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Optimal Resource Allocation in Networks: Optimization, Game Theoretical Models, and Algorithms

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Jocelyne Elias

Committee:

Reviewers:
Prof. André-Luc Beylot
Dr. Johanne Cohen
Prof. Rachid El-Azouzi

Examiners:
Dr. Eitan Altman
Prof. Matteo Cesana
Dr. Vania Conan
Dr. Marcelo Dias De Amorim
Prof. Marwan Krunz
Prof. Pavlos Moraitis
Prof. Farid Nait-Abdesselam

Abstract

This thesis summarizes my main research activities conducted during the *last ten* years. I have worked in the field of *network optimization*, developing both *centralized* and *distributed approaches*, while focusing on three main research areas: (1) Wireless Body Area Networks, (2) Cognitive Radio Networks, and (3) Virtual Networks and Cloud Computing.

In fact, all these technologies have contributed to shape modern networks, starting from *sensing*, and its applications to medical and healthcare environments, *intelligent spectrum utilization*, which enables improved network performance, and *virtualization*, that allows scalability and dynamic implementation of novel network services, with reduced costs. Specifically, I have investigated resource allocation, network planning, spectrum management, interference and congestion mitigation as well as various optimization problems in such networks.

To efficiently address these problems, I have used and developed the most appropriate mathematical modeling tools, like integer, linear and nonlinear programming, stochastic models, and game theory, as well as performance evaluation techniques involving extensive simulations.

As a *"fil rouge"* of all these works, I always address the research problems I investigate starting from their mathematical modeling, since their theoretical analysis allows me to identify the fundamental relationships necessary to design an efficient and practical solution with higher value for the technology's audience. Such an approach has proven particularly fruitful in recent years, since the rapid growth of all information and communication technology (ICT) sectors requires a careful redesign of the existing technologies to consider new communication paradigms (Internet of Things, 5G networks, Cloud Computing, Network Function Virtualization, Software Defined Networking ...) and performance metrics (e.g., energy/spectral efficiency, wireless network capacity, signal-to-interference-plus-noise ratio, pricing ...), to design next generation Internet architectures and protocols.

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Chapter 1

Introduction

Today's networks offer a large range of applications of great (social) benefit for users. Think, for example, to the impressive progress of sensor applications for healthcare systems, along with the seamless mobility, ubiquitous connectivity and improved performance provided by 5G mobile systems. Current networks are highly heterogeneous and need to interact with different types of recently emerging infrastructures, such as *Internet of Things*, *Cloud Computing* data centers and *Mobile Edge Computing* facilities. This phenomenon has dramatically increased the complexity of such networks and has encouraged infrastructure and service providers to leverage *Virtualization* techniques and implement novel mechanisms for efficiently managing, optimizing and orchestrating their physical/virtual resources in a flexible manner.

For these reasons, in the last ten years, I have focused on *three* main research areas, which constitute, in my view, fundamental building blocks of current and next-generation networks: (1) Wireless Body Area Networks, (2) Cognitive Radio Networks, and (3) Virtual Networks and Cloud Computing. Specifically, I have worked in the field of *network optimization*, developing both *centralized* and *distributed approaches* for such networks. I have addressed various optimization problems related to resource allocation, network planning, spectrum management, interference and congestion mitigation, using mathematical modeling tools, such as linear, nonlinear, stochastic programming and game theory.

My main contributions in the aforementioned 3 research areas are summarized hereafter, and then a more detailed description is given for each of them in the next Chapters (2–4). Chapter 5 summarizes other contributions I provided in the same period. Finally, Chapter 6 provides conclusions and future perspectives, including my research project for the next five years.

1.1 Wireless Body Area Networks and Body-to-Body Networks

Wireless Body Area Networks (WBANs) have emerged as an effective means to provide several promising applications in different domains, such as remote healthcare, athletic performance monitoring, military and multimedia [1, 2, 3, 4, 5, 6], to cite a few. In general, a WBAN topology comprises a set of sensor nodes, which have to be very simple, cheap and energy efficient, and a sink node. Sensors are usually placed in the clothes, on the body or under the skin, and they collect information about the person and send it through one-hop or multi-hop wireless paths to the sink, in order to be processed or relayed to other networks. Since WBAN sensors are small and use the wireless medium, which is prone to interference and collisions, to transmit their data, they present very stringent power requirements. Hence, energy-efficient reliable data delivery and scheduling are mandatory in a WBAN scenario. Of course, mobility and security are additional challenging issues in WBANs, and require energy-efficient and secure mobility-aware communication mechanisms.

Furthermore, the co-existence of several WBANs and the interaction between each other as well as with their surrounding environment form a large-scale network called *Body-to-Body network*, which presents various challenges at different levels, such as data delivery and routing among WBANs, communication links scheduling and interference mitigation, etc.

Main Contributions:
In our works, we investigated the WBAN design optimization problem, reliable data communication, routing and handover mechanisms for WBANs, interference mitigation in Body-to-Body Networks (BBNs), using centralized as well as distributed optimization approaches. The main contributions are summarized as follows:

- ***Optimal, energy-efficient design of Wireless Body Area Networks***: In [7, 8, 9], we have proposed energy-aware optimal design models for WBANs. The main idea was to deploy some relay nodes in the network in order to relay the data of sensors far away from the sink through multi-hop links. This reduces the energy consumption of sensors and hence improves the network lifetime. The optimal WBAN topology design model was evaluated considering different body postures' scenarios (i.e., standing, sitting and walking). Our contributions in this area have served as a baseline reference for future research activities.

- ***Cross-layer routing and handover in Wireless Body Area Networks***: In [10], we have proposed a priority-based cross-layer medium access control and intra- and extra-body routing protocols for healthcare monitoring applications. These protocols are based on a set of defined healthcare monitoring applications (or traffic categories) that represent general monitoring traffic data, high priority and emergency data.
  A multi-attribute decision making handover algorithm for WBANs is proposed in [11]. The main feature of our handover algorithm is to choose, in a soft and seamless way, the best network to which WBAN data should be relayed, taking into account some quality of service attributes – choose the network with the best signal quality and smallest delay – using the mobile phone radio interfaces (i.e., 4G, WiFi, etc.).

- ***Interference Mitigation in Body-to-Body Area Networks***: In [12, 13, 14, 15, 16], we have first addressed the interference mitigation problem in BBNs (networks of WBANs), using a centralized optimization approach. We have developed an integer linear programming model and a set of efficient heuristics that guarantee low interference and high throughput. We have then proposed a distributed game-theoretic approach for minimizing the interference; each WBAN in the BBN plays the role of a player, and its objective is to select a wireless channel in order to minimize the signal-to-interference-plus-noise ratio.

Our contributions in this research area are further detailed in Chapter 2.

1.2 Cognitive Radio Networks

Cognitive radio networks (CRNs) are envisioned to deliver high bandwidth to mobile users via heterogeneous wireless architectures and dynamic spectrum access techniques [17]. Such networks provide the capability to share the wireless channel with primary users in an opportunistic manner. In CRNs, a primary (or licensed) user has a license to operate in a certain spectrum band; his access is generally controlled by the Primary Operator (PO) and should not be affected by the operations of any other unlicensed user. On the other hand, unlicensed (secondary) users have no spectrum license, and they implement additional functionalities to share the licensed spectrum band without interfering with primary users.

Similarly, in TV White Space networks, idle TV channels – those unused by TV stations and called "TV White Spaces" – are made available for use to (non-primary or secondary) mobile devices, as in the case of CRNs, in an opportunistic manner. The TV channel allocation scheme should guarantee low inteference with TV stations (primary users) and other secondary devices residing in the same geographic area.

Main Contributions:
Cognitive radio nodes can opportunistically exploit (and aggregate) underutilized licensed and unlicensed spectrum to transmit at higher data rates. These devices are in general geographically distributed, and aim at maximizing their own throughput. Therefore, Game Theory is a good candidate to investigate the spectrum access problem in CRNs where each CR device plays the role of a player [18, 19, 20].

- ***Non-cooperative spectrum access***. We have studied in [18, 19] the spectrum access problem in CRNs proposing a non-cooperative spectrum access game. In this game, the secondary users (or the players) access simultaneously multiple spectrum bands left available by primary users, minimizing the interference with primary users as well as with the other competing secondary users.

- ***Pricing and network selection.*** In [20], we considered a Cognitive Radio scenario which consists of a secondary network that coexists with a primary network, as well as a large set of cognitive users, and we address the joint pricing and network selection problem. The problem was formulated as a Stackelberg (leader-follower) game where first the Primary and Secondary operators compete with each other and set the network subscription price to maximize their revenues. Then, users perform the network selection process, deciding whether to choose the primary network and pay more for a guaranteed service, or use a cheaper, best-effort secondary network, where congestion and low throughput may be experienced.

- ***Distributed TV White space access.*** Since very encouraging results were obtained in our previous works [18, 19, 20], we extended the idea of adopting a game theoretic approach to the *TV White Space* context, and proposed in [21, 22] non-cooperative games for channel allocation in TV White Space networks, which have in common with CRNs the fact that the mobile user can exploit channels left free by TV stations (or primary users); however, this network scenario imposes different, peculiar technological constraints that must be modeled accurately (i.e., the TV spectrum, the maximum transmission power, ...).

Chapter 3 describes in more detail our main contributions on these topics.

1.3 Virtualization and Cloud Computing

Network Functions Virtualization (NFV) aims to evolve standard IT virtualization technology to consolidate many network equipment types onto industry standard high volume servers, switches and storage. It involves implementing network functions in software that can run on a range of industry standard server hardware, and that can be moved to, or instantiated in, various locations in the network as required, without the need to install new equipment [23, 24]. NFV technology has emerged as a means to reduce capital and operational expenditures (CAPEX/OPEX) of telecommunication operators, to offer them some flexibility in operating and orchestrating the resources of their physical infrastructure [23, 24]. Virtualization comes hand in hand with *Cloud Computing* [25, 26] in order to provide users with large scale storage and computation services. Cloud Computing has emerged as a means to facilitate the transition from a stationary IT model, where information is locally processed and stored in a physical device to a distributed model that promotes the use of remote resources in an abstract environment.

Main Contributions:
Optimal resource allocation constitutes a major issue in NFV-based networks and Cloud computing, wherein the main goal of the physical infrastructure provider is to allocate resources in an efficient way in order to satisfy end-users' demands while maximizing its revenue. Our main contributions to address this problem are summarized hereafter.

- ***Resource orchestration in NFV-based networks.*** In [27, 28], we have studied, respectively, the *congestion mitigation* problem using a centralized optimization approach and the *resource orchestration* problem by the means of a game theoretic approach in NFV-based networks, and we have proposed several models and efficient algorithms to minimize the per-link worst congestion and/or the total congestion in the network.

- ***Resource allocation optimization in Cloud Computing.*** In [29, 30, 31], we focused on the Infrastructure as a Service (IaaS) model of Cloud computing and developed a Column Generation-based optimization approach for optimizing the resource allocation problem, satisfying IaaS users' requests with quality of service requirements, while maximizing the revenue of the Cloud provider.

Chapter 4 develops our contributions addressing the aforementioned problems.

Chapter 2

Optimal design and interference mitigation in Wireless Body Area Networks

The ongoing evolution of wireless technologies has fostered the development of innovative network paradigms like the Internet of Things (IoT), where the pervasive deployment of wearable devices, endowed with sensing capabilities, interweaves the physical and digital worlds, thus enabling the development of enhanced services. Mobile medical applications and wearable devices for remote monitoring, entertainment, sport and medical data collection represent important application areas of IoT. Wireless Body Area Networks (WBANs), and more generally Body-to-Body Area Networks (BBNs), are emerging solutions for the monitoring of people's behavior and their interaction with the surrounding environment. These networks represent a key building block of the IoT paradigm. In this context, we tackle two major problems, which are intrinsic to WBANs: the *optimal topology design* problem and the *interference mitigation* problem. These two problems are described in Section 2.1 and Section 2.2, respectively.

2.1 Optimization and Reliable data communication in Wireless Body Area Networks

Reliable body-aware communication and routing protocols are of great importance in healthcare applications. Therefore, we have investigated in [7, 8] the *optimal design of wireless body area networks* by studying the *joint data routing and relay positioning problem*, in order to increase at the same time communication reliability and network lifetime. To this end, we have proposed an integer linear programming model, which optimizes the number and location of relays to be deployed on the body and ensures reliable data delivery towards the sink, minimizing both the network installation cost and the energy consumed by wireless sensors and relays. This problem has been further tackled in [9] taking into account the WBAN's mobility as well as different body postures' scenarios, such as standing, sitting and walking. It is worth noting that this work was conducted by *Dr. Javier Salazar* during his Master ("Master Informatique 2ème année") under my supervision, with collaboration with other colleagues from University of Ottawa (Prof. Ahmed Karmouch and Dr. Abdallah Jarray). [1]

Hereafter (in Subsection 2.1.1), I will develop one of my main contributions presented in [7, 8, 9], which is the optimal, energy-aware WBAN topology design model.

2.1.1 Energy-aware Topology Design for Wireless Body Area Networks

In this work, we consider a WBAN scenario, which is illustrated in Figure 2.1, where the body is in a standing position with arms hanging along the side. Biosensors are placed on the body for data collection, and they communicate wirelessly with a sink node through a set of special nodes, called *relays*. Such relays form a wireless backbone network which transports the data collected by biosensors to the sink. Hence, the wireless body area network is composed of three types of nodes: the biosensors, the sink node (which collects and processes data from all sensors) and the relays. We assume that biosensors can share the same radio spectrum in a time division multiple access manner, and therefore, there is no interference between such wireless devices within a single WBAN [32, 33, 34, 35]. The proposed optimization framework for the Stand scenario represented for us a starting point for understanding the impact of the WBAN topology on energy-efficiency and network lifetime, and it can be easily extended to more general or dynamic WBAN scenarios.

Our model aims at *minimizing* at the same time *the total network installation cost (i.e., the total number of relays)* and *the overall energy consumed by the network*, while ensuring

[1]This work was published in IEEE Globecom 2013: J.Elias, A. Jarray, J. Salazar, A. Karmouch, A. Mehaoua, A Reliable Design of Wireless Body Area Networks, in Proceedings of IEEE Globecom 2013, Atlanta, GA, USA, December 2013 (DOI: 10.1109/GLOCOM.2013.6831489).

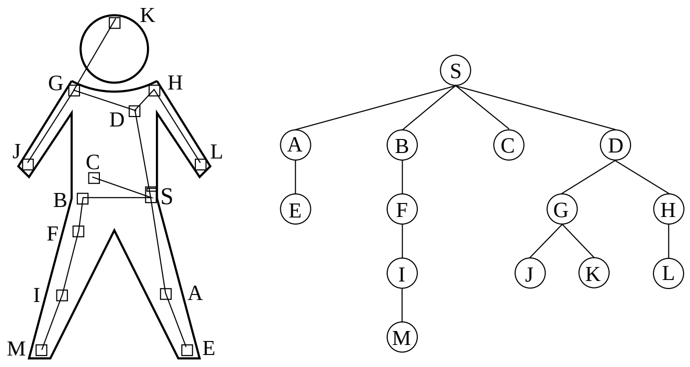


Figure 2.1: WBAN topology with 13 sensors, and the corresponding tree topology under the multi-hop approach.

full coverage of all sensors and effective routing of medical data towards the sink node.

To calculate the energy consumed by a wireless node (either a sensor or a relay), we assume that the sensing energy and the processing energy are negligible with respect to communication energy (this assumption is commonly adopted in the literature). Therefore, the total energy consumption of a node is represented by the total transmission and reception energy. Hence, the energy consumed by the whole network is simply the sum of the total energy consumed by all wireless nodes. The energy the radio dissipates to run the circuitry for the transmitter and receiver are denoted by E_{TXelec} and E_{RXelec}, respectively. $E_{amp}(n_{ij})$ represents the energy for the transmit amplifier, and D_{ij} is the distance between nodes i and j. The transmission energy can therefore be computed as $w[E_{TXelec} + E_{amp}(n_{ij})D_{ij}^{n_{ij}}]$, while the reception energy is wE_{RXelec}, where w is the total number of transmitted/received bits.

Before presenting the proposed model in a nutshell, let us first introduce some notations. Let $S = \{1, \ldots, s\}$ denote the set of sensors, $P = \{1, \ldots, p\}$ the set of Candidate Sites (CSs) where relays can be positioned, and $N = \{1, \ldots, n\}$ the set of sinks. We assume that we may have several sinks that can collect and process the data, thus making the model more general. The cost associated with installing a relay in CS j is denoted by c_j^I, and its capacity is denoted by $v_j, \forall j \in P$. Furthermore, the traffic generated by sensor i towards sink k is denoted by w_{ik}, $i \in S, k \in N$.

Decision variables of our problem include:

- Sensor assignment variables x_{ij}, $i \in S, j \in P$:

$$x_{ij} = \begin{cases} 1 & \text{if sensor } i \text{ is assigned to a relay installed in CS } j \\ 0 & \text{otherwise} \end{cases}$$

- Relays' installation variables z_j, $j \in P$:

$$z_j = \begin{cases} 1 & \text{if a relay is installed in CS } j \\ 0 & \text{otherwise} \end{cases}$$

- Flow variables f_{jl}^k, which denote the traffic flow routed on link (j, l) destined to sink $k \in N$. The special variables f_{jk}^t denote the total traffic flow between the relay installed in CS j and the sink k.

Therefore, the objective function, which accounts for the total installation cost and the total energy consumption, is defined as:

$$Min \quad \Bigg\{ \sum_{j \in P} c_j^I z_j + \alpha \Big(\sum_{i \in S, j \in P, k \in N} w_{ik} x_{ij} (E_{TXelec} + E_{amp}(n_{ij}) D_{ij}^{n_{ij}}) + \\ + \sum_{i \in S, j \in P, k \in N} w_{ik} x_{ij} E_{RXelec} + \sum_{j,l \in P, k \in N} f_{jl}^k (E_{TXelec} + E_{amp}(n_{jl}) D_{jl}^{n_{jl}}) + \\ + \sum_{j \in P, k \in N} f_{jk}^t (E_{TXelec} + E_{amp}(n_{jk}) D_{jk}^{n_{jk}}) + \sum_{j,l \in P, k \in N} f_{jl}^k E_{RXelec} \Big) \Bigg\} \tag{2.1}$$

More in detail, the first term, $\sum_{j \in P} c_j^I z_j$, takes into account the relay nodes installation cost, while the second term represents the total energy consumed by the network (relays and sensors), including the transmission and reception energy, α being a parameter that permits to give more weight to one component with respect to the other. For large α values, the first component becomes negligible and the model minimizes only the energy consumed by the network; on the other hand, for small α values the model minimizes the relays' installation costs. Hence, α should be set carefully in order to guarantee both low energy consumption and a small number of installed relays, as we will show in the Performance Evaluation section.

The energy-aware WBAN design (EAWD) model includes the set of constraints outlined in the following:

- *Coverage constraints*: These constraints are used to ensure full coverage of all sensors. It is worth noting that sensor i can be covered by CS j only if a relay is installed in j and i can be connected to j (relay j is in the communication range of sensor i).

- *Flow conservation constraints*: they define the flow balance in a relay node j for all the traffic destined towards sink node k. These constraints are very similar to those adopted for classical multicommodity flow problems. Note that these constraints define the multi-hop paths (i.e., the routing) for all the traffic that is transmitted in the WBAN.

- *Connectivity constraints*: they define the existence of a link between CS j and CS l, depending on the installation of relays in j and l and the connectivity parameters between CS j and CS l. These latter may depend on the proximity of CSs j and l.

- *Capacity constraints*: they impose, for each relay node j, that the ingress traffic (from all covered sensors and neighbors) serviced by such network device does not exceed its capacity v_j.

- *Proximity constraints*: they enforce each sensor to be assigned to the closest installed relay.

- *Integrality constraints* for the binary decision variables.

Note that we can consider alternative formulations to this model. For example, we can easily take into account the requirement that sensors must be connected to more than one relay, for redundancy. Furthermore, a constraint on the total number of relays that can be installed (or, alternatively, on their total installation cost) can be easily introduced ($\sum_{j \in P} z_j \leq N$).

We further observe that our model can be easily extended taking into account sensor positioning. In fact, if there exist also several candidate sites where to place sensors, the extended model can decide at the same time the optimal number and positions of sensors and relays, as well as the traffic routing, in order to minimize further the energy consumed by the network.

Performance Evaluation

We evaluate the performance of our model considering the WBAN topology depicted in Figure 2.1. For the multi-hop approach, we assume that the routes from the sensors to the sink are those illustrated by straight lines on the left-hand side of the figure, and hence the corresponding tree topology is the one shown on its right-hand side. The distances (in meters) between sensors and the sink for the single-hop case, and between sensors and the nearest node for the multi-hop case are given in Table 2.1.

We further assume that candidate sites for placing relays are chosen uniformly at random on the surface of ellipsoidal areas, along the clothes of the patient, as illustrated in Figure 2.2. However, it is noteworthy that relays, besides biosensors, should be placed on the human body in an intelligent manner without causing any discomfort for the person, with reduced disturbance to her/his daily activities. For example, in the case of e-health applications seeking continuous monitoring of chronically ill patients, it would be impractical to place a sensor/relay on the stomach or on the back, thus limiting significantly their daily activities, like sitting and sleeping. Hence, these physical constraints are accurately considered in the choice of candidate areas while designing our wireless body area network.

We compare our model's performance to that of the single-hop, multi-hop and Relay Network approaches [36, 37], in terms of the energy consumption and the number of relays installed in the WBAN. The *single-hop* approach consists in transmitting all data directly from each sensor to the sink node. In the *multi-hop* approach, the traffic is relayed by intermediate sensor nodes towards the sink. The *Relay Network* approach aims at installing relays in the WBAN until each sensor and relay have at least one relay node in line of sight.

Table 2.2 reports the average value of the total energy (E_{tot}), the energy consumed by each sensor (E_s), and the number of relays installed in the WBAN, using our *Energy-Aware WBAN Design (EAWD)* model (with $p = 200$ CSs) and under the single-hop, multi-hop and Relay Network [37] approaches.

It can be observed that the EAWD model reduces consistently both energies E_{tot} and E_s with respect to the single-hop and multi-hop approaches. This is due to the beneficial effect of installing relays for reducing the energy consumption: in fact, the total energy consumed by the network without deploying relays is in average 127.74 and 4.202 μJ/bit for the single

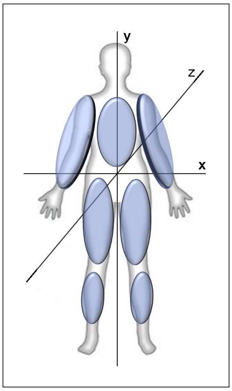


Figure 2.2: Candidate sites for placing relays are chosen uniformly at random on the surface of ellipsoidal areas, along the clothes of the patient.

and multi-hop approaches, respectively, while the installation of relays permits to decrease such values significantly. On the other hand, if we focus on the energy consumed by each sensor to send one bit of traffic to the sink, we can observe that, with our model, such energy is significantly lower (0.017 μJ) than the one obtained with the single-hop (9.826 μJ) and multi-hop (0.323 μJ) approaches.

Note that our model chooses in average 11 relays, among 200 candidate sites, to route one bit of traffic from all sensors to the sink, consuming in average 1.923 μJ/bit. As for the Relay

Table 2.1: Distances (in meters) between sensors and the sink for the single-hop case, and between sensors and the nearest node for the multi-hop case.

Sensor	A	B	C	D	E	F	G	H	I	J	K	L	M
Single-hop	0.6	0.3	0.2	0.5	1.2	0.6	0.7	0.6	0.8	1.0	0.8	0.8	1.5
Multi-hop	0.6	0.3	0.2	0.5	0.6	0.3	0.2	0.1	0.3	0.6	0.4	0.6	0.6

Table 2.2: WBAN scenario: Total energy per bit consumed by (1) the whole network and (2) each sensor, and (3) number of relays installed in the WBAN (in average), in the single-hop, multi-hop, Relay Network approaches and with the EAWD model.

model	E_{tot} (μJ/bit)	E_s (μJ/bit)	N_R
Single-hop	127.740	9.826	-
Multi-hop	4.202	0.323	-
Relay Network	1.383	0.017	22
EAWD ($p = 200$)	**1.923**	**0.017**	**11**

Network approach, 22 relays are installed in the WBAN with a total energy consumption equal to 1.383 μJ/bit. The number of relays N_R with this latter approach increases dramatically with the number of sensors, and in some WBAN scenarios it is impractical to have a large N_R which may limit the activity or mobility of the patient. For example, to relay the data of an additional sensor situated far away from the sink (i.e., at 1.5 m from the sink), the Relay Network approach should install 4 additional relays (obtaining in total 26 relays), thus limiting the patient's movement; on the contrary, by using our model we do not need to install additional relays, but of course at the cost of slightly higher per-relay energy consumption.

Summary. Our energy-aware WBAN design model guarantees that all biosensors consume the least possible energy (0.017 μJ/bit), minimizing at the same time the number of relays (installing 50% less of relays with respect to the Relay Network approach) at the cost of slightly higher energy consumption for relays. We can conclude that the EAWD model provides a good compromise between the energy consumption and the number of relays installed in the WBAN, thus improving the patient comfort and mobility.

To conclude this section, I would like to underline that we have also tested the sensitivity of our model to different parameters like the number of candidate sites and biosensors, the traffic demands, as well as the α value in objective function (2.1), which permits to express a trade-off between planning cost-effective and energy-efficient networks. The obtained results are discussed in detail in [7, 8, 9] and are not reported in this manuscript for the sake of brevity.

2.2 Interference Mitigation in Body-to-Body Area Networks

We now broaden our vision from a single WBAN to a scenario where multiple such networks co-exist and communicate. A *Body-to-Body Area Network (BBN)* consists of several WBANs, and each of which is composed of sensor nodes that are usually placed in the clothes, on the body or under the skin. These sensors collect information about the person and send it to the sink (i.e., a Mobile Terminal or a Personal Digital Assistant, PDA), in order to be processed or relayed to other networks (an example of BBNs is illustrated in Figure 2.3). In BBNs, several transmission technologies like 802.11 and 802.15.4, that share the same unlicensed band (namely the industrial, scientific and medical (ISM) band), coexist, increasing dramatically the level of interference and, in turn, negatively affecting network's performance. For this reason, in [12, 13, 14, 15, 16] we have investigated the *Cross-Technology Interference Mitigation (CTIM) problem* caused by the utilization of different transmission technologies that share the same radio spectrum. This problem was studied by first considering in [12, 13] a *centralized* interference minimizing optimization framework. A set of integer linear programming models and heuristics (greedy, tabu search, sequential fixing) have been developed to obtain optimal and efficient sub-optimal interference mitigation solutions. Next, in [14, 15, 16], we have addressed the CTIM problem by proposing a *distributed approach* based on Game Theory and the Nash equilibrium concept. The proposed game theoretic approach performs channel allocation in two stages: at the BBN stage for inter-

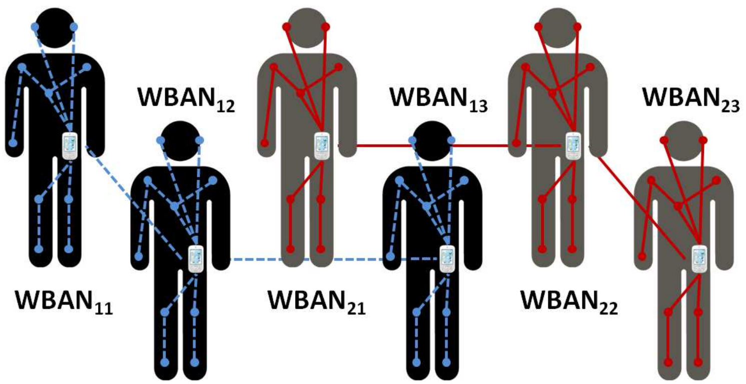


Figure 2.3: Two Body-to-Body Area Networks (BBNs) corresponding to two different groups of people (i.e., blue and red) are using the same unlicensed spectrum.

WBAN communications (WiFi-802.11 channel allocation stage) and at the WBAN stage for intra-WBAN communications (ZigBee-802.15.4 channel allocation stage). Our Nash equilibrium solutions were compared to relevant state-of-art power control solutions [38, 39], exhibiting significantly improved performance.

I would like to emphasize that this latter problem was deeply investigated under my supervision by Ph.D. student *Dr. Amira Meharouech*, who defended her Ph.D. in December 2016. Furthermore, works [10, 11] have been investigated while supervising Dr. Hadda Ben Elhadj within a collaboration with LETI Laboratory, Sfax University, Tunisia. Dr. Ben Elhadj has visited us at the LIPADE Lab. for 3 months in 2013.

In Subsection 2.2.1, I will present the problem of cross-technology interference mitigation in BBNs that we have modeled and solved using a *distributed (Game Theoretic) approach*.

2.2.1 Interference mitigation in body-to-body networks: A game theoretical approach

In this section, we first present the body-to-body network model, then, we introduce the main ideas behind our interference mitigation game theoretical approach and finally, we illustrate a numerical example showing the good performance of our proposal.

Body-to-Body Network Model

We consider a BBN scenario composed of a set $\mathcal{N}$ of WBANs, which are located in the same geographical area (i.e., a medical center, a rest or a care home). We assume that each WBAN is equipped with a wearable Mobile Terminal (MT)[2], that uses both the 802.15.4 protocol (i.e., ZigBee) to communicate with the sensor nodes within its WBAN, and the IEEE 802.11

[2]The *WBAN* and her/his corresponding *Mobile Terminal* will be used as synonyms throughout this section.

wireless standard (i.e., WiFi) to create a backhaul infrastructure for inter-WBANs' communications. We further assume that all WBANs share the same unlicensed 2.4 GHz Industrial, Scientific and Medical (ISM) band, and we denote by $\mathcal{C}^w$ and $\mathcal{C}^z$, respectively, the set of WiFi and ZigBee channels in this band. Since we are also assuming that WBANs can move and interact with their surrounding environment, we find ourselves in a quite dynamic BBN scenario, and therefore, we decide to consider the notion of time and divide the operating time of the whole system into a set T of consecutive epochs, and during each epoch $t \in T$ we suppose that the network topology and environment conditions do not change.

The set $\mathcal{L}^w(t)$ represents all WiFi unidirectional links established by mobile terminals, due to the interaction among WBANs, during the epoch $t \in T$; $\mathcal{L}^w(t)$ may vary between two consecutive epochs due to WBANs' mobility. Similarly, the set $\mathcal{L}^z$ represents the ZigBee unidirectional links used for intra-WBAN communication among the sensors and does not change with time.

In summary, our network model has focused on the following relevant points:

- Every single WBAN's MT, equipped with one WiFi antenna and one ZigBee antenna, should dispose of non overlapping WiFi and ZigBee channels.

- No interference is present within a WBAN; we assume a TDMA-based medium access control implemented in each WBAN to deal with collisions. Note in addition that there is no interference between adjacent ZigBee channels since there is no overlapping.

- As in [40, 41], and differently from [13, 42, 43, 44, 45], which considered the binary model to represent overlapping between channels, the degree of interference between (partially) overlapping WiFi channels m and n is a fractional value, given by the following expression:

$$w_{mn} = \frac{\int_{-\infty}^{+\infty} F_m(w)F_n(w)dw}{\int_{-\infty}^{+\infty} F_m^2(w)dw}, \tag{2.2}$$

  where $F_m(w)$ and $F_n(w)$ denote the Power Spectral Density (PSD) functions of the band-pass filters (i.e., *raised cosine filters*) for channels m and n, respectively, which can be obtained from the channels' frequency responses.

- The interference between overlapping WiFi and ZigBee channels c_1 and c_2 is represented by a binary value: $a_{c_1 c_2} = 1$ if WiFi channel c_1 overlaps with ZigBee channel c_2 (0 otherwise).

- To preserve the network connectivity within a BBN, we assume that its WBANs WiFi interfaces are tuned on the same channel. Therefore, we use the $|\mathcal{L}^w| \times |\mathcal{L}^w|$ matrix $B(t)$, whose element b_{ij} is a binary value: $b_{ij} = 1$ if WiFi links i and j belong to the same BBN at time epoch $t \in \mathcal{T}$ (0 otherwise).

- Finally, WBANs use a higher transmission power on the inter-WBAN communication channel than on the channel used for intra-WBAN communications (i.e. $p^w >> p^z$).

Note that data transmissions within ZigBee networks can completely starve due to WiFi communications, which use 10 to 100 times higher transmission power [13].

Signal-to-Interference-Ratio (SIR)

In order to minimize the total interference within BBNs involving several wireless technologies (WiFi and ZigBee in our scenario), it is advantageous to observe every interference component separately, thus we can specify two-kind interference scenarios:

- ***The Mutual interference***:
  - *WiFi-WiFi interference* at the MT receiver, that occurs while receiving collected data from a nearby WBAN of the same BBN and interfering with adjacent BBNs' WiFi links. Such component includes as well the co-channel interference.
  - *ZigBee-ZigBee interference* at the MT receiver, that happens when a ZigBee link of a WBAN interferes with a ZigBee link of another WBAN belonging to the same or to a different BBN, when they are allocated the same channel.
- ***The Cross-Technology interference***: WiFi-ZigBee, among adjacent WBANs, where each WBAN (MT) is communicating with other WBANs over a WiFi link and is prone to interference from nearby ZigBee links, and vice versa.

The *Interference issue* and the *Signal-to-Interference-Ratio (SIR) metric* are tightly related. Thus, in this work, we determine the SIR in decibel format by:

$$SIR_i(t)(dB) = 10log(\frac{g_{ii}(t)p^i}{\sum_{j\neq i} g_{ij}(t)p_j}), \tag{2.3}$$

where p^i is the transmission power of transmitter i, $g_{ij}(t)$ is the link gain from transmitter j to receiver i at time epoch t. Since WBANs can move in their surrounding environment, the links' gains $g_{ij}(t)$ vary over time, and the SIR in turn has been further expressed as a function of time t. The gain parameters are calculated taking into account the average channel gain evaluated at the reference distance $d_0 = 1\ m$ and with a path loss exponent $n(\alpha)$, according to the following formula [46]:

$$g_{ij}(t)|_{dB} = G(d_0, \alpha)|_{dB} - 10 \times n(\alpha) \times log_{10}(d/d_0), \quad \forall i, j \in \mathcal{L}^w(t) \cup \mathcal{L}^z \tag{2.4}$$

A Two-Stage Cross-Technology Interference Mitigation game

The lack of a centralized control and prioritization of access to the radio spectrum, in addition to the restricted knowledge of the global network status, motivate us to model our cross-technology interference mitigation problem by using *Game Theory*. We propose a *two-stage interference mitigation game*, which is divided into the *BBN-stage/WiFi-level game* and *WBAN-stage/ZigBee-level game*, in which *players are social* and hence they consider their own payoffs as well as those of their neighbors, to optimize their strategies while relying on their surrounding network information.

More specifically, our two-stage socially-aware interference mitigation game proceeds as follows:

- At a first stage, each BBN takes a decision on the WiFi channel that should be assigned to his WiFi transmission links, ensuring minimal interference with his surrounding environment, through a local interaction game with his neighboring BBNs. More precisely, each group of WBANs communicating between each other (i.e., each sub-BBN) is represented by a special player (a delegate or a leader of the group) who decides which WiFi channel to choose. Indeed, to ensure network connectivity all WBANs within the same sub-BBN should be tuned to the same WiFi channel, and we consider this special player that acts on behalf of the entire sub-BBN.

- At the second stage, given the WiFi channel assignment for each BBN, a local interaction game takes place among the WBANs belonging to the same BBN. After playing this game, each WBAN (more precisely, each MT) will be assigned a ZigBee channel to his ZigBee radio interface, and such assignment guarantees the minimal interference of the WBAN with his neighboring WBANs.

Hence, in the proposed game, the players are the set of links $\mathcal{L}(t) = \mathcal{L}^w(t) \cup \mathcal{L}^z$ associated with the set $\mathcal{N} = \{1, ..., n\}$ of WBANs. More specifically, each player is represented by a couple of links (l, h), such that $l \in \mathcal{L}^w(t)$ and $h \in \mathcal{L}^z$ are a WiFi and a ZigBee link corresponding to a given WBAN $i \in \mathcal{N}$ assimilated to its MT. At time epoch $t \in T$, each player chooses a couple of strategies $(s^l(t), s^h(t)) \subset S(t)$, such as $s^l(t)$ is the strategy to allocate a WiFi channel $c_1 \in \mathcal{C}^w$ to the WiFi link $l \in \mathcal{L}^w(t)$ at time epoch $t \in \mathcal{T}$, denoted by $x^l_{c_1}$, and $s^h(t)$ is the strategy to allocate a ZigBee channel $c_2 \in \mathcal{C}^z$ to the ZigBee link $h \in \mathcal{L}^z$, denoted by $y^h_{c_2}$. $S(t)$ is obviously the set of the total channel allocation strategies of all players of the BBN scenario.

Thereby, we can define the **BBN-stage/WiFi-level game ($\mathcal{G}_1$)** as follows:

- *Players:* the set of BBNs represented by their delegates, such as a delegate player per sub-BBN. For the BBN-stage, the player is assimilated to its WiFi link l.

- *Strategies/actions:* $s^l(t) = x^l_{c_1}(t)$, the strategy to choose a WiFi channel c_1 for WiFi link l from the set of available channels in $\mathcal{C}^w$.

- *Utility function:* To ensure a realistic representation of the game, we use the worst SIR values perceived by the two radio interfaces, WiFi and ZigBee, as utility function.

Hereafter, we determine the SIR, previously given in Equation (2.3), that we extend to consider interfering transmitters using different technologies. It is worth noting that Equation (2.5) can be easily extended to more than two radio technologies, considering further for example Bluetooth. However, to simplify the analysis we conduct the study with only two components, corresponding to WiFi and ZigBee, respectively. Whence, the SIR (in dB) of the player $l \in \mathcal{L}^w$, considering the WiFi interface, is given by:

$$SIR^w(x^l_{c_1})(t) = 10log(\frac{g_{ll}p^l_w}{I^w_{c_1}(x^l_{c_1}) + I^w(x^l_{c_1}) + I^{wz}(x^l_{c_1})}), \tag{2.5}$$

where

$I^w_{c_1}(x^l_{c_1})$: Co-channel interference from WiFi links of other sub-BBNs sharing WiFi channel c_1 with WiFi link l.

$I^w(x^l_{c_1})$: Mutual interference from WiFi links of other sub-BBNs using WiFi channels that overlap with c_1.

$I^{wz}(x^l_{c_1})$: Cross-interference from ZigBee links using ZigBee channels overlapping with WiFi channel c_1.

g_{ll} is the channel gain of link l and p^l_w is the WiFi transmit power.

Similarly, the **WBAN-stage/ZigBee-level game** ($\mathcal{G}_2$) is defined as follows:

- *Players:* set $\mathcal{N}$ of WBANs. The player is assimilated to his ZigBee link h.
- *Strategies/actions:* $s^h(t) = y^h_{c_2}(t)$, the strategy to choose a ZigBee channel c_2 for ZigBee link h from the set of available channels in $\mathcal{C}^z$.
- *Utility function:* is defined as a function of the SIR at the ZigBee interface, which is used for intra-WBAN communications. Such SIR (denoted as SIR^z, in dB) is given by:

$$SIR^z(y^h_{c_2})(t) = 10log(\frac{g_{hh}p^h_z}{I^{wz}(y^h_{c_2}) + I^z(y^h_{c_2})}), \tag{2.6}$$

$I^{wz}(y^h_{c_2})$ represents the *cross-technology* interference caused by mobile terminals using WiFi channels that overlap with the ZigBee channel c_2 on which WBAN link h is tuned.

$I^z(y^h_{c_2})$ accounts for the *co-channel interference* of nearby WBANs sharing the same ZigBee channel c_2 of player h.

g_{hh} is the channel gain of link h and p^h_z is the ZigBee transmit power.

Before illustrating a numerical example for the game evaluation, we would like to underline that the BBN-stage and the WBAN-stage games are *potential* games, and therefore, the existence of at least one pure-strategy Nash Equilibrium (NE) and the convergence of a

Best Response[3] algorithm to a NE is guaranteed [47, 48]. Indeed, potential games have two appealing properties: they admit at least one pure-strategy NE which can be obtained through a best-response dynamics carried out by each player, and they have the Finite Improvement Property (FIP), which ensures the convergence to a NE within a finite number of iterations. We refer the reader to our works [14, 15, 16] for all the details and the demonstrations regarding our games' properties.

A Numerical Example

We now illustrate and discuss some numerical results obtained in an example of a BBN scenario, where 40 mobile WBANs are randomly deployed in a $1000 \times 1000m^2$ area, and grouped into four overlapping BBNs (Figure 2.4). The mobility is simulated using the common *random way-point model* [49]. We consider the first five overlapping WiFi channels of the ISM band ($\mathcal{C}^w = \{1, 5\}$) and the whole band of ZigBee channels ($\mathcal{C}^z = \{11, 26\}$) in order to simulate the mutual and the cross-technology interference scenarios. To compute channel gains, we refer to the BBN-specific channel gain model in [46]. The WiFi and ZigBee transmission powers are set to 100 mW and 1 mW, respectively.

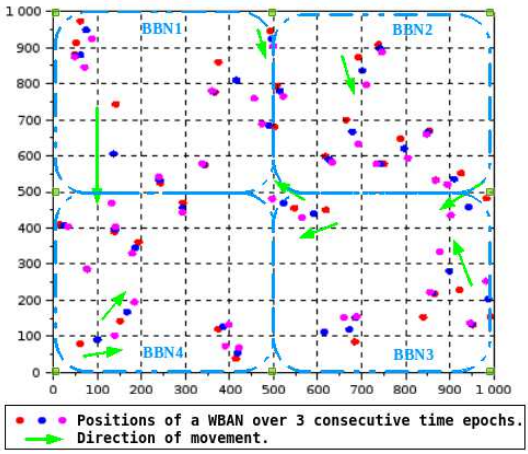
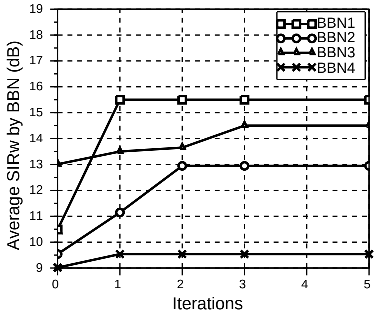


Figure 2.4: Simulation scenario for N=40 WBANs

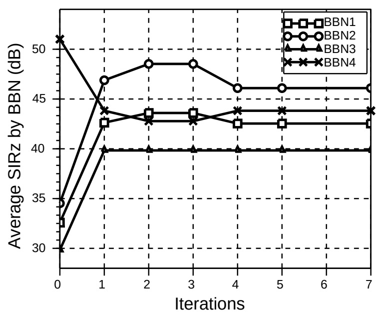
The curves on Figure 2.5 illustrate the dynamics of the Best Response. More specifically, Figure 2.5a and Figure 2.5b show the average WiFi SIR (SIRw in Equation (2.5)) and ZigBee SIR (SIRz in Equation (2.6)), respectively. Figure 2.5c further shows the convergence of the SIR at the ZigBee interface of a subset of players under the Best Response algorithm.

We notice at the Nash Equilibrium that the worst WiFi SIR (SIRw of BBN4 stabilizes at 9.5 dB), measured with the standard transmission power of 20 dBm (100 mW) is always above the receiver sensitivity of most commercial cards (the lowest receiver sensitivity for

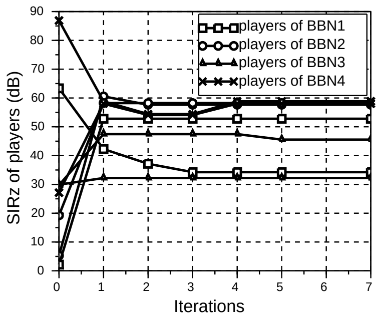
[3]The Best Response of a player is an action (i.e., a strategy) that maximizes its objective function/payoff for a given action tuple of the other players, subject to the played game's constraints if any.



(a) Average WiFi SIR (SIRw)



(b) Average ZigBee SIR (SIRz)



(c) SIRz of a subset of players

Figure 2.5: Dynamics of the Best Response for each BBN, with N=40 WBANs

the Atheros chipset is -95 dB), even when considering other effects like fading and thermal noise. The same conclusions are observed for the worst ZigBee SIR measured by all four BBNs (i.e., the WBAN that experiences the worst SIR in a BBN), which stabilizes at 40 dB for BBN3 after a small number of iterations. Note that the worst SIR measured at the ZigBee interface is higher than the value measured at the WiFi interface due to the small number of WiFi channels used in the simulation, thus resulting in highly conflicting WiFi transmissions. Yet, the performance of the Best Response is ensured since it provides a rather fair, socially-aware channel allocation, so that both WiFi and ZigBee SIR stabilize at quite good values at the Nash Equilibrium. Finally, we close this section by underlining that we further compare our distributed (NE) solutions to the distributed power control algorithm proposed in [38] and to the joint relay selection and transmit power control algorithm proposed in [39], demonstrating the good performance of our game with respect to these latter. The corresponding results are discussed in detail in our work [14].

Chapter 3

Spectrum access in Cognitive Radio and TV White Space Networks: A Game Theoretical Perspective

The frequency spectrum is the scarcest resource for wireless communications, and it is becoming more and more so over the last few years with the rapid proliferation of smartphones, tablets and other smart mobile devices, as well as the emergence of IoT. However, it may result underutilized: at any given time and location, much of the prized spectrum lies idle. For this reason, cognitive radio networks have emerged as a solution to deliver high bandwidth to mobile users, ensuring better utilization of the available (idle) spectrum, thus reducing its wastage. Similarly, with the aim to better utilize the spectrum and make available more radio resources for mobile users, the Federal Communications Commission (FCC) has recently allowed wireless devices to opportunistically access the unused spectrum in the TV bands (also called "white space"). It is in this context that we tackled two main problems, presented hereafter, 1) spectrum access/network selection in cognitive radio scenarios (Section 3.1) and 2) distributed spectrum management in TV White Space networks (Section 3.2).

For the sake of space, in this chapter I chose to describe in more detail one of my main contributions to the problem of distributed spectrum management in TV White Space networks [1].

3.1 Spectrum Access, network selection and pricing in Cognitive Radio Networks

Cognitive Radio Networks (CRNs), also referred to as xG networks, are envisioned to deliver high bandwidth to mobile users via heterogeneous wireless architectures and dynamic

[1] This choice is further justified by the fact that this work is conducted under an international collaboration with professor Marwan Krunz from the University of Arizona.

spectrum access techniques. In CRNs, a Primary (or licensed) User has a license to operate in a certain spectrum band; his access is generally controlled by the Primary Operator and should not be affected by the operations of any other unlicensed user. On the other hand, the Secondary Operator has no spectrum license; therefore, Secondary Users must implement additional functionalities to share the licensed spectrum band without interfering with primary users.

An example scenario is illustrated in Figure 3.1. In [20], we considered a CR scenario which consists of primary and secondary networks, as well as a large set of cognitive users, and we addressed the joint pricing and network selection problem. The problem was formulated as a Stackelberg (leader-follower) game, where first the Primary and Secondary operators compete with each other and set the network subscription price to maximize their revenues. Then, users perform the network selection process, deciding whether to choose the primary network and pay more for a guaranteed service, or use a cheaper, best-effort secondary network, where congestion and low throughput may be experienced. In this regard, we studied both practical cases where (1) the Primary and Secondary operators fix access prices at the same time, and (2) the Primary operator exploits his dominant position by playing first, anticipating the choices of the Secondary operator. Then, network users react to the prices set by the operators, choosing which network they should connect to, therefore acting either like primary or secondary users.

In [18, 19], we studied the spectrum access problem in CRNs from a game theoretical perspective. More specifically, the problem was modeled as a non-cooperative spectrum access game where secondary users access simultaneously multiple spectrum bands left available by primary users, optimizing their objective function (i.e., minimizing a cost function). As a key innovative feature, we *modeled accurately the interference* between secondary users, capturing the effect of spatial reuse, and we considered both elastic and non-elastic user traffic, to model real-time as well as data transfer applications. We determined the sufficient conditions for the existence and uniqueness of the Nash equilibrium, and we derived equilibrium flow settings. Finally, we performed a thorough numerical analysis of the proposed model,

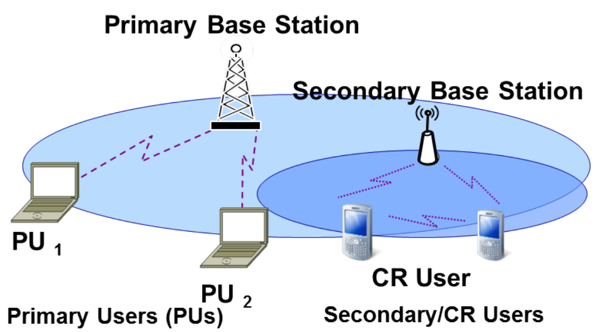


Figure 3.1: Cognitive Radio Networks (CRNs), with Primary and Secondary Users coexisting in the same physical environment, sharing available spectrum opportunistically.

studying the impact of several parameters, like the number of secondary users and wireless channels as well as the interference between secondary users, on the game efficiency.
The works described in [18, 19, 20] are conducted under a tight and fruitful collaboration with Dr. Eitan Altman from Inria NEO team at Sophia-Antipolis.

3.2 Distributed Spectrum Management in TV White Space Networks

As observed before, the radio frequency (RF) spectrum is a scarce resource that has become particularly critical with the increased wireless demand. For this reason, the FCC has recently allowed for opportunistic access to the unused spectrum in the TV bands (also called "white space") [50, 51]. With opportunistic access, however, there is a need to deploy enhanced channel allocation and power control techniques to mitigate interference, including in particular Adjacent-Channel Interference (ACI). TV White Space (TVWS) spectrum access is often investigated in the literature [52, 53, 54] without taking into account ACI between the transmissions of TV Bands Devices (TVBDs) and licensed TV stations. Guard Bands are an effective solution to protect data transmissions and mitigate the ACI problem. Therefore, in [21, 22], we have considered a scenario, illustrated in Figure 3.2, where the spectrum database is administrated by a database operator, and an opportunistic secondary system is composed of TVBDs, each of which is equipped with a single antenna that can be tuned to a *subset of licensed channels*. This can be done, for example, through adaptive channel aggregation or bonding techniques [55, 56, 57]. We have investigated the *distributed spectrum management problem* in opportunistic TVWS systems using a *game theoretical approach* that accounts for both adjacent channel interference and spatial reuse. TVBDs compete to access idle TV channels and select channel "blocks" that optimize their objective function. This function provides a tradeoff between the achieved rate and a cost factor that depends on the interference between TVBDs. We have considered practical cases where *contiguous* or *non-contiguous* channels can be accessed by TVBDs, imposing realistic constraints on the maximum frequency span between the aggregated/bonded channels. We have shown that, under general conditions, the proposed TVWS management games admit a potential function. Accordingly, a "best response" strategy allows us to determine the spectrum assignment of all players. This algorithm is shown to converge in few iterations, in most practical network scenarios, to a Nash Equilibrium. Furthermore, we have proposed an effective algorithm based on *Imitation dynamics/learning*, where a TVBD probabilistically imitates successful selection strategies of other TVBDs in order to improve its own objective function. Numerical results showed that our game theoretical framework provides a very effective tradeoff (close to optimal, centralized spectrum allocations) between efficient TV spectrum use and reduction of interference between TVBDs.

The rest of this chapter will be devoted to present in some detail our contributions to this problem. Therefore, it will be organized as follows. First, we will present the system model and the two proposed spectrum management games, and finally we will discuss a numerical

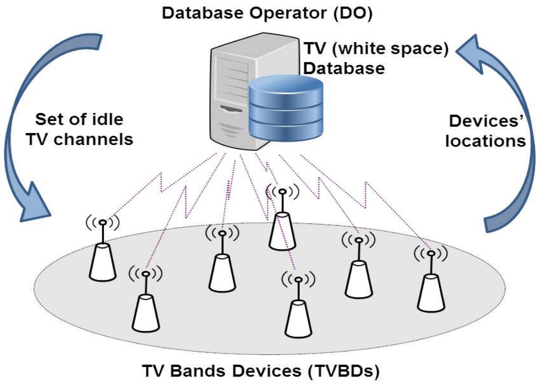


Figure 3.2: A TV White Space scenario composed of a set of TVBDs and a TV/white space Database operated by a third-party Database Operator (DO). The DO receives the TVBDs' locations and then provides them with the set of idle TV channels.

example with the aim to show the good performance of our games.

3.2.1 System Model

We consider the TV White Space scenario of Figure 3.2, where a spectrum database is administrated by a third party Database Operator (DO). The DO serves a set $\mathcal{N}$ of unlicensed TVBDs.

Potentially available TV channels include channels 2 to 51 (except channels 3, 4 and 37) in the case of fixed TVBDs, or channels 21 to 51 (except channel 37) for personal/portable TVBDs [50, 51].

Following the FCC's 3rd Memorandum Opinion and Order [51], we remark that *"fixed devices may operate only on vacant TV channels that are not adjacent to occupied TV channels, while personal/portable devices may operate adjacent to occupied channels if their maximum EIRP is reduced to no more than 40 mWatt (instead of 100 mWatt EIRP)"*. Furthermore, TVBDs must incorporate a geo-location capability and a means to access the database to retrieve a list of idle TV channels that may be used at a given location [50, 51]. They use a fixed transmission power, i.e., power control is not applied, and they may also perform spectrum sensing to determine the relative utilization of a given channel.

Therefore, in our work we assume that the DO first provides all TVBDs with the set of idle, guard band, and occupied channels. Based on such information, each TVBD i chooses at most n_{max} idle channels so as to optimize its objective function. Note that if the TVBD chooses non-contiguous idle channels, it is necessary to guarantee that the distance between the chosen channels does not exceed a given value d_{max}, determined by hardware constraints and aggregation overhead.

We assume that TVBDs are located in the same geographical area, and therefore they perceive the same TV spectrum status. Let $\mathcal{M}$ denote the set of idle TV channels and

B the TV channel bandwidth in MHz (same for all channels). Figure 3.3 illustrates an example. We classify channels into idle, busy, and guard band channels. In Figure 3.3, channels $\{8, 10, 16, 17\}$ are busy, and channels $\{7, 9, 11, 15, 18\}$ are guard bands. Thus, $\mathcal{M} = \{5, 6, 12, 13, 14, 19, 20, 21, 22\}$.

Let d_i be the rate demand (in Mbps) required by TVBD i, and let r_j be the maximum data rate that can be supported by TV channel j. In fact, r_j can be deterministic (ideal channel quality) or random if we assume that channel quality varies due to multi-path fading and shadowing, as well as due to the unpredictability of TVBDs activities. Note that under poor channel conditions, we expect that our games will allocate more channels to TVBDs to guarantee their minimum rate demands.

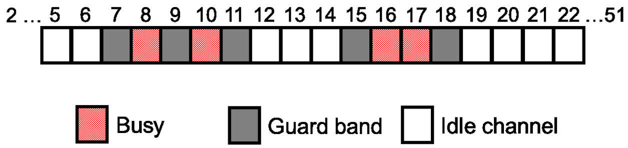


Figure 3.3: Example illustrating idle, busy, and guard band channels in the TV spectrum. The set of idle TV channels is given as $\mathcal{M} = \{5, 6, 12, 13, 14, 19, 20, 21, 22\}$.

3.2.2 TV White Space spectrum management games

We address the TVWS spectrum management problem in a fully distributed fashion using a game theoretic approach. Given the spectrum status that is provided by the Database operator, each TVBD locally selects a set of idle channels (at most n_{max}) for its communications so as to optimize an objective function (3.4), which accounts for the *utility* perceived by using the chosen channels and a *cost term*, expressed as a function of the experienced interference.

This section will first describe in details the player's (the TVBD) objective function and then present the two proposed games for TVWS spectrum management. Let us first define the notation used hereafter.

Let $x_{ij}, \forall i \in \mathcal{N}, j \in \mathcal{M}$ be the binary decision variables defined as follows:

$$x_{ij} = \begin{cases} 1 & \text{if idle channel } j \text{ is assigned to TVBD } i\text{'s transmission} \\ 0 & \text{otherwise.} \end{cases}$$

Hence, $\boldsymbol{x}_i = \{x_{i1}, x_{i2}, \ldots, x_{i|\mathcal{M}|}\}$ represents the set of channel selection strategies of TVBD i.

We denote by E_j the interference matrix associated with idle channel j. Let $e_{ik}^{(j)}$ be the (i, k)th element of E_j, the interference parameter between TVBDs i and k on channel j. Note that E_j needs not be symmetric.

More specifically, $e_{ik}^{(j)}$, for $i, k \in \mathcal{N}$ and $j \in \mathcal{M}$, is defined as follows:

$$e_{ik}^{(j)} = \begin{cases} 1 & \text{if TVBD } i \text{ interferes with TVBD } k \text{ on channel } j \\ 0 & \text{otherwise.} \end{cases}$$

TVBD's Objective Function

In this work, we focus on TVBDs characterized by a minimum data rate requirement (d_i) and an elastic traffic: the goal of each device is to maximize the difference between its utility (U_i) and cost (J_i).

We begin by illustrating the *cost function* J_i of TVBD i, which represents a congestion cost that the device incurs due to its *interference* with other devices that operate on the same channel j. J_i is given by:

$$J_i = \sum_{j \in \mathcal{M}} r_j x_{ij} \cdot [\alpha_j \cdot (\sum_{k \in \mathcal{N}} r_j e_{ki}^{(j)} x_{kj})^{\beta_j} + \gamma_j], \tag{3.1}$$

where the coefficients α_j and γ_j are two positive numbers that model the overhead caused by choosing a wireless channel j, and β_j is a positive integer greater than or equal to 1 (the larger is β_j, the higher is the impact of interference among TVBDs). This cost function well captures the network congestion level and it is commonly used in the literature [18, 58]. More specifically, for each channel j we consider an increasing and convex function of the form:

$$\alpha_j \cdot (\sum_{k \in \mathcal{N}} r_j e_{ki}^{(j)} x_{kj})^{\beta_j} + \gamma_j \tag{3.2}$$

where $r_j x_{kj}$ is the traffic of TVBD k over channel j. We observe that (3.2) represents the per traffic unit congestion cost experienced by the TVBD on a single channel. Therefore, the total cost incurred by device i due to the overall network congestion is obtained by summing the cost over all channels.

J_i represents the penalty that TVBD i pays due to interference. It is monotone in the number of TVBDs sharing the same band, and is used to incite them to choose idle or underutilized bands. In other words, this cost is naturally proposed to discourage TVBDs from choosing "crowded" channels, thus reducing the interference. Hence, each TVBD i is better off minimizing J_i.

As for the utility, we consider an affine utility function of the form:

$$U_i = \sum_{j \in \mathcal{M}} \delta_{ij} r_j x_{ij} \tag{3.3}$$

where δ_{ij} is a positive parameter that represents the significance (priority) of channel j for

TVBD i. Hence, the objective function that (elastic) TVBD i aims to maximize is given by:

$$\begin{aligned} OF_i =& U_i - J_i \\ =& \sum_{j \in \mathcal{M}} \delta_{ij} r_j x_{ij} - \sum_{j \in \mathcal{M}} r_j x_{ij} \cdot [\alpha_j \cdot (\sum_{k \in \mathcal{N}} r_j e_{ki}^{(j)} x_{kj})^{\beta_j} + \gamma_j]. \end{aligned} \tag{3.4}$$

It is worth noting that there is a tradeoff between minimizing the number of chosen idle channels and minimizing the interference with other TVBDs.

Spectrum management games

We study and compare two variants of the TVWS spectrum management game:

- Game $\mathcal{G}_1$ (*Channel Aggregation*-based TVWS Spectrum Management): Given the spectrum status, TVBDs play the game choosing *at most* n_{max} *idle channels*, which are *not necessarily contiguous*. However, the chosen idle channels must be separated by no more than d_{max} channels. This feature is used to take into account hardware constraints and the cost of aggregating distant channels.

  In $\mathcal{G}_1$ each player i aims at maximizing OF_i in (3.4) subject to the following constraints:

  - Rate demand constraint:
  $$\sum_{j \in \mathcal{M}} r_j x_{ij} \geq d_i \tag{3.5}$$
  - Maximum number of channels constraint (at most n_{max} channels can be chosen by a TVBD):
  $$\sum_{j \in \mathcal{M}} x_{ij} \leq n_{max} \tag{3.6}$$
  - Maximum frequency-separation constraint (which guarantees that the maximum separation between any chosen channels j_1 and j_2 does not exceed d_{max}):
  $$j_1 x_{ij_1} - j_2 x_{ij_2} \leq d_{max} + (1 - x_{ij_2}) \cdot |\mathcal{M}|, \forall j_1, j_2 \in \mathcal{M} : j_1 > j_2 \tag{3.7}$$
  - Integrality constraints:
  $$x_{ij} \in \{0, 1\}, \forall j \in \mathcal{M} \tag{3.8}$$

- Game $\mathcal{G}_2$ (*Channel Bonding*-based TVWS Spectrum Management): Given the spectrum status, TVBDs play the game choosing *at most* n_{max} *contiguous idle channels*. This condition is used to minimize the system complexity (aggregation overhead, hardware costs), guaranteeing a fair access to TVWS, independent of rate demands.

In $\mathcal{G}_2$ player i maximizes his objective function OF_i subject to constraints (3.5), (3.6), and (3.8) defined in $\mathcal{G}_1$. In addition, the following single frequency block constraint (contiguous channels) is imposed:

$$j_1 x_{ij_1} - j_2 x_{ij_2} \leq n_{max} - 1 + (1 - x_{ij_2})|\mathcal{M}|, \forall j_1, j_2 \in \mathcal{M} : j_1 > j_2 \qquad (3.9)$$

Let us elaborate on $\mathcal{G}_1$ and $\mathcal{G}_2$, considering the example in Figure 3.3. We focus on channels 5 to 18, for simplicity. According to $\mathcal{G}_1$, if the TVBD can choose at most $n_{max} = 2$ idle channels separated by a distance of at most $d_{max} = 6$, then its possible choices are: $\{5, 6\}$, $\{6, 12\}$, $\{12, 13\}$, $\{12, 14\}$, and $\{13, 14\}$. On the other hand, in $\mathcal{G}_2$, if the TVBD can choose at most $n_{max} = 2$ contiguous idle channels, then it has the following alternatives: $\{5, 6\}$, $\{12, 13\}$, and $\{13, 14\}$, besides choosing each of these channels separately. Of course, the strategy space of the TVBD in $\mathcal{G}_1$ is in general larger than that of $\mathcal{G}_2$.

Finally, we demonstrate that both games $\mathcal{G}_1$ and $\mathcal{G}_2$ exhibit desirable properties since they are *potential*, and possess at least one pure-strategy Nash Equilibrium (NE). Hence, a Best Response algorithm can be used to converge to a NE. The *Best Response* of a player (or a TVBD) is an action (i.e., a set of idle channels) that maximizes its objective function OF_i for a given action tuple of the other players, subject to constraints (3.5)-(3.8) for $\mathcal{G}_1$, and to constraints (3.5), (3.6), (3.8) and (3.9) for $\mathcal{G}_2$. The same procedure is repeated for all TVBDs in the network, and such procedure converges iteratively to a NE of our games. To determine the NE solutions, we have implemented three algorithms that converge to these latter in few iterations:

1. a Best Response algorithm,
2. the Krasnoselskij algorithm [59, 60], which is similar to the Best Response algorithm, however, only a fraction (i.e., 20%, 30%) of TVBDs change their strategies at the same time at each iteration to improve their objective function and
3. an Imitation algorithm, where a player can imitate another player chosen randomly, by playing the same strategy at the next iteration of the algorithm.

All the details regarding the pseudo-code of the above three algorithms as well as the extensive numerical evaluation can be found in [22]. A numerical example is illustrated hereafter in order to show that our three TVWS spectrum management algorithms perform quite good in terms of the quality of the obtained solution and the number of iterations to converge to the NE solution.

A numerical example

We consider here a TV white space system composed of M TV channels and N fixed TVBDs randomly scattered over a 1500 meter $\times$ 1500 meter area. The transmission power of a TVBD is fixed to 20 dBm, the bandwidth of each TV channel is 6 MHz, and the rate r_j supported by TV channel j can be either deterministic or vary according to a random distribution. In

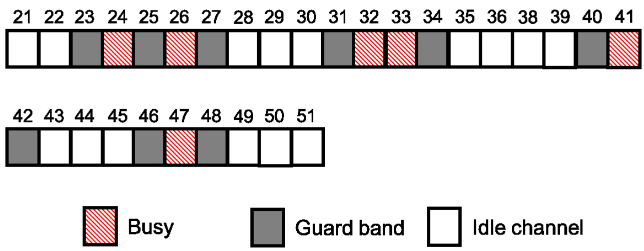


Figure 3.4: Set of TV channels ($\{21, \ldots, 51\} \setminus \{37\}$) considered in the numerical analysis.

this example, we assume that r_j is deterministic and equal to 10 Mbps. Figure 3.4 illustrates an example of the TV spectrum that we consider in our numerical analysis.

We assume that TVBDs rate demands d_i are homogeneous and equal to 20 Mb/s, and we consider two cases for the set of idle channels: case (i) $\mathcal{M}$ consists of all idle channels of the spectrum depicted in Figure 3.4, while in case (ii) $\mathcal{M} = \{21, 22, 28, 29, 30, 35, 36, 38, 39\}$. The aim behind considering case (ii) is to study the system's behavior when a smaller number of idle channels is available for TVBDs, thus increasing the interference. We further assume a free-space path loss model between any two unlicensed devices. We vary the number of TVBDs in the range $[1, 20]$ to show the impact of this parameter on the interference among the devices.

Parameters α_j, β_j, γ_j, and δ_{ij} are set to 1, 1, 0, and 100, respectively, for all $i \in \mathcal{N}$ and channels $j \in \mathcal{M}$, $d_{max} = 10$, $n_{max} = 3$ and $\lambda = 0.2$ (i.e., 20% of players change strategy in each iteration of the Krasnoselskij-based DSM algorithm, K-DSM).

Note that the SBR-DSM algorithm (sequential best response dynamics) is guaranteed to converge in both games $\mathcal{G}_1$ and $\mathcal{G}_2$ in a finite number of iterations, due to the fact that we demonstrated in [22] that these games are potential. In practice we observed that, in all the scenarios we simulated and for all parameters settings, the distributed algorithms we considered in this paper always converge in few iterations to equilibrium conditions. More specifically we observed that, in the worst case, up to 5 iterations are needed for a TVBD to converge to a stable point, while in average less than 3 iterations are sufficient.

Figure 3.5(a) shows the average value of the objective function obtained by all the proposed algorithms (SBR-DSM, BR-DSM, K-DSM and IM-DSM, as summarized in Table 3.1) for game $\mathcal{G}_1$ (solid lines in the figure) and game $\mathcal{G}_2$ (dotted lines) as a function of the total number of players (unlicensed devices), considering the entire set of idle channels (case (i)). Similarly, Figure 3.5(b) shows the same performance measure when only a subset of idle channels is available (case (ii)).

Several key findings can be drawn from the observation of these results, namely in terms of the impact of the number of TVBDs and idle TV channels, which we discuss in the following.

Acronym	Description
SBR-DSM	Sequential Best Response-based DSM
BR-DSM	Best Response-based DSM
K-DSM	Krasnoselskij-based DSM
IM-DSM	Imitation-based DSM

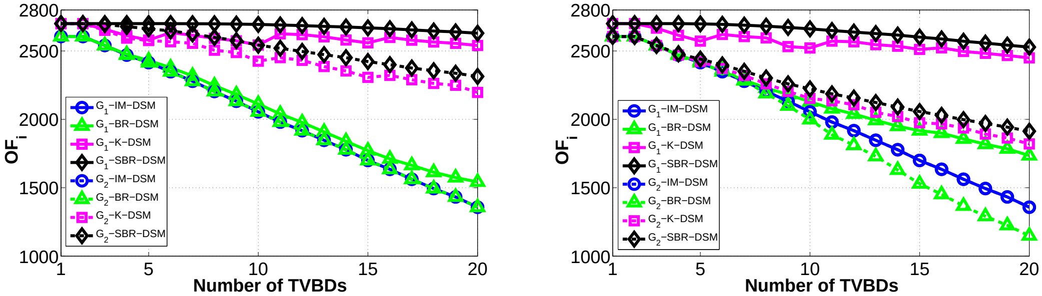
Table 3.1: Summary of the Distributed Spectrum Management (DSM) algorithms considered in our study.

Effect of the number of TVBDs: As expected, it can be seen in Figures 3.5(a) and 3.5(b) that the objective function (OF_i average value) decreases when increasing the number of players, and this is in fact due to the increase in the interference between TVBDs. It can also be observed that SBR-DSM and K-DSM have very similar trends for both games, and they exhibit better performance values than IM-DSM and BR-DSM, especially when the number of players is higher than 5. SBR-DSM shows the best performance among all the distributed algorithms. In fact, at each iteration of the algorithm, each device chooses the best channels knowing those chosen by the previous players in the same round or iteration. Therefore, since this algorithm relies on a most up-to-date information, it is not surprising that the sequential BR algorithm exhibits the best performance.

Effect of the number of idle TV channels: We observe from Figure 3.5(a) and Figure 3.5(b) that a player gets, on average, in case (ii) an objective function value lower than that perceived in case (i). For example, under SBR-DSM and K-DSM, when game $\mathcal{G}_2$ is played, each TVBD achieves an objective function value under case (i) that is, on average, 1.3 times higher than the one obtained under case (ii). This is justified by the fact that in case (i) the set of players' strategies is larger than the one in case (ii) and hence TVBDs can better optimize their performance in the former case. This is particularly true for SBR-DSM and K-DSM; IM-DSM however exhibits the same trend in the two cases, since the imitation algorithm is more sensible to the number of players than the size of the set of strategies that players can explore.

Effect of traffic distributions: We further measure the impact of the traffic pattern by considering different realistic distributions for the traffic demand. More specifically, we consider: a) deterministic traffic with rate of 20 Mb/s, b) uniformly distributed traffic with rate between 10 and 30 Mb/s, and c) truncated normally distributed traffic with mean and standard deviation of 20 and 5 Mb/s, respectively. Figure 3.6(a) and Figure 3.6(b) show the average value of OF_i versus the number of TVBDs for uniformly distributed traffic[2]. By comparing Figures 3.5 and 3.6, it can be observed that the impact of different traffic distributions on all the proposed algorithms is limited (i.e., practically almost negligible). Therefore, we can conclude that our proposed algorithms are quite robust against different traffic patterns.

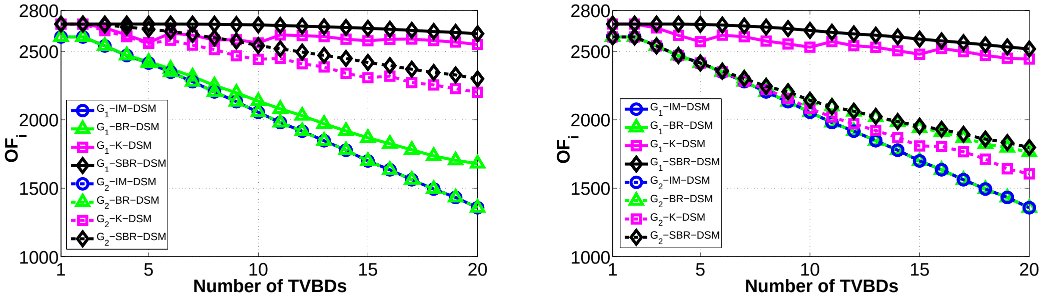
[2] Similar results were obtained when we assume that the traffic follows a truncated normal distribution.



(a) Deterministic traffic, d_{max}=10, case (i)

(b) Deterministic traffic, d_{max}=10, case (ii)

Figure 3.5: Static TVWS scenario: Average objective function values (the players' total utility) as a function of the number of TVBDs ($[1, 20]$), and for two different sets of available idle channels (traffic demand $d_i = 20$ Mb/s).



(a) Uniform dist., d_{max}=10, case (i)

(b) Uniform dist., d_{max}=10, case (ii)

Figure 3.6: Static TVWS scenario: Average objective function values (the players' total utility) versus the number of TVBDs ($[1, 20]$), and for two different sets of available idle channels (uniformly distributed traffic with rate between 10 and 30 Mb/s).

We conclude this chapter by highlighting that we also evaluated the performance of the proposed algorithms in dynamic TVWS scenarios, in which TVBDs are mobile, and through the determination of the Price of Anarchy (PoA)[3] [61], in order to assess the Nash equilibria quality. For the sake of brevity, these results are not reported in this chapter, and we invite the reader to refer to our work [22] for all the details regarding these results.

[3]The PoA is defined in our context as the ratio between the utility of the socially optimal solution and that of the worst Nash equilibrium.

Chapter 4

Optimal Resource Allocation in Virtual Networks and Cloud Computing

Traditional telecommunication infrastructures are composed of property hardware operated by a single entity to offer communication services to their final users. While this architecture simplifies the design and optimization of the network equipment for specific tasks, its low flexibility represents the main limitation for the evolution of the network infrastructure. For this reason, network operators and equipment manufacturers have started the standardization process of several virtualization solutions that have been developed in recent years for enabling the sharing of general-purpose resources and increasing the flexibility of their network architectures. Such a process has led to the specification of the *Network Functions Virtualization* (NFV) technology [24], which promises to bring about several benefits, such as reduced CAPEX and OPEX (CAPital and OPerational EXpenditure), low time-to-market for new network services, higher flexibility to scale up and down the services according to users' demand, simple and cheap testing of new services. Furthermore, *Virtualization techniques* allow to setup cost-effective Data Centers (DCs) infrastructures for storing large volumes of data and hosting large-scale service applications [26]. Large companies like Google, Facebook, and Amazon have made large investment in massive virtualized data centers supporting Cloud services that require large-scale computations and storage. With the emergence of *Cloud Computing* (CloudNaaS, EC2, SS3, etc.), service hosting in DCs has become a profitable business that plays a crucial role in the future of Internet. The *resource allocation optimization* problem is a key, challenging issue in both virtual networks and Cloud computing, and the main goal of the Virtual Operator (VO) on one hand, and the Cloud Provider (CP) on the other hand is to allocate resources in an efficient way in order to satisfy end-users' demands while maximizing its own profit.

This problem is described in the following sections (Section 4.1 for *Virtual Networks* and Section 4.2 for *Cloud Computing*), dedicating more space for this latter since it was

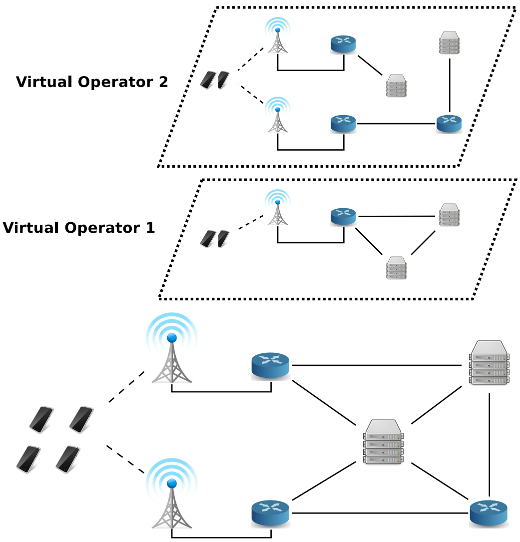


Figure 4.1: Example Network Scenario: A single physical infrastructure (bottom figure) is shared among two Virtual Operators. The network topology, the transmission services of network links, and the services executed by network nodes are selected according to the virtual operator needs in order to minimize the physical network congestion.

investigated by a Ph.D. student I co-supervised, Dr. Javier Salazar, under an international collaboration project with University of Ottawa (Prof. Ahmed Karmouch and Dr. Abdallah Jarray).

4.1 Congestion mitigation in Virtual (NFV-based) networks

The necessity to reduce CAPEX/OPEX for telecommunication operators is becoming a very challenging issue to design Next Generation Internet Architectures. The NFV technology has emerged as a means to address such issue allowing different (virtual or service) operators to share a single physical network infrastructure, as illustrated in the example network scenario of Figure 4.1. Indeed, the flexibility provided by NFV permits to compose communication services independently of the underlying equipment and quickly reconfigure the infrastructure. However, the utilization of the same resources can increase their congestion due to the spatio-temporal correlation of traffic demands and computational loads. Therefore, in [27, 28], we analyzed the congestion resulting from the sharing of the physical infrastructure and proposed innovative orchestration mechanisms based on both *centralized* and *distributed* approaches, aimed at unleashing the potential of the NFV technology.

In particular, we have first formulated the network functions composition problem as a *non-linear optimization model* to accurately capture the congestion of physical resources and to dynamically control traffic flows and system configurations in order to prevent the congestion of network resources. While centralized solutions, like [27], permit to optimally control the system, the associated costs and responsibilities for satisfying the service (i.e., SLA and corresponding penalties) represent one of the main obstacles for the operator of the physical infrastructure. Therefore, the NFV technology further calls for distributed approaches where the best operational point of the system results from individual decisions performed independently by virtual operators according to the network status and customers' requests. In this context, game theory provides the natural framework for both analyzing the evolution of NFV-based systems and designing the rules (e.g., incentives/prices and use policy) to coordinate network allocation decisions of virtual operators.

As a second key contribution of [28], we analyze the congestion resulting from the sharing of the physical infrastructure from a distributed (game theoretic) point of view. We formulate the distributed congestion minimization problem as a game, proposing a *dynamic pricing strategy* of network resources, proving that the resulting system achieves a stable equilibrium in a completely distributed fashion, even when all virtual operators independently select their best network configuration. We demonstrate that the NFV congestion mitigation game admits a unique Nash Equilibrium, under very general conditions, and that efficient solutions can be easily computed in a distributed fashion. We further compare our distributed solution to a centralized approach, using both an optimization model and an efficient heuristic based on the Shortest Path Tree algorithm. Numerical results showed that the proposed distributed model significantly decreases network congestion, thus representing a very promising approach for operators to manage network resources in an efficient, fully distributed and dynamic fashion. Furthermore, it well approaches the performance of centralized optimization models, which can hardly be solved to the optimum in real network scenarios.

4.2 Resource Allocation Optimization of Infrastructure As A Service in Cloud Computing

Advances in communications and IT technology have profoundly influenced many aspects of our life, making available an extensive range of new applications which undoubtedly have had a great impact on society's lifestyle. New technologies, such as virtualization, remote storage or virtual private networks, enable users to access their data, content (streaming/video on demand services) or even their work terminals from anywhere, at any time. It is in this context that *Cloud Computing* facilitates the transition from a stationary IT model, where information is locally processed and stored in a physical device to a distributed model that promotes the use of remote resources in an abstract environment. Essentially, this architecture gives end users the impression of having unlimited resources available in the cloud. As this is what makes cloud computing attractive to end users, it is imperative that providers adopt models that optimize the management of their resources to satisfy all user requests (hence maintaining this perception of the end user), while maximizing their revenue.

The first contribution of this work was the identification of a novel architecture to improve performance and maximize the revenue of the Cloud Provider (CP) in a general cloud computing context. In this respect, our approach incorporates the cutting edge solutions pro-

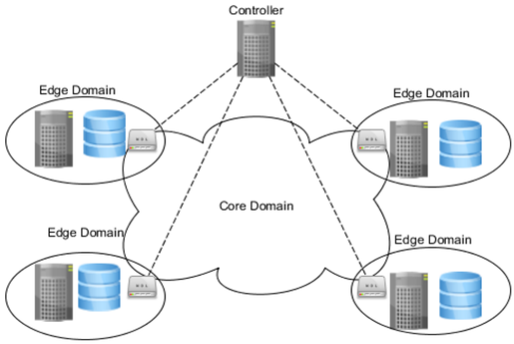


Figure 4.2: Networked Edge Datacenters Architecture.

posed in the literature – a distributed Data Center scenario where end users are able to access the same CP's infrastructure from different locations, and networked Edge DC architecture –in a single model (An example is illustrated in Figure 4.2).

We focused on *Infrastructure as a Service (IaaS)* resources, which constitute the physical infrastructure of the Cloud and which are contained in Data Centers (DCs). An IaaS request is defined through two main requirements: Hosting and Networking resources (i.e., computing, storage, memory and bandwidth resources). When an IaaS request arrives, the CP has to determine whether to accept or reject it, and the main guideline of his decision will be based on both the availability of Networked Edge DCs resources and the economic benefit (cost) of accepting an IaaS request. We start with studying the resource allocation optimization problem in the general IaaS context in [29, 30], with and without consideration of quality of service, and then in the Multimedia Cloud-based IaaS context [31]. We propose different resource allocation optimization models for both IaaS cloud computing scenarios. The proposed models are based on a *large-scale* optimization technique known as *Column Generation (CG)*, which allows large and complex mathematical problems to be solved within acceptable computational times. We evaluated the performance of our models in the several realistic network scenarios, comparing them to state-of-the-art algorithms (Greedy, Bin packing and Multi-Site). Simulation results demonstrated that the proposed CG-IaaS optimization approach effectively reduces the costs of the resources used by the CP, while exhibiting low blocking ratio of IaaS requests with respect to other algorithms. In sum, we can affirm that our approach proved to be effective not only in reducing costs but also in jointly allocating different types of resources while ensuring that part of the infrastructure is always available to serve future requests.

In the rest of this chapter, we will present in a concise, yet clear, manner our CG-based resource allocation approach for the classic IaaS Cloud computing scenario. We refer the reader to our recent work [31] for the resource allocation optimization approach introduced in the specific, yet more challenging, case of Multimedia Cloud-based IaaS. Hence, the rest of this chapter (Section 4.2.1) is organized as follows: first, we will present the network model, then, we will describe the resource allocation approach, and finally, we will conclude by illustrating and discussing some numerical results showing the good features and insights behind our proposed optimization approach.

4.2.1 Column-generation-based IaaS resource allocation approach

Network model

We adopt a Networked Edge DCs infrastructure (illustrated in Figure 4.2), to handle IaaS user requests. We represent the DC physical infrastructure by an undirected graph $G_d = (S_d, H_d, L_d)$, where S_d denotes the set of backbone switching nodes, H_d the set of DC server locations (hosting nodes), and L_d the set of network links. Each physical link between DC server locations $l \in L_d$ has a bandwidth capacity b_l. Each DC hosting node $u \in H_d$ offers a computing capacity p_u. A Cloud IaaS request is denoted by a Virtual Network I_n, where $n \in \mathcal{N} = \{1, 2, \ldots, N\}$ and represented by a directed graph $G_n = (A_n, S_n, E_n)$, where A_n, S_n, and E_n denote, respectively, the set of virtual hosting nodes and switching nodes, and the set of virtual networking links. The QoS requirements of virtual link $e \in E_n$, belonging to QoS class $j \in J_B$, are defined by the pair of parameters (b_j, d_j), where b_j is the required bandwidth and d_j is the end-to-end delay of a routing path measured through the number of switching nodes between the two end points of the routing path. Similarly, the QoS requirements of virtual node $a \in A_n$, belonging to class $j \in J_U$, are defined by the pair (p_j, t_j), where p_j is the required CPU for QoS class j and t_j is the set of potential embedding hosting locations that guarantees QoS requirements of class j.

The mapping of each IaaS user request is decomposed into the *hosting* and the *network mapping* as follows:

- *IaaS Hosting*: virtual hosting nodes of IaaS request n ($\forall a \in A_n$) are mapped to different substrate hosting nodes $u \in H_d$ by the mapping M_N: $A_n \to H_d$. Similarly, virtual switching nodes ($\forall s \in S_n$) of request n are mapped to different substrate switching nodes $v \in S_d$ by mapping M_N: $S_n \to S_d$.

- *IaaS Inter-Edge DCs Networking*: each virtual link $e \in E_n$ from request n is mapped to a set of substrate paths $\pi^e_{uv} \subset \Pi^s$ by mapping M_L: $E_n \to \Pi^s$, where (u, v) are substrate nodes assigned to virtual nodes (s, d) source and destination nodes of virtual link e, respectively.

Cloud Provider (CP)'s objective function

When an IaaS request arrives, the CP decides whether to accept or reject it. This decision depends on three important aspects: the IaaS's QoS requirements, the availability of cloud DCs resources and the economic cost due to accepting the IaaS request.

In this work, we focus on computing and bandwidth as the main substrate resources, and therefore we propose to calculate the mapping cost of each IaaS request $I_n, \forall n \in \mathcal{N}$, represented by $G_n = (A_n, S_n, E_n)$, as follows:

$$COST[I_n] = COST[M_N(A_n), M_N(S_n), M_L(E_n)] \tag{4.1}$$

Column Generation Formulation for IaaS Resource Allocation (CG-IaaS)

Since the IaaS mapping problem is known to be NP-hard and the Column Generation (CG) [62] represents a good candidate solution for reducing the problem complexity and the execution time to obtain the solution, we decide in this work to use such a technique to solve our problem.

The proposed CG-QoS-IaaS optimization model formulates the IaaS mapping problem in terms of Independent Cloud Mapping Configurations (ICMCs), where *each ICMC* provides an IaaS mapping solution of *a set of (one or more) IaaS requests*. We denote by $\mathcal{C}$ the set of all possible ICMCs. An ICMC configuration $c, \forall c \in \mathcal{C}$ is defined by the vector $(a_n^c)_{n \in N}$, such that: $a_n^c = 1$ if ICMC c serves IaaS request I_n and 0 otherwise. Accordingly, our problem can be formulated with respect to the variables $\lambda_c, \forall c \in \mathcal{C}$, where λ_c is equal to 1 if a configuration c is used for serving a IaaS request and 0 otherwise. Thus, our model consists in selecting at maximum N ICMCs, if each IaaS request is served by a distinguished ICMC.

Therefore, the original IaaS mapping problem is decomposed into two subproblems:

- the *Master problem*:
  It takes into account the constraints related to the optimal partitioning of available substrate resources among QoS classes. By using the CG technique, we only solve a restricted form of this problem, i.e., with a restricted number of columns (ICMCs[1]). The objective function of the master problem that we want to minimize is given as:

  $$\sum_{n \in \mathcal{N}} COST[I_n] = \sum_{c \in \mathcal{C}} \mathrm{COST}_c \lambda_c + \sum_{l \in L_d} \sum_{j \in J_B} c_l b_l^j + \sum_{u \in H_d} \sum_{j \in J_U} c_u p_u^j, \tag{4.2}$$

  where COST_c, the cost of configuration c, corresponds to the costs of the used substrate resources (bandwidth and computing) for the mapping of IaaS request granted by ICMC c. It is defined as follows:

  $$\mathrm{COST}_c = \sum_{l \in L_c} c_l b_c(l) + \sum_{u \in H_c} c_u p_c(u), \tag{4.3}$$

  where $b_c(l)$ and $p_c(u)$ are the used substrate bandwidth and computing resources by ICMC c, respectively. $L_c \subset L_d$ and $H_c \subset H_d$ define, respectively, the set of physical links and hosting nodes used by ICMC c.
  The variable $b_l^j (\in \mathbb{N}, \leq b_{max})$ defines the amount of bandwidth to be setup on link l for

[1]Each ICMC provides an IaaS mapping solution of a set of IaaS requests.

QoS class $j \in J_B$ and the variable $p_u^j (\in \mathbb{N}, \leq p_{max})$ defines the amount of computing capacity to be setup on hosting node u for QoS class $j \in J_U$.

- The *pricing problem*:
  It corresponds to the problem of *generating an additional column* to the constraint matrix of the restricted master problem, i.e., it generates an ICMC that improves the current value of the objective function (*an ICMC with negative reduced cost*). It includes the following constraints which are related to the mapping of IaaS requests respecting QoS requirements:

  – Mapping of hosting nodes and switching nodes of IaaS requests:
    * Mapping is done for all nodes of an accepted request I_n
    * A virtual hosting node a of an IaaS request I_n can be assigned to only one physical hosting node u.
    * A virtual switching node s of I_n can be assigned to only one physical switching node v.

  – Mapping of networking links of IaaS requests: at least one mapping path π is selected between a pair of substrate nodes (u, v) assigned to end virtual nodes (s, d) of virtual link $e \in E_n$.

  The reduced cost of ICMC c is expressed as a function of the cost COST_c and the variables of the pricing problem and the coefficients of the master problem.

For a detailed description of the formulations of the master and pricing problem we refer the reader to our works [29, 30].

Recall that the main objective of the CG-QoS-IaaS model is to determine the optimal QoS-based partitioning of networked edge data centers' resources among QoS IaaS demand classes. Let MIP(M) denotes the continuous relaxation of the original master problem, obtained by relaxing the integrality constraints on variables λ_c; $\lambda_c \in \mathbb{R}^+, \forall c \in \mathcal{C}$. Moreover, let LP(M) denotes the continuous relaxation of MIP(M); LP(M) is obtained by relaxing the integrality constraints on variables b_l^j and p_u^j. Since the number of ICMC configurations is important, LP(M) is initialized by a subset of possible artificial configurations. Then, the restricted master problem is solved until optimality. To check the optimality of the obtained solution within the original problem, it is required to check the existence of a variable λ_c with a *negative reduced cost*. If such a variable exists, it is added to the master problem and this latter is solved again. Otherwise, LP(M) is solved to optimality.

Hence, to solve the MIP(M) problem, we use a CG-based QoS-IaaS mapping algorithm, which proceeds as follows:

1. Relax the integrality of Data Center design variables as follows: $b_l^j \in \mathbb{R}, l \in L_d, j \in J_B$ and $p_u^j \in \mathbb{R}, u \in H_d, j \in J_U$.

2. Call procedure *Column_Generation()* to solve the resulting LP(M) to optimality,

3. Convert the design variables from continuous to integer values (b_l^j and $p_u^j \in \mathbb{N}$), while keeping the variables λ_c continuous. The obtained mixed ILP program is MIP(M).

4. Use the MILP CPLEX solver to solve the resulting MIP(M) program.

5. To calculate an integer solution, re-establish integrality constraint on variable λ_c and proceed with a branch-and-bound procedure using CPLEX package on selected columns in MIP(M) solution.

Procedure Column_Generation:

1. Solve the LP(M) master problem using CPLEX algorithm.

2. Solve the pricing problem.

3. Add the resulting column to the current master problem, and re-iterate with Steps 1 and 2 until no column can be found with a negative reduced cost. In such a case the master problem is solved to optimality.

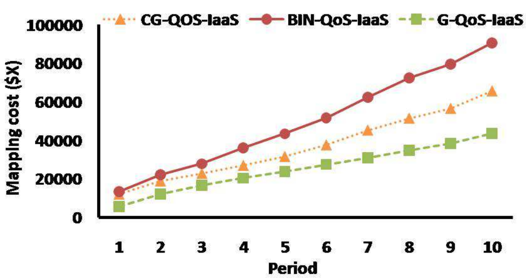
In the next section, we present some numerical results that show the efficiency of the proposed CG-based QoS IaaS resource allocation approach, compared to literature; the Bin packing [63] (BIN-QoS-IaaS), where computing and bandwidth requirements are mapped using a CPU Bin and bandwidth Bin, respectively, and the Greedy computing node mapping combined with a K-shortest path algorithm (G-QoS-IaaS) [64].

Numerical results

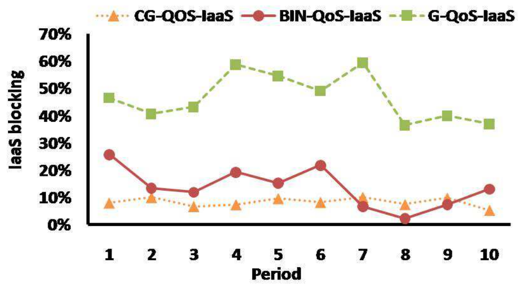
We consider a physical infrastructure of four edge data centers connected through the NSFNet topology [65]. The backbone network includes 14 nodes located at different cities in the United States. In each IaaS request, the number of virtual nodes is generated randomly according to a uniform distribution in the range [2,20]. The minimum connectivity degree is fixed to 2 links. QoS requirements of new IaaS requests are randomly generated from a uniform distribution among $|J_B| = 5$ QoS classes for IaaS nodes and among $|J_U| = 5$ QoS classes for IaaS links. Bandwidth and computing unit costs are expressed in terms of $\$X$, which represents the price of 1 Mb of bandwidth or 1 unit of computing capacity.

Figure 4.3(a) and Figure 4.3(b) plot, respectively, the cumulative IaaS mapping cost for the cloud provider and the blocking ratio of IaaS requests versus the allocation time periods. Furthermore, Figure 4.3(c) and Figure 4.3(d) show, respectively, the percentage of bandwidth utilization and substrate nodal CPU utilization versus the allocation time periods. In these figures, we compare the performance of our CG-QoS-IaaS model with the BIN-QoS-IaaS and G-QoS-IaaS benchmark models.

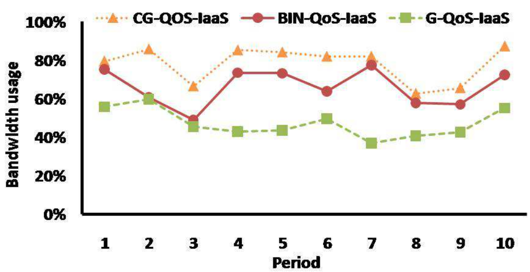
The results show that G-QoS-IaaS model provides the lowest mapping cost (the highest blocking ratio). It rejects 36% up to 59% of the requests; this includes the ones using QoS classes that require larger amounts of resources and therefore are more expensive. On the other hand, the Bin-IaaS approach accepts more requests but still present a high blocking ratio on some periods and also larger cumulative mapping cost. In this aspect, the proposed CG-QoS-IaaS model maintains a uniform, low blocking ratio through all time periods, while reducing effectively the mapping cost guaranteeing at the same time the satisfaction of requests' QoS requirements.



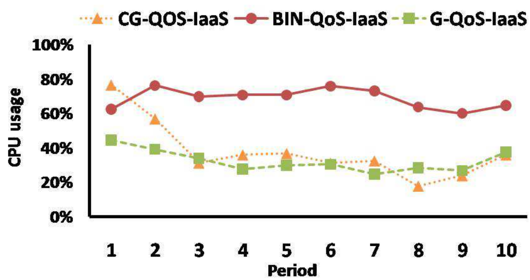
(a) IaaS mapping cost



(b) IaaS blocking ratio



(c) Bandwidth usage



(d) CPU usage

Figure 4.3: The IaaS mapping cost for the Cloud Provider, the blocking ratio of the IaaS requests, the bandwidth and the CPU usage versus the allocation time periods.

Moreover, the CG-QoS-IaaS model provides the highest bandwidth utilization; indeed, it provides on average an utilization of 78% of the networks' bandwidth resources through all the planning period of time, where Bin packing and Greedy mapping used an average of 66% and 47%, respectively. This is due to the fact that our model maintains a higher bandwidth utilization to deal with the entire users' requests of different classes of QoS. The contrary applies for the other two models, which showed a high rejection rate. Finally, it can be observed that the CG-QoS-IaaS model permits an average utilization of 38% of nodal CPU resources, while the Bin Packing and Greedy mapping approaches use on average the 68% and 32%, respectively. This trend is tightly related to the fact that the Greedy and Bin Packing approaches performed a sort of myopic mapping of hosting resources, with a lack of coordination among the requirements in terms of bandwidth and CPU usage, thus exhibiting a high blocking ratio.

Chapter 5

Summary of other works

In this chapter, I present a summary on a selection of additional research achievements I obtained in the past ten years on *distributed network design*, optimal *geographic content caching* in cellular networks and *energy storage control* in smart grids, which can be regarded as extensions (and variants) of the works presented in the previous chapters.

- The work on distributed network design was developed during my regular stays (in the period: 2008-2013) at the MAESTRO (now, NEO) team at INRIA Sophia Antipolis, where I collaborated with Dr. Konstantin Avrachenkov and Dr. Giovanni Neglia.

- The two research activities on geographic content caching and energy storage control were conducted with, respectively, Dr. Bartłomiej Błaszczyszyn and Dr. Ana Busic and her Ph.D. student I co-supervised (Dr. M.U. Hashmi), during my 2-year "delegation" in the DYOGENE team at INRIA Paris.

5.1 Network Design – A Game Theoretical Perspective

In many scenarios network design is not enforced by a central authority, but arises from the interactions of several self-interested agents. This is the case of the Internet, where connectivity is due to Autonomous Systems' choices, but also of overlay/virtual networks, where each user client can decide the set of connections to establish. Therefore, in [66, 67], we studied the network design problem from a game theoretic perspective and propose *socially*-aware network design games (the social aspect means that users are in part social, and contribute all together to minimize the network cost). Finally, we provided bounds on the Price of Anarchy – which represents the loss of efficiency as the ratio between the cost of a specific stable network and the cost of the optimal network – and other efficiency measures, and evaluated the performance of the proposed schemes in several network scenarios.

However, considering almost exclusively networks designed by selfish users can result in/lead to consistently suboptimal solutions. Therefore, in [68, 69], we addressed the network design issue using cooperative game theory, and we extended the Nash bargaining solution

(NBS) approach to the case of multiple players and give an explicit expression for users' cost allocations. We further provided a distributed algorithm for computing the Nash bargaining solution. Then, we compared the NBS to the Shapley value and the Nash equilibrium solution in several network scenarios, including real ISP topologies, showing its advantages and appealing properties in terms of cost allocation to users and computation time to obtain the solution.

5.2 Optimal Geographic Caching in Cellular Networks with Linear Content Coding

We stated and solved in [70][1] the problem of optimal geographic caching of content in cellular networks, where linear combinations of contents are stored in the caches of base stations. We considered a general content popularity distribution and a general distribution of the number of stations covering the typical location in the network. We looked for a policy of content caching maximizing the probability of serving the typical content request from the caches of covering stations. The problem has a special form of monotone sub-modular set function maximization. Using dynamic programming, we found a deterministic policy solving the problem. We also considered two natural greedy caching policies. We evaluated our policies considering two popular stochastic geometric coverage models: the Boolean and the Signal-to-Interference-and-Noise-Ratio models, assuming Zipf popularity distribution. Our numerical results show that the proposed deterministic policies are in general better than randomized policies considered in the literature, and can further improve the total hit probability in the moderately high coverage regime.

5.3 Optimal Control of Storage under Time Varying Electricity Prices

End users equipped with storage may exploit time variations in electricity prices to earn profit by doing energy arbitrage, i.e., buying energy when it is cheap and selling it when it is expensive. We proposed in [71][2] an algorithm to find an optimal solution of the energy arbitrage problem under given time varying electricity prices. Our algorithm is based on the discretization of optimal Lagrange multipliers of a convex problem and has a structure in which the optimal control decisions are independent of past or future prices beyond a certain time horizon. The proposed algorithm has a run time complexity of $O(N^2)$ in the worst case, where N denotes the time horizon. To show the effectiveness of the proposed algorithm, we compare its runtime performance with other algorithms used in MATLAB's constrained optimization solvers. Our algorithm is found to be at least ten times faster, and hence has the

[1]This work was conducted with Dr. Bartomiej Baszczyszyn from Inria and Ecole Normale Supérieure, Paris, France.

[2]This work was conducted with Dr. Ana Busic from Inria and Ecole Normale Supérieure.

potential to be used in real-time scenarios. Using the proposed algorithm, we also evaluated the benefits of performing energy arbitrage over an extended period of time for which price signals are available from some ISO's in USA and Europe.

Chapter 6

Conclusion and Future Perspectives

This last chapter presents the conclusions of this manuscript, and then outlines the perspectives I deem more promising, which constitute my research project for the next five years.

6.1 Conclusion

This manuscript presented the main research activities I carried out in the past ten years; it is structured into three main chapters (Chapter 2–Chapter 4), corresponding to three major research areas: (1) Wireless Body Area Networks, (2) Cognitive Radio Networks, and (3) Virtual Networks and Cloud Computing.

In **Chapter 2**, we investigated several optimization problems related to *planning* optimal, energy-efficient and cost-effective *Wireless Body Area Networks (WBANs)*, reliable *data delivery* and *routing in WBANs*, and *cross-technology interference mitigation in Body-to-Body Networks*. In particular, we introduced centralized optimization frameworks to address each of these problems, using (mixed) integer linear programming. Since solving the cross-technology interference mitigation problem may take a long computation time (several hours) to obtain the optimal solution in large BBN network instances, we further developed a set of efficient heuristics that build upon the sequential fixing technique, randomized rounding, and tabu search. Furthermore, we proposed a distributed, game theoretic approach for this latter problem, where each WBAN, which plays the role of a player in the interference mitigation game, aims at maximizing its own signal-to-interference ratio by selecting the best available channels (the best strategies) in the ISM band shared among all WBANs.

Chapter 3 focuses on the problem of *opportunistic and dynamic spectrum access in Cognitive Radio (CR) and TV White Space (TVWS) systems*. Since CR nodes and TVWS devices are geographically distributed and aim at maximizing their own utility *in a selfish manner*, a game theoretic approach constitutes a good candidate solution to address the distributed spectrum access problem in these networks. In this context, we first formulated and studied a spectrum access game, where players (CR nodes) choose the channels that maximize their utility. Then, we proposed a Stackelberg (leader-follower) game for modeling and solving the *joint pricing and network selection problem* in CRNs. In this problem, the leaders are the primary and secondary operators that set the prices for accessing their network, while the followers are the CRs that select the primary or the secondary network according to the cost function that they want to minimize. Finally, we introduced two types of TVWS spectrum management games, where the goal is to allocate the available TV channels to TVWS devices ensuring low interference among them.

Chapter 4 studies the *resource allocation problem* in two environments which are tightly related: *NFV (Network Function Virtualization)-based Networks* and *Cloud Computing*. We first proposed an optimization framework for congestion mitigation in NFV-based networks, using mathematical programming tools. The goal of the operator of the physical infrastructure is to minimize the total congestion and the worst (per link) congestion in the network. Then, we dealt with the congestion mitigation from a distributed point of view; each virtual operator aims at performing routing, while guaranteeing that its flow passes through a predefined set of nodes with required network functions. Finally, we focused on the resource allocation problem for Infrastructure as a Service (IaaS) in Cloud computing. We proposed an optimization approach for IaaS resource allocation, taking into account users' QoS requirements. This approach leverages the Column Generation technique, which allows us to drastically reduce the problem complexity.

Additional work was conducted in parallel, and was briefly presented in **Chapter 5**. This work is articulated around *distributed network design*, optimal *geographic caching in cellular networks* and *optimal storage control in smart grids*.

6.2 Future Perspectives – Research Project

In the continuity of the research activities I presented in this manuscript, I think that a promising research topic that deserves to be investigated is the resource allocation problem in next generation networks, which include the Internet of Things (IoT), as well as the access and the Core of mobile networks that leverage network function virtualization techniques. Hence, my research project for the next five years will be articulated around three main activities:

- joint routing and interference mitigation in next-generation networking scenarios;
- optimal resource allocation in (Cloud-based) radio access networks;
- optimal planning of next-generation mobile networks.

Context and position

Recent advances in networking, communications, computation, software, and hardware technologies have revolutionized the way *Humans*, *Smart Things*, and *Engineered Systems* interact and exchange information. The Internet of Things paradigm [72, 73, 74], which is one of the major contributors to this area, will fuel the realization of this new, globally interconnected world. Therefore, today's networks are becoming highly heterogeneous and need to interact with different recently emerging infrastructures, such as *Internet of Things*, *Cloud Computing* data centers and *Mobile Edge computing* facilities in order to provide users with seamless mobility, ubiquitous connectivity and remote data access. This phenomenon has further increased such networks complexity and incited infrastructure and service providers to implement novel mechanisms for efficiently managing, optimizing and orchestrating their physical/virtual resources in a flexible manner. It is in this context that *Virtualization* has attracted the attention of the research community and Industry.

Research goals: The main objective of my research project is to design and develop a novel and efficient resource optimization framework tailored for current and future networks, which build upon virtualization techniques (both at the *access* and at the *core* of the network) in order to reduce the operational and capital costs of the operators. More specifically, I will start by designing *centralized* resource optimization approaches using the most suitable tools from mathematical programming, auction theory and cooperative game theory. However, in large scale networks, which can be owned and operated by different parties, a *distributed* approach is more suitable, and hence in this case, I will design distributed approaches using concepts from non-cooperative game theory or adaptive local/distributed learning.

My research project will be logically structured into 3 interrelated activities. The first activity focuses on IoT, and more specifically on Body-to-Body area networks that provide healthcare applications and need to exchange information both *inside* the network as well as *outside*, for processing purposes, for example. In order to achieve fast communications and data exchange, necessary to such IoT networks, an efficient mobile infrastructure that can be dimensioned dynamically, and on-the-fly, is hence necessary; designing and carefully planning it, leveraging the concept of *virtualization* both at the access (Cloud-RAN concept) and in the core (Evolved Packet Core), is the focus of Activities 2 and 3, respectively. Indeed, these activities are tightly coupled since integrating flexible network optimization both in the access and core part of mobile networks is vital to provide all the necessary chain of services needed to serve the traffic offered to the network.

A reference networking scenario: An example is illustrated in Figure 6.1, where at the center we have a Body-to-Body (or Human-to-Human) Network (BBN). A BBN can be seen as a group of humans, equipped with wearable sensors/devices and smartphones, who desire to interact with each other and their surrounding environment, and want to exchange data in real-time. For example, wearable sensors can measure the physiological signals or the activity of the user and send such data to her/his smartphone for visualization or processing, or for forwarding to the Cloud when deep learning/decision making or intensive processing are necessary. Furthermore, sensors deployed in the environment (i.e., a smart home, a smart city ...) can collect data (i.e., traffic information) and send it to the user's smartphone, using wireless communication (WiFi, Bluetooth or ZigBee technology) or potentially through the Internet, and then the smartphone can be used to share such data in real-time with other users within the same BBN (in the same geographical area).

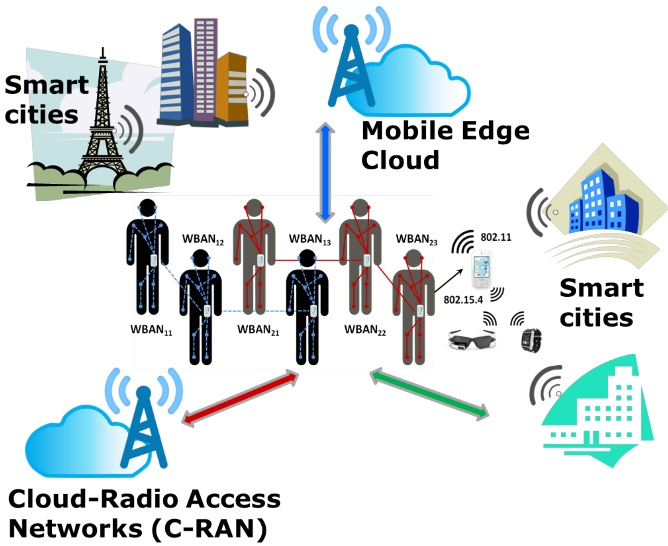


Figure 6.1: An example of a networking scenario, which includes IoT, Cloud-Radio Access Networks (C-RAN) and Mobile Edge Computing technologies.

Data processing in the Cloud and data exchange in real-time among BBN mobile users represent two challenging tasks for mobile operators, which need to upgrade their infrastructure in order to deliver on-the-fly high bandwidth, with low latency. It is in this context that virtualization has gained momentum in mobile networks infrastructure, and virtualization techniques have been deployed at the access network with the emergence of Cloud-Radio Access Networks (C-RAN) [75, 76], and at the core of the mobile network with vEPC (Virtual Evolved Packet Core) [77, 78, 79]. Virtualization indeed allows mobile operators to dimension and orchestrate the mobile infrastructure resources on-the-fly in a flexible manner, and guarantee a low OPEX and CAPEX costs for the operator and end-to-end QoS for end-users. For this reason, in Figure 6.1 we show a BBN that needs to interact with sensors in its surrounding environment (smart cities) and at the same time with the Cloud-RAN and Mobile Edge computing facilities. The vEPC is in the backhaul of the mobile operator infrastructure and hence it is not shown on the figure.

Open questions: In this networking scenario, several challenging questions arise at different levels, and some of these questions, especially those situated at my expertise level (i.e., networking and physical levels, as well as network planning and resource optimization), will be tackled and solved within my research project:

1. How to perform optimal data delivery/data routing taking into account the interference mitigation issue [12, 14, 15] in a highly dynamic scenario (in a BBN), where people can join and leave the network randomly? Which solutions could be devised? The routing strategy depends on the situation: 1) We may need to route data end-to-end,

via the access radio network and then through the mobile core network or 2) we may use another communication technology (i.e., in hotspots), and forward data from one BBN user to another until data reaches the destination, like some routing protocols do in mobile Ad Hoc networks.

2. What kind of challenges will be faced by augmenting the BBN scenario with smart environment services, a Cloud RAN and Cloud computing facilities at the mobile edge network? How to efficiently and dynamically allocate resources at the access/edge and core parts of the mobile network?

The central goal of my research project is to answer the above questions by designing and developing an efficient optimization framework tailored for such challenging networking scenarios. To deal with uncertainty and dynamicity, which are intrinsic to these latter, I plan to use *(Stochastic) Mathematical Programming* tools. Furthermore, to address large-scale and distributed scenario cases, *Game Theory* and *Learning algorithms* will be used to help devices learn, self-adapt and self-organize in order to perform efficiently data routing and interference mitigation between each other.

The main objectives of my research project as well as the strategic and technological ideas to concretely address each of them are detailed hereafter.

6.2.1 Joint routing and interference mitigation in the future/next-generation networking scenarios

This research activity is structured into the following three sub-activities:

(1A) Joint routing and interference mitigation in Body-to-Body networks

The main goal of this first activity is to develop and integrate an interference mitigation model along with a routing mechanism into a cross-layer optimization approach for the *intra-BBN communication scenario*, building upon and extending our previous works [12, 14, 15]. Since sensors and wireless/wearable devices should, on one hand, exhibit low-power operations and, on the other hand, share the same wireless medium, in this research activity I will first define novel and efficient routing metrics that take into account the wireless devices activities at the PHY-MAC layers, and then optimize the wireless communication link selection/scheduling by using mathematical tools from Integer Programming and Game Theory, thus guaranteeing low interference between devices.

(1B) BBN Cloudification in a Smart environment

The goal of this activity is to extend the basic scenario of BBN to a more general one, which includes cloud computing facilities (storage, computing, processing ...), due to the emergence of Edge mobile computing and Cloud-RAN, and interaction, through wireless communications links, with the surrounding environment of a smart city with smart sensors/actuators, smart buildings, smart transportation systems that could provide user-profile-based services. This activity is the basis for **Activity 1C**, and will describe, define and model from a technical and strategical point of view the different relationships and interactions between the different actors (wearable and wireless devices, the Edge Cloud, Smartphones accessing the Cloud-RAN) involved in the networking scenario shown in Figure 6.1.

(1C) Optimal resource allocation and management in the global network scenario

This activity is central for the project and poses interdisciplinary challenges related to the coexistence of different key technologies, involved in the considered network scenario of Figure 6.1, which are:

1. WiFi/ZigBee/Bluetooth wireless technologies used by RFID sensors, wearable devices, smartphones radio interfaces, WiFi access points in hotspots (i.e., airports, railway stations);

2. the Cloud computing technology offering to BBN users ubiquitous data access with low latency and computing services [25, 80].

In addition to the technology coexistence issues, I plan to consider the mobility of users who ask for ubiquitous services, and anywhere/anytime connectivity despite the fact that they are mobile.

To realize the goals of this activity, I will first extend the solutions developed in **Activity (1A)** to the more general networking scenario involving the mobile and cloud environments. Adopting a centralized approach may have critical limitations in terms of overhead and computation time, and therefore as an alternative, a distributed approach will be carefully designed and developed in this general context, providing us a good tradeoff between complexity/overhead and optimality/quality of the solutions. A natural, final step of **Activity 1** will be dedicated to implementation and validation in order to provide useful proposals for the research community and industry. This step is discussed in more details in the Methodology section (Section 6.2.4).

6.2.2 Resource Allocation Optimization in Cloud-based Radio Access Networks (C-RAN)

C-RAN, sometimes referred to as Centralized-RAN or Virtualized-RAN, is a novel mobile network architecture which aims at addressing a number of challenges mobile operators are facing today, when trying to support ever growing end-users' needs [75, 76]. These include support to Machine-to-Machine (M2M) communications, which are growing considerably in terms of traffic volume due to the success of sensors and their applications. End users have thus stringent constraints related to end-to-end QoS guarantees, real-time data exchange, storage and computing/processing services.

The main idea behind C-RAN is to pool the Baseband Units (BBUs) from multiple base stations into a centralized BBU Pool for statistical multiplexing gain, while shifting the burden to the high-speed wireline transmission of In-phase and Quadrature (IQ) data. C-RAN enables energy efficient network operation, cost savings on baseband resources and improvement of the network capacity by performing load balancing and cooperative processing of signals originating from several base stations [75]. Figure 6.2 illustrates an example scenario of a C-RAN, where we have a set of users asking for blocks of resources to the Mobile Virtual Network Operators (MVNOs), which in turn, based on users' requests, ask for resources to the Cloud operator. Therefore, in this research activity, I will focus on the following optimization problems for the C-RAN context:

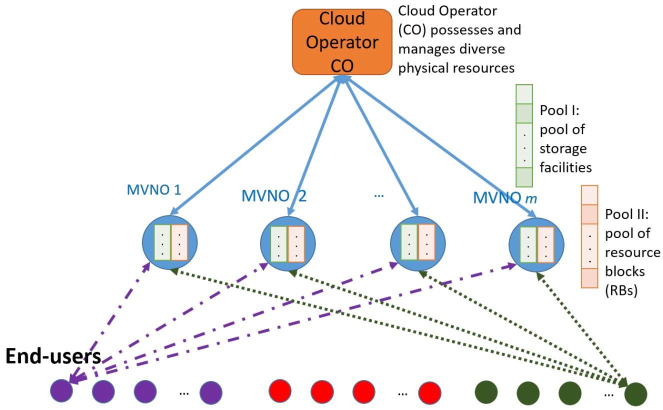


Figure 6.2: An example of a C-RAN, which includes a set of mobile users, several Mobile Virtual Network Operators (MVNOs) and a Cloud operator.

Auction-based Resource Allocation

In general, the C-RAN scenario, as illustrated in Figure 6.2, consists of three main actors: the mobile users, the Mobile Virtual Network Operators (MVNOs) and the Cloud Operator (CO) who owns the physical resources. Mobile users can ask the MVNOs for various types of resources (radio, processing or computation resources) and MVNOs in turn, based on the underlying users' requests, ask the CO for the needed resources. It is easy to see that the resource allocation approach can be decomposed into two-levels: *low-level* – between mobile users and MVNOs – and *high-level* – between MVNOs and the CO. Given the hierarchical structure of the considered networking scenario, *Auction Theory* [81, 82] represents a very good mathematical tool to model and solve the low-level and the high-level resource allocation problem. In fact, auctions are economically well-adapted in markets where sellers (or auctioneers) want to maximize their revenues and technically, can significantly increase the efficiency of the resource utilization. We can easily imagine that a *low-level auction* takes place between users and MVNOs and a *high-level auction* between MVNOs and the CO.

In the considered scenario, each mobile user will submit her/his bid to one or more MVNOs, and the bid contains for instance the number of blocks of spectrum, the amount of storage, a time interval for computation (i.e., starting and ending time), and at last the price the user is willing to pay. Each MVNO in turn bids the total amounts of resources it needs, based on users' demands, and the price it is willing to pay to the C-RAN operator. The MVNO and the C-RAN operator naturally aim at maximizing their revenues.

It is worth noting that the consideration of various types of resources (more than one pool of resources at the CO) can significantly complicate the problem. Therefore, as a starting point, I will study, model and solve a special case considering only one type of resources (i.e., the number of spectrum blocks) requested by users. Then, an extension, with at least two different types of resources, will be investigated. Finally, this research activity will include a theoretical study to demonstrate that the auction mechanisms satisfy a set of desirable economical properties: individual rationality, efficiency, incentive compatibility, and budget balance.

Optimal Resource Matching

Reconsidering the networking scenario in Figure 6.2, the wireless resource management problem can be alternatively posed as a *matching problem* between resources and users at the low and high levels. According to the survey in [83], entitled *Matching Theory for Future Wireless Networks: Fundamentals and Applications*, the resources can be of different abstraction levels, representing base stations, time-frequency chunks, power, or others. Users can be devices, stations or smartphone applications. Each user and resource has a *quota* that defines the maximum number of players with which it can be matched. The main goal of matching is to *optimally match* resources and users, given their individual, often different objectives and learned information. Matching theory has been considered in different wireless network contexts – cognitive radio networks [84], heterogeneous small cell-based networks [85, 86] and Device-to-Device communications [87], and the obtained results confirm that it is indeed an effective method to address challenging wireless resource allocation/management problems. Therefore, in this research activity, I plan to use matching theory to model and solve the resource allocation problem between users and MVNOs in the low-level and between MVNOs and the CO in the higher one. Using such method in the C-RAN context is indeed exciting and could provide efficient solutions; however, it is worth noting that I expect that a resource allocation approach based on matching theory could be complex, and approximation algorithms will hence be developed, giving us a good compromise between optimality (performance) and complexity.

Radio Resource Calendaring

Bandwidth calendaring (termed as calendering for brevity) refers to the possibility of shifting some bulk data transfers, typically of large size with less stringent real-time constraints, to be scheduled on future occasions, when the network is less congested [88, 89]. One such example is an update for a popular application which could be pushed towards user devices at night. It exploits the knowledge, or estimation, of future arrivals to pack current and future demands in an optimal way in the network.

Calendaring gained momentum in transferring large, inter-datacenter traffic through Wide-Area Networks (WAN) which constitute expensive and business-critical resources [90, 91]. It has been made possible thanks to Software-Defined Networking (SDN), which allows for logically centralized control of resources [92].

The main idea behind resource calendaring is to (re-)schedule some flexible connections (those without hard or real-time constraints) later in time thus utilizing more efficiently the available bandwidth and reducing both the call blocking rate and interference. For this reason, in this activity, I will study the calendaring problem in the C-RAN context, which, as a centrally controlled entity, is a natural candidate for applying such a technique. I plan to consider two broad categories of user flows: *shiftable* and *non-shiftable*, but at the same time I will model the whole range between these two extreme users' preferences in terms of the experienced delay before being served. To this aim, the first step will be to formulate the problem through an Integer Linear Program (ILP), to perform the optimal calendaring of users' connections while maximizing some pertinent metric like, for example, the social welfare. The second step will be to propose heuristics approaches, starting from greedy algorithms. A thorough simulation campaign will be needed to test our models and algorithms in several case studies, varying several key system parameters to measure the effectiveness of our proposed approach and models to improve the performance of C-RAN systems.

6.2.3 Optimal Planning of Next-generation Mobile Networks

As mentioned earlier in my research project, mobile traffic from smartphones and portable devices, along with Device-to-Device (D2D) or M2M applications, are creating huge volumes of mobile data traffic. The signaling overhead necessary for handling these diverse applications, which is even more critical than the capacity needs, requires a radical transformation of the actual mobile network architecture (i.e., the Evolved Packet Core of LTE network). This has encouraged mobile operators to leverage virtualization techniques (i.e., Network Function Virtualization (NFV) and Software Defined Networking (SDN)) in their network infrastructure, promoting the new paradigm of *virtualized Evolved Packet Core (vEPC)* [77, 78, 79]. vEPC combines diverse packet core functions and provides those network functions as virtualized services, in order to scale capacity on-the-fly and introduce new services in a fast and cost-effective way according to mobile data traffic dynamics. For example, M-CORD [93] is an open source reference solution for carriers deploying 5G mobile wireless networks. This solution is built on SDN, NFV and cloud technologies, and includes both virtualization of RAN functions and a vEPC to enable mobile edge applications and innovative services. Moreover, the Telecom Infra Project [94] includes a set of groups, which were created to support three strategic network areas: Access, Backhaul and Core Management.

A key feature of *mobile core network function virtualization* is its ability to provide intelligent resource management and network orchestration by dynamically scaling packet core functions to adapt the system to actual needs, in a flexible way. Virtualization allows mobile operators to get rid of building out a packet core infrastructure dimensioned for peak capacity and to elastically create or take down resources on-the-fly. It also reduces both CAPEX and OPEX, giving operators the possibility of replacing purpose-built hardware with standardized computing and storage platforms while, at the same time, helping the packet core infrastructure run more efficiently, reducing the network footprint, and simplifying network configuration and maintenance.

Deploying virtualization techniques in core mobile networks in order to increase network flexibility and performance while reducing services deployment cost has been investigated by few recent works [77, 78, 79]. Differently from these related works, this research activity will provide a clear representation of the structure of the underlying computational infrastructure as well as a detailed description and modeling of the interrelations between the different elements (the mobile core functions) composing the EPC. These issues were completely or in part ignored in the previous works.

More specifically, I will first propose novel optimization models for optimal planning of vEPC that consider time-varying traffic patterns based on real traces. These models will optimize the placement of virtual network functions in data centers and their interconnections, by satisfying a some order while interconnecting these functions. I will answer to questions like: Where is it better to instantiate network functions? How to interconnect them? Furthermore, a set of constraints will be proposed in order to define the end-to-end delay, the DC maximum capacity and processing delay.

This optimization problem is very challenging and complex. Therefore, my strategy will be to focus on one or maximum two types of user applications as a starting point to model and formulate the optimal vEPC planning problem. To obtain good solutions in a short computation time, I will develop approximate algorithms which scale in a polynomial time in case of large scenarios including a very large number of mobiles users. Then, the proposed models and algorithms will be extended to scenarios with diverse types and a large number of applications, along with the required network functionalities. Finally, the optimal vEPC planning problem will be addressed and solved not only in its off-line version, but potentially in the on-line context.

6.2.4 Methodology

To realize my aforementioned objectives, I plan to use the most adequate optimization and mathematical tools, such as Mixed Integer Linear Programming, Stochastic Programming and Game Theory, to model and formulate on one hand the joint routing and interference mitigation problems of BBN-centric IoT scenarios and on the other hand, the resource optimization problems in the Cloud-RAN and the mobile core network. I will then perform numerical analysis and simulations in order to study the sensitivity of the proposed models and algorithms to the system parameters and evaluate them.

Methodologically, this project addresses a topic at the nexus of IoT, Sensor Networking, Virtualization and Cloud computing, by using mathematical tools in stochastic optimization, game theory, distributed learning, algorithm design and analysis. Optimization techniques (combinatory optimization) will be applied to solve the formulated optimization problems and analyze the structural properties of the solutions and the correspondent tradeoffs. Efficient heuristics will be proposed to scale up to realistic network sizes, thus studying the performance limit. Dynamical system analysis and distributed learning methods are further employed in the investigation of the convergence and stability properties of the proposed distributed algorithms for online sensor network reconfiguration. Finally, game theory (along with auction and matching theory) will play an essential role in the design of efficient and robust distributed algorithms and protocols, and their performance characterization and analysis. I have already used these tools in some of my previous works like [12, 18, 20, 29, 31, 15] with success, and I plan to further deepen into such fundamental knowledge to tackle the challenges proposed in this project.

The mathematical framework developed for each of the objectives should be followed by a practical design of protocols and implementation plans to ensure deploy ability and maximal diffusion in standards and real-life networks. For this reason, an additional, interesting step will be to validate our solutions on *experimentation platforms* for IoT (to this aim, I plan to use platforms like the FIT IoT-Lab - https://www.iot-lab.info/, which is a very large scale open WSN testbed), and recently available platforms for 5G mobile networks based on NFV, SDN and Cloud technologies [93, 94] (M-CORD and TIP Community Labs).

To the best of my knowledge, very few research projects convey a good tradeoff between robust mathematical foundations, and experimentation/prototyping like this project does.

Appendix A

List of Publications

International Peer-Reviewed ("avec comité de lecture") Journals

1. M. Morcos[1], T. Chahed, L. Chen, J. ELIAS, F. Martignon, A Two-level Auction for Resource Allocation in Multi-tenant C-RAN, *accepted for publication in Elsevier Computer Networks*, February 2018.

2. A. Jarray, A. Karmouch, J. Salazar, J. ELIAS, A. Mehaoua, F. Zaman, Efficient resource allocation and dimensioning of media edge clouds infrastructure, *Journal of Cloud Computing: Advances, Systems and Applications*, vol. 6, issue 1, 27 pages, December 2017.

3. J. ELIAS, F. Martignon, L. Chen, M. Krunz, Distributed Spectrum Management in TV White Space Networks, *IEEE Transactions on Vehicular Technology*, vol. 66, issue 5, pages 4161–4172, 3 August 2016.

4. M. Mangili, J. ELIAS, F. Martignon, A. Capone, Optimal Planning of Virtual Content Delivery Networks under Uncertain Traffic Demands, *Elsevier Computer Networks*, vol. 106, pages 186–195, 4 September 2016.

5. H.B. Elhadj, J. ELIAS, L. Chaari, L. Kamoun, Multi Attribute Decision Making Handover Algorithm for Wireless Body Area Networks,*Elsevier Computer Communications*, vol. 81, pages 97–108, 1 May 2016.

6. A. Meharouech, J. ELIAS, A. Mehaoua, A Two-Stage Game Theoretical Approach for Interference Mitigation in Body-to-Body Networks, *Elsevier Computer Networks*, vol. 95, pages 15–34, 11 February 2016.

7. H.B. Elhadj, J. ELIAS, L. Chaari, L. Kamoun, A Priority based Cross Layer Routing Protocol for healthcare applications, *Elsevier Ad Hoc Networks*, vol. 42, pages 1–18, 15 May 2016.

8. J. ELIAS, F. Martignon, S. Paris, J. Wang, Efficient Orchestration Mechanisms for Congestion Mitigation in NFV: Models and Algorithms, *IEEE Transactions on Services Computing*, 5 November 2015.

[1]I underline in this list of publications the name of the Ph.D. students I co-supervised in the last ten years.

9. K. Avrachenkov, J. ELIAS, F. Martignon, G. Neglia, L. Petrosyan, Cooperative Network Design: a Nash bargaining solution approach, *Elsevier Computer Networks*, vol. 83, pages 265–279, 4 June 2015.

10. J. ELIAS, S. Paris, M. Krunz, Cross Technology Interference Mitigation in Body Area Networks: an Optimization Approach, *IEEE Transactions on Vehicular Technology*, September 2014.

11. J. ELIAS, Optimal design of energy-efficient and cost-effective Wireless Body Area Networks, *Elsevier Ad Hoc Networks*, vol. 13, pages 560–574, February 2014.

12. J. ELIAS, F. Martignon, L. Chen, E. Altman, Joint Operator Pricing and Network Selection Game in Cognitive Radio Networks: Equilibrium, System Dynamics and Price of Anarchy, *IEEE Transactions on Vehicular Technology*, vol. 62, issue 9, pages 1–14, November 2013.

13. J. ELIAS, F. Martignon, G. Carello, Very Large-Scale Neighborhood Search Algorithms for the Design of Service Overlay Networks, *Telecommunication Systems*, vol. 49, no. 4, pages 391–408, 2012.

14. J. ELIAS, F. Martignon, A. Capone, E. Altman, Non-Cooperative Spectrum Access in Cognitive Radio Networks: a Game Theoretical Model, *selected best papers from WiOpt 2010, Elsevier Computer Networks*, vol. 55, no. 17, pages 3832–3846, December 2011.

15. J. ELIAS, F. Martignon, K. Avrachenkov, G. Neglia, A Game Theoretic Analysis of Network Design with Socially-Aware Users, *Elsevier Computer Networks*, vol. 55, no. 1, pages 106–118, January 2011.

16. A Capone, J. ELIAS, F. Martignon, Routing and Resource Optimization in Service Overlay Networks, *Elsevier Computer Networks*, vol. 53, no. 2, pages 180–190, February 2009.

17. A Capone, J. ELIAS, F. Martignon, Models and Algorithms for the Design of Service Overlay Networks, *IEEE Transactions on Network and Service Management*, vol. 5, no. 3, pages 143–156, September 2008.

18. J. ELIAS, F. Martignon, A. Capone, G. Pujolle, A New Approach to Dynamic Bandwidth Allocation in Quality of Service Networks: Performance and Bounds, *Elsevier Computer Networks*, vol. 51, no. 10, pages 2833–2853, 11 July 2007.

19. J. ELIAS, F. Martignon, A. Capone, G. Pujolle, Distributed Algorithms for Dynamic Bandwidth Provisioning in Communication Networks, *Journal of Communications (JCM)*, vol. 1, no. 7, pages 47–56, November-December 2006.

International Peer-Reviewed Conferences

1. J. ELIAS, F. Martignon, M. Mangili, A. Capone, Optimal Planning of Virtual Mobile Networks, *accepted for publication in IEEE WCNC 2018*, Barcelona, Spain, 15-18 April, 2018.

2. J. ELIAS, F. Martignon, M. Morcos, L. Chen, T. Chahed, Radio Resource Calendaring in Cloud-based Radio Access Networks, *accepted for publication in the 10th Wireless Days Conference*, Dubai, April 2018.

3. M.U. Hashmi, A. Mukhopadhyay, A. Busic, J. ELIAS, Optimal Control of Storage under Time Varying Electricity Prices, *in Proc. of IEEE International Conference on Smart Grid Communications (SmartGridComm): Control and Operation of Responsive Grids symposium*, 21 July 2017.

4. J. ELIAS, B. Blaszczyszyn, Optimal geographic caching in cellular networks with linear content coding, *in the 15th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt 2017): The 2nd Content Caching and Delivery in Wireless Networks Workshop (CCDWN)*, Paris, France, 15-19 May 2017.

5. A. Meharouech, J. ELIAS, A. Mehaoua, Joint Epidemic Control and Routing in Mass Gathering Areas using Body-to-Body Networks, *in the 13th International Wireless Communications and Mobile Computing Conference (IWCMC 2017): e-Health Symposium*, Valencia, Spain, 26-30 June, 2017.

6. M. Morcos, T. Chahed, L. Chen, J. ELIAS, F. Martignon, A Two-level Auction for C-RAN Resource Allocation, *ICC 2017: International workshop on the main trends in 5G networks (MT5Gnet)*, Paris, France, 21-25 May 2017.

7. L. Lahlou, A. Meharouech, J. ELIAS, A. Mehaoua, MAC-Network Cross-Layer Energy Optimization model for Wireless Body Area Networks, *Joint 16th CFIP & 12th NOTERE*, Paris, France, July 2015.

8. A. Meharouech, J. ELIAS, A. Mehaoua, Future Body-to-Body Networks for Ubiquitous Healthcare: A Survey, Taxonomy and Challenges, *Ubi-HealthTech 2015*, Beijing, China, 28-30 May 2015.

9. J. ELIAS, M. Krunz, Distributed Spectrum Management in TV White Space Cognitive Radio Networks, *in Proceedings of IFIP Networking 2015*, Toulouse, France, May 2015.

10. A. Meharouech, J. ELIAS, S. Paris, A. Mehaoua, A Game Theoretical Approach for Interference Mitigation in Body-to-Body Networks, *IEEE ICC'15 - Workshop on ICT-enabled services and technologies for eHealth and Ambient Assisted Living*, London, UK, June 2015.

11. A. Jarray, J. Salazar, A. Karmouch, J. ELIAS, A. Mehaoua, QoS-based Cloud Resources Partitioning Aware Networked Edge Datacenters, *IFIP/IEEE IM 2015*, Ottawa, Canada, May 2015.

12. J. ELIAS, F. Martignon, S. Paris, J. Wang, Optimization Models for Congestion Mitigation in Virtual Networks, *in Proceedings of the 22nd IEEE International Conference on Network Protocols (ICNP 2014)*, Concise Papers Track (acceptance rate: 18.9%, 15 papers out of 79 submissions).

13. A. Meharouech, J. ELIAS, S. Paris, A. Mehaoua, Socially-Aware Interference Mitigation Game in Body-to-Body Networks, *in Proceedings of the International Conference on NETwork Games COntrol and oPtimization 2014 (NETGCOOP 2014)*, short paper, Trento, Italy, October 29-31, 2014.

14. A. Jarray, J. Salazar, A. Karmouch, J. ELIAS, A. Mehaoua, Column Generation based-Approach for IaaS Aware Networked Edge Data-Centers, *in Proceedings of IEEE Globecom 2014 Workshop - The 2nd International Workshop on Cloud Computing Systems, Networks, and Applications (CCSNA)*, Austin, Texas, December 2014.

15. J. ELIAS, A. Jarray, J. Salazar, A. Karmouch, A. Mehaoua, A Reliable Design of Wireless Body Area Networks, *in Proceedings of IEEE GLOBECOM 2013*, Atlanta, USA, December 2013.

16. S. Paris, J. ELIAS, A. Mehaoua, Cross Technology Interference Mitigation in Body-to-Body Area Networks, *in Proceedings of IEEE WoWMoM 2013*, Madrid, Spain, June 4-7, 2013.

17. J. ELIAS, F. Martignon, E. Altman, Joint Pricing and Cognitive Radio Network Selection: a Game Theoretical Approach, *in Proceedings of WiOpt 2012*, Paderborn, Germany, May 2012.

18. J. ELIAS, A. Mehaoua, Energy-aware Topology Design for Wireless Body Area Networks, *in Proceedings of IEEE ICC 2012*, Ottawa, Canada, June 2012 (79 citations).

19. K. Avrachenkov, J. ELIAS, F. Martignon, G. Neglia, L. Petrosyan, A Nash bargaining solution for Cooperative Network Formation Games, *in Proceedings of Networking 2011*, Valencia, Spain, May 2011.

20. J. ELIAS, F. Martignon, A. Capone, E. Altman, Competitive Interference-aware Spectrum Access in Cognitive Radio Networks, *in Proc. of the 8th Intl. Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks, WiOpt 2010*, Avignon, France, June 2010.

21. J. ELIAS, F. Martignon, Joint Spectrum Access and Pricing in Cognitive Radio Networks with Elastic Traffic, *in IEEE ICC 2010*, Cape Town, South Africa, May 2010.

22. J. ELIAS, F. Martignon, Joint QoS Routing and Dynamic Capacity Dimensioning with Elastic Traffic: A Game Theoretical Perspective, *in IEEE International Conference on Communications, ICC 2010*, Cape Town, South Africa, May 2010.

23. J. ELIAS, F. Martignon, K. Avrachenkov, G. Neglia, Socially-Aware Network Design Games, *in Proceedings of the 29th IEEE Conference on Computer Communications (INFOCOM 2010)*, March 2010, San Diego, CA, USA.

24. E. Altman, J. ELIAS, F. Martignon, A Game Theoretic Framework for joint Routing and Pricing in Networks with Elastic Demands, *in Proceedings of the 4th International Conference on Performance Evaluation Methodologies and Tools (VALUETOOLS 2009)*, October 2009, Pisa, Italy.

25. A. Capone, J. ELIAS, F. Martignon, Optimal Design of Service Overlay Networks, *in Proceedings of the Fourth International Telecommunication Networking Workshop on QoS in Multiservice IP Networks, IT-NEWS 2008*, Venice, Italy, February 2008.

26. J. ELIAS, F. Martignon, A. Capone, An Efficient Dynamic Bandwidth Allocation Algorithm for Quality of Service Networks, *in Autonomic Networking 2006 (INTELLCOMM 2006)*, Paris, France, 27-29 September 2006, *also published in Springer Lecture Notes in Computer Science*, Volume #4195, pp. 132–145 (acceptance rate: 25%).

27. A. Capone, J. ELIAS, F. Martignon, G. Pujolle, Dynamic Resource Allocation in Communication Networks, *in Networking 2006*, Coimbra, Portugal, 15-19 May 2006, *also published in Springer Lecture Notes in Computer Science*, Volume #3976, pp. 892–903 (acceptance rate: 20%).

28. A. Capone, J. ELIAS, F. Martignon, G. Pujolle, Dynamic Resource Allocation in Quality of Service Networks, *Springer Lecture Notes in Computer Science*, Volume #3883, pp. 184–19, 2006.

29. A. Capone, J. ELIAS, F. Martignon, G. Pujolle, Distributed Dynamic Bandwidth Provisioning in Quality of Service Networks, *in Proceedings of the Third EuroNGI Workshop on QoS and Traffic Control*, Ecole Normale Supérieure (ENS), Paris, France, December 7-9 2005.

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1. J. ELIAS, M. Mangili, F. Martignon, A. Capone, Stochastic Optimization Models for Virtual Content Delivery Network Planning, *ROADEF 2016*, February 11, 2016.

2. J. ELIAS, F. Martignon, G. Carello, Very Large-Scale Neighborhood Search Algorithms for the Design of Service Overlay Networks, *Italian Networking Workshop*, Cortina d'Ampezzo, Italy, January 2009.

3. J. ELIAS, F. Martignon, A. Capone, G. Pujolle, Dynamic Bandwidth Allocation in Communication Networks, *Italian Networking Workshop*, Bardonecchia, Italy, January 2007.

4. J. ELIAS, D. Gaiti, Contrle de MPLS par l'utilisation des Systèmes Multiagents, *DNAC-PARIS'04*, Paris, France, November-December 2004.

5. J. ELIAS, D. Gati, G. Pujolle, Optimisation du Protocole MPLS par l'utilisation des Systèmes Multiagents, *in Proceedings of 6èmes Journées Doctorales Informatique et Réseau (JDIR'04)*, Lannion, France Télécom R&D, France, 2–4 November 2004.

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