ALTERNATIVE SPECTRUM TRADING ARCHITECTURES IN COGNITIVE RADIO NETWORKS: SPECTRUM EXCHANGE, CRM, STRICT POWER CONTROL

by

Gülfem IŞIKLAR ALPTEKİN

B.S., in Computer Engineering, Galatasaray University, 2001

M.S., in Industrial Engineering, Galatasaray University, 2003

Submitted to the Institute for Graduate Studies in
Science and Engineering in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy

Graduate Program in Computer Engineering

Boğaziçi University

2010

ACKNOWLEDGMENTS

I would like to express my gratitude to my advisor Assist. Prof. Ayşe Bener, whose expertise, understanding and guidance throughout my study in Boğaziçi University added considerably to my experience. I appreciate her vast knowledge and skill in many areas, especially her immense help in directing and influencing my work, as well as in my vision in life. I wish to thank Prof. Cem Ersoy for his support and insightful and constructive comments both professionally and personally. I would also like to thank the other members of my committee, Prof. Taner Bilgiç, Prof. Ünal Zenginobuz and Assoc. Prof. Orhan Feyzioğlu, for the valuable time and advices they have shared on my research. I am grateful to all of them for accepting to participate in my progress and defense committee. Finally, I owe great thanks to Assoc. Prof. Tuna Tuğcu, who has considerable contributions to the dissertation in terms of technical feedbacks.

I would also like to thank my family for the support they provided me through my entire life and in particular, I must acknowledge my husband and best friend, Emre, without whose love, encouragement and editing assistance, I would not have finished this thesis.

ABSTRACT

ALTERNATIVE SPECTRUM TRADING ARCHITECTURES IN COGNITIVE RADIO NETWORKS: SPECTRUM EXCHANGE, CRM, STRICT POWER CONTROL

The underutilization of spectrum coupled with developments in network technologies has prompted a number of proposals for managing spectrum. Dynamic spectrum access radio technology, which is based on cognitive radio technology, promises to increase spectrum sharing and thus overcome the lack of available spectrum for new communication services. It allows unlicensed secondary systems to share the spectrum with the licensed systems. In this dissertation, different architectures are investigated in a cognitive radio environment. The considered network is assumed to consist of multiple primary service providers which have some unutilized bandwidth, and multiple secondary users that require bandwidth. Secondary users are assumed to pay the primary service providers for short term usage of their available spectrum bands; which is referred as the spectrum trading. The proposed architectures all aim at establishing a framework where each type of users satisfies with the services. As each new entrant secondary user creates interference on the incumbent users, controlling the power emission in a cognitive radio network is crucial in spectrum trading. Furthermore, proposed architectures examine the unit spectrum prices that primary service providers set in the multiple-seller and multiple-buyer environment.

Modeling the competitive relationships among network elements as games ensures analyzing all elements’ behaviors and actions in a formalized way. The existence of various network elements that want to maximize its own profits makes the problem very complex, with usually conflicting objective functions. Therefore, the proposed pricing models have their basis on the game theory in order to deal with the severe competition in spectrum trading markets.

ÖZET

BİLİŞSEL AĞLAR İÇİN ÖNERİLMİŞ FARKLI SPEKTRUM TİCARETİ MİMARİLERİ: SPEKTRUM DEĞİŞİMİ, MÜŞTERİ İLİŞKİLERİ YÖNETİMİ (MİY), KATI GÜÇ GÖZETİMİ

Kablosuz ağlar için geliştirilen teknolojilerin özellikleri değişiklik gösterse de, hepsi kablosuz iletişim temellidir ve hepsi aynı frekans spektrumunu kullanırlar. Frekans spektrumu, tüm bu teknolojiler arasında düzgün, adil ve etkin bir biçimde paylaştırılmalıdır. Her bir teknolojiye ait donanım, veri aktarımı için aynı ortamı kullandıkları için, birbirleri üzerinde girişim yaratmaktadırlar. Dolayısıyla, spektrum yönetiminin vazgeçilmez bir bileşeni güç yönetimi olmalıdır. Ayrıca zaman içinde yapılan ölçüm çalışmalarıyla, spektrum kullanımının hiç etkin olmadığı görülmüştür.

Bu araştırmada, bu sorunlara çözüm bulmayı hedeflenerek, bilişsel ağlar için farklı mimariler önerilmiştir. Araştırmanın ana amacı, spektrum ticareti pazarında, her tip kullanıcının hem bant genişliği, hem de kalite seviyesiyle ilgili beklentilerini karşılayabilecek bir altyapı ortaya koymaktır. Ayrıca, birim spektrum fiyatlarının belirlenmesi de, bilişsel ağlar için önemli bir problemdir. Ağda iletişim yapan her bir yeni kullanıcı, diğer kullanıcılar üzerinde girişim yaratmaktadır. Yarattığı girişim, kullandığı güç seviyesiyle doğru orantılıdır. Dolayısıyla, bilişsel ağlarda güç yayılımının kontrolünü sağlamak, servis sağlayıcıların en önemli amaçlarından biri olmalıdır. Modellenilen bilişsel ağda, birden fazla Birincil Servis Sağlayıcı (BSS) olduğu varsayılmıştır. Birçok pazarda, özellikle telekomünikasyon pazarında, müşteriler gittikçe daha talepkâr bir hale gelmektedirler. Bununla birlikte, rekabetin sürekli artması, kullanıcılara servis sağlayıcılarını her an değiştirebilme özgürlüğü vermiştir. Verilen problemde birden fazla satıcı olduğundan ve her bir satıcının kendi kârını ençoklamak istemesinden dolayı, klasik eniyileme yöntemleri yetersiz kalmaktadır. Bu yüzden önerilen fiyat belirleme modelleri, oyun teorisi temellerine dayandırılarak, işbirliksiz bir oyun biçiminde çözülmüştür.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS / ABBREVIATIONS

a_i	Weight coefficient of cost due to the quality degradation
b_j	Size of the spectrum that SU_j buys (shared bandwidth)
$b_j^{\min}$	Minimum desired bandwidth of SU_j
B	Bandwidth of the channel
B_k^i	Bandwidth requirement of PU_k of PSP_i
BF	Band factor
BIF	Band interval factor
C	Channel capacity
d_i	Weight coefficient of cost due to the interference created by SUs
d_{ij}	Distance between the BS of PSP_i and the SU_j
D_j	Demand function of SU_j
$D_{ik}(\mathbf{p}, \mathbf{q})$	Demand that NP_i experiences from ASP_j
$h_{i,j}$	Channel gain between the BS of PSP_i and the SU_j
$h_{PU_i \rightarrow BS_i}$	Channel gain between the BS of PSP_i and the PU_i
$h_{SU_j \rightarrow BS_i}$	Channel gain between the BS of PSP_i and the SU_j
l_l	Lower bound for $SINR_j$ and $SINR_i$ values
l_u	Upper bound for $SINR_j$ and $SINR_i$ values
L	Spreading gain
LF	Location factor
m	Total number of calls belonging to the customer
M	Number of SUs in region R
n_{PU_i}	Number of PUs in PSP_i's network
OC_{ik}	Opportunity cost
p	Unit price of the offered spectrum band
p	Price vector
p_i	Unit price offered to SUs by PSP_i
$\overline{p_i}$	Fixed fee that PU_i pays
p_{ik}	Price that NP_i charges ASP_k per unit demand
p^{NE}	Equilibrium price of the *T_Broker*

q	Quality vector
q_1	First component of the quality of the spectrum band (Received signal power)
q_2	Second component of the quality of the spectrum band (Location)
q_3	Third component of the quality of the spectrum band (Band type)
q_{ik}	Quality measure of the spectrum band offered by NP_i to ASP_k
q^{NE}	Equilibrium price of the *V_Broker*
r_1	Constant utility of service provider
r_2	Extra utility of service provider
s_j^{II}	Transmission power of SU_j
s_k^i	Transmission power of PU_k in the PSP_i's network
S_{ik}	Strategy space
SPS_T	Total surplus of service providers
SW	Social welfare
U	Utility function
v	Quality related parameter
W_i	Total size of the spectrum of PSP_i
x	Valuation of the service provider for frequency brokers in the unit interval
x_{CV}	Call value
x_{CRM}^i	CRM value of the i^{th} participants
x_{CTV}	Call type value
x_{ECL}	Expected call length of the customer
x_{CL}^i	The i^{th} call length of the customer
α	Path loss exponent
β_j	Positive constant that represents to what extent the SU_j is influenced from price offered by PSP_i
γ_{jk}	Positive constants that represent to what extent the SU_j is influenced from prices offered by the competitors of PSP_i
δ_j	Base demand of SU_j
δ_{ik}	Base demand of ASP_k from NP_i
ξ	Coefficient of resource winning ratio
φ	Coefficient of expected call length

π_i	Profit function of PSP_i
π_T	Profit of the *T_Broker*
π_V	Profit of the *V_Broker*
ρ_1, ρ_2	Importance weight coefficients of the quality parameters
σ^2	Background noise power
τ	Quality related parameters
ψ	Coefficient of caller's CRM value
ω	Coefficient of total call value

AP	Access Point
ASP	Application Service Provider
BS	Base Station
BSC	Base Station Controller
BSS	Birincil Servis Sağlayıcı
BTS	Base Transceiver Station
CP	Coordinated Pricing
CRM	Customer Relationship Management
DARPA	Defense Advanced Research Projects Agency
DSA	Dynamic Spectrum Access
DTV	Digital TV
FCFS	First-Come First-Serve
FCC	Federal Communications Commission
FDMA	Frequency-Division Multiple Access
GAMS	General Algebraic Modeling System
GEO	Geostationary Earth Orbit
ISM	Industrial, Scientific and Medical
ITU	International Telecommunication Union
MAC	Medium Access Control
MNO	Mobile Network Operator
NE	Nash Equilibrium
NP	Network Provider
NTIA	National Telecommunications and Information Administration
OFDM	Orthogonal Frequency-Division Multiplexing

PSP	Primary Service Provider
PU	Primary User
QoS	Quality of Service
RACH	Random Access Channel
RLAN	Radio Local Area Network
RUP	Resource Usability Parameter
SCC	Standards Coordinating Committee
SDR	Software-defined Radio
SLA	Service Level Agreement
SU	Secondary User
TCA	Telecommunication Coordinating Authority
TDMA	Time-Division Multiple Access
TK	Telekomünikasyon Koordinatörü
UHF	Ultra High Frequency
U-NII	Unlicensed National Information Infrastructure
WMAN	Wireless Metropolitan Area Network
WRAN	Wireless Regional Area Network
WSP	Wireless Service Provider

1. INTRODUCTION

1.1. Motivation

All different technologies rely on radio communications and the most fundamental resource is the frequency spectrum. Each technology requires unique hardware which is appropriate to send and receive these different radio waves. In order to minimize interference among them, each is restricted to specific bands of the spectrum. Radio frequency spectrum usage therefore needs to be shared amongst the various radio services and it must be used efficiently, optimally and economically in conformity with the provisions of national and international policies.

The traditional way of spectrum management is to let government agencies statically allocate communication frequencies to different wireless service providers (WSPs) for large geographical areas and for long periods of time. This approach is referred as the *command and control* model. The government opens a radio frequency band for bidding and specifies a certain type of wireless technology/application for this particular radio frequency band (e.g. TV broadcast, cellular services, etc.). Any interested user/company submits the bid and the government determines the winning user/company, which is generally the user/company offering highest bid. The allocation process of the spectrum bands is referred as the *spectrum auction*. Although the government-issued licenses intend to enhance the efficiency of spectrum usage by specifying user rights and obligations, they can cause inefficient spectrum usage.

The radio frequency spectrum allocation of United States is given in Figure 1.1. As seen from the chart, the current spectrum allocation leaves no available bandwidth for future wireless systems. Moreover, actual measurements of spectrum utilization show that most of the time spectrum is underutilized at a given location (FCC, 2002) (Rubinstein, 2007) (Weiss and Jondral, 2004) (Shared Spectrum report, 2007). Measurements in the 30-300 MHz band show that utilization of some of the radio channels is less than one percent, whereas the average occupancy over all the frequency bands is only 5.2 percent (Vilimpoc and McHenry, 2006). Surprisingly, the maximum total spectrum occupancy for New York City during one such measurement was found to be only 13.1 percent, in the 30 MHz-3GHz band. Even during the peak hours of usage, it is possible to find free spaces in the spectrum (Prasad et al., 2008).

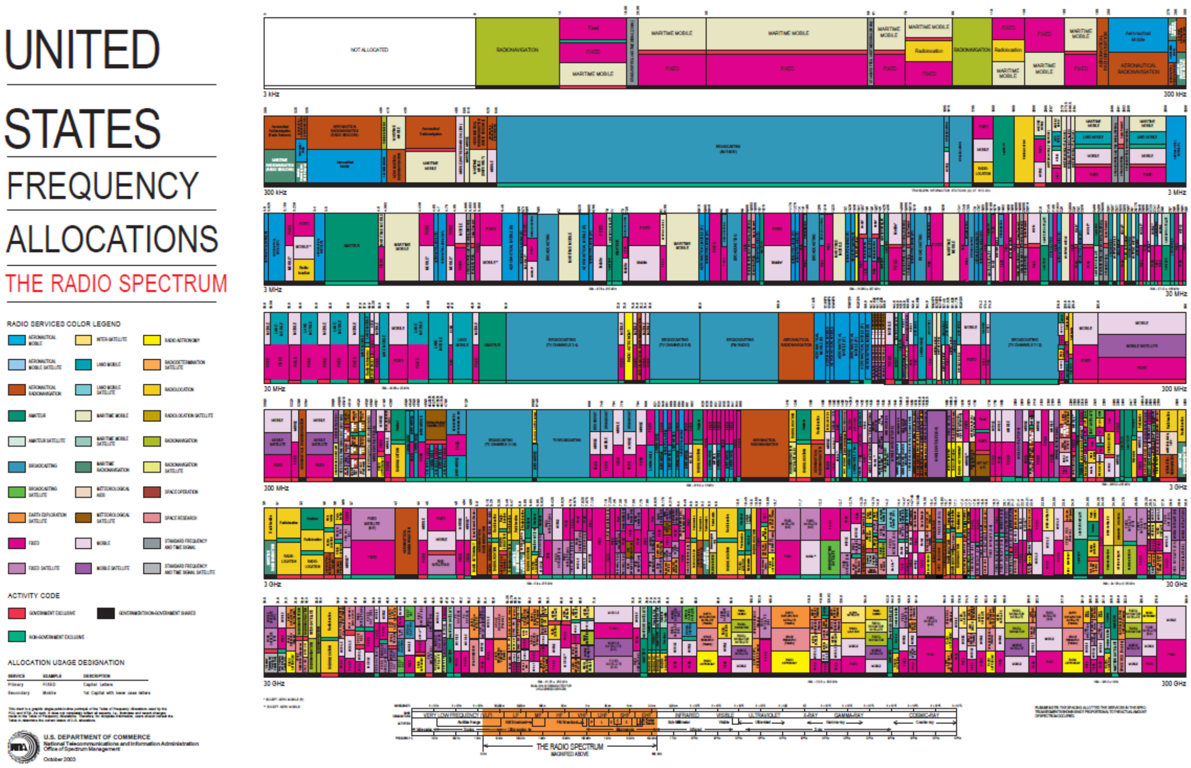

Figure 1.1. The frequency allocation chart of the National Telecommunications and Information Administration (NTIA, 2003)

Apart from the spectrum scarcity, the limitations on the wireless technology put by regulatory requirements are the causes of spectrum usage inefficiency. The limitations may prevent an authorized user from changing its wireless transmission techniques and services according to market demand. The measurements seriously question the suitability of the current regulatory regime and possibly provide the opportunity to solve the spectrum bottleneck.

The results conduct many regulators to consider alternative approaches for more efficient use of spectrum resources. In 2004, International Telecommunication Union (ITU), in Geneva, found that “many TV channels are unused over significant geographical areas" and concluded that "dynamic spectrum access (DSA) techniques appear to be a promising approach" for using spectrum more efficiently. It is the cognitive radio technology that enables a DSA network using or sharing a wide range of available spectrum in an opportunistic manner. Cognitive radio is based on software-defined radio (SDR) technology, and it has emerged as a new approach to improve the flexibility and adaptability of wireless communication systems. (Akyıldız et al., 2006). The statement of ITU has not escaped the attention of the Federal Communications Commission (FCC), and in 2004, FCC legalized secondary markets for spectrum and issued a request for industry comment on sharing of the unused TV bands. UK regulator Ofcom has so far taken the decision of deregulate the airwaves in such a way that the licensee can relicense (sub-lease) some of its rights to other parties, instead of filling underutilized bands with smarter and smarter radios (Qinetiq report, 2007). In such a way, Ofcom plans to have exclusive use of certain frequencies. Ofcom expects to convert more than 70 per cent of the UK's spectrum to the new regime by 2010 (Rubinstein, 2007). These different approaches can provide significant economic and social benefits only if they become widely available and utilized, i.e. if they are commercially successful (Chapin and Lehr, 2007). From a technical perspective, a spectrum management system needs to ensure the lowest interference and the highest utilization of the radio frequency band. From an economic perspective, the system needs to have an economic model which is related to the revenue and satisfaction of the spectrum licensee.

A WSP buys spectrum with a certain price from the telecommunication regulatory authority, and then sells the spectrum to its end users in the form of services (bandwidth) (Sengupta et al., 2007). The WSPs that are the long-term spectrum owners are referred as the *primary service providers* (PSPs). The regular customers of the PSPs are referred to as the *primary users* (PUs). The PSPs have the opportunity to sell the spectrum opportunities to *secondary service providers* or *secondary users* (SUs), when their allocated spectrum is not fully utilized. This is called as *spectrum trading* or *secondary trading of spectrum* (Niyato and Hossain, 2008a). Price is the fundamental component of the economic model, since it indicates the value of the spectrum to both seller and buyer. For the buyer, the price paid to the spectrum seller would depend on the satisfaction achieved through the usage of that spectrum. For the spectrum seller, the price determines its revenue and hence, its profit. The spectrum price should be set based on the demand of the buyers (SUs) and the supply of the seller. Also, competition among buyers/sellers has an impact on price setting. In this regard, it is important to investigate the economic issues that arise due to the presence of multiple service providers. Another important component in a spectrum management system is the power control. Power control serves as a means for both battery savings at the mobile equipment, and interference management. When power emission is not controlled, the intended quality of service (QoS) levels can be achieved at arbitrary high power levels. This leads to interference on PUs, as well as on the other SUs.

In this dissertation, our main objective is to propose a robust pricing model to be used in next generation wireless networks. Our research has begun with a utility-based pricing model for cellular networks, where there was only one service provider in the telecommunication market. Then, we have applied a similar utility-based pricing and resource allocation model to satellite networks. With the appearance of cognitive radio networks and the concept of open spectrum environment in years 2005-2006, we have focused on these kind of networks. As the competition is the major issue in cognitive radio networks, game theory has been the basis of our pricing models. Our first proposed game theory-based model were including a brokering architecture, where a frequency broker was managing the available spectrum bands of service providers and was helping the service provider to sell them to end users. Then we have extended our architecture to a spectrum exchange marketplace, where there was not any intermediary broker among service providers and end users. As a final work, we have established a pricing model in a secondary market in the presence of multiple competing PSPs. The proposed secondary market consists of SUs who seek for spectrum bands, the PSPs who have available spectrum bands to sell and a telecommunications coordinating authority (TCA) who assures the satisfaction of all the players in the market. In most markets, especially in telecommunication markets, the customers are becoming ever more demanding and they have options to deviate among service providers. *Churning* is defined as the migration of users from one service provider to another, mostly due to dissatisfaction with perceived quality of service and competitive offerings of new services by other providers (Das et al., 2004). The new network element that is introduced in this research, the TCA, is assumed to be formed by the association of PSPs to help them keep their long-term customer satisfaction and minimize the churning rate. Since the air interface is a shared medium, each SU’s transmission is a source of interference to other players in the network. Besides, the SUs need to guarantee their minimum quality requirements, which create a tradeoff between transmission power levels and resulting interference. The TCA aims at managing the transmission powers of SUs so as to maximize the QoS both SUs and PSPs' regular customers get. By considering these optimum power values, PSPs determine which SUs are more profitable for them to serve. Then, as the second step, PSPs decide on the unit price of their spectrum bands. The pricing model of spectrum bands is based on a non cooperative game, where the PSPs are the players. Solving the game, the mutual best response strategies that determine the equilibrium point(s) are studied. With the optimum prices, the PSPs calculate their actual demands and maximum possible profits. We use a heuristic which we call the Coordinated Pricing (CP) algorithm to model interactions in the proposed framework.

1.2. Contributions

The contributions of this research are relevant both for academia and practice:

- The use of Customer Relationship Management (CRM) tool into the resource allocation and pricing framework: We make use of the CRM tool in order to segment the customers of the spectrum buyers. We evaluate the positive impact of knowing the customers and segmenting them in respect to their demographic information and usage behaviors to the profitability of spectrum buyers.

- Integration of a coordinating market authority for power management: The coordinating authority, which operates on the behalf of PSPs, directs them keeping their PUs' satisfaction. We evaluate the positive impact of such an authority to the profitability and to the social welfare of the network by comparing the proposed framework with the one having no power management authority.

- Simultaneous transmission of SUs and PUs in the same spectrum band: The power control component of the proposed framework puts some limitations on the transmission powers. Hence, it allows SUs to transmit simultaneously with the PUs in the same frequency band, as long as the level of interference to PUs and to other SUs remains within an acceptable range.

- Examination of the impact of transmission power on the profit maximization, as well as the unit spectrum prices: The research on spectrum trading do not focus on the power control issue within the spectrum pricing model. Besides, the research on pricing and power control in cognitive radio networks usually includes the concept of pricing in order to control power. Prior to this dissertation, no study was performed to investigate the impact of transmission power on the profits of PSPs, as well as on their unit spectrum prices.

- Flexibility of the size of the offered spectrum band: We let the PSP sell more spectrum band than that is available, by accepting the resulting quality degradation and interference costs.

- Optimum price setting in a multiple-seller and multiple-buyer environment: If there was a single PSP with a single objective function, the pricing problem would be solved using the classical optimization approaches. However, there are multiple PSPs in the problem, and each one needs to maximize its own profit. Hence, the pricing problem of PSPs in this context is considered from a game theoretical perspective, with a non cooperative setup.

- A heuristic that encapsulates the power control process within the price setting problem: We propose a five-step algorithm that involves the optimization of transmission powers of SUs and the non cooperative pricing game played by PSPs. The runtime of the algorithm is shown to be in the acceptable range up to nine SUs in the same region.

- Comparison of two spectrum access models: The spectrum shortage problem is believed to be resulted from the spectrum management policy rather than the physical scarcity of usable spectrum. Then, different spectrum access models are proposed for different scenarios. In this dissertation, we compare two major spectrum access models: The command and control and exclusive use approaches.

1.3. Thesis Organization

The dissertation is structured into six chapters. Chapter 2 first introduces the cognitive radio networks in a broad sense with their capabilities, main functions, and architectural and standardization issues. Then, we present the concept of dynamic spectrum access by introducing common spectrum access models and different DSA architectures. The main topic of the dissertation is the pricing models for next generation wireless networks. Hence, we describe the role of pricing in computer networks as well as the concept of spectrum trading in the same chapter. Chapter 3 discusses the related work in the literature and our research questions. We also summarize our recent works on the same research area in the same chapter. The common methodology in the proposed frameworks is the game theory. We have given an introduction and main concepts of the game theory which had been useful in our proposed architectures in Chapter 4. Chapter 5 encapsulates the architectures that answer to all of our research questions. We have given four different architectures for spectrum trading. We provide in depth analysis of the formulation of all the frameworks. The same chapter includes the elaboration on numerical simulations and comparisons regarding the performance of the proposed frameworks. Chapter 6 ends this dissertation with a conclusion and an outlook on the future research directions.

2. BACKGROUND

This chapter is organized as four main sections and it summarizes the necessary background on cognitive radio, dynamic spectrum access, pricing in communication networks and spectrum trading. The pricing model in this dissertation is proposed for cognitive radio networks; hence we first define cognitive radio, its capabilities and its main functions. The first section ends with the architectural and standardization issues of cognitive radio networks. Then, we describe the management systems in the DSA networks in the second section. This section involves common spectrum access models and common architectural propositions for DSA networks. We give the notion of pricing and the importance of churning in communication networks in the third section. We conclude the chapter by the fourth section which involves the definition and the main structures of spectrum trading.

2.1. Background on Cognitive Radio

2.1.1. Definition

While many researchers and public officials agree that upgrading a software radio's control processes will add significant value to software radio, there is currently some disagreement over the precise definition of a cognitive radio (Neel, 2006).

Joseph Mitola III first defines a cognitive radio as (Mitola, 1999):

"*A radio that employs model based reasoning to achieve a specified level of competence in radio-related domains.*"

In his recent popularly cited paper, Simon Haykin defines a cognitive radio as (Haykin, 2005):

"*An intelligent wireless communication system that is aware of its surrounding environment, and uses the methodology of understanding-by-building to learn from the* *environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g. transmit power, carrier frequency, modulation strategy) in real-time, with two primary objective in mind: High reliable communications whenever and wherever needed, and efficient utilization of the radio spectrum.*"

By the time IEEE 1900.1 group defines cognitive radio, there have been various definitions made by FCC, National Telecommunications and Information Administration (NTIA) and ITU. In 2006, the IEEE 1900.1 group, which studies on the terminology and concepts for next generation radio systems and spectrum management, defines cognitive radio as (IEEE 1900.1, 2006):

"*A type of radio that can sense and autonomously reason about its environment and adapt accordingly. This radio could employ knowledge representation, automated reasoning and machine learning mechanisms in establishing, conducting, or terminating communication or networking functions with other radios. Cognitive radios can be trained to dynamically and autonomously adjust its operating parameters.*"

Despite of the fact that there are several definitions for cognitive radio, these definitions have some common conceptions. All of them assume that cognition will be implemented as a control process, presumably as part of a SDR. All the definitions imply some capability of autonomous operation. They all assume that the radio is capable of acquiring information about its operating environment, changing its waveform and applying information towards a purposeful goal (Neel, 2006).

2.1.2. Main Functions of Cognitive Radio

A cognitive radio supports the capabilities to acquire information about its environment and select the best available channel. Next, it makes the network protocols adaptive to the available spectrum. Hence, cognitive radio networks require new functionalities in order to come up with these challenges. The main functions for cognitive radio can be summarized as (Akyıldız et al., 2006) (Hossain et al., 2009):

- Spectrum sensing: The objective of spectrum sensing is to determine the status of the spectrum band; in other words, spectrum sensing is periodically detecting if there are active PUs in the target spectrum band. The spectrum portions (i.e. band, location or time) where a PU is not active are called as *spectrum holes*. The cognitive radio transceiver detects these spectrum holes that do not interfere with the transmission of a PU.
- Spectrum management: Information from spectrum sensing is analyzed to have knowledge on the spectrum holes. Then, a decision to access the spectrum (e.g. frequency, bandwidth, modulation mode, transmit power, location and duration) is made by optimizing the system performance given the desired objective and constraints.
- Spectrum mobility: It is the function of changing the operating spectrum band of SUs in any environmental change (e.g. a PU starts transmitting on that radio channel, SU moves, or network traffic changes). This change is referred as *spectrum handoff*. The protocol parameters at different layers of the protocol stacks have to be adjusted to match the new operating frequency band.
- Spectrum sharing: This functionality is needed when a SU decides to operate on a spectrum hole. The cognitive medium access control (MAC) protocol has to avoid collisions with PUs and also with other SUs in the channel. A cognitive MAC protocol could be based on a fixed allocation MAC (e.g. FDMA, TDMA, CDMA) or a random access MAC (e.g. ALOHA, CSMA/CD) (Neel, 2006) (Buddhikot, 2007).

2.1.3. Cognitive Radio Architecture

The Defense Advanced Research Projects Agency (DARPA) initiated the NeXt Generation (XG) program in 2003, in order to use the DSA mechanism through cognitive radio (DARPA XG, 2003). The locations of the main functions in the XG network protocol stack are shown in Figure 2.1 (Akyıldız *et al*., 2006) (Hossain *et al*., 2009). The XG network architecture consists of two main wireless systems: Primary (licensed) and secondary (unlicensed / XG) network systems.

The existing network infrastructure, which has an exclusive right to a certain band, is generally referred as the *primary network*. The primary base station (BS) or access point provides wireless connections for PUs. The XG network does not have license to operate in a desired band. The XG network may or may not use an infrastructure. If the XG network has an infrastructure, an XG BS is used to control the spectrum access by SUs. Otherwise, an ad hoc access mode is used for communication among SUs, and an XG network gateway can be used to connect the XG network to the primary network.

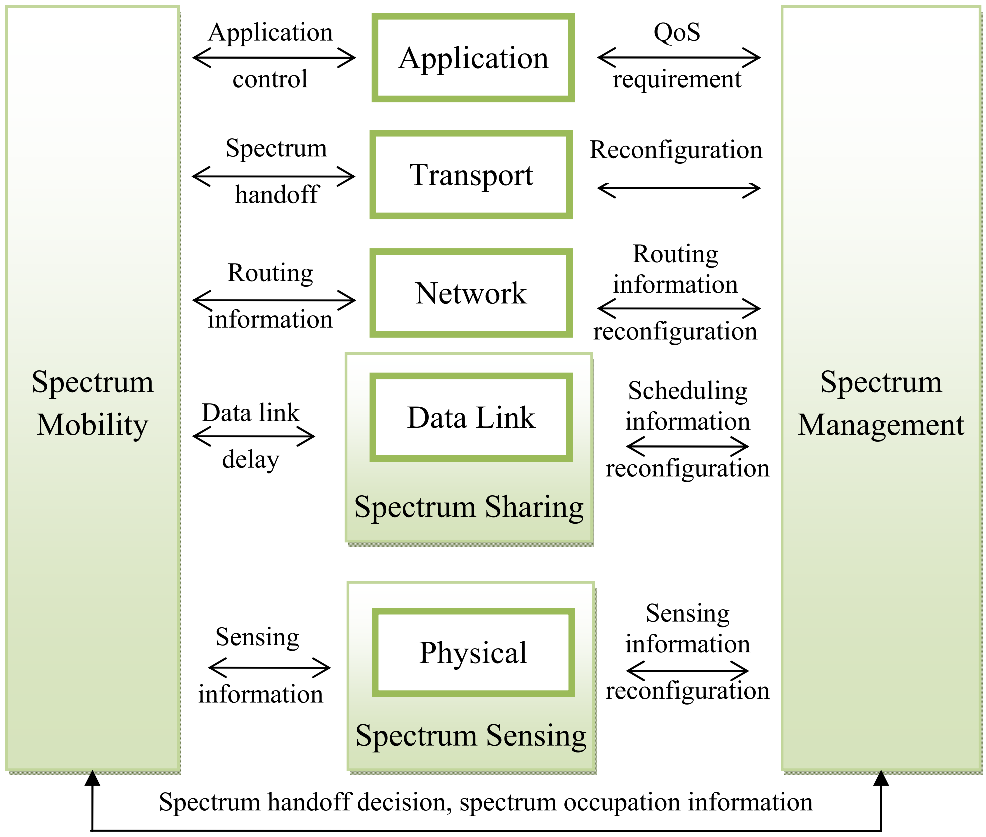

Figure 2.1. Protocol stack for XG networks (Akyıldız *et al*., 2006) (Hossain *et al*., 2009)

2.1.4. Cognitive Radio Standardization

Many technical, managerial, and economic aspects are associated with cognitive radio concepts. It necessitates strong coordination among regulators, academia, and product developers. Hence, there is need to standardize processes, terms, and so on. In this section, we present two main standardization processes.

- IEEE SCC 41: In 2005, realizing the importance of coordinated work around cognitive radio standardization, the IEEE created the IEEE SCC 41 to address the issues related to the deployment of next generation radio systems and advanced spectrum management (IEEE 1900 Std., 2010) (Prasad *et al*., 2008). IEEE SCC 41 was preceded by the IEEE 1900 task force, which initiated the IEEE standards setting effort in this area. IEEE SCC 41 is composed of four working groups and one study group. Each of these groups is responsible for initiating standardization processes for different aspects of a cognitive radio system.

- IEEE 1900.1: This working group is to identify and explain a glossary of terms and concepts related to spectrum management, SDR, adaptive radio, and other relevant technologies.
- IEEE 1900.2: This working group focuses on developing a common standard platform to resolve any conflict occurring as a result of the coexistence of many wireless devices and services in the same location at the same time.
- IEEE 1900.3: The role of this working group is to develop a common standard platform on software modules in wireless devices.
- IEEE 1900.4: This working group is related to the coexistence support for the heterogeneous wireless technologies and corresponding protocol.
- IEEE 1900.A: This group is responsible from the certification of DSA-based devices. They work on developing new methodologies and testing procedures to ensure that the certified device will not interfere with the transmission of a licensed device.

- *IEEE 802.22:* IEEE 802.22 is a standard for Wireless Regional Area Network (WRAN) which aims at using cognitive radio technologies to allow sharing the unused spectrum that is allocated for Television Broadcast Service. The 802.22 system specifies spectral efficiencies in the range of 0.5 bit/(sec/Hz). If we consider an average of 3 bits/sec/Hz, this would correspond to a data rate of 18 Mbps in a 6 MHz TV channel. This means that 12 simultaneous users can obtain 1.5 Mbps per user in the downstream direction (Cordeiro *et al*., 2006). These 6 MHz TV bands can be used for data communication. The TV bands are mostly in the low-frequency spectrum (e.g. 54-862 MHz in North America and 41-910 MHz internationally); therefore their propagation characteristics are more suitable for long-range transmissions. Since 802.22 is mostly targeted at rural and remote areas, its coverage range is considerably larger than 802.16

Wireless Metropolitan Area Network (WMAN) standard. The BS coverage range in 802 standards can go up to 100 km, if power is not an issue.

2.2. Background on Dynamic Spectrum Access Models

As mentioned earlier, the traditional command and control licensing model results in inefficiency of spectrum usage. The reasons of that inefficiency can be summarized as (Hossain *et al*., 2009):

- The spectrum is assigned to a specific WSP. If the assigned portion is not utilized, it cannot be assigned to another WSP which requires it.
- The spectrum is assigned for a specific wireless technology and it cannot be changed. For instance, a 6 MHz spectrum band allocated to an analog TV services cannot be used for another service.
- The spectrum license is location-invariant. For instance, the radio spectrum could be allocated to a cellular service in an entire region (urban and suburban). The spectrum could be heavily used in urban areas, but be underutilized in suburban areas. However, WSP cannot use the underutilized portions for other services.
- The granularity of spectrum usage is fixed. For instance, the spectrum allocation for cellular service is made only in large chunks (e.g. 50 MHz in the 800 MHz band).
- The spectrum cannot be utilized by licensed and unlicensed users simultaneously. The spectrum can be unutilized only by the licensed users at a given time in a specific region. WSP cannot assign this portion to unlicensed users in order to improve spectrum utilization and increase its profit.

The spectrum shortage problem results from the spectrum management policy rather than the physical scarcity of usable spectrum (Zhao and Sadler, 2007). In order to break away from the inflexibilities and inefficiencies of static command and control allocation, the concepts of open spectrum and dynamic spectrum access are being investigated by network and radio engineers, policy makers, and economists. The *open spectrum* concept defines a set of techniques and models to support dynamic management of spectrum bands for wireless communication systems. Except from command and control model, three different spectrum access and licensing models and their variants have been proposed (Buddhikot, 2007) (Niyato and Hossain, 2008a) (Zhao and Sadler, 2007) (Figure 2.2).

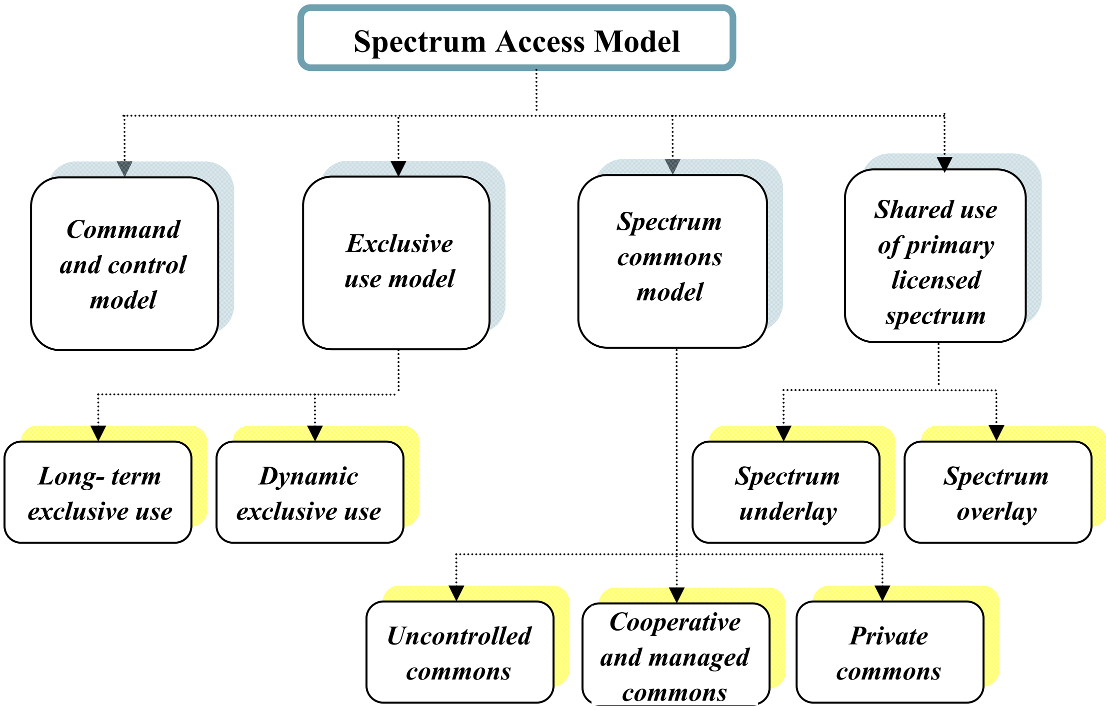

Figure 2.2. Spectrum access models

2.2.1. Spectrum Access Models

2.2.1.1. Exclusive Use Model: The licensee is authorized to use a specific frequency band or channel for whatever service or purpose they desire. These rights are subject to general emission rules that are designed not to interfere with neighboring spectrum users. The main idea is to introduce flexibility to improve spectrum efficiency. The spectrum owner may grant the spectrum rights to cognitive radio users, if its allocated spectrum is not fully utilized in all times and in all locations. In this case, the spectrum owner is referred as the licensed user; whereas the cognitive radio user is referred to as the unlicensed user in the shared frequency band.

In the exclusive use model, two variants are possible: The long-term exclusive use (spectrum property rights) and dynamic exclusive-use (dynamic spectrum allocation). The *long-term exclusive use* model involves sell and trading of radio resources to a licensed user/ service provider for some period of time (e.g. few weeks). It allows licensees freely choose technology. In a *dynamic exclusive-use model*, only one user can exclusively access the spectrum at any particular point in time. However, at different points in time, the users accessing the spectrum and the types of wireless service using that spectrum can be changed. Thus, the spectrum owner can earn revenue from trading its owned spectrum. This trading is referred as a *secondary market* (Peha and Panichpapiboon, 2004).

Three different sub-models of a secondary market are defined (Hossain *et al*., 2009):

- Non real-time secondary market: The trading and allocation are performed before the spectrum is accessed.
- Real-time secondary market for homogeneous multi-operator sharing: The spectrum can be traded and allocated to a SU in an on-demand basis. However, the wireless service type cannot be changed. When a SU needs spectrum, he/ she can request to buy the spectrum from the owner. This spectrum trading is known as *spectrum leasing* since the agreement between a spectrum owner and a SU is a temporary one.
- Real-time secondary market for heterogeneous multi-operator sharing: Similar to homogeneous sharing, the spectrum can be traded and allocated on an on-demand basis. However, the wireless service type over the allocated spectrum can be changed. For example, the spectrum can be traded between a TV broadcaster and a broadband WSP.

The exclusive use model consists of a trading environment. Therefore the economic issues and pricing become vital. Our proposed framework is suitable to employ in all sub models of exclusive use model. It is important to note that, the algorithm of a pricing model for real-time secondary markets needs to run fast enough to respond to the demand of SUs.

<u>2.2.1.2. Spectrum Commons Model</u>: The development of spectrum for unlicensed user is seen as crucial in supporting innovation processes and in maximizing the benefits from advanced mobile communications. Due to the original nature of this approach, researchers in engineering community generally support this regime. Current examples are IEEE 802.11 standards, fixed 802.16 standard, and 2.4 GHz ISM band. Under this regime, no

intervention form a regulator for any services exists. All SUs have the same rights to access the radio spectrum. Spectrum trading is out of the question because licensing is free. The potential gains from unlicensed use include: Eliminating the requirement for administrative licensing that would lower barriers to market entry, encouraging market competition, and fostering benefits to consumers by increasing innovation and competition. However, most opponents of this approach assert the possibility of a "tragedy of common" problem (Hwang and Yoon, 2009). This problem describes a situation in which multiple individuals, acting independently, and solely and rationally consulting their own-interest, will ultimately reduce a shared limited resource even when it is clear that it is not in anyone's long-term interest for this to happen (Mas-Colell *et al*., 1995).

There are three variants of spectrum commons model:

- Uncontrolled commons: The spectrum is not owned by any entity. This sub-model is already being used in the ISM (2.4 GHz) and U-NII (Unlicensed National Information Infrastructure) (5 GHz) unlicensed bands. In this sub-model, only the maximum transmit power constraint applies to a SU. However, since there is no control on spectrum access, a SU suffers from interference.
- Managed commons: This sub-model considers radio spectrum as a resource which needs to be controlled jointly by a group of cognitive radios. There should be a management protocol that has the objective of supporting advanced and efficient device design, services and business model, minimizing communication and coordination overheads for spectrum access, providing flexibility for protocol changes in the future, and promoting fair spectrum access among cognitive radio users (Hossain *et al*., 2009). Although there are spectrum rules, there could be some SUs who violate the spectrum access environment.
- Private-commons: The spectrum owner can specify a technology and a protocol for the SUs to access the spectrum. A SU may receive a command from the spectrum owner. This command may contain the transmission parameters (e.g. time, frequency band, transmission power) to be used. Alternatively, a SU may opportunistically sense and access the spectrum without interrupting a spectrum owner.

<u>2.2.1.3. Shared Use of Primary Licensed Spectrum</u>: In the shared use spectrum access model, the radio spectrum can be simultaneously shared between a PU and a SU. The basic idea is to open licensed spectrum to SUs while limiting the interference perceived by PUs. This regime is the middle between the spectrum commons model and command and control model. Two approaches to spectrum sharing have been considered:

- Spectrum underlay: In the case of spectrum underlay, a SU can transmit concurrently with a PU (Figure 2.3). However, the transmission power of the SU should be limited so that the interference caused to the PUs remains below a certain threshold. Emerging technology such as the UWB unlicensed system makes it possible to improve spectrum utilization with low power transmission below the noise floor so that interference can be protected. The IEEE 802.15 standard is the current standardization group.

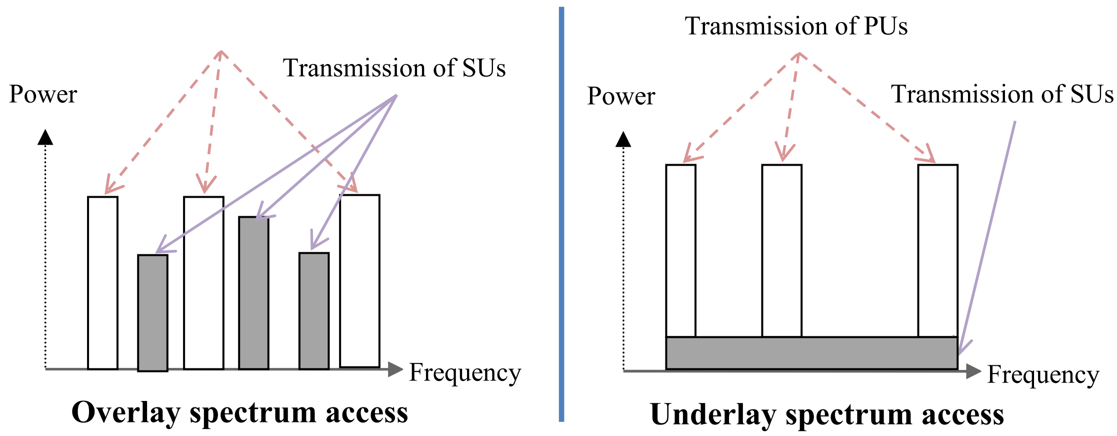

Figure 2.3. Spectrum overlay and spectrum underlay

- Spectrum overlay: It was first envisioned by Mitola under the term spectrum pooling and then investigated by the DARPA XG program under the *opportunistic spectrum access* (Mitola, 1999). The opportunistic spectrum access approach does not necessitate severe restrictions on the transmission power, but it necessitates severe restrictions on when and where to transmit. In case of a spectrum overlay, a PU receives an exclusive right to spectrum access. However, at a particular time or frequency, if the spectrum is not utilized by a PU, it can be opportunistically accessed by a SU. Therefore, to access a spectrum band, a SU has to perform spectrum sensing to detect if a PU is active in that band. If a spectrum hole is found, SU may access the spectrum (Figure 2.3). Spectrum overlay can be used for cognitive radio in FDMA (Frequency-division multiple access), TDMA (Time-division multiple access), and OFDM (Orthogonal frequency-division multiplexing) wireless systems. It is used by RLANs in the 5 GHz range. The RLANs use spectrum band that is also used by radar systems.

Table 2.1. Comparisons of different spectrum access models (Hwang and Yoon, 2007)

	Command and Control	Exclusive Use	Spectrum Commons	Share Use
Spectrum efficiency	Low	High	Very high	Very high
Innovation	Low	High	Very high	Very high
Interference	Very low	Low	Can be high	Can be high
QoS guarantee	High	High	Low	Low
Management processing time	Very long	Short	Very short	Very short
Social cost	High	Can be high	Low	Very low
Market competition	Low	High	High	Very high
Management	Easy	Normal	Difficult	Difficult
Degree of regulation	Very high	Low	Low	Very low

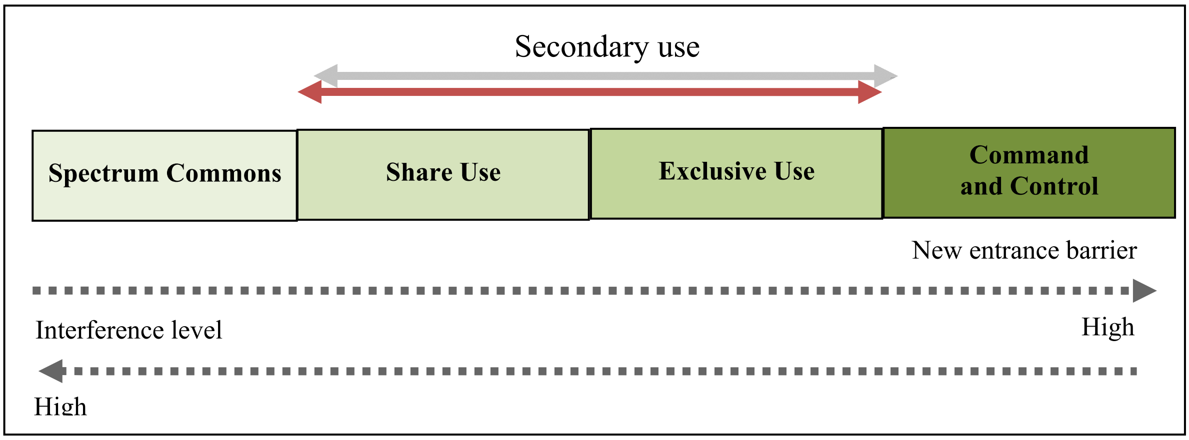

Figure 2.4. Basic attributes of different regimes

The comparisons of different spectrum access models based on basic attributes are summarized in Table 2.1. In Figure 2.4, the interference and the new entrance barrier of each regime is compared to the command and control model. Compared to the exclusive use model and spectrum commons model, the shared use model can be viewed as the most compatible with our proposed framework. In this dissertation, we do not focus on which model is the most efficient one. We aim at proposing a spectrum trading architecture that can fit to each one of spectrum access models with slight modifications.

2.2.2. International Trends on Spectrum Access

Currently some countries are developing the midterm spectrum frameworks to allow secondary markets and auctions using the market mechanism. The recent big issue about new spectrum allocation is a Digital TV (DTV) band reallocation method after analog TV broadcasting ends. FCC in the USA auctioned this band and many third parties such as Google and Apple were interested in this opportunity; alternatively, some of this band would be unlicensed.

There are not many successful secondary market examples. In many cases, the matter is still being discussed. In countries such as New Zealand, Australia, Guatemala, the United Kingdom, and the USA, which have already allowed spectrum trading, it has not been widely activated. For example, in Australia, less than 10 per cent of the total available trading band is being traded and even much of this is in the low-frequency band (Hwang and Yoon, 2009).

2.2.3. Dynamic Spectrum Access Architectures

Dynamic spectrum access architecture can be either centralized or distributed, and the corresponding protocols depend on the behavior (i.e. cooperative and non cooperative) of the cognitive radio entities. The different network architectures and protocol behaviors for cognitive radio can be described as follows (Niyato and Hossain, 2008a):

- Centralized cooperative dynamic spectrum access: In a centralized architecture, a centralized controller (e.g. PSP, spectrum owner) gathers information on the cognitive radio environment (e.g. spectrum opportunity, spectrum demand). Based on the complete information, the centralized controller makes the decision of bandwidth assignment and transmission power allocation. In this type of architecture, even though an optimal solution can be achieved, this may incur a large communication overhead.

- Centralized non cooperative dynamic spectrum access: Complete information on the cognitive radio environment are again gathered in a centralized controller; but this time, the solution that satisfies all the entities is obtained. Nobody can achieve a better solution by changing his/ her action. This is the definition of Nash equilibrium in a game theory formulation. We propose our pricing framework for this type of architecture.
- Distributed cooperative dynamic spectrum access: In a distributed architecture, the cognitive radio entities will observe and make decisions independently. There is not a centralized controller. The cognitive radio entities can improve the efficiency and the fairness in their networks by making cooperation with their competitors. However, the signaling and information exchange among entities would incur communication overhead.
- Distributed non cooperative dynamic spectrum access: In a non cooperative environment, cognitive radio entities make decisions non cooperatively to achieve their individual objectives. This architecture is common for cognitive radio networks in which no prior network information is available to the cognitive radio entities. Also, an entity may have its individual interest; therefore, cooperation may be infeasible to establish. Estimation and learning algorithms are required to model such situations.

2.3. Background on Pricing in Communication Networks

We are in the midst of a revolution in communications services. In a world that is thoroughly changing because of the impact of communications services, the pricing of these services play an important role (Das *et al*., 2004). The presence of multiple WSPs in any geographic region together with the freedom of users in switching WSPs is forcing a competitive environment where each WSP is trying to maximize its profit. A price must be charged for something if service providers are to recover their costs and remain in business (Courcoubetis and Weber, 2003).

There are two main factors influencing the price setting: User demand and competition among service providers (Niyato and Hossain, 2008c). Price and demand are functions of each other. If demand is high, a high price can be charged by a service provider to earn more revenue. On the other hand, if demand is low, the price must be reduced to attract more mobile users. Competition among the service providers also impacts the price setting. In particular, the service providers can compete with each other to offer wireless access services through price adjustment. A price increase of a service provider results in a decrease in its demand, while the price increases of its competitors cause an increase in its demand. The transformation from a monopolistic to a competitive market brings forth significant research issues and challenges in the design of architectures, algorithms, and protocols.

2.3.1. The Impact of Churn

Churning is defined as the migration of users from one service provider to another, mostly due to dissatisfaction with perceived quality of service and competitive offerings of new services by other providers (Das *et al*., 2004). There are many factors that influence customer churning. They include marketing advertisement and promotional packages offered by the WSPs, resource management policies, network coverage and reliability, pricing, QoS, service features offered, and so on. Thus, effective network architectures and management algorithms must include all these factors to keep the churn rate under control.

The statistics from 2003 show that most WSPs experienced an average churn rate of 2-3 percent/month, translating to about 30 percent/year (Das *et al*., 2004) (AT&T Report). With the implementation of wireless local number portability and severe competition, this number is bound to rise even more sharply. The cost of churn to a provider is reported as high as $300 (AT&T Report). With a churn rate of 33 per cent, then, for a WSP with a customer base of 1 million, the churning causes a loss of about $100 million. These results offer significant challenges to WSPs to retain a steady customer base.

The statistics mentioned above are mostly done for cellular networks; however, we believe that the same problem is valid for cognitive radio networks. Indeed, the churn rate would be even higher in cognitive radio networks, since cognitive radio users are considered to have the freedom to change their service providers on the basis of application. Furthermore, in telecommunication market, retaining the existing subscribers is as costly as acquiring new ones (Hwang *et al*., 2004). The different spectrum trading architectures that we propose in this dissertation aim at setting the unit spectrum prices in an appropriate way to satisfy PSPs' steady customer bases.

2.3.2. The Role of Economics

The success of a technology or business is directly related to its economic viability. To retain its customer base, a WSP must make sure that customers are satisfied with the QoS they receive for the price they pay. Consistent economic models should guide the creation of demand on content, services, and applications. This approach would require new algorithms and protocols, the development of which must combine ideas from economics and networking research. (DaSilva, 2000a).

The deployment of new wireless services is also impeded by the lack of market incentives to improve network services and applications. Recent history has demonstrated that even with all the technological successes, perhaps the bottleneck for better services still lies in economics. The failure of Motorola's satellite-based Iridium system and Metricom Ricochet's high-speed data services in wide area wireless networks are two concrete examples that are failed due to the lack of a robust economical model (DaSilva, 2000a).

2.3.3. Pricing in Homogeneous Wireless Networks

Pricing models for service providers that aim at selling homogeneous products can be roughly examined into three classes:

- Market-Equilibrium-Based Pricing Model: In this type of model, it is assumed that the primary service is not aware of others. In real life, this may happen due to the lack of any centralized controller or information exchange among primary services. As a result, at the seller side, the primary service naively sets the price according to the spectrum demand of the secondary service. This price setting is based on the willingness of the primary service to sell spectrum which is generally determined by *the supply function*. For a given price, supply function indicates the size of radio spectrum to be shared by a primary service with the secondary service. At the buyer side, the willingness of a secondary service to buy spectrum is determined by *the demand function*. Again, for a given price, demand function determines the size of radio spectrum required by a secondary service. In this spectrum trading, market-equilibrium price denotes the price for which spectrum supplied by the primary service is equal to the spectrum demand from the secondary service. This market-equilibrium price ensures that there is no excess supply in the market and spectrum supply meets all spectrum demand.

- Non Competitive Pricing: Optimization-Based Approach: A non competitive pricing model consists of one WSP who adjusts its offered unit price to maximize its revenue. We can use an optimization formulation with an objective function and a set of constraints. This type of pricing model is suitable for cellular systems in which the cellular operator tries to serve maximum number of users simultaneously.
- Competitive Pricing: Game Theoretic Approach: With the market environment changing from monopolistic to competitive, WSPs must continuously play with and manipulate different parameters so they can retain a steady customer base and also generate revenue. In general, a wireless system may consist of multiple WSPs whose objectives are different and probably conflict with each other. In such a case, a solution which is optimal from the global point of view, may not be desirable by all the entities (Niyato and Hossain, 2008c). Cognitive radio entities here refer to the primary users/ primary service providers/ spectrum sellers and secondary users/ cognitive radio users/ spectrum buyers. In this multi-entity environment, non cooperative game theory can be used to obtain the optimal pricing policy. Here, the competition can be either among user entities, who compete for the radio resource, or among WSPs, who offer wireless services to the users. The most popular solution of this competitive situation is the Nash equilibrium concept, which guarantees that none of the entities in the system wants to change its strategy, given that other entities stick to the Nash equilibrium (Nash, 1951). We present game theory in more details in Section 4.3.

2.4. Background on Spectrum Trading

To design efficient and effective dynamic spectrum access techniques for a cognitive radio network, the related technical aspects (e.g. channel allocation, power control) as well as economic aspects (e.g. pricing, spectrum auction) need to be considered. In this dissertation, we propose a pricing framework that fits the requirements of the exclusive use spectrum access model. Since the exclusive use model defines the incentive for licensed users to yield the right of spectrum access to unlicensed users, the economic issues are crucial. The economic issues are also important for dynamic spectrum access based on the shared use and spectrum commons models, because they determine the competition and cooperation between the licensed and unlicensed users.

2.4.1. Definition

In economics, *trading* is defined as the process of exchanging goods or services in a market (Mas-Colell *et al*., 1995). This exchange can be performed directly between goods and services or using a medium of exchange. In general, license for spectrum access is provided to a PU or a PSP through an auction process in a primary market (Figure 2.5).

At the top of this hierarchy, the regulating authority (e.g. FCC or Ofcom) issues relatively long-term spectrum leases, say for a 10 year period, on contiguous blocks to spectrum owners, for large geographical regions. We refer to this market as the *primary marketplace*. When the allocated spectrum is underutilized, the spectrum owner can temporarily lease the spectrum in a secondary market to potential buyers. These offered spectrum bands could be from any frequency band interval. If the spectrum buyer accepts the spectrum offer, the required portion is allocated to it for the duration of the time period.

The concept of trading can be applied to spectrum leasing in the secondary market, which constitutes the concept of spectrum trading. Spectrum trading is defined as a process of selling and buying of spectrum resources in different dimensions (e.g. frequency band, time slot). It is obvious that, pricing is the most important issue here both the license owners (PSPs) selling the spectrum and the unlicensed users (SUs) buying the spectrum.

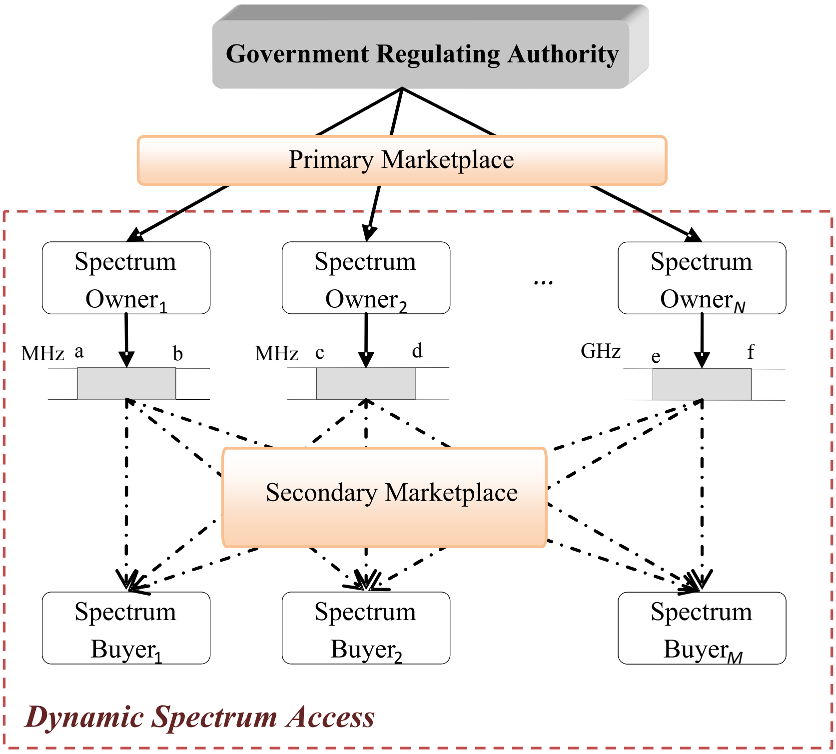

Figure 2.5. Primary and secondary marketplace

Dynamic spectrum access encapsulates many functionalities including spectrum sensing at the physical and medium access control layers, routing, and cognitive MAC. Spectrum trading can be considered as one of these components. Spectrum pricing, which is the main topic of our dissertation, is the major research area in the spectrum trading.

2.4.2. Structures of Spectrum Trading

Two major structures of spectrum trading are as follows (Hossain *et al*., 2009):

- Single seller, monopoly: It is the simplest structure of spectrum trading. It arises when there is only a single seller in the market. This gives the seller the ability to optimize spectrum trading to achieve the highest profit based on the demand from buyers. This type of market can be either *seller-driven* or *buyer-driven*. In the seller-driven case, the seller sets the price and broadcasts the information on available spectrum. The buyer determines the spectrum demand and proceeds to buy the spectrum. These steps can be performed in a single-shot or repeated fashion. In the buyer-driven case, the buyer and seller can negotiate on the price and the requested spectrum repeatedly until the desired solution for both entities is obtained (Niyato and Hossain, 2008a). The markets in which the buyer proposes the price and the requested spectrum are also referred as buyer-driven.

- Multiple sellers, oligopoly: The markets which consist of multiple sellers are referred as oligopoly markets, and the sellers in these markets are referred as oligopolists. Multiple sellers offer radio spectrum to the market. The buyer chooses the best offer to maximize its satisfaction in both performance and price. The oligopoly markets contain competition among oligopolists; hence the profit of a spectrum seller is always less than that in the monopoly market. The trading process can be realized in one shot, if information on all the sellers are available. In real life, generally, the information on the sellers are not available; so buyers and sellers make a negotiation among them to reach a solution.

In spectrum trading, the objective of a seller is to maximize the revenue/profit, while that of a buyer is to maximize the utility of spectrum usage. Here, the utility of a spectrum buyer depends on both the received bandwidth and its unit price. However, these objectives generally conflict with each other. As the seller increases the price to achieve higher revenue, the utility of a buyer decreases due to the higher cost. A similar effect on the QoS performance is observed when the amount of spectrum allocated to a SU is varied. As the spectrum size allocated to a SU increases to a degree, the utility of a SU increases; but the performance of a licensed user degrades. Therefore, an optimal and stable solution for spectrum trading in terms of price and allocated spectrum would be required so that the revenue and utility are maximized, while both the seller and the buyer are satisfied and do not want to deviate from the solution.

2.4.3. Techniques for Designing Spectrum Trading Models

There are different techniques that are useful in modeling the spectrum trading process:

- Microeconomic approach: Microeconomic theory can be used to model spectrum trading in a cognitive radio environment where there are a spectrum seller and a spectrum buyer. The solution is obtained from the market-equilibrium, where the demand is equal to the supply. At this point, both the profit of the seller and the satisfaction of the buyer are maximized.

- Classical optimization theory: A classical optimization formulation consists of an objective to be minimized or maximized and a set of constraints. Therefore, we can use an optimization problem to model the spectrum trading process. The objective function can be selected by PSPs according to their preferences. A PSP may want to maximize its profit, other PSP may want to maximize the utility of its SUs, or another PSP may want to minimize the quality degradation into its network. The constraints can be to maintain transmission quality at the target level or maintain the interference level in the network below a certain level.
- Non cooperative game approach: In a non cooperative game model, more than one entity are involved in the market and they have different and possibly conflicting interests. The solution to the game model satisfies all the entities involved.
- Bargaining game approach: It can be useful in situations where cognitive radio entities can cooperate and each entity can influence the action of other entities during spectrum trading. The entities can negotiate and bargain with each other until reaching a fair and efficient solution. A general solution of the bargaining game is the Nash solution, which can ensure efficiency and fairness.
- Auction approach: An auction is a sale in which the price of an item is determined by bidding. An auction can be viewed as a partial information game in which the valuations that each bidder places on the items for sale is hidden from the auctioneer and the other bidders (Courcoubetis and Weber, 2003). In an auction process, the buyers submit their spectrum bids and the profit of spectrum seller is maximized by allocating spectrum to the buyer(s) submitting the highest bidding price. This technique is suitable for a situation where price of the resource is undetermined and is variable with the buyers' requirements.

Auction theory can be applied to a cognitive radio network, allowing a licensed user or a spectrum owner to sell its licensed spectrum to SUs. The main objectives of spectrum are: Determining the clearing price of the spectrum to be sold, and determining the parameter of spectrum access (e.g. frequency band, time slot, and transmit power) by a SU (Hossain *et al*., 2009).

3. RELATED WORK

The underutilization of spectrum has stimulated a flurry of exciting activities in engineering, economics, and regulation communities in searching for better spectrum management policies and techniques (MacKenzie and DaSilva, 2006). In this chapter, we have categorized the works related to our research topic under three main titles: Research on pricing model for communication networks, research on secondary markets and research on the application of game theory in cognitive radio networks, especially for the pricing problems. Over the past few years, our research has also evolved into the issue of charging in cognitive radio networks. Therefore, we have included our recent work in each category at the end of each corresponding section.

3.1. Related Work on Pricing Models in Communication Networks (from Internet to 3G)

The first studies on network economy have begun by examining the pricing in the Internet. One of the first studies is presented by MacKie-Mason and Varian in 1995 (Mackie-Mason and Varian, 1995). They have described the technology and cost structure of the NSFNET backbone of the Internet, and have discussed how one might price Internet access and use. They have argued that usage-based pricing is likely to be necessary to control congestion on the Internet and have proposed a particular implementation of usage-based pricing using a “smart market”. D.D. Clark in 1995, explores issues in the pricing of the Internet, in particular the relationship between the range of service actually offered to users and the cost of providing these services. Based on this analysis, it identifies a new scheme for resource allocation and pricing, expected capacity allocation (Clark, 1995). DaSilva *et al.*, argue for a policy with three price components (set-up, allocation and usage) for multi-service networks that allocate resources according to a Service Level Agreement (DaSilva *et al.*, 1997) (DaSilva *et al.*, 2000b).

For Internet pricing, the heterogeneity in user preferences is proposed by Odlyzko, who also introduced the term *Paris Metro Pricing* (Odylzko, 1999). The major advantage of *Paris Metro Pricing* over traditional QoS-differentiating mechanisms (such as (Mendelson, 1985), (Mandjes, 2003), (Mendelson and Whang, 1990)) is its low complexity from a technological point of view. As in *Paris Metro Pricing* the customers join the subnetworks of their preference, the network elements (routers) can just do the service on a First-Come First-Serve basis, and as a consequence in these sub-networks no prioritization is required. In one other work, a spot pricing framework is established on a nonlinear pricing scheme for cost recovery (Gupta, 2006). They have used a utility based options pricing approach to account for the uncertainties in delivering loss guarantees.

Following the Internet pricing structures, a group of work concentrates on the pricing concepts on 2G, 2.5G and 3G networks. Soursos et al. adapt the Differentiated Services framework and apply it over the GPRS air interface in order to provide various levels of service differentiation (Soursos *et al*., 2001). They also focus on applying a charging technique so as to publish a unit price for each service class. Başar and Srikant consider a network where each user is charged a fixed price per unit bandwidth used, but where there is no congestion-dependent pricing. They answer the question on how should the network choose the price to maximize its overall revenue. They consider a single link accessed by many users where the capacity is increased in proportion to the number of users (Başar and Srikant, 2002).

A large group of these studies use game theoretic approaches to reflect the competitive nature of the telecommunication market. A game theoretic framework for bandwidth allocation for elastic services in high-speed networks is given (Yaiche and Mazumdar, 2000). This framework is based on the idea of the Nash bargaining solution from cooperative game theory. This means that the solution provides the rate settings of users that are Pareto optimal from the point of view of the whole system as well as they are consistent with the fairness axioms of game theory. Das et al. investigate the role and importance of the economic aspects that are vital to the success of wireless services deployment and provider selection by users in a competitive environment. They model the interaction between a service provider and its customers as a non cooperative game. They propose a cross-layer resource management framework for integrated admission and rate control in CDMA networks (Das *et al*., 2004). Zhang et al. analyze a communication network providing differentiated services for heterogeneous users by Paris Metro Pricing scheme. They answer the question on how should the service provider optimally set prices and allocate resources for different services to maximize revenue of overall services. They model the interaction between the service provider and the users as a Stackelberg game, in which the service provider allocates the network resources and sets up prices for different services as a leader, while each user responds with a demand to maximize his/ her surplus as a follower (Zhang *et al.*, 2004). Dai et al. consider the pricing strategies of multiple firms providing the same service in competition for a common pool of customers in a revenue management context. The firms have finite capacities and the demand at each firm depends on the selling prices charged by all firms, each of which satisfies demand up to a given capacity limit. They use the game theory to analyze the systems when firms face either deterministic demand or a general stochastic demand (Dai *et al.*, 2005). A model with two firms and two classes of customers are analyzed in another work (Mandjes and Timmer, 2007). These customers' classes are characterized by their attitude towards congestion. In the first stage of the game, the providers set their prices, whereas in the second stage the customers choose the provider for given prices. They prove that the stage-2 game has a unique equilibrium.

Our first studies in the area of pricing in communication networks were on the 2.5G and 3G networks. In our very first work, we have proposed a simple pricing structure to publish a unit price for each wireless product class by taking into account of the issues of social welfare maximization and price determination (Işıklar and Bener, 2005). We have assumed that each WSP has j classes of products, which are differentiated according to their bandwidth occupancy. The Class 1 with the highest priority includes the premium products, which require mostly a large amount of bandwidth and are very sensitive to delays. At the packet level, applications of this class are forwarded with the highest priority that the system can offer to the customers. Class 2 and class 3 have respectively lower priority than class 1 and are suitable for applications requiring less bandwidth. Although there was not any limitation on the number of time periods, we have used just two distinct periods of time to signify peak hours and non-peak hours in the proposed model. The utility function represents the net benefits of individual end users from different products. We have taken the external effects of a marginal increase in flow in order to determine the local maximum points in that model.

The proposed utility-based pricing model first determines the amount of bandwidth that should be allocated to different product classes which enables WSPs and end users to obtain highest utilities. For instance, with two product classes and a logarithmic utility function, the bandwidth allocation is depicted in Figure 3.1. The curve can be interpreted as: When 30 per cent of the bandwidth capacity is allocated for the first product class and 38 per cent of the capacity is allocated for the second product class, then the end user obtains the maximum net utility. Accordingly, the WSP determines the unit price values in this equilibrium point that brings its profit to a maximum level.

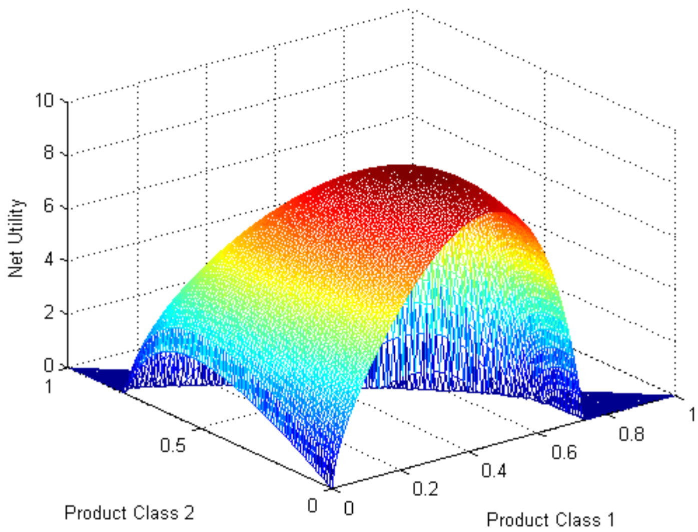

Figure 3.1. Bandwidth allocation to two product classes

Next, we have extended our proposed utility-based approach to a two-stage algorithm to allocate bandwidth in Geostationary Earth Orbit (GEO) satellite networks (Işıklar *et al*., 2006a). The first stage of the algorithm involves determining the portion of bandwidth that should be offered to a satellite gateway, while the second stage consists of sharing this allocated bandwidth among different traffic flow types. At this point, the strategic pricing concept which means building a balance between the customer's desires and the network operator's profits emerges. The proposed approach has the objective to solve simultaneously these two consecutive allocation problems and moreover to propose their pricing scheme.

Another application area of our research had been the mobile commerce services. We have proposed a pricing model for mobile commerce services, by integrating the CRM tool into the pricing problem (Işıklar *et al*., 2006b). In this research, we have first segmented customers according to their CRM values, in order to differentiate the QoS that they receive. CRM is a tool which enables organizations to better understand the needs of their customers. CRM helps the mobile network operators (MNOs) to have customer-specific strategies so that the MNO can improve its service offering as well as increase its revenues. In the second step, we have differentiated the mobile services/products according to their bandwidth requirements and their tolerances to delays. We aim to come up with a unit price for each mobile service/product class.

3.2. Related Work on Secondary Market Models

The success of dynamic spectrum access radio technology relies on their commercial success (Niyato and Hossain, 2008a). For this to occur, the wireless services market itself must evolve. Secondary spectrum market is one of these proposals.

Peha and Panichpapiboon showed that many secondary users can access spectrum with little impact on the primary cellular customers (Peha and Panichpapiboon, 2004). They have differentiated the secondary access from secondary market. Secondary access is defined as the transmission of a secondary device when it does not interfere with the licensed user. In secondary access, SUs usually get no QoS guarantees, because a licensed user may need the spectrum. However, with a secondary market, the guarantees are possible, through explicit coordination between license owner and SUs. Their paper quantitatively assesses real-time secondary market structures. Bai and Chen proposed a flexible spectrum allocation method for secondary markets. They formulated an optimization problem with the objective of profit maximization. They aimed that their model would be useful for network providers to determine appropriate amounts of spectrum for assigning to cognitive users (Bai and Chen, 2006). Al Daoud *et al*. studied the pricing model of a secondary spectrum market where a primary license holder aims at leasing the spectrum rights in a given subset of its coverage area (Al Daoud *et al*., 2009). They have formulated an optimization problem, with the objective of profit maximization. They have modeled traffic in the network. Their simulation results have emphasized importance of effective pricing strategies in bringing secondary markets to full realization.

We have also investigated the secondary spectrum market environment in an economic point of view. In our first proposed model, we have presented a theoretic framework and its process flow in a dynamic spectrum access network, and gave a related pricing model including service providers, spectrum brokers and end users (Işıklar Alptekin and Bener, 2008a). The integration of brokers into the telecommunication business model is given by Di Sorte and Reali. They consider an IP-based communication platform where barrier-free business and market interactions can be performed. They use the network commodity concept in order to define a new usage-based tariff model (Di Sorte and Reali, 2005).

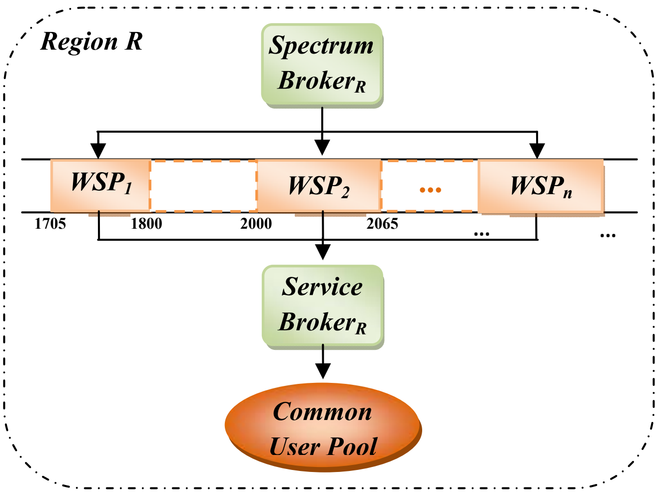

Figure 3.2. Secondary spectrum market architecture with spectrum broker

In the market architecture, a spectrum broker which is at the top of the hierarchy owns licensed portions of spectrum and only leases them for a specified time periods to the WSPs or directly to end users (Figure 3.2). In that way, big player syndrome where only big service providers can operate networks will be ended. This will increase the competition among service providers which will contribute to decreases in telecommunication service prices. A spectrum broker is assumed to be aware of the static characteristics, supported radio frequency ranges, signal processing and various waveform capabilities of WSPs in its region. The objective of a spectrum broker in the given architecture is to obtain revenue from leasing the licensed spectrum bands belonging to WSPs; whereas the objective of a WSP is to offer the best possible service in order not to lose any customer.

A difference of this proposed scenario is that all the users in a region coexist in a common pool. In other words, they are not regular customers of any WSP. The presence of multiple operators in geographic regions together with the freedom of users in switching them is forcing a competitive environment. Thus, we need a network element that provides with the coordination among user pool and WSPs: the service broker. A user, upon entering to a region gets connected to the regional service broker. Certain fixed frequencies are reserved as spectrum information channels that are unidirectional from the service broker to end user's terminal. The service broker first collects demographic information as well as the location of the user. This information will then be utilized when offering a satisfying service to the user.

Next, as a second research, we have proposed a secondary market environment without any broker, in order to be able to get rid of the communication overhead. The framework was based on a spectrum exchange market architecture (Işıklar Alptekin and Bener, 2009a). We will represent this framework in detail in Chapter 5.

3.3. Related Work on the Application of Game Theory in Spectrum Trading

Game theory has been extensively applied in microeconomics, and recently has received attention as a useful tool to design and analyze spectrum management and pricing algorithms (Başar and Olsder, 1995).

Dusit Niyato and Ekram Hossain are the researchers who have been conducting extensive research on the spectrum trading and related pricing models. One of their earliest works on spectrum trading is the one, in which they have proposed a Bertrand game in an oligopoly market consisting of few firms and a customer (Niyato and Hossain, 2007a). In their work, they have considered *spectrum substitutability* which represents the ability that the secondary service can switch among the operating frequency spectrum offered by different service providers. They have used the Nash equilibrium to find the optimal solution in such an oligopoly. Also they have presented distributed iterative algorithm for a dynamic spectrum sharing when the primary services cannot observe the profit for each other. Their model considers that there is only one customer in the market; therefore the demand is known. However, in real life situations, we have more than one customer in the market who require spectrum bands.

Next, they have proposed a Stackelberg leader-follower game to obtain pricing solution for bandwidth sharing (Niyato and Hossain, 2007b). They have considered an integrated WiMAX/WiFi network, where the licensed WiMAX spectrum is shared by the WiFi access points/ routers. They have used a genetic algorithm to iteratively obtain the solution of this game when complete bandwidth demand information is not available. In their work, they have not considered the power control of SUs in network providers' networks. In another work, Niyato and Hossain have considered the problem of hierarchical spectrum sharing in cognitive radio environment (Niyato and Hossain, 2007d). They have formulated the problem of hierarchical spectrum sharing as an interrelated market model in which a multiple-level market is established among the primary, secondary, and tertiary services. They have used the concept of demand and supply functions in economics to obtain the partial equilibrium for which all services are satisfied with the shared spectrum size and the charging price.

Niyato and Hossain consider the problem of spectrum sharing among a primary user and multiple secondary users (Niyato and Hossain, 2007c). They formulate this problem as an oligopoly market competition and use a Cournot game to obtain the spectrum allocation for secondary users. A Cournot game includes more than one firm that produce a homogeneous product. The firms do not cooperate and they compete in quantities that are chosen simultaneously. In another work, they have considered a scenario where routers in the SUs' network form a wireless infrastructure mesh network, and they have investigated two levels of competitions (Niyato and Hossain, 2008c). The first level of competition is among the PSPs to choose the price for spectrum opportunities to maximize their revenues. The second level of competition is among the SUs for spectrum usage to choose the source rate to maximize their utilities.

Different network architectures and protocol behaviors for dynamic spectrum sharing as well as the spectrum sharing models are summarized in (Niyato and Hossain, 2008a). Furthermore, they have introduced a market-equilibrium-based spectrum trading mechanism that uses spectrum demand and supply of the PSPs and SUs, respectively.

Since spectrum supply is stochastic in nature, a distributed and adaptive learning algorithm is used for the SUs to estimate spectrum price and adjust the spectrum demand accordingly so that the market equilibrium can be reached. A comparison of different pricing models is investigated in (Niyato and Hossain, 2008b). In each model, the PSPs have different behavior. Specifically, in market equilibrium pricing model, the objective of spectrum trading is to satisfy spectrum demand from the SUs, and there is neither competition nor cooperation among PSPs. In the competitive pricing, the objective is to maximize the individual profit, and there is competition among PSPs. In cooperative pricing, the objective of spectrum trading is to maximize the total profit, and cooperation exists among PSPs. They have proposed distributed algorithms to achieve the pricing solutions of these pricing algorithms and have analyzed stability of these distributed algorithms.

Recently, they have proposed a spectrum trading problem with multiple primary and secondary users (Niyato and Hossain, 2009). They have used an evolutionary game to model the selection process of secondary users. Their model determines which one of the offered bands are selected by which SUs. Then, a non cooperative game is formulated among primary users in order to determine the size and price of the spectrum that they offer. However, this work does not consider the issue of power management.

Apart from Niyato and Hossain, there are various valuable research which apply game theory in cognitive radio networks, especially in spectrum trading. The convergence conditions for various game models in cognitive radio networks were investigated by Neel et al. (Neel et al., 2004). A game theoretic framework to analyze the behavior of cognitive radios for distributed adaptive channel allocation (Nie and Comaniciu, 2005). Based on the utility definition for cooperative users, they have shown that the channel allocation problem can be formulated as a potential game. They have implemented a no-regret learning algorithm to find the solution of the game. In his dissertation, Neel has presented techniques for modeling and analyzing the interactions of cognitive radio for improving the design of cognitive radio and distributed radio resource management algorithms (Neel, 2006). He has established a non cooperative potential game in order to determine the waveforms of cognitive radios.

Bloem et al., have suggested a Stackelberg game model that allows cognitive radio pairs to update their transmission powers and frequencies simultaneously (Bloem *et al*., 2007). Then, they define the virtual prices for communicating over a licensed channel. In the paper, the price values are computed using two different algorithm: Unidirectional and bidirectional update algorithms. A cooperative game theory model to analyze a scenario is proposed by Suris et al. where nodes in a multi-hop wireless network need to agree on a fair allocation of spectrum (Suris *et al*., 2007). In another research, two different buyer populations, the quality sensitive and the price sensitive are investigated in a cooperative game setup, where players are the network operators and their strategies are the decision of price and QoS level. They have used a stochastic learning algorithm.

Table 3.1 summarizes the most fundamental approaches that we have mentioned above. Non cooperative game, auction structure, bargaining game, optimization approaches, microeconomic approaches have all been utilized as a solution approach for spectrum trading problems.

The research on spectrum trading do not focus on the power control issue within the spectrum pricing model (Al Daoud *et al*., 2007) (Niyato and Hossain, 2008b) (Niyato and Hossain, 2009). Saraydar et al., have presented a power control solution based on a game theoretical framework for wireless data (Saraydar *et al*., 2002). They have stated that the pricing approach for power control is especially helpful in a heavily loaded system. Mwangoka et al. have developed a mechanism that enables joint spectrum allocation, revenue maximization and power control through pricing while achieving a desired QoS performance (Mwangoka *et al*., 2009). They cited the fact that the spectrum is owned by the state, and hence they considered monopoly as the mode of management. Alpcan *et al*., have presented a game-theoretic model of distributed power control in CDMA wireless systems (Alpcan *et al*., 2002). They have set a price per unit transmission power in order to minimize transmission powers; in other words, they observed the effect of price setting on power management.

Prior to the extended research in this dissertation, we have proposed a game theoretic-based model which was considering a brokering architecture for next generation cognitive radio-based communication platform (Işıklar Alptekin and Bener, 2008b). This system and its results will be described in Chapter 5.

3.4. Research Questions

Our main research problem in this dissertation concerns the pricing problem in computer networks. It was referred as *network economy* when Internet and the cellular networks were in consideration; however after the appearance of cognitive radio technologies and dynamic spectrum access networks, now, it is referred as *spectrum trading*.

We have initiated our studies by examining the models proposed for Internet pricing, in 2004. Our first work was a utility-based pricing model for a MNO in a cellular network (Işıklar and Bener, 2005). This work was differentiating the wireless services according to their tolerance to delays. We have determined the price of each type of service, as well as the amount of bandwidth that the operator has to allocate to each type of service. Then, we have applied a similar model to a GEO satellite network (Işıklar *et al*., 2006) so as to make a bandwidth allocation among satellite gateways, furthermore among different types of services. The model was more complicated, since it was implemented in both stages. The proposed framework was based on an optimization problem that maximizes a utility function. The model was not considering any competition in the environment.

Next, we have made an application of a similar model in order to determine the unit prices of different mobile commerce products; but this time we have differentiated the end users according to their Customer Relationship Management (CRM) values (Işıklar *et al*., 2006). From the simulation results, we have seen that, understanding the customer preferences and directing the marketing plans to a target market increases both the revenues of service providers and the utilities of customers. With this inference in mind, we have integrated the CRM tool into the resource allocation process in cellular networks (Kastro *et al*., 2009).

Table 3.1. Summary of research that utilize game theory as a solution approach

	Structure, Behavior	Approach	Players	Strategy	Payoff
Demand responsive pricing (İleri *et al*., 2005)	Distributed, non cooperative	Non cooperative game / auction	Network operators	(offered rate, price)	Expected profit of all operators
Adaptive channel allocation in spectrum etiquette (Nie and Comanicu, 2005)	Distributed, non cooperative	Non cooperative game / potential game	Cognitive radios	(transmission parameters &frequency)	Perceived utility by cognitive radios
Distributed radio resource management algorithm (Neel, 2006)	Distributed, non cooperative	Non cooperative game / potential game	Cognitive radios	(waveform)	Perceived utility by cognitive radios
Dynamic pricing in competitive spectrum access (Xing *et al*., 2007) (Işıklar Alptekin and Bener, 2008b)	Distributed, non cooperative/ cooperative	Non cooperative game / stochastic learning algorithm	Network operators	(quality, price)	Utility of spectrum buyers
Stackelberg game for power control &channel allocation (Bloem *et al*., 2007)	Distributed, non cooperative	Stackelberg game	Cognitive radios	(power level, available channel)	Utility of each cognitive radio

Table 3.1. Summary of research that utilize game theory as a solution approach (continue)

	Structure, Behavior	Approach	Players	Strategy	Payoff / Solution
Optimal price competition (Niyato and Hossain, 2007a)	Distributed, non cooperative	Bertrand game	Primary network operators	(offered price)	Profit of each primary network operator
Optimal pricing for integration of WiMAX and WiFi (Niyato and Hossain, 2007b)	Centralized, non cooperative	Stackelberg game/ Genetic algorithm	Leader: WiMAX BS, Follower: WiFi APs	Leader: (price) Follower: (required bandwidth)	Profit of the leader and the followers
Oligopoly market competition (Niyato and Hossain, 2007c)	Distributed, non cooperative	Cournot game	SUs	(allocated spectrum size)	Profit of SUs
Competitive spectrum sharing (Niyato and Hossain, 2008c)	Distributed, non cooperative	Non cooperative game	Traffic flows of SUs	(source rate)	Utility of SUs
Multiple-seller multiple-buyer spectrum trading (Niyato and Hossain, 2009)	Non cooperative	Evolutionary game/ Non cooperative game	SUs/ PSPs	Decision on buying spectrum from among the PSPs / offered price	Utility of SUs / Net utility of PSPs

Table 3.1. Summary of research that utilize game theory as a solution approach (continue)

	Structure, Behavior	Approach	Players	Strategy	Payoff / Solution
Distributed fair spectrum allocation using cooperative game (Suris *et al*., 2007) (Işıklar and Bener, 2005)	Distributed, cooperative	Nash bargaining solution	Transmitting nodes	(available channel)	Received utility by transmitting nodes
Hierarchical spectrum/ bandwidth sharing (Niyato and Hossain, 2007) (Işıklar Alptekin and Bener, 2008a)	Distributed, non cooperative	Microeconomic approach	-	-	Market-equilibrium of price
Market-equilibrium-approach in spectrum trading (Niyato and Hossain, 2008a)	Distributed	Microeconomic approach / Market equilibrium	-	-	Market demand = Market supply
Analysis and comparison of three pricing models (Niyato and Hossain, 2008b)	Distributed, cooperative / non cooperative	Market equilibrium/ Non cooperative game/ Cooperative game	SUs	(requested/ allocated spectrum size)	Market demand = Market supply/ Nash equilibrium/ Optimal price

We have claimed that, using the call information together with the personal information and usage behaviors of the customers rather than using only the technical network parameters, improves the revenue of network operators. The results validate our claim, since the proposed approach allows network operator to make an 8 per cent of extra revenue for the scenarios that we have studied. Again, this work was always considering that there was only one entity in the market.

Since an optimization-based formulation maximizes/ minimizes the given objective function which is defined for the system as a whole, the solution may not satisfy all the related entities individually. In real life spectrum trading environments, there are multiple service providers that are selfish and needs to maximize their own profit. Game theory is one of the most popular mathematical models used to analyze the interaction among multiple entities (Fudenberg and Tirole, 1991). In contrast to an optimization-based approach, a game theoretic formulation aims at providing individually optimal solutions, which are more suitable for a situation where many entities interact with each other to achieve their interests.

In a secondary market where service providers trade their available spectrum bands, there are various entities that interact with each other. The demand, supply, received revenues and offered prices all depend on each other. Therefore, it is important to make an analysis in order to quantify these relationships. Besides, the trading architecture itself is important in spectrum trading; since the owners of the available spectrum need to inform potential buyers; and also, the SUs that seek for spectrum bands need to inform the spectrum owners on their requests. There could be some private or governmental agencies in the networks, which have the role of an intermediator or a broker. However, the existence of such a frequency broker in a network environment may cause severe communication overhead. Furthermore, as the broker is expected to be a third part agency, service providers would pay a brokerage commission. These additional costs may reduce the desire towards spectrum trading process.

Companies are becoming increasingly aware of many potential benefits provided by customer-oriented business strategies. In telecommunication market, retaining the existing subscribers is as costly as acquiring new ones (Hwang *et al*., 2004). Therefore, integrating the customer preferences, their demographic information and their usage behaviors in the pricing system may have an impact on both the satisfaction of customers and on the profits of spectrum owners.

Moreover, the research on spectrum trading do not focus on the power control issue within the spectrum pricing model (Al Daoud *et al*, 2007) (Niyato and Hossain, 2008b) (Niyato and Hossain, 2009). The research on pricing and power control in cognitive radio networks usually includes the concept of pricing in order to control power (Mwangoka *et al*., 2009) (Alpcan *et al*., 2002). The transmission power control is one of the major QoS parameters in a dynamic spectrum access network, since it is directly related to the interference level that the PUs experience. A PSP has to keep the service quality of its PUs up to a certain threshold value. On the other hand, SUs tend to increase their transmission powers in order to improve their communication qualities. This will cause interference on the PUs, as well as on other SUs. Hence, a spectrum trading process needs to include a power control component. Especially, the impact of power management into the price setting process needs to be examined.

The service providers are expected to offer the spectrum bands that are not utilized by their PUs (Mwangoka *et al*., 2009) (Hwang and Yoon, 2009). However, selling more bandwidth than the unutilized portion may be more profitable for a PSP in some cases. A PSP could have the flexibility on the size of the offered bandwidth by keeping the service quality of its PUs in an acceptable range.

As mentioned earlier, the PSPs compete with each other to sell the spectrum opportunities to potential SUs. Each PSP should carefully set its price so as to maximize its profit. On the other hand, the price is important to grab maximum number of SUs. If the offered price is too high, the SU has the freedom to deviate and buy spectrum from another PSP. Multiple-seller and multiple-buyer environment is studied by Niyato *et al*. (Niyato *et al*., 2009). They model the dynamic buying behavior of SUs using the theory of evolutionary game. This game foresees the number of SUs that will communicate in each PSP's network. Then, PSPs play a non cooperative game to determine their unit prices. However, such a set up does not take into consideration the power control of SUs.

Therefore, in this research, we state six research questions, and in the rest of the dissertation, we will look for empirical evidences for the answers to these questions:

- How can we structure a basic model which sets relationships among network demand, service providers' profit and service prices?
- What would be the effect of intermediary agency in spectrum trading?
- What kind of impact the CRM tool has on the profit maximization?
- What kind of impact transmission power has on the profit maximization, as well as on the unit spectrum prices?
- What kind of impact the flexibility on the amount of offered spectrum bands has on profit maximization, as well as on the unit spectrum prices?
- How can we structure a market where each PSP determines its target customers and their potential demand and then determine their unit prices?

4. METHODOLOGY: GAME THEORY

We use the game theory as a methodology to solve competitive price setting problem of PSPs. Game theory can be defined as the study of mathematical models of conflict and cooperation between intelligent rational decision-makers. It provides general mathematical techniques for analyzing situations in which two or more individuals make decisions that will influence one another's welfare (Myerson, 1991). These situations are referred as the *interactive decision processes*. Like other sciences, game theory consists of a collection of models. A *model* is an abstraction that we use to understand our observations and experiences (Osborne, 2004). In this section, the concepts and the elements of game theory is discussed.

4.1. Basic Elements of a Game

Whether implicitly or explicitly, every game includes the following elements (Neel, 2006):

- A set of *players*,
- *Strategies* for each of the players,
- Some method for determining the *payoffs (outcomes)* according to the actions chosen by the players,
- *Preferences* for each of the players defined all the possible outcomes,
- *Rules* specific to the model, e.g. the order of play**.**

The elements in a game are related to specific components of the interactive decision process (Table 4.1).

Table 4.1. Relationships between game elements and interactive decision process components (Neel, 2006)

Game	⇔	Interactive Decision Process
Player	⇔	Decision Maker
Strategies	⇔	Inputs
Payoffs	⇔	Outputs
Preferences	⇔	Decision Maker Objectives
Rules	⇔	Decision Timings

4.1.1. Players

The *players* are the decision making entities in the interactive decision process. There are two basic assumptions that game theorist generally make about players: They are rational and they are intelligent. A decision maker is *rational* if he makes decisions consistently in pursuit of his objectives (Myerson, 1991). Each player is assumed to have a consistent set of rankings (values or payoffs) over all the logically possible outcomes and to calculate the strategy that best serves these interests (Dixit *et al*., 2009). Thus, rationality has two essential ingredients: Complete knowledge of one's own interests and flawless calculation of what actions will best serve those interests. As a rule, games only consider situations where there are two or more players.

4.1.2. Strategies/ Actions

In game theory, a player's *strategy* is a complete contingent plan of action for whatever situation might arise. The strategy of a player determines the action the player will take at any stage of the game, for every possible history of play up to that stage. If a game has purely simultaneous moves made only once, then each player's strategy is just the action taken on that single occasion. But if a game has sequential moves, then the actions of a player who moves later in the game can respond to what other players have done (or what he himself has done) are earlier points. An example of a strategy would be:

"If my rival does A, then I will do X but, it my rival does B, then I will do Y."

4.1.3. Payoffs/ Outcomes

Although the objective of a player is though “to win” by most of the people, very few games are purely zero-sum or win-lose. For instance, in research and development competition, if your product is slightly better than the nearest rival’s, your patent may be more open to challenge.

Each player in a game is given a complete numerical scale with which to compare all outcomes of the game, corresponding to each available combination of choices of strategies by all the players. The numerical value associated with each possible outcome is called that player’s *payoff* for that outcome. The payoffs can be simple numerical ratings, such as 1 for the worst, 2 for the next worst, and so on. Other games can have more natural numerical scales, such as money income, profit of a firm, ratings for televisions, etc. The payoffs for a player should capture everything in the outcomes that the player cares. In many cases, the payoff function is represented by a *utility function*, which assigns a number to each possible outcome, with higher utilities representing more desirable outcomes.

4.1.4. Preferences

Preference is a concept, used in the social sciences, particularly in economics. In a game, it is assumed that each player knows which strategy he prefers or which strategies are equally desirable for him. These preferences are assumed to be consistent; in other words, if the player prefers the action *a* to action *b*, and the action *b* to action *c*, then he prefers the action *a* to the action *c*.

For small games, we can list all of the preference relations for every player over all possible outcomes. However, as the size of the game grows this can quickly become unwieldy. The reason to employ a utility function is to capture these preference relations in a more compact way.

4.1.5. Rules

At some level, the players are assumed to have a common understanding of the rules of the game. Game theory cannot properly analyze a situation where one player does not know whether another player is participating in the game, what the entire sets of actions available to the other players, or what their value systems are. But in actual strategic interactions, some of the biggest gains are to be made by taking advantage of the elements of surprise and doing something that your rivals never thought you capable of (Dixit *et al*., 2009). The strict definition of game theory leaves out a very important aspect of strategic behavior. However, the theory can be formulated so that each player attaches some small probability to the situation where such dramatically different strategies are available to the other players.

4.2. Basic Game Models

The analysis of any game or conflict situation must begin with the specification of a model that describes the game. Of course, the elements of a model vary from decision process to decision process, but it is possible to consider broad classes of game model.

4.2.1. Cooperative and Non Cooperative Games

A *cooperative game* is a game where groups of players may enforce cooperative behavior. This type of games considers the competition between coalitions of players, rather than between individual players. A *non cooperative game* is one in which players make decisions independently. It is not defined as games in which players do not cooperate, but as games in which any cooperation must be self-enforcing. If the information is strictly limited to local information, the non cooperative game might be the only choice for each player to play.

4.2.2. Simultaneous Move and Sequential Move Games

Simultaneous move games are games where players must move without knowledge of what their rivals have chosen to do. Hence, the players choose their actions at exactly the same time. A game is said to be simultaneous when players choose their actions in isolation, with no information about what other players have done or will do, even if the choices are made at different hours (For this reason, simultaneous move games are said to have *imperfect information*.). In s*equential move games*, players take turns making their actions, and they know what players who have gone before them have done.

4.2.3. Perfect Information and Imperfect Information Games

The game of perfect information is a subset of sequential games. A game is said to have perfect information if each player, at each point where it is his turn to act, knows the full history of the game up to that point, including the results at any random actions taken by nature or previous actions of other players in the game, including pure actions as well as the actual outcomes of any mixed strategies they may play. Otherwise, the game is said to have imperfect information.

4.2.4. Supermodular Games

The concept of supermodularity is used in the social sciences to analyze how one player's decision affects the incentives of others. Supermodular games constitute an interesting class of games that exhibits strategic complementarity, which means that if any player i chooses a higher s_i, all other players j have an incentive to raise their strategies s_j too (Levin, 2003). The supermodular games are interesting for several reasons. They encompass many applied models like existence of pure strategy Nash equilibrium, dominance solvability, identical bounds on joint strategy space etc (Saraydar *et al*., 2002). Supermodular games are also important for mechanism designers as it is observed that supermodularity has a strong connection with convergence to the Nash equilibrium. Much of the theory is due to (Topkis, 1979), (Vives, 1999) and (Milgrom and Roberts, 1990). The conditions of supermodularity are checked using the following theorem in (Milgrom and Roberts, 1990):

Theorem 1 : The game *G* is supermodular if (A1)-(A4) below are satisfied:

(A1) S_n is an interval in $\Re^N$, that is $S_n = \left[\underline{y}_n, \bar{y}_n\right] = \left\{x \middle| \underline{y}_n \leq \bar{y}_n\right\}$;

(A2) f_n is twice continuously differentiable on S_n;

(A3) $\frac{\partial^2 f_n}{\partial x_{ni} \partial x_{nj}} \geq 0$ for all *n* and all $1 \leq i < j \leq N$;

(A4) $\frac{\partial^2 f_n}{\partial x_{ni} \partial x_{mj}} \geq 0$ for all $n \neq m, 1 \leq i \leq N$ and $1 \leq j \leq M$.

Then a pure Nash equilibrium is a strategy tuple $x = (x_n; n \in N)$ such that each x_n maximizes $f\left(\hat{x}_n, x_{-n}\right)$ over S_n. Any pure Nash equilibrium is by definition also a mixed Nash equilibrium and a correlated equilibrium.

4.3. Nash Equilibrium and Best Response Analysis

In this section, we will ask the question of: "What actions will be chosen by players in a strategic game?" In the theory of a rational decision-maker, it is assumed that each player chooses the best available action. In a game, the best action for any given player depends, in general, on the other players' actions. Therefore, when choosing an action a player must have in mind the actions the other players will choose. The player must form a *belief* about the other players' actions (Osborne, 2004). Each player's belief is derived from his/ her past experience playing the game. The actions of the opponents are not known, but the previous involvement in the game leads him/ her to be sure of these actions.

The solution that we study has two components: First, each player chooses his/ her action according to the model of rational choice given his/ her belief about the other players' actions. Second, every player's belief about the other players' actions is correct. These two components form the definition of Nash equilibrium (NE) (Osborne, 2004):

"*A Nash equilibrium is an action profile a* with the property that no player I can do better by choosing an action different from* a_i^**, given that every other player j adheres to* a_j^*."

In game theory, the most frequently discussed steady state is the NE. The NE is defined as the solution of a game. It is the set of strategies adopted by the players such that none of the players wants to deviate from it. In this equilibrium, each player's chosen strategy is optimal given that every other player chooses the equilibrium strategy as well (Başar and Olsder, 1995). Osborne interprets NE as: "*A steady state where each player holds a correct expectation of the other players' behavior and acts rationally* (Osborne, 1994)."

The second component of the NE, which says that the players' beliefs about each other's actions are correct, implies that two players' beliefs about a third player's action are the same. For this reason, the condition is sometimes referred to as the requirement that the players' expectations are coordinated.

Let *a* be an action profile, in which the action of each player *i* is a_i. Let a'_i be any action of player *i*. Then $(a'_i,\ a_{-i})$ denotes the action profile in which every player *j* except *i* chooses her action a_j as specified by *a*, whereas player *i* chooses a'_i. The *–i* subscript on *a* stands for "except *i*". That is, $(a'_i,\ a_{-i})$ is the action profile in which all the players other than *i* adhere to a while *i* deviates to a'_i.

An action profile *a** is a NE, if no player *i* has any action a_i for which she prefers $\left(a_i,\ a^*_{-i}\right)$ to *a**. Equivalently, for every player *i* and every action a_i of player *i*, the action profile *a** is at least as good for player *i* as the action profile $\left(a_i,\ a^*_{-i}\right)$.

The action profile *a** in a strategic game is a *Nash equilibrium* if, for every player *i* and every action a_i of player *i*, *a** is at least as good according to player *i*'s preferences as the action profile $\left(a_i,\ a^*_{-i}\right)$ in which player *i* chooses a_i while every other player *j* chooses a^*_j. For every player *i*,

$u_i\left(a^*\right) \geq u_i\left(a_i, a^*_{-i}\right)$ for every action a_i of player *i*,

where u_i is a payoff function that represents player *i*'s preferences (Osborne, 2004).

This definition implies neither that a strategic game necessarily has a Nash equilibrium, nor that it has at most one.

4.4. Best Response Analysis

The Nash equilibria of a game in which each player has only a few actions can be found by examining each action in turn to see is it satisfies the conditions for equilibrium. In more complicated games, it is better to work with the players' best response functions.

Consider a player, say player *i*. For any given actions of the players other than *i*, player *i*'s actions yield his/ her various payoffs. We are interested in the best actions, those that yield him/ her the highest profit. A NE is defined as the action profile for which every player's action is a best response to the other players' actions. The best response function of player *i* is defined as (Fudenberg and Tirole, 1991):

$$B_i\left(a_{-i}\right) = \arg\max_{a_i \in A} u_i\left(a_i, a_{-i}\right) \tag{4.1}$$

Every member of the set $B_i(a_{-i})$ is a best response of player *i* to a_{-i}: if each of the other players adheres to a_{-i}, then player *i* can do no better than choose a member of $B_i(a_{-i})$. The action profile a* is a NE of a strategic game if and only if every player's action is a best response to the other players' actions:

a_i^* is in $B_i\left(a_{-i}^*\right)$ for every player *i*.

Best response analysis is a comprehensive way of locating all possible Nash equilibria of a game. The best response is the strategy that is optimal for one player, given the strategies actually played by the other players, or the belief of this player about the other players' strategy choices (Dixit *et al*., 2009).

5. PROPOSED MODELS FOR SPECTRUM TRADING AND RESULTS

In this chapter, we represent four alternative spectrum trading architectures that are proposed to answer to our research questions. In the first section, we describe the brokering and pricing architecture which is proposed to find main economic relationships among network elements. This was also our first research question. In the second section, we introduce the spectrum exchange architecture. We have proposed such an exchange architecture to get rid of the communication overhead caused by frequency brokers, which is also our second research question. The third section includes the use and the contributions of the CRM tool into the spectrum exchange market environment. Finally, the last section represents the spectrum trading architecture with a power control. It is our most developed pricing model with power control mechanism and it looks to find the answers to our last three research questions.

5.1. Brokering and Pricing Architecture

Our objective in this architecture was to answer to our first research question, which is: “How can we structure a basic model which sets relationships among network demand, service providers’ profit and service prices?” Doing so, we have come up with a network environment where the frequency brokers (FBs) have the role of an intermediary agency among service providers (SPs) and end users.

5.1.1. Network Architecture and Elements

We assume that the cognitive radio value chain includes the frequency brokers that have direct interaction with service providers in the brokering architecture (Işıklar Alptekin and Bener, 2008b) (Figure 5.1). The essence was to bring out the nexus between wireless network technology and economics, often ignored by researchers. The simple model determines the socially optimal prices for different QoS levels that maximize the social welfare of all the players in the communication market.

In the proposed model, the SPs have subscribers with whom they have signed a Service Level Agreement (SLA). Similarly, the SPs have SLAs with one or more FBs. We consider a number of independent FBs, which have the task of providing the most appropriate frequency band in response to a request at the least possible price. They detect the SP's network on regular basis to discover the temporarily unused spectrum holes. The SPs' objective is to utilize their unused resources at that time to fulfill their subscribers' requests. The end users do not necessarily demand a share of the spectrum directly, but may require a certain service instead. These services' requirements are then converted into an optimal amount of spectrum (e.g. bandwidth) by the SP. Below is the information flow of the proposed framework:

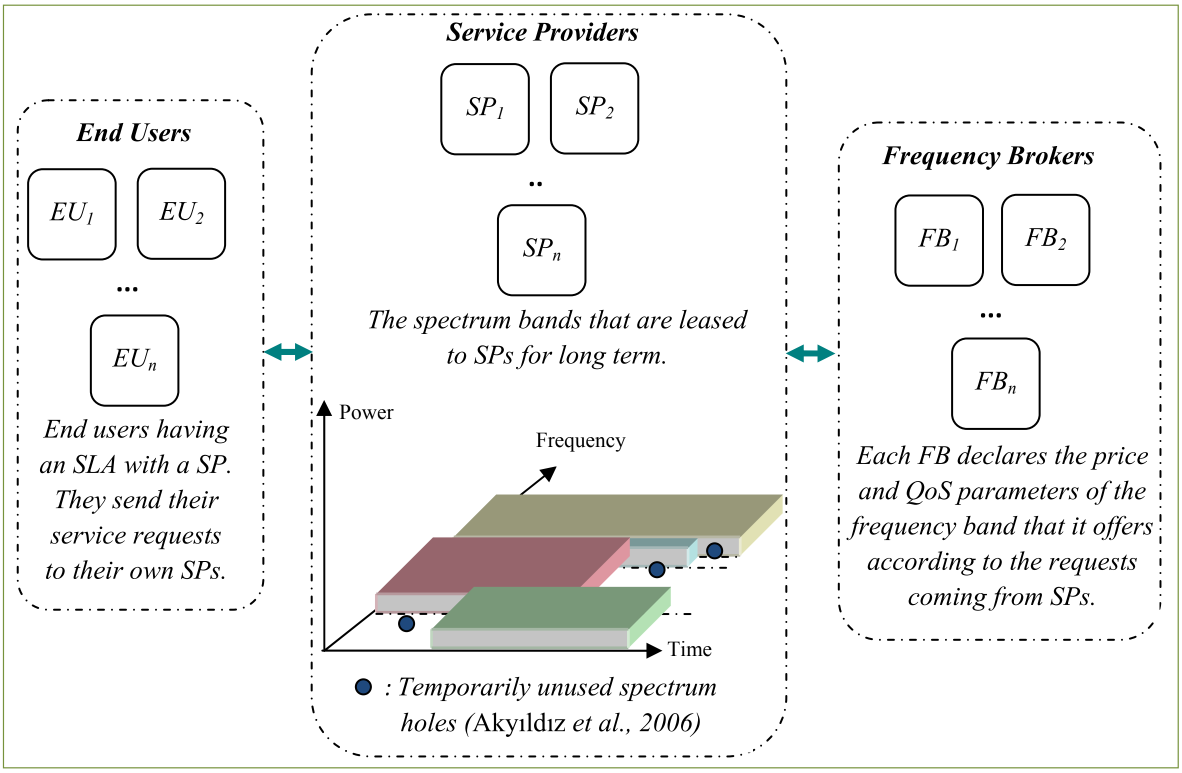

Figure 5.1. Cognitive radio-based brokering architecture

(i) The end users send their service requests to their service providers.

(ii) The service provider offers the service; if it has sufficient resources.

(iii) Otherwise, the service provider requests the necessary resources from the frequency brokers.

(iv) The frequency brokers' declare their offers that include the QoS parameters values and the price.

(v) The service provider decides which frequency offer to buy by comparing the QoS parameters values and prices.

The competitive wireless network market is a good example of a non cooperative game (Başar and Olsder, 1995). The FBs, on one hand, want to maximize their own revenues. The SPs, on the other hand, want to maximize their own QoS satisfactions at minimum expense, given that a SP has the freedom to leave the current FB and sign a SLA with a better one in the competitive market. These two goals are different and often conflict with each other. In such a competitive environment, the FBs try to make a SLA with maximum number of SPs. Thus, the *players* in the proposed game are the FBs. The brokers' revenues are modeled as their *payoffs*. Their *strategies* are the choices of the unit spectrum prices in respect to the given QoS parameters. The FBs have no apparent motivation to cooperate with each other to achieve a single optimal goal. The QoS satisfaction of a SP is directly related to the QoS satisfaction of its customers, since the SP offer the resources to satisfy the requests of services of its customers.

For the sake of simplicity, we suppose that the industry consists of two risk neutral FBs and two SPs. That means that they all want to maximize their own profits. We assume that the SPs require the same type of frequency band that the FBs offer (i.e. they both require/ offer GSM frequencies or TV broadcasting frequencies). Let us assume that a FB has two strategies:

(i) Offer the required frequency band,
(ii) Not to offer it.

The SP seeking resources also has two strategies:

(i) Buy the frequency band offered by the broker,
(ii) Not to buy it.

In our scenario, we characterized two SPs by the letters *T* and *V*; and two FBs by *T_Broker* and *V_Broker*. *T_Broker* listens the *T* network in order to detect the unused frequency bands. *T* can buy a frequency band from both *V_Broker* and *T_Broker*. The difference is that; if T buys T's frequency bands; it receives extra utility r_1, because T can utilize its own value-added services. Additionally, the reason that we have incorporated this extra utility is that a SP has the tendency to prefer its own unused resources, if its rival's bands are at the same price or at higher prices to a certain degree. If T buys V's frequency bands, it does not have this extra utility. Similarly, if V buys V's frequency bands, it receives an extra utility of r_2.

We assume that the SPs are uniformly distributed along the unit interval [0, 1]. Their positions in that interval reveal their valuations for the two FBs. Here the valuation is utilized interchangeably with the utility value that a SP can have from a FB. The valuation of the SP in the unit interval is denoted by x. We assume that the maximum utility value that a SP can have from a FB is located in different locations in the unit interval. The SP attaching higher value to *T_Broker* is positioned closer to zero (left half of the interval), while the SP attaching higher value to *V_Broker* is positioned closer to one (right half of the interval) (Figure 5.2) (Özertan and Çevik, 2003). The SPs have three options:

(i) Buying its own unused frequency band,
(ii) Buying its rival's unused frequency band,
(iii) Not buying any frequency band.

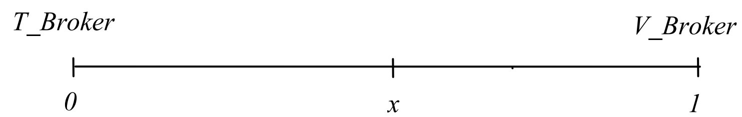

Figure 5.2. Positioning of the service providers when valuating brokers

The prices of the frequency bands depend on several parameters. First of all, the offered frequency band should be the same type as the required frequency band (q_{3k}). This means that, if we require an AM broadcasting band; the FB cannot offer us a GSM band. Secondly, we consider the received signal power (q_{1k}) by the SP which is measured for each period by the FB. The utility value that the SP receives is proportional to the signal power value. Finally, we consider the location of the SP into the variable q_{2k}, to include the congestion and popularity level. All these parameters add up to the quality of the offered frequency band. This value is also equal to the valuation of the offered frequency band by SPs.

$$quality = (\rho_{1k}.q_{1k} + \rho_{2k}.q_{2k})(1 - q_{3k}), \quad k \in \{T\_Broker, V\_Broker\} \tag{5.1}$$

In our model, we do not consider that the FB offers different types of frequency bands from different ranges; therefore as the quality of the k^{th} frequency broker, we only care about the parameters q_{1k} and q_{2k}. ρ_{1k} and ρ_{2k} are the importance weight coefficients of the quality parameters which are set by the k^{th} frequency broker.

The FBs are located at each end of the unit interval (Figure 5.2). *T_Broker* is located at 0, and *V_Broker* is located at 1. The value attached to *T*'s frequency bands by the SPs is maximized at 0 and is equal to $(\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T})$, which is equal to the quality of the band, where $(\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}) > 0$. Similarly, the value attached to *V*'s bands by the SPs is maximized at 1 and is equal to $(\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V})$, where $(\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V}) > 0$. Both *V* and *T* want to maximize their profits. Given the quality levels, each FB sets profit-maximizing prices and they both incur fixed costs. We assume that all the resources are required for an equal period of time, thus the time parameter is not included in our formulations.

5.1.2. Service Provider Behavior

We assume that the preferences of the SPs can be described by a utility function *U*. Our first assumption is that both SPs may buy their own unused frequency bands and their rival's unused bands. The other possibility is not buying any frequency band. If *T* located at *x* buys the band offered by *T_Broker* at price *p*, it will get its valuation $(1 - x)\,.\,(\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T})$ and a constant utility r_1 by utilizing the value-added services yielding the net utility:

$$(1 - x)\,.\,(\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}) + r_1 - p \tag{5.2}$$

Similarly, let $x.(\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V})$ be the value attached to *V_Broker*'s frequency bands by the SP located at *x*. Then, the above argument applies and the net utility that *V* receive will be

$$x.(\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V}) + r_2 - q \tag{5.3}$$

If *T* or *V* does not buy any band, their utilities are zero. If *V* located at *x* buys the frequency band offered by *T_Broker*, it only gets its valuation:

$$(1-x).(\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}) - q \tag{5.4}$$

Similarly, if *T* located at *x* buys the frequency band offered by *V_Broker*, its net utility will be:

$$x.(\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V}) - q \tag{5.5}$$

5.1.3. Demand Function of the Service Providers

The demand functions are calculated by using the indifference points between the utility curves. For instance, *T* is indifferent between buying *T*'s bands and buying *V*'s bands if and only if his expected returns from buying them are equal. The indifference points of *T* between buying *T*'s bands and buying *V* ones can be obtained by the equation:

$$(1-x).(\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}) + r_1 - p = x.(\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V}) - q \tag{5.6}$$

Likewise, the indifference points of *T* between buying *T*'s bands and buying nothing at all can be obtained by the equation:

$$(1-x).(\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}) + r_1 - p = 0 \tag{5.7}$$

The demand functions of the encapsulated all the utility functions are given as follows:

$$D_T^T = \frac{(\rho_{1T}.q_{1T}+\rho_{2T}.q_{2T})-p+q+r_1}{(\rho_{1T}.q_{1T}+\rho_{2T}.q_{2T})+(\rho_{1V}.q_{1V}+\rho_{2V}.q_{2V})} \tag{5.8}$$

$$D_V^T = \frac{(\rho_{1V}.q_{1V}+\rho_{2V}.q_{2V})+p-q-r_1}{(\rho_{1T}.q_{1T}+\rho_{2T}.q_{2T})+(\rho_{1V}.q_{1V}+\rho_{2V}.q_{2V})} \tag{5.9}$$

$$D_V^V = \frac{(\rho_{1V}.q_{1V}+\rho_{2V}.q_{2V})+p-q+r_2}{(\rho_{1T}.q_{1T}+\rho_{2T}.q_{2T})+(\rho_{1V}.q_{1V}+\rho_{2V}.q_{2V})} \tag{5.10}$$

$$D_T^V = \frac{(\rho_{1T}.q_{1T}+\rho_{2T}.q_{2T})-p+q-r_2}{(\rho_{1T}.q_{1T}+\rho_{2T}.q_{2T})+(\rho_{1V}.q_{1V}+\rho_{2V}.q_{2V})} \tag{5.11}$$

where D_T^T is the *T* frequency band demand of *T*, D_V^T is the *V* frequency band demand of *T*, D_V^V is the *V* frequency band demand of *V* and D_T^V is the *T* frequency band demand of *V*. We have D_V^T = 1 - D_T^T, and D_T^V = 1 - D_V^V. The total demand to *T_Broker* (D_T) or *V_Broker* (D_V)'s bands is the sum of the demand of the two SPs of *T* or *V*'s bands.

5.1.4. Equilibrium of the Game

In this subsection, we are interested in finding p^{NE} and q^{NE} that are defined as the equilibrium prices of *T_Broker* and *V_Broker*, respectively. When *T* buys *T_Broker*'s bands, it lies in the interval [0, *x*). We sum the expected net revenue of *T* over [0, *x*) to get the total surplus. Hence, the total surplus of *T* when buying *T*'s bands is given by the integral:

$$\int\limits_{over\ D_T^T} ((1-x).(\rho_{1T}.q_{1T}+\rho_{2T}.q_{2T})+r_1-p^{NE}).dx \tag{5.12}$$

Similarly the total surplus of *T* when buying *V* bands is given by the integral:

$$\int\limits_{over\ D_V^T} (x.(\rho_{1V}.q_{1V}+\rho_{2V}.q_{2V})-q^{NE}).dx \tag{5.13}$$

On the other hand, when *V* buys *V_Broker*'s frequency bands, it lies in the interval (*x*, 1]. The total surplus of *V* when buying *V* bands and the total surplus of *V* when buying *T*'s bands is given in (5.14) and (5.15), respectively.

$$\int\limits_{over\ D_V^V} (x.(\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V}) + r_2 - q^{NE}).dx \tag{5.14}$$

$$\int\limits_{over\ D_T^V} ((1-x).(\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}) - p^{NE}).dx \tag{5.15}$$

The two FBs want to maximize their profits π_T and π_V with respect to p and q, respectively. We assume that the FBs face costs which increase with the value of the frequency band and the given value-added services. We define $C_T\left((\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}), r_1\right)$ and $C_V\left((\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V}), r_2\right)$ to be the costs incurred by *T_Broker* and *V_Broker*, respectively. Therefore, the frequency brokers' profits are:

$$\pi_T = p.D_T - C_T((\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}), r_1) \tag{5.16}$$

$$\pi_V = q.D_V - C_V((\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V}), r_2) \tag{5.17}$$

A SP's surplus is the difference between what the provider is willing to pay for a good and what the provider actually pays for it. In our case, SP surplus is the difference between the value attached to the frequency band and its price. SPS_T is the total surplus of T and V buying T's frequency bands, while SPS_V is the total surplus of T and V buying V's frequency bands.

$$\begin{aligned} SPS_T = &\int\limits_{overD_T^T} \left((1-x).(\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}) + r_1 - p^{NE}\right).dx + \\ &\int\limits_{overD_T^V} \left((1-x).(\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}) - p^{NE}\right).dx \end{aligned} \tag{5.18}$$

$$\begin{aligned} SPS_V = &\int\limits_{over\ D_V^T} (x.(\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V}) - q^{NE}).dx + \\ &\int\limits_{over\ D_V^V} (x.(\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V}) + r_2 - q^{NE}).dx \end{aligned} \tag{5.19}$$

Social welfare, *SW*, is the sum of total SPs' surpluses and brokers' profits.

$$SW = SPS_T + SPS_V + \pi_T + \pi_V \tag{5.20}$$

<u>5.1.4.1. Concavity of the objective function</u>: The objective function of the problem is:

$$\max \quad \pi_i, \quad i \in \{T\_Broker, V\_Broker\} \tag{5.21}$$

Let us inspect if the profit functions of FBs (π_T and π_V) are concaves on *p* and *q*, respectively, given the quality of the offered frequency bands. The profit of *T_Broker* can be expressed as:

$$\pi_T = p.\left(\left(\frac{K_1-p+q+r_1}{K_1+K_2}\right) + \left(\frac{K_2+p-q-r_1}{K_1+K_2}\right)\right) - C_T \tag{5.22}$$

with

$$K_1 = \rho_{1T}.q_{1T} + \rho_{2T}.q_{2T} \text{ and } K_2 = \rho_{1V}.q_{1V} + \rho_{2V}.q_{2V} \tag{5.23}$$

We have:

$$\frac{\partial^2 \pi_T}{\partial p^2} = 0 \leq 0 \tag{5.24}$$

Similarly, the profit of *V_Broker* can be expressed as:

$$\pi_V = q.\left(\left(\frac{K_2+p-q+r_2}{K_1+K_2}\right) + \left(\frac{K_1-p+q-r_2}{K_1+K_2}\right)\right) - C_V \tag{5.25}$$

$$\frac{\partial^2 \pi_V}{\partial q^2} = 0 \leq 0 \tag{5.26}$$

Therefore, we can conclude that the objective function is concave on *p*, given the quality of the offered frequency bands. Hence, the equilibrium point of the given problem is the global optimum point of the problem.

5.1.5. Numerical Examples and Results

The optimum price levels for each frequency band can be analytically calculated by taking the first order conditions of the profit functions of each FB. Here are the results:

$$p^{NE} = \frac{2.(\rho_{1T}.q_{1T}+\rho_{2T}.q_{2T})+r_1}{4} \tag{5.27}$$

$$q^{NE} = \frac{2.(\rho_{1V}.q_{1V}+\rho_{2V}.q_{2V})+2.p+r_2-r_1}{4} \tag{5.28}$$

In the remaining part of the simulations, we will show the relationships between two brokers' prices and the net utility value. During the simulations, we assume that the costs that two FBs face are zero. The qualities of the frequency bands that *T_Broker* and *V_Broker* offer are taken as equal in value $((\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}) = 1,\ (\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V}) = 1)$. Furthermore, their extra utility values from the value-added services are also taken as equal ($r_1 = 0.1$, $r_2 = 0.1$). We have increased the *p* and *q* values in the range of 0 to 1, by 0.01; in order to see the values of the social welfare in every combination of (*p*, *q*).

Figure 5.3 shows the net utility values as a function of *T_Broker* price (*p*) and *V_Broker* price (*q*). It is easy to see from Figure 5.3, that there are plural maximum points on the diagonal which are the Nash Equilibrium points. The reason is that all of our quality and extra utility value assumptions have a symmetric nature. If the demand to a FB increases, the demand to the other one decreases. At a fixed price *p*/*q*, *T_Broker*/ *V_Broker*'s profit increases, when *q*/*p* increases; since the demand to *T*/*V* frequency bands will increase. In this situation, the surplus of *T_Broker*/*V_Broker* will also increase as do its total demand.

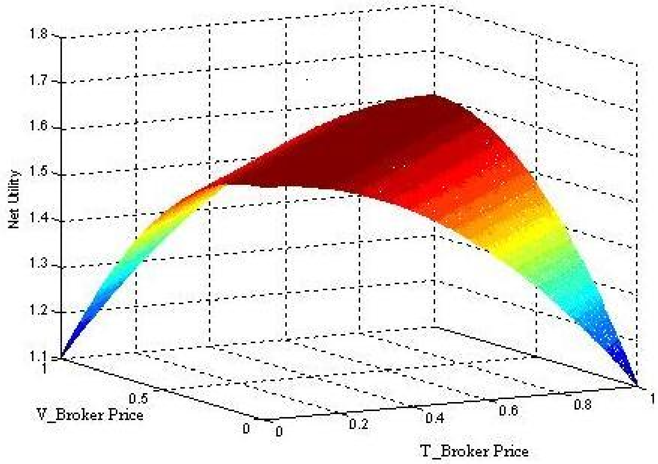

Figure 5.3. Net utility function with respect to *p* and *q* for the first case

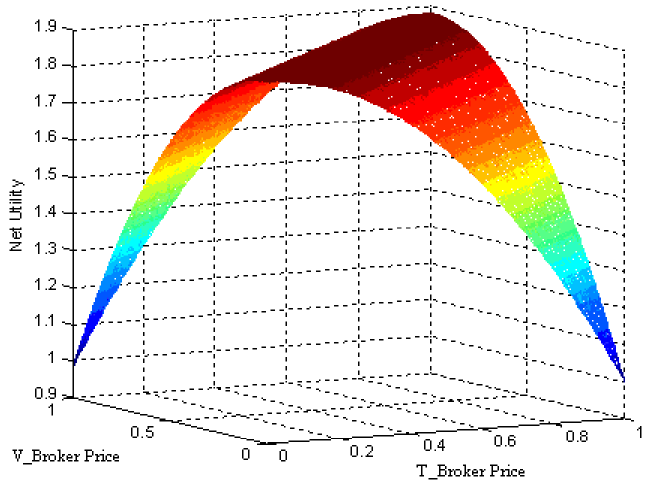

Figure 5.4. Net utility function with respect to *p* and *q* for the second case

For the second part of our simulations, we assume that the quality of the *T_Broker*'s frequency bands are higher than that of *V_Broker*'s $((\rho_{1T}.q_{1T} + \rho_{2T}.q_{2T}) = 1,\ (\rho_{1V}.q_{1V} + \rho_{2V}.q_{2V}) = 0.5)$. However, their extra utility values from the value-added services are assumed to be equal (r_1 = 0.1 r_2 = 0.1). As in the first part, the *p* and *q* values are increased from 0 to 1 by 0.01, in order to see the values of the social welfare in every combination of (*p*, *q*). Figure 5.4 shows the net utility as a function of *T_Broker* price (*p*) and *V_Broker* price (*q*).

In the second case, the multiple Nash Equilibrium points are also on the diagonal similar to the first case. However, the difference here is that, the total demand values of two FBs are not equal, which directly influence their profits and surplus. At a fixed price *p*, when *q* increases, the total demand to *T_Broker* increases; since it sells higher quality frequency bands at a lower price. This incurs an increase in its profit and surplus value also. On the contrary, in the same situation the demand to *V*'s frequency bands falls; since it is possible to find higher quality frequency bands at a lower price. Accordingly, it causes a decrease in *V_Broker*'s profit and surplus value.

5.2. Spectrum Exchange Architecture

Although the brokering architecture gives the main relationships among the network elements of a spectrum trading process, brokering may cause severe communication overhead. Moreover, as the broker is expected to be a third part agency, service providers would pay a brokerage commission. Hence, we have established a trading architecture without an intermediary element, as a response to our second research question: "What would be the effect of intermediary agency in spectrum trading"

5.2.1. Network Architecture and Elements

In the spectrum exchange architecture, we focus on the sub-lease process of the underutilized bands of a spectrum license holder, under the control of a regulator (Işıklar Alptekin and Bener, 2009c). We first introduce a general architecture of a possible future scenario which includes a competitive spectrum exchange marketplace (a secondary marketplace) where the license holders and the application service providers (ASPs) that seek for spectrum come together. Our proposed pricing approach is based on game theory and aims at calculating the unit band prices that maximize the net profit of license holders while simultaneously satisfying buyers. To do so, we come up with a non cooperative game, where the players are the spectrum holders and their strategy is the choice of the unit price of the offered band subject to QoS constraints.

The different components of the architecture in the region *R* are shown in Figure 5.5. At the top of this hierarchy, the regulatory body (e.g. FCC or Ofcom) issues relatively long-term spectrum leases, say for a 10 year period, on contiguous blocks to spectrum holding network providers (NPs), for large geographical regions. This market is referred as the primary marketplace. The marketplace that we have concentrated on was the second one, where the long-term license owners (NPs) sub-lease previously bought spectrum to potential buyers (WSPs). These offered spectrum bands could be from any frequency band interval. The trading is realized under the control of a spectrum exchange regulator, a governmental agency or a private one. This could be the same regulatory body as the one at the top of the hierarchy. In this architecture, the interference management within and at the boundaries of the license would remain the responsibility of the spectrum license holder. If the WSP accepts the spectrum offer, the required portion is allocated to it for the duration of the time period. At the lowest level, we have the customers of the WSPs; but we have focused mainly on the relationships among spectrum holders and buyers for this model.

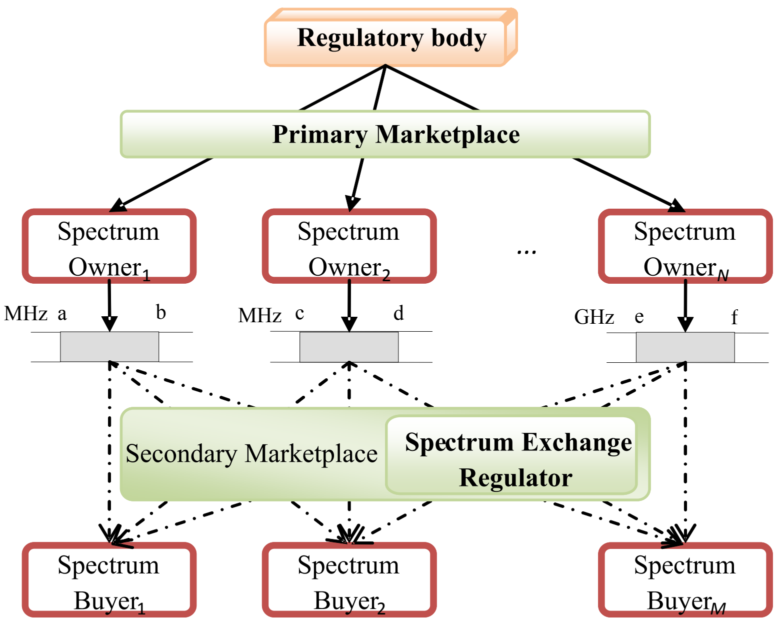

Figure 5.5. Frequency spectrum exchange architecture for region *R*

5.2.2. Proposed System Model

We model our pricing problem as the outcome of a non cooperative game, whose properties are:

- Players: The network providers. They compete with each other to sub-lease maximum part of their unutilized bands.

- Actions/ Strategies: The choice of the unit price of the offered frequency band.

- Payoffs: The net revenues of NPs.

- Commodity of the spectrum exchange market: The frequency spectrum band.

In analyzing the outcome of the game, as the players make decisions independently and are influenced by the other players' decisions, we are interested to determine if there exists a convergence point, from which no player would deviate anymore, i.e. Nash equilibrium.

The spectrum exchange game that we consider consists of a set of *N* NPs holding spectrum licenses, NPs, denoted by $\mathbf{I} = \{1, 2, \ldots, N\}$. Each provider's spectrum band has two service parameters: $(\mathbf{p}, \mathbf{q}) \in \Re_{+}^{2N}$. $\mathbf{p} = \{p_{1k}, \ldots, p_{Nk}\}$ is the unit price vector where p_{ik} is the unit price that NP_i charges ASP_k per unit demand, and $\mathbf{q} = \{q_{1k}, \ldots, q_{Nk}\}$ where q_{ik} is the quality measure of the spectrum band offered by NP_i to ASP_k. We assume that the quality vector (q) is given.

NP_i experiences a demand from ASP_j for its bands which is symbolized by $D_{ik}(\mathbf{p}, \mathbf{q}) : \Re_{+}^{2N} \rightarrow \Re_{+}$. The important aspect of our model is that the demand to NP_i depends not only on its own parameters p_i and q_i but also on the prices and the QoS levels offered by its competitors. In other words, $D_{ik}(\mathbf{p},\ \mathbf{q})$ depends on the entire price vector p and the entire QoS vector q. The payoff or utility functions of the NP_i from ASP_k is given by $U_{ik}(\mathbf{p},\ \mathbf{q}) : \Re_{+}^{2N} \rightarrow \Re_{+}$, while the strategy space, S_{ik}, of NP_i with the upper and lower bound constraints is given by the subset of :

$$S_{ik} = \left\{(p_{ik},\ q_{ik}) :\ 0 \leq p_{ik}^{\min} \leq p_{ik} \leq p_{ik}^{\max};\ 0 \leq q_{ik}^{\min} \leq q_{ik} \leq q_{ik}^{\max}\right\} \quad (5.29)$$

Beyond some price, demand will be zero whatever the prices and QoS levels of competitors are. Accordingly, the NP itself or the central regulator defines an upper bound on price. The lower bound is set so as to keep the net profit of the NP positive.

5.2.3. Demand Function of Application Service Providers

In our model, we assume that the average demand, $D_{ik}(\mathbf{p},\ \mathbf{q})$ is linear in all prices and QoS levels. A price increase of an NP results in a decrease in its demand, while the price increases of its competitors cause an increase in its demand. Furthermore, a QoS level increase of an NP results in an increase on its demand, while the QoS increases of its competitors cause a decrease in its demand. Thus we can write a linear demand function in the following form (Bernstein and Federgruen, 2004):

$$D_{ik}(\mathrm{p},\ \mathrm{q}) = \delta_{ik} - \beta_{ik} \cdot p_{ik} + \sum_{j \in I, j \neq i} \gamma_{ijkl} \cdot p_{jk} + \nu_{ik} \cdot q_{ik} - \sum_{j \in I, j \neq i} \tau_{ijkl} \cdot q_{jk} \tag{5.30}$$

with δ_{ik} is the base demand of ASP_k from NP_i and β_{ik}, γ_{ijkl}, ν_{ik}, τ_{ijkl} are positive constants that represent to what extent the ASPs are influenced from price and quality variations. For instance, γ_{ijkl} is the coefficient that represents to what extent ASP_l is influenced from the price that NP_i proposes to ASP_k, when ASP_l is served by NP_k, where $l \in \{1,\ 2,\ ...,\ M\}$.

In the rest of the model description, the expressions, d_{ik} and $D_{ik}(\mathbf{p},\ \mathbf{q})$ are utilized interchangeably and we assume that the following assumption holds: The constants β and γ satisfy:

$$\beta_{ik} > \sum_{j \neq i} \gamma_{ijkl}\ , i, j \in I \text{ and } k,\ l\ \in \{1,\ 2,\ ...,\ M\} \tag{5.31}$$

It implies that the influence of an NP's price is significantly greater on its own demand than are the prices of its competitors. This assumption represents the presence of customer loyalties and/or imperfect knowledge of competitors' prices (NCC Regulations, 2002). Moreover, we assume that $D_{ik}(\mathbf{p},\ \mathbf{q})$ is non-negative over the strategy space.

5.2.4. Quality of the Spectrum Band

ASPs should be able to differentiate spectrum bands in the market according to some quality of service parameters. First of all, the band which is offered to ASP_k by NP_i should be in the operating intervals of the ASP_k. If the ASP requires an UHF band for mobile services, any VHF band will not serve it. Therefore, we incorporate a binary variable, q_{ikl}, that shows if the band is suitable for the ASP in question.

$$q_{ik1} = \begin{cases} 0, & \text{if the offered band is in the operating intervals} \\ 1, & \text{otherwise.} \end{cases} \tag{5.32}$$

Secondly, we consider an interference related factor, q_{ik2}, that sets aside the spectrum band that will create interference. The main idea of the spectrum sensing is to detect the unused spectrum holes that will not interfere with the existing users. Interference generally limits the useable range and effectiveness of communication signals.

We assume that the q_{ik2} parameter represents the normalized value (in the range (0-1]) of the interference temperature of a spectrum band. In our proposed model, we use it to differentiate bands according to their interference levels. If it is above the given threshold, q_{ik2} is taken as zero.

Finally the third quality parameter, q_{ik3}, has to be selected as a distinctive quality of service metric by the ASP. It depends on which type of network that ASP will operate. For instance, modulation error ratio, jitter, path loss or signal propagation characteristics are possible QoS measures for digital TV networks. The interval of the spectrum band can be taken as a quality parameter for cellular networks; since the signal propagate farther and penetrate buildings better in lower frequency bands. The band interval factors (*BIF*) for cellular networks can be defined as in Table 5.1 (NCC Regulations, 2002).

All these parameters add up to the quality of the offered spectrum band by NP_i:

$$q_{ik} = (1 - q_{ik1}) \cdot q_{ik2} \cdot q_{ik3} \tag{5.33}$$

5.2.5. Opportunity Cost of the Spectrum Band

We assume that NPs sub-lease their unused resources (the spectrum bands or bandwidths) to the ASPs. Hence, NPs should also consider their opportunity costs when setting the prices.

Table 5.1. Band interval and band interval factors

BIF	Band interval
0.5	10.5 GHz
0.625	< 700 MHz
0.625	2.5-3.5 GHz
0.625	> 10.5 GHz
0.75	2.0-2.5 GHz
0.8	900 MHz-1.8 GHz
0.875	1.8/1.9 MHz
1	700/800/900 MHz

The *opportunity cost* is defined as the value of an asset or resource in the next best alternative that is foregone by virtue of its actual use (Cave, 2002). In our proposed model, it is the value of the unused spectrum bands to the NP that derives the highest benefit from being able to use it. Spectrum has a non-zero opportunity cost if there is excess demand for it now or in the future from current and potential alternative uses.

Some pricing algorithms in the literature include the calculation of opportunity cost of a spectrum band. In his research, Doyle addresses the question of how a radio spectrum manager can use estimates of opportunity costs to determine spectrum prices and use to promote efficiency (Doyle, 2007). He shows that it is not necessary to know in detail the entire marginal benefit functions in order to compute spectrum prices. The pricing algorithm that he uses is called the Smith-NERA methodology (Smith-NERA, 1996).

United Kingdom has used the "Administered Incentive Pricing" (AIP) since 1998, which has its basis from the Smith-NERA algorithm. The Smith-NERA and AIP algorithms have originally been proposed to calculate the license prices of spectrum, and we make use of their basic ideas to determine the opportunity cost of spectrum bands for NPs. Although the chosen cost parameters and their importance may depend on NPs, we have formulated the opportunity cost of NP_i received from ASP_k as:

$$OC_{ik}(d_{ik}) = [w_{\mathrm{ik1}}.BF_{ik} + w_{\mathrm{ik2}}.\ LF_{ik}].\ d_{ik}.p_{ik} \tag{5.34}$$

with BF_i, the band factor and LF_i, the location factor. They are both defined in the [0-1] range. The location factor increases proportional to the congestion of the region that the spectrum portion will be in use. The band factor increases with the number of technologies that can operate on this band; since NPs will have the opportunity to reach more ASPs. This is not the same factor as the band interval factor. It is the ASP that defines the band interval factor, while it is the NP that defines the band factor. The importance weights, w_{ik1} and w_{ik2}, are used to adjust the cost value according to the marketing preferences of NPs, where w_{ik1} and w_{ik2} are positives and $w_{ik1} + w_{ik2} = 1$.

5.2.6. Utility Model of Network Provider

The net profit (net revenue) of NP_i is given by the sum of the differences of its opportunity cost (OC_{ik}) and its revenues from all the ASPs,

$$U_i(\mathrm{p},\mathrm{q}) = \sum_{k\in\{1,..,M\}} \left(p_{ik}.d_{ik} - OC_{ik}(d_{ik})\right). \tag{5.35}$$

We assume that $U_i = U_i(\mathbf{p},\mathbf{q})$, $i \in \mathbf{I}$, where $d_{ik} = D_{ik}(\mathbf{p},\mathbf{q})$ is continuous in $(\mathbf{p},\mathbf{q})$ and concave in (p_{ik}, q_{ik}), for all $i \in \mathbf{I}$ and $\mathbf{k} \in \{1,2,...,M\}$. The NP can use this utility expression while making the decision of whether it should sub-lease the spectrum band or not. The sub-lease process is thought to have business value when its net profit ($U_i(\mathbf{p},\mathbf{q})$) is positive, and to be unprofitable when it is negative. Among a set of spectrum alternatives, the one with the highest $U_i(\mathbf{p},\mathbf{q})$ generates the most value, and should be favored over the others. Hence, our result space consists of the values which make the net profit positive.

5.2.7. Equilibrium of the Game

Our question is that when we can ensure the existence and uniqueness of the resulting equilibrium across NPs under general assumptions on data and model functions. In their research, Milgrom and Roberst studied a rich class of non cooperative games that includes the model of oligopoly competition (Milgrom and Roberts, 1990). They show that for these games, the sets of pure strategy Nash equilibria, correlated equilibria, and rationalizable strategies have identical bounds. We will make use of their theorems and proofs, while finding the equilibrium points of our model. We consider the single-parameter price game where the QoS levels of the NPs (q_{ik}) are given.

Definition of the single-parameter Nash equilibrium: Let $U_i\left(\mathbf{p},\mathbf{q}\right)$ be the net revenue of NP_i, when the vector of prices set by all providers, $\mathbf{p}$, and the vector of QoS parameters, $\mathbf{q}$, of all providers is fixed at values, $q_{1k}, q_{2k}, \ldots, q_{Nk}$. Then, a single-parameter Nash equilibrium in $\mathbf{p}$ at $\mathbf{q}$ is the vector $\mathbf{p}*$ that solves for all i:

$$U_i(\text{p}^*, \text{q}) = \max_{(p_{ik}, \text{q}) \in \Re_i} U_i\left(p^*_{1k}, \ldots, p^*_{(i-1)k}, p_{ik}, p^*_{(i+1)k}, \ldots, p^*_{Nk}, \text{q}\right) \tag{5.36}$$

Theorem 1: A single-parameter price game has a unique equilibrium p^*_{ik} (q), with

p^*_{ik} (q) $= (I - T_{ik})^{-1}\Gamma^{-1}X_{ik}$, where $\Gamma = \text{diag}\,(2\beta_{1k}, 2\beta_{2k}, \ \ldots, 2\beta_{Nk})$, $T_{ii} = 0$, $T_{ij} = \frac{\gamma_{ijkl}}{2\beta_{jk}}$ for $i \neq j$, and $X_i = \delta_{ik} + \beta_{ik}.q_{ik} - \sum_{j \in I, j \neq i} \tau_{ijkl}.q_{jk}$.

<u>5.2.7.1. Concavity of the objective function</u>: The objective function of the problem is:

$$\max \quad U_i\left(\text{p},\text{q}\right), \quad i \in \{1,\ldots,N\} \tag{5.37}$$

Let us inspect if the net revenue functions of NPs are concaves. We have:

$$\frac{\partial^2 U(\text{p},\text{q})}{\partial {p_i}^2} = 2\beta_i.\left(w_{i1}.BF_i + w_{i2}.LF_i - 1\right) \leq 0 \tag{5.38}$$

since a NP prefers sub-leasing its spectrum bands, if the opportunity cost is less than the net profit. Namely, when $w_{i1}.BF_i + w_{i2}.LF_i < 1$. Therefore, we can conclude that the objective function is concave. Hence, the equilibrium point of the given problem is the global optimum point of the problem.

<u>5.2.7.2. Existence of the Nash Equilibrium</u>: The existence of the Nash equilibrium point will be proved by using the supermodularity of the utility function.

The feasible strategy space of our game:

$S_i = \{p_i : 0 \le p^{\min} \le p_i \le p^{\max};\ i = 1, 2, ..., N\}$ is a compact sublattice of $\Re^N$.

$$\frac{\partial U(\mathbf{p},\mathbf{q})}{\partial p_i} = [1 - (w_{i1}.BF_i + w_{i2}.LF_i)] . [D_i(\mathbf{p},\mathbf{q}) - \beta_i.p_i] = 0 \tag{5.39}$$

$$\frac{\partial^2 U(\mathrm{p},\mathrm{q})}{\partial {p_i}^2} = 2\beta_i . (w_{i1}.BF_i + w_{i2}.LF_i - 1) \le 0 \tag{5.40}$$

since a network provider prefers sub-leasing its spectrum bands, if the opportunity cost is less than the net profit. Namely, when $w_{i1}.BF_i + w_{i2}.LF_i < 1$.

Because $p * (\mathbf{q})$ is a Nash equilibrium, it follows that for all $i \in \mathbf{I}$, $\mathbf{p}_i^*$ is a global maximum of the single variable function $U_i\left(\mathbf{p}\left|p_{-i}^*, \mathbf{q}\right.\right)$. It follows that $\mathbf{p}_i^*$ is the unique solution to the equation (5.39). It is equal to:

$$[1 - (w_{i1}.BF_i + w_{i2}.LF_i)] \left[\delta_i - 2\beta_i.p_i + \sum_{i \ne j} \gamma_{ij}.p_j + \nu_i.q_i - \sum_{i \ne j} \tau_{ij}.q_j\right] = 0 \tag{5.41}$$

$$2\beta_i.p_i - \sum_{i \ne j} \gamma_{ij}.p_j = \delta_i + \nu_i.q_i - \sum_{i \ne j} \tau_{ij}.q_j,\ i \in I \tag{5.42}$$

This is a linear system of equation in *p*, which in matrix form can be written as:

$$Ap = \left[\delta_i + \nu_i.q_i - \sum_{i \ne j} \tau_{ij}.q_j\right] \tag{5.43}$$

where

$$A = \begin{pmatrix} 2\beta_1 & -\gamma_{12} & \cdots & -\gamma_{1N} \\ \cdots & & & \cdots \\ & & \ddots & \\ -\gamma_{(N-1)1} & & & -\gamma_{(N-1)N} \\ -\gamma_{N1} & -\gamma_{N2} & \cdots & 2\beta_N \end{pmatrix} = \Gamma(I - T), \tag{5.44}$$

with $\Gamma = diag\,(2\beta_1, 2\beta_2, ..., 2\beta_N)$, and

$$T = \begin{pmatrix} 0 & \cdots & \frac{\gamma_{1N}}{2\beta_1} \\ \vdots & \ddots & \vdots \\ \frac{\gamma_{N1}}{2\beta_N} & \cdots & 0 \end{pmatrix} \tag{5.45}$$

Thus $A^{-1} = (I-T)^{-1}.\Gamma^{-1}$ and $\mathbf{p}* = A^{-1}.X = (I-T)^{-1}\Gamma^{-1}.X$ (5.46)

with $X = \delta_i + \nu_i.q_i - \sum\limits_{i \neq j} \tau_{ij}.q_j$

$$\mathbf{p}_i^* = \sum_{j=1}^{N} A_{ij}^{-1}.\delta_i + \left(A_{ii}^{-1}.\nu_i - \sum_{i \neq j} A_{ij}^{-1}.\tau_{ji}\right).q_i + \sum_{j \neq i}\left(A_{ij}^{-1}.\nu_j - \sum_{l \neq j} A_{il}^{-1}.\tau_{li}\right).q_j \tag{5.47}$$

proving the claims in the Theorem 1.

5.2.7.3. Uniqueness of the Nash Equilibrium: To prove the uniqueness of the equilibrium point, we use the *contraction* approach (Vives, 1999). We have:

$$\begin{aligned} &\beta_i.\left(w_{i1}.BF_i + w_{i2}.LF_i - 1\right) + \sum_{i \neq j} \gamma_{ij}\left[1 - \left(w_{i1}.BF_i + w_{i2}.LF_i\right)\right] = \\ &(\beta_i - \sum_{i \neq j} \gamma_{ij})\left[\left(w_{i1}.BF_i + w_{i2}.LF_i\right) - 1\right] \end{aligned} \tag{5.48}$$

We use the assumptions of $\beta_i > \sum\limits_{j \neq i} \gamma_{ij}\,, i \in I$ and $w_{i1}.BF_i + w_{i2}.LF_i < 1$ to prove that the above expression is negative.

5.2.8. Numerical Examples and Results

For our simulations, in order to reflect the competition, we consider a secondary marketplace where two spectrum holders NP_1 and NP_2, and two spectrum buyers, ASP_1 and ASP_2, come together. We assume that NP_1 has 2 x 6 MHz of spectrum band (704-710 MHz and 734-740 MHz) that is owned from the FCC auction, and that NP_2 has 2 x 6 MHz of band (1856-1862 MHz and 1872-1878 MHz) that is too much for its customer pool and their utilization profiles. NP_2 wants to lease its extra bands that usually remain underutilized to different SPs for making money. In our simulations, we assume that both ASPs require 12 MHz of bandwidth, which is paired in the form of 2 x 6 MHz for a time period of one week in region *R*. They require these paired bands to operate their cellular networks. We have differentiated ASPs according to their attitudes towards prices and QoS levels of the offered spectrums. The *high profile* ASP (ASP_1) is assumed to attach great importance to the quality of the band, where the price takes the second place. On the contrary, the price of the band is assumed to be more significant than its quality level for the *low profile* ASP (ASP_2).

We summarize the values of the quality parameters in Table 5.2. The band interval factors (BIF_i) are taken as given in Table 5.1. The spectrum bands are in the intervals that the ASPs can operate, thus q_{1k1} and q_{1k2} are set to 1. As all the quality parameters are taken in the range [0-1], they can be thought as percentage values.

Next, we give the values of each NP's opportunity cost with its parameters' values in Table 5.3. As the spectrum bands are assumed to be utilized in the same region, the location factor LF_i would be the same for both bands. The band factors (BF_i) are determined in respect to the number of technologies that is suitable for the band and to its popularity level. For the sake of simplicity, we assume that these two criteria have equal importance for the NPs; hence their importance weight values are set to 0.5.

Table 5.2. Parameter values of quality

	$NP_1 \rightarrow ASP_1$	$NP_1 \rightarrow ASP_2$	$NP_2 \rightarrow ASP_1$	$NP_2 \rightarrow ASP_2$
Interference temperature (q_{ik2})	0.8	0.6	0.8	0.55
BIF (q_{ik3})	0.875	1	0.875	1
Quality level of the band (q_{ik})	0.7	0.6	0.7	0.55

The next step is the identification of the demand functions. It is important to note that, the profiles of the ASPs have direct influence on these parameters. As the high profile ASP prioritizes the quality of the band, the QoS related parameters (v and τ) values should be higher than the price related parameters (β and γ). On the contrary, the QoS related parameters of the low profile ASP should be lower than the price related ones.

Table 5.3. Opportunity cost and its parameters

	NP_1		NP_2	
	ASP_1	ASP_2	ASP_1	ASP_2
w_1	0.5		0.5	
w_2	0.5		0.5	
BF	0.9		0.75	
LF	0.75		0.75	
Opportunity cost	1.757	1.239	1.161	0.914

For this given scenario, the non cooperative price game has the following equilibrium points (Table 5.4). It gives the equilibrium prices for the required spectrum bands that maximize both the net utilities of NPs and satisfaction levels of ASPs.

Table 5.4. Results in the equilibrium

	NP_1		NP_2	
	ASP_1	ASP_2	ASP_1	ASP_2
p*	2.3891	2.3013	1.7292	1.6751
Demand	9.5566	9.2053	11.7591	11.3911
Utility	3.9956	4.4081	4.4465	4.7705

Figure 5.6 and Figure 5.7 represent the impact of QoS level variations on the demand and utility functions, respectively. For these simulations, we have fixed all the interference temperature and only change the interference temperature of the bands of NP_1 which is offered to ASP_1 (ASP_1-NP_1). Under different qualities, the Nash equilibrium is located at different points. We can observe that, the increase in the quality level of NP_1 induces an increase on the demand and net utility of NP_1, while causing a decrease on NP_2. The demand variations that ASP_2 causes on the NPs are relatively low, but still we can see the decreasing trend. The reason is that ASP_2 has low profile, which means it prioritizes the price variations instead of the quality variations in its decisions. In Figure 5.7, we can easily observe the positive or negative effects of quality on the received utility. When its competitor increases its quality level when serving ASP_1, NP_2 sees a dramatic decrease in its net utility.

Figure 5.8 illustrates the price variations as a function of the interference temperature of the bands of NP_1 which is offered to ASP_1 (ASP_1-NP_1), similar to the previous figures. We can see that all the other price offers decrease.

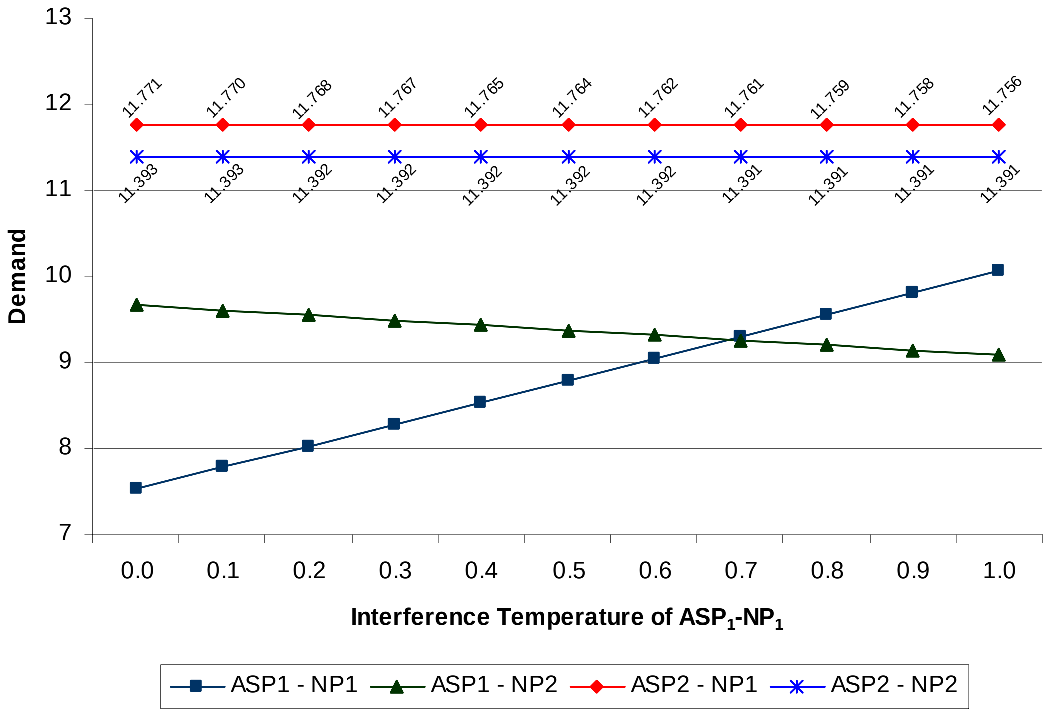

Figure 5.6. Demand functions variation as a function of interference temperature

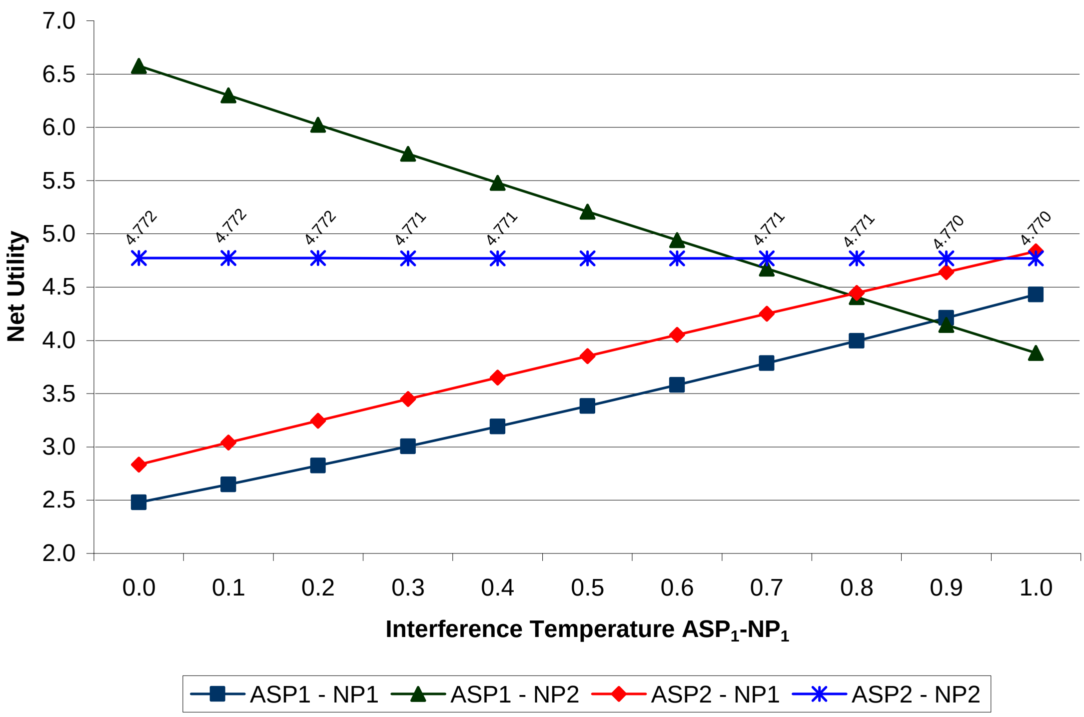

Figure 5.7. Net utility variations as a function of interference temperature

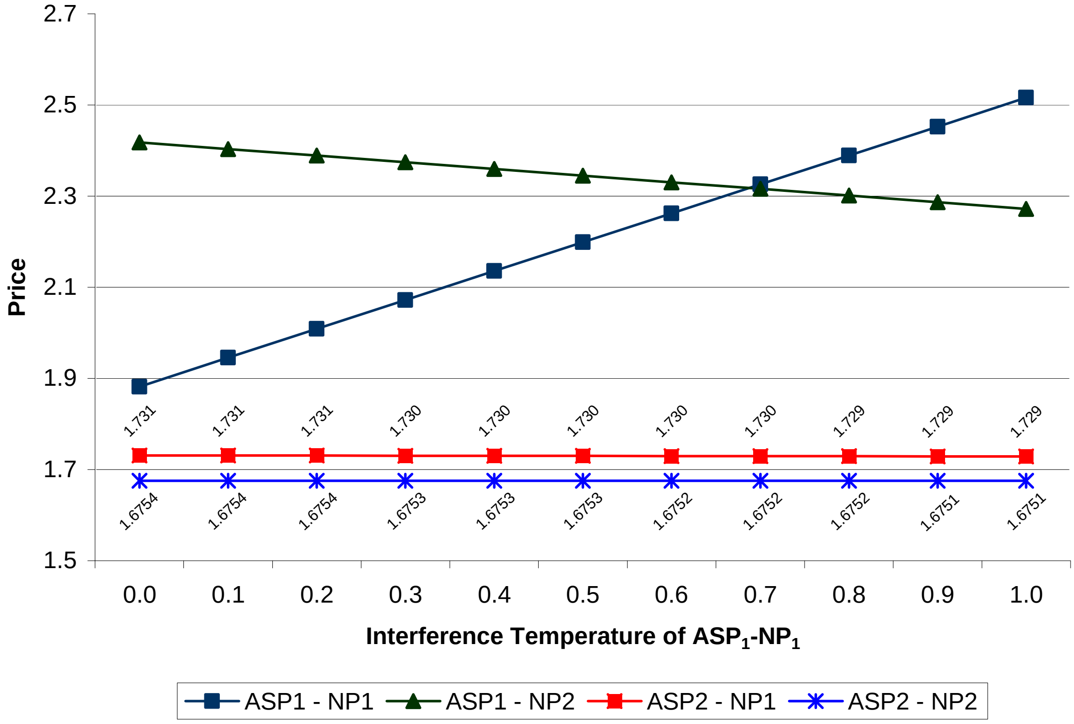

Figure 5.8. Price variations as a function of interference

5.3. CRM-based Architecture

As a response to our third research question, which is: "What kind of impact the CRM tool has on the profit maximization, as well as on the pricing process?", we have extended the spectrum exchange architecture to include the CRM characteristics of SUs (Işıklar Alptekin and Bener, 2009b).

Companies are becoming increasingly aware of the many potential benefits provided by customer-oriented business strategies. When evaluating customer profitability, marketing managers are often reminded of the rule of Pareto Optimality (80 per cent of the profits are produced by top 20 per cent of profitable customers and 80 per cent of the costs are produced by top 20 per cent of unprofitable customers) (Kim *et al.*, 2006) (Dubois, 1992). In telecommunication market, retaining the existing subscribers is as costly as acquiring new ones (Hwang *et al.*, 2004). Therefore this model aims at both increasing the revenue of an ASP and offering a satisfactory level of QoS to its customers through a customer-oriented approach. The focus is to build a flexible resource allocation strategy that would work under different scenarios over the lifetime of the network. It is assumed that the network is already configured. In this respect, a novel parameter, "Resource Usability Parameter (RUP)" is proposed (Kastro *et al.*, 2009).

5.3.1. The Spectrum Exchange Architecture with the Integration of CRM

The proposed model is very similar to the one in the previous sub-section, but we have extended it by integrating the customers of the spectrum buyers in the hierarchy (Figure 5.9). In spectrum exchange architecture, the equilibrium prices of spectrum bands were calculated using a competitive non cooperative game for the secondary market (Işıklar and Bener, 2008). It was assumed that the spectrum holders shall adapt a pricing formula that reflects the economic value of the bands in order to encourage its efficient usage. The pricing problem was modeled as the outcome of a non cooperative game, where the players are the spectrum holders. However, this game was not considering the relationships among ASPs and their subscribers.

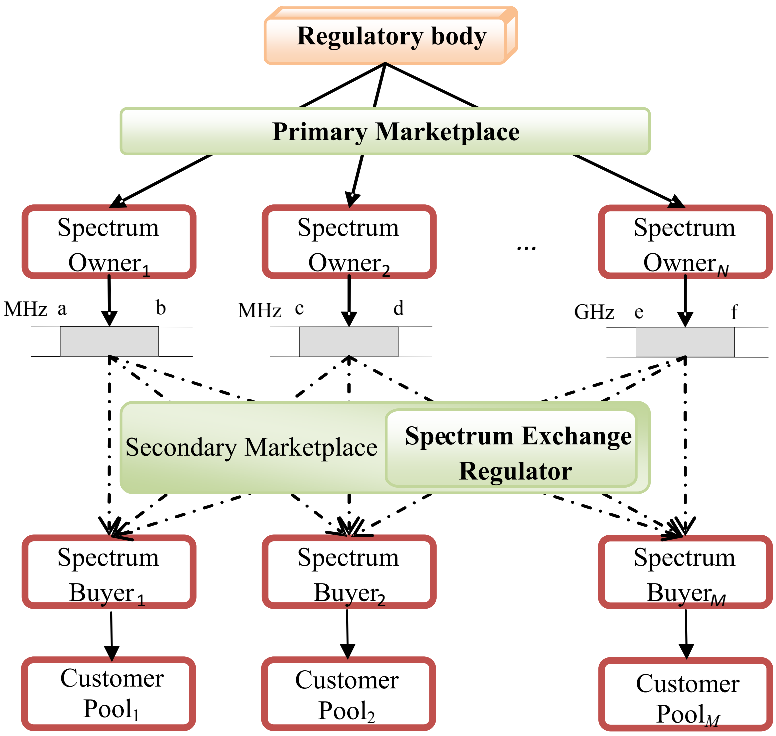

Figure 5.9. Frequency spectrum exchange architecture with the integration of CRM

In this architecture, we have concentrated on the lowest level, where the ASPs allocate sub-leased bands to their subscribers. It is challenged if the maximum possible revenue of an ASP could be increased by integrating both the transaction and customer information into the resource allocation process. It is assumed that the spectrum prices at the secondary marketplace are calculated as in the spectrum exchange architecture (Işıklar and Bener, 2008). The RUP value which is calculated for each subscriber before her/ his connection attempt depends upon four parameters is presented in the next sub-sections. The numerical results are generated to analyze the net utility variations that ASPs receive from subscribers of different profiles.

5.3.2. The RUP Value and its Constituents

5.3.2.1. Customer Relationships Management Value: As competition increases, many firms use a CRM system to improve business intelligence, to make better decisions, to enhance customer relations, and to increase QoS and product offerings. CRM could be defined as the strategies, processes, people and technologies used by companies to successfully attract and retain customers for maximum corporate growth and profit (Roh *et al*., 2005).

In the proposed model, it is assumed that each subscriber has a CRM value defined by the MNO's marketing division (Kastro *et al*., 2008). The CRM value of a subscriber is taken in the range of [0,1]. The range could depend on many factors such as customer's service usage rate, job position, duration of subscription or any other factors identified by the service provider. Telecommunications industry is highly competitive and hence the customer churn rates are quite high (Hwang *et al*., 2004). Therefore precise evaluation of CRM value and targeted customer segmentation are the critical success factors of a CRM system especially in the wireless communications market. However, in this research it is assumed that each service provider evaluates customers' CRM values by using its own method. The CRM value is updated by each ASP on a regular basis.

As far as the proposed model is concerned, the CRM value is one of the variables that reflects the marketing perspective of the service provider. For example one service provider may prefer to address the low-CRM-valued customers to encourage them to become higher-valued; while another may disregard the low-CRM-valued customers and focus on further increasing CRM values of the high-CRM-valued ones. This is the same case in cognitive radio networks, since despite the type of network, service providers have to attract and retain its customer pool to keep their market share.

5.3.2.2. Call Value: The next element involved is the value of the current call defined in the range of [0-1]. This can be considered as the types of services that the application service provider offers. An ASP could sub-lease some spectrum blocks in the secondary market to operate any kind of network technology. For instance in cellular networks, this could be a call between two subscribers, a call between more than two subscribers, mobile Internet services or different entertainment services. However, in the case of cognitive radio the offered services depend on the network type. Each service has its own resource requirements and has its own priority with respect to the number of involving subscribers. The call type could be one of the criteria influencing the call value. The current call could be either a data transfer of one customer or a voice call between two customers or a video conference among six customers. A call containing multi-parties would be more valuable than a data transfer of a single customer. Therefore the call type value of a video conference could be set as higher value than the value of a voice call. Similarly the call type value of a voice call would be higher than the value of a one-way data transfer. This value assessment can be assumed reasonable in terms of both ASP's profitability and the total annoyance of customers in case a call drops. Thus, calls are primarily differentiated by considering their types. The number of participants is also a significant criterion. The call value does not only depend on the number of participants, but also it depends on the CRM values of them. To give an example; a low-CRM-valued customer could make use of the resources just because she/ he is making a call with a high-CRM-valued customer.

Below is the expression for a call with *n* participants:

$$x_{CV} = a.\left[\frac{x_{CRM}^{\max}+(n-1).x_{CRM}^{avg}}{n}\right] + b.x_{CTV} \tag{5.49}$$

with x_{CV} = The call value

x_{CRM}^{i} = The CRM value of the i^{th} participants

x_{CTV} = The call type value

$x_{CRM}^{\max} = \max\left(x_{CRM}^{1}, x_{CRM}^{2}, ..., x_{CRM}^{n}\right)$

$$x_{CRM}^{avg} = \frac{\sum_{i=1}^{n} x^{i}_{CRM}}{n}$$

$$a + b = 1$$

The first term represents the CRM values of the customers. When computing the overall CRM value, the highest-CRM-valued participant in the first place and then the average CRM value of the other participants in the second place are taken into consideration. The reason is to identify the customer who has the highest CRM value among all customers. Then the call value is determined as a function of the CRM value of that customer. The value of the second term depends on the type of the call initiated. The positive weight coefficients *a* and *b* enable the ASPs to reflect their preferences in the call value expression.

5.3.2.3. Resource Winning Ratio: This ratio, in the range of [0-1], is inserted into the model to avoid the continuous special treatment of the customers who have relatively high RUP value. If there is continuous special treatment of high RUP valued customers, the least profitable customer may never get the resource whatever the type of application is. This could be a cellular network channel or an AM broadcasting band. The resource winning ratio gives the percentage of resource assignment to a customer in a given time period. For instance; let us consider two customers: The first one has received the required resource at her/ his call initiation in the last ten times she/ he needs it because she/ he has a high RUP value. Her/ his value is 1 (100 per cent). However, the second one has received the resource just twice in her/ his last ten requests because of her/ his low RUP value. Therefore, her/ his value is 0.2 (20 per cent). In such a case, the ASP could choose to assign the resource to the second customer in order not to lose her/ him; or else the ASP could always assign resources to the first customer, who is a business class customer ready to pay whatever it takes to get the best service. This parameter is assumed to be updated on a regular basis.

5.3.2.4. Expected Call Length: The last component is the expected length of a customer call. During the computation, it is considered that a customer's recent call lengths, which reveal her/ his recent habits, are as significant as her/ his average call length. An anthropologist and industrial designer, Jan Chipchase, travels around the world and he observes the mobile phone usage attitudes of different cultures for Nokia (Chipchase, 2006). He has stated that an ordinary customer makes seven calls and sends five SMS daily. Therefore, taking the average of the ten recent calls is assumed to be sufficient to understand her/ his recent behavior, and the location information. If this number is below a certain threshold, attributes of the call may not reflect the real behavior of the customer. If it is above, the recent changes in behavior may be missed. For example, the customer may be out of the country for a week and prefer to make shorter calls. Therefore, the expected call length value has the following expression:

$$x_{ECL} = \frac{1}{2}\left[\frac{\sum_{i=1}^{m} x_{CL}^{i}}{m} + \frac{\sum_{i=0}^{9} x_{CL}^{m-i}}{10}\right] \tag{5.50}$$

with x_{ECL} = The expected call length of the customer

x_{CL}^{i} = The i^{th} call length of the customer

m = Total number of calls belonging to the customer

The RUP value of the t^{th} customer of i^{th} ASP encapsulating all the above mentioned parameters can be represented as follows:

$$RUP_t^i = \psi.x_{CRM} + \omega.x_{CV} + \varphi.x_{ECL} + \xi.x_{RWR} \tag{5.51}$$

with $\psi + \omega + \xi + \varphi = 1$

The coefficients (ψ, ω, φ, ξ) are designed for adjusting the preferences of the ASP (Figure 5.10).

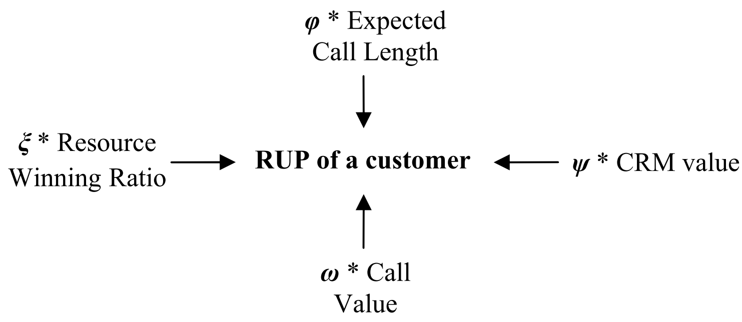

Figure 5.10. The RUP value and its components

5.3.3. Application Scenarios of the Proposed Approach in Cellular Network Environment

As mentioned in the previous sub-section, it is assumed that the ASPs have leased some spectrum bands in the spectrum exchange market and that the ASPs will utilize them for their cellular networks. Now, the concentration is on the next process of ASP, namely the efficient allocation of these resources to subscribers. The proposed framework may be used as a part of a decision support system that runs several scenarios. The ASP would be able to make decisions to maximize its profits by evaluating accurate RUP values. In this research, the RUP is utilized as a parameter that is directly proportional to the profitability of the ASP. However, RUP could also be used as a parameter to differentiate customers in order to prioritize a service level. In the next part, three major scenarios for cellular networks in which this approach may be used are presented: "Handoff Decision", "Resource Allocation at Call Initiation" and "Profit Maximization in Allocation of Mobile Base Stations".

<u>5.3.3.1. Handoff Decision</u>: Efficient resource allocation during handoff is still a hot research topic in cellular networks (Sang *et al.*, 2007) (Li *et al.*, 2006) (Akan and Baykal, 2005). Mobile terminals are assigned a base station for service, namely a cell. Each customer, who is using a mobile terminal, must use a certain channel in a cell. The handoff process begins when the mobile terminal leaves this initial cell while the call is in progress. When the mobile terminal is around the boundary of cells, it will pluck the strongest received signal; hence the mobile server will be serviced by the base station providing the strongest field. In this manner, the call in progress will not terminate since the mobile

terminal establishes a connection in its new base station without losing the initial connection. This process is called the handoff process. In some cases, the new cell might not contain free traffic channels (TCHs) to accept the newcomer customer. In such a situation, the only approach is downgrading the voice quality in this cell and dividing the current channel into two sub-channels with less quality. If all the channels are already downgraded, the only choice is to drop the call. These two situations are known as the most annoying events for the customer (Li *et al*., 2006).

At this point, the profitability needs to be considered since the dropped or downgraded customer might be a profitable customer. The basic idea behind this scenario is; determining the “least profitable customer” in the cell when the ASP is obliged to drop or downgrade a customer’s call. It is done by calculating the RUP value for each customer and choosing the least-valued one. It is important to note that, “the most profitable” may not always mean “the longest speaker”, since the definition of profitable customer will differ as per the marketing strategy of each ASP. This will be determined by the RUP value coefficients of that ASP.

Traditionally the resource allocation is used to favor the decrease of call dropping rate even if it produces an increase in call blocking rate (Schiller, 2003). The RUP approach can be used both for choosing the call to drop and to downgrade. This scenario can be extended to a preemptive level. As mentioned in the handoff scenario, one of the least profitable customers might be preempted to open up an available channel to a more profitable newcomer. Although, this preemptive scenario is quite uncommon in literature; it can still be utilized in highly competitive cellular networks markets.

<u>5.3.3.2. Resource Allocation at Call Initiation</u>: The second scenario where the RUP can be effectively used is the resource allocation process when more than one customer simultaneously wants to initiate a connection. A mobile terminal sends its call request using the Random Access Channels (RACH) to Base Transceiver Station (BTS). It is BTS that initiates the call and transfers required messages to Base Station Controller (BSC). However in some cases, the cell might be fully utilized except for a single available channel. This scenario considers a rare case such that two call requests of two different customers arrive in the same time-slot within a cell. The traditional action is allocating the

channel as First-Come, First-Served (FCFS) basis (Schiller, 2003). The approach in this paper proposes that the ASP should examine the RUP values of each concurrent customer in order to assign the resource. In the end, the customer with the highest RUP should grab the channel since she/ he is the most profitable customer for the ASP.

5.3.3.3. Profit Maximization in Allocation of Mobile Base Stations: The ASPs typically have a set of vehicles with base stations mounted on top of them. These units are called the *Mobile Base Stations* or the *Vehicle-Mounted Base Stations*. They are dynamically located in a way that, the channel capacity should be enlarged in specific cases (e.g. Concerts, football games, or unexpected over-utilizations), by allowing more customers to benefit from TCHs. Additionally, it serves to decrease the channel utilization and call-blocking rate. Let us assume that, after 2 years the spectrum bands that a mobile network operator has will not be sufficient to meet the demand in a specific region, where a football stadium and a concert hall are located. Let us think that this operator will sub-lease several spectrum bands. The operator should decide to which event it should send the mobile base station.

There is a problem when a mobile base station has more than one location to be sent. In general, the ASPs have the tendency to send the mobile base station to the most crowded location. The proposed approach claims that sending the mobile base station to the most crowded location may not be the most profitable decision for an ASP. It suggests calculating the sum of the RUP values in each location to determine the location with the highest total RUP value. This information would enable the ASP to make the most profitable decision by sending the mobile base station to the most suitable location. This decision is also the best for the customers who constitute the premium class of this ASP.

This scenario is quite common especially for cellular networks where over-utilization is often seen. The scenario could be extended by incorporating the opportunity cost of moving the base station to a specified location. However in this framework, only the decision of where to send the mobile base stations is considered.

5.3.4. The System Model

The proposed resource allocation model consists of a set of *N* ASPs, denoted by $\mathbf{I} = \{1,\ 2, \ldots, N\}$, which sub-lease several spectrum bands from NPs. $\mathbf{p} = \{p_1, \ldots, p_N\}$ is the price vector where p_i is the price that the NP charges the ASP_i per unit demand. ASP_i experiences a demand from its subscribers which is symbolized by d_i. The payoff or utility function of ASP_i is given by U_i. For the rest of the model and simulations, it is assumed that the price vector p and demand function d_i are calculated as the outcome of a non cooperative game among ASPs (Işıklar and Bener, 2008).

Although the chosen cost parameters and their importance may depend on network providers, the opportunity cost expression is formulated as:

$$OC_i\,(d_i) = \text{Opportunity cost of } ASP_i = \ [w_{i1}.BIF_i + w_{i2}.\ LF_i]\,.\ d_i.p_i.\,(1 - \mathrm{RUP}_i) \quad (5.52)$$

with $RUP_i = \frac{1}{T_i}\sum_{t=1}^{T_i} RUP_t^i$,

T_i is the total number of subscribers of ASP_i. BIF_i is the band interval factor and LF_i is the location factor. They are both defined in the [0-1] range. The location factor increases proportional to the congestion of the region that the spectrum portion will be in use. The interval of the spectrum band is also significant since at lower frequencies, signal propagate farther and penetrate buildings better. Operating in 700 MHz band rather than 1.8 GHz band is shown to make a 90 percent decrease in infrastructure costs, because fewer cells will be required, given the longer distances signals travel (Rast, 2005). The importance weights, w_{i1} and w_{i2}, are used to adjust the cost value according to the marketing preferences of ASPs, where w_{i1} and w_{i2} are positives and $w_{i1} + w_{i2} = 1$. The last term of opportunity cost which includes the demographic information and usage behavior of the subscribers is inserted to make a difference. According to the assumptions, the higher the RUP value, the profitable the subscriber is for the ASP. Furthermore, the higher the RUP value, the lower the opportunity cost should be. Hence, the RUP value is integrated in the form of (1 - RUP_i).

The net profit (net revenue) of ASP_i is given by the subtraction of its opportunity cost (OC_i) from its revenue from subscribers,

$$U_i = p_i.d_i - OC_i\left(d_i\right) \tag{5.53}$$

5.3.5. Numerical Examples and Results

In this sub-section, the performance of the proposed model is evaluated by running various simulations covering all the three scenarios mentioned in the previous sub-section. The *efficiency* refers to the comparison of the proposed model with the First-Come First-Serve based model. The proposed approach has two components: monetary and non-monetary. Monetary component represents the expected profit as a function of expected call length and unit price. Non-monetary component, on the other hand, considers CRM value, Resource Winning Ratio and Call Value. It is ASP's expectation that non-monetary component will eventually be earned in monetary terms.

The regulatory authorities of the telecommunication industry around the world prepare statistical reports that include several data on the telecommunication systems usage in that country. These data constitute average transaction numbers and corresponding average revenues of the mobile market. The US regulator, FCC, has detailed reports that contain the duration of residential wireless calls, the distribution of residential interstate wireless minutes by day and time, the average revenue per minute or the telecommunication revenues reported by type of services (FCC report). They are obtained by taking the average of usage characteristics of the people all over the country, or the state. The reports include the average data that belongs to the customers from different classes (gold, silver, bronze, etc.) of all ASPs in its state or in its country. The monetary component of the proposed model can be calculated by similar data. Likewise, the non-monetary component necessitates the demographic information and usage behavior of an ASP's subscribers. In constructing the simulations of the third scenario, it is assumed that a stadium or a concert full of people would be the representative of whole nation/ state. Therefore, the publicly available average transaction and customer data is taken as the basis.

The simulations are built on two sets which focus on different parameters. In the first part the simulations observe the case where the *student package* subscriber and the *business package* subscriber compete with each other for a call initiation or a handoff process. The second part consists of the decision to send a mobile base station to one of the two groups of subscribers.

The model necessitates the determination of net utilities for each ASP, which includes the calculation of RUP value of each subscriber in his each call attempt. Total net utility value that the ASP receives from a group of subscribers is calculated by the sum of the net utility values received from each subscriber. For simulation purposes, a subscriber's call value is described with a normal random variable with mean μ and variance σ^2.

Property 1: Let X_1, X_2, ….., X_n be n random variables. Their sum is also a random variable (Soong, 2004).

According to the Property 1, the sum of call values of N subscribers is again a normal random variable with:

$$\text{Mean: } \sum_{i=1}^{N} \mu_i \quad \text{Variance: } \sum_{i=1}^{N} \sigma_i^2$$

The expected call length is generated as exponentially distributed with mean μ. The first and the second part of the simulations consider resource allocation processes when two or more subscribers are simultaneously competing for the same resource. Wherever there is a competition for limited resources queuing is likely to occur. Therefore during the simulations, queuing theory principles are used in the calculation of the resource winning ratio. ASP's channels (or bands) are modeled as servers with limited space and the subscribers are First-Come First-Queued clients (Bertsekas and Gallager, 1992). Each subscriber's resource winning ratio value is updated, depending on previous channel grabbing statistics. This ratio is then used to select the candidate, during the channel assignment in limited resource scenarios. Finally, the CRM value is generated as randomly distributed from a normal distribution, where the mean is an input parameter to the simulator.

A simulator, implemented as a Visual Basic Win32 Application running on .Net Framework, is programmed for this specific purpose. A timer randomizer is used for generating the queuing theory based random seed numbers. Simulations are run on a single CPU PC on Windows XP SP2 Operating System.

5.3.5.1. Simulations for Handoff Decision and Call Initiation: Let us consider the ASP_1 sub-leases 12 MHz of spectrum bands on the high season of a touristic region for one week. ASP decides to use the RUP value as a decision support tool in handoff or call initiation processes during this week. Assume there are two subscribers, one from the student package and the other from the business package, who are in competition to grab the existing band. During the simulations, it is focused on the effect of RUP value when serving to the business package customers. The simulations are interested in finding out whether there is a positive impact on the ASP's profitability when the ASP takes business package subscribers as the target group. The remaining part of this subsection is composed of two cases which are built to show impact of the RUP value when it is set considering the target group subscribers.

- Case 1: Coefficients of RUP parameters are the same.

In this case, the subscribers are differentiated as *students* and *businessmen*; by defining their mean values for the four RUP parameters (Table 5.5). The assumption is that; if the proposed model is not in use, the channel (band) will always be assigned to the first subscriber, which is the student here. This assumption is the same as not considering the RUP value when allocating resources. Therefore, in this case the proposed approach is compared with the First-Come First-Serve based approach.

Table 5.5: Simulation parameters values for the case 1

Coefficient Name	**Value**
Coefficient of Caller's CRM Value (ψ)	0.25
Coefficient of Total Call Value (ω)	0.25
Coefficient of Resource Winning Ratio (ξ)	0.25
Coefficient of Expected Call Length (φ)	0.25
Total	1.00

The mean values representing two different subscriber groups are given in Table 5.6. The mean values are defined by quantifying several discussions with CRM managers of the leading mobile network operators in Turkey. The simulation is run 100 times to calculate the overall efficiency (Table 5.7).

Even though RUP value is not used in an optimum manner (all the weight coefficients are the same), the results show us that in 45 per cent of the competitions, businessman grabs the band. In order to ignore the effect of RUP value for the First-Come First-Serve based approach, it is fixed to 0.5. If the efficiency of the First-Come First-Serve model is assumed as 100 per cent, the RUP based approach produces a 3.05 per cent efficiency increase to the ASP for the scenario that we have studied. This increase in efficiency is supposed to signify a positive impact on the ASP's profitability.

Table 5.6: Subscriber groups' characteristics mean values

Attribute Name	**Mean of Student Package**	**Mean of Business Package**
Avg. of Caller's CRM Value	50	55
Avg. of Call Value	45	55
Avg. of Resource Winning Ratio	55	55
Avg. of Expected Call Length	50	35

Table 5.7: Simulation results for the case 1

Measure	**Efficiency of the model**
RUP value is fixed to 0.5 ($OC_i=[w_{i1}.BIF_i+w_{i2}. LF_i]. d_i.p_i.(1\text{-}0.5)$	100%
RUP value is fixed to 0.5 ($OC_i=[w_{i1}.BIF_i+w_{i2}. LF_i]. d_i.p_i.(1\text{-}RUP_i)$	103.05%

- Case 2: Coefficients of RUP parameters are defined in an optimum way.

In this case, subscribers are again differentiated as *students* and *businessmen*; by defining their mean values for the four RUP parameters (Table 5.6). However this time, the ASP has defined the coefficient of the RUP parameters in a way that reflects their marketing perspective (Table 5.8). For instance, this ASP wants to prioritize its high CRM-valued and high call-valued customers, by taking the coefficients of these parameters as

0.4. As the concentration is on the business package customers during these simulations, it is logical to keep these two coefficients as high as possible in order to prioritize the businessmen package. The simulation steps are repeated 100 times to calculate the overall efficiency (see Table 5.9). The results of the experiments show that businessman grabs the resource in 85 per cent of the competitions which produces a 5.61 per cent efficiency increase to the ASP compared to the First-Come First-Serve based approach for the scenario that we have studied.

Table 5.8: Simulation parameters values for the case 2

Coefficient Name	**Value**
Coefficient of Caller's CRM Value (ψ)	0.40
Coefficient of Call Value (ω)	0.40
Coefficient of Resource Winning Ratio (ξ)	0.10
Coefficient of Expected Call Length (φ)	0.10
Total	**1.00**

Table 5.9: Simulation results for the case 1

Measure	**Efficiency of the model**
RUP value is fixed to 0.5 ($OC_i=[w_{i1}.BIF_i+w_{i2}. LF_i]. d_i.p_i.(1\text{-}0.5)$)	100%
RUP value is fixed to 0.5 ($OC_i=[w_{i1}.BIF_i+w_{i2}. LF_i]. d_i.p_i.(1\text{-}RUP_i)$)	105.61%

5.3.5.2. Simulations for Allocation of Mobile Base Stations: In this second part, the simulations compare the conventional strategy and the RUP based approach when allocating mobile base stations. Let us consider ASP_1 sub-leased 12 MHz of spectrum band as in the first part of the simulations. During this week, there is an international exposition and a concert of a famous singer that occur at the same time. The conventional resource allocation strategy is the First-Come First-Serve based approach, where the channel is always assigned to the first subscriber. In this context, the mobile base station is always sent to the first group, the group A. The other strategy in the comparison includes the usage of RUP values. The coefficients, represented in Table 5.10, reflect a sample marketing strategy of an ASP. This ASP in question prefers to favor the subscribers who are used to make respectively longer calls. The remaining part of this subsection is composed of two cases which are built to investigate performance limits of the proposed approach.

Table 5.10: Simulation parameters values

Coefficient Name	**Value**
Coefficient of Caller's CRM Value (ψ)	0.10
Coefficient of Call Value (ω)	0.20
Coefficient of Resource Winning Ratio (ξ)	0.10
Coefficient of Expected Call Length (φ)	0.60
Total	**1.00**

- Case 1: Each customer group has equal number of customers.

There are two different groups of subscriber who are located in two different locations. For comparison purposes, both subscriber groups are assumed to contain 100 customers and they both have the same average mean values for each parameter (Table 5.10). The first ten simulation results are represented in Table 5.11. In the given table, *profitability*$_1$ represents the extra profitability that the ASP obtains from sending the base station to the winner group instead of the other one, whereas *profitability*$_2$ represents the extra profitability received with the integration of RUP value.

Table 5.11: Details of the first ten simulations

No	**Utility received from group A with RUP**	**Utility received from group B with RUP**	**Utility received with RUP=0.5**	**Winner**	***Profitability*$_1$**	***Profitability*$_2$**
1	1290.301	1309.459	1218.945	B	1.47%	7.42%
2	1310.338	1305.622	1218.945	A	0.03%	7.49%
3	1296.272	1346.389	1218.945	B	3.80%	10.40%
4	1262.375	1308.672	1218.945	B	3.66%	7.40%
5	1340.600	1278.483	1218.945	A	4.80%	9.90%
6	1298.126	1342.240	1218.945	B	3.30%	10.10%
7	1351.247	1282.019	1218.945	A	5.40%	10.80%
8	1324.616	1315.953	1218.945	A	0.60%	8.60%
9	1316.138	1323.637	1218.945	B	0.50%	8.60%
10	1323.639	1267.179	1218.945	A	4.40%	8.58%

If a First-Come First-Serve approach is used, in each case the mobile base station will be sent to the subscriber group A. However, with the inclusion of the RUP-based approach into decision making process; in 57 per cent of the cases, the mobile base station is sent to the subscriber group B instead of A. This 57 per cent represents the cases where the total net utility of the ASP received from the group B is greater than the one of the group A. Consequently, in 57 per cent of the cases, the ASP prefers the group B over group A by taking into consideration the RUP values.

The $profitability_1$ represents the extra profitability that the ASP obtains from sending the base station to the winner group instead of the other one. Next, the $profitability_2$, that is considered to be more significant, stands for the extra profitability that the RUP based approach brings to the ASP. The simulation results reveal an average of 9.49 per cent increase in received net utility which will have direct impact on the profitability of ASP.

- *Case 2:* Customer group A has variable number of subscribers.

In this case, the number of subscribers in group A is increased starting from 1000 to 2000 with an increment of 50 people each time whereas the number of subscriber in the other group (group B) remains constant. For each population change, the simulations are repeated. By changing the ratio of group populations, the change in the efficiency of the model is observed (Table 5.12). The *efficiency* signifies the ratio of the total net utility value which is obtained by using the decision strategy to the total net utility value without using it. The coefficients and attributes in these simulations are set again as in Table 5.10 and Table 5.11. Until the ratio of the subscribers reaches 1.95, it is possible to see an increase in the efficiency. This result proves that an ASP should not always make its decision by just looking at the population size of subscriber groups.

This architecture differs from the other research in the same area by taking customer information into consideration. It allows the service provider to include customer relationship strategy into its marketing strategy. It is shown that the proposed approach positively contributes to the profitability of service providers when compared to First-Come First-Serve approach. These architectures that we have mentioned in the previous sub-sections were all positively contributing to the profitability of the service providers, by considering the satisfaction of the network users. However, even an economic model needs to be robust in the physical level. Hence, we have turn back to the physical characteristics of the network and have examined the power management issues of the SUs in the network.

Table 5.12: Ratio of subscribers in the group and efficiency calculation for each ratio considering the case 2

Ratio of Subscribers	Efficiency of RUP-based Model
1.00	9.49%
1.05	8.98%
1.10	8.47%
1.15	8.01%
1.20	7.50%
1.25	6.99%
1.30	6.53%
1.35	6.02%
1.40	5.56%
1.45	5.05%
1.50	4.60%
1.55	4.10%
1.60	3.85%
1.65	3.15%
1.70	2.64%
1.75	2.19%
1.80	1.69%
1.85	1.24%
1.90	0.74%
1.95	0.29%

5.4. Spectrum Trading Architecture with Power Control Mechanism

Our lastly proposed framework looks for empirical evidence to our next three research questions: “What kind of impact transmission power has on the profit maximization, as well as on the unit spectrum prices?” “What kind of impact the flexibility on the amount of offered spectrum bands has on profit maximization, as well as on the unit spectrum prices?" "How can we structure a market where each PSP determines its target customers and their potential demand and then determine their unit prices?"

The models that have been mentioned above were all considering the QoS requirements of customers. In the brokering architecture, we were considering the quality as an integration of two factors: The received signal power and the location factor. The received signal power is an appropriate quality factor; however we were not calculating it in respect to the distances of customers to the base stations of service providers. Instead, they were predetermined. In the spectrum exchange architecture, the quality was depending on the interference temperature. However, we have encountered that FCC has abandoned the interference temperature concept due to a number of negative comments of industry players on its feasibility (Zayen *et al*., 2008). Furthermore, this metric should be measured at the receiver rather than in the radio channel. Thus, it may be questionable to use this metric without giving a detailed explanation on its background and its current status. Hence, we have given up the interference temperature and have focused on the signal to interference and noise ratio (SINR) as the quality metric. As mentioned earlier, in the literature there are several studies that look at the impact of pricing on power control (Saraydar *et al*., 2002) (Mwangoka *et al*., 2009) (Alpcan *et al*., 2002); however to the best of our knowledge, no one has considered the impact of power control on profit maximization and on price setting of PSPs. Thus, with our proposed framework, we have focused to answer to the question: "What kind of impact transmission power has on the profit maximization, as well as on the unit spectrum prices?"

In previous works, we have always taken the size of the available or underutilized spectrum bands as given. We were determining the unit spectrum prices as the size of the available portion is constant during the trading process. However, we believe that the flexibility on the size of the offered bands could bring more profit to spectrum owners by not disturbing the regular customers. Hence, this framework considers another research question: "What kind of impact the flexibility on the amount of offered spectrum bands has on profit maximization, as well as on the unit spectrum prices?".

Our last research question is about to build a framework that considers a competitive spectrum trading marketplace with multiple spectrum owners and multiple potential spectrum buyers. There are more than one entity in the marketplace; therefore we cannot utilize classical optimization techniques. Moreover, we aim at analyzing the impact of limiting the target customers of spectrum owners to the spectrum demand, profit and unit prices. Hence, our proposed framework with power management includes the answer to the question: "How can we structure a market where each PSP determines its target customers and their potential demand and then determine their unit prices?"

5.4.1. Framework Information Flow

The framework introduced in the dissertation consists of a cognitive radio system with multiple PSPs and multiple SUs who are co-located in the same geographical region *R*. SUs are randomly distributed over the geographical area. Each PSP has its own frequency band and its own regular costumers (i.e. PUs) in region *R*. PSPs intend to sell portions of their unutilized spectrum to SUs in order to obtain additional revenue. Also, this spectrum trading process enables SUs to satisfy their spectrum requirements. For analytical purposes, a single cell wireless CDMA data network is considered where the PUs and SUs of a PSP transmit simultaneously in a common frequency band. The model concentrates on the power control for the uplink communication in the given carrier frequency. Thus, the base station (BS) of a PSP receives independent signals transmitted from multiple SUs. The proposed framework can be extended to other types of wireless networks with slight modifications. Each BS is assumed to have perfect knowledge of channel information from SUs to BS and PUs to BS. In practice, certain cooperation is needed between secondary and primary network in order to have such perfect information. This might be in terms of parameter feedback which is carried out directly by the primary network or indirectly through a spectrum manager or spectrum broker that mediates between the two networks (Buddhikot *et al*., 2005) (İleri *et al*., 2007) (İleri and Zander, 2009).

Figure 5.11 illustrates the system information flow. The flow is activated by the declaration of minimum desired bandwidths of SUs in region *R*. The messages are broadcasted to PSPs in the same region periodically, in order to prevent multiple individual attempts. Knowing the demand behavior and bandwidth requirements of SUs, each PSP wants to find out which SU(s) are more profitable to serve. Obviously, if serving a SU does not bring any positive profit to a PSP, then the PSP does not join the spectrum trading process. Moreover, the PSPs have to follow the power level limitations in order to keep their PUs quality level above a certain threshold. A new network element, the *telecommunication coordinating authority* (*TCA*), has the role of a power management system. The TCA's aim is to preserve the social welfare of each network in region *R*. The TCA supervises PSPs by computing the optimum transmission power levels that the SUs in their network have to set. The PSPs then select which SU(s) are more profitable to serve. Accordingly, each PSP determines the unit price of its available bandwidth considering the other PSPs' strategies. Then, the unit prices are offered to SUs. To summarize:

(i) SUs broadcast their minimum bandwidth requirements to all the PSPs in the same region.

(ii) PSPs send the channel information and minimum desired bandwidths of the SUs to the TCA.

(iii) The TCA computes the optimum transmission power levels of SUs, for each PSP individually. It sends the optimum transmission power values to PSPs.

(iv) Using an initial price vector and the optimum transmission power values, each PSP determines the best set/ combination of SUs to serve (the set that gives more profit).

(v) Using the optimum transmission power values, PSPs play the pricing game and they each determine their unit spectrum price. (The TCA is not an element of the pricing game. The pricing game is played among PSPs. The TCA determines the transmission power of SUs prior to the pricing game. The TCA calculates its unit spectrum price by making an assumption that each offered bandwidth to SUs will be bought by SUs.)

(vi) The unit spectrum prices are offered to SUs in the region.

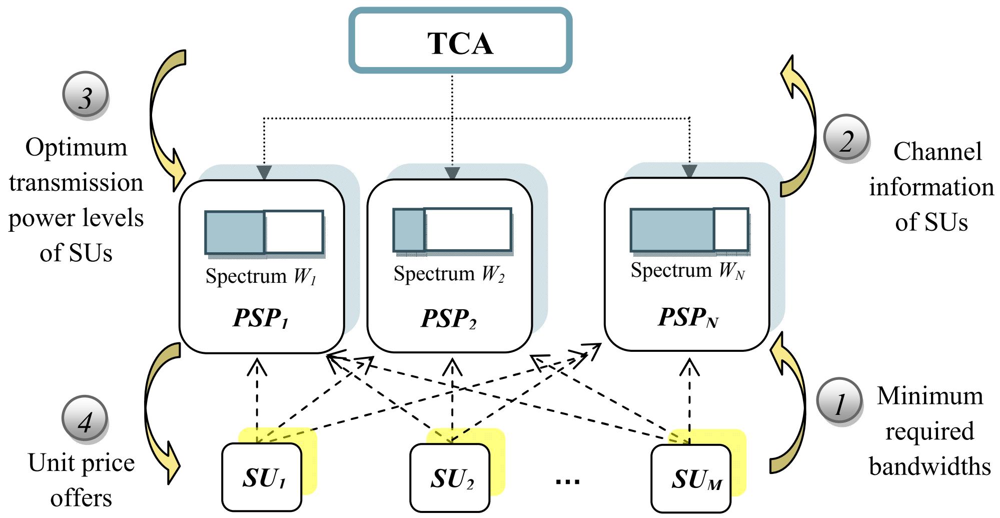

Figure 5.11. System information flow

5.4.2. Network Architecture and Elements

5.4.2.1. Telecommunication Coordinating Authority (TCA): In wireless networks, user's satisfaction highly depends on the physical conditions, especially on the received signal quality. The receiver can decode the message successfully, only if the signal is significantly stronger than ambient noise and other interfering signals. Since the same frequency bands are reused by multiple PUs and SUs; links operating over the same frequency interfere with each other. SINR value is a quality measure for such networks that represents the overall ratio of the wanted signal to any other unwanted power at the receiver side (Walke *et al*., 2007).

We introduce the TCA, as a response to our fourth research question. The TCA is assumed to be formed by the association of PSPs to manage the spectrum trading process. It operates on behalf of the PSPs, with a role of a central controller. The TCA directs PSPs keeping their PUs' satisfaction by balancing the tradeoff between transmission quality and resulting interference. Finding a good balance between these two conflicting objectives is the primary focus of an efficient power control component. With the information coming from the PSPs in region *R*, the TCA computes the optimum transmission power levels of SUs for each PSP. By the time PSPs declare their unit spectrum price, we do not know how SU and PSP matching takes place. This will be determined by the TCA taking transmission power levels of SUs into consideration for each combination of selection.

These power levels maximize the SINR levels for both SUs and PUs; in other words, they are the smallest transmission powers to achieve the best transmission quality for SUs. The PSPs use the results to choose which SU(s) to offer the spectrum. By investing in the TCA, PSPs seek to minimize their churning rate and maximize their profits in long-term by keeping their primary customer base. In the literature so far, there are several studies that look at the impact of pricing on power control (Saraydar *et al*., 2002) (Mwangoka *et al*., 2009) (Alpcan *et al*., 2002); however to the best of our knowledge no one has considered the impact of power control on profit maximization and on price setting of PSPs. In the dissertation, our focus is to find out how power control affects pricing with a controlling authority such as TCA.

5.4.2.2. Primary Service Providers (PSPs): The regular customers of the PSPs are referred to as the *primary users*. A part of the revenue of a PSP is obtained from what the PUs pay for the services. We assume that the PSP_i receives a fixed amount of fee ($\overline{p_i}$) from each PU, in return for a guarantee of a minimum bandwidth (B_k^i) and a minimum quality of service level in terms of SINR, call dropping probability and call blocking probability. In this framework, we have considered the SINR value as an indicator of the quality of service level. The number of PUs in region *R* (n_{PU_i}) can vary over time due to random arrivals and departures; however during the spectrum trading process, it is assumed to be constant. Moreover, we assume that the prices are calculated fast enough to assume the PUs and SUs have not moved too much during the trading process. Otherwise, the corresponding channel gains cannot remain constant during the convergence of transmission powers.

When their allocated spectrum of size W_i is not fully utilized by PUs, the PSPs (spectrum owners) have the opportunity to lease/sell these spectrum opportunities to SUs in order to obtain additional revenue. This is consistent with the exclusive-use spectrum access model. Each spectrum owner sets its own price (p_i) per unit of spectrum. The unit of spectrum is measured by a bandwidth measurement unit, Hertz. The PSPs compete with each other to sell extra spectrum to SUs by setting the optimal price that maximizes their utilities. In this regard, the price should be set properly by considering both the demand of SUs and the price strategies of other PSPs.

Our fifth research question, the flexibility of spectrum supply of PSP, is investigated in its profit function. In spectrum trading models, a PSP usually sells the spectrum band that left over the regular customers' utilization (Niyato and Hossain, 2008b) (Işıklar Alptekin and Bener, 2009a). The spectrum shortage problem results from the spectrum management policy rather than the physical scarcity of usable spectrum (Zhao and Sadler, 2007). Therefore in this research, we aim at proposing an alternative management model by integrating a new coordinating authority, as well as by allowing PSPs to sell more spectrum than they have. If the PSP_i sells too much spectrum to SUs, this will cause degradation on B_k^i. Therefore, PSP_i has to be penalized with a cost of quality degradation. This profit diminution can be considered as a discount which is offered to PUs. A similar approach is envisioned by Niyato and Hossain (Niyato and Hossain, 2008b), but they introduce a cost for each spectrum band which is shared by SUs. The difference of our model is that in our model, a PSP does not experience any cost, if the minimum quality requirements of its PUs are met. Apart from excessive spectrum sell, the interference which arises from undue transmission power also degrades the service quality of PUs. Even if the power emission is controlled by the TCA, a PSP should be penalized because of the power emission of SUs (s_j^{II}) in its network. To summarize, the profit of the PSP_i can be expressed as follows:

Profit$_i$ *= Revenue from PUs + Revenue from spectrum sell – Cost of quality degradation on PUs (if any) – Cost of transmission power of SUs*

<u>5.4.2.3. Secondary Users (SUs)</u>: Each SU is assumed to have a minimum desired bandwidth ($b_j^{\min}$) at a point in time. The SU broadcasts its requirement to all the PSPs in the same region. They then receive price offers from the PSPs. The spectrum offered by a PSP should meet the minimum desired bandwidth requirement of a SU. The PSPs' price offers also include the transmission power level information, which is set by the TCA. A SU has to obey this power limitation of the PSP, if this PSP is chosen as the seller. A SU chooses the offer that provides the best utility in terms of received quality and price. SUs are free to choose and buy spectrum opportunities. They are interested in getting high quality service at a low cost and they pay for the spectrum they accessed.

In order to examine the multiple-seller and multiple-buyer trading environment, which is also our sixth research question, sellers (PSPs) make use of the demand functions of buyers (SUs). PSPs are assumed to know SUs' demand function and they utilize them into their profit functions when determining their price strategies. We constitute a heuristic, called the Coordinated Pricing (CP) algorithm, to solve this entire spectrum trading process in a multiple-seller and multiple-buyer environment. The pseudocode of CP algorithm will be given after describing the problem formulation and game model in detail.

5.4.3. Problem Formulation

5.4.3.1. Objective Function of the Telecommunication Coordinating Authority: As previously mentioned, the role of the TCA is to provide with an optimum power control by considering the social welfare of all the users in the given network. It is important to note that the TCA is not an element of the proposed pricing game. One way to reach the optimum points in a network is to satisfy data rates of both PUs and SUs in the system. Shannon's channel capacity establishes the bound of the maximum amount of error-free digital data that can be transmitted with a specified bandwidth in the presence of the noise (Shannon, 1949) (Zayen *et al.*, 2008). In other words, it is the achievable data rate of the user on the given bandwidth. It is formulated as:

$$C = B.\log_2(1 + SINR) \tag{5.54}$$

where B is the bandwidth of the channel in Hertz and C is the channel capacity in bits/second. For spread spectrum transmission, the SINR of SU_j at the base station of PSP_i can be represented as (Alpcan *et al.*, 2002) (Bloem *et al.*, 2007) (Le and Hossain, 2008) (Kastrinogiannis and Papavassiliou, 2009) (Hossain *et al.*, 2009):

$$SINR^i_{SU_j} = \frac{L\, s^{II}_j \left|h_{SU_j \to BS_i}\right|^2}{\sum\limits_{k=1,\, k\neq j}^{M} s^{II}_k \left|h_{SU_k \to BS_i}\right|^2 + \sum\limits_{k=1}^{n_{PU_i}} s^i_k \left|h_{PU_k \to BS_i}\right|^2 + \sigma^2} \tag{5.55}$$

The SINR of the k^{th} primary user of PSP_i (PU^i_k) at the base station of PSP_i can be represented as:

$$SINR^{i}_{PU_k} = \frac{L\, s^i_k \left| h_{PU_k \to BS_i} \right|^2}{\sum\limits_{j=1}^{M} s^{II}_j \left| h_{SU_j \to BS_i} \right|^2 + \sigma^2} \tag{5.56}$$

where

L : Spreading gain
s^{II}_j: Transmission power of SU_j
s^i_k: Transmission power of PU^i_k in the PSP_i's network
$h_{PU_i \to BS_i}$: Channel gain between the BS of PSP_i and the PU^i_k
$h_{SU_j \to BS_i}$: Channel gain between the BS of PSP_i and the SU_j
σ^2: Background noise power
n_{PU_i}: Number of PUs in the PSP_i's network
M : Number of SUs in region R

The *spreading gain* (processing gain) of the CDMA system is equal to $L = W/R$, where W is the chip rate and R is the total rate (Alpcan *et al*., 2002) (Schwartz, 2005). The spreading gain is usually required to be larger than a particular positive value. The larger the spreading gain L, the more users can be accommodated. It is simply equal to 1 for other multiple access technologies such as FDMA (Le and Hossain, 2008). The background noise power is assumed to be the same for all users. The channel gain between the BS of PSP_i and the SU_j is modeled as (Kastrinogiannis and Papavassiliou, 2009):

$$h_{i->j} = \frac{1}{d^{\alpha}_{ij}} \tag{5.57}$$

where

d_{ij} : The distance between the BS of PSP_i and the SU_j
α : The path loss exponent

Using the above functions, the TCA aims at adopting the transmission powers of SUs in order to maximize their cognitive capacity, while maximizing their SINR and minimizing the interference in the environment. We do not propose adjusting the power levels of PUs. They are taken from a lookup table which involves the average transmission power values with respect to distance. It is always possible to let the transmission powers of PUs be variable and optimize them; however in this research, we want to examine the impact of our proposed approach on the secondary market separately.

For a PSP with n_{PU_i} PUs and M SUs in the region, the objective function of the TCA is expressed in (5.52). The TCA uses this objective function for each PSP individually and calculates the optimum transmission powers of SUs:

$$\max_{s_j^{II}} \sum_{j=1}^{M} b_j^{\min} \log_2 \left(1 + SINR_{SU_j}^{i}\right) + \sum_{k=1}^{n_{PU_i}} B_k^i \log_2 \left(1 + SINR_{PU_k}^{i}\right) \tag{5.58}$$

s.t.

$$l_l \leq SINR_t \leq l_u \,, \quad t \in \{SU, PU\} \tag{5.59}$$

$$0 < s_j^{II} \leq 2 \,, \quad \forall j \tag{5.60}$$

where

$b_j^{\min}$: Minimum desired bandwidth of SU_j

B_k^i: Bandwidth requirement of PU_k of PSP_i

l_l: Lower bound for $SINR_j$ and $SINR_i$ values

l_u: Upper bound for $SINR_j$ and $SINR_i$ values

The transmission powers of SUs are bounded by a lower limit of 0 and upper limit of 2 Watts. Similarly, the SINR values are bounded with a lower and upper limit, depending on the SU's application type.

5.4.3.2. Profit Function of Primary Service Providers: The PSP is considered the spectrum seller in the spectrum trading process, while the SU is the spectrum buyer. A PSP can sell spectrum bands to more than one SU; however a SU is assumed to buy its required spectrum band from only one PSP. The set $M_i \subset \{SU_1, SU_2, \ldots, SU_M\}$ represents the set of the SUs that are selected to serve by PSP_i. $M_k \subset \{SU_1, SU_2, \ldots, SU_M\}$ represents the set of the SUs that are selected by other PSPs, $\forall k \neq i$, $i,k \in \{1,..,N\}$. The profit function of PSP_i can be expressed as:

$$\pi_i = \bar{p}_i n_{PU_i} + p_i \sum_{j \in M_i} b_j - a_i \max\left\{ \sum_{j \in M_i} b_j - \left(W_i - B_k^i n_{PU_i}\right), 0 \right\} - d_i \sum_{j \in M_i} s_j^{II} \quad (5.61)$$

s.t

$$p_i \geq 0, \quad \forall i \quad (5.62)$$

$$b_j \geq b_j^{\min}, \forall j. \quad (5.63)$$

$$\sum_{j \in M_i} b_j \leq W_i, \forall i \quad (5.64)$$

where

$\bar{p}_i$: Fixed fee that PU_k^i pays
p_i : Unit price offered to SUs by PSP_i
b_j: Size of the spectrum that SU_j buys (actual demanded bandwidth)
W_i : Total size of spectrum of PSP_i
a_i : Weight coefficient of cost due to the quality degradation
d_i : Weight coefficient of cost due to the interference created by SUs

The factors a_i and d_i are the weight coefficients, as well as the factors that convert utility units to currency. Therefore, the unit of the profit function can be assumed as TL. The higher the a_i, the more the PSP is penalized for quality degradation. The lower bound of the offered bandwidth determines the upper bound of the offered price, and it is set by (5.57). The $b_j^{\min}$ is the minimum desired bandwidth of SU_j that is broadcasted to PSPs in the same region. By setting an initial average price vector, PSP_i calculates its initial profit for each case by using the power levels (s_j^{II}) given by the TCA. PSP_i chooses the case that brings it the highest positive profit. In other words, PSP_i selects the SUs that it is going to offer its available spectrum band. Then PSPs play a game among each other for unit price setting. The details of the game among PSPs will be discussed in the next sub-section.

5.4.3.3. Demand Function of Secondary Users: We assume that the demand coming from a SU shows a linearly decreasing trend when the price offered by PSP_i increases. Besides, it shows a linearly increasing trend when other PSPs' prices increase. Therefore, demand is a function of PSPs' price decisions as well as a function of competitors' price decisions. The linear demand function D_j has the following properties and expression, respectively:

$$\frac{\partial D_j}{\partial p_i} \leq 0, \frac{\partial D_j}{\partial p_k} \geq 0, \text{ where } k \in \{1, .., N\}, k \neq i \tag{5.65}$$

$$D_j = \delta_j - \beta_j p_i + \sum_{k=1,\, k\neq i}^{N} \gamma_{jk} p_k \tag{5.66}$$

where

δ_j : Base demand of SU_j

β_j : Positive constant that represents to what extent the SU_j is influenced from price offered by PSP_i

γ_{jk} : Positive constants that represent to what extent the SU_j is influenced from prices offered by the competitors of PSP_i

δ_j denotes the fixed bandwidth demand (i.e. when the price is zero), and β_j denotes the elasticity of the demand function. If δ_j is large, the bandwidth demand is high. If β_j is high, the elasticity of the demand increases. This means that the SU is more sensitive to the increase/ decrease in price.

We assume that the influence of a PSP_i's price on SU_j's demand is greater than the influence of the competitors' prices. The following assumption will be utilized when proving the uniqueness of the equilibrium point.

$$\beta_j > \frac{1}{2} \sum_{k=1,k\neq i}^{N} \gamma_{jk} \tag{5.67}$$

5.4.4. Game Model

The game theory is defined as the collection of models and analytical tools used to study interactive decision processes (DaSilva, 2000a). When determining the unit spectrum prices, we want to analyze the competition and interactions among PSPs. Game theory provides us to deal with the interactive nature of the price setting process.

The elements of the proposed pricing game are as follows:

- Players: Primary service providers.
- Strategy of players (s_i): The unit price of the offered bandwidth.
- Payoff of players: Profit function of PSPs.

Each PSP tries to maximize its own *payoff* (profit) function without considering the effect of its actions on other users. The one shot game is a part of our proposed framework. It begins by the optimum transmission power levels coming from the TCA to PSPs, and the game ends by the declaration of unit prices of PSPs. The optimum unit price of a PSP depends on the unit prices (strategies) that other PSPs determine. Solving such a game means predicting the strategy of each PSP. One can see that if the strategies from the players are mutual best responses to each other, no player would have a reason to deviate from the given strategies and the game would reach a steady state. Such a point is called the Nash equilibrium (NE) point of the game (Nash, 1951).

In the pricing game, PSPs determine their unit spectrum price independently and the information is strictly limited to local information. Hence, the game has a non cooperative setup. It is important to note that, a PSP does not know if the SUs that are offered bandwidth will choose this PSP as the seller. Therefore, the PSP calculates its maximum expected demand and maximum possible profit using the equilibrium point of the game. Our proposed framework has some common ground with the game proposed by Niyato and Hossain (Niyato and Hossain, 2009). They determine both the size and the price of the spectrum that they offer in their proposed game model; however they do not consider the issue of power management.

The PSPs use the demand information to adjust their price strategies. The shared bandwidth (b_j) in the profit function of PSP_i (5.61) is replaced with the demand function of SU_j (5.66):

$$\begin{aligned}\pi_i = {} & \bar{p}_i n_{PU_i} + \sum_{j\in M_i} p_i \left(\delta_j - \beta_j p_i + \sum_{k\in M_k} \gamma_{jk} p_k\right) \\ & - a_i \max\left\{ \sum_{j\in M_i} \left(\delta_j - \beta_j p_i + \sum_{k\in M_k} \gamma_{jk} p_k\right) - \left(W_i - B_k^i n_{PU_i}\right), 0 \right\} - d_i \sum_{j\in M_i} s_j^{II}\end{aligned} \tag{5.68}$$

s.t. $p_i \geq 0, \quad \forall i$

$$\delta_j - \beta_j\, p_i + \sum_{k=1,\, k\neq i}^{N} \gamma_{jk}\, p_k \geq b_j^{\min}, \forall j \tag{5.69}$$

$$\sum_{j\in M_i} (\delta_j - \beta_j\, p_i + \sum_{k=1,\, k\neq i}^{N} \gamma_{jk}\, p_k) \leq W_i, \forall i \tag{5.70}$$

The vector $\mathbf{p}^* = [p_1^*, p_2^*, .., p_i^*, .., p_N^*]$ denotes the solution (the NE) of this game for:

$$p_i^* = BR_i\left(\mathbf{p}_{-i}^*\right) \tag{5.71}$$

where $\mathbf{p}_{-i}^*$ represents the vector of best responses for player *j* for $j \neq i$. The NE is the point that solves the set of equations: $\frac{\partial \pi_i}{\partial p_i} = 0$ for all *i*. The set of equations is given as:

$$\frac{\partial \pi_i}{p_i} = \begin{cases} \sum_{j\in M_i}\left(\delta_j - 2\beta_j p_i + \sum_{k\in M_k} \gamma_{jk} p_k\right) + a_i \sum_{j\in M_i} \beta_j & , \textit{if} \sum_{j\in M_i} b_j > W_i - B_k^i n_{PU_i} \\ \sum_{j\in M_i}\left(\delta_j - 2\beta_j p_i + \sum_{k\in M_k} \gamma_{jk} p_k\right) & , \textit{otherwise} \end{cases} \tag{5.72}$$

<u>5.4.4.1. Convexity of the objective function</u>: A convex optimization problem is a problem where all of the constraints are convex functions, and the objective is a convex function if minimizing, or a concave function if maximizing (Bazaraa et al., 2006). With a convex objective and a convex feasible region, there can be only one optimum solution, which is globally optimum. Furthermore, a function *f* is concave if *–f* is convex.

First, we convert the profit maximizing objective function of PSPs (5.68) to a convex minimization problem form by taking its opposite:

$$\min_{p_i}\ (-\pi_i) =$$
$$= \min_{p_i}\ - \left(\begin{array}{l} \overline{p_i}.n_{PU_i} + \sum_{j\in M_i} p_i \left(\delta_j - \beta_j p_i + \sum_{k\in M_k} \gamma_{jk} p_k\right) \\ - a_i \max\left\{ \sum_{j\in M_i}\left(\delta_j - \beta_j p_i + \sum_{k\in M_k} \gamma_{jk} p_k\right) - \left(W_i - B_k^i n_{PU_i}\right), 0 \right\} - d_i \sum_{j\in M_i} s_j^{II} \end{array} \right) \tag{5.73}$$

s.t.

$$-\delta_j + \beta_j\, p_i - \sum_{k=1,\, k\neq i}^{N} \gamma_{jk}\, p_k + b_j^{\min} \leq 0, \forall j \tag{5.74}$$

$$\sum_{j\in M_i} (\delta_j - \beta_j\, p_i + \sum_{k=1,\, k\neq i}^{N} \gamma_{jk}\, p_k - W_i) \leq 0, \forall i \tag{5.75}$$

$$-p_i \leq 0, \quad \forall i \tag{5.76}$$

Let us look at whether the given objective function and the constraints are convexes. Hence, we examine if $\frac{\partial^2 \pi_i}{\partial p_i^2}$ is positive given p_k, for $\forall k \neq i$.

$$\frac{\partial^2 \pi_i}{\partial p_i^2} = \begin{cases} \sum_{j\in M_i} 2\beta_j, & if \sum_{j\in M_i} b_j > W_i - B_k^i n_{PU_i} \\ \sum_{j\in M_i} 2\beta_j, & otherwise \end{cases} \geq 0 \tag{5.77}$$

Then, we can say that given $p_k, \forall k \neq i$, the profit function (π_i) is convex on p_i. Now, we inspect if the constraints are convexes. The three constraints are all linear; so they are convexes. We have proved that we have a complex optimization problem. The vector $\mathbf{p}^* = [p_1^*, p_2^*, .., p_i^*, .., p_N^*]$ which is the solution to the set of equation $\frac{\partial \pi_i}{\partial p_i} = 0$ for all i is the Nash equilibrium of the proposed game. It is also the global optimum of the given problem.

5.4.4.2. Existence of the Nash Equilibrium: The existence of the Nash equilibrium point will be proved by using the supermodularity of the profit function.

The feasible strategy space of the proposed game $S_i = \{p_i : 0 \leq p_i \leq p^{\max};\ i = 1,\, 2,\, ...,\, N\}$ is a compact sublattice of $\Re^N$. The upper bound on the price is set by the minimum desired bandwidth of the SUs.

$$\frac{\partial^2 \pi_i}{\partial p_i^2} = \begin{cases} -\sum_{j\in M_i} 2\beta_j, & if \sum_{j\in M_i} b_j > W_i - B_k^i n_{PU_i} \\ -\sum_{j\in M_i} 2\beta_j, & otherwise \end{cases} \leq 0 \tag{5.78}$$

$$\frac{\partial^2\pi_i}{\partial p_i \partial p_k} = \begin{cases} \sum\limits_{j\in M_i}\sum\limits_{k\in M_k}\gamma_{jk}, & if \sum\limits_{j\in M_i} b_j > W_i - B_k^i n_{PU_i} \\ \sum\limits_{j\in M_i}\sum\limits_{k\in M_k}\gamma_{jk}, & otherwise \end{cases} \geq 0 \tag{5.79}$$

$$\frac{\partial^2\pi_i}{\partial p_k^2} = \begin{cases} 0, & if \sum\limits_{j\in M_i} b_j > W_i - B_k^i n_{PU_i} \\ 0, & otherwise \end{cases} \leq 0 \tag{5.80}$$

Given p_k, the profit function is concave on p_i.

$$\frac{\partial^2\pi_i}{\partial p_k \partial p_i} = \begin{cases} \sum\limits_{j\in M_i}\gamma_{jk}, & if \sum\limits_{j\in M_i} b_j > W_i - B_k^i n_{PU_i} \\ \sum\limits_{j\in M_i}\gamma_{jk}, & otherwise \end{cases} \geq 0 \tag{5.81}$$

Then, the vector $\mathbf{p}^* = [p_1^*, p_2^*, .., p_i^*, .., p_N^*]$ which is the solution to the set of equation $\frac{\partial\pi_i}{\partial p_i} = 0$ for all i is the Nash equilibrium of the proposed game.

5.4.4.3. Uniqueness of the Nash Equilibrium: To prove the uniqueness of the equilibrium point, the *contraction* approach is used (Vives, 1999). Vives says that the contraction condition is the easiest to check, but it is also the strongest. r_i (·) is defined as the best reply function of player i to actions a_{-i} of rivals. The approach is based on showing that the best-reply map r (·) ≡ (r_1 (·), …, r_n (·)) is a contraction. A sufficient condition for r (·) to be a contraction is

$$\frac{\partial^2\pi_i}{\partial {p_i}^2} + \sum_{i\neq k}\left|\frac{\partial^2\pi_i}{\partial p_i \partial p_k}\right| < 0 \tag{5.82}$$

which is equal to

$$\sum_{j\in M_i}(-2\beta_j + \sum_{k\in M_k}\gamma_{jk}) < 0 \tag{5.83}$$

with the assumption of $\beta_j > \frac{1}{2}\sum\limits_{k\in M_k}\gamma_{jk}$ expressed in (5.67), the expression (5.83) is proven to be negative.

5.4.5. The Coordinated Pricing (CP) Algorithm

The proposed heuristics that encapsulates the power control process of the TCA and the price setting game of the PSPs are summarized in the form of a pseudecode (Figure 5.12). From the practical implementation point of view, the complexity of the CP algorithm comes from the computation of SINR values for all the PSPs, as well as the optimum transmission powers. In each run, the algorithm calculates ($N.2^M$) optimum transmission power. The number of SUs increases the runtime of the algorithm. We have run the algorithm on an Intel Core 2 Quad 2.66 GHz microprocessor using MATLAB. The runtime of the algorithm is in the acceptable range up to 9 SUs in the same region. The CP algorithm is run periodically thus, 9 SUs for one shot game is a realistic number for real life scenarios. Moreover, with more powerful processor systems, the algorithm can support higher number of SUs.

We have used the function *fmincon* in order to maximize the social welfare function. The function *fmincon* enables us to maximize the social welfare function which is a nonlinear and multivariable function. The function *fmincon* may solve the given problem using different algorithm. We have used the *interior-point* and *active-set* algorithms, and we have seen that they both give the same results. Moreover, when we have changed the initial points of the algorithm, we have obtained the same results. It shows us, we have obtained the global optimum of the problem.

We have used the function *lsqlin* in order to calculate the optimum unit price values of the PSPs. We give the best response functions of the PSPs with the corresponding constraints. The function *lsqlin* solves constrained linear least-squares problems. With the specified model parameter values, the function gives the same result. Note that, if the result is optimum, then the corresponding residual value should be zero.

The first module of the CP algorithm consists of calculating of the optimum transmission power values of SUs. Doing so, the TCA takes the spreading gain, the channel gains, background noise power, the number of PUs, the transmission power of PUs, the guaranteed bandwidth to PUs, and the minimum desired bandwidth requirement of SUs as input. These inputs are sufficient to calculate the SINR values of SUs and PUs, using equations (5.55) and (5.56). Then, the TCA finds the optimum transmission power values by maximizing the objective function in equation (5.58) by considering the constraints. The first module of the algorithm gives the optimum transmission power of SUs in each PSP's network in each case, as the output.

The remaining modules of the algorithm are run by the PSP. The PSP receives the optimum transmission power values of the SUs and using an initial price vector, it calculates its initial profit in each case by the equation (5.68). Before doing so, it eliminates the cases where the sum of the offered bandwidth exceeds its total capacity. We have assumed that the initial price value is equal to the flat fee that the PUs pay. Indeed, the magnitude of the initial price is not so significant; since this initial profit is used to rank the alternatives of SU selection. The PSP chooses the SU(s) that are more profitable to serve by looking at this initial profit value. Therefore, the output of the second module of the CP algorithm is the set of SUs that gives PSP the highest profit.

After determining the target customer set, the PSPs play a pricing game with each other in order to set their unit spectrum prices. The algorithm simultaneously solves the best response function of each PSP, given with the equation (5.72), considering each of their constraints. Thus, the third module gives the optimum spectrum price values of each PSP as the output.

In the last two modules, the PSP calculates its total demand using equation (5.66), and its maximum possible profit using equation (5.61), respectively. As a PSP does not know which SU(s) will choose it as the buyer, it can only calculate maximum possible profit.

Telecommunications Coordinating Authority:
inputs: $L, h_{PU_i \to SU_j}, h_{PU_i \to BS_i}, h_{SU_j \to BS_i}, \sigma^2, n_{PU_i}, s_k^i, B_k^i, b_j^{\min}$
output: s^{II} of SUs

1
```
for each PSP (from 1 to N)
      for each combination (from 1 to 2^M)
            calculate SINR of all SUs and PUs (5.49) - (5.50)
            find s^II values that optimize obj. function of TCA (5.52)
      end for
end for
```

Primary Service Providers:
input: s^{II} of SUs
output: Best SU combination to serve for each PSP

2
```
for each PSP (from 1 to N)
      ignore combinations where ∑_j b_j > W_i
            for remaining combinations
                  calculate Profit_PSP (5.62)
                  choose the combination that maximizes Profit_PSP (5.62)
            end for
end for
```

input: Best SU combination to serve
output: Optimum price vector (p*)

3
```
for each PSP (from 1 to N)
      compute best responses given other PSPs' current prices (5.66)
end for
```

input: Optimum price vector (p*)
output: Actual demanded bandwidth of SUs

4
```
for each PSP (from 1 to N)
      for each SU
      calculate Actual demanded bandwidth_SU (5.60)
      end for
end for
```

input: Actual demanded bandwidth of SUs
*output:*Maximum possible profit of PSPs

5
```
for each PSP (from 1 to N)
      calculate Maximum possible profit_PSP (5.55)
end for
```

Figure 5.12. The coordinated pricing algorithm

5.4.6. Numerical Examples and Results

Cognitive radio seems to be a very promising technology in theory, but it is much harder to put into practice in real-time applications mainly because of the possibility of shadowing or fading in the environment (Attar *et al*., 2008). In this research, we consider a feasible real life architecture which considers the reuse of licensed spectrum bands that are unutilized.

This section attempts to reveal the performance of the proposed power control and pricing mechanism. The framework is simulated numerically using MATLAB on three different demonstrative network examples. The first demonstrative example represents a case without competition, while the second and the third one correspond to competitive cases. As the parameters are scaled for a less-congested network, the scenario can be considered to reflect a real-life situation. We start by giving some possible spectrum trading scenarios.

<u>5.4.6.1. Possible Spectrum Trading Scenarios</u>: The underutilization of spectrum bands is a common case for TV broadcasting bands. Consider the following example: A TV company in a rural area has leased a frequency band from the telecommunication regulator for 10 years, but after 5 years of operation the company has been obliged to cease its broadcasting service. This company would like to retrieve its losses by sub-leasing its resources to other service providers (SPs). On the other hand, consider a SP that wants to enter the market with its technological infrastructure and spectrum resources. However, there is not any spectrum band left for this new entrant. So, it has two alternatives: It will ask for available spectrum bands to each license holder in order to lease them for a specified period of time. Or, there will be regional spectrum trading under the control of a centralized controller in a periodic manner. Here the SPs do not own any spectrum, instead they obtain time bound rights from the spectrum holder. In this scenario, the SP is considered as the SU. The SP should not necessarily be a new entrant one, but a SP with its spectrum license that seeks for extra resources. Whenever a SP encounters a temporary high traffic demand which cannot be satisfied by its own spectrum, it can lease one or two blocks (Nekoogar, 2005).

A similar scenario is also suitable for the United States 700 MHz FCC wireless spectrum auction. FCC started, the so-called Auction 73, in January 2008 for the licenses to operate the 700 MHz frequency band (FCC, Auctions Home Page). This auction stands to be the one of the most significant airwave auctions in U.S. history, potentially affecting everything from the cost of the wireless services to the competitive landscape among U.S. mobile operators for years to come. The 700 MHz spectrum was previously used for analog television broadcasting, but they are all wanted to be switched to digital television. To do so, the license holders of the 747 to 792 MHz portion of the spectrum, known as *C Block*, will hand their chunk of spectrum band back in return for new UHF (Ultra High Frequency) spectrum. FCC auctioned the remaining part of these bands. These bands are suitable for widely distributed mobile networks, broadcast applications for mobile devices, public safety applications or dynamic-access spectrum. They are said to be ideal for cellular services, since signals at those frequencies propagate farther and penetrate buildings better than signals in today's cellular bands, which go up to 1.9 GHz. Cellular network operators expect infrastructure costs to be reduced by 90 percent, because fewer cells will be required, given the longer distances signals travel (Rast, 2005). Due to such advantages, the cellular network operators are likely to have heavy competition for this valuable bandwidth. The bidders of this auction have asked that the blocks of spectrum be free to lease to different providers. This spectrum real estate is intended for the rental market: The buyers will act as land-lords, leasing the spectrum to third parties for short periods of time. Auction 73 concluded with 1090 provisionally winning bids covering 1091 licenses and it raised a total of $18.957.582.150 in net winning bids.

For another scenario of spectrum trading, consider a one hour social gathering of a game company at a city park which attracts a sudden influx of 200 end users in a single cell (Mwangoka *et al*., 2009). Assume 80 of these end users are video game freaks. The 80 gamers start playing an online video game which will demand a bandwidth range of 450-550 Kbps/per-stream/per-user. When all gamers are active, the aggregate cell throughput required is between 36 and 44 Mbps. Considering the demand from the other 120 guests, the number can be thought as 50 Mbps. Assume that the game company has a license of 15 MHz of spectrum block and can activate 11 1.25 MHz carriers, and each downlink channel can offer a maximum of 3.1 Mbps. In theory, the 11 carriers cannot satisfy the sustained constant bit rate demand from gamers. If the game company can acquire additional spectrum to activate 6 more carriers in real time, it may able to meet the demand of the unexpected traffic.

- Demonstrative example 1 : One PSP and two SUs in the region

The first example is a simple network with one PSP (PSP_1), its PU (PU_1) and two SUs (SU_1 and SU_2) (Figure 5.13). The simulation parameters are chosen as in Table 5.13.

The spreading gain L = 128 is taken in accordance with IS-95 standard (Rapaport, 1996). Multimedia QoS requirements are used from Diao and Li (2007) who showed that voice requires 3-10 dB SINR values, constant bit rate (CBR) digital audio requires 5-15 dB SINR values, and CBR and variable bit rate video require 6-21 dB SINR values (Diao and Li, 2007). In all simulations, the upper (l_u) and lower bound (l_l) of SINR values are taken 6 and 22 dB, respectively.

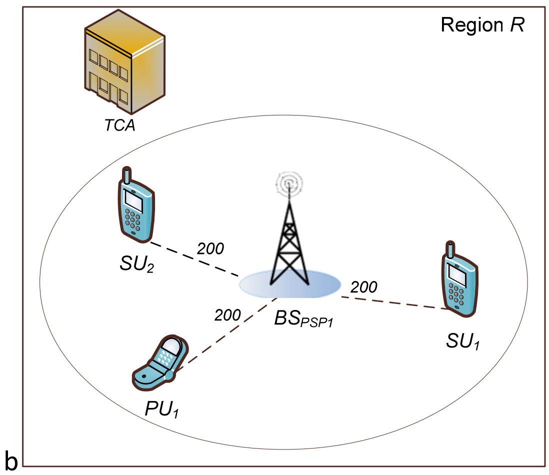

Figure 5.13. The demonstrative example 1 with one PSP, one PU, and two SUs

The SUs are differentiated as *price sensitive* and *quality sensitive*, with the minimum desired bandwidths of $b_1^{\min}$ = 0.34 MHz, and $b_2^{\min}$ = 0.46 MHz, respectively. They are differentiated according to their sensitivities on offered unit prices. SU_1 is the price sensitive one with a higher β_1 value, while SU_2 is the quality sensitive one.

Table 5.13. Parameters of the demonstrative example 1

Spreading gain (L)	128
Background noise (σ^2)	0
Min. bandwidth requirement of PU_1 (B_1^1)	0.46 MHz
Path loss exponent (α)	4
Total size of the spectrum (W_1)	1.5 MHz
Flat price ($\bar{p}_1$)	4
Transmission powers of PU (s_1^1)	0.5 Watt
Initial price (p_1)	4
Coefficient of cost due to the quality degradation of PSP_1 (a_1)	2.5
Coefficient of cost due to the interference created by SUs of PSP_1 (d_1)	2
Minimum desired bandwidth of SU_1 ($b_1^{\min}$)	0.34 MHz
Minimum desired bandwidth of SU_2 ($b_2^{\min}$)	0.46 MHz
Base demand of SU ($\delta_1 = \delta_2$)	1.8 MHz
Coefficients representing to what extent the SU_1 is influenced from PSP_1's price (β_1)	0.3
Coefficients representing to what extent the SU_2 is influenced from PSP_1's price (β_2)	0.2

In the given example with two SUs, PSP_1 has four choices:

- Offering only to SU_1,
- Offering only to SU_2,
- Offering to both SU_1 and SU_2, and
- Not offering any spectrum bands to SUs.

As the first step, the TCA calculates optimum transmission powers of SU_1 and SU_2 in each one of these cases. Taking these power values and an average price vector, PSP_1 calculates its initial profits in each one of the cases, using the CP algorithm. It finds out that serving both SUs is the most profitable decision for this example (Table 5.14).

Table 5.14. *PSP_1*'s initial profits in each case

Case	Offer no band	Offer SU_2	Offer SU_1	Offer both SU_1 and SU_2
Initial profit of PSP_1	4.000	7.1924	5.5924	**7.4272**

Next, PSP_1 determines its unit price by running the CP algorithm. PSP calculates the unit price by assuming that the offered bands will be bought by the SUs. Using the unit price value, PSP_1 can easily calculate its actual demanded bandwidth from SUs and the maximum possible profit (Table 5.15). In case PSP_1 does not trade its available spectrum, it will only receive the flat fee coming from PU, which is equal to 4. By employing the proposed spectrum trading framework, PSP_1 makes up to 7.7272 of profit, which is equal to 193 per cent of extra profit without disturbing PU_1 and with the total satisfaction of two SUs.

In order to determine the performance of our proposed framework, especially to separate the effect of the TCA to the profit, we compare it with a model without any power control. As the benchmark model, we consider the same model with same formulations; however the TCA does not optimize the transmission powers of SUs. Instead, transmission powers are randomly selected from the interval [0.03, 2] Watts. The results show that, there is not a significant increase in social welfare (1 per cent); but PSP_1 makes a 132 per cent of extra profit when the TCA manages the transmission powers. This is the maximum possible profit that the TCA can make. The offered prices are the same in both models because, in each model, the PSP is assumed to offer bands to both SUs. As the price is directly related to the demand, the offered prices are the same. This result validates the positive impact of the power control mechanism in the price setting process, even in a non competitive environment.

The convergence of the SINR values of PU and SUs, and the social welfare at the equilibrium point are depicted in Figure 5.14 and Figure 5.15, respectively.

The TCA's objective is to optimize the data rates of PU and SUs at the same time. During all the simulations, the transmission power levels of *PUs* are taken as constant; however the SINR value of PU_1 fluctuates with the SUs' transmission powers variations.

As the distances of both SUs to BS_{PSP1} are equal, but the minimum desired bandwidth of SU_1 is lower than SU_2; SINR of SU_1 converges to 15.6 dB, while SU_2 converges to 19.1 dB.

Table 5.15. Price, demand and profit values in the demonstrative example 1

	Model with power control (with TCA)		***Model without power control (without TCA)***	
	PSP_1		***PSP_1***	
	SU_1	***SU_2***	***SU_1***	***SU_2***
Offered price	4.85		4.85	
Demanded bandwidth	0.3450	0.8300	0.3450	0.8300
Maximum possible profit	7.7272		5.8253 (**- 132%**)	
Social welfare in *PSP_1*'s network	5.2922		5.2367 (**- 1%**)	
SINR (dB)	15.64	19.11	15.06	22.40
Transmission power (Watt)	0.29	0.50	0.44	1.28

The TCA allows SU_2 to increase its SINR up to 19.1 dB in order to provide it with its higher bandwidth requirement. The minimum bandwidth requirement of PU is equal to SU_2's requirement; hence SINR of PU converges to 19.1 dB, as well. Accordingly, the social welfare of the PSP_1's network converges to its optimum point, 5.292 (Figure 5.15).

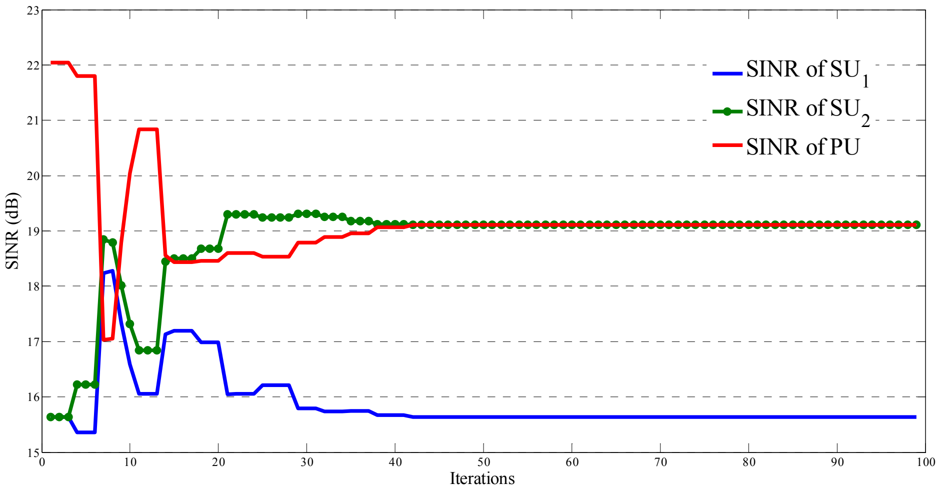

Figure 5.14. Convergence of SINR values

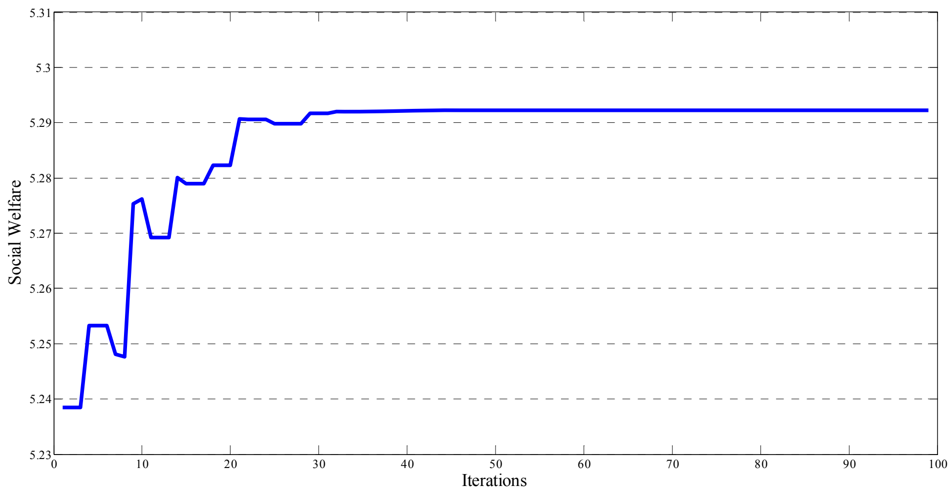

Figure 5.15. Convergence of social welfare

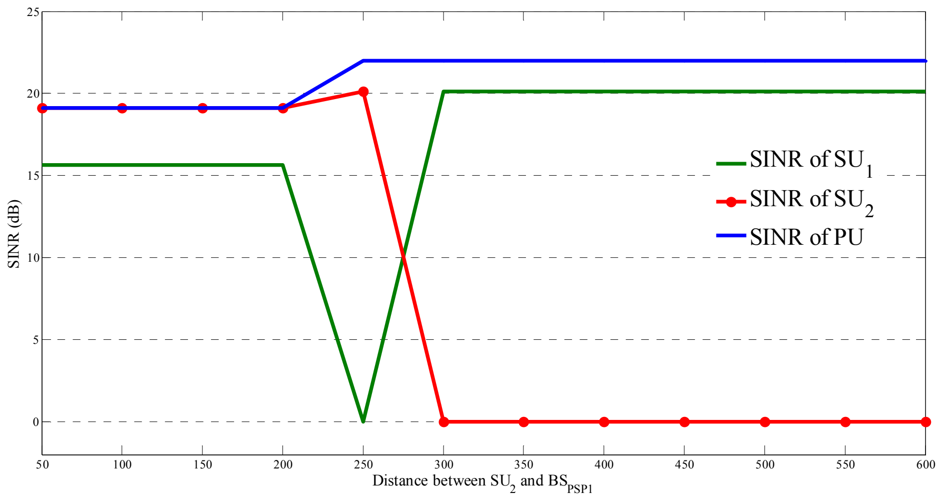

Figure 5.16. SINR variations in respect to distance

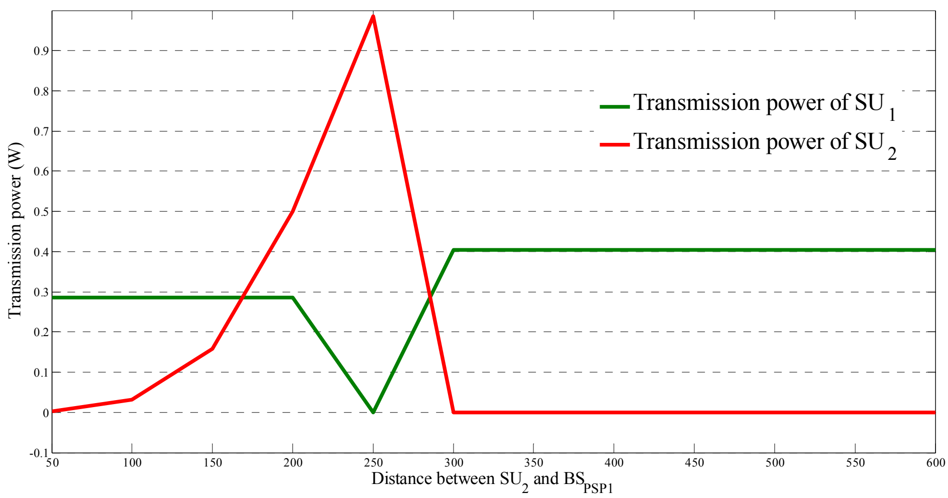

Figure 5.17. Transmission power variations in respect to distance

Figure 5.16 and Figure 5.17 represent the variations of SINR values and transmission powers in respect to distance. The distance of SU_2 to BS_{PSP1} is varied over the range from 50 to 600, while all other parameters are kept constant. We explain our observations as follows:

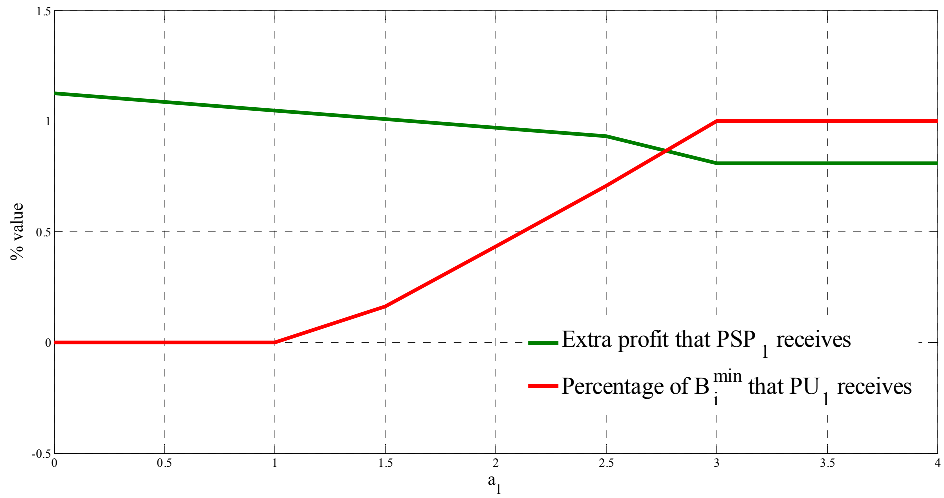

Figure 5.18. The profit and allocation size variations in respect to a_1

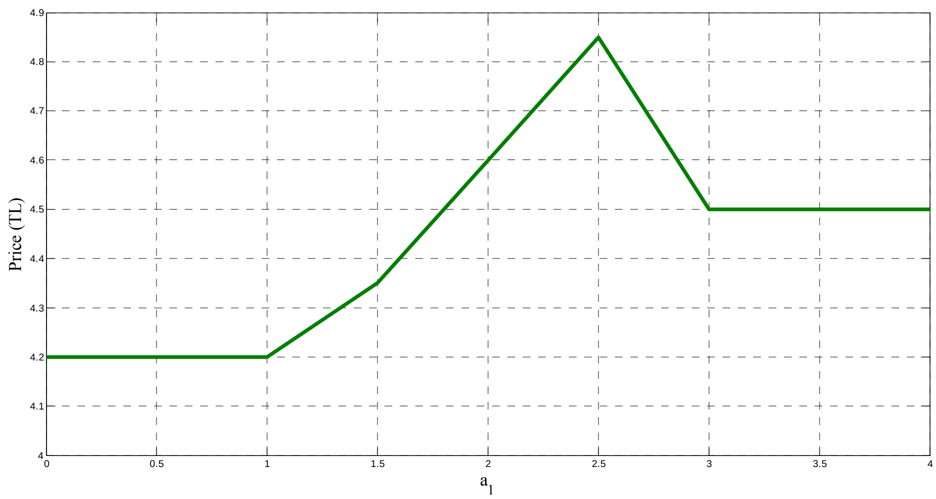

Figure 5.19. The price variations in respect to a_1

The SINR of SU_2 shows a constant trend up to a certain distance value (200), since SU_2 increase its transmission power in order to keep its data rate above its minimum threshold. Up to the distance value of 200, PSP_1 serves both SUs. For distance values between 200 and 250, PSP_1 receives more profit when serving only SU_2. On the contrary, for distance values higher than 250, it stops serving SU_2 and serves only SU_1.

Consequently, the transmission power and SINR of SU_2 drop to zero. The power decrease of SU_2 allows SU_1 and PU_1 increase their SINR levels. The minimum desired bandwidth of PU_1 (0.46 MHz) is higher than the one of SU_1 (0.34 MHz), hence PU_1 has a higher SINR value than SU_1 (21.9 dB > 20.1 dB). Figure 5.17 shows the power increase of SU_1, after SU_2 is stopped serving.

As mentioned earlier, if PSP_1 does not sell any of its unutilized bands, it will receive only the flat fee from the PU_1, which is equal to 4. In Figure 5.18, the extra profit that PSP_1 earns from selling spectrum is depicted as the function a_1 value. When $a_1 = 0$, which means that PSP_1 does not pay any cost for quality degradation due to the excessive sell of spectrum, it receives its maximum profit, 8.50. This means, PSP_1 makes an extra profit of 112 per cent. However in this case, it has to sell all of its bandwidth (1.5 MHz) to SUs; in other words, PU_1 receives 0 per cent of its required bandwidth. It is shown with the second curve in Figure 5.18. When $a_1 = 3$, PU_1 receives 100 per cent of its minimum bandwidth requirement. The increase in a_1 value causes a decrease on the profit of PSP_1, hence PSP_1 tries to compensate its profit loss by increasing its price (Figure 5.19). However, when $a_1 > 2.5$, PSP_1 cannot support to serve both SUs, and it stops serving one of them. This causes a sharp decrease in its demand which results in a sharp decrease in its price. It is the PSP's choice how to set the a_1 value, according to its marketing perspective.

The following six figures (Figure 5.20 - Figure 5.25) depict the variations of different parameters of the model in respect to the minimum desired bandwidth of SU_1 ($b_1^{\min}$). Except for the $b_1^{\min}$, all other parameters are fixed.

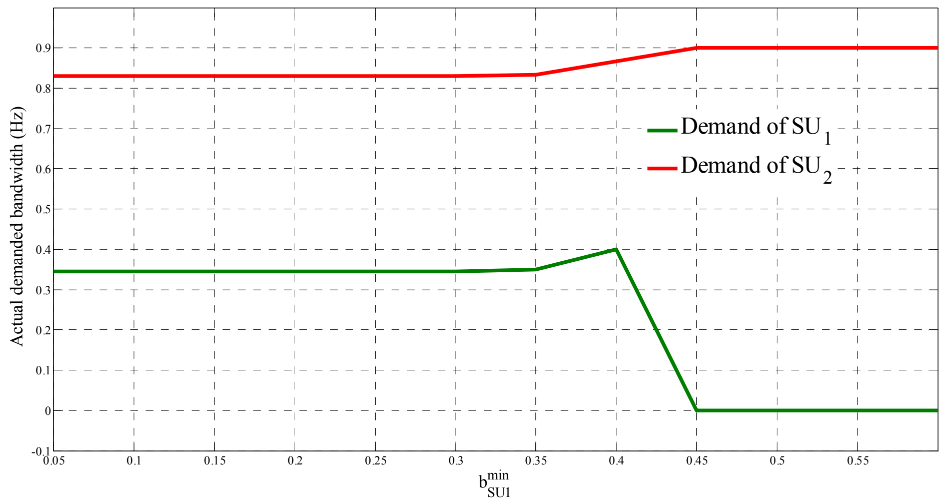

Figure 5.20. Variations of demand in respect to $b_{SU_1}^{min}$

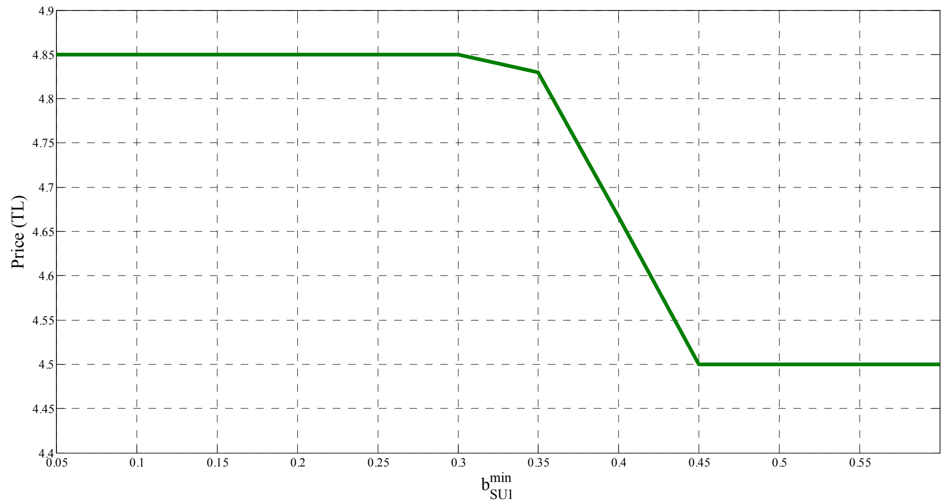

Figure 5.21. Variations of price in respect to $b_{SU_1}^{min}$

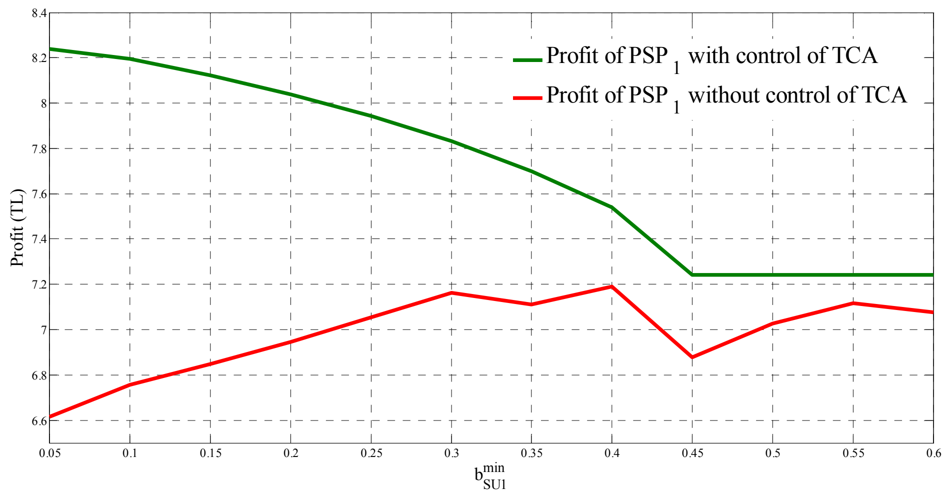

Figure 5.22. Variations of profit in respect to $b_{SU_1}^{min}$

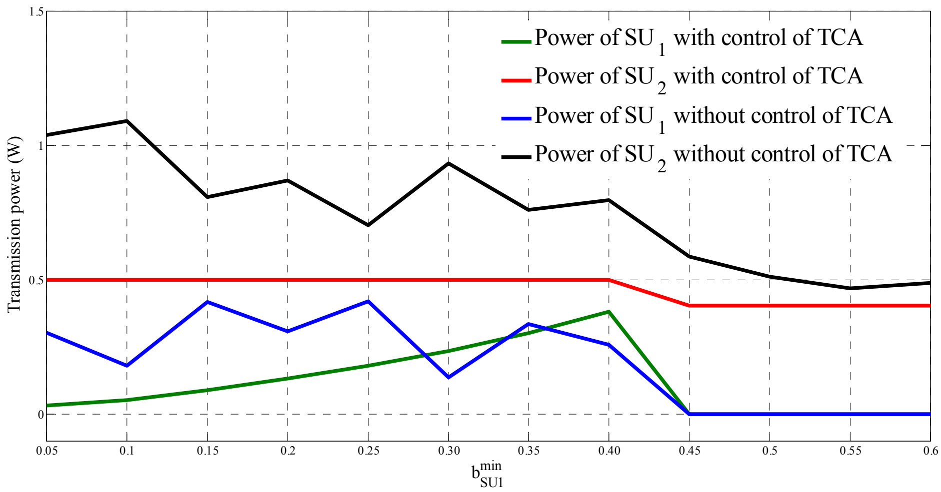

Figure 5.23. Variations of transmission power in respect to $b_{SU_1}^{\min}$

The actual demanded bandwidths of SUs are examined in Figure 5.20. Up to $b_1^{\min}$ = 0.4 MHz, PSP_1 can serve both SU_1 and SU_2. However when $b_1^{\min}$ > 0.4, PSP_1 cannot offer any spectrum band to SU_1, instead its offer to SU_2 increases. At this point, the actual demand of SU_1 decreases sharply, while the demand of SU_2 to PSP_1 increases. It is possible to see the impact of demand decrease on the price in Figure 5.21.

The behaviors of actual demands have a direct impact on the profit of the PSP. In Figure 5.22, we compare the profit of PSP_1 in the proposed model with the benchmark model. The results show that controlling transmission power of SUs is more beneficial for PSP_1 in terms of profit than not controlling it. At the equilibrium point of the given scenario, PSP_1 can make up to 132 per cent of additional profit when applying the power limitations coming from the TCA (Table 5.15). The simulation results prove that for each value of $b_1^{\min}$, PSP_1's profit is significantly higher than the one in the benchmark model (Figure 5.22).

SU_1 is not served by PSP_1 when $b_1^{\min}$ > 0.4 MHz, then the transmission power of SU_1 in the PSP_1's network drops to 0 (Figure 5.23). The increase of the minimum desired bandwidth ($b_1^{\min}$) of SU_1 makes an increasing effect on its transmission power. $b_1^{\min}$ is a weight coefficient in the SUs' cognitive capacity formulation in the TCA's objective function (5.53). When this coefficient increases, the TCA tends to increase the related SINR value, hence the transmission power. After $b_1^{\min}$ > 0.4 MHz, PSP_2 stops serving SU_1, therefore its transmission power drops to zero. The results show that, the proposed framework enables lower transmission power levels for each $b_1^{\min}$ value, when compared with the benchmark model.

Lower transmission powers are not sufficient for declaring the efficiency of the proposed model. The SINR values should be in the acceptable range [6-22 dB] and the social welfare of each network should be at least equal to the one in the benchmark model. In Figure 5.24 and Figure 5.25, we focus on the issues of social welfare and SINR, respectively.

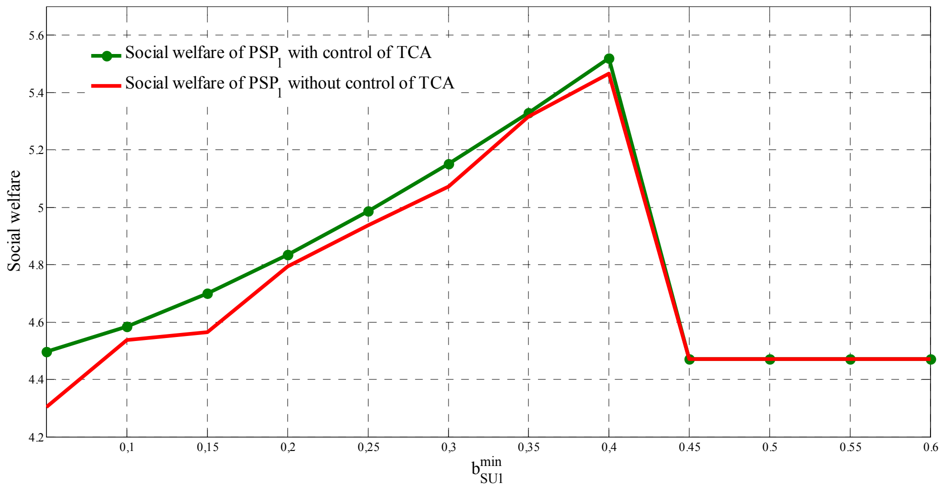

Figure 5.24. Variations of social welfare in respect to $b_{SU_1}^{\min}$

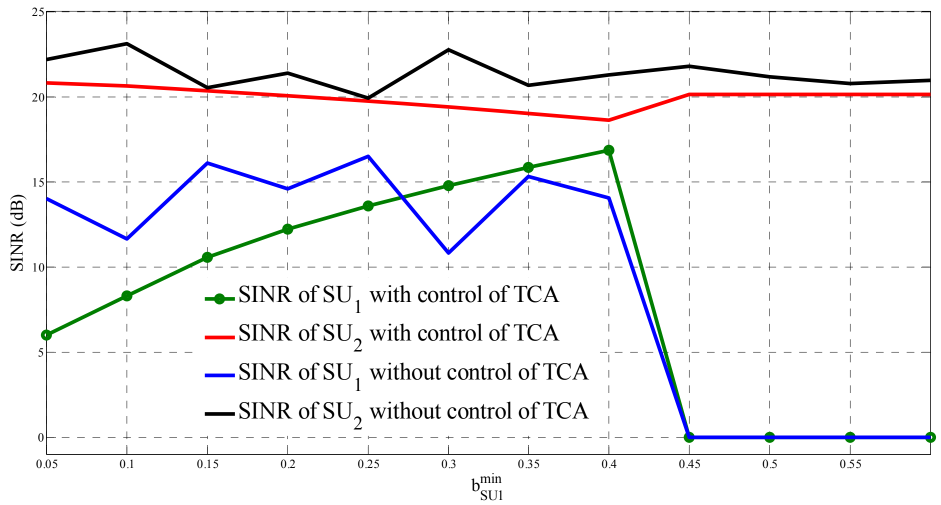

Figure 5.25. Variations of SINR in respect to $b_{SU_1}^{\min}$

The transmission power increase of SU_1 (Figure 5.23) makes a positive impact on its SINR value (Figure 5.25). However, the increase of power of SU_1 causes interference on the network, which causes a slight decrease on the SINR value of SU_2 (Figure 5.25). Figure 5.24 compares the social welfare of PSP_1 in the proposed model with the one in the benchmark model. It is clear that, the social welfare in PSP_1's network increases proportional to the increase of transmission power of SU_1. It falls dramatically when PSP_1 stops serving SU_1, i.e. $b_1^{\min}$ > 0.4 MHz. The results prove that the social welfare in the proposed model is as well as the one in the benchmark model; even it has higher values for most of the $b_1^{\min}$ values.

- Demonstrative example 2 : Two PSPs and two SUs in the region

The second simulation example includes two PSPs (PSP_1 and PSP_2), one PU for each one (PU_1^1 and PU_2^1) and two SUs (SU_1 and SU_2) (Figure 5.26). The simulation parameters are chosen as in Table 5.16.

The PSPs are differentiated as *price sensitive* and *quality sensitive,* according to their attitudes toward quality degradation of PUs. PSP_1 is the quality sensitive one with a higher a_1 value, $a_1 = 3.5$, while PSP_2 is the price sensitive one with $a_2 = 2.75$. In the same way, the SUs are differentiated as *price sensitive* and *quality sensitive*, with the minimum desired bandwidths of $b_1^{\min}$ = 0.34 MHz, and $b_2^{\min}$ = 0.46 MHz, respectively. They are differentiated according to their sensitivities on offered unit prices. SU_1 is the price sensitive one with a higher β_1 and γ_1 value, while SU_2 is the quality sensitive one.

In this example with two SUs, PSPs have again four choices, similar to the demonstrative example 1. The TCA operates on behalf of PSP_1 and PSP_2, and calculates optimum transmission powers of SU_1 and SU_2 in each one of these cases for each PSP.

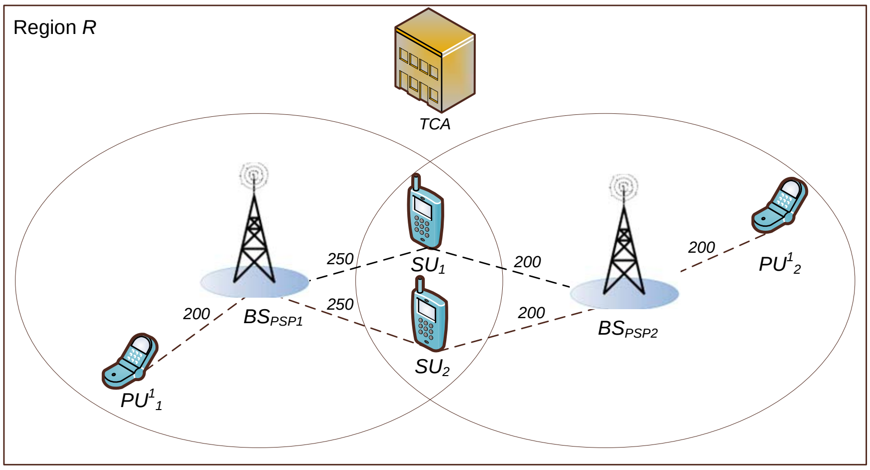

Figure 5.26. The demonstrative example with two PSPs, two PUs and two SUs

Table 5.16. Parameters of the demonstrative example 2

Spreading gain (L)	128
Background noise (σ^2)	0
Min. bandwidth requirement of PU ($B_1^1 = B_1^2$)	0.46 MHz
Path loss exponent (α)	4
Total size of the spectrum ($W_1 = W_2$)	1.5 MHz
Flat price ($\bar{p}_1 = \bar{p}_2$)	4
Transmission powers of PUs (s_k^i)	0.5 Watt
Initial price ($p_1 = p_2$)	4
Coefficient of cost due to the quality degradation of PSP_1 and PSP_2 (a_1 and a_2)	3.5 and 2.75
Coefficient of cost due to the interference created by SUs of PSP_1 and PSP_2 ($d_1 = d_2$)	2
Min. desired bandwidth of SU_1 (b_1^{min})	0.34 MHz
Min. desired bandwidth of SU_2 (b_2^{min})	0.46 MHz
Base demand of SU ($\delta_1 = \delta_2$)	1.8 MHz
Coefficients representing to what extent the SU_1 and SU_2 are influenced from PSP_i's price (β_1, β_2)	0.4 and 0.25
Coefficients representing to what extent the SU_1 and SU_2 are influenced from other PSP_i's prices (γ_1, γ_2)	0.15 and 0.03

Taking these power values and an initial price vector, PSPs calculate their initial profits (Table 5.17).

Table 5.17. PSPs' initial profits in each case

Case	Offer no band	Offer SU_2	Offer SU_1	Offer both SU_1 and SU_2
Initial profit of PSP_1	4.000	**5.7083**	5.2283	4.6603
Initial profit of PSP_2	4.000	6.8724	6.3924	**7.4372**

The results reveal that, PSP_1 has higher profit when serving only SU_2, but serving both SU_1 and SU_2 is more profitable for PSP_2. After determining which SUs to serve, each PSP decides on its unit price as a result of the pricing game (Table 5.18). The results of the comparison of the proposed framework with the benchmark model are given in the same table.

Note that, the power values have a direct effect on the profit of PSPs: The profit of PSP decreases by the increase of the transmission power levels of SUs in its network. The power values do not have a direct effect on unit prices. However, PSPs determine which SUs to serve by considering their profits, and accordingly, they set their unit prices.

Table 5.18. Price and demand values in the demonstrative example 2 at the equilibrium

	Model with power control (with the TCA)				***Model without power control (without the TCA)***			
	PSP_1		***PSP_2***		***PSP_1***		***PSP_2***	
	SU_1	***SU_2***	***SU_1***	***SU_2***	***SU_1***	***SU_2***	***SU_1***	***SU_2***
Offered price	3.8809		4.6816		3.8809		4.6816	
Demanded bandwidth	-	0.9702	0.5095	0.7460	-	0.9702	0.5095	0.7460
Maximum possible profit	5.7936		7.4587		4.3307 (**-34%**)		6.6268 (**-13%)**	
Soc.welf. in PSP_i network	4.4712		5.2922		4.4712 (**0%**)		5.2417 (**-1%**)	

Hence, we can conclude that the transmission power levels effects the unit prices. During the comparison simulations, we have taken the cases where the PSP serves both SUs, for the accuracy of the simulations. For this reason, the unit prices of the PSPs are the same, as well as the demands coming from SUs. It is the maximum possible profits of PSPs and the social welfare in their networks which will evaluate the efficiency of our proposed model with a coordinating authority.

PSP_1 will not serve SU_1, hence it only offers a unit price to SU_2, which is 3.8809. PSP_1 expects that the demand from SU_2 will be 0.9702 with this price. SU_2 has another spectrum offer with the unit price of 4.6816. SU_1's actual demand to PSP_2 is 0.5095 MHz and SU_2's actual demand to PSP_2 is 0.7460 MHz, with this price. The results reveal that the proposed spectrum trading framework with power control allows PSP_1 to make 45 per cent and PSP_2 to make 86 per cent of additional profit without violating the social welfare in the networks. These values correspond to the maximum possible profits that the PSPs can make. Our proposed framework is also more profitable when compared to the benchmark model without power control. The PSPs can make up to 34 per cent of additional profit by controlling the transmission powers (Table 5.18).

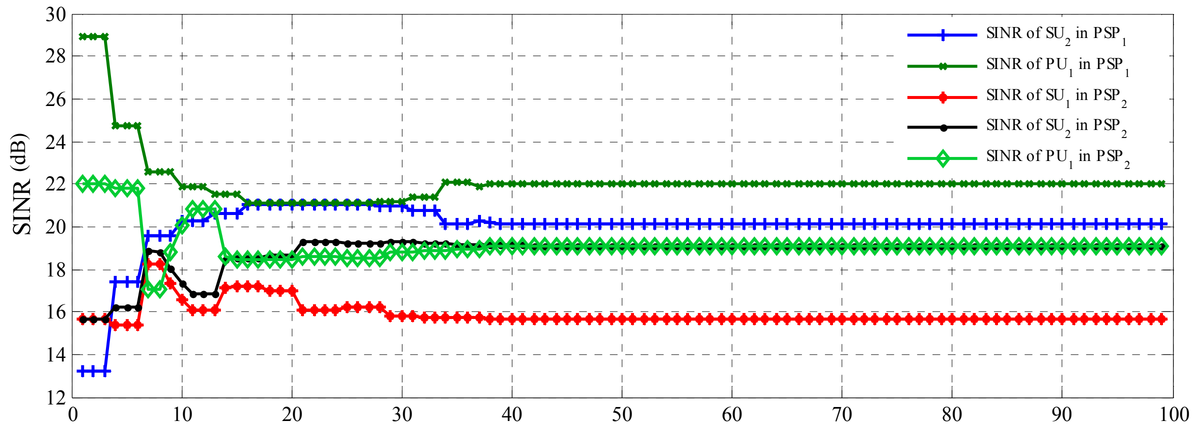

Figure 5.27. Convergence of SINRs

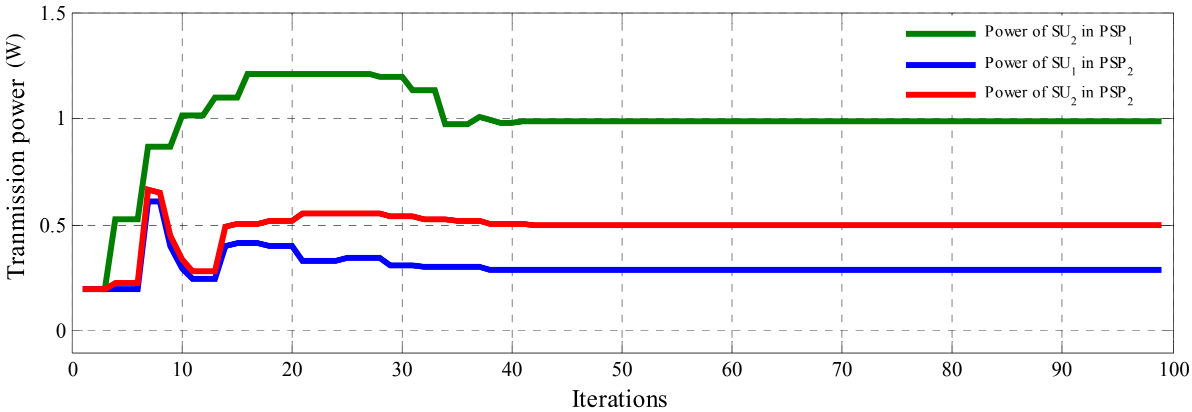

Figure 5.28. Convergence of power

The convergences of SINR and transmission power values are found by the CP algorithm after 99 iterations (Figure 5.27 and Figure 5.28). SU_1 is not served by PSP_1, hence its SINR value is not given in Figure 5.27.

The following six figures (Figure 5.29 - Figure 5.34) depict the variations of different parameters of the model in respect to the minimum desired bandwidth of SU_1 ($b_1^{\min}$) in a competitive environment. Except for the $b_1^{\min}$, all other parameters are fixed. Figure 5.29 examines the actual demanded bandwidths of SUs. Up to $b_1^{\min}$ = 0.1 MHz, PSP_1 can serve both SU_1 and SU_2. However when $b_1^{\min}$ > 0.1, PSP_1 cannot offer any spectrum band to SU_1, instead its offer to SU_2 increases. At this point, the actual demand of SU_1 decreases sharply, while the demand of SU_2 to PSP_1 increases. It is possible to see the impact of demand decrease on the price in Figure 5.30, by the sharp price decrease of PSP_1. SU_1's demand to PSP_2 is influenced from the PSP_1's sharp decrease of price and the actual demand of SU_1 to PSP_2 slightly decreases. PSP_2 serves both SU_1 and SU_2 up to $b_1^{\min}$ = 0.46 MHz. Then it stops serving SU_1 and gives more bandwidth to SU_2. This sharp decrease is also visible in the price fall of PSP_2 (Figure 5.30).

The behaviors of actual demands have a direct impact on the profits of PSPs. In Figure 5.31, we compare the maximum possible profits of PSPs in the proposed model with the benchmark model. The results show that controlling transmission power of SUs is more beneficial for PSPs in terms of profit than not controlling it. At the equilibrium point of the given scenario, PSP_1 can make up to 34 per cent of additional profit, while PSP_2 can make up to 13 per cent when applying the power limitations coming from the TCA (Table 5.18).

SU_1 is not served by PSP_1 when $b_1^{\min}$ > 0.1 MHz, then the transmission power of SU_1 in the PSP_1's network drops to 0 (Figure 5.32). The increase of the minimum desired bandwidth ($b_1^{\min}$) of SU_1 makes an increasing effect on its transmission power. $b_1^{\min}$ is a weight coefficient in the SUs' cognitive capacity formulation in the TCA's objective function (5.54). When this coefficient increases, the TCA tends to increase the related SINR value, hence the transmission power. After $b_1^{\min}$ > 0.46 MHz, PSP_2 stops serving SU_1, therefore its transmission power drops to zero. The results show that, the proposed framework enables lower transmission power levels in both networks, when compared to the benchmark model.

The efficiency of the proposed model will be demonstrated by showing the SINR values are in the acceptable range [6-22 dB] and the social welfare of each network is at least equal to the one in the benchmark model. In Figure 5.33 and Figure 5.34, we focus on the issues of SINR and social welfare, respectively. The transmission power increase of SU_1 in PSP_2's network (Figure 5.32) makes a positive impact on its SINR value (Figure 5.33). However, the increase of power of SU_1 causes interference on PSP_2's network, which causes a slight decrease on the SINR value of SU_2 (Figure 5.33). Figure 5.34 compares the social welfares of PSP_1's and PSP_2's networks in the proposed model with their social welfares in the benchmark model. It is clear that, the social welfare in PSP_1's network increases proportional to the increase of transmission power of SU_1. It falls dramatically when PSP_1 stops serving SU_1, i.e. $b_1^{\min} > 0.46$ MHz.

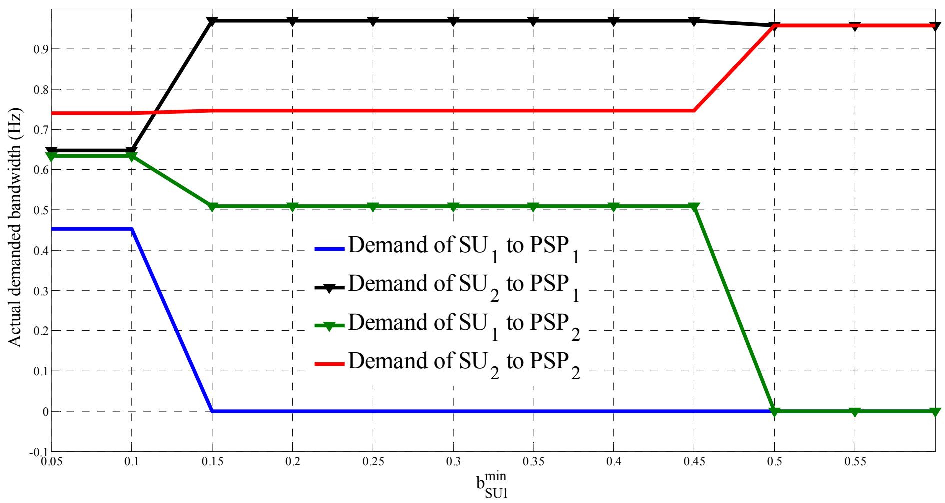

Figure 5.29. Variations of demand in respect to $b_{SU_1}^{\min}$

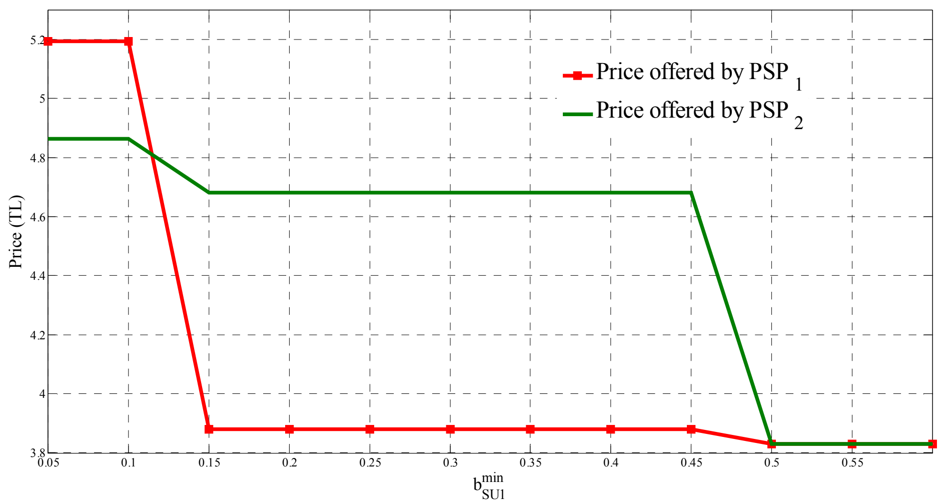

Figure 5.30. Variations of price in respect to $b_{SU_1}^{\min}$

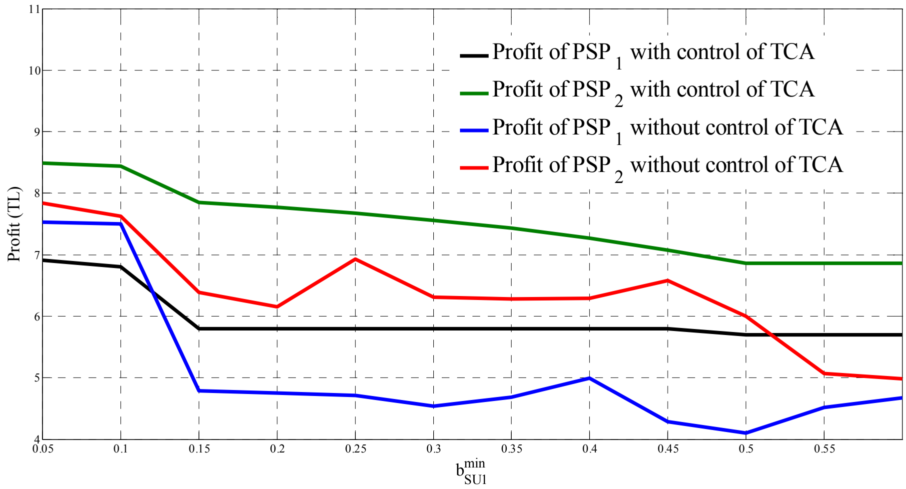

Figure 5.31. Variations of profit in respect to $b_{SU_1}^{\min}$

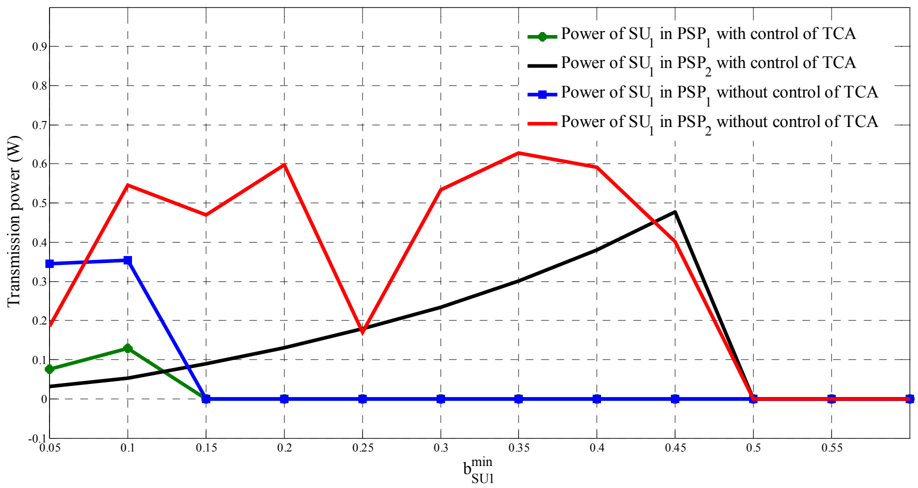

Figure 5.32. Variations of transmission power in respect to $b_{SU_1}^{\min}$

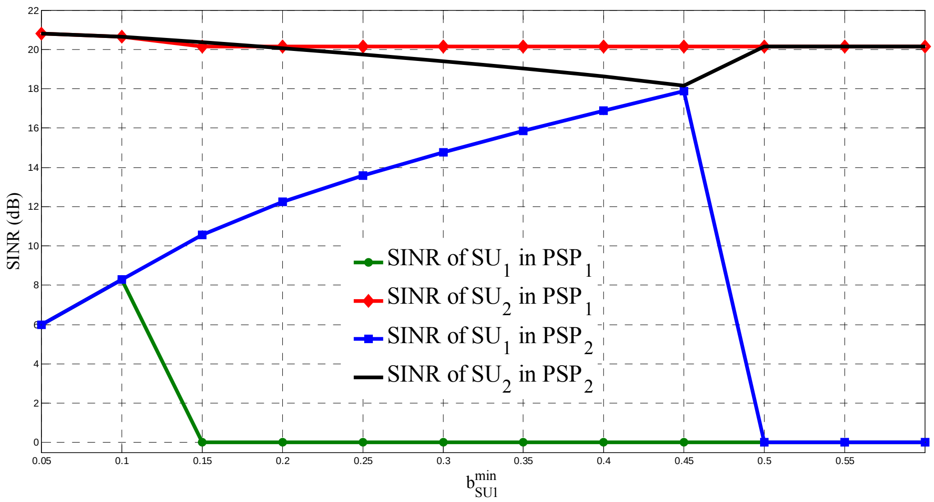

Figure 5.33. Variations of SINR in respect to $b_{SU_1}^{\min}$

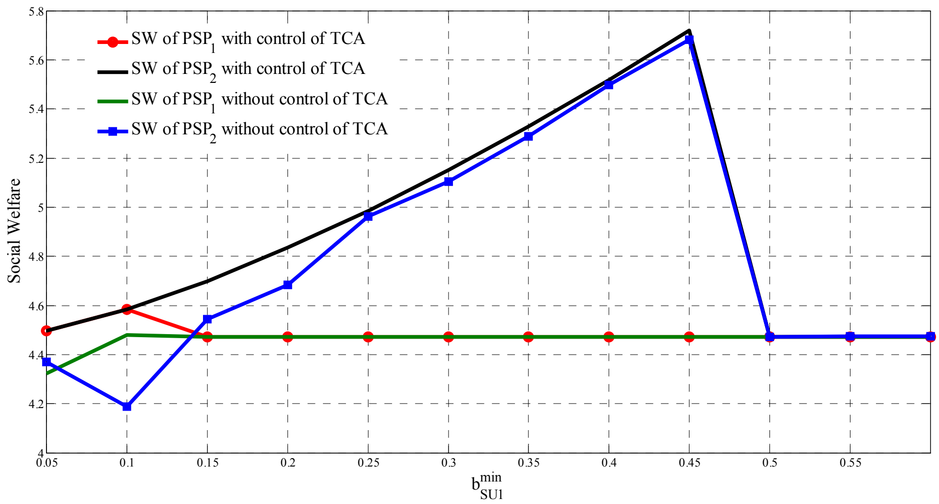

Figure 5.34. Variations of social welfare in respect to $b_{SU_1}^{\min}$

The results show that PSPs' social welfares in their networks are higher when the transmission powers are controlled by the TCA.

In Figure 5.35, the additional profit that PSP_2 can earn from selling spectrum is depicted as the function of a_2 value. When $a_2 = 0$, which means that PSP_2 does not pay any cost for quality degradation due to the excessive sell of spectrum, it receives maximum possible profit, 9.57. This means, PSP_2 can make a profit of 139 per cent. However in this case, it has to sell all of its bandwidth (1.5 MHz) to SUs. For the a_2 values higher than 3.45, PU_1^2 receives 100 per cent of its minimum desired bandwidth. The effect of a_2 value is similar to the non competitive scenario (Demonstrative example 1).

Figure 5.36 shows the reaction of PSP_2 to its profit loss: PSP_2 reacts to the loss by increasing its price. At the point $a_2 = 2$, PU starts to receive some of its required bandwidth, hence the available bandwidth of PSP_2 starts to decrease. PSP_2 continues to increase the price until $a_2 = 3.5$, where PSP_2 stops serving SU_1 and offers the same price as PSP_1.

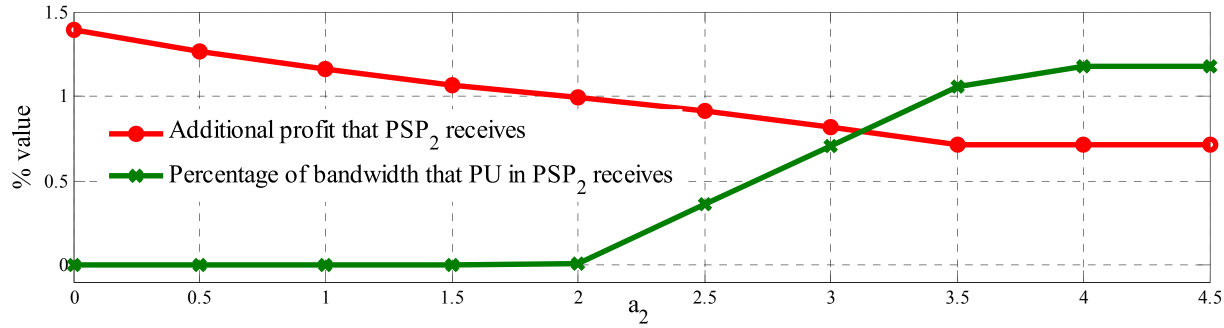

Figure 5.35. Percentage variations in respect to a_2

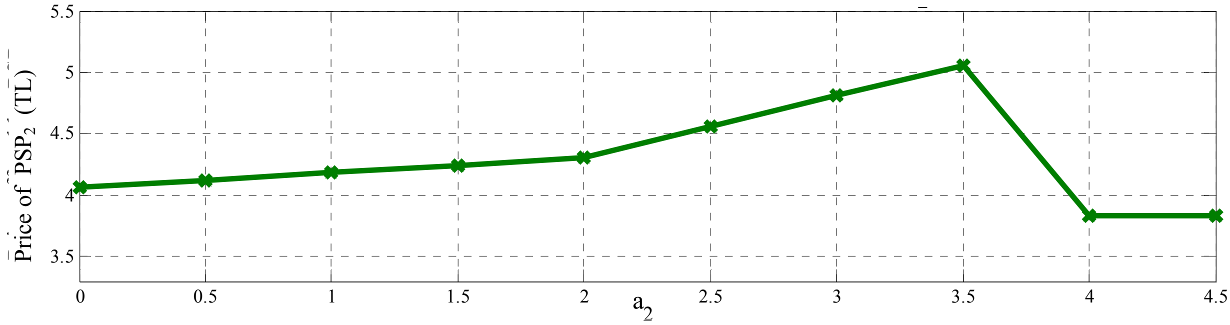

Figure 5.36. Variations of price in respect to a_2

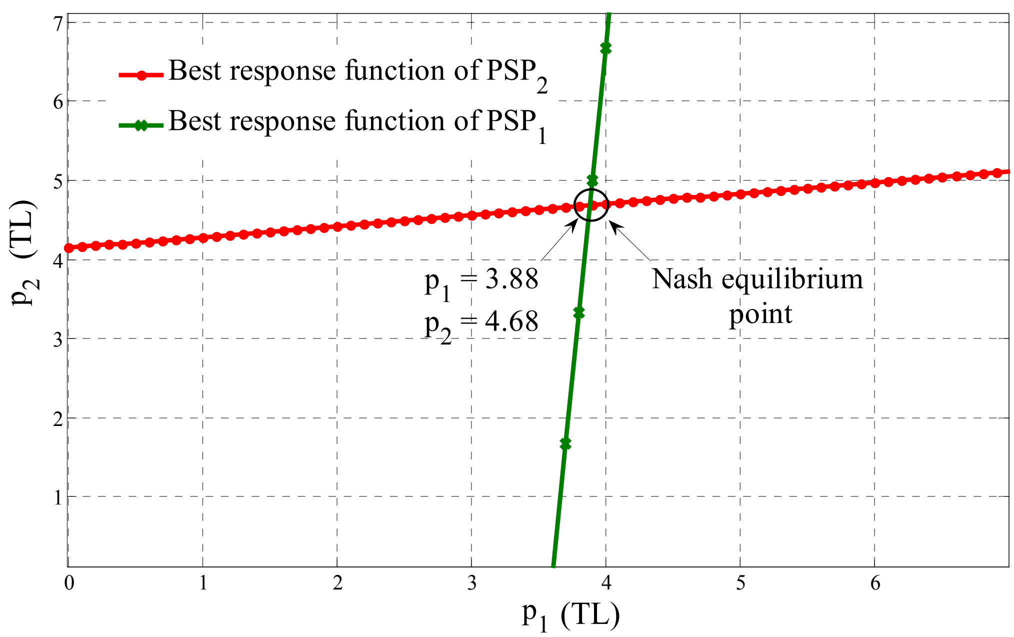

Figure 5.37. Best response functions of *PSP_1* and *PSP_2*

Figure 5.37 shows the best responses of PSPs in the non cooperative pricing game. The best response of a PSP is a linear function of price offered by the other PSP. The Nash equilibrium is located where the best response functions intersect.

- Demonstrative example 3: Two PSPs, constant number of PUs and variable number of SUs in the region

In order to investigate the impact of number of SUs in the region on PSPs' maximum possible profit, as well as on the performance of the CP algorithm, we randomly locate SUs in the region (Figure 5.38). The number of PUs is kept constant in both networks in order to separate the influence of the number of SUs in the region to the profitability of the PSPs. We assume that the distances of SUs from the BSs are normally distributed in the interval [50, 300]. The other parameters are taken as in Table 5.16. All the SUs are assumed to be price sensitive, with the same demand parameters.

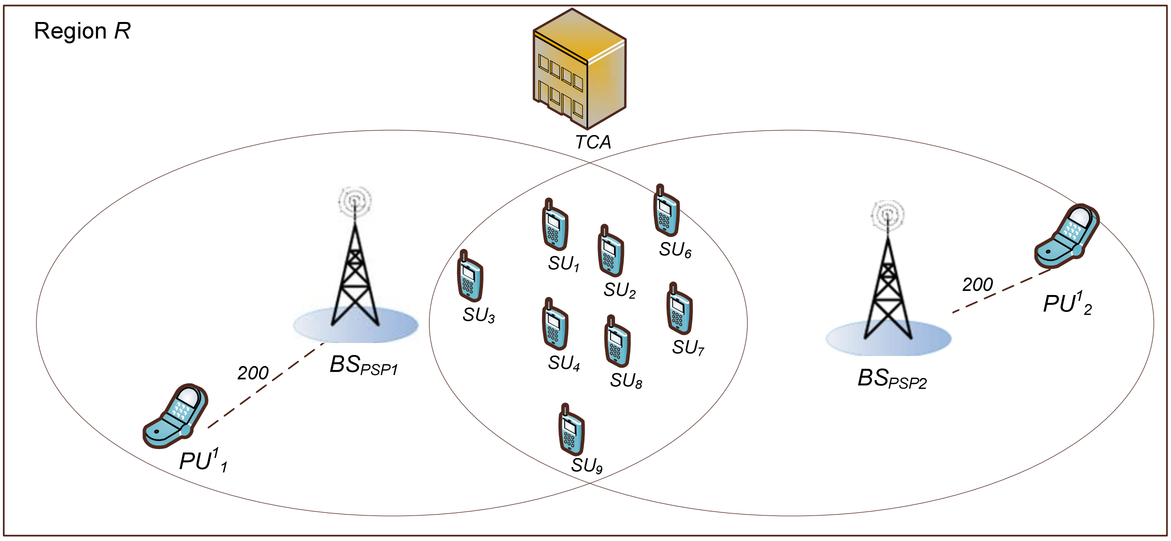

Figure 5.38. The demonstrative example 3 with two PSPs and variable number of SUs in the region

Even though the number of SUs in the region increases, the PSPs select the best combination of SUs to serve. Table 5.19 presents the selected SUs in each case, with the maximum profit values of both PSPs. The simulation results show that in each case, the PSPs select two SUs to serve, since they have limited available bands. Depending on the locations of the selected SUs, their maximum possible profits vary (Figure 5.39). We can see that the profit of both PSPs show increasing trends. The reason is that, the more SUs are in the region, the more alternative that the PSPs have. Hence, the PSPs have the chance to find more profitable SUs.

Table 5.19. The selection of SUs by PSPs to serve

# of SUs	Selection of PSP_1									Selection of PSP_2									Max. possible profit of PSP_1	Max. possible profit of PSP_2
	SU_1	SU_2	SU_3	SU_4	SU_5	SU_6	SU_7	SU_8	SU_9	SU_1	SU_2	SU_3	SU_4	SU_5	SU_6	SU_7	SU_8	SU_9		
2	X	X								X	X								7.2690	6.6000
3	X	X	-							-	X	X							7.7064	6.7736
4	X	-	X	-						-	-	X	X						7.7745	7.2274
5	-	X	X	-	-					X	-	X	-	-					7.7923	7.5230
6	-	-	X	-	X	-				-	-	X	X	-	-				8.0932	7.7801
7	-	-	-	-	-	X	X			-	-	-	-	X	X	-			8.1681	7.7974
8	X	-	-	-	-	-	-	X		X	-	-	-	-	-	-	X		8.2834	7.8323
9	-	-	X	X	-	-	-	-	-	-	-	X	X	-	-	-	-	-	8.2901	7.9211

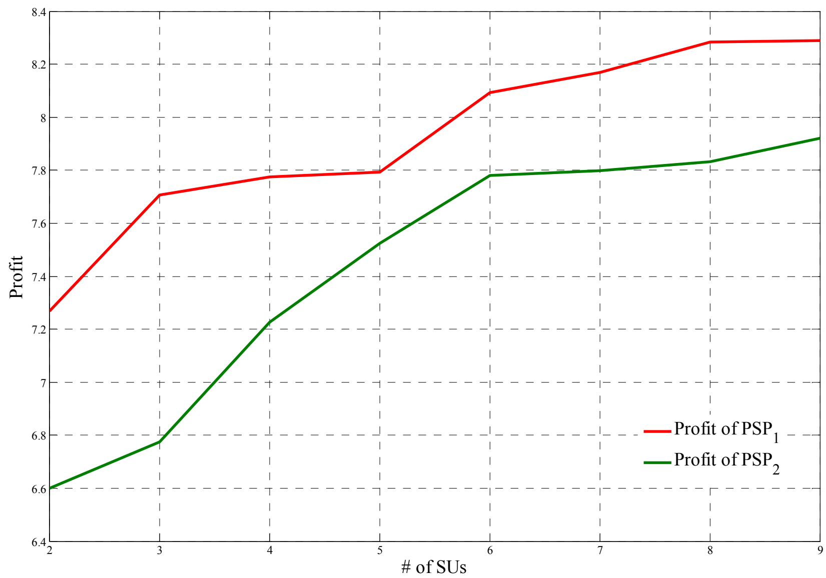

Figure 5.39. Variations of maximum possible profit in respect to the number of SUs in the region

5.4.7. Discussion

We have grouped simulations into three categories. The first set consists of a non competitive environment where only one PSP trades its available spectrum bands to SUs in its region. For the second case, we have established a competitive market where two PSPs join the spectrum trading process. We have aimed at examining all the effects of the problem parameters to the results in case of a competition. In the third part of the simulations, we have enforced the proposed algorithm to see the maximum number of SUs to support.

The principal objective of this dissertation was to propose a pricing model which would be valid for every spectrum access mode and for more than one type of network technology by making slight modifications. We have performed the simulations for the uplink transmissions in a CDMA network, however by adjusting the given formulations; we can run the framework on downlink transmissions or opportunistic IEEE 802.22-based WRANs. The on-demand basis spectrum trading or the real-time secondary market environments necessitate that the decision making process is fast enough to grab the SU as a buyer. With our simulations, we have demonstrated that until nine SUs in the same region; the running time of the algorithm is in the milliseconds range. Hence, it is of great use for on-demand basis markets and real-time secondary markets. For more users in the region, a non real-time secondary market structure is much more convenient.

The very first observation of the simulation results is that PSP always receive a positive amount of profit when it offers the available spectrum resources to potential buyers, namely trading the available spectrum. The first set of simulations consist of a non competitive spectrum trading, where only one PSP's spectrum bands are on the market. With the parameters given for this numerical example, we have shown that the PSP can receive a 193 per cent of additional profit when joining such a trading process. Our concern in this dissertation was not only proposing a price setting solution to the PSPs, but also examining the effects of power management into the profit maximization of PSPs and also to the unit spectrum prices set by PSPs. In our proposed framework, it is the TCA that controls the transmission power of SUs. Hence, we have established a benchmark model without any component of power control, in order to investigate the contribution of the TCA. The results reveal that, the contribution of the TCA, in this non competitive environment, was a 132 per cent of profit increase for PSP. Obviously, by just looking at the profit increase of PSP, we cannot conclude that the proposed pricing framework is efficient. We need to control if the regular customers of PSPs (PUs) and also the SUs receive a satisfying quality level for the offered services. We have used the SINR value as a quality metric and the results reveal that the SINR of SU_1 and PU converges to 19.1 dB, whereas the SINR of SU_1 converges to 15.9 dB, where the acceptable range is [6-22] dB. The SINR values belonging to PUs and SUs are also in the acceptable range, in the second demonstrative example.

The second demonstrative example consists of a competitive environment, with two PSPs. The first observation was that the offered unit spectrum prices by PSP_1 and PSP_2 was lower than the unit price offered in the demonstrative example 1. It validates the fact that the competition results in a decrease in offered prices. The decrease in prices directly had an influence on profits. By trading their spectrum bands, PSP_1 had 45 per cent, and PSP_2 had 86 per cent of additional profits. They are lower than 193 per cent, which is obtained in the non competitive scenario. The contribution of the power management component to the profit had been 34 per cent and 13 per cent for PSP_1 and PSP_2, respectively.

The third part of the simulations considers more than two SUs in the region. As the complexity of the algorithm increases more with the number of SUs than with the number of PSPs, we have chosen to enforce the algorithm by the number of SUs. Besides, it is more likely to have many SUs in a given region than many PSPs. It is expected that, as the unit prices offered by PSPs increase proportional to the number of SUs, because of the increase in demand. However, the algorithm does not work in this way. Under the power control set by the TCA, a PSP selects the SUs which provide it with more additional profit, considering its available spectrum limitations. In our numerical case, both PSPs have available bands to satisfy at most two SUs. Even if the number of SUs in region R is 25, they will be able to select only two SUs among them. The location and the minimum required bandwidth of the SUs have an effect for PSPs on the selection of best combination to serve. The numerical analysis shows that the increase in the number of SUs in the region results in an increase in both PSPs' maximum possible profits.

5.4.8. Threats to Validity

The runtime of the CP algorithm is still in an acceptable range, when there are nine SUs in the region. As the complexity of the algorithm is $N.\ 2^M$, where N is the number of PSPs and M is the number of SUs, the runtime increases exponentially by the increase of M and increases linearly by the increase of N. The CP algorithm is run by the telecommunication controlling authority and by the PSPs periodically, namely for each one-shot game. Therefore, nine SUs in one-shot game can be considered as acceptable. Besides, we have run the simulations on an Intel Core 2 Quad 2.66 GHz microprocessor using MATLAB. This microprocessor is a quite weak equipment to be a part of the decision making process of a telecommunication service provider. Hence, more complex problems can be solved by more powerful microprocessor systems. Moreover, it is possible to use more efficient modeling systems than MATLAB, such as GAMS (General Algebraic Modeling System) or complex problems may be solved by making some approximations on the proposed model.

Our proposed framework is suitable for centralized non cooperative dynamic spectrum access architecture. In this type of architecture, the information on the cognitive radio environment are gathered in a centralized controller, i.e. the TCA. This may incur a large communication overhead. Also, deployment of a centralized controller may be infeasible in some scenarios (e.g. in ad hoc or sensor networking scenarios). The PSP needs to consider its network properties, the expected churn cost per user and the expected communication overhead before joining the association to form a centralized authority.

In the computation of unit prices, the base demand (δ), the constant that represents to what extent SU is influenced from rival's price (β), and the constant that represents to what extent the SU is influenced from prices offered by the competitors (γ), are of great importance. They determine both the magnitude of the unit price and the proportion of the unit prices offered to different types of SUs. Therefore, they have to be selected with great care. The big suppliers/ providers such as telecommunication service providers, food suppliers, banks or insurance companies, are assumed to know the customers and to have experience on segmenting them according to their demographic information and usage behaviors. Moreover, the suppliers/ providers have their own marketing perspectives and target customers. They have to set their fixed fee ($\bar{p}$), the weight coefficient of cost due to the quality degradation (a_i) and the weight coefficient of cost due to the interference created by SUs (d_i) by considering their perspectives.

During the simulations, the transmission powers of PUs are taken from a lookup table; in other words during the simulation we are not adjusting their power levels. However, this is not the case in CDMA networks. CDMA networks always adjust the transmission power levels of the PUs to reach to the minimum SINR values. The power management element in the network, the TCA, is newly proposed for this framework. Hence, we wanted to separate its impact to the results and see if it is efficient to integrate such a power control mechanism in a spectrum trading process. It is the reason that we did not let the transmission powers of PUs variable.

Managing the power emission in its network is itself a challenging task for a wireless telecommunication operator. The number of connecting users in a network varies depending on the number of arriving and departing users. In the proposed spectrum trading architecture with power control, we assume that the number of PUs in the network is constant during the trading process. However, this may not be the case in real life scenarios. We believe that this is not a disturbing assumption, since the trading process is realized in a few milliseconds.

6. CONCLUSIONS AND FUTURE DIRECTIONS

In wireless communication, the rising demand for freely available spectrum goes along with an increasing necessity for coordination of spectrum utilization, to meet quality requirements. The unlicensed spectrum is limited, and additional unlicensed spectrum will not be available in the foreseeable future, because regulatory changes from licensed to unlicensed bands are complicated and usually take a long time. Therefore, opportunistic spectrum access modes become more and more important for both spectrum owners and spectrum users. An efficient unit spectrum band pricing model which considers the interference limitations of network users is the main focus of this thesis.

6.1. Theoretical Contributions

In this research, we have asked six research questions. The first one was: “How can we structure a basic model which sets relationships among network demand, service providers’ profit and service prices?” Doing so, we have established a network environment where the frequency brokers have the role of an intermediary agency among service providers and end users. The proposed brokering architecture was a theoretical framework rather than a practical one, because of the severe communication overhead among service providers and frequency broker. However, in this simple model, we have been able to demonstrate the dependence of the prices to quality level, the relationship between indifference curves and demand, the relationship between demand and total surplus, and also the relationship between total surplus and social welfare. Moreover, it was an original architecture and has had its place in the spectrum trading literature.

Our second research question was: “What would be the effect of intermediary agency in spectrum trading” Therefore, we have changed our framework to the one without any intermediary network element. The proposed spectrum exchange architecture focuses on the sub-lease process of the underutilized bands of a spectrum license holder, under the control of a regulator. To do so, we come up with a non cooperative game, where the players are the spectrum holders and their strategy is the choice of the unit price of the offered band. We have used a linear demand function and the supermodularity of the proposed game to prove the existence of the Nash equilibrium points. It is the unique work in the literature that considers the opportunity cost of the spectrum band as the cost of the spectrum owner.

Our third research question was: “What kind of impact the CRM tool has on the profit maximization?” In brokering and spectrum exchange architecture, we were investigating the relationships among spectrum sellers and spectrum buyers. We have extended the spectrum exchange architecture and have considered a lower level in the hierarchy, the end users. We have again used the same pricing game as in the spectrum exchange architecture. However, when allocating the spectrum bands to the end users, we have proposed to segment the end users according to their CRM values. It is the first study in literature that has utilized the CRM tool into the resource allocation process. We have proved that the proposed resource allocation approach is more profitable than the First-Come First-Serve-based approach.

Our fourth research question was: “What kind of impact transmission power has on the profit maximization, as well as on the unit spectrum prices?” We have introduced a new market authority, the telecommunication regulating authority, as a response. The role of the TCA is to direct PSPs keeping their PUs’ satisfaction by balancing the tradeoff between transmission quality and resulting interference. We have seen that, the power limitations directly influence the supply decisions of the PSPs. This type of power control element in a spectrum trading marketplace is new in the literature.

Our fifth research question was: “What kind of impact the flexibility on the offered spectrum size has on profit maximization, as well as on the unit spectrum prices?” We have look the answers to this question in the spectrum trading architecture with power control. The approach of letting PSPs free when determining the size of the offered spectrum bands, was a new one in the related literature. The results show that degrading the received quality of PUs may be very profitable for PSPs in some cases, and this can happen without disturbing any user in the network.

Our last research question was: How can we structure a market where each PSP determines its target customers and their potential demand and then determine their unit prices? We have addressed this question by establishing a multiple-buyer (PSPs) and multiple-seller (SUs) market environment. PSPs compete with each other to sell the spectrum opportunities to potential SUs. In each of the three architecture, we have introduced non cooperative games, where each PSP determines its unit price by maximizing its own profit. The application of game theory offers an intelligent but also complex interaction. In the pricing game of the spectrum trading architecture with power control, PSPs take consideration the power limitations in order to keep the interference level in their network at its minimum level. We have introduced a novel algorithm, called the Coordinated Pricing algorithm, which encapsulates all the answers to the research questions.

The proposed framework of spectrum trading with power control is flexible. In this dissertation, we have assumed that the TCA has the objective of maximizing the data rates of all the users in the network. However, in another study, the TCA may have the objective of minimizing the delay in the network, setting a price cap to the offered prices, etc. The TCA may even have multi objectives. Furthermore, PSPs may have alternative profit functions. They may incorporate the CRM approach into the process of selecting the best combination of SUs to serve. The demand behaviors of SUs are also flexible. Their demand may have a logarithmic trend, exponential trend according to the market conditions. Hence, our proposed spectrum trading framework is a base model which can be adopted to different scenarios or different types of networks with slight modifications.

6.2. Practical Contributions

In the spectrum exchange architecture, we have used the Smith-NERA algorithm when calculating the opportunity cost of the spectrum band. The similar algorithms have been used by OFCOM for defining the spectrum license fees. We have shown that it is possible to make use of it for determining unit spectrum prices.

The simulation results of the spectrum exchange framework based on CRM have proven that, using customer demographic information and usage behavior has made a positive impact of up to 5.6 per cent on the total profit of the spectrum buyer when compared to the First-Come First-Serve approach.

The numerical analysis has showed that, spectrum trading with a centralized controller allows PSPs to increase their profit up to 193 per cent in a non competitive environment and up to 86 per cent in a competitive environment, by protecting the satisfaction of their primary customer base. We have compared our proposed model with the one that does not have a centralized power manager. We have shown that the PSPs can make up to 132 per cent of additional profit in a non cooperative environment, and up to 34 per cent of additional profit in a competitive environment by controlling the transmission powers. It is important to note that, the integration of such a centralized controller may require some communication overhead among base stations and the controller. PSPs should make a trade-off considering their marketing objectives.

The proposed five-step Coordinated Pricing algorithm can be used as a decision support tool for service providers in telecommunication market. We have showed that the algorithm performs well for many spectrum buyers in the same region.

6.3. Future Directions

In this dissertation, the transmission powers of PUs are taken from a lookup table, in other words they are fixed during the optimization of social welfare. The table is assumed to include the average transmission power values as a function of the distance of the PU to the base station of the PSP. Going forward, the power levels of PUs can be taken as variable, and be adjusted just like the power of SUs.

We do not consider the decision process of SUs in the spectrum trading architecture with strict power control. Actually, we have only considered the relationships among PSPs, since only the demand function of SUs are taken into consideration. An extended framework may be proposed for the relationships among PSPs, as well as the relationships among PSPs and SUs. There can be another game among SUs, when selecting the best PSP to buy spectrum bands.

In the proposed spectrum trading framework with power control, PSPs are assumed to completely know the demand behavior of SUs. Furthermore, PSPs negotiate with each other to reach the optimal unit prices; hence, they know the unit prices offered by other players. In practical systems these assumptions may not be valid. In this case, we can use learning or evolutionary algorithms to reach the equilibrium.

In the proposed spectrum trading framework with power control, the numbers of PUs in PSPs' networks are constant. In real life systems, this assumption may not be valid; hence an extended framework may be proposed which also takes into account the arrival and departure rates of the mobile users in a region.

The profit values that are calculated in the spectrum trading framework with power control are the maximum possible profit values for the PSPs. The reason is that a PSP does not know if its offered bandwidth will be bought by the SU. The SUs have the possibility to have more than one bandwidth offer; hence each SU chooses the best offer among them. The framework may be extended by integrating another game into the framework in order to determine the exact demand of the PSPs.

In the near future, commercial broadband and cellular networks will still require exclusive spectrum access to enable QoS guarantees to the customers. This will accelerate to propose more efficient, more flexible licensing modes to facilitate rapid developments in the wireless communication market. The flexibility of the proposed framework will enable us to adjust it to a newly proposed market structure.

REFERENCES

Akan, O.B and B. Baykal, 2005, "Handoff performance improvement with latency reduction in next generation wireless networks", *Wireless Networks*, Vol. 11, pp. 319-332.

Akyıldız, I.F., W.Y. Lee, M.C. Vuran and S. Mohanty, 2006, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey", *Computer Networks,* Vol. 50, pp. 2127-2159.

Al Daoud A, M. Alanyalı and D. Starobinski, 2007, "On pricing of spectrum in secondary markets", *Proceedings of the Information Theory and Applications Workshop*, pp. 11-15, 2007.

Al Daoud A., M. Alanyalı and D. Starobinski, 2009, "Pricing strategies for spectrum lease in secondary markets", *IEEE/ACM Transactions on Networking*, pp. 1-14.

Alpcan, T., T. Başar, R. Srikant and E. Alpman, 2002, "CDMA uplink power control as a noncooperative game", *Wireless Networks*, Vol. 8, pp. 659-670.

AT&T Wireless Annual Report, 2002, www.attws.com/press/annual_2002/dnload_pdf.pdf

Attar, A., S.A. Ghorashi, M. Sooriyabandara and A.H. Aghvami, 2008, "Challenges of real-time secondary usage of spectrum", *Computer Networks*, Vol. 52, No. 4, pp. 816-830.

Bai, Y. and L. Chen, 2006, "Flexible spectrum allocation methods for wireless network providers", *Proceedings of the IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, pp. 1-5.

Başar, T. and R. Srikant, 2002, “Revenue-maximizing pricing and capacity expansion in a many-users regime”, *Proceedings of the IEEE Conference on Computer Communications (INFOCOM)*, Vol. 1, pp. 294-301.

Bazaraa, M.S., H.D. Sherali and C.M. Shetty, 2006, *Nonlinear Programming Theory and Algorithms*, John Wiley & Sons, Inc., Hoboken, New Jersey.

Bernstein, F. and A. Federgruen, 2004, “A general equilibrium model for decentralized supply chains with price- and service-competition”, *Operations Research*, Vol. 52, No. 6, pp. 868-886.

Bertsekas, D. and R. Gallager, 1992, *Data Networks*, Prentice Hall, 2nd edition, Upper Saddle River, NJ.

Bloem, M., R. Alpcan and T. Başar, 2007, “A Stackelberg game for power control and channel allocation in cognitive radio networks”, *Proceedings of the International Conference on Performance Evaluation Methodologies and Tools (ValueTools 2007)*, Article no: 4.

Boyd, S.P. and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.

Buddhikot, M.M., P. Kolodzy, S. Miller, K. Ryan and J. Evans, 2005, “DIMSUMnet: New directions in wireless networking using coordinated dynamic spectrum”, *Proceedings of the IEEE International Symposium on a World of Wireless Mobile and Multimedia Networks*, pp. 78-85.

Buddhikot M.M., 2007, “Understanding dynamic spectrum access: models, taxonomy and challenges”, *Proceedings of the IEEE International Dynamic Spectrum Access Networks DySPAN*, pp. 649-663.

Cave, M., 2002, “Review of Radio Spectrum Management, for Department of Trade and Industry and HM Treasury”.

Chapin, J.M. and W.H. Lehr, 2007, "The Path to Market Success for Dynamic Spectrum Access Technology", *IEEE Communications Magazine*, pp. 96-103, May.

Chipchase, J., 2006, "Ethnography to inform and inspire design", Istanbul Technical University, available online: http://research.nokia.com/people/jan_chipchase/index.html.

Clark, D.D., 1995, "A Model for Cost Allocation and Pricing in the Internet", *Proceedings of MIT Workshop on Internet Economics*, March 1995.

Cordeiro, C., K. Challapali, D. Birru and S.N. Shankar, 2006, "IEEE 802.22: An Introduction to the first Wireless Standard based on Cognitive Radios", *Journal of Communications,* Vol. 1, No. 1, pp. 38-47.

Courcoubetis, C. and R. Weber, 2003, *Pricing Communication Networks: Economics, Technology and Modelling*. John Wiley & Sons, Ltd.

Dai, Y., X. Chao, S.C. Fang and H.L.W. Nuttle, 2005, "Pricing in revenue management for multiple firms competing for customers", *International Journal of Production Economics*, Vol. 98, pp. 1-16.

DARPA XG Working Group, 2003, "The XG Architectural Framework v1.0", Technical report.

Das, S.K., H. Lin and M. Chatterjee, 2004, "An Econometric Model for Resource Management in Competitive Wireless Data Networks", *IEEE Network*, pp. 20-26.

DaSilva L.A., 2000a, "Pricing for QoS-Enables Networks: A Survey", *IEEE Communications Surveys*, Second Quarter, pp. 2-8.

DaSilva, L.A., D.W. Petr and N. Akar, 2000b, "Static Pricing and Quality of Service in Multiple Service Networks", *Proceedings of the Fifth Joint Conference of Information Sciences*, Atlantic City, NJ, Vol. 1, pp. 355-358.

Diao, Z. and V.O.K. Li, 2007, "Fading-aware packet scheduling algorithm in OFDM-MIMO systems", *EURASIP Journal on Wireless Communications and Networking*, pp.1-10.

Di Sorte, D. and G. Reali, 2005, "Pricing and brokering services over interconnected IP networks", *Journal of Network and Computer Applications*, Vol. 28, pp. 245-283.

Dixit, A., S. Skeath and D.H. Reiley, 2009, *Games of Strategy*, W.W. Norton & Company, Inc., Third Edition.

Doyle, C., 2007, "The pricing of radio spectrum: using incentives mechanisms to achieve efficiency", *Proceedings of the ITU Workshop on Market Mechanisms for Spectrum Management*.

Dubois, R.S., 1992, "Marketing to maximize profitability", *The Journal of Business Strategy*, Vol. 13, pp. 10-13.

FCC, 2002, "Federal Communications Commission: Spectrum Policy Task Force Report", FCC ET Docket 02-135.

FCC Auctions Home Page, 2009, http://wireless.fcc.gov/auctions /default.htm?job= auctions _home

Fudenberg, D. and J. Tirole, 1991, *Game Theory*, MIT Press, Cambridge, MA.

Gupta, A., S. Kalyanaraman and L. Zhang, 2006, "Pricing of risk for loss guaranteed intra-domain internet service contract", *Computer Networks*, Vol. 50, pp. 2787-2804.

Haykin, S., 2005, "Cognitive Radio: Brain-Empowered Wireless Communications", *IEEE Journal on Selected Areas in Communications*, Vol. 23, No. 2, pp. 201-220.

Hossain, E., D. Niyato and Z. Han, 2009, *Dynamic Spectrum Access and Management in Cognitive Radio Networks*. Cambridge University Press.

Hwang, H., T. Jung and E. Suh, 2004, "An LTV model and customer segmentation based on customer value: a case study on the wireless telecommunication industry", *Expert Systems with Applications*, Vol. 26, pp. 181-188.

Hwang, J. and H. Yoon, 2009, "A mixed spectrum management framework for the future wireless service based on techno-economic analysis: The Korean spectrum policy study", *Telecommunications Policy*, Vol. 33, pp. 407-421.

IEEE 1900 Std., 2010, Committee, IEEE SCC41 home page: http://www.scc41.org.

IEEE 1900.1, 2006, "Standard Definitions and Concepts for Spectrum Management and Advanced Radio System Technologies", Draft Document.

Işıklar, G. and A.B. Bener, 2005, "A Simple Approach to Charging and Billing of Packetized Applications," *Proceedings of the IEEE Wireless Communications and Networking Conference*, New Orleans, Vol. 4, pp. 2440-2445.

Işıklar Alptekin, G. and A.B. Bener, 2008a, "Business Model Specific Charging Mechanism in Cognitive Radio", *Proceedings of the Euromicro Conference on Software Engineering and Advanced Applications*, pp. 156-163.

Işıklar Alptekin, G. and A.B. Bener, 2008b, "Brokering and Pricing Architecture over Cognitive Radio Wireless Networks", *Proceedings of the IEEE Consumer Communications and Networking (CCNC)*, pp. 1004-1008.

Işıklar Alptekin, G. and A.B. Bener, 2009a, "Pricing Model for the Secondary Market Architecture in Cognitive Radio Networks", *Proceedings of the IEEE International Conference on Game Theory for Networks* (*Gamenets*).

Işıklar Alptekin, G. and A.B. Bener, 2009b, "Customer oriented resource allocation framework in cognitive radio", *Computers & Industrial Engineering*, article in press, DOI: 10.1016/j.cie.2009.03.2009.

Işıklar Alptekin, G. and A.B. Bener, 2009c, “An Efficient Spectrum Management Mechanism for Cognitive Radio Networks”, *Proceedings of the IFIP/IEEE International Symposium on Integrated Network Management*, New York, pp. 653-660.

Işıklar, G., A.B. Bener and F. Alagöz, 2006a, “A New Bandwidth Allocation Strategy in GEO Satellite Networks and Pricing the Differentiated Services”, *Proceedings of the IEEE International Conference on Communications*, Vol. 4, pp. 1855-1860.

Işıklar, G., M. Üner and A.B. Bener, 2006b, “A Pricing Model for M-Commerce Services using CRM-Based Approach”, *Proceedings of the IEEE/ICETE International Conference on e-Business*, pp. 118-125.

İleri, Ö., D. Samardzija and N.B. Mandayam, 2007, “Dynamic Property Rights Spectrum Access: Flexible Ownership Based Spectrum Allocation via a Spectrum Server”, *Proceedings of the IEEE Symposium on New Frontiers in Dynamic Spectrum Access Networks* (*DySPAN*), pp. 254-265.

İleri, Ö. and J. Zander, 2009, “Broker Coordination in Demand Responsive Dynamic Spectrum Access Settings”, *Proceedings of the IEEE International Conference on Communications* (*ICC*), pp. 1-6.

Kastrinogiannis, T. and S. Papavassiliou, 2009, “Game theoretic distributed uplink power control for CDMA networks with real-time services”, *Computer Communications*, Vol. 32, pp. 376-385.

Kastro, Y., G. Işıklar and A.B. Bener, 2009, “A Decision Strategy for Resource Allocation in Cellular Networks-based on Operator’s Marketing Preferences”, *Wireless Networks*, article in press, DOI: 10.1007/s11276-008-0112-7.

Kim, S.T., T.S. Jung, E.H. Suh and H.S. Hwang, 2006, “Customer segmentation and strategy development based on customer lifetime value: A case study”, *Expert Systems with Applications*, Vol. 31, pp. 101-107.

Le, L.B. and E. Hossain, 2008, “Resource Allocation for Spectrum Underlay in Cognitive Radio Networks”, *IEEE Transactions on Wireless Communications*, Vol. 7, No. 12, pp. 5306-5315.

Levin, J. 2003, Lecture Notes, https://www.cds.caltech.edu/help/uploads/wiki/files/187/SupermodularGames.pdf

Li, M., H. Zhu, I. Chlamtac and B. Prabhakaran, 2006, “End-to-end QoS framework for heterogeneous wired-cum-wireless networks”, *Wireless Networks*, Vol. 12, pp. 439-450.

MacKenzie, A.B. and L. DaSilva, 2006, *Game Theory for Wireless Engineers*, Morgan & Claypool Publishers, USA.

Mackie-Mason, J.K. and H.R. Varian, 1995, *Pricing the Internet*. In B. Kahin and J. Keller, editors, Public Access to the Internet. Prentice-Hall, Englewood Cliffs, NJ.

Mandjes, M., 2003, “Pricing strategies under heterogeneous service requirements”, *Computer Networks,* Vol. 42, pp. 231-249.

Mandjes, M. and J. Timmer, 2007, “A duopoly model with heterogeneous congestion-sensitive customers”, *European Journal of Operational Research*, Vol. 176, pp. 445-467.

Mas-Colell, A., M.D. Whinston and J.R. Green, 1995, *Microeconomic Theory*, Oxford University Press, USA.

Mendelson, H., 1985, “Pricing computer services: Queuing effects”, *Communications of the ACM*, Vol. 28, pp. 312-321.

Mendelson, H.and S. Whang, 1990, “Optimal incentive-compatible priority pricing for the M/M/1 queue”, *Operations Research*, Vol. 38, pp. 870-883.

Milgrom, P. and J. Roberts, 1990, "Rationalizability and Learning in Games with Strategic Complementarities", *Econometrica*, Vol. 58, pp. 1255-1278.

Mitola III.J., 1999, "Cognitive Radio for Flexible Multimedia Communications", *Proceedings of the IEEE International Workshop on Mobile Multimedia Communications*, pp. 3-10.

Mwangoka, J.W., K.B. Letaief and Z. Cao, 2009, "Joint power control and spectrum allocation for cognitive radio networks via pricing", *Physical Communication*, Vol. 2, No. 1-2, pp. 103-115.

Myerson, R.B., 1991, *Game Theory Analysis of Conflict*, Harvard University Press.

Nigerian Communication Commission (NCC), Frequency Spectrum Fees and Pricing Regulations, 2002, available online: http://www.ncc.gov.ng/RegulatorFramework/Frequency %20 spectrum%20Fees%20and%20Pricing%20Regulations.pdf

Nekoogar, F., 2005, *Introduction to Ultra-Wideband Communications*, Prentice Hall, Inc.

Nash, J., 1951, "Non-Cooperative Games", *The Annals of Mathematics*, Vol. 54, No. 2, pp. 286-295.

Neel, J.O., J.H. Reed and R.P. Gilles, 2004, "Convergence of Cognitive Radio Networks", *Proceedings of the IEEE Wireless Communications and Networking Conference*, Vol. 4, pp. 2250-2255.

Neel, J.O., 2006, "Analysis and Design of Cognitive Radio Networks and Distributed Radio Resource Management Algorithms", Ph.D. Dissertation, Virginia Polytechnic Institute and state University.

Nie, N. and C. Comaniciu, 2005, “Adaptive channel allocation spectrum etiquette for cognitive radio networks”, *Proceedings of the IEEE International Conference on New Frontiers in Dynamic Spectrum Access Networks* (*DySPAN*), pp. 269-278.

Niyato, D. and E. Hossain, 2007a, “Optimal Price Competition for Spectrum Sharing in Cognitive Radio: A Dynamic Game-Theoretic Approach”, Proceedings of the IEEE Global Telecommunications Conference, pp. 4625-4629.

Niyato, D. and E. Hossain, 2007b, “Integration of WiMAX and WiFi: Optimal Pricing for Bandwidth Sharing”, *IEEE Communications Magazine*, Vol. 45, No. 5, pp. 140-146.

Niyato, D. and E. Hossain, 2007c, “A Game-Theoretic Approach to Competitive Spectrum Sharing in Cognitive Radio Networks”, *Proceedings of the IEEE Wireless Communications and Networking Conference* (*WCNC*), pp. 16-20.

Niyato, D. and E. Hossain, 2007d, “Hierarchical Spectrum Sharing in Cognitive Radio: A Microeconomic Approach”, *Proceedings of the IEEE Wireless Communications and Networking Conference* (*WCNC*), pp. 3822-3826.

Niyato, D. and E. Hossain, 2008a, “Spectrum trading in cognitive radio networks: A market-equilibrium-based approach”, *IEEE Wireless Communications*, pp. 71-80.

Niyato, D. and E. Hossain, 2008b, “Market-equilibrium, competitive, and cooperative pricing for spectrum sharing in cognitive radio networks: Analysis and comparison”, *IEEE Transactions on Wireless Communications*, Vol. 7, No. 11, pp. 4273-4283.

Niyato, D. and E. Hossain, 2008c, “Competitive Pricing in Heterogeneous Wireless Access Networks: Issues and Approaches”, *IEEE Network*, Vol. 22, No. 6, pp. 4-11.

Niyato, D., E. Hossain and. Z. Han, 2009, “Dynamics of Multiple-Seller and Multiple-Buyer Spectrum Trading in Cognitive Radio Networks: A Game-Theoretic Modeling Approach”, *IEEE Transactions on Mobile Computing*, Vol. 8, No. 8, pp. 1009-1022.

NTIA, 2003, The National Telecommunications and Information Administration's frequency allocation chart, http://www.ntia.doc.gov/osmhome/allochrt.pdf

Odlyzko, A., 1999, "Paris Metro Pricing: The minimalist differentiated services solution", *Proceedings of the IEEE Seventh International Workshop on Quality of Service* (*IWQoS'99*), New York, pp.159-161.

Osborne, M.J., 2004, *An introduction to Game Theory*, Oxford University Press.

Özertan, G. and B. Çevik, 2003, "A Simulation Analysis of Pricing Strategies and Protection Under Presence of Software Piracy", Mimeo, Boğaziçi University, Department of Economics.

Peha, J.M. and S. Panichpapiboon, 2004, "Real-time secondary markets for spectrum", *Telecommunications Policy*, Vol. 28, No. 7-8, pp. 603-618.

Prasad, R.V., P. Pawelczak, J.A. Hoffmeyer and H.S. Berger, 2008, "Cognitive Functionality in Next Generation Wireless Networks: Standardization Efforts", *IEEE Communications Magazine*, Vol. 46, No. 4, pp. 72-78.

Rapaport, T.S., 1996, *Wireless Communications: Principles and Practice*, Prentice Hall, Upper Saddle River, NJ.

Rast, R.M., 2005, "The Dawn of Digital TV", *IEEE Spectrum*, October 2005.

Roh, T.H., C.K. Ahn and I. Han, 2005, "The priority factor model for customer relationship management system success", *Expert Systems and Applications*, pp. 641-654.

Rubenstein, R., 2007, "Radios Get Smart", *IEEE Spectrum*, February.

Sang, A., X.Wang, M. Madihian and R.D. Gitlin, 2007, "Coordinated load balancing, handoff/cell-site selection, and scheduling in multi-cell packet data systems", article in press: DOI 10.2007/s11276-006-8533-7.

Saraydar, C.U., N.B. Mandayam and D.J. Goodman, 2002, "Efficient power control via pricing in wireless data networks", *IEEE Transactions on Communications*, Vol. 50, No. 2, pp. 291-303.

Schiller, J., 2003, *Mobile Communications*, Pearson Education Limited, 2nd Edition, Great Britain.

Schwartz, M., 2005, *Mobile Wireless Communications*, Cambridge University Press.

Sengupta, S., M. Chatterjee and S. Ganguly, 2007, "An economic framework for spectrum allocation and service pricing with competitive wireless service providers", *Proceedings of the International Conference on New Frontiers in Dynamic Spectrum Access Networks* (*DySPAN*), pp. 89-98.

Shannon, C.E., 1949, *"Communication in the presence of noise"*, *Proceedings of the Institute of Radio Engineers*, Vol. 37, No. 1 pp. 10–21, http://www.stanford.edu /class/ee104/shannonpaper.pdf.

Shared Spectrum report, 2007, available online: http://www.sharedspectrum.com/ measurements/ download/Ireland_Spectrum_Occupancy_Measurements_v2.pdf / .

Smith-NERA, 1996, "Study into the use of spectrum pricing", *Report for the Radiocommunications Agency by NERA and Smith System Engineering*, April.

Soong, T.T., 2004, *Fundamentals of Probability and Statistics for Engineers*, John Wiley & Sons Ltd, England.

Soursos, S., C. Courcoubetis and G.C. Polyzos, 2001, "Pricing Differentiated Services in the GPRS Environment", *Wireless Mobile Internet*, pp. 62-68.

Suris, J.E., L.A. DaSilva, Z. Han, and A.B. MacKenzie, 2007, "Cooperative Game Theory for Distributed Spectrum Sharing", *Proceedings of the IEEE International Conference on Communications* (*ICC*), pp. 5282-5287.

Qinetiq, 2007, "Cognitive Radio Technology, A Study for Ofcom – Vol. 1", http://www.ofcom.org.uk/research/technology/research/emer_tech/cograd/cograd_main.pdf

Topkis, D., 1979, "Equilibrium Points in Non-Zero Sum *n*-Person Submodular Games," *SIAM Journal of Control and Optimization*, Vol. 17, No. 6, pp. 773-787.

Vilimpoc, M. and M. McHenry, 2006, "Dupont Circle Spectrum Utilization During Peak Hours", http://www.newamerica.net/files/archive/Doc_File_183_1.pdf

Vives, X., 1999, *Oligopoly Pricing Old Ideas and New Tools*, The MIT Press.

Walke, H., S. Mangold and L. Berlemann, 2007, *IEEE 802 Wireless Systems: Protocols, Multi-Hop Mesh/Relaying, Performance and Spectrum Coexistence*, Wiley.

Weiss, T.A. and F.K. Jondral, 2004, "Spectrum pooling: an innovative strategy for the enhancement of spectrum efficiency", *IEEE Communications Magazine*, Vol. 42, No. 3, pp. 8-14.

Xing, Y., R. Chandramouli and C.M. Cordeiro, 2007, "Price dynamics in competitive agile spectrum access markets", *IEEE Journal on Selected Areas in Communications*, Vol. 25, No. 3, pp. 613-621.

Yaiche, H. and R.R. Mazumdar, 2000, "A Game Theoretic Framework for Bandwidth Allocation and Pricing in Broadband Networks", *IEEE/ACM Transactions on Networking*, Vol. 8, No. 5, pp. 667-678.

Zayen, B., M. Haddad, A. Hayar, and G.E. Oien, 2008, “Binary power allocation for cognitive radio networks with centralized and distributed user selection strategies”, *Physical Communication*, Vol. 1, No. 3, pp. 183-193.

Zhang, G., W. Cheng, Y. Liu and Z. Dasheng, 2004, “Revenue-maximizing pricing and resource allocation of differentiated services”, *Proceedings of the IEEE Region 10 Conference* (*TENCON*), pp. 605-608.

Zhao, Q., B.M. Sadler, 2007, “A survey of dynamic spectrum access: Signal processing, networking, and regulatory policy”, *IEEE Signal Processing Magazine*, Vol. 24, No. 3, pp. 79-89.

REFERENCES NOT CITED

Kastro, Y., G. Işıklar and A.B. Bener, 2010, "Resource allocation in cellular networks based on marketing preferences", *Wireless Networks*, Vol. 16, No. 1, pp. 27-38.

Alptekin, G.I. and A. Bener, 2010, "Customer Oriented Resource Allocation Framework in Cognitive Radio", C*omputers & Industrial Engineering*, Vol. 58, No. 3, pp. 401-410.

Alptekin, G.I. and A. Bener, 2009, "Pricing Model for the Secondary Market Architecture in Cognitive Radio Networks"**,** *Proceedings of the IFIP/IEEE Game Theory for Networks (GAMENETS)*, pp. 479-483.

Alptekin, G.I. and A. Bener, 2009, "An Efficient Spectrum Management Mechanism for Cognitive Radio Networks", *Proceedings of the IFIP/IEEE International Symposium on Integrated Network Management (IM)*, pp. 653-660.

Alptekin, G.I. and A. Bener, 2008, "Business Model Specific Charging Mechanism in Cognitive Radio", *Proceedings of the 34th Euromicro Conference on Software Engineering and Advanced Applications (SEAA'08)*, pp. 156-163.

Işıklar, G. and A. Bener, 2008, "Brokering and Pricing Architecture over Cognitive Radio Wireless Networks", *Proceedings of the IEEE Consumer Communications& Networking Conference (CCNC)*, Workshop on Cognitive Radio Networks, pp. 1004-1008.

Kastro, Y., G. Işıklar and A. Bener, 2007, "The Use of Customer Relationship Management in Resource Allocation: The Case of Cellular Networks", *Proceedings of Computers & Industrial Engineering Conference*, pp. 119-125.

Işıklar, G., M. Üner and A. Bener, 2006, "A CRM-based pricing model for m-commerce services", *Proceedings of the IEEE International Joint Conference on E-Business and Communications (ICETE/ ICE-B 2006)*, pp. 118-125.

Işıklar, G., A. Bener and F. Alagöz, 2006, "A New Bandwidth Allocation Strategy in GEO Satellite Networks and Pricing the Differentiated Services", *Proceedings of the IEEE International Conference on Communications (ICC)*, Vol. 4, pp. 1855-1860.

Işıklar, G. and A. Bener, 2005, "A Simple Approach to Charging and Billing of Packetized Applications", *Proceedings of the IEEE Wireless Communications and Networking Conference* (*WCNC*), Vol. 4, pp. 2440-2445.

Işıklar, G. and A. Bener, 2006, "Hücresel ağlarda kaynak atamasına alternatif bir yaklaşım", *GAP 2006*, Harran Üniversitesi, Şanlıurfa.

Işıklar, G. and A. Bener, 2005, "Ağdaki paket uygulamalar için önerilmiş fiyatlandırma modeli", *Akademik Bilişim 2005*, Gaziantep Üniversitesi.