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Spectrum sharing in mobile cellular networks: an alternative approach for efficient resource utilization

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The dissertation of Luca Anchora is approved.

Program Coordinator: Prof. Rocco De Nicola, IMT Institute for Advanced Studies, Lucca

Supervisor: Dr. Leonardo Badia, University of Padova

Tutor: Dr. Leonardo Badia, University of Padova

The dissertation of Luca Anchora has been reviewed by:

Prof. Dr.-Ing. Frank H.P. Fitzek, University of Aalborg, Denmark

Prof. Dr.-Ing. Eduard Jorswieck, Technische Universität Dresden, Germany

Dr. Eleftherios Karipidis, University of Linköping, Sweden

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To my family and to those who made this possible

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List of Abbreviations

3GPP	Third Generation Partnership Project
AMC	Adaptive Modulation and Coding
B3G	Beyond 3G
BS	Base Station
CDMA	Code Division Multiple Access
CQI	Channel Quality Indicator
CR	Cognitive Radio
CSI	Channel State Information
ECR	Effective Code Rate
eNB	eNodeB
FCC	Federal Communications Commission
FDD	Frequency Division Duplexing
FDMA	Frequency Division Multiple Access
FS-IFC	Frequency Selective Interference Channel
GPL	General Public License
GSM	Global System for Mobile Communications

IFC	Interference Channel
IMT	International Mobile Telecommunications
LTE	Long Term Evolution
LTE-A	LTE-Advanced
MCS	Modulation and Coding Scheme
MIMO	Multiple Input Multiple Output
MISO	Multiple Input Single Output
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
QAM	Quadrature Amplitude Modulation
QPSK	Quadrature Phase Shift Keying
RAN	Radio Access Network
RB	Resource Block
RRA	Radio Resource Allocator
RRM	Radio Resource Management
SC-FDMA	Single Carrier Frequency Division Multiple Access
SDR	Software Defined Radio
SINR	Signal-to-Interference-plus-Noise Ratio
SISO	Single Input Single Output
SNR	Signal-to-Noise Ratio
TDD	Time Division Duplexing
TDMA	Time Division Multiple Access

TTI	Transmission Time Interval
UE	User Equipment
UMTS	Universal Mobile Telecommunications System
UTRAN	UMTS Terrestrial Radio Access Network
WWRF	Wireless World Research Forum

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Vita

June 29, 1983	Born in Galatina, Lecce, Italy
2005	Laurea Triennale Degree in Information Engineering Final mark: 110/110 cum laude University of Lecce, Lecce, Italy
2007	Contract on project DIALOGO with the following assignment: "Analysis of RFID technologies applied to commodities distribution and storage systems". Institute: University of Salento, Lecce, Italy
2008	Teaching of a 32 hour course on the VoIP technology and on network security with open source solutions (Netfilter). Institute: "BLUESEA Formazione Professionale", Magliano (Lecce), Italy
2008	Teaching of a 20 hour course on the VoIP technology. Institute: "Associazione Campus Formazione Lavoro", Campi Salentina (Lecce), Italy
2008	Master of Science (M.Sc.) Degree in Information Engineering Final mark: 110/110 cum laude University of Salento, Lecce, Italy
2010-2011	Visiting Ph.D. student at the Division for Communication Systems at Linköping University in Sweden, under the supervision of prof. Erik G. Larsson and Dr. Eleftherios Karipidis

Publications

1. Luca Anchora, Luca Canzian, Leonardo Badia, and Michele Zorzi, "A Characterization of Resource Allocation in LTE Systems Aimed at Game Theoretical Approaches," *in Proceedings of 15th International Workshop on Computer Aided Modeling, Analysis and Design of Communication Links and Networks (CAMAD)*, 2010.

   Abstract.*This paper proposes a novel approach, based on game theory, for radio resource allocation in the downlink of cellular networks based on Orthogonal Frequency Division Multiple Access. The technology of reference is the Long Term Evolution (LTE) of the 3GPP UTRAN. The main contribution is to identify a model for the allocation objectives, and how to approach them in a tunable manner. The resource management issue is framed in the context of* spectrum sharing, *where multiple entities agree on utilizing the radio access channel simultaneously. A trade-off between sum-rate throughput and fairness among the users is identified, and it is shown how it can be addressed by means of game theory, i.e., moving the system operating point towards a stable Pareto efficient point. Such a methodology can be implemented with low complexity and ensuring logical modularity of the resource allocator from higher and lower layers. Numerical results are also shown to exemplify the validity of the proposed approach.*
   I am the main contributor of this work. My effort includes the proposal of the game theoretic model, the proposal of the algorithm for the dynamic estimation of the system parameter D and the implementation of the simulation platform, which in this case was developed from scratch. All the parts of this paper, used in Chapter 3 of this thesis, belong to my own contribution.

2. Luca Anchora, Leonardo Badia, and Michele Zorzi, "Joint Scheduling and Resource Allocation for LTE Downlink Using Nash Bargaining Theory," *International Conference on Communications (ICC) - Workshop on Game Theory for Resource Allocation*, 2011.

   Abstract. *We propose a game theoretical model for joint scheduling and radio resource allocation in the downlink of a Long Term Evolution system, where Orthogonal Frequency Division Multiple Access is used as the multiple access scheme. The context is that of* spectrum sharing, *with multiple users competing for simultaneous access to the radio channel. We first give a layered system representation and then model it through a game theoretic formulation using Nash Bargaining theory, where players cooperate to achieve a better common payoff. A trade-off between fairness and throughput is identified and addressed. In addition, we also propose an efficient algorithm that drives the system toward a* balanced Pareto

efficient *operating point represented by the Nash Bargaining Solution. Numerical results are also provided to show the validity of the proposed approach.*
For this paper, I am the main contributor. I proposed the Nash Bargaining model for the system, solved it and developed the algorithm to find the optimal solution. I also implemented this algorithm into the ns-3 simulator and run all the necessary simulations. All the parts of this paper, included in Chapter 3 of this thesis, belong to my own contribution

3. Luca Anchora, "From Intra-Cell Resource Allocation to Inter-Cell Multi-Operator Spectrum Sharing," *PhD Forum Discussion of IEEE Int. Symposium on a World of Wireless Mobile and Multimedia Networks (WoWMoM)*, 2011.

   Abstract. *This research work deals with efficient resource utilization in the downlink of cellular networks which use Orthogonal Frequency Division Multiple Access, as the Long Term Evolution of 3GPP technology. Efficiency is considered first of all in an intra-cell context, where Base Stations exploit the multiuser diversity by adaptive resource allocation. Then, the focus is extended to a scenario with several adjacent Base Stations belonging to different network operators, and a new paradigm is explored. Instead of the classical* static orthogonal division *of the spectrum, a* spectrum sharing *approach is introduced where operators share part of their frequencies. Game Theory is the mathematical tool used to model the systems in both steps. Simulative approach is employed for the quantitative evaluation.*

4. Luca Anchora, Marco Mezzavilla, Leonardo Badia, and Michele Zorzi, "Simulation Models for the Performance Evaluation of Spectrum Sharing Techniques in OFDMA Networks," *in Proceedings of 14th ACM Int. Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM)*, 2011.

   Abstract. *Cooperation in wireless networks is an important means to improve the resource utilization efficiency. It finds an interesting application in the context of spectrum sharing, where multiple wireless users put their licensed frequency bands in common in order to achieve a better resource usage. Due to the complexity of the problem, mathematical analysis is typically focused on simple scenarios. However, we believe that, in order to obtain a concrete proof of concept of the sharing paradigm, it is mandatory to assess its performance in realistic situations, i.e., with a larger number of nodes and a wider range of applications. Therefore, the support of a proper simulation environment is fundamental for high-quality applied research. In this paper we present and evaluate an original extension of the well known ns-3 network simulator which focuses on multiple operators of the most up-to-date cellular scenarios, i.e., the Long Term Evolution of UMTS employing OFDMA multiplexing. We describe the software architecture that enables the spectrum sharing and, in particular, allows operators to interact in order to agree on a spectrum division. A sample sharing policy is given as well, and a detailed simulation campaign is run to validate the proposed architecture, assess its*

efficiency, and evaluate the simulation time related to scenarios with an increasing number of nodes.
I am the main contributor of this work. My contribution includes mainly the design and implementation of the software architecture for the support to multi-operator spectrum sharing scenarios in ns-3. I also contributed to the design of the intra-cell allocation policies and the inter-cell contention resolution mechanisms. All the material of this paper used in this thesis, in particular in Chapters 4 and 5, refers to my contributions.

5. Luca Anchora, Leonardo Badia, Haibin Zhang, Torsten Fahldieck, Jianshu Zhang, Michał Szydelko, Martin Schubert, and Eleftherios Karipidis, "The SAPHYRE approach to resource allocation and management for wireless networks with shared physical resources," *Submitted to the Future Network and Mobile Summit 2012 (FNMS)*, 2011.

   Abstract. *We discuss the development of strategies for the allocation of communication resources within the EU-FP7 project SAPHYRE. The context of our investigation involves next-generation network scenarios, where physical resources are shared among the operators. This primarily implies cooperative usage of the available radio frequencies, but also infrastructure sharing and other forms of collaboration among the operators are addressed. While SAPHYRE deals with the effectiveness of sharing physical resources in wireless networks, in this paper we specifically investigate the development of practical allocation strategies that the operators may implement. Under this umbrella, we specifically address the translation from physical-layer approaches to a more general network vision, where allocation strategies are defined with a cross-layer approach across the whole protocol stack. We also briefly describe advancements brought by the project for what concerns modelling of users' and operators' preferences and evaluation of the system performance through simulation. The main findings of our investigations quantify the effectiveness of our sharing rationale and set new interesting perspectives for the operators of next-generation networks.*
   For this paper, I am the main contributor. I lead the organization and editing of the paper and contributed to the investigation of spectrum sharing on short time-scale. This one is the only part of this work that I exploited in this thesis, in particular to write part of Chapter 4.

6. Luca Anchora, Marco Mezzavilla, Leonardo Badia, and Michele Zorzi, "A Performance Evaluation Tool for Spectrum Sharing in Multi-Operator LTE Networks," *Submitted to Journal of Computer and Communications (ComCom), Elsevier*, 2012.

   Abstract. *Recent advances in wireless networking introduce the concept of resource sharing as one promising way to enhance the performance of radio communications. As the wireless spectrum is a scarce resource, and its usage is often found to be inefficient, it may be meaningful to design solutions where multiple operators join their efforts, so that wireless access of their terminals takes place on*

shared, rather than proprietary to a single operator, frequency bands. In spite of the conceptual simplicity of this idea, the resulting mathematical analysis may be very complex, since it involves analytical representation of multiple wireless channels. In this sense, simulation studies may be extremely useful to grasp a correct performance characterization of wireless networks with shared resources. In this spirit, the present paper introduces and evaluates an original extension of the well known ns-3 network simulator which focuses on multiple operators of the most up-to-date cellular scenarios, i.e., the Long Term Evolution of UMTS employing OFDMA multiplexing. Spectrum sharing is represented through a proper software architecture where several sharing policies can be framed. A detailed simulation campaign is run to assess the computational performance of the proposed architecture, and to show its effectiveness in analyzing realistic scenarios.
For this work, I am the main contributor. I designed and implemented the extension of ns-3, contributed to the design of all the algorithms introduced and run all the necessary simulations. All the material of this paper used in this thesis, in particular in Chapters 4 and 5, refers to my contributions.

Other Publications

1. Gabriella Convertino, Silvio Oliva, Francesco Sigona, and Luca Anchora, "An Adaptive FEC Scheme to Reduce Bursty Losses in a 802.11 Network," *in IEEE Global Communications Conference (GLOBECOM)*, San Francisco, 2006.
2. Luca Anchora, Luca Casone, Giovanni Ciccarese, Mario De Blasi, Pierluigi Marra, and Cosimo Palazzo, "An Optimal Setting for the Parameters of an Intelligent Flooding Scheme in VANETs," *in Proceedings of European Wireless (EW)*, Lucca, 2010.
3. Luca Anchora, Antonio Capone, and Luigi Patrono, "An Asynchronous Scheduler to Minimize Energy Consumption in Wireless Sensor Networks," *in Proceedings of 11th International Conference on Next Generation Wired/Wireless Advanced Networking (NEW2AN)*, St. Petersburg, 2011.

Presentations

1. Luca Anchora, Luca Canzian, Leonardo Badia, "Spectrum Sharing Games in Wireless Networks," *Poster session of the NEWCOM++ Spring School on Cognitive Wireless Communication Networks*, May 4-7, 2010, Lucca.

2. Luca Anchora, “Joint Scheduling and Resource Allocation in the Downlink of an LTE Network using Nash Bargaining Theory,” *Seminar at Linköping University (LiU), Division for Communication Systems (CommSys)*, October 22, 2010.
3. Luca Anchora, “Spectrum Sharing in Multi-Operator Cellular Networks,” *Seminar at Linköping University (LiU), Division for Communication Systems (CommSys)*, February 11, 2011.
4. Luca Anchora, “From Intra-Cell Resource Allocation to Inter-Cell Multi-Operator Spectrum Sharing”, *Poster Session within the Ph.D. Forum Discussion in IEEE WoWMoM*, 2011, Lucca.
5. Luca Anchora, “Orthogonal spectrum sharing in multi-operator cellular networks,” *Seminar at the SIGNET laboratory of the University of Padova*, December 16, 2011.

Abstract

Mobile cellular communications have been becoming the leading technology in data transmissions: trillions of devices will serve billions of people in few years, not only for simple phone calls but also for application data transfer. The rapid diffusion of this technology goes with an increasing use of resources, in particular of bandwidth, whose scarcity and expensiveness make efficient management necessary. To this aim, a dynamic allocation of the spectrum is preferred to an inefficient static allocation. In this way, the waste of resources is reduced by assigning the unused frequencies to nodes that need them. Many flexible ways to use the resource can be thought of, provided that the quality of service requirements of each user are respected.

In this thesis the problem of efficient spectrum usage is considered in a two-fold manner, namely considering the intra-cell and the inter-cell context. In the former, the need for an efficient resource utilization in the downlink is traded-off with fairness among the user flows, so a possible system model is discussed and some allocation algorithms are proposed. Two algorithms for the dynamic setting of a structural parameter are proposed and validated thus showing the efficiency of the operating point into which the radio resource manager is lead. Regarding the inter-cell context, a particular type of scenario is considered, a multi-operator cellular network. In this case, an alternative to the classical static frequency allocation is proposed: spectrum sharing. By allowing operators to share part of the spectrum that they receive by the regulation body, a gain in terms of cell throughput can be achieved thanks to a better utilization of the shared resources. In this case, a crucial

issue is the access mechanism to the common spectrum. Two algorithms that define the upper bound and the lower bound on the system performance are given. Another possible mechanism that takes into consideration priorities on the access to the common resources is analyzed as well. The main result is that there is an asymptotic gain for the operators in sharing their resources, which is a fundamental point for the diffusion of this proposal. This opens the door to the implementation of effective algorithms of spectrum sharing in scenarios with realistic constraints. Moreover, the main factors that impact on the value of such a gain have been identified and analyzed.

Most of the mathematical models considered all over this thesis are based on the Game Theory. Multi-agent systems perfectly fit such a framework, through which equilibrium points and efficiency of solutions can be evaluated together with possible cooperative strategies. However, in many situations the intrinsic complexity of the sytem or the consideration of realistic scenarios may make the analytical treatment tough. Therefore, the validation through simulations is important as well. A modular framework, obtained through the extension of a well-known simulation platform, has been developed for the support to the scenarios of interest and has been used for the validation of all the proposed algorithms. The details of its software architecture are given as well.

Chapter 1

Introduction

Mobile cellular networks have seen an incredible evolution in the last two decades and have been changing our everyday life. Thanks to the technological progress it has been possible to build devices always smaller and smaller that we can easily carry and that enable us to be constantly in contact with the rest of the world. Wherever we are, we can not only make phone calls, but also browse the web, check our email, etc. The key factors that have pushed the evolution of the cellular networks can be identified in (i) the strong need of communication of people and (ii) the ever increasing use of the web and of all the other network applications based on the Internet, that have become an essential part of our lives. At the very beginning there was a neat separation between voice and data applications and the relative streams were kept separate and managed in a different way. Since a few years ago, we have been witnessing a convergence of the two types of flows, i.e., both started to exploit the same infrastructure. Cellular networks can now be used as well as an access network to the Internet, thus enabling people to use all the network applications they used to run on their PCs or laptops. This phenomenon has lead to a proliferation of devices and a huge amount of data traffic that has overloaded the network and has evidenced some fundamental problems related to an inadequate infrastructure and the inefficient and expensive resource management. According to some forecasts formulated by the

Wireless World Research Forum (WWRF) in 2008 [40], 7 trillion wireless devices will serve 7 billion people by 2017 and mobile users expect reliable high-data rate services with strict delay constraints and ubiquitous and permanent access according to the paradigm *anywhere anytime*. Pervasive ubiquitous computing is the hot topic of the moment, not only for voice traffic but also for an ever increasing application data traffic (e.g., real-time streaming). Radio spectrum and physical infrastructures must be used in a proper way by the network operators. Actually, as almost everything in life, resources are scarce and thus must be managed in a proper way. Moreover, their cost is not negligible: currently, the transmission frequencies are not for free while installation and maintenance of the whole infrastructure (e.g., masts, antenna, backhauls) require a huge investment of capitals. The challenge of future wireless networks designers is the development of cost-, energy- and spectrum-efficient solutions that enable the network operators to satisfy the increasing demand for high-quality services yet keeping the amount of money and the necessary effort at a reasonable level. This is to be considered as a key factor for the evolution of cellular networks. The history of the technology is full of examples of promising technologies that did not have a large diffusion because of their cost. On the other hand, a cheap technology providing a scarce quality of service would not have a great impact on the market because it would not be able to meet the current trend in consumers' needs.

In this thesis the focus is on the problem of spectrum usage in a multiuser cellular network, while the infrastructure management is left as future work. Hereinafter, if not otherwise specified, the term *resource* is used with reference to the sole spectrum component. It is mainly an access problem, where several competitors (i.e., the users) try to access a shared resource (i.e., the spectrum) for their transmission. An inefficient situation might result if no arbitration is introduced because of the interference problem. Even tough interference might not always prevent a communication, in this thesis the focus is mainly on an *orthogonal* use of the transmission channel, where no more than one user can access the shared resource. Of course, this leads to the problem of the users scheduling for the channel access. Some proposals are evaluated to improve the

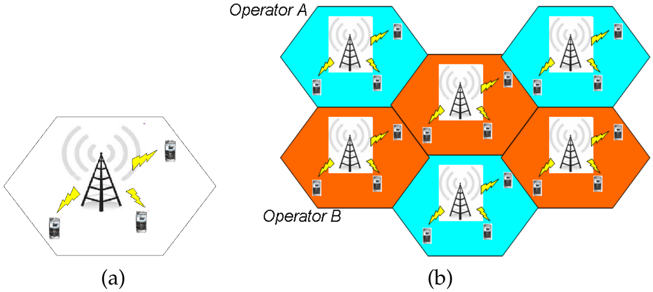


Figure 1: Single-cell (a) and multi-cell multi-operator (b) scenario

radio interface efficiency and are discussed in the following chapters. We decided to tackle the problem at two layers, with a bottom-up approach. First, we considered the downlink of a single cell (*intra-cell* resource allocation), then we moved to a wider and more realistic scenario, i.e., several adjacent cells managed by different network operators (*inter-cell multi-operator* resource allocation). Figure 1 shows this double context. In both cases, the reference technology considered was the Long Term Evolution (LTE) of the 3GPP UTRAN [6].

For the intra-cell scenario a joint scheduling and resource allocation solution has been evaluated which takes into account not only efficiency but also fairness. All the users of the system are expected to receive a service level conforming to their requirements, and thus the flows they generate need to be scheduled in a proper way so as to guarantee fairness and a good service level. On the other hand, particularly for the case of wide-band systems where the portion of the spectrum used for transmission cannot be considered as a flat-fading channel, each user may experience a different channel quality on different sub-carriers (so called *multiuser diversity* effect). A smart resource allocation can improve spectrum efficiency by exploiting such diversities, i.e., trying to give to each user the best available resources, as long as this is possible. Of course, this requires a cross-layer communication in the system. However, a trade-off between efficiency and fairness may arise. If the resource allocation is driven only by the efficiency goal, then this may result in an unfair situation from the point of view of the system users because those experiencing a better channel condition (e.g., closer to the base station) are given more service. On the other hand, if the only objective is the fairness of the allocation, then this may lead to an inefficient result due to a limited exploitation of users' different conditions. Starting from this trade-off, a two-layer representation of the system is proposed in Chapter 3 and modeled in a game theoretic perspective. The Resource Allocator and the Packet Scheduler can be seen as the two players of a game. Game theory allows us to study the existence and optimality of equilibrium points. Both *non-cooperative* and *cooperative* approach are used, and in both cases a feasible algorithm is proposed that leads the system in a (Pareto) efficient operating point by the dynamic estimation of a structural parameter.

Although multi-operator coexistence is quite common in modern cellular networks, few studies are available in the literature. Historically, in cellular networks, resources have been allocated in a static manner in order to avoid interference: each operator has its own portion and is entitled to use only it, without any overlapping. This type of allocation is commonly referred to as *orthogonal*. Earlier radio transceivers were not able to distinguish between different transmissions on a single frequency and were also limited in memory and signal processing power, so the only way for multiple users to share the radio spectrum was to divide it into orthogonal slices. Each of these ones was assigned to an operator through licensing, the so called *command and control* approach. Auction mechanisms were (and are still) used for that purpose. The most important shortcoming of this solution is its inefficiency. When a node has nothing to transmit, its resources are unused while they could be assigned to other nodes plenty of traffic to get through. Moreover, the cost for installing and maintaining a complete infrastructure is remarkable and represents a big barrier for accessing the market. The use of a unique shared infrastructure would be a possible solution to reduce costs for each one. For these reasons, the operators, together with the scientific community, have been starting considering the benefits of alternative and more flexible solutions in the direction of both spectrum and physical infrastructures sharing. As already said before, in this work we focus only on the former research direction. We explore the idea of **spectrum sharing** among cellular network operators. A *common pool* of frequencies is created and can be seen as a virtual extension of the initial spectrum they are given by the regulator (see Figure 2). The aim is to show how this new paradigm of radio spectrum usage can increase the efficiency and the user satisfaction level if the shared resources are properly used. This is an innovative idea whose results are interesting not only from an academic but also an industrial and regulatory point of view. Industrial partners may be attracted by the potentials of such a paradigm and regulation bodies might decide to encourage operators in sharing their resources and to regulate this market. Moreover, introducing this technique does not require a complete change in the existing hardware either for the users or for the operators, and this is important for its rapid diffusion on the market. In this thesis the problem of the access to the common set of frequencies is addressed. Two main categories of schemes are identified, i.e., *orthogonal* and *non-orthogonal*. In the former case the access is mutually exclusive while in the second case several operators can exploit the same resource at the same time. In this work we focus only on the former while the approach to the latter is only touched and left as future work. The main challenge faced refers to the arbitration of the access conflicts on the common pool of frequencies that may arise. An upper bound and a lower bound algorithm are proposed when the joint cell sum capacity is considered as the system performance metric. The identification of a sharing gain for the network operators is the most important achievement that justifies additional research activities in this field, maybe according to the lines given as future works in last Chapter of this thesis.

Besides mathematical modeling, all the algorithms proposed in this work for both intra-cell and inter-cell scenarios are validated by means of simulations. The validation was done by using the well-known network simulator ns-3 [2] with its module for LTE networks [1]. In particular, for the spectrum sharing case we developed an extension able to support such scenarios and flexible enough to permit the validation of many new user-defined spectrum sharing algorithms that can be easily plugged in

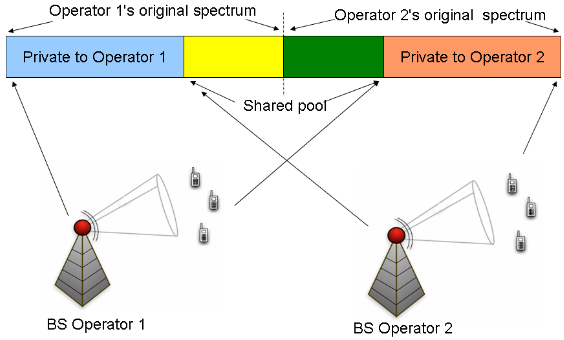


Figure 2: Spectrum sharing

[12]. The architecture, as described later on in this work, is completely modular, free and also open source. It is publicly available, under the GNU GPLv3 license, at the URL
http://code.nsnam.org/lanchora/ns-3-lte-SpectrumSharing/.
Therefore, another important achievement of this thesis work has been the release to the research community of such a simulation framework for spectrum sharing.

To sum up, the main contributions of this thesis go into three directions:

1. Intra-cell resource allocation. A game theoretic model for the trade-off between resource allocator and packet scheduler is defined, according first to non-cooperative and then to cooperative games. A couple of algorithms for the dynamic estimation of a structural parameters are described;

2. Inter-cell multi-operator spectrum sharing. The orthogonal sharing of the common resources is analyzed and several algorithms for the conflicts resolution are proposed. In particular, an upper bound on the sharing gain is identified;

3. NS-3 extension. A modular extension of the well-known network simulator ns-3 has been designed and implemented to support multi-

operator spectrum sharing scenarios.

The remainder of this thesis is organized as follows. Chapter 2 gives a detailed overview of the state of the art regarding interference in wireless networks and dynamic spectrum allocation in both intra-cell and inter-cell perspective; moreover, a short introduction about the main game theory concepts and about the LTE technology is given there as a support to improve the clearness of the whole work. The intra-cell scenario is analyzed in Chapter 3 by using both non-cooperative and cooperative game theory, while the inter-cell case is discussed in Chapter 4. In Chapter 5 some more information is given regarding the ns-3 extension developed for the simulative support to this thesis. Conclusions and possible future evolutions of this work are given in Chapter 6.

The chapters were written by exploiting the material published in the papers reported in the section "Publications", inserted at the beginning of this thesis (and recalled also in the final Reference section). More specifically, the mapping is as follow:

1. Chapter 3 is based on the papers 1, 2 and 3;

2. Chapter 4 is based on the papers 3, 4, 5 and 6;

3. Chapter 5 is based on the papers 4 and 6.

Chapter 2

State of the Art

In this chapter we give a review of the main works in the literature that face the problem of efficient spectrum usage in multi-user wireless networks. Both intra-cell and inter-cell scenarios can be framed within this context.

The Interference Channel

The coexistence of multiple wireless systems in mobile environments using the same spectrum in a non-orthogonal way (i.e., at the same time and in the same geographical area) leads to interference at the air interface, a problem typically analyzed within the context of *interference channels* (IFC). Usually, an IFC is defined as a communication medium shared by M sender-receiver pairs, where transmissions of information from each transmitter to the corresponding receiver interfere with communications between the other pairs. Information theory literature contains several studies on the IFC, made by researchers since many years ago, with interesting results. Many mathematical models are constructed starting from different assumptions (e.g., memoryless channel, Gaussian noise channel), and try to derive the maximum rate each sender can reach in that situation. [7, 18, 21, 32] have provided various achievable rate regions (i.e., the set of all the possible rates that the senders can jointly reach), but the identification of the exact capacity region of the general

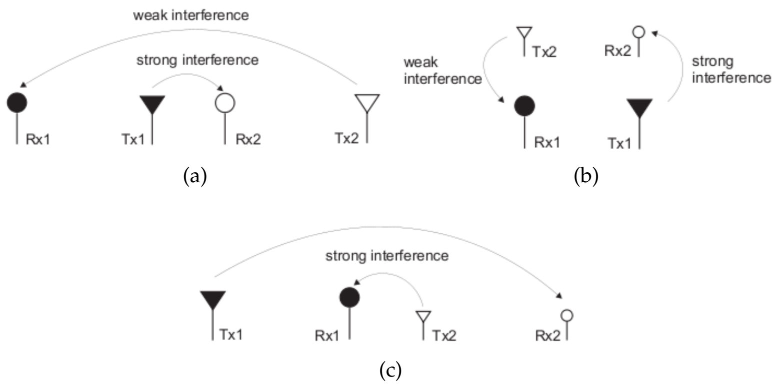


Figure 3: Examples of interference in bandwidth sharing [27]

IFC is still an open problem. The achievable rates depend also on the amount of information available at the transmitter and on the co-operation at the transmitter and at the receiver side. The more information is known, the greater the rates that can be realized. A fundamental objective of resource sharing is to find a stable system operating point based on certain fairness and efficiency criteria. In [16] authors model a system made of two pairs of nodes by using game theory and then characterize the subset of the interference channel capacity region that can be achieved as Nash equilibria, giving also explicit coding schemes that permit to realize those rates. An important conclusion is that in all the cases there are always efficient Nash equilibria.

Figure 3 illustrates three common examples of interference due to spectrum sharing [27]. This effect mainly depends on the transmission power used by the sender and on the distance from it: the greater the power, the larger the area covered; the lower the distance from another transmitter, the lower the power needed to disturb communications. In scenario (a) both systems have similar power capabilities but, due to the locations of transmitters and receivers, one system receives large interference while the other does not. On the other hand, scenarios (b) and (c) describe situations where a high power system shares spectrum with a low power one. In the first case all the gains are comparable, so, intuitively, the weak system is in disadvantage; in the second case, due to asymmetry in the gains, both systems can interfere with each other and we can imagine that a more fair situation may result.

The simplest way for multiple users to share the spectrum without any interference is to divide it into *orthogonal slices* and assign them to each user. From a communications engineering perspective, the orthogonality can be realized in different domains, i.e., frequency, time, physical space and space of coding, depending on the type of interference that characterizes the system. Users receive the available resources (i.e., *slices*) according to some pre-defined allocation policy. Some well-known examples for users in a cellular network operated by one operator (intra-cell interference avoidance) are: TDMA combined with FDMA in GSM systems, CDMA combined with TDMA/FDMA in 3G systems. A promising multiple-access technique for high data rate transmission is the Orthogonal Frequency Division Multiple Access (OFDMA), which is able to exploit the multiuser diversity by adaptive resource allocation. Regarding the multi-cell contexts, typically an operator uses different frequency reuse factors to control inter-cell interference. However, an aggressive (i.e., too low) reuse factor might still lead to some interference in cells rather close to each other. Since OFDMA is the scheme used in the downlink of LTE networks, which is the reference technology for the following chapters,hereafter we discuss some literature related to that access scheme. Moreover, in Section 2.1 we give a short overview of LTE as well, just to introduce the main concepts and parameters that are used in the other chapters.

OFDMA - Constrained Optimization Formulation

Many studies have been conducted to tackle the problem of resource allocation in OFDMA cellular networks, for both the uplink and the downlink. Most of them assume perfect knowledge of instantaneous Channel State Information (CSI) at the base station, so as to exploit multiuser diversity and increase efficiency. Several formulations of the problem exist and different mathematical tools have been used, stressing different aspects. A first powerful tool is the constrained optimization, with the objective function related to the (weighted) sum rate. For any fixed sub-channel assignment, the optimum can be reached by multilevel water-filling [35] for the continuous rate relaxation, or by greedy and bisection allocation [44] for the discrete case. However, the sum rate maximization may not result in a fair allocation, especially for non-symmetric channels and non-uniform traffic patterns [71]. Therefore, some studies tried to consider a joint solution for an efficient yet fair allocation [8, 41, 71]. In general, exact optimization approaches suffer from the issue that the optimal sub-channel assignment is a combinatorial problem whose complexity increases exponentially with the number of sub-carriers. Moreover, typically the computation of an optimal solution is centralized and requires complete knowledge of the network. In [35], an efficient suboptimal algorithm is found considering a convex relaxation. In [67] a solution is found by using Lagrangian dual decomposition and considering that the duality gap goes to zero when the number of sub-carriers tends to infinity.

OFDMA - Game Theoretic Formulation

Another way to approach the problem of resource allocation is through game theory. Terminals requesting access to the shared resources can be seen as players of a game who compete in order to maximize their own utility, e.g., their data rate. In this way, the efficiency and the evolution of the game are analyzed together with schemes that force players to move towards an efficient operating point. An overview of spectrum sharing games is given in [27] and [42]. Many alternatives are described, from the simple non-cooperative approach to the more sophisticated bargaining and auction-based games. From a practical point of view, game theory is also seen as a way to derive efficient distributed algorithms for dynamic spectrum sharing with agents having only local information. Such solutions are easier to implement than a centralized one, which needs complete knowledge, even though they might lead to a sub-optimal result and involve an iterative process. As examples closely related to the present work, we mention [74], where a second-price auction mechanism is proposed to model user competition in a wireless fading channel, and bids are posed based on the perceived channel quality. The existence of a Nash equilibrium is proved, together with its Pareto optimality. The Nash Bargaining Solution (NBS) and coalitions are employed in [33] to formulate a problem of fair rate maximization and to find a sub-optimal distributed algorithm for uplink access. NBS and coalitions are also used in [60] for the case of OFDMA-based relay networks. The authors tackle spectrum and power allocation among relay nodes within the same coalition, and subsequently the inter-coalition coordination, and finally propose some greedy algorithms able to enhance the total system capacity and maintain the user fairness. Some more details about the game theory and its application to wireless networks are given in Section 2.2.

Multi-operator Scenarios

With reference to the multi-operator case, few works address that specific scenario. In [55] and [15] the concept of resource sharing among cellular network operators is introduced and its impact on achievable capacity and total delay is evaluated. The main differences with the work we present in Chapter 4 are that: (i) a time division duplexing radio access is employed where operators are allocated slots in a super-frame; (ii) operators share resources only as a "last resort" solution; (iii) sharing algorithms are not distributed. An example of game theoretical perspective of inter-operator spectrum sharing has been given in [14]. A one-shot *Stackelberg* game [1] is proposed to model a network where secondary operators can use the frequencies of the primaries only as long as they do not need them. In our research work no hierarchy is introduced and the repetitive nature of the game is considered.

[1] In game theory, a Stackelberg game is a strategic game whose players are a *leader* and a *follower* and they compete on quantity. The leader is the first to move, then the follower decides its action accordingly.

Cognitive Radio

With reference to the multi-cell context and, more in general, to multi-transmitter networks, another recent technology must be mentioned as well, for the sake of completeness: the Cognitive Radio (CR) . This assumes that the nodes of the network have the possibility to adapt their behavior according to the presence of other transmitters and decide on the strategy to take. CR is made possible by the introduction of Software Defined Radios (SDR) , where most of the radio interface parameters are no longer fixed in the hardware but are decided by a controlling software and can be tuned at runtime. According to the FCC (Federal Communications Commission) definition, SDR encompasses any "radio that includes a transmitter in which operating parameters such as frequency range, modulation type or maximum output power can be altered by software without making any changes to hardware components that affect the radio frequency emission". Mitola [37] took the definition of an SDR one step further, and envisioned a radio that could make decisions as to the network, modulation, and/or coding parameters based on its surroundings, and called this a "cognitive radio". Di Benedetto et al. [25] defined it a new way of thinking and researching about wireless communications; indeed, CR is currently one of the key candidates for the fourth-generation (4G) wireless systems. The whole idea behind CR use is that it should prompt effective spectrum use, since intelligence and learning processes aid the radio system to perform the access in an efficient way. The system collects information about its operating environment and uses them to adapt its internal state and its operating parameters in such a way that highly reliable communication and efficient utilization of the radio system can be achieved. Thus, the key words are awareness, learning, adaptivity, reliability and efficiency [17]. All these capabilities have been applied to the case of spectrum sharing among transmitters in order to increase transmission rates by smartly using available information. In [24] the authors present some results on the fundamental information and communication limits of CR by modeling the concept of cognition in the form of nodes having side information about the wireless environment. They explore a situation (see Figure 4) in which two transmitters, say *X1* and *X2*, can send their data to two distinct receivers, say *Y1* and *Y2*, at the same time and in the same band of frequencies just supposing that one of them is a cognitive radio and has a priori knowledge of what the other is going to transmit (by means of a certain "genie"). Having this context in mind they explore the achievable region for such channels, called *cognitive radio channels*.

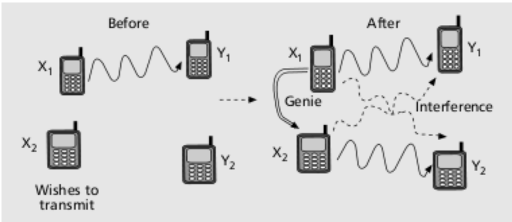


Figure 4: The cognitive radio channel [24]

In [17, 37] the issue of coexistence of licensed and unlicensed users is considered. *Spectrum pooling* is addressed as a mechanism where the current spectrum owners allow portions of their spectrum to be utilized by unlicensed users, which apply the CR system. As some portions of the spectrum are rarely used by the owners, the other nodes can use them as long as they are sensed free and release the resource when it is required by the entitled node. In this case users are divided into two classes, licensed and unlicensed (also *primary* and *secondary*), with reference to the spectrum access priority (see Figure 5 for an example); the latter use their cognitive capabilities to detect holes in the spectrum and occupy them until when they are needed by the former. This is the approach proposed in many research projects about cellular networks, in opposition to the one that we propose in Chapter 4, where an *egalitarian* system is considered with all the nodes competing for the access to the common resources. In that case the competitors are Base Stations of different cells who are not supposed to have cognitive capabilities and bargain for the access to the common medium.

In [65] Scutari et al. as well face the issue of hierarchical cognitive net-

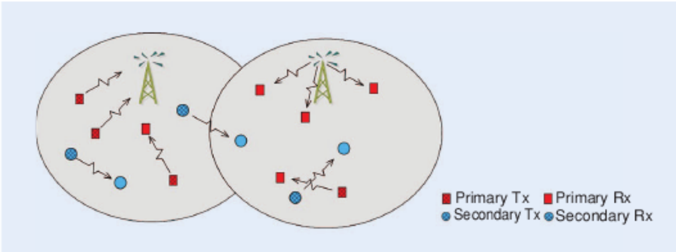


Figure 5: Hierarchical cognitive radio network [65]

works and provide a game theoretic model of the system, with secondary users competing against each other to maximize their performance, under the constraint on the maximum interference induced to the primary users. They design decentralized algorithms able to reach the equilibrium points with minimal coordination among nodes.

Another evidence of the increasing interest addressed to the problem of resource sharing is represented by the significant number of projects and research initiatives approved all over the world in the past few years. Most of them aim at improving the efficiency in resource usage in order to avoid wastes by resorting to some of the aforementioned techniques (i.e., CR, SDR, advanced signal processing). Some examples are:

- SAPHYRE (Sharing Physical Resources), which investigates a voluntary physical resource sharing in cellular networks, with an innovative use of radio spectrum and network infrastructure under economic and regulatory constraints. In particular, the use of game theoretic models and cross-layering is proposed.
  The topic generalizes what discussed in this thesis by extending the definition of resource to the physical devices (e.g., antenna, masts). Moreover, innovative signal processing techniques for interference cancellation are developed.

- E^3 (End-to-End Efficiency), which aims at integrating cognitive wireless systems in the Beyond 3G (B3G) world, evolving current heterogeneous wireless system infrastructures into an integrated, scal-

able and efficiently managed B3G cognitive system framework.
With respect to this thesis, the focus is on the cognitive paradigm.

- SOCRATES (Self-Optimization and self-Configuration in wireless networks), which aims at the development of self-organization methods to enhance the operations of wireless access networks, by integrating network planning, configuration and optimization into a single, mostly automated process requiring minimal manual intervention.
  With respect to this thesis, the focus of such project is on algorithms for the self-configuration of the devices.

- PHYDYAS (Physical Layer for Dynamic Spectrum Access and Cognitive Radio), which exploits an advanced physical layer to overcome the lack of flexibility of the classical OFDM. In particular, a filter bank-based multi-carrier transmission is used for the support to dynamic access spectrum management and cognitive radio.
  The main difference with this thesis is that we do not consider any physical layer improvement.

- WINTSEC (Wireless Interoperability for Security), which explores a mix of complementary solutions to overcome the barriers for wireless interoperability across different security agencies, enabling first responders with incompatible legacy radios to communicate in a crisis situation. SDR is exploited.
  The scenario taken into consideration in this case is quite different from that of this thesis; the resource management is aimed at addressing particular situations of danger.

- AN P2 (Ambient Networks Phase Two), which aims at developing a Multi-Radio Resource Management that provides an advanced joint management of radio resources, including access advertisement, access discovery, access selection and load sharing between different radio accesses.
  In this thesis all the functionalities of call admission are not considered.

Cross-layer

Another important research topic related to the channel utilization efficiency is represented by the *cross-layer* approach. Breaking up the traditional way of handling interference requires a cross-layer optimization too. Cross-layering is a new way to manage the division of functionalities in the protocol stack that has been introduced few years ago. The traditional way to do that was the division of network functionalities among layers, each one concerning with a particular problem and with a sharp separation of one another. Cross-layering aims at increasing overall performances by reducing this separation and introducing a flow of information between different layers, even though not adjacent. In particular situations and/or environments, these additional data can be exploited by protocols to take more proper decisions. It was introduced with regard to wireless systems because of three main reasons: the unique problems created by wireless links, the possibility of opportunistic communications on wireless links, and the new modalities of communication offered by the medium. In such networks the channel creates many new problems that cannot be handled in the framework of layered architectures, so this new idea has been widely explored. With reference to the area of spectrum sharing and interference management, for example, it has been shown that interference can be efficiently reduced by *jointly* performing signal processing and resource allocation (for example see the SAPHYRE project [3]). Moreover, resource allocation can be more efficient if adapted to the channel state information and link quality, that is why a joint PHY/MAC design is often considered useful. The adaptation of networking protocols is also a viable solution. A lot of work has been done showing improvements with respect to the classical ISO/OSI model. Several algorithms have been proposed which operate using information from other layers. In this way, some of the main points of strength of the traditional model, i.e., modularity and de-coupling, are violated in the name of efficiency and improvement of performances (see Figure 6).

This observation has led to criticism against the change of a consolidated paradigm. On the other side, considering the problems and the

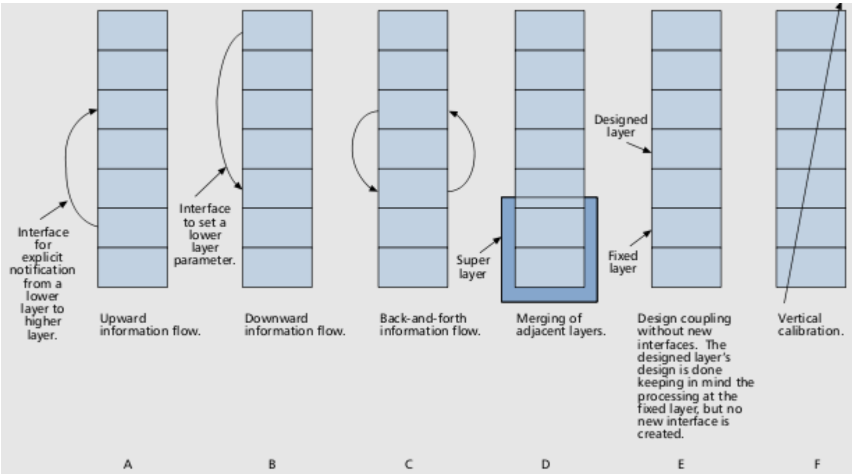


Figure 6: Different kinds of cross-layer design proposals [72]

new challenges introduced by the wireless channel with respect to the wired case, on which the standard architecture was tailored, the introduction of additional information flows is not so bad. Let's think about the fact that the bad performance of TCP protocol on wireless links is mainly due to its association of packet losses with network congestion, which is almost true in the wired (error-free) case but not for sure in the wireless (error-prone) case. For example, knowledge about the channel quality and the level of interference experienced by the receiver(s) may be important for adapting transmitters' behavior, e.g., by the variation of the coding and modulation schemes or the reduction/increase of the application data rate [19, 43]. In many cases, especially in presence of a central base station deciding the scheduling and/or the resource allocation, more chances are given to stations seeing a better channel. In several OFDMA systems proposals, the resource allocator assigns each subchannel to the user characterized by less fading on those frequencies, thus requiring less power expenditure to transmit [80] (*multiuser diversity*). Of course, this choice may result in a lack of fairness (both short-term and long-term) for stations with strong persistent fading, so QoS parameters must be taken into account when associating a utility function to a node as well. In this way, several proposals of channel-aware schedulers and joint Scheduling/Resource Allocation have been evaluated. Badia et al. in [13] describe the principles of joint scheduling and resource allocation for IEEE 802.16 networks operating in AMC mode (Adaptive Modulation and Coding), and discuss the critical role played by physical layer considerations. The scheduler determines which packets must be passed to the allocator and their order (according to an internal scheduling policy); the allocator selects for transmission the subset of them which maximizes the advantages of multiuser diversity. This is the same system model that we have adopted for the work presented in Chapter 3 and that is summarized in the papers [10, 11]. In our case, a game theoretical perspective is presented. In [36, 41] a mathematical formulation of the problem is provided together with possible algorithms. Short-term fairness is difficult to reach, but long-term fairness can be guaranteed. In [69] Song et al. provide a theoretical framework for cross-layer optimization for OFDM wireless networks with multiuser frequency-selective fading. They build a bridge between the MAC and the PHY layers and balance the efficiency and fairness of resource allocation. They formalize the problem as the maximization of the average utility of all active users subject to certain constraints due to resource allocation schemes. In [70] the same authors depict possible algorithms for efficient and fair resource allocation in such systems. Two surveys about cross-layer proposals are reported in [64,72], with the latter giving also some hints on possible evolutions.

In all the analysis that we present in the next chapters, some cross-layering is always exploited to help base stations in taking resource allocation decisions. In particular, channel state information is used with the aim to exploit the multiuser diversity.

2.1 Introduction to LTE

This section is meant to give some basic information about the LTE standard as a support for understanding the other Chapters, where the LTE cellular networks are used as the reference scenario. For more indepth details the reader can refer directly to the standards [5, 6], or to some books [22, 23, 68].

LTE is a set of improvements to the Universal Mobile Telecommunications System (UMTS) introduced in the 3rd Generation Partnership Project (3GPP) Release 8 [4]. It represents efficient packet-based radio access networks allowing high throughput, low latency and low operating costs. Small enhancements to LTE specifications have been introduced in Release 9 [6]. The next step for LTE evolution is LTE-Advanced, currently standardized in Release 10 [5], the major candidate technology for the so-called International Mobile Telecommunications (IMT)-Advanced.

In the LTE standard, the Base Station managing a cell is called eNodeB (eNB) while all the registered devices are referred to as User Equipments (UE). In the rest of this work we will use interchangeably the terms Base Station (or BS) and eNB. Rel-8 LTE supports both Frequency Division Duplexing (FDD) and Time Division Duplexing (TDD) and uses multiple transmission bandwidths (i.e., 1.4, 3, 5, 10, 15 and 20 MHz) and multiple modulation schemes (i.e., QPSK, 16QAM and 64QAM) allowing peak rates of 300 Mbps in downlink and 75 Mbps in uplink. In the uplink, in order to maintain user orthogonality in frequency domain, a Single Carrier Frequency Division Multiple Access (SC-FDMA) is adopted. Uplink and downlink are separated in frequency.

The physical layer for the downlink uses an OFDMA access scheme. In this way, a multi-user transmission is possible by exploiting different sub-carriers for different users. In particular, the frequency plane in LTE is organized into groups of 12 adjacent sub-carriers. Hereinafter, these groups will be referred to as (frequency) *sub-channels*. Sub-carriers have a 15 kHz spacing, for a total bandwidth of 180 kHz. The OFDMA scheme is used in combination with Time Division Multiple Access (TDMA), such that the resources are partitioned in the time-frequency plane, i.e., groups of sub-carriers for a specific time duration. Such time-frequency blocks are called Resource Blocks (RBs). The time-frequency resources are subdivided in the following way: the time is organized in radio frames of 10 ms, which are further subdivided into ten 1 ms sub-frames. Each sub-

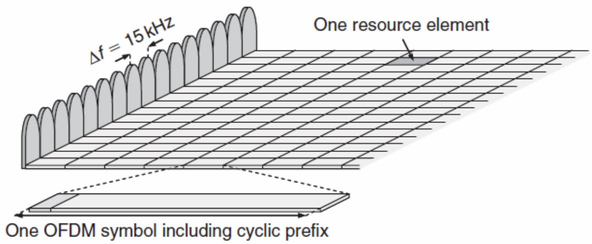


Figure 7: The LTE downlink physical resource [23]

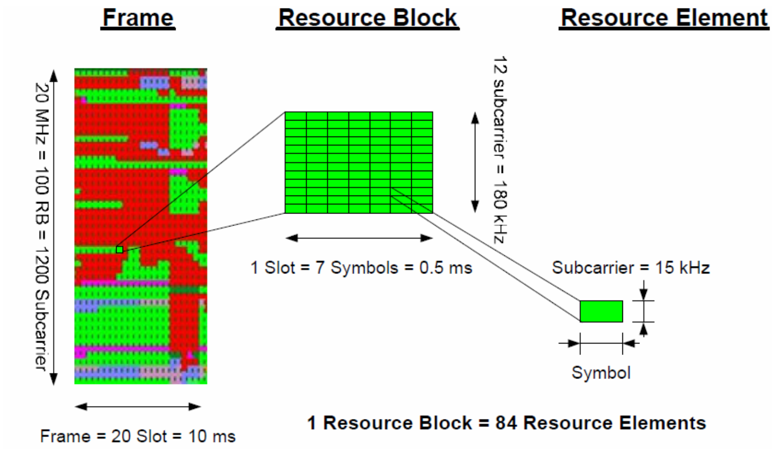


Figure 8: Structure of an LTE frame

frame is split into two 0.5 ms slots. Each slot comprises 7 or 6 OFDM symbols, depending on the cell configuration. Such a parameter configuration makes LTE suitable for high mobility networks, up to 350 or even 500 km/h. Figures 7 and 8 show graphically the time-frequency organization.

The use of the OFDMA scheme in downlink enables OFDM to take advantage of the multiuser diversity. Each UE sends periodically a feedback to the eNB with the indication of the frequency-selective channel conditions it is perceiving. This feedback is called Channel Quality Indi-

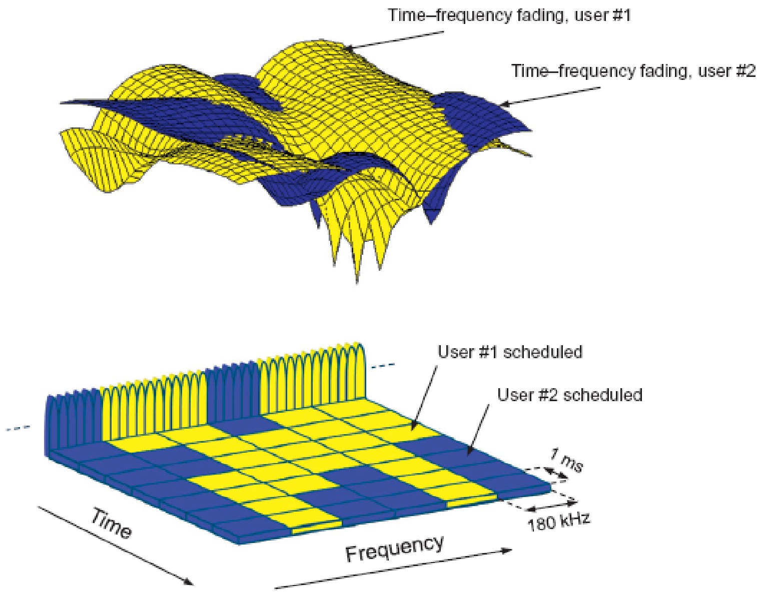


Figure 9: Downlink channel-dependent scheduling in LTE [22]

cator (CQI) and can be exploited by the eNB to perform adaptive user-to-subcarrier assignment, enhancing considerably the total system spectral efficiency compared to single-user OFDM systems. This is called *channel-dependent scheduling* and is represented in Figure 9. Actually, what happens is that the transmitter can adapt its modulation and coding scheme (MCS) according to the receiver's channel quality. As reported in Table 1, LTE identifies 15 different values of CQI, where ECR stands for Effective Code Rate and represents the robustness of the selected coding scheme. Hence, the MCS determines the quantity of bits that can be actually transmitted in the sub-frame on a certain sub-channel.

It is important to note that the resource allocation decision can be taken also every sub-frame. This is the shortest time-scale introduced by the standard, so as to exploit the multiuser diversity as much as possible even in high mobility contexts (i.e., with a short channel coherence time).

CQI	Modulation	ECR	Spectral Efficiency
1	QPSK	0.0762	0.15
2	QPSK	0.1172	0.23
3	QPSK	0.1885	0.38
4	QPSK	0.3008	0.6
5	QPSK	0.4385	0.88
6	QPSK	0.5879	1.18
7	16QAM	0.3691	1.48
8	16QAM	0.4785	1.91
9	16QAM	0.6016	2.41
10	64QAM	0.4551	2.73
11	64QAM	0.5537	3.32
12	64QAM	0.6504	3.9
13	64QAM	0.7539	4.52
14	64QAM	0.8525	5.12
15	64QAM	0.9258	5.55

Table 1: LTE MCS and CQI

The main parameters for the downlink access are summarized in Table 2.

2.2 Game Theory applied to communication networks

In this section we introduce the main concepts of the game theory that are used in the next chapters. Therefore, only a subset of all the possible concepts belonging to this discipline are described and also their presentation is rather divulgative and not technical. In particular, the focus is mainly on static games in normal form with perfect information and on the Nash Bargaining theory. The aim is to give just a rough idea to the reader not confident with this theory. For a more thorough analysis please refer to [28,29,58].

In recent years, communication networks researchers have devolved an ever increasing interest towards game theory as a tool to analyze con-

Parameter	Value
Downlink bandwidth	[2110, 2170] MHz
Possible transmission bandwidths	1.4, 3, 5, 10, 15 and 20 MHz
Subcarrier bandwidth	15 kHz
$RB_{bandwidth}$	180 kHz
$RB_{sub-carriers}$	12
$RB_{OFDM symbols}$	7 (or 6)
Frame duration	10 ms
TTI–Transmission Time Interval (i.e., sub-frame duration)	1 ms

Table 2: Main LTE downlink parameters

flicts among agents. Game theory is a branch of mathematics that provides a tool set for analyzing optimization problems with multiple users (*players*) having conflicting objective functions. Developed since the first half of the 20th century, this discipline has been widely applied to economics (both micro and macro), political science, psychology, logic and biology. Starting from a few years ago it has also been considered in Computer Science and Engineering, where several game theoretic models have been proposed for congestion control, routing, power control, topology control, trust management and other issues in wired and wireless communication systems. The strength of this mathematical tool is that it lets us to naturally model the interaction among interdependent decision makers where no centralized control is present.

The fundamental elements of the theory are: ***Game***, ***player***, ***strategy*** and ***payoff***. A Game describes an interaction among a set of agents (not necessarily humans), the players, which try to optimize their utility function, the payoff, by performing some choices, the strategies. Each player's payoff depends not only on its choices but also on the others', and in most cases there is a conflict, i.e., increasing one player's utility implies decreasing someone else's. A fundamental assumption that is behind this theory is the "rationality" of the players in performing their choices. In other words, each player does always the best action [2] that it can do to optimize the prefixed payoff, according to the level of information it is provided with.

A game $\mathcal{G}$ is typically formalized as a triple

$$\mathcal{G} = (\mathcal{P}, \mathcal{S}, \mathcal{U})$$

where $\mathcal{P}$ is the set of players, $\mathcal{S}$ is the strategy space and $\mathcal{U}$ is the set of payoffs, one for each player. We have:

- $\mathcal{P} = \{1, \dots, N\}$, where N is the number of players;
- $\mathcal{S} = \mathcal{S}_1 \times \cdots \times \mathcal{S}_N$, with $\mathcal{S}_i$ the strategy space of user i;
- $\mathcal{U} = (u_1, \dots, u_N)$, where $u_i = u_i(s_1, \dots, s_N)$ is the payoff of user i and is defined as $u_i : \mathcal{S} \to \mathbb{R}$ (for what concerns this thesis we can assume that payoff functions are real functions, without loss of generality).

The game theory deals with the formulation and resolution of games, where solving a game means identifying the strategy that in the end will be played by each player and the related outcome that will be reached. The formulation is not always an obvious operation since it depends on the rules followed by the agents in their interactions. Such constraints may be imposed by some regulator, the society, the nature itself, the technology or, in general, by the environment. This has led to the proliferation of a big variety of games. Possible taxonomies are:

- *static* vs *dynamic* games. In the case of a static game all the players do their choices independently without having any information on each others, as if they were moving at the same time. On the other hand, in the dynamic case moves are not simultaneous but ordered.

[2] In this simple treatment we use interchangeably the terms *action* and *strategy*. They coincide in the case of static games, but not in general. An action is one of the choices (or moves) that a player can perform at some point in the game. A strategy is something more structured and indicates a complete plan of action for whatever situation might arise; this fully determines the player's behavior. A player's strategy will determine the action the player will take at any stage of the game, for every possible history of play up to that stage.

A particular category of dynamic games is represented by the *repeated games*, i.e., a game $\mathcal{G}_R$ where each step is the repetition of the same static game $\mathcal{G}$ (called stage game).

- *complete* vs *incomplete information* games. In the case of complete information everybody's payoff is common knowledge, while in the other situation there is some uncertainty;

- *perfect* vs *imperfect information* games. In the former case each player has always a complete view of the moves of the others (e.g., the tic-tac-toe game), while in the latter there is some knowledge lack (e.g., card games);

- *non-cooperative* vs *cooperative* games. In the former games players strictly compete and cannot make deals, while in the latter they can negotiate with one another and form joint strategies.

When a player has to choose its strategy, it has to take into consideration the possible choices of the others and all the possible revenues it can obtain. When referring to possible strategies, some typical definitions are:

- *strictly dominated strategy*. A strategy $s_i \in \mathcal{S}_i$ of player $i \in \mathcal{P}$ is strictly dominated by strategy $s_i' \in \mathcal{S}_i$ if, for each strategy of the other players, s_i' always makes him reach a better payoff than s_i;

- *Nash equilibrium*. The strategies $(s_1^*, s_2^*, ..., s_N^*)$ are a Nash equilibrium if, for each player i, s_i^* is the best choice (also best response) he can make given the strategies played by the others, i.e.:

$$\begin{aligned} \forall i \in \mathcal{P}, \quad u_i(s_i^*, \dots, s_{i-1}^*, s_i^*, s_{i+1}^*, \dots, s_N^*) \geq \\ u_i(s_i^*, \dots, s_{i-1}^*, s_i, s_{i+1}^*, \dots, s_N^*) \quad \forall s_i \in \mathcal{S}_i \end{aligned} \tag{2.1}$$

  In other words, no player has an interest in deviating from that situation;

- *Pareto efficiency*. The strategies $(s_1, s_2, ..., s_n)$ are Pareto efficient if no player can improve its payoff without making another player worse off.

- *mixed strategy*. A mixed strategy for a player is defined as a probability distribution on the action space. It can be interpreted as a player's uncertainty about what the other players will do [29]. Each single strategy s_i in the strategy space can be seen as a particular mixed strategy where the probability associated to s_i is 1 while for the others it is 0. This is referred to as a *pure strategy*.

A game can admit zero, one or more Nash equilibria if the only pure strategies are considered. A Nash equilibrium, if present, is considered as the natural evolution of the game even if it is not Pareto efficient. Actually, in 1950 the famous mathematician John F. Nash proved a theorem about the existence of a Nash Equilibrum.

Theorem 2.2.1 (Nash, 1950) *In the n-player game, if n is finite and the action space for each player is finite as well, then there exists at least a Nash equilibrium, possibly involving mixed strategies.*

There are several particular types of games for which some theoretical results (not valid in general) have been derived. Among them there are the **zero-sum games** [79] and the **coordination games** [20]. The former include all those games where the sum of the payoffs for each strategy set is always zero, i.e., a player's gain (or loss) of utility is balanced by the loss (or gain) of the utility of another player(s). Instead, coordination games are a class of games with multiple pure strategy Nash equilibria in which players choose the same or corresponding strategies. A typical example is represented by the "Battle of the sexes", very well-known in the literature [49].[3]

A generalization of the Nash equilibrium concept is represented by the **subgame perfect (Nash) equilibrium**, which is used in the context of dynamic games where the moves of the players are organized into steps (i.e., first a player, then another, and so on). In this case it is important to distinguish the concept of action from that of strategy: the former refers

[3]In game theory, battle of the sexes (BoS), also called Bach or Stravinsky, is a two-player coordination game. It can be formulated as follows. Imagine a couple that want to go to the cinema. The husband would most of all like to watch an action movie. The wife would like to watch a romantic movie. Both would prefer to stay together and watch the same movie, but which one?

to the choice that a player can do in a certain situation, while the latter is the set of choices that the player can perform according to the situation he has to deal with (i.e., according to what the others have chosen before him). We say that a strategy profile is a subgame perfect equilibrium if it represents a Nash equilibrium of every *subgame* of the original game. Roughly speaking, without going into the details of the definition of the subgame concept, if (a) the players played any smaller game that consisted of only one part of the larger game and (b) their behavior represents a Nash equilibrium of that smaller game, then their behavior is a subgame perfect equilibrium of the larger game.

Game theory has been used to address a variety of interrelated resource allocation problems in communication networks. For example, it has been applied to CDMA power control problems and medium access control in ALOHA systems [51,52], in the analysis of ad hoc networks [73] and of the Internet and its protocols [61]. A survey of its applications in wireless communications is reported in a recent book of MacKenzie and DaSilva [50].

As already mentioned in the previous section, there is a quite rich literature on applications of game theory to spectrum conflicts in wireless systems. Preliminary studies of the spectrum sharing problem from a game theoretic point of view have focused on the search for fair, effective, and self-enforcing protocols, as in [27]. The authors argue that players should be compelled to use proportional fair and Pareto efficient operating strategies. The strategy enforcement idea is backed by the use of a repeated game where users can punish one another if deviating from a desired strategy. Specifically, if a player defects from the proposed fair and globally efficient power strategy, the other players would also defect by punishing it with a lower utility corresponding to the Nash equilibrium strategy. Consequently, no player has any incentive in defecting. In [46] the authors characterize the conditions under which the Nash equilibrium is inefficient for a two player spectrum sharing game, and introduce a distributed coordination algorithm in order to improve the performance of the system by optimizing the frequency allocation among the users.

The spectrum sharing problem in the context of cognitive radio has been formulated as both a static and a dynamic (repeated) Cournot game [57]. [4] Here, the setup is described as an oligopoly market, and the objective is to maximize the payoffs of the secondary users. In [77], a repeated game is analyzed for a spectrum sharing situation in cognitive radio that can be described as a ”prisoner’s dilemma” game. [5] In order to achieve higher outcomes, the iterated prisoner’s dilemma is used by applying different decision rules, which indicate the moves of a player in response to the actions of the others. A comparison of several algorithms is performed. A further work is the power control game presented in [31]. In this case, a pricing-based approach is used to obtain efficient operating points. It is found that when a cost function is inserted into the defined utility function, the players reduce their powers simultaneously and achieve higher payoffs at the Nash equilibrium point.

Cooperative and non-cooperative schemes for power control optimization in interference networks have been proposed [9]. Cooperation has been used to agree on a fair allocation of the spectrum in [75] too. An interesting application to the interference channel of the concepts of cooperative game theory such as coalitions, co-ordination and Nash Bargaining Theory is given in [45, 47, 48, 53]. In particular, in [45] Larsson et al. discuss the application of both cooperative and non-cooperative game theory to the flat-fading interference channel, and give some examples for the SISO, MISO and MIMO case. In [47] and [48] Leshem and Zehavi address the case of a frequency-selective interference channel, with both non-cooperative and cooperative perspective. They show how, under some conditions about the orthogonality of the access, the Nash bar-

[4] A Cournot game is a game between two firms which are the only producer of a certain good, i.e., in a duopoly condition. The price they receive is a decreasing function of the total quantity of goods that the firms produce. That function is known to both firms. Each chooses a quantity to produce without knowing how much the other will produce

[5] The prisoner’s dilemma is a canonical example of a game that shows why two individuals might not cooperate, even if it appears that it is in their best interest to do so. It can be formulated in the following way: << *Two men are arrested, but the police do not possess enough information for a conviction. Following the separation of the two men, the police offer both a similar deal. If one testifies against his partner (defects/betrays), and the other remains silent (co-operates/assists), the betrayer goes free and the cooperator receives the full one-year sentence. If both remain silent, both are sentenced to only one month in jail for a minor charge. If each testifies against the other, each receives a three-month sentence. Each prisoner must choose either to betray or remain silent; the decision of each is kept quiet.* >> [63].

gaining solution can be modeled as a convex optimization problem and solved through a proper algorithm. In Chapter 4, when discussing the non-orthogonal spectrum sharing, we consider a system model similar to this but without the assumption on the orthogonality of the access. In that case, we show how the problem becomes non-convex and thus of tough solution.

2.2.1 The Nash Bargaining Problem

Let $\mathcal{P} = \{1, \dots, N\}$ be the set of players of the game, and $\mathcal{H}$ denote a closed and convex set of $\mathbb{R}^n$ representing the set of all feasible payoffs that the players can get if they work together. We also assume that if no agreement is reached, i.e., the players do not cooperate, they get a payoff denoted by $\mathbf{d} = (d_1, \cdots, d_N) \in \mathcal{H}$, which is called *disagreement point*. Suppose that the set $\{\mathbf{y} \in \mathcal{H} | y_i \geq d_i, \forall i \in \mathcal{N}\}$ is non-empty and bounded. Then, the pair $(\mathcal{H}, \mathbf{d})$ is called an *n-person bargaining problem*.

Within set $\mathcal{H}$, we use Pareto optimality as a selection criterion for the bargaining solutions. The number of Pareto optimal points might be infinite. Among all of them, the Nash Bargaining Solution provides a unique result under the following conditions, which represent the characteristics that a solution is supposed to satisfy in Nash's theory, and are thus considered as axioms.

Definition 1 *A specific solution to the bargaining problem $(\mathcal{H}, \mathbf{d})$, denoted as $\phi(\mathcal{H}, \mathbf{d})$, is called a **Nash Bargaining Solution (NBS)**, if the following axioms are satisfied.*

1. *Weak Pareto Efficiency: there is no other vector $\mathbf{y} \in \mathcal{H}$ such that $\forall i \in \mathcal{P}, y_i > \phi_i(\mathcal{H}, \mathbf{d})$.*

2. *Individual Rationality: $\phi(\mathcal{H}, \mathbf{d}) \succeq \mathbf{d}$ (where $\succeq$ is $\geq$ element-wise).*

3. *Invariance: For any affine transformation ψ of $\mathcal{H}$ onto itself, $\psi(\phi(\mathcal{H}, \mathbf{d})) = \phi(\psi(\mathcal{H}), \psi(\mathbf{d}))$.*

4. *Independence of Irrelevant Alternatives: For any closed convex set $\mathcal{G} \subseteq \mathcal{H}$, if $\phi(\mathcal{H}, \mathbf{d}) \in \mathcal{G}$, then $\phi(\mathcal{G}, \mathbf{d}) = \phi(\mathcal{H}, \mathbf{d})$. This means that if the solution belongs to a subset of $\mathcal{H}$, it is also the solution of the bargaining problem restricted to that subset.*

5. *Symmetry: If $\mathcal{H}$ is invariant under all exchanges of players, then $\forall i, j \in \mathcal{P}, \phi_i(\mathcal{H}, \mathbf{d}) = \phi_j(\mathcal{H}, \mathbf{d})$.*

Given the above axioms, there is only one NBS satisfying them, as stated in the following theorem [59].

Theorem 2.2.2 (Existence and Uniqueness of NBS) *There exists a unique solution to the bargaining problem that satisfies all the axioms in* Definition 1, *given by*

$$\phi(\mathcal{H}, \mathbf{d}) = \underset{\mathbf{h} \in \mathcal{H}, h_i \geq d_i \forall i}{\operatorname{argmax}} \prod_{i=1}^{N} (h_i - d_i) \tag{2.2}$$

Following these theoretical notions, the cooperative game in a multi-player system can be seen as follows. Every player has its own payoff function, which is upper bounded and has a nonempty, closed and convex support. The NBS can be regarded as a way to maximize all these functions at the same time, i.e., to find an operating point in $\mathcal{H}$ which is optimal and fair (i.e., not good only for some players).

In this thesis work we resort to the Nash bargaining theory in Chapters 3 and 4. In the former, we try to model the trade-off between end users' fairness and spectrum allocation efficiency as a bargaining problem and apply this theory to find the solution. In the latter, we consider this approach for studying the capacity region of the non-orthogonal spectrum sharing.

Chapter 3

Intra-cell resource allocation

As a first step for the analysis of efficient resource allocation we start from the single cell scenario, where the Base Station (BS) managing the cell has to serve a certain number of registered users trying to guarantee a minimum level of service to each one of them and, at the same time, to exploit the available resources as much as possible. In particular, in the following the focus is on downlink transmissions.

Radio resource allocation on wireless channels is known to involve several design choices from the algorithmic point of view. One key issue involves the definition of the main allocation objective: since the channel quality is perceived differently by different users, it may be thought of allocating most of the resources to the users with the best channel conditions. However, this choice leads to unfairness from the network users' perspective since those with a bad channel (e.g., located further from the BS) will starve. Alternatively, some form of fairness may be sought, which imposes sometimes not to allocate the users with the best channel conditions (and thereby potentially decreasing the allocation efficiency). Typically, this trade-off is solved with a priori choices, by fixing some parameters. However, these solutions are not easy to set up, nor they can be dynamically adapted. Conversely, game theory can be used to solve this problem in a more efficient manner, by putting the burden of the trade-off resolution on some preference utility definitions, which are much easier to define from the operator's standpoint, and also enable dynamic adaptation of the allocation.

A sample challenge of this kind arises in multiple access schemes using OFDMA, such as the downlink of LTE systems. Assume that several users need to be served by allocating packets belonging to their flows on the OFDMA resource block (i.e., a frequency sub-channel for a time slot). Since their perceived channel quality is different (and, additionally, varies from one sub-carrier to the other) the problem becomes a complex task (combinatorial in nature), in view of the high number of possible allocations among which to choose. Additionally, the aforementioned trade-off between maximizing the throughput and achieving fairness (at least in a long term perspective) further complicates the problem. In the LTE standards, the design of policies for resource management is intentionally left open to allow developers to implement their own strategy of choice.

To study the problem through a game theoretical approach, we follow the model proposed in [13]. Here, a modular representation is introduced, where the Radio Resource Management is split between two functional entities, i.e., a packet scheduler and the actual Radio Resource Allocator (RRA) (see Figure 10). The former determines which packets, taken from the different flows, are candidates to be served in the next allocation round. The latter associates the packets with the available resources. In this choice, the RRA exploits a degree of freedom represented by the number of packets selected by the scheduler, which is greater than the number of available resources (i.e., time-frequency blocks). Indeed, the allocator selects for transmission a subset of them with the aim of maximizing the advantages of multiuser diversity. In this case only a loose cross-layer is introduced, guaranteeing a certain modularity between the involved entities. The resulting allocation can be regulated according to a trade-off between two contrasting objectives, i.e., that of throughput maximization, which is achieved by selecting the packets only according to a channel quality rationale, and fairness among the flows, which requires to pursue equity among the achieved rates. Indeed, this trade-off is re-

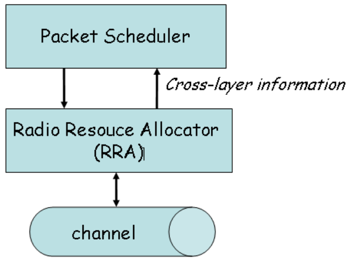


Figure 10: High level view of the system model

flected by the number of packets selected by the scheduler: when it is minimum, i.e., only the packets that fit the set of available OFDMA resources are selected, all packets are allocated and the resource allocator has no choice. Here the allocation is determined only by the credit-based scheduler, which guarantees fairness. Conversely, if the number of selected packets is high, the resource allocator can restrict the selection to the packets of the users with the best quality, entirely neglecting any fairness among flows.

Within this framework, in this chapter we propose a game theoretical view of the system aimed at the resolution of this trade-off between contrasting objectives. In fact, the idea is to define two virtual players, one representing the scheduler needs, i.e., to ensure fairness among the users, and the other reproducing the resource allocator perspective, i.e., to select those users which are experiencing better channel quality. A coordination game is established between these two players, which leads to the derivation of simple yet effective algorithms to identify a Pareto-efficient trade-off point. Both non-cooperative and cooperative models are used. In the former, we suppose that the two players do not cooperate and act only to optimize their own payoffs. In the latter, a cooperation is established between the players, which aim at optimizing a common utility function still being rational.

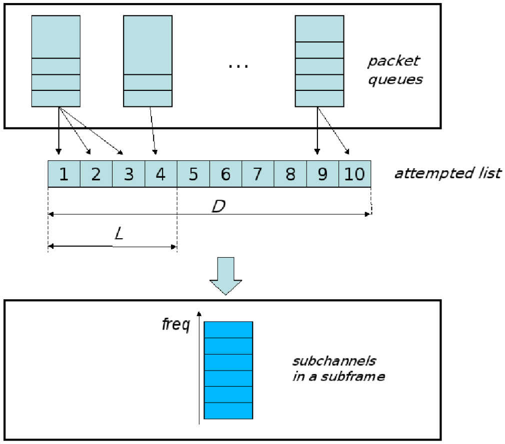


Figure 11: Detailed view of the two layer system model for the RRM

3.1 System Model and Game Theoretical view

Call L the number of physical resource blocks that the resource allocator is entitled to assign. This is subject to the constraint $L \leq L_{\max}$, where $L_{\max}$ is the maximum number of allocable resources. $L = L_{\max}$ corresponds to assigning every resource block (i.e., saturation condition). The value assigned to L is communicated to the scheduler by the resource allocator (cross-layer communication). Upon knowing L, the RRM determines a number D of packets the scheduler can send to the resource allocator, where in general $D \geq L$. The exact choice of D influences the entire allocation. As a matter of fact, if $D = L$ the resource allocator has no degree of freedom as to which packets to allocate (while, obviously, it must allocate the packets to the best channels as perceived by the users). By increasing D, the resource allocator can achieve a higher throughput by selecting only L packets out of D, according to a channel-aware policy, although at the price of a possibly decreased fairness. A graphical representation of the system is given in Figure 11 (whose PHY layer is drawn from an LTE scenario, where the resources to be allocated are the frequency sub-channels), while Figure 12 shows the qualitative impact of

	Fairness	**Throughput**
$D = L$	Max	Min
$D > L$	$\Downarrow$	$\Uparrow$

Figure 12: Impact of D on fairness and throughput

D on fairness and throughput.

The communication between the two entities is realized through an attempted list of candidate packets for transmission. The scheduler fills it while the RRA empties it. The length of this buffer is exactly D. In particular, the resource allocation in Figure 11 takes into account only the frequency domain since it is implicitly assumed that the allocation algorithm is run in every sub-frame, which corresponds to the finest granularity possible according to the LTE standard.

The choice of D determines a trade-off between the possible objectives of throughput and fairness. Through a process of abstraction we can see the scheduler-RRA as a two player game. The scheduler and the RRA are the players of a game whose aim is the decision of the value for D. Both players make a proposal s_j, with $j = 1, 2$, respectively (i.e., s_1 for the scheduler and s_2 for the RRA). The game is inspired by a particular type of *coordination games* [20], where two players get non-zero payoff only if they converge on a common agreement (see Section 2.2). [1] In our case, if proposals s_1 and s_2 coincide, D is assigned their common value. However, the choice of s_1 and s_2 is also done according to the utility of the proposer, i.e., the fairness for the scheduler and the throughput for the RRA, respectively.

Consider a network scenario with M, $M > 2$, network users (in this case we assume one data flow per user); these are not to be confused with the two "virtual" players of the game, i.e., the scheduler and the RRA. We model the system as a static game in normal form, as follows:

- The players are the scheduler and the RRA.

[1]One can think of this situation as a generalization of the "battle of the sexes" game described in Section 2.2.

		Resource Allocator			
		L	$L{+}1$	$\dots$	ML
	L	$1, T_{\min}$	$0, 0$	$0, 0$	$0, 0$
Scheduler	$L+1$	$0, 0$	$\dots$	$0, 0$	$0, 0$
	$\dots$	$0, 0$	$0, 0$	$\dots$	$0, 0$
	ML	$0, 0$	$0, 0$	$0, 0$	$\frac{1}{M}, T_{\max}$

Figure 13: Bi-matrix representation of the game.

- Their action spaces are the set of values of D that can be proposed, i.e., $S_1 = S_2 = \{L, L+1, \dots, ML\}$.
- Both payoffs are 0 if the proposals s_1 and s_2 do not coincide, i.e., there is no agreement on the value of D. This assumption is drawn from the more general theory about coordination games.
- When $s_1 = s_2$, the payoffs are assigned to the throughput $T(s_1, s_2)$ for the RRA and to fairness $F(s_1, s_2)$ for the scheduler, the latter calculated by using Jain's index [38],

  $$F = \frac{(\sum_{i=1}^{M} x_i)^2}{(M \cdot \sum_{i=1}^{M} x_i^2)} \tag{3.1}$$

  where x_i is the number of bytes transmitted of flow i. We can simplify the notation by writing $T(s, s) = T(s)$ and $F(s, s) = F(s)$.

The last point is arbitrary, as other definitions can be used; the important requirement is that $F(s)$ and $T(s)$ are decreasing and increasing in s, respectively. The resulting bi-matrix representation of the game is given in Figure 13. The fairness is a decreasing function of D: according to its definition, its maximum value is 1 while the minimum is $1/M$. On the other hand, the throughput is an increasing function of D varying in the range $[T_{\min}, T_{\max}]$, where $T_{\min}$ is achieved when no degree of freedom is given to the allocator, while $T_{\max}$ is obtained when the RRA has enough freedom to allocate only the best L resources. Both maximum throughput and minimum fairness are reached for $D = ML$, under the assumption that there are always at least L packets available for selection by the scheduler from each queue. All the strategies along the diagonal are Pareto efficient Nash equilibria. This means that improving the payoff of one player results in worsening the other's outcome. Thus, once the value of L is fixed, there is no unique evolution of the game and, in any case, a trade-off is encountered.

In the following we discuss two game theoretical approaches to solve the game and determine a proper value of D. Our proposed methodology enables a dynamic setup of D without any need for a preliminary evaluation, e.g., where D is set to some arbitrary fixed value. The choice of D is directly derived from the definitions of the contrasting utilities between which a trade-off is sought (specifically, throughput and fairness). Together with the separation of the resource management process into two functional entities (scheduler and RRA), this is key to achieve a computationally efficient online allocation strategy. The approaches described in the following sections refer to a non-cooperative and a cooperative view of the system, according to what we presented in [11] and [10].

3.2 Non-Cooperative Approach

In this perspective, the two players are considered as two rational selfish entities which try to optimize their own utility function, without any effort of cooperation among them. To determine a trade-off point, we propose an algorithm which tries to automatically estimate an efficient value of D for each sub-frame. The value is chosen considering the entire history of the game, thus the model we propose is a *repeated game with perfect information*. The aim is to reach an acceptable level for both payoffs after a number of repetitions. The main steps are the following.
1) Both scheduler and RRA randomly pick a value for D within their action spaces.
2) If the choices coincide, D is set and the game ends, otherwise an iterative phase starts and goes on until a common value is chosen. Every time the players disagree, both get zero payoff.

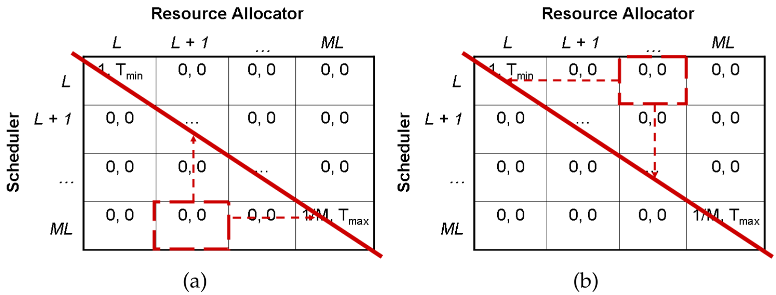


Figure 14: Movements in the bi-matrix

The goal of each repetition of the iterative phase is moving towards the diagonal of the bi-matrix in Figure 13 step-by-step. Each player decides whether or not to change its previous proposal based on its *level of satisfaction*, i.e., the ratio between the payoff actually achieved and the maximum achievable. The higher the satisfaction, the higher the probability that a player changes its proposal with a value more convenient for the other. If S_D and RRA_D are the proposals for D made by the scheduler and the allocator, respectively, and S_s and RRA_s the respective levels of satisfaction when the game is played, we select the changes as follows.

- If $S\_D > RRA\_D$, we are in the lower triangle of the matrix (Figure 14a). We can move towards the diagonal by going up (decrement of S_D), or right (increment of RRA_D), or in both directions. For both players, these options lead to higher values in their own utility function to the detriment of the other's, thus the willingness to change should be a decreasing function of the respective satisfaction level. Thus, we select

$$Prob\{S\_D\ up\} = 1 - S\_s \tag{3.2}$$

$$Prob\{RRA\_D\ right\} = 1 - RRA\_s \tag{3.3}$$

- If $S\_D < RRA\_D$, we are in the upper triangle of the matrix (Figure 14b). The diagonal can be reached by going down (S_D increment), or left (RRA_D decrement), or in both directions. The situation is now reversed, as a deviation in its own action implies a reduction in the payoff of each player in favor of the other's. Therefore, the probability of moving must be an increasing function of the respective satisfaction, which is obtained for example by choosing

$$Prob\{S\_D\ down\} = S\_s \tag{3.4}$$

$$Prob\{RRA\_D\ left\} = RRA\_s \tag{3.5}$$

In this manner, we define an algorithm whose goal is to lead the choice of D towards an intermediate value which offers both good throughput and satisfactory fairness. The approach can still be considered non-cooperative since there is no common (social) function to be optmized and each player aims to optimize its own utility function. The algorithm converges asymptotically towards the diagonal of the bi-matrix in a limited amount of time, as noted from the simulations run.

3.2.1 Simulation Model and Numerical Results

In this section we present numerical results obtained after a simulation campaign for the validation of the algorithm presented above. We used the independent run simulation method, with all the measured performance indices characterized by a 95% confidence interval with a maximum relative error of 5%.

For these simulations we developed a simple asynchronous event-driven simulator, written in C++, which reproduces a base station transmitting to some users. The base station contains a packet scheduler managing some flow queues (one for each flow), the RRA module and the radio channel. The scheduler is credit-based and tries to guarantee fairness by selecting packets from the queues according to their residual credit. We considered a simple scenario with two equal priority flows having always backlogged traffic. The RRA manages the resource allocation according to a greedy criterion: the match between resource blocks and packets is done trying to maximize the total throughput given the channel condition at each user.

Parameter	value
number of flows	2
packet size	500 bytes
$Pr\{GOOD \rightarrow GOOD\}$	0.9
$Pr\{BAD \rightarrow BAD\}$	0.8
number of sub-carriers	16
time slots per frame	24
frame duration	5 ms
transmission power per slot	1 mW

Table 3: Main system parameters for the non-cooperative approach

We considered an LTE-like access system, with an OFDMA/TDMA access scheme. The number of frequency sub-channels is 16 while the time slots for each time frame are 24, for a total of 384 resource allocation blocks. With reference to the channel model, for each frequency sub-channel we used a two-state Markov channel, a Gilbert-Elliot model [26,30]. The two channel states in this model are generelly referred to as GOOD (or gap) and BAD (or burst). Each state has a different probability of transmitting a bit correctly, of course higher in the former. In our scenario, a different average noise power has been associated with each of the two states of the chain, thus different values of capacity can be reached (according to the Shannon formula). For simplicity, when the Gilbert-Elliot channel is in the state GOOD, interference and noise power are treated as a random variable with uniform distribution between 1 and 2 mW; similarly, in case of channel in the state BAD, the interference plus noise power is uniformly distributed among 1 and 200 mW. The transmission power per slot is fixed to 1 mW. The channel state is updated after each time slot to take channel correlation over time into account. The main system parameters are summarized in Table 3. The assumptions made are quite simple since the aim of this first bunch of simulations was just to confirm the relationship between fairness, throughput and the value of D and to validate the effectiveness of the proposed algorithm.

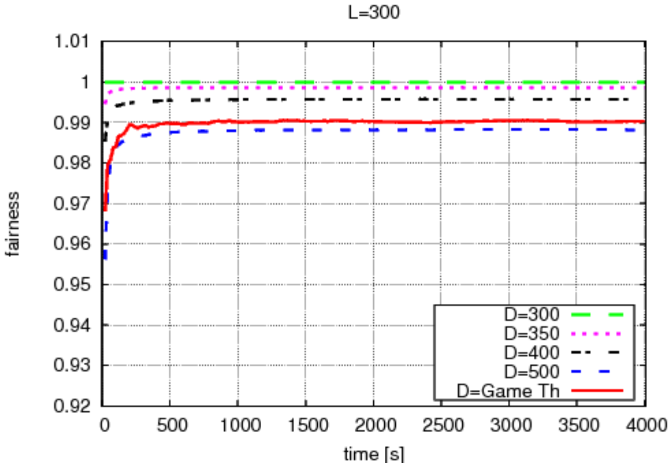


Figure 15: Fairness over time for different values of D - non-cooperative approach

Nonetheless, they are not restrictive for the validity of the considerations that can be drawn. The performance indices considered for the analysis are the fairness (Jain's index) and the normalized throughput, i.e., the ratio between the actual value of cell sum throughput and the maximum value reachable when D is set the its maximum ML.

In Figures 15– 16 the fairness and the normalized throughput as function of the time are shown for several values of D having fixed L to 300 packets. They confirm what expected from our analysis: the fairness is a decreasing function of D while the throughput increases. When $D = L$, we have that the fairness is always 1, the maximum value according to Jain's index. On the other hand, the normalized throughput has its minimum value because the resource allocator has no freedom in the choice of the packets to transmit and the user diversity is limited.

When D is increased, the two performance indices considered have contrasting behaviors, as already expressed in the previous analysis: the fairness undergoes a decrease while the throughput starts to increase. The introduction of a certain freedom in the allocation choice shows its effects

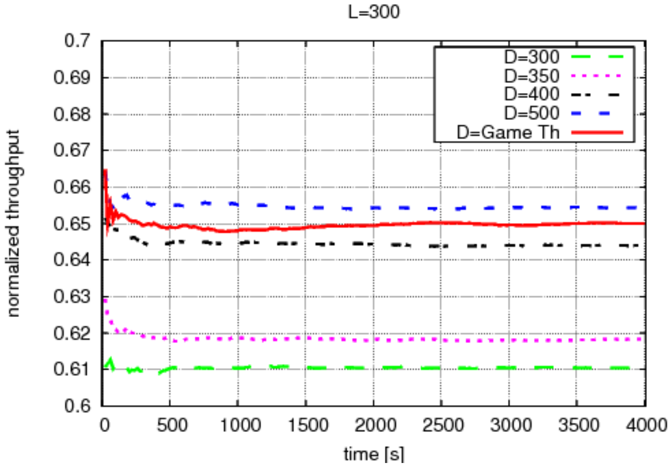


Figure 16: Normalized throughput over time for different values of D - non-cooperative approach

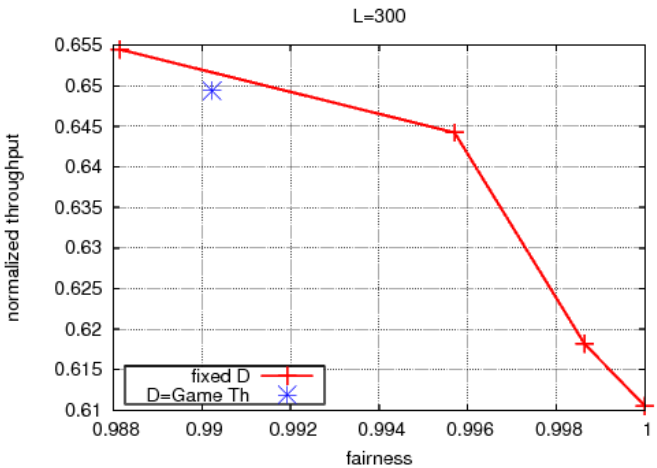


Figure 17: Pareto boundary and operating point of the non-cooperative algorithm

and the trade-off among the payoff of the two players becomes evident. Figure 17 clearly shows this situation: the points along the curve are the Pareto solutions of the game, one for each value of D, and there is no possibility to reach a better solution for one player without worsening the other's.

In all the figures, the outcome of the game theoretic algorithm is shown as well. Both in Fig. 15 and Fig. 16, the application of the proposed algorithm for the automatic choice of D leads to an intermediate value of both performance indices. This means that each player reduces a little bit its own payoff in the sake of a better joint solution. In Fig. 17 it is shown that this new operating point is localized close to the Pareto boundary. Moreover, the proposed algorithm is quite simple and the convergence to a common value of D is extremely fast, thus it is suitable for an online implementation. Indeed, in Figs. 15–16 the warm-up period is quite short, about 300 ms.

For completeness, we ran other tests by varying L in the range $[100, 350]$. In all the cases we obtained that the fairness increased with the value of D while the throughput decreased. The operating point reached by the proposed algorithm always approximately lies on the Pareto boundary.

3.3 Cooperative Approach

In the cooperative version we consider the interaction scheduler-RRA as a bargaining process. The goal is to achieve a balance between the two interests, with a solution that does not favor either of the players. The two players are still rational but aim at optimizing a kind of "social welfare" function. According to this view, we can think of modeling this situation by using the Nash bargaining theory [56, 59], whose solution represents a Pareto-efficient *fair* point, where in this definition *fair* refers to an equal distribution of the payoffs between the scheduler and the RRA (i.e., the two players). According to what described in Section 2.2.1, this theory is based on some axioms. In order to fit our problem within this framework, we introduce some assumptions:

1. The payoff functions $F(D)$ and $T(D)$ are properly translated and

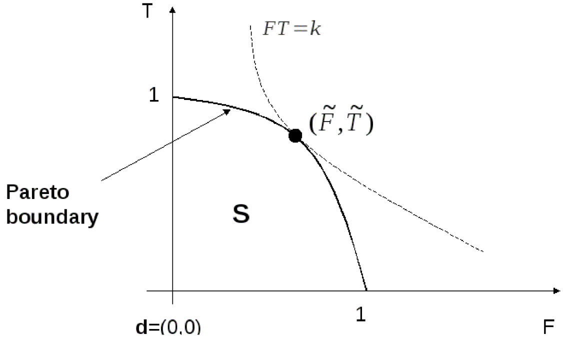


Figure 18: Pareto boundary and NBS

scaled in the interval [0,1], which is admissible since the NBS is (by axiom) independent of affine transformations. For ease of notation, in the following we still refer to the transformed functions as $F(D)$ and $T(D)$, and to the transformed set of joint payoffs $(F(D), T(D))$ as $\mathcal{S}$.

2. D is treated as a continuous value.

3. $F, T \in \mathcal{C}^1(\mathbb{R})$, i.e., $F(D)$ and $T(D)$ and their first-order derivatives are continuous functions;

4. When the players propose different values of D, their payoffs vary with continuity in [0,1] and are upper bounded by the Pareto frontier of all the agreement points (see Figure 18). In this way, the set of all feasible payoffs, $\mathcal{S}$, is a closed and convex set. This is still sensible since in the bi-matrix in Figure 13 the choice of giving payoff zero for all the points out of the main diagonal is totally arbitrary.

5. The disagreement point is set to $\mathbf{d} = (0, 0)$.

According to the theory we have to find the point

$$(\widetilde{F}, \widetilde{T}) = \underset{(F,T)\in\mathcal{S}}{\operatorname{argmax}}(FT) \tag{3.6}$$

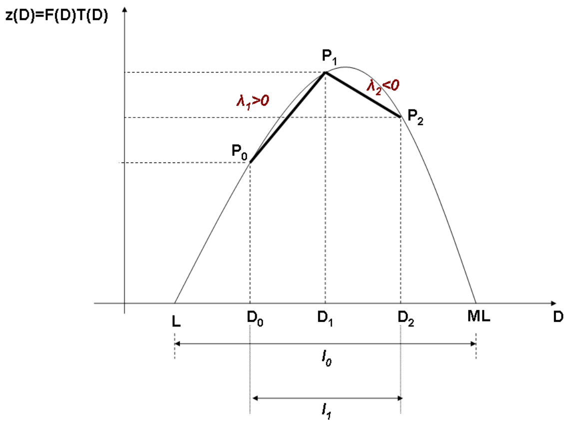


Figure 19: Example of $\widetilde{D}$ estimation

which means finding the value $\widetilde{D}$ that generates $(\widetilde{F}, \widetilde{T}) = (F(\widetilde{D}), T(\widetilde{D}))$; it is worth noting that the image of $\widetilde{D}$ lies on the Pareto frontier and not within the convex set $\mathcal{S}$. From a geometric point of view, the NBS represents the unique point of tangency between the feasible convex set $\mathcal{S}$ and the generic hyperbola $FT = k, k > 0$. These hyperbolas are the contour lines of the function $z(F, T) = FT$ (see Figure 18). An advantage of modeling the system as a Nash bargaining problem is that the theory guarantees the existence and uniqueness of the solution, in addition to the fact that this solution represents an *equity* point between the players. Sometimes this is also referred to by saying that the NBS realizes the *maximum utility transfer*: by moving away from that point, the proportional increment in the payoff of one user is less then the proportional decrement sustained by the other user, thus the overall benefit is negative.

To determine the point $\widetilde{D}$ we propose an effective yet efficient algorithm. Note that the algorithm is run within the Base Station at every allocation opportunity, thus it is always the same physical entity that calculates the value of D. In this way we enable the dynamic estimation of the optimal value of D (with respect to the NBS) based on the current network state, instead of using a static value fixed a priori that could lead the system in an inefficient operating point because unable to adapt to the system variations. The algorithm is iterative. The search interval is exponentially reduced, so the complexity is logarithmic. We select some increasing values of D in the initial interval, compute the corresponding points through the Nash bargaining function $z(F(D), T(D)) = F(D)T(D)$ and measure the slope of the segments connecting them. Taking into account that the derivative of a $\mathcal{C}^1(\mathbb{R})$ function is positive before the point of maximum and negative after it, we can restrict the interval of interest (see Figure 19). For example, if the slopes of the segments are all positive, then D_0 and D_1 must be lower than the point of maximum. Thus, the lower bound of the interest interval can be set to D_1. Similar considerations apply to the other combinations of signs, leading to the decision tree in point 5) below. We iterate until the interest interval is small enough, below a fixed precision $\epsilon > 0$, meaning that we are sufficiently close to the exact value. The steps are the following:

1. Set $a = L$, $b = ML$. Call $I = b - a$;

2. if($I \leq \epsilon$) then return (int)($I/2 + a$);

3. choose $D_0 < D_1 < D_2$ in the interval $[a, b]$ such that $D_i = a + \frac{1}{4}(i + 1)I,\ i = 0, 1, 2$;

4. find the point $P_i = (D_i, z(D_i))$, and determine the slopes λ_1 and λ_2 of the segments $\overline{P_1 P_0}$ and $\overline{P_2 P_1}$;

5. change the extremes a and b of the interval according to the sign of the slopes. In particular:

   - if($\lambda_1 > 0$) then $a = D_0$;
   - if($\lambda_1 \leq 0$) then $b = D_1$; jump to 6);
   - if($\lambda_2 > 0$) then $a = D_1$; jump to 6);
   - if($\lambda_2 \leq 0$) then $b = D_2$;

6. update I; jump to 2);

Note that the value of D is eventually rounded down to an integer.

Proposition 1 *The algorithm described above has complexity* $\Theta(\log_2(\frac{I_0}{\epsilon}))$*, where* I_0 *is the initial length of the interval of interest.*

Proof For any choice of the three points D_0, D_1 and D_2, the pairwise distance is $\frac{1}{4}I$. According to point 4), at each iteration at least one of the extremes of the interval is changed and its total length is halved. Therefore, after n steps the length of the interval is $I_n = I_0(\frac{1}{2})^n$. From the inequality $I_n \leq \epsilon$, we obtain the logarithmic complexity stated in *Proposition 1*. ∎

3.3.1 Simulation Model and Numerical Results

We verified the effectiveness of the proposed solution by means of simulation. All the performance indices shown hereafter are characterized by a 95% confidence interval with a maximum relative error of 5%.

To carry out our tests we used the ns-3 simulator with the extension for LTE systems described in [1]. We modified the MAC layer by introducing our scheduler and RRA modules. The first one adopts a credit-based policy and guarantees fairness by selecting packets from the flow queues according to their residual credit. Flows are assumed to be always backlogged. The second module deals with resource allocation by using a greedy criterion: blocks and packets are matched in order to maximize the total throughput given the channel condition. This information is obtained by the base station through periodic feedbacks sent by its UEs according to what indicated in the LTE standard. We assumed a low mobility scenario such that the channel coherence time is greater than the feedback interval, in our case equal to one sub-frame duration (i.e., 1 ms). The radio propagation model takes into account the effects of path loss, penetration loss, shadowing and multipath fading. The shadowing is modeled according to a log-normal distribution with parameters $\mu = 0$ dB and $\sigma = 8$ dB, while for the multipath Jakes' model [39] is considered with a number of scatterers between 6 and 12. The penetration loss is of 10 dB. Each resource unit allocable to users has a duration of one sub-frame and is made of 12 adjacent sub-carriers with 15 kHz spacing (equal to one sub-channel of 180 kHz). We considered 80 frequency sub-channels for the downlink plus 20 for the uplink, for a total

Parameter	Value
number of flows	2
packet size	500 bytes
number of sub-channels for the downlink	80
number of sub-channels for the uplink	20
frame duration	10 ms
sub-frame duration	1 ms
downlink transmission power	43 dBm

Table 4: Main system parameters for the cooperative approach

of 20 MHz bandwidth. The scheduling and allocation decisions are made at the beginning of each sub-frame and are immediately communicated to the registered UEs. The values for the main system parameters are reported in Table 4, with the air interface defined according to indications of the LTE standard. The performance indices considered are, as in the previous section, fairness and normalized throughput.

Figures 20 and 21 show the two normalized payoff functions versus time for several values of D. Like in the Figs. 15–16, also here the trade-off expected from the theory is confirmed: once the value of L is fixed, Jain's fairness decreases in D while the throughput increases. From a quantitative point of view, the variation depends on several factors, e.g., the number of users in the cell, the channel conditions, the transmission power, the number of available sub-channels. For the sake of completeness, we ran additional simulations by changing some of these parameters. We do not report all the results which would not add any information since, in every case, the mutual relations among the curves for different values of D were found to be the same.

In both Fig. 20 and Fig. 21 we can note that the proposed algorithm for the estimation of D leads to an intermediate value of both performance indices. The two functions cannot be jointly maximized. Indeed, what is maximized is a common utility function, represented by the product of each player's payoff. This situation is summarized in Fig. 22, where both

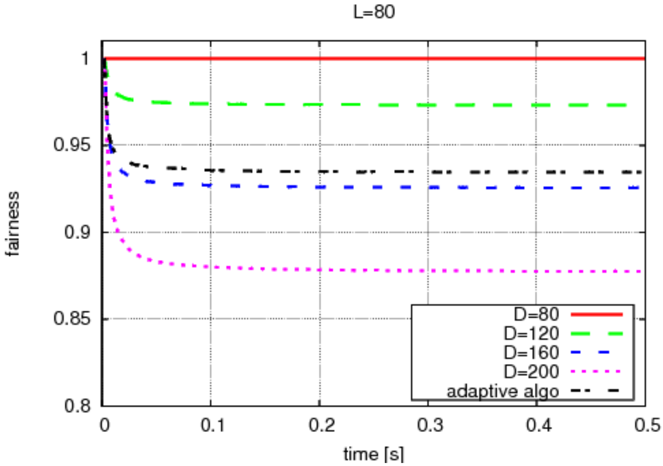


Figure 20: Fairness over time for different values of D - cooperative approach

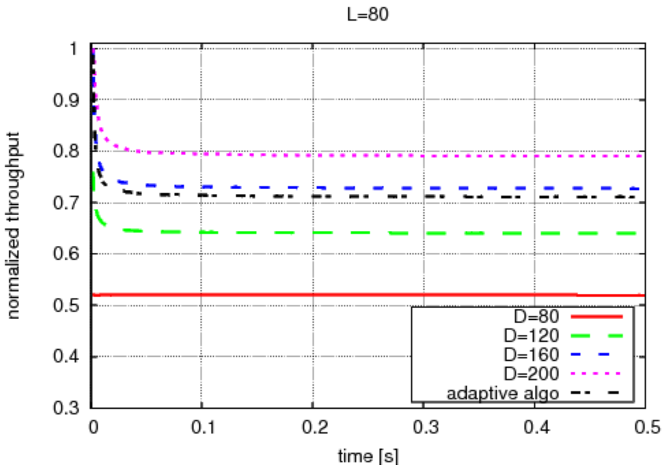


Figure 21: Normalized throughput over time for different values of D - cooperative approach

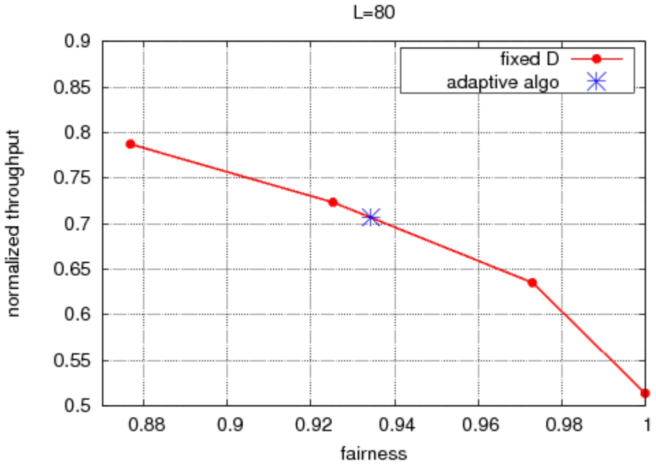


Figure 22: Pareto boundary of the game and operating point of the NBS algorithm. The disagreement point is in (0,0)

the Pareto boundary and the NBS point are drawn. This point lies on the frontier, as expected from the theoretical analysis.

We think it is worth stressing again that the strength of the proposed solution is its adaptivity. One could think of fixing D a priori, after a preliminary study, but the system performance is context dependent, thus the value should be re-computed every time a change occurs, which is not practical. On the other hand, the algorithm above discussed is able to to determine at runtime the best value in an efficient way.

3.4 Applications of the Proposed Approach in a Multi-Agent Context

The algorithms proposed above reach a Pareto efficient point, which trades throughput for fairness in an efficient and tunable manner. However, this should not be seen just as a way to set the equilibrium between contrasting needs. In fact, a direct extension may be identified to cases where the multiple players of the game are not just *virtual* agents representing different layers of the same entity, e.g., the radio resource management procedure at one base station. Rather, the game may be extended to a wider population of actors, where still coordination is sought but among different classes of actors.

A first extension of this game theoretical setup involves the interaction between multiple base stations, possibly belonging to different operators (this may be also partially applied to the case where the operator is the same, but the exchange of management policies among the base stations is made difficult by some externalities). This case, which can be analyzed in a practical scenario similar to those studied by [54] can be framed in the context of *games with incomplete information*. A multitude of games may be used to represent the different base stations, each one of them using two virtual players to represent the contrasting needs of throughput and fairness. In other words, the game discussed above, as well as some specific procedure to solve it, is played several times at the same time. Under the assumption of perfectly rational players, it may still be assumed that a Pareto efficient equilibrium point is sought by all base stations. However, due to interference caused by neighboring cells, a repeated version of this game may also be considered in order to reach a further equilibrium among the games played locally.

A further extension may involve the management of contrasting objectives among different operators. In this case, the game agents are not only virtual players which are assumed to blindly pursue the task of finding an efficient trade-off between throughput and fairness (or any other objective). Rather, the operators also try to drive the whole allocation of the system toward a favorable allocation for them, which is possibly reflected by the virtual players at one base station trying to influence the outcomes of other games. The extension of such games, which involves further utility modeling and possibly extension to Bayesian games, is a possible direction for further study.

Chapter 4

Inter-cell spectrum sharing

In this chapter we move one step ahead with respect to the previous one and consider a wider scenario with several cells, each serving several users. The focus is always on downlink transmissions. We consider the LTE standard as the reference technology. The main technical details, or at least those relevant to our treatment, are reported in Section 2.1.

A particular scenario of multi-cell network is hereafter considered, the *multi-operator* case, i.e., a multi-cell network where cells are managed by different operators. Such a situation is quite important and innovative. Most of the telecommunication companies have their own Base Stations close to those of other companies, thus a multi-operator context is quite common. The main innovation of our research work is the exploration of a concept which might change significantly the current market of this sector: ***spectrum sharing*** among network operators.

Currently, in most countries each operator is allocated a separate portion of the spectrum by the regulator (e.g., by an auction mechanism), thus no inter-cell inter-operator interference can happen. So, when a BS performs the resource allocation for its users it needs not to take into consideration what the BSs belonging to the other operators are doing, even when the cells overlap each other (e.g., think of a site sharing). Only intra-operator interference needs to be managed, e.g., by setting a proper frequency reuse factor. On one hand, an orthogonal allocation like that of the spectrum gives each operator a clear idea of the amount of spectrum it is entitled to use, how many users it can serve and the quality of service it can guarantee. On the other hand, it may result in an inefficient use of the resource. First of all, operators experimenting a peak of requests cannot exploit frequencies unused by other operators. Second, the exploitation of multi-user diversity effects in the downlink of a BS is limited to the frequencies it is assigned, even though it could reach a higher efficiency by employing frequencies not used by other operators. These are some of the classical drawbacks related to static allocation schemes. As for the case of circuit commutation and packet commutation networks [76], in the same way a fixed orthogonal resource allocation can lead to some flaws in the efficiency and quality of service guaranteed to the users. The introduction of a certain (regulated) overlapping between the spectra assigned to network operators seems a possible way to tackle the problem. Of course, this solution requires a certain level of signaling/synchronization among the involved operators to define which part of their spectrum they are willing to share and how it can be accessed. In the literature, very few studies have been presented so far that face such a situation. In this thesis we do not consider the business and legal aspects of this operation, even though they are interesting. What we investigate is the gain that the companies operating in the telecommunications sector can obtain in terms of increase of the QoS guaranteed to their users or in terms of higher number of users served.

Once that a group of operators agree on sharing part of their initial spectrum, the main problem that arises regards the access to the common resource. It is important to develop efficient schemes in order to avoid the "Tragedy of the Commons" problem, very well-known in the game theory literature. [1] This issue is rather challenging from the point of view of the research. Two directions are possible: ***orthogonal*** and ***non-orthogonal*** sharing. In the former, the access to each common sub-channel is mutually exclusive, thus no inter-operator interference can happen. On the

[1] The "Tragedy of the Commons" is a classical example of inefficient competition among selfish rational agents. It arises when multiple individuals, acting independently, selfishly and rationally will ultimately deplete a shared limited resource even though this leads to a non-optimal situation for each of them [34].

contrary, in the latter more transmitters can contemporaneously exploit the same resource and generate mutual interference provided that the Signal to Interference-plus-Noise Ratio (SINR) to the respective intended receivers is still acceptable.

For the orthogonal sharing, we have proposed and evaluated some algorithms. In particular, an upper bound on the total sum capacity has been identified that shows the existence of a sharing gain. In Section 4.1 we discuss extensively the main achievements done in this research direction. The implementation and evaluation of the presented mechanisms has been done by exploiting an ad-hoc extension of the ns-3 simulator that we designed for the support to the spectrum sharing [12], as explained in Chapter 5.

Regarding the non-orthogonal case, it basically adds the power control issue. We can frame it as the so-called *frequency-selective interference channel* (FS-IFC) problem, which is still open since the capacity region of such a channel has not been derived in the general case when power constraints on each sub-channel and on the whole transmission are considered [48, 66]. A game can be identified among the BSs, which try to optimize their payoffs (e.g., sum rates) by choosing an appropriate power distribution on the sub-channels. The application of the Nash bargaining theory is quite difficult in this case, since the resulting model is a non-convex optimization problem, of difficult solution itself, whose rigorous formalization is made harder as the Nash equilibrium, required in the Nash product definition, might neither exist nor be unique. The situation becomes even worse when the achievable rate region gets non-convex, since in that case the NBS is not defined properly anymore. However, the solution of this problem is out of the scope of this work.

For both classes of sharing policies, it is important to understand what are the main factors impacting on the system performance and that are worth to investigate. A first issue is the time granularity at which the resource allocation is performed. Short, intermediate and long time-scale policies are possible, with the related advantages and drawbacks. Very frequent allocation choices (short time-scale) are more adaptive to channel changes and thus make the system more flexible. However, since they

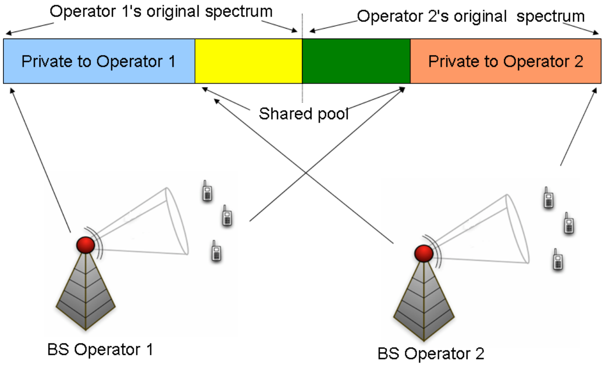


Figure 23: Example of inter-operator spectrum sharing

are executed very often, a low complexity is a key issue together with the signaling overhead for synchronization among BSs. On the other hand, an algorithm run on a long time-scale has less constraints on the convergence time but is less reactive to the channel variations. In our study we have considered the shortest time scale, i.e., an allocation every LTE subframe, so as to exploit all the channel fluctuations that arise mainly due to the channel fading.

The number of UEs in the cell and, more in general, the traffic load are important parameters to be taken into consideration. Some considerations on their effect are made later on. Besides all, a fundamental element necessary to justify the spectrum sharing is frequency diversity. If the channel for each UE of a BS is almost flat, then there is no incentive in using others' frequencies since they have the same quality, and thus there is no added value in resorting to the spectrum sharing solution. Therefore, the greater the diversity among sub-channels the greater the expected sharing gain [78].

All over this work, for the sake of simplicity, we consider only scenarios with two network operators, each one with its own Radio Access Network (RAN), managing two adjacent cells. In every cell there is a BS (called BS1 and BS2, respectively) which manages a certain number of registered User Equipments (UE) (see Fig. 23). The discussion can be naturally extended to a generic number of involved operators.

The remainder of this chapter contains first a description of the work done for the orthogonal sharing, including the simulation results obtained after the validation of some algorithms. Then, the non-orthogonal sharing is introduced together with the main issues that come with it.

4.1 Orthogonal Spectrum Sharing

According to the LTE radio interface definition for the downlink (see Section 2.1), the spectrum is divided into bundles of adjacent sub-carriers, called *sub-channels*, and each one of them is assigned to a single user for an entire time sub-frame. We can model this situation as in Figure 24. We assume that the original spectra assigned to each operator by the regulation authority are adjacent. The orthogonal access hypothesis is not in contrast with the sharing concept. We can still talk of a spectrum sharing context since spectrum allocation is dynamic in time and, more important, each operator can exploit additional frequencies out of the original set it was assigned by the regulator. As a consequence of this assumption, we have to consider the case when the same (common) resource is needed by both the operators, i.e., there is an access contention.

In the following of this section, we give first a possible system model that formalizes the situation under analysis, then we discuss some possible *orthogonal sharing algorithms*.

Call $\mathcal{K}$ and K respectively the set and the number of available sub-channels for the downlink. These resources are divided into two subsets, $\mathcal{K}_1$ and $\mathcal{K}_2$, of cardinality K_1 and K_2, assigned respectively to operator 1 and 2. Let $\alpha_i \in [0, 1], i = 1, 2$ be the sharing percentage for operator i, i.e., the percentage of spectrum it decides to share. Without loss of generality, we assume that $K_1 = K_2 = k$ and $\alpha_1 = \alpha_2 = \alpha$. The k sub-channels are split into a part $k^s = k\alpha$ that is shared, and a part k^p that remains private to the operator, with $k = k^s + k^p$ (see Fig. 24). In this way, each operator i has a final set of k^F available sub-channels that is made of its initial k

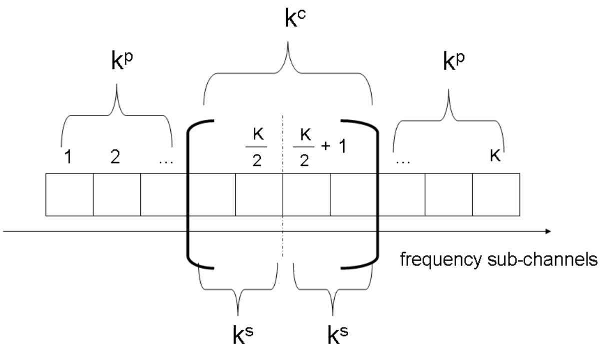


Figure 24: Frequency sub-channels

plus the k^s shared by the other,

$$k^F = k(1 + \alpha). \tag{4.1}$$

We denote with k^c the number of sub-channels in the common pool, i.e., $k^c = 2k^s$.

Each BS first runs independently its resource allocation procedure, then the trading for the common pool usage starts. Therefore, two phases can be identified, (i) the proposal of resource allocation and (ii) the contention resolution.

We assume that the BS manages a different flow for each UE registered to it, and these flows are always backlogged so that, every time a flow is selected there is always a packet to be transmitted. Another fundamental assumption that we do in our work is represented by the fact that flows are scheduled for transmission according to a maximum throughput criterion only, without taking into consideration the fairness among the UEs. This assumption is due to the fact that in this study we are interested in the fundamental limit of spectrum sharing among operators. If fairness were taken into consideration then the total throughput reached by a BS would be reduced since the achievement of a fair situation could force the allocator to sub-optimal choices (as deeply discussed in Chapter 3). Some results for a fair scheduling are given in Section 5.4

of Chapter 5. Note that each operator exploits all the spectrum that it can access, i.e., its k^p private sub-channels plus the whole common pool, thus the number of available resources is k^F, which is greater than the original k since a larger set of sub-channels is available. However, since the k^c sub-channels are to be shared with the other operator and in order to avoid overbooking situations, we allow each BS to use only k of those resources at maximum at the same time. In this way we are sure that no more than K users can be scheduled for transmission, thus respecting the limit imposed by the maximum number of available resources. Note that, since the downlink access is an OFDMA, no interference can occur among different sub-channels and thus the transmission power on each one of them can be set to the maximum possible. At the end of the intra-cell allocation procedure, the BS determines a channel allocation map, i.e., a map that determines for each sub-channel whether it is allocated and the user it is assigned to. Since the problem of selecting the set of sub-channels that maximizes the throughput is combinatorial in nature (and thus with a high computational complexity), we opted for a greedy algorithm that trades off efficiency with optimality. In particular, our algorithm puts the couples <*user, sub-channel*> in decreasing order of channel state value and selects the k best couples (with the constraint that no more than one user can be scheduled per sub-channel because of the orthogonality of the scheme).

Once each BS has determined its proposal of resource allocation, then the trading phase starts in order to solve all the possible contentions for resource access and determine the final allocation maps. Many algorithms can be proposed to fix the conflicts. In Sections 4.1.1, 4.1.2 and 4.1.3 we discuss three of them and give some numerical results as well. An important taxonomy relevant to the problem considered here indicates two broad categories of algorithms, *centralized* and *decentralized*. The former are characterized by the presence of a central entity (a kind of "God" or "Oracle") having a complete information about the state of the whole network and able to take in each moment the best decision (absolute optimum). Of course, this solution is in most cases impractical since would require a lot of overhead for the communication with the central node, which could need a huge amount of memory and computational capabilities to take every time the right decision. Moreover, in many cases exact optimization algorithms are characterized by a non-trivial time complexity (see Chapter 2 when discussing about the constrained optimization applied to OFDMA) thus resulting not suitable for a real-time system like a Base Station of a cellular network. In some cases it is also illegal to introduce a controller. Nonetheless, centralized solutions are valid from a theoretical point of view since can lead to the identification of limit performance of the system. On the other hand, the distributed algorithms exploit only an information local to each node, without anyone having a complete view of the system. In this way, the decision taken by the algorithm might not be the optimum but a sub-optimum, and an iterative procedure might be required as well to reach a stable state. However, they represent a more practical way to solve a problem and sometimes are directly derived from a centralized algorithm.

As already said before, the reference scenario is an LTE cellular network. The main system parameters considered for the simulation campaigns are summarized in Table 5.

The performance indices used to evaluate the algorithms are:

- the **Cell Sum Capacity**, which represents the sum of the Shannon capacity reached in a cell on each sub-channel. It is given by

$$\begin{gathered} C = \sum_{i=1}^{N_{UE}} \sum_{j=1}^{N_{subc}} \left(B \cdot \log_2(1 + SINR_{ij} \cdot \delta_{ij}) \right), \\ \delta_{ij} = \begin{cases} 1, & \text{UE}_i \text{ allocated to subchannel}_j \\ 0, & \text{otherwise} \end{cases} \end{gathered} \tag{4.2}$$

  where B is the sub-channel bandwidth, N_{UE} and N_{subc} are, respectively, the number of UEs in the cell and and the number of available sub-channels, while $SINR_{i,j}$ is the SINR perceived by UE i on sub-channel j;

- the **Cell Sum Throughput** T of the cell, i.e., the sum of the actual data rate achieved on each sub-channel allocated to a UE. Of course, this value is lower than the previous since it is calculated by taking

Parameter	Value
1st sub-channel frequency	2110 MHz
Downlink Channel Bandwidth	20 MHz
Sub-carrier Bandwidth	15 kHz
Doppler frequency	60 Hz
$RB_{bandwidth}$	180 kHz
$RB_{subcarriers}$	12
$RB_{OFDMsymbols}$	7
BS downlink TX power	43 dBm
Noise spectral density (N_0)	-174 dBm/Hz
Pathloss	$128.1 + (37.6 \cdot \log_{10}(R))$ dB
Shadow fading	log-normal ($\mu = 0, \sigma = 8$ dB)
Multipath	Jakes model with 6 to 12 scatterers
Wall penetration loss	10 dB
Frame duration	10 ms
TTI (sub-frame duration)	1 ms

Table 5: Main system parameters for the spectrum sharing simulations

into consideration the actual modulation and coding scheme (MCS) used by the transmitter;

- the **capacity gain** (i.e., the sharing gain), calculated as the ratio between the capacity achieved by the algorithm and that achieved without sharing;

- the **total sum capacity** of the two cells.

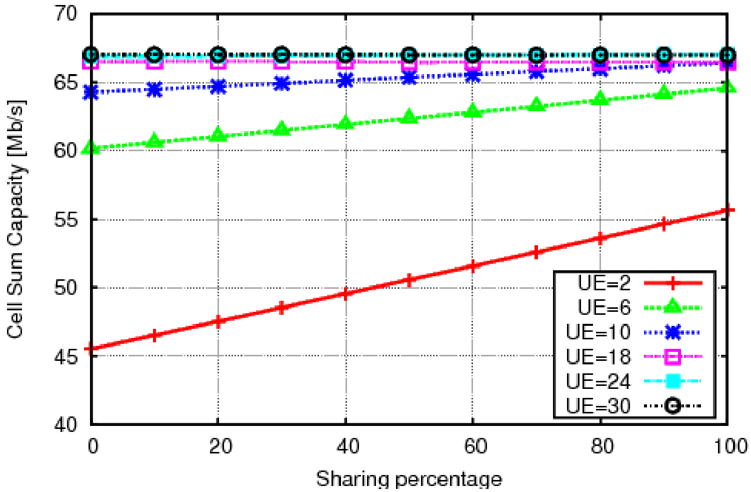
All the results shown hereinafter are characterized by a 95% confidence interval with a maximum relative error lower tha 1%.

4.1.1 *Upper Bound* Algorithm

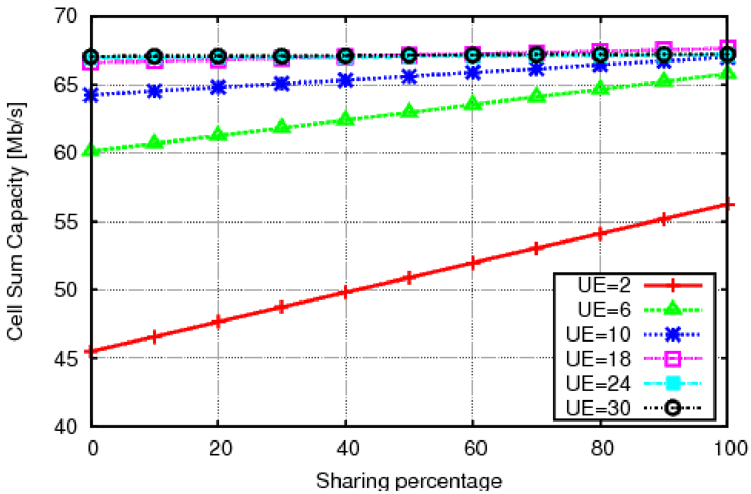
This is a centralized algorithm that we have introduced in order to obtain an upper bound on the gain that can be achieved by resorting to the orthogonal spectrum sharing. Despite its inapplicability in a real scenario, it is useful from a theoretical perspective since can be used for the comparison with other effective schemes. In particular, the proposed solution aims at maximizing the total cell sum capacity. To do that the operators behave as if they were a unique entity, a kind of monopolist having a complete information on both cells, and allocate each sub-channel to the best UE, i.e., the one having the greatest Channel Quality Indicator (CQI), without taking into consideration any fairness constraint. The resulting capacity is the maximum achievable, the theoretical limit.

Figure 25 shows the cell sum capacity reached by each BS, for a different number of UEs, when the sharing percentage increases. Since both cells are statistically equivalent (for number of UEs, channel state, traffic load), also the final performance is the same. First of all, a clear increment of the capacity with the number of users can be noted, which is a direct consequence of the multiuser diversity. The greater the number of UEs, the higher the probability that for each sub-channel there is at least one UE with a good channel quality. However, for a denser cell, the improvement is quite low because for almost all the sub-channels there is at least one user in a good situation. The second important observation that can be done is that there is a neat *sharing gain*. The cell sum capacity increases with the sharing percentage, thus there is an incentive for the network operators to share part of their frequencies. For a small number of UEs a 20% gain can be reached over the non-sharing case. The corresponding capacity gain value is shown in Figure 26 for BS1 (for BS2 it is same). As discussed above, it is greater for scenarios with few UEs, and tends to reduce for denser situations where the effect of the multiuser diversity is less apparent. Of course, a lot depends also on the intra-cell allocation policy adopted by the BS. In this example we are not considering at all the fairness among the flows and for each sub-channel the best UE is always chosen. By introducing some fairness the figures would change significantly (in Chapter 5 some sample results for a fair algorithm are shown).

In Figure 27 the cell sum throughput for the cell managed by BS1 is shown (for BS2 is the same). As expected, the actual throughput value



(a)



(b)

Figure 25: Cell sum capacity of BS1 (a) and BS2 (b) for the *upper bound allocation* algorithm

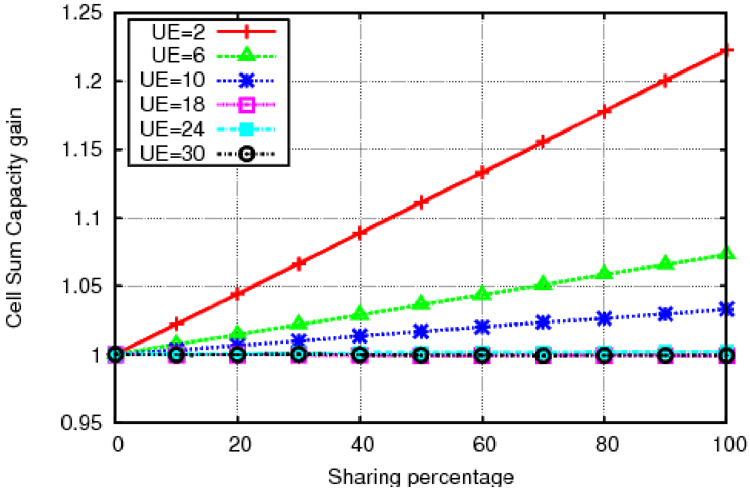


Figure 26: Cell Sum Capacity Gain of BS1

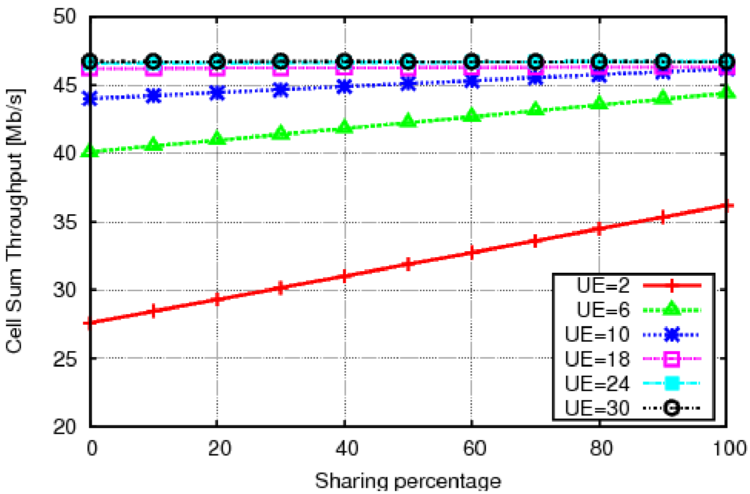


Figure 27: Cell Sum Throughput for BS1

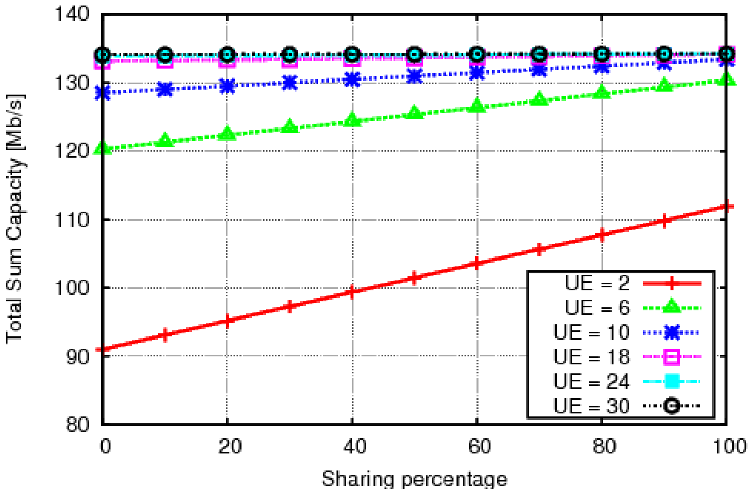


Figure 28: Upper bound on the joint sum capacity of the two cells

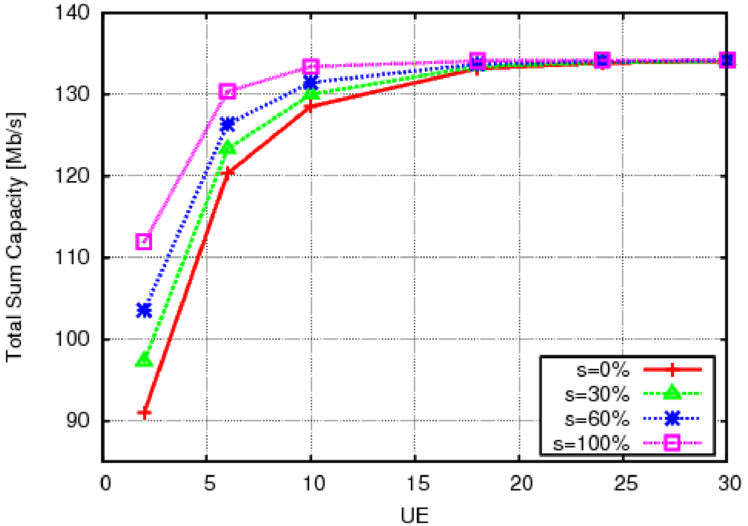


Figure 29: Total sum capacity of the two cells versus the number of UEs per cell

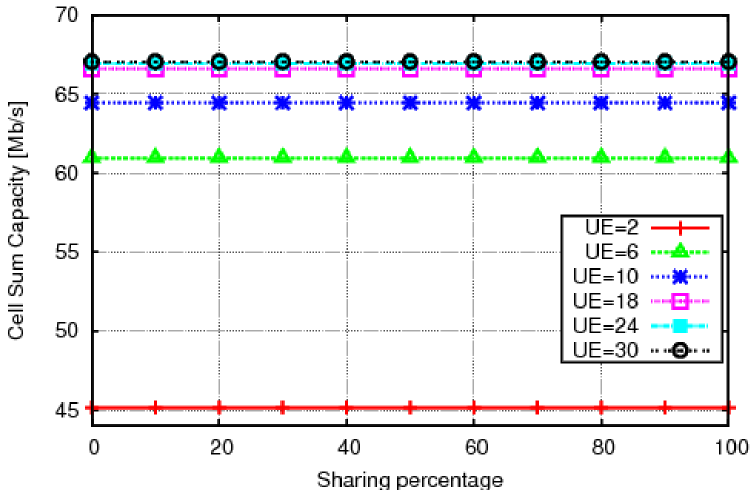
is significantly below the channel capacity, which represents a theoretical limit. The actual amount of data transmitted depends on the Effective Code Rate (ECR) (shown in Section 2.1, Table 1), which indicates the robustness of the selected coding scheme. However, the behavior of both capacity and throughput as functions of the sharing percentage for different numbers of users is qualitatively similar, meaning that they differ only by a scaling factor due to the use of a real MCS.

Figure 28 shows the joint sum capacity of both BSs that can be achieved for a different number of UEs per cell when the spectrum sharing percentage increases. Since the cell sum capacities of both BSs increase in the sharing percentage, also in this figure all the curves have an increasing trend. In Fig. 29 the same results are depicted in a different perspective, i.e., by considering the total sum capacity as a function of the number of UEs in the cell. In this case the saturation effect for denser cells is more evident: after 18 UEs the improvement of the capacity is almost negligible, as discussed above.

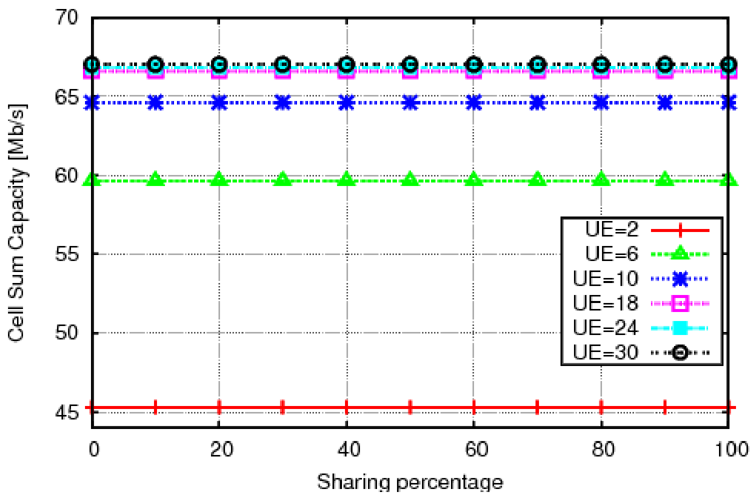
However, it is important to remind that these values were obtained for a scenario under saturation. In the case of asymmetric cell traffic load, a BS might have only few active flows and the other BS could opportunistically exploit most of the unused resources. Therefore, we can consider the results presented in Figure 28 as the worst-case upper bound. More significant results are expected by considering different and more realistic scenarios. For example, it is quite difficult in a real situation to have always both cells under saturation, while it is sensible to consider cases in which one of the two operators has far more traffic than the other and thus can opportunistically exploit the unused (common) resources to serve some more UEs of its. This situation is analyzed in Section 4.1.4.

4.1.2 *Safest Allocation Choice* Algorithm

This algorithm represents a sort of lower bound on the system performance with no resource waste. Together with the previous algorithm they define a performance region (with an upper and a lower bound) for all the many possible sharing mechanisms that do not realize any re-



(a)



(b)

Figure 30: Cell sum capacity of BS1 (a) and BS2 (b) for the *safest allocation choice* algorithm

source waste, i.e., do not perform less than non-sharing case. Therefore, they represent a sort of comparison meter.

It is an example of how the contention can be solved in an easy way, but with a very poor gain. If the allocation maps proposed by each BS do not overlap, i.e., there is no contention at all, then the common spectrum is used according to the proposals. On the contrary, if there is contention on at least one sub-channel then the BSs resort to the non-sharing solution. The good point of this scheme is that it does not perform worse than the non-sharing case; on the other hand, in most of the cases it does not introduce any gain. Indeed, the probability of collision is not negligible, and increases with the sharing percentage. Moreover, as already remarked, a significant frequency diversity is an important factor for boosting spectrum sharing. If a channel is flat then it is less likely that a BS will resort to others' frequencies, so the average number of conflicts decreases.

In Figure 30 the cell sum capacities for both BS1 and BS2 are shown. Since the two cells are statistically equivalent, also the result is the same. We can still note the effect of the multiuser diversity, which leads to an increase in the capacity with the number of UEs per cell. On the other hand, it can be seen that there is no gain at all when the sharing percentage increases, as expected. Indeed, all the curves are flat when the percentage of shared spectrum increases, meaning that the influence of this factor is almost negligible.

4.1.3 Algorithm with Priorities

In this section we show how spectrum sharing might lead to an inefficient outcome if not implemented in a proper way. In this case we suppose that each operator keeps a higher access priority on the k^s sub-channels it shares so that, in case of contention for the access to one of them, it has higher chances of using them. In particular, we use a deterministic priority mechanism where each operator has probability 1 of winning the contention on its portion of the k^c sub-channels and probability 0 on the other part. Of course, a mechanism with probabilities $(p, 1-p)$ can be evaluated as well. In this way, in case of contention on the access

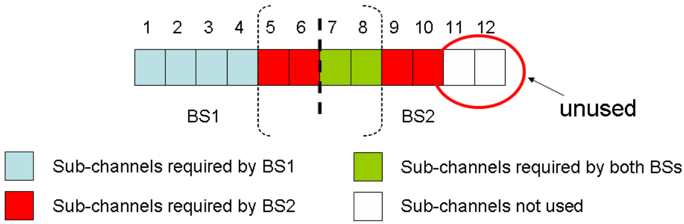


Figure 31: Example of inefficiency for the allocation by priority

to one of the common resources, the original owner always wins. Such a choice could seem interesting for telecommunication companies, which can use their frequencies as long as they need them even if required by the other competitors.

This way of managing contentions may lead to a resource waste, i.e., situations in which not all the sub-channels have been assigned. For example, suppose that BS1 tries to use the part of the common pool shared by BS2, while BS2 tries to use the whole common pool. According to the sharing policy above described, BS2 would access the whole common pool while BS1 would be prevented to access it. So BS1 should use only its k^p private resources, which are less than k, while some of BS2's private resources would remain unallocated. Figure 31 depicts such a situation, and it is not difficult to imagine that the final sharing gain obtained after the application of this algorithm for the conflicts resolution may be less than 1, i.e., lower than the non-sharing solution. Moreover, also an unfair allocation results from this example. Indeed, BS2 will win the contention on the sub-channels 7 and 8 because it has greater priority, and it will get also the sub-channels 5 and 6 since there is no contention on them. So, BS2 will get 6 sub-channels (the whole common pool plus 2 private) while BS1 will get only 4 resources.

Actually, the amount of wasted resources depends on the sharing percentage and on the frequency selectivity of the channel. Indeed, for a flat-fading channel it is unlikely that a BS tries to access the resources of the other (since their quality is almost the same of its ones) and thus it is less probable to have situations in which one BS monopolizes the common pool.

Some results are shown in 5.4, where the priority algorithm has been used for the validation of the simulator.

The performance of this algorithm are meaningful since let us understand in a clear way that spectrum sharing is not *always* positive for network operators. It lets us see how an improper way of managing the common resources may lead to a performance loss. However, the amount of this loss might be mitigated by other parameters, like the scarce frequency diversity.

4.1.4 The case of asymmetric cell traffic load

In this section we consider a situation slightly different from what done up to now. An asymmetric cell-load is evaluated, i.e., a situation in which the amount of traffic the two BSs have to manage is different, with one cell more loaded than the other. In this case, the BS having more load can opportunistically exploit the common resources not used by the other, and thus has the possibility to serve a number of UEs higher than what it could do without any sharing.

We run some simulations for the *upper bound algorithm* by considering the following scenario. Each BS guarantees to its UEs no more than two sub-channels at each allocation opportunity (i.e., every sub-frame). The UEs are always allocated according to their CQI, so as to exploiting the multiuser diversity as much as possible. In particular, each BS tries to give 2 resources to each of its users as long as there are free sub-channels in the part of the spectrum it can access. Therefore, the asymmetric load is generated by varying the number of users. Cell 1 is overloaded and has 40 UEs to serve, thus needs 80 sub-channels. For cell 2 we considered a different number of UEs, ranging from 2 up to 40. When the sharing percentage is 0%, BS1 cannot use more than 50 sub-channels, independently from the load of cell 2. This leads to an incredible resource waste when the latter is underloaded. When the sharing percentage increases, BS1 is entitled to use sub-channels of the other operator and thus a greater number of UEs can be served, taking into consideration that BS2 has to satisfy

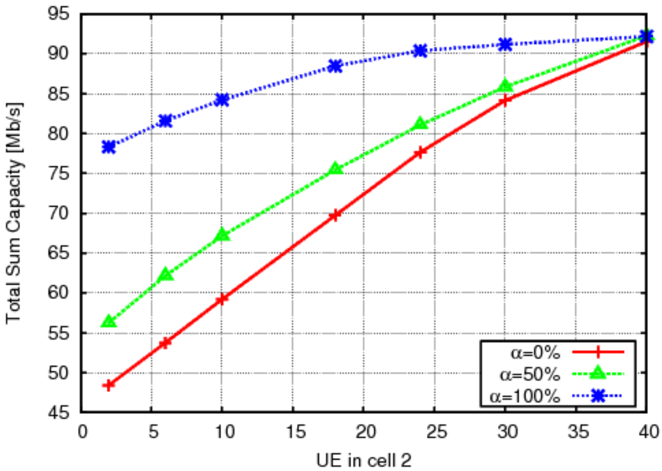


Figure 32: Total cell sum capacity upper bound for the asymmetric traffic load scenario

its requests too and thus some contention may arise. Therefore, the performance of BS1 are limited by the sharing percentage an by the load of cell 2. Of course, when both cells have the same load, also the capacity realized is the same since the distribution of the UEs in the coverage area and the channel gains are statistically the same.

In Figure 32 the total cell sum capacity for the upper bound algorithm is shown. The x-axis represents the number of UEs in cell 2, and three values of spectrum sharing percentage α have been considered, i.e., 0, 50 and 100%. For $\alpha = 0\%$ the curve is increasing due to the increasing number of UEs that are served in cell 2, while for cell 1 the capacity is constant since all the 50 resources are always allocated. For the other values of α the curves still increase in UE for the same reason aforementioned; moreover, there is a joint increase due to the fact that BS1 is entitled to use a higher portion of the spectrum and thus can serve more UEs. It should be noted that after a certain number of UEs in cell 2 has been reached (in this case 25 since the number of initial sub-channels per cell is 50), there are no free resources that BS1 can exploit from cell 2 and any additional increment in the total sum capacity is only due to the multiuser diversity, which still benefits from an increasing number of users (even though the marginal improvement decreases for denser networks).

4.2 Non-orthogonal Spectrum Sharing

The non-orthogonal sharing case is expected to achieve a higher capacity gain since the constraint of mutual exclusion for the access to the common resources is eliminated. Unlike the previous case, a more complex signaling exchange is expected and this makes the development of feasible distributed algorithms harder. However, also in this case it is important to have a theoretical framework for the derivation of the limit capacity.

Since the access to the common resource is no longer exclusive, both the BSs can use contemporaneously the same sub-channel to transmit to their UEs. This means that some interference may arise and may prevent the intended receivers from detecting correctly the corresponding transmissions. This leads to the necessity to introduce a power control scheme in order to guarantee that the SINR to the intended receivers is above a certain threshold in order to have an acceptable QoS in reception. Such a system represents an example of *frequency-selective interference channel*. Since the choice of the power level to feed the sub-channels can be seen as a bargaining process among the transmitters, we can think of using the Nash bargaining theory (see Section 2.2.1) for a possible mathematical formulation.

Call $\mathcal{N} = \{1, 2\}$ the set of transmitters (i.e., the BSs) and $\mathcal{K} = \{1, \ldots, K\}$ the set of sub-channels.

- The players are the two BSs;
- The actions that player $i \in \mathcal{N}$ can take are represented by the power levels $p_{i,k} \in [0, P]$ that it can feed on sub-channel $k \in \mathcal{K}$, subject to a total power constraint $\overline{P}$.
- The utility function for player i is the sum of the rates on each sub-

channel, and is given by the following expression

$$R_i^{\text{FS}} = \sum_{k=1}^{K} \log_2 \left(1 + \frac{G_{ii}^k p_{i,k}}{\sigma_{i,k}^2 + \sum_{j \neq i} G_{ji}^k p_{j,k}} \right) \tag{4.3}$$

where $G_{ij} = |h_{ij}|^2$ and h_{ij} is the cross-talk between transmitter i and receiver j. The channel is Gaussian, $\sigma_{i,k}^2$ representing the noise power on sub-channel k at user i, and the interference is treated as noise by the receivers.

Call $R_i^{\text{FS, NE}}, i \in \mathcal{N}$, the payoffs at the Nash equilibrium for the non-cooperative case (the disagreement point). In this case the Nash equilibrium point $\mathbf{R}^{\text{FS, NE}}$ can be obtained by applying the iterative waterfilling algorithm.

The formulation for the Nash Bargaining Solution with both the power constraints can be posed as an optimization problem:

$$\mathbf{R}^{\text{FS, NBS}} = \text{argmax} \prod_{i=1}^{2} \left(R_i^{\text{FS}} - R_i^{\text{FS, NE}} \right) \tag{4.4}$$

$$\text{s.t.} \quad p_{i,k} \leq P \qquad \forall i \in \mathcal{N}, k \in \mathcal{K} \tag{4.5a}$$

$$\sum_{k=1}^{k=K} p_{i,k} \leq \overline{P} \qquad \forall i \in \mathcal{N} \tag{4.5b}$$

$$\overline{P} < KP \tag{4.5c}$$

The main drawback of this formulation is the non-convexity of the problem, both utilities and region. The Nash bargaining theory assumes the satisfaction of some axioms and, more important, requires the convexity of the problem. As observed in some studies, for example in [75], this is not always true for the FS-IFC and in that case the treatment becomes quite difficult. Moreover, in this particular type of system we do not have a closed form expression for the Nash equilibrium in the non-cooperative case, we only know that it can be reached by using the iterative waterfilling algorithm, whose convergence is not always guaranteed [66]. Sufficient conditions exist, but the algorithm is not globally stable Another way to tackle to problem has to be found, but this is out of the scope of this thesis.

Chapter 5

NS-3 extension for spectrum sharing

One of the main contributions of this thesis work regards the extension of the network simulator ns-3 for the support of multi-cell multi-operator scenarios and of the inter-operator spectrum sharing, with the related need for the introduction of a flexible structure to manage contentions. The availability of a suitable simulation platform for testing protocols and algorithms is quite important, in particular for all those scenarios where the mathematical analysis becomes complex or cannot produce a solution in closed form. The support of a valid simulation platform is important for the execution of system-level simulation campaigns where a complete and complex network scenario is considered.

5.1 Introduction

The network simulator-3 (ns-3) [2] is a very well known tool widely used in the research community for the simulation of heterogeneous communication networks. It is an event-driven asynchronous simulator entirely open source, free and managed by an active community of developers. It is written in C++, so its execution is quite efficient because that programming language is compiled and not interpreted. The whole

TCP/IP protocol stack is implemented, with the most important protocols at the transport, network, and datalink layers (e.g., TCP, UDP, IP, ARP, IEEE 802.11, IEEE 802.16). Several types of applications are provided with the basic version of the code (e.g., CBR, VBR) and many others can be implemented just by extending the base classes. The transmission channel is implemented as well, both wired and wireless. The level of detail in the channel definition is not extremely deep (e.g., no symbol-level operations), even though it has been definitely improved with respect to the previous version of the software, ns-2. The code includes as well built-in data structures and functions to deal with several types of networks, from sensors to satellite communications.

Besides its great flexibility, one of the main features of this simulator is the modularity. The implementation is not monolithic at all and this makes its extension simpler. This is particularly appealing for our purposes, since the analysis of spectrum sharing, while involving physical and datalink layers, implies important consequences in protocol design at higher layers as well, thus being an inherently cross-layer problem. These reasons motivated our choice to employ ns-3 as the system level simulator. The extended version proposed in [62] was considered because of its capability to support the Long Term Evolution of the UMTS. It was already possible to create Base Stations (called eNodeBs, or eNBs) and user terminals (called UEs) which could communicate with the eNBs. Most of the functionalities of the physical channel and medium access were implemented, while some of them were still empty or a sample code was provided, thus giving the programmer the opportunity to introduce and test new algorithms. This is the starting point of the implementation and validation work done in this thesis. The main contribution in this direction was the introduction of a novel software extension of this version of ns-3 to simulate spectrum sharing scenarios where cooperation is established among multiple operators, each with a considerable number of nodes. To this aim, original software structures were introduced. First of all, the support to multi-cell multi-operator networks with overlapping spectra in the downlink was provided. Then, a class describing a virtual *frequency market* was inserted in the simulator structure. This class implements the functionalities of a virtual arbitrator, and does not represent a physical entity of the network, but rather it determines the sharing policy of the frequencies belonging to the common pool. In other words, its role is to abstract the set of rules agreed by the operators when determining the shared portion of the spectrum. Both orthogonal and non-orthogonal policies can be implemented. In both cases, the arbitrator structure is required to give an abstract representation of every other sharing policy detail, such as priority rules among the operators in case of conflicting assignments. Since for this thesis work we have mainly focused on orthogonal sharing (as discussed in Chapter 4), the architecture up to now implemented refers to that case. However, the extension to the non-orthogonal case is under development. Some sharing policies were implemented and tested in order to assess the computational performance of the proposed architecture and to show its effectiveness in analyzing realistic scenarios. With reference to the software modifications, more details are given in [12]. The code is publicly available at the URL http://code.nsnam.org/lanchora/ns-3-lte-SpectrumSharing/.

5.1.1 System model

We consider a short time-scale spectrum sharing, where the inter-operator trading of the resources is done on a fine-grained basis, in our case corresponding to the LTE sub-frame duration, i.e., 1 ms.

To have a complete system characterization, we need to consider the spectrum management parameters, i.e., physical details such as center frequencies, channel bandwidth, and sharing percentages. In particular, the set of licensed frequencies that the operators are willing to share and the access mechanism must be defined. The policy behind such a cooperation agreement is out of the scope of the present paper, as it is more related to the economic agreement between the operators and to their business models. However, along with different allocation and coordination techniques, it represents an interesting research topic and, thanks to this contribution, various approaches can be quantitatively evaluated. Our choice is to be fully compliant with the LTE standard and to treat

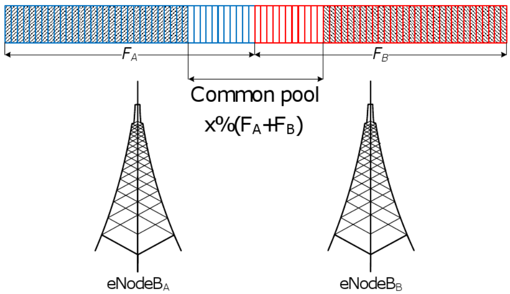


Figure 33: Spectrum sharing

OFDMA resource blocks as perfectly fluidic and transferrable entities, subject to licensing constraints (that is, they can be shared only if the legitimate owner agrees to it). Figure 33 shows the scheme adopted to define the system sharing capabilities. According to the selected bandwidth percentage to be shared, the eNBs will allow partial access to UEs belonging to other domains.

After these preliminaries, in the following subsections we describe two original parts of our contribution which complete the system description. First, we need to discuss local scheduling and resource allocation algorithms that must be executed in each eNB in order to generate an allocation map (i.e., the association <sub-channel, UE>), the downlink serving scheme, which will be detailed in Section 5.1.1. Moreover, we consider a *virtual market* to be in charge of collecting this information and deriving serving schemes that must be adopted by each eNB, according to the chosen contention solving policy, which will be illustrated in Section 5.1.1.

Intra-cell allocation

The cell capabilities are fully characterized when the physical components have been defined. Then, a joint scheduling and resource allocation algorithm is needed to design a proper downlink transmission scheme.

		Users										max throughput		fairness	
		1	2	3	4	5	6	7	8	9	10				
Private RBs	RB 1	7	9	4	15	13	8	14	9	3	7	UE4	15	UE4	15
	RB 2	7	9	4	15	12	8	14	8	3	7	UE4	15	UE7	14
	RB 3	7	9	4	15	13	8	14	8	3	7	UE4	15	UE5	13
	RB 4	8	9	5	14	13	8	15	9	4	8	UE7	15	UE2	9
	RB 5	7	8	4	15	13	7	14	8	4	8	UE4	15	UE8	8
	RB 6	8	8	5	14	13	8	14	9	4	7	UE4	14	UE1	8
Shared RBs	RB 7	8	9	4	15	12	8	14	9	3	8	UE4	15	UE6	8
	RB 8	8	9	4	15	12	8	15	8	4	7	UE4	15	UE10	7
	RB 9	7	9	4	14	13	7	15	8	3	8	UE7	15	UE3	4
	RB10	7	8	5	14	13	7	14	8	4	7	UE4	14	UE9	4

CQI values

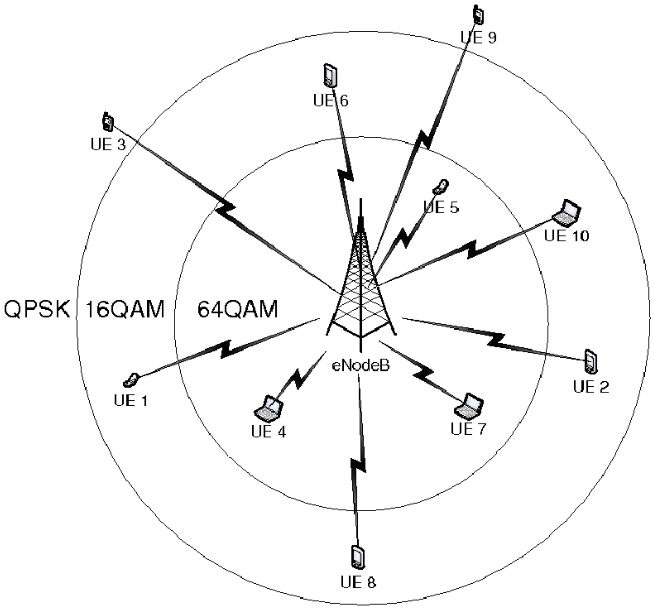


Figure 34: Intra-cell allocation

The definition and the analysis of efficient schemes are not directly investigated here. However, the architecture of the simulator considered here makes it simple to plug-in any of such algorithms and validate their performance (an example is given in [10] and is discussed in Chapter 3).

For what concerns the scope of this discussion, which is explicitly on the architecture of the simulator and not on the algorithms themselves, two basic algorithms have been implemented and compared: on one hand, *max throughput* that represents an allocation scheme for which the resources are always allocated to the best UEs, without taking into account fairness among users (actually, this is the intra-cell algorithm considered in Chapter 4 when discussing the inter-cell coordination). On the other hand, a fair approach is proposed, denominated *fairness*, where the available system resources are distributed among the users in a Round Robin way, thus lowering the overall throughput but increasing the average level of service received by each UE. Figure 34 depicts a sample scenario, where 10 UEs and 10 resources, hereinafter referred to as allocation tiles (ATs), are considered (note that an AT is made of two RBs, defined in 2.1, in two consecutive time slots). For the particular case of LTE networks, each AT lasts 1 ms and spans in frequency for 12 sub-carriers. By selecting the first approach, i.e., *max throughput*, all the available resources are allocated to the UEs with the best channel quality indicator (CQI). Thus, by exploiting multiuser diversity, the system throughput can be very high. However, UEs with lower CQIs will never be served. On the contrary, the *fairness* mechanism will provide service to all the registered UEs, as visible in the figure. Indeed, each AT is still allocated to the best UE, but each user will be given at least a certain amount of resources thus preventing starvation. In particular, the distribution of the ATs happens in a Round Robin way starting from the UEs with the best CQI and moving to those in a worse condition. During the first allocation round each UE is given a number of ATs equal to

$$TH_{min} = \left\lfloor \frac{N_{AT}}{N_{UE}} \right\rfloor , \tag{5.1}$$

where N_{AT} and N_{UE} are, respectively, the total number of ATs and of registered UEs in the cell. Then, once that this minimum threshold has been guaranteed to all the users, all the remaining ATs are distributed again with a Round Robin policy by assigning 1 AT per UE starting again from those with better channel conditions. In the proposed example, the threshold in equation (5.1) is equal to 1, so all the UEs will be allocated a single AT.

Inter-cell coordination

The sharing contention policy is implemented in a separate module, here called *virtual market*. The relevant class (we refer to an Object-Oriented Programming, or OOP, paradigm) implements an arbitration rule which defines how the operators bargain the access to the common portion of the spectrum. Any complex strategy can be implemented within this class, possibly involving further extensions. In particular, this is the place where to implement, in an entirely modular manner, some procedures inspired by game theoretic principles.

Each eNB, after generating its own allocation map, sends it to the *virtual market* who gathers all the cells' allocation information and rearranges the allocation maps according to the sharing policy (see Figure 35). It is useful to point out that this class does not represent a real entity, i.e., a kind of central node controlling the network. On the contrary, it is just an implementation choice to separate the function of contention resolution from the rest of the architecture. In a real context this function might be implemented by each eNB, in a distributed way, or might be delegated to a real central node, in the case of a centralized structure (even though the latter proposal is rather impractical for cellular networks).

For the validation phase we propose immediate implementations of scheduling and resource allocation algorithms, as well as a simple procedure to handle the contentions among operators. Each eNB is assigned a *priority* value per frequency sub-channel, defined as

$$PR_{eNB_j,AT_{pool,i}} = \begin{cases} p, & AT_{pool,i} \in F_{eNB_j} \\ 1-p, & \text{otherwise} \end{cases}, \tag{5.2}$$

where $j \in \{1, ..., m\}$ represents the eNB identifier, m is the total number of eNBs involved in the sharing process, $p \in [0, 1]$ is the priority level

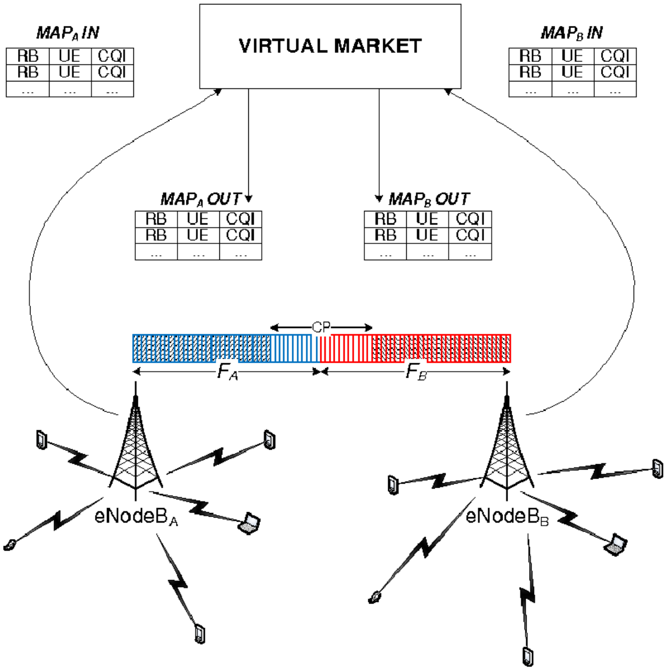


Figure 35: Inter-cell coordination

given to the eNB, $F_{eNB_j} = \{AT_{j,1}, ..., AT_{j,n_j}\}$, n_j is the total number of ATs available at eNB$_j$, and $AT_{pool,i} \in F_{eNB_1} \cap ... \cap F_{eNB_m}$. Contentions on the shared resources are fixed according to these priority levels. The proposed approach can be made even simpler if we assume $p = 1$ and $m = 2$: an eNB will assign to its UEs the shared resources belonging to the *competitor* eNB, referred to as eNB$_c$, only if these are not allocated to UEs belonging to eNB$_c$. Therefore, when multiple players request the same resource, only the one with the highest priority will get it. The others end up with no assignment, which is in general inefficient.

We stress that this general strategy is not given as an optimal allocation, which ought to be derived from a (game) theoretic perspective. Rather, such an intentionally non-optimized (and actually inefficient) policy serves to show the effectiveness of our software implementation. Moreover, it can be thought of as a characterization of the inefficient Nash equilibria in the games with *competitive* sharing, while the goal of spectrum sharing should rather be a *collaborative* assignment of frequencies. Thus, our reference allocation policy correctly reflects that, if the whole common pool is shared competitively, in the long run only inefficient and unfair allocations will be achieved. However, we also remark that more efficient solutions derived through game theory, either available in the literature or originally developed, can be tested and validated within the modular framework proposed, so as to determine the choice that better suits the operator needs. Chapter 4 discusses the algorithmic aspect in more details and the simulations there presented were run by using the ns-3 extension described in this chapter.

5.2 NS-3 LTE extension

The reference implementation of LTE to which we have applied our modifications is the one presented in [62] and included in the release ns-3.9 of the simulator. Our extension introduced two main features, i.e., the implementation of multi-cell multi-operator scenarios and the design of the inter-operator downlink spectrum sharing infrastructure. In this way, we have prepared a framework that can be used as is or extended again to simulate a broader category of scenarios. This is made possible by the extreme modularity of ns-3. It is also worth mentioning that our extension is entirely backward compatible with the previous releases of ns-3.

5.2.1 Multi-cell multi-operator scenario

The definition of a multi-cell scenario requires first of all the definition of a separate object of class *LteHelper* for each cell. Such an object contains a reference (i.e., C++ pointers) to the eNB and to all its UEs and therefore manages the creation and configuration of all the members of a cell (e.g., registration of a UE). Different cells are managed by different *LteHelper*s.

A further modification that was required with respect to [62] regards the management of the time by each eNB. The class *LtePhy* is the base class for modeling the physical layer of eNBs and UEs. Then *EnbLtePhy* and *UeLtePhy* are derived classes that implement particular features of the physical layer for the two types of nodes, such as transmission and reception of signals on the wireless channel. The *LtePhy* class has in its private fields two *static* counters, one for the frame index and another for the sub-frame index within the current frame. They are incremented every time a new frame/sub-frame is started, a functionality that is implemented by the *EnbLtePhy* class, methods *StartFrame* and *StartSubFrame*, since it is up to the eNB to decide when to start the new frame/sub-frame. In a multi-cell scenario there are many eNBs, each with its own *EnbLtePhy*, and all these counters need to be incremented. Therefore, two possible solutions are available: either only an eNB increments those counters or each eNB has its own counter and increments it independently. In our implementation we have chosen the latter, thus each eNB has its private view of the time index. In our case they are all synchronized, hence they start each (sub)frame at the same time, but this implementation choice does not prevent further more realistic extensions where the eNBs are not synchronized.

5.2.2 Downlink spectrum sharing

Regarding the implementation of the inter-cell downlink spectrum sharing, several modifications to the base model have been written. First of all, we made eNBs aware of the additional sub-channels they can use for downlink resource allocation. The original implementation assigns to each *EnbLtePhy* and *UeLtePhy* a vector of sub-channels which represents the available resources they can use. In our implementation we have associated to each node an extended vector containing not only the sub-channels originally assigned to it, but also those that the other eNBs are willing to share (calculated as a percentage of the original spectrum size) together with the sub-channel priority access information. This vector is the set of frequencies that is actually used by the resource allocator of the eNB. The way it is used depends on the scheduling and allocation policy implemented. In particular, to customize these functionalities, it is sufficient to write a new class which extends the *PacketScheduler* class, thereby inheriting its methods, and to override the method *DoRunPacketScheduler*, i.e., the routine called by the eNB at the beginning of each sub-frame when a new set of packets must be selected for transmission.

As a further point, we have implemented the communication and trading mechanisms among the eNBs for the sharing of the common pool. Each eNB calculates its allocation map independently, according to an internal scheduling and resource allocation policy. Then, a virtual entity has been introduced to implement the exchange of the maps and the resolution of the conflicts. In a real system, this phase requires that the eNBs communicate (e.g., through a backhaul) and agree on a final allocation map to which all of them must adhere. This virtual entity is an object defined as an instance of the class *VirtualMarket*; at the beginning of each sub-frame, it receives the resource allocation maps proposed by all the eNBs (competitors) and decides the final map according to some policy. Developers can implement whatever policy they need, just by modifying that class or by extending it and overriding the method *GetAllocationMap()* which deals with the contention resolution. The *VirtualMarket* has a collection of eNB entities, which can communicate with it through its

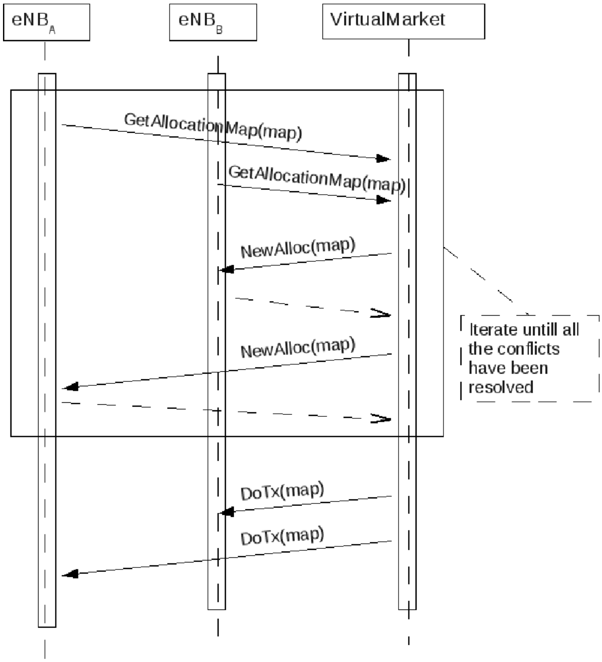


Figure 36: Sequence diagram for resource allocation conflicts resolution

public interface. In Figure 36 an example of such a communication is shown by means of a sequence diagram, which is also able to catch the temporal dimension of the activity. The particular sharing mechanism shown is that based on priorities as described in the previous section. An iteration is shown as well since every time a competitor cannot use a sub-channel for some UEs (i.e., it loses the contention), it is invited to reschedule those UEs on other free resources (if any).

5.3 Simulation scenario

In order to test the software architecture that we have implemented and show its functionalities, we have run some simulations. The algo-

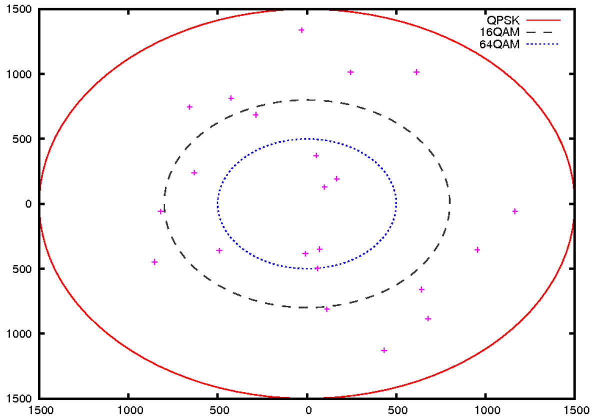


Figure 37: Deployment of the UEs around the eNB

rithms used are meant to be just an example to show how things work, so they are not expected to be the optimal solution. We are more interested in the performance and the usability of the simulator itself. In the following we present the results of a simulation campaign conducted with the extended framework for spectrum sharing in ns-3.

The scenario consists of two co-located eNBs, both with a coverage radius of 1500 m. An increasing number of UEs, characterized by low mobility, are registered to each station, and are uniformly distributed within the eNB coverage area (Figure 37). Each user is supposed to be always backlogged and so the network operates in saturation conditions. Each user perceives a different quality of the channel according to its position and to radio propagation effects (e.g., shadow and multipath fading). An ideal uplink channel is established between each UE and the corresponding eNB, used for the transmission of the CQIs associated to each AT. The main system parameters are provided in Table 6.

The objective of the simulation campaign was twofold. On one hand, we measured the performance of the proposed framework in terms of execution time; on the other hand, we used the simulator to analyze some spectrum sharing algorithms for LTE networks, in terms of cell sum capacity and aggregate throughput, thus showing the effectiveness of the proposed software and its flexibility for the implementation and comparison of different algorithms. More specifically, the performance metrics taken into consideration are:

- **Cell Sum Capacity**, which represents the sum of the Shannon capacity reachable in a cell on each sub-channel to each UE. It is given by

$$C = \sum_{i=1}^{N_{UE}} \sum_{j=1}^{N_{subc}} \left(B \cdot \log_2(1 + SINR_{ij} \cdot \delta_{ij}) \right), \qquad \delta_{ij} = \begin{cases} 1, & \text{UE}_i \text{ allocated to subchannel}_j \\ 0, & \text{otherwise} \end{cases} \tag{5.3}$$

  where B is the sub-channel bandwidth, N_{UE} and N_{subc} are, respectively, the number of UEs in the cell and and the number of available sub-channels, while $SINR_{i,j}$ is the SINR perceived by UE i on sub-channel j. Note that, since we are considering only the orthogonal spectrum sharing and the downlink employs and OFDMA multi-user access, each sub-channel can be allocated at 1 UE at maximum and there is never interference. Thus, in this case the SINR becomes an SNR (Signal-to-Noise Ratio).

- **Cell Sum Throughput**, which represents the aggregation of the actual data rates delivered to each UE by using the MCSs listed in Table 1, Section 2.1. Of course, the Shannon capacity is the upper bound of the troughput.

- **Execution time**, which represents the actual time required for the execution of a simulation run. We expect an increasing behavior in the number of UEs and in the sharing percentage because of the higher computational complexity needed to perform a greater number of operations. The reference machine is a server with 48 Pentium CPUs, 64 GB RAM and running GNU/Linux Ubuntu 11.04 as the operating system. It must be noted that, even though the number of available processors is considerable, the ns-3 software is

Parameter	Value
1st sub-channel frequency	2110 MHz
Channel Bandwidth	20 MHz
Subcarrier Bandwidth	15 kHz
Doppler frequency	60 Hz
$AT_{bandwidth}$	180 kHz
$AT_{subcarriers}$	12
$AT_{OFDMsymbols}$	14
eNodeB TX power per sub-channel	26.98 dBm
Noise spectral density (N_0)	-174 dBm/Hz
Pathloss	$128.1 + (37.6 \cdot \log_{10}(R))$ dB
Shadow fading	log-normal ($\mu = 0, \sigma = 8$ dB)
Multipath	Jakes model with 6 to 12 scatterers
Wall penetration loss	10 dB
Frame duration	10 ms
TTI	1 ms

Table 6: Main system parameters for the validation of the simulator

inherently non-parallel and thus all the runs were always executed on a single processor as if it were a single CPU machine. The only advantage of having more CPUs derived from the possibility to execute several simulations in parallel, one for each different combination of the input parameters (i.e., number of UEs and sharing percentage).

All the results shown hereinafter are characterized by a 95% confidence interval with a maximum relative error lower tha 1%.

5.4 Simulation Results

Figures 38–39 show the performance in terms of sum capacity and throughput achieved by each cell for both *max throughput* and *fairness* intra-cell allocation algorithms for a different number of cell users. The

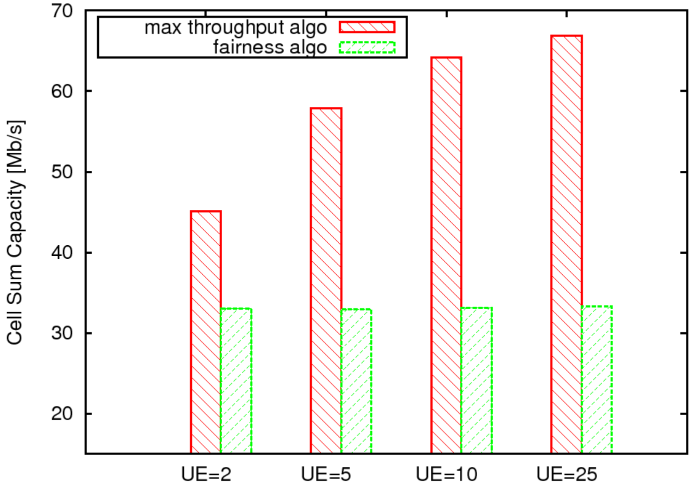


Figure 38: Comparison of the Cell Sum Capacity for the *max throughput* and the *fairness* allocation algorithms, with a sharing percentage of 100%

sharing percentage α was fixed to 100%. In this case we are considering a symmetric cell load, thus both cells have the same number of UEs and are statistically equivalent. For this reason, only the results for one of them are reported. As expected, the actual throughput value is significantly below the cell sum capacity, as defined in equation (5.3), which represents the upper bound on the data rate achievable for a given channel condition. The actual amount of data transmitted depends on the ECR. However, the behavior of both sum capacity and throughput as functions of the sharing percentage for different numbers of users is qualitatively similar, meaning that they differ only by a scaling factor due to the use of real coding and modulation schemes.

In both figures the trade-off between the *max-throughput* and the *fairness* allocation algorithms is clearly shown. The former always makes the system reach a better performance because the application of a fair scheduling policy requires the allocation of ATs also to the UEs with lower CQI. This is true for all values of the number of UEs.

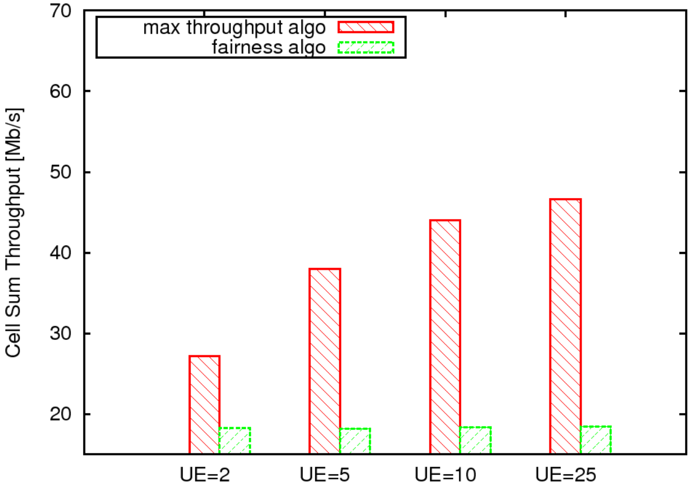


Figure 39: Comparison of the Cell Sum Throughput for the *max throughput* and the *fairness* allocation algorithms, with a sharing percentage of 100%

Another important effect that can be noted from Figures 38–39 is the increment of both performance indices with the number of UEs. As expected, this is due to the multiuser diversity effect: the larger the number of UEs, the higher the probability that for each sub-channel there is at least one of them with a good CQI. Of course, this might lead to some (short term) unfairness in favor of the users with a good channel quality. On the contrary, if the fairness constraint must be taken into consideration, then the effect of the multiuser diversity is significantly reduced. That is the reason for which in both figures, the increment of the performance indices for the *fairness* approach is almost negligible. For a possible discussion of this trade-off from a game-theoretic perspective, see [10,11] and Chapter 3. Moreover, the marginal increment of efficiency decreases when a certain user density has been reached in the cell. When more users are in the system, then for almost all the sub-channels there is a user with good CQI. Thus, a saturation effect appears.

To sum up, the results validate the reliability of our simulator in spite of an inefficient sharing policy, which was not the scope of this simulation campaign. Thanks to the modularity introduced, the contention technique can be adapted to different needs, and in particular to pursue a cooperative sharing, where system capacity and throughput increase when the spectrum sharing percentage becomes higher. A more thorough discussion on the algorithms is reported in Chapter 4.

Finally, the execution time is analyzed. In Figure 40, as expected, an increase in the number of UEs and in the spectrum sharing percentage can be noted. A greater number of UEs requires more memory and computational resources to store and manage all the necessary objects and thus a higher execution time. On the other hand, a greater number of shared resources implies more contentions and thus more iterations of the conflict resolution algorithm. The increment of the execution time in the sharing percentage is also due to the higher degree of freedom that the allocation algorithm has. Even though the values reported in the figure might seem too large, we want to remark that the tracing option was enabled during the simulation in order to log the performance indices and calculate statistics. Disk accesses are quite time consuming and can slow down the

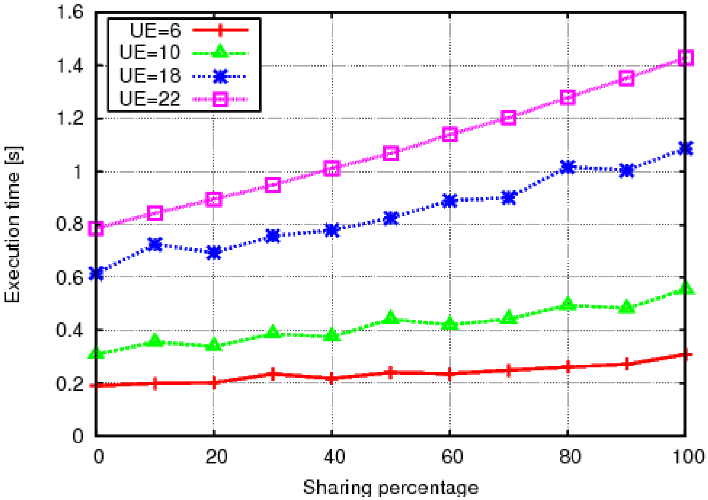


Figure 40: Execution time

execution by more than 10 times the normal duration. However, in spite of all these points, the computational complexity scales almost linearly with the number of users and with the sharing percentage, and can thus be considered acceptable for realistic and detailed simulation campaigns.

Chapter 6

Conclusions and Future Work

In the previous chapters we presented the main research directions followed in our thesis and the results that have been achieved. Basically, we have investigated the problem of efficient spectrum allocation in next generation mobile cellular networks.

Nowadays, this is a very hot problem because of the increasing traffic on cellular networks due to the enhancements in the technology and the ever increasing services available to customers. To address this situation one might think of increasing the bandwidth allocated to each network operator. However, the spectrum is a scarce resource and is also very expensive. Moreover, several studies have shown that a high percentage of the spectrum allocated for the telecommunications is not used, or at least is not permanently used. Therefore, a more sensible solution to be followed is the increase of the spectrum usage by a smarter allocation. Several studies have been done in the field of Dynamic Spectrum Allocation, but only few of them have focused on the multi-operator case and even fewer have considered the opportunity to change the current way to distribute the resources among several competing operators.

The present thesis has faced the efficiency issue by following a bottom-up approach. As a first step, we considered the allocation issue within a single cell and proposed some models and algorithms. Then, we moved to a multi-operator multi-cell scenario where BSs are not isolated but interact with each other. In this context we introduced, as a possible way to improve the spectrum usage efficiency, the idea of multi-operator spectrum sharing. Therefore, the main contribution of this thesis work is threefold and can be summarized as follows:

1. **Intra-cell resource allocation**. We have identified and discussed the trade-off between allocation efficiency and fairness among the network users that a BS faces every time it has to take an allocation decision in its downlink. Starting from that consideration, we have modeled the system in a game theoretic perspective and we have given some efficient algorithms to lead the system into a Pareto efficient operating point, i.e., a good balance between fairness and efficiency.

2. **Multi-operator spectrum sharing in a multi-cell network**. We have introduced the innovative idea of *spectrum sharing*. Instead of keeping separate the portion of spectrum allocated to each cellular network operator, they could share part of them so that each one can see a spectrum virtually larger than its original. Of course, this mechanism implies problems related to the arbitration of the common resources usage in order to avoid wastes and unfair situations. A deep discussion and classification about the possible algorithms has been done, and some algorithms have been analyzed. In particular, an upper bound and a kind of lower bound on the system performance have been identified. Moreover, the key factors that impact on the success of the spectrum sharing have been discussed.

3. **Simulator support to the previous two points**. All the algorithms presented in the previous two points have been validated by means of simulations. It is important to have a simulator able to reproduce realistic scenarios, in particular when the mathematical analysis becomes difficult to carry out because of the complexity of the system. To this aim, we have enhanced a network simulator very well-known and widely used in the research community, ns-3 [2]. We

have introduced a modular framework for the multi-cell spectrum sharing, thus making it a valid support for everyone doing research in this field. The code has been tested and is publicly available.

We do not expect this work to be complete and exhaustive. Some ideas have been introduced and evaluated, mainly by means of system level simulations. Some others are just sketched. Future evolutions include:

- extension of the work presented for the intra-cell case to a wider multi-cell scenario. In this case, some of the parameters used by each BS must be bargained with the other adjacent BSs, in order to reduce the interference and guarantee fairness;

- evaluation of some smart mechanisms for the orthogonal spectrum sharing by using both mathematical analysis and simulations;

- analysis of the non-orthogonal approach for the spectrum sharing case. In this thesis work only a few ideas and models have been sketched, but a robust analysis is needed. We still plan to consider a cooperative behavior of the players. However, we need to define a proper utility function which should include also a punishment for cheating players, in order to make the solution self-enforcing (i.e., encouraging players in cooperating).

- enhancement of the ns-3 simulator by adding the inter-cell interference management. In this way the simulation platform will become a complete and valuable support for the validation of spectrum sharing policies, both orthogonal and non-orthogonal.

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