two classes of mobile network nodes, stubborn (*i.e.*, selfish) and conciliatory (*i.e.*, cooperative), respectively, with $S + C = N$, and Z a physical location in the network, whose state at any point in time is a binary variable $z \in \{0, 1\}$. Assume also that pairwise node encounters form uniform Poisson processes of rate λ and that all nodes hit Z with Poisson rate h. Stubborn nodes persistently advertise that z is in state 0; whereas, conciliatory nodes update their information about z upon two kinds of encounters. Whenever they meet a stubborn node, they adopt its claim about z, *i.e.*, $z = 0$. In parallel, they may themselves hit Z and update their knowledge about its state. When nodes of the same type encounter each other, they do not update their information but rather stick to what they know. If $x_1(t),\ 0 \leq x_1(t) \leq N - C$ denotes the number of nodes over time, whose information about z is *not* in sync with what the S nodes propagate, then its evolution over time is a stochastic process coming under the broader family of density-based Continuous Time Markov processes. Drawing on the mean-field theoretic arguments in [Kurtz, 1970], the evolution of $E[x_1(t)]$ for large N can be approximated by the deterministic solution of the ordinary differential equation (ODE)

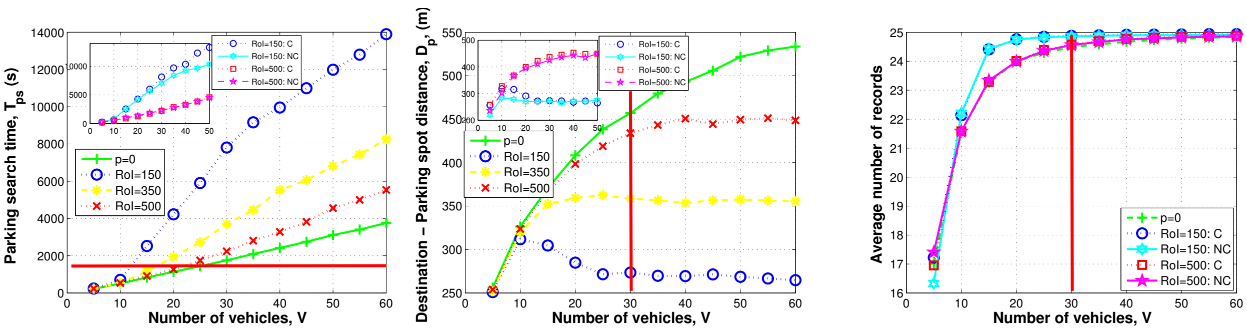
$$\dot{x}(t) = h(C - x(t)) - \lambda S x(t) \tag{5.24}$$

This is a first-order linear ODE with initial condition $x(0) = C = N - S$ and solution

$$x(t) \doteq E[x_1(t)] = \frac{N-S}{h+\lambda S}[h + \lambda S e^{-(h+\lambda S)t}] \tag{5.25}$$

Namely, the average number of nodes that maintain their own assessment of the status of z reduces over time to $\frac{(N-S)h}{h+\lambda S}$.

Now, consider adding to the network R "bona fide" storage nodes relaying information about z. When a storage node encounters a stubborn node, it synchronizes with it, and when it encounters a conciliatory node, it propagates its own information to it. Essentially, the three types of nodes form a three-level hierarchy regarding their capacity to impose their information, with conciliatory nodes at the bottom level and stubborn ones at the top level. If $x_1(t), x_2(t)$ denote the number of conciliatory and storage nodes, respectively, that are not in sync with the stubborn nodes, their evolution over time is a two-dimensional Markov process and, with similar arguments as before, it can be approximated by the deterministic solution of the non-linear system of ODEs



(a) Average parking search time (b) Average dest-spot distance (c) Average number of records in memory

Figure 5.25: Mobile Storage Nodes and *Information Forgery*: hotspot road, $p = 0.3$.

$$\dot{x}(t) = (C - x(t))h - x(t)(R+S)\lambda + \lambda C y(t) \tag{5.26}$$

$$\dot{y}(t) = -y(t)(h+\lambda S) + hR \tag{5.27}$$

with initial values $x(0) = C$ and $y(0) = R$. Solving initially the first-order linear ODE for $y(t)$ and replacing to obtain another first-order linear ODE for $x(t)$, we obtain:

$$x(t) \doteq E[x_1(t)] = \frac{N-S}{h+\lambda S}[h + \lambda S e^{-(h+\lambda S)t}] \tag{5.28}$$

$$y(t) \doteq E[x_2(t)] = \frac{R}{h+\lambda S}[h + \lambda S e^{-(h+\lambda S)t}] \tag{5.29}$$

The expression for $E[x_1(t)]$ coincides with that without storage nodes in (5.25). Hence, the Mobile Storage Nodes do not really alter the dynamics, through which stubborn (*a.k.a.* selfish) nodes synchronize the conciliatory (*a.k.a.* cooperative) nodes to their (deliberately falsified) information.

Chapter 6

Information consumption

The advances in the broader information and communication technologies (ICT) sector have dramatically changed the role of end users and resulted in unprecedented rates of information generation and diffusion. Besides generating information, the end users may be actively involved in its dissemination, as discussed and explored in Chapter 5, and even make use of it for their own good and benefit. In the following sections, we study scenarios, where some *non-excludable finite resource* is of interest to a population of distributed users and the information that is generated and may be shared concerns the *resource demand* and *supply*. When the amount of resource is large and the interested user population is small, users can readily opt for using it. When, however, the resource's supply cannot satisfy the demand for it, an inherent competition for the resource emerges that should be factored by users in their decision to opt for accessing this resource or not. The underlying assumption here is that the decision to opt for the finite resource under high competition bears the risk of an excess cost in case of a failure (*i.e.*, go for the limited resource but find it unavailable). This cost captures the impact of congestion phenomena that appear in various ICT sectors when distributed and uncoordinated high volume demand appears for some limited service.

Indeed, in several instances of ICT systems and applications a number of selfish agents compete over a limited-capacity and low-cost resource. In several studies, the way the competition is resolved in different autonomic environments has been addressed in game theoretic terms. Starting from a transportation paradigm in [Holzman & Lev-Tov, 2003], the drivers choose between a number of routes from a common-to-all origin to a common-to-all destination. The cost incurred by each user is a non-decreasing function of the number of other users also follow the same trajectory. Likewise, in an instance of the access-point association problem, a number of mobiles compete over a finite number of access points where high access delays (low throughput) occur when many users associate with the same wireless access point [Hasan *et al.*, 2012]. In [Shi *et al.*, 2012], nodes' access in a shared communication channel is regulated by the CSMA/CA protocol whereby the backoff rates are determined in distributed manner by self-organized nodes that either act selfishly (optimize their own throughput) or are willing to cooperate aiming at a global optimal solution. In [Saad *et al.*, 2012], the authors present the technical challenges in design, control, and implementations of smart grids and propose game theoretic frameworks to describe the interaction-competition between the loads over the energy resources as well as between the sources over the supply of energy.

In such settings, various critical decisions need to be taken by the entities that are involved in the production, dissemination and consumption of information. Indeed, the decision to acquire and distribute the information or not, may account for own-interest priorities, such as preserving own resources or hiding information from potential competitors. In the following sections, we focus on the way the entities make use of the accumulated knowledge. Essentially, the main dilemma faced by the end user possessing resource information is *whether to compete or not* for using these resources. This very fundamental question is investigated by factoring cognitive heuristics/biases in the human-driven decision-making process. Overall, the high-level question that we address is how efficiently the competition about the resources is resolved under different assumptions about the way the agents make their decisions. The efficiency depends not just on the quality of the information about the resources that is provided to the users but also on the way the provided information is used ("consumed") by users. Therefore, information may be precise and complete or imperfect and limited; whereas users may exhibit different levels of rationality in the way they process the provided information and determine their actions.

In essence, we are more concerned with the comparison of the decision-making under *full* and *bounded rationality* conditions. The key assumption is that human activity takes place within a fairly autonomic networking environment, where each agent runs a service resource selection task and seeks to maximize his benefit, driven by self-oriented interests and biases. As the full rationality reference, we frame the case where the agents (typically software engines) avail all the information they need to reach decisions and, most importantly, are capable of exploiting all information they have at hand; whereas users of bounded rationality either possess partial information about the resources or they are totally aware of them but it might be too complex in time and computational resources to exploit all the available information. Typically, decision-makers respond to these complexity constraints by acting heuristically. At the same time, their behavior is prone to case-sensitive biases that may lead to perceptual variations or distortions and inaccurate/not rational judgments that shape their competitiveness.

In a different research direction, the competitive networking environment is addressed as a market field and centralized auction-based mechanisms are proposed to alleviate congestion phenomena that result from the uncoordinated selfish behavior of decision-makers.

6.1 Impact of perfect rationality

6.1.1 Introduction

The research questions as posed in the first paragraphs of Section 6 can be concretized and most importantly find direct applicability to a daily routine activity for many of us in urban environments, the search for parking space. As we thoroughly present in previous chapters, academic research but also public and/or private initiatives have been primarily directed towards the design and deployment of *parking assistance systems*. Common to these systems is the exploitation of wireless communications and sensing technologies to collect and broadcast (in centralized systems, *i.e.*, [Mathur *et al.*, 2010], [Wang & He, 2011]) or share (in distributed systems, *i.e.*, [Caliskan *et al.*, 2006], [Delot *et al.*, 2009]) information about the supply of (and demand for) parking resources. This information ideally saves drivers from redundant cruising trips in search of a parking spot and assists in the management of parking resources, with centralized systems even implementing parking spot reservation. Parking assistance systems may also enable smart demand-responsive pricing schemes on the parking facilities, resulting in higher parking availability in overused parking zones and preventing double-parking and excessive cruising phenomena (*i.e.*, in SFpark[1]).

In the following sections we seek to systematically explore the fundamental limits on the efficiency of these assistance systems to alleviate the congestion effects, when the parking resource allocation is not controlled by a centralized entity, *e.g.*, through a reservation mechanism. To this end, it is ideally assumed that drivers become *completely* aware of the competition intensity, parking capacity and applied pricing policies on the parking facilities. We take a game-theoretic approach and view the drivers as rational strategic selfish agents that try to minimize the cost they pay for the acquired parking space. More precisely, we assume that the decisions are made by automatic software agent implementations on-board the vehicles rather than humans and the drivers' actions fully comply with the agents' suggestions. We formulate the uncoordinated parking spot selection problem as an instance of *resource selection games*. The drivers choose independently to either compete for the inexpensive but scarce on-street public parking spots or head for the more expensive private parking lot(s)[2]. In the first case, they run the risk of failing to get a spot and having to *a posteriori* take the more expensive alternative, this time suffering the additional *cruising* cost in terms of time, fuel consumption (and stress) of the failed attempt. Drivers make their decisions drawing on perfect information about the number of drivers, the availability of parking spots and the pricing policy, which is broadcast from the parking service operator. We derive the equilibrium behaviors of the drivers and compare the induced social cost against the optimal one via the Price of Anarchy metric. Most importantly, we show that the optimization of the equilibrium social cost is feasible by properly choosing the pricing and location of the private parking facilities.

[1]SFpark: parking application for San Francisco, available online in $http://sfpark.org/$

[2]The terms *public* parking spots and *private* parking facilities denote *on-street* parking spots and parking lots, respectively. Their context in this thesis should not be confused with that of public/private goods in economics.

6.1.2 Modeling the parking spot selection process

The traffic and environmental burden of the parking space search process depends on several factors. The potential overlap in drivers' travel destinations, personal parking preferences, and the drivers' unwillingness to park beyond the proximity of their destination have been identified as causes for major congestion problems. These are further aggravated due to specific parking regulations-restrictions, which are often in place especially in center areas of big cities, *e.g.*, business districts. Typically, parking in these areas is completely forbidden or restricted in whole sets of road blocks so that the effective curbside is scarce. Thus, drivers may have to settle for parking spots that hardly satisfy personal search criteria (*i.e.*, short walking distance to their destinations). More fundamentally, drivers are faced with a decision whether to compete for the low-cost but scarce on-street parking space or directly head for the over-dimensioned but more expensive parking lots.

In our model, drivers are faced with this dilemma, that is, whether to compete or not for the scarce on-street parking space. Those who manage to park in curbside pay $c_{osp,s}$ per-time cost units, whereas those heading directly for the safer parking lot option pay $c_{pl} = \beta \cdot c_{osp,s}, \beta > 1$, per-time cost units. However, drivers that decide first to search for low-cost parking spots but fail to acquire one and finally resort to a parking lot, pay $c_{osp,f} = \gamma \cdot c_{osp,s}, \gamma > \beta$, per-time cost units. The excess cost $\delta \cdot c_{osp,s}$, with $\delta = \gamma - \beta > 0$, reflects the actual cost of cruising and the "virtual" cost of wasted time till eventually reaching the more expensive parking facility. Parking facilities of both types are managed by a single operator, *e.g.*, municipal authorities, and all parking facilities of the same type are assumed to be of similar value to the drivers –we discuss this assumption further in Chapter 8. Thus, the drivers' decisions are essentially made on the two *sets* of parking facilities, *i.e.*, on-street parking space *vs.* parking lots, rather than individual set items, *i.e.*, parking spots.

Optimal centralized parking spot allocation: Under the optimal centralized parking-spot-allocation scheme, the full information processing and decision-making tasks lie with a central entity. Drivers issue their parking requests to a central server, which monitors the parking space, possesses precise information about its availability, and assigns it so that the overall cost paid by drivers is minimized (typically, the case when the municipality runs centralized parking assistance services). Thus, in an urban environment with R on-street parking spots, whereby such an ideal centralized system serves the parking requests of $N > R$ drivers, exactly R ($N - R$) drivers would be directed to the low-cost (respectively, more expensive) facilities and no one would pay the excess cruising cost.

Uncoordinated parking spot selection: In the absence of central coordination, each driver acts selfishly, aimed at minimizing the parking cost. However, the intuitive tendency to head for the low-cost on-street parking space, combined with its scarcity in urban center areas, give rise to *tragedy of commons* effects [Hardin, 1968] and highlight the game-theoretic dynamics behind the parking spot selection task. Thus, the collective decision-making on parking space selection can be formulated as an instance of *resource selection games*, whereby N players (*i.e.*, drivers/software agents) compete against each other for a finite number R of common resources (*i.e.*, curbside parking) [Ashlagi *et al.*, 2006]. In this game-theoretic view of the parking spot selection process, the agents are assumed rational strategic players. They explicitly consider the presence of identical counteractors that also make rational decisions, weight the costs related to every possible action profile, and act as cost minimizers.

6.1.3 Parking spot selection under complete knowledge of parking demand

In addition to the number of parking spots and the parking fees, which are assumed to be known throughout this study, drivers are assumed to also possess perfect information about the level of parking demand, *i.e.*, the number of drivers searching for parking space. Then, the one-shot parking spot selection game under complete information is defined as follows:

Definition 6.1.1. *A strategic Parking Spot Selection Game is a tuple* $\Gamma(N) = (\mathcal{N}, \mathcal{R}, (A_i)_{i\in\mathcal{N}}, (w_j)_{j\in(osp,pl)})$, *where:*

- $\mathcal{N} = \{1, ..., N\}$, $N > 1$ *is the set of drivers who seek for parking space,*
- $\mathcal{R} = \mathcal{R}_{osp} \cup \mathcal{R}_{pl}$ *is the set of parking spots;* $\mathcal{R}_{osp}$ *is the set of on-street spots, with* $R = |\mathcal{R}_{osp}| \geq 1$*;* $\mathcal{R}_{pl}$ *is the set of spots in parking lot, with* $|\mathcal{R}_{pl}| \geq N$*,*

- $A_i = \{osp, pl\}$ *is the action set for each driver* $i \in \mathcal{N}$*, comprising of the actions "on-street" (osp) and "parking lot" (pl),*

- $w_{osp}(\cdot)$ *and* $w_{pl}(\cdot)$ *are the cost functions of the two actions, respectively*[3].

The parking spot selection game falls under the broader family of *congestion games*. The players' payoffs (here: costs) are non-decreasing functions of the *number* of players competing for the parking capacity, rather than their identities, and common to all players. More specifically, drivers who decide to compete for the curbside parking space undergo the risk of not being among the R winner drivers to get a spot. In this case, they have to eventually resort to a parking lot only after wasting extra time and fuel (plus patience supply) on the failed attempt. The expected cost for a driver that plays the action osp, $w_{osp} : A_1 \times ... \times A_N \to \mathbb{R}$, is therefore a function of the number of drivers k taking it and is given by

$$w_{osp}(k) = min(1, R/k)c_{osp,s} + [1 - min(1, R/k)]c_{osp,f} \tag{6.1}$$

On the other hand, the cost for those that head directly to the parking lot facilities is fixed

$$w_{pl}(k) = c_{pl} = \beta \cdot c_{osp,s} \tag{6.2}$$

Figure 6.1 plots the cost functions against the number of drivers, for both parking options, under different pricing schemes.

We denote an action *profile* by the vector $a = (a_i, a_{-i}) \in \times_{k=1}^{N} A_k$, where a_{-i} denotes the actions of all other drivers, except for player i in profile a. In addition to the two *pure* actions reflecting the pursuit of parking spots in curbside and in parking lots, the drivers may also randomize over them. In particular, if $\Delta(A_i)$ is the set of probability distributions over the action set of player i, a player's *mixed action* corresponds to a vector $p = (p_{osp}, p_{pl}) \in \Delta(A_i)$, where p_{osp} and p_{pl} are the probabilities of the two pure actions, with $p_{osp} + p_{pl} = 1$, while its cost is a weighted sum of the cost functions $w_{osp}(\cdot)$ and $w_{pl}(\cdot)$ of the pure actions. We draw on concepts in [Koutsoupias & Papadimitriou,

[3]Note that the cost functions are defined over the action set of each user; in the original definition of resource selection games in [Ashlagi *et al.*, 2006], cost functions are defined over the resources, but the resource set coincides with the action set.

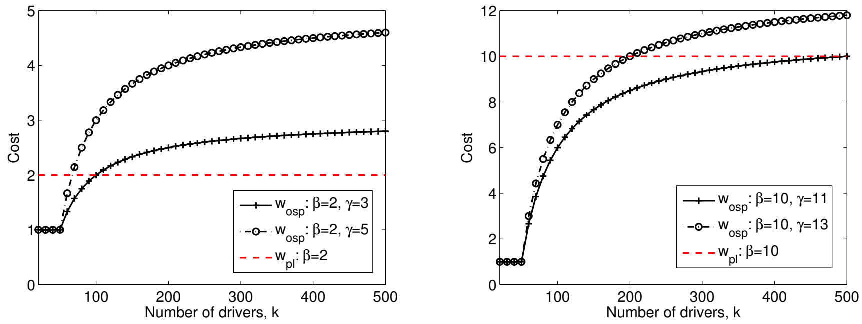


Figure 6.1: The cost functions for parking spots in curbside and in parking lots: $R = 50$, $c_{osp,s} = 1$.

2009] and theoretical results in [Ashlagi *et al.*, 2006] and [Cheng *et al.*, 2004] to derive the equilibrium strategies for the game $\Gamma(N)$ and assess their (in)efficiency.

Pure equilibrium strategies

Existence: The parking spot selection game constitutes a symmetric game, where the action set is common to all players and consists of two possible actions, *i.e.*, *osp* and *pl*. Cheng *et al.* have shown in ([Cheng *et al.*, 2004], Theorem 1) that every symmetric congestion game with two strategies has an equilibrium in pure strategies.

Derivation: Due to the game's symmetry, the full set of 2^N different action profiles maps into $N+1$ different action *meta-profiles*. Each meta-profile $a(m), m \in [0, N]$, encompasses all $\binom{N}{m}$ different action profiles that correspond to the same number of drivers competing for on-street parking space. The expected costs for these m drivers and for the $N-m$ drivers directly choosing the parking lot alternative are functions of $a(m)$ rather than the exact action profile. In general, the cost for driver i under the action profile $a = (a_i, a_{-i})$ is

$$c_i^N(a_i, a_{-i}) = \begin{cases} w_{osp}(N_{osp}(a)), & \text{for } \; a_i = osp \\ w_{pl}(N - N_{osp}(a)), & \text{for } \; a_i = pl \end{cases} \tag{6.3}$$

where $N_{osp}(a)$ is the number of competing drivers for on-street parking under action profile a. Equilibrium action profiles combine the players' *best responses* to their opponents' actions. Formally, an action profile $a = (a_i, a_{-i})$ is a pure Nash equilibrium (NE) if, for all $i \in \mathcal{N}$, it holds that $a_i \in \arg\min_{a'_i \in A_i}(c_i^N(a'_i, a_{-i}))$, so that no player has anything to gain by changing his decision unilaterally. Therefore, to derive the equilibrium states, we determine the conditions on N_{osp} that break the equilibrium definition and reverse them. More specifically, given an action profile a with $N_{osp}(a)$ competing drivers, a player gains by changing his decision to play action a_i in two circumstances, *i.e.*, :

$$when\ a_i = pl \text{ and } w_{osp}(N_{osp}(a) + 1) < c_{pl} \tag{6.4}$$

$$when\ a_i = osp \text{ and } w_{osp}(N_{osp}(a)) > c_{pl} \tag{6.5}$$

Lemma 6.1.1. *In $\Gamma(N)$, a driver is motivated to change his action a_i in the following circumstances:*

- $a_i = pl$ *and (a)* $N_{osp}(a) < R \leq N$ *or*

  (b) $R \leq N_{osp}(a) < N_0 - 1 \leq N$ *or*

  (c) $N_{osp}(a) < N \leq R$ (6.6)

- $a_i = osp$ *and* $R < N_0 < N_{osp}(a) \leq N$ (6.7)

where $N_0 = \frac{R(\gamma-1)}{\delta} \in \mathbb{R}$.

Proof. Conditions (6.6a) and (6.6c) are trivial. Since the current number of competing vehicles is less than the on-street parking capacity, every driver having originally chosen the parking lot option has the incentive to change his decision due to the price differential between $c_{osp,s}$ and c_{pl}. When $N_{osp}(a)$ exceeds the curbside parking supply, a driver who has decided to avoid competition, profits from switching his action when (6.4) holds, which when combined with (6.1) yields (6.6b). Similarly, a driver that first decides to compete profits by switching his action if (6.5) holds, which combined with (6.1) yields (6.7). □

Theorem 6.1.1. *The game $\Gamma(N)$ has the following*

(a) *for $N \leq N_0$, a unique NE profile a^* with $N_{osp}(a^*) = N_{osp}^{NE,1} = N$;*

(b.1) *for $N > N_0$ and $N_0 \in (R, N) \backslash \mathbb{N}^*$, $\binom{N}{\lfloor N_0 \rfloor}$ NE profiles a' with $N_{osp}(a') = N_{osp}^{NE,2} = \lfloor N_0 \rfloor$;*

(b.2) *for $N > N_0$ and $N_0 \in [R+1, N] \cap \mathbb{N}^*$, $\binom{N}{N_0}$ NE profiles a' with $N_{osp}(a') = N_{osp}^{NE,2} = N_0$ and $\binom{N}{N_0-1}$ NE profiles $a^\star$ with $N_{osp}(a^\star) = N_{osp}^{NE,3} = N_0 - 1$.*

Proof. Theorem 6.1.1 follows directly from Lemma 6.1.1. The equilibrium states satisfy both the conditions $N_{osp} \geq N_0 - 1$ and $N_{osp} \leq N_0$. Thus, the game has two equilibrium states on N_{osp} for $N > N_0$ with integer N_0 (case b.2), or a unique state, otherwise (cases a, b.1). □

An alternative way to derive the equilibria of $\Gamma(N)$ is via potential functions. The game $\Gamma(N)$ is a congestion game; thus, it accepts an exact potential function $\Phi(\cdot)$ [Monderer & Shapley, 1996]. As already explained, the 2^N different action profiles of $\Gamma(N)$ can be grouped into $N+1$ different meta-profiles $(m, N-m), 0 \leq m \leq N$, where m is the number of drivers that decide to compete for on-street parking. Therefore, the potential function is effectively a function of m and can be written as

$$\Phi(a) \sim \Phi(m) = \sum_{j \in \mathcal{R}} \sum_{k=0}^{n_j(a)} w_j(k) \tag{6.8}$$

where $n_j(a)$ the number of drivers using resource j under action profile a. Therefore, for $m \leq R$,

$$\Phi(m) = (N-m)c_{pl} + \sum_{k=1}^{m} c_{osp,s} = c_{osp,s}[\beta N - (\beta - 1)m] \tag{6.9}$$

whereas, for $m > R$

$$\begin{aligned}
\Phi(m) &= (N-m)c_{pl} + \sum_{k=1}^{m} min\left(1, \frac{R}{k}\right) c_{osp,s} + \left[1 - min\left(1, \frac{R}{k}\right)\right] c_{osp,f} \\
&= c_{osp,s}\left[\beta N + \delta m - R(\gamma - 1) + R(1-\gamma) \cdot \sum_{k=R+1}^{m} \frac{1}{k}\right] \\
&= c_{osp,s}\left[\beta N + \delta m - R(\gamma - 1) + R(1-\gamma) \cdot (H_m - H_{R+1})\right] \qquad (6.10)
\end{aligned}$$

$H_n = \underline{\gamma} + log(n) + O(1/n)$ is the n^{th} harmonic number; and $\underline{\gamma}$ the Euler constant. The pure NE strategies coincide with the local minima of the potential function. For $m \leq R$, $\partial\Phi(m)/\partial m < 0$ and the minimum is obtained at m, as derived in Theorem 6.1.1.

For $m > R$, demanding $\partial\Phi(m)/\partial m = 0$ we get $\delta + \frac{R(1-\gamma)}{m_{NE}} = 0$, which yields $m_{NE} = \frac{R(\gamma-1)}{\delta} = N_0$, *i.e.*, the value we got through Lemma 6.1.1.

Efficiency: The efficiency of the equilibria is assessed through the broadly used metric of the PoA [Koutsoupias & Papadimitriou, 2009]. It expresses the ratio of the social cost in the worst-case equilibria over the optimal social cost under ideal coordination of the drivers' strategies.

Proposition 6.1.1. *In* $\Gamma(N)$, *the pure PoA equals:*

$$\texttt{PoA} = \begin{cases} \frac{\gamma N-(\gamma-1)\min(N,R)}{\min(N,R)+\beta\max(0,N-R)}, & if\ N_0 \geq N \\ \\ \frac{\lfloor N_0 \rfloor \delta - R(\gamma-1)+\beta N}{R+\beta(N-R)}, & if\ N_0 < N \end{cases}$$

Proof. The social cost under action profile a equals:

$$C(N_{osp}(a)) = \sum_{i=1}^{N} c_i^N(a) = c_{osp,s}\left[N\beta - N_{osp}(a)(\beta - 1)\right] \quad (6.11)$$

if $N_{osp}(a) \leq R$ and

$$C(N_{osp}(a)) = \sum_{i=1}^{N} c_i^N(a) = c_{osp,s}\left[N_{osp}(a)\delta - R(\gamma - 1) + \beta N\right] \quad (6.12)$$

if $R < N_{osp}(a) \leq N$. The numerators of the two ratios are directly obtained by replacing the first two N_{osp}^{NE} values (a) and (b.1) (worst cases) computed in Theorem 6.1.1. On the other hand, under the socially optimal action profile a_{opt}, exactly R drivers pursue on-street parking space, and, hence, no drivers have to pay the additional cruising cost. The optimal social cost C_{opt} is given by:

$$C_{opt} = \sum_{i=1}^{N} c_i^N(a_{opt}) = c_{osp,s}[min(N,R) + \beta \cdot max(0, N - R)]$$

□

Proposition 6.1.2. *In* $\Gamma(N)$, *the pure PoA is upper-bounded by* $\frac{1}{1-R/N}$ *with* $N > R$.

Proof. The condition is obtained directly from Proposition 6.1.1, when $N > R$. □

Mixed-action equilibrium strategies

We consider *symmetric* mixed-action equilibria since these can be more helpful in dictating practical strategies in real systems (asymmetric mixed-action equilibria are discussed at the end of the section).

Existence: In ([Ashlagi *et al.*, 2006], Theorem 1) it is proven that a unique symmetric mixed equilibrium exists for the broader family of resource selection games with more than two players and increasing cost functions. This is easily shown to hold for the game

$\Gamma(N)$, with $N > R$ and cost functions $w_{osp}(\cdot)$ and $w_{pl}(\cdot)$ that are non-decreasing functions of the number of players.

Derivation: The expected costs of choosing parking spots in curbside and in parking lot, when all other drivers play the mixed action $p = (p_{osp}, p_{pl})$ are given by $c_i^N(pl, p) = c_{pl}$ and

$$c_i^N(osp, p) = \sum_{N_{osp}=0}^{N-1} w_{osp}(N_{osp} + 1)B(N_{osp}; N-1, p_{osp})$$

where $B(N_{osp}; N-1, p_{osp})$ is the Binomial probability distribution with parameters $N-1$ and p_{osp}, for N_{osp} drivers choosing curbside parking. The cost of the symmetric profile where everyone plays the mixed-action p is given by

$$c_i^N(p, p) = p_{osp} \cdot c_i^N(osp, p) + p_{pl} \cdot c_i^N(pl, p) \tag{6.13}$$

We can now postulate the following Theorem.

Theorem 6.1.2. *The game $\Gamma(N)$ has a unique symmetric mixed-action Nash equilibrium $p^{NE} = (p_{osp}^{NE}, p_{pl}^{NE})$, where $p_{osp}^{NE} = 1$, if $N \leq N_0$ and $p_{osp}^{NE} = \frac{N_0}{N}$, if $N > N_0$, with $p_{osp}^{NE} + p_{pl}^{NE} = 1$ and $N_0 \in \mathbb{R}$.*

Proof. The symmetric equilibrium for $N \leq N_0$ corresponds to the pure NE we derived in Theorem 6.1.1. To compute the equilibrium for $N > N_0$ we invoke the condition that equilibrium profiles must fulfil

$$c_i^N(osp, p^{NE}) = c_i^N(pl, p^{NE}) \tag{6.14}$$

namely, the costs of each pure action belonging to the support of the equilibrium mixed-action strategy are equal. Hence, from (6.13) and (6.14) the symmetric mixed-action equilibrium $p^{NE} = (p_{osp}^{NE}, p_{pl}^{NE})$ solves the equation

$$f(p) = -\beta + \sum_{k=0}^{N-1} \left[\gamma - \min\left(1, \frac{R}{k+1}\right) \cdot (\gamma - 1)\right] B(k; N-1, p) = 0 \tag{6.15}$$

A closed-form expression for the equilibrium p_{osp}^{NE} is not straightforward. However, it holds that:

$$\lim_{p \to 0} f(p) = -\beta + 1 < 0 \text{ and } \lim_{p \to 1} f(p) = \delta(1 - \frac{N_0}{N}) > 0 \tag{6.16}$$

and $f(p)$ is a continuous and strictly increasing function in p since

$$f'(p) = \sum_{k=0}^{N-1} \left[\gamma - \min\left(1, \frac{R}{k+1}\right) \cdot (\gamma - 1)\right] B'(k; N-1, p) > \sum_{k=0}^{N-1} B'(k; N-1, p) = 0$$

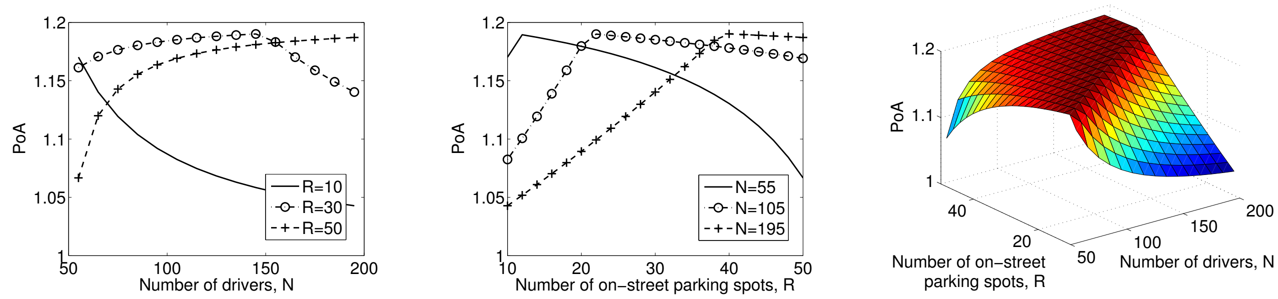
Hence, $f(p)$ has a single solution. It may be checked with replacement that $f(N_0/N) = 0$. □

Asymmetric mixed-action equilibria: In paragraph "Pure equilibrium strategies" in this section, we showed that there may exist asymmetric pure equilibria, when the number of drivers exceeds N_0. In general, the derivation of results for asymmetric mixed-action equilibria is much harder than for either their pure or their symmetric counterparts since the search space is much larger. Moreover, asymmetric mixed-action equilibria have two more undesirable properties: (a) they do not treat all players equally, *i.e.*, different players end up with *a-priori* worse chances to come up with an inexpensive parking spot; (b) their realization in practical situations is much more difficult than that of their symmetric counterparts. Therefore, we focus our analysis and discussion on symmetric equilibria and their (in)efficiency.

6.1.4 Numerical results

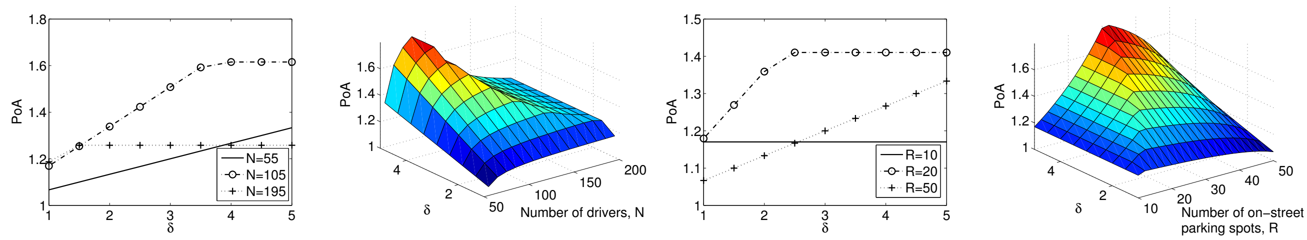
The analysis in Section 6.1.3 suggests that the charging policy for on-street and private parking space and their relative location, which determines the overhead parameter δ of failed attempts for on-street parking space, affect to a large extent the (in)efficiency of the game equilibrium profiles. In the following, we illustrate their impact on the game outcome and discuss their implications for real systems.

For the numerical results we adopt per-time unit normalized values used in the typical municipal parking systems in big European cities[4]. The parking fee for on-street space is set to $c_{osp,s} = 1$ unit whereas the cost of parking lot β ranges in $(1, 16]$ units and the excess cruising cost parameter δ varies within $[1, 5]$ units.



(a) $2D$ PoA(N) (b) $2D$ PoA(R) (c) $3D$ PoA(N, R)

Figure 6.2: Price of Anarchy as a function of the parking demand and supply, under fixed pricing scheme $\beta = 5, \delta = 1$.



(a) $2D$ PoA$(N, \delta), R = 50$ (b) $3D$ PoA$(N, \delta), R = 50$ (c) $2D$ PoA$(R, \delta), N = 55$ (d) $3D$ PoA$(R, \delta), N = 55$

Figure 6.3: Price of Anarchy as a function of the parking demand and supply, under variable cruising cost δ and fixed parking fee $\beta = 5$.

Impact of parking demand and on-street parking supply

An optimal (centralized) mechanism would assign exactly $\min(N, R)$ on-street parking spots to $\min(N, R)$ drivers. If $N \leq R$, in the absence of (central) coordination, all drivers go for the on-street parking space and, trivially, $PoA = 1$. Hereafter, we focus on the more interesting case $N > R$, where a number of drivers end up paying the extra cruising cost $\delta c_{osp,s}$ (Ref. Lemma 6.1.1, Theorem 6.1.1). Under a fixed pricing scheme, this inefficiency depends on N and R. In Figure 6.2, we plot the PoA against N and R ranging in $[55, 195]$ and $[10, 50]$, respectively. The following remarks suggest joint conditions on N and R that result in more efficient parking search.

Varying N or R: For $N \leq N_0$ or, equivalently, for $R \geq \frac{N\delta}{\gamma-1}$, it holds that $\frac{\vartheta PoA}{\vartheta N} > 0$ and $\frac{\vartheta PoA}{\vartheta R} < 0$. Therefore, the PoA is strictly increasing in N and decreasing in R. On the contrary, for $N > N_0$ or $R < \frac{N\delta}{\gamma-1}$, the PoA is strictly decreasing in N and increasing in R, since $\frac{\vartheta PoA}{\vartheta N} < 0$ and $\frac{\vartheta PoA}{\vartheta R} > 0$.

[4] $http://www.city-parking-in-europe.eu/$

When all drivers choose to compete, that is, if $N \leq N_0$ or $R \geq \frac{N\delta}{\gamma-1}$, exactly R drivers pay $c_{osp,s}$, whereas the rest of them, *i.e.*, $N-R$ drivers, pay $\gamma c_{osp,s}$. Thus, under a fixed pricing scheme, the social cost is optimized when the maximum charging cost ($\gamma c_{osp,s}$) is incurred by the minimum possible set of drivers, namely when the parking demand is the lowest possible one ($N = R+1$) or, equivalently, as R is increased so that only one driver fails the competition for the low-cost parking spots. On the other hand, when $N > N_0$ or $R < \frac{N\delta}{\gamma-1}$, R drivers pay $c_{osp,s}$, $N-N_0$ drivers pay $\beta c_{osp,s}$ and N_0-R drivers pay $\gamma c_{osp,s}$. Under the optimal operation of the service, the latter two sets of drivers directly head for space in parking lot. Thus, the efficiency of the uncoordinated parking search is improved as the parking demand increases, making the total cost paid by the $N-N_0$ drivers the most critical factor for the overall social cost and hence minimizing the impact of the total cost paid by the N_0-R drivers due to the lack of coordination. Equivalently, the set of $N_0-R = \frac{R(\beta-1)}{\delta}$ drivers that fail the competition is minimized when the on-street parking capacity becomes the lowest possible one, *i.e.*, $R=1$.

On the other hand, the extra cruising cost δ may change as the result of, for example, an addition of a parking lot closer to the search area or a change in driving conditions. Figure 6.3 displays the PoA against δ and suggests the following trends:

Varying δ: For $N \leq N_0$ or, equivalently, for $\delta \leq \frac{R(\beta-1)}{N-R}$, it holds that $\frac{\vartheta PoA}{\vartheta\delta} > 0$. Therefore, the PoA is strictly increasing in δ. For $\delta > \frac{R(\beta-1)}{N-R}$, we get $\frac{\vartheta PoA}{\vartheta\delta} = 0$. Hence, if δ exceeds $\frac{R(\beta-1)}{N-R}$, PoA is insensitive to changes of the excess cost δ.

For given charging costs and on-street parking capacity, the construction of expensive parking lots in the proximity of the on-street parking area does not work effectively, when the competition is high (Ref. Figures 6.3(a) and 6.3(b) for high N values and Figures 6.3(c) and 6.3(d) for low R values). Otherwise, under medium or low competition, there is a monotonic trend that suggests, if possible, to decrease the distance between the two options to increase the efficiency of the parking search process. Overall, changes in this distance and, hence, the cruising cost are meaningless for high δ values, over $\frac{R(\beta-1)}{N-R}$. In this case, when $N > N_0$, $N_0 - R = \frac{R(\beta-1)}{\delta}$ drivers pay the extra cruising cost and end up in a parking lot together with the $N-N_0$ drivers that head directly for this kind of parking space. Thus, the increase of cruising cost has a double-edge effect. On the one hand, drivers are discouraged from competing so that fewer end up paying the cruising overhead. On the other hand, failing the competition for on-street parking costs more. In addition, the total number of drivers that incur the more (less) expensive parking fee is $N - R$ (R), irrespective of the exact δ value. As a result, changes in δ do not affect either the total cost spent for space in the on-street or parking lot facilities, or the aggregate cruising overhead. Thus, the social cost can be decreased by locating a parking lot in the proximity of the on-street parking area so that the additional travel distance is reduced to the point of bringing the excess cost δ below $\frac{R(\beta-1)}{N-R}$.

Although low PoA values denote high efficiency in the parking search process, they are not always coupled with low *absolute* social costs. For instance, this may happen under very intense competition, namely, under high parking demand for very low curbside capacity (*i.e.*, Ref. Figure 6.2 at $N = 195$, $R = 10$). In the following, we study the sensitivity of the social cost to the parking demand and supply, and the prices charged for the two types of parking facilities.

Impact of pricing scheme

Figure 6.4 plots the social costs $C(N_{osp})$ under pure (Eq. 6.11, 6.12) and $C(p_{osp})$ under mixed-action strategies as a function of the number of competing drivers N_{osp} and competition probability p_{osp}, respectively, where

$$C(p) \quad = \quad c_{osp,s} \sum_{n=0}^{N} \binom{N}{n} p^n (1-p)^{N-n} [min(n, R) + max(0, n-R)\gamma + (N-n)\beta] \qquad (6.17)$$

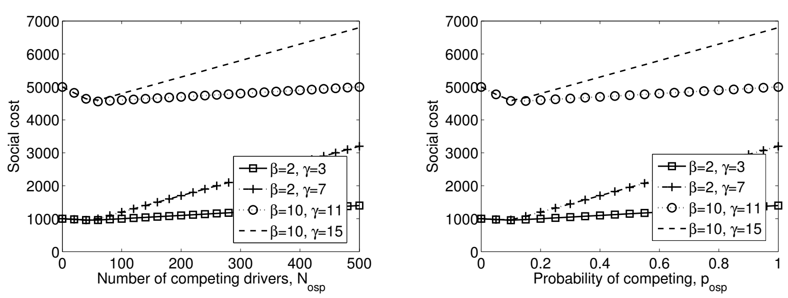
Figure 6.4 motivates two remarks. First, the social cost curves for pure and mixed-action profiles have the same shape. This comes as no surprise since, for given N, any value for the expected number of competing players $0 \leq N_{osp} \leq N$ can be realized through an appropriate choice of the symmetric mixed-action profile p. Second, the cost is minimized when the number of competing drivers is equal to the number of on-street parking spots. The cost rises when either the competition exceeds the available on-street parking capacity or the drivers are overconservative in (and refrain more than they should from) competing for on-street parking. In both cases, the drivers pay the penalty for the lack of coordination in their decisions. The deviation from the optimal case grows faster with increasing price differential between the on-street spots and the space in parking lot (*i.e.*, β) or the distance between the on-street and parking lot facilities (*i.e.*, δ).

If $N > R$, in the worst-case equilibrium (*i.e.*, the equilibrium state with the maximum number of competing drivers and, hence, the maximum social cost among all equilibria), the number of drivers that actually compete for on-street parking spots exceeds the real curbside parking capacity by a factor which is a function of β and γ (equivalently, δ) (Ref. Lemma 6.1.1 and Theorem 6.1.1). This inefficiency is captured in the PoA plots in Figures 6.5(a) and 6.5(b) for β and δ ranging in $[1.1, 16]$ and $[1, 5]$, respectively. The plots illustrate the following trends:

Varying β: For $N \leq N_0$ or, equivalently, for $\beta \geq \frac{\delta(N-R)+R}{R}$, it holds that $\frac{\vartheta PoA}{\vartheta \beta} < 0$ and therefore, the PoA is strictly decreasing in β. On the contrary, for $\beta < \frac{\delta(N-R)+R}{R}$, the PoA is strictly increasing in β, since $\frac{\vartheta PoA}{\vartheta \beta} > 0$.

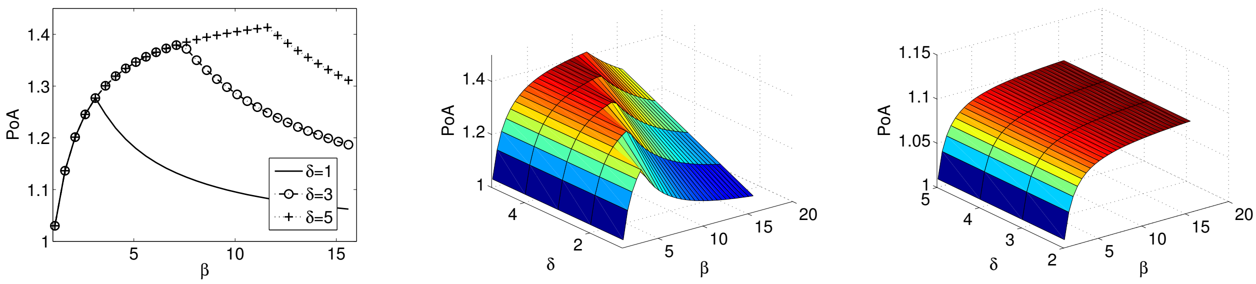
Practically, the equilibrium strategy emerging from this kind of assisted parking search behavior can approximate the optimal coordinated mechanism, provided that the operation of parking lots properly accounts for the drivers' preferences and estimates of the typical parking demand and supply. More specifically, if, as part of the pricing policy, the fee of parking lot is less than $\frac{\delta(N-R)+R}{R}$ times the cost of on-street parking, then the social cost in the equilibrium profile approximates the optimal social cost as the price differential between on-street and parking lots decreases. This result is in line with the statement in [Larson & Sasanuma, 2010], arguing that "*price differentials between on-street and off-street parking should be reduced in order to reduce traffic congestion*".

Note that the PoA metric also monotonically decreases for high values of the parking lot fee, specifically when the parking operator desires to gain more than $\frac{\delta(N-R)+R}{R}$ times



(a) Pure-action profiles (b) Symmetric mixed-action profiles

Figure 6.4: Social cost for $N = 500$ drivers when N_{osp} drivers compete (a) or when all drivers decide to compete with probability p_{osp} (b), for $R = 50$.



(a) $2D$ $\texttt{PoA}(\beta), R = 160$ (b) $3D$ $\texttt{PoA}(\beta, \delta), R = 160$ (c) $3D$ $\texttt{PoA}(\beta, \delta), R = 50$

Figure 6.5: Price of Anarchy for $N = 500$ and varying R, under different pricing schemes.

the cost of on-street parking, towards a bound that depends on the excess cost δ. Nevertheless, these operating points correspond to high absolute social cost, *i.e.*, the minimum achievable social cost is already unfavorable due to the high fee paid by the $N - R$ drivers that use space in parking lots (Ref. Figure 6.4, large β). However, there are instances, as in the case of $R = 50$ (Ref. Figure 6.5(c)), where the value $\frac{\delta(N-R)+R}{R}$ corresponds to a non-realistic (too large) option for the cost of the space in parking lots, already for $\delta > 1$. Thus, in contrast with the previous case, the PoA only improves as the cost for parking lot decreases.

6.1.5 Trading public parking space

In previous sections of Chapter 6, we have formulated and studied the game that arises from the conventional parking search behavior under a fixed parking cost model. In this section, we ask whether and how much can centralized parking assistance systems combined with more aggressive pricing schemes improve the outcome for both the on-street parking space operator *and* the drivers. More specifically, we propose different *auction* mechanisms for the assignment of on-street parking space. In fact, auction mechanisms have been used under various concepts in different disciplines. In network science, research efforts on node transactions devise auction-based schemes to address the challenge of resource (energy, bandwidth and storage space) sharing among multiple networking users [Iosifidis & Koutsopoulos, 2010]. The study presented in the following sections approaches the process of parking space selection in urban environments as a network resource allocation problem. Indeed, the auctioning of parking spots is a promising key-idea that has only recently started to gain interest[5]. The number of available auctioned spots is announced to the drivers, who submit their bids for them, expressing what they are willing to pay for a parking spot in that particular occasion with complete information for the overall parking demand. As central mechanisms, auctions determine who gets a parking spot and at what cost, saving the additional expenses of cruising in the non-assisted, uncoordinated parking search, while unleashing the conventional buying rules in public parking operation. Indeed, in the following sections we show that, as expected, auctions always raise the revenue of the public parking operator since they adapt payments to what drivers are willing to pay for on-street parking space. Nevertheless, this does not come necessarily at the expense of drivers, who save the cruising cost and find the auctioning system less expensive on average, under various combinations of parking demand and pricing policies.

6.1.6 The parking spot selection game

In previous sections we formulate the collective decision-making on parking space selection as an instance of the strategic *resource selection games*, whereby N players (*i.e.*, drivers) compete against each other for a finite number of S on-street public parking spots[6]. More specifically, drivers who decide to compete for the cheaper on-street public parking space undergo the risk of not being among the S winner-drivers to get a public spot. In this case, they have to eventually resort to private parking space (parking lot), only after wasting extra time and fuel (plus patience supply) on the failed attempt.

Recall by Section 6.1.3 that the resulting aggregate drivers' cost C_g under the equilibrium states of the game amounts to

$$C_g \equiv C(N) = c_{osp,s}\left[N\gamma - \min(N,S)(\gamma-1)\right], \text{ if } N \leq N_0 \text{ and}$$

$$C_g \equiv C(N_0) = c_{osp,s}\beta N, \text{ if } N > N_0 \tag{6.18}$$

which, for $N > S$, exceeds the optimal cost value $C_{g,opt} \equiv C(S) = c_{osp,s}\left[S + \beta(N-S)\right]$, the ratio $C_g/C_{g,opt}$ expressing the "price of anarchy" of the game and quantifying the penalty of lack of coordination across the drivers. On the other hand, the revenue R_g for

[5] $https://web.chapman.edu/parking/$

[6] In previous sections the number of on-street public parking spots is denoted by R. Herein the notation is changed to avoid misleading with other indices that are introduced in the following sections.

the public parking space operator becomes

$$R_g \equiv R(N) = \min(N, S)c_{osp,s}, \text{ if } N \leq N_0 \text{ and}$$

$$R_g \equiv R(N_0) = Sc_{osp,s}, \text{ if } N > N_0 \tag{6.19}$$

6.1.7 The auction-based parking allocation

Parking assistance schemes can help overcome the inefficiencies that result from the uncoordinated selfish behavior of drivers. These systems rely on wireless communication systems for delegating the parking space assignment task to a central server, which: (a) gets informed about the status of on-street public parking spots; (b) collects the requests and bids of drivers for parking space; and (c) determines who is assigned a public parking spot and at what cost, and notifies the drivers. In the sequel, we propose and analyze an *auction-based* system for the management of the public parking space drawing on the theory of *multi-unit auctions with single-unit demand* [Krishna, 2010].

In particular, N drivers (buyers) bid in a single auction for no more than one of S spare on-street public parking spots (non-divisible, physically identical goods). Drivers (bidders) are assumed to be symmetric: their valuations of parking spots are i.i.d RVs continuously distributed in the same interval $[v_{min}, v_{max}]$ and $F_V(), f_V()$ are their cumulative distribution and probability density functions, respectively. An appropriate choice for this interval is $[c_{osp,s}, c_{pl}]$. In other words, the operator of the public parking resources will typically impose a threshold on the selling price, *i.e.*, a reserve price, that will be no less than the on-street public parking spot price under fixed cost. Drivers, in turn, will account for this lower bound in their bidding decisions, while they will not be willing to pay more than what the private parking operator charges. Although each driver is aware of the distribution of his competitors' valuations, upon bidding, he can only know the realization of his own RV (*i.e.*, his bid). Bidders are also assumed to be risk-neutral, *i.e.*, they seek to maximize their expected profit from bidding, and free of budget constraints [Krishna, 2010].

In general, if $\mathcal{N} = \{1, ..., N\}$ with N > 1 is the set of drivers who seek parking space, a selling auction mechanism consists of three components: the set of *bids* $\mathcal{B}_i$ (increasing functions of valuations) for each driver $i \in \mathcal{N}$; an *allocation rule* $\pi : \mathcal{B}_1 \times ... \times \mathcal{B}_N \to \mathcal{D}(\mathcal{N})$, where $\mathcal{D}$ is the set of probability distributions over $\mathcal{N}$ determining who are awarded parking spots, and a *payment rule* $p : \mathcal{B}_1 \times ... \times \mathcal{B}_N \to \mathbb{R}^N$ for the selling price of each allocated spot. Out of the variety of options, hereafter we consider the three most thoroughly analyzed implementations, the *uniform-price*, *discriminatory-price* and *Vickrey* auctions. All three auction formats are *standard* in that they assign the parking spots to the users that submit the highest bids. Under single-unit demand and symmetric risk-neutral bidders, all three auctions are also *efficient* in the sense that they assign the parking spots to the users that value them most[7]. In other words, they induce equilibrium states, whereby the top-bids are submitted by the drivers that value the parking spots most. On the other hand, whereas all three auctioning mechanisms follow the same allocation rule, they differ in the payment rule they apply.

- Under the *uniform-price auction* (*upa*) and the *Vickrey auction* (*va*), all parking spots are sold at the same price, the "market-clearing price", which is equal to the first losing bid, *i.e.*, the $(S+1)^{th}$ highest over all drivers' bids.

- Under the *discriminatory-price auction* (*dpa*), the winning drivers pay an amount equal to their individual bids.

In the sequel, we first define the equilibrium bidding strategies when the drivers are aware of the number of competitors; for instance, because the parking assistance system provides them with this information. We then discuss their effectiveness from the bidders' and operator's perspective, given that the auctioned parking spots do not suffice to fulfil the entire parking demand. Otherwise, it is trivial to show that the centralized auction's and the distributed practice's outcomes (*i.e.*, parking spot allocation and winners' payments) coincide.

[7]In general, reserve prices introduce a positive probability that the auctioned object remains unsold impacting on the efficiency of the mechanism. Herein, however, this event is excluded, since drivers' bids range in $[c_{osp,s}, c_{pl}]$.

Uniform-price and Vickrey auction

Both the single-unit demand uniform-price and Vickrey auction mechanisms come under the broader category of incentive-compatible (truthful) mechanisms in that the equilibrium strategy, $\beta(v)$ for the drivers is to bid their real valuations v,

$$\beta_{upa}(v) = \beta_{va}(v) = v \tag{6.20}$$

For $N > S$, the conditional expectation of the driver's payment for a given valuation v is

$$\begin{aligned} p_{upa}(v) = p_{va}(v) &= Pr(V_{(N-S,N-1)} < v)E\{V_{(N-S,N-1)}|V_{(N-S,N-1)} < v\} \\ &= \int_{v_{min}}^{v} y f_{V_{(N-S,N-1)}}(y)dy \end{aligned} \tag{6.21}$$

where $E\{\cdot\}$ is the expectation operator and $V_{(k,n)}$ is the k^{th} order statistic of the n competing valuations (*i.e.*, the k^{th} smallest out of n samples drawn from RVs $V_1, ..., V_n$) with probability density function $f_{V_{(k,n)}}(y) = \{B(k, n-k+1)\}^{-1}\{F_V(y)\}^{k-1}\{1-F_V(y)\}^{n-k} f_V(y)$, where $B(\cdot,\cdot)$ stands for the complete Beta function [Balakrishnan & Rao, 1998].

Therefore, the unconditional (*ex ante*) expectation of the driver's payment is given by

$$\begin{aligned} p_{upa} = p_{va} &= \int_{v_{min}}^{v_{max}} p_{upa}(v) f_V(v)dv \\ &= \frac{S}{N} E\{V_{(N-S,N)}\} \end{aligned} \tag{6.22}$$

while the *expected* revenue of the public parking operator becomes

$$\begin{aligned} R_a \equiv E\{R_{upa}\} = E\{R_{va}\} &= N p_{va} \\ &= S E\{V_{(N-S,N)}\} \end{aligned} \tag{6.23}$$

and is collected from the drivers with the top S bids.

On the other hand, drivers with the $N - S$ lowest bids resort to private parking facilities, all paying the fixed cost $v_{max} = c_{pl}$. Thus, the *expected* aggregate drivers' cost turns out to be

$$C_a \equiv E\{C_{upa}\} = E\{C_{va}\} = S E\{V_{(N-S,N)}\} + (N - S)v_{max} \tag{6.24}$$

For $N \leq S$, it is trivial to show that,

$$p_{upa} = p_{va} = v_{min}$$

$$R_a \equiv E\{R_{upa}\} = E\{R_{va}\} = Nv_{min} \quad (6.25)$$

$$C_a \equiv E\{C_{upa}\} = E\{C_{va}\} = Nv_{min} \quad (6.26)$$

Discriminatory-price auction

The discriminatory-price auction mechanism is the multi-unit counterpart of the single-unit *first-price* auctions. Vickrey, already in [Vickrey, 1962], showed that the expected revenue for all multi-unit auctions with single-unit demand featuring the same allocation rule is the same, a demonstration of the *revenue equivalence principle*. Therefore,

$$p_{dpa}(v) = p_{upa}(v) = p_{va}(v),$$

$$R_a = E\{R_{dpa}\} \text{ and } C_a = E\{C_{dpa}\} \quad (6.27)$$

For $N > S$, the equilibrium bidding strategy equals

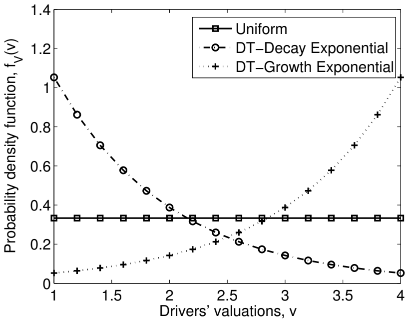
$$\beta_{dpa}(v) = E\{V_{(N-S,N-1)} | V_{(N-S,N-1)} < v\} = \frac{1}{F_{V_{(N-S,N-1)}}(v)} \int_{v_{min}}^{v} y \cdot f_{V_{(N-S,N-1)}}(y) dy \quad (6.28)$$

Otherwise,

$$\beta_{dpa}(v) = v_{min} \quad (6.29)$$

6.1.8 Numerical results

In Sections 6.1.6 and 6.1.7 we have outlined the analytical formulations of the two main practices in managing on-street public parking space and derived the equilibrium behaviors they induce. Under conventional uncoordinated search for on-street public parking, drivers have the chance to pay a lower parking fee when they succeed in getting a public parking spot. However, they run the risk of paying a normalized per-hour



Distribution of drivers' valuations	$f_V(v)$
Uniform	$\frac{1}{v_{max}-v_{min}}$
Doubly-truncated *decay* exponential	$\frac{e^{-v}}{e^{-v_{min}}-e^{-v_{max}}}$
Doubly-truncated *growth* exponential	$\frac{e^{v}}{e^{v_{max}}-e^{v_{min}}}$

Figure 6.6: Probability density functions for drivers' valuations of public parking spots, $c_{osp,s} = 1$, $\beta = 4$.

cruising cost $\delta c_{osp,s}$, on top of the private more expensive parking fee, when they fail to seize a public parking spot and, eventually, drive to a private parking lot. On the other hand, the auctioning of public parking places exploits the diverse drivers' personalities and level of interest for parking and allows for higher payments for public parking space, while saving the "price of anarchy" paid in the absence of coordination as under the aforementioned game formulation. In this section, we explore how different pricing schemes and the drivers' personalities and interest in parking (as captured in their valuation distributions) affect (a) the revenue achievable by the public parking service operator; and (b) the resulting per-driver expected cost of the parking service, under the two radically different paradigms of parking space management.

For the pricing policy, we adopt values used in the municipal parking system in the city of Athens[8]. In particular, $c_{osp,s} \leq 2$ €, and $\beta \leq 7$, for 60-minute period. The cruising cost parameter δ is allowed to range in $(0, 10]$. On the other hand, we consider three alternatives for the distribution of the drivers' valuations, $f_V(v)$. In all three of them, V lies within an interval $[v_{min}, v_{max}] = [c_{osp,s}, \beta c_{osp,s}]$, yet the mass of the distribution is spread differently over this interval (Ref. Figure 6.6):

Doubly-truncated decay exponential valuations: This instance of valuation function corresponds to scenarios, whereby drivers are not willing to pay high for a parking spot. It could model driving in the center during leisure hours, where the acquisition of a parking spot is less urgent. The moments of the $(N - S)^{th}$ order statistic can be computed numerically through the recurrence relations derived by Joshi in [Joshi, 1979].

[8] $http://www.cityofathens.gr/en/city-athens-municipal-parking-system-0$

Doubly-truncated growth exponential valuations: The mass in this valuation distribution is concentrated towards the rightmost values of its support. Compared with the doubly-truncated decay exponential distribution, this one can model driving in the city center during busy hours for business purposes.

Uniform valuations: This is the intermediate scenario, where the valuation of parking spots for individual drivers may lie anywhere in $[v_{min}, v_{max}]$ equiprobably. In this case, the expected value of the $(N-S)^{th}$ order statistic can be also computed through the mean value of the generalized Beta distribution $f(v; N-S, S+1)$, for $v \in [v_{min}, v_{max}]$, that is,

$$E\{X_{N-S,N}\} = v_{min} + \frac{N-S}{N+1}(v_{max} - v_{min}) \tag{6.30}$$

We consider medium to high parking demand levels (up to 160 drivers) and limited public parking supply ($S = 20$ spots) during the time window over which the parking requests are issued.

Figures 6.8(a) and 6.8(b) plot the aggregate drivers' cost as a function of the parking demand intensity (*i.e.*, number of drivers, N), under the distributed parking spot selection game and centralized parking auctioning system, respectively. In line with intuition, the aggregate drivers' cost increases with the parking demand under both parking allocation approaches. Under the distributed game (Ref. Figure 6.8(a)), the aggregate drivers' cost grows as the penalty cost for cruising between the public and private parking facilities (*i.e.*, δ) increases. Under the auctioning system (Ref. Figure 6.8(b)), the valuation distribution induces the following ordering of the aggregate drivers' costs

$$C_a^g \geq C_a^u \geq C_a^d \tag{6.31}$$

where the superscripts g, u and d indicate quantities derived under growth exponential, uniform and decay exponential valuations, respectively.

Indeed, we note that there are first-order stochastic dominance relationships between the three cumulative distribution functions, that is

$$F_V^g(v) \prec F_V^u(v) \prec F_V^d(v) \tag{6.32}$$

as can be readily seen in the following Figure.

In addition, the cumulative distribution function of the $(N-S)^{th}$ order statistic is

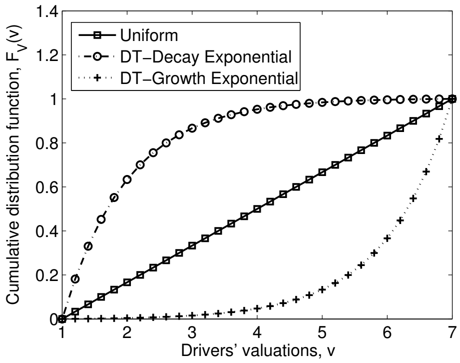


Figure 6.7: Stochastic ordering of the three valuation functions $F_V(v)$, ($v_{min} = 1$, $v_{max} = 7$).

written [Balakrishnan & Rao, 1998]

$$F_{(N-S,N)}(v) = \int_0^{F(v)} \frac{N!}{S!(N-S-1)!} t^{N-S-1}(1-t)^S dt \tag{6.33}$$

Therefore, the first-order dominance relationships in the drivers' valuations as given in (6.32) is inherited by their $(N-S)^{th}$ order statistics. As a result it holds that,

$$F^g_{V_{(N-S,N)}}(v) \prec F^u_{V_{(N-S,N)}}(v) \prec F^d_{V_{(N-S,N)}}(v) \tag{6.34}$$

Finally, the ordering in (6.31) emerges directly when relating the expected values of the valuations to their cumulative distribution functions through a general relation concerning non-negative RVs [Ross, 1998],

$$E\{X_{(N-S,N)}\} = \int_0^{\infty} \left(1 - F_{(N-S,N)}(x)\right) dx \tag{6.35}$$

On the parking operator's side, the revenue from auctioning the public parking spots exceeds that under the fixed-cost distributed parking service provision (Ref. Figure 6.8(c)). This is expected since the same number of drivers park in public space under both practices and these drivers pay *at least* $c_{osp,s}$ in the first case, while they pay *exactly* $c_{osp,s}$ in the latter case. The operator exploits the differentiated drivers' interest in the lower-cost public parking space and adapts the payments to what they are willing to pay for it. Thus, the revenue under the three valuation distributions is strictly ordered, with the growth exponential valuations inducing the highest revenue values and the decay exponential valuations the lowest values.

On the drivers' side, the picture is mixed as some drivers pay more and some pay

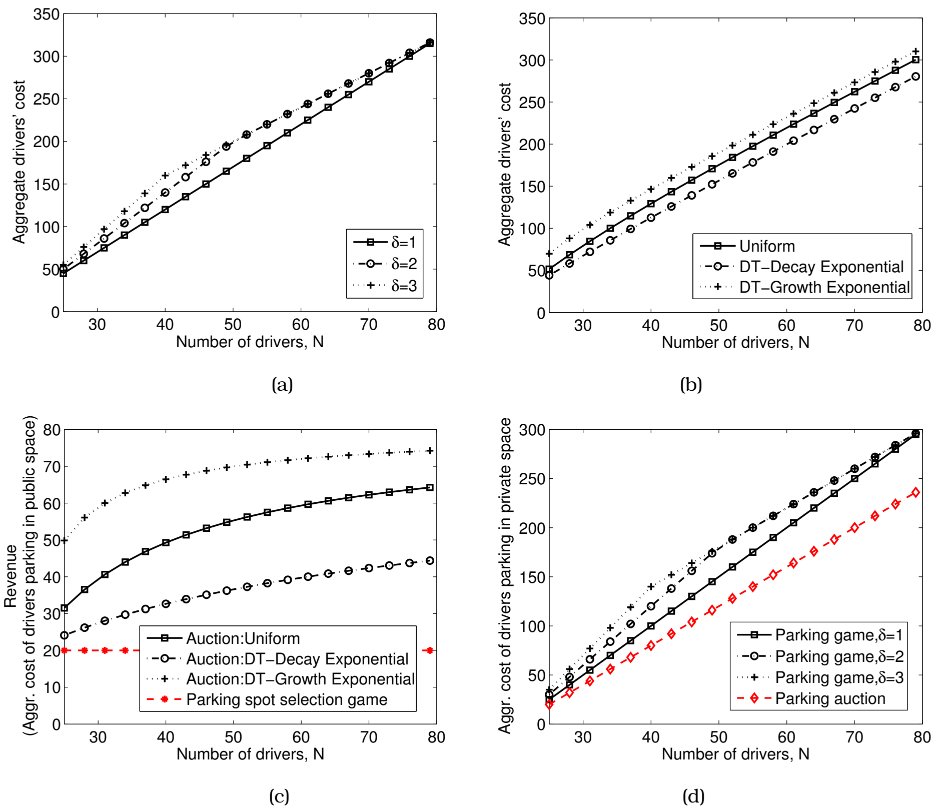


Figure 6.8: Aggregate drivers' costs and revenues as functions of the number of drivers, $c_{osp,s} = 1, \beta = 4$: (a) Aggregate drivers' cost under the parking spot selection game (for $\delta \in \{1, 2, 3\}$); (b) Aggregate drivers' cost under the auctioning system (for the three valuation distributions); (c) Operator's revenue under the auctioning system and the parking spot selection game; (d) Aggregate cost of the drivers parking in private parking space under the auctioning system and the parking spot selection game.

less for public parking space under the auctioning system. Specifically, on one hand, the aggregate cost of the drivers parking in public space (*i.e.*, operator's revenue) under the auctioning system exceeds that under the parking spot selection game, as Figure 6.8(c) illustrates. On the other hand, the aggregate cost of the drivers parking in private space under the auctioning system is lower than that under the parking spot selection game, as shown in Figure 6.8(d). This is due to the fact that under the auctioning system all bidders that are not awarded public parking spots enjoy the benefits from the coordination of drivers' parking spot selection, avoid the "price of anarchy" and end up paying the same fixed cost c_{pl}, irrespective of their valuations.

Overall, when the excess cost (in terms of fuel and time wasted on cruising) due to the lack of coordination in the distributed parking game, exceeds the excess cost from bidding *over* the fixed minimum cost $c_{osp,s}$ (collected by the operator), *both* the drivers and the operator are doing better under the auctioning system. Otherwise, the distributed parking spot selection represents a less expensive practice for the drivers. In the remainder of this section, we compare the per-driver cost under the two parking space management practices and explore the conditions on the number of drivers and the cruising, public and private costs under which the aforementioned win-win situation emerges in the auctioning practice.

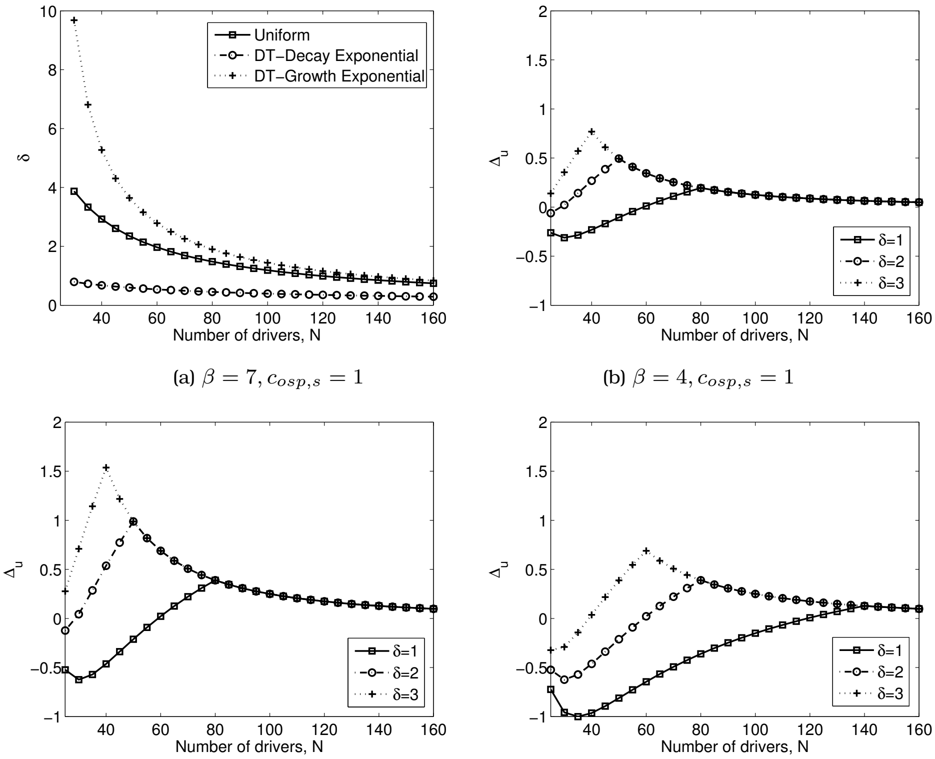
Let Δ denote the difference between the per-driver cost under the conventional distributed parking spot selection game, C_g/N, and its counterpart under the centralized auction-based allocation, C_a/N, that is,

$$\Delta = \frac{1}{N}(C_g - C_a) \tag{6.36}$$

For $\Delta > 0$ ($\Delta < 0$), this difference expresses the *excess* cost that drivers pay in the parking spot selection game (auctioning system) compared to the auctioning system (parking spot selection game). Drivers are indifferent over the two approaches for $\Delta = 0$.

Case $N > N_0$: By equations (6.18) and (6.36) we have that

$$\begin{aligned} \Delta &= \frac{1}{N}\left(N\beta c_{osp,s} - C_a\right) \\ &= \frac{1}{N}\left[N\beta c_{osp,s} - \left[R_a + (N-S)\beta c_{osp,s}\right]\right] \\ &= \frac{S}{N}\left(\beta c_{osp,s} - E\{V_{N-S,N}\}\right) > 0 \end{aligned} \tag{6.37}$$



(a) $\beta = 7, c_{osp,s} = 1$

(b) $\beta = 4, c_{osp,s} = 1$

(c) $\beta = 4, c_{osp,s} = 2$

(d) $\beta = 7, c_{osp,s} = 1$

Figure 6.9: (a): Values of cruising cost that zero difference Δ for different number of drivers; (b), (c), (d): Difference Δ_u as a function of the number of drivers, under various pricing schemes.

since the per-spot expected payment $E\{V_{N-S,N}\}$ is strictly smaller than the cost of private parking space. Therefore, for $N > N_0$, with $N_0 = \frac{S(\gamma-1)}{\delta}$, drivers are always better off with the auctioning system. Consequently, if the demand is high enough, win-win situations always emerge under the auctioning practice.

Case $N \leq N_0$: Unlike the first case, when $N \leq N_0$ (*i.e.*, $\delta \leq \frac{S(\beta-1)}{N-S}$) the picture is not clear from the drivers' perspective. By equations (6.18) and (6.36) we have that

$$\Delta = \frac{1}{N}\left[c_{osp,s}[N\gamma - S(\gamma-1)] - C_a\right] \tag{6.38}$$

Therefore, the two parking assignment options can be equivalent or either of them prevail. In particular, the two parking assignment options become equivalent when

$$\delta = \frac{1}{N-S}\left[\frac{C_a}{c_{osp,s}} + S(\beta-1) - N\beta\right] \tag{6.39}$$

The cruising cost that achieves equivalence is plotted in Figure 6.9(a) as a function of the parking demand. By equation (6.39) and as shown in Figure 6.9(a), the equivalence is possible by decreasing (increasing) the cruising cost as the parking demand increases (decreases). In addition, the higher the drivers' valuations are, the higher revenue the operator gains, the higher the aggregate drivers' cost the auctioning system induces and, finally, the more the cruising between the area of public and private parking should cost to counterbalance the higher payments of drivers under the auctioning system. This causal relation between valuations and cruising cost parameter is clearly seen in Figure 6.9(a).

In order to proceed further and identify conditions under which the win-win situations emerge (*i.e.*, $\Delta > 0$), we need a specific valuation distribution to consider. In the sequel, we study the difference $\Delta_u = \frac{1}{N}(C_g - C_{a,u})$ between the induced *per-driver* cost under the parking spot selection game and that under the auctioning system with uniformly distributed drivers' valuations. By equations (6.18), (6.24) and (6.30), with $[v_{min}, v_{max}] = [c_{osp,s}, \beta c_{osp,s}]$, the difference Δ_u is

$$\Delta_u = \begin{cases} c_{osp,s}\frac{(N-S)}{N}\left[\delta - (\beta-1)\frac{S}{N+1}\right], \text{if } N \leq N_0 \\ c_{osp,s}(\beta-1)\frac{S(S+1)}{N(N+1)}, \text{if } N > N_0 \end{cases} \quad (6.40)$$

As Figures 6.9(b), (c), (d) and equation (6.40) suggest, the shape of Δ_u function is primarily determined by the relation between the number of drivers N and the number $N_0 = \frac{S(\gamma-1)}{\delta}$. The turning point at $N = N_0$ is shifted to the left as (a) the public parking capacity, S, decreases; or (b) the cruising cost, δ, increases; or (c) the cost of private parking space, β, drops.

Impact of number of drivers: For given public parking capacity and charging parameters and if $N > N_0$, we have already shown that drivers always prefer the auctioning system (*i.e.*, $\Delta_u > 0$). However, as Figures 6.9(b), (c) and (d) also illustrate, Δ_u approaches zero as the demand increases which suggests that the auctioning system will have marginal advantage, irrespective of the applied charging scheme. Indeed, the difference Δ_u is strictly decreasing with N since,

$$\frac{\vartheta \Delta_u}{\vartheta N} = -c_{osp,s}(\beta-1)\frac{S(S+1)(2N+1)}{[N(N+1)]^2} < 0 \quad (6.41)$$

On the contrary, under lower parking demand ($N \leq N_0$), no scheme dominates. Drivers end up paying less on average under the auctioning scheme only if $\frac{S(\beta-1)}{\delta} - 1 < N \leq N_0$.

Impact of cruising, private and public parking costs: For given parking demand and supply, Δ_u increases with the cruising cost, δ, as shown in Figures 6.9(b), (c), (d) and captured in equation (6.42),

$$\frac{\vartheta \Delta_u}{\vartheta \delta} = \begin{cases} c_{osp,s}\frac{(N-S)}{N} > 0, \text{if } \delta \leq \frac{S(\beta-1)}{N-S} \\ 0, \text{if } \delta > \frac{S(\beta-1)}{N-S} \end{cases} \quad (6.42)$$

The dependance of Δ_u from the private parking cost, β, can be analyzed from equation (6.43). Namely, Δ_u increases with β under high parking demand (*i.e.*, $N > N_0$ or equivalently $\beta < 1 + \frac{\delta(N-S)}{S}$), thus motivating more drivers to compete for the scarce on-street parking space and increasing the "price of anarchy" of the uncoordinated parking search. However, under low-to-medium parking demand (*i.e.*, $N \leq N_0$ or equivalently $\beta \geq 1 + \frac{\delta(N-S)}{S}$), any increase in β raises the payments in the auctioning system and hence, reduces the advantage of saving the cruising cost. This trend is also shown in Figures 6.9(b), (d).

$$\frac{\vartheta \Delta_u}{\vartheta \beta} = \begin{cases} c_{osp,s}\frac{-S(N-S)}{N(N+1)} < 0, \text{if } \beta \geq 1 + \frac{\delta(N-S)}{S} \\ c_{osp,s}\frac{S(S+1)}{N(N+1)} > 0, \text{if } \beta < 1 + \frac{\delta(N-S)}{S} \end{cases} \quad (6.43)$$

Finally, by equation (6.44) we infer that Δ_u increases as the public parking gets more expensive (cheaper), while the distance between public and private parking is significant (close). Namely, drivers benefit from the auctioning system if the cruising cost outweighs the cost of bidding over a higher reserve price. This effect is also shown in Figures 6.9(b), (c).

$$\frac{\vartheta \Delta_u}{\vartheta c_{osp,s}} = \begin{cases} (\beta-1)\frac{S(S+1)}{N(N+1)} > 0, \text{if } \delta > \frac{S(\beta-1)}{N-S} \\ \frac{(N-S)}{N}\left[\delta - (\beta-1)\frac{S}{N+1}\right] \geq 0, \text{if } \frac{S(\beta-1)}{N+1} \leq \delta \leq \frac{S(\beta-1)}{N-S} \\ \frac{(N-S)}{N}\left[\delta - (\beta-1)\frac{S}{N+1}\right] < 0, \text{otherwise} \end{cases} \quad (6.44)$$

6.2 Impact of bounded rationality

6.2.1 Introduction

In the emerging networking environments the behavior of the end-user node, expressed through his social interests and interaction with the environment, affects in a great scale the performance of the network operations and services. On top of that, the self-awareness of human agents that, in many cases, undertake the operation of the networking nodes, impacts on the way some networking functionalities work. The self-awareness refers to the ability to manage one's own thoughts and behavior and to act and respond to stimuli and depends on the innate human rationality constraints together with cognitive biases.

Therefore it is of critical importance to assess how cognitive heuristics/biases in human behavior and especially in the decision-making process, affect the performance of ICT systems/applications. Following the analysis in Section 6.1, the prime assumption in this assessment is that human activity takes place within a fairly autonomic networking environment where each element runs a service resource selection task. User-nodes are typically self-owned and managed and there is no central entity orchestrating them. Therefore, their behavior and actions are not controllable and may well be in conflict with those of others. Indeed, in general, users, driven by self-oriented interests and objectives, act as benefit maximizers. In a second assumption, the resources are not adequate to satisfy demand, raising competition effects between the users.

The maximization of user benefit under perfect and real-time information about the dynamic characteristics of the environments, as described in Section 6.1, is a clearly unrealistic assumption for individuals' decision-making. In this section, we iterate on several expressions of *bounded rationality* in decision-making. This is an umbrella term for different deviations from the fully rational paradigm: incomplete information about environment and other people's behavior, time, computational and processing constraints, and cognitive biases in assessing/comparing alternatives. Experimental work shows that, practically, people exhibit such bounded rationality symptoms and rely on simple rules of thumb (heuristic cues) to reach their decisions in various occasions and tasks. Overall, we have identified the following instances of bounded rationality as worth exploring and assessing in the context of the resource selection task:

Incomplete information about the demand - The most apparent deviation from the perfect information norm relates to the amount of information agents have at their disposal. As two distinct variations hereby, we consider probabilistic (stochastic) information and full uncertainty.

The four-fold pattern of risk aversion - Particular experimental data show that human decisions exhibit biases of different kinds, in comparing alternatives. For instance, a huge volume of experimental evidence confirms the fourfold pattern of risk attitudes, namely, people's tendency to be risk-averse for alternatives that bring gains and risk-prone for alternatives that cost losses, when these alternatives occur with high probability; and the opposite risk attitudes for alternatives of low probability [Tversky & Kahneman, 1992].

Own-payoff effects - This is another type of bias that was spotted in the context of experimentation with even simple two-person games, such as the generalized matching pennies game. Theoretically, in these matching pennies games, a change in a player's own payoff that comes with a particular strategy/choice, must not affect that player's choice probability. However, people's interest for a particular strategy/choice is shown to increase as the corresponding payoff gets higher values. This behavior makes choice probabilities range continuously within 0 and 1 and not jump from 0 to 1 as soon as the corresponding choice gives the highest payoff. This bias gives further credit to Simon's early arguments ([Simon, 1955], [Simon, 1956]) that humans are satisficers rather than maximizers, *i.e.*, that they are more likely to select better choices than worse choices, in terms of the utility that comes with them, but do not necessarily succeed in selecting the very best choice.

Heuristic reasoning - Cognitive science suggests that people draw inferences (*i.e.*, predict probabilities of an uncertain event, assess the relevance or value of incoming information *etc.*), exploiting simple heuristic principles.

In the following sections, all these effects are incorporated in distinct decision-making analytical models. We account for symmetric scenarios whereby the entire population exhibits the same instance of bounded rationality and the knowledge of this deviation from full rationality is common among individuals.

6.2.2 Deviations from full rationality

In this section we study the decision-making process under four levels of agents' rationality which result in difference degrees of responsiveness to specific price differentials between low-cost and expensive resources. In particular, we describe (qualitatively) four elements of competitive networking resource selection settings, consisting in imperfect information availability and behavioral biases, whereby end-users' decisions are made under bounded rationality conditions. We present how these four bounded rationality expressions can be modelled in a way that enables their analysis and the quantitative assessment of their impact on the efficiency of the resource selection task. In all cases, we derive the agents' choices in the stable operational conditions in which all competing influences are balanced.

Bayesian and pre-Bayesian models

Practically, within a dynamic and complex environment, perfectly accurate information about the resource demand is hard to obtain. For instance, the resource operator may, depending on the network and information sensing infrastructure at his disposal, provide the competing agents with different amounts of information about the demand for resources; for example, historical statistical data about the utilization of the low-cost resources. Thus, in this case, the information is impaired in accuracy since it contains only some estimates on the parameters of the environment.

In the same vein, in this paragraph we assume a more realistic realization of the resource selection task where decision-makers have only knowledge constraints, while they satisfy all other criteria of full rationality, *i.e.*, they are selfish agents who are capable of defining their actions in order to minimize the cost of occupying a resource. That is, no computational or time constraints deteriorate the quality of their decisions. However, they either share common probabilistic information about the overall resource demand or are totally uncertain about it. From a modeling point of view, we apply this general concept to a particular case-study: the parking search assistance, whereby the drivers are the selfish agents and the public on-street together with the private parking spots are the resources. We extend the game formulation for the full rationality case (Ref. Section 6.1) to accommodate the two expressions of uncertainty. In particular, we formulate this type of bounded rationality drawing on Bayesian and pre-Bayesian models and prescriptions of classical Game Theory.

Probabilistic knowledge of parking demand

In the *Bayesian* model of the game, the drivers determine their actions on the basis of private information, *i.e.*, their *types*. The type in this game is a binary variable indicating whether a driver is in search of parking space (*active* player) or not. Every driver knows his own type along with the strategy space and the cost functions, and draws on common *prior* probabilistic information about the types of other drivers to estimate the expected cost of his actions. Formally, the Bayesian parking spot selection game is defined as follows:

Definition 6.2.1. *A Bayesian Parking Spot Selection Game is a tuple* $\Gamma_B(N) = (\mathcal{N}, \mathcal{R}, (A_i)_{i\in\mathcal{N}}, (w_j)_{j\in(osp,pl)}, (\Theta_i)_{i\in\mathcal{N}}, f_\Theta)$, *where* $\mathcal{N}$ *and* $\mathcal{R}$ *are as defined for* $\Gamma(N)$ *(Ref. Section 6.1.3) and*

- $A_i = \{osp, pl, \oslash\}$ *is the set of potential actions for each driver* $i \in \mathcal{N}$*;*

- $\Theta_i = \{0, 1\}$ *is the set of types for each driver* $i \in \mathcal{N}$*, where* 1 *(*0*) stands for active (inactive) drivers;*

- $S_i : \Theta_i \to A_i$ *is the set of possible strategies for each driver* $i \in \mathcal{N}$*;*

- $c_i^{N_B}(s(\vartheta), \vartheta)$ *is the cost functions for each driver* $i \in \mathcal{N}$*, for every type profile* $\vartheta \in \times_{k=1}^{N}\Theta_k$ *and strategy profile* $s(\vartheta) \in \times_{k=1}^{N} S_k$*, that are functions of* $w_{osp}(\cdot)$ *and* $w_{pl}(\cdot)$*, as defined for* $\Gamma(N)$*, and also written as* $c_i^{N_B}(s(\vartheta), \vartheta) = c_i^{N_B}(s_i(\vartheta_i), s_{-i}(\vartheta_{-i}), \vartheta_i, \vartheta_{-i})$*;*

- p_{act} *is the probability for a driver to be active.*

In $\Gamma_B(N)$, for all inactive drivers i, $s_i(\vartheta_i = 0) = \oslash$. For active players i, $s_i(\vartheta_i = 1) \in \{osp, pl\}$, under pure-action strategy, or $s_i(\vartheta_i = 1) \in \Delta(\{osp, pl\})$, when they randomize over this subset of A_i under mixed-action strategy. The game is symmetric when, in addition to the action set, drivers share the same activity probability p_{act} and, hence, the same prior joint probability distribution of the drivers' activity (types) f_Θ. The number of active players upon each time depends on their types and is given by $n_{act} = \sum_k \vartheta_k$. The action profile is the effect of players' strategies on their types and is noted as $a = (s(\vartheta), \vartheta) \in \times_{k=1}^{N} A_k$.

Equilibria: For the game $\Gamma_B(N)$, the strategy profile $s' \in \times_{k=1}^{N} S_k(\vartheta_k = 1)$ is a Bayesian NE if, for all $i \in \mathcal{N}$ with $\vartheta_i = 1$

$$s_i(\vartheta_i) \in \arg\min_{s_i' \in S_i} c_i^{N_B}(s_i(\vartheta_i), s_{-i}(\vartheta_{-i}), \vartheta_i, \vartheta_{-i}) \qquad \text{or,}$$

$$s_i(\vartheta_i) \in \arg\min_{s_i' \in S_i} \sum_{\vartheta_{-i}} f_\Theta(\vartheta_{-i}/\vartheta_i) c_i^{\sum_k \vartheta_k}(s_i', s_{-i}(\vartheta_{-i}), \vartheta_i, \vartheta_{-i})$$

where $c_i^{\sum_k \vartheta_k}(s_i', s_{-i}(\vartheta_{-i}), \vartheta_i, \vartheta_{-i})$, with $s_l(\vartheta_l = 0) = pl$, $\forall l \neq i$, is the cost $c_i^m(s_i', s_{-i})$ of driver i under profile s in the game $\Gamma(m)$ with $m = \sum_k \vartheta_k$ drivers, and $f_\Theta(\vartheta_{-i}/\vartheta_i)$ the posterior conditional probability of the active drivers *given that* user i is active, as derived from the application of the Bayesian rule. Therefore, s' minimizes the expected cost over all possible combinations of the other drivers' types and strategies so that no active player can further lower its expected cost by unilaterally changing the strategy.

Theorem 6.2.1. *The game $\Gamma_B(N)$ has unique symmetric equilibrium profiles $p^{NE_B} = (p_{osp}^{NE_B}, p_{pl}^{NE_B})$, with $p_{osp}^{NE_B} + p_{pl}^{NE_B} = 1$. More specifically, with $N_0 \in \mathbb{R}$, we have the following:*

- *a unique pure (Bayesian Nash) equilibrium with $p_{osp}^{NE_B} = 1$, if $p_{act} < \frac{N_0}{N}$;*
- *a unique symmetric mixed-action Bayesian NE with $p_{osp}^{NE_B} = \frac{N_0}{N p_{act}}$, if $p_{act} \geq \min(\frac{N_0}{N}, 1)$.*

Proof. Inline with the reasoning in the proof of Theorem 6.1.2, any symmetric mixed-action equilibrium p^{NE_B} must fulfil

$$c_i^{N_B}(osp, p^{NE_B}) = c_i^{N_B}(pl, p^{NE_B}) \tag{6.45}$$

Since $c_i^{N_B}(pl, p) = c_{pl}$ and $c_i^{N_B}(osp, p) = \sum_{n_{act}=0}^{N-1} c_i^{n_{act}+1}(osp, p) B(n_{act}; N-1, p_{act})$, a few algebraic manipulations suffice to derive that the symmetric mixed-action equilibrium p^{NE_B} solves the equation

$$h(p) \;=\; -\beta + \sum_{n_{act}=0}^{N-1} B(n_{act}; N-1, p_{act}) \cdot \sum_{k=0}^{n_{act}} \left[\gamma - \min\left(\frac{R}{k+1}, 1\right) \cdot (\gamma - 1)\right] B(k; n_{act}, p) = 0 \tag{6.46}$$

The function $h(p)$ is continuous and strictly increasing in p for all $p_{act} \in [0, 1]$ since

$$\begin{aligned}
h'(p) &= \sum_{n_{act}=0}^{N-1} B(n_{act}; N-1, p_{act}) \cdot \sum_{k=0}^{n_{act}} \left[\gamma - \min\left(\frac{R}{k+1}, 1\right) \cdot (\gamma - 1)\right] B'(k; n_{act}, p) \\
&> \sum_{n_{act}=0}^{N-1} B(n_{act}; N-1, p_{act}) \sum_{k=0}^{n_{act}} B'(k; n_{act}, p) \\
&= \sum_{n_{act}=0}^{N-1} B(n_{act}; N-1, p_{act}) \left(\sum_{k=0}^{n_{act}} B(k; n_{act}, p)\right)' = 0
\end{aligned}$$

since the weights of the rightmost Binomial coefficients in the second line are not smaller than one,

$$\gamma - \min\left(\frac{R}{k+1}, 1\right) \cdot (\gamma - 1) > 1, \forall k \in [0, N-1]$$

Likewise, for $p_{act} \in [0, 1]$, its leftmost value is $\lim_{p \to 0} h(p) = -\beta + 1 < 0$ and its rightmost value is

$$\lim_{p \to 1} h(p) = -\beta + \sum_{n_{act}=0}^{N-1} B(n_{act}; N-1, p_{act}) \left[\gamma - \min\left(1, \frac{R}{n_{act}+1}\right) \cdot (\gamma - 1)\right] = f(p_{act}) \tag{6.47}$$

In the proof of Theorem 6.1.2 we showed that the function $f(p)$ is strictly increasing in p and has a single solution $p = N_0/N$. Therefore, as long as $p_{act} \in [0, N_0/N)$, $\lim_{p \to 1} h(p) < 0$, and $c_i^{N_B}(osp, p) < c_i^{N_B}(pl, p)$ $\forall p \in (0, 1)$; namely, it is a dominant strategy for all drivers to compete for on-street parking. On the contrary, for $p_{act} \in [N_0/N, 1]$, $\lim_{p \to 1} h(p)$ gets positive values and $h(p) = 0$ has a single solution $p = \frac{N_0}{N p_{act}}$ (can be checked with replacement). □

Strictly incomplete information about parking demand

The worst-case scenario with respect to the information possessed by the drivers is represented by the *pre-Bayesian* game variant, under which the drivers are aware of only the upper limit of the vehicles that are *potential* competitors for parking resources.

Pre-Bayesian games do not necessarily have *ex-post* Nash equilibria, even in mixed actions. The ex-post NE consists of strategies that, for every joint type profile, result in actions that are in NE in the corresponding strategic game. On the other hand, all quasi-concave pre-Bayesian games *do* have at least one mixed-strategy *safety-level equilibrium* [Ashlagi *et al.*, 2006]. In the safety-level equilibrium, every player minimizes over his strategy set S_i the worst-case (maximum) cost that he may suffer over all possible types and actions of his competitors (S_{-i}, Θ_{-i}). The result of interest for our pre-Bayesian variant of the parking spot selection model $\Gamma_{pB}(N)$ is the following proposition, due to [Ashlagi *et al.*, 2006], whose implications for the efficiency of the equilibrium behaviors of the drivers are discussed in Section 6.2.3.

Proposition 6.2.1. *An action profile a is the unique symmetric mixed-action safety-level equilibrium of the pre-Bayesian parking spot selection game $\Gamma_{pB}(N)$ with non-decreasing resource cost functions, iff a is the unique symmetric mixed-action equilibrium of the respective strategic game with deterministic knowledge of the number of players $\Gamma(N)$.*

In Table 6.1 we summarize the equilibrium strategies for the three variants of the parking spot selection game.

For years, the main approaches to collective decision-making, whereby the decisions of one agent affect the gain/cost experienced by others, draw on Expected Utility Theory (EUT). Agents are considered as strategic and fully rational, namely, they can compute the expected utility of all possible action profiles exploiting all available information about their own and the others' utilities (*i.e.*, the expected utility of one's action equals the sum of his utilities for all possible opponents' actions times the probabilities of their occurrence). In such setting, the classical solution concept of the game is embodied by the Nash Equilibrium (NE), the action profile that no agent would like to unilaterally deviate from. Essentially, the NE captures the agents' best responses in terms of expected utility maximization.

However, experimental data suggest that human decisions reflect certain limitations, that is, they exhibit biases of different kinds in comparing alternatives and maximizing their welfare in terms of the expected utility that comes with an alternative. To accommodate the empirical findings, researchers from economics, sociology and cognitive

Table 6.1: Equilibrium strategies for the strategic, Bayesian and pre-Bayesian parking spot selection game

strategic Parking Spot Selection Game, $\Gamma(N)$		
Condition	Equilibrium type	Equilibrium expression
$N \leq N_0$, $N_0 \in \mathbb{R}$	pure Nash Eq	$N_{osp}^{NE} = N$
$N > N_0$, $N_0 \in (R, N) \backslash \mathbb{N}^*$	pure Nash Eq	$N_{osp}^{NE} = \lfloor N_0 \rfloor$
$N > N_0$, $N_0 \in [R+1, N] \cap \mathbb{N}^*$	pure Nash Eq	$N_{osp}^{NE} = N_0$, $N_{osp}^{NE} = N_0 - 1$
$N > N_0$, $N_0 \in \mathbb{R}$	mixed-action Nash Eq	$p_{osp}^{NE} = \frac{N_0}{N}$
Bayesian Parking Spot Selection Game, $\Gamma_B(N)$		
Condition	Equilibrium type	Equilibrium expression
$p_{act} < \frac{N_0}{N}$, $N_0 \in \mathbb{R}$	pure Bayesian Nash Eq	$p_{osp}^{NE_B} = 1$
$p_{act} \geq \min(\frac{N_0}{N}, 1)$, $N_0 \in \mathbb{R}$	mixed-action Bayesian Nash Eq	$p_{osp}^{NE_B} = \frac{N_0}{N p_{act}}$
pre-Bayesian Parking Spot Selection Game, $\Gamma_{pB}(N)$		
Condition	Equilibrium type	Equilibrium expression
$N \leq N_0$, $N_0 \in \mathbb{R}$	pure safety-level Eq	$p_{osp}^{NE_{pB}} = 1$
$N > N_0$, $N_0 \in \mathbb{R}$	mixed-action safety-level Eq	$p_{osp}^{NE_{pB}} = \frac{N_0}{N}$

psychology, have tried either to expand/adapt the Expected Utility framework or completely depart from it and devise alternative theories as to how decision alternatives are assessed and decisions are eventually taken.

In the following sections we first give the general analytical framework of the decision-making model and then its application to the resource selection task as introduced in Section 6.2.1. We apply the general competition concept to scenarios whereby the agents make their decision independently within a particular time window over which they start the resource selection task. In connection with the analysis presented in Section 6.1, we consider settings where N agents are called to decide between two alternative sets of resources. The first set consists of R low-cost resources while the second one is unlimited but with more expensive items. Those who manage to use the low-cost resources pay $c_{l,s}$ cost units, whereas those heading directly for the safer, but more expensive option pay $c_u = \beta \cdot c_{l,s}, \beta > 1$, cost units. However, agents that first decide to compete for the low-cost resources but fail to acquire one suffering the results of congestion, pay $c_{l,f} = \gamma \cdot c_{l,s}, \gamma > \beta$ cost units. The excess penalty cost $\delta \cdot c_{l,s}$, with $\delta = \gamma - \beta > 0$, reflects the "virtual" cost of wasted time till eventually being served by the more expensive option.

Cumulative Prospect Theory

Tversky and Kahneman in [Tversky & Kahneman, 1992] proposed the Cumulative Prospect Theory (CPT) framework to explain, among others, why people buy lottery tickets and insurance policies at the same time or the fourfold pattern of risk attitude (Ref. Section 6.2.1). According to EUT, if X denotes the set of possible outcomes of a lottery, its expected utility equals the sum of the outcomes' utilities, $U(x), x \in X$, times the probabilities of their occurrence, $pr(x)$, that is, $EU = \sum_{x \in X} pr(x)U(x)$. In CPT, the desirability of the alternatives-lotteries (now termed prospects) is still given by a weighted sum of prospect utilities, only now both components of the EUT (*i.e.*, outcomes and probabilities) are modified. However, agents are still maximizers, *i.e.*, they try to maximize the expected utilities of their prospects.

The CPT value for prospect X is given by

$$CPT_X = \sum_{i=1}^{k} \pi_i^- u(x_i) + \sum_{i=k+1}^{n} \pi_i^+ u(x_i) \tag{6.48}$$

where $x_1 \leq ... \leq x_k$ are negative outcomes/losses and $x_{k+1} \leq ... \leq x_n$ positive outcomes/gains.

In particular, the decision weights π_i^-, π_i^+ are functions of the cumulative probabilities of obtaining an outcome x or anything better (for positive outcomes) or worse (negative outcomes) than x. They are defined as follows:

$$\begin{aligned} \pi_1^- &= w^-(pr_1) \\ \pi_i^- &= w^-(pr_1 + ... + pr_i) - w^-(pr_1 + ... + pr_{i-1}), \\ & \qquad 2 \leq i \leq k \end{aligned} \tag{6.49}$$

$$\begin{aligned} \pi_n^+ &= w^+(pr_n) \\ \pi_i^+ &= w^+(pr_i + ... + pr_n) - w^+(pr_{i+1} + ... + pr_n), \\ & \qquad k+1 \leq i \leq n-1 \end{aligned} \tag{6.50}$$

In [Tversky & Kahneman, 1992], the authors propose concrete functions for both weighting and utility functions,

$$u(x_i) = \begin{cases} x_i^a, \text{ if } x_i \geq 0 \\ -\lambda(-x_i)^b, \text{ if } x_i < 0 \end{cases} \tag{6.51}$$

$$w^+(p) = p^c / \left[p^c + (1-p)^c\right]^{1/c} \tag{6.52}$$

$$w^-(p) = p^d / \left[p^d + (1-p)^d\right]^{1/d} \tag{6.53}$$

$$w^+(0) = w^-(0) = 0 \tag{6.54}$$

$$w^+(1) = w^-(1) = 1 \tag{6.55}$$

Both functions are consistent with experimental evidence on risk preferences. Indeed, empirical measurements reveal a particular pattern of behavior, termed as loss aversion and diminishing sensitivity. Loss aversion refers to the fact that people tend to be more sensitive to decreases than to increases in their wealth (*i.e.*, a loss of 80 is felt more that a gain of 80); whereas diminishing sensitivity (appeared in both the value and the weighting function) argues that people are more sensitive to extreme outcomes and less in intermediate ones.

The parameter $\lambda \geq 1$ measures the degree of loss aversion, while the parameters $a, b \leq 1$ the degree of diminishing sensitivity. The curvature of the weighting function as well as the point where it crosses the $45°$ line are modulated by the parameters c and d. Tversky and Kahneman estimated the parametric values that best fit their experimental data at $\lambda = 2.25, a = b = 0.88, c = 0.61, d = 0.69$.

Applying Cumulative Prospect Theory to the resource selection task In the uncoordinated resource selection problem, the decisions are made on two alternatives/prospects: the low-cost, limited-capacity resource set, on one side and the more expensive but unlimited resource set, on the other side. In addition, both prospects consist only of negative outcomes/costs.

The CPT value for the low-cost prospect is given by

$$CPT_l = \sum_{n=1}^{N} \pi_n^- u(g_l(n)) \tag{6.56}$$

where $g_l(k)$, with $g_l(1) \leq ... \leq g_l(N)$, is the expected cost for an agent that plays the action "low-cost/limited-capacity resource set". It is a function of the number of agents k taking this action, and is given by

$$g_l(k) = min(1, R/k)c_{l,s} + (1 - min(1, R/k))c_{l,f} \tag{6.57}$$

The decision weights and utility functions are defined by equations (6.49)-(6.55). The possible $n \leq N$ outcomes, for the number n of agents choosing the low-cost resources, occur with probability pr_n that follows the Binomial probability distribution $B(n; N, p_l^{CPT})$, with parameters the total number of agents, N, and the probability to compete for the low-cost resources, p_l^{CPT}.

The CPT value for the certain prospect "expensive/unlimited resource set" is given by (6.51) and equals

$$CPT_u = u(c_u) \tag{6.58}$$

It is possible to extend the equilibrium concept inline with the principles of CPT. Namely, under an equilibrium state, no agent has the incentive to deviate from this unilaterally because by changing his decision, he will only find himself with more expected cost. Thus, the symmetric mixed-action equilibrium strategy $p^{CPT} = (p_l^{CPT}, p_u^{CPT})$, $p_u^{CPT} = 1 - p_l^{CPT}$, is derived when equalizing the CPT values of the two prospects, $CPT_l = CPT_u$.

Rosenthal and Quantal Response Equilibria and their application to the resource selection task

Both casual empiricism as well as experimental work suggested systematic deviations from the prescriptions of EUT and hence, classical Game Theory (Nash Equilibrium predictions). In Section 6.2.1 we briefly present the own-payoff effects that constitute the most common pattern of deviations from Nash predictions in matching pennies games. Triggered by this kind of observations, Rosenthal in [Rosenthal, 1989] and, later, McKelvey and Palfrey in [McKelvey & Palfrey, 1995], propose alternative solution concepts to the Nash equilibrium. The underlying idea in both proposals is that "individuals are more likely to select better choices than worse choices, but do not necessarily succeed in selecting the very best choice". Rosenthal argued that "the difference in probabilities with which two actions x and y are played is proportional to the difference of the corresponding expected gains (costs)". For the actions "low-cost/limited-capacity resource set" and "expensive/unlimited resource set", the Rosenthal equilibrium strategy $p^{RE} = (p_l^{RE}, p_u^{RE})$, $p_u^{RE} = 1 - p_l^{RE}$ is given as a fixed-point solution of the equation

$$p_l^{RE} - p_u^{RE} = -t(c(l, p^{RE}) - c(u, p^{RE})) \tag{6.59}$$

where $c(l, p)$ and $c(u, p)$ are the expected costs for choosing "low-cost/limited-capacity resource set" and "expensive/unlimited resource set", when all other agents play the mixed-action $p = (p_l, p_u)$, namely,

$$c(l, p) = \sum_{n=0}^{N-1} g_l(n+1) B(n; N-1, p_l) \tag{6.60}$$

and

$$c(u, p) = c_u \tag{6.61}$$

The degree of freedom $t \in [0, \infty]$[9] quantifies the rationality of agents, here seen as a synonym of the knowledge they possess and, primarily, their capacity to assess the difference in the utilities between two outcomes. Thus, the model's solution converges to the Nash equilibrium as parameter t goes to infinity.

In a similar view of people's rationality, McKelvey and Palfrey have shown that these "own-payoff effects", *i.e.*, people's inability to play always the strategy that maximizes (minimizes) the expected utility (cost), can be explained by introducing some randomness into the decision-making process. Actually, one can think this kind of randomness and, ultimately, these inaccurate/not rational judgments with respect to cost minimization, as reflecting the effects of estimation/computational errors, individual's mood, perceptual variations or cognitive biases. McKelvey and Palfrey implement these effects into a new equilibrium concept, the Quantal Response equilibrium. For instance, if the randomness

[9] In the Rosenthal equilibrium the rationality parameter t is subject to the constraint that the resulting probabilities range in [0,1].

follows an exponential distribution (*i.e.*, *logistic errors*, iid mistakes with an extreme value distribution, smaller mistakes are more likely to occur than more serious ones), the response function/probability to play the action "low-cost/limited-capacity resource set" in this equilibrium state $p^{QRE} = (p_l^{QRE}, p_u^{QRE})$, $p_u^{QRE} = 1 - p_l^{QRE}$ is given using (6.60) and (6.61) by,

$$p_l^{QRE} = \frac{e^{-tc(l,p^{QRE})}}{e^{-tc(l,p^{QRE})} + e^{-tc(u,p^{QRE})}} \tag{6.62}$$

Likewise, the free parameter t plays the same role, abstracting the rationality level.

Addressing human behavior in real-life choice problems by using alternative equilibrium solutions emerges as a typical approach for analytical investigations. In a similar study in [Chen *et al.*, 2012], a capacity-constrained supplier divides the limited supply among prospective retailers. The latter are assigned quantities proportional to their orders, so they have an incentive to inflate their orders to secure more favorable allocated quantities (when facing capacity constraints). They choose their orders strategically but not always perfectly rationally; the optimization of individual payoffs is prone to errors in line with the quantal response model. Other studies, take explicitly into account similar deviations from perfect rationality in attackers' behavior to improve security systems. In [Yang *et al.*, 2011], the defender has a limited number of resources to protect a set of targets (*i.e.*, flights) and selects the optimal mixed strategy, which describes the probability that each target will be protected by a resource. The attacker chooses a target to attack after observing this mixed strategy. This context can be encountered in selective checking applications where the (human) adversaries monitor and exploit the checking patterns to launch an attack on a single target.

Heuristic decision-making and its application to the resource selection task

In a more radical approach, models that rely on heuristic rules reflect better Simon's early arguments in [Simon, 1955], [Simon, 1956] that humans are satisficers rather than maximizers. These heuristics rely on related rules for search that have been suggested from other domains (*i.e.*, psychology, economics) and criteria that have been identified as important for drivers such as the parking fee, parking time limits, distance from drivers' travel destination, accessibility and security level [Goot, 1982], [Golias *et al.*, 2002].

In an effort to get the satisficing notion in our competitive resource selection setting, we came up with a simple kind of heuristic rule arguing that instead of computing/comparing the expected costs of choices, individuals estimate the probability to get one of the "popular" resources and play according to this. In essence, as common sense suggests, agents appear overconfident under low demand for the scarce low-cost resources and underconfident otherwise. Similar to equilibrium solutions in previous paragraphs, we define the equilibrium heuristic strategy $p^{HE} = (p_l^{HE}, p_u^{HE})$, $p_u^{HE} = 1 - p_l^{HE}$, by the fixed-point equation

$$p_l^{HE} = \sum_{n=0}^{R-1} B(n; N-1, p_l^{HE}) \tag{6.63}$$

where $B(n; N-1, p_l^{HE})$ is the Binomial probability distribution with parameters $N-1$ and p_l^{HE}, for n agents competing for the low-cost resources.

6.2.3 Numerical results

In Section 6.2.2, we iterate on decision-making models for individuals that exhibit systematically deviations from the full rational behavior and show how the agents resolve in distributed manner the problem of coordinating, that is, which partition of agents will gain the low-cost resources and which will pay the service more expensively. In this section, we first discuss how the efficiency of the parking search process is affected when it is executed under probabilistic information and uncertainty, considering the game variant under complete information as a comparison reference for the efficiency of the uncoordinated parking spot selection process. We then compare the Cumulative Prospect Theory decision-making model, the Rosenthal and Quantal Response equilibria as well as the heuristic reasoning against what the fully rational decision-making yields (Ref. Theorem 6.1.2). In addition, we plot the different types of equilibria against the optimal/ideal centralized resource allocation, where the full information processing and decision-making tasks lie with a central entity. Agents issue their requests to a central server, which monitors the limited-capacity resource set, possesses precise information about its availability, and assigns it so that the overall cost paid by agents is minimized.

Thus, in an environment with R low-cost resources, whereby such an ideal centralized system serves the requests of $N \geq R$ agents, exactly R ($N - R$) agents would be directed to the low-cost (respectively, more expensive) option and no one would pay the excess penalty cost.

Bayesian and pre-Bayesian models

Looking at the mixed-action equilibria, Theorem 6.1.2 indicates that drivers' intention to compete for on-street parking resources is shaped by the pricing schemes, the number of players, and the curbside parking capacity. Indeed, players start to withdraw from competition as the competition intensity rises over the threshold $N_0 = \frac{R(\gamma-1)}{\delta}$. For the Bayesian implementation, the rationale behind the active players' behavior is almost the same. The only difference is that the players adjust their strategies based on estimations for the demand level, as expressed in the commonly known probabilistic information of competition. Therefore, the probability to compete decreases with the expected number of competitors Np_{act} if this number exceeds the threshold N_0 of the strategic games (Ref. Theorem 6.2.1). Furthermore, for both game formulations, players start to renege from competition as the distance between on-street and parking lot facilities (*i.e.*, δ) is increased, the number of opportunities for curbside parking (*i.e.*, R) decreases, or the price for space reservation in parking lot (*i.e.*, β) drops. Figure 6.10 shows the effect of these parameters on the equilibrium mixed-action, for strategic ($p_{act} = 1$) and Bayesian ($p_{act} \in \{0.5, 0.7\}$) games.

Less-is-more phenomena under uncertainty: Less intuitive are the game dynamics in its pre-Bayesian variant, when users only possess an estimate of the maximum number of drivers that are *potentially* interested in parking space. From Proposition 6.2.1, the mixed-action safety-level equilibrium corresponds to the mixed-action equilibrium of the strategic game $\Gamma(N)$. However, we have seen that, when the players outnumber the on-street parking capacity, the mixed-action equilibrium in the strategic game generates a higher expected number of competitors than the optimal value R (Ref. Theorem 6.1.2), the social cost conditionally increases with the probability of competing (Ref. Figure 6.4(b), for $p_{osp} > \frac{R}{N}$), and the probability of competition decreases with N (Ref. Figure 6.10, for $N > N_0$). Therefore, at the safety-level equilibrium of the game, the drivers end up randomizing the pure action “on-street” with a lower probability than that corresponding to the game that they actually play, with $k \leq N$ players. Hence, the resulting number of competing vehicles is smaller, and cumulatively, they may end up paying less than they would if they knew deterministically the competition they face.

One question that becomes relevant is for which (real) number K of competing players do the drivers end up paying the *optimal* cost. Practically, if $p_N^{NE} = (p_{osp,N}^{NE}, p_{pl,N}^{NE})$ denotes the symmetric mixed-action equilibrium for $\Gamma(N)$, we are looking for the value of K satisfying the following:

$$Kp_{osp,N} = R \Rightarrow K = \frac{RN}{N_0} = \frac{\delta}{\gamma - 1}N$$

That is, when $\frac{\delta}{\gamma-1}N$ (rounded to the nearest integer) drivers are seeking parking space under uncertainty conditions, in the induced equilibrium they end up paying the minimum possible cost, which is better than what they would pay under complete information about the parking demand.

In the remainder of this section, we consider the resource selection task described in Section 6.2.2 and plot the derived bounded rational agents' choices along with the associated per-user costs incurred in the equilibrium states of the system, under different charging schemes for the two resource sets. The average per-user cost in the symmetric case where every agent performs the mixed-action $p = (p_l, p_u)$ is given by (6.60) and (6.61), as follows

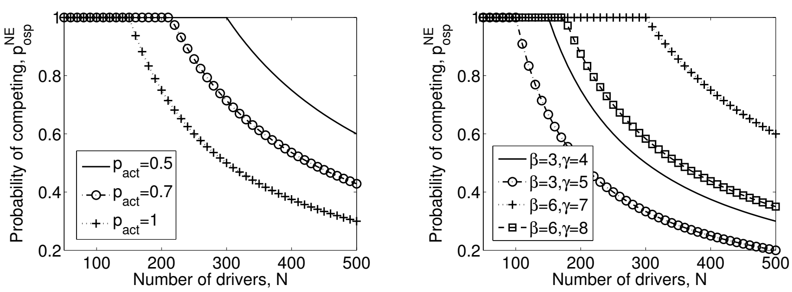


Figure 6.10: Probability of competing in equilibrium, for $R = 50$. Left: Strategic and Bayesian games under fixed pricing scheme $\beta = 5, \gamma = 7$. Right: Strategic games under various pricing schemes $\beta \in \{3, 6\}, \gamma \in \{4, 5, 7, 8\}$.

Table 6.2: Sensitivity analysis of the CPT parameter b: $N = 100, R = 50, \beta = 4, \gamma = 8$

b **value**	0.616 (-30%)	0.704 (-20%)	0.792 (-10%)	0.88 (0%)	0.968 $(+10\%)$
p_l^{CPT}	0.8837	0.8836	0.8835	0.8834	0.8834

Table 6.3: Sensitivity analysis of the CPT parameter d: $N = 100, R = 50, \beta = 4, \gamma = 8$

d **value**	0.552 (-20%)	0.621 (-10%)	0.69 (0%)	0.7590 $(+10\%)$	0.828 $(+20\%)$
p_l^{CPT}	0.8934	0.8876	0.8834	0.8805	0.8786

$$C(p) = p_l c(l,p) + p_u c(u,p) \tag{6.64}$$

For the numerical results, usage of the limited resources costs $c_{l,s} = 1$ unit whereas the cost of the more expensive resources β and the excess penalty cost parameter δ range in $[3, 12]$ and $[1, 16]$ units, respectively.

Cumulative Prospect Theory

Although the CPT model was originally suggested to rationalize empirical findings in financial lottery experiments, it has been successfully exploited to accommodate data sets for different decision-making models. In [Booij *et al.*, 2010], the authors review empirical estimates of prospect theory under different (parametric) assumptions, incentives, tasks and samples. In a transportation paradigm more similar to our setting, Avineri *et al.* in [Avineri & Prashker, 2004] first conduct a route-choice stated-preference experiment and then explain the results parametrizing their route choice model with values similar to the ones that Tversky and Kahneman found for their archetypal model in [Tversky & Kahneman, 1992]. In the absence of proper experiment measurements on the particular resource selection paradigm that could validate this theory, it is not suggested that the parameter set $b = 0.88, d = 0.69, \lambda = 2.25$, as was introduced in Section 6.2.2, reflects the actual agents' choices. Thus, we use the default parametric values to explore the existence (or not) of the same risk attitudes towards losses in the particular environment (Ref. Section 6.2.2) and conduct a sensitivity analysis on the parameters b, d, λ in the end of the section to address these concerns.

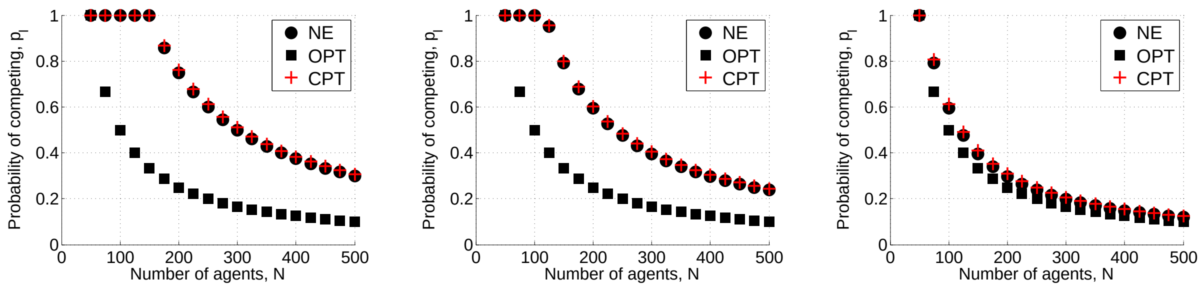
Table 6.4: Sensitivity analysis of the CPT parameter λ: $N = 100, R = 50, \beta = 4, \gamma = 8$

λ **value**	1.8 (-20%)	2.025 (-10%)	2.25 (0%)	2.475 $(+10\%)$	2.7 $(+20\%)$
p_l^{CPT}	0.8834	0.8834	0.8834	0.8834	0.8834

Motivated by the simple experiments on preferences about positive and negative prospects that, eventually, reveal the four-fold pattern of risk attitude [Tversky & Kahneman, 1992], we iterate on the most interesting case studies for the cost differentials between the certain prospect (*i.e.*, c_u for the expensive/unlimited resource set) and the best or worst outcome of the risky one (*i.e.*, $c_{l,s}$ or $c_{l,f}$ for the low-cost/limited-capacity resource set). As Figures 6.11(a), 6.11(b) suggest, when the agents have the opportunity to experience a marginally or significantly lower charging cost at low or high risk, respectively, their biased risk-seeking behavior turns to be full rational, and thus, minimizes the expected cost over others' preferences. On the contrary, in the face of a highly risky option reflected in significant extra penalty cost (Figure 6.11(c)), the risk attitude under the two types of rationality starts to differ. For instance, when $N = 100$ agents compete for $R = 50$ low-cost resources, the expected utility maximization framework results in the Nash equilibrium $p_l^{NE} = \frac{R(\gamma-1)}{\delta N} = 0.59$, with expected cost values $c(l, p^{NE}) = c(u, p^{NE}) = c_u$ whereas the CPT suggests playing with $p_l^{CPT} = 0.61$ that equalizes the relevant values $CPT_l = CPT_u = -7.62$. Under the prescriptions of CPT, at the mixed-action $p^{NE} = (0.59, 0.41)$, the cumulative prospect values become $CPT_l = -6.74$ and $CPT_u = -7.62$ which leads to a risk-prone behavior, in line with the theory for losses: an agent may decrease the prospect cost by switching his decision from the certain more expensive resource set to the risky low-cost one. On the other hand, at the mixed-action p^{CPT} the expected costs for the two options differ, namely, $c(l, p^{CPT}) = 4.49$ and $c(u, p^{CPT}) = c_u = 4$.

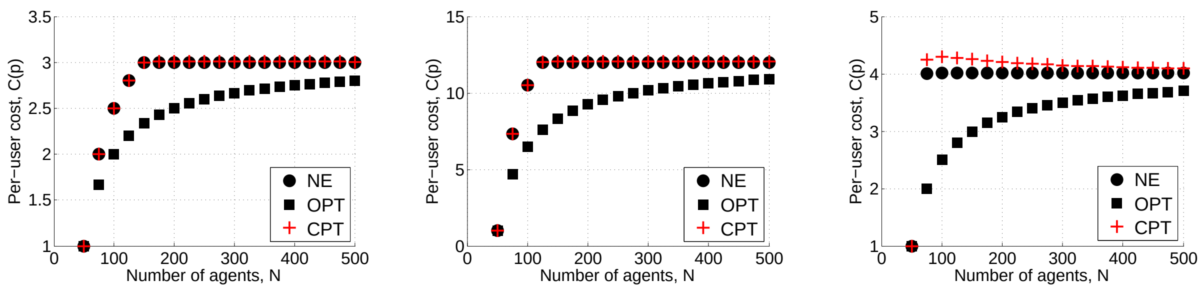
Overall and as Figure 6.12 implies, both the full rational and the biased practice are more risk-seeking than they should be, increasing the actual per-user cost (or equivalently, the social cost) over the optimal levels. As a result, being prone to biased behaviors cannot score better than acting full rationally.

The sensitivity of these results to the particular CPT parametric values $b = 0.88, d = 0.69, \lambda = 2.25$, can be drawn from Tables 6.2, 6.3 and 6.4, respectively. The CPT model



(a) $\beta = 3, \gamma = 4$ (b) $\beta = 12, \gamma = 20$ (c) $\beta = 4, \gamma = 20$

Figure 6.11: Probability of competing in CPT equilibrium, for $R = 50$, under different charging schemes.



(a) $\beta = 3, \gamma = 4$ (b) $\beta = 12, \gamma = 20$ (c) $\beta = 4, \gamma = 20$

Figure 6.12: Per-user cost in CPT equilibrium, for $R = 50$, under different charging schemes.

evolves to the expected utility maximization one that gives $p_l^{NE} = 0.875$, as the parameters go to one. In general, although we admit that the ultimate validation of our analytical results would come out of real, yet costly and difficult experimentation with in-field measurements, the effect of the parameters is shown to be limited.

Rosenthal and Quantal Response Equilibria

Within the typical game-theoretic setting, the agents' expected costs from different strategies are determined by their beliefs about others' preferences. Eventually, these beliefs may generate choice probabilities according to a particular response function that is not necessarily *best*, in line with the expected utility maximization norms. Yet under this kind of response functions, such as those in the form of (6.59) or (6.62), the resulting - Rosenthal and Quantal Response - equilibria impose the requirement that the beliefs match the equilibrium choice probabilities, as in the Nash equilibrium solutions.

Figures 6.13 and 6.14 plot these two alternative types of equilibrium strategies and the resulting per-user costs when individuals cannot always choose the actions that best satisfy their preferences, that is when the rationality parameter t is 3. First, the implementation of bounded rationality increases randomness into agents' choices and hence, draws choice probabilities towards 0.5. As a result, when competition exceeds the capacity of the low-cost resources, computational limitations lead to more conservative actions comparing to the Nash equilibrium competing probabilities when $N < \frac{2R(\gamma-1)}{\delta}$ and less, otherwise. Second, the more different the - expected - costs of the two options are, the less the Rosenthal and Quantal Response equilibrium differ from the Nash one, since the identification of the best action becomes easier. Thus, we notice almost no or limited difference when the risk to compete for a very small benefit is high due to the significant extra penalty cost δ (Figure 6.14(a)) or the high demand for the resources (Figure 6.13(a), $N > 300$). The same reason underlies the differences between the Rosenthal and the Quantal Response equilibrium. Essentially, the three types of equilibrium form a three-level hierarchy with respect to their capacity to identify the less costly resource option, with the Quantal Response equilibrium at the bottom level and the Nash one at the top level.

Since the per-user cost is minimized at lower competing probabilities, the inaccurate but frugal computation of the best action saves not only time and computational resources but also, usage cost when $N < \frac{2R(\gamma-1)}{\delta}$ (Figure 6.13(b)).

The impact of computational limitations becomes more sharp at even lower values of the rationality parameter. In Figures 6.15 and 6.16, we plot the probability of competing for the low-cost resources and the resulting per-user cost, when $t = 0.2$. Again higher differences in behavior are observed in settings where it is not clear which of the two resource options costs less. This is the case of Figure 6.15(a), where the choices are decided almost randomly. On the other hand, when the risk is high when choosing the limited resources, as in Figure 6.16(a), even that low rationality level generates decisions similar to the full rational ones.

Interestingly, when $\beta = 3$, $\gamma = 4$ and $N < \frac{2R(\gamma-1)}{\delta}$, the decrease in competing probability that comes with imperfect rationality, draws the per-user cost to near-optimal

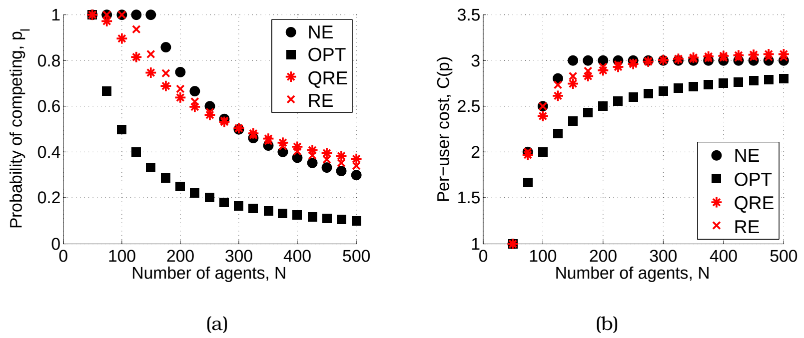


Figure 6.13: Probability of competing in the Quantal Response and Rosenthal equilibria and the resulting per-user cost, for $R = 50$, $\beta = 3, \gamma = 4$, $t = 3$.

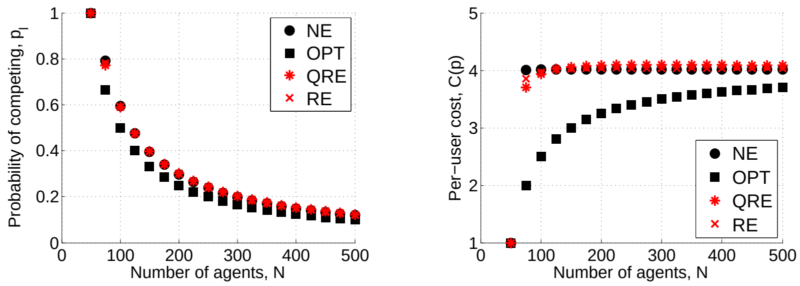
levels (Figure 6.15(b)). However, when the penalty cost is high, any - limited - increase in competitiveness due to inaccurate cost discrimination causes significant overhead (Figure 6.16(b)).

As a last note, Figure 6.17 illustrates the impact of the rationality parameter t on the equilibrium choice probabilities. Starting with a difference $\delta_{prob,t\sim0} = p_l^{QRE,RE} - p_l^{NE} = 1/2 - \frac{R(\gamma-1)}{\delta N}$ under a pure stochastic decision-making model, the bounded rational reasoning approximates the full rational practice, as t goes to infinity. When $N \sim (N-1)$, as in our setting, this difference in competing probability can be translated in gains (less cost) or losses (more cost) in the ultimate per-user cost, by (6.64), as follows:

$$\begin{aligned}\delta_{cost,t} &= C(p^{QRE,RE}) - C(p^{NE}) \\ &\approx \delta_{prob,t} \cdot \delta c_{l,s}, \quad \text{if } \ R/((N-1)(p_l^{NE} + \delta_{prob,t})) < 1 \\ &\approx c_{l,s}(p_l^{NE} + \delta_{prob,t} - R/(N-1)) - c_{l,f}(p_l^{NE} - R/(N-1)) - \delta_{prob,t}c_{pl}, \quad \text{o/w}\end{aligned}$$

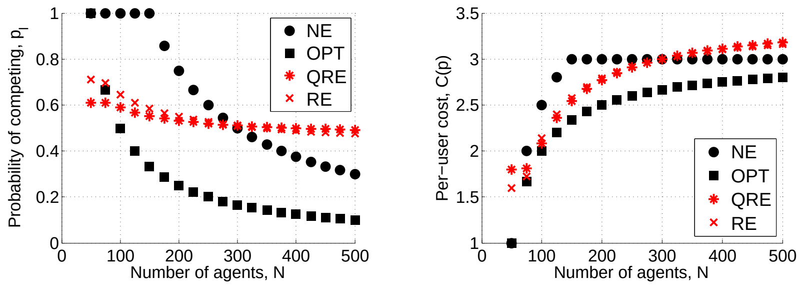
Heuristic decision-making

Typically, under time and processing limitations, the heuristic reasoning approach emerges as the only solution. Within a highly competitive environment and in the face of a penalty cost ($\delta c_{l,s}$), the heuristic reasoning just estimates the competition levels (*i.e.*, according to (6.63)) and plays according to this. At equilibrium, the beliefs that formulate the competition level match the actual choice probabilities, as in paragraph



(a) (b)

Figure 6.14: Probability of competing in the Quantal Response and Rosenthal equilibria and the resulting per-user cost, for $R = 50$, $\beta = 4, \gamma = 20$, $t = 3$.



(a) (b)

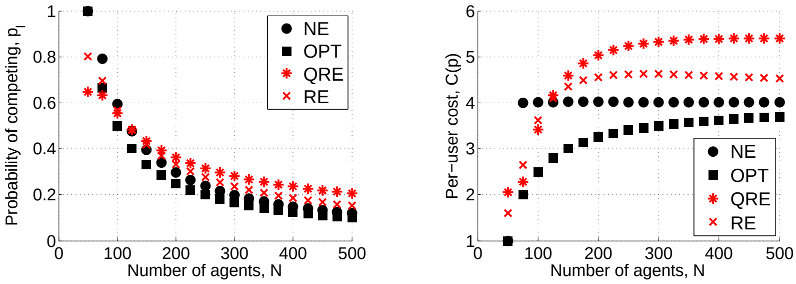
Figure 6.15: Probability of competing in the Quantal Response and Rosenthal equilibria and the resulting per-user cost, for $R = 50$, $\beta = 3, \gamma = 4$, $t = 0.2$.

"Rosenthal and Quantal Response Equilibria" in this section.

Interestingly, this trivial modeling approach leads to near-optimal results. Unlike CPT or the alternative equilibrium solutions, it does not take into account the charging costs. Yet, this reasoning mode expresses a pessimistic attitude that takes for granted the failure in a possible competition with competitors that outnumber the resources. As a result, it implicitly seeks to avoid the tragedy of common effects and hence, eventually, yields a socially beneficial solution.

6.2.4 The parking search as a sequential search problem

As discussed in Section 6.2.2, the various analytic models of bounded rationality coming from the areas of Cognitive Psychology and Behavioral Economics depart from the norms of classical rationality as expressed in the Expected Utility Theory framework. However, people do not seem to perform all these calculations, at least not under all



(a) (b)

Figure 6.16: Probability of competing in the Quantal Response and Rosenthal equilibria and the resulting per-user cost, for $R = 50$, $\beta = 4, \gamma = 20$, $t = 0.2$.

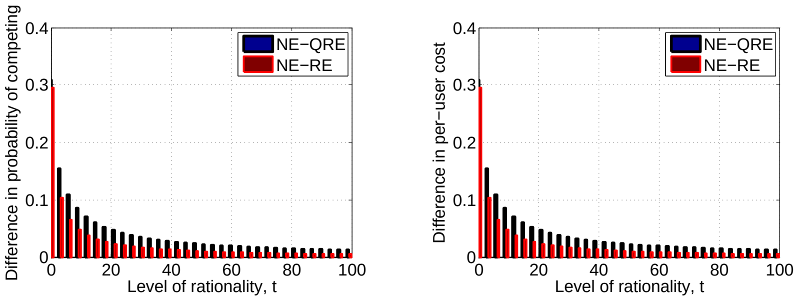


Figure 6.17: Difference between the probability of competing in the Quantal Response, Rosenthal equilibria and that in Nash equilibrium (left) and the resulting per-user cost difference (right), for $R = 50, N = 180$, under fixed charging scheme $\beta = 3, \gamma = 4$ and $t = [0.1, 100]$ (from imperfect to perfect rationality).

conditions and especially in situations where there is pressure to be “rational” (*e.g.*, route and parking spot selection). In other words, a criticism against these models is that they no longer aim at describing the processes (cognitive, neural, or hormonal) underlying a decision but just at predicting the final people’s choices for a large chunk of choice problems. Furthermore, they give no insight as to how should the corresponding models be parametrized each time.

On the other hand, the cognitive heuristics are fast, frugal, adaptive strategies that allow humans (organisms, in general) to reduce complex decision tasks of predicting, assessing, computing to simpler reasoning processes. In the salient of heuristic-based decision theory, notions such as recognition, priority, availability, fluency, familiarity, accessibility, representativeness and adjustment - and - anchoring stand out. One of the simplest and well - studied heuristic is the recognition heuristic [Goldstein & Gigerenzer, 2002]. It is applied as follows: “If there are N alternatives, then rank all n recognized al-

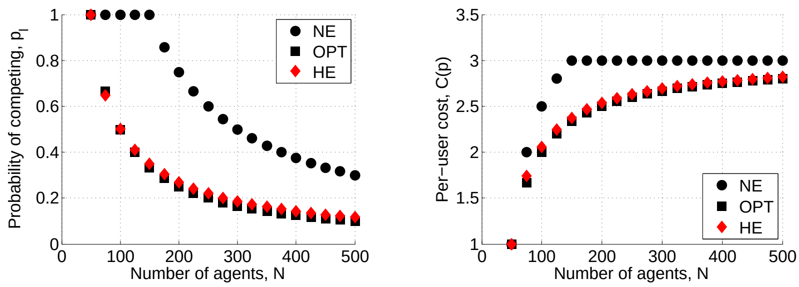


Figure 6.18: Probability of competing in heuristic equilibrium (left) and the resulting per-user cost (right), for $R = 50$, under fixed charging scheme $\beta = 3, \gamma = 4$.

ternatives higher on the criterion under consideration than the $N - n$ unrecognized ones". The order at which different reasons are examined to make a final decision is defined by the priority heuristic [Brandstatter *et al.*, 2006]. The availability heuristic is stated as "a graded distinction among items in memory, measured by the order or speed with which they come to mind or the number of instances of categories one can generate". Cognitive researchers have conceptualized a distinct version of availability heuristic, named as fluency heuristic. In particular, the authors in [Schooler & Hertwig, 2005] give the definition: "a strategy that artfully probes memory for encapsulated frequency information that can veridically reflect statistical regularities in the world". What is more, "the degree of knowledge a person has of a task or object" is termed as familiarity [Griggs & Cox, 1982]. The accessibility heuristic [Koriat, 1995] argues that "feeling - of - knowing judgments are based on the amount and intensity of partial information that rememberers retrieve when they cannot recall a target answer". Following the representativeness heuristic, people answer probabilistic questions by evaluating the degree to which a given event/object resembles/is highly representative of another one. When people adjust a given initial value to yield a numerical prediction, they devise the adjustment - and - anchoring heuristic. Tversky and Kahneman in [Tversky & Kahneman, 1974] discuss biases to which some of the abovementioned heuristics could lead, digging people's responses that are in favor of or against a specific set of alternative choices.

Models that rely on cognitive heuristics constitute more radical approaches to the decision-making task that originate from the cognitive psychology domain and specify the underlying cognitive processes while they make quantitative predictions. In fact, the cognitive heuristics operate as adaptive strategies that allow agents to turn complex decision tasks of predicting others' preferences, assessing corresponding utilities or costs, determining best or better actions, to simpler decision-making tasks.

As such, one may argue that heuristics are more transparent than other approaches and could be more acceptable to the consumers of transportation decision modeling (*e.g.*, policy-makers) [Katsikopoulos, 2011]. Indeed, to effectively alleviate congestion phenomena in city areas caused by the circulation of large numbers of vehicles in search for available parking space, transportation engineers need to be able to understand how drivers make their decisions concerning route planning and parking spot choices. However, modeling the real-world interaction of drivers' decisions in the emerging smart city environments, admittedly, can be proved to be a very complicated task. On one side the inherent challenging city planning, including the route and parking layout and, on the other side, the uncertainty in the human attitude towards different routing/parking options, induce significant complexity in analytically evaluating the performance of different strategies for route or parking spot selection.

We close Section 6.2 by considering a simplified structure of a city environment and representative behavioral profiles that help overcome computational hindrances and reduce complexity. In particular, we consider the road topology that Hutchinson, Fanselow and Todd introduce in [Todd. *et al.*, 2012], that is, a long dead-end street, two one-directional lanes leading to and away from a destination and a parking strip between the two lanes, as shown in Figure 6.19.

As it will become clear in the next section, searching for an empty parking spot in such parking lot arrangement amounts to a type of a sequential search. Typically, empirical evidence shows that decision-makers respond to the complexity of sequential search problems (*e.g.*, mate choice, secretary problem, parking search) by acting heuristically. Interestingly, albeit the human cognitive limitations, time constraints and lack of full information in those reasoning contexts, simple rules of thumb can frequently perform as well as more sophisticated search approaches by exploiting the structure of the information in the environment (Ref. *ecological rationality* in [Goldstein & Gigerenzer, 2002]). In this investigation, the drivers employ a decision rule based on their distance from the destination, namely the *fixed-distance heuristic*, which ignores all places until

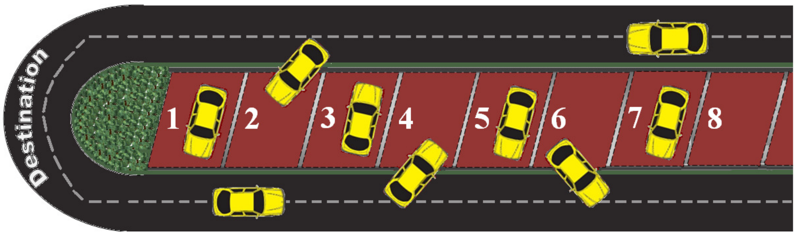


Figure 6.19: The structure of the parking environment.

the driver reaches a specific distance from the destination and then takes the first vacant one. Ultimately, we seek to systematically study the efficiency of the fixed-distance heuristic within the sequential parking search context. It is important to notice that this instance of heuristics incorporates two fundamental practices in behavioral decision theory, one-at-a-time processing of pieces of information and the use of thresholds [Katsikopoulos, 2011]. The fixed-distance heuristic decision strategy is considered in this study by factoring in knowledge that the driver may or may not have about the status (empty or occupied) of the next to the currently inspected parking spot in the direction towards the destination. This knowledge leads to distinct behaviors and realizations of the empty/occupied spots and thus, two distinct case-studies of the fixed-distance heuristic decision-making: *with view-ahead* (w-VA) and *without view ahead* (w/o-VA).

6.2.5 Game setting

Implementing the basic assumptions introduced in Section 6.2.4, we consider a parking lot of R parking spots arranged as shown in Figure 6.19 and N drivers that seek available parking space within this lot. The drivers employ in their search the fixed-distance heuristic decision rule which ignores all places until the driver reaches as close as D places from the destination and then takes the first vacant one. The collective decision-making on parking place selection can be formulated in the following game setting:

Definition 6.2.2. *A Heuristic-Strategy Parking Game is a tuple* $\Gamma_H(N) = (\mathcal{N}, \mathcal{R}, \mathcal{D}, c(k), c'(k))$, *where:*

- $\mathcal{N} = \{1, ..., N\}, N > 1$ *is the set of drivers who seek parking space,*
- $\mathcal{R} = \{1, ..., R\}, R \geq N$ *is the set of parking spots, with set items in increasing order with*

respect to their distance from the destination (i.e., the closest-to-destination spot is the first set item),

• $\mathcal{D} = \{1, ..., N\}$*, (recall* $R \geq N$*), is the set of the fixed-distance heuristic strategies with set items that denote at which distance from the destination the drivers initiate their search,*

• $c(k)$ *and* $c'(k)$ *are the cost functions for occupying the* kth *parking spot after travelling across the approach lane only, or both lanes, respectively.*

In particular, let $a, b, d, e \geq 0$ be the cost weights (more precisely, cost per distance unit, where a distance unit is defined to be the - assumed constant - distance between two consecutive parking spots) for walking (a), driving through the approach lane (b), driving through the return lane (e) and driving away from a particular parking spot (d) (Ref. Figure 6.20). For example, $a > b, d$ would mean "prefer driving a bit more rather than walk for long" and $e > b$ would imply "it hurts more if we reach the end of the street and still have not found a spot, hence, have to take a turn and start". Thus, the cost incurred by a driver that parks at the kth parking spot while travelling in the approach lane is

$$c(k) = b(R - k) + d(R - k) + 2ak, \quad 1 \leq k \leq R \tag{6.65}$$

whereas ending in the same parking spot while travelling in the return lane entails a higher cost, that is

$$c'(k) = bR + e(k - 1) + d(R - k) + 2ak, \quad 1 \leq k \leq R \tag{6.66}$$

Indeed, the order of a parking event together with the adopted heuristic strategies determine the specific spot at which a driver parks (*i.e.*, the ith parking event, with $1 \leq i \leq N$, occurs at the kth parking spot) and whether this spot is reached through the approach or the return lane.

In the following two sections, we derive the equilibrium states of the game and assess their (in)efficiency under two distinct case-studies: parking search with and without view of the availability status of the parking spots ahead. As in the original treatment of the problem, we distinguish between the aspiration level (*i.e.*, adopted distance threshold) of a single "mutant" driver (D_m, $D_m \in \mathcal{D}$) and the - assumed to be common - aspiration level of the rest of the population (D_p, $D_p \in \mathcal{D}$). Indeed, we seek symmetric equilibria[10] whereby

[10]The derivation of asymmetric equilibria is much harder and their realization in practical situations is much more difficult than that of their symmetric counterparts.

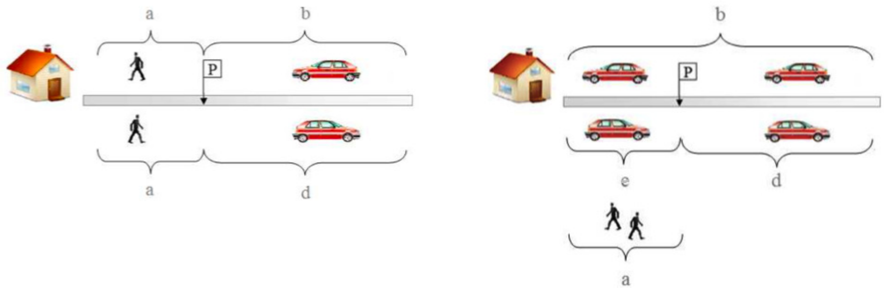


Figure 6.20: Cost weights for walking and driving in the approach and return lane, when the driver travels across only the approach lane (left) or both lanes (right) to reach his parking spot.

the expected cost for the mutant driver is minimized at $D_m = D_p$. The efficiency of the satisficing fixed-distance heuristic strategy is assessed by comparing the cost induced by the equilibrium strategy profiles to that under the optimal parking spot allocation, whereby no driver continues his search in the return lane and hence, the overall cost paid by drivers is minimized. Typically, this is the case when the full information processing and decision-making tasks lie with a centralized parking assistance service.

As last notes, it should be pointed out that the drivers are viewed as decision-makers that, by repeated and varied attempts, adjust their strategy to minimize the incurred cost and hence, they reach those equilibria. In addition, this study implies that all drivers share the same chance of parking at a specific order and none leaves his parking place before the last arrival. This assumption could correspond, for instance, to a scenario where drivers arrive at the business district area in the morning within a given time window, *e.g.*, 8.30-9.00, park for the duration of the working day, and leave the spots in the afternoon to go back home.

6.2.6 Fixed-distance heuristic parking strategy with view ahead

In this section we study the fixed-distance heuristic parking strategy in an environment whereby *the drivers never occupy a place if the place right next to it is also vacant, on their way to the destination.* This is in accordance with the initial formulation in [Todd. *et al.*, 2012] and would correspond to a side-by-side arrangement of parking spots across some street. In such environments the parking spot area fills sequentially, starting from the destination dead-end. Hence, the ith parking event, with $1 \leq i \leq N$, occurs at the ith parking spot, irrespective of the employed D_m and D_p. However, the corresponding cost

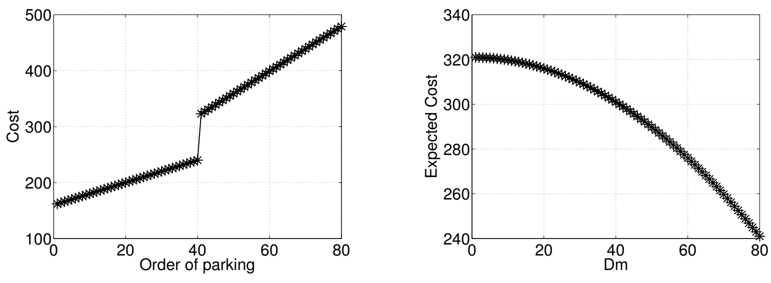


Figure 6.21: Parking w-VA: Cost of playing $D_m = R/2$ as a function of the order of parking (left) and expected cost of the fixed-distance heuristic parking strategy (right), $N = R = 80, a = 2, b = d = e = 1$.

does depend on the aspiration level of the driver associated with the ith parking event; namely, the mutant driver pays $c(i)$, if $i \leq D_m$ and $c'(i)$ if $i > D_m$. Figure 6.21(a) plots the cost incurred by the driver associated with the ith parking event as a function of i. By invoking equations (6.65) and (6.66), the expected cost of playing D_m is given by

$$\begin{aligned} E[C] &= \frac{1}{N}\left[\sum_{i=1}^{D_m} c(i) + \sum_{i=D_m+1}^{N} c'(i)\right] \\ &= \frac{1}{2N} D_m(1+D_m)(2a-b-d) + R(b+d) + \frac{N-D_m}{2N}\left[(1+D_m+N)(2a+e-d) - 2e\right] \end{aligned} \quad (6.67)$$

Note that this cost is independent of D_p. Therefore, in symmetric equilibrium (where all drivers adopt the same strategy) all drivers start their search for parking place once they have reached a distance D_m that minimizes the expected cost function in equation (6.67). Since $\frac{dE[C]}{dD_m} < 0$, the expected cost is minimized for the maximum value that D_m may assume, which is N. Thus, starting the search for available parking space from the very beginning, seems the most rational strategy to minimize the expected cost, irrespective of others' preferences (*e.g.*, Ref. Figure 6.21(b)). In terms of Game Theory, this strategy is the best response for all players; namely the game has exactly one (symmetric) equilibrium strategy $D^{eq} = N$. The intuition is that having a view of the next parking place's status brings benefits to the drivers when this is possible (there are empty spots ahead). Hence, by exercising this very simple heuristic strategy at the equilibrium aspiration level D^{eq}, drivers will never end up paying the extra penalty of e cost units of driving in the return lane.

6.2.7 Fixed-distance heuristic parking strategy without view ahead

In this section, *the drivers take the first empty place they encounter within a distance of at most D places from the destination, on their way to the destination.* This would correspond to a dispersed yet uniform arrangement of parking spots across a street, so that the status of the next spot is not visible when the drivers reach the immediately previous one. Unlike the case in Section 6.2.6, the expected cost for using a parking spot depends on both realized strategies D_m and D_p. In order to systematically analyze the consequences of a strategy profile (D_m, D_p), we explicitly discriminate between two cases, featuring $D_m > D_p$ and $D_m \leq D_p$, respectively.

Strategy profiles with $D_m > D_p$

In this case, the following observations may be made for the parking patterns (Ref. Figure 6.22(a)):

• drivers (other than the mutant driver) will first fill in all the spots in segment $< destination, D_p >$ while approaching the destination, and then start filling up the spots in segment $< D_p, D_m >$ while moving away from the destination. Hence, there is no possibility that the mutant driver encounters an occupied spot in segment $< D_p, D_m >$ as long as there exists at least one empty spot in segment $< destination, D_p >$,

• the mutant driver parks at least D_m places away from the destination.

If the mutant driver is associated with the ith parking event, he will park at a distance of $max(D_m, i)$ spots away from the destination. The corresponding cost is $c(D_m)$, if $i \leq D_m$ and $c'(i)$, if $i > D_m$. Thus, if $D_m > D_p$ the expected cost becomes

$$\begin{aligned} E[C] &= \frac{D_m}{N} c(D_m) + \frac{1}{N} \sum_{i=D_m+1}^{N} c'(i) \\ &= \frac{N-D_m}{2N}(1+D_m+N)(2a+e-d) + \frac{D_m}{N}\left[D_m(2a-d-b)+e\right] + R(b+d) - e \end{aligned} \quad (6.68)$$

The analysis of this function gives that $\frac{dE[C]}{dD_m} = \frac{1}{N}\left[-D_m[2(b-a)+d+e] - a + \frac{d+e}{2}\right]$ and $\frac{d^2E[C]}{dD_m^2} = -\frac{1}{N}[2(b-a)+d+e]$. Hence, if $2(b-a)+d+e \geq 0$, then $E[C]$ is concave and monotonically decreasing with D_m. Otherwise, $E[C]$ is convex. Therefore, the expected cost function assumes its minimum value at

(a) $D_m > D_p$ (b) $D_m \leq D_p$

Figure 6.22: Parking w/o-VA: Available parking options for a driver with strategy D_m, given the strategy D_p of the rest of the population.

$$D_{m\,min} = \begin{cases} N, \text{ if } 2(b-a)+d+e \geq 0 \\ \frac{d+e-2a}{2[2(b-a)+d+e]}, \text{ if } 2(b-a)+d+e < 0 \end{cases} \tag{6.69}$$

Strategy profiles with $D_m \leq D_p$

When the mutant driver exposes a more risky behavior comparing to others, the following observations may be made for the parking patterns (Ref. Figure 6.22(b)):

• the drivers fill in sequentially all spots from the parking place D_p towards the destination. Hence, there is no possibility that the mutant driver encounters an occupied spot in segment $< destination, D_m >$ as long as there exists at least one empty spot in segment $< D_m, D_p >$,

• the mutant driver parks either at segment $< destination, D_m >$ or at least D_p places away from the destination.

If the mutant driver is associated with the ith parking event, it holds that: if $i > D_p$, the mutant driver parks at the ith spot at a cost of $c'(i)$ units; if $D_p - D_m < i \leq D_p$, he parks at the $(D_p - i + 1)th$ spot at a cost of $c(D_p - i + 1)$ units; and if $i \leq D_p - D_m$, he parks at the $D_m th$ spot at a cost of $c(D_m)$ units. Figure 6.23 plots the resulting cost of parking events of particular order. Thus, if $D_m \leq D_p$, the expected cost equals

$$\begin{aligned} E[C] &= \frac{1}{N}\sum_{i=D_p+1}^{N} c'(i) + \frac{1}{N}\sum_{i=D_p-D_m+1}^{D_p} c(D_p - i + 1) + \frac{D_p - D_m}{N} c(D_m) \\ &= \frac{N-D_p}{2N}\left[(1+D_p+N)(2a+e-d)-2e\right] + R(b+d) + \frac{D_m}{2N}\left(D_m - 2D_p - 1\right)(b+d-2a) \end{aligned} \tag{6.70}$$

The analysis of the expected cost function for the monotonicity and concavity trends gives that $\frac{dE[C]}{dD_m} = \frac{1}{N}(b+d-2a)\left(D_m - D_p - \frac{1}{2}\right)$ and $\frac{d^2E[C]}{dD_m^2} = \frac{1}{N}(b+d-2a)$. If $b+d-2a > 0$, then $E[C]$ is convex and monotonically decreasing with D_m, whereas if $b+d-2a < 0$, then

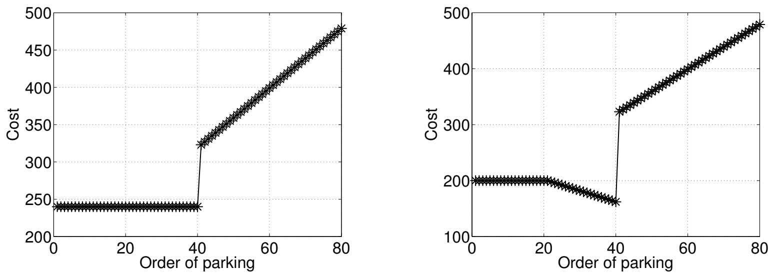


Figure 6.23: Parking w/o-VA: Cost of playing $D_m = R/2$ (left) and $D_m = R/4$ (right) against a population who plays $D_p = R/4$ (left) and $D_p = R/2$ (right) as a function of the order of parking, $N = R = 80, a = 2, b = d = e = 1$.

$E[C]$ is concave and monotonically increasing with D_m. (Otherwise, $E[C]$ is a constant function and the driver experiences the same expected cost irrespective of his strategy of preference.) Ultimately, if $D_m \leq D_p$, the mutant driver minimizes his expected cost if he starts his search for parking space from

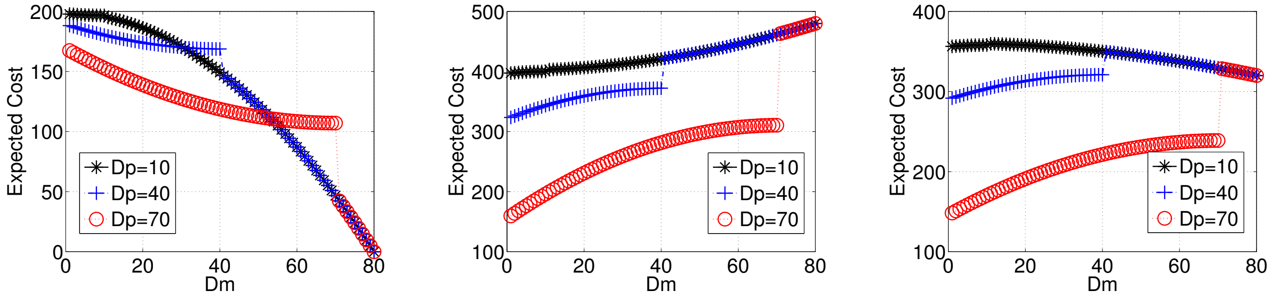
$$D_{m_{min}} = \begin{cases} D_p, \text{ if } b + d - 2a > 0 \\ 1, \text{ if } b + d - 2a < 0 \end{cases} \tag{6.71}$$

Hence, the expected cost exhibits one of three possible minimum values[11], depending on specific conditions on the cost weights. More precisely, by (6.69) and (6.71), the expected cost function for the parking search without view ahead assumes its minimum value at

$$D_{m_{min}} \begin{cases} = N, \text{ if } b + d - 2a \geq 0 \\ \in \arg\min_{D_m{}' \in \{1, \frac{d+e-2a}{2[2(b-a)+d+e]}\}} E[C/D_m = D_m{}'], \text{ if } 2(b-a) + d + e < 0 \\ \in \arg\min_{D_m{}' \in \{1, N\}} E[C/D_m = D_m{}'], \text{ if } 2(b-a) + d + e \geq 0 \text{ and } b + d - 2a < 0 \end{cases} \tag{6.72}$$

Figure 6.24 depicts the expected cost for the mutant driver, when he exposes a risk-seeking ($D_m \leq D_p$) or risk-averse ($D_m > D_p$) attitude, given three different values of D_p. As Figure 6.24 and equation (6.68) suggest, all three cases of D_p share the same cost results when $D_m > D_p$. On the contrary, the curves differ on their left part, since the expected cost for $D_m \leq D_p$ is a function of D_p (Ref. equation (6.70)). In all plots the minimum expected costs satisfy the results in (6.72).

[11] By comparing the left end point $E[C/D_m = D_p + 1]$ of the branch $D_m > D_p$, with the right end point $E[C/D_m = D_p]$ of the branch $D_m \leq D_p$, we have that $E[C/D_m = D_p] > E[C/D_m = D_p + 1]$ if $b + d - 2a \geq 0$ and $E[C/D_m = D_p] < E[C/D_m = D_p + 1]$ if $2(b-a) + d + e < 0$ and $D_p > 1$, or if $2(b-a) + d + e < -b$ and $D_p = 1$.



(a) $a = 0, b = 1, d = 1, e = 2$ (b) $a = 3, b = 1, d = 0, e = 2$ (c) $a = 2, b = 1, d = 0, e = 3$

Figure 6.24: Expected cost for the fixed-distance heuristic parking strategy w/o-VA, $N = R = 80$.

Overall, if we restrict our interest to only symmetric equilibria, the analysis of this section concludes that there is always at most one symmetric equilibrium whereby the drivers demonstrate either a fully conservative attitude, $D^{eq} = N$, starting their search from the beginning (when $b+d-2a \geq 0$, *e.g.*, Ref. Figure 6.24(a)) or a fully aggressive one, $D^{eq} = 1$, anticipating a vacancy adjacent to the destination (when $2(b-a)+b+d+e < 0$, *e.g.*, Ref. Figure 6.24(b)). The intuition in the first equilibrium case is that drivers prefer walking than driving and hence, by choosing $D^{eq} = N$ drivers park at the first available parking spot on their way towards the destination, avoiding excess driving in the approach or the return lane. In the second equilibrium case, drivers prefer driving than walking and hence, they are drawn towards spots close to the destination, seeking to minimize the walking overhead. Contrary to the first equilibrium case whereby the simple fixed-distance heuristic rule minimizes the overall social cost, in the second case all but one drivers end up paying the extra penalty of e cost units. In between the two extreme values 1 and N, there is no other symmetric equilibrium since there are no cost weights that - satisfy both the conditions $b+d-2a \geq 0$ (constant or decreasing $E[C]$, for $D_m \leq D_p$) and $2(b-a)+d+e < 0$ (convex $E[C]$, for $D_m > D_p$) and - allow the expected cost to exhibit its minimum value at $D_m = D_p$, with $1 < D_p < N$.

Finally, when $2(b-a)+d+e \geq 0$ and $b+d-2a < 0$, there is no symmetric equilibrium since the value D_{mmin} decreases with D_p. In particular, the two possible minimum expected costs that may appear are $E[C/D_m = 1, D_m \leq D_p]$ and $E[C/D_m = N, D_m > D_p]$. However, the strategy selected by the population, D_p, affects the minimum expected cost of the mutant driver, only if he demonstrates a risk-seeking behavior, expressed in the strategy $D_m = 1$. Furthermore, if $D_m = 1$, the expected cost is a decreasing function of D_p, since $\frac{dE[C/D_m=1, D_m \leq D_p]}{dD_p} < 0$, while it holds that $E[C/D_m = 1, D_p = 1] > E[C/D_m = N, D_p = 1]$ and $E[C/D_m = 1, D_p = N] < E[C/D_m = N, D_p = N]$. The intuition behind this result is that when the drivers do not have a clear preference over walking or driving (*i.e.*, $2(b-a)+d+e \geq 0$ and $b+d-2a < 0$) the mutant driver profits from exhibiting the opposite attitude with respect to what all the rest of the population do (Ref. Figure 6.24(c)). Namely, by choosing high (low) D_m values under low (high) D_p values, the driving (walking) savings counterbalance the walking (driving) overhead.

6.2.8 The two-player game $\Gamma_H(2)$

In this section we focus our attention on the interaction of exactly two drivers within the reference parking area. Table 6.5 shows the resulting game matrix for the strategy profiles.

Table 6.5: Game matrix for the parking game $\Gamma_H(2)$.

	$D_p = 1$	$D_p = 2$
$D_m = 1$	A, A	B, C
$D_m = 2$	C, B	D, D

We arbitrarily consider the row player as the mutant driver and the column player as the driver that constitutes the rest of the population. With A, B, C, D we denote the expected costs for the row player (or the column player, as they are symmetric) when he responds with $D_m = 1$ to the population strategy $D_p = 1$, or with $D_m = 1$ to $D_p = 2$, or with $D_m = 2$ to $D_p = 1$, or finally, with $D_m = 2$ to $D_p = 2$, respectively. By (6.68) and (6.70) the expressions for A, B, C and D are

$$A = \left(R - \frac{1}{2}\right)(b+d) + 3a - d + \frac{1}{2}e$$

$$B = (R-1)(b+d) + 2a$$

$$C = (R-2)(b+d) + 4a$$

$$D = \left(R - \frac{3}{2}\right)(b+d) + 3a$$

In order to determine the equilibrium states in the parking game, we compare the expected costs that are induced by either strategy and, hence, define the best responses for every player. Then, we draw similarities between the two-player parking game and well-known archetypal games that present the same equilibria, under the same assumptions for the dominance of the strategies. Thus, it is possible to expand our understanding of the interaction of the drivers by exploiting known results from the theoretic investigation of those classical games (*e.g.*, results regarding the iterative versions of the games).

$2(b-a)+d+e<-b$: Given the particular condition for the costs, we derive that B < D < A < C and hence, the equilibrium state is $D_m = D_p = 1$. This is an instance of the Prisoner's Dilemma. Therefore, the parking game converges to the "bad" (most expensive) symmetric strategy profile.

$b+d-2a>0$: This condition results in the ordering $C<D<B<A$, if $2a+b+e-d>0$ and $C<D<A<B$, if $2a+b+e-d<0$. This is an instance of the Deadlock Game and, unlike the Prisoner's Dilemma, the action $D_m = D_p = 2$ that is mutually most beneficial (less expensive) is also dominant.

$2(b-a)+d+e>-b$ and $b+d-2a<0$: These conditions result in $B<D<C<A$ and yield the two asymmetric equilibria $D_m = 1$, $D_p = 2$ and $D_m = 2$, $D_p = 1$. This is an instance of the Chicken Game (or Hawk-Dove Game), whereby the players are called to choose whether to back off or risk fighting, with one of the two symmetric strategy profiles (fighting) being disastrous for both. The game, also, exhibits a symmetric mixed-strategy equilibrium where both players randomize over their pure-strategy space.

Part III

Effectiveness and side-issues in managing public goods through vehicular social applications

Chapter 7

Social parking applications: turning common goods to private goods?

More than ever before, information and communication technologies (ICT) help people around the globe overcome the physical separation constraints and exchange information while working or in their leisure. On the one hand stands the integration of sensing devices of various sizes and capabilities with mobile communication devices. This enables the generation and collection of huge amounts of information, of very different spatial and temporal context, by leveraging the heterogeneity of users' interests, preferences and mobility. When sensing and radio communication technologies are mounted on vehicles, in particular, they convert them into pervasive sensing platforms. These platforms can then collect various types of information about the urban environment, ranging from natural environment status indices (humidity, temperature) to traffic conditions and parking space availability.

On the other hand, online social networking applications provide a fast and easy way to publish and share this *information* among their users. More importantly, they often process it in various ways to generate *knowledge*, which can find use in various vehicular network applications such as safety, traffic management, and infotainment applications. At the same time, these social applications instantiate virtual spaces, over which their users interact, communicate and collaborate with each other. Examples of such virtual social communities are the drivers (commuters, in general) who follow similar trajectories in their daily driving routines.

In this section, we focus on an emerging generation of *social parking applications* that seek to transform the way the search for parking space is carried out in busy urban environments, where the demand for parking space may exceed its supply. Social parking applications have been deployed over the last couple of years in different European and North American cities, including Athens ("ParkingDefenders"[1]), Paris ("PlaceLib"[2]), New York ("ParkShark"[3]), San Francisco ("Kurb"[4]). Several features are common across them: they run on smartphones, support multiple operating systems, and enable drivers to hand over parking spots to each other. Application users can offer their parking spot to other users seeking one; or find a parking spot for themselves by claiming a spot another user is offering. Most applications embed social comparison and gamification mechanisms in their design to incentivize users. Users are rewarded for their offers with non-monetary credits and their current credit-based ranking is monitored and published by the application. High-credit users then enjoy higher chances to be chosen by a parking spot sharer (defender) when they seek a parking spot ("ParkingDefenders"); or get informed about a vacant spot prior to other seekers ("ParkShark"); or consume some of their credits when they seek available space ("PlaceLib")("Kurb").

Although some of these applications are currently in use, we are aware of no systematic study of their performance and scalability properties. Questions that arise in this respect are:

- How is the advantage of the application users over non-user drivers affected by the penetration rate?
- For given penetration levels, do the application users end up largely monopolizing the parking resources so that non-user drivers are, in essence, almost excluded from using public parking spots (goods)?
- Does the virtual credit incentive mechanism induce rich-club phenomena, whereby a subset of users in a population of drivers with identical needs for parking space,

[1] ParkingDefenders: parking application for Athens (Greece), available online in $http://www.parkingd.com$

[2] PlaceLib: parking application for Paris, available online in $http://www.placelib.com$

[3] ParkShark: parking application for New York City, available online in $http://www.parkshark.mobi/www/$

[4] Kurb: parking application for San Francisco, available online in $http://www.kurbkarma.com$

seizes the parking resources by handing over spots among them and hence, continually increasing their ranking?

To address these questions, we model the two fundamental elements that are encountered in different instances of social parking services: the awareness (*i.e.*, information) and the incentive (*i.e.*, rankings) mechanisms. In the same section we present the details of three different driver profiles: the application users that (have access to information/services provided by the application and) share their parking spots (*i.e.*, Defenders) or simply seek parking space but do not share theirs (*i.e.*, Seekers) and the traditional drivers that do not subscribe to any such application. The model has taken into account data from recent surveys and statistics and has employed a queuing model that approximates the size of the driver population for given parking demand levels.

Overall, we are interested in understanding the impact of the application operation on both its users and the rest of the driver population, as well as identify key parameters, such as the penetration rate or the parking supply and demand, that can affect these social applications' efficiency. We set up focused scenarios that help us explore particular aspects of these applications as the parking demand scales up and competition phenomena emerge. The operation of these applications is shown to yield a significant advantage for their users at the expense of only slight (or moderate, at high-penetration-rate environments) deterioration of traditional drivers. The incentive mechanism, especially, is shown to operate efficiently, offering preferential treatment to those fully cooperating, yet it induces rich-club phenomena. Those problems are mitigated as the number of parking spot offers by application users drops. In a final scenario, drivers' behavior is allowed to alternate between the three different users' profiles. In this dynamic environment, we show that old and new application subscribers end up with similar probabilities to win the competition for parking space, indicating that dynamicity creates the conditions for a fair treatment of newcomers to such an application.

7.1 Modeling the social parking application

The primary objective in this study is to illuminate fundamental properties that are common across the different social parking applications launched over the last couple of years. To this end, we have developed a discrete-event simulation environment that abstracts the precise details of the individual applications and rather focuses on their two critical components: the *collective awareness layer* they induce and the *(pseudo)credit-based mechanism* they implement for motivating their users to cooperate in the handover of spots.

Our environment is initialized with R parking spots and N driver nodes. Each driver node alternates among four possible states, $parked_{os}$, $parked_{pl}$, *search*, *idle*. Its residence time at the idle state is described by a Random Variable, t_i, and is closely related to its parking attempt rate. Upon a parking attempt, it enters the *search* state and stays there for a maximum time of T_s^{max}. If it succeeds in seizing an on-street parking spot within this time, it jumps to the $parked_{os}$ state; otherwise, it enters the $parked_{pl}$ state (*e.g.*, equivalent to driving to a parking lot). In either case it remains parked for time t_p, which follows the parking time distribution, before returning to the idle state.

Three driver node profiles are implemented in this environment: (a) the *traditional driver*, who seeks a parking spot without assistance from any application; (b) the *parking defender* who uses the social parking application and facilitates other users of the application by informing the system when leaving a parking spot and handing over its spot to another application user who is looking for parking in the same area; and (c) the *parking seeker*, who uses the application only for getting informed about vacant spots and parking offers, but neither informs the application when he vacates a spot nor does he wait to hand it over to another application user. The traditional driver profile represents the traditional practice in searching for on-street parking space, while the other two profiles are induced by the social parking applications, instantiating the favorable cooperative norm and the annoying free-riding phenomenon, respectively. The aforementioned three profiles are described in more detail below.

Defender profile: When an application user shares a parking spot[5]

1. locates his parking spot on the map and informs the application,

2. reviews the existing requests for the particular spot, accepts and replies to one

[5]In realized systems, user nodes that offer a parking place, may also indicate when they intend to free the spot, wait until the time they declared when they made the offer ends and watch the selected vehicle approaching before they leave the spot.

based on some criterion (such as, the requesters' rating and their distance from the spot at the time of the request),

3. earns some rating in reward of his offer.

Seeker profile: When an application user seeks available parking spot[6]

1. submits a request of interest to every relevant offer available until the acceptance of his request or until the detection of a vacant parking spot,

2. if the request is accepted, parks at the particular spot, rates the Defender driver and remains parked for a time interval according to some probability distribution,

3. when the parking time ends, abstains from competition for a parking space for a time interval according to some probability distribution, before initiating another parking searching attempt.

Traditional driver profile: It refers to drivers that ignore the social parking application and

1. abstain from competing for a parking spot for a time interval that follows some probability distribution,

2. when the latter time interval expires, they start wandering randomly in search for a parking spot,

3. park at the first encountered vacant parking spot for a time interval according to some probability distribution.

Application users might exercise both profiles: they may operate as Defenders and assist others in anticipation of non-monetary credits that will increase their rating, or operate exclusively as Seekers hoping to benefit from the advantage that application users have over the traditional drivers. In environments with mixed populations, when no Seeker (or Defender) is interested in parking or when a traditional driver or Seeker vacates a spot, all interested drivers have the same chance to be served.

[6]In realized systems, user nodes that seek a parking spot, define the search area for available parking spots and choose one to send a request of interest. If the request is accepted, they are provided with driving directions to the spot and if they end up parking at the particular spot, they rate the Defender driver.

7.2 Model parametrization and performance metrics

To populate our simulator with meaningful numbers, we have drawn on real maps of on-street parking space in the city of Athens, Greece. We consider one of the busiest areas at the Athens city center featuring 140 controlled on-street parking spots. According to the report in [INTERREG IIIC: City Parking in Europe, 2006], the average parking demand, L_p, in these districts, as inferred by accounting for illegally parked vehicles, can be up to 150% of the on-street parking space supply. We simulate drivers who enter this area and search for parking space once a day, on average, resulting in exponentially distributed t_i with mean equal to one day. The maximum search time before quitting search is set to $T_s^{max} = 15min$ [le Fauconnier & Gantelet, 2006] [Polycarpou *et al.*, 2013]. Finally, parking times t_p are assumed exponential with mean equal to one hour. The duration of simulations is ten days, which is enough time to generate a significant number of parking events for all drivers.

To compute the equivalent driver population N that yields a given over-demand ratio L_p, we devise and solve (reverse engineering) a stochastic finite-source queuing model for the parking search process. In particular, we formulate a 2D continuous-time Markov chain with states (x, y), where x represents the number of drivers occupying an on-street parking spot or in search for one (referring to as the active population) and y represents the number of drivers that have quitted the search for an on-street spot and have ended up in a parking lot (referring to as the inactive population). If λ, μ and γ denote the rates $E[t_i]^{-1}$, $E[t_p]^{-1}$ and $E[t_s]^{-1}$, respectively, there are four different types of transitions from an initial state (i, j) to a next state (i', j') occurring at rate $q_{(i,j;i',j')}$.

Transitions that increase the size i of the active population

$$q_{(i,j;i+1,j)} = (N - i - j)\lambda, \quad 0 \leq j \leq N - R, 0 \leq i < N - j$$

Transitions that decrease the size i of the active population

$$q_{(i,j;i-1,j)} = \begin{cases} i\mu, 0 \leq j \leq N - R \text{ and } 1 \leq i < R \\ R\mu, 0 \leq j \leq N - R \text{ and } R \leq i \leq N - j \end{cases}$$

Transitions that decrease the size j of the inactive population

$$q_{(i,j;i,j-1)} = j\mu, \quad 1 \le j \le N-R, 0 \le i \le N-j$$

Transitions due to a driver quitting his search for a parking spot

$$q_{(i,j;i-1,j+1)} = (i-R)\gamma, \quad 0 \le j < N-R, R < i \le N-j$$

In our scenarios, we generally account for mixed populations of users and non-users of the application letting the application penetration rate, r_p vary in $[0, 100]\%$. Likewise, the percentage of Seekers over the application users, r_s, varies over $\{0, 30, 50, 70\}\%$. User rankings are initialized to values uniformly drawn from the intervals $[0, 2]$ (default case) or $[0, 9]$ and each parking spot handover by a parking Defender to another application user is thereafter rewarded by C credits (default value, $C = 3$) that do not age. A parking Defender offers his parking spot to the requester with the highest ranking (accumulated credit).

The impact of a social parking application on the drivers (both users and non-users) is quantified through two metrics: the parking success rate, r_{suc}, measured as the percentage of a driver's successful parking attempts; and, the time t_s spent in search for a parking spot till either capturing a parking spot or heading for a parking lot ($t_s = T_s^{max}$).

7.3 Simulation results-experimentation

In this section we derive various simulation results under different mixtures of user profiles, aiming at depicting (a) the extent to which on-street public parking resources are hijacked by the social parking application users at the expense of traditional drivers and (b) the effectiveness and hidden fairness issues concerning the incentive mechanism and whether newcomers to the application are well integrated and not unfairly treated compared to existing application users.

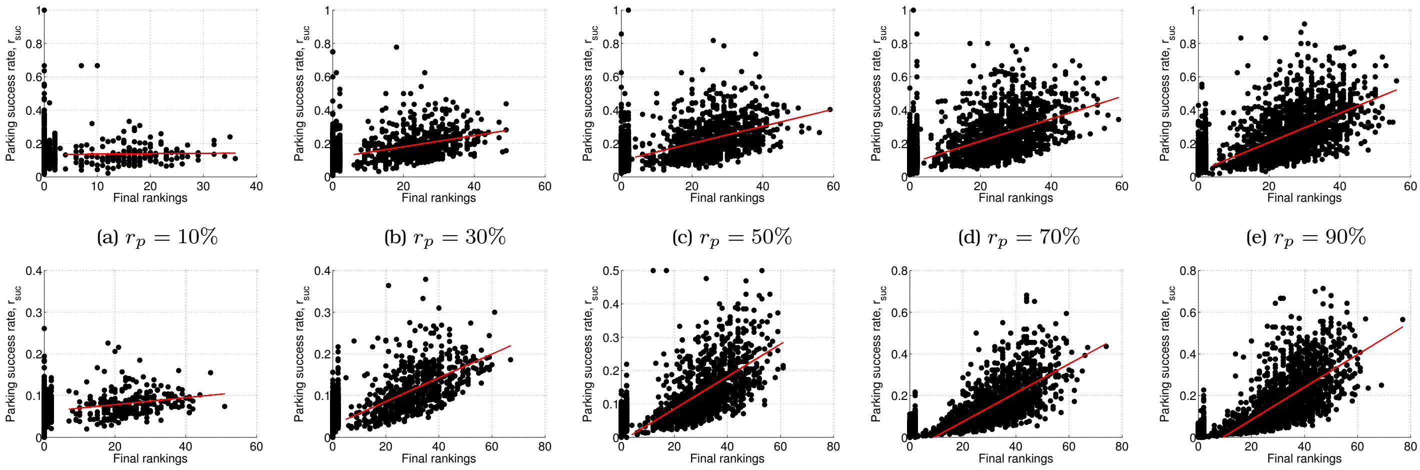
7.3.1 Effectiveness of the social parking application and impact on traditional drivers' performance

A number of smart mobile applications for efficient parking spot management have recently been developed. The first version of the system "ParkShark" (New York) was released in 2010. Two years later, the systems "PlaceLib" (Paris) (with 10.800 users and 5024 parking spots), "ParkingDefenders" (Athens, Greece) and "Kurb" (San Francisco) started their operation. Albeit new and under-dimensioned, the systems have emerged as breakthrough applications with strong potentials for large-scale development in the near future [Polycarpou *et al.*, 2013]. However, it is unlike that the entire driver population will subscribe to such parking systems, independently of whether a fee will or will not be charged for the provided parking assistance service. In the first case, the applied fee might discourage possible clients, while in the second case, the requirement for acquiring and operating advanced devices or even the lack of proper promotion of the services might hinder their growth.

Two questions become relevant in this respect: (a) How the penetration rate affects the advantage of application users over traditional drivers; and (b) whether the application tends to exclude traditional drivers from utilizing public parking places. By addressing these questions, we seek to comment on the boundaries that vouch high efficiency without turning a rivalrous (*i.e.*, occupation of a parking spot by one driver prevents simultaneous occupation by other drivers) but non-excludable (*i.e.*, drivers that have not subscribed cannot be prevented from accessing parking spots) public good into an excludable one.

Figure 7.1 plots the ultimate parking success rates against the drivers' rankings as shaped by the end of the simulation time, for two scenarios that differ in the intensity of the parking requests. Rankings of zero value in the plots correspond to traditional drivers, while Seekers and Defenders end up with rankings $0-2$ and above 2, respectively. Figures 7.2 and 7.3 plot the corresponding average parking success rates for different penetration rates.

In line with intuition, the higher the penetration rate, the more frequent the handovers of parking spots between application users and thus, the lower the parking opportunities for traditional drivers. A notable advantage of exploiting the parking service



(a) $r_p = 10\%$ (b) $r_p = 30\%$ (c) $r_p = 50\%$ (d) $r_p = 70\%$ (e) $r_p = 90\%$

(a) $r_p = 10\%$ (b) $r_p = 30\%$ (c) $r_p = 50\%$ (d) $r_p = 70\%$ (e) $r_p = 90\%$

Figure 7.1: Impact of penetration rates $r_p \in [10, 90]\%$ and parking request intensity $L_p \in \{150$ (first row), 165 (second row)$\}$, on the final satisfaction of traditional drivers and application users with Seekers' ratio $r_s = 50\%$. The red line corresponds to the simple linear regression model.

emerges, especially for the Defenders, even at low penetration rates and low intensity of requests (*i.e.*, Ref. first row of results in Figure 7.1). Under intense parking demand (*i.e.*, Ref. Figure 7.2 and second row of results in Figure 7.1), the abovementioned advantage emerges at even lower levels of penetration rate. Indeed, as the penetration rate and/or the intensity of request increase, upon a parking spot offer by a Defender, traditional drivers compete against at least one application user with high probability. Interestingly, this performance improvement of application users, both in terms of success rate and the ultimate search time, comes at the expense of only slight deterioration of the performance of traditional drivers, as depicted in Figure 7.2. Indeed, even in pure cooperative environments whereby the entire application user population participates in the handover/credit-building processes, users' improved performance is mostly due to the increased efficiency they generate in the parking search process, rather than excluding traditional drivers from the public parking resources (Ref. Figure 7.3).

7.3.2 Effectiveness of the incentive mechanism and some concerns on its fairness

The incentive (for cooperation) mechanism is central to the operation of the social parking application and the implementation of the Defender profile. On one hand, it is

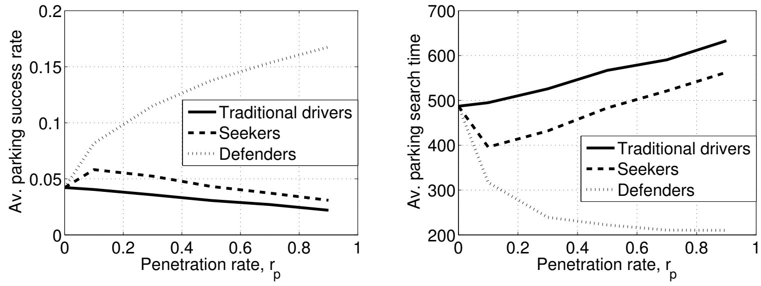


Figure 7.2: Average parking success rates and search times for $L_p = 165$, $r_s = 50\%$.

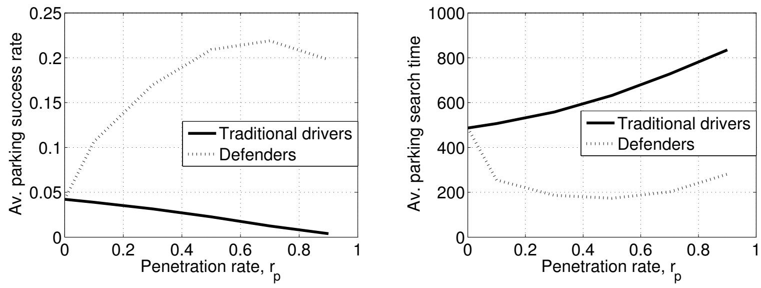
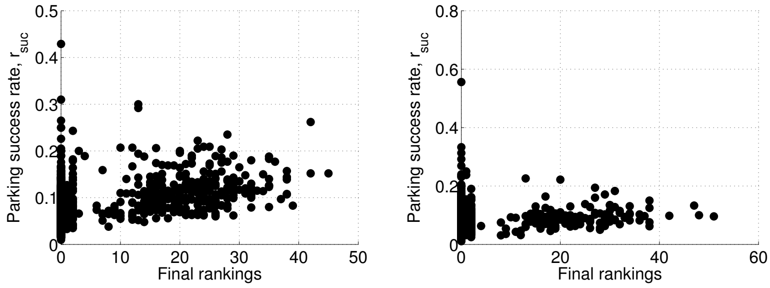


Figure 7.3: Average parking success rates and search times for $L_p = 165$, $r_s = 0\%$.

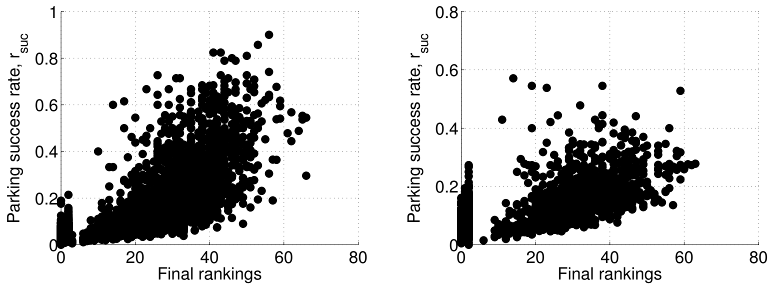
expected that an effective such mechanism would result in rewarding and providing better service to the most cooperative users. On the other hand, such a mechanism should not discriminate against users with similar interests, needs and attitude towards cooperation, or against newcomers to the application. Unfortunately, incentive mechanisms that are based on the accumulation of credit occurring over time and at a rate that depends on the frequency of interactions tend to yield some discrimination, as shown below.

First, we consider environments of various penetration rates and examine the degree of correlation between ranking and satisfaction, in order to assess the effectiveness of the incentive mechanism. Indeed, the plots in Figure 7.1 provide useful insights regarding the effectiveness of the incentive mechanism and the resulting parking service provided to the application users. In particular, plots referring to high-penetration-rate environments (*i.e.*, $r_p > 50\%$) show a strong relation between users' rankings and induced success rate, with (expected) higher success rates being coupled with higher rankings, suggesting that the incentive mechanism is effective. Table 7.1 provides the values of the coefficient of determination for the simple regression model that is drawn as a red line in the data point sets of Figure 7.1. The coefficient values increase with the penetration rate. Hence, the observed outcomes/rankings are better replicated by the regression model as the



(a) $r_s = 30\%$ (b) $r_s = 70\%$

Figure 7.4: Impact of the Seekers' ratio, r_s, on the final satisfaction of application users and traditional drivers, under $r_p = 10\%$ and $L_p = 157$.



(a) $r_s = 30\%$ (b) $r_s = 70\%$

Figure 7.5: Impact of the Seekers' ratio, r_s, on the final satisfaction of application users and traditional drivers, under $r_p = 80\%$ and $L_p = 157$.

penetration rate increases. This relation seems to present non-linear characteristics for very high penetration rates, which is a concern, due to the risk of having a few users, achieving high ranking, almost monopolize the resources and discourage otherwise fully cooperative users who happened to achieve lower ranking. Indeed, such concerns were founded through observations during the simulations showing that once a user wins in the initial competition round (whereby the differences in user rankings are limited and hence, the success probabilities similar for all), he immediately starts enjoying a competitive edge in the following rounds over other users with the same (Defender) profile, through the continuous credit accumulation. This rich-get-richer effect sharpens as the frequency at which drivers enter the parking search area increases, resulting in higher L_p (*i.e.*, $L_p = 165$) and, eventually, high probability for one to compete against higher-ranked drivers.

The application users' profile (*i.e.*, mixture of Defenders and Seekers) also affects the way the rankings and most importantly, drivers' satisfaction are shaped. Environments whereby the parking spot handover process is less frequent (*i.e.*, in the presence of a good portion of Seekers) provide fewer opportunities for credit-building and emergence of high rankings, thus preventing the monopolization of the parking resources by a few Defenders. Instances of these environments are depicted in Figures 7.4(b) and 7.5(b), where the majority of the users abstain from parking spot sharing (only 3% and 24% are Defenders in these plots). Although the Defenders enjoy the benefits of the good ranking and a higher success probability, application users might instead decide to follow the Seeker profile for a number of reasons; for instance, they may not desire to wait for the implementation of the parking spot handover process.

In view of the above discussions, it becomes clear that when the applications' penetration is high and a good portion of the application users follow the Defender profile, Defenders with very low ranking are very difficult to compete against those with high ranking and improve their success rate. Such very low-ranking Defenders would be newcomers to the social parking application desiring to fully cooperate upon joining the application. This could be an issue with the application as it would not encourage (or welcome) newcomers under the above (static) conditions. As application users are strongly guided in their behavior by a strong social/behavioral layer, it is very likely that the environment in which a social parking application will operate will be a dynamic one, where users occasionally modify their profile. In real environments, traditional drivers may subscribe to the application from time to time, while users may alternate between the two application user profiles. In this context, we question whether traditional drivers have the incentive to subscribe to the application. In particular, we simulate scenarios with low initial penetration rate ($r_p = 30\%$) whereby traditional drivers stochastically (with 10% probability) become application users, while users change profiles in response to the success rate they experience. That is, Seekers that win less that one fifth of the times they compete for an offered spot, start offering their place to others in anticipation of their credits (*i.e.*, assume the Defender profile). On the other hand, Defenders that see their success rate rise over 40%, might feel that there is no need for extra credits and hence, abstain from offering their place. Figure 7.6 illustrates the drivers' final success rates against their initial rankings without any profile transition (left plot) and with profile transitions as described above (right plot). In the first case, zero rankings yield

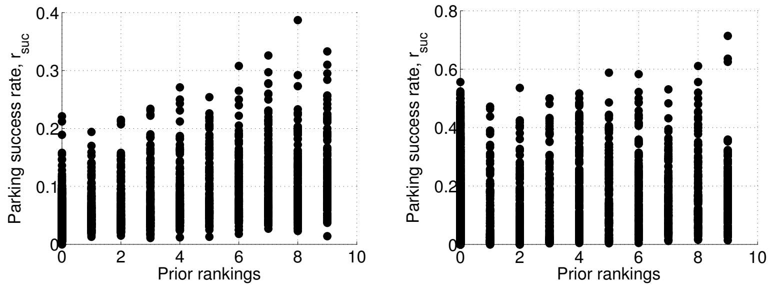


Figure 7.6: Final parking success rates in driver populations with static (left) and dynamic (right) drivers' profiles, under (initial rates) $r_p = 30\%$, $r_s = 50\%$, $L_p = 165$.

Table 7.1: Coefficient of determination, R^2 for the simple regression models on the data point sets in Figure 7.1.

		r_p				
		10%	30%	50%	70%	90%
L_p	150	$4.2 \cdot 10^{-4}$	0.09	0.15	0.19	0.28
	165	0.043	0.29	0.35	0.45	0.44

lower success rates. On the other hand, when these profile transition rules are applied (dynamic environment), initially traditional drivers are well integrated into the application as inferred by the similar satisfaction scores they achieve (right plot).

Chapter 8

Conclusions

In the last chapter, we present the main results of Parts II, III and introduce possible extensions for future work.

In Part II, we investigate the effectiveness and side-issues in building and exploitation of collective awareness in competitive environments. The part starts with Chapter 5 which explores information dissemination within competitive networking urban environments where networked vehicular user nodes have to autonomously decide whether to dispose private information. Information is essentially a kind of asset; sharing it, user nodes assist their potential competitors, in anticipation of their support in due course. We consider realistic scenarios of an opportunistic parking assistance system that instantiates such environments and systematically analyze its capacity to assist the provision of a real-world service, *i.e.*, the parking space search in city areas. In Section 5.1, the opportunistically-assisted scheme is investigated under the assumption that the vehicular nodes are fully cooperative and reliable and compared against a centralized scheme that has the sole responsibility for collecting information on parking space availability and deciding on its allocation to vehicles; as well as the current-practice unassisted scheme, where vehicles drive randomly around their travel destinations in search of parking space. The three schemes represent distinct, sometimes even extreme, paradigms as to how much they exploit spatially distributed and dynamically changing information to assist the parking search task.

Our results suggest that no search practice solution can always serve optimally the users' expectations. On the contrary, the particular drivers' preferences, *e.g.*, travel destinations, and the density of traffic may dramatically modulate the relative performance of the centralized and opportunistic approaches and give rise to tradeoffs that only the user can resolve. Specifically, when users tend to travel towards destinations randomly spread in space, the cooperative opportunistic scheme leverages the vehicle mobility and, for moderate-to-high traffic density, can collect and disseminate fast information with broad spatial scope. The benefits from the information diffusion across the vehicles outweigh the increased competition due to overlapping interests in parking spots. On the contrary, the performance of the centralized scheme deteriorates more quickly with the traffic intensity and its reservation system appears to cancel the flexibility of more self-organizing schemes to make use of the spatially distributed parking space resource. This relative performance of the three parking strategies seems to be independent of the average parking time.

When traffic concentrates in a smaller section of the area (*e.g.*, a road), the centralized system consistently yields the minimum search times and travelled distances. With global knowledge of parking space availability throughout the area, it can resolve better the competition amongst the vehicles for the few parking places around the common destinations. The user is faced with a hard tradeoff: either he goes for shorter parking search times and routes and parks his vehicle further away from his travel destination (centralized system); or he prefers to spend much more time and fuel in favor of a parking spot closer to his travel destination (opportunistic scheme). Notably, what he gets in the second case is marginally better than he would achieve by randomly wandering around the area (road) of interest since the opportunistic system ends up recycling information that synchronizes the movement patterns of the vehicles and intensifies their competition. Even for moderate number of vehicles, the opportunistic scheme effectively “degenerates" to the non-assisted scheme. One way to strengthen the dissemination performance of the system without further aggravating competition, is through the introduction of Mobile Storage Nodes. At low competition burden, these dedicated nodes further strengthen the information dissemination overlay and result in more favorable parking space assignments. In this study, we also expand the simulation study and furnish analytical arguments that support the credibility of the simulation findings and give further insights to the problem dynamics. Indeed, we introduce an analytical model for the centralized parking assistance system to derive its main performance measures. The validation of the model shows excellent agreement with simulation results.

Chapter 5 continues with Section 5.2 that has looked into the vulnerability of opportunistic parking assistance systems to drivers' selfish behaviors. In this study drivers are let behave as free riders that benefit from information other vehicles collect and share but do not share theirs; and selfish liars that falsify information in their caches in order to increase their chances to find a spot close to their destinations. The problem under consideration features strong spatiotemporal dynamics that are not conducive to analytical investigation.

Notably, the results do not lie always in line with intuition. In almost all cases misbehaving nodes fail to obtain distinctly better performance than cooperative nodes. Both types of misbehavior, through different mechanisms, tend to reduce the destination-spot distances and increase the parking search times for *all* vehicles, the latter increase becoming quickly prohibitive when drivers' destinations overlap. This *fate-sharing* effect essentially weakens vehicles' incentives to misbehave and increases the system resilience to selfishly-thinking drivers. On the other hand, neither of the two misbehaviors attenuates the *synchronization phenomena* emerging at the cache contents, and subsequently, the mobility patterns of vehicles when their destinations overlap. The introduction of Mobile Storage Nodes in this case, which collect and share parking information with parking-seeking vehicles, has a sharply different impact on the two misbehavior instances. Whereas, in the presence of free riders, a few of them suffice to restore the information flow at the levels of a cooperative system, they have negligible impact in the presence of selfish liars: even a few misbehaving vehicles suffice to overwrite the fresh information Mobile Storage Nodes carry and convert them into relays of forged information. To strengthen our confidence in the simulation results, we formulate simple analytical arguments that capture surprising well the fundamental behavior of the opportunistic system without accounting for the finer practical details of the context (*i.e.*, vehicles, parking spots), let alone for the finer details of the application (*i.e.*, road grid and vehicle movement patterns). Such a model would enable a more systematic investigation of the tradeoff that arises between more informed search and increased competition.

The implementation of Mobile Storage Nodes is one, rather proactive countermeasure, for the two types of misbehaviors. The online detection and penalization of misbehaviors would be the other apparent solution for enhancing the system resilience. Yet, the misbehavior detection for the particular application is further complicated by the aging dynamics of disseminated information (*a.k.a.* change of parking spots' status). For example, misbehaving nodes that forge information may inadvertently correct outdated information (*i.e.*, turn the availability status of the advertised parking spots to their real up-to-date values) and, hence, end up assisting the dissemination process. Furthermore, the information hits a node after traversing several vehicular nodes, over which it may be forged multiple times. Nodes would then need to: (a) become aware of (and maintain state about) the space-time paths traversed by the information in the vehicular network; and (b) make rather complex computations using historic data about the parking space availability to draw inferences about the validity of transmitted information and the trustworthiness of each node. Despite the involved challenges (or precisely because of them), the design of misbehavior detection and penalization mechanisms for these misbehaviors is an interesting research direction out of this work.

An equally interesting direction for future work is the study of the opportunistic parking assistance system as a dynamic system, where the populations of cooperative and non-cooperative nodes evolve over time in response to their experienced levels of satisfaction when adopting the one or the other behavior/strategy. This implies that the software running onboard the vehicles avails learning mechanisms and the flexibility to adapt its functionality over time. From a methodological point of view, a good starting point for exploring the outcome of the vehicular nodes' interactions over time would be the solid framework provided by the Evolutionary Game Theory (*e.g.*, [Smith, 1982]).

In the second and last chapter of Part II, *i.e.*, Chapter 6, we investigate how competition awareness affects users' decisions, that is, how users exploit awareness of their environment to meet their own needs and achieve certain individual objectives. In essence, in this chapter we are concerned with comparing decision-making under full versus bounded rationality conditions in fairly autonomic networking environment where each networked entity runs a service resource selection task. In particular, we consider environments where tragedy of commons effects emerge on a limited-capacity set of inexpensive resources. Agents choose independently to either compete for these resources running the risk of failing the competition and having to take an unlimited, yet more expensive option after paying a penalty cost, or prefer from the beginning the more secure but expensive option. In their decisions, they consult (or not) information about the competition level (*i.e.*, demand), the supply (*i.e.*, capacity) and the employed pricing policy on the resources. This content might be available through ad-hoc/opportunistic interaction or broadcast from the resource operators, through information assistance systems.

In Section 6.1 we consider the ideal reference model of the perfectly rational decision-making. Here the main assumption is that the decision-maker is a software engine that in the absence of central coordination, acts as rational strategic agent that explicitly considers the presence of identical counter-actors to make rational, yet selfish decisions aiming at minimizing what he will pay for a single resource. They also avail themselves of all the information they need to reach decisions and, most important, are capable of exploiting all the information they have at hand. The intuitive tendency to head for the low-cost resources, combined with their scarcity in the considered environments, give rise to tragedy of commons effects and highlight the game-theoretic dynamics behind the resource selection task.

Indeed, the collective full-rational decision-making can be formulated as an instance of *resource selection games*, whereby a number of players compete against each other for a finite number of common resources [Ashlagi *et al.*, 2006]. We have analyzed the strategic resource selection game in the context of parking search application whereby drivers are faced with a decision as to whether to compete for the low-cost but scarce on-street parking space or directly head for the typically over-dimensioned but more expensive parking lots. An assistance service announces information of perfect accuracy about the demand (number of users interested in the resources/parking spots), supply (number of low-cost resources/on-street parking spots) and pricing policy, that eventually, manages to steer drivers' decisions. We derive the equilibrium behaviors of the drivers and compare the costs paid at the equilibrium against those induced by the ideal centralized system that optimally assigns the low-cost resources and minimizes the social cost. We quantify the efficiency of the service using the Price of Anarchy (PoA) metric, computed as the ratio of the two costs (*i.e.*, worst-case equilibrium cost over optimal cost).

In general, we show that PoA deviates from one, implying that, at equilibrium, the number of user nodes choosing to compete for the low-cost resources exceeds their supply. The PoA can be reduced by properly manipulating the price differentials between the two types of resources. Notably, our results are in line with earlier findings about *congestion pricing* (*i.e.*, imposition of a usage fee on a limited-capacity resource set during times of high demand), in a work with different scope and modeling approach [Larson & Sasanuma, 2010]. The results of this study serve as a benchmark for assessing the impact of different rationality levels and cognitive biases on the efficiency of the resource selection process, which is the focus of Section 6.2.

The formulation of the parking spot selection game assumes that drivers do not have any preference order over the on-street parking spots. This could be the case when these spots are quite close to each other, resulting in practically similar driving times to them and walking times from them to the drivers' ultimate destinations. When drivers express preferences over different parking spots, we come up with an instance of the *stable marriage problem*, potentially with indifference [Irving, 1994], whereby the option of the more expensive parking lot would commonly rank as the last one for all drivers. The problem objective is to derive a matching between drivers and parking spots/lots such that no subset of the drivers could be better off if they exchanged their allocated spots with each other. At a theoretical level, the search is for mechanisms that treat all drivers fairly, are strategy-proof, *i.e.*, the drivers are motivated to advertise their true preference orders because they cannot gain by lying about them, and efficient in some Pareto-optimality sense.

Section 6.1 closes with centralized parking assistance systems that are combined with more aggressive schemes to improve the outcome of parking service for both the on-street public parking space operator (*i.e.*, increase revenue) and the drivers (*i.e.*, resolve competition and avoid "price of anarchy"). In particular, we propose auction-based mechanisms for allocation of public parking space and analyze their effectiveness in terms of the induced drivers' cost and achievable revenue by the public parking operator. These mechanisms are compared against the conventional uncoordinated parking space search with fixed parking service cost. While the operator profits from auctioning the public parking resources, exploiting the diverse drivers' personalities and interest in parking (as captured by their valuation distributions), the comparative study reveals that drivers also benefit due to the savings of the “price of anarchy”. A detailed analytical study determines the conditions under which such win-win situations emerge. It turns out that this is always the case under high parking demand.

The efficiency of advanced (wireless) networking technologies that can improve certain processes and operations in urban environments ultimately depend not just on the quality of the information they can provide but also on the way the provided information is used (“consumed”) by end-users. Therefore, information may be precise and complete or imperfect and limited; whereas users may exhibit different levels of rationality in the way they process the provided information and determine their actions. In Section 6.2, we explore four elements of real-life resource selection applications, consisting in imperfect information availability and behavioral biases, whereby users’ decisions are made under bounded rationality conditions.

Bayesian and pre-Bayesian variants of the strategic resource selection game are investigated to express incompleteness in agents’ knowledge and provide normative prescriptions for the impact of the information factor on agents’ decisions. Following the investigation of Section 6.1, we apply our study to a real-life parking search scenario. The study describes how different amounts of information for the parking demand steer the equilibrium strategies, reduce the inefficiency of the parking search process, and favor the social welfare. Actually, the dissemination of parking information constitutes an instance of service provision within competitive networking environments, where more information does not necessarily improve the efficiency of service delivery but, even worse, may hamstring users’ efforts to maximize their benefit. This result has direct practical implications since it challenges the need for more elaborate information mechanisms and promotes certain policies for information dissemination on the service provider side. On the other hand, people’s biased behavior within the competitive resource selection environment is captured via the Cumulative Prospect Theory framework. We view the resource alternatives as prospects and verify numerically the agents’ risk-prone attitude under particular charging schemes on the resources. Alternative equilibria solutions (Rosenthal and Quantal Response) model the impact of people’s time-processing limitations on their decisions, in line with Simon’s argument that humans are satisficers rather than maximizers. We tune the rationality parameter in the Rosenthal and Quantal Response equilibria, to model agents of different rationality levels and thus, different degrees of responsiveness to various cost differentials between the two resource options, ranging from pure guessing to perfectly rational reasoning (Nash equilibrium). We identify environments where the impaired reasoning, as expressed by the two alternative equilibrium concepts, leads to less costly choices compared to the Nash solutions. In the more radical approach, the agents decide heuristically based on the estimated probability to win the competition for the low-cost resources. Interestingly and unlike the other models, the heuristic decision-making results in near-optimal per-user/social cost, albeit far from what the perfect rationality yields.

A criticism against these decision-making models is that they no longer aim at describing the processes (cognitive, neural, or hormonal) underlying people's decisions but just at predicting them. In response to this, we draw inputs from Behavioral Decision Theory in order to analytical investigate drivers' decision-making concerning parking spot selection in city environments. Hence, Part II, closes by addressing the parking search problem within the framework of sequential search/optimal stopping problems, whereby decision-makers devise simple heuristic strategies (rules of thumb) to overcome the complexity of finding the optimal decision. In particular, we envisage that drivers use the *fixed-distance heuristic* according to which drivers start searching for available parking space after they reach as close as a specific distance from their travel destination. Through a game-theoretic investigation, we show that when the drivers are risk-averse (namely, they prefer walking than driving), the simple fixed-distance heuristic strategy leads to optimal parking spot allocation (minimum social cost). Motivated by these results, our intention is to explore scenarios with a richer mix of drivers' preferences for walking and driving, factoring in dynamic scenarios as well, where the drivers leave their parking spots while others still enter the parking area. We expect that this can yield symmetric equilibrium strategies that depart from the fully risky or conservative attitude. The ultimate evaluation of these results would come out of field experimentation, or in a more convenient alternative, dynamic driving emulators that allow for generating the appropriate scenarios and experimenting with real subjects.

With the emergence of social networking applications new opportunities arise for mobile networking, that facilitate, furthermore, the information diffusion within urban environments. In the last part of the thesis, *i.e.*, Part III, we explore the effectiveness and appropriateness of competition awareness-driven, distributed, public resource management applications with specific focus on the emerging challenge to protect public/common resources/goods and secure their availability to users and non-users of such applications. We have specifically looked into some key properties of a particular instance of vehicular social applications with respect to the parking search process. In our study, we model two fundamental elements that are commonly encountered in various realized parking systems: the awareness-information and the incentive-ranking mechanisms, and investigate the induced effectiveness and fairness of service. The simulation results reveal a high advantage for the application users over the traditional drivers. As the penetration rate and/or the competition (parking demand) are intensified, the traditional drivers suffer only slight to moderate service deterioration with respect to what they experience in the absence of the application. In addition, it is shown that the incentive mechanisms are effective in the sense that they do provide preferential treatment to those fully cooperating, yet they induce rich-club phenomena whereby a subset of users with high ranking seizes the parking resources. Different conditions (*i.e.*, awareness/incentive mechanism, selection criterion for parking spot handovers) might change these side-effects. This may be a concern and an issue worth looking into more carefully in the future.

8.1 Directions for further investigation

In this thesis we described modeling approaches for the decision-making under full and bounded rationality assumptions in competitive resource selection environments. The models refer to symmetric scenarios whereby the entire population exhibits the same instance of bounded rationality and the knowledge of this deviation from full rationality is common among individuals. However, modern networking environments consist of large-scale virtual worlds and communities that people with different socio-psychological profile use as spaces to socialize. The formation and efficient operation of many of these communities (*e.g.*, collective awareness platforms, crowdsourcing, social applications for decentralized management of urban operations) largely rely on the collaboration and contributions of autonomous human entities, whose personalities and attitudes are shaped by real and virtual communities they participate in and combine different behavioral paradigms in different mixtures: (pure) altruism, rational selfishness, socio-psychological and cognitive biases.

From a methodological point of view, a natural direction for further investigation is to explore scenarios with a richer mix of agents' behaviors, catering for various expressions of rationality that interact with each other. A good starting point for exploring asymmetric scenarios would be the "cognitive hierarchy" framework provided by the Behavioral Game Theory. This approach assumes a distribution of cognitive steps of iterated reasoning, where the zero-step agents just randomize over their strategy space while higher-step agents take account of the intelligence and complexity of others' reasoning [Camerer & Fehr, 2006].

Implementation-wise, it becomes compelling to address problems that stem from the fact that the design of many ICT applications is mainly driven by technology and not the knowledge of computer-mediated human communications and reactions. Examples of such problems are the phenomena of many ICT applications which can in principle meet common needs, be developed but never actually adopted or other applications that need to overcome the concerns of end users (candidate contributors) about the privacy of their data and locations. Overall, in order to design effective platforms for virtual interaction and address issues as that of poor user involvement we need to implement mechanisms that first, identify users' characteristics (personalities and attitudes, socio-psychological and cognitive biases) and second, personalize their experience in participating in such virtual information communities. In this task, it is of paramount importance to revisit some assumptions about the amount and nature of information that is generated and presented to the users and, especially, investigate how the stimulus generated by the ICT infrastructure can be diversifying to match it to the individuals and hence, stimulate targeted reactions.

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