© 2007

Omer Ileri

ALL RIGHTS RESERVED

DYNAMIC SPECTRUM ACCESS MODELS: TOWARDS AN ENGINEERING PERSPECTIVE IN THE SPECTRUM DEBATE

BY OMER ILERI

A dissertation submitted to the

Graduate School—New Brunswick

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

Graduate Program in Electrical and Computer Engineering

Written under the direction of

Prof. Narayan B. Mandayam

and approved by

New Brunswick, New Jersey

October, 2007

ABSTRACT OF THE DISSERTATION

Dynamic Spectrum Access Models: Towards an Engineering Perspective in the Spectrum Debate

by Omer Ileri

Dissertation Director: Prof. Narayan B. Mandayam

The increased demand for wireless communications services, and innovations in smart radio technologies have spurred a debate in the recent past regarding the efficiency of the spectrum governance policy of the Federal Communications Commission (FCC). The two main camps that have emerged in this yet non-conclusive debate are the ones that are proponents of (i) the spectrum property rights and (ii) the spectrum commons. In this dissertation, we first present a detailed overview of the ongoing spectrum debate and then present two engineering models that allow certain types of realistic comparisons to be made.

We call these models dynamic property-rights spectrum access (D-Pass) and dynamic-commons property-rights spectrum access (D-CPass). While both models introduced retain a bias toward the spectrum property rights approach based usage of spectrum, they also promote dynamic access and short term dedication of spectrum resources. Specifically, we consider a framework where operators compete for spectrum and users in a geographical area. A spectrum policy server (SPS) functions as a controller/enforcer

as well as a clearinghouse for spectrum allocations.

In the D-Pass model, the operators pay the SPS for the exact amount of bandwidth they are allocated, irrespective of the utilization of the bandwidth. Each operator competes for users via rate and price offers for utilizing the spectrum portion under its short term “ownership”. We model the operator competition in the form of a SPS-mediated iterative bidding scheme that is reminiscent of a simultaneous ascending auction. In the D-CPass model, all operators have access to all the available bandwidth during the competition phase. The operators pay the SPS for the portion of the spectrum that they actually utilize (pay-as-you-go). They compete for each user via rate and price offers through an SPS-mediated iterative bidding scheme that is reminiscent of a single-item ascending auction. Our results indicate that both the spectrum access mechanism and the market forces play an important role in determining the resulting bandwidth utilization. Furthermore, under negligible spectrum usage costs, the commons-like model (D-CPass) promotes greater utilization of spectrum resources.

Acknowledgements

I would like to thank my advisor Prof. Narayan Mandayam for his guidance throughout my graduate studies. He has taken the trouble to motivate me at the very beginning for the challenging studies I have undertaken here at Rutgers. He has been an excellent advisor, making himself available even during his busiest days and he has shared his insight in wireless communications technologies. He has also given me valuable hints on how to approach problems but he has also made sure that I learn how to navigate by myself. He has truly inspired me for the better, and I owe him a lot in this respect.

I would also like to thank Prof. Yates, Prof. Comaniciu and Prof. Raychaudhuri for being on my thesis committee. Their feedback has greatly improved the quality of the work presented here. I would also like to extend my appreciation to Dr. Samardzija of Alcatel-Lucent Technologies, for being my mentor during my internship there and directly contributing to many of the results presented in this thesis. All Winlab faculty has, in one way or another, helped me learn a great deal, and more importantly they have set inspiring examples for me. I feel blessed to have had the opportunity to spend six years with them.

I would also like to thank my friends here in New Brunswick, simply for being good friends. I have enjoyed being with them, and will miss them, even though I will always be in touch with them. Last, but certainly not the least, I want to thank my beloved family, my parents, my sister and my brother-in-law. Certainly they have always encouraged me for the better since the first days of my life. I owe them everything! Thank you.

Table of Contents

List of Figures

Chapter 1

Introduction

Efficient regimes for spectrum management have been a research focus since the earliest days of radio communications. Recent advances in radio technology coupled with the success of communications services in the unlicensed bands has produced a new and lively debate. The two opposing camps in this debate argue for the following spectrum governance regimes: (1) Property rights based spectrum governance and (2) Lightly regulated access to "spectrum commons". Unfortunately, the different approaches and languages adopted by the mix of technologists, economists, lawyers, lawmakers and businessmen in this debate has made communication and consensus difficult, and no solid conclusions have emerged.

Traditional spectrum governance in the form of a command and control approach has long been employed by the FCC. It had the goal of meeting important needs, and protecting those important users from destructive interference. It has thus tended toward the static, long-term exclusivity of spectrum use in large geographic areas, often based on the radio technologies employed at the time of decision making.

In the command and control spectrum management model, the government is responsible for allocating the spectrum and specifying the terms of usage for every spectrum portion individually. It specifies the kinds of services that could be provided over any spectrum portion (TV broadcast, emergency services, PCS, etc.) and also enforces physical layer constraints (spectrum mask) [1].

This approach has led to many successful applications like broadcasting and cellular, which can be cited by the proponents of spectrum property rights, but has also been criticized as inefficient in the overall use of spectrum. A recent report presenting statistics regarding spectrum utilization shows that even during the high demand period of a political convention such as the one held between August 31 and September 1 of 2004 in New York City, only about 13% of the spectrum opportunities were utilized [2].

In the past two decades, a relatively small regulatory experiment for creating "unlicensed spectrum access" in the ISM (Industrial/Scientific/Medical) bands has resulted in much innovation and popular use (cordless telephony and WiFi being well-known examples) and has supported a new paradigm in which regulation (or perhaps a judicial reduction in regulation) drives dramatic advances in technology. In these bands, the communicating parties need not acquire a license for operation, and can use these bands as long as they abide by some specific technical rules set forth by the FCC. The success of these applications, in terms of massive usage with relatively few problems, can be cited by the proponents of spectrum commons, but these experiments are still relatively new, and involve applications which are generally short range and non-critical in terms of public safety.

These developments and observations have sparked a hot debate regarding how the spectrum governance employed by the FCC should be improved, so that the new spectrum policy alleviates artificial spectrum scarcity, and also encourages innovation. However, this debate has very quickly surpassed the technical comparisons and generated, as pointed out in [3], more passionate rhetoric than logic.

As mentioned above, the proposals for new governance regimes fall into two categories: spectrum property rights, and spectrum commons. These models have first appeared in the form of alternative overarching-legal regimes, and the discussions so far have focused mostly on the ways in which the FCC should allocate the resources. Detailed algorithms as to how spectrum access would be realized in end user level have not yet been specified.

The spectrum property rights approach is motivated by the landmark work of R.H.

Coase [4], in which it is suggested that spectrum can be treated just like land, and private ownership of spectrum is viable. The proponents of spectrum ownership, believe that the spectrum should be allocated to the prospective spectrum holders through market forces. The spectrum holders would then be able to exclusively use the spectrum portion they possess, without suffering interference from other parties. Alternatively they would be able to trade the spectrum portion in a secondary market. The use of spectrum would be flexible, in that the authorized party could use the spectrum portion for any purpose. Thus the focus, in this approach, is on transferring the ownership of the spectrum from the government to private parties and substituting market forces for traditional spectrum regulation, overcoming two sources of inefficiency in the status quo regime.

The spectrum commons approach, encouraged by the unlicensed spectrum band experiments, argues that with developing smart technologies, the spectrum will become “unscarce” as communicating devices become able to avoid interference through mutual cooperation and coexistence. The emergence of cognitive and software defined radio concepts, multiple antenna and multicarrier techniques as well as UWB technologies and mesh network topologies, provide a “technology panacea” that the supporters of this approach use in favor of their arguments. The communicating devices will be able to efficiently share a specified spectrum band through the enforcement of technical restrictions and multiple-access protocols, without requiring exclusive access or private ownership.

The lack of specific models which detail the above approaches, describing how spectrum allocation would actually be implemented in each, has led to vague and lengthy discussions that have not resolved the opposing views of these camps. The supporters of spectrum commons refer to the risk of monopolization and holdup, emphasizing that spectrum access should not be granted only to those who can pay. Those who side with the property rights camp emphasize the risk referred to as the tragedy of commons which predicts the overuse and exploitation of the common resources [5]. Political and philosophical arguments that relate to freedom of speech and the first amendment also find their place in this ongoing battle. Thus, what started as a technical challenge related to avoiding spectrum scarcity has turned into a passionate debate with political and philosophical overtones and no clear path toward resolution. On the positive side, there have been recent calls (such as for example in [3] and [5]) for the need for specific spectrum access and management models for implementation of the above-mentioned governance regimes, and to develop detailed schemes and investigative tools that would permit both technical and political/philosophical comparisons of such approaches to spectrum governance.

In this thesis we present two simple but realistic exemplifier models for specifying spectrum access and operator competition in a dynamic spectrum access setting. The dynamic spectrum access models considered here rely on a quasi-centralized mechanism that coordinates spectrum sharing while retaining the distributed decision making of users. The framework here is enabled by the presence of a spectrum policy server [6–8], which functions as a controller/enforcer as well as a clearinghouse for spectrum allocations. In this framework, there is a dynamic competition phase in which operators compete for the users of spectrum. This phase is followed by a spectrum usage phase in which exclusive rights to spectrum are granted to the operators and users. The access models we present are called "dynamic property rights spectrum access (D-Pass)" and "dynamic-commons property-rights spectrum access (D-CPass)". While both models promote exclusive use of spectrum resources, thus retaining a bias toward the spectrum-property-rights-based usage, they also make use of dynamic access and short term spectrum allocations. Specifically, as will be seen later, the D-CPass model in conjunction with the spectrum policy server, has the flavor of commons-like shared managed access (i.e., in the competition phase before usage). In both models, the operators compete with each other for customers through demand responsive pricing where users assert their preferences for the rate and prices offered by the operators [9].

1.1 Scope of the Dissertation

We develop our models based primarily on technology issues while addressing economic issues relating to feasibility and operator profits as well. Our emphasis is on presenting an engineering perspective towards developing practical models for use in the spectrum debate. We do not, consider the other economic dimensions like the secondary markets formed in a property rights regime, or the dispute resolution protocols and transaction costs that would be of interest to completely characterize a spectrum governance scheme in terms of its macroeconomic consequences.

It is also important to note that this dissertation does not aim to have the final say regarding alternative spectrum governance regimes. It does, nevertheless, strive to demonstrate the importance of specifying models and detailed algorithms for spectrum management that need to be used in the spectrum debate, beyond the usual over-arching legal and socio-political issues.

The outline of the rest of the dissertation is as follows. In chapter 2, we present a brief discussion of the spectrum debate, describing in greater detail the spectrum property rights and spectrum commons approaches. In chapter 3, we present the generic system model and provide an overview of the system architectures, models proposed and the modelling of user appreciation. In chapters 4 and 5 we present the D-Pass and D-CPass models respectively. We provide some analytical insight and also present illustrative numerical results. In chapter 6, we elaborate on numerical comparisons regarding the performance of each model. In chapter 7, we propose various approaches to address the privacy, complexity and scalability issues surrounding these models. Finally, we conclude the dissertation providing a brief overview of our contributions and identifying some future research directions.

Chapter 2

The Spectrum Debate

The spectrum resources of most nations are under the direct control of the appropriate national regulatory bodies established by their governments. The regulatory bodies for spectrum usage have been formed historically to serve several purposes. These include protection and safeguards for communications related to applications in the defense of the country, public safety, broadcast for entertainment and several others that offer benefits to the society. As a result, the decisions and policies made by such regulatory agencies are affected by many issues beyond just technological ones. They are notably influenced by economics, law, business as well as social and political factors.

The national regulatory bodies cooperate with each other through the international organizations which make sure national spectrum regulations provide the means for interoperability and that harmful interference between different countries is avoided. Currently, the Radio Regulations unit under the ITU (International Telecommunication Union) is in charge of the spectrum management decisions on an international level. The ITU functions as an agency of the United Nations and provides a platform for establishing coherence among the national regulators [10].

2.1 Brief History of Spectrum Regulations in the USA

The early days of radio communications in the US were dominated by ship-to-shore telephony for maritime communications, particulary for the Navy. The communication failures experienced during the Titanic disaster [11] as well as the failures to fully exploit the wireless communication technologies for the allied navies during WWI created the drive to improve maritime communications in the US in the post WWI period. This further reinforced the dominance of military communications in this period.

Starting in 1921, broadcast radios based in the east coast urban centers like New York and Pittsburgh started to emerge. The deployment of such broadcast stations made it mandatory to enforce some spectrum allocations for broadcasters to avoid unwanted interference. Given the communication technologies at the time, the only way to avoid interference was to make sure that the broadcasters operated at different frequencies. Thus, a regulation paradigm which imposed the technical approach of allocating non-overlapping spectrum portions to spectrum demanding parties emerged. As will be seen later in this chapter, this paradigm of exclusive spectrum usage transformed into a rigid governance regime, namely the command and control regime, and has stayed in effect to date. The enforcement of this approach is through the distribution of licenses. Each broadcaster needs a license to operate. The license specifies the frequency band the user is authorized to operate on, the geographical area, the expiration date for the permission to operate, as well as the applications and the technologies that are to be employed in the indicated band.

Responding to the need for a central regulator, the congress initiated the Federal Radio Agency, through the Radio Act of 1927. The Federal Radio Agency was considered as the sole authority in determining who could use which portion of the available spectrum and for what purpose. The Federal Communications Commission (FCC) was created replacing the Federal Radio Agency through the Communications Act of 1934 and it took over the responsibilities for spectrum allocations for commercial parties [11]. The FCC has functioned as the sole authority for spectrum allocation to date.

The implementations for the exclusive allocation of spectrum portions across the broadcasters have varied over the years. The early implementations were in the form of a simple rule: "priority in use", which proposed that the first broadcaster to operate in a given spectrum portion owned it. The "priority in use" regulation has created chaos and has also been challenged by various court rulings [11].

Another such implementation was through the"Comparative Hearings", in which the competing parties would present the FCC with a description of the ways in which they would utilize the allocated spectrum if granted the license. Such hearings, also referred to by many as "beauty contests" would result in one party being granted the usage license for the spectrum portion considered. The winning party would only be able to use the spectrum portion awarded in line with the license specifications. This procedure for allocating licenses was critiqued to be very prone to political inefficiencies and rent seeking as it is based on a very subjective evaluation process [11].

The FCC also used lotteries in the past, for a brief period, for issuing analog cellular licenses. This approach, has been critiqued by many for the apparent lack of intelligent decision making in regard to the best use of spectrum resources from a societal point of view.

Starting in the 1990's, the FCC has started auctioning available spectrum resources to interested parties. In this system, chunks of spectrum portions are awarded to those bidders who can offer the greatest payments to the FCC. The winners in auctions are given operation licences and they are obliged to follow the restrictions specified on the licenses. The licenses are subject to renewal after expiration [11].

Such spectrum auctions have raised billions of dollars for the FCC and are considered by many as an efficient way of allocating spectrum resources, as they promote awarding spectrum resources to those who value them the most. This view is bolstered by the belief that such awardees are more likely to make the most efficient use of spectrum resources they own. However, such auctions have been recently challenged by many [12] who believe that these have deteriorated into fund raising activities encouraged by the government, and they do not necessarily invoke the most efficient allocation from a societal point of view. It has also been argued that such auctions induce high barriers for market entry and also drain the financial resources of the telecommunications industry.

It is also well known in the economics literature, that auction mechanisms can eventually result in destructively high prices for the participants and push the winners to make offers which can lead them to bankruptcy. Such situations are often referred to as the "winner's curse" [13].

2.2 Aspects of Spectrum Management Regimes

It is important to note that any spectrum policy needs to clearly describe practical aspects of management. The way spectrum portions are to be allocated, the way licences are to be renewed, for example, need to be clarified to understand the implementation details that a given regime would lead to. The efficiency of the governance regime in effect heavily depends on these practical considerations. In [10] these practical aspects are referred to as "characteristics of a spectrum management regime".

The below are the aspects for identifying any spectrum governance regime that are often mentioned in the discussions surrounding the spectrum management options.

1. **Allocation Mechanism**: As mentioned above, there are different means of allocating spectrum resources to consuming parties. These allocation mechanisms could be based on administrative fiat, as in beauty contests or lotteries, or through employing market tools, such as spectrum auctions.

2. **Duration of Transmission Rights**: The spectrum usage rights can be awarded to consuming parties either on a temporary basis or permanently. The duration of a temporary transmission right can vary across different implementations, yielding different outcomes for each. Transmissions rights might also be transferred in certain regimes.

3. **Spectrum Sharing**: Different regimes can impose different limits on spectrum sharing. Regimes in effect today (with the exception of unlicensed bands) are exclusive-use based regimes, in which spectrum portions are dedicated to usage

by certain parties only, and the spectrum users exclude all others at all times, even when the spectrum is idle.

4. **Flexibility of usage**: There might be different restrictions on the licenses awarded to consumers. Some regimes can even allow the licensee to utilize the spectrum portion awarded in any way it wants through any technology it prefers.

5. **Dispute Resolution**: Dispute resolution refers to the set of procedures followed in case unwanted interference is observed between two different parties. The legal system, as well as the national regulators are often part of the process. Different spectrum management regimes require different dispute resolution procedures.

Note that in reality there are some other aspects of interest that are not mentioned in the above list. We believe the above are the most important ones and focus more on the first three while developing our models.

2.3 Command and Control Spectrum Management Regime

In this section we provide an overview of the current governance regime in effect. The current management policies of the FCC are predominantly in the form of a "command and control" structure. In this approach, the FCC functions as the sole, centralized decision maker responsible for all spectrum allocation decisions and usage rules. Specifically, the FCC directs the (i) use for any specified spectrum portion, (ii) physical layer constraints (transmit power, modulation, etc...) and (iii) who will have access to spectrum [14].

This centralized regime has in fact evolved over time, and has been mostly shaped by the needs and concerns of the telecommunications industry. The solutions proposed, as mentioned earlier, have been heavily based on the communication technologies employed at the time of decision making. The main motivation was to avoid unwanted interference between transmitters. Given the communication technologies employed at the time of the decision making, the only way to achieve this purpose was to make sure that the transmitters operate on non-overlapping spectrum portions. Thus, the command and control regime dictates exclusive usage of spectrum resources. The spectrum allocation decisions are static in the sense that they are valid for long time intervals (usually 10 years) and over large geographical regions. As mentioned earlier, the FCC has taken steps to increase the effect of markets on spectrum allocation decisions by initiating spectrum auctions beginning in the 1990's.

Reference [15] identifies some benefits to such a centralized system. One is that in this regime the central administration (the FCC) can make sure that some applications which do not actually have great returns for the license holders, but nevertheless are very useful for users who can not pay much are offered (through controlling the use for the spectrum portions). Another benefit is that the FCC can represent the national industry during international negotiations. Finally, in such a centralized scheme, the FCC can enforce standardization and thus enable interoperability. Besides these, the proliferation of TV broadcast services can be seen as an evidence that such exclusive use of resources with static allocation has actually benefitted certain services.

Nevertheless, many have voiced their concerns regarding the blocking of innovation in this regime. Since the FCC specifies many of the technological constraints regarding the spectrum portions, there often is very little room left for technological innovation. Also, the auction mechanisms employed produce very high market entry barriers, effectively cartelizing the industry and limiting the freedom of speech [12]. Many also critique the regime due to its static allocation and inability to catchup with the dynamics of the market. Political inefficiency and rent seeking are also seen by many [16] as an inherent problem with any government based centralized scheme, which also affects the command and control regime currently employed by the FCC.

Note also that even though the spectrum resources are predominantly governed in the command and control structure described above, some portions (ISM, UNII) are dedicated to unlicensed operation. In these portions, the transmitters do not need licenses for operations, and any transmitter is authorized to operate in these bands as long as they abide by certain technical constraints related to transmit power and interference. The present day 802.11 networks, garage door openers, walkie talkies and bluetooth systems are all examples of systems that operate in these bands. As will be seen later in the text, the success of these regulatory experiments in unlicensed bands have actually contributed to the open access and commons argument for spectrum usage.

2.4 Alternative Governance Regimes

The observance of the severe under utilization of spectrum resources [2] has encouraged the view that the scarcity experienced is an artificial one caused by the current spectrum governance regime employed. The static nature of the allocation decisions were first considered to be the cause for the inefficiency, however soon enough researchers started to point out many other drawbacks of the current regime including the ones mentioned in the previous section.

As possible alternatives to the current regime, two alternative proposeals regimes seemed to emerge; (1) property rights based spectrum usage (2) treating spectrum as "common" property open to all.

2.4.1 The Spectrum Property Rights Model

The property rights model basically argues that spectrum management should completely be left to market forces. The preliminary ideas in this direction have originated due to the economic critique of administrative spectrum regulation in an article by Leo Herzel, in 1951, who was a law student at the time [17]. The main critique was that licenses for spectrum portions are economics goods and economics goods are most efficiently allocated by market forces [18]. This concept was later emphasized in the landmark work of Ronald Coase [4] in 1959.

Coase argued that spectrum portions should be treated like land and private ownership of spectrum portions should be viable. The spectrum owners should be able to exclusively use their portions, or alternatively they should be able to buy, sell, and trade these portions among each other. The spectrum owners should be able to use their spectrum for any purpose they want (flexible usage). Thus, this approach can be considered as a call for fee-simple ownership of spectrum resources.

More specifically, in the proposed model, the available bandwidth is to be partitioned into non-overlapping blocks. The government employs certain market tools to determine the initial owners of these blocks, who will have the right to exercise exclusive usage of these blocks. The acceptable interference levels between the blocks will be determined by the government and they will be enforced [19]. The initial owners will then be able to trade or lease these blocks possibly in secondary markets.

Note that the property rights model is not the same as the licensing approach employed recently. It is true that the FCC has taken a big step forward in implementing a market based allocation through the initiation of spectrum auctions for distributing licenses. However important differences persist. As opposed to the rigidity of the command and control regime, in the property rights model, the owners of spectrum blocks have total control over their portion while enjoying flexible usage. The spectrum allocation in the property rights model is not static, as in the current regime, and blocks of spectrum can change hands. The allocation is not centralized, and market forces determine the final outcome. The transmission rights are permanently awarded to the license holders, instead of for limited periods, as in the case of command and control model.

The proponents of the spectrum spectrum property rights model argue that this model encourages innovation and most efficient use of spectrum resources, as the owners of spectrum will not suffer from political inefficiencies and will try to make the best use of their property. In fact they view this mechanism as one in which competition will be encouraged. Many also claim that in such a scheme, the transaction costs associated with license distributions and renewals will be avoided [11, 15].

2.4.2 The Spectrum Commons Model

The spectrum commons approach develops more of an engineering perspective. It is mostly inspired by the success and popularity of systems operating in the unlicensed bands. The proponents of the spectrum commons argue that the developing communication technologies have the ability to transform the spectrum resources into unscarce commodities by enabling the transmitters to share spectrum through cooperation and/or coexistence [3]. The communicating devices in such settings would avoid interfering with each other by a variety of techniques that could be implemented in a distributed manner.

Thus the proposed mechanism considers the available spectrum resources as common property, and the spectrum usage is to be non-exclusive and free of charge. All parties should be able to use the spectrum resources as long as they abide by some usage rules and restrictions, in the form of protocols or etiquettes [3, 18].

There are a variety of analogies used when analyzing the commons model. Those who put the emphasis on the prediction that the emerging technologies will transform the spectrum into "unscarce" resources use analogies with those of ships trying to avoid each other in a vast ocean [5], while those who put more focus on the interference avoidance capabilities of these emerging technologies put forth the analogy with highways [16]. In order to drive in a lane on a highway, the motorist does not need to ask for permission, or own the lane. He/she is free to drive on any lane as long as he/she abides by some driving rules. The moment a person starts violating the rules, (hopefully) he/she is pulled over and, in many cases, denied further access to the highway.

The highway analogy illustrates that the spectrum commons regime would be implemented in the form of a lightly controlled shared access [20]. This form of managed shared access raises the question of who would be the controller in such a scenario. The two main approaches are that the restrictions and rules governing the use of spectrum resources would be determined by the government, or by the private owners (this would be implemented under the framework of a spectrum property rights regime) [3]. However, the current agreement seems to be that the government (regulator) would be in charge of controlling the spectrum resources [16]. Note that this kind of implementation would correspond to the expansion of the unlicensed bands.

As mentioned earlier, the emergence of cognitive and software defined radio concepts, multiple antenna and multicarrier techniques as well as ultra wide band technologies and mesh network topologies, provide the potential tools that would enable the implementation of the spectrum commons approach [5]. These technologies would enable interference avoiding networks through overlay (using, for example, agile radios) or underlay architectures (using, for example, ultra wide band (UWB) technologies). They can also reduce interference by using lower transmit powers (mesh networks).

The proponents of the spectrum commons approach base their proposals on two arguments: (i) the theoretical insight which suggest that "removal of fences" in the spectrum space would lead to greater efficiency [11] and (ii) empirical evidence showing that regulatory experiments in the unlicensed bands have enjoyed popularity and technological innovation.

There are many advantages identified by the proponents of spectrum commons. They claim that such an approach would enable dynamic sharing of spectrum resources thus avoiding the inefficiency caused by static allocation. It would also enable applications that are not suitable for licensed applications (for example peer-to-peer applications) [15]. On top of these, a commons regime would also lower the transaction costs, and provide economies of scale, as the communicating parties would enjoy "unfenced usage" of spectrum resources. A common pool would also enhance mobility and range of services [21].

2.4.3 The Spectrum Debate

As mentioned earlier, the debate between the proponents of the spectrum property rights and the spectrum commons has not yet reached any tangible resolution or conclusion.

The spectrum property rights model is critiqued for potentially leading to the "holdup" problem [5] and artificial scarcity [18]. The holdup problem refers to the situation in which aggregation of resources become very difficult due to the private owners who ask for very large payments for contributing their pieces. This problem is well know in law and economics, and many of those advocating the spectrum commons approach believe a spectrum property rights model would eventually yield similar problems. It is also argued that the spectrum property rights model might violate the first amendment, as it restricts the freedom of speech [12].

The spectrum commons approach is most critiqued for its seeming vulnerability to the "tragedy of the commons" [5]. The overuse of common, yet scarce resources, like the open ocean fisheries, might lead to exploitation and even destruction of these common resources. Many argue that the spectrum commons approach would only be feasible in situations where spectrum is not a scarce resource. Given the overwhelming demand, they believe that spectrum will necessarily be scarce and a commons regime will yield very inefficient outcomes. As will be explained later in the text, some proponents of the spectrum commons believe this critique is a result of the misuse of terminologies and a confusion between the open access regimes and the spectrum commons regime.

[16] argues that the apparent need for a controller in the spectrum commons regime will lead to the regulator taking control of the spectrum resources and impose usage restrictions to enable the shared access. This situation, it contends, will inevitably lead

to the political inefficiencies that already plague the currently employed command and control regime.

Other voiced concerns regarding the spectrum commons model include the lack of QoS guarantees (due to unlimited number of users) and possible restraints on the technologies used due to coexistence rules [15].

The main problem in the ongoing debate is that the performance evaluation of the two approaches discussed above is not trivial. There seems to be a variety of performance metrics, some qualitative in nature, that could be used as a basis for evaluation. The ability of the proposed regime to induce technological innovation, the transaction costs associated with spectrum allocation, social welfare achieved can all be comparison metrics. However, an engineering oriented approach would be to compare the models based on system performance metrics, like the bandwidth utilization or user satisfaction (communication quality) in the system.

Note that in order to be able to make the above comparisons, both regimes need to be defined in detail for all management aspects listed in Section 2.2. However, the two regimes proposed are not clearly defined in terms of these aspects of spectrum management. On top of that, there seems to be no practical models which clearly specify how spectrum access and utilization would be implemented in either of the two regimes proposed. Even though the generic descriptions of the two proposals seem to be clear, the lack of precise modeling raises many unanswered questions regarding the implementation details. The exact nature of the controller or the enforcer mechanisms in both models are vaguely defined. The government's role in managing the controlled access in a spectrum commons regime, for example, is not clear. This lack of clarity also pervades the many issues related to transferability and duration of transmission rights, transactions costs and specific mechanisms involved in allocating the spectrum when needed. It is not clear, for example, how often the transmission rights are anticipated to change hands in a spectrum property rights model.

The ensuing gaps in the definitions, coupled with the inconsistent terminologies employed by the participating researchers lead to confusion and miscommunication. A striking example would be the “tragedy-of-taxonomy” as pointed out in [16], which refers to the apparent confusion between the terms open-access regimes and the spectrum commons, particularly as encountered in the engineering communities. The open access regime, considered by some to be yet another alternative to the existing proposals for governance models, refers to a scheme where spectrum has no owner, and access to spectrum is open to all with no limits or control at all. Thus, it is not the same as a spectrum commons. This confusion can partly be seen in discussions regarding the work of Noam [12], in which he proposes an “open access” scheme in which temporary (exclusive) spectrum access is granted to parties through congestion-based pricing. This work is often cited by those in favor of the spectrum commons approach, whereas many others argue that this approach can not be classified under either the open access or the spectrum commons models, and could in fact be considered as a form of exclusive usage [22].

2.4.4 Current Trends in the Debate and the Motivation for the Dissertation

There have been some recent calls ([3,5]) for the need for specific spectrum access and management models for implementation of the above-mentioned governance regimes. It is argued that development of such detailed schemes would provide the means for both technical and political/philosophical comparisons of the two approaches to spectrum governance. Another encouraging development is that some parties from both sides have managed to agree that the two models are not polar opposites and that there is a need for governance regimes that support both the exclusivity of property rights and the dynamic nature of shared managed access to a spectrum commons. Some hybrid schemes have been proposed, including end-state regulation, and the property rights with non-interfering easement. End-state regulation is a regulatory scheme that contains bands dedicated for spectrum property rights governance along with other spectrum portions allocated for commons [5]. In property rights with non-interfering easement, the owner of any given spectrum portion (primary user) is supposed to permit secondary users to communicate in that band as long as they do not interfere with the transmission of the primary user [5].

In this dissertation, motivated by the calls for practical models and the efforts to come up with compromise solutions, we introduce the D-Pass and the D-CPass models. In these models, we use the following characteristics to embody certain aspects of both proposals in the spectrum debate, and alleviate the static nature of the command and control structure leading to inefficiencies: (i) dynamic allocation of spectrum resources, (ii) market based allocation of spectrum resources, (iii) temporary exclusive usage.

We develop these models in the framework of a commercial network where a number of operators serve a geographical region populated with a number of users. The spectrum resources are allocated among the operators/users by a spectrum policy server (SPS) on a short term basis. The SPS is a central entity which determines the optimal partition of the available spectrum to maximize a predefined objective function in the system. Given the spectrum allocation decisions, the operators compete for users (customers) through demand responsive pricing. In this dissertation, we have focused on objective functions which reflect the bandwidth utilization or metrics which quantify user appreciation for services.

The focus is to illustrate that performance comparisons for different management regimes need solid models which describe the operational details of spectrum access. In this sense, we aim to emphasize an engineering perspective in the debate. We also aim to show that all aspects of management, including spectrum allocation, duration of transmission rights, as well economics, play major roles in the performance outcomes [23].

Chapter 3

The System Model

3.1 The Spectrum Policy Server and Dynamic Spectrum Access Models

The dynamic spectrum access approach raises the issue of enabling architectures for coordinated spectrum access. In [6–8, 24, 25], this issue is addressed via the introduction of a (spectrum policy server) SPS. The SPS is a central server responsible for coordinating spectrum access in a specified geographical region, as shown in Fig. 3.1. While the SPS, in a broad sense, can act as a broker for mediating spectrum access across heterogeneous systems and settings (see [26]), the role of the SPS in this work will be coordinating dynamic spectrum access in a local interference region. In this sense, the SPS's operation can be likened to that of the domain name server (DNS) or dynamic host configuration protocol (DHCP) in internet engineering. We assume that the geographical boundaries of the interference region that the SPS serves can be governed, for example, by either a signal strength threshold or a minimum throughput requirement that the SPS can use to determine whether a given user is located in the region it serves. We assume that the spectrum resources are owned by the government, and portions of spectrum available in the interference region are leased on a temporary basis through the SPS which acts like a clearinghouse.

We believe that with the advances in cognitive radio technologies, it will be possible for radios in a geographical region to identify and negotiate access to spectrum via the SPS for the serving area. Specifically, we assume that the SPS collects user-specific information, upon the entry of the user into the system, and mediates operator interactions to form a basis for spectrum allocation decisions. The user specific information can be gathered from the user through any of several mechanisms, e.g. a control channel that is dedicated to establishing associations between the users and the local SPS. The allocation decisions of the SPS could be based on maximization of any relevant prespecified criteria such as the bandwidth utilization in the system, the sum rate achieved or other system performance metrics. The assumption here is that with advances in cognitive radio technology, the radio nodes (users) will be able to participate in such dynamic spectrum allocation schemes that include market forces.

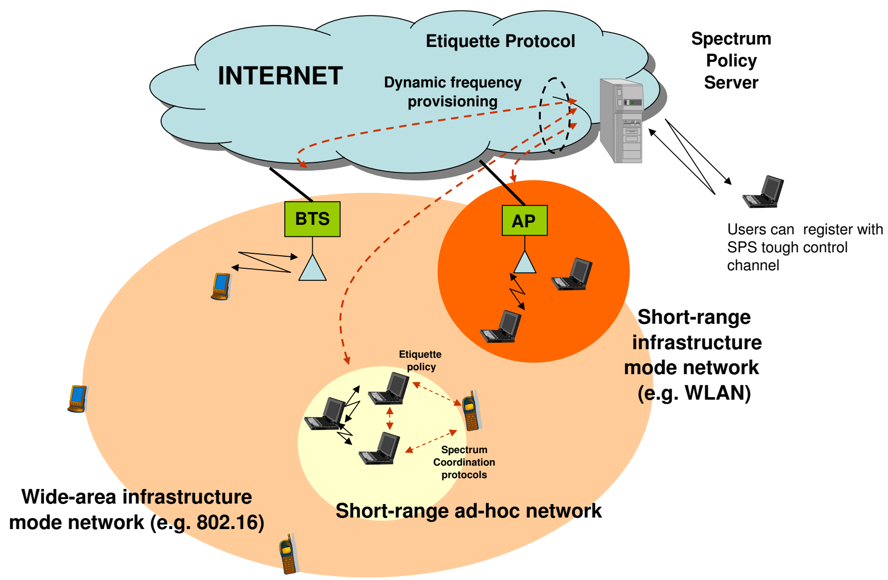


Figure 3.1: Spectrum Policy Server (SPS) enabling dynamic spectrum access in heterogenous environments.

In the D-Pass model, the operators are allocated portions of spectrum by the SPS and they compete for the potential users (customers) given this allocation through demand responsive pricing which will be described in the next section. The operators pay for the amount of bandwidth they were assigned by the SPS whether or not they actually utilize all of it (spectrum ownership). The partition of the bandwidth is valid for a short term duration which could be as short as a single communication session or possibly longer. Further, no operator can use the portion of spectrum which is assigned to its competitors. In this sense, the spectrum resource is considered under the framework of property rights with short term dedication. The SPS determines the optimal partition of the available spectrum among the operators to maximize a specified objective function. Various choices for the objective function will be explained later in the next chapter. The SPS mediates the operator competition through the realization of an iterative bidding scheme reminiscent of a simultaneous ascending auction [27].

In the D-CPass model, the operators dynamically compete for the spectrum as well as the customers through demand responsive pricing. Portions of spectrum are devoted to any operator that provides service to a user. The operators in return pay the SPS for the portion of the spectrum that they actually utilize. The operators compete for each user through an SPS-mediated iterative bidding scheme [6] that is reminiscent of a single-item ascending auction [28]. The result is that the SPS optimally partitions the total available bandwidth among the different user-operator sessions in order to maximize the specified objective function. Note that during the competition phase, there is no exclusivity and all operators have access to all the available bandwidth even though the contention is still regulated by the SPS. The spectrum usage is still exclusive; the operators transmit only in bandwidth portions allocated to users which they serve.

Note that both schemes consider operator competition settings in which users are free to select their providers on a short-term basis and both propose dynamic solutions where allocation of spectrum is short-term.

However, it is important to emphasize that these schemes differ in two major ways in terms of spectrum management: (1) In the D-CPass model, all available spectrum is open to all operators during the bidding (competition) period, while in the D-Pass model, operators have access only to the portion they are allocated individually; (2) In the D-CPass model, operators pay for bandwidth based on their usage (pay-as-you-go), while in the D-Pass model, operators pay for the portions allocated to them, whether or not they are actually able to utilize the whole spectrum portion.

3.2 Demand Responsive Pricing

Given that both models propose competitive spectrum allocation in which operators compete for the users, it is important to model user appreciation for the service. The user's response to any operator's offered transmission rate R [bps] with price asked P [units] is modeled through an acceptance probability $A(R, P)$ which reflects its willingness to buy the offered service at the asked price. In both models, the operators try to attract any given user by inducing a higher acceptance probability from the user.

The operators are distinguished by the fact that they may have different service spectral efficiencies r [bps/Hz] and also different costs involved in serving any given user. Note that the spectral efficiency may depend on various parameters like the technology used by the operator and the user, the density of the base stations belonging to the operator in the considered geographical region, and the location of the user. The result is that each operator offers a specific transmission rate R [bps] at a corresponding price P [units] to each potential customer. Note that the offered transmission rate R utilizes R/r $[Hz]$ of bandwidth, and the bandwidth utilization for any offered rate R changes across the operators due to differing spectral efficiencies. The operators determine their offers through maximizing a payoff function which reflects their expected profit. Operator profit models will be described in detail later in the text.

Intuitively, the acceptance probability $A(R, P)$ should have the following qualitative properties. It should be an increasing function of the rate R the user enjoys for a fixed price asked P while decreasing in P for fixed R. Mathematically, these properties are formulated as:

$$
\begin{aligned}
&\frac{\partial A}{\partial R} \geq 0, && \frac{\partial A}{\partial P} \leq 0, && \\
&\forall P > 0, && \lim_{R \to 0} A(R, P) && = 0, \\
& && \lim_{R \to \infty} A(R, P) && = 1, \\
&\forall R > 0, && \lim_{P \to 0} A(R, P) && = 1, \\
& && \lim_{P \to \infty} A(R, P) && = 0.
\end{aligned}
\tag{3.1}
$$

While there are several candidate choices for the function $A(R, P)$, we follow [9,29] and choose

$$
A(R, P) = 1 - e^{-Cu(R)^{\mu} P^{-\epsilon}} \tag{3.2}
$$

where μ is the utility sensitivity of the user, ϵ is the price sensitivity, and C is an appropriate constant. R affects the acceptance probability through $u(R)$ which stands for the utility a user achieves given it communicates with rate R. In this work, for simplicity, we ignore the role of transmit power in the user utility and instead parameterize u as a function of offered rate R only[1].

Note that the above formulation provides a means to tune each user's preference. In the limiting special case when $A(R, P) \approx CR^{\mu} P^{-\epsilon}$, acceptance probability is very similar to the Cobb-Douglas utility curves [31] that are used in economics to characterize the sensitivity to various inputs. A common example is characterizing the effects of inputs such as labor and capital on the production output. In our setting, the acceptance probability is the output that results as a function of the input parameters, namely the rate and price offers.

Note that there are several choices for the mapping $u(R)$ which assigns a utility level

[1]It is possible to consider the role of transmit power in the user utility as has been done in [30].

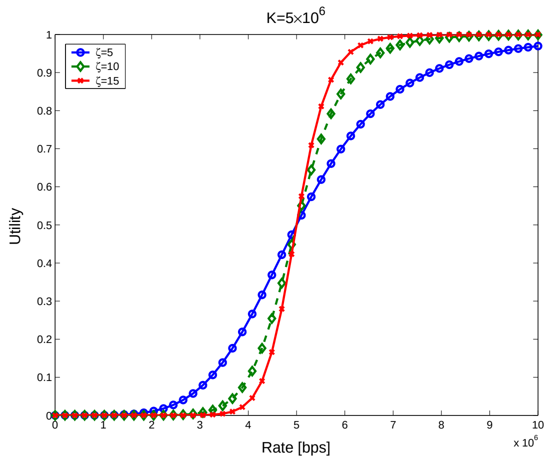


Figure 3.2: Utility for $K = 5 \times 10^6$ [bps].

for any given communication rate R. For example, in systems delivering voice services only, a step like mapping in which the utility level is zero for all values of R which are lower than a determined threshold R_{Thresh}, and, is maximum for all $R > R_{Thresh}$ seems to be the most appropriate. A concave utility function which achieves a single peak along the R dimension seems to be a good fit for delay tolerant data services (Email, http, etc.). In this work we consider a sigmoid utility expression that obeys a law of diminishing returns such as in [9, 29, 31]. Such sigmoid utility expressions are considered appropriate for real time applications. The generic form for a sigmoid utility is as expressed in (3.3).

$$u(R) = \frac{(R/K)^{\zeta}}{1 + (R/K)^{\zeta}} \tag{3.3}$$

where K $[bps]$ and ζ are parameters that determine the exact shape of the above sigmoid function. More specifically, K specifies the rate input at which the slope of the utility function is greatest. Note that the above expression gives normalized utility values in the interval $[0, 1)$ with the rate $R = K$ yielding a utility of $1/2$. The utility as a function of rate with $K = 5 \times 10^6$ [bps] for different values of ζ is illustrated in Fig. 3.2.

Fig. 3.3 illustrates the acceptance probability surface as a function of offered rate

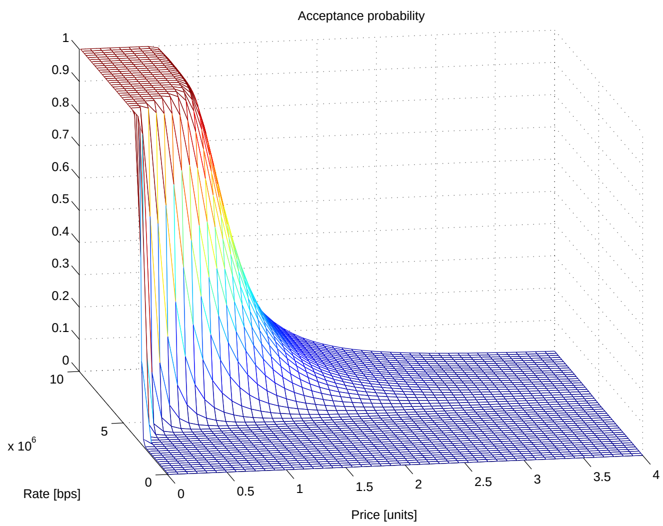


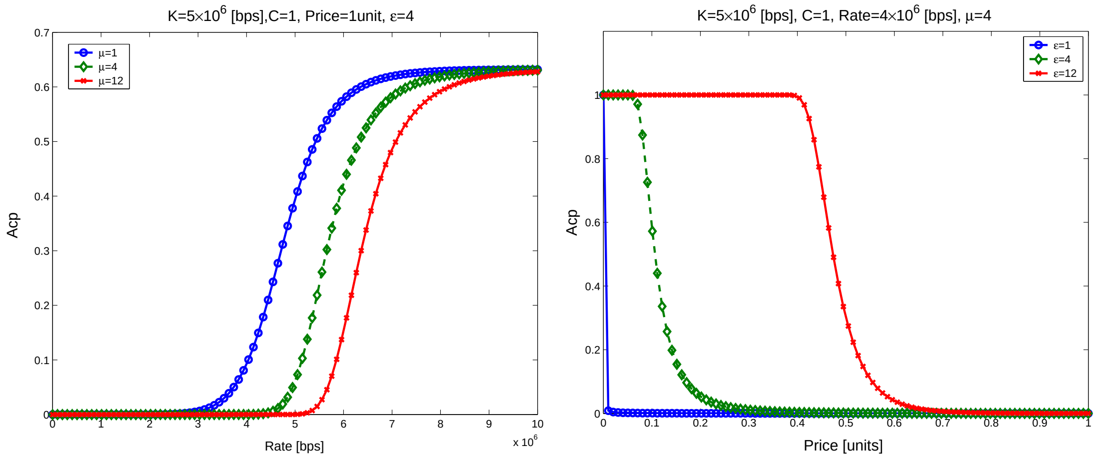
Figure 3.3: The acceptance probability for $K = 5 \times 10^6$[bps], $\zeta = 10$, $C = 1$, $\epsilon = 4$, $\mu = 4$.

R [bps] and asked price P [$units$] for the parameter values $K = 5 \times 10^6$ [bps], $\zeta = 10$, $C = 1$, $\epsilon = 4$ and $\mu = 4$. As expected, the acceptance probability is decreasing with price. We also note the effect of diminishing returns. Specifically, even for a low price, if the user is offered rates in excess of 5 Mbps its acceptance probability will not increase in this example. Figs. 3.4(a) and 3.4(b) illustrate the acceptance probability as functions of rate and price with various values of μ and ϵ, respectively.

3.3 SPS Based Dynamic Spectrum Access

A limited interference region where SPS has control of the available W_{A} is considered. A set of M operators compete to provide services to an arbitrary set of N users within the specified region. Each operator provides access to the users through its base stations (access points) that are located in the serving area.

Note that the "interference region" over which the SPS has control of spectrum allocations is an abstraction. The interference region is a geographical locality in which no two different operator-user pairs can use the same frequency band, due to interference. In principle, the spatial scale over which the SPS operates is determined by many factors, including the communication technologies employed by the operators (coverage)



(a) (b)

Figure 3.4: Rate and Price cross-sections for acceptance probability function with $K = 5 \times 10^6$ [bps], $\zeta = 10$, $C = 1$, for (a) $Price = 1$ [units] and (b) $Rate = 4 \times 10^6$ [bps].

as well as the location of the region (regulation). In this work, we assume that the SPS employs a simple physical layer mechanism in which it compares the receives signal strength or throughput to certain threshold values to determine whether a given user is in the region it serves.

For simplicity of illustration, we consider a session based system. Note that there could be several ways to define a session. In some contexts, every phone call can be a session. Alternatively sessions can be defined on a time scale basis in which each time slot corresponds to a session, or on a packet basis, in which transmission of a number of packets would correspond to a session. In this work, in our numerical evaluations, we assume that the channels between the operators and users are time-invariant and the path loss between any two entities in the system depends only on the distance between them. Therefore we envision a session to be based on user locations and define the session to be the time interval between any two consecutive changes in user locations. Thus, a new communication session is initiated which a change in any user's location. Note that such a model would be relevant to settings like office spaces in which end user occasionally change locations. Scenarios in which there is perpetual mobility could

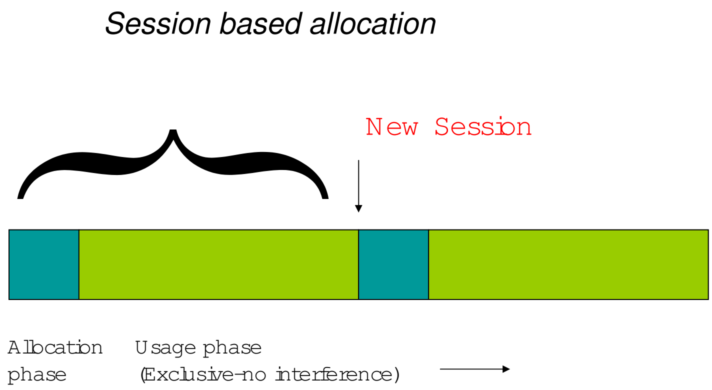


Figure 3.5: Session based allocation of spectrum resources.

be addressed by considering the various averaging approaches, in which the allocation decisions are based on averages over the duration of a given session.

Each session is made up of the spectrum allocation phase and the spectrum usage phase (Fig. 3.5). In the spectrum allocation phase, the spectrum resources are allocated to users or operators by the SPS. The spectrum allocations are valid for the remaining part of the session, the spectrum usage phase, until a new session is initiated.

In addition to the spectrum decision allocation, the associations between the users and operators are also finalized in the spectrum allocation phase. The potential users in the system have no long term subscription to any operator. The operators compete for the users in the spectrum allocation phase and the user-operator associations achieved at the end of the competition are valid for the immediate communication session only.

The spectrum allocation decisions in the spectrum allocation phase lead to an "interference free" system in which users are served in non-overlapping spectrum portions, i.e. at each point in the frequency spectrum, there is at most one user-operator pair communicating at a time. In this sense, the spectrum usage phase denotes exclusive use of spectrum resources by the communicating parties.

It should be noted here that the two models introduced in this dissertation denote two different mechanisms regarding the SPS assisted spectrum resource allocations and operator competitions. Thus the two models differ in the spectrum allocation phase alone.

The final spectrum allocation among the operators and users in the spectrum allocation phase is the result of a hierarchical (two-tier) optimization process. Each spectrum allocation vector declared by the SPS in the upper tier induces an operator competition in the lower tier resulting in a set of rate and price offers as well as user acceptance probabilities. The SPS iteratively produces that allocation vector which a predefined objective function. This objective function could be any metric of relevance to the system. The three different objective functions considered in this work relate to the expected bandwidth utilization, the mean acceptance probability for the users or the minimum acceptance probability. The precise definitions for these functions will be given in the next chapter. Fig. 3.6 illustrates this iterative optimization process, that is discussed in greater detail in Chapter 4 and Chapter 5.

3.4 SPS as a Coordinator and Mediator

We envision that the dynamic spectrum allocation mechanisms outlined in this dissertation can be implemented with minimal user involvement. Specifically, the user, upon entering into the system gets connected to the SPS through a control channel[2]. The SPS first collects the user specific information about its acceptance probability profile. It then mediates the competition between the operators to determine the one that could offer service to the user. Each operator adjusts its service offer in order to maximize

[2]This initial connection can be considered to be analogous to the operation of either domain name server (DNS) or dynamic host configuration protocol (DHCP) in internet engineering.

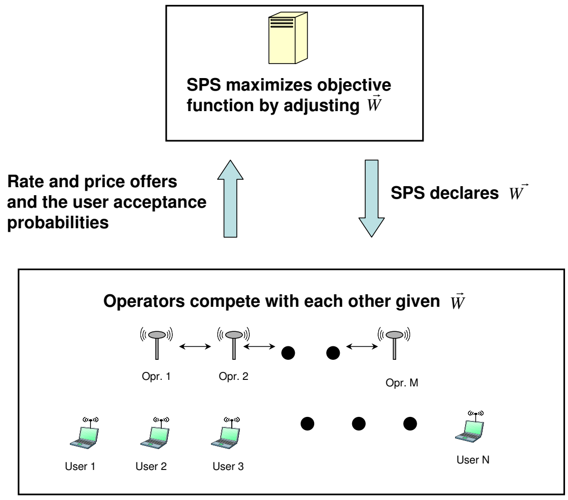


Figure 3.6: SPS based hierarchical optimization for maximizing the pre-defined system function.

its expected profit in the presence of competition. During the competition, each operator needs to be aware of the acceptance probability profiles for the users as well as the spectral service efficiencies it enjoys serving them. Note that in reality the service spectral efficiency with which any given operator serves a given user depends on many technical parameters. Recall that in this work, for the sake of simplicity, we assume that the service spectral efficiency is a function of the distance between the operator base station and the user location. We also assume that the operators find out about their service spectral efficiencies serving a user after some initial control messaging with the user. This initial control messaging and the initial registration of the user to the SPS constitutes the only interaction the user is involved during the spectrum allocation phase.

The scheme is composed of three steps (Fig. 3.7):

- Step 1: *New user(s) gets connected to the SPS. Acceptance profile $A(R, P)$ is communicated to the SPS. The operators determine the service spectral efficiencies for the user.*

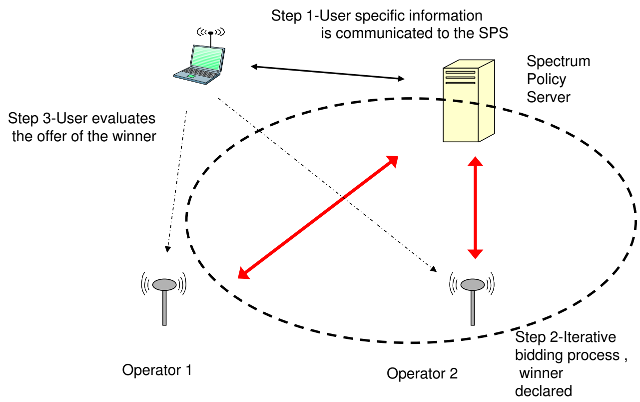


Figure 3.7: SPS as a mediator.

- Step 2: *Operators compete for users through rate and price offers. SPS mediates the operator competition through auction like schemes - either* D-Pass *or* D-CPass.
- Step 3: *The winning operator offers the winning bid* (R_{winner}, P_{winner}). *The winning bid is determined by the offer which induces the highest acceptance probability. The user decides to accept the service with probability* $A\left(R_{winner}, P_{winner}\right)$.

Note that at the end of Step 1, the SPS and the operators have all the relevant information regarding the user. Steps 2 and 3 denote actual execution and completion of the competition phase. During the spectrum allocation phase, the SPS acts on the user's behalf. Consequently, in Step 2, only the SPS and the operators are involved. In Step 3, the user makes the final decision whether or not to take the service offer of the winning operator. After step 3, the actual usage phase begins depending on the user's acceptance probability. We consider the allocation to be fixed for the entire session. With each new session, steps $1-3$ are repeated to determine the allocation followed by a new usage scenario for the session.

Three practical concerns that might arise due to the above algorithm are the privacy issues, the algorithm complexities and the scalability concerns.

As mentioned earlier, since the SPS acts on behalf of the user, it needs to have access to the acceptance probability profile for any given user. While it is true that collection of such user specific information is alerting from a privacy point of view, we believe that information regarding consumer preferences is only seldomly a potential threat to communication security. Data mining and consumer preference analysis are already commonly employed by commercial sites which try to make convincing shopping offers to their subscribers. Note also that in this algorithm, the exact location of the user in the system need not be known by either the SPS or the operators. The operators need to have knowledge of the path loss the signals undergo reaching the user. Such information can reliably be acquired by control messaging between the operators and users. In this sense, the algorithm outlined here can be considered as a secure one which can protect or flexibly be improved to protect privacy information relating to the users.

Note that, in case a user is overly concerned regarding the SPS collecting its acceptance probability profile, due to some reasons, the SPS simply could let the user be involved in the operator competition real time. Note however, that such an involvement would drastically increase the amount of control messaging between the operators and the user. Such a modification in the algorithm would not affect the operation of the mechanisms presented in this dissertation.

Another way to address the privacy concerns is through conveying partial information of the acceptance probability profile to the SPS. In this case, the SPS and the operators would have access to only part of the profile, and all allocation decisions would be based on this partial information. In Chapter 7, we model such an approach and study the effect of incomplete information of the acceptance probability profile, on the resulting system performance.

Note that the proposed models involve complicated operator competition procedures and computationally expensive optimization problems. The operator competition procedures involve iterative bidding algorithms, which could potentially take a number of iterations to converge. In Chapter 7 we address this issue by studying the performance degradation in the system when simplified operator competition algorithms are employed.

In both models, the SPS determines the optimum allocation vector through iterative mechanisms in which all possible spectrum allocation vectors are tested. Thus, it is apparent that there will be scalability issues in the presence of a large number of users or operators. Based on the fact that the number of users is almost always much greater than the number of operators, along with the fact that the number of operators in a real life system is often limited by regulations or entry barriers, we believe the main problem related to scaling is the case when there are too many users. As will be discussed later in the dissertation, we believe there can be a number of ways to avoid such scalability problems. One way would be to let the SPS have location information from the users (in expense of reduced privacy) and form a database mapping most plausible network geometries (user numbers and user locations) to optimum spectrum allocation vectors. Such a database can be prepared off-line before system initiation through simulations or it can be gradually built in time through real life cases. Once the database is mature, the SPS optimization algorithms can be reduced to a table lookup process, significantly reducing the convergence time. We believe there may be other ways of solving the scaling problem. Clustering the users into groups and treating each group as a single user might help reduce the complexity and convergence time. Such approaches will be discussed in Chapter 7.

Chapter 4

The D-Pass Model

In this model, the total available bandwidth W_A is partitioned into non-overlapping spectrum portions, each of which is allocated to an operator. The allocation vector $\vec{W} = (W_1, W_2, ..., W_M)$ for the M operators is determined by the SPS as a result of a optimization problem in which the system related performance function is maximized. Given the allocation vector, the operators compete simultaneously for the N users with rate and price offers (vectors). While making their vectoral offers the operators are constrained not to exceed the bandwidth allocated to each and they try to maximize their expected profit. The underlying operator competition results in an iterative bidding process that is reminiscent of a simultaneous ascending auction [27] where the bidding process is finalized when there are no new rate and price offers for any of the users. The SPS charges the operators for the amount of spectrum they are allocated, regardless of the extent of actual utilization.

Given any specific bandwidth partition among the operators, the operators try to attract users through demand responsive pricing [9,29]. Enjoying differing service spectral efficiencies $r\,[bps/Hz]$ for any given user, they make rate $R\,[bps]$ offers in exchange of a price P $[units]$ for the given user. The user's willingness to accept the service is modeled through an acceptance probability $A\,(R, P)$. Each offer an operator makes to a given user invokes an expected income to the operator associated with the $A\,(R, P)$ as well as the price asked P and the related fixed operational costs (independent of the offered rate R). The operator's total profit depends on the total expected income it achieves from serving the users and its payment for the spectrum portion it was allocated by the SPS.

The operator competition for the users is modeled in the form of an iterative bidding scheme inspired by the simultaneous ascending auction [27,32]. The simultaneous ascending auction was first introduced by the FCC in 1994 to sell spectrum licences and proved to be a practical and profitable means of spectrum allocation for the FCC. The operators make vectoral offers of $\vec{R}$ in exchange of vectoral prices $\vec{P}$ at each round, with each component of the $\vec{R}$ and $\vec{P}$ vectors denoting the rate offer and the price asked for the corresponding user. In each bidding round, the operators try to achieve the greatest acceptance probabilities for the users they would benefit from serving, while also maximizing their expected profits. In making their rate offers, the operators are obliged not to consume more bandwidth than that of the spectrum portion allocated by the SPS. The bidding process is terminated the first round there are no new bids for any user.

4.1 Operator Income Model

It is beneficial for the operators to stay in operation only if the total expected profit they achieve serving the users compensates the payments they make to the SPS for the spectrum portion purchased as well as the fixed operational costs involved in serving the users.

The individual expected income operator $i \in \{1, ..., M\}$ achieves serving any arbitrary user $n \in \{1, ..., N\}$ is expressed as

$$I_{i,n}\left(R_{i,n}, P_{i,n}\right) = A\left(R_{i,n}, P_{i,n}\right)\left(P_{i,n} - F_i\right), \tag{4.1}$$

where $R_{i,n}$ and $P_{i,n}$ are the offered rate and price, respectively, corresponding to user n. $F_i\,[units]$ is the fixed operational cost incurred by operator i while serving any user.

It is important to note the difference between the fixed operational cost F_i and sunk cost frequently encountered in pricing literature. Sunk cost refers to the type of cost that is incurred whether the service is provided or not. The fixed operational cost, on the other hand, is incurred only if the service is provided, and it does not depend on the quality(amount) of service. In our formulations we do not include the sunk cost. It is straightforward to prove that inclusion of the sunk cost in the profit expression does not affect the resulting performance of the mechanisms we develop in this chapter. Note that in most cases, the fixed operational cost F_i is implicitly related to the efficiency r_i. One would expect operators with higher fixed operational cost to be able to sustain greater efficiencies resulting from superior infrastructure [33]. A detailed discussion of the parameters involved in determination of F_i for a given operator is beyond the scope of this work, but a relevant reference on cost estimation for further reading is [28].

Note that the total expected profit of an operator i is the difference between the sum of the individual expected incomes from the users it serves and its payment for the bandwidth it has purchased from the SPS at the beginning of the communication session. This can mathematically be expressed as:

$$\begin{aligned} Q_i\left(\vec{R}_i, \vec{P}_i\right) = \sum_n A\left(R_{i,n}, P_{i,n}\right)\left(P_{i,n} - F_i\right) - W_i V, \\ i \in \{1, ..., M\}, \quad n \in \mathbf{N}^{'}, \end{aligned} \tag{4.2}$$

where n is the user index, and $\mathbf{N}^{'}$ is the set of users the specified operator makes offers to. $\left(\vec{R}_i, \vec{P}_i\right)$ are the offer vectors which specify the offers for each user. W_i is the amount of bandwidth owned by the operator and V $[units/Hz]$ is the unit bandwidth cost the operator need to pay to the SPS for unit spectrum they purchase. In this model we assume the unit bandwidth cost declared by the SPS is the same throughout its service area and it is the same for all operators.

4.2 SPS Based Dynamic Spectrum Allocation in D-Pass Model

At the beginning of every communication session, the available spectrum is partitioned among the operators. Spectrum portions allocated to operators are non-overlapping, with $\sum_{i=1}^{M} W_i \leq W_A$, where W_A is the total available bandwidth while W_i is the bandwidth of the spectrum portion allocated to operator i. Note that, in such a "property rights" scheme where the operators need to make payments for the total amount of spectrum they buy, irrespective of the extent of utilization, it is possible for the operators to end up in a loss. Such a loss would be realized in case the total expected income the operator achieves as a result of the operator competition is not high enough to compensate for its payments to the SPS for the spectrum portions it purchases. This is much like a company making investments to enter consumer markets and facing bankruptcy due to wrong assumptions regarding the market conditions. In our work, we assume that the SPS not only mediates the allocation of spectrum resources, but it also ensures a fair allocation in the sense that all operators are prevented from negative profits. Note that in order to accomplish this, the SPS might allocate zero bandwidth for those operators who would otherwise have negative profits, thus practically leaving them out of operation for the current session.

The exact bandwidth allocation vector $\vec{W} = (W_1, ..., W_M)$ is determined as a result of a maximization process in which the SPS maximizes a predefined system related objective function. The generic notation for the objective function in terms of system parameters is $Obj\left(\mathbf{r}, \vec{F}, V, \vec{W}\right)$. In this notation, $\mathbf{r}$ refers to the $N \times M$ dimensional spectral efficiency matrix with each element r_{ij}, $i \in \{1, ..., M\}$, $j \in \{1, ..., N\}$ corresponding to the spectral efficiency the operator i enjoys while serving user j. Note that this matrix depends on the exact locations of the users. $\vec{F}$ is the vector of fixed costs with each element denoting the fixed operational cost for the corresponding operators. V is the unit bandwidth cost the operators need to pay to the SPS for unit spectrum they utilize. The role of these cost variables in the operator competition is described in detail later in the text. Having emphasized the effect of system geometry and cost structure on the objective function, we will use the notation $Obj(., \vec{W})$ for the sake of brevity in the rest of the thesis.

The SPS maximizes the objective function subject to the constraints that the total allocated bandwidth does not exceed the total available bandwidth W_{A} and that no operator ends up with negative profit for the current session. Consequently, the SPS optimization problem can be expressed as:

$$\begin{aligned} \max_{\vec{W}} \; Obj\left(., \vec{W}\right) \quad \text{st.} \; & \sum_{i=1}^{M} W_i \leq W_{\mathrm{A}} \\ & Q_i^S \geq 0, i \in \{1, 2, ..., M\}. \end{aligned} \tag{4.3}$$

Q_i^S refers to the total expected profit of operator i for the considered session. Note that the maximum achievable values for $Obj\left(., \vec{W}\right)$ depend on many parameters including the user locations, cost structures and the service spectral efficiencies of the operators.

The SPS optimization problem is solved using a sequential search method in which all combinations of bandwidth allocations among the operators are tested and the one which achieves the greatest objective value is chosen as the optimum allocation. For any tested allocation vector $\vec{W}$, the operators compete with each other for the users considering the bandwidth constraints imposed by the allocation vector, as illustrated for the case of $M = 2$ operators in Fig. 5.1.

In this work, we consider the following objective functions for the SPS: (1) total expected bandwidth utilization in the system (EBU) ; (2) the average acceptance probability that a user accepts the offered service ($\overline{Acp}$); (3) the minimum acceptance probability that a user accepts the offered service (Acp_{min}). Note that these objective functions are defined below.

1. Maximizing the Expected Bandwidth Utilization (EBU):

$EBU(.,\vec{W})$ [Hz] is defined as the sum of the expected bandwidth utilizations of the users. In this sense, it is a function of the bandwidth allocation vector $\vec{W}$ as well as the user locations and the cost parameters in the system:

$$EBU\left(.,\vec{W}\right) = \sum_{n=1}^{N} A_n^f\left(.,\vec{W}\right) W_n^f\left(.,\vec{W}\right). \tag{4.4}$$

In the above equation, A_n^f and W_n^f refer to the winning bid acceptance probability and bandwidth usage achieved as a result of the operator competition over user n. W_n^f depends on the winning rate offer and the winning operator's spectral efficiency through the relation $W_n^f = R_{winner}/r_{winner}$.

2. Maximizing the Average Acceptance Probability ($\overline{Acp}$):

   The average acceptance probability of the users is defined as:

$$\overline{Acp}\left(.,\vec{W}\right) = \frac{1}{N}\sum_{n=1}^{N} A_n^f\left(.,\vec{W}\right). \tag{4.5}$$

   where N and A_n^f are as defined above.

3. Maximizing the Minimum Acceptance Probability (Acp_{min}):

   The minimum acceptance probability is defined as:

$$Acp_{min}\left(.,\vec{W}\right) = \min\left(A_1^f\left(.,\vec{W}\right),...,A_N^f\left(.,\vec{W}\right)\right) \tag{4.6}$$

   In maximizing the minimum acceptance probability, the SPS follows a max-min fairness criteria and achieves that acceptance probability vector $\vec{A^f} = [A_1^f A_2^f ... A_N^f]$ for which A_n^f can not be increased without decreasing $A_{n^*}^f$ for some n^* such that $A_{n^*}^f \leq A_n^f$. Thus in maximizing the above quantity the SPS emphasizes a fairer allocation as opposed to those considered earlier.

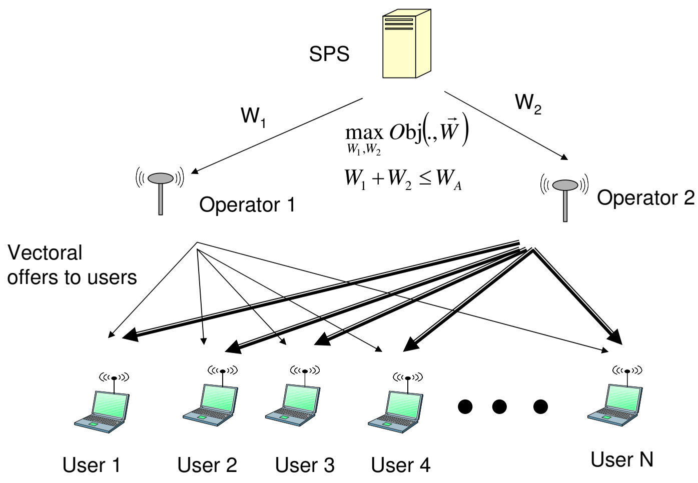


Figure 4.1: SPS mediating iterative bidding processes among 2 operators for N users.

The operators compete with each other in the form of an iterative bidding scheme that is reminiscent of simultaneous ascending auctions. In this scheme, details of which will be described later in the text, the operators make bids in rounds in the form of vectors $\left(\vec{R}_i, \vec{P}_i\right) \in R^{N+} \times R^{N+}$ where i is the index for the operator making the offer. Each of the N entries of the offer vectors $\left(\vec{R}_i, \vec{P}_i\right)$ specify the rate offers and the price asked by the operator i for the corresponding user. The result of the operator competition determines at most one of the operators as the winner for each user, who then makes its respective winning service offer as the final offer.

4.3 Operator Competition and Iterative Bidding in D-Pass Model

We assume that in the presence of a number of service offers from different operators, any specified user accepts the service offer of the operator which induces the greatest acceptance probability, with that corresponding acceptance probability, and ignores all other offers (practically setting their relevant acceptance probabilities to zero). Thus, in order to gain the right to serve any given user, an operator needs to make the offer which induces the greatest acceptance probability among all other operators.

Consequently, the operator competition for the users can be modeled as an iterative bidding mechanism in which the operators make bids in rounds, in the form of rate and price offer vectors. The goal of the operators at each round is to come up with offers that would maximize their expected profits by inducing greater acceptance probabilities than those of the competing offers for each user.

Note that while competing for a number of users simultaneously, each operator is making use of the limited spectrum portion allocated to it, partitioning it among the rate offers it makes to different users. In this sense, the operator competition can be likened to a situation in which a number of goods (users) are to be partitioned among a number of buyers (operators) with budget constraints. The multi-item auction theory in the economics literature [34] presents many different mechanisms through which multiple items can be assigned to numerous bidders in such settings.

In this work, we have developed a bidding mechanism which is similar to simultaneous ascending auctions [27, 32] in terms of implementation. Even though simultaneous ascending auction mechanisms do not always achieve the optimal operating points, as frequently mentioned in auction theory literature, we believe it is a good match for wireless communications settings due to the simplicity of the mechanism.

Below, we first present a brief discussion on simultaneous ascending bid auctions before proceeding to provide a detailed overview of the proposed bidding scheme considered here.

4.3.1 The Simultaneous Ascending Auction

The simultaneous ascending auction was first developed in 1994 for use in the US FCC's spectrum auctions. It is a simple extension of the single item ascending (English) auction to the case in which a number of bidders (buyers) simultaneously compete for multiple items.

The bidding occurs in rounds. At each round the bidders make price bids for the items they are interested in. At the end of each round the auctioneer declares the "standing high bid" and the corresponding highbidder, for each item. The auctioneer also declares the minimum bid for each item for the next round, as the sum of the standing high bid and a predetermined bid increment for the item. The predetermined bid increments are often the larger of a fixed amount and a fixed percentage (usually 5% or 10%) of the standing high bid [27, 32]. A participant who is not the current highbidder for an item it is interested in, needs to increase it's price bid next round to exceed the current standing high bid by at least the bid increment amount, in order to be in the winning position. Note that the enforcement of the minimum bid rule aims at avoiding lengthy bidding periods in which bidders exceed the standing high bids only by negligible amounts each round. The bidding is finalized at the first round in which no bidder can raise its bid on any of the items anymore. Each item is awarded to the bidder who holds the current standing high bid for the item.

In such auction settings, the bidders can often end up with only part of what they desire. Such situations can often lead to the exposure problem in which the bidder ends up with items that are not useful to it by themselves only, and only are profitable to own in the company of some other items which have been sold to different parties. A simple example is an operator who wins only one of the two adjacent spectrum portions which is not sufficient for profitable operation by itself. In order to avoid this problem, in most versions of the simultaneous ascending auctions, the bidders are allowed to withdraw their bids. Such withdrawals, however are often punished with penalties. In some other versions, bid withdrawal is not allowed. The bid for any item is considered as a commitment by the bidder.

Fig. 4.2 provides a simple illustration. Two bidders compete for two objects (cell phones). Bidder 1 has a budget of 5 dollars while bidder 2 has a budget of 4.5 dollars. The minimum bid increment is assumed to be 0.5 dollars. At the first round, bidder

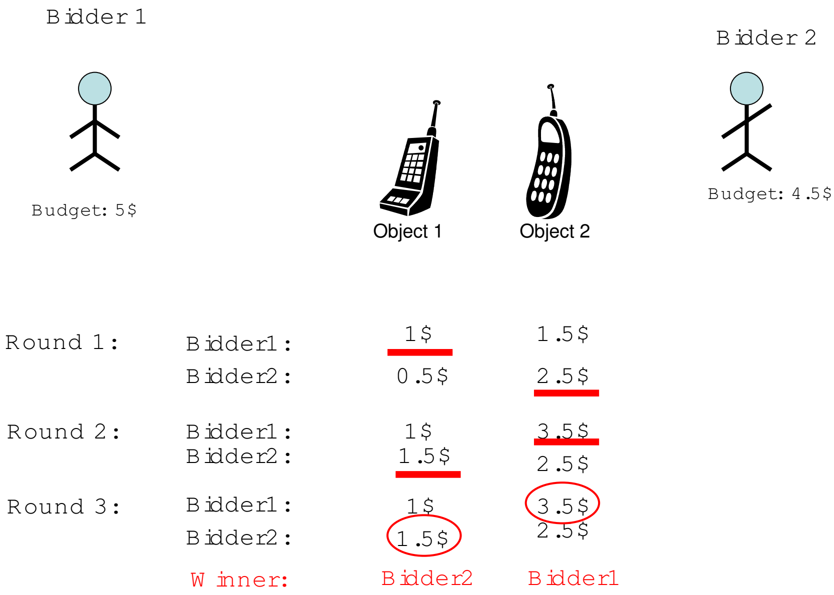


Figure 4.2: Illustration of simultaneous ascending auction.

1 is the highbidder for the first object and bidder two is the highbidder for the second object. In the second round, bidder 1 exceeds bidder 2 for the second object and bidder 2 exceeds bidder 1 for the first object. Note that, the standing high bids for each object from round 1 are not withdrawn. Since the bidders reach their budget limit, they can not make any new offers and the auction is finalized in round 3. Note that this example is meant to illustrate the mechanism of bidding. We are not considering the valuations of the bidders for the objects, and we do not reflect on the bidding strategies in this particular illustration.

The simultaneous ascending auction mechanisms also specify rules regarding the activity and eligibility of the bidders. Interested readers can find discussions relevant to these rules in [27, 32].

4.4 The Iterative Bidding

Inspired by the generic rules cited above for a simultaneous ascending auction, we propose a simple bidding scheme, as a means of operator competition.

In the proposed bidding scheme, the operators make bids in rounds. The bids are in the form of rate and price offer vectors. At any given round, for any specified user n, the greatest induced acceptance probability by the offers made is declared by the SPS as standing high acceptance probability (H_n) for that user. At the end of each round, the SPS computes the minimum acceptance probabilities ($M_{i,n}$) for the next round for each user-operator pair considering the standing high acceptance probability H_n for the user and the minimum acceptance probability increments enforced ($I_{i,n}$) for any given operator i regarding user n. Note that $I_{i,n}$ may differ for different operators for a given user n, as the operator who is currently the highest bidder (H bearer) need not increase its acceptance probability in the next round, while the opponent operators need to exceed H_n by at least some predetermined value δ_n in order to claim the user. Note that δ_n can be considered as an auction design parameter and is determined by the SPS. In case a number of operators simultaneously induce the H for the user in any given round, only one of them (randomly determined by the SPS) is treated as the current winner, while the rest are obliged to make more attractive offers for the user in the next round in order to be in the winning position. The SPS declares the M values for the next round in the form of $\vec{M_i} \in [0,1)^N$ vectors where each element in $\vec{M_i}$ refers to the minimum acceptance probability operator i needs to induce next round in order to be in the winning position for the corresponding user. The iterative bidding is initialized by allowing the operators to choose their service offers without consideration of the opponent strategy. It is finalized the first round in which there is no new offers (no increase in H) for any of the users.

A technical issue related to the minimum increment policy is the fact that for any positive price $P > 0$, the acceptance probability, by definition, is always less than 1; $A(R, P) < 1$.

Considering the above, we define the M for any user n and operator i as:

$$M_{i,n} = \min\left(H_n + I_{i,n}, A_{max}\right) \tag{4.7}$$

where $A_{max} < 1$ is a predefined constant, which is set as close to 1 as possible. H_n is the standing high acceptance probability for the user from the previous round and $I_{i,n} \geq 0$ is the minimum acceptance probability increment for operator i regarding user n, declared by the SPS. $I_{i,n}$ is defined as:

$$I_{i,n} = \begin{cases} 0 & \text{if operator } i \text{ has the greater bid from last round,} \\ \delta_n & \text{otherwise,} \end{cases} \tag{4.8}$$

where $\delta_n > 0$ is the increment amount set by the SPS. There can be different approaches for setting δ_n.

In this work, we have considered two different approaches for determining δ_n: increasing increment and decreasing increment. In the increasing increments approach, the increment is set to be a certain percentage of the H,

$$\delta_n = \eta \times H_n,$$

where η is a predefined percentage. Note that in this approach the SPS imposed increments increase throughout the bidding period, since H_n increases (or stays the same) with each iteration. We have also considered diminishing increments where

$$\delta_n = \eta \times (1 - H_n).$$

In this approach, the increment is actually diminishing in each round. Our observation is that the specific choice of increment policy among these alternatives does not significantly affect the comparisons presented in this thesis.

We further impose the rule that if any operator happens to make an offer inducing acceptance probability A_{max} for any user, it wins the competition for the user and the other operators may no longer make any offers for the specified user. In case more than one operator makes the offer inducing acceptance probability A_{max} for the first time simultaneously, one of them is chosen by the SPS as the winner randomly. The SPS declares the user for which the auction is finalized this way in the form of a boolean vector $\vec{K} \in \{0,1\}^N$. For those users for whom the competition is finalized, the corresponding element of $\vec{K}$ is set to zero, while for others it is set to 1.

While making their bids, the operators consider their costs and maximize their expected profits at each round, subject to the bandwidth constraints set by the allocation vector and the bidding rules mentioned above. As in some versions of simultaneous ascending bid auctions, we enforce the additional rule that the current H inducing offers should not be withdrawn; if operator i is the one who has achieved the H_n for the specific user n in the previous round, it can not make an offer which implies a lower acceptance probability than H_n for that user, otherwise it is penalized (with negative infinity payoff).

Considering the rules cited above, the total expected profit optimization problem for any operator at each round can be mathematically expressed as:

$$\max_{\vec{R}_i,\vec{P}_i} \left(\sum_{n=1}^{N} \beta_{i,n} \left(R_{i,n}, P_{i,n} \right) - W_i V \right) \text{ st. } \sum_{n=1}^{N} Wo_{i,n} \leq W_i. \tag{4.9}$$

In the above formulation, i is the index for the operator. $\vec{R_i}$ and $\vec{P_i}$ refer to the offered rate and price vectors for the operator, respectively. W_i is the spectrum portion allocated to operator i and $\beta_{i,n}$ is a function which reflects the expected income from user n for operator i as defined in (4.1), subject to the rules of the iterative bidding cited above. $Wo_{i,n}$ is the bandwidth consumption relevant to the rate offer for user n.

$\beta_{i,n}$ can mathematically be expressed as follows:

$$\beta_{i,n}\left(R_{i,n}, P_{i,n}\right) = \begin{cases} 0 & \text{if } \left(A\left(R_{i,n}, P_{i,n}\right) < M_{i,n} \text{ or } \vec{K}_n = 0\right) \text{ and } I_{i,n} \neq 0 \\ -\infty & \text{if } A\left(R_{i,n}, P_{i,n}\right) < M_{i,n} \text{ and } I_{i,n} = 0 \\ A\left(R_{i,n}, P_{i,n}\right)\left(P_{i,n} - F_i\right) & \text{if } A\left(R_{i,n}, P_{i,n}\right) \geq M_{i,n}, \end{cases} \tag{4.10}$$

where $M_{i,n}$ stands for minimum bid required for user n regarding operator i, as defined in (5.7). $Wo_{i,n}$ can be expressed as:

$$Wo_{i,n} = R_{i,n}/r_{i,n} \tag{4.11}$$

where $r_{i,n}$ $[bps/Hz]$ is the spectral efficiency of operator i for user n.

Note that the definition implies that for any given user n, if the operator does not exceed the H by the minimum increment even though it is not the H bearer from the previous iteration, or if the competition for the user is already blocked by the SPS, the operator will gain zero income. If the operator is the H bearer from the previous round and it lowers the acceptance probability it has induced in the previous iteration, it is penalized by receiving negative infinity payoff. An operator who is either the H bearer from the previous round (and does not lower the acceptance probability), or who successfully induces greater acceptance probability for the user, than that of the H from the previous round, simply achieves the expected income as defined in (4.1).

Note that operators trying to maximize their total profits with $\beta_{i,n}$ defined as above avoid bid withdrawal (M bearers do not lower induced acceptance probability), try to exceed the SHAP relevant to users and avoid making any offers for users for whom competition is finalized by the SPS (due to another operator already achieving A_{max}).

The iterative bidding, by design, is finished in a finite number of iterations for both the increasing increments and diminishing increments approaches. This follows from the fact that no bid withdrawal is permitted (for offers inducing the standing high acceptance probability) and that there should be an increase (by the corresponding minimum bid increment) for at least one of the users in the system at each iteration as long as the iterative bidding is not finalized.

We now state a theorem on the properties of the solution to problem in (4.9). This theorem also shows that in the D-Pass model, the operators economize on spectrum, in a way similar to the Faulhaber's predictions in a property-rights regime [5].

Theorem 4.4.1. *For any operator i, the solution of the optimization problem in (4.9) satisfies the constraint with equality;* $\sum_{n=1}^{N} Wo_{i,n} = W_i$.

Proof. Consider any fixed price offer vector $\vec{P_i}$ and any rate offer vector $\vec{R_i}$ such that $\sum_{n=1}^{N} Wo_{i,n} < W_i$. Assume that the rate offer for an arbitrary user a, is increased by some specified value Δ, i.e., increased from $R_{i,a}$ to $R_{i,a} + \Delta$. This increases the associated acceptance probability to $A\left(R_{i,a} + \Delta, P_{i,a}\right)$. Considering (4.10), such an increase would potentially also increase $\sum_{n=1}^{N} \beta_{i,n}\left(R_{i,n}, P_{i,n}\right)$ (never decreasing it), not altering the second term $(W_i V)$ of the objective function in (4.9). Consequently the overall effect of such an increase would be an increase in the achieved total expected profit. Thus, the operator would keep increasing offered rates as long as the allocated bandwidth is not exceeded. It thus follows that the solution of the problem should always saturate the constraint $\sum_{n=1}^{N} Wo_{i,n} \leq W_i$. □

The above theorem shows that in all rounds, both operators will offer all of the spectrum portions allocated to them by the SPS. This can be considered as a natural result of operating in a property rights like regime; since the operators are charged for all of the spectrum portions they control, irrespective of the extent of utilization, it is always better to fully utilize them. Thus, they are encouraged to economize on spectrum.

Theorem 4.4.2. *For any given fixed system geometry (user locations and number of users) and fixed operational costs $F_i, i \in 1, 2, ..., M$, the maximum achievable SPS objective function is decreasing in unit bandwidth cost V $[units/Hz]$.*

Proof. Consider the operator optimization in (4.9). Note that the solution of the operator optimization problem does not depend on V, as V is only included in the second term of the objective function which does not involve any of the optimization parameters. Consequently, for any declared $\vec{W}$, the value of objective function $Obj(., \vec{W})$ does not depend on V. On the other hand, the resulting operator profits diminish with increasing V as their income from the users do not change and payments to SPS increase linearly with V. Thus, the space of allocation vectors $\vec{W}$ for which the operators achieve non negative total profits diminish with increasing V. Consequently, the optimization domain for the SPS in optimization problem (4.3) shrinks, leading to potential decrease in the maximum achieved value for the objective function, i.e., $Obj^* (V, .) \geq Obj^* (V + \Delta, .)$ for $\Delta > 0$. □

This theorem shows that increasing unit bandwidth cost hurts the SPS objectives considered in this thesis.

4.5 Long Term Allocation of spectrum resources in D-Pass Model

So far the scheme we have described considers spectrum resource allocation for a single communication session only. We now briefly describe how this scheme could be extended to address those cases in which the spectrum allocation is considered for longer durations.

We parameterize the duration of spectrum allocation decision by T which denotes the number of communication sessions for which the decisions are valid. Note that with increasing T, the scheme approaches to a static allocation approach.

The bandwidth allocation vector chosen by the SPS is valid for T sessions in a row. Although the SPS decisions are made considering T sessions, we assume that the operators still compete for users at each instantiation of user locations (only the spectrum management is in the form of static governance for the T sessions), through the iterative bidding described in section 4.4 . Consequently, the long term SPS optimization problem can be expressed as:

$$\begin{aligned} & \max_{\vec{W_T}} \overline{Obj_T}\left(., \vec{W_T}\right) \\ & \text{st.} \sum_{i=1}^{M} W_i \leq W_{\text{A}}, \qquad Q_i^T \geq 0, \forall i \in \{1, 2, ..., M\} \end{aligned} \tag{4.12}$$

where $\vec{W_T}$ refers to the allocation vector which is valid for T communication sessions and Q_i^T is the final profit of operator i at the end of T sessions, which is defined as the sum of the session based profits for each of the T sessions. $\overline{Obj_T}$ is the average value for the SPS objective function considered over T sessions.

Note that the above described operation model is similar to the operation of present day service providers. The service providers purchase licenses for spectrum portions from the FCC for long durations (approximately 10 years, subject to extension). Their decision to actually purchase the spectrum portions at the requested prices depends on their long term profitability. However, they keep changing their market penetration strategies several times during the 10 years they have the right to use the specified spectrum portions.

4.6 Numerical Experiments for the D-Pass Model

In this section we provide numerical results corresponding to the D-Pass schemes described earlier in the text. As our experimental setup, we consider $M = 2$ operators located in a simple linear region. Each operator has only one base station. Recall that

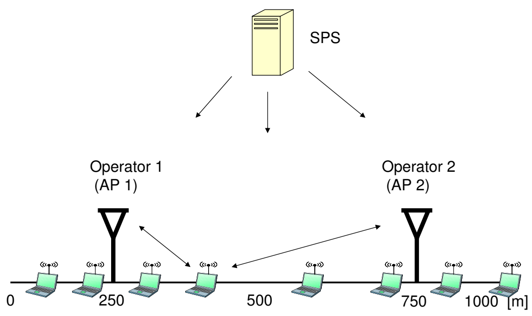


Figure 4.3: Geographical region with two operators.

in our numerical experiments each change in user locations denote the beginning of a new communications session. The linear region and the locations of the base stations are as depicted in Fig. 4.3, which shows an instantiation of user locations for 8 users.

The base station locations are fixed and the user locations are randomly determined assuming a uniform distribution for each user. Each data point is generated by testing 300 different instantiations of user locations (communication sessions). The results are then averaged over all 300 different realizations and the average values are presented in the following figures.

The spectral efficiency between base station i, where i is the index for the operator, and the user's mobile terminal is determined as

$$r_i = \log_2 \left[1 + \frac{P_\mathrm{s}}{N_o} \left(\frac{d_i}{L/4} \right)^{-2} \right], \tag{4.13}$$

where P_s is the signal power, N_o is the AWGN variance, d_i is the distance between the base station i and the terminal, and L is the total length of the linear region in Fig. 4.3 ($L = 1000$ m). We set $P_\mathrm{s} = 2N_o$, which guarantees a SNR $= 3$ dB at the distance of $L/4 = 250$ m from the base station.

The available bandwidth considered is $W_A = 10$ MHz and the users are assumed to have utility parameters used in Fig. 3.2.

In order to keep the exhaustive search tractable, the bandwidth is quantized to be made of basic units of approximately 380 kHz wide. The SPS optimization problem is then solved using a brute force search method in which all combinations of bandwidth allocations among users are tested and the one which achieves the greatest objective value is chosen as the optimum allocation.

Recall that the fixed operational cost F_i for operator 1 and 2 can be a complicated function of many parameters including the number of base stations, physical layer technology used and the like. In this thesis, for the sake of simplicity we consider a symmetric cost structure with $F_1 = F_2 = F$ [units]. We also assume that the SPS will be charging both operators at the same variable cost rate V [units/Hz].

In the numerical experiments, we test four different schemes. As mentioned in section 4.2, we consider the expected bandwidth utilization EBU maximizing scheme , average acceptance ($\overline{Acp}$) maximizing scheme and the minimum acceptance probability (Acp_{min}) maximizing scheme. For comparison purposes, we also consider the equal partition (EP) scheme in which each operator is allocated exactly half of the available spectrum, subject to the constraint that the operator achieves positive profit at the end of the competition, otherwise it is allocated no bandwidth.

Fig. 4.4 shows the achieved expected bandwidth utilization in a 8 user system, as function of cost parameters F and V, for the EBU maximizing scheme. It is observed that, the achieved expected bandwidth utilization is decreasing in both cost parameters F and V. We also observe (not shown here) that the same decreasing pattern remains for the schemes where the SPS either maximizes the minimum acceptance probability or equally partitions the bandwidth.

To develop a better understanding for possible comparisons among the considered schemes as well as the effect of increasing cost on various performance metrics, we consider two different trajectories in the F-V plane shown in Fig. 4.4. We conduct

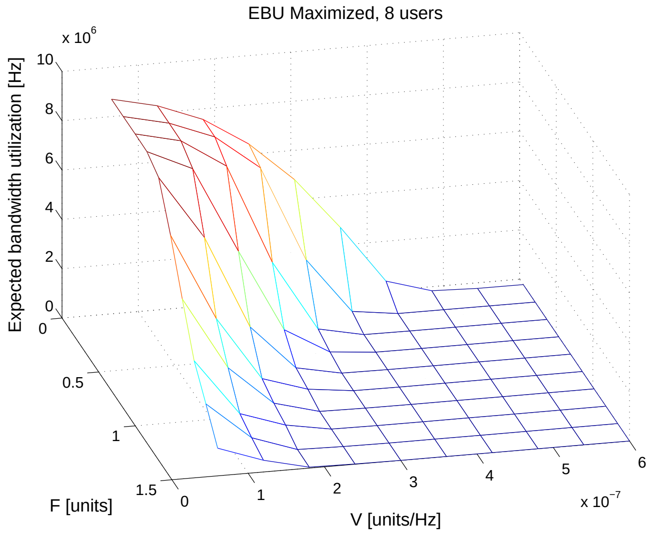


Figure 4.4: Expected bandwidth utilization in EBU maximizing system in a 8-user system.

experiments for many (F, V) pairs on these two trajectories that are shown in Fig. 4.5. One of the trajectories follows (F, V) pairs along a line such that $VW_A/F = 0.5$. The other trajectory follows (F, V) pairs along a line such that $VW_A/F = 4$. Note that the former trajectory reflects a cost structure in which the variable spectrum cost VW_A has relatively lower weight against F, as opposed to the latter trajectory. Consequently, we refer to the first trajectory as the F-dominated trajectory and the latter one as the V-dominated trajectory throughout the rest of the dissertation.

We parameterize points on the trajectories by the total cost metric $F + VW_A$. Each value of $F + VW_A$ denotes a unique (F, V) pair on the considered trajectory and increasing $F + VW_A$ corresponds to progressing along the trajectory further away from the origin.

In Figs. 4.6 and 4.7, we present the expected bandwidth utilization and the average number of users served, as functions of the cost metric $F+VW_A$ $[units]$, with $VW_A/F =$ 0.5 (F- dominated) and $VW_A/F = 4$ (V-dominated), respectively. The average number of users served in the system refers to the number of users for which the final offered rates as well as the final acceptance probabilities are positive.

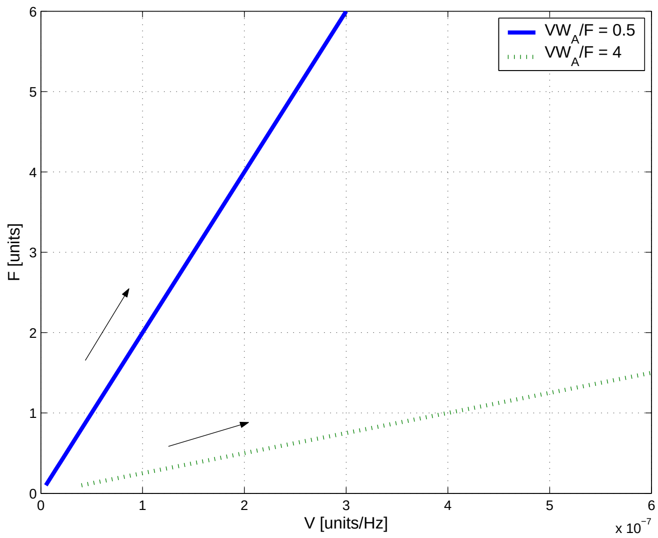
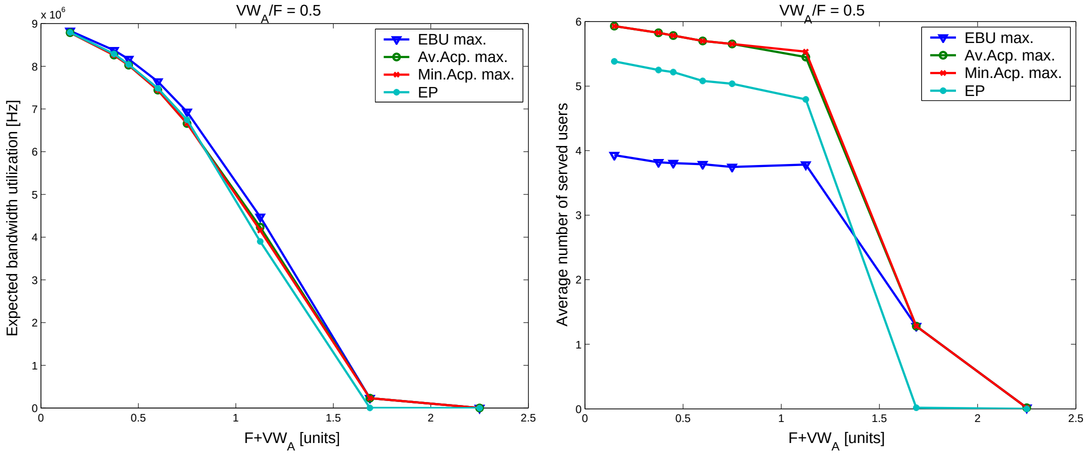


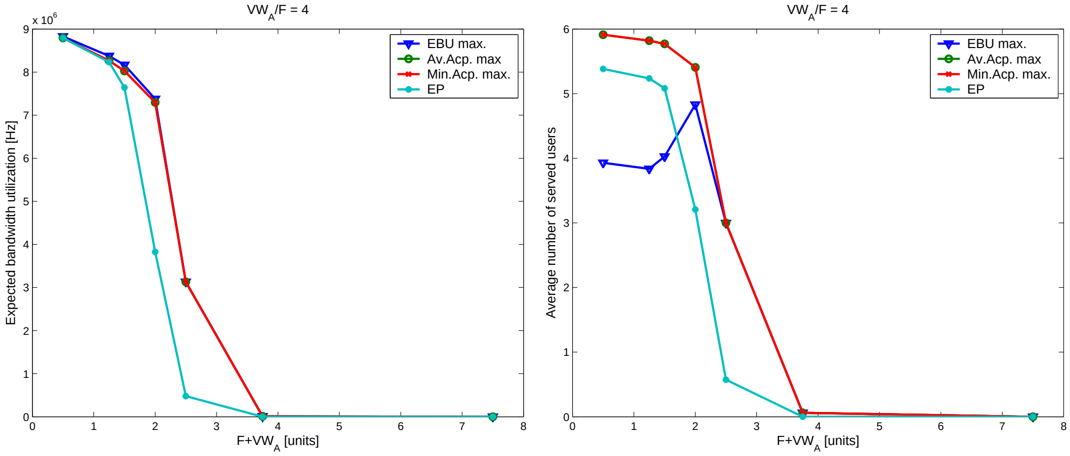
Figure 4.5: Illustration of the trajectories.

Figs. 4.6(a) and 4.7(a) show that with increasing cost metric the bandwidth utilization diminishes. The considered schemes achieve very similar bandwidth utilizations for low values of the cost metric along both the F-dominated and V-dominated trajectories. As the cost metric is increased, it is observed that the schemes perform differently, with the EBU maximizing scheme achieving the best utilization, and the EP scheme performing the worst. The difference in the bandwidth utilizations of the schemes observed with increasing cost metric is more dramatic along the V-dominated trajectory. These results collectively suggest that the achieved bandwidth utilization becomes more sensitive to the specific scheme employed with increasing cost. It is seen that SPS based optimization schemes are more helpful (as opposed to the EP scheme) when the unit bandwidth is relatively costly. This result is intuitive, given that with increasing cost, it becomes more difficult for operators to maintain positive profit when allocated exactly half of the available spectrum. Thus, with increasing cost, the EP scheme often results in allocating no bandwidth to at least one of the operators, decreasing the performance. The SPS based optimization schemes, on the other hand, support a more efficient bandwidth allocation approach, and make sure that only affordable amount of spectrum is



(a) Expected bandwidth utilization (b) Average number of users served

Figure 4.6: F-dominated trajectory



(a) Expected bandwidth utilization (b) Average number of users served

Figure 4.7: V-dominated trajectory

allocated to the operators.

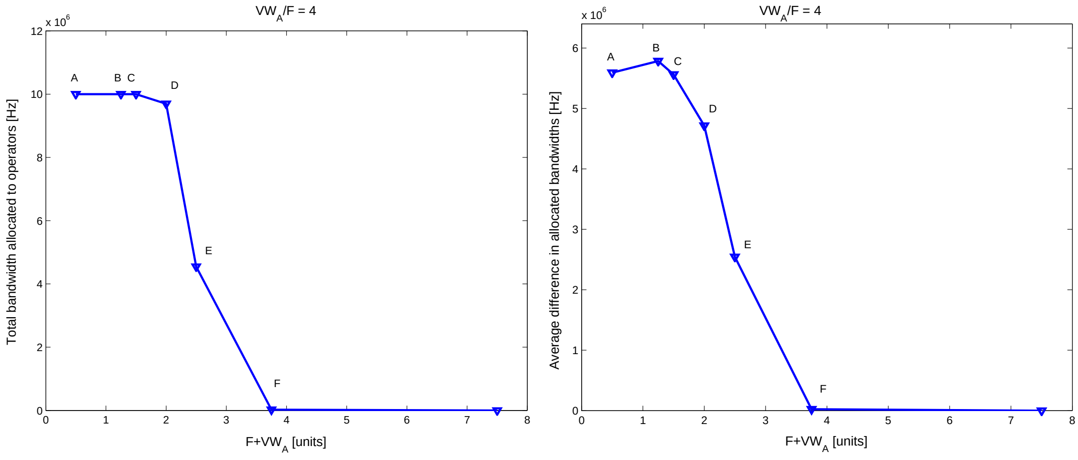
Figs. 4.6(b) and 4.7(b) show that the Acp_{min} maximizing scheme always achieves the greatest average number of users served in the system. This is intuitive since the Acp_{min} maximizing scheme promotes a max-min fairness criterion for the users. It is also observed that $\overline{Acp}$ maximization scheme performs similar to the Acp_{min} scheme. The number of users served is decreasing in cost metric for the Acp_{min} maximization, $\overline{Acp}$ maximization and EP schemes, along both trajectories. It is observed that for low values of the cost metric $F + VW_A$, the EBU maximization scheme results in the lowest number of users served. For the EBU maximization scheme, as the cost metric is increased, a slight decrease is followed by an increase and a final decrease, along both trajectories. This pattern is more apparent along the V-dominated trajectory (see Fig. 4.7(b)).

We now present an interpretation of the above trend regarding the average number of users served for the EBU maximizing scheme. Our detailed observations suggest that in the EBU maximizing scheme, the SPS is in the tendency of allocating most of the bandwidth to the operator who can serve users which enjoy greater service spectral efficiencies. This is much like a water-filling solution encountered in classical resource allocation, in which users with good channels are allocated more resources. Note that, considering the definition of EBU in section 4.2, such an allocation would increase the EBU. Note also that, in the other schemes, there is no such incentive. Consequently, for low cost values, the SPS partitions the spectrum among the operators in such a way that those users who are relatively further away from the access points are not served at all. This often means that the operator who is more likely to serve the distant users is allocated little bandwidth by the SPS, forcing it to effectively deny service to distant users and serve relatively low number of users. However, as the cost is increased, the operator that is allocated small spectrum portions is not able to maintain positive profit anymore. Thus the SPS is obliged to allocate more resources to such an operator, who in turn serves more users. This pattern is more evident in curves along the V-dominated trajectory simply because the variable cost VW_i (for operator i) in (4.9) is the major factor in determining the affordability of spectrum allocations, as F is compensated on a per user basis. As the costs are further increased, a decrease is observed since with even higher costs, the operators face diminishing returns and can not make convincing offers to the users.

Figs. 4.8(a) and 4.8(b) support the above interpretation. They show the total allocated bandwidth to the operators and the average difference between bandwidths of spectrum portions allocated to operators along the V-dominated trajectory for the EBU maximizing scheme. The points on the curves corresponding to data points in Fig. 4.7(b) are labeled. It is easy to see that for the data points with low cost metric (points A,B,C,D), the average difference between spectrum portions for operators is considerably large, verifying the above intuition that the operator likely to serve distant users is given considerably less bandwidth. With increasing cost the total allocated bandwidth stays more or less constant for the first four data points (A,B,C,D), while the average difference is reduced, supporting the above intuition that spectrum resources are more fairly distributed in this region. This explains the increase in the average number of users served from C to D (see Fig. 4.7(b)). As the cost is further increased, the total allocated bandwidth diminishes, suggesting that in this region the high cost makes it difficult for operators afford spectrum portions allocated to them.

Note that, when the bandwidth usage cost is zero ($V = 0$), the above trends do not hold, and the number of users served in the EBU maximizing scheme is always less than those achieved in the other schemes, as illustrated in Fig. 4.9.

Fig. 4.10 shows the achieved expected bandwidth utilizations and the average number of users served as functions of the number of users in the system, for two different cost pairs (F, V). Note that these plots are representative for other cost pairs tested in the F-V plane illustrated in Fig. 4.4. We refer to Figs. 4.10(a) and 4.10(b) as the lower



(a) Total bandwidth allocated

(b) Average difference in allocated bandwidths.

Figure 4.8: Bandwidth allocation among the operators along V-dominated trajectory for the EBU maximizing scheme.

cost regime (close to origin) and Figs. 4.10(c) and 4.10(d) as the higher cost regime (further away from the origin). We note that along any given trajectory, as the cost pair (F, V) considered is relatively closer to the origin, the trends observed are as in Figs. 4.10(a) and 4.10(b). Similarly, when the cost pair (F, V) considered is further away from the origin, for any trajectory, the trends observed are as in Figs. 4.10(c) and 4.10(d). Note that in these figures the expected bandwidth utilization achieved does not necessarily increase with the number of users (see Fig. 4.10(a)). More specifically, for low cost, the bandwidth utilization achieved by the three schemes considered decrease with number of users, where as it increases with the number of users for high cost. The interpretation here is that at high cost, it is difficult to find affordable spectrum allocations for the operators (allocations for which operators have positive profit - see Eq. 4.3) by the SPS, given the large payment for spectrum. With increasing number of users, there is more opportunity to make profit for the operators. Thus it is easier for the SPS to determine affordable allocations for the operators. Thus the optimization domain is enlarged and the achieved expected bandwidth utilization increases, for all three objective functions considered. For low cost (see Fig. 4.10(a)), on the other

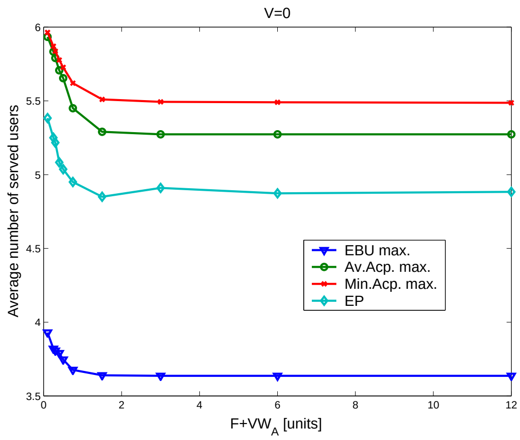


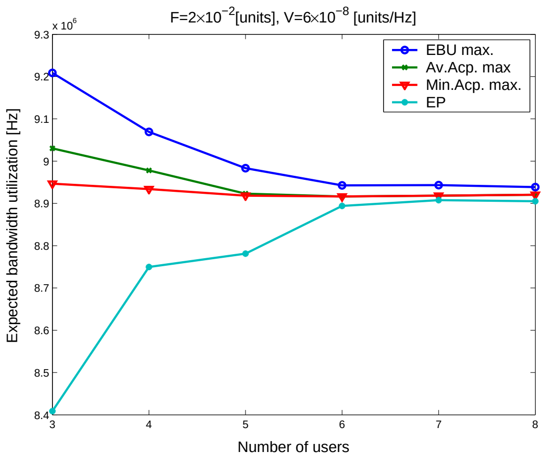
Figure 4.9: Average number of users served for $V = 0$ trajectory.

hand, increasing the number of users does not affect the optimization domain for the SPS, since the cost is already low. However, profit seeking operators distribute their resources among more users, with increasing number of users. Thus, the spectrum portions are not concentrated at the users with best spectral efficiency. Thus, there is a decrease in the bandwidth utilization achieved.

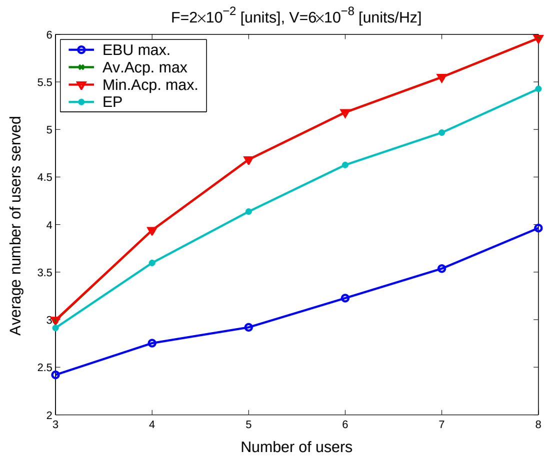
In Figs. 4.11(a) and 4.11(b), we present the illustrative results for longer term dedication of system resources in an EBU maximizing scheme for the F-dominated and V-dominated trajectories, respectively. The $T = 1$ curves refer to the scheme in which the SPS updates the spectrum allocation vector every communication session, e.g. every time a change in user locations is detected. The $T = 5$ and $T = 10$ curves refer to longer term spectrum allocation schemes in which the SPS updates the allocation vector every 5 sessions and every 10 sessions, respectively. Recall that no matter what T is set to be, the operators compete with each other each time there is a change in user locations. The values plotted for $T > 1$ refer to the average values per communication session.

As the updates in spectrum allocation become less frequent, the SPS is restricted to use the same allocation vector for greater number of sessions. This seems to constrain the SPS thus potentially

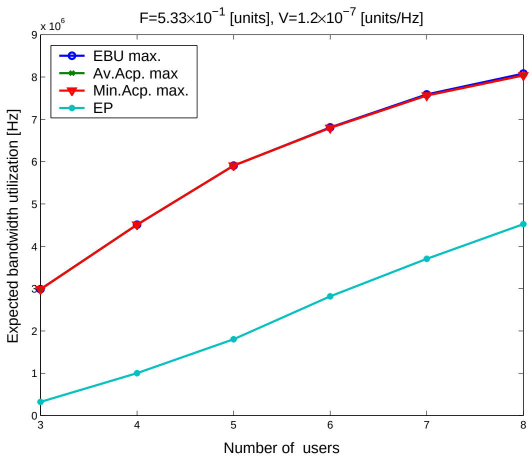
reducing the achieved expected bandwidth utilization. On the other hand, the



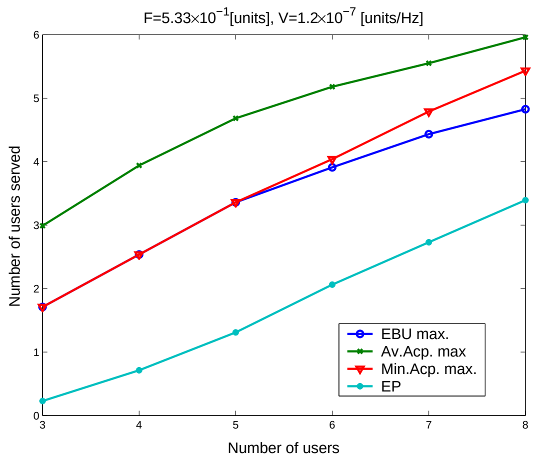
(a) Expected bandwidth utilization



(b) Average number of users served

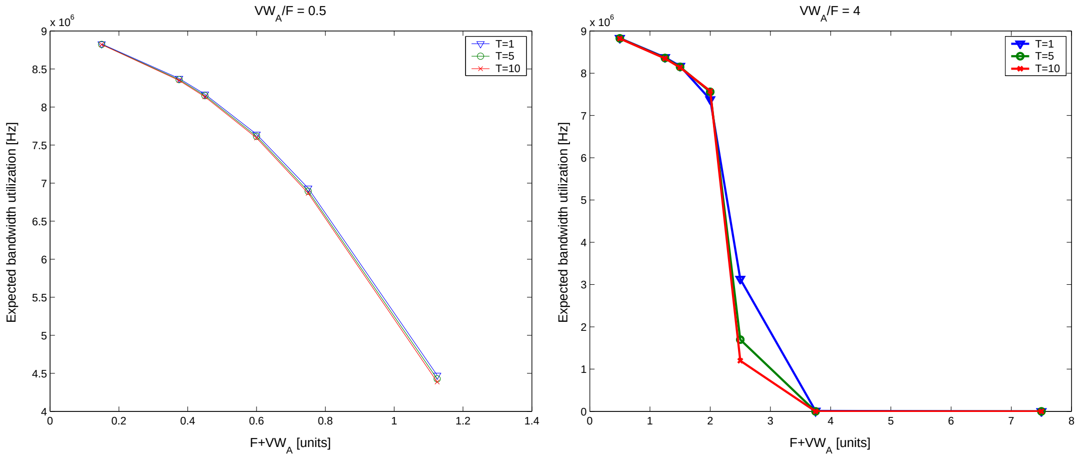


(c) Expected bandwidth utilization



(d) Average number of users served

Figure 4.10: Performance of the schemes with respect to number of users.



(a) $VW_A/F = 0.5$

(b) $VW_A/F = 4$

Figure 4.11: Effect of long term dedication of spectrum resources for the EBU maximizing scheme.

constraints on the final profits of the operators are relaxed as opposed to $T = 1$, as the operators need to end up with positive profit only at the end of T sessions, as opposed to every single session as in $T = 1$. This seems to be in favor of increasing performance.

The plots shows that for the F-dominated trajectory, all three updating schemes achieve similar performance, with $T = 1$ performing slightly better than the other two. For the V-dominated trajectory, the $T = 1$ scheme achieves significantly greater bandwidth utilization for high cost values. These plots, thus, suggest that employing short term allocation of resources could potentially lead to performance gains as opposed to more slowly changing (or static) allocation of resources, especially in regimes where the bandwidth is expensive.

We can summarize the experimental findings in this chapter as follows. As a function of cost, the considered schemes,(EBU) maximizing, average acceptance ($\overline{Acp}$) maximizing scheme and the minimum acceptance probability (Acp_{min}) maximizing schemes all perform superior to the equal partition EP scheme considered for benchmark purposes, in terms of achieved bandwidth utilization. The performance difference is more apparent along the V-dominated (variable cost dominated) trajectory. The (EBU) maximizing scheme promotes a water-filling type of solution where the available spectrum is concentrated at users which can be served with high spectral efficiency. Consequently, the (EBU) maximizing scheme induces less number of users served, especially at low cost. The ($\overline{Acp}$) maximizing scheme and the minimum acceptance probability (Acp_{min}) maximizing schemes perform well in terms of number of users served in the system.

As a function of the number of users in the system, it is observed that the specific cost values considered make a difference. For low costs, the bandwidth utilization achieved for (EBU) maximizing, average acceptance ($\overline{Acp}$) maximizing scheme and the minimum acceptance probability (Acp_{min}) maximizing schemes decrease with increasing number of users. For all three schemes, at high cost, the bandwidth utilization increases with increasing number of users. It should also be noted that for the EP scheme, the expected bandwidth utilization always increases with number of users.

Chapter 5

The D-CPass Model

In this model the SPS partitions the total available spectrum W_{A} into N non-overlapping portions where N is the number of users in the system. The exact partition is determined as a solution of the optimization problem where SPS maximizes any one of the objective functions introduced in the previous chapter, with respect to bandwidth allocation vector $\vec{W} = (W_1, W_2, ..., W_N)$ where W_n refers to the spectrum portion allocated for serving user n.

Given the partition, the operators compete for each user individually. For any given user, they have differing service spectral efficiencies r [bps/Hz], and offer a rate R [bps] as well as a total price P [*units*]. Each offer invokes an *expected profit* for the operator making the offer. This profit is related to the associated $A\,(R, P)$ as well as the price asked P, the related fixed operational costs (independent of the offered rate R) and variable costs that depend on the actual spectrum usage. The operators compete with each other in order to ensure that the user accepts their service offer with the highest probability. We formulate the operator competition for any given user as a non-cooperative game and propose an SPS-centered iterative bidding scheme reminiscent of a single-item ascending (English) auction that achieves a Nash equilibrium of the operator game.

5.1 Per User Operator Profit in the D-CPass Model

The operators considered in the model are able to provide spectral efficiencies of r_i [bps/Hz] to a specified user, where $i \in \{1, ..., M\}$ is the index denoting the operator. For the offered rate R_i and price P_i, the profit $Q_i(R_i, P_i)$ can be expressed as:

$$Q_i(R_i, P_i) = P_i - F_i - VR_i/r_i \tag{5.1}$$

where $F_i\,[units]$ is the fixed operational cost incurred by the operator, and $V\,[units/\mathrm{Hz}]$ is the price per unit bandwidth that the SPS charges the operator. Recall from previous chapter that we assume the unit bandwidth cost declared by the SPS is global and it is the same for all operators. The last term denotes the usage-based variable cost for the operator.

Considering the user's acceptance probability, the expected profit for operator i is

$$\overline{Q_i}(R_i, P_i) = A(R_i, P_i)\, Q_i(R_i, P_i)\,. \tag{5.2}$$

Note that for fixed r_i, the acceptance probability $A(R_i, P_i)$ is increasing in R_i and decreasing in P_i while the profit $Q_i(R_i, P_i)$ is decreasing in R_i (due to increased bandwidth consumption) and increasing in P_i.

5.2 SPS Based Dynamic Spectrum Allocation in D-CPass Model

The SPS determines the exact N- dimensional partition vector $\vec{W}$, specifying the spectrum portions allocated for each user, as a result of the maximization of one of the following objective functions:

1. total expected bandwidth utilization in the system (EBU);

2. the average acceptance probability ($\overline{Acp}$) that a user accepts the offered service ;

3. the minimum acceptance probability (Acp_{min}) that a user accepts the offered service.

Recall that these objective functions are defined in the previous chapter.

Each portion W_n is dedicated to serving user n alone. The operators compete with each other for any user n through rate and price offers, in the form of an iterative bidding scheme reminiscent of ascending bid auctions. In this scheme, details of which will be described later in the text, the operators iteratively make rate and price offers to exceed the acceptance probability associated with their opponent's most recent offer. The operators competing for user n are subject to the constraint that they may not make offers that require bandwidths greater than W_n. This portion of spectrum devoted for serving the user n is open to both operators during the competition as long as they use the specified portion for making offers to the corresponding user only. The result of the operator competition for user n determines at most one of the operators as the winner who can make a final service offer to the user. The user accepts this final offer of the winning operator with the associated acceptance probability, as described in section 3.2. The SPS charges the winning operator for its spectrum usage only if the user actually accepts the offer.

The SPS maximizes the objective function subject to the constraint that the total allocated bandwidth does not exceed the total available bandwidth W_{A}. Consequently, the SPS optimization problem can be expressed as:

$$\max_{\vec{W}} Obj\left(.,\vec{W}\right) \qquad \text{st.} \sum_{n=1}^{N} W_n \leq W_{\mathrm{A}}. \tag{5.3}$$

When maximizing the objective function $Obj(.,\vec{W})$ over $\vec{W}$, the SPS performs a centralized optimization whose result is a vector $\vec{W}^*$ that maximizes the relevant objective function. In order to determine $\vec{W}^*$, the SPS performs an exhaustive search in which it declares all possible $\vec{W}$s one at a time. For any declared allocation vector

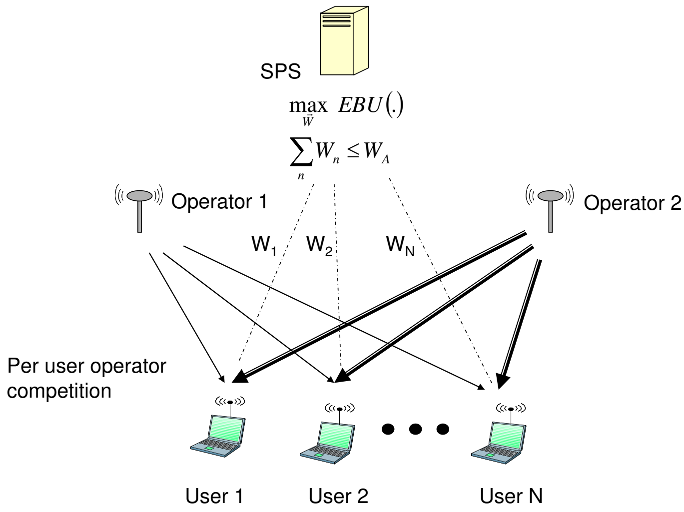


Figure 5.1: SPS mediating iterative bidding processes for N users.

$\vec{W}$, the operators compete with each other for each user independently considering the bandwidth constraints imposed by the allocation vector, as illustrated in Fig. 5.1.

5.3 Per User Operator Competition and Iterative Bidding in the D-CPass model

In this section we first describe in detail the operator competition for any given user n in the form of a non-cooperative game. We characterize the Nash equilibria of the game and then propose the iterative bidding algorithm through which a Nash equilibrium for the game is achieved.

The user response to an offer (R, P) is modelled as in (3.2). In the presence of a number of offers from different operators, the offers for which $A(R, P)$ are lower are ignored by the user. The offer with the greatest associated acceptance probability is then accepted with the associated acceptance probability. When there are two or more operators which induce the greatest acceptance probability (offers invoking equal acceptance probabilities), we assume that each such offer is equally likely to be accepted.

In the context of operators competing for resources and the user preference, the game can be represented by $G = [I, \{S_i\}, \beta_i]$ where $I = \{1, ..., M\}$ is the index set of the players (operators), S_i is the strategy space available to operator i, and $\beta_i(.)$ is the resulting expected profit associated with the operator with index i. The strategy space S_i for operator i consists of all (R, P) pairs which satisfy the bandwidth constraint:

$$S_i = \left\{ \forall (R, P) \mid \begin{array}{c} F_i + VR_i/r_i \leq P, \\ 0 \leq R \leq W_n \times r_i. \end{array} \right\} \tag{5.4}$$

where W_n is the bandwidth allocated by the SPS for serving user n as described in section 5.2. We further impose the constraint that the standalone profits (without consideration of the opponents' strategies) are necessarily nonnegative.

The resulting expected profit β_i of operator i given the strategy of the opponent operator j is

$$\beta_i(R_i, P_i, ..., R_M, P_M) = \begin{cases} 0 & \text{if } A(R_i, P_i) < A^*(R, P), \\ \frac{1}{Z}\overline{Q_i}(R_i, P_i) & \text{if } A(R_i, P_i) = A^*(R, P). \end{cases} \tag{5.5}$$

In the above equation, $A^*(R, P)$ refers to the greatest acceptance probability induced by the offers for the user and Z is the number of operators inducing $A^*(R, P)$.

The non-cooperative operator game can now be formally stated as

$$\max_{(R_i, P_i) \in S_i} \beta_i(R_i, P_i, ..., R_M, P_M), \quad i \in \{1, ..., M\}. \tag{5.6}$$

We now state the following theorem which is a necessary condition for the Nash equilibrium of the above game.

Theorem 5.3.1. *At any Nash equilibrium for the game G, at most one of the operators has non-zero expected profit.*

Proof. By contradiction: Assume there exist the equilibrium strategies (R_i^*, P_i^*), where $i \in \{1, ..., M\}$ is the index for the operators, such that the best responses $\beta_j(.) > 0$ where $j \in \mathbf{P}$ is the index of operators for which the equilibrium profit is strictly positive. Considering (5.5), the only way this can be achieved is to have equality between the achieved acceptance probabilities for all operators $j \in \mathbf{P}$; $A\left(R_j^*, P_j^*\right) = Acp$ $\forall j \in \mathbf{P}$, where Acp is a constant between 0 and 1. In this situation, in accordance with (5.5), the corresponding payoffs would be $\beta_j\left(R_j^*, P_j^*\right) = \frac{1}{|\mathbf{P}|}\overline{Q_j}\left(R_j^*, P_j^*\right)$, where $\mid \mathbf{P} \mid$ is the cardinality of $\mathbf{P}$. Note that the assumption of non-zero profits implies that $\frac{1}{|\mathbf{P}|}\overline{Q_j}\left(R_j^*, P_j^*\right) > 0$. Consider any given operator $k \in \mathbf{P}$ without loss of generality. If operator k were now to deviate from the strategy (R_k^*, P_k^*) to $(R_k^*, P_k^* - \Delta_P)$ by lowering its price offer by an infinitesimal amount Δ_P, then it follows that $A(R_k^*, P_k^* - \Delta_P) > Acp$. Further, from (5.5) it follows that the resulting expected profit for operator k is $\overline{Q_k}(R_k^*, P_k^* - \Delta_P)$. By continuity of the profit function, it follows that $|\overline{Q_k}(R_k^*, P_k^* - \Delta_P) - \overline{Q_k}(R_k^*, P_k^*)| < \delta$ for arbitrarily small $\delta > 0$. We can thus bound the change in payoff of operator k, i.e.,

$$\overline{Q_k}(R_k^*, P_k^* - \Delta_P) - \frac{1}{\mid \mathbf{P} \mid}\overline{Q_k}(R_k^*, P_k^*)$$

as

$$\frac{1}{2}\overline{Q_1}(R_1^*, P_1^*) - \delta < \overline{Q_1}(R_1^*, P_1^* - \Delta_P) - \frac{1}{\mid \mathbf{P} \mid}\overline{Q_k}(R_k^*, P_k^*) < \frac{1}{\mid \mathbf{P} \mid}\overline{Q_k}(R_k^*, P_k^*) + \delta$$

. Given that $\frac{1}{|\mathbf{P}|}\overline{Q_k}(R_k^*, P_k^*) > 0$ and δ is arbitrarily small, it follows that the change in payoff for operator k is strictly positive. Therefore the strategy (R_k^*, P_k^*) can never be the best response of operator k. This contradicts the initial assumption that at equilibrium $\beta_j(.)$ are the best responses for $j \in \mathbf{P}$ which lead to positive profit. $\square$

5.3.1 Iterative Bidding

In the iterative bidding process for any given user, the operators make offers in each iteration. The strategy of each operator is to make the offer such that $A(R, P)$ associated with its offer is greater than the one associated with its opponent's offer from last iteration while simultaneously maximizing the resulting expected profit.

The iterative bidding is initialized by allowing the operators to choose their service offers without consideration of the opponent strategy.

It is clear from the structure of $\beta_i(.)$ in (5.5) that the iteration process is terminated when a zero value for expected profit is declared by all but at most one operator. More specifically, when an operator realizes that it can not achieve positive profit anymore, it does not update its offer any more and keeps its most recent offer (thus practically quitting the iterative bidding). The opportunity to offer service to the user is then given to the operator that still maintains positive profit (if any). The winning operator uses its most recent bid $(R_{\text{winner}}, P_{\text{winner}})$, as a service offering to the user. Note that the iterative bidding process by definition should converge to a Nash equilibrium of the game G, since at the convergence point all operators employ their best response strategies given the actions of the opponent operators. Note also that at the convergence point, there is at most one operator which achieves positive profit, in accordance with the necessary condition for the Nash equilibrium as stated in Thm. 5.3.1. If all operators declare zero expected profit at the same iteration, all are dismissed. This degenerate situation can happen when all operators have identical fixed costs and the user is located in a geographical location where the spectral efficiencies of all operators are identical. Such an operating point is also a Nash equilibrium. In such a case, we assume that the SPS randomly selects one operator to offer service.

Note that in terms of the competition mechanism, the iterative bidding process is reminiscent of the ascending bid auctions (English Auctions) [13]. In the following, we first present a brief discussion on English Auctions and then provide a detailed description for the proposed iterative bidding in the upcoming sections.

5.3.2 Single Item Ascending (English) Auctions

In English auctions, there are a number of bidders competing for an item on display. The bidding is conducted in rounds. At each round, the bidders make their price bids for the item. At the end of each round, the auctioneer declares the highest bid for the item. The bidders keep increasing their price bids beyond the standing high bid from the previous rounds. The bidding is finalized the first round at which there is no new bids, and the item is awarded to the bidder who holds the most recent standing high bid for the item, at the price corresponding to the standing high bid. Fig. 5.2 illustrates this procedure. There are a number of rules in literature, which focus on ways to improve the convergence speed of such auctions. One typical measure employed to ensure timely completion of the bidding process is the minimum bid increment rule. According to this rule, the auctioneer declares a minimum bid increment amount and the bidders need to exceed the current standing high bid by at least that amount to be in the winning position for the item. Detailed descriptions for standard auction types for single item transactions can be found in [13].

5.4 Practical Issues in Iterative Bidding

In this section we consider the iterative bidding process for any given user in more detail and discuss critical issues regarding the convergence time and the precision of the achieved equilibrium. We then propose a practical algorithm to address these issues.

5.4.1 Implementation of Iterative Bidding - Traditional Approach

The strategy of each operator in each iteration is to make the offer such that the $A(R, P)$ associated with its offer is greater than the ones associated with its opponents' offers

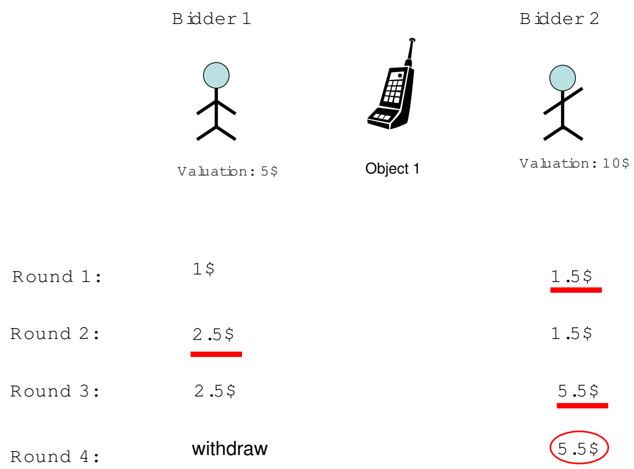


Figure 5.2: Illustration of single item ascending aution.

while simultaneously maximizing the resulting expected profit. The operators stay in competition as long as they are able to achieve positive expected profit, else they do not make any new offers thus practically quitting competition.

At any given round, for any specified user n, the offer which induces the greatest acceptance probability is declared by the SPS as the standing high acceptance probability, which we represent by (H) for that user. At the end of each round, the SPS computes the minimum acceptance probabilities (M_i) for the next round for each operator considering the standing high acceptance probability H for the user and the minimum acceptance probability increments enforced (I_i) for any given operator i regarding the user.

Note that I_i may differ for different operators for a given user n, as the operator who is currently the highest bidder (H bearer) need not increase its acceptance probability in the next round, while the opponent operators need to exceed H by at least some predetermined value δ in order to claim the user. δ can be considered as an auction design parameter and is determined by the SPS. In case a number of operators simultaneously induce the H for the user in any given round, only one of them (randomly determined by the SPS) is treated as the current winner, while the rest are obliged to make more attractive offers for the user in the next round in order to be in the winning position. The SPS declares the M values for the next round in the form of $\vec{M_i} \in [0,1)^N$ vectors where each element in $\vec{M_i}$ refers to the minimum acceptance probability operator i needs to induce next round in order to be in the winning position for the corresponding user. The iterative bidding is initialized by allowing the operators to choose their service offers without consideration of the opponent strategy. It is finalized the first round in which there is no new offers (no increase in H) for any of the users.

A technical issue related to the minimum bid increment policy is the fact that for any positive price $P > 0$, the acceptance probability, by definition, is always less than 1; $A(R, P) < 1$.

Considering the above, we define the M for operator i as:

$$M_i = \min\left(H + I_i, A_{max}\right) \tag{5.7}$$

where $A_{max} < 1$ is a predefined constant, which is set as close to 1 as possible. H is the standing high acceptance probability for the user from the previous round and $I_i \geq 0$ is the minimum acceptance probability increment for operator i regarding user n, declared by the SPS. I_i is defined as:

$$I_i = \begin{cases} 0 & \text{if operator } i \text{ has the} \\ & \text{greater bid from last round,} \\ \delta_i & \text{otherwise,} \end{cases} \tag{5.8}$$

where $\delta_i > 0$ is the increment amount set by the SPS. There can be different approaches for setting δ_i.

Consequently, the optimization problem for any operator at each round can be written as:

$$\max_{(R_i,P_i)\in S_i} \beta_i\left(R_i,P_i\right) \qquad \text{st.} \quad i\in\{1,2\}. \tag{5.9}$$

R_i and P_i refer to the offered rate and price to user n by operator i, respectively. r_i is the spectral efficiency achieved when operator i serves the user. W_n is the spectrum portion allocated by the SPS for serving user n and β_i is the expected payoff for operator i which is defined as:

$$\beta_i\left(R_i,P_i,R_j,P_j\right)=\begin{cases} 0 & \text{if } A\left(R_i,P_i\right)<M_i, \\ \overline{Q_i}\left(R_i,P_i\right) & \text{if } A\left(R_i,P_i\right)\geq M_i. \end{cases} \tag{5.10}$$

The main tradeoff in such a bidding algorithm is the correct choice of minimum bid increment δ_i for every user-operator pair. Note that large values of δ_i will provide fast convergence of the scheme while they will fail to stop at a precise Nash equilibrium of the game G deviating from the true equilibrium, while smaller values of δ improve precision at the expense of prolonged runtime.

5.4.2 Improved Implementation Approach

Considering the importance of runtime length in a wireless communications setting, and also addressing the need for a correct algorithm which converges to the true Nash equilibria of the game, we now propose an alternative approach. This approach is inspired by the equivalence of second price sealed bid single-item auctions to ascending bid single-item auctions frequently mentioned in auction theory literature [13]. The details of this equivalence is beyond the scope of this work, and thus will not be discussed here.

The improved algorithm is a two step one in which in the first step each operator declares the greatest acceptance probability it can support with nonnegative profit for any user n. This value is declared taking into account the cost structure, allocated bandwidth W_n and the spectral efficiencies. The winner is declared by the SPS right after this step to be the one which has declared the greatest acceptance probability. In the second step, the winner makes its final offer to the user, maximizing its expected profit subject to the constraint that the final acceptance probability should be greater than or equal to the second greatest acceptance probability declared among all its opponents in the first step.

Theorem 5.4.1. *Consider the iterative bidding (traditional approach) for any specified user n with $\delta_i \to 0$ $\forall i$. Let $\{A_1^{max}, ..., A_M^{max}\}$ denote the greatest acceptance probabilities that operators can offer to the user subject to the constraint that they achieve nonnegative expected profits. If there exists an operator k such that $A_k^{max} > A_j^{max}$ $\forall k \neq j$, then the following are true:*

1. *The winner of the iterative bidding is operator k where $k = \arg\max_i \left(A_i^{max}\right)$*
2. *The final offer is determined through the following profit maximization:*

$$\max_{(R_k,P_k)\in S_k} \beta_k \left(R_k, P_k, R_j, P_j\right)$$
$$st.\ A_k \left(R_k, P_k\right) \geq \max\left(A_1^{max}, .., A_{k-1}^{max}, A_{k+1}^{max}, ..., A_M^{max}\right)$$

Proof. Let A_{High}^r denote the standing high bid in acceptance probability at the end of round r. Note that A_{High}^r is increasing in r as long as $r < r_{final}$ where r_{final} is the final round at which there is no new offers.

Assume that there exists an operator i for whom $A_i^{max} > A_j^{max}$ $\forall i \neq j$. Note that this implies that operator i can afford to make offers such that $A_i \left(R_i, P_i\right) > \max(A_1^{max}, .., A_{i-1}^{max}, A_{i+1}^{max},..., A_M^{max})$. Thus, it will be the last operator staying in the iterative bidding, as A_{High}^r gradually increases beyond $\max\left(A_1^{max}, .., A_{i-1}^{max}, A_{i+1}^{max}, ..., A_M^{max}\right)$. This proves the first part of the theorem.

Let A_{loser}^f denote the acceptance probability associated with the final offer of the last surviving operator(s) (except the winner) before quitting. Note that since it is the final bid, the losing operators should not be able to make any further bids beyond that of the winner's final offer while still maintaining positive profit, i.e., $A^f_{winner} + \delta \geq \max\left(A^{max}_1, .., A^{max}_{i-1}, A^{max}_{i+1}, ..., A^{max}_M\right)$ where δ is the minimum bid increment. Also, by definition of the iterative bidding algorithm $A^f_{winner} \geq A^f_{loser} + \delta$. Consequently, the final bid should be determined as the result of the optimization problem:

$$\begin{aligned} &\max_{(R_i,P_i)} \beta_k\left(R_i, P_i, R_j, P_j\right) \\ &\qquad \text{st. } A_i\left(R_i, P_i\right) \geq \max\left(A^f_{loser} + \delta, \max\left(A^{max}_1, .., A^{max}_{i-1}, A^{max}_{i+1}, ..., A^{max}_M\right) - \delta\right), \\ &\qquad\qquad R_k/r_k \leq W_n \end{aligned} \tag{5.11}$$

where the constraint on acceptance probability follows from the above discussed facts:

$$\begin{aligned} A_i\left(R_i, P_i\right) &\geq \max\left(A^{max}_1, .., A^{max}_{i-1}, A^{max}_{i+1}, ..., A^{max}_M\right) - \delta \quad \text{and} \\ A_i\left(R_i, P_i\right) &\geq A^f_{loser} + \delta. \end{aligned}$$

Let the losing operator(s)'s last bid be $\left(R^f_{loser}, P^f_{loser}\right)$. Since this offer has been made, the resulting expected profit for the losing operator should have been positive. This implies $A^f_{loser} < \max\left(A^{max}_1, .., A^{max}_{i-1}, A^{max}_{i+1}, ..., A^{max}_M\right)$. Consequently

$$\lim_{\delta\to 0} \max\left(A^f_{loser} + \delta, \max\left(A^{max}_1, .., A^{max}_{i-1}, A^{max}_{i+1}, ..., A^{max}_M\right) - \delta\right) \to$$

$$\max\left(A^{max}_1, .., A^{max}_{i-1}, A^{max}_{i+1}, ..., A^{max}_M\right).$$

Thus, for $lim_{\delta\to 0}$ (5.11) can equivalently be written as:

$$\max_{(R_i,P_i)\in S_i} \beta_i\left(R_i, P_i, R_j, P_j\right) \quad A_i\left(R_i, P_i\right) \geq \max\left(A^{max}_1, .., A^{max}_{i-1}, A^{max}_{i+1}, ..., A^{max}_M\right)$$

This proves the second part of the theorem. □

This theorem indicates that the improved algorithm achieves the same results as the traditional one described in the previous section when $\delta_i \to 0\ \forall i$. Note that this ensures convergence to the exact equilibrium in only 2 iterations.

5.5 Some intuition about the D-CPass Model

In this section, we provide some more analytical findings to improve the understanding of the D-CPass model.

Theorem 5.5.1. *For a given system with symmetric cost structure; $F_1 = \cdots = F_M$, the winning operator of the iterative bidding for any specified user is that one which has the highest service spectral efficiency for that user.*

Proof. Recall from Theorem 5.4.1 that the winning operator is the one which can support the greatest acceptance probability with non-negative profit. Note that when the operational fixed costs for the operators are the same, the operator which can induce the highest acceptance probability with non-negative profit is the one which enjoys highest spectral efficiency, since for any given price P and bandwidth consumption W, the operator with the highest spectral efficiency can provide greater connection rate thus achieving higher acceptance probability.

□

5.6 Numerical Experiments for the D-CPass Model

In this section we provide numerical results corresponding to the D-CPass schemes described earlier in this chapter. In our experimental setup, we consider $M = 2$ operators located in the simple linear region illustrated in Fig. 4.3 in the previous chapter.

The experiments are conducted for 6 user systems, and the spectrum efficiency calculations, system parameters, cost structures as well as user utility parameter are the

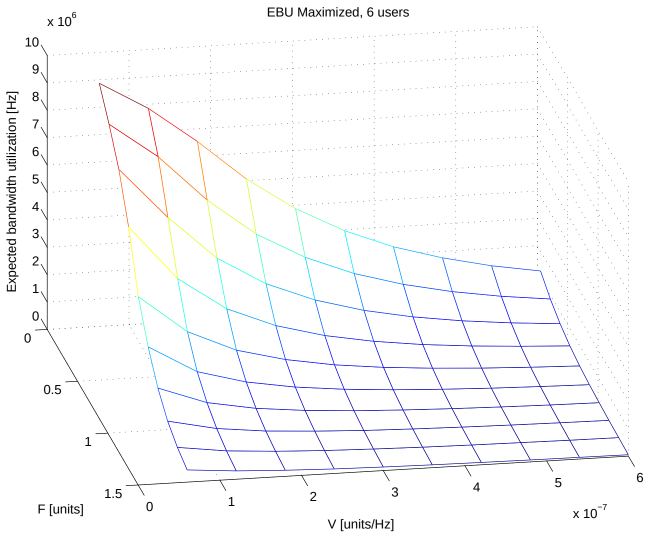
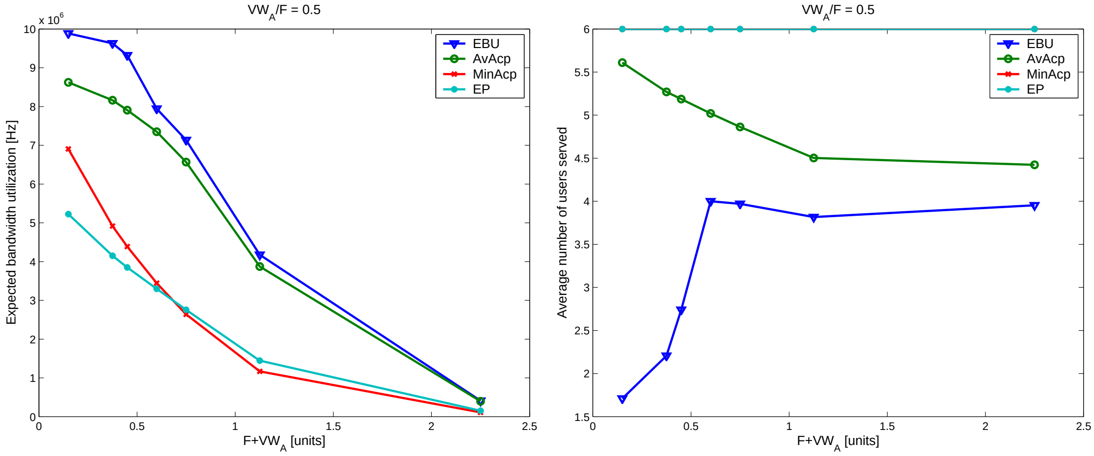


Figure 5.3: Expected bandwidth utilization in EBU maximizing system in a 6-user system.

same as in section 4.6. Recall that the base station locations are fixed and the user locations are randomly determined assuming a uniform distribution for each user. Each data point is generated by testing 300 different instantiations of user locations (communication sessions). The results are then averaged over all 300 different realizations and the average values are presented in the following figures.

In the numerical experiments, we test four different schemes each with different SPS objectives. As mentioned earlier in section 4.2, we consider the expected bandwidth utilization (EBU) maximizing scheme, average acceptance probability ($\overline{Acp}$) maximizing scheme and the minimum acceptance probability (Acp_{min}) maximizing scheme. For comparison purposes, we also consider the equal partition (EP) scheme in which the available bandwidth (W_A) is equally divided between the users in the system, with no SPS optimization.

Fig. 5.3 shows the achieved expected bandwidth utilization, as a function of cost parameters F and V, for the EBU maximizing scheme. It is observed that, the achieved expected bandwidth utilization is decreasing in both cost parameters F and V. We also observe (not shown here) that the same decreasing pattern remains for the schemes where the SPS either maximizes the mean or the minimum acceptance probability, or



(a) Expected bandwidth utilization

(b) Average number of users served

Figure 5.4: F-dominated trajectory

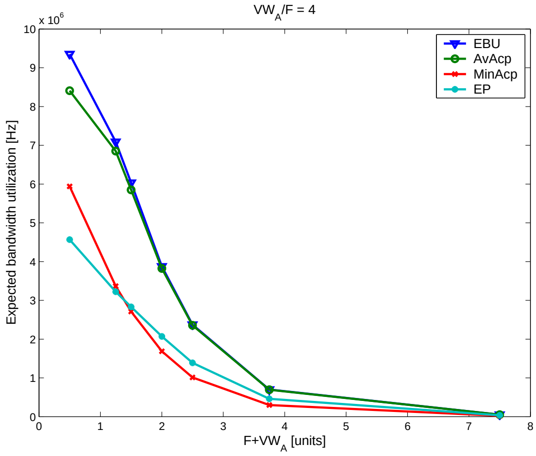
equally partitions the bandwidth.

To develop a better understanding for possible comparisons among the considered schemes as well as the effect of increasing cost on various performance metrics, we consider the two trajectories shown in Fig. 4.5 (section 4.6), and conduct experiments over the (F, V) pairs on them.

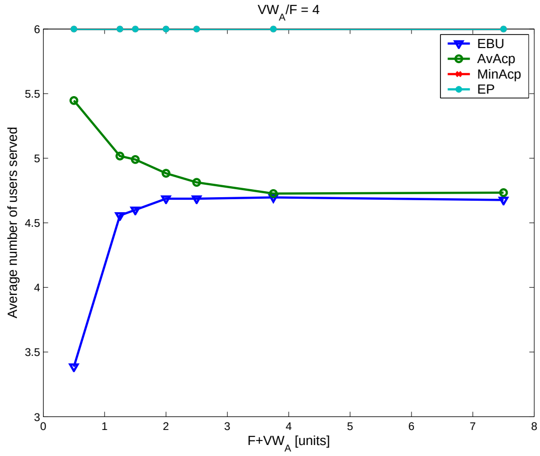
In Figs. 5.4 and 5.5, we present the expected bandwidth utilization and the average number of users served, as functions of the cost metric $F+VW_A$ $[units]$, with $VW_A/F = 0.5$ (F- dominated) and $VW_A/F = 4$ (V-dominated), respectively. The average number of users served in the system refers to the number of users for which the final offered rates as well as the final acceptance probabilities are positive.

Figs. 5.4(a) and 5.5(a) show that, in both trajectories, with increasing cost metric the bandwidth utilization diminishes for all schemes. It is observed that the EBU maximizing and $\overline{Acp}$ maximizing schemes perform significantly better than the EP and Acp_{min} maximizing schemes in achieved expected bandwidth utilization.

In Figs. 5.4(b) and 5.5(b), it is observed that in the Acp_{min} maximization and EP schemes, all users present in the system are being served. This result is intuitive considering that in the EP scheme all users are assigned some nonzero bandwidth in any case,



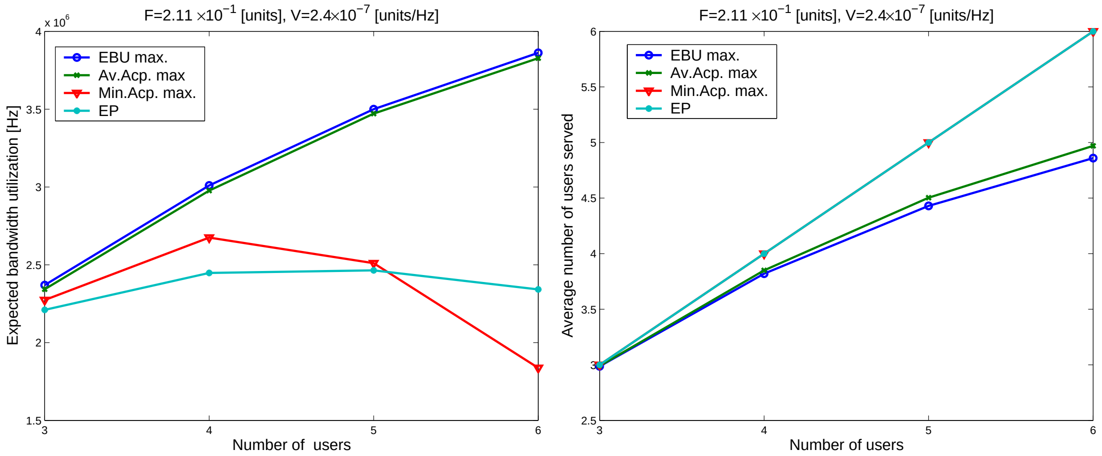
(a) Expected bandwidth utilization



(b) Average number of users served

Figure 5.5: V-dominated trajectory

and in the Acp_{min} maximization scheme, the SPS optimization is likely to force nonzero minimum acceptance probability which means that all users are active. It is observed, on the other hand that for the $\overline{Acp}$ maximization and EBU maximization schemes, the number of active users is less than the total number of users in the system. In the EBU maximization and $\overline{Acp}$ maximization schemes, the SPS would like to concentrate the bandwidth to users which could be served with high acceptance probability only, thus resulting in some users not being offered any bandwidth at all. The number of users served is decreasing in cost metric for the $\overline{Acp}$ maximizing, Acp_{min} maximization and EP schemes, along both trajectories. It is observed that for low values of the cost metric $F + VW_A$, the EBU maximization scheme results in the lowest number of users served. For the EBU maximization scheme, as the cost metric is increased, a drastic increase is followed by a slight decrease, along both trajectories. This observation is also intuitive. When the cost parameters are low, bandwidth is allocated to a few users in the EBU maximizing scheme, however, as the cost is increased, concentrating all spectrum in a few users does not help, since the operators will not use all the bandwidth to make offers in such a case. Thus, the available bandwidth is spread across the users, increasing the average number of users served.



(a) Expected bandwidth utilization

(b) Average number of users served

Figure 5.6: Performance of the schemes as functions of the number of users in the system.

In Fig. 5.6, we show the expected bandwidth utilization and the average number of users served by the tested schemes as functions of the number of users in the system, for an arbitrary cost structure. It is important to note that the patterns observed in these plots are valid for other cost structures that have been tested.

In Fig. 5.6(a), it is observed that $\overline{Acp}$ maximization scheme achieves comparable bandwidth utilization with the EBU maximization scheme, which by definition achieves the greatest. On the other hand, the Acp_{min} maximization scheme and the EP scheme achieve substantially lower bandwidth utilization than the other two, with increasing number of users. It is also observed that the expected bandwidth utilizations relevant to the EBU maximizing and $\overline{Acp}$ maximizing schemes are increasing in number of users while Acp_{min} maximization and EP schemes form a bell shape with expected bandwidth utilization first increasing in number of users and then decreasing. Note that, as the number of users is increased, each user is allocated decreasing bandwidths in the EP scheme. Thus, the acceptance probability resulting from the operator competition also diminish. This affect initially leads to an increase in achieved expected bandwidth utilization (due to increased number of users), and followed a decrease in bandwidth utilization (as the increase in the number of served users can not compensate the decrease in resulting acceptance probability anymore). Note that in Fig. 5.6(b), it is seen that the EBU maximizing scheme does not support as many users as others. This illustrates the water filling nature of the EBU maximizing solution.

We can summarize the experimental findings in this chapter as follows. As a function of cost, EBU maximizing and average acceptance ($\overline{Acp}$) maximizing schemes perform superior to the equal partition EP scheme and the minimum acceptance probability (Acp_{min}) maximizing schemes. The EBU maximizing scheme induces less number of users served, especially at low cost. The EP and the minimum acceptance probability (Acp_{min}) maximizing schemes perform well in terms of number of users served in the system.

As a function of the number of users in the system, it is observed that the (EBU) maximizing and average acceptance ($\overline{Acp}$) maximizing schemes achieve increasing expected bandwidth utilization while the EP and (Acp_{min}) maximizing schemes induce diminishing bandwidth utilizations.

Chapter 6

Comparisons between the Models

In this chapter we present some performance comparisons between the D-Pass and the D-CPass models. In all numerical experiments presented in the chapter, we consider EBU maximizing schemes in the context of the D-Pass and the D-CPass models. Fig. 6.1 shows the ratio of the expected bandwidth utilization achieved in the D-Pass scheme to that achieved in the D-CPass scheme as a function of the fixed operational cost F [units] and the variable cost V [units/Hz] in an 8-user system (linear geometry). Each data point on the curves denotes the average values for the 300 realizations of user locations considered before. All relevant user parameters are the same as in previous chapters. Note also that in all experiments results of which are presented in this chapter, the SPS maximizes the expected bandwidth utilization in the system.

Fig. 6.2 shows the expected bandwidth utilizations achieved in both models as a function of $F+VW_A$ along different trajectories in the $F-V$ plane displayed in Fig. 6.1. Fig. 6.2(a) shows the performance comparison for the $F = 0$ (zero fixed operational cost) trajectory while Fig. 6.2(d) considers the $V = 0$ (zero bandwidth usage cost) trajectory.

Note that figures 6.2(b) (V-dominated) and 6.2(c) (F-dominated) refer to non-zero F and V values, and they collectively suggest that for values of F and V sufficiently close to zero (negligible costs), the D-CPass model seems to slightly outperform the D-Pass model, with $EBU_{DP}/EBU_{DC} \approx 1$. It is also observed that the expected bandwidth utilization is decreasing in both models with increasing costs. As the values of F and V become non-negligible, the D-Pass model initially starts to achieve greater expected

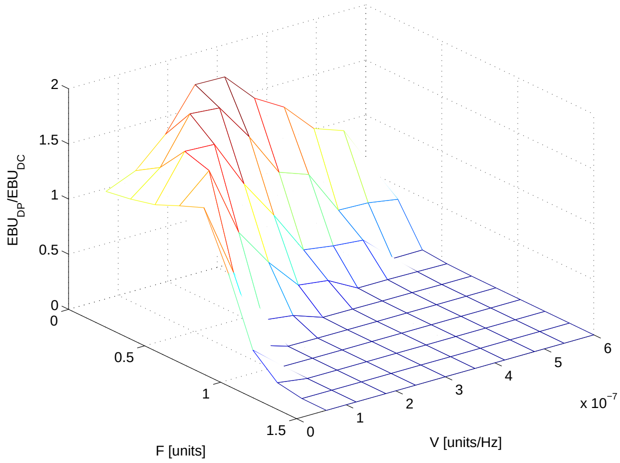


Figure 6.1: Performance comparison between *D-Pass* and *D-CPass* models: Ratio of expected bandwidth utilization in *D-Pass* to *D-CPass* (EBU_{DP}/EBU_{DC})

bandwidth utilization as opposed to the D-CPass model. However, when the cost pair (F, V) grow much higher, this trend is reversed and the D-CPass model performs better. This trend is more apparent along the V-dominated trajectory.

Considering figures 6.2(a) and 6.2(d), it is observed that when $V = 0$ (bandwidth usage cost is zero), the D-CPass model always performs superior irrespective of the value of F. When $F = 0$, on the other hand, the performance comparison depends on the value of V. D-CPass model outperforms the D-Pass model for very small values of V and for large values for V.

Figure 6.3 shows the performance comparisons over different trajectories for non-zero F and V. Note that in these trajectories, either F or V is fixed, aiming to achieve a better understanding of the effects of changes in V only or F only on the achieved performance. Figs. 6.3(a) and 6.3(b) display the performance comparisons for $F = 0.25$ (low fixed operational cost) and $F = 1.5$ (high fixed operational cost)respectively. Figs. 6.3(c) and 6.3(d) display the performance comparisons for $V = 0.125 \times 10^{-7}$ (low unit bandwidth cost) and $V = 3 \times 10^{-7}$ (high unit bandwidth cost) respectively. These plots emphasize the earlier observation that when unit bandwidth cost (V) is sufficiently low, the D-CPass scheme always performs superior. Also, when either one of F or V is

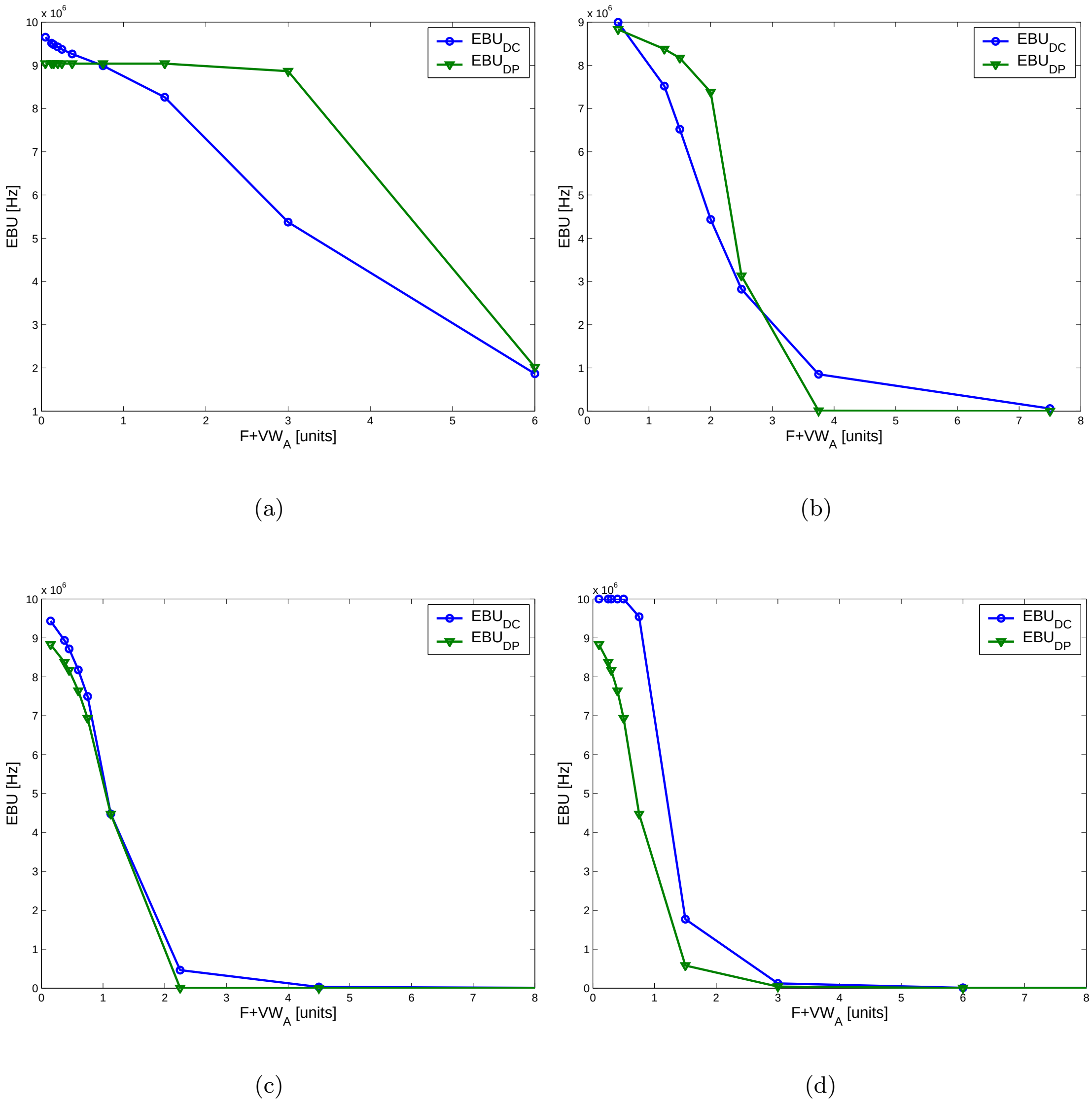
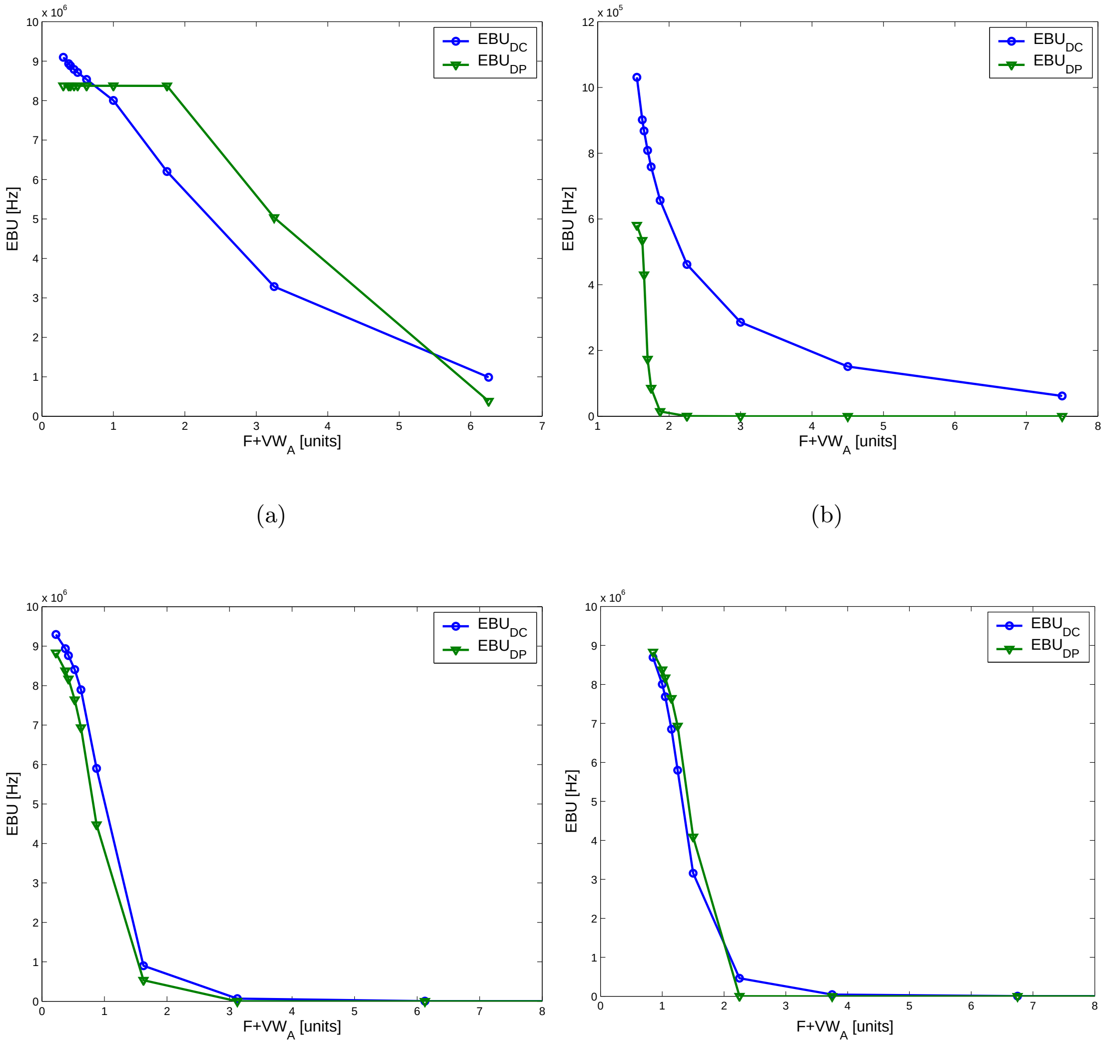
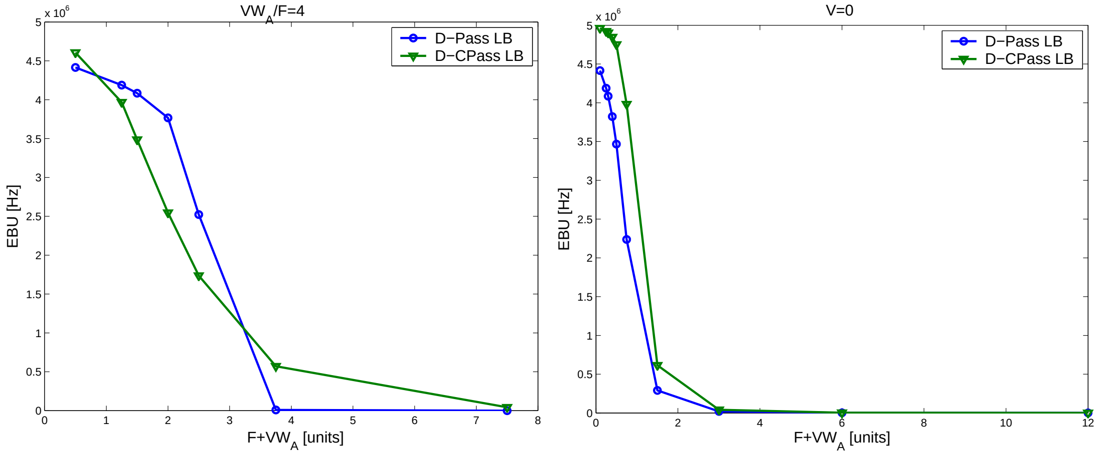


Figure 6.2: Expected bandwidth utilization (EBU) in *D-CPass* and *D-Pass* models for (a)$F = 0$ and $W_A = 10^7$ Hz; (b) $VW_A/F = 4$ and $W_A = 10^7$ Hz; (c)$VW_A/F = 0.5$ and $W_A = 10^7$ Hz; (d) $V = 0$ and $W_A = 10^7$ Hz .



(a) (b) (c) (d)

Figure 6.3: Expected bandwidth utilization (EBU) in *D-CPass* and *D-Pass* models for (a)$F = 0.25$ units and $W_A = 10^7$ Hz; (b) $F = 1.5$ units and $W_A = 10^7$ Hz; (c)$V = 0.125 \times 10^{-7}$ units/Hz and $W_A = 10^7$ Hz; (d)$V = 3 \times 10^{-7}$ units/Hz and $W_A = 10^7$ Hz.



(a) (b)

Figure 6.4: Expected bandwidth utilization (EBU) in *D-CPass* and *D-Pass* models for (a) $VW_A/F = 4$ and $W_A = 5 \times 10^6$ Hz; (c) $V = 0$ and $W_A = 5 \times 10^6$ Hz .

sufficiently large, the D-CPass model achieves greater utilization.

In Fig. 6.4, we show the comparisons of the two models along the $VW_A/F = 4$ and $V = 0$ trajectories for $W_A = 5 \times 10^6$ Hz (low bandwidth). It is observed that the qualitative results observed in the previous plots are valid; the D-CPass scheme performs superior for negligible costs and sufficiently high costs. Our observations suggest that changing the available bandwidth does not affect these comparisons.

We have also considered the case of a two dimensional system, such as the one presented in Fig. 6.5. Fig. 6.6 presents the comparisons for $VW_A/F = 4$ and $V = 0$ trajectories. It is observed that the observations for the one dimensional experimental setting are also valid for the two-dimensional settings.

Overall, our conclusion is that the cost structure plays an important role in the resulting comparison between the models. The effect of unit bandwidth cost V seems to be somewhat dominant. When the bandwidth usage cost is negligible, the superior scheme is the D-CPass model. For both F and V negligible, it is apparent that D-CPass is the better choice. With increasing cost in either F and V, the D-Pass model starts to outperform. However, if any one of F or V is sufficiently large, the D-CPass

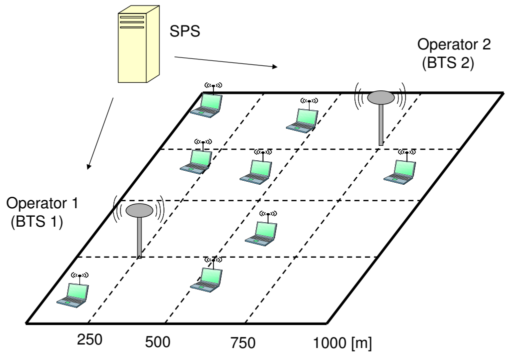


Figure 6.5: Two-Dimensional experimental setting.

outperforms D-Pass.

We now present an interpretation of the above trends in relation to the two models considered. In both models there are factors related to the dynamic access as well as market forces (cost and payment mechanisms) that affect the bandwidth utilization that is achieved. In the D-Pass model, only part of the spectrum is available to each operator which can cause inefficiencies. Thus, when the costs are very low (virtually free bandwidth), the D-CPass scheme enjoys superior performance due to greater control of the SPS in optimizations (user level optimizations), as well as the shared access. However, the SPS enforced allocation mechanism in D-Pass requires the operators to pre-competitively invest in spectrum portions. Thus, this mechanism induces greater incentives for the operator to make attractive rate offers to the users, thereby increasing the bandwidth utilization (see Thm. 4.4.1). The above explains the initial improvement in the bandwidth utilization in the D-Pass scheme as the costs increase from zero. However, when the costs become much higher, the SPS is unable to produce allocation vectors affordable to the operators. In this case, since the payment for the spectrum is due regardless of the utilization (see equation(4.2)), the operators are unable to make rate and price offers that are attractive to the users, resulting in reduced values of the induced acceptance probability. This results in the operators opting out (SPS unable

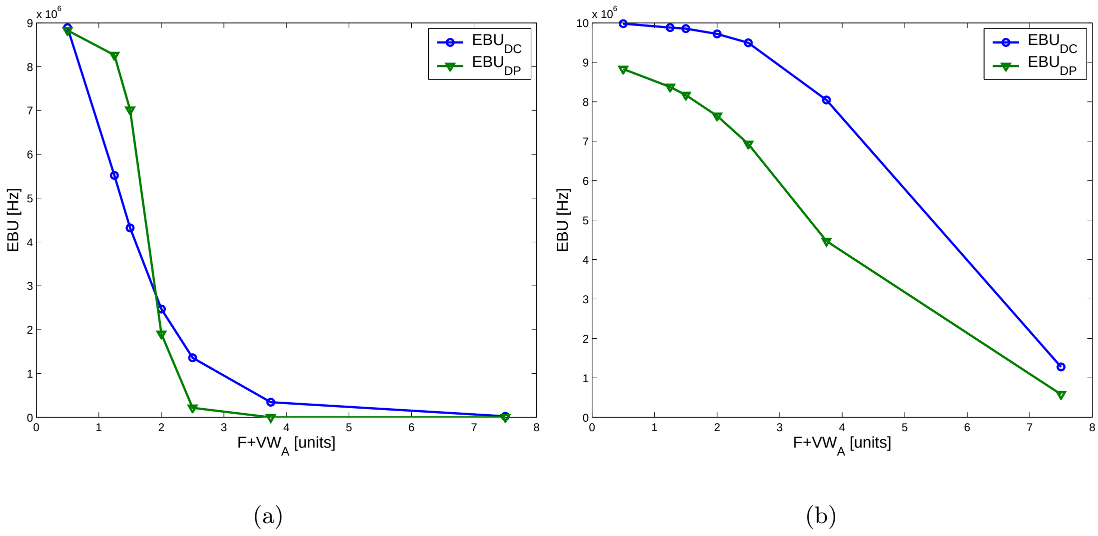


Figure 6.6: Expected bandwidth utilization (EBU) (Two-Dim) in *D-CPass* and *D-Pass* models for (a)$V/F = 4 \times 10^{-7}$ and $W_A = 10^7$ Hz; (b) $V = 0$ and $W_A = 10^7$ Hz;

to maintain positive operator profit) in the short-term, thereby reducing the bandwidth utilization below that of the D-CPass model. Note that the payment mechanism in the D-CPass model does not require pre-competitive payments and the operators pay for the part of spectrum they actually use (see Eq. (5.2)). The operators have access to all available bandwidth during the competition phase and they determine the amount of bandwidth they purchase for any given user. Thus the above mentioned market forces relevant to the D-Pass model are not present in case of the D-CPass model.

These results demonstrate that in addition to the specific spectrum access mechanism, the market forces employed and the relevant payment schemes in the models have an important role in determining the achieved performance.

Chapter 7

Practical Issues in the Implementation of the Models

The previous chapters have focused on theoretical modelling of the dynamic spectrum access schemes proposed. An improved bidding algorithm is proposed in the context of the *D-CPass* model, which achieves convergence in only two iterations. This algorithm is considered as an important step in addressing the practical needs concerning the implementation of the models.

Nevertheless, a variety of potential problems related to practical implementations persist. Some of these are mentioned in Chapter 2,where a generic overview of the system model is presented. These problems include *complexity issues*, *scalability concerns* and *privacy concerns*.

Note that the D-CPass model requires the SPS to optimize the spectrum allocated to every single operator-user association in the system. Similarly, in the D-Pass scheme, the SPS optimizes the spectrum bandwidth allocated to a given operator, nevertheless, the operators need to optimally partition their spectrum resources among different users. Furthermore, the SPS objective functions and the operator payoffs are not convex or concave functions. Thus, the optimizations mentioned are performed in an iterative manner in which all possible spectrum partition vectors need be tested to determine the optimum allocation. Note also that the operator competitions in the D-Pass model is a very complex algorithm possibly converging in many iterations. Consequently it is apparent that the models proposed are complex and thus the computational cost for the system increases drastically with increasing number of users. These constitute the complexity and scaling problems.

Another practical issue worth addressing is the privacy problem. Recall from Chapter 3 that upon entry into the system, the user is supposed to convey a fully descriptive acceptance probability profile that maps any given rate and price offer to an acceptance probability. This requirement does not seem to be more intrusive then many of the currently employed data mining methods employed by the commercial companies. Nevertheless, it is evident that there might be incidents in which the user would not be willing to convey its full acceptance probability profile. Instead, it could communicate a partial description.

In this chapter, we first propose methods to overcome the complexity and scaling problems, evaluating their performances. We then study the effect on performance of privacy aware users who convey only partial description of their acceptance probability profiles.

7.1 Clustering Approach (Scaling Issues)

In this approach, the considered geographical area is divided into smaller regions. Each of these smaller regions denotes a cluster, and every user located in the region is associated with the cluster.

The operators and the SPS treat each user as if they are located at the center of the cluster they belong to. We assume that the clusters are homogeneous in shape and they are in the form of regular geometrical shapes (we consider squares for this work). When the SPS or operators optimize spectrum allocation across the users, they consider every user in a given cluster to be located at the center. We also impose the constraint that every user in a given cluster is to be allocated exactly the same amount of spectrum in the D-CPass model. Similarly, the operators are to make the same price and rate offers to all users in a given cluster. Note that this constraint is reasonable since every user in a given cluster is assumed to be located at the same point. Thus, in the D-CPass model, the SPS optimization which used to be a multidimensional optimization with

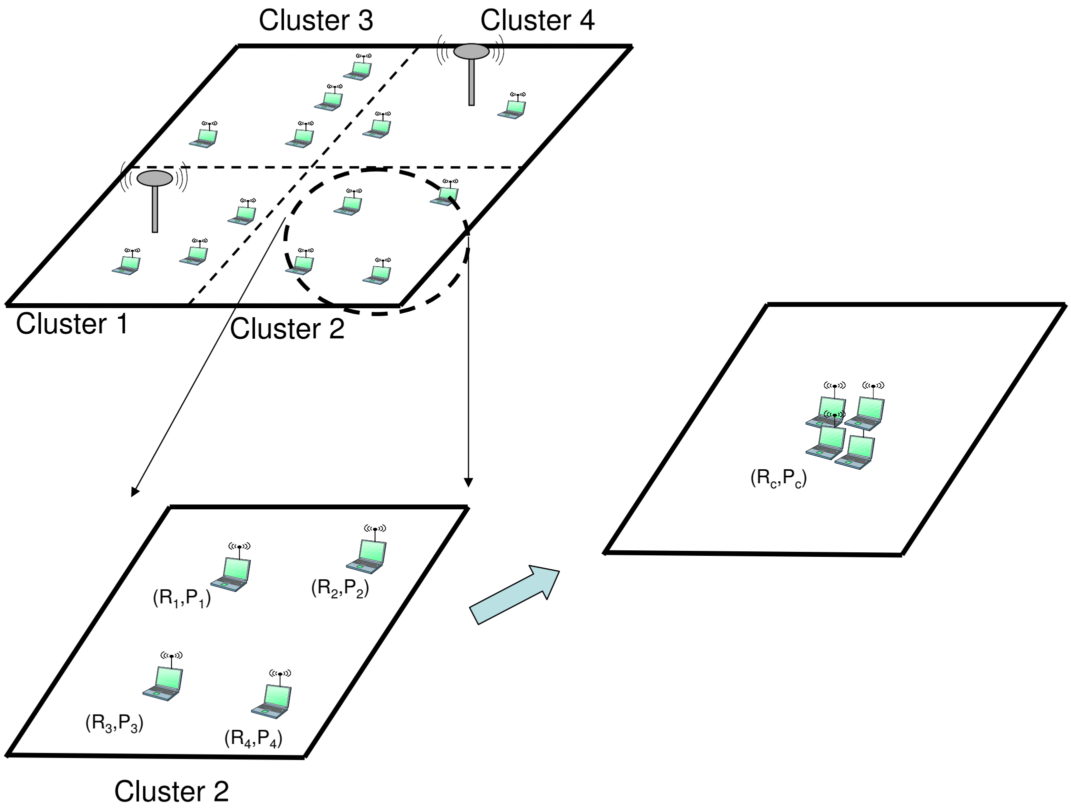


Figure 7.1: Clustering procedure; the geographic region is divided into 4 clusters (square). Each user in a cluster is treated as if it is located at the center of the cluster. For the case of cluster 2, 4 user parameters are reduced into one cluster-wide parameter.

the number of variables being equal to the number of users, is reduced to a simpler optimization in which the number of variables is equal to the number of clusters in the system. Similarly, in the D-Pass model, the number of optimization parameters in the operator competition is reduced.

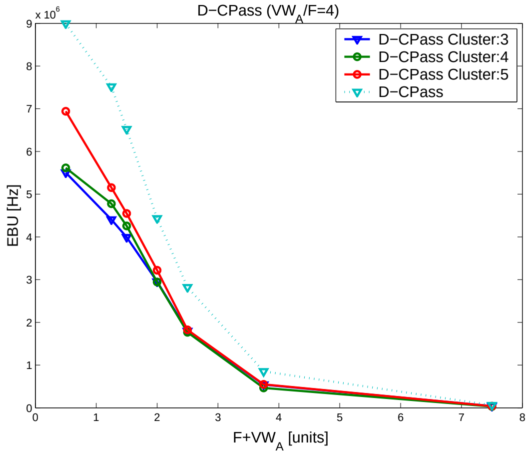
An illustration of the clustering procedure is shown in Fig. 7.1.1. In this figure, the whole region the SPS serves is divided into 4 clusters in the form of smaller squares. All users in a cluster are treated as if they are located in the center of the cluster. Also, all offers to the users are constrained to be equal to each other. Thus, the number of free parameters in the optimization problems are drastically reduced.

7.1.1 Performance Degradation in the Clustering Approach

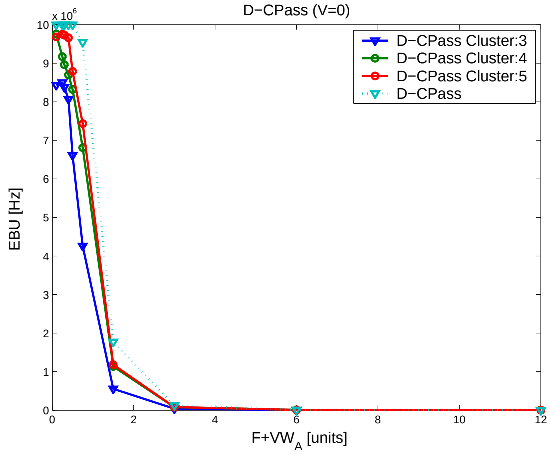
In order to compare the performance of a clustered system to that of a non-clustered one, experiments for the linear geometry in Fig. 4.6 have been conducted. Fig. 7.2 shows these comparisons. Note that in all these experiments the SPS maximizes the expected bandwidth utilization in the system. It is observed that, the clustering system performs inferior than the corresponding non-clustered system. Nevertheless, the difference between the performance diminishes as the number of clusters in the system is increased. This result is intuitive, since as the number of clusters is increased, the difference between the real location of a given user and its perceived location (as the center of the cluster) is reduced, thus yielding a better approximation to the true result. Recall also that in the clustered system, the SPS (in D-CPass) and the operators (in D-Pass) are constrained to make the same allocation decisions for all users in a given cluster. This constraint shrinks the optimization domain for the SPS optimization and operators optimizations. Thus, decreasing the number of clusters makes this constraint more severe, as the number of users per cluster increases with decreasing cluster number.

In Fig. 7.3, we show the comparisons between the D-CPass and D-Pass schemes for the linear geometry with 8 users. The users in the system are clustered into 4 groups. It is observed that the performance comparisons yield similar conclusions as in the non-clustered cases, detailed in the previous chapter. It is observed that for $V = 0$ trajectory, the D-CPass scheme always achieves superior. For the $VW_A/F = 4$ trajectory (variable cost dominated trajectory), the D-Pass scheme achieves superior for low cost regime, however performs poorly when cost is increased.

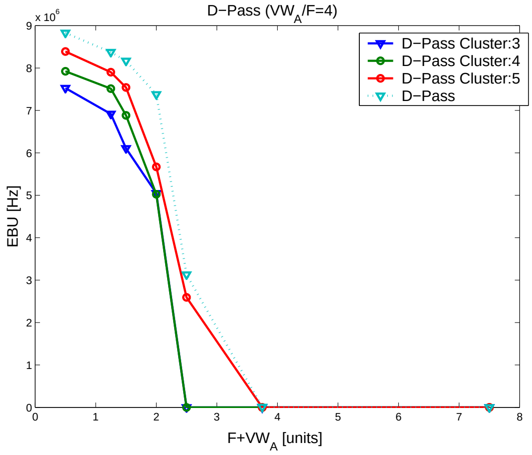
Finally, we present the performance comparisons between the clustered D-CPass and D-Pass schemes for the case of a two dimensional setting, as in Fig. 6.5. The considered system is populated with 20 users. The SPS maximizes the expected bandwidth



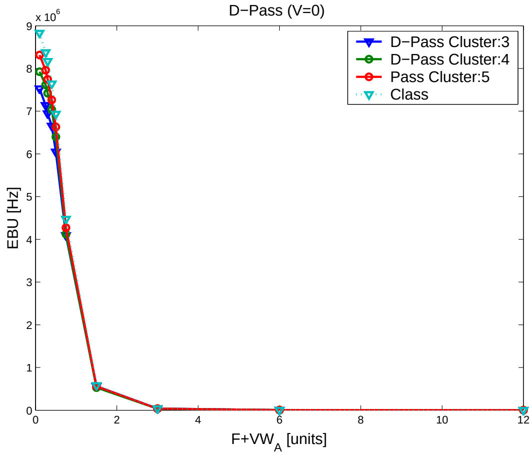
(a)



(b)

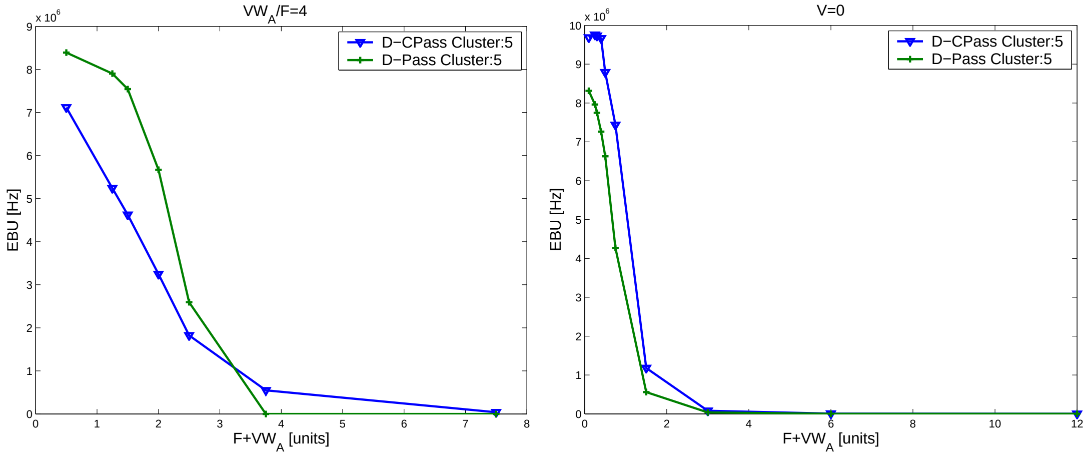


(c)



(d)

Figure 7.2: Performance of the clustering approach in an 8-user system (a)$VW_A/F = 4$ and $W_A = 10^7$ Hz (D-CPass); (b) $V = 0$ and $W_A = 10^7$ Hz (D-CPass); (c)$VW_A/F = 4$ and $W_A = 10^7$ Hz (D-Pass); (d)$V = 0$ and $W_A = 10^7$ Hz (D-Pass);



(a) (b)

Figure 7.3: Performance of the clustering approach in an 8-user system for (a)$VW_A/F = 4$ and $W_A = 10^7$ Hz; (b) $V = 0$ and $W_A = 10^7$ Hz.

utilization. We consider the variable cost dominated trajectory in Fig. 7.4. It is observed that the earlier conclusions regarding the comparisons between the two models are valid in the case of a two dimensional 20 user system.

7.2 Simplifying the Operator Competition

Yet another way to reduce the computational complexity of the schemes is to simplify the operator competitions. Recall that in the context of the D-CPass model, an improved bidding algorithm was proposed in Chapter 5 to increase the convergence rate of the iterative bidding procedure. In this section we propose another algorithm which simplifies the operator competition, at the expense of reduced acceptance probability for the users. Note that the simplification of the operator competition does not necessarily help the scaling problem, as it does not reduce the number of optimization variables to be considered by the SPS.

In this section we consider a simple approach for the operator competitions. Instead of iterative bidding, we propose a two step bidding approach as follows. In the first step each user is associated with the closest base station based on the greatest signal strength

][t]

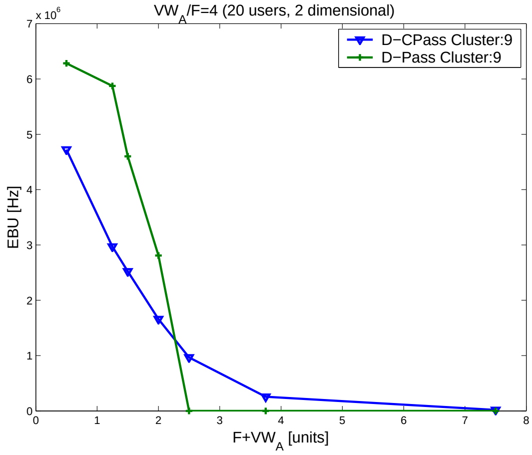
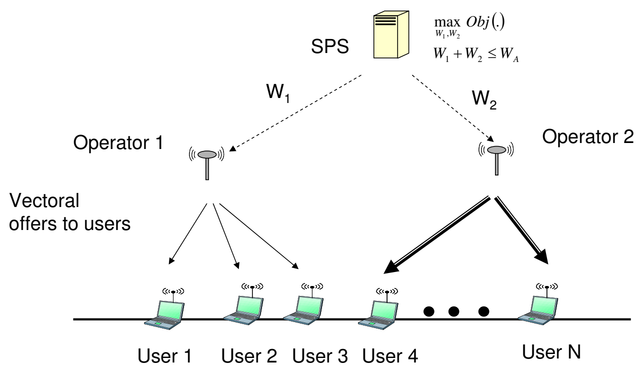


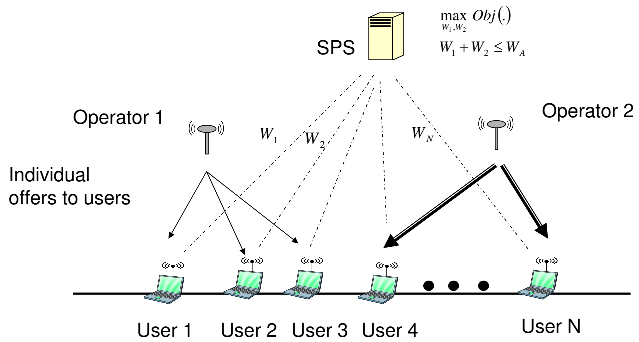
Figure 7.4: Performance comparison between *D-Pass* and *D-CPass* models for $VW_A/F = 4$ and $W_A = 10^7$ Hz). (2 dimensional system with 20 users).

it sees. In the second step, the operators make their best offers to only those users who are associated with them in the first step. In the case of the D-CPass model each operator makes independent offers to each associated user, considering the bandwidth consumption constraint imposed by the SPS for the specified user. In the D-Pass model, the operators make vectoral rate and price offers to the associated users only, given the bandwidth allocated by the SPS, with no consideration of their opponents and the users which are not associated. Thus, in all cases the final operator offers are determined in only one iteration, and, the operators practically do not compete with each other. Note that this approach only affects the lower level of the SPS based hierarchical optimization structure shown in Fig. 3.6, the upper level SPS optimization is still in effect.

Fig. 7.6 shows the performance comparisons between the schemes where the simplified operator competition is employed and the ones in which the normal iterative bidding described in previous chapters is employed. A linear geometry populated with 8 users is considered. It is seen that the simplified operator competition is a very close approximation to the D-Pass scheme for both cost structures shown in Fig. 7.6(c) and 7.6(d). The D-CPass scheme, however, seems to be severely affected for negligible bandwidth usage costs ($V = 0$) as observed in Fig. 7.6(b). Overall, it is seen that

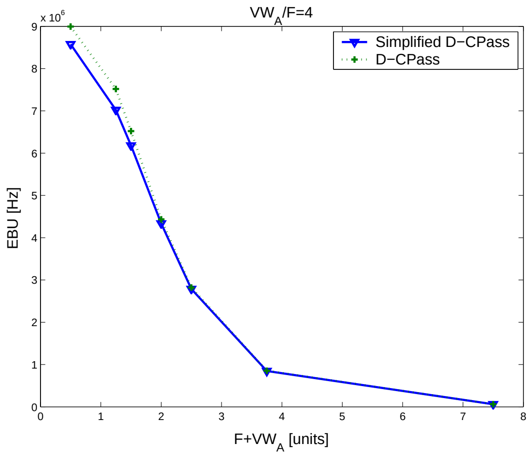


(a)

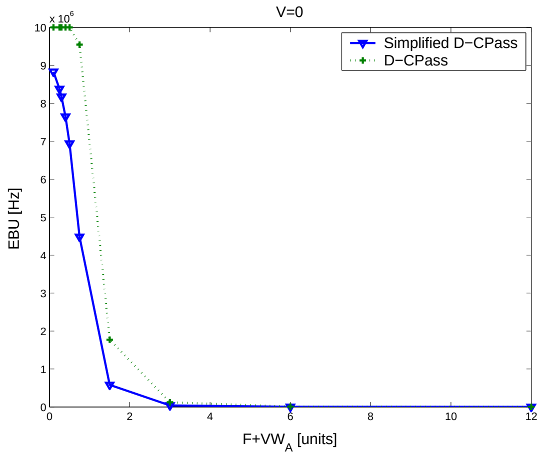


(b)

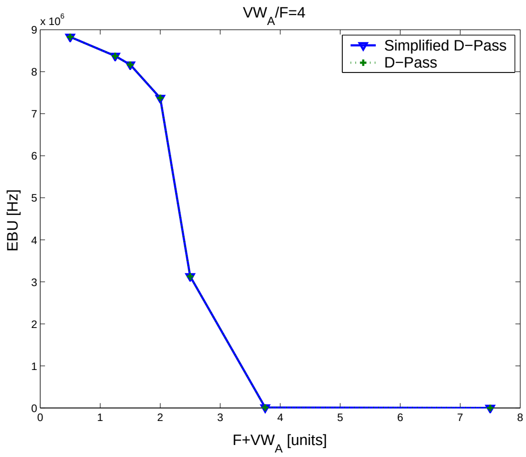
Figure 7.5: Illustration of the simplified operator competition approach in (a) D-Pass (b) D-CPass.



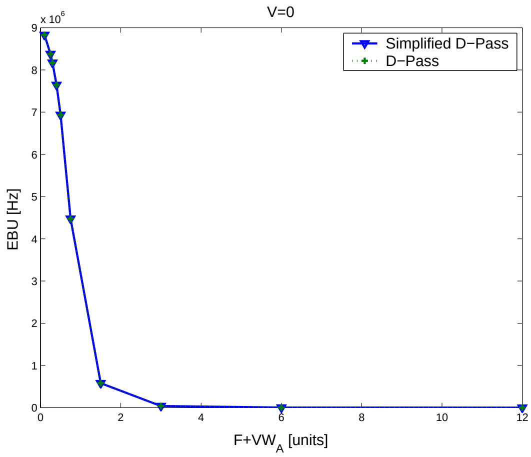
(a)



(b)

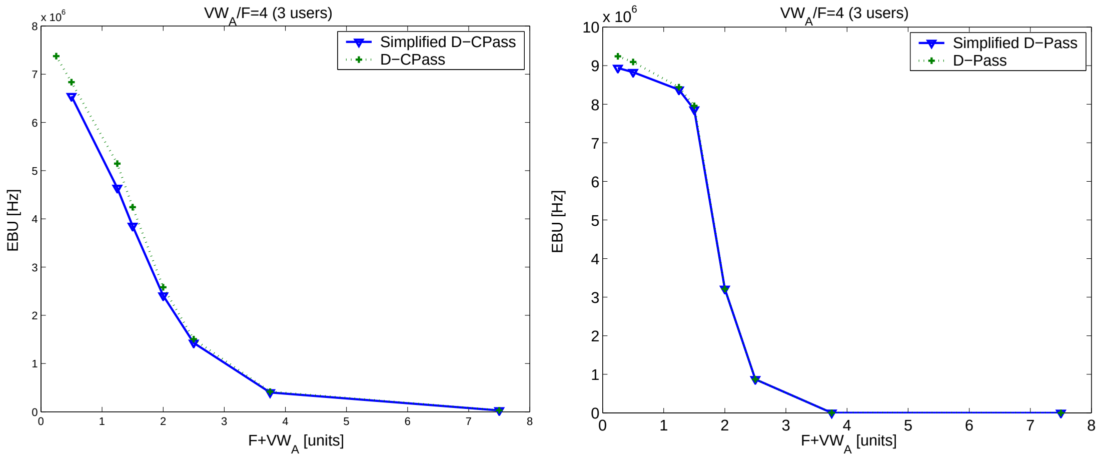


(c)



(d)

Figure 7.6: Performance of the simplified operator competition approach in a 8-user system (a)$VW_A/F = 4$ and $W_A = 10^7$ Hz (D-CPass); (b) $V = 0$ and $W_A = 10^7$ Hz (D-CPass);(c)$VW_A/F = 4$ and $W_A = 10^7$ Hz (D-Pass); (d) $V = 0$ and $W_A = 10^7$ Hz (D-Pass)



(a) (b)

Figure 7.7: Performance of the simplified operator competition approach in a 3-user system (a)$VW_A/F = 4$ and $W_A = 10^7$ Hz (D-CPass); (b) $VW_A/F = 4$ and $W_A = 10^7$ Hz (D-Pass)

the simplified operator competition approach is a good approximation for both models when costs are non-negligible. These results also indicate that in the D-CPass model, the operator competition is more effective when the costs are lower (i.e., results in increased bandwidth efficiency). On the other hand, in the D-Pass scheme, since each operator directly competes for all users, the result is that users closest to any operator are made favorable rate and price offers. This maximizes operator profits and intuitively suggests bandwidth utilization similar to the simplified connection model. The degradation effects are more visible in a 3 user setting shown in Fig. 7.7. Note that in the 3-user setting, there is even degradation for the D-Pass model, at negligible costs.

7.3 Incomplete Acceptance Profile Information

Recall that for the proposed models to work the user needs to convey its acceptance probability profile to the SPS upon entry into the serving area. However, privacy concerns may not allow the user to convey the complete acceptance probability profile. It could only try to "give an idea" about it's preferences instead. Quantifying the effect of incomplete acceptance probability profile on the resulting system performance is an

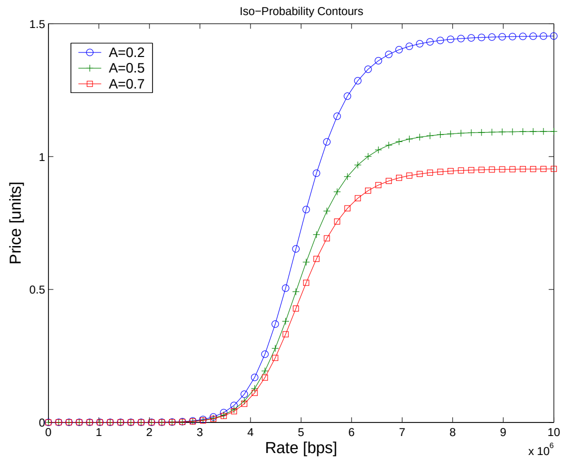


Figure 7.8: Illustration of Iso-Probability contours

interesting research question that is addressed in the following.

Note that the user might convey partial information about it's acceptance probability profile in different ways. Similarly, the operators and the SPS can interpret and use this partial information in several different ways. In this section, we consider simple, straightforward ways of conveying and using partial information about the acceptance probability profile of a user.

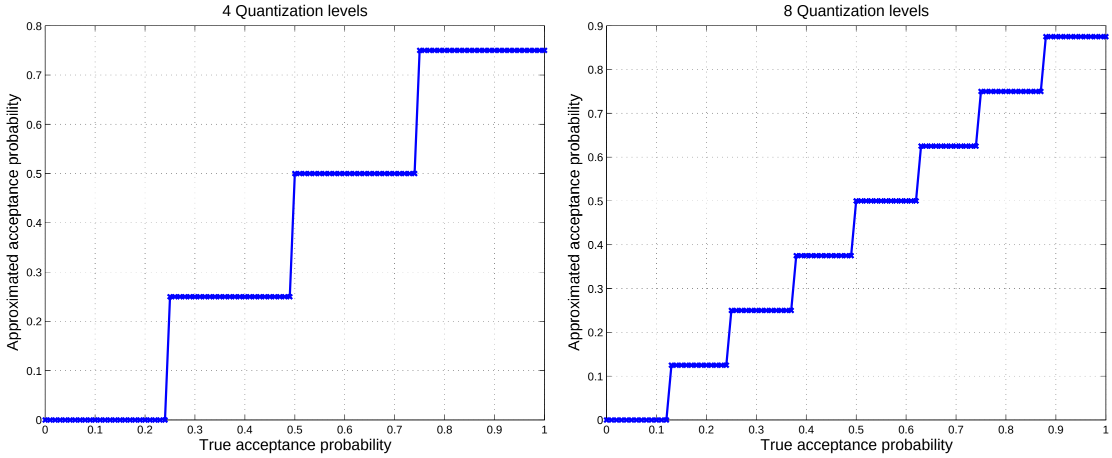
We consider a scenario in which the user, upon entry into the system, conveys sets of (R, P) pairs corresponding to a discrete set of acceptance probability values. For example, the user could convey the (R, P) values for which $A(R, P) = 0.5$ only. Instead, it could convey all (R_1, P_1) and (R_2, P_2) pairs, such that $A(R_1, P_1) = A_1$ and $A(R_2, P_2) = A_2$ for arbitrary A_1 and A_2, $0 < A_1, A_2 < 1$. In other words, the user conveys a few iso-probability contours on the P-R plane. Each point on a given contour induces the same acceptance probability. Fig. 7.8 illustrates examples of such contours.

The SPS and the operators come up with an approximation of the complete acceptance probability profile by using the conveyed contours by the user. Note that such approximations can me made through several ways. For instance, any (R, P) pair on the plane could be mapped to the acceptance probability of the contour that lies closest to the it. Yet another example (chosen here) is one where the SPS and the operators map any (R, P) pair in the R-P plane to a contour that corresponds to the greatest lower bound among all known contours with positive acceptance probability. If no such contour exists, then the (R, P) pair in question is mapped to an acceptance probability of zero.

To better illustrate this procedure, consider the case in which the user conveys the contours for 0.25 and 0.75 probabilities. In this case, any (R, P) pair which in reality would correspond to an acceptance probability A such that $0.25 \leq A < 0.75$ would be considered to induce an acceptance probability of 0.25. Similarly, any offer pair which in reality would induce an acceptance probability $A \geq 0.75$ would be considered as inducing an acceptance probability of 0.75. (R, P) pairs which in reality induce acceptance probabilities $A < 0.25$ would be considered to correspond to zero acceptance probability.

Note that this procedure is similar to quantizing the true acceptance probability induced by an (R, P) pair into discrete levels. This follows a uniform quantization procedure for the acceptance probability, in which the step-size is determined by the division $1/Q$ where Q stands for the number of quantization levels. The decision thresholds are $D = \{0, 1/Q, 2/Q, ..., 1 - 1/Q\}$. Any given true acceptance probability is approximated using the mapping $Acp_{App} = m_k$ if $m_k \leq Acp_{true} < m_{k+1}$, where Acp_App is the approximation, Acp_{true} is the true value for the acceptance probability and m_k is the decision threshold with index k. Thus, for a 4-quantization level scenario, we assume the decision thresholds are $0, 0.25, 0.50$ and 0.75 and the user conveys the contours for 0.25, 0.50 and 0.75 (there is no contour for 0). Fig. 7.9 illustrates this. The horizontal axis denotes the true acceptance probability that a given (R, P) pair corresponds to. The staircaselike mapping shows the approximated acceptance probability.

Fig. 7.10 shows how the resulting acceptance probability looks like as a function of R and P. These approximated acceptance probability surfaces are based on the true

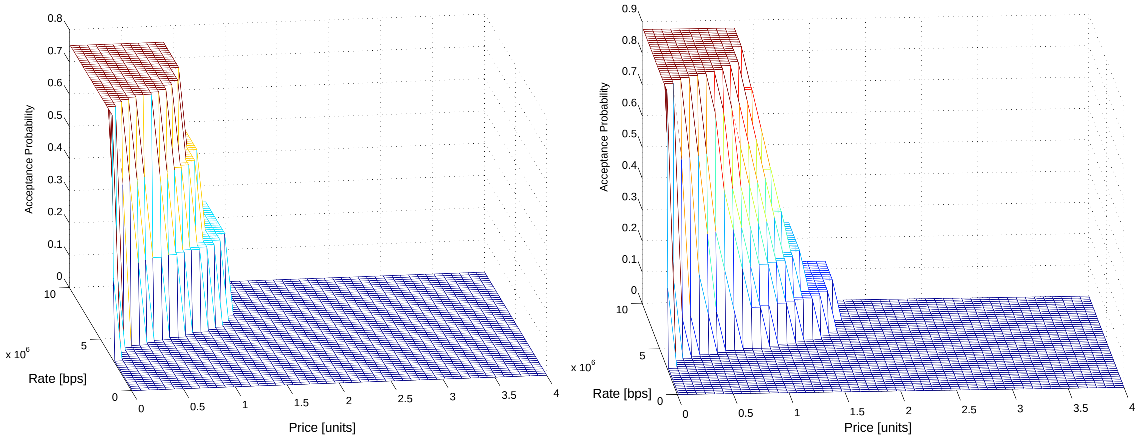


(a) (b)

Figure 7.9: Mapping from true acceptance probability to approximated acceptance probability.

probability surface shown in Fig. 3.2. Note that with increasing number of quantization levels, the value of the greatest decision level increases. In the given figures, the value of the greatest threshold for 4-quantization levels is 0.75 while the corresponding value is 0.875 for 8-quantization levels. Another interesting inference is that the operator will always make their offers to fall on the contours provided by the user. This is caused by the fact that if an operator makes and offer that induces a true acceptance probability which falls in between two decision thresholds, the approximate acceptance probability profile would give the lower decision threshold as the output. Thus, an operator would always increase the price asked P until it hits the contour, as such an increase would increase its expected profit.

Fig. 7.11 shows the performance results for the acceptance probability approximation with different quantization levels. It is observed that as the number of quantization levels is increased, the results approach the true values. It is also observed that for low cost regimes, the approximating acceptance probability achieves lower expected bandwidth utilization as opposed to true values. As the costs are increased, the achieved



(a) (b)

Figure 7.10: Approximated acceptance probability for the true probability surface in Fig. 3.2: (a) 4 quantization levels; (b) 8 quantization levels.

results get closer to the true values. We explain this behavior as follows. As mentioned earlier, the operators when using an approximate acceptance probability profile always make offers which induce true acceptance probabilities equal to one of the decision thresholds. This strategy is conservative and underachieves in terms of inducing higher acceptance probabilities. For example, in the case of the 4 level quantization, the operators would make offers which would induce true acceptance probability of 0, 0.25, 0.50 or 0.75. When the costs are very low, the best an operator can do is to induce an acceptance probability of 0.75, when in reality it would have induced a much higher acceptance probability if it knew the complete profile. Thus for low cost, the approximation of the acceptance probability profile degrades the performance. With increasing costs, the acceptance probability induced by the approximate method on an average can either underestimate or overestimate the true acceptance probability. Thus, the resulting average bandwidth utilizations are comparable.

Fig. 7.12 shows the performance comparisons for between the D-CPass and D-Pass models using 4 level quantization approximation. It is observed that the earlier observations regarding the performance comparisons are also valid for this case.

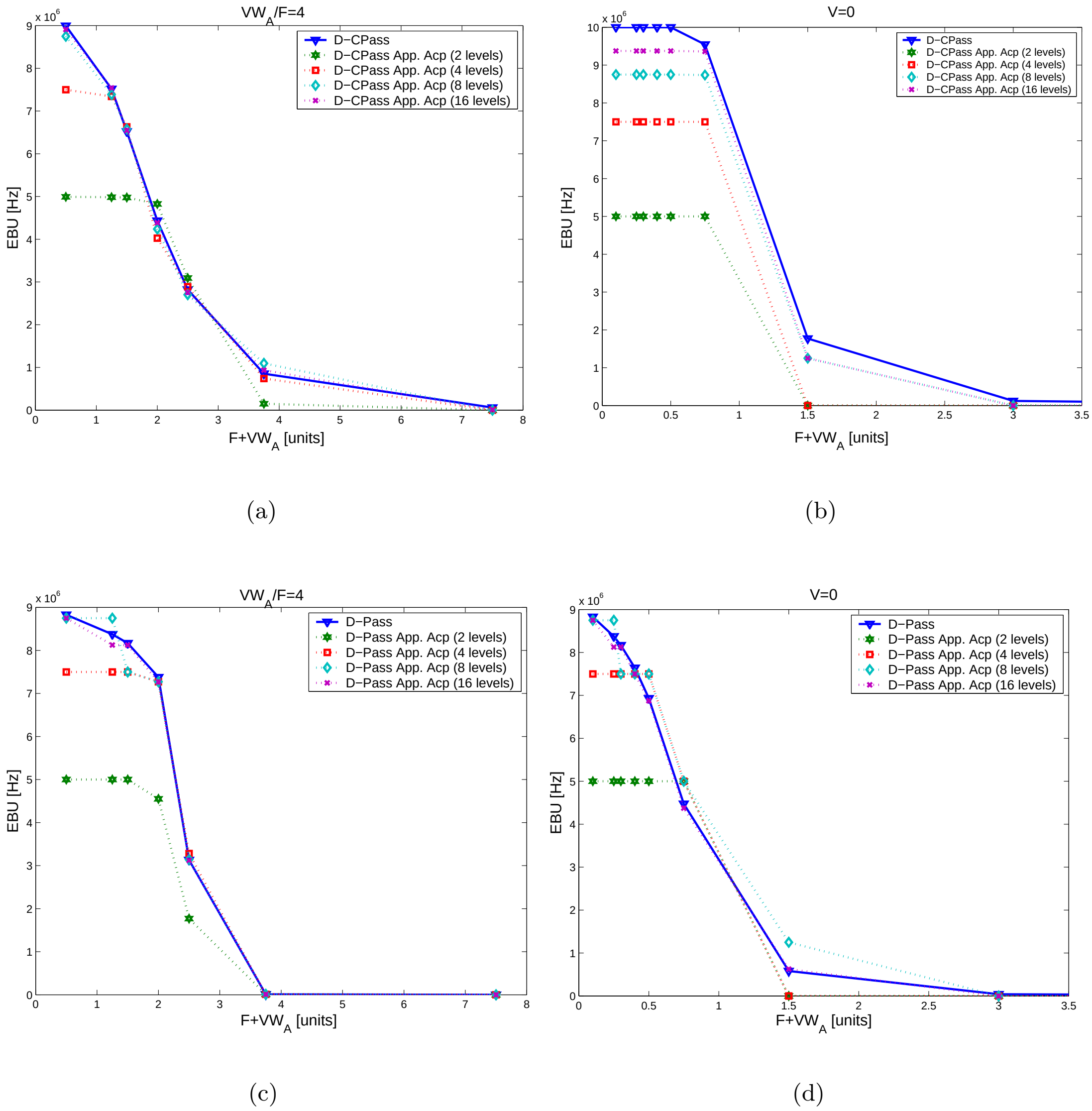
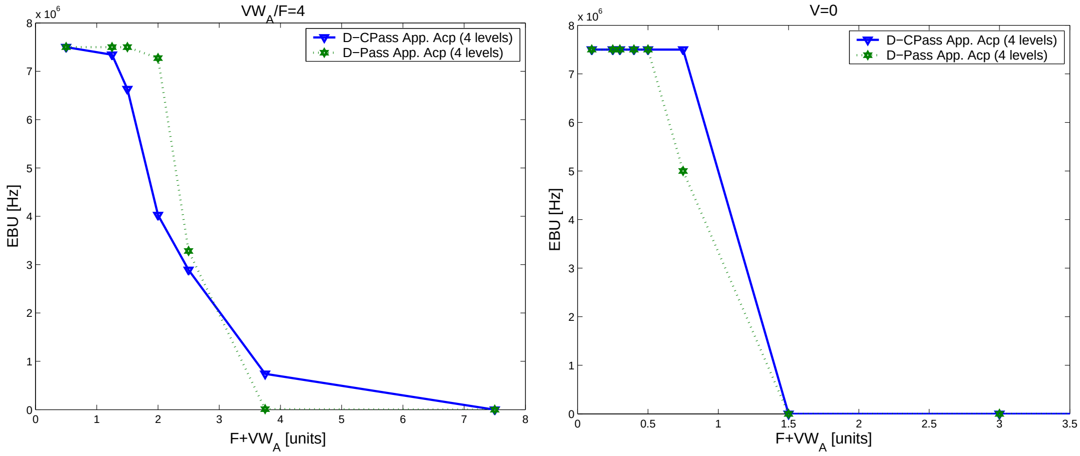


Figure 7.11: Performance of the acceptance probability approximation approach in a 8-user system (a)$VW_A/F = 4$ and $W_A = 10^7$ Hz (D-CPass); (b) $V = 0$ and $W_A = 10^7$ Hz (D-CPass); (c) $VW_A/F = 4$ and $W_A = 10^7$ Hz (D-Pass) ; (d) $V = 0$ and $W_A = 10^7$ Hz (D-Pass).



(a) (b)

Figure 7.12: Performance comparison between *D-Pass* and *D-CPass* models for a 8 user system (linear geometry).

7.4 Remarks

In this chapter, we have introduced some simple approaches to mitigate the scaling, complexity and privacy issues related to the models. Our conclusion is that all the approaches introduced here come at the expense of reduced performance. However, the degradation of the performance is not severe enough to alter the tradeoff patterns observed with the true algorithms. Furthermore, as seen in the clustering and acceptance probability approximation approaches, the tradeoff between performance and scalability or privacy can be tuned.

Chapter 8

Conclusions

The motivation for this thesis was to bring an engineering perspective to the ongoing spectrum debate. The spectrum debate strives to identify alternative spectrum governance regimes that would mitigate the artificial spectrum scarcity caused by the currently enforced, pre-dominantly command and control type spectrum governance. The inherent governmental inefficiencies, static nature of spectrum allocations are identified as the major reasons for the inefficiency observed. The two proposal that have emerged in this debate are the spectrum property rights and the spectrum commons approaches. Even though the generic definitions of these proposals seem clear, lack of precise modelling of the relevant spectrum allocation algorithms, monetary transactions and other spectrum management aspects have created gaps, and the ensuing tragedy of taxonomy has avoided any conclusion or consensus at the time of writing.

Inspired by the call for practical models, and the recent focus of research efforts to produce compromise approaches, we proposed two models, dynamic property-rights spectrum access (D-Pass) and dynamic-commons property-rights spectrum access (D-CPass). While both models introduced retain a bias toward the spectrum property rights approach based usage of spectrum, they also promote dynamic access and short term dedication of spectrum resources. In the D-Pass model, the operators pay the SPS for the exact amount of bandwidth they are allocated, irrespective of the utilization of the bandwidth. Given the spectrum allocations, each operator competes for users via rate and price offers for utilizing the spectrum portion under its short term "ownership". We model the operator competition in the form of a SPS-mediated iterative bidding scheme that is reminiscent of a simultaneous ascending auction. In the D-CPass model, all operators have access to all the available bandwidth during the competition phase, suggesting the flavor of a spectrum commons model. The operators pay the SPS for the portion of the spectrum that they actually utilize (pay-as-you-go). They compete for each user via rate and price offers through an SPS-mediated iterative bidding scheme that is reminiscent of a single-item ascending auction.

We considered three different objective functions for the SPS maximization: (i) expected bandwidth utilization (EBU), (ii) average acceptance probability ($\overline{Acp}$), and, (iii) minimum acceptance probability (Acp_{min}). For comparisons purposes, we also consider a equal partition approach, in which the available spectrum is allocated equally (EP) among the operators (D-Pass) or users (D-CPass). We considered different cost structures to understand the trade-offs between these objective functions. We concluded that the exact trade-offs strongly depend on these parameters. Our observation is that in both the D-Pass and the D-CPass models, use of SPS based maximization schemes are beneficial as opposed to the simple equal partition (EP) scheme. However, the EBU maximizing scheme can cause a decrease in the number of users served. The bandwidth utilization performance improvement through the SPS based optimizations is more apparent in high bandwidth cost regimes for the D-Pass model.

We also considered performance comparisons between the D-CPass and D-Pass models. We considered EBU maximizing schemes for both models and compared the two models in terms of the expected bandwidth utilization they achieved. Our results indicated that both the spectrum access mechanism and the market forces play an important role in the resulting bandwidth utilization. More specifically, we observed that when the bandwidth cost is negligible, the D-CPass model outperforms the D-Pass model, due to the open-access nature of the competition phase. As the costs are increased, however, the D-Pass scheme initially outperforms. Further increasing costs degrade the performance of the D-Pass model, as it becomes more difficult for the SPS to identify allocation vectors for which the operators achieve positive profit. These observations suggest that for negligible costs and very high costs, the D-CPass model seems to be the more reasonable choice. Else, employing the D-Pass model is more beneficial.

The proposed models suffer from three drawbacks; (i) the operator competitions are computationally intensive, (ii) the SPS optimizations involve iterative algorithms which require exhaustive search, thus creating a scaling problem, and (iii) the privacy concerns could cause the users to give up their complete acceptance probability profiles. We addressed these concerns by developing simple approaches. We proposed a clustering approach in which users are grouped into clusters and allocation/offer decisions are made on a cluster basis instead of user basis. This approach reduces the scaling problem. Our experiments showed that the clustering approach degrades the performance for the models. However, it was also observed that the qualitative results regarding the performance comparisons between the models are valid in the clustering approach. As the users are divided into increasing number of clusters, the performance gap is diminished. We also proposed a simplified operator competition approach in which the users get connected to the closest operator. Then the operators make their optimum offers, with no competition. It was observed that this approach induced similar performance results to the true results for low cost structure. We also addressed the privacy issue by investigating the effect of incomplete information on the SPS side, regarding a specified user's acceptance probability profile. We observed that lack of such information degrades the system performance, especially for low cost structures.

As mentioned earlier in the thesis, we aimed to initiate an engineering perspective in the spectrum debate, by considering quantitative performance metrics and also emphasizing the effect of economics as well as specific allocation mechanisms on the resulting performances. In this sense, the models presented in this thesis provide a foundation for more realistic engineering models that can shape spectrum policy.

There are a number of ways in which this thesis could be expanded. An interesting research direction would be to investigate ways in which the models proposed in this work can be applied to networks in which there is constant mobility. In our numerical evaluations, we assumed that the service spectral efficiency an operator enjoys serving a given users depends only on the users location (distance between the user's location and the operator's base station). How would the models work in scenarios in which the users are constantly moving (as opposed to occasional movement model in this work), or if the channels are time varying? Would our results be still valid if we considered the different propagation and pathloss characteristics for different frequency bands? These are interesting research questions worth exploring for the curious minds.

A more ambitious research direction would be to try to model a scheme which can be considered to be a pure spectrum commons approach. Such an approach would probably not involve payments or such monetary transactions as the spectrum usage in a spectrum commons model is often envisioned to be free of charge. How could such a model be compared to a spectrum -property rights based model where market forces play a major role? How can we ensure a fair, system wide comparison? These questions are difficult ones, and finding answers for them would be a major contribution to the spectrum debate.

References

[1] D. N. Hatfield and P. J. Weiser, "Property rights in spectrum: taking the next step," in *IEEE DySpan 2005*, 2005.

[2] M. McHenry and D. McCloskey, "New York City spectrum occupancy measurements september 2004," Tech. Rep., December 2004. [Online]. Available: http://www.sharedspectrum.com/inc/content/measurements/nsf/NYC_report.pdf

[3] J. M.Peha, "Approaches to spectrum sharing," *IEEE Communications Magazine*, vol. 43, no. 2, pp. 10–12, February 2005.

[4] R. H. Coase, "The federal communications commission," *Journal of Law and Economics*, vol. 2, pp. 1–40, Oct. 1959.

[5] G. R. Faulhaber, "The question of spectrum: Technology, management and regime change," in *The Conference on the Economics, Technology and Policy of Unlicensed Spectrum, East Lansing, MI*, 2005. [Online]. Available: http://quello.msu.edu/conferences/spectrum/program.htm

[6] O. Ileri, D. Samardzija, T. Sizer, and N. B. Mandayam, "Demand responsive pricing and competitive spectrum allocation via a spectrum server," in *Proceedings of the IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySpan), Baltimore, MD, USA,* 8-11 *Nov., 2005*, pp. 194–202.

[7] C. Raman, R. Yates, and N. B. Mandayam, "Scheduling variable rate links via a spectrum server," in *Proceedings of the IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySpan), Baltimore, MD, USA,* 8-11 *Nov., 2005*, pp. 110–118.

[8] N. Mandayam, "Cognitive algorithms and architectures for open access to spectrum," in *The Conference on the Economics, Technology and Policy of Unlicensed Spectrum, East Lansing, MI*, 2005. [Online]. Available: http://quello.msu.edu/conferences/spectrum/program.htm

[9] L. Badia, M. Lindstrom, J. Zander, and M. Zorzi, "Demand and pricing effects on the radio resource allocation of multimedia communication systems," in *Proceedings of the Global Telecommunications Conference (GLOBECOM), San Francisco, CA, USA, Dec., 2003.*

[10] O. Queseth, "Coexistence and competition in unlicensed spectrum," Ph.D. dissertation, KTH Royal Institute of Technology, Stockholm, Sweden, 2005.

[11] G. R. Faulhaber and D. Farber, "Spectrum management: Property rights, markets, and the commons," in *Telecommunications Policy Research Conference Proceedings*, 2003.

[12] E. Noam, "Spectrum auctions: Yesterday's heresy, today's orthodoxy, tomorrow's anachronism. taking the next step to open spectrum access," *Journal of Law and Economics*, vol. 41, no. 2, pp. 765–790, Oct. 1998.

[13] P. Klemperer, "Auction theory: A guide to the literature," *Journal of Economic Surveys*, vol. 13, no. 3, pp. 227–286, July 1999.

[14] S. Galicia, M. Sirbu, and J. Peha, "A narrowband approach to efficient pcs spectrum sharing through decentralized dca access policies," *IEEE Personal Communications Magazine*, pp. 24–34, February 1997.

[15] J. Peha, "Spectrum management policy options," 1998. [Online]. Available: citeseer.ist.psu.edu/peha98spectrum.html

[16] J. Brito, "The spectrum commons in theory and practice," 2006, working paper in regulatory studies.

[17] L. Herzel, ""public interest" and the market in color television regulation," *University of Chicago Law Review*.

[18] Y. Benkler, "Overcoming agoraphobia: Building the commons of the digitally networked environment," *Harv. J. L. Tech.*, vol. 11, no. 2, pp. 287–400, 1998.

[19] C. Ting, S. Wildman, and J. Bauer, "Modeling the efficiency properties of spectrum management regimes," 2004.

[20] K. Werbach, "Supercommons: Toward a unified theory of wireless communications," *Texas Law Review*, vol. 82, pp. 863–973, March 2004.

[21] S. Buck, "Replacing spectrum auctions with a spectrum commons," *2002 STAN. TECH. L. REV. 2*. [Online]. Available: http://stlr.stanford.edu/STLR/Articles/02_STLR_2

[22] T. Hazlett, "Spectrum flash dance: Eli noam's proposal for "open access" to radio waves," *J. Law and Economics*, pp. 805–820, Oct. 1998.

[23] O. Ileri and N. Mandayam, "Dynamic spectrum access models: Towards an engineering perspective in the spectrum debate," *Accepted for publication in the IEEE Communications Magazine*.

[24] O. Ileri, D. Samardzija, and N. B. Mandayam, "Dynamic property rights spectrum access: Flexible ownership based spectrum management," in *Proceedings of the IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySpan), Dublin, Ireland,* 17-20 *Apr.*, 2007.

[25] J. Acharya and R. Yates, "Profit maximizing pricing strategies for dynamic spectrum allocation," in *Proceedings of the IEEE CISS, 14-16 March 2007*.

[26] M. M. Buddhikot, P. Kolodzy, S. Miller, K. Ryan, and J. Evans, "Dimsumnet: New directions in wireless networking using coordinated dynamic spectrum access," in *Proceedings of the IEEE WoWMoM05, 13-16 June 2005*, June, pp. 78–85.

[27] P. Milgrom, "Putting auction theory to work: The simultaneous ascending auction," 1997. [Online]. Available: citeseer.ist.psu.edu/milgrom99putting.html

[28] C. Courcoubetis and R. Weber, *Pricing Communication Networks*. Wiley, John Sons, Incorporated, 2003.

[29] M. Lindstrom, "Demand responsive resource management for cellular networks," Ph.D. dissertation, KTH Royal Institute of Technology, Stockholm, Sweden, 2005.

[30] C. Saraydar, N. B. Mandayam, and D. J. Goodman, "Efficient power control via pricing in wireless data networks," *IEEE Trans. on Communications*, vol. 50, no. 2, pp. 291–303, February 2002.

[31] H. R. Varian, *Intermediate Microeconomics: A Modern Approach.* New York, W.W. Norton, 1987.

[32] P. Cramton, "Simultaneous ascending auction," 2004.

[33] K. Johansson, A. Furuskar, P. Karlsson, and J. Zander, "Relation between cost structure and base station characteristics in cellular systems," in *IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, September 2005.

[34] V. Krishna, *Auction Theory.* Academic Press, 2002.

Vita

Omer Ileri

2001 B.S. in Electrical and Electronic Engineering, Bogazici University, Istanbul, Turkey.

2001-2002 Teaching Assistant, Department of Electrical and Computer Engineering, Rutgers University, Piscataway, NJ.

2001-2007 Graduate Research Assistant, WINLAB, Department of Electrical and Computer Engineering, Rutgers University, Piscataway, NJ.

2003 M.S. in Electrical and Computer Engineering, Rutgers University, Piscataway, NJ.

2003 S. Seker, A. Morgul, O. Ileri, "A discrete approach for modelling the EM wave attenuation in tunnels", The 9th Asia-Pacific Conference on Communications APCC 2003.

2004 O. Ileri, S.-C. Mau, N. Mandayam, "Pricing for Enabling Forwarding in Self-Configuring Ad Hoc Networks", IEEE Wireless Communications and Networking Conference (WCNC) 2004, Atlanta.

2005 O. Ileri, S.-C. Mau, N. Mandayam, "Pricing for Enabling Forwarding in Self-Configuring Ad Hoc Networks", IEEE Journal on Selected Areas in Communications (IEEE J-SAC), Special Issue on Wireless Ad Hoc Networks, vol. 23, No. 1, pp. 151-162, January 2005.

2005 O. Ileri, D. Samardzija, T. Sizer and N. B. Mandayam, "Demand Responsive Pricing and Competitive Spectrum Allocation via a Spectrum Server", IEEE Symposium on new frontiers in Dynamic Spectrum Access Networks (DySpan) 2005, November 2005, Baltimore.

2007 O. Ileri, D. Samardzija and N. B. Mandayam,"Dynamic Property Rights Spectrum Access: Flexible Ownership Based Spectrum Management", IEEE Symposium on new frontiers in Dynamic Spectrum Access Networks (DySpan) 2007, June 2007, Dublin, Ireland.

2007 O. Ileri and N. B. Mandayam,"Dynamic Spectrum Access Models: Towards an Engineering Perspective in the Spectrum Debate", to appear in the IEEE Communications Magazine, September 2007.

2007 Ph.D. in Electrical and Computer Engineering, Rutgers University, Piscataway, NJ.