Spectrum Pricing for Cognitive Radio

Abdulkarim Ayopo Oloyede

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Abstract

This thesis examines how the price paid by the end users via an auction model can be used in regulating and controlling the admission process given a dynamic spectrum access and a heterogeneous small cell network. The performance of the system is judged by the energy consumed, the system throughput and the delay.

A first price auction model with a reserve price is designed to take into consideration the signal to noise ratio of the users by introducing a novel tax and subsidy scheme called the green payments. Furthermore, the use of multiple bidding process and an admittance threshold, known as the probability of being among the highest bidders, helps in further reducing the energy consumed and improves the system throughput. A utility function is also found useful in determining the satisfaction of the users and in formulating a theoretical model for the admission process.

Bid learning performance using Linear Reinforcement learning, Q learning, and Bayesian learning is compared and the results show that Bayesian learning converges faster because it incorporates prior information. It is shown that incorporating a price based utility function into the punishment or the reward weighting factor can help the learning process to converge at the optimal bidding price. A game model is formulated to allow all users in the system to learn depending on their priority. This enables users to learn different parameters such as the best offered bid price and the appropriate time to participate in the auction process. Results show that provided all the users take part in the learning process, a Nash Equilibrium can be established. The energy and the delay associated with the auction process are also further reduced when all the users are learning the different parameters.

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Dedication

This work is dedicated to my Dad, Professor Is-haq Olanrewaju Oloyede (OFR).

Acknowledgement

It would not have been possible to pursue this doctoral program or even dream of writing a doctoral thesis without the approval and support of God Almighty and the kind people around me. It is not be possible to mention everyone here, but I am extremely grateful to everyone who contributed one way or the other towards me having a PhD degree.

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Declaration

Some of the research presented in this thesis have already resulted in some publications, in conference proceeding and workshop proceedings. A list of the publications is provided below. Some of these results are also under consideration for publications in journals and conference proceedings.

All contributions presented in this thesis as original are as such to the best knowledge of the author. References and acknowledgments to other researchers have been given as appropriate.

Publications

A. Oloyede and D. Grace, "Energy efficient soft real-time spectrum auction for dynamic spectrum access," *Telecommunications (ICT), 2013 20th International Conference on*, vol., no., pp.1-5, 6-8 May 2013

A. Oloyede and D. Grace, " Energy Efficient Learning Based Auction Process for Cognitive Radio Systems" *IEEE Consumer Communications and Networking Conference (CCNC)*, Las Vegas, 10-13 January, 2014

A. Oloyede and D. Grace, " Learning Based Auction for Cognitive Radio Networks" *Cost Action IC0902 MC Meeting and 4th Workshop,* Rome October 9-11 2013.

Chapter 1

Introduction

Contents

1.1 Overview

The radio spectrum is a precious natural resource that lies in the electromagnetic band from about 2 Hz up to around 300 GHz. Across the globe, the different regulatory authorities allocate different parts of the band to a range of wireless technologies. However, in recent years, wireless mobile technology has required more and more bandwidth and the demand for use of the radio spectrum is increasing exponentially [1]. This trend of exponential growth is expected to continue according to most forecasts [2]. A search to accommodate the increase in traffic has led to the concepts like Cognitive Radio (CR), Licensed Shared Access (LSA), Authorised Shared Access (ASA), heterogeneous and small cell networks. Heterogonous networks allow different protocols to be combined on the same network. Using smaller cells encourages low-powered radio access and better frequency reuse. Hence with the help of these concepts, future wireless networks are expected to deliver more in terms of higher data rates, reduction in energy and a significant increase in the data carrying capacity. The reduction in energy consumption can also help in reducing the financial cost associated with the running of the network thereby, reducing the cost to the end users [3].

Presently, the users of the radio spectrum can either be licensed or unlicensed. The licensed bands are exclusively allocated to individual service providers while the unlicensed bands are open to any user provided they meet the set criteria [4]. However, both are regulated by the regulating agencies. Presently, the licenced part of the radio spectrum is allocated in a static manner, known as the "*command and control*" allocation mechanism. The static allocation mechanism is an approach where the regulating agency allocates the spectrum band to different wireless service providers in space and time for long term use (usually years). This is done to prevent interference from adjacent bands. The technique has led to artificial *scarcity* of the radio spectrum [5]. The scarcity has been found to be artificial because the existing users of the radio spectrum are not fully utilising the allocated bands in space and time [6]. However, new technologies are finding it difficult to get bands allocated to them [6]. Research showed that the inability of the static spectrum allocation scheme to cope with the increasing demand is not as a result of over utilization of the radio spectrum, but due to the allocation mechanism [4]. Research also showed that most of the desirable spectrum for mobile communications lies in the licensed bands of radio spectrum [7]. Figure 1.1 is a set of readings from Vienna, VA, USA, which is located approximately 18 km from Washington, DC taken over a three and a half day period for a frequency range of 30 *MHz* to 3 *GHz*. It shows that the spectrum is not utilized *100%* of the time in that location and this is the same for most other locations. This shows that the scarcity of the radio spectrum might be as a result of the adopted static allocation mechanism. Hence, one of the ways of making the present wireless network more efficient and robust lies with a change in the allocation mechanism.

Dynamic Spectrum Access (DSA) has been proposed as a solution to the regulation and more efficient use of the radio spectrum [8-10]. The main aim of introducing DSA is to help to meet the increasing demand for the radio spectrum. It also aims to allow for better technological innovation in the use of the spectrum. This should allow new devices to gain easy access to the radio spectrum [11]. Furthermore, for the effective implementation of DSA there is a need to develop a good pricing mechanism combined with an energy efficient policy. Therefore, DSA should trigger a shift from the fixed time based pricing scheme to a usage based scheme. This is because resource allocation and spectrum trading should go hand-in-hand. Pricing mechanisms such as the use of an auction can be used to reflect the value of the radio spectrum to users. Hence, this thesis examines the use of an auction in allocating the radio spectrum dynamically.

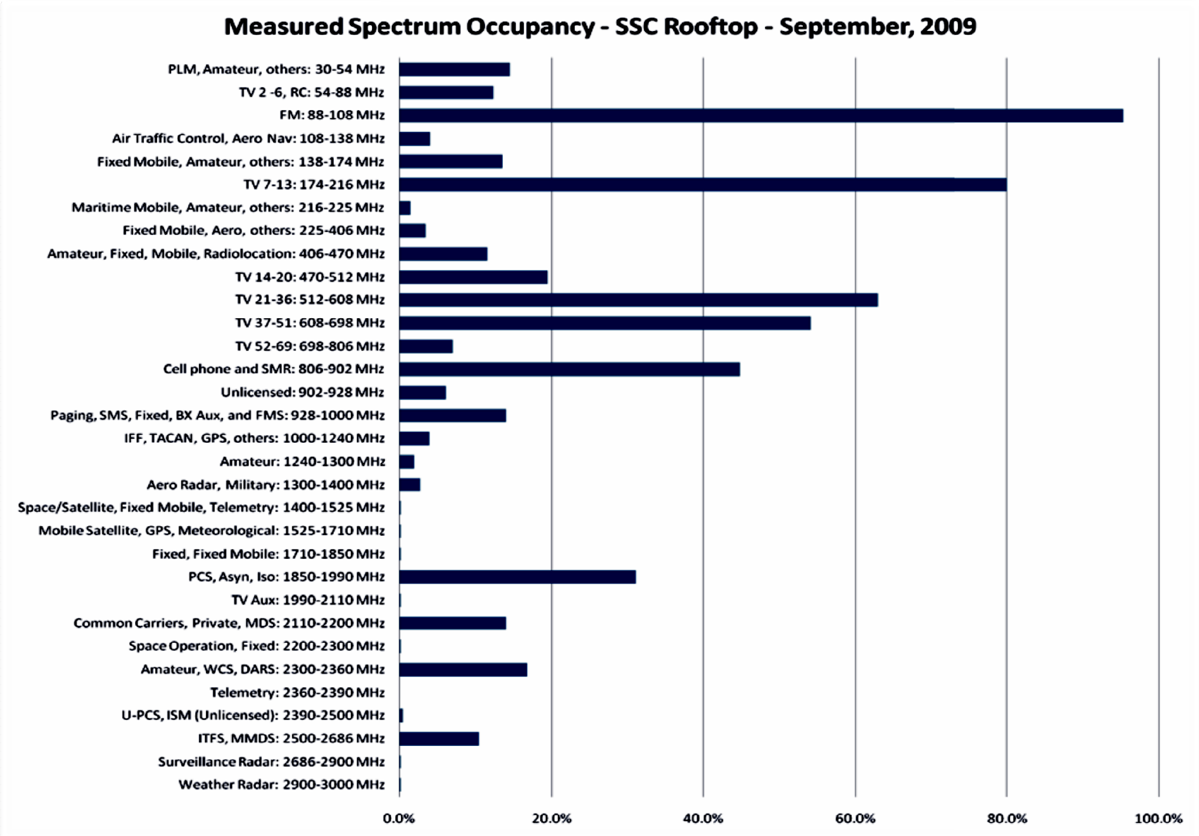

Figure 1.1. Measurement taken from SSC roof top for a 3 day period (copied from [7])

The model aims at using an auction in a manner that does not introduce additional delay into the system, while remaining energy efficient. Therefore the concept of a *green payment* is introduced. This is meant to tax power inefficient users and subsidise power efficient users. This is done to encourage efficient use of the radio spectrum. This study was carried out because interference management and power control are also some of the fundamental factors that should be considered when trying to improve spectrum usage and provide more capacity to wireless users. According to the Shannon theorem, the capacity of any wireless network is dependent on the interference from other users. Hence, a primary aim is to develop a pricing mechanism that can help to improve the efficient use of the spectrum.

1.2 Hypothesis

The price paid by users of the radio spectrum can be used to regulate the spectrum admission process and aid energy efficiency in an auction based DSA network.

1.3 Purpose

The main aim of this research is to propose an auction based DSA scheme with an incentive to encourage the efficient use of the radio spectrum. The purpose is to use price to regulate the admission process of wireless users based on the concept of DSA. Pricing/price is not the only method that can be used to control the admission process of the secondary users. Other methods include the use of power constraints so that users above a certain interference threshold are denied access. [12] used the interference temperature model in assigning the spectrum in an auction. The work allocates power to users in a manner that can maximise the Signal to Noise plus Interference Ratio (SNIR) but minimise the interference temperature.

However this work uses price in combination with the power received at the base station because these two factors are important to both the service provider and the users.

1.4 General System Scenario

This thesis proposes the use of an auction to allocate the radio spectrum dynamically for short term use. This involves the use of a broker as the central entity. The price acceptance is done by the spectrum broker and subsequent allocation of the channels for a fixed transmission period of time is carried out by the service provider. The proposed auction process is repeated for each allocation period. After each allocation and transmission period, the allocated channels are released for another auction to take place. The number of available channels (availability of spectrum), budget of the user, the green payments, number of bidders at a particular auction period, the transmit power and the SNR are the most important determinants of who wins the bidding process. The use of a database is assumed throughout this thesis. The database provides information about the available channels to the spectrum broker. This prevents harmful interference to a scheduled primary user in the system. The proposed auction model also involves the use of the reserve price and a novel concept known as the green payment. This novel concept is introduced in order to provide an incentive to wireless users towards the more efficient (power efficiency) use of the radio spectrum. The concept of the green payment is divided into two parts: tax and subsidy. The users that are not power efficient during the use of the radio spectrum based on the received Signal to Noise Ratio (SNR) at the base station pay the tax, while those that are power efficient based on the received SNR are subsidised. The modelling is done with the use of the MATLAB simulation tool. An auction model with a reserve price is adopted to allow the scheme to be profitable for the Wireless Service Provider (WSP). This is because the demand for the radio spectrum is space and time dependant. After the auction process, the successful bidder(s) are allocated the spectrum.

The use of an auction to allocate the radio spectrum for short term use was proposed in [13]. This work showed that in the near future, wireless users would be selecting a service provider based on a file by file basis and each wireless user selects a service provider based on price. This work among others inspired the formulation of this thesis. Figure 1.2 shows the general overview of the proposed model using an example. This example assumes that two channels are available with a large number of users in the cell. "*A*" shows that seven of the users require the use of the spectrum at time t. The seven users indicate their interest by submitting a sealed bid to the spectrum broker. The spectrum broker calculates the reserve price using a defined method and arrives at a Reserve Price (RP) of 1.75. This leaves only one eligible user to be allocated the radio spectrum. Two channels are available but only one is allocated due to the reserve price.

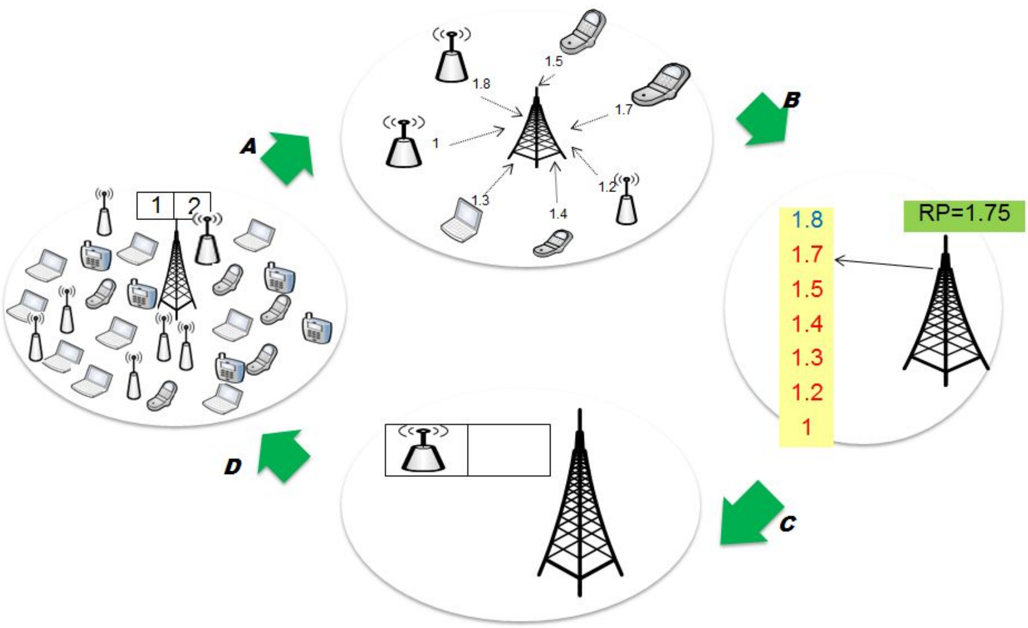

Figure 1.2 General modelling scenario

The above example illustrates and summarised how the radio spectrum is assigned using an auction process as proposed in this thesis. It also shows some of the fundamental problems, such as delay, that might be associated with the use of an auction to allocate the spectrum. Hence, this thesis aims to investigate some of these problems.

1.5 Thesis Structure

This thesis is divided into nine chapters. Chapter 2 gives a literature review by providing the necessary relevant background to the research work. Firstly, CR and DSA are introduced and extensively examined. The chapter also introduces the concept of spectrum pricing and the suitable pricing models. This is followed by examining the need for energy conservation and how this thesis can achieve energy conservation using an auction model. Machine learning and game theory for wireless communication are also examined in this chapter. Chapter 3 shall provide an introduction to the modelling techniques adopted in this thesis. Firstly, this chapter examines and compares the different modelling techniques that can be used. Afterwards it explains the reasons for choosing a particular modelling technique. The performance measurement used in the modelling scenarios is also examined. Different propagation models are considered and examined before arriving at the model used in this thesis. This is followed by the general formulation of the energy model, the green payment model and a general overview of the modelling scenario adopted in this work.

Chapter 4 investigates and formulates the concept of green payments and the application to dynamic spectrum management. It examines how best to apply the green payments equation without introducing additional delay into the system. Firstly it formulates the green payment equation with reasons, after which it examines how the parameters in the green payment equation can be chosen in order to achieve the aims of this thesis. The chapter also examines how green payment can be made self-sustaining. It also examines different scenarios that could result if the green model is adopted for future wireless communication networks.

Chapter 5 examines the performance of the proposed model in terms of energy consumption and congestion control. The concept of a utility function is introduced and used to formulate a mathematical model for the proposed green payment based auction scenario. The concept of single bidding and multiple bidding processes are also reviewed in order to improve on the performance of the system in chapter 4 in terms of delay and energy consumption. The chapter also examines the effects of making the reserve price either public or private.

Chapter 6 introduces the concept of learning using reinforcement learning. This was done to aid energy efficiency in the proposed model and to reduce delay associated with the use of an auction in allocating the spectrum for short term use. The effects of linear reinforcement learning, Q learning and Bayesian learning are examined. This chapter scrutinizes the learning rate and the learning efficiency for the different learning models.

Chapter 7 adopts the concept of a game model in the dynamic spectrum auction in order to aid energy efficiency. The chapter follows up from chapter 6 by using the developed learning model to formulate a game with three players and examines the interaction between the players by the formulation of utility functions for each of the players. The utility functions are formulated in a way that the satisfaction of the players can be examined. Finally, this chapter compares the results based on the delay and energy consumption as a result of the users adopting the learning model (in chapters 6 and 7) compared to the non-learning models (in chapters 4 and 5).

Chapter 8 provides some details on how the research work can be further examined. Chapter 9 presents the main conclusions in this thesis and novel contributions to knowledge.

Chapter 2

Introduction to Related Techniques

Contents

2.1 Introduction

The purpose of this chapter is to examine and explain some of the essential background knowledge and concepts related to the formulation of the ideas during the implementation of this thesis. The information provided in this chapter should aid the better understanding of the techniques used in other chapters. A review of the concept of Cognitive Radio (CR) and some of the proposed models of CR networks is provided in section 2.2. After that, the concepts and reasons behind DSA are provided is section 2.3. This is followed by some state of the art pricing mechanisms, and the principle of auction theory is examined in section 2.4. The need for energy conservation in wireless communication and its application to wireless cognitive radio networks is described in section 2.5. Machine learning and its application to wireless communication is reviewed in section 2.6. Game theory in relation to wireless communications is also discussed in section 2.7. The conclusions are given in section 2.8.

2.2 Cognitive Radio

The huge shift to wireless communications brought about by the advent of smartphones and related devices with access to different services such as social media networks has fundamentally increased the number of devices seeking access to the wireless networks. More importantly, as mobile technology advances, a large and growing part of the applications and functions offered by devices like smartphones are relying more on the use of the radio spectrum. This is leading to congestion of the radio spectrum. The cause of the congestion is associated with the traditional fixed spectrum allocation schemes put in place by the different regulatory authorities [14]. The fixed allocation guards against interference from anyone apart from the person the band was allocated to. This allocation mechanism worked perfectly in the past, but because of the rapid increase in the demand for the radio spectrum, the scheme is leading to "*artificial spectrum scarcity*"[14]. It is artificial because the perceived congestion is not as a result of non-availability of the radio spectrum but due to the confinement of users to the assigned frequency band [14, 15].

The basic concepts behind the proposed cognitive radio network are observation, learning, planning and decision making process as shown in figure 2.1. The observation methods that can be used by CR includes determining which parts of the spectrum are free by listening to the radio network, the use of the database approach, sending special signals to obtain information about the surroundings among others, some of which are discussed later. The learning process involves the extraction of useful information either from the present or previous transmission carried out by the network. The planning process involves setting goals, priority and constraints to meet the system requirements, and the decision making process allows the use of the data obtained in the learning and planning process to make a decision. The decision making processes is based on the best available resources and information obtained.

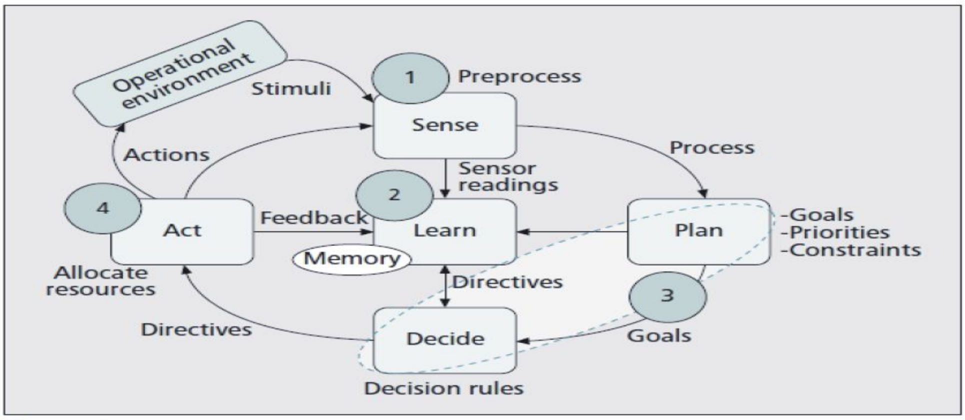

Figure 2.1. Cognitive cycle (copied from [16])

The basic idea of CR is to allow unlicensed or secondary users to have access to the radio spectrum in a non-interfering manner. The aim is to increase the number of users gaining access to the radio spectrum simultaneously and over time, thereby increasing spectrum usage and efficiency. Cognitive radios which are defined as intelligent systems are also expected to possess the capabilities to be aware of the wireless environment. They should allow for intelligent scanning and detection of holes in the radio spectrum [5]. They also support the subsequent allocation of the detected holes to users who require the use of the radio spectrum. This is as shown in figure 2.2.

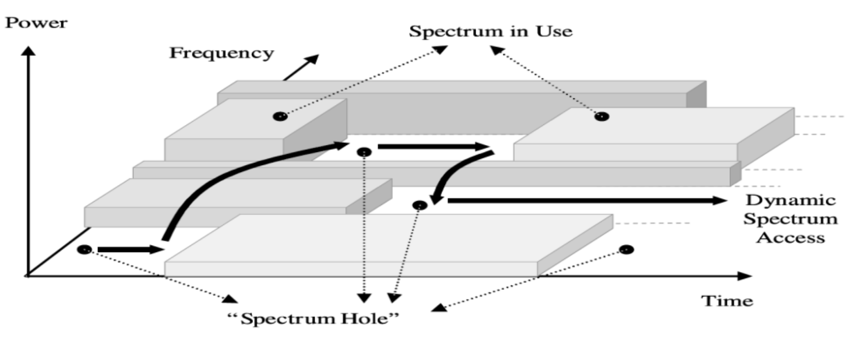

Figure 2.2. Spectrum holes copied from [17]

The spectrum holes are the unutilized or underutilized allocated spectrum bands in the radio spectrum in a given geographical location [18]. They are sometimes referred to as the spectrum white space [19]. An example of this is the TV white space which was extensively discussed in [20]. The research about CR is not all about holes detection and allocation; it also includes making the radios spectrum more flexible and reconfigurable in the presence of interference. CR is expected to all allow quick adaptation of the transmission characteristics by making intelligent decision on the basis of spectrum usage within the given vicinity.

Aims of CR

- To help improve the utilisation of the radio spectrum by taking advantage of spectrum holes.
- Elimination of the rigid or coarse spectrum allocation policy and help in switching to the demand based approach.
- There is evidence that CR can help in generating more revenue for spectrum owners and provide better quality of service to the cognitive radio users [21].

Advantages

- Improve link performance.
- Improve spectrum utilization.
- Better QoS range.
- Improved cross layer optimization.

Disadvantages

- Complex to build and cost intensive.
- May involve significant computation which might be power consuming.
- It carries all the limitations of the existing standards.

- Hidden node problem.

There are a wide range of proposed models of CR networks in the literature; however this thesis categorises the different models as shown below:

2.2.1 Centralised Geolocation Database Approach

In the database approach for implementing CR, a centralised mediating entity known as the Database (DB) is needed to provide information on the spectrum usage to the Wireless Service Device (WSD) seeking access to the radio spectrum. The database stores the information regarding the allocated and the free spectrum bands in both space and time. [22, 23] proposed the use of the DB in space to cover different geographic locations. This removes the need for sensing at the mobile and allows dynamic access to the radio spectrum. This method requires the radios to be connected to the database all the time. In the design of a database system, the information in the database can be provided by different sources as proposed in [24]. Then the user domain can access the database before connection to the radio spectrum. This is as illustrated in figure 2.3 using the TV White Space (TVWS). This figure shows the authentication process that can take place when using the database from 1 to 6 as explained in [24].

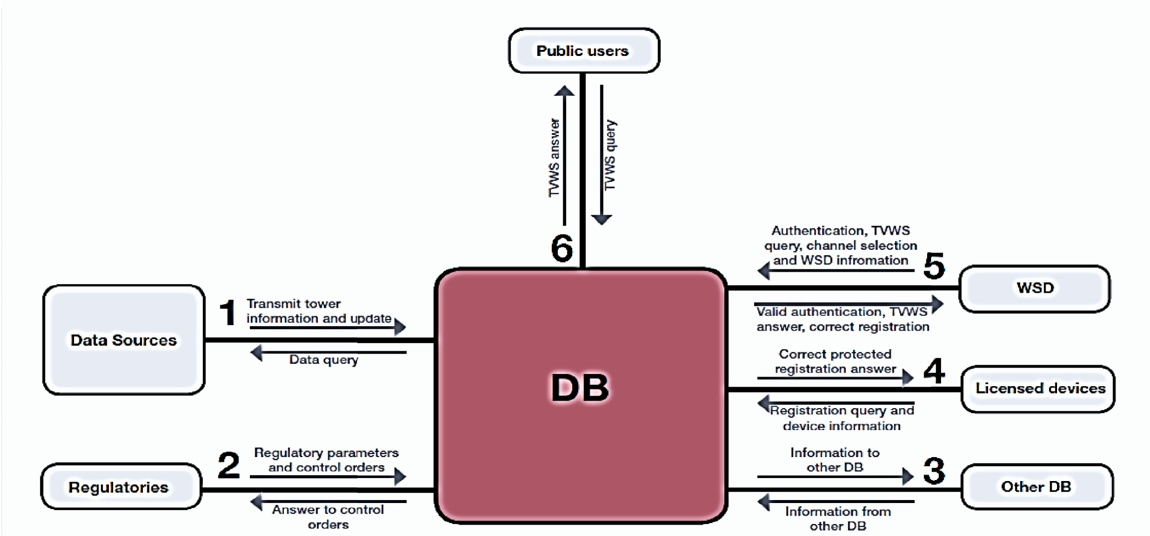

Figure 2.3. Database system for cognitive radio application copied from [24]

The database approach is widely used in this thesis mainly because it has more potential and can easily be implemented without the use of the complex sensing methods. This approach for TV white space was tested in a European Union project called COGEU. The project allowed for the testing of the geolocation database approach in a real life spectrum auction scenario [25]. The geolocation database was designed for the Munich area specifically for LTE systems. In most parts of this thesis, the database approach that is used can be described as shown in figure 2.4 below. The users who require the spectrum send a request to the spectrum broker. The spectrum broker receives information regarding the available spectrum from the database and the available spectrum is allocated to the users who require it.

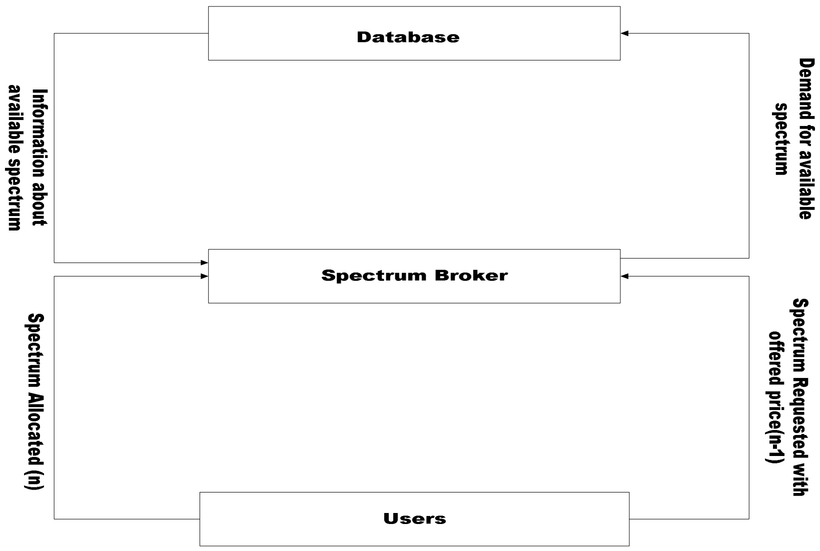

Figure 2.4. The database approach

The Spectrum Broker

The spectrum broker is the central platform that facilitates the trading and allocation of spectrum to different users. In this work, the goal of the spectrum broker is to maximise profit by granting access to the highest bidder(s). The maximisation of profit by the spectrum broker can be seen as maximising social welfare if the spectrum broker is same the service provider or the regulating agency (which is usually an arm of the government) because the radio spectrum belongs to all. Hence, one of the aims of this thesis is to help maximise the profit of the spectrum broker/wireless service provider. This is the main reason for introducing the reserve price (as done later) in this thesis. The spectrum broker controls the manner in which the radio spectrum is allocated to the users and also determines the type of auction to be adopted. The broker might also determine the maximum allowable transmit power for each part of the allocated spectrum. The spectrum broker can be the regulatory authority or it can be formed by users coming together to form another mediating entity. In this work, it is assumed that the spectrum broker is put in place by the regulatory authority just as a mediating entity between the users and the WSP for the sole purpose of carrying out an auction.

The Interference Temperature Model

Depending on the distance of transmission, the transmit power of the present transmitters are designed to approach a prescribed noise floor. They are known as transmitter-centric systems [18]. However in wireless networks, it is possible for some other sources to create some form of interference in the system leading to the degradation of the network [18]. To prevent this from happening, an interference temperature threshold model based on a real time approach was proposed by the FCC in 2002 as a metric used in assessing the interference at the primary receiver. In the proposed system, the interference temperature threshold for a given location is determined by the regulator [18, 26]. It is a measure of the radio frequency power generated by other noise sources or emitters at the receiver [27, 28]. The equation for the interference temperature is as given below [18, 26]

$$\mathrm{T}\,(f_c, B) = \frac{P(f_c,B)}{k_b B} \tag{2.1}$$

Where $P(f_c, B)$ is the average interference in $Watts$ centred at f_c covering bandwidth B measured in Hertz and k_b is Boltzmann’s constant. The aim of the equation is to allow the cognitive system to understand the difference between interference and noise. The model allows for a situation where both the primary and secondary users can use the spectrum simultaneously but the interference of the secondary users on the primary users must not exceed a certain threshold. Before a secondary user is allowed to transmit, it must keep the interference temperature below this threshold. This method is not widely in use because of the difficulty in the separation of interference from noise and because the proposed model was built for the worst case scenario. FCC has also abandoned the use of this model since 2007.

The Beacon Concept

The beacon concept is a primary user operator assisted signalling mechanism. It was proposed in [29]. The concept allows secondary users to be granted access to the radio spectrum via the use of the beacon signal which can be from the primary users. The advantage of this approach over the other methods described in this thesis is the fact that the signal gives a reliable knowledge of what is happening in the radio spectrum. It informs users whether the frequency is in use or the transmit power level that cause interference to the transmitting users without necessary knowing where the receivers are. The concept as proposed allows for receivers to be transmitting and transmitters can also be receivers using different frequencies. But the frequencies in use must be near enough to have good path loss correlation but far enough to allow for duplexing [30]. The receiver transmits a beacon and any terminal that can hear the beacon on a particular frequency must reduce its transmit power depending on the strength of the received beacon as shown in the figure 2.5 below. This method is not used in this thesis because of the overhead involved in the exchange of information.

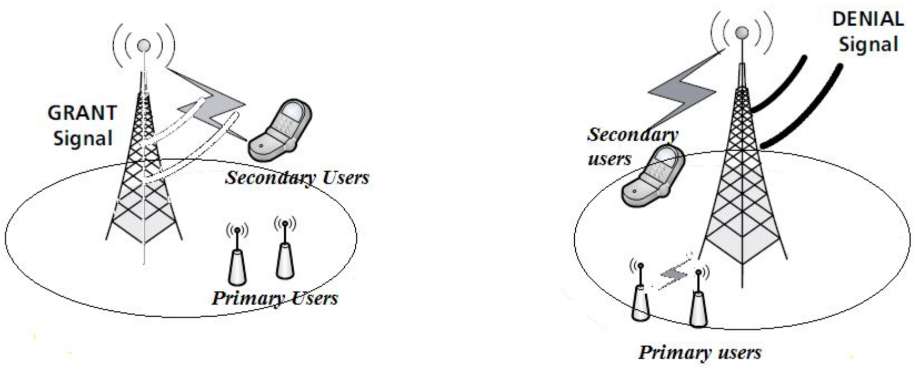

Figure 2.5. The Beacon concept

The Spectrum Sensing Model

Spectrum sensing allows for secondary or unlicensed users to scan the radio spectrum to determine if a primary or licensed user is transmitting or not. After the scanning process, the secondary/unlicensed user then occupies the radio spectrum if free. This method is used to obtain some awareness of the spectrum usage or existence of primary users on the radio spectrum as required in a cognitive network. In order to employ the use of the cognitive network, the secondary radios must be able to determine if a particular band is available for use or not. Spectrum sensing has been widely researched in [31]. There are numerous proposed models for spectrum sensing such as the cyclostationarity-based sensing, covariance based sensing, energy detection based sensing, matched filtering and coherent detection among others [32].The method of spectrum sensing is not used in this thesis because of its complexity, the hardware requirements, the security issues with sensing the radio spectrum during transmission among others [33]. The complexity of spectrum sensing is due to the possibility of having a false alarm.

2.3 Dynamic Spectrum Access

The concept of DSA has been popular among researchers in recent years because of the perceived scarcity of the radio spectrum and the advent of CR systems. This is due to the increases in devices seeking access to the radio spectrum especially in the last decade, making the radio spectrum one of the most important infrastructures around the world [34, 35]. As the demand grows, there is a need to adopt management techniques and avoid excessive interference among the competing users. This is because if spectrum users transmit on the same frequency and significantly close to each other, they are likely to interfere with each other. Therefore, spectrum management deals with the coordination, planning, regulation and allocating of the radio spectrum to promote efficient usage [36]. The present approach (static spectrum allocation scheme) makes it difficult for new technologies to diffuse into the market [37] hence, there is a need for dynamic schemes in managing the radio spectrum. For efficient and reliable spectrum management to be implemented, some factors are very crucial. This includes pricing, licensing period and the power allocation mechanism. They are very important because the price of the radio spectrum determines who and at what cost access is granted to the radio spectrum. This also reflects the economic importance of the radio spectrum to the user, the service provider and the nation at large. The transmit powers among other factors also determine the distance needed to prevent interference from devices using the same frequency band. Furthermore, the use of DSA allows a change from the present situation where service providers are restricted to a modulation and filtering scheme due to the effects of adjacent channel interference. DSA allows incentives to be provided to encourage efficient use of the radio spectrum. This is necessary to prevent congestion and bad practices on the radio spectrum. Hence, this thesis examines the concept of tax and subsidy in DSA.

DSA as proposed in [38], allows secondary access to spectrum holes. It also allows for faster deployment of wireless technology using the unused or underutilized spectrum serving as a remedy to the static spectrum allocation problem. [39] proposed a DSA scheme in the form of a Coordinated Access Band (CAB). The concept allows for a chunk of spectrum to be reserved for centralised and controlled dynamic access to the radio spectrum. In the proposed system, the spectrum broker owns the spectrum and leases the spectrum out on request to wireless users. The concept of CAB is widely explored in this thesis. [40] proposed spectrum pooling based on Orthogonal Frequency Division Multiplexing (OFDM). The scheme allows for the unused spectrum to be put together for access by the secondary users.

However, according to [5] the spectrum used by fast moving objects such as satellites cannot be pooled. A hierarchical dynamic access model was proposed in [37].

2.4 Spectrum Pricing and Auction Theory

Pricing mechanisms can also be used as a form of regulation in order to eliminate bad practices in a commodity market and it can also be used to offer incentive to users to encourage the sale of a commodity. It can also be used as a fair means of allocating scarce resources. Therefore there are links between traffic management in the wireless networks and the pricing mechanism because price paid can be used in controlling the admission process. Spectrum pricing can also help in implementing the concept of CR and DSA. This is by allowing sellers and buyers to indicate the value they hold for the radio spectrum.

The radio spectrum provides a significant source of income to most countries around the world. According to [41] the estimated economic benefit arising from the use of the radio spectrum in the UK for 2005/6 was £42 *billion* compared to £28 *billion* in 2002. It also contributed about £37 *billion* to the UK Gross Domestic Product (GDP) in 2006. According to [42, 43] the value the radio spectrum contributing to the economy has grown in real terms by over 50% from 2006 to 2008 and the global telecom market was worth about 1.340 *billion USD* in 2008 and 1.348 *billion USD* in 2009. Hence, one of the aims of this work is to use pricing (which is very important to all parties) to regulate the use of the spectrum.

In wireless communications, the pricing scheme adopted is dependent on several factors. However, these factors can be broadly divided into two: static and dynamic pricing schemes [44]. The static pricing scheme which is generally in use presently is leading to a decline in the revenue of the service provider compared to the traffic and the cost of the network as seen in figure 2.6. However, it is estimated that the radio spectrum can generate more revenue if dynamic spectrum trading is implemented as part of efforts to encourage spectrum efficiency [43]. This is because dynamic pricing scheme changes with network conditions unlike the present static scheme.

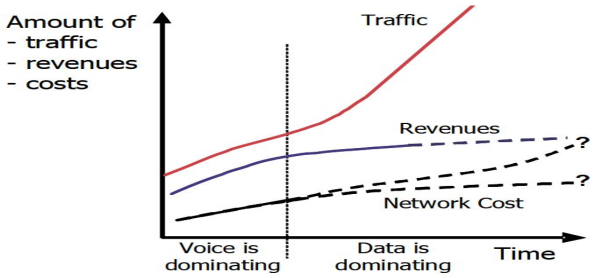

Figure 2.6. Traffic and revenue for increasing data (copied from [45])

2.4.1 Static Pricing Schemes

Static pricing schemes allow prices to be set without consideration for the network resources or amount of usage. The prices paid by these types of schemes are generally fixed by the service provider and they do not depend on the current network conditions[46]. They are also easy to implement. Below are some of the proposed or implemented static pricing schemes found in the literature.

2.4.2 Flat Rate Pricing Scheme

This pricing scheme allows the WSP or regulators to fix price based on their assumed market price for the spectrum for an unlimited amount of access to the wireless network for a period of time [44]. This is the traditional approach to spectrum pricing that does not take into consideration the Quality of Service (QOS). This does not allow for flexibility and cannot guarantee maximum profit for the WSP because congestion cost is not taken into consideration. This scheme does not provide incentives for QOS. According to [45], the scheme creates a revenue gap for operators providing mobile broadband service despite the increase in traffic.

2.4.3 Parameter Based Pricing Scheme

This pricing mechanism is based on some parameters such as the opportunity cost of the radio spectrum as proposed by OFCOM with the use of Administrative Incentive Pricing (AIP). These factors are considered by the WSP or regulator as a measure of incentive towards a more productive use of the radio spectrum. This parameter does not change over a period of time. This is a more fair and flexible method of charging for the use of the spectrum than the flat rate pricing scheme [44].

2.4.4 Adaptation Pricing Scheme

This is a scheme that uses the previous data from the network in fixing the price of the spectrum. This static method allows for cooperation between different service providers and it helps in predicting the future price of the spectrum. This scheme does not put into consideration the QOS and changes in traffic demand as proposed in [47].

2.4.5 Dynamic Pricing Schemes

This allows the WSP to adjust the price of the spectrum based on the QOS and the demand for the spectrum at a particular time and in a particular environment. This scheme requires more processing of the price and it is more sophisticated than the static scheme [46]. They are also flexible regarding the immediate changes in the network parameters and generally they can guarantee more profit when the demand is high and can help the end users obtain better QOS. Some of the examples are explained below:

Priority Pricing Scheme

This is a pricing mechanism that allows the system to adjust the price based on changes noted by the system. It also allows an end user to prioritise the services but the priority can be modified based on the QOS. This mechanism helps to manage the resources of the network by guaranteeing available bandwidth to end users [48].

Assignment Pricing Scheme

This scheme is also known as a hotspot based scheme. It is based on the base station a user is connected to. A user is charged more when connected to a base station which is not the home base station. The home base station is the user's favourite location for making a connection to the network [44]. Presently, this scheme is widely in use by GSM operators in Nigeria.

Rate Adaptation Pricing Scheme

The price of the spectrum based on the impact the users have on other users. Congestion is used as an incentive for the end users. This can be used in regulating new users of handoff in order to provide better QOS [49].

Probabilistic Pricing Scheme

This method uses historical data and mathematical formulation and assumptions to determine the price of the spectrum. This formulation allows network to predict the network demand. Such demands is ultimately used to determine the price of the spectrum [49]. This method is discussed and used in [44] for indifferent prices.

Auction Based Pricing Scheme

An auction is a process where bids are taken from interested parties and a winner(s) is determined based on some established criteria. According to the Oxford dictionary, "an auction involves the public sale of a good to the highest bidder". It can be used as the centralised market mechanism for allocating the radio spectrum. An auction usually involves a single seller and multiple buyers. This pricing scheme is quite interesting and can help to determine the appropriate market price for commodities such as the wireless radio spectrum. This is because the price of the radio spectrum depends on space and time and sometimes the application offered. One main advantage of an auction process is that it requires little or no interaction between the seller and the buyer because a spectrum broker is employed who serves as the middle man. An auction process is prone to sellers and buyers acting selfishly as they tend to maximise each other's benefit. In any auction process, there are three rules that must be made very clear before an auction begins: the bidding rule, the allocation rule and the payment rule. The bidding rule informs all the potential buyers of how the bids are carried out either an open or closed bid, or if it is open it can be increasing/decreasing auction. The allocation rule states what each bidder gets if they emerge victorious and the payment rule states the amount to be paid. The rules determine the auction schemes. Auctions can also be categorised either as single item auction or multiple item auctions. In a single item auction only one item is up for sale however multiple items are up for sale in a multi-item auction. An auction process can be applied in the allocation of the radio spectrum to promote efficient use by granting access to those who value it the most.

Recently around the world, an auction processes has been widely adopted in allocating licenses to wireless service providers because of the advantage it offers. However the aim of this thesis is to use an auction process to allocate short term access to the radio spectrum unlike in the present situation where it has been used for a long term spectrum access. Using an auction to allocate the spectrum helps in determining the actual value of the spectrum. This is because the value of the spectrum is space and time dependent. An auction process is used throughout this thesis.

2.4.6 Auction Theory for DSA

Auction theory deals with the economics behind an auction. There are different models of auction some of which are explained below.

First Price Sealed Bid Auction

This is a simple auction process where the highest bidder wins and pays the bid value submitted. This is usually carried out in a concealed fashion. It is widely used in wireless communication and it is used throughout this thesis because it requires less computation complexity [50].

Vickrey Auction

This is a kind of auction where the highest bidder is allocated the item on auction but the highest bidder pays the price offered by the second highest bidder. Vickrey auctions are usually carried out using the sealed bid auction process. This encourages bidders to put forward bid which shows their true valuation of the radio spectrum. This method is disadvantageous if more than one winner emerges from the auction process. It also does not allow for price discovery and cannot maximise profit (it might even generate zero revenue to the auctioneer) hence, the reason for not using it in this thesis. The Vickery auction model was adopted in [51] to capture the interaction between end users and spectrum brokers. This model is not used in this thesis because of the complexity in determining the second highest bidder in a multi-winner scenario.

Sealed bid Auction

In sealed bid auctions, the bids of the users are submitted in a concealed fashion. The submitted bids are then compared and the winner emerges depending on the auction model adopted. A sealed bid auction model cannot be applied in isolation. It has to be implemented in conjunction with other models such as the first or second price auction. This auction guards against collusion among users and it is widely used in spectrum allocations because it allows users to simultaneously submit their bids thereby reducing delay in the system [52].

This is because delay is an important factor in any wireless communication system. This model in combination with others is adopted throughout this thesis.

Simultaneous Ascending Auction (Dutch auction)

This method involves bidding in rounds. The auctioneer specifies the minimum bid increment and the bidder increases their bids above the minimum increment. This method can be time consuming. In this auction process the buyers might resolve to the "live and let live" situation. This is where in the early stages of the auction process, when prices are low, buyers collude to allow everyone to win a band and tactically agree to stop pushing prices up. In some part of this thesis, an approach similar to this is implemented, where the bidders increases their bids after losing in the previous bidding round.

The Reserve Price Auction

This is a type of auction that guarantees that the sellers only sell above a minimum price. If a buyer bids below the specified minimum price, the sellers can refuse to sell. The reserve price can be public or private knowledge. However, usually the reserve price is not always announced but it must be realistic. Chapter 5 of this thesis shall investigate the effects of public knowledge of the reserve price. An auction with a reserve price can help to increase the revenue of the seller above the cost price. If a realistic reserve price is not set it could impact negatively on the auction. This method was adopted in this research because it guarantees that the costs of using the spectrum can be met and it helps in maximising the revenue of the WSP regardless of the traffic load in the system. There are many pricing mechanisms but the proposed pricing mechanism in this work is unique because it reflects the variation in demand which occurs daily and in different locations. Also it prevents a loss in a situation where there are few bidders. An auction process with a reserve price is used throughout this thesis because it is a useful scheme when the demand and supply of a good or services is space and time dependent.

Homogeneous Sealed Bid Auction

This type of auction is a multiple bid auction in which the buyers submit their bid in a vector format (*b1, b2,* and *b3….bn*). Where each bid stands for the amount the buyer is willing to pay for a particular commodity. The maximum total amount the bidder is willing to pay for all the commodities is the sum of *b1, b2,…bn*. In this type of auction the buyer puts in a bid for different commodities such as different bands of the radio spectrum. Using this auction process the bidder might lose some of the items it bid for and win some [53].

Uniform Pricing Scheme

A uniform pricing scheme is an auction process where all the winning bidders pay the same amount. This scheme is popular for a multi-unit auction. In this scheme, the auctioneer might be the one to determine the clearing price that maximise the auctioneer's revenue based on the average bid submitted. This scheme can also be implemented with the winners paying an amount which is the lowest offered price of all the winning bids. An example is if there are 3 channels available and 5 users offered a price of £1, £2, £3, £4, £5 the three highest bidders either pay a value set by auctioneer which might be any value between £1 and £5 or all 3 winning bids pay £3, which is the lower value of the winning bid. This type of pricing scheme prone to collusion among bidders and it is less fair creating an unsettled market [26].

Discriminatory Pricing scheme

In discriminatory pricing, identical goods are sold at different prices to different users. This pricing scheme is adopted throughout this thesis. A discriminatory pricing system is adopted because a multi-channel system is assumed and therefore more than one user can win access to the channel and the amount paid by each user may vary slightly based on their offered price. Discriminatory pricing is adopted because it allows for profit maximisation by the WSP as different user's value the spectrum differently. An example is a situation where 3 channels are available and 5 users are interested in offering to pay £1, £2, £3, £4 and £5 respectively. If a flat pricing system is adopted each winning bidder pays £3 pounds making a total of £9 for the WSP but in the case of discriminatory pricing scheme the WSP makes a total of £12, making £3 more profit.

2.4.7 Implementation of Spectrum Pricing in DSA

The use of the price paid by the users in allocation the radio spectrum can help to reduce the congestion in the radio spectrum by allowing users with the highest valuations for the radio spectrum to have priority access. However, the use of the price alone to allocate the radio spectrum might not be efficient. This is because the radio spectrum is a shared resource, hence the transmit power of the user is also an important factor that should be taken into consideration. Therefore, in terms of practical implementation of the use of price in allocating the radio spectrum, the transmit power should also be taken into consideration as done throughout this thesis. The use of price in allocating the radio spectrum can either be for a short term or long term period. This thesis however focuses on short term spectrum allocation. Throughout this thesis, a session by session price allocation mechanism is modelled. However this might not be too practical for implementation because of the overhead involved, as it would be explained in section 2.4.6. However in terms of practical implementation, this can be done based on time intervals such as every hour of every two hours. This should help in reducing the frequency of the auction process. Furthermore because of the delay and uncertainty of winning associate with an auction process, a scenario where users can bid in advance for the radio spectrum can be implemented such as the "day ahead pricing scheme" that is proposed in [54]. In this scheme, the day is divided into 24 bidding periods and each winning bidder is allocated the radio spectrum for one hour however the auction process is carried out a day before the channels are allocated. The auction period can be represented as shown below:

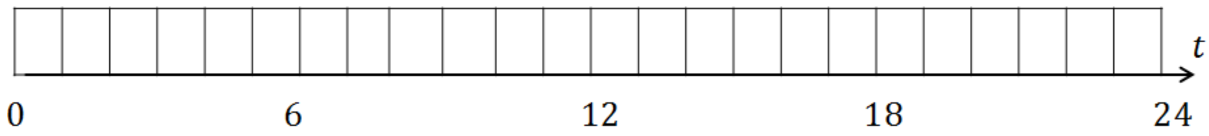

Figure 2.7: Example of 24 daily day ahead auction periods

In addition to this, the proposed auction model can be implemented with a non-auction based model, such that a user has the choice of either using the auction based system or a non-auction based. However the auction based scenario should be attractive and must include an incentive such as the proposed green payments in this thesis for it to be attractive to users. These two models can be combined because in the case of the auction process, a user is not sure of access to the radio spectrum until after the auction process is complete and sometimes users are insensitive to price and want instant access rather than having to wait. However some applications such as software updates, movie downloads, and cloud data synchronisation can be delayed until when a user has cheaper access to the radio spectrum via an auction, hence the need for the incentive in order to encourage the use of the auction based scheme. The proposed combined model is summarised in figure 2.8. It can be seen that it is important for the auction based mechanism to be efficient in terms of price in order for it to be attractive to the end user. The price optimiser compares the two rates and makes a judgment as to which scheme is cheaper. The historical information allows for the system to take into consideration the usage partner of the end user based on previous usage. This information can then be used in planning ahead to determine if and when an auction process is required. The traffic and network monitor observes the current traffic situation and into is taken into consideration before choosing between the available options.

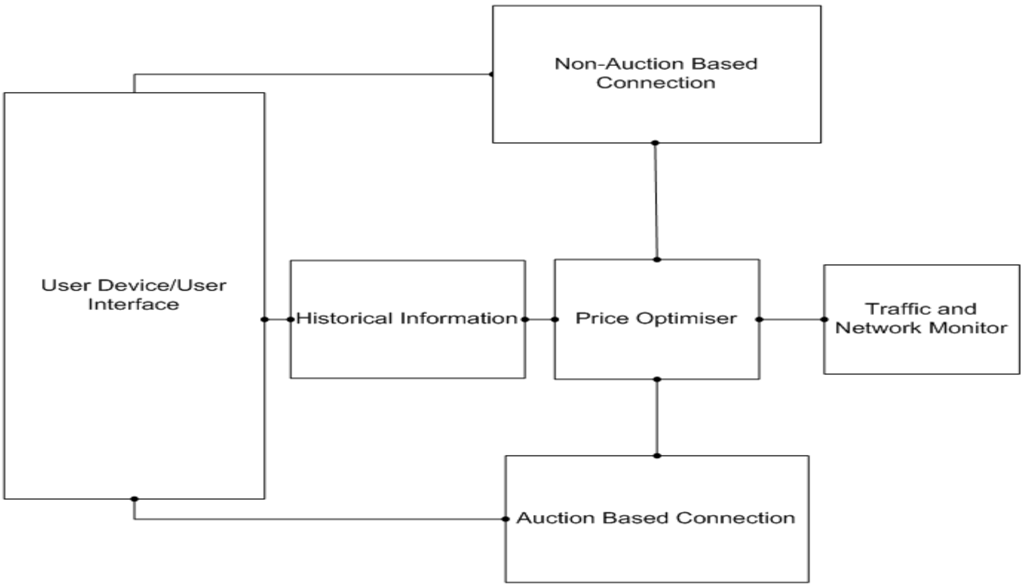

Figure 2.8: Architecture showing how the auction and non-auction model can be implemented

The auction process can be implemented by the interactive software located in the auction based connection. This should be interfaced with the user device such that the users can indicate their minimum, price increment and maximum price in order for the auction process to be carried out using an automated system. This system can be similar to the present auction process on eBay where a biding user indicates the minimum price, the price increment and the maximum price for an item of interest. Another example of this is a software presently available to iPhone and Android phones called *Datawiz*. This app allows users to track and manage Wi-Fi and cellular connection after a week of usage. The app suggest daily and monthly cap, it also allows the users to enter a daily/monthly cap manually or automatically. In addition to this, the software can increase the initial bid of all the users depending on what values the other users are entering. This allows minimal human interaction with the auction process. The software should be designed in such a way the budget entered is spread evenly across the number of hours/days specified by the user while carrying out the auction process. The users can also be allowed to specify priority periods for important messages. The software should also be interactive enough to tell the user the amount that has been spent, the remaining amount to be spent, when the budget is about to be exceeded either on hourly/daily/monthly basis. A user should also be allowed to change the settings on an hourly/daily/monthly basis or even more frequently to accommodate changes in life style or situation.

2.4.8 Pricing Mechanism: The Past and the Future

Traditionally with the advent of commercial mobile communications in the 1990's, a mobile devices was only used for calls and text messages [55]. The customers were charged per minute of calls and text messages were charged at fixed rate but quite expensive [55]. This pricing mechanism was replaced with the per-second billing system. This allows for more flexibility and more fairness because users are charged for only what is consumed. Sooner with the advent of smart mobiles devices, data communication become more popular. Flat rate pricing schemes were introduced in order to encourage users to adopt the applications that were introduced as a result of the advent of the smart mobile phones. Furthermore research soon discovered that there is less traffic at night compared to during the day time hence there was a shift from flat rate pricing scheme to day/night pricing scheme. This pricing scheme was widely implemented in Asia and Africa [55]. However with the growth and ever increasing data applications over a short period of time, the service providers were forced to shift to a more flexible time dependent pricing schemes especially in Europe and America [55]. This allow the WSP's to offer lower prices to customers during the periods of minimal congestion. However, the problem of congestion is still persistent and the demand for data applications is still on the increase, hence the auction based scheme is proposed in this work as one of the possible solution. The auction based scheme allows users who can pay the most to have access to the radio spectrum especially during the period of congestion. Consequently, it is thought that the future of spectrum pricing lies with short term spectrum auction with incentives.

Furthermore, an auction based scheme might face some challenges in terms of implementation and usage, some of these challenges are discussed below:

2.4.9 Challenges Associated with the use of an Auction in Allocating the Radio Spectrum for Short Term Use

Increase in Delay:

The use of an auction in allocating the radio spectrum for short term use might introduce additional delay into the system. This is because an auction process needs time for processing the bid of the users in order to determine winners. This might introduce additional delay into the wireless network. The duration of the delay is determined by the type of auction process adopted. Different applications have different delay tolerance levels. Data communications and broadcasting networks can tolerate more delay than voice communications. Hence, the application must take into consideration the design of an auction process for wireless networks.

Increase in Energy Consumption:

An auction process for DSA might increase the energy consumption of the system because of the overhead involved in the auction process. This problem might be more pronounced if the auction process allows for a reserve price. This is because the use of a reserve price might give rise to a situation where the bids are rejected, when there are network resources available for use. The available resource cannot be allocated to the user seeking access because the user’s bid is below the reserve price. Furthermore, in an auction process, users might consume additional energy in order to participate in the auction. This thesis examines this problem extensively.

Allocation of Spectrum to Mobile Users:

The use of an auction in allocating the spectrum for short term use might be a problem for mobile users. This is because mobile users might change location after winning the auction process. This might give rise to a problem because the availability of the spectrum is space and time dependent. Therefore, a mobile user might have problems transmitting after winning the auction process due to a location change.

Auction Overhead:

The use of an auction introduces additional information overhead to wireless users in terms of the exchange of communications between the users and the auctioneer. The additional overhead as a result of the exchange of information between the wireless devices and the auctioneer might give rise to some problems in wireless communication because the transmitting medium is not lossless.

Security of the Auction Process:

Another problem that might arise with the use of an auction process is the security issues which might arise around the auction process itself. It is quite important to make sure that the platform for the auction process is secured in order to gain the confidence of the users using the process. Furthermore, a secured platform prevents collusion in the system and therefore there is a need to make the auction process secure when designing an auction process for short term spectrum allocation.

2.5 Energy Conservation and Dynamic Spectrum Access

ICT contributes about 2% to the world's energy consumption and this figure is increasing daily, judging by the growth in the number of devices seeking access and the ever increasing demand for higher data rate by end users [56]. According to [56], the use of wireless mobile phone network consumes about 0.12% of the daily primary energy usage. Hence, there is a need to introduce energy efficiency into wireless communication networks. Furthermore, energy conservation is an important aspect in DSA because of the problems associated with carbon emission and global warming [57]. It is also very important in a cognitive or DSA network because these schemes allow for coexistence of different devices sharing the same spectrum band. In sharing of the radio spectrum, devices close to each other cannot use or share the same frequency band at the same time because of the problem of interference. However, the distance of separation for devices sharing the same frequency band depends mainly on the transmit power. Hence, if the transmit power can be reduced, then spectrum sharing can be made easier and the problem of spectrum scarcity can also be solved. Energy and power are linearly related and a reduction in power leads to a reduction in energy. The reduction in energy consumption also helps to prolong the operating time of battery powered devices. Generally, there is an on-going improvement in equipment and signal processing in wireless communications however there is also a need to make some saving at the admission and control level. It can be seen from figure 2.7 that the network cost and traffic is increasing but green communications can help to reduce the amount of energy consumed. The aim of this thesis is to provide energy efficient solutions in an auction based DSA scheme.

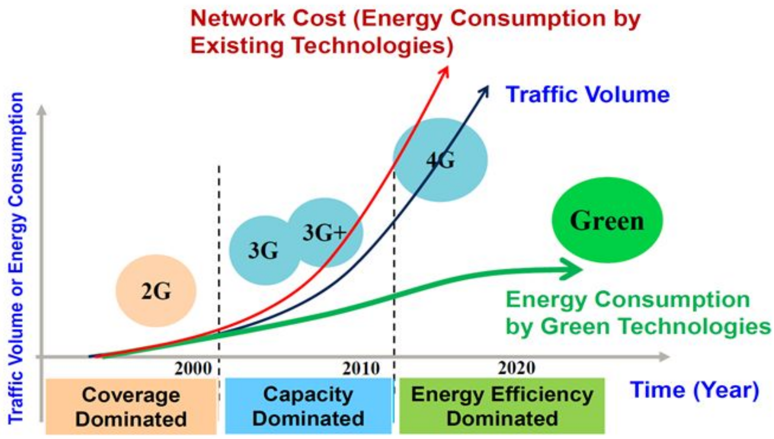

Figure 2.9. Energy consumption of existing technology (copied from [42])

2.6 Machine Learning in Wireless Communications

Machine learning or artificial intelligence deals with instances where users/devices use some data or information to pass judgements or take decisions regarding an action to be taken [58, 59]. The use of machine learning is based on one of the promises behind the concept of a cognitive radio systems to implement an intelligent radio that can learn and adapt to the wireless radio environment. In wireless communications, Reinforcement Learning (RL) is widely used. It involves the use of a simple feedback reward mechanism by the learning user(s). However, one of the main problems of reinforcement learning is the slowness in convergence [60]. This is because of the large number of trials involved in order for the learning process to be effective. A wide range of model based approaches have been proposed in order to modify and aid the fast convergence of RL. Fast reinforcement learning for energy efficient communications was proposed in [61] to aid point-to-point transmission of delay sensitive multimedia data for a fading channel. Two stage reinforcement learning was proposed in [62] for distributive cognitive radio sharing. Reinforcement learning has also been used for dynamic spectrum auction. [58, 63] proposed a Q learning bidding algorithm for DSA while [64] modelled a repeated auction learning process for secondary users. This is based on a distributed learning algorithm for a single channel network for second price auction with an entry fee. In the paper, the bidders can either choose to bid or stay out depending on if the user's requirement is met. The results show that the scheme performs better in resource allocation compared to a bidding process without learning. [65] proposed a double auction reinforcement learning to improve performance in terms of packet loss, bidding efficiency and transmission rate.

A learning based auction is also relevant in this thesis because in chapter 4, where an auction model is designed for DSA, it is evident that the players, who are the users generating the bids are likely to be software agents rather than humans. Therefore, there is a need to allow the players to have complete information or have the ability to independently use learning algorithms to decode incomplete information that might be provided in a fast and energy efficient manner.

Generally, the learning process is based on a form of reward and penalty which accumulates additively. This can be with or without a discount factor. The learning agent uses the information learnt at time t based on action $a_t \in A(S_t)$ to transit from one state (s) to another at time $t + 1$, receiving a reward (r_t). The main objective is to maximise such reward $(\pi: S \rightarrow A)$. Where $A(S_t)$ and π is the set of available action and policy at time t respectively

2.6.1 Q Learning

Q Learning is a form of reinforcement learning in the Markovian domain [66]. It works by learning the value function and using such to update the Q table. The main advantage of Q learning is that is that it compares the expected utility of the actions with the best action. This allows the agent to acquire optimal knowledge from the reward function without prior knowledge. The $Q(s, a)$ is the value and it is defined to be the expected discounted sum of future payoffs obtained by taking action a from state s. After these values have been learned, the optimal action from any state is the one with the highest Q-value. After the initialization to arbitrary numbers, Q-values are then estimated on the basis of experience.

$$Q'(S,a) = Q(s,a) + x[r + \gamma max Q(s',b) - Q_t(s,a)] \quad (2.2)$$

Where x is the learning rate and $0 < \gamma < 1$ is the discount factor.

2.6.2 Bayesian Learning

Bayesian learning allows a learning agent to compute the posterior probability given a prior probability by using Bayes formula. Rather than a learning agent choosing the most likely solution, the learning agent computes the most likely posterior probability for all the given training examples. One of the main characteristics of Bayesian learning is that a prior probability is always required. Bayes formula is as shown below:

$$P_r\left(\frac{h}{D}\right) = \frac{P_r(D/h)P_r(h)}{P_r(D)} \quad (2.3)$$

- $P_r(h)$ = Prior probability of hypothesis h
- $P_r(D)$= Prior probability of training data D
- $P_r(h|D)$=Probability of h given D
- $P_r(D|h)$=Probaility of D given h

2.6.3 Application of Learning to an Auction Based DSA Network

Different forms of learning can be applied to wireless networks. [62] applied reinforcement learning to the assignment of the channels to users. This was done by showing that reinforcement learning can be used to assign a channel effectively to users. [67] proposed a multi-agent reinforcement learning scheme for an auction process by combining a market based mechanism with reinforcement learning. [58] proposed a Q learning bidding algorithm for spectrum auction and showed that Q learning is effective in an auction process.

2.6.4 Transfer Learning

Transfer learning is a method to improve learning or learning time by transferring the knowledge learnt from one task (source task) onto another (target task). Most machine learning algorithms are designed to learn a single task or to be used by the individual agents [68]. The development of transfer learning allows the sharing of knowledge among multiple agents to improve learning. However negative transfer can occur when transfer learning decreases performance. Another reason for adopting transfer learning might be as a result of data constantly changing [69]. Bayesian learning which is used in this thesis is a form of transfer learning because the learning user incorporates prior knowledge in taking decisions. Transfer learning for an indoor based Wi-Fi system was designed in [70]. The paper developed an algorithm to solve the problems with transfer learning while data is transferred using a mapping. It showed that the performance of the proposed system performs better with transfer learning. [71] proposed a method of transfer learning to speed up Q learning. It showed that transfer learning from one agent to the other can help to speed up the convergence.

2.7 Game Theory for Wireless Communications

Game theory is an analytical tool that can be used in the understanding of decision making by providing a mathematical basis for the analysis [72]. It also helps in predicting the outcome of the interactions among different competing agents. A game is made up of three components, the players, a set of actions or strategy and the utility. The players are the main decision makers and they determine the game strategy by taking an action among the available actions and receive a form of utility depending on the action taken. The player knows the goal of the game and takes decisions that maximise the utility. The strategies are the actions available to the players to achieve a feasible game. The payoff determines the strategy of the player. Different strategies give different payoffs. The utility or pay off attached to any strategy determines the attitude of the players towards the strategy. Although game theory has mostly been used in economics, it can also be applied to wireless communications. This section defines a game and it applications to wireless communications.

2.7.1 Important Concepts in Game Theory

Some of the important concepts in game theory are as explained below:

Cooperative Game and Non-cooperative Game

A game is cooperative if the players in the game form a coalition depending on the actions in the game. In a cooperative game, the players negotiate with one another in order to decide on the action to be taken. The players attempt to maximize the overall profit function of all the players in a fair manner. A cooperative game provides a higher overall profit and it shows some level of fairness. On the other hand a non-cooperative game allows each of the players acts selfishly. In a non-cooperative game each player is selfish and unconcerned about the performance of other players. Each player chooses a strategy to optimise the performance metric under the assumption that all other players are rational and they are also adopting a selfish behaviour. Hence, a non-cooperative game studies the interaction among competing players. A non-cooperative game is the most widely used game in studying the interaction that occurs in wireless communications. This is because most devices accessing the wireless network are known to act selfishly.

Game with Perfect and Imperfect Information

A game is said to have perfect information if all the factors in the game are of common knowledge to all the players (Each of the player's is fully aware of the other players in the game). However, with imperfect information, the players are unaware of the actions chosen by others [72]. They also do not know the strategy the utility of others. They know others do exist. The Prisoners' dilemma is an example of incomplete information game.

Decision Making and Utility Function

Decision making is core to game theory because the basic principle of game theory is allowing multiple agents to decide on actions to take. The decision taken by any of the players attracts an outcome known as the utility. Hence, the utility function and decision making goes hand in hand with game modelling. The utility function represents preference and is used to measure the satisfaction of a user or how close a user is to the optimal value. The concept of a utility function is widely used in chapters 5 to 7 of this thesis. Generally preference or utility can take different binary forms as long as they are transitive, complete and continuous. Completeness means that the preference can of different objects. An example of this is if one prefers a car to laptop. Transitivity means absolute distinction between objects such as a cup of tea with two spoons of sugar or a cup of tea with three spoons of sugar. They binary relationship can be expressed using $\geq$ or $>$. Such as $> y \Leftrightarrow u(x) > u(y), x, y \in \boldsymbol{X}$. This means that utility function is a mapping from objects to certain values.

Let $\boldsymbol{X}$ be a set of outcomes. The preference relationship $x \succeq y$ is read as x is weakly preferred to y. Where $x, y \in \boldsymbol{X}$.

Game solution

Generally, the best solution to a game is known as the Nash Equilibrium. A Nash Equilibrium exists in a game if there is a set of strategies which have the property that no player can increase their payoff by changing their strategy while the other players keep their strategy unchanged. A Nash Equilibrium gives the best utility to the players. More formally a Nash Equilibrium is a strategy profile a such that for all $a_i \in A_i$. Where A_i contains all the possible strategy profiles.

$$U(a_i, a_i) \geq U(a_i' a_{-i}') \tag{2.4}$$

Where a' denotes the other strategies for player i and a_{-i} denotes the other strategies for the other players except player i. Strategy $a_i' \neq a_i$.

2.7.2 Applying Game Theory to Wireless Communications and Dynamic Spectrum Access

In recent times, game theory has been applied to the field of telecommunications in order to study the interactions that exist among the different competing element seeking access to the radio spectrum. This is because optimization problems are often NP hard and are becoming unsolvable computationally. Game theory on the other hand can be used in analyzing a complex solution since is it highly scalable. However according to [72], one of the pitfalls is the application of game theory to wireless communication is mistaking a simple optimization problem for a game. This thesis focuses on non-cooperative game. This is because the scenario just like most of the emerging trends in wireless communication can be analyzed using a non-cooperative game and such a game allows for an interaction through a predefined mechanism.

[73] proposed an economic framework for DSA using game theory. The paper captures the interactions that can exist between a spectrum broker, service provider and the users in a multi-provider scenario using the concept of CAB. The paper shows that a Nash Equilibrium can be achieved if the players maintain some threshold and that pricing can be used to provide an incentive to WSP. [74] proposed a double auction scheme that allows unlicensed

users to obtain the spectrum using the concept of a game and an auction. It studied the completion among the different users in order to achieve the best solution (Nash Equilibrium).

2.8 Conclusions

This chapter has provided the background related to the formulation of the concept used in this thesis. This chapter established the concept of cognitive radio networks and DSA as the possible solutions to the problem of spectrum scarcity. It also examined different models of each scheme. Furthermore it examined spectrum pricing and the economics of spectrum pricing known as auction model. It also discussed how spectrum pricing can be used in regulating the radio spectrum via the use of an auction process. Finally, machine learning and game modelling are discussed with a view of implementing them in an auction based wireless communications network.

Chapter 3

System and Performance Modelling

Contents

3.1 Introduction

Performance modelling is used to capture or analyse the behaviour of systems which are large or complex. This allows the use of a model to capture the essential characteristics in order to be able to reproduce the performance of the system. In modern technology, the use of modelling techniques is quite important and cannot be underestimated. It is more important during the planning stages of complex systems under development, such as the proposed dynamic spectrum network in this thesis. This is important in order to predict the changes or predict the possible optimizations that can be performed such that the performance of the communication network is improved. The use of modelling techniques is also important because the wireless communications protocol or networks in the real world is complex and require careful attention to detail. Such attention can be provided by choosing good and suitable modelling techniques among the available options depending on the aspect of the network under observation.

This chapter presents the key research methodologies and techniques used in characterising the essential models used in subsequent chapters of this thesis. It also explains some main performance measures used in analysing the research work carried out in later chapters.

The remaining part of this chapter is organised as follows. The next section introduces the general system modelling approach. This is followed by examining some modelling techniques in section 3.3. The simulation modelling technique adopted in this thesis is explained with justification in section 3.4. The performance measurements used during the modelling are introduced and explained in section 3.5. The propagation models are introduced in section 3.6. The energy model used throughout this work is formulated and explained in section 3.7. Section 3.8 describes the green payment model. In section 3.9, the proposed general auction model scenario is described with the general parameters and assumptions used in the formulation of this thesis. The verification method adopted in this thesis is described in section 3.10. Finally, the conclusions are given in section 3.11.

3.2 System Modelling

Complex, large or expensive systems or networks can be modelled in a simplified form using a *simulator.* Generally, a simulator can imitate the operation of a real world system using a developed model. A simulator can also be used in investigating the performance of complex systems using computer modelling software with some inputs similar to the parameters in a real world scenario. The results obtained after the simulation process should be similar to results if the actual test was carried out [75]. This approach is now widely used in conducting research in the field of Engineering and Technology.

In this work, considerable effort has been put into the development of the modelling techniques used during the investigation of the different proposed scenarios. Generally, a multi-winner auction model for dynamic spectrum access is developed where the effects of an auction process is examined on the system performance characteristics. The modelling technique is used because the system that is modelled in this thesis is quite difficult to analyse mathematically and too expensive to develop using a physical prototype or test beds.

3.3 System Modelling Techniques

The simulation of wireless networks can be done in several ways, using a range of different simulators which have been developed over the years. Below are some of the characteristics of MATLAB, the chosen simulator and some of the other techniques considered before choosing MATLAB.

3.3.1 MATLAB

MATLAB stands for Matrix Laboratory and has been developed by MATHWORKS Inc [76]. It is a popular tool used in the industry and among academia of different disciplines. It was initially developed for numerical analysis of linear control systems. MATLAB is very interactive, easy to use, and flexible. It often used for numerical algorithms. It can be used on different platforms like Windows, Linux, and Apple. It employs the use of technical computation that integrates visualisation tools and mathematical computation for developing algorithms and applications based on different functions. It also allows for structure like loops and selection using linear algebra systems for vector and matric manipulations and plotting of data. MATLAB is compatible with C, C++ and the FORTRAN programming language. MATLAB allows for development of prototypes of models using simulation.

MATLAB has a graphical interface called SIMULINK, which is an additional package that usually comes with MATLAB but it is not used in this research. The disadvantage of MATLAB is that it can be slower than C++ and might require more memory for complex scenarios.

3.3.2 OMNeT++

OMNeT++ is a discrete event simulation tools that has been available since 1997 for non-commercial use and for academic purposes. It provides a framework to simulate a network in a sophisticated environment. It is based on C++ and allows open source discrete event simulation in a hierarchical manner. Its hierarchical nature allows for large scale simulation [77]. The tool consists of "simple modules" which can be grouped into "compound modules" which allow for packets/files to be sent via a module or directly to the destination. This simulation tool can be used on Linux, Unix-like and on windows systems, thereby providing a powerful Graphical User Interface (GUI). The GUI interface allows for easy debugging. The software is reported to be relatively easy to use but the simulation time for large networks can be cumbersome [51].

3.3.3 OPNET

OPNET is an event based network level simulation tool which is quite powerful because it has the ability to investigate and examine a wide variety of scenarios in wireless communications in research and during development. It operates at the packet level to simulate a network. It was originally developed in 1986 for military use, but it is used nowadays commercially and for educational purposes [78]. It was constructed from high level languages like C and C++ using a hierarchical structure which can be divided into network, node, parameter and process domains. Different layers of a communication system can be modelled using the External Model Access (EMA) such ad C++ and External System Domain (ESD) available on OPNET. The simulation tool (OPNET) has been reported to have a high usage threshold for the developers but low threshold for end users. Some end users find it to be a demanding tool [78, 79].

3.3.4 ***N*S (Version *2)***

NS2 is an open source, object oriented, event driven, discrete network simulator, which was first developed in 1989 using the REAL network simulator. It is constructed based on C++. It is quite popular for non-specific network simulators. It can be operated on Linux and Cygwin operating systems. It is mainly used for local and wide area network simulation implementing protocols like TCP, UDP and FTP and can support a considerable range of protocols in all layers [80]. It also implements multicasting and some of the MAC layer protocols. According to [81], the simulation tool separates the data path implementation from control path implementations therefore, the packets containing data can be observed separately from the ones delving control information or acknowledgements. This is done to reduce the number of control packets in the system so that the event processing time can be reduced.

It is reported to be a difficult tool to use by a beginner, as a beginner needs to master the scripting language and modelling technique before usage [79]. It is more time consuming and complex compared to simulation software like MATLAB according to [82]. Also the results cannot be interpreted easily you need an “awk” file to interpret it, and graphs are also difficult to plot. It also has difficulty in simulating more than 100 nodes, and has a scalability problem [82].

3.3.5 NS (Version 3)

NS3 is a discrete event network simulator which is targeted primarily for research on the workings of the Internet. It is quite different from NS2 and they are not compatible. NS3 helps to improve the technical rigor of simulating a network. It allows simulation in time, based on discrete jumps from event to event using mainly simulation which involves a number of independent repeated simulations, usually written in C++ but can also be written in Python. The simulation of packets in NS3 is carried out in an advanced structure and allows for fragmentation and reassembling of packets used for real and virtual data applications [83].

NS3 has features like helper and containers (containers group similar objects for convenience sake) which are better than the helpers in NS2 as users can help to improve the helper. The reported disadvantage of NS3 is that the helper is not generic, and does not allow for code reuse [83].

3.4 Model Adopted in this Thesis

An event based simulation in MATLAB was considered to be the most appropriate tool for this research because of the advantages and the flexibility it offers. Using an event based simulation allowed us to model the operation of the system as a sequence of events which occurs at some particular time instants. The execution of each step gives rise to a change of state in the system. This is unlike the continuous or time based simulation which performs some operations only between time constant steps making it time dependant. A Monte Carlo simulation technique is used because it is an helpful tool especially when it is not infeasible to compute an exact results while using a deterministic algorithm [84]. The technique relies on repeated random sampling and provides multiple results from the same parameters rather than a single result. It uses a large number of trials to reduce the effect of randomness in the system making the results more accurate.

The general process for the event based simulation is as illustrated in Figure 3.1. The simulator generates the locations of the users and the central entity. It also generates the propagation environment, bidding price and the arrival and departure time based on some predefined parameters. The bids are received by the auctioneer and channels are allocated as defined later. The channels are then released after transmission. This is repeated for a large number of events and the results are obtained at the end of the simulation process.

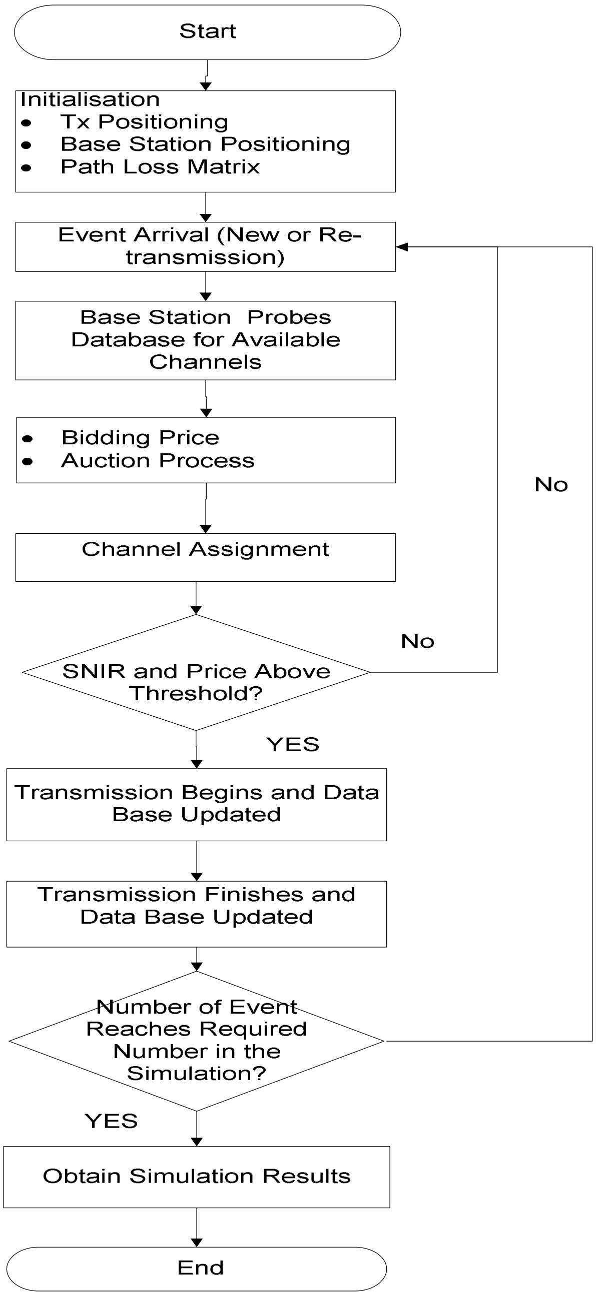

Figure 3.1. Typical event based spectrum auction simulation process

3.5 Performance Measures

The performance parameters are used to evaluate the working capabilities of the system. In order to analyse the performance of the proposed system, some parameters which are explained below are used.

3.5.1 Throughput (Thr)

Throughput is the average rate of successful information delivered over a communication network [85]. It is usually dependent on the number of available channels, bandwidth and SNIR requirement of the system. It is one of the key measures of quality in a wireless system network. It is usually expressed in a metric of bits-per-second or Erlang. The metric of Erlang is used throughout this thesis. The throughput in Erlang for one channel is defined as shown in equation 3.1. Where N_{FS} is the number of files sent successfully, F_s is the file size in bits, T_r is the average transmission rate in bits per seconds and t_s is the simulation time in seconds.

$$Thr(Erlang) = \frac{N_{FS}F_S}{T_r t_s} \tag{3.1}$$

An adaptive modulation technique is adopted using the Truncated Shannon Bound (TSB) as proposed in [86] in order to determine the transmission rate (T_r) at time (t). The average transmission rate is updated frequently during the simulation. TSB is a model that captures the behaviour of adaptive modulation techniques. It is as described below

$$T_r = \begin{cases} 0 & SNIR < SNIR_{threshold} \\ \alpha . S(SNIR) & SNIR_{threshold} < SNIR < SNIR_{max} \\ Thr_{max} & SNIR > SNIR_{max} \end{cases} \tag{3.2}$$

$$S(SNIR) = log_2(1 + SNIR)$$

Where $S(SNIR)$ is the Shannon bound and α is the rate reduction factor as defined in chapter 3, Thr_{max} is the maximum throughput for the codeset and Thr is the throughput of the system. Thr_{max} and $SNIR_{threshold}$ are specified in the parameter table. The $SNIR_{threshold}$ is the minimum threshold that allows the detection of the information at the receiver and $SNIR_{max}$ is the maximum SNIR beyond which there is no change in throughput. The TSB is used to represent the transmission rates that can be achieved in practice given an adaptive modulation scheme in a real world scenario. This is dependent on the SNIR of the user.

3.5.2 Cumulative Density Function (CDF).

A CDF describes the probability that a real-valued random variable X with a given probability distribution will be found at a value less than or equal to x.

$$f_X(x) = P(X \leq x) \tag{3.3}$$

A CDF gives the probability of the value less than *x, P(x)* goes to 0 as *x* get smaller and *P(x)* is a non-decreasing number. CDF is used to analyse the bidding price paid for the use of the spectrum in this work.

3.5.3 Delay (Δ)

Delay in the wireless network is the difference between the time (in seconds) a file (i) is generated (t_{F_G}) and the time (in seconds) when the same file i is successfully sent (t_{F_S}) and it is usually measured in seconds. Delay is an important parameter in a network as the delay determines the usefulness of the network. For example a voice communication network cannot tolerate a high value of delay unlike a data network, and also a TV broadcast network cannot tolerate as much as a data network especially with live transmission.

$$\Delta(Seconds) = t_{F_S}(i) - t_{F_G}(i) \tag{3.4}$$

Delay can be measured in different ways as discussed in [87], but for the purpose of this research, delay is measured as the time taken from when the packet is generated to the time the packet was sent successfully in the system. If a file is unable to be sent, it is rescheduled and resent at the next available time until it is sent successfully. Hence the delay in the system increases with the number of attempts before a file is sent successfully. In this work, the delay is only measured for files which were eventually sent before the end of the simulation. Files generated but not sent during the lifespan of the simulation are not considered and the delay for such packet is not added to the total delay in the system.

3.5.4 Signal to Interference Plus Noise Ratio (SNIR)

SNIR is generally defined by the quotient between the average received signal power and the average received co-channel interference power plus the noise power from other sources. The equation used to calculate SNIR in this thesis is as shown below:

$$SNIR_i = \frac{G_{ii} P_i}{\sum_{k=1}^{m} G_{ik} P_k + n_i} \quad , i \neq k \qquad (3.5)$$

Where G_{ii} represents the channel gain of user i G_{ik}, while the gain between the transmitter of link i and interfering user k where P_i and P_k is the transmit power in watts of signal i and interference transmit power (P_k) respectively and n_i represents the noise from user i, $i \neq k$ and m is the total number of interfering users.

3.5.5 Blocking Probability

Blocking probability is the probability of losses due to non-availability of the transmission channel. The blocking probability at time t is defined as shown below [88]:

$$P_b(t) = \frac{N_b(t)}{N_{FG}(t)} \qquad (3.6)$$

Where $P_b(t)$ is the blocking probability up to time t. $N_b(t)$ is the total number of blocked activation in the system up to time t and $N_{FG}(t)$ is the total number attempted activation to send a file up to time t.

3.6 Propagation Models

Propagation loss is a burden on communication networks as antennas are obstructed by obstacles, reflecting surfaces around the antenna's propagation path between the transmitter and receivers. This is as a result of the propagated wave traveling from the transmitter to one or more receivers. The mobile units also move from time to time which varies the path of communication between the transmitters and the receiver(s). Therefore, researchers have developed a wide variety of experimental and theoretical models to study propagation loss using various frequency bands and environments. A reliable propagation model will help network planners to optimise the cell coverage size and to use the correct transmit powers. Some of the proposed models are discussed below.

3.4.1 Free Space Loss Model

The free space model gives the theoretical minimum propagation loss that is achievable. This model is most appropriate as a starting point for good propagation prediction because it assumes unobstructed direct line of sight propagation and useful for a point to point fixed links over short distances in an open area [85]. It can be represented by

$$P_{re}(Watts) = \frac{P_t G_t G_r \lambda^2}{(4\pi d)^2} \tag{3.7}$$

$$L_s(Watts) = P_{tr} - P_{re} \tag{3.8}$$

Where P_{tr} is the transmitted power in watts, P_{re} is the received power in watts, G_{tr} and G_{re} are the gains of the transmitter and receiver, d is the distance of separation between the transmitter and the receiver in meters, L_s is the measured loss in watt and λ is the frequency wavelength.

3.4.2 Okumura/Hata Model

This is one of the models relevant to the present day radio systems. It provides the foundation for most propagation models. It covers a range of frequencies between 150 MHz to 1920 MHz. The Okumura model is an empirical model which was developed as a result of extensive experimental readings and statistics taken by Okumura in Tokyo, Japan. After taking these readings, Hata performed some curved fitting on the readings to produce the equations. Over the years some correction factors have been introduced into the equation to fit into other environments such as urban, small urban, suburban and rural areas [85]. The empirical model generated using this model can be summarised as shown below as obtained from [85], where L represents the path loss in decibel:

$$L_s(dB) = 69.55 + 26.16log_{10}(f_c) - 13.82log_{10}h_b - a(h_m) + 44. -6.55log_{10}(h_b)log_{10}d \quad (3.9)$$

For a medium or small city

$$a(h_m) = 1.1log_{10}\,(f_c)0.7h_m - 1,.56\;log_{10}(f_c)0.8 \quad (3.10)$$

For a large city where $f_c \leq 200$ *MHz*

$$a(h_m)\;8.29(log_{10}(1.54\;h_m)^2 - 1.1 \quad (3.11)$$

For suburban areas

$$L_s(dB) = 69.55 + 26.1log_{10}\,(f_c) - 13.8\;log_{10}\,h_b - 2(log_{10}(\frac{f_c}{28})^2 - 5.4 \quad (3.12)$$

For an open area

$$L_s(dB) = 69.6 - 26.2(f_c) - 18.8log_{10}h_b - 4.7(log_{10}f_c)^2 + 18.3log_{10}(f_c) - 20.9 \quad (3.13)$$

Where f_c the central frequency, h_b is the height of base station in meters, h_m is height of mobile station in meters, d = distance between receiving and transmitting antennas in meters.

3.4.3 WINNER II Model

The WINNER II project [89] evolved from the WINNER I project. The aim of the project was to develop a comprehensive propagation model for a wide range of scenarios in a communication network. This model covers scenarios such as indoor, indoor to outdoor, urban, suburban and rural. The main focus of this model is multiple inputs and multiple outputs (MIMO) channels. The model also gives reading for both Line of Sight (LOS) and Non-Line of Sight (NLOS) conditions and it is valid form 2-6 GHz and up to 100 MHz of the radio frequency bandwidth. It also supports multiple antenna technology (MIMO) but it separates the propagation parameters from the antenna [89].

Generally the model can be summarised below

$$L_s(dB) = Alog_{10}d(m) + B + Clog_{10}\left(\frac{f_c}{5}\right) + X \tag{3.14}$$

While for a typical urban microcell with LOS it can be as shown below:

$$L_s(dB) = 40log_{10}(d) + 9.45 - 17.3log_{10}(h_b) - 17.3log_{10}(h_m) + 2.7log_{10}\left(\frac{f_c}{5}\right) \tag{3.15}$$

For a typical urban microcell with NLOS:

$$L_s(dB) = L(LOS) + 20 - 12.5n_j + 10n_j log_{10}(d) + log_{10}\frac{fc}{5} \tag{3.16}$$

$$\text{Where } n_j = \text{Max}(2.8 - 0.0024(d)1.84) \tag{3.17}$$

For a suburban area with LOS:

$$L_s(dB) = 40.0log_{10}d + 11.65 - 16.2log_{10}(hb) - 16.2log_{10}(hm) + 3.8log_{10}(\frac{fc}{5}) \tag{3.18}$$

For suburban area with NLOS

$$L_s(dB) = 44.9 - 6.55log_{10}(hb)log_{10}d + 31.46 + 5.83log_{10}hm + 6.0log_{10}(\frac{fc}{5}) \tag{4.17}$$

The WINNER II B2 propagation model as detailed in [89] is used throughout this thesis. This is because it provides for both short and long range communication environments which are scalable with the proposed scenario.

3.7 The Proposed Model (General Scenario)

The proposed model for an auction based dynamic spectrum access with green payment can be summarised as outlined below:

- The spectrum broker requests the available channels from the database and the database provides the information regarding all the free channels to the spectrum broker.
- The users who require the use of the spectrum submit their request with the price they intend to pay for the use of the spectrum in the form of a sealed bid.
- Based on the received request and received SNR the spectrum broker applies the green payment to the received bid by subsidising the power efficient users and by applying a tax to the submitted bid of those who are not power efficient.
- After the application of the green payment, the users with the highest set of bids are offered the available channels. The number winning users is dependent on the number of available channels.
- Then the highest bidders whose bids are above the reserve price and the SNIR value is above the SNIR threshold are allowed to transmit. However, any user who does not meet the SNIR or reserve price threshold is not allowed to transmit after the channel allocation (the check of the price against the reserve price is done at this stage because in calculating the reserve price the number of users arriving is used and this can only be known to the auctioneer after all bids has been submitted this is in addition to that other reasons explained later).
- The least interfered channel assignment scheme is used where the highest bidder is allocated the least interfered channel and the lowest bidder (among the highest set of bidders) is allocated the most interfered channel.

The important features of the system are the database, the spectrum broker, the users and the green payment. The green payment is an incentive for DSA to help conserve the energy usage on the spectrum because it is a shared resource. The spectrum broker is responsible for coordinating the access for all users requiring the use of the radio spectrum. It is also assumed that the spectrum broker knows the user locations for all the users within the same cell or close to each other. Hence such users who are in close proximity cannot be assigned the same channel at the same time.

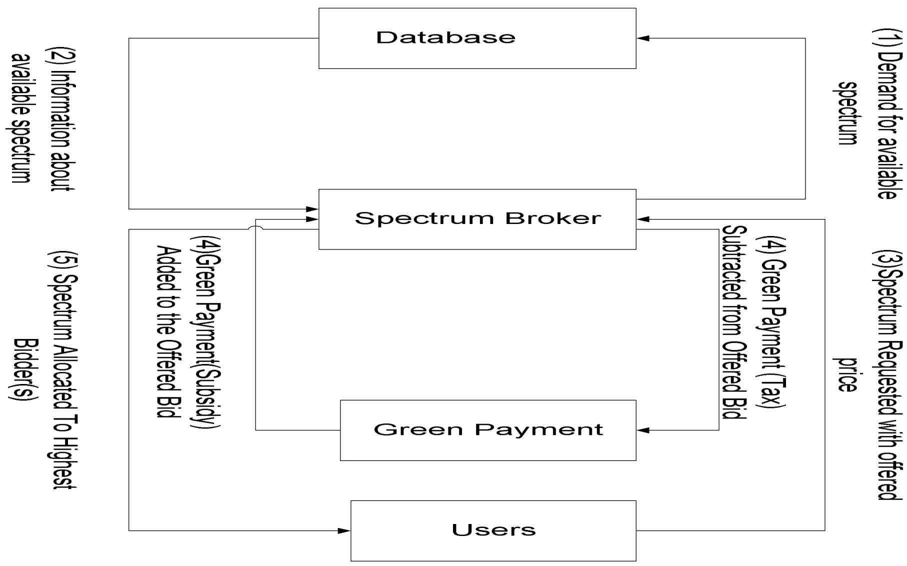

Figure 3.2. General modelling scenario

3.8 The Model

3.8.1. The User Model

Throughout this thesis, two types of users are considered: the High Powered Users (HPU) and the Low Powered Users (LPU). These two types of users are considered because it is assumed that the future wireless system would be homogeneous, where different types of users with a varying level of transmit power competing on the same frequency band using the concept of DSA. The users are divided into just two groups in this thesis for ease of understanding and for simplicity purposes. In practice, more classification can be used or the use of fuzzy logic can be adopted. This should not have any significant effect on the results obtained later in this thesis. It would not have any significant effect, because the classification does not have any significance, what matters is the interference caused by using a particular transmit power and the number of users that either pay a tax or receive a subsidy. As long as a group or groups are taxed and others are subsidised in a balanced manner, such that the tax is paying for the subsidy and the user's that are causing significant interference are paying the tax, then there should be no significant change in result. As seen later in this thesis in chapter 4, the tax paid by the users should subsidies the users receiving the subsidy.

3.8.2. The Energy Model

The energy model used for the mobile users in an uplink configuration throughout this thesis can be represented as a 2 state Markov chain as shown in figure 3.2 below. In the energy model a user can transit from 1 to 4 as shown and explained below:

1. A user who has file(s) to send moves into the OFF state and continue to be in this state until such user is among the winning bidders.
2. A user who is among the winning bidders moves from the OFF state to the ON state.
3. The user remains in the ON state until after transmission if transmission is successful or until when the user receives a failed signal either due to low offered bid compared to the reserve price or due to poor quality channel.
4. After transmission the user moves back to the OFF state before switching completely off if no file is to be sent again. However if the user has another file to send, the user remains and attempt again in the off state. The complete off mode (not in figure 3.2) is the mode a user is in when there is no file to be sent.

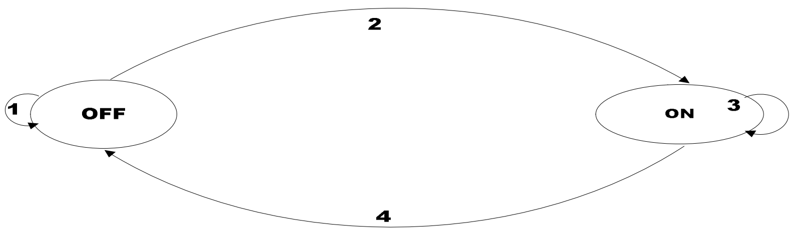

Figure 3.3 Energy and system model as a two state Markov chain

In the ON state, it is assumed that a transmission is successful provided the Signal to Noise plus Interference Ratio (SNIR) and the reserve price are above the set thresholds, after which the user moves back to the OFF state. If the user moves from the ON state to the OFF state, and the thresholds are not met, then the energy consumed in processing the request of the user during the state transition is considered as energy wasted. A processing time which is the time taken to process the received bid is also assumed. All users that move from the ON state to the OFF state have the same processing time.

3.9 The Green Payments Model

This thesis models a subsidy/tax scheme known as green payments. To maximise profit given the unique characteristic of the radio spectrum, a tax/subsidy scheme is designed to encourage efficient use of the radio spectrum in order to maximise both the social benefit of the radio spectrum and the revenue of the auctioneer. This unique characteristic of the radio spectrum makes it reusable provided the radios that are sharing the same band are not within a certain distance interfering with each other. The minimum separation distance depends on the transmit power. Hence, the green payment scheme is proposed and the details are explained in chapter 4.

3.10 The Overall Auction Setup

The general setup for the auction process for all the modelling chapters (4-7) is explained in this section. This is done in order to understand the general overview and the aims of each of the proposed models. Furthermore the possible scenarios for the practical implementation are examined and reasons are stated for the scenarios that are not practical. Throughout this thesis, N users are assumed to be present in the system and their positions in each cell are initially generated randomly within each cell but the positions of each of the user are then fixed throughout the remaining modelling process. The number of cells is indicated in the parameter table 3.1. The auction process is carried out by the auctioneer as explained later. Each auction period is called a bidding period. First, the implementation setup of the single and multiple bidding process is introduced as this forms the foundation of the models. They are also explained further in chapter 5.

Single Bidding Process (SBP): The implementation concept of the SBP can be described as shown in the example in figure 3.4. In this example, it is assumed that 5 users are arriving out of the N possible users in the system during each of the shown bidding periods. The bidding period is represented as t with their bidding price represented as BP, 3 bidding periods (t_1 to t_3) are shown in this example. The users are represented as N_i^a, where the subscript i represents the user number and superscript a represent the packet number. Hence N_1^2 means that user number one is about to send packet number two. 3 channels are also assumed to be available in each bidding period (in our modelling process, the number of available channel varies and the information regarding the available channel is provided by the database). The Reserve Price (RP) is assumed to be 4 and it is placed below the bidding period because the auctioneer in this case is not aware of this value (the reason for this is further explained later in this chapter). The transmission period is represented as T. In the first bidding period, users number 1 to 5 arrive into the system and each with a bidding value as indicated in the figure 3.4, since 3 channels are available, the auctioneer picks the 3 users with the highest biding values (N_1, N_5 and N_4). However only N_1 and N_5 are allowed to transmit because of the reserve price. Furthermore in the proposed model throughout this thesis, all the users that are not successful in a bidding period retries in the next bidding period. Hence it can be seen from the example that users 2 to 4 are also bidding again in t_2. This is in addition to user 6 and 1. User 6 is a new bidder who is attempting to send the first file as seen from the superscript (N_6^1) but user 1 is attempting to send the second file after the initial success in the first bidding and transmission period. In period T_2, only one user is successful. However 3 users are successful in period T_3. In order to reduce the number of times when channels are available but not put to use the concepts of MBP and bid learning is examined in chapter 5 and 6 respectively. It can also be seen that despite having more than 3 users offering a bid above the reserve price during period t_3, only 3 users are picked as winners and those 3 are allocated the transmitting channels during transmission period T_3.

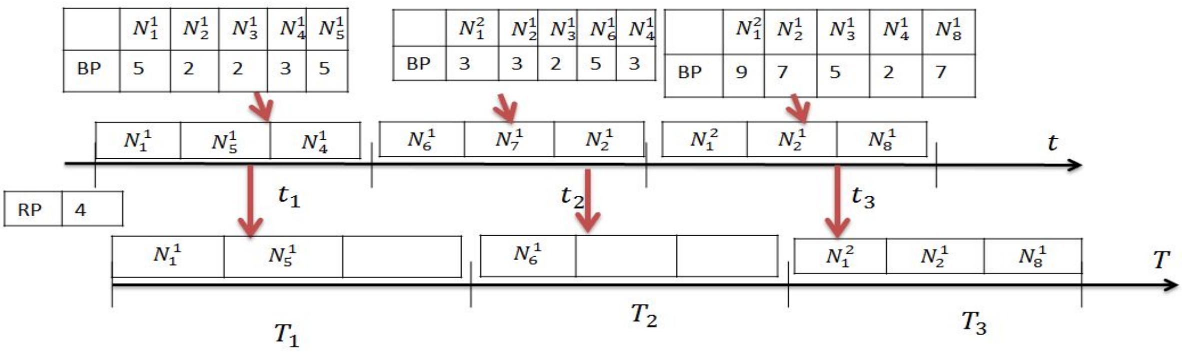

Figure 3.4 Single Bidding Process

Multiple Bidding Process (MBP): The concept of MBP allows for a losing bidder to attempt again in the same bidding period as shown in figure 3.5. This is explained in more details in chapter 5. If this concept is used then there is no need for users to learn the best biding price. This is because a user can attempt more than once during the same auction period. In the example in figure 3.5, only one bidding and transmission period is shown. However 3 auction rounds were conducted during the bidding period. The reserve price is placed above the bidding period this time because in this case, it is assumed that the auctioneer is aware of the reserve price. This assumption is necessary because if the auctioneer is not aware of the reserve price then there is no way of carrying out a MBP. This is because the auctioneer only sends bidders whose bids are above the reserve price to the WSP for the allocation of transmission channels. During the first bidding round, only user 5 has a bid above the RP, and then during the second bidding round users 1 also has a bid above the RP. Finally in the third bidding round user 2 also offers a bid above the RP. It can also be seen that even though in the third bidding round, user 3 has a bidding value above that of user 5 but since user 5 has already placed a bid above the RP in the first bidding round then such bidder cannot be replaced in the third bidding round even though it is in the same bidding period. This rule is applied throughout this thesis when the MBP is used. It can be seen that after 3 bidders whose bids are above the reserve price have emerged the transmission process begins.

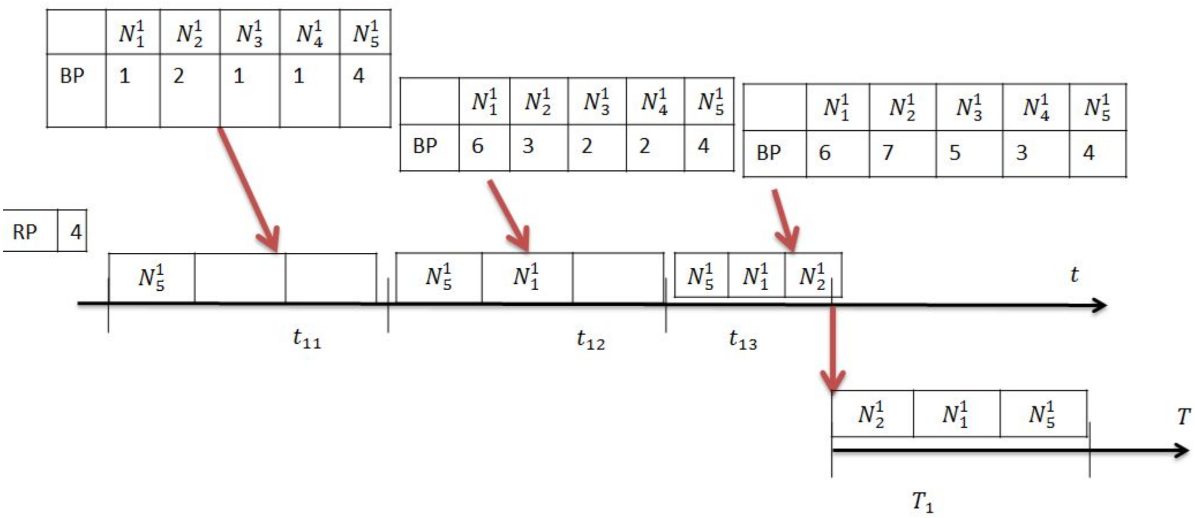

Figure 3.5 Multiple Bidding Periods

Furthermore from other similar research that proposed the use of an auction in allocating the radio spectrum in future wireless networks, two types of auctioneers can be deduced: the auctioneer can either be same as the regulator as proposed in [90] or an auctioneer can be just a middle man out to make profit. This middle man is out to make some profit by selling unused spectrum after pooling the unused spectrum together as proposed in [63]. Hence, throughout this thesis, these two types of auctioneer can either be assumed in order to explore the consequences attached to each. In this chapter, the auctioneer who is an agent of the regulator whose aim is to only regulate the spectrum is called the non-profit oriented auctioneer while the one whose aim is to make profit is called the profit oriented auctioneer. Furthermore, the term profit or non-profit oriented auctioneer is only used in this chapter for explanation purposes and for easy understanding of the reasons behind the future models. Hence this classification is not used in subsequent chapters. The scenario that determines this classifications are explained below:

Profit oriented auctioneer: This type of auctioneer is like a middle man whose aim is to maximise profit as a result of congestion and popularity of the wireless network. If this type of auctioneer is adopted in practice, it would not be appropriate for the auctioneer to be the one to fix or have the knowledge of the reserve price. The reason is because the auctioneer can fix a high RP in order to maximise profit at the expense of other factors. Hence, in some part of this thesis where this type of auctioneer is considered, the RP is never known to the auctioneer. Hence this is the only scenario that is considered from the first branch in figure 3.6. In this scenario, the database informs the auctioneer of the number of available channels and the auctioneer carries out the auction process and passes on the winners who are the highest bidders to the WSP. The WSP now checks that the offered bid is above or below the set RP before transmission begins. Therefore the price is checked against the reserve price after the auction process. In this case only the SBP is possible. This is because the MBP as explained earlier requires the auctioneer to have the knowledge of the reserve price. Furthermore, since a user can only try once during a bidding period (single bidding process) learning the best bid price might be a good idea. This is one of the reasons for introducing learning in chapters 6 and 7 of this thesis. This is also summarised in figure 3.6.

Non-profit oriented auctioneer: Another type of auctioneer is the non-profit oriented auctioneer. This can be but in place by the regulator with the intension of maximise the social welfare of the radio spectrum. Hence if the aim of the auctioneer is not to make money as the middle man then the value of the RP can be known or fixed by the auctioneer. In chapter 5 of this thesis where this type of auctioneer is assumed, the concept of MBP is used. From figure 3.6 the branch of the non-profit oriented auctioneer is dived into known and unknown reserve price because these are the possible scenarios. If the reserve price is unknown then only the SBP can be used otherwise the MBP can be used. There is also no need for learning the best bidding price when using the MBP because the users can attempt more than once during the same bidding period unlike the SBP as seen from figure 3.6.

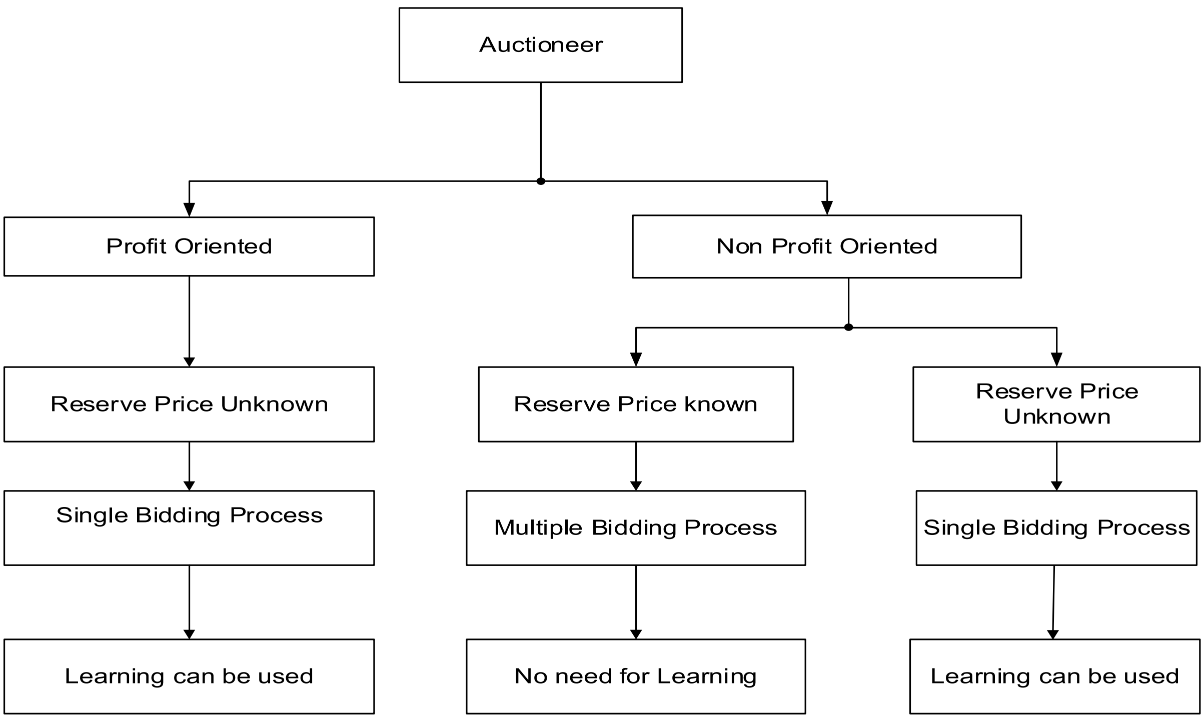

Figure 3.6: The Overall Possible Auctioneer Scenarios

Common Parameters and Assumptions

The common parameters used throughout this thesis are as shown in table 3.1. The other parameters which are specific to each chapter are specified in each of the chapters.

Parameters	**Value**
Cell radius	$2km$
Interference threshold	-40dBm
Users in a cell	200
Number of cell	19
Noise floor	-114 *dB/MHz*
$SINR_{max}$	21 *dB*
$SINR_{threshold}$	1.8 *dB*
Cr	0.7
Max number of channels per cell	4
Bid reduction	10%
Height of base station	15 m
Height of mobile station	1 m
Budget	100000 Price Units
Transmit power for LPU (P_{LPU})	0.09 *W/bit*
Transmit power for HPU (P_{HPU})	0.9 *W/bit*
Energy consumed by device	0.5 *Watt sec*
Transmit power used in bidding	0.25% of the transmit power

Table 3.1 Parameters used

The following assumptions are made throughout this thesis

- First price auction model with reserve price is used except where specified.
- The TSB is assumed throughout.
- A users whose bid is above the reserve price and SNIR is above SNIR threshold and allocated a transmitting channel is allowed to transmit and it is assumed that transmission cannot be interrupted.
- A losing bidder attempts in the next bidding round until success is achieved.
- Two stages are assumed before successful transmission of any file. The first state is where users submit their bids and the second stage is where the bids and the SNIR of the winning users are checked against the reserve price and the SNIR threshold respectively if the reserve price is unknown to the auctioneer. However if the reserve price is known to the auctioneer then the price is checked against the reserve price in both stages.

- If the reserve price is unknown to the auctioneer then it can never be known by the users. This is because the auctioneer is always the middle man between the users and the WSP.
- A user can only bid for one channel at a time and only one channel is needed by any user at a time.
- The channels are allocated in such a way that the highest bidder is allocated the least interfered channel among the available channels and the lowest bidder among the winning bidders is allocated the most interfered channel that is available.

3.11 Model Verification

Auction models under some certain strict conditions can be verified using the revenue equivalence theorem [91]. However the auction model used in this thesis takes into account some certain restrictions making the theorem not suitable and therefore there is no known analytical model that can be used. The learning model used in chapters 6 and 7 involve multi-agent learning and no analytical model is available for this type of scenario. This thesis uses mainly some established scenarios and Monte Carlo simulation to evaluate the performance of the different schemes. It also uses some mathematical formulation such as probabilities and utility functions to evaluate the schemes in chapters 5 to 7. Detailed analysis is given in each chapter while examining the various scenarios. The different learning models examined are also compared in chapter 6 and, the last part of chapter 7 compares the models used from chapters 4 to 7 where applicable.

3.12 Conclusions

This chapter describes the modelling techniques used in this thesis. The different simulation tools used in this thesis was discussed. The chapter also explained the reasons why the MATLAB simulation tool was used throughout this thesis. The key measurement parameters were also examined with the general parameters and assumptions. Furthermore, a brief discussion about the green payment and energy model approach is given. Lastly, the general modelling scenario was explained.

Chapter 4

Energy Efficient Dynamic Spectrum Pricing Using the Concept of Green Payments

Contents

4.1 Introduction

As previously stated in chapters 1 and 2, the number of the devices seeking access to the radio spectrum is on the increase [92]. Consequently, there is *scarcity* of the most useful band for voice and data communications [93]. Furthermore to increase spectrum availability to devices, the cell structure is becoming smaller [94]. In addition to smaller cells, there are proposals to increase spectrum availability by allowing the already licensed spectrum to be shared using concepts like the Licensed Shared Access (LSA), the Authorised Shared Access (ASA) both defined in [95], the coordinated access band as defined in chapter 2 among other various proposals. This is because with bandwidth limitations as a result of spectrum "*scarcity*", high data rate applications might tend to operate with high transmit power, to obtain a SNIR to sustain the required high data rate [96]. In a communication network, there must be a trade-off between the transmit power and the bandwidth used [97]. However, with the cell structure becoming smaller, the introduction of DSA and heterogeneous networks, the use of high power with less bandwidth to deliver high data rate is not a sustainable solution

[98]. This is because of the interference by users sharing the same channel in a multiple access network.

There is also a need to design a fair means of allocating the radio spectrum without introducing additional delay into the system. Hence, a spectrum auction has been proposed as a fair means of granting access to the radio spectrum in [99]. This chapter introduces a short term spectrum auction mechanism which encourages low power transmission by using a novel concept known as *green payments*. The green payment is in form of a tax or a subsidy depending on the received SNR at the central base station. This is introduced because the use of only the user's financial power in allocation the radio spectrum might result into interference in the system. Hence, this chapter examines the effects of the green payments on the energy consumed, the delay in the system and how to implement the model to make the system to generate enough revenue to finance the subsidy scheme.

The rest of this chapter is organised as follows, section 4.2 describes the energy model, the bidding period, and the auction model used. The green payment system is described in section 4.3 while section 4.4 gives the modelling scenario adopted for this chapter. Results are analysed and discussed in section 4.5 and the conclusions are given is section 4.6.

4.2 The Models

Using the concept of the green payments, two types of user group with different levels of transmit power are assumed. Only these two groups of users are assumed in other to simplify the modelling process. According to [3], the future wireless network would be homogeneous, consisting of different devices with a wide range of transmit power sharing the same network however; this is simplified into two groups in this thesis for simplification purposes. Furthermore, the general model examined in this work is based on two stages: The first stage is the submission of bids and application of the green payment to the received bid. After which the highest bidders are allocated the spectrum according to the allocation scheme which is explained later. Then in the second stage the final bids (after the tax and subsidy) is checked against the reserve price and the SNIR threshold. Before explaining the general model, the sub-models that make up the general model are first explained as shown below:

4.2.1 The Users, Auction Model and the Reserve Price

An infrastructure based network is considered in this work; therefore the users transmit via a centralised based station in an uplink scenario. The spectrum broker is located at the base station and has the knowledge regarding the location of all the users in the system. Throughout this thesis, the users requiring low transmit power are referred to as the Low Powered Users (LPU) while those requiring high transmit power are referred to as High Powered Users (HPU). The system consists of N users in total and N_{USA} users are seeking access to the radio spectrum at time t by submitting a bid. N_{AC} is the number of channels that is available in the system during an auction period out of the total transmission channels in the system (N_{TC}). The information regarding the number of available channels is provided to the auctioneer by the database as described in chapter 3. Furthermore, N_{WU} represents the number of the winning users that emerge in any auction period and N_{UT} represents the number of users who are able to transmit after the auction and allocation process. Throughout this thesis, N_{AC} is equal to N_{WU} ($N_{AC} = N_{WU}$) because the number of users that emerge as winners is always the same as the number of available channels but N_{UT} can be equal or less than N_{WU} and N_{AC} ($N_{UT} \leq N_{WU}$ and $N_{UT} \leq N_{AC}$) because not all the winning users are able to transmit due to reasons explained later. A multi-winner first price auction with a reserve price is used. In the auction model, N_{USA} bidders among the N possible users in the system submit a sealed bid simultaneously. The highest N_{AC}/N_{WU} bidders win the bidding process and are subsequently allocated the spectrum. The amount paid by any of the winning bidders depends on bids submitted by the users and the payment rules put in place by the auctioneer as explained in chapter two. Two types of payment rules are examined in this chapter: The discriminatory payment rule and the uniform payment rule.

Furthermore, the reserve price (r) is the minimum price paid before the spectrum is allocated. The reserve price is introduced because the demand for the radio spectrum is both time and space dependent therefore, when the demand is low the reserve price helps to retain the minimum selling price of the service provider. The reserve price might also prevent the use of the spectrum if the value is set too high. Hence, the reserve price is formulated by taking into account the current traffic load in the system, the frequency band in use, the total number of channels in the system and the number of channels in use as shown below:

$$r(Price\ Unit) = C_f N_{TC} C_r \tag{4.1}$$

Where C_r is a constant in price units which is used to specify the value of a spectrum band in use. This value is determined from common knowledge regarding the common price of the radio spectrum. It also represents the valuation of the auctioneer for the spectrum band. This is introduced because the value of the spectrum varies depending on the frequency and the application that requires the use of the spectrum. Generally, it is known that data and voice communications on mobile devices are better with lower frequencies while satellite communication networks can cope well at higher frequencies [100]. This is because at lower frequencies, the transmitted waves have better propagation characteristics. This makes them to penetrate and bend around obstructions such as walls, buildings and trees better than at higher frequencies hence, the reason for having C_r in the reserve price equation. Furthermore, users believe that the bigger the size of the network, the better the quality of service offered hence, the total number of channels in the system is also taken into consideration when calculating the reserve price. Consequently, the reserve price increases as the size of the network. The congestion factor (C_f) is introduced because of the laws of demand and supply. The lower the demand the lesser the price and the higher the demand the higher the price of a commodity as explained in [101]. The congestion factor (C_f) is the number of requesting users per channel during an auction period as shown below:

$$C_f = \frac{N_{USA}}{N_{AC}} \tag{4.2}$$

The C_f is the same for all the users who want to transmit within the same bidding period (t). In the proposed auction model, a user can only bid for one channel and a maximum of one channel can be allocated to any of the winning bidders. A user cannot transmit on more than one channel simultaneously.

4.2.2 The User Bid, the Auction Period (t) and the Transmitting Period (T)

The bid of a user is the amount submitted by the users to the auctioneer as the valuation for the use of the radio spectrum. The proposed model assumes that all the users are truthful and submit a true valuation. Such valuation reflects the user's private value to access the radio spectrum. This assumption was made because the issue with truthful bidding and bid shading which dominates auction theory in the perspective of an economist is more of an economic problem than an engineering problem. Hence, it is not considered in this work. Truthful bidding allows the bidders to bid their true valuation [102], while bid shading is a situation where some bidders lower their valuations in order to get some added advantage during the auction process [103]. The users in this thesis have a similar valuation for the radio spectrum as widely done in auction theory. The valuation of the users show their willingness to pay and it is drawn from a range of values represented as $[V_{max}\ V_{min}]$. This is formulated based on the conventional settings in economics where users has private valuation has done in [104]. Each bidding user independently draws their bid value with a probability density function as shown below:

$$f_V(v_i) = \frac{1}{V_{max}(i) - V_{min}(i)} \tag{4.3}$$

Where V_{max} and V_{min} are the maximum and the minimum possible bid valuation a user can have respectively in price unit. The valuation (V_i) depends on the user's budget per file and it is always less than the users maximum budget. Hence throughout this thesis, a situation where the bidding user does not have enough to cover the necessary payments is not considered. The budget for all the users in the system is the same and it is as specified in the parameters table 3.1. Each of the bidders generates a bid using the distribution as shown below:

$$b_i(Price\ Unit) = \frac{(N_{USA} - N_{AC})V_i}{N_{AC}} + V_{min} \text{ For } i = 1,2 \ldots .N_{USA} \text{ and } N_{USA} > N_{AC} \tag{4.4}$$

The above equation was formulated to reflect the conventional economic theory of demand and supply because with an essential commodity like the radio spectrum, demand and supply plays an important role in determining its economic value. The conventional theory of demand and supply can be found in [87]. V_i is derived from equation 4.3. Using equation 4.4, each of the users intending to transmit generates a bid within the given range and submits the same to the auctioneer. This must be done within a given time window known as the bidding period (t). The value of the N_{USA} is always greater than the N_{AC} for an auction to take place. In order to formulate the above equation, it is assumed that all the users have knowledge of N_{AC} and N_{USA}. This assumption is quite strong but reasonable, since it enables the understanding of how an auction process can be implemented for short term spectrum access. Due to the assumption being strong, it shall be relaxed in the future chapters.

4.2.3 The Bidding / Auction Period

An auction period (t) represents the time window in which users that require the use of the radio spectrum submit their bids to the auctioneer. Only bids submitted within this time frame are considered by the auctioneer and only such users are considered as the contenders for the next available transmit channel slots. The number of available channel slots (N_{AC}) is provided to the auctioneer by the database. The number of users seeking access (N_{USA}) that submit a bid during the auction period is dependent on the number of users who require the use of the spectrum. Hence, it depends on the user's arrival process at any particular auction period. The appropriate bidding period is examined because a long bidding period allows more bidders to arrive and submit their bids, but this can introduce additional delay into the system. A short bidding period might not allow enough users to arrive for an auction to be carried out. Another implication of more users arriving as seen from equation (4.4) is that the bids of the users depend on the value of N_{USA}, while N_{USA} depends on the bidding period (t) as explained. Therefore, the higher the number of arrivals (N_{USA}), the higher the bids submitted by the users. This might be considered as a positive implication because the revenue obtained by the WSP is dependent on the user's bid. The higher the bidding values, the higher the revenue of the auctioneer. The number of arriving bidders also determines the reserve price set by the auctioneer as seen from equation (4.1). Therefore, in the modelling scenario it can be concluded that the longer the bidding period, the longer the delay introduced into the system and the shorter the bidding period, the smaller the value of the revenue obtained by the WSP. Hence, the bidding period is an important factor that needs to be examined and chosen appropriately in order to balance the trade-off between the auctioneer's revenue and the delay in the system. Also there is a need to consider the transmission period. This is because in this work the bidding and transmission are carried out simultaneously as explained later but a longer bidding period than the transmission period also means delay in the system.

4.2.4 The Bidding Period

To obtain the appropriate bidding period which allows the number of bidding users arriving to be more than the number of channels. The number of bidders that are able to transmit after the allocation of the radio spectrum is defined as N_{UT}. N_{UT} is less than or equal to N_{WU} or N_{AC}. This is because some of the winning users are not able to transmit after being allocated the spectrum because their bids are below the reserve price or they do not meet the transmission requirement such as the SNIR threshold. It is also assumed that each of the users has only one file to send at any giving time hence, the number of files arriving is the same as the N_{USA}. This assumption is reasonable because before each file is sent an auction must take place. This is also summarised as shown

$$N_{WU} = N_{AC} \tag{4.5}$$

$$N_{UT} \leq N_{AC} \; or \; N_{WU} \tag{4.6}$$

The appropriate auction period should allow for N_{USA} to be greater than N_{AC}. Such bidding periods should also not introduce additional delay into the system. First, an expression for the probability of N_{USA} in any auction period is defined using a Bernoulli distribution to model the independent time interval between the user's arrivals. The bidding period is assumed to be t and the probability (P_r) of a user arrival in each trial as shown in equation 4.7. The bidding period t is divided into smaller periods called the trial periods. If no user arrives during a trial period this is termed as a failure but a user arrival during this trail period is known as a success.

$$P_r = \frac{\lambda t}{N_{tr}} \tag{4.7}$$

Where λ is the average user arrival rate and N_{tr} is the number of trials in period t. The number of failed attempts (failure) is $N_{tr} - N_{USA}$. The probability of N_{USA} users arriving in N_{tr} trials is given by the binomial distribution as shown below [105]:

$$P_r(N_{USA}\ out\ of\ N_{tr}) = \frac{N_{tr}!}{N_{USA}!(N_{tr}-N_{USA}!)}p^{N_{USA}}(1-p)^{N_{tr}-N_{USA}} \tag{4.8}$$

Substituting (4.7) into (4.8):

$$(N_{USA}) = \frac{N_{tr}!}{N_{USA}!(N_{tr}-N_{USA}!)}\frac{\lambda t}{N_{tr}}^{N_{USA}}(1-\frac{\lambda t}{N_{tr}})^{N_{tr}-N_{USA}} \tag{4.9}$$

Assuming the probability of a user arrival is small and assumed as shown below:

$$(1-\frac{\lambda t}{N_{tr}})^{N_{tr}} \cong e^{-\lambda t} \tag{4.10}$$

Therefore, the standard expression for the Poisson distribution is obtained:

$$P_r(N_{USA}\ \text{users arriving in } t) = \frac{e^{-\lambda t}(\lambda t)^{N_{USA}}}{N_{USA}!} \tag{4.11}$$

The above expression shows that the probability depends on the arrival rate and therefore, the equation represents the most likely number of bids to be received in any auction period t. User's arrival is used interchangeably with file arrival because it is assumed that each of the users only has one file to send at a given time. This bidding period must allow an auction to take place, therefore N_{USA} must be greater than N_{AC} ($N_{USA} > N_{AC}$). N_{AC} is assumed to be fixed in this section. Furthermore, an expression to allow at least $N_{AC}+1$ bids to be submitted in an auction period is derived. This is because if the number of bids received is less than the number of available channels, there is no need for an auction to be carried out. Therefore, substituting $\lambda = \frac{T_L}{h_t}$ into equation (4.11) and varying the period, where T_L is the traffic load in the system in Erlang and h_t is the holding time obtained from figure 4.1. The other parameters used are as given in table 4.1 and an average data rate of of $3.8bps/Hz$ and N_{AC} is 4.

From figure 4.1, it can be concluded that the appropriate bidding period that allows exactly 5 arrivals $(N_{AC}+1)$ decreases with the traffic load in the system when examined for all traffic loads. This is because the probability of arrivals depends on the traffic load in the system.

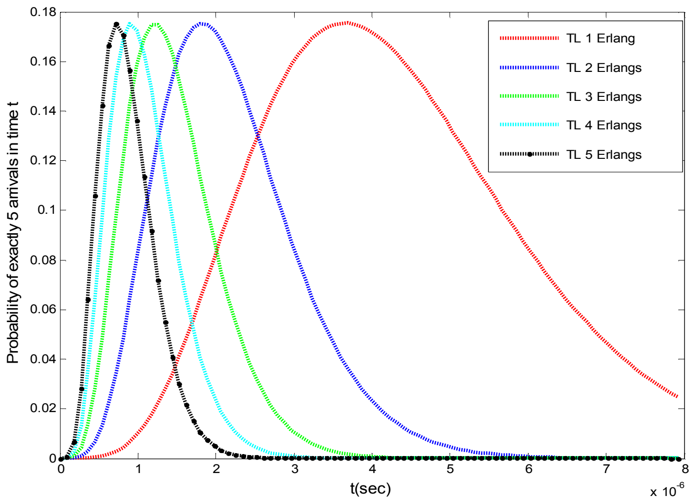

Figure 4.1. Probability of at exactly 5 arrivals in time $\boldsymbol{t}$

Furthermore, because the auction process takes time depending on the traffic load in the system, a scenario where the auction process and transmission process are carried out simultaneously is modelled. The auction process for transmission period T_1 is carried out during the transmission period T_0. This means that users submit their bids during an auction (bidding) period t_0 are only able to transmit during transmission period T_1 as shown below:

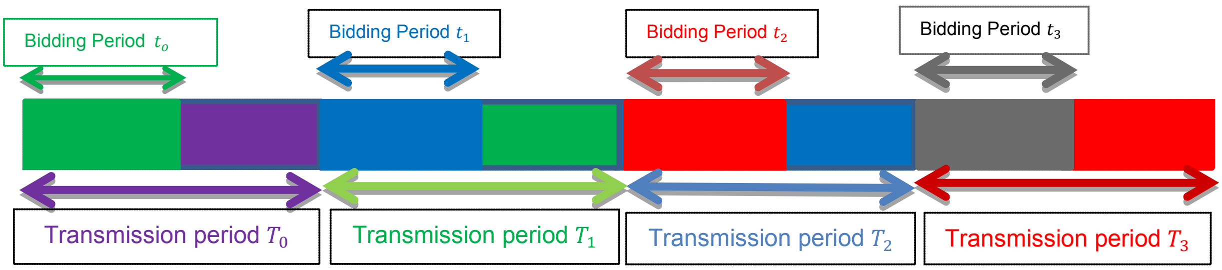

Figure 4.2 Relationship between auction and transmission period

The bidding process is carried out simultaneously as the transmission period to reduce the delays that the short term periodic auction process can introduce into the system. From the above figure, it can be seen that the bidding period for t_1 is carried out during the transmission period T_o

4.2.5 The Auctioneers Revenue

The expected revenue (R_e) of the auctioneer from one bidder during a single auction period is as shown below:

$$R_e(Price\ Unit) = b_i \tag{4.12}$$

Substituting equation (4.4) into above, the expected revenue is as shown below:

$$R_e(Price\ Unit) = \frac{(N_{USA} - N_{AC})V_i}{N_{AC}} + V_{min} \tag{4.13}$$

The total revenue obtained by the auctioneer during all the auction periods (t_n) can be represented as shown below:

$$R_{e_{total}}\ (Price\ Unit) = \sum_{1}^{t_n} \sum_{1}^{N_{AC}} R_e \tag{4.14}$$

It can be seen from the equation (4.13) that as N_{USA} increases the expected revenue also increases. The number of arriving users (N_{USA}) can only increase provided the bidding period is increasing. Therefore, the bidding period has a direct relationship with the revenue of the WSP. This also shows that the bidding period is an important factor that needs to be considered carefully when using an auction to allocate the spectrum. Another important factor that is considered throughout this thesis is the energy consumed.

4.2.6 The Energy Model

According to [106], the energy consumed by wireless devices consists of the energy used in generating and processing the signals. It also includes the energy consumed by the power amplifiers and other components. Hence, throughout this thesis, the total energy consumed by each user is the sum of all the energy consumed by each of the components during the period a user is active and the transmit power. The energy model is as explained in section 3.7.

As mentioned earlier the device can require a high transmit power or a low transmit power when in the ON mode. The transmit power for each group of users is fixed but both groups can switch to the OFF mode. Generally, in this work, the HPU transmit at higher bit rate compared with the LPU depending on the users SNIR based on the truncated Shannon bound as defined in chapter 3. Therefore, the energy consumption is modelled as a function of the bit rate which is directly proportional to the transmit power level. The energy consumed in transmitting one file by user i is as shown below:

$$E_i(Joules) = \frac{P_i\, S_f}{B_r} + P_D t_d \tag{4.15}$$

Where P_w is the transmit power for user i in watts, S_f is the file size in bits and B_r is the bit rate in bits/seconds, P_D is the power used in powering the user device in Watts and t_d is the time in seconds in which the device is powered on. The device is assumed to be powered on during the bidding and the transmission periods. It is assumed that all users are transmitting the same file size. Therefore, a higher bit rate means transmitting for a shorter period for the HPU compared to the LPU. The total energy (E_T) consumed by the system in Joules is

$$E_T(Joules) = \sum_{i=1}^{N} E_i\, N_{FG_{i_i}} \tag{4.16}$$

Where N_{FG_i} is the total number of file generated for user i (both successfully sent and the ones not successful sent) and N is the total number of users in the system. The average energy consumption per file sent is calculated as shown below. Where N_{FS_i} is the total number of files successfully sent by user(i) in the system.

$$E = \frac{E_T}{\sum_{i=1}^{N} N_{FS_i}} \tag{4.17}$$

4.3 The Green Payment (R)

The green payment (R) is either in the form of a tax or a subsidy and the main aim of introducing the green payments is to allow the bids of the LPU to be subsidised, the bids of the HPU to be taxed and to increase the probability of LPU winning the bid. This is because all the users (LPU and the HPU) are all opportunistic spectrum users and such users need to reduce their interference to other users by keeping their transmit power level low. Hence, the aim is to use the green payment to encourage the users to keep their interference level to be as low as possible. This is because this thesis wants the primary users which are not considered in this work but assumed to be present to perceive the interference as a form of noise rather than interference. The auction modelling scheme allows the granting of access to the radio spectrum to the HPU only when the bid of the HPU after the tax is above the reserve price and above the bids of the LPU with the subsidy. This is because sometimes due to the value of money involved, low demand for the use of the spectrum or the importance of the application seeking the use, the HPU should be allowed to transmit after paying the price for using such transmit power. An equation derived from the inverse of the Truncated Shannon Bound (TSB) is obtained to either tax or subsidise the users. The TSB represents the transmission rates that can be achieved in practice given an adaptive modulation scheme in a real world scenario. This is dependent on the SNIR of the user as shown in the TSB equation. In order to use the green payments to control the interference caused by the users requiring high SNIR in a fair manner, and to penalise or subsidise users based on the interference they contribute into the system, an equation related to the TSB is used to derive the green payment equation. The reason for using this equation is due to the fact that the transmission rate is an important parameter in a wireless communication system. This is because the transmission rate is dependent on the SNIR and SNIR is dependent on transmit power and interference. The derived green payments equation is shown below as formulated from the TSB:

$$\text{R(Price Unit)} = \begin{cases} 2^{1+ß\theta} - 1 & For\ green\ payment\ subsidy \\ 2^{1+ß\theta} + 1 & For\ green\ paymnet\ tax \end{cases} \quad (4.18)$$

Where ß is the green payment factor derived later in this chapter. The value of ß is chosen in such a way that the green payments dose not introduce too much tax/subsidy into the system leading to delay or reduction in the system throughput, hence the reason for it being called the green payment factor. θ is the absolute value of the linear difference between the SNR value of a user i (ψ_i) and the value of the SNR of a set threshold (ψ_j).

$$\theta_i = |\psi_i - \psi_j| \text{ for } i=1, 2, 4 \ldots N_{USA} \quad (4.19)$$

The set threshold (ψ_j) is derived by first arranging the received SNR of the N_{USA} users who are seeking access to the radio spectrum at time t in an ascending order

$$\boldsymbol{\psi}_t = [\psi_1, \psi_2, \psi_3 \ldots \psi_{N_{USA}}] \quad (4.20)$$

Then to determine which of the SNR at time t is the set threshold, the equation below is used, where P_c is the desired percentile. The appropriate value of the desired percentile is obtained later in this chapter. A percentile is usually used in statistics to indicate what percentage of scores is less than set threshold in an investigation.

$$|j| = \left\lfloor \frac{P_c N_{USA}}{100} + \frac{1}{2} \right\rfloor \quad (4.21)$$

The above equation gives an absolute value (integer) known as the percentile rank. This shows that whatever the value of j, the j^{th} SNR in equation (4.20) is the set threshold (ψ_j). For example if j is 2, then the second SNR (ψ_2) in equation 4.2 is the set threshold, therefore $\psi_j = \psi_2$ with this example. The set threshold is not the same or related to the SNIR threshold ($SNIR_{threshold}$) in the TSB equation. The value of the percentile rank used has an effect on the total revenue needed to subsidise the bids of the users as seen from equation (4.21). As P_c increases the percentile ranks also increases. This means that the number of users falling below the percentile rank increases and percentile value of 100 means that all the users are subsidised and no user is taxed. As explained earlier, the green payment is derived from equation (4.19) can either be a tax or subsidy. In order to determine if the green payment of any user in the system is either a tax or subsidy, the scenarios that determines the users paying a tax or subsidy at any traffic load can is summarised into case 1 to 3 as explained below:

Case 1: Most of the N_{USA} Users Arriving in Period t are Low Powered Users:

This happens when all or most of the bids received in an auction period are from the LPU. When this scenario occurs some of the LPU whose SNR is above the percentile value appear to fall in the tax category. As an example when N_{USA} is 6, and 4 transmit channels are available in the system. Where $\boldsymbol{\psi}_{\boldsymbol{A}}^{\boldsymbol{C}}$ represents the SNR of all the users attempting to transmit at any period arranged in ascending order and superscript C can either be LPU or HPU indicating low powered or high powered users respectively and subscript A represents the position number of each of the SNR values in ascending order. Therefore, in the above example, A varies from 1-6 since there are 6 bidders seeking access to the radio spectrum during the auction period and the SNR is represented as shown below:

$$\boldsymbol{\psi}_{\boldsymbol{A}}^{\boldsymbol{C}} = [\psi_1^{LPU}, \psi_2^{LPU}, \psi_3^{LPU}, \psi_4^{LPU}, \psi_5^{LPU}, \psi_6^{HPU}] \tag{4.22}$$

Assuming the percentile rank (J) which is calculated from equation (4.21) is 3 then $\psi_J^c = \psi_3^{LPU}$. Therefore, ψ_4^{LPU}, ψ_5^{LPU}, $\psi_6^{HPU} > \psi_3^{LPU}$. This means that the SNR of users 4 and 5 who are LPU fall above the percentile value and the corresponding green payment for users 4 and 5 appear to be a tax. However, if this happens a tax is not be applied to the bid of the users (4 and 5 in the example) and neither is their bid subsidised, but users whose SNR are less than the value of percentile rank (users 1 and 2 in this example) are subsidised by adding the value of the green payment to their original bid and a tax is deducted from the bid of user 6. This is done so that only the set of users with the lowest values of SNR are subsidised and this subsidy is only when necessary. In the above example, the HPU (user 6) has the least priority to transmit and user 4 is able to transmit if the bid is above the reserve price but the bidder is not subsidised.

Case 2: Most of the Bidders Requiring the Use of the Spectrum are High Powered Users.

Some of the HPU have an SNR value less than the value of the percentile rank, using the same illustration as in the example above.

$$\boldsymbol{\psi}_{\boldsymbol{A}}^{\boldsymbol{C}} = [\psi_1^{LPU}, \psi_2^{HPU}, \psi_3^{HPU}, \psi_4^{HPU}, \psi_5^{HPU}, \psi_6^{HPU}] \tag{4.23}$$

Assuming the percentile rank is 3, user 2 appears to fall into the category of users receiving subsidy, but in the work this set of users is not subsidised or taxed as the percentile rank that is used in this case is 2 rather than 3. Therefore, user 3 is paying the minimum possible tax. This is done to prevent the bid of such user from going below the reserve price thereby making some of the available channels idle and lowering the system throughput.

Case 3: The Arriving Bidders Fall Equally In-between the High Powered Users and Low Powered Users.

This is when the value of the percentile rank falls somewhere in-between the HPU and the LPU: In this case each of the users is taxed or subsidised accordingly as illustrated below using the same illustration as previous examples:

$$\boldsymbol{\psi}_A^C = [\psi_1^{LPU}, \psi_2^{LPU}, \psi_3^{LPU}, \psi_4^{HPU}, \psi_5^{HPU}, \psi_6^{HPU}] \quad (4.24)$$

Users 1 and 2 are subsidised and user 3 is neither taxed nor subsidised and the other users are taxed with user 4 paying the least amount of tax.

The aim of adopting the above rules is to subsidise users only when it is necessary, thereby preventing users from paying tax when the spectrum is not in use by the LPU. The rule also allows the tax received to be able to subsidise the bids of the LPU and prevent unnecessary denial of access to the HPU thereby, reducing the system throughput. As an example, substituting N_{USA}=5 and P_c=30 into the equation (4.21) gives j an approximate value of 2 meaning that in the event of at least 5 arrivals, 2 falls below the percentile rank. These two users should be able to transmit because their bids are either subsidised or they are paying the minimum amount of tax using the green payment equation. This also means that only two of the transitting users are subsidised thereby helping in balancing the value of the tax and subsidy making the system self-sustaining.

The green payment (R) as explained earlier is then applied to each of the received bids as shown below:

$$b_i^{final} = \begin{cases} b_i + R_i & \text{For } \psi_i^C < and\ i\ is\ a\ LPU \psi_A^C = \psi_A^{LPU} \\ b_i - R_i & For\ \psi_i^C > \psi_j^C \text{and } i\ is\ a\ HPU \\ b_i & For\ Others \end{cases} \quad (4.25)$$

For i = 1,2,3 ... N_{USA} and j is the percentile rank of the threshold as

Where b_i and R_i are representing the bid submitted by user i and the value of the green payments paid to user i for a bidding period.

4.4 General System Description

One spectrum broker and N wireless users are considered modelling an infrastructure based uplink wireless network. The users require short term access to the radio spectrum. It is assumed that the users in the same group transmit at the same constant power which can be represented as either P_H or P_L, representing high power or low power respectively. On average, the LPU transmit at a lower bit rate compared to the HPU depending on the SNIR as defined by the truncated Shannon bound as explained in chapter 3. A hexagonal cell structure where cells that are located next to each other cannot share the same channel is assumed. A frequency reuse factor as specified in the table of parameters in chapter 3 is used. This chapter assumes a fixed total number of channels (N_{TC}) is available in all the cells. The channels are assumed to have similar characteristics and in the absence of interference no channel is better in quality than the other. Hence, the users are allocated the least interfered channels based on their offered bid. The user with the highest bid is offered the least interfered channel and the winning bidder with the least bid is offered the most interfered channel. The file arrival process conforms to a Poisson distribution and the channel holding time is exponentially distributed. Each of the users who want to transmit during each auction period submits a uniform sealed bid $b_i \, (i = 1,2,3, \dots . N_{USA})$ to the spectrum broker. A period t allowing a minimum of $N_{AC} + 1$ arrival is assumed for the bidding period depending on the traffic load in the system as explained earlier. The auction process is also carried out as explained earlier where multiple users (N_{WU}) can emerge as winners depending on the number of available channels (N_{AC}) after applying the green payments to the bid of the users as explained earlier. The flow chart is shown in figure 4.3 below.

The winning bidders are subsequently allocated to the available channels. Each user that is allocated a channel transmits successfully provided the SNIR of such user is above the SNIR threshold ($SNIR_i \geq SNIR_{Treshold}$) and the final bid price is above the reserve price ($b_i^{final} \geq$

r). N_{UT} represents the number of users that are able to transmit successfully after the auction and allocation process. The signal to noise ratio for each user is calculated using the SNIR equation in 3.5. Each of the users in each group transmits at a different bit rate according to the users received SNIR level, as determined by the TSB as explained in [7].

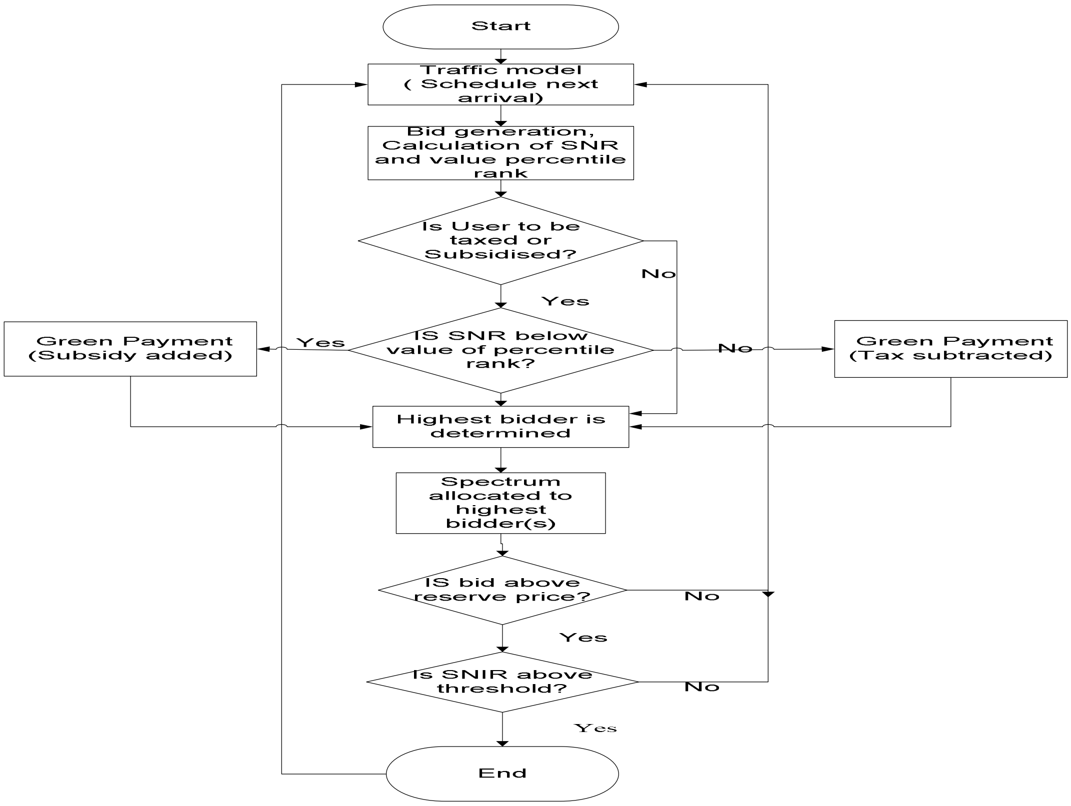

Figure 4.3. System flow chart

4.5Results and Discussion

The first problem formulated here is to determine the range of values of the green payments that maximise the system performance over different traffic loads. Such value should make the system profitable and maximise the system capacity. It must also minimise the energy consumed by the cellular network. The WINNER II B2 propagation model as detailed in [89] is adopted. The parameters specified in table 3.1 are used here together with the ones specified in table 4.1 below.

Parameter	Value
$[V_{min} V_{max}]$	[5 8]

Table 4.1 Parameter used

The value of the green payment factor (ß) in equation (4.19) is varied from 0 to 0.1 for different traffic loads to obtain a range of values for ß at different traffic loads in order to examine if the aim of this work is achieved. The aim is to allow the HPU to access the radio spectrum mainly when the LPU are not transmitting, to make the tax obtained pay for the subsidy given out, not to introduce significant delay into the system and to allow the system to be able to operate at maximum capacity when required. It is worth pointing out that the system performance used in this work is per cell.

Furthermore from equation (4.21), it can be seen that as the percentile value increases, the percentile rank also increases, meaning that the number of users to be subsidised also increases as explained in the three modelling scenarios earlier in section 4.2.5 named case 1 to 3. Therefore in order to examine the effects of varying the green payment factor (ß) and the value of the percentile used on the value of the total green payment, the value of the green payment is varied. The total green payment (R_{tot}) is calculated as shown below:

$$R_{tot}(Price\ unit) = R_{ttp} - R_{tsp} \tag{4.26}$$

Where R_{ttp} and R_{tsp}represents the total tax and total subsidy paid in price unit respectively.

Figure 4.4 shows the results obtained by varying the value of the green payment factor (ß) in equation (4.18) for different percentile values. It can be seen that with the percentile value of 10, the value of the green payment factor can be increased up to 0.08 before the total green payment value goes below the zero margin. This is because the percentile equation as specified determines the number of users to be taxed or subsidised. This result is examined because the aim is to make the tax received to be able to pay for the subsidy. Therefore the auctioneer does not have to set aside some amount to pay for the subsidy. It can be seen from this figure that as long as the value of ß is less than 0.05, then the system is self-sustaining for all the percentile value examined. As the percentile value increases the system can no longer be self-sustaining especially at high values of ß, as the tax received cannot finance the subsidy. This does not pose a major problem if the subsidy is coming from an external source such as the government. However, in this work one of the aims is to allow the tax paid by HPU to be able to subsidise the LPU who are receiving a subsidy, hence the 30th percentile is used for all the remaining results throughout this thesis. Furthermore it can be seen that it is important to examine the range of values of ß that allows the system to be self-sustaining after having a fixed value of the percentile.

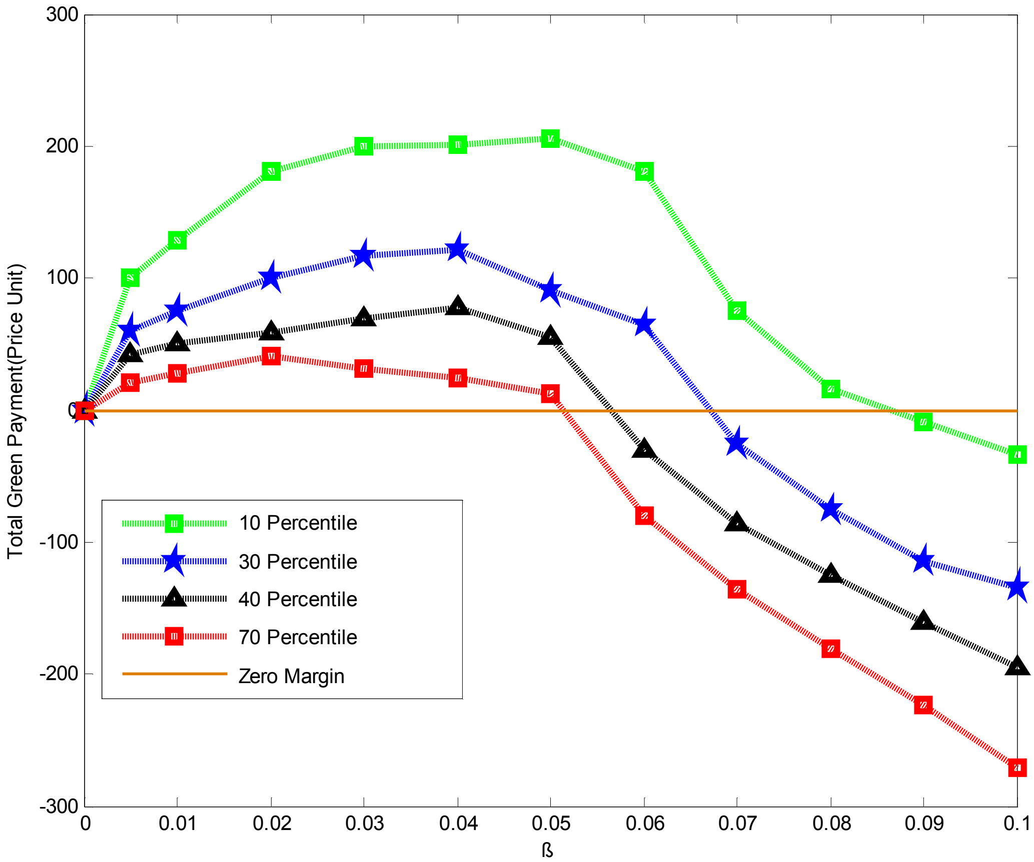

Figure 4.4. Green Payments against ß for different Percentile Value

After selecting the 30th percentile based on the above reasons, the value is now kept constant to determine the range of values for ß that would make the tax pay for the subsidy. This is necessary because one of the aims of this thesis is to allow the tax to pay for the subsidy. Figure 4.5 shows the green payment against the tax. The total green payments for all traffic loads are initially zero because no tax or subsidy is paid when ß is 0. The total green payments rise after the initially zero value because as seen from equations (4.18 to 4.21), the subsidy paid increases with increases in ß and also the tax increases with ß. However as the value of ß increases, more HPU are squeezed out and the number of HPU paying a tax reduces in the process. Therefore, as the HPU are squeezed out gradually, the tax paid can no longer pay for the subsidy, thereby decreasing the value of the total green payment gradually until the total green payments goes to negative. The total green payment is negative when most or all the HPU in the system have been squeezed out. In terms of allowing the tax paid to pay for the subsidy and allowing the system to be self-sustainable the most suitable range of ß can be obtained to be between 0.01 and 0.05 for all the traffic loads examined.

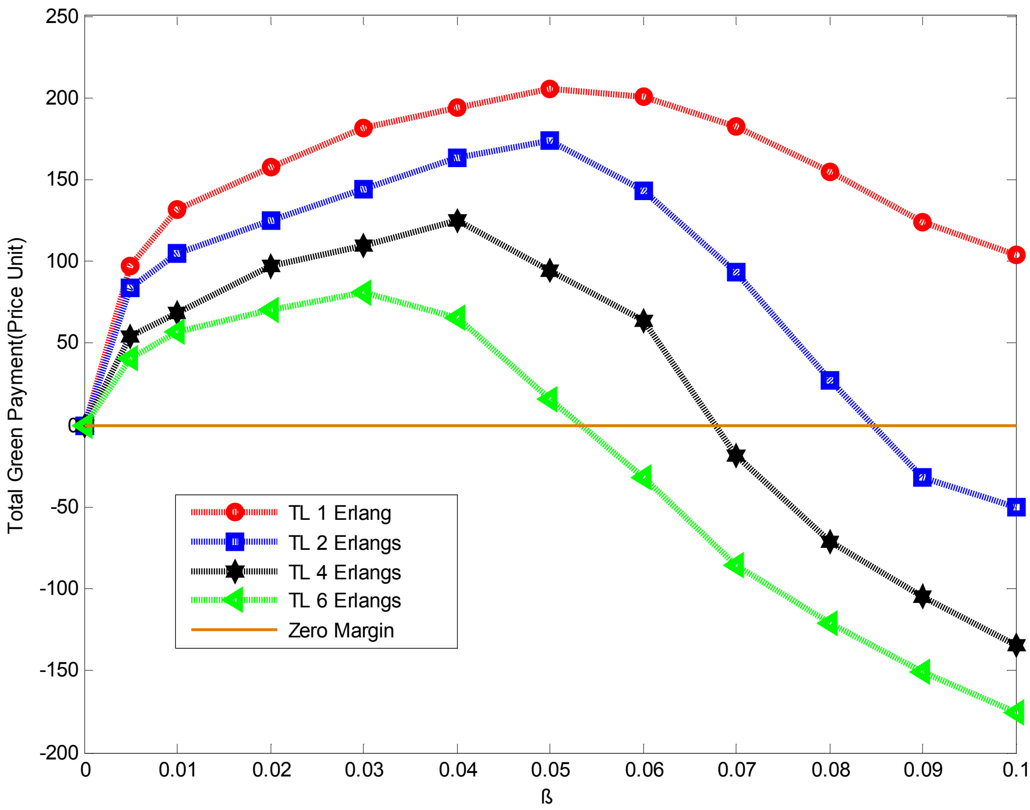

Figure 4.5. The Revenue from the Green Payment against ß

The aim of the green payment is not to completely squeeze out all the HPU in the system. Hence, the ratio of HPU to LPU during transmission is examined to determine the value of ß that would not completely squeeze out all the HPU in the system depending on the traffic load in the system. It is important to show the ratio of the HPU to LPU in the system while varying ß because it helps to verify the fact that the reduction in the total green payment value is due to a reduction in the number of HPU in the system. As seen from figure 4.6 below, the ratio of the successful transmit files of the HPU compared to that of the LPU decreases as the value of ß increases from 0 to 0.1 for all the traffic loads examined. First, this result shows that there is a need to only test the range between 0 and 0.1 because as the value of ß approaches 0.1 the ratio decreases to zero. The decreasing ratio can especially be noticed at a traffic load above 2 Erlangs and it is as a result of the HPU being completely squeezed out due to the increase in the tax paid. As the tax increases, the bid of the HPU is subsequently below the reserve price. Therefore, a value of ß above 0.1 means the HPU are never granted access to the radio spectrum unless the overall budget is increased. This also means that no HPU are allowed access to the spectrum and there is no way of subsidising the bids of the LPU. It can be argued that if no HPU is granted access then there is no need to subsidise the LPU. However, the aim of this work is not to completely squeeze out the HPU but to grant the HPU access when the interference caused does not have a significant impact on the primary users in the system, or when LPU are not transmitting and the power can be spread over a wider bandwidth. It can be concluded from this that the higher the probability of LPU arriving, the lesser the chances the HPU are having of getting through. The result shows that the range of values for ß that allows a significant proportion of the HPU to transmit when the system is not in use by the LPU (if only the ratio is considered) is between 0 and 0.06 for all traffic loads between 1 and 6 Erlangs. Squeezing out the HPU and leaving the system empty or below its capacity is not an ideal situation because this gives a low value of throughput to the system. The system is operating below capacity because there are times when channels are available but because the offered bid of the HPU is below the reserve price as a result of the excess tax paid. Hence, there is a need to examine the throughput of the system with a varying value of ß. It is also important to examine the performance of the system as the value of ß is varied. This is because the performance of the system in terms of delay and throughput is important to any wireless system.

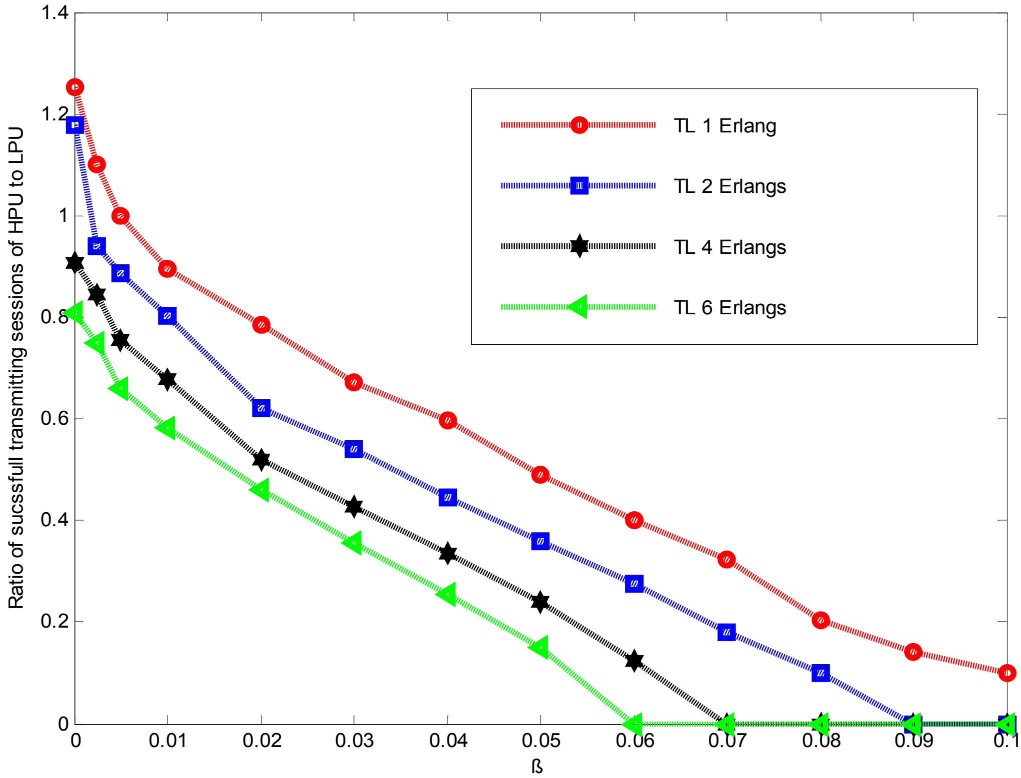

Figure 4.6. Ratio of transmitting files of HPU to LPU against ß for different traffic loads

Figure 4.7(a) shows the corresponding throughput value as ß increases from 0 to 0.1 when the least interference channel assignment scheme is used. It can be seen that at traffic loads of 1 and 2 Erlangs the throughput decreases at higher values of ß. This is because the system is not loaded to capacity. This can also be because most of the HPU are completely denied access even when the LPU are not transmitting or because N_{UT} is less than N_{AC}. Furthermore, at traffic loads of 4 and 6 Erlangs and at lower values of ß, the throughput is lower because of the interference from the HPU transmitting. At low traffic loads the LPU can avoid using the same channels as the HPU transmitting in other cells because of the least interfered channel assignment scheme in use. The avoidance is possible since more channels are available than the number of channels required. However, at higher traffic loads when the system is approaching maximum capacity, the least interfered channel assignment scheme has no effect. This is because the LPU has little or no option of transmit channels to choose from.

This is because all the channels are busy most of the time due to the increase in the traffic load. In order to determine if it is the reserve price that is preventing the system from operating at full capacity below 4 Erlangs, the reserve price is removed. Figure 4.7(b) shows that removing the reserve price does not have any significant effect on the throughput at lower values of ß, but it does increase the throughput at higher values of the green payment factor (ß) at traffic loads between 1 to 4 Erlangs. This signifies that at values of ß above 0.05, there is a need to make the reserve price constant, especially at low traffic loads. Furthermore, the reserve price has no significant effect at higher traffic load above 4 Erlangs because the LPU who are getting subsidies are always transmitting on the radio spectrum and there is no need for the HPU to come into the system. From the throughput point of view, the range of values of the green payment factor that maximises the throughput is between 0.03 and 0.55. This is because at this value the system can be operated to capacity.

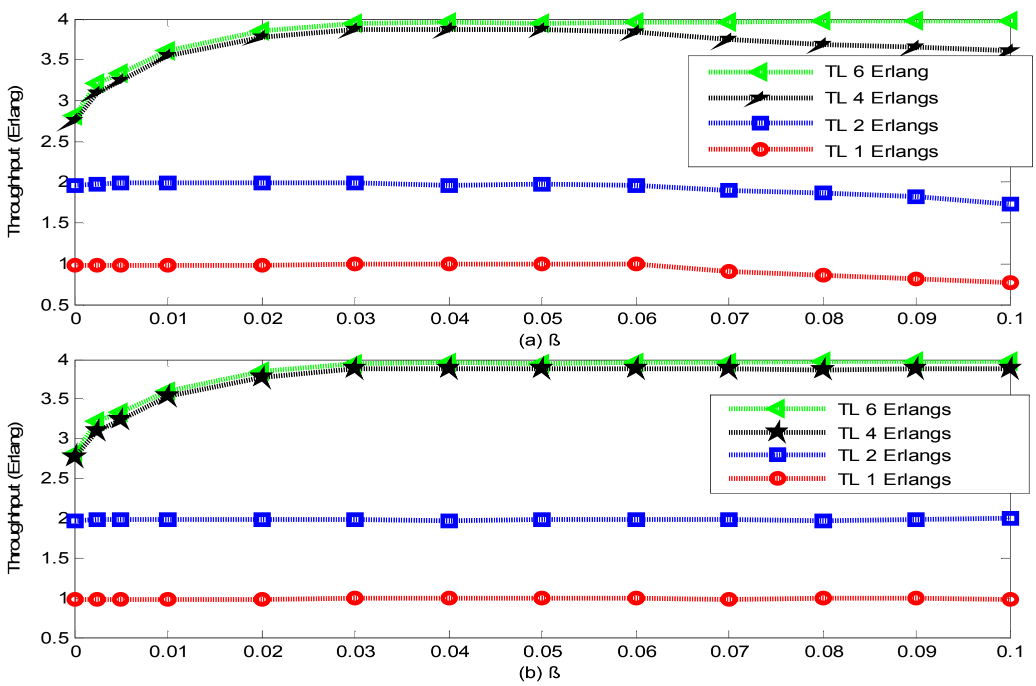

Figure 4.7. Throughput against ß for different traffic loads for without and without reserve price

After considering the throughput of the system, another important factor that is considered is the amount of energy consumed by the system. This is because one of the important features in many of the proposed future wireless systems is energy conservation. Figure 4.8 shows that the average energy consumed per successful file sent. The energy consumed here is the total energy consumed by only the users who are among the winning bidders (N_{WU}) and this is divided by the number of bidders who are able to transmit successfully (N_{UT}). It is worth pointing out that that the number of winning bidder (N_{WU}) is always less than or equal to the number of bidders who are able to transmit successfully after the transmission period (N_{UT}). The energy consumed reduces initially because the amount of energy consumed by the winning bidders reduces as the value of ß increases. This is because as ß increases more of the winning (N_{WU}) bidders are LPU as a result of the tax being paid by the HPU. However, as the value of ß increases the value of N_{UT} also reduces. This is because more of the HPU who are among the winning bidders are not able to transmit successfully. Initially, the reduction in the value of N_{UT} is gradual until it gets to a point where there are channels available but they are not put to use and all the users who are able to transmit successfully are only the LPU. This is because the HPU who are among the winning bidders are not always able to transmit. This is also because the value of the tax paid is higher as ß increases, thereby making the bid value of the HPU go below the reserve price. At the point when only the LPU are able to transmit, the average energy is flat as seen for values of ß above 0.06. This is because on the average the number of HPU who are among the N_{UT} becomes constant and the traffic load is also constant. The rise in the value of the average energy consumed after a value of ß is equal to 0.05 is because there is a sudden reduction in the value of N_{UT} without a corresponding reduction in the value of the energy consumed. The sudden reduction in the value of N_{UT} is because the HPU are almost completely squeezed out of the system at higher values of ß. At high values of ß more of the winning bidders are LPU, but the number of LPU among the winning bidder is not enough to occupy all the available channels and the aim of the proposed model is not to make the system to work below its capacity. Therefore in terms of energy consumed by the system, the range of values of ß that significantly reduces the consumed energy per file has a range between 0.04 and 0.05. This is because at those range of values, the average energy consumed per successful file sent is minimised for all traffic loads.

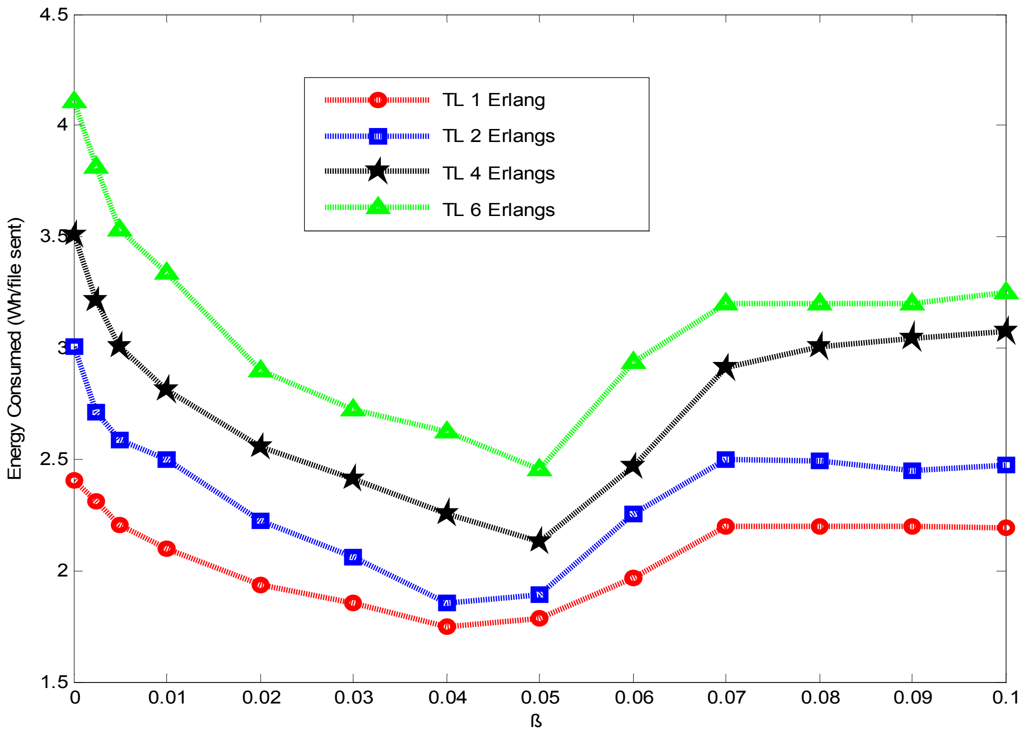

Figure 4.8. Energy consumption against ß *for different traffic loads*

Taking all the above reasons into consideration ß is chosen to be 0.045. This value is chosen in order to obtain an optimal value that maximises all the aims of this thesis. This value is seen as the optimal value of ß because when the throughput and energy are taken into consideration, the optimal value is the point where the least energy is consumed. This value is also optimal because it makes the system to be self-sustainable (the tax received can pay for the subsidy paid out).

4.4.1 General System Performance

Using the optimal ß value of 0.045 the system performance with and without the green payment and without the reserve price is examined in order to determine how each affects the general performance of the system. It is assumed that the bidders derive their bid using a uniform random distribution as explained earlier and a user does not pay if the data transmission is not successful but energy can still be consumed.

In order to determine the effects of either using the discriminatory or uniform price increase as explained in chapter 3, this two price increase are examined together with 50% and random price increase. By random price increase it is meant that the user uses equation (4.4) during any bidding period to generate their bids all the time. However, with the 50% price increase the bidders such as bidder (i) uses equation (4.4) to generate their new bid at time t represented as b_i^t but also add 50% of the last value of bid submitted (b_i^{t-1}) to the new bidding value provided the user is not among the winners in the last bidding period in which the user participated. This is done in order to understand the effects of the price generation mechanism on the revenue of the auctioneer and it is summarised using the equation below:

$$b_i(Price\ Unit) = b_i^t + \frac{b_i^{t-1}}{2} \tag{4.29}$$

Figure 4.9 shows the revenue obtained by the WSP using the 50% price increases or the random price increases either with a discriminatory auction or uniform auction. From the results the discriminatory (50% or random price increase) performs slightly worse than the uniform price (50% or random price increase). It can be seen that the price increase per session (50% or random) does not have any significant difference in the result obtained for the revenue of the WSP. The reasons are explained better with figure 4.10.

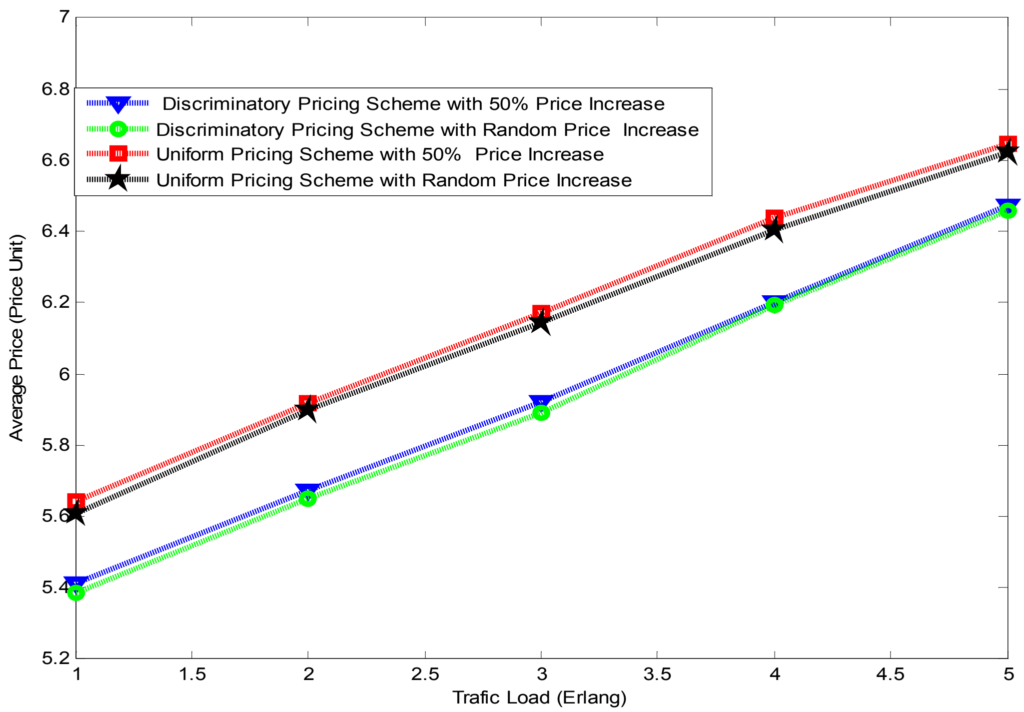

Figure 4.9. Average revenue per file for different payment Schemes

However, from figure 4.10 the throughput of the system performs worse with the 50% price increase. This is because it (50%) gives an advantage to the HPU to be able to win the auction process at the expense of the LPU thereby lowering the system performance. From the throughput result, it can be seen that the discriminatory or random price increase does not affect the throughput of the system. This is because the discriminatory or uniform price increase only has an effect on the average revenue of the service provider while the price increase per file (50% or random) determines if the bid of the user is accepted or rejected and subsequently if the file is sent or not.

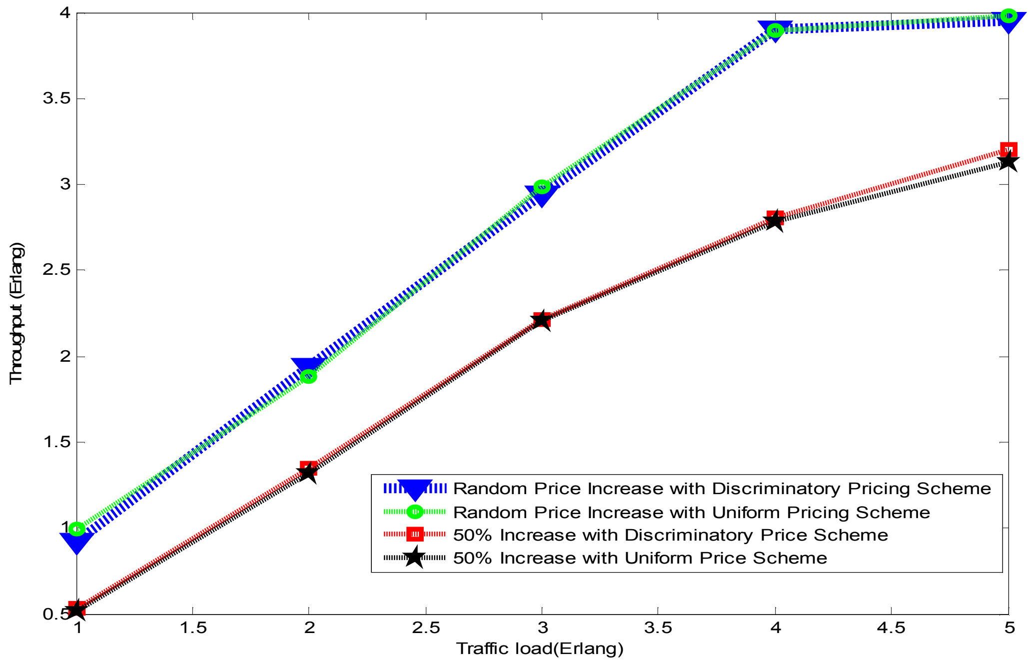

Figure 4.10. Traffic Load against Throughput for Different Payment Schemes

In order to determine the effects of the green payment and the reserve price on the performance of the system, the models with and without the green payment and reserve price are considered.

Figure 4.11 shows the traffic load against the throughput using the optimal value of ß for scenarios with and without the green payment and with the green payment but with and without a reserve price. The throughput results without the green payment are significantly lower because without the green payment the HPU is always interfering significantly with the LPU and other HPU in the other cells with whom they share the same channel, thereby making the system to operate at a lower throughput. The schemes with the reserve price perform worse compared to the schemes without the reserve price because the reserve price sometimes hinders the transmission of users in the system. The hindrance is as a result of the users not being able to transmit when channels are available but they (channels) are not offered to the users because the offered bids are below the reserve price. However, the importance of the reserve price is demonstrated later with figure 4.14. Furthermore, chapters 5-7 are aimed at helping the users to pick a bid price that is above the reserve price in order to avoid the scenario as demonstrated with this figure. The throughput also saturates close to 4 Erlangs per cell because 4 Erlangs is the maximum throughput per cell that can be achieved since 4 channels are available in each of the cells at the maximum.

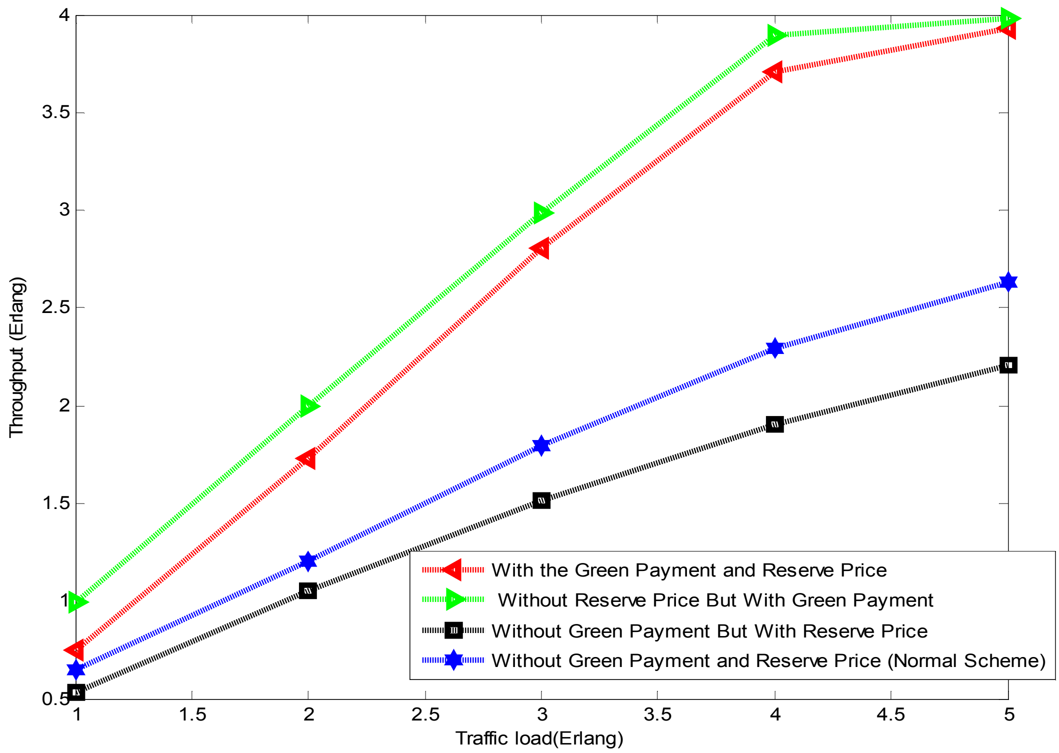

Figure 4.11. Throughput per cell against traffic load for scenario with and without green payment and without reserve price

Another important performance parameter is the energy consumed by the system. Figure 4.12 shows the energy consumption per file sent with and without the green payment and with and without the reserve price. The energy consumed increases with the traffic load because as the traffic load increases the collision in the system also increases. Furthermore energy consumption increases with the traffic load. The increase in collision is because whenever a bid is rejected energy is wasted as explained with the energy model. The energy consumed using the green payment with a reserve price is slightly above the scenario without the reserve price. This is because a few of the bids are rejected as a result of the offered bid going below the reserve price. The difference is about 20% on the average which is very low compared to over 120% average increase without the green payment. The energy consumed without the green payment is significantly more because more packets are being dropped as a result of HPU interfering and making the SNIR of the interfered signal fall below the SNIR threshold. This result also showed that the use of the reserve price increase the energy consumed by the system. However, chapters 5-7 demonstrates how the users can place their bids only above the reserve price because of the importance of the reserve price as explained earlier and this is shown later in figure 4.14.

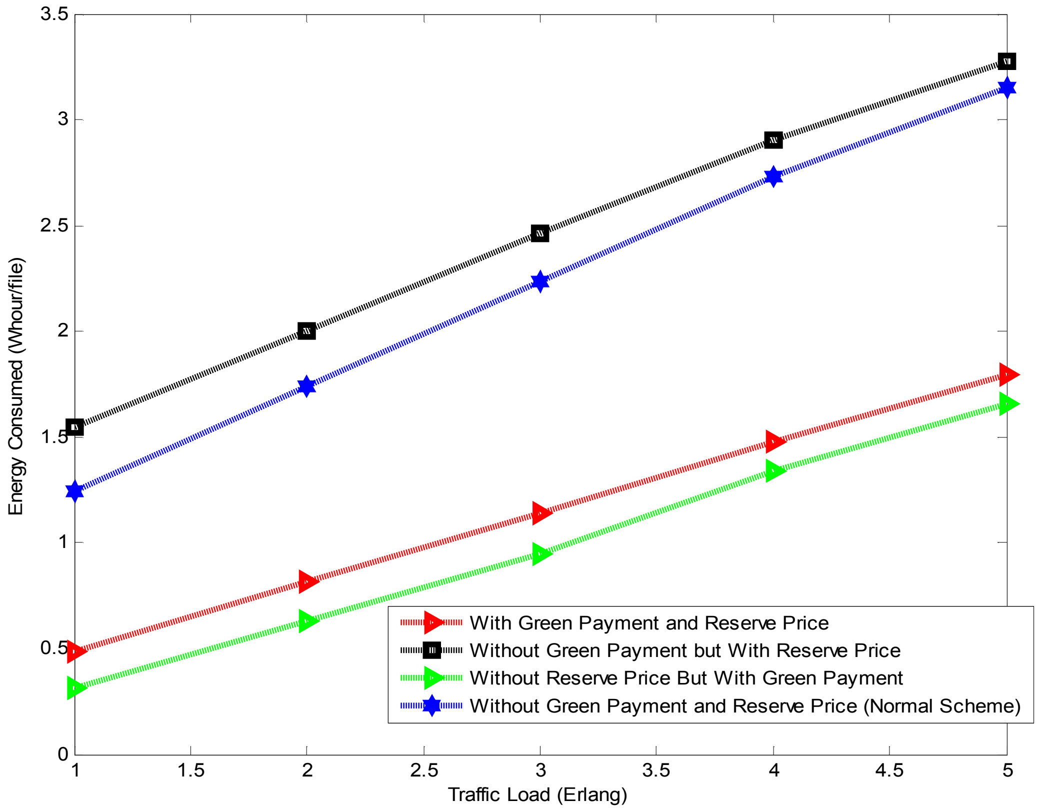

Figure 4.12. Energy consumption against traffic load with and without green payment and without reserve price

Figure 4.13 shows the traffic load against the delay. It can be seen that the delay increases with the traffic load for all the examined scenarios. However, without the green payment the delay is significantly more when compared with the scheme with the green payment. The scheme without the reserve price also performs better than the scheme with the reserve price. The reasons are the same as the reasons explained for the energy consumed in figure 4.12.

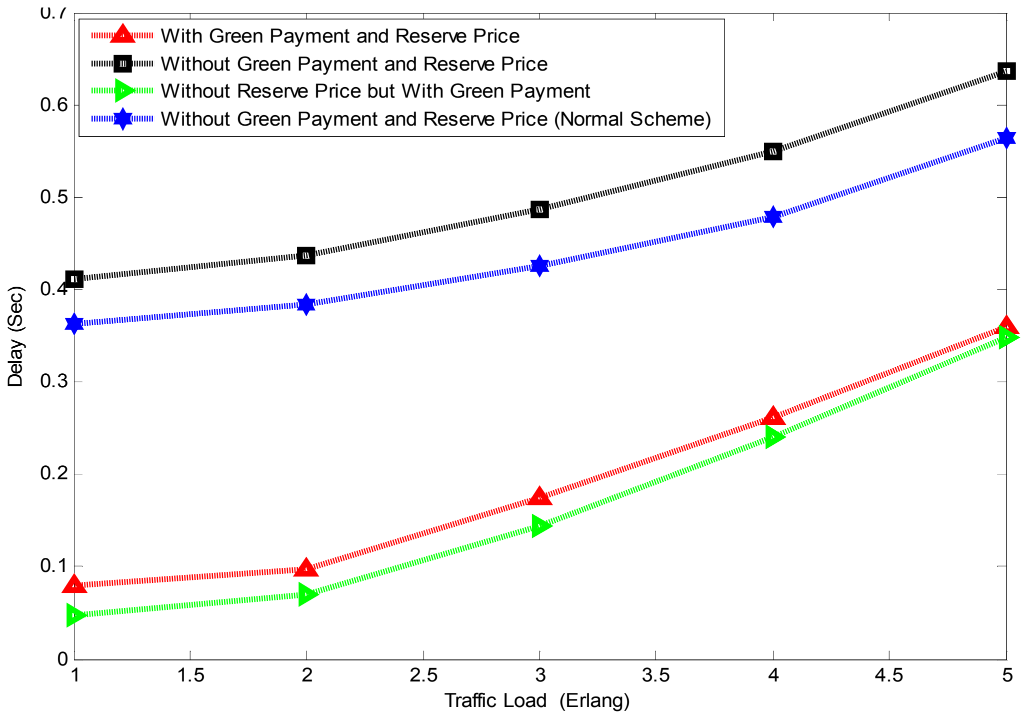

Figure 4.13. Delay against throughput for scenario with and without green payment and without reserve price

Figure 4.14 shows the average revenue with and without the green payment, with the green payment but without the reserve price and without both the green payment and reserve price. The price paid per file for all the scenarios increases with the traffic load because as the traffic load increases the competition in the system increases. From the bid equation the bids also increases in order for the bids to be above the reserve price if there is a reserve price. The revenue increases with the traffic load with and without the green payment until when the traffic load is 4 Erlang and begins to flatten out because the maximum capacity of the system has been reached. The revenue without both the green payments and the reserve price is lower compared to all the others because the accepted bids are not necessarily above the reserve price. The crossover between the scenario with green payments and without a reserve price and with a reserve price is because at lower traffic loads the bids accepted without the reserve price is lower but as the traffic load increases, the green payments also increase thereby making the average revenue to increase above the reserve price.

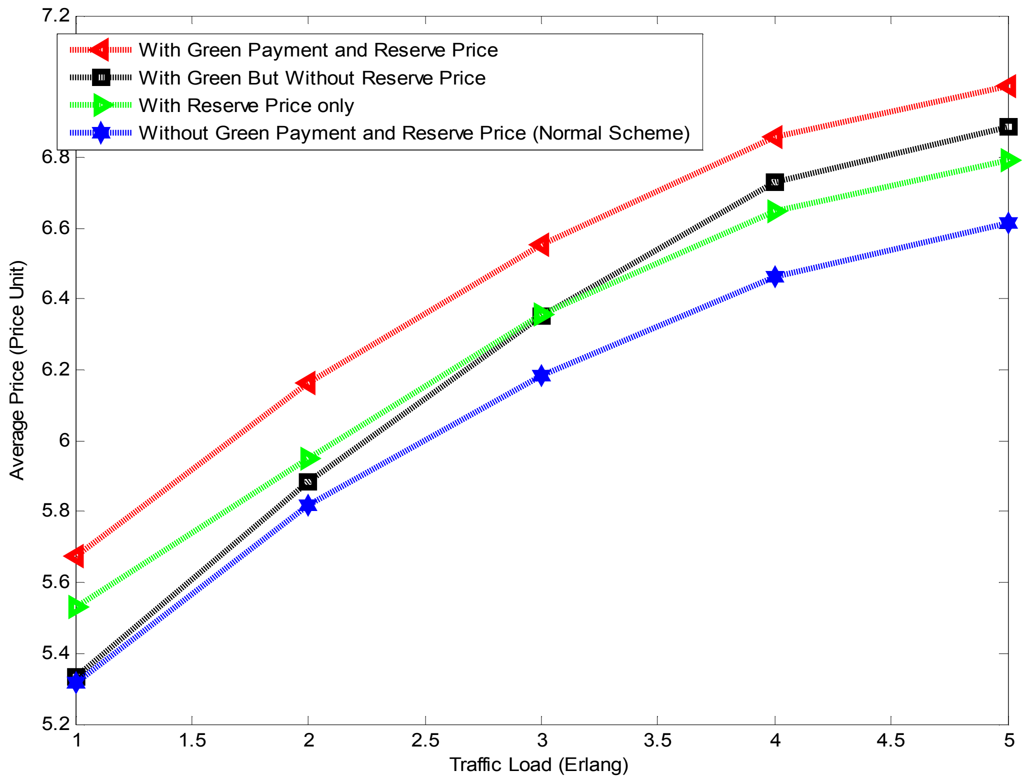

Figure 4.14. Average price per packet sent against traffic load for scenario with and without green payment and without reserve price

The reserve price is useful at lower traffic loads because the users put in a bid which is relative to the traffic load. At traffic load of 1 Erlang the slight difference between the two scenarios without the reserve price is because of the green payment.

Finally, in order to determine if the system can be self-sustaining the average and total green payment (tax and subsidy) is examined. Figure 4.15(a) shows the total subsidy and tax paid against the corresponding traffic load. The total subsidy paid increases with an increase in traffic load while the total tax decreases as the traffic load increases. The total tax decreases because as the traffic load increases fewer HPU are granted access to the spectrum thereby reducing the total amount of tax paid. It can also be seen from equation 4.21 that as the number of arriving users (N_{USA}) increases (traffic load), the value of j also increases meaning that more of the admitted users are falling below the SNR threshold (because the capacity of the system does not increase) hence, more subsidy is paid out and less users are paying a tax especially when case 1 as explained in section 4.3 occurs more often than case 2 or three. Case 1 is the situating where most of the arriving users (N_{USA}) arriving in the same period are LPU. It is worth pointing out that the occurrence of any of the three cases occurring depends on the user's arrival model explained in section 4.4 for all the traffic loads. However, as seen in figure 4.15(b) the average tax paid per successful transmitted file for each of the users is more than the average subsidy but the average tax per successful transmission for the HPU is relatively flat. This is because the total value of the tax paid is decreasing with the number of HPU who are able to transmit successfully. This is unlike the LPU who are able to receive more subsidies and the average files transmitted successfully is slightly more. The tax paid decreases with traffic load also because none of the equations formulating the green payments increases with traffic loads (Equation 4.20 depends on SNR not SNIR) but the number of HPU paying a tax or admitted into the system reduces with traffic load because more subsidy is paid out. The average subsidy however increases with the traffic load because more users are subsidised as the traffic load is increasing. It can be seen from the result that if the traffic load continues to increase or if a higher value of the green payment factor is used, a time would come when the total tax paid would not be able to finance the total subsidy. Hence, in the next chapter a congestion charge is introduced which helps to increase the value of the tax as the traffic load increases.

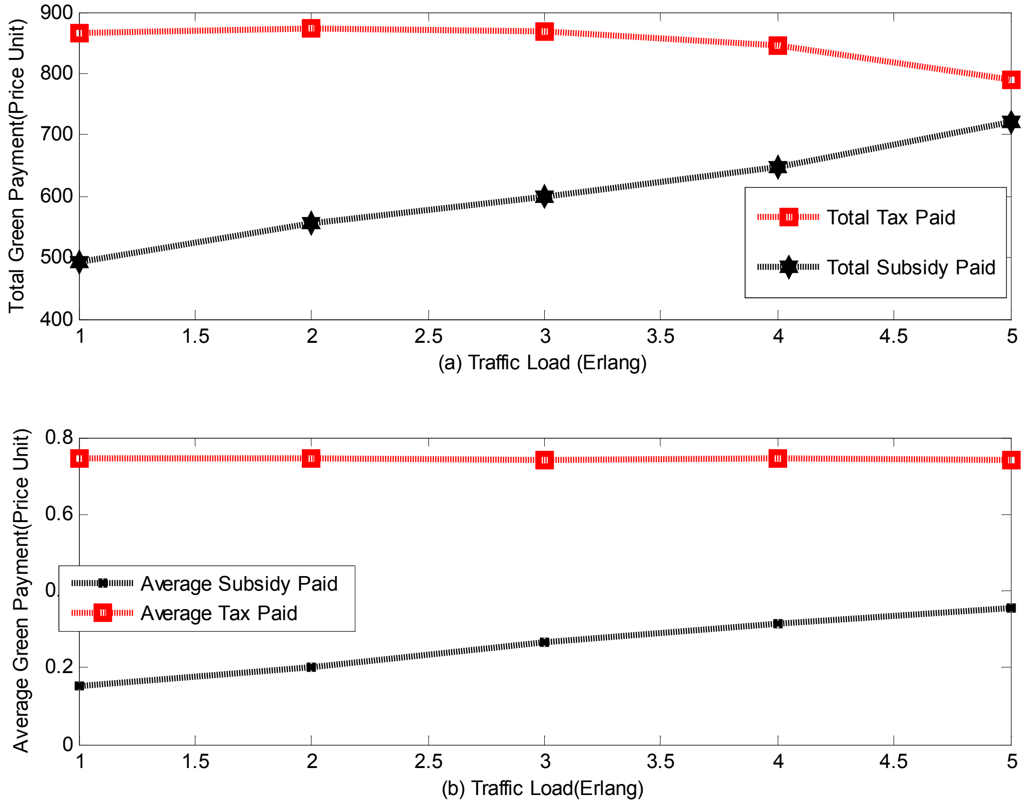

Figure 4.15. Total tax and subsidy paid and Average Subsidy paid per packet sent

4.6 Conclusions

An energy efficient dynamic pricing mechanism to assign the radio spectrum using a sealed bid auction process with a reserve price along with a green payment to help energy efficient users has been proposed. The green payment was derived from the inverse of Shannon's equation with some variables such as the green payment factor (ß) introduced. After examining the effect of varying ß on the ratio of successful transmission sessions of HPU compared to LPU in the system, the system throughput, the revenue of the WSP and the energy consumption in the system, the optimal value of the green payment factor (ß) is approximated to be 0.045. This showed that the energy consumption level of the system can be varied with the green payment. This chapter also examined the effect of the reserve price and the random channel assignment scheme and the assignment scheme with the least interfered channel on the throughput and discovered that both affects the system especially when the system is not fully loaded. Hence it was discovered that there is a need to make sure that the reserve price is set to reflect the current traffic in the system and that the presence of the reserve price helps in increasing the revenue of the WSP at lower traffic load and that the green payment increases the gross revenue of the WSP. The chapter further showed that using the optimal value of ß, the green payment scheme preforms better than the scheme without the green payment in terms of increase in revenue, throughput delay and more importantly energy consumed.

Chapter 5

Energy Efficient Dynamic Spectrum Auction Process with Utility Function

Contents

5.1 Introduction

In chapter 4, the green payment to be used in conjunction with DSA auctions was introduced. However, during the modelling process, it was discovered that the use of an auction with reserve price in allocating the spectrum for short term use highlights a number of problems. Such problems include having a number of transmit channels available based on the information provided by the database but the channels are not put to use (after the auction and the allocation process). This is because the value of the bids submitted is below the reserve price. This occurs mostly at low traffic loads. Lowering the reserve price might be an option but reducing the value of the reserve price might alter the profitability of the system. Hence, there is a need to find an alternative solution to the problem. Another problem is congestion and the total green payments subsidy going above the total green payment tax as the traffic load increases. This is because the bids of the users increase with the traffic load as given in equation 4.4 but the number of users paying the green tax and the total value of the green tax reduces with traffic load increase as seen from figure 4.15. These problems might waste more energy and hence, this chapter aim to investigate some solutions. Therefore, in addition to the green payment, the inefficient users are further penalised as the system gets congested by introducing a congestion charge. This is introduced because according to [107] penalising inappropriate behaviour can help in solving energy consumption and congestion problems in wireless systems. This chapter also investigates the use of a probability threshold measure known as the probability of being among the highest N_{AC} bidders ($P_{r_{N_{AC}}}$). Where N_{AC} is the number of available channels. This chapter also examines how the concepts of multiple bidding process and utility function can be formulated to aid energy efficiency in the proposed model.

The rest of this chapter is organised as follows. The system architecture is introduced and defined along with the major elements of the system in section 5.1. In section 5.2, the energy model and the proposed green payment model are defined and explained. Section 5.3 derives the theoretical model as formulated in chapter 3 using probabilities and utility functions. Section 5.4 describes the overall simulation model and section 5.5 presents the results. The chapter concludes in Section 5.6.

5.2 System Architecture

5.2.1 The Users Bid

The bids of the users is formulated as explained in section 4.2.2 and shown below:

$$b_i(Price\ Unit)=\frac{(N_{USA}-N_{AC})V_i}{N_{AC}}+V_{min}\quad For\ i=1,2,3\ \ldots\ldots N_{USA} \tag{5.1}$$

In some part of this chapter, it is assumed that the users can estimate the value of the reserve price based on information provided by the broker unlike in chapter 4. Therefore, it is assumed that such users generate a bid above the reserve price as shown in equation (5.2)

(This does not increase the user's budget). Hence, if a user possesses such information the user uses equation 5.2 as shown below rather than 5.1 to generate the offered bid value:

$$b_i = \frac{(N_{USA} - N_{AC})V_i}{N_{AC}} + r_{\mathrm{Est}} \quad For\ i = 1,2,3 \ldots \ldots N_{USA}. \tag{5.2}$$

Where r_{EST} is the estimated value of the reserve price. The above assumption is formulated in order to examine the effects of making the reserve price either known to the users or privately known to the auctioneer only. The equations were derived from conventional economics theory as explained in chapter 4.

5.2.2 *The Reserve Price*

The reserve price r is the minimum acceptable bid by the broker as shown below:

$$r_i(\,price\ Unit) = C_f N_{TC} C_r \tag{5.3}$$

C_f is the congestion factor, C_r is a constant in price units and N_{TC} is the total number of channels in the system both used and unused as explained in chapter 4.

$$C_f = \frac{N_{USA}}{N_{AC}} \tag{5.4}$$

5.2.3 *Green Payments and Congestion Charge*

The green payment concept is as explained and defined in chapter 4. It is as shown below:

$$\mathrm{R(Price\ Unit)} = \begin{cases} 2^{1+ß\theta} - 1 & For\ green\ payment\ subsidy \\ 2^{1+ß\theta} + 1 & For\ green\ payment\ tax \end{cases} \tag{5.5}$$

Where the green payment factor (ß) is a constant and it was determined from chapter 4 and θ is the absolute value of the linear difference between the SNR value for user i and the value of a set threshold represented as the j^{th} SNR value as shown in equation (5.6) below. The parameters are exactly as explained in chapter 4.

$$\theta_i = |\psi_i - \psi_j| \quad \text{for } i=1, 2, 4 \ldots N_{USA} \tag{5.6}$$

$$|j| = \lfloor \frac{P_c N_{USA}}{100} + \frac{1}{2} \rfloor \tag{5.7}$$

P_c is the desired percentile. It can be of any value between 0 and 100 ($0 \leq P_c \leq 100$). The SNR of N_{USA} arriving users can be arranged in ascending order as shown below:

$$\boldsymbol{\psi}_t = [\psi_1, \psi_2, \psi_3 \ldots \psi_{N_{USA}}] \tag{5.8}$$

The HPU users are further charged a congestion charge which increases as the traffic load increases as shown in equation (5.9). The aim of the congestion charge is to use price to regulate the amount of congestion in the system and to increase the value of the tax paid as the traffic load increases as shown below. Furthermore in the modelling scenarios, a situation where the final bid value of any user remains positive after the deduction of green tax and the congestion charge is only examined. It is important to highlight here that the only changes made in this model so far compared to the model in chapter 4 is the introduction of r_{Est} in equation 5.2 and L in equation 5.9 below:

$$b_i^{final}(price\ Unit) = \begin{cases} b_i + R_i & For \text{ LPU} \\ b_i - LR_i & For HPU \end{cases} \tag{5.9}$$

For i= 1, 2, 3….N_{USA}

Where L is the traffic load in Erlang, b_{final} and R_i is the final value of the bid in price unit and the green payment for user i respectively after the deduction or addition of the congestion and green tax, ψ_i^C represents the SNR of user i and the superscripts C can either be LPU or HPU. After the tax (green tax and congestion charge) and subsidy is applied as shown in equation (5.9), the highest N_{AC} bidders are afterwards allocated a channel.

5.2.4 *Energy Model and Energy Consumption Calculation*

To measure and compare the energy consumed by the users in the system, a definition of measuring the user throughput compared to the energy consumed and the traffic load in the system as defined in chapter 4 is proposed. The transmission rate is a function of the SNIR of the user. The dependence of SNIR on the transmission rate used in this chapter is as given by the TSB as defined in chapter 3. This is similar to the model in [108].

5.2.5 *Probability of a User Being Among the Highest N_{AC} Bidders ($P_{r_{N_{AC}}}$)*

The probability ($P_{r_{N_{AC}}}$) is introduced in this chapter to prevent users who have a low probability of winning from attempting to transmit. Using the probability helps in reducing the number of users who attempt to transmit and eventually lose the auction process thereby wasting energy in the process. The scheme prevents such users from going into the transmission mode (ON) unnecessarily. The ON/OFF mode is as explained in section 3.8.2. The probability is dependent on the bid submitted by a user and the number of available channels in the system as shown below:

$$P_{r_{N_{AC}}}(i) = \left(\frac{b_i - b_r}{V_{max} - b_r}\right)^{N_{USA} - N_{AC}}, \; N_{USA} > N_{AC} \tag{5.10}$$

Where b_r can be the value of the reserve price if known to the user otherwise it is the minimum possible bid by user i based on the user's budget. V_{max} is the maximum possible valuation for a user. The probability is calculated for all the users intending to transmit during any bidding period. If the value of the probability is greater than or equal to a set probability threshold $P_{r_{Threshold}}$ ($P_{r_{N_{AC}}}(i) \geq P_{r_{Threshold}}$) the user is allowed to attempt otherwise the user stays out of the process. This is further explained in section 5.3.

5.2.6 Blocking

In this chapter, two types of blocking are considered. Blocking that occurs because of price and blocking due to insufficient transmission resources.

Blocking due to insufficient resources (B_{IR}): A user(s) is blocked due to insufficient resources when the SNIR is below the SNIR threshold or due to non-availability of transmission channel. This is the same as the blocking probability defined in chapter 3. This is calculated and shown as a fraction to differentiate it from the blocking due to price. Where $N_{FAR}(t)$ represents the number of failed transmission trials due to insufficient resources up to time t and N_{tr} represents the total number of trials up to time t

$$B_{IR} = \frac{N_{FAR}(t)}{N_{tr}(t)} \tag{5.11}$$

Blocking due to price (B_P): A user is blocked due to price if the bid is below the reserve price or because of the ${P_r}_{N_{AC}}$ is below the threshold. If any of the users are blocked due to price, then the number of users transmitting after the auction and allocation process N_{UT} is less than the number of available channels (N_{AC}) or the number or winning bidders (N_{WU}). That is ($N_{UT} < N_{AC}\ or\ N_{WU}$). It is calculated as shown below in percentage in this chapter. Where N_{FAP} represents the total number of failed trials due to price up to time t.

$$B_P(\%) = \frac{N_{FAP}}{N_{tr}(t)} \tag{5.12}$$

5.3 Theoretical Evaluation and Utility Function

This section develops the mathematical formulation of the proposed system using utility functions. The following assumptions were made in formulating this section.

- The word "tax" is used to mean both the green payment and the congestion charge.

- The revenue of the auctioneer does not include the tax. This is because the tax paid by HPU is assumed to be used in subsidising the LPU. Hence, the tax is just redistributed.

$$R_e(Price\ Unit) = \begin{cases} b_i - tax & For\ HPU \\ b_i + subsidy & For\ LPU \end{cases} \tag{5.13}$$

Two stages are also assumed in this chapter before a successful transmission however a threshold check is added to stage 1 as explained below:

STAGE 1: A user places a bid in the OFF mode: Provided the user's $P_{r_{N_{AC}}}$ is above the set threshold, the user moves to the second stage ($P_{r_{N_{AC}}}(i) > P_{r_{Threshold}}$).

STAGE 2: In the 2nd stage the energy mode of the user is changed to the transmitting mode (ON) and the user is successful in the second stage if the offered bid is above the reserve price and the SNIR is above the SNIR threshold. The number of users who successfully transmit after this stage is represented as N_{UT}.

Comparing the bids of the two user groups, the following are the possible outcomes (*PO*) after the tax and subsidy is applied to the offered bids.

PO 1. *The final bid of the HPU is greater than that of the LPU* ($b_{HPU}^{final} > b_{LPU}^{final}$). If this occurs then the subsidy has not had a significant impact or changed the winning bidder from a HPU to a LPU but has lowered the income of the auctioneer since b_{HPU} has been taxed.

PO 2. *The final bid of the LPU is greater than that of the high powered user* ($b_{LPU}^{final} > b_{HPU}^{final}$). This occurrence means that the subsidy might have made a difference to the winning bid; if initially $b_{LPU} > b_{HPU}$ before the green payment is applied. This has helped in increasing the revenue of the auctioneer.

Under no circumstances is any user allowed to transmit if the final bid (after the tax or subsidy) is below the reserve price leading to possible outcome 3 and 4.

PO 3. *The initial bid and the final bid of the HPU is greater than the reserve price (r).*

$b_i > r_i$. Such users is allowed to transmit provided b_i is among the highest N_{AC} bids.

PO 4. *The initial bid of the LPU is below the reserve price but after the subsidy the final bid is greater than the reserve price (r).* $b_i^{final} > r > b_i$. In this case the subsidy ensures the bid of user i is above the reserve price.

Above are some of the scenarios that may occur and they are examined later. First, the effects of the public or private knowledge of the reserve price is examined:

5.3.1 Auction Model With and Without the Public Knowledge of the Reserve Price

A probability scheme can be used to analyse the energy consumed by the system when the reserve price is feedback to the users. Let P_r represent the probability of winning, $1 - P_r$ represents the probability of not winning the bid and E_i represents the amount of energy consumed by user i in putting in a bid (The probability that is calculated here is not the same as the probability of being among the highest bidder ($P_{r_{N_{AC}}}$), but the probability of the user's bid being above the reserve price). The probability threshold ($P_{r_{N_{AC}}}$) described here is carried in stage two of the modelling scenario as described in section 5.3. It is also assumed here that the user wins once the offered bid is above the reserve price the user wins and the trials comes to an end (this assumption is reasonable because no user can transmit if the offered bid is below the reserve price). The total energy consumption with the probability is as shown below:

$$\boldsymbol{E_T} = \sum_{i=1}^{N_{USA}} (1 - P_r)^{n-1} P_r(i) E_i \tag{5.14}$$

In the above equation if the entire user wins the auction process at the first attempt the first part of the equation is 1. Then the total energy consumed is calculated by multiplying the remaining part of the equation by 1. The total energy consumed if the user does not win on the first attempt is the cumulative sum of all failures before success assuming independent arrivals. As an example if it takes 3 attempts before success in the 4th attempt for all the users transmitting in the system, the cumulative energy consumed for $P_r = 0.5$ and the total energy consumed by user i is represented as E_i for all trials up till the first success is as shown below:

$$\boldsymbol{E_T} = \sum_{i=1}^{N_{UT}} ((1 - P_r)(i)^{1-1} P_r(i) + (1 - P_r)(i)^{2-1} P_r(i) + (1 - P_r)(i)^{3-1} P_r(i)$$

$$+ (1 - P_r)(i)^{4-1} P_r(i)) E_i \tag{5.15}$$

Substituting into the above equation gives:

$$E_T = \sum_{i=1}^{N_{UT}} (0.5(i) + 0.25(i) + 0.125(i) + 0.0625(i)) E_i \tag{5.16}$$

From the above equations, it can be seen that the energy consumed increases as the number of attempts before success (each arrival is independent). Hence if a user does not attempt to participate in the auction process except when the user is sure that the offered bid is above the reserve price, less energy is consumed. This shows that the public knowledge of the reserve price helps in reducing the amount of energy wasted. This is because a user cannot be sure of offering a price above the reserve price if the reserve price is not a known to the user (i.e. not known to the public).

5.3.2 Utility Function

The utility function plays an important role in determining the achievable performance of a system. It describes the level of satisfaction or the preference of a user based on the QoS received [109]. It can be used in radio resource management to determine the level of satisfaction of the users. The utility function can be described using different ways, but the choice of the function is critical in achieving the desired performance. In [110] the utility functions were divided into two categories, “the absolute utility” and “the relative utility”. The absolute utility function involves the direct use of the performance metric to measure the utility while the relative utility involves using transformed metrics to represent the level of satisfaction. [111] used a concave utility function for resource allocation by using the function to prove the performance of the system compared to some other resource allocation mechanisms. [112] also used a utility function to show how the proposed price based call admission control mechanism performs better than the admission mechanism without pricing in controlling network congestion. In wireless networks, the utility of the social welfare (U_{SW}) is sometimes considered as being more important than the individual utility since the network is a shared resource. Utility of the social welfare is a function or the aggregate of the individual utility of a group. According to [113], it is defined as:

$$U_{Sw} = f(U_1, U_2, \dots \dots \dots . U_n) \tag{5.17}$$

Where U_1 is the utility function of a user say i and $i = 1.2 \dots \dots n$.

Individual wireless users are known to act selfishly in order to maximise their utility. Defining a relative utility function can be complicated but this chapter uses the design objective of the system to determine the overall desired utility. Generally, when different performance metrics are used to determine the utility of a system, the weighted power is used to show the importance of each of the individual metrics that forms the overall utility function depending on the objective of the system. However, in the later part of this chapter, all the metrics are assigned the same weighted power. This is because a generic form of utility function that can be modified based on the application of the system in the future is proposed.

A relative utility function that incorporates the important system performance to determine the utility function is used. The performance of the system such as delay, data rate and the probability of blocking due to price are used to determine the user's utility function. The throughput is used to determine the utility function of the WSP. Furthermore the throughput per energy consumed is used to determine the overall system performance per unit of energy consumed, assuming that individual user's act selfishly in order to maximise their individual utility and the system is bandwidth limited. These performance metrics are used since they determine the user's level of satisfaction. An increasing strictly concave utility function is used since an elastic traffic as explained in [114] is modelled. Concave functions also help in representing scenarios when utility drops sharply. The following performance metric was adopted to determine the utility function for the users similar to [115]. All the performance metrics were formulated to allow the value of the utility function for each user to only vary between 0 and 1. An exponential function is used with a base of 2 throughout this thesis to show the exponential growth. This is because users satisfaction towards a commodity is usually modelled as exponential [103]. The value of 2 is also used throughout because the aim is not allow the utility growth to be too steep or grow too fast.

Data Rate: In a wireless network, different types or class of users require access to the radio spectrum using different access techniques. Access techniques such as Code Division Multiple Access (CDMA) and Wideband Code Divisional Access (W-CDMA) require users in the same class to share a frequency band. This is also true for DSA as described in this chapter. However, in order for different/the same classes to share the same frequency, the attainable QOS of a sharing user are affected by the transmit power of other sharing users. According to the TSB defined in chapter 3, the data rate is dependent on the SNIR of the user and therefore, the data rate of the user is also a measure of the user's utility. The higher the data rate of a user the higher the satisfaction of such user. Thus, each user aim to achieve a high SNIR depending on the data rate required. This means that generally the HPU will have a higher value of utility in terms of data rate compared to the LPU if both are sharing the same channel. This is shown below:

$$U_D = 2^{\frac{D_i}{D_{max}}} - 1 \text{ For } i = 1,2,3..N \text{ and } D_i < D_{max} \tag{5.18}$$

$$0 \leq U_D \leq 1$$

D_i is the data rate of user i and D_{max} is the maximum achievable data rate of the system.

Delay (Δ): All wireless applications have a maximum delay that can be tolerated for the system to achieve the desired operation. Beyond such a threshold, the system is not feasible. Generally voice based applications cannot tolerate delay as much as packet/file based applications. In general it is assumed that the lower the value of the delay, the better the satisfaction of the user and the once the delay is above the set threshold the system is not feasible, hence here a zero value of utility is assumed.

$$U_\Delta = \begin{cases} 2^{1-\frac{\Delta_i}{\Delta_{max}}} - 1 & For\ \Delta_i < \Delta_{max} \\ 0 & For\ \Delta_i > \Delta_{max} \end{cases} \tag{5.19}$$

$$0 \leq U_\Delta \leq 1\ and\ \Delta_i < \Delta_{max}$$

Where Δ_i is the delay experienced by user i and Δ_{max} is the maximum possible delay of the system to make the system feasible.

Blocking Due to Price (B_P): The proposed system employs the use of an auction process for allocating the radio spectrum with a reserve price. A user whose bid is below the reserve price (also in some parts of this chapter, the probability of being among the N_{AC} highest bidders is used) is not allocated the spectrum. As explained earlier, any user whose bid is below the reserve price or whose probability is below the threshold is assumed to be blocked. In terms of the utility of the user the lower the value of the blocking due to price the more satisfied the user is as shown below:

$$U_{B_P} = 2^{(1-B_P)} - 1 \tag{5.20}$$

$$0 \leq U_{B_P} \leq 1$$

General Utility before the Admission Process (U_G): The general performance is analysed in order to provide a fair and balanced combination of the different individual performance metrics. Putting all the above utility functions together, and examining the overall utility of each of the users, the model multiplies the individual utility together. This is because if one of the components which form the utility function in this chapter has a value of zero, the file transmitted by the user is not successful transmitted. Hence, the reason for the multiplication (However, it would be discovered in the next chapter, that the utilities are not always multiplied together because the aim of the model is different compared to the one in this chapter). As an example if a user has a zero utility value in terms of delay, then the delay that the user experienced during the file transmission cannot support the application of the user. Hence the general utility is as defined below:

$$U_G = U_{\Delta} U_D U_{B_P} \tag{5.21}$$

$$0 \leq U_G \leq 1$$

From equation (5.21) it can be seen that if any of U_{Δ}, U_D, U_{B_P} is zero, then the overall general utility of the user is zero because the system is not feasible for such user. Hence, any user with such value cannot be admitted into the system. The above utility function defines the mathematical model for the admission process. This shows that no user can be admitted if the delay experienced cannot be tolerated by the application in demand, the data rate required by the application cannot be provided or the offered bid price is below the reserve price.

After analysing the general utility as shown above, the utility in terms of price is also examined. The utility in terms of price is separated from the general utility function because this research work is focused on the use of price to regulate the radio spectrum. Furthermore the price utility function is separated because the utility function in terms of price using an auction process works differently compared to other utility functions especially when combined as seen later in equation 5.28.

General Utility with Pricing (U_p): Wireless users are generally selfish and aim to maximise their total utility in order to allow for fairness pricing is introduced. Generally, the utility of a user decreases as the value of the offered bid decreases. This is because users prefer to win the bid with a lower price in order to maximise their utility. The equation is shown below:

$$U_p = 2^{1-\frac{b_i}{b_{max}}} - 1 \tag{5.22}$$

$$0 \leq U_p \leq 1$$

Where b_{max} is the maximum bid, no bidder can bid above the maximum bid value, therefore a user bidding the maximum is deemed to have a utility of zero and b_i is the bid submitted by user i who is a winning bidder. Any bidder who is not among the winning bidders has a utility value of 1 in terms of price. It can be seen from the above equation that when using an auction process the lower the value of utility in terms of price the better for the user. This is because price paid is always defined as a cost(i.e. negative) and users do not usually want to incur high cost however, in order to combine the price function into the overall utility function the equation is modified as shown later in equation 5.28. Therefore, the overall utility of the users individually is:

$$U = U_G - U_p \tag{5.23}$$

The above result shows that the winning users paying the least actually have the highest utility provided the general utility of all the users are the same. It is also worth pointing out that an auction process is used. This allows the highest bidder to gain access to the spectrum. However, the price function considered above examined the utility in terms of the price paid by the winning bidders because the users want to win with the least possible amount.

The utility functions defined until this point represents the utility functions for the individual user. It is assumed that since the spectrum is a shared resource, the utility function of the social welfare is more important than of the individual. However, as shown in equation (5.24) the utility of the social welfare is a function of the individual utility hence, the utility of the social welfare is defined.

Utility of Social Welfare

There are different objectives that can be met in the design of an auction such as efficiency. An efficient auction should maximise the social welfare. The utility of the social welfare is defined as the average of the total utility of all the users in the system. The individual utility contributes to the utility of the social welfare and therefore, there must be some level of satisfaction from the individual user that maximises the utility of the social welfare.

$$U_{sw} = \frac{\sum_{i=1}^{N} U_i}{N} \tag{5.24}$$

To maximise the utility of the social welfare there must be an optimal individual utility.

Definition 5.1: For a total number of N users in a system. The maximum possible individual utility after pricing can maximise the utility of the social welfare. Where the maximum possible social welfare utility is represented as U_{sw}^{*}.

$$U_{sw}^{*} = \frac{\sum_{i=1}^{N} Max(U_i)}{N} \tag{5.25}$$

Proof: By definition it is known that $U_{sw}^{*} \geq U_{sw}$ because U^{*} can be achieved by maximising the sum of the individual utility therefore, maximising individual utility also maximises the utility of the social welfare.

This helped to prove the definition of the utility of the social welfare as a function of the individual utility. In order to show the scheme works, the utility is defined in terms of the user's admission process. This is because the scheme as defined in this work aims to use pricing to control the users admission process.

Utility in Terms of Admission Process (U_a): This part shows how the price paid by each user affects the admission process. An expression for the utility of each of the users in terms of the green payment is firstly defined, and then it is combine it with the utility in terms of price as shown in equation (5.28) to determine the utility in terms of the admission process.

Utility in Terms of the Green Payments *(U_R):* The green payment is divided in two, the tax and the subsidy. If a user is taxed, the utility function is as defined below:

$$U_R = -(2^{\left(\frac{R_i^t}{R_{max}^t}\right)} - 1) \tag{5.26}$$

$$\text{For } i = 1,2,3,\ldots N_{USA_t}$$

Where R_i^t is the green tax paid by the user, R_{max}^t is the maximum tax paid by any of the users and N_{USA_t} is the total number of bidder paying a tax among the N_{USA} bidders who are attempting to gain access to the channel. From equation (5.26), it can be seen that a user paying a tax has a negative utility. The utility for a user receiving a subsidy is:

$$U_R = (2^{\left(\frac{R_i^S}{R_{max}^S}\right)} - 1) \tag{5.27}$$

For $i = 1,2,3, \dots N_{USA}$

Where R_i^s is the subsidy paid by user i, $R_{max}^s$is the maximum subsidy paid by any of the users and N_{USA} is the total number of bidder receiving a form of subsidy among the N_{USA} bidders who are attempting to gain access to the channel. Combining the utility for the price and the green payment:

$$U_a = \frac{(1-U_P)+U_R}{2} \tag{5.28}$$

If the U_a values of all the bidders who wants to gain access to the channel at bidding round t is represented by set $\boldsymbol{N_{USA}}$ below in descending order then a maximum of N_{AC} users who are having the highest U_a utility value is admitted into the system provided their bid is above the reserve price and can be represented by $N_{N_{AC}}$ where $\boldsymbol{N_{K_c}} \subset \boldsymbol{N}_{N_{USA}}$.

$$\boldsymbol{N}_{N_{USA}}(t) = [U_a^1\ U_a^2\ U_a^3..U_a^{N_{AC}}\ U_a^{N_{AC}+1}\ U_a^{N_{AC}+2} \dots U_a^{N_{USA}}] \tag{5.29}$$

$$\boldsymbol{N_{K_c}}(t) = [U_a^1 U_a^2 U_a^3..U_a^{N_{AC}}] \tag{5.30}$$

From the above equation, the following can be concluded:

- The utility in terms of the admission process varies from 0 or 1.
- A user who is taxed and whose bid is low in value has a negative or a low utility.
- A user who is paying a low tax and has a high offered bid has a high utility value and therefore might be admitted into the system to transmit.

- A user who is receiving a high subsidy and whose initial bid is low may or may not be admitted into the system to transmit depending on the utility of others at time t.
- A user who is receiving a high value of subsidy and whose initial bid is high has a very high probability of been admitted into the system.
- This also explains *PO1* to *PO4* as defined at the beginning of this section.
- This also shows that the N_{WU} or N_{AC} bidders admitted have the highest utility.

Utility of the Wireless Service Provider

The utility of the WSP is determined by the number of users admitted simultaneously into the system. This is because spectrum reuse in adjacent cells is assumed. As a result of spectrum reuse if a user is causing significant interference on a channel, which is being used by another user in another cell, then the user that is being interfered with will be forced to abort the transmission. In order to calculate the utility of the WSP, a user whose SNIR is below the threshold is being significantly interfered with. This is because a fixed transmit power is assumed for all the users provided they belong to the same group. The assumed transmit power allows the worst case user to transmit successfully if there is no interference from other users. The utility of the WSP is as given below:

$$U_{wsp}(t) = 2^{\frac{\sum N_{CAU}(t)}{\sum N_{TC}(t)}} - 1 \tag{5.31}$$

Where $\sum N_{CAU}(t)$ gives the cumulative sum of all channels (after each iteration) in use in all the cells up to time t and $\sum N_{TC}(t)$ gives the cumulative sum (after each iteration) of all available channels in all the cells up to time t. The utility of the WSP explains the reason why the LPU are been subsidised at the expense of the HPU. This is because if the HPU are allowed at the expense of LPU, The HPU might be causing significant interference to the LPU who are assigned the radio spectrum forcing them to abort transmission thereby reducing the utility of the WSP. In addition, the utility of the WSP is related to the revenue obtained by the WSP because the users do not pay for a channel that is not in use.

5.4 System Model Description

One spectrum broker and the N users are modelled in an infrastructure based uplink scenario, where each user is transmitting at a fixed power (high or low) level depending on the group the user belongs too. On average the LPU transmit at a lower bit rate compared to the HPU depending on the received SNIR. This work is based on the hexagonal cell structure with a fixed frequency reuse factor as specified in the table 3.1. The channel assignment scheme is based on the least interfered channel. A Poisson distribution process with arrival rate (λ) and inter arrival rate described by an exponential distribution is assumed. Each of the users who want to transmit at each auction round submits a uniform sealed bid b_i ($i = 1,2,3, \dots . N_{USA}$) to the spectrum broker depending on the user's budget based on equation (5.1) or (5.2). This is as explained earlier in section 5.2, the valuation of each of the users follows a uniform continuous random distribution drawn from the known distribution range. A bidder who loses a bid in a bidding round during time t increases their bid in the next bidding period ($t + 1$) as shown in the flow chart below.

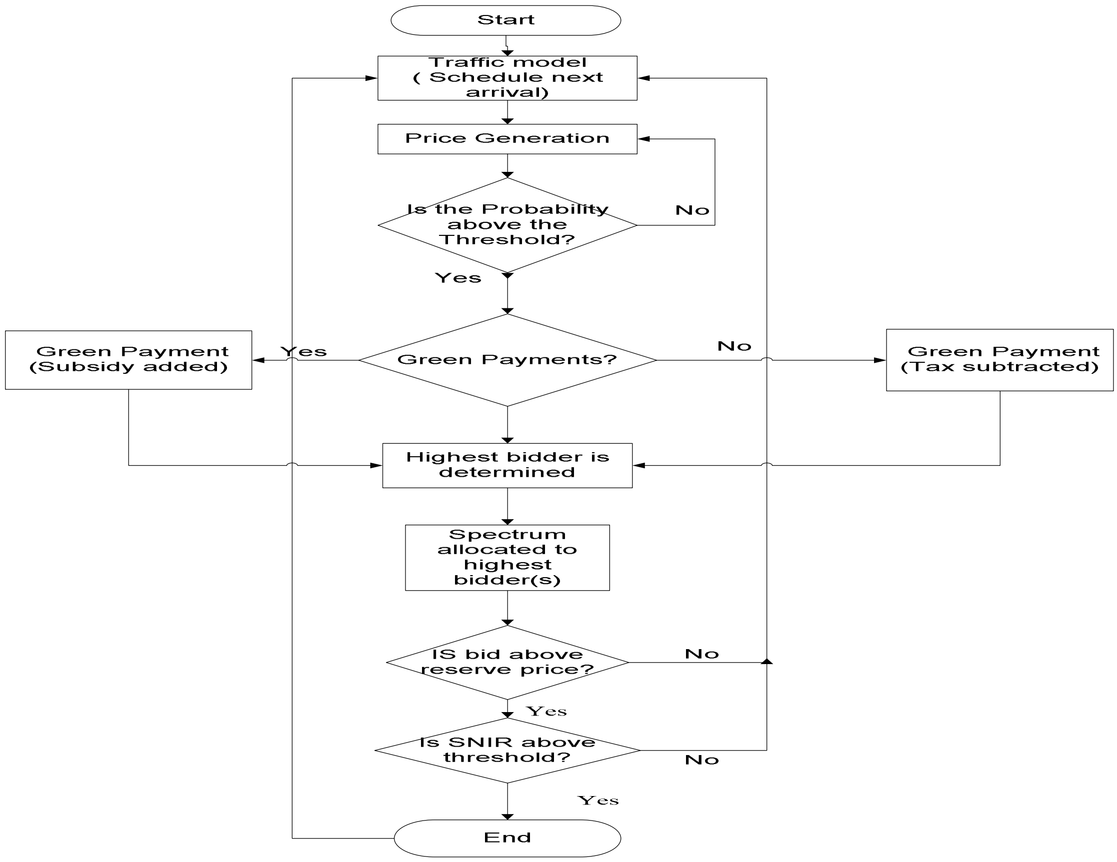

Figure 5.1 System flow chart

This increase is drawn from a uniform distribution represented as $F(v)$ with range $[v_{min}, v_{max}]$. The bid of a winning user is reduced in the bidding period $t+1$ by a fixed percentage as specified in the parameters table. This value is chosen in order to gradually reduce the bid of the user and prevents the user from paying a high price for the use of the spectrum. This also ensures that the user maintains a high value of utility based on the price paid as explained earlier. This process is repeated until a steady state is reached. The path loss is based on the WINNER II B2 model. A bid is submitted by a user after the calculation of the probability of being among the highest N_{AC} bidder ($P_{N_{AC}}$) as specified. If the probability calculated by a user is above the set threshold ($P_{r_{N_{AC}}}(i) \geq P_r(T_{threshold})$) then the green payment and congestion charge is applied as explained using equation 5.9. A user is assumed to have transmitted successfully provided the SNIR and final bid price is above the SNIR threshold and the reserve price. After the auction process, the number of winning bidders that emerges is represented as N_{WU} and N_{UT} is the number of successful bidders.

This chapter considers three different scenarios for the auction process. The first scenario is the Single Bidding Process (SBP), which involves the users bidding in a single round before the transmission period. As an example say at bidding period t_0. At this time, each of the users requesting access to the radio spectrum submits a bid. The user whose probability of being among the N_{AC} highest bidders is below the set threshold do not attempt to transmit while a user whose probabilities are above the threshold goes into the ON state in order to attempt to transmit during the transmission period T_1. This is as shown in figure 5.2. If none of the users, or if the number of users whose threshold is above the set threshold, is less that the number of channels ($N_{WU} < N_{AC}$) then all or some of the channels are left vacant. This is because the bidding for transmission period T_1 is carried out in bidding period t_0, which is simultaneously carried out with transmission period T_0 as shown in figure 5.2. In the second scenario, an improvement is made by increasing the number of bidding rounds/periods before the transmission period (T).

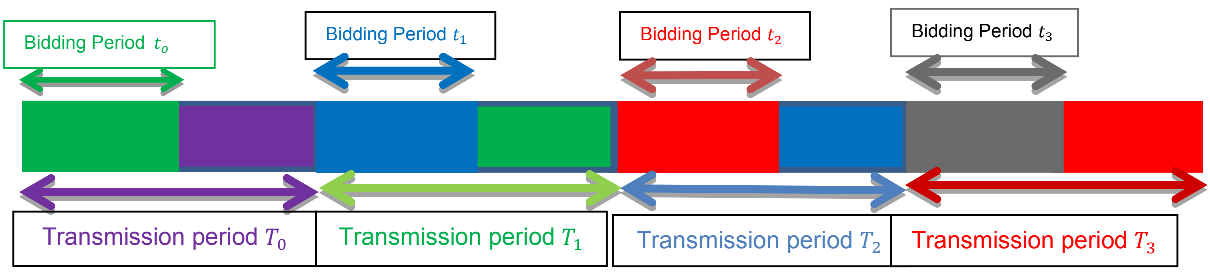

Figure 5.2. Single bidding process

As an example, 3 bidding periods $t_0^1, t_0^2, \dots t_0^x$. Where x is the number of bidding periods carried out before a transmission period (T_1). This scenario is called the Multiple Bidding Process (MBP) as shown below. To clearly present the scenario, the auction and bidding rounds are sometimes not on the same line.

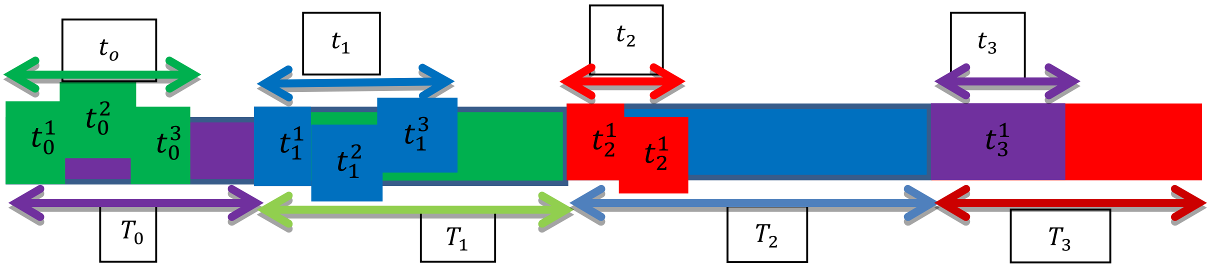

Figure 5.3 Multiple bidding process

Here, the system is assumed to have a buffer to queue the winning bidders as they come into the system. The actual number of bidding rounds carried out is dependent on the number of winners emerging in each round and the number of channel available. The auction round only stops when $N_{AC} = N_{WU}$. This is quite different from chapter 4 because in this case the emerging N_{WU} winners are likely going to have an offered bid price above the reserve price. Hence there is more likelihood that N_{WU} is equal or almost equal to N_{UT} after the transmission process. If the two values are not equal then it is most likely not due to price but due to the SNIR threshold level or the channel quality. Therefore, the green payment can help solve the problem of channel quality by penalising the high powered users who are causing the interference. As an illustration for MBP, assuming $x = 4$ and $N_{USA} = 8$. If in the first bidding round only 2 bidders out the 8 bidders has a probability above the set threshold. The two users are admitted and queued in the buffer. The remaining 6 bidders increase their bids accordingly. The number of available channels (N_{AC}) used in equation (5.2) also changes to 2. If 2 winners emerge in the second round then the bidding round is closed and the 4 winning bidders are assigned the channel in period T_1. This is as illustrated in figure (5.2). In this chapter, the bidding period is chosen in a way to allow for N_{AC} bidding periods before a transmission period. The method of determine the bidding and transmission period is as explained in chapter 4. The third method considered in this work is when the auctioneer is assumed to be feeding back the reserve price and the estimated tax of each of the user back to the users, in addition to the MBP. This is done in order to improve the probability of blocking due to price. It can be seen from equation (5.22) that the closer the user is to the maximum possible bid value, the better the probability of winning the auction.

5.5 Results and Discussion

This section shows and explains the results obtained from the simulation. Firstly, the threshold for the probability of being among the highest N_{AC} bidders ($P_{r_{N_{AC}}}$) is varied to determine the effect of the probability on the number of users admitted into the system. Based on this, the value for the threshold that helps in reducing the energy consumed by the system without reducing the other system performance metric significantly is determined. The other parameters used are given in the table 5.1. These are in addition to the parameters given in table 3.1. The values for the desired percentile and β were derived from chapter 4.

Table 5.1 Parameters used

Parameters	**Value**
$[V_{min} V_{max}]$	[5 8]
Bid reduction	10%
Desired Percentile	30
β	0.045

It is quite important to show that introducing the threshold helps in reducing the number of users who are blocked as a result of offering a bid price below the reserve price. Hence, the percentage of users blocked against the threshold is examined. Figure 5.4 shows the probability of blocking due to price per files generated when the threshold ($P_r(T_{threshold})$) of $P_{r_{N_{AC}}}$ is varied from 0 to 1. In general, for all the 3 scenarios examined, the number of users that are blocked due to price is reducing as the threshold is increasing. This is because when the threshold is 0 all the users entering the system are attempting but a significant amount of them are blocked because the offered bid price is below the reserve price. However as the threshold is introduced and as it is increasing some of the users whose probability of being among the highest N_{AC} bidders are no longer attempting, hence the number of users that are blocked due to price is reducing with an increase in the threshold. When the threshold is set to a value of 1, all the users attempting are offering a bid value that is above the reserve price. Hence, this is the reason why none of the users are blocked. The MBP with knowledge of reserve price performs best because on the average the users are placing only a bid that is above the reserve price. However, the final bid of some of the users might end up going below the reserve price after a tax is removed from the bid price. This occurs mainly when the value of the set threshold is low. This is because at high values of the set threshold only high bid values are accepted giving equation 5.10. It can also be seen from the result that the multiple bidding process without the knowledge of the reserve price has no significant effect on the number of users who are blocked due to price when compared to the single bidding process at low values of the threshold. This is because the result examined here only deals with the number of users whose bid are above the reserve price and it does not matter if the multiple or single bidding process is used, as long as the use are bidding below the reserve price. However as the value of the set threshold increases, the users with lower values of bid compared to the reserve price are not attempting. Hence the number of users that are blocked is reducing compared to the single bidding process. As this value of the set threshold increases above about 0.6 the percentage of users that are blocked using the MBP begin to increase again. This is because the number of users attempting has reduced significantly. When the value of the set threshold is high, most of the users attempting are having a value that is below the set threshold, hence only a few users are attempting and fewer users are getting blocked due to price. However, because the percentage is calculated relative to the number of users attempting, the value in terms of the percentage is higher compared to values at lower values of the set threshold.

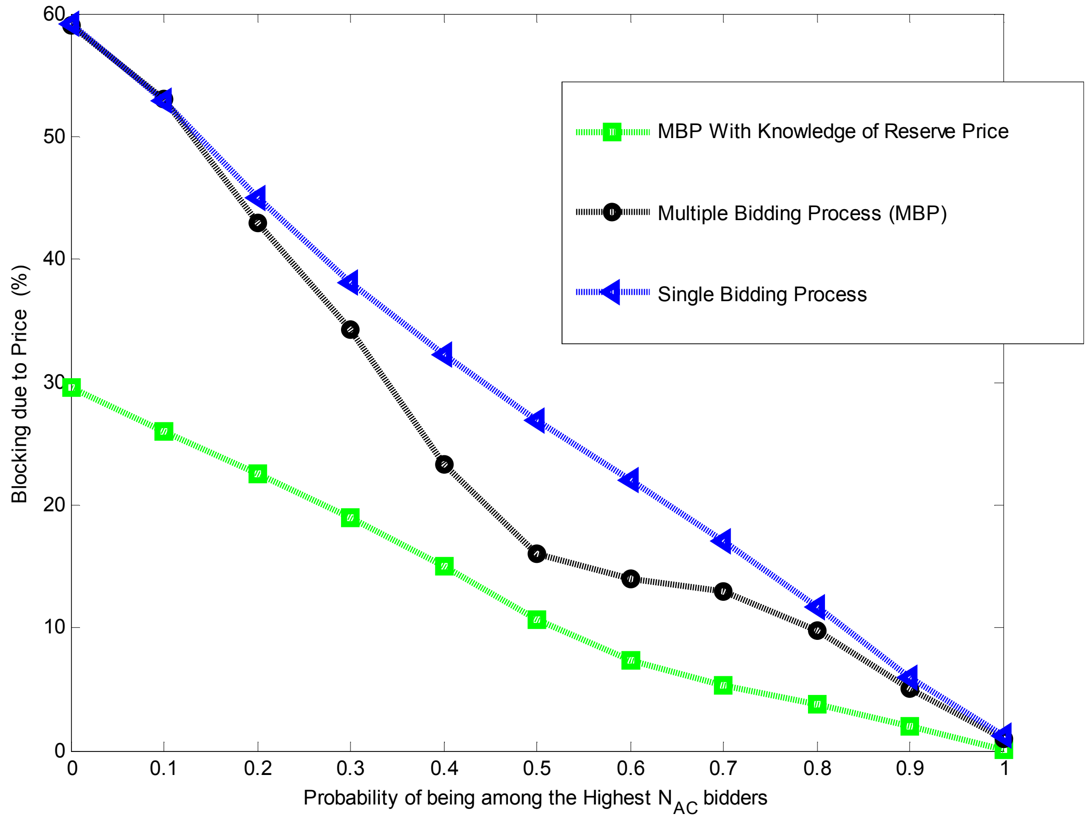

Figure 5.4. Effects blocking due to price per file generated for single bidding process, multiple bidding process and multiple bidding process with knowledge of reserve price

In order to demonstrate the importance of $P_{r_{Threshold}}$ and find the appropriate value to set $P_{r_{Threshold}}$ to, the value of $P_{r_{Threshold}}$ is now varied against throughput, delay and energy consumed. Figures 5.5 is the results obtained when the probability threshold is varied from 0 to 1. The result is obtained after the first stage of the modelling process as explained in section 5.3. The first stage represents the stage where the users are placing their bids and checking it (the bid) against the probability threshold as explained. If after generating the bid and the probability of the users being among the highest N_{AC} bidder is below the threshold (the threshold is varied in this result) the user does not attempt to move to stage two. From figure 5.4, it can be seen that if the threshold is set too low the numbers of users attempting and failing are high and if it is set too high only a few are offering a bid below the reserve price. However, the result (figure 5.4) does not show if setting the value too high affects the performance of the system especially in terms of throughput. This is because the system might be operating below its capacity if the threshold is set too high. Therefore, there is a need to examine the performance of the system in terms of throughput. It is also important to examine the throughput so that the appropriate threshold can be selected with respect to the other performance metric required in a standard wireless network such as delay and blocking probability.

Figure 5.5 shows the throughput against the threshold of $P_{r_{N_{AC}}}$. A user is assumed to get through provided the user succeeds in having a probability value from equation 5.10 to be above the set threshold in both stages and the SNIR is above the SNIR threshold. It can be seen that with the Single Bidding Process (SBP) the throughput reduces drastically with the increase in the threshold. This is because as the threshold increases the number of admitted users into the system reduces. This is due to fewer users having a probability above the threshold therefore, more channels are available that the number of admitted users after an auction round, leaving some of the transmit channels idle. With the multiple bidding process, the throughput reduces initially because at lower threshold values, some of the users actually get through stage 1 but fail at stage 2. The failure in stage 2 considered here is only due to the users offering a bid price below the reserve price. As the probability increases more users are only attempting when their offered bid price is above the reserve price. With the knowledge of the reserve price a user that gets through in stage one is more likely to have an offered bid that is above the reserve price especially as the threshold is increasing. However, the throughput reduces slightly as the threshold increases because only users offering bids close to V_{max} can move from stage one to stage two. As the threshold increases and the traffic load are relatively constant the system is sometimes loaded below its capacity. Hence, the reason for having a lower throughput that the maximum throughput that the system can support.

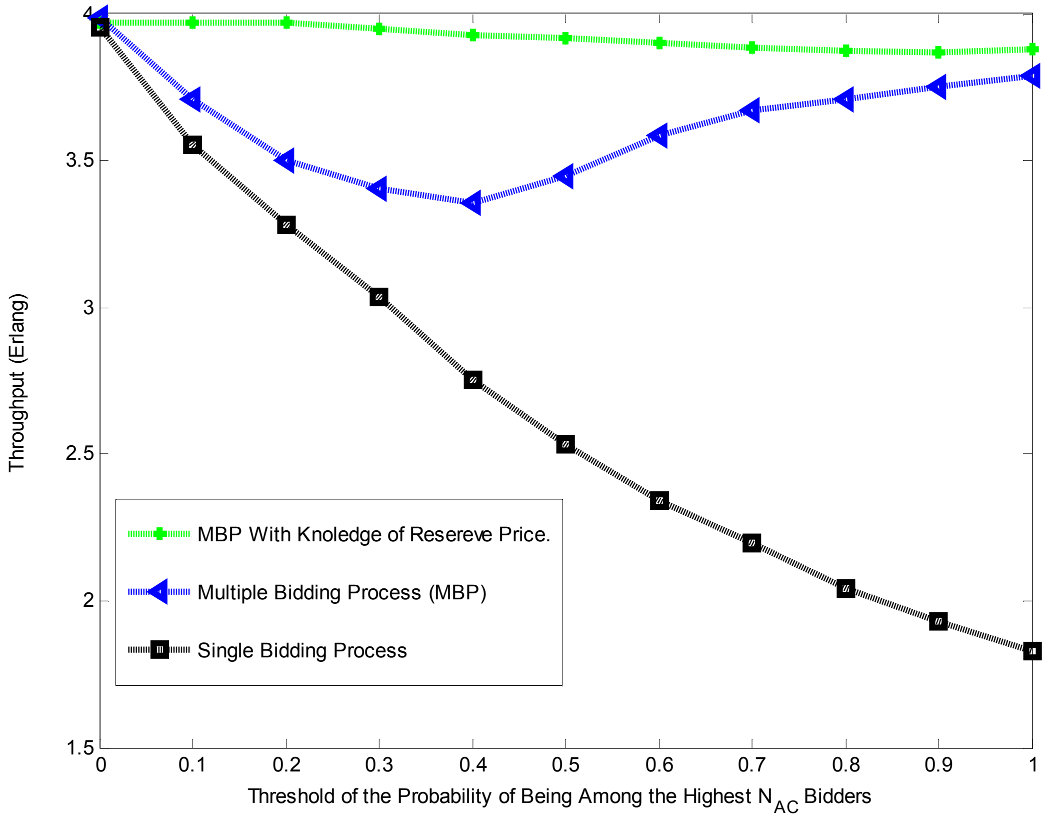

Figure 5.5 System performance in terms of throughput for single bidding process, multiple bidding process and multiple bidding process with knowledge of reserve price

Another important performance that is examined is the delay. This is because one of the aims of this thesis is to propose a model that does not introduce significant delay into the system. Figure 5.6 shows the average delay per successful file sent against the threshold of $P_{r_{N_{AC}}}$. The delay experience by the users when moving from stage 1 to stage 2 of the modelling process as explained in section 5.3 is divided by the number of files successfully sent after stage 2. The average delay experience is reducing as the threshold is increasing because as the value of the threshold is increasing more of the users moving from stage 1 to 2 are able to send their files successfully after stage 2. The single bidding round has the highest value of delay because when using the single bidding process the users experience more delay compared to the multiple bidding process. This is because when using the multiple bidding process all the available channels are put to use when needed. The scheme with the knowledge of the reserve price performs best because when the users are having the knowledge of the reserve price there is less likelihood that their bids fall below the reserve price and subsequently the less the likelihood that the bids of a user is rejected due to price at stage 2.

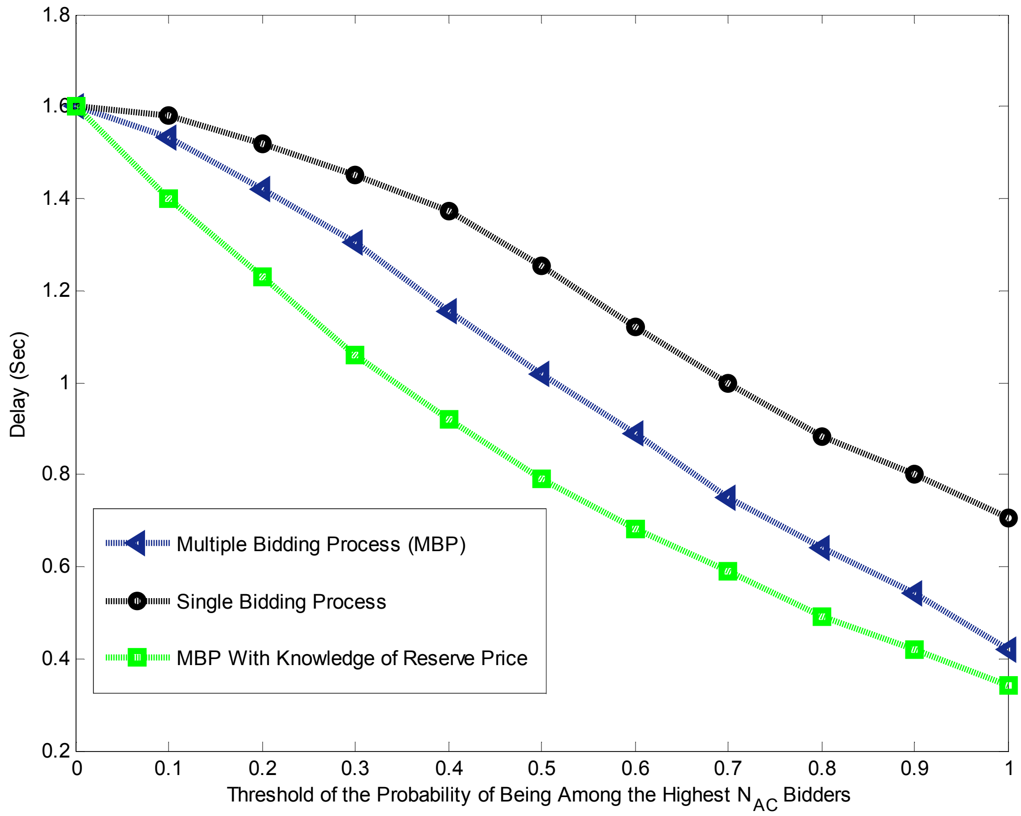

Figure 5.6. The average delay for SBP, MBD and MBP with knowledge of reserve price

Apart from the throughput and delay results already shown another important performance parameter that is considered in this thesis is the energy consumed. Figure 5.7 shows the total energy consumed by the system as the probability threshold ($P_{r_{Threshold}}$) increases. The total energy reduces with $P_{r_{Threshold}}$ because as $P_{r_{Threshold}}$ increases, it is less likely for a user to lose the bid when in stage two. The single bidding process consumes more energy because more users lose out after getting into the transmitting mode than the other two scenarios. The reasons for this are the same as those explained for figures 5.5 and 5.6.

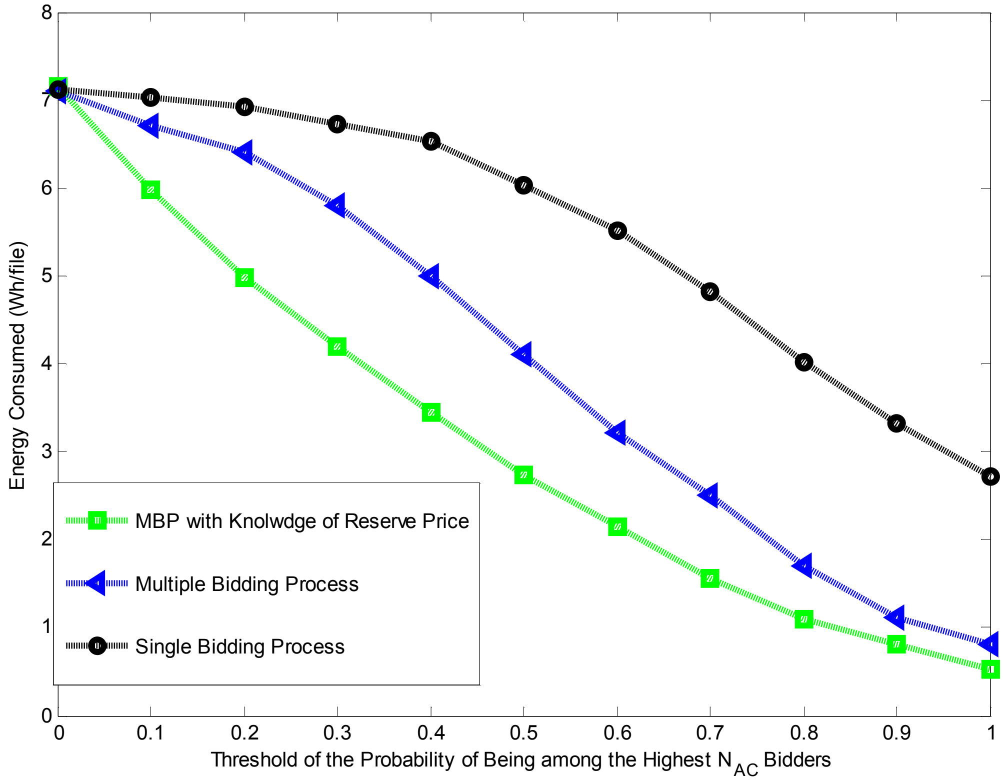

Figure 5.7. The energy consumed by the system for SBP, MBD and MBP with knowledge of reserve price

So far, the threshold helps in reducing the number of users that not able to transmit after winning the auction process. Hence it is important to determine the appropriate value for $P_{r_{Threshold}}$. This value should take into account all the factors such as delay, throughput energy consumed and blocking probability in such a way that none of this performance metrics is badly affected. To determine the appropriate value for the probability threshold ($P_{r_{Threshold}}$) to be used in the future analysis, the deviation of the performance metrics (delay, energy consumed, throughput and probability of blocking) as shown in equation 5.32 is normalised called the Normalised Difference (ND). Where $M_{V_{i_i}}$ is the value obtained at point i for the metric under consideration $M_{V_{max}}$ and $M_{V_{min}}$ is the maximum and minimum value for the performance metric under consideration respectively.

$$ND = \frac{M_{V_{max}} - M_{V_i}}{M_{V_{max}} - M_{V_{min}}} \tag{5.32}$$

As an example, from Figure 5.7, the metric under consideration is the energy consumed using the MBP. The obtained value of M_{V_i}at a threshold of the probability of being among the highest bidder at 0.5 is 3.90 watt hour per file. $M_{V_{max}}$and $M_{V_{min}}$ are 7 and 0.72 Watt hour per file respectively. Equation 5.32 is normalised to obtain 0.45. This is obtained for all the four performance metrics in order to obtain Figure 5.8. This normalization has no unit. A scenario with known knowledge of the reserve price and MBP to obtain the result is used. The probability of blocking is increasing while others are decreasing because more users are blocked as the threshold is increasing.

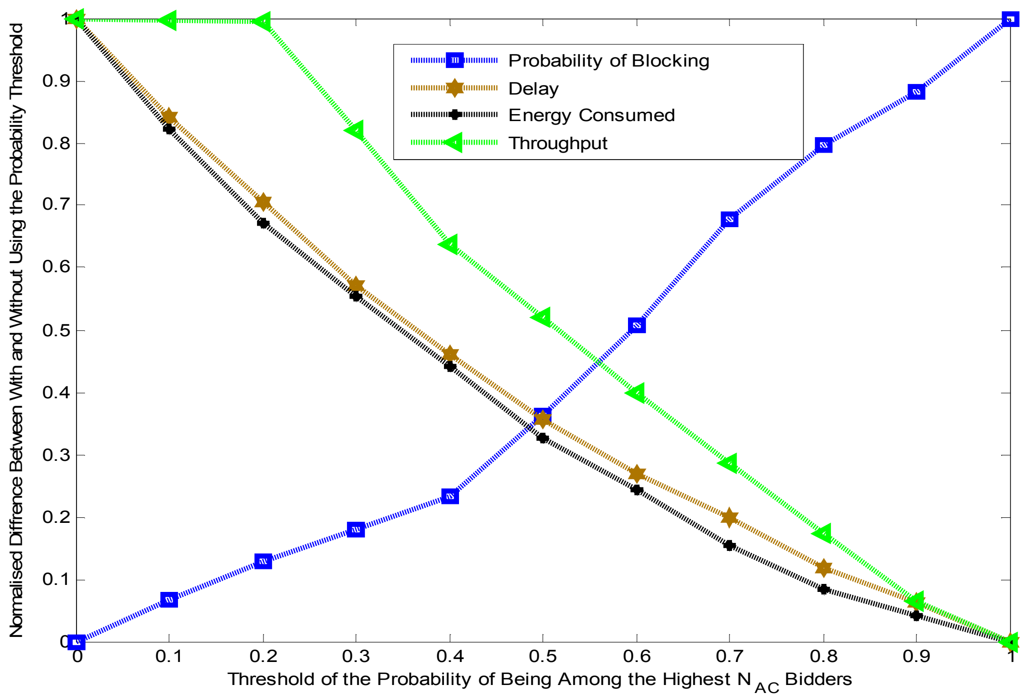

Figure 5.8. The normalised difference for blocking, delay energy consumed and throughput

To balance all the performance parameters without trading off one of the other performance parameters too much, the midpoint between the cross over point is picked. From the figure below, this is 0.55 and this is used as the probability threshold. Using this, the performance of the system is examined with the green payment alone without using the probability of being among the highest N_{AC} bidder ($P_{r_{N_{AC}}}$) to determine the admission process, and the green payments with MBP and MBP with the knowledge of reserve price. After determining the appropriate threshold to use, so that most of the users attempting are offering a bid value above the reserve price, it is important to show the performance of the system in terms of throughput, delay, energy consumption and blocking. This is important to demonstrate the improvement achieved if the admittance threshold is used.

Figure 5.9 shows throughput against the traffic load. The MBP without the knowledge of the reserve price performs slightly below the other two as expected. This is because with the multiple bidding process with the reserve price, N_{UT} is equal or almost equal to N_{AC}. This is unlike the SBP or the MBP without the knowledge of the reserve price where the throughput of the system is significantly less than the traffic load because N_{UT} is not always or almost equal to N_{AC}. This shows that the MBP can only provide a better performance if the users have the knowledge of the reserve price or better still if the users are aware of the green payment if paying a tax.

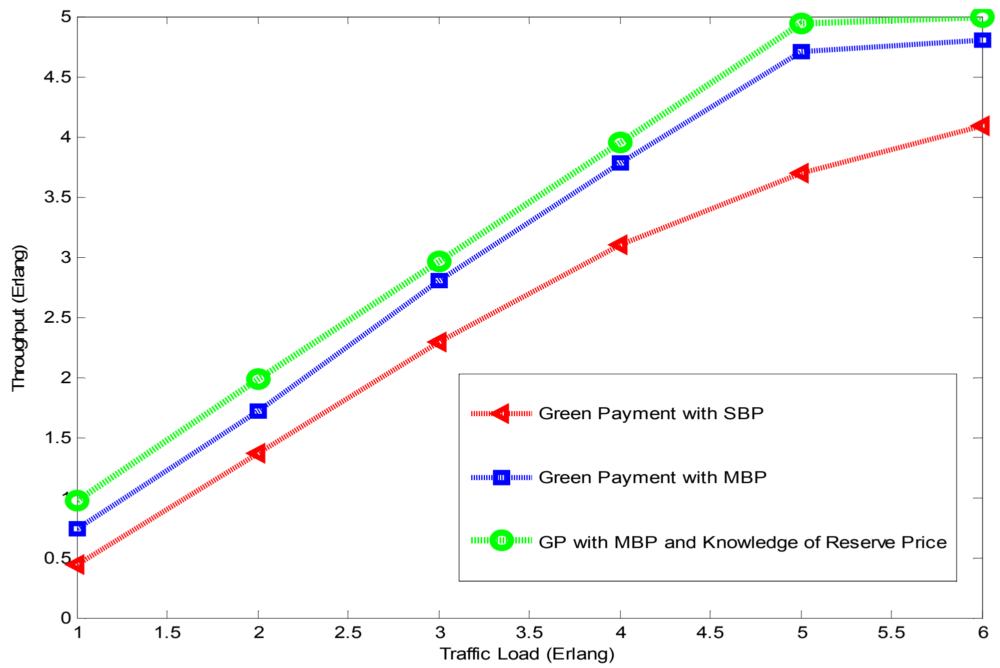

Figure 5.9 The throughput of the system with green payments, multiple bidding process and multiple bidding process and knowledge of the reserve price

However, the average delay per file sent as seen in figure 5.10 performs better with when using the probability to determine the admission process compared to the scheme with the green payment alone. The delay with known knowledge of the reserve price performs best of the three scenarios. The delay is increasing with the traffic load because as the traffic load increases the collision in the system also increases.

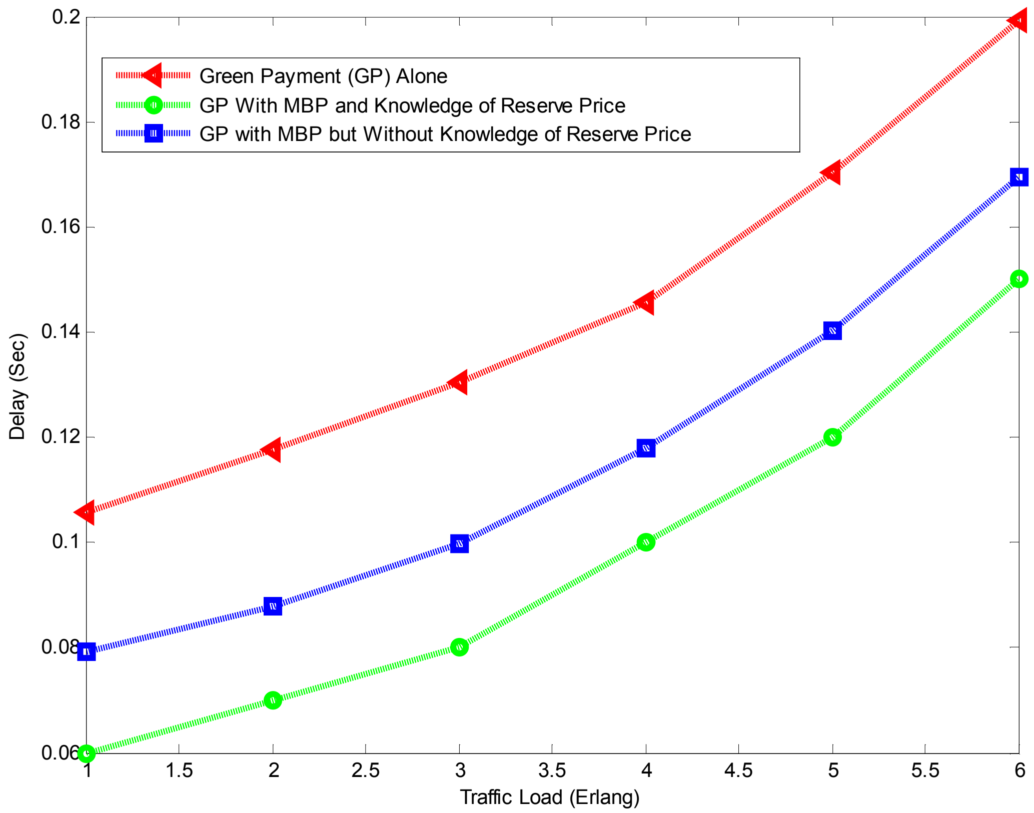

Figure 5.10 The average delay experienced by the system for schemes with green payments, green payments with MBP and MBP and knowledge of reserve price

Another important performance metric is the energy consumed. From figure 5.11, using the green payment alone, the energy increases linearly with the traffic load. However, with the probability introduced, the increases can no longer be described as linear but similar to a parabola as the traffic load increases. As the traffic load increases, fewer actually go into the transmitting mode and are not able to transmit successfully. The knowledge of the reserve price algorithm performs best because of the reasons stated earlier in figures 5.9 and 5.10.

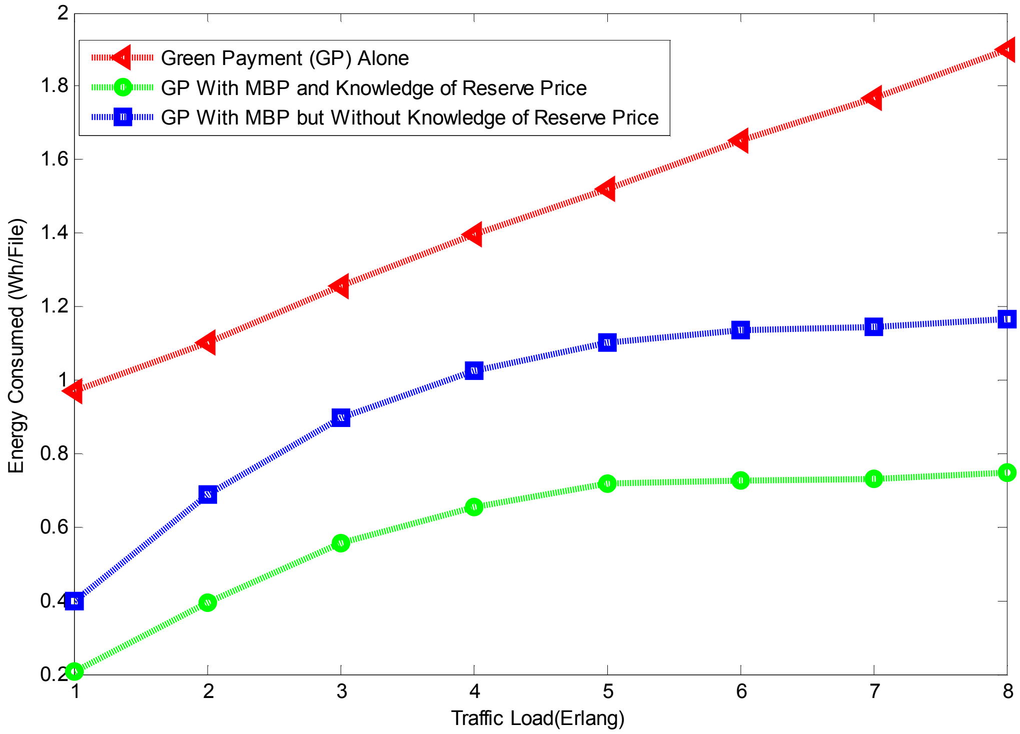

Figure 5.11. The energy consumption level of the system for schemes with green payments, MBP and knowledge of reserve price

Furthermore, Figure 5.12 shows the average price paid per file sent. The result shows that with or without the knowledge of the reserve price, the average revenue is almost the same. This shows that the price difference between having and not having the knowledge of the reserve price is quite small, however compared with the loss in terms of energy consumed and delay, having the knowledge of the reserve price is important. The average price also increases with the traffic load because the reserve price and the bids of the users increase the traffic load. To determine if the scheme helps with congestion control, the blocking probability of the system especially as the traffic load approaches the maximum traffic load is examined. While calculating the blocking probability, a situation when a user is blocked because of the SNIR being below the SNIR threshold is considered.

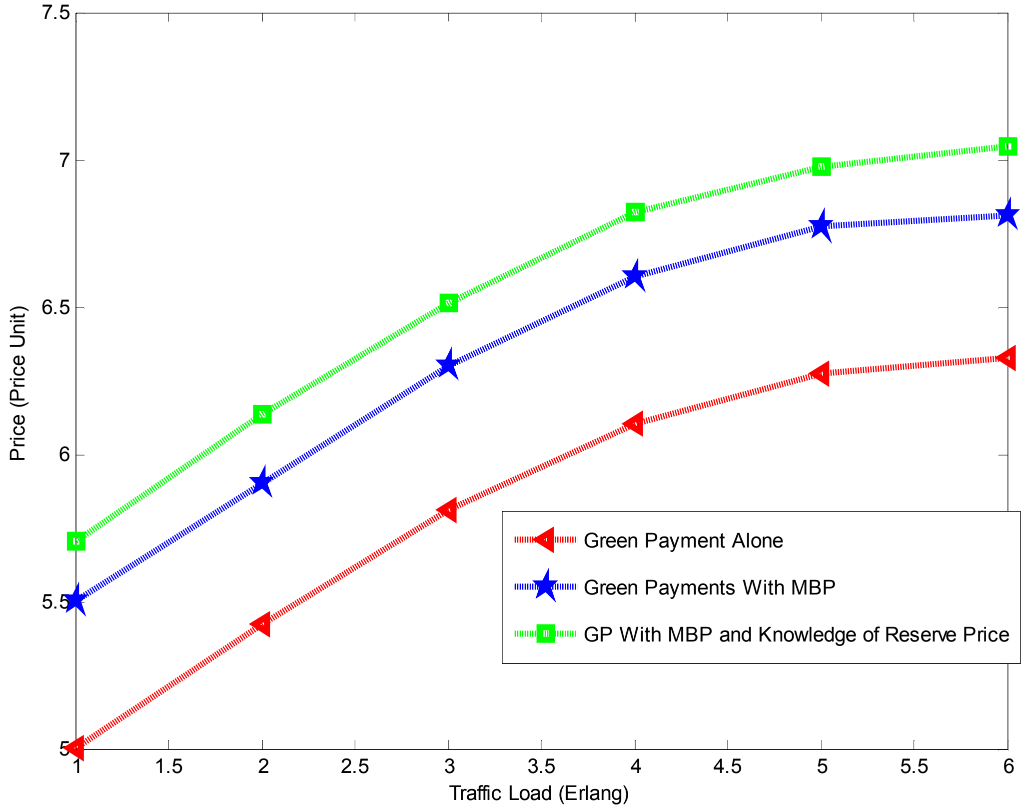

Figure 5.12 The average revenues of the system for schemes with green payments, green payments with MBP and knowledge of reserve price

It is important to show the improvement achieved in terms of blocking because the blocking probability is one of the important performance metric in any wireless network. Figure 5.13 shows that without using the green payments the blocking probability is very high due to the HPU interfering with the LPU because they have equal access right to the spectrum. With the introduction of the green payments, the blocking probability reduces significantly because the green payment helps in controlling the admission process. This can be improved further if the probability is used in the admission process as seen below.

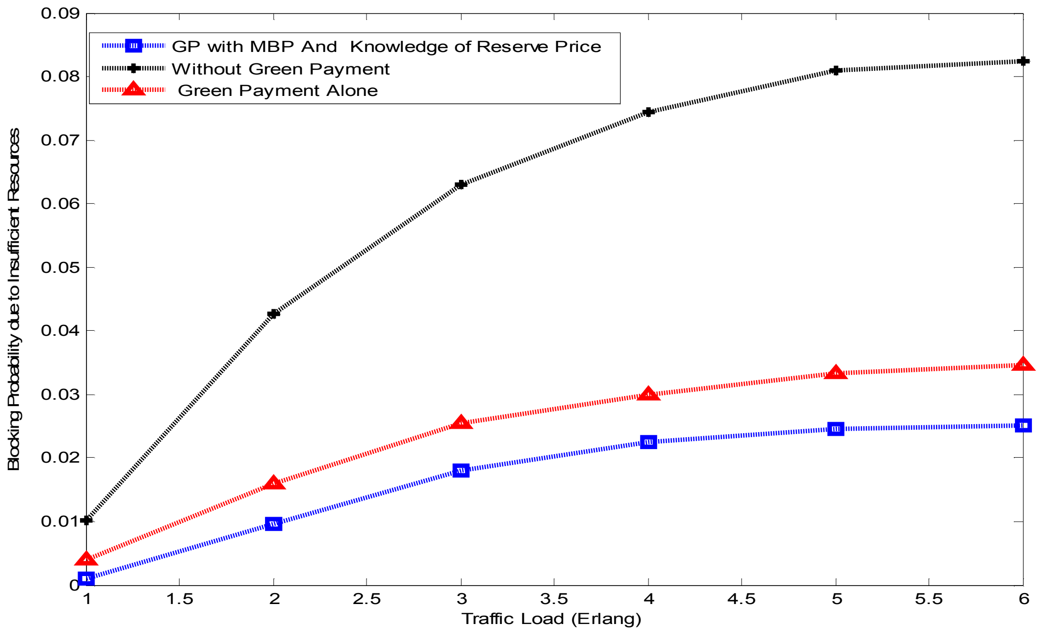

Figure 5.13. The blocking probability of the system using different schemes

This chapter introduced and used the concept of utility function in section 5.3.2. Hence, the performances of the system in terms of the defined utility functions are shown in figures 5.14 and 5.15. Figure 5.14(a) shows the general user utility against traffic load with and without the green payments. The scheme with the green payments involves MBP. The utility of the LPU without the green payments decreases with increases in traffic load as a result of the interference caused by the HPU to the LPU. At low traffic loads there are more channels available than required. Therefore, the LPU can avoid sharing the same channel with the HPU. This changes as the traffic in the system increases leading to the LPU not been able to achieve the maximum data rate possible and longer delays. Without the green payment the LPU receives no incentive and therefore, their bids are sometimes rejected due to price. The utility of the LPU with the green payments is relatively constant. This is because of the incentive received from the green payments. The LPU does not attempt to transmit when the probability of being among the highest bidder is below the set threshold while using the MBP. The utility of the HPU with the green payment decreases slightly as the traffic load increases because they get squeezed out as the traffic load increases, thereby leading to more delay. Using the probability threshold with the MBP allows the utility of the HPU to be relatively high because the HPU only transmits when their calculated probability is above the threshold. This is due to calculating the utility for the delay and data rate being calculated only when a user is admitted into the system. However, without the green payments the general utility of the HPU is higher because they dominate the system. This is an undesirable effect because the utility of the social welfare should be of concern.

This can be seen in figure 5.14(b) with the combined utility of all the users showing the utility of the social welfare. The scheme without the green payments is better than the scheme with the green payments. This also shows that with the green payments the HPU are disadvantaged but the system gives a better performance as a whole. The utility without the green payments falls with the traffic load because as the traffic load increases the LPU are performing worse. This is because they have a low value in all the utility factors (Delay, data rate and bid being below reserve price) that was taken into account while calculating the utility. However, with the green payments, the HPU experiences more delay, but the higher data rate compensates for the loss due to the delay. The LPU has a lower data rate compared to the HPU but they make up for this with shorter delay. The relative increases of the utility with the green payments as the traffic load increases is because as the traffic load increases the HPU are squeezed out therefore compared to the admitted users the LPU has a high utility for data rate and all the other factors. This is because the utility is calculated in terms of date rate and delay only if a user is admitted into the system.

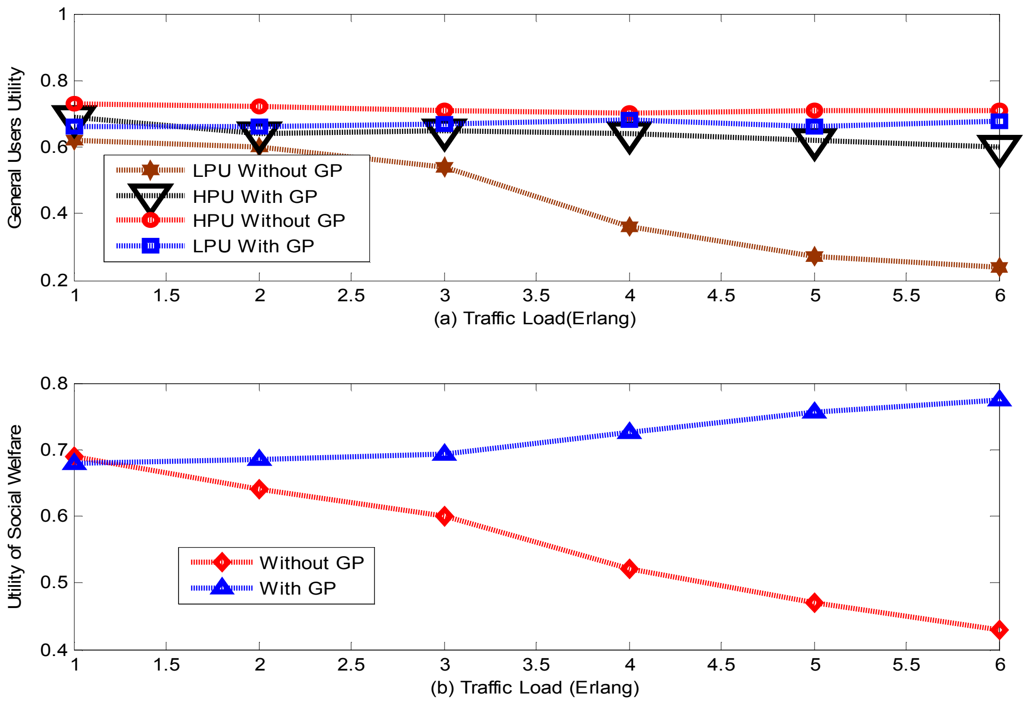

Figure 5.14. (a) General utility of users for LPU and HPU with and without the green payment (b) Utility of the social welfare with and without green payments

Figure 5.15 shows the utility of the service provider against the traffic load with and without the green payments. The utility increases with the traffic load for the two schemes because as the traffic load in the system increases the number of channels in use also increases. At low traffic loads the two schemes perform similarly because at low traffic with or without the green payments the LPU can avoid the interference caused by the HPU because of availability of channels. However, as the traffic load increases the schemes with the green payments perform better. This is because without the green payments, when the LPU wins the auction process, they sometimes cannot transmit because their SNIR is below the set threshold. Therefore the channel which ought to be in use is not used. The scheme with the green payments avoids this and therefore the scheme with green payment gives a better utility to the WSP.

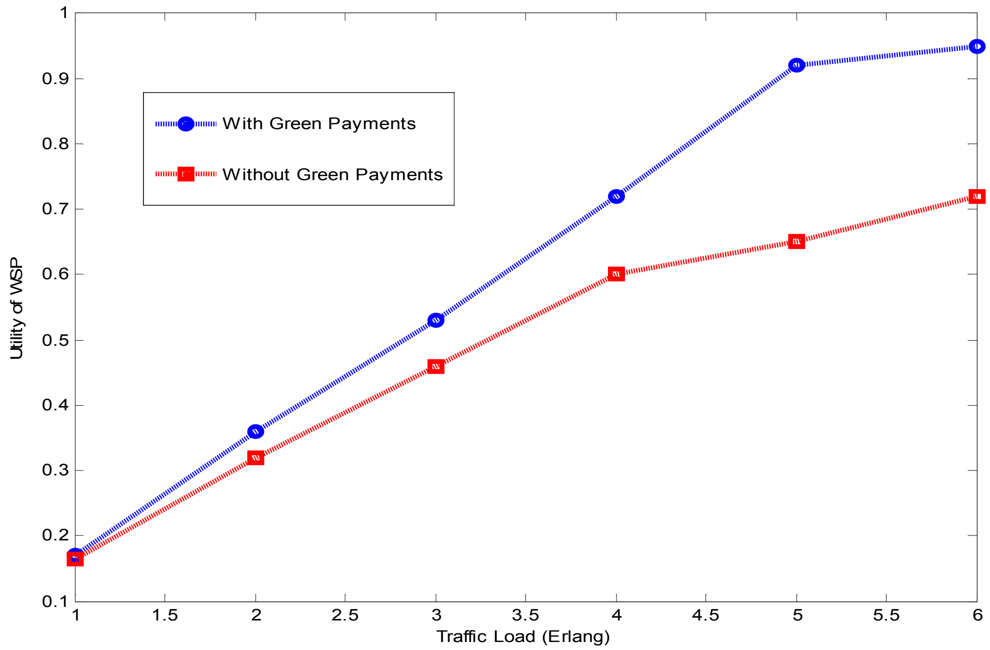

Figure 5.15 Utility of the WSP with and without the green payments against traffic load

5.6 Conclusions

This chapter has proposed an energy efficient admission and congestion control scheme for future wireless systems using green payments and an auction process to control the admission process of the users. Firstly, this chapter showed how the effects of using the probability of being among the highest N_{AC} bidder ($P_{r_{N_{AC}}}$) and the multiple bidding process affect the system performance such as delay and throughput. It showed that if an appropriate value of the threshold of the probability is set, the amount of energy consumed by the system and the delay can be reduced. It also showed that the energy consumed by the system and other system performance measures can be improved when the users have the knowledge of the reserve price and the approximated tax to be paid as a result of the green payments. It showed that the knowledge of the reserve price has no effect on the revenue of the WSP since truthful bidding was assumed in this chapter. Finally the chapter showed that the proposed scheme could be used to improve the congestion in the system and provide a better utility to optimise the social welfare of the users and provide better utility to the service provider.

Chapter 6

Energy Efficient Bid Learning Process in an Auction Based Cognitive Radio Network

Contents

6.1 Introduction

This chapter examines how artificial intelligence can be used in learning the bid price given an auction based DSA network. This chapter is formulated in order to further help in solving the problem associated with the reserve price as formulated and explained in chapter 5. This is necessary because some strong assumptions were made in order to solve the problem in chapter 5. Using an auction with a reserve price in allocating the radio spectrum might introduce additional delay and increase the energy consumption of the system. This is because sometimes the offered bid is below the reserve price as explained in the previous chapters. Furthermore, an auction process for DSA is slightly different from a conventional auction because energy and other resources are consumed to conduct the auction itself. However, this chapter examines if learning the best bidding price can help in improving the efficiency of the auction process and the system. As explained with the energy model in chapter 3, the losers during the auction process waste energy in participating, whereas they could be better off not participating. Hence, the learning process should help the bidders learn the appropriate bid value that is above the reserve. This chapter examines if machine learning is suitable for DSA, the different types of learning model that can be used in an auction based DSA scheme. It is important to introduce machine learning in this work because the auction process is ideally be carried out using an automated system installed in the user device and bidding above the reserve price is very important. A user need to bid above the reserve price in order to get access to the radio spectrum and as explained in chapter 3 using the SBP, when the reserve price is unknown to both the users and the auctioneer. Furthermore there is a need to learn so that the user does not pay too much for the radio spectrum because machine learning allows for historical information to be incorporated. Learning can also help in reducing the amount of energy wasted as a result of losing an auction process. However, it is also important to understand that if all the users in the system adopt the same method of learning, the learning process might have a difficulty in achieving convergence. This is because all the users are learning about the others and they might just keep increasing their bids until they run out of budget. Hence in this chapter only few of the users in the system adopt the learning model.

The rest of this chapter is organised as follows: The modelling parameters are discussed in section 6.2. Section 6.3 explains the learning model. The simulation scenario is given in section 6.4. Section 6.5, evaluates the scenario where learning can be used in an auction based DSA process. Based on the scenario where learning is applicable, the performance of different learning techniques is analysed in section 6.6. Conclusions are drawn in the last section.

6.2 System Model

The important models and changes made to the models discussed in the previous chapters are presented in this section.

6.2.1 The Reserve Price

The reserve price is the minimum acceptable offered bid price as used in previous chapters:

$$r\ (price\ unit) = \frac{N_{USA} C_r N_{TC}}{N_{AC}} \tag{6.1}$$

6.2.2 The Users Bid

The bid of a user is the price offered to gain access to the radio spectrum. In the previous two chapters, the bid or the valuation of a user is determined using a random process. However, in order to simplify and understand the analysis done in the later part of this chapter, it is assumed in this chapter that the offered bid that can be picked by each of the users is from a fixed range of discrete values and the values depend on the traffic arrivals (N_{USA}). Therefore, the range is referred to as the traffic load bin. The range for each traffic load bin is determined by first examining the average minimum and maximum number of users requesting the use of the channels. It is known from chapter 4 that the number of users arriving depends on the traffic load in the system. Hence, the average minimum and maximum number of users arriving for each traffic load bin (${N_{USA}}_{min}^{T_L}$ and ${N_{USA}}_{max}^{T_L}$, where superscript T_L is the traffic load) is determined as explained below where L_p represents the traffic load bins:

$$L_p = \begin{cases} \lfloor C_r {N_{USA}}_{min}^{T_L} \rfloor, & \text{For the lower range of bid values} \\ \lfloor C_r {N_{USA}}_{max}^{LT_L} N_{TC} \rfloor, & \text{For the upper range of bid values} \end{cases} \tag{6.2}$$

For the lower range, it is assumed that $N_{AC} = N_{TC}$ in equation 6.1. This is in order to determine the minimum possible reserve price. For the upper range (for each traffic loads), it is assumed that N_{AC}=1, in order to determine the maximum possible reserve price for a particular traffic load. The value of N_{USA} used in both cases is the average arrival for each traffic load as investigated in chapter 4. The range is then approximated to the nearest integer number as stated in table 6.1. Hence, it is assumed that each of the users intending to transmit on the radio spectrum picks an offered bid value from one of the bins depending on the belief of the user regarding the traffic load in the system. Five traffic load bins are assumed in this chapter as shown below:

Table 6.1 Traffic Load Bin

Traffic Load Bin (L_P)	*Value of offered Bid*
1	12-40
2	35-45
3	40-50
4	45-55
5	48-60

The traffic load bins reflect the increase in competition occurring in the system as the traffic load increases. As shown in the table, the values overlap for each traffic load because the estimated value of N_{USA} is overlapping too. In some other scenarios (not considered in this work), the bidding values in each of the bins can be associated with the quality of service that the user expects from the WSP.

6.2.3 The Utility Function

Utility functions are used to determine a preference given a number of options. In this chapter, the available option is the different offered bid values that the users submit during the auction process. A bidding round starts when the users intending to transmit at transmitting time T_1 submit a bid during the bidding period t_o. The winners of the auction process are then allocated the spectrum. It is assumed that the aim of any bidder is to win the auction process with the least possible amount. Therefore, this chapter uses the utility function to measure how much a user deviates from the lowest winning bid as shown below:

$$\boldsymbol{N_{WU}} = \{b_1, b_2, b_3 \dots b_{N_{WU}}\} \tag{6.3}$$

$$\delta = min\ \boldsymbol{N}_{WU} \tag{6.4}$$

$$U_i(t) = \begin{cases} 2^{\frac{\delta}{b_i}} - 1 & \text{For winning bidders} \\ 0 & \text{otherwise} \end{cases} \tag{6.5}$$

Where set $\boldsymbol{N_{WU}}$ contains the bids of the winning bidders and b_i represents the bid of user i. A power utility function is used because of its rapidly increasing nature as explained in chapter 5. The closer the bids of the winning bidders to the minimum winning bid the higher the utility of such bidder. If a user is not among the winning bidders then the utility of such user is zero.

6.3 The Learning Model

In wireless networks, Reinforcement Learning (RL) is the most widely learning model used [116]. Hence, reinforcement learning with some modifications is examined.

6.3.1 Linear Reinforcement Learning

Reinforcement learning involves the interaction of learning agents with an environment. The agents are learning from the environment by using a process of trial and error [117]. A learning user obtains a reward after exploring each of the available actions or the possible bidding values, as is the case in this chapter. This is done to understand the consequences associated with each bidding value. After the exploration process, the learning users begin exploiting the best action learnt.

Linear Reinforcement Learning (LRL) [88] is usually described using a Markov decision process and using a tuple such as $(\boldsymbol{S_s}, \boldsymbol{A_s}, P(s|s'), \boldsymbol{R_s}(s|s'), \gamma_s)$. Where $\boldsymbol{S_s}$ is set containing the finite states available, $\boldsymbol{A_s}$ is the set containing the finite number of actions available at each state $\boldsymbol{S_s}$, $P(s|s')$ is the probability that an action by user i leads to a another action s', $\boldsymbol{R_s}(s|s')$ is the reward or punishment for a user and γ_s is the reward discount factor. Usually γ_s has a value between 0 - 1. $(s|s')$ represents the transition from an initial state s to another state s'. The learning process can be described as Markov because at time t, the current state is the only information required by a learning user to move from one state to the other since $s|s' = [s_{t+1}|s_1 \ldots\ldots s_t]$. This is true until a point when the learning process converges. The present state captures all the relevant historical information. Therefore the previous history is no longer necessary. The reward/punishment can sometimes be discounted, because the undiscounted reward might not fully represent the uncertainty in the learning process [62, 118]. According to [117], the optimal outcome $(V^{\pi^*}(s))$ can be learnt using the value function defined as $V^{\pi}(s)$. The learning agent updates its knowledge based on the feedback from the value function. There are different approaches that can be used to update a value function [119]. However, this chapter adopts a linear value function because of the simplicity associated with the updating rule [119]. Linear approximation allows for a linear weight to be associated with the previous weight as shown below:

$$W(t) = \gamma_1 W_{t-1} + \gamma_2 W_t \tag{6.6}$$

Where $W(t)$ is the final weight, W_{t-1} is the weight at time $t-1$, W_t is the weight at time t which is added to the previous weight to give the weight for the present time. γ_1 and γ_2 are the weighting factors associating with the learning process for each state. The weighting factors may or may not be the same and the ways in which the weight W_{t-1} (the addition of

$\gamma_2 W_t)$ is updated in time t to give $W(t)$ is known as the updating rule. The summary of weighting factor used in this chapter is as shown in table 6.2.

Table 6.2 Weight factor values

SCHEMES	Reward	Punishment
Discounted Reward $f(U(b_i))$	$f(U(b_i))$	0

The reward function $f(U(b_i))$ means that the weight of the reward is dependent of the value of the utility function based on the bid submitted as explained in section 6.2.3. One of the main problems of reinforcement learning is its slowness to converge [60]. This is because of the large number of trials involved for the learning process to be effective. It uses different methods to allow for faster convergence such as taking the average, using the greedy policy and Q learning. Some other methods can be found in [120].

6.3.2 Q Reinforcemenet Learning (QL)

The policy adopted by the learning user usually affects the learning convergence speed. QL is a type of reinforcement learning which assigns values to pairs of the state actions. Every state has a number of possible actions and the reward earned depends on the action taken (scalar reward). The reward received by taking an action is based on how close the action taking is to the best known action. In the proposed auction process where users aim is to win with the least possible amount, the closer the bid of any of the winning bidder to the minimum winning bid the higher the reward obtained. This is because the acceptable values of the winning bids can be any value down to the reserve price. The Q learning algorithm is similar to the reinforcement learning earlier explained. However, the difference is in the update of the Q table. The Q learning for policy π is updated as shown below [66]:

$$Q^{\pi}(s,a) = R_s + \gamma_s \max_a Q(s',a') \tag{6.7}$$

Where R_s is the reward obtained by observing the new state by taking action a, γ_s is the weighting factor and $\max_a Q(s', a')$ is the maximum possible reward for the new state that the learning user moves into by taking action a.

The QL approach used in this chapter is similar to [121]. The bidders only have information regarding their own bid history and not that of any other user in the system. Only a single bid can be submitted by a user in a bidding round. In this chapter, the reserve price is not known to the bidders. This is because the reserve price is set by the WSP whose aim is to maximise profit. However, in a real world auction model, it is likely that if the reserve price is known, the bidders might only offer bids slightly above the reserve price hence, the reason why this assumption is modified from the one made in chapter 5. An auction process is started by asking the bidders to submit their sealed bids to the WSP. Based on the value of the submitted bid, the bidders obtain a utility value using the utility equation in (6.5). The aim of the user is to win the bid with a high utility value, however, the lower the offered price of the bidder, the lower the probability of the bidder winning the bid and the higher the bid of the user, the higher the probability of the user paying too much for the spectrum compared to the price paid by others. Therefore, any of the two extremes can lead to a lower value of utility. Hence, the dilemma faced by a bidder is to decide the best bid that offers the best utility value.

Using the QRL, each of the possible bidding values has a reward received after a learning event. A learning event occurs after each iteration, meaning that after each bidder submits a bid value, a reward is obtained. The reward is added to the previous reward weight. After the conclusion of the learning exploration, the learning user exploits the bidding value that gives the highest weight as stated in equation 6.12. The reward (R_s) is obtained as explained below:

First, all the possible bidding values for a traffic load bin (L_p) can be represented in an ascending order as shown in equation 6.8, where subscript p represents each of the traffic load bins (i.e. 1 to 5 in this case) and the superscript y represents each of the discrete ascending values which fall in the p^{th} traffic load bin:

$$L_p = [b_p^1, b_p^2, b_p^3, \ldots . b_p^y] \tag{6.8}$$

A user picks one of the possible bid values and the winning ratio (W_R) as shown below. Where N_{SW} is the number of times a user selects and wins with a particular bid value divided by $N_{\tau_a}(t)$. This is the total number of iterations carried out up until time t for a bid value.

$$W_R\ (t) = \frac{N_{SW}(t).}{N_{\tau_a}(t)} \tag{6.9}$$

The winning ratio is then multiplied by the utility function obtained from equation 6.5 to obtain the weight as shown below:

$$R_W = W_R U \tag{6.10}$$

The reward associated with a bidding value is updated using equation 6.17 to obtain the total weight as shown below:

$$W_p^y = \sum_{1}^{t} R_W \tag{6.11}$$

Where W_p^y is the learning weight which is the summation of the reward the users obtained for learning up to time t using a specific offered bid value from traffic load bin p. The weight for all the possible bids in the single traffic load bin p (L_p) value can be as shown below:

$$w_p = [w_p^1, w_p^2, w_p^3 \ldots w_p^y] \tag{6.12}$$

A learning user then picks the bid value that has the maximum weight (π^*) after the exploration period as shown below:

$$\pi^* = \max\ (w_p) \tag{6.13}$$

In some of the scenarios considered, where the user picks from any of the traffic load bins the weight for all the traffic load bins is as shown below in form of a matrix.

$$\boldsymbol{W} = \begin{array}{cccccc} & 1 & 2 & 3 & \dots & y \\ 1 & w_1^1 & w_1^2 & w_1^3 & \dots & w_1^y \\ 2 & w_2^1 & w_2^2 & w_2^3 & & w_2^y \\ \cdot & \cdot & \cdot & \cdot & \dots & \cdot \\ p & w_p^1 & w_p^2 & w_p^3 & & w_p^y \end{array} \tag{6.14}$$

The reason for using this method is mainly due to the fact that a scenario where the users want to win with the least possible amount is modelled hence, the utility function is used in obtaining the weights during the learning process.

The summary of the Q learning process is as shown below:

1: Users pick a bid value randomly from the bin.

2: The utility function of the user based on the bid is calculated.

3: Other records are also calculated in equation (6.8).

4: The weight table is computed at time t.

5: After τ trials, the best bidding value is exploited π^*=max (W).

Another learning method that is considered in this chapter is the Bayesian reinforcement learning as explained below:

6.3.3 Bayesian framework for Reinforcemnet Learning (BRL)

The problems with uncertainty and delay associated with random exploration in reinforcement and Q learning might lead to a sub-optimal convergence point if the exploration period is not long enough. This brings about the need to manage the uncertainty and enhance the exploration process. One such approach is Bayesian learning. The Bayesian algorithm allows the learning agent to make a decision based on the most likely events that could happen, using prior experience. Bayesian learning can be implemented in an auction based DSA as proposed in this work because the users are bidding very often to request for the spectrum. Therefore, the users use the previous bidding rounds as the prior knowledge and update it as the bidding progresses. This allows for a faster and smooth movement from the exploration to exploitation behavior. Bayes' theorem is applied as shown below:

$$P_r(A\backslash B) = \frac{P_r(B\backslash A) \times P_r(A)}{P_r(B)} \tag{6.15}$$

Where $P_r(A)$ is the prior probability distribution of hypothesis A, $P_r(B)$ is the probability of the training data B(likelihood) and $P_r(B\backslash A)$ is the probability of A given B (posterior probability). Bayesian learning offers several advantages over the previous model. It provides an ideal format to reach a compromise between the exploration and the exploitation stages by providing information on states which the player might not have explored. It also allows for the incorporation of prior probabilities to determine the user's transition. However, it has a disadvantage in that it can only be applied when prior information is available.

In this chapter, a learning user generates the initial prior knowledge based on an assumption regarding the common knowledge of the price for the spectrum and the utility of the user. The transition matrix is assumed to be sparse as only a certain number of the bid values in the bins have a non-zero probability. The results examine the concept of uniform and non-uniform prior probabilities known as the rectangular and triangular prior probabilities respectively. The rectangular prior probability assumes the same values of the utility function for all possible bidding values except the bidding values which fall below the reserve price. They are assigned a zero prior probability. While for the triangular prior probability the utility function is calculated using equation (6.16).

$$Prior\ probability = U_i b_i \tag{6.16}$$

The posterior probability is calculated using the Bayes equation after converting the likelihood into a probability. After then the same process as explained in the Q learning model is used except that the total number of iterations to be carried out (τ) is reduced. This is further explained in the simulation description. There are other methods of calculating the prior and the likelihood. A similar method can be found in [122]. In a real world scenario, the prior probability distribution can be based on facts such as users bidding above or below a certain percentage of the guide price as assumed in [123]. The posterior distribution represents the uncertainty in the system for the transition probability for each of the state action pair as explained in section 6.3.2. The summary is stated below:

1: u and the prior probabilities are calculated.

2: The likelihood is generated from QL and converted into probability.

3: Bayes rule is applied.

4: Users pick the action with the highest utility and the winning percentage (π^*).

6.3.4 Learning Rate (LR) and Learning Efficiency (LE)

Learning rate is generally a time dependent factor which decreases as the time of learning increases. Generally, it is inversely proportional to the time it takes to learn.

$$LR = \left(\frac{1}{\tau}\right) t_a \tag{6.17}$$

Where τ is the number of iterations before a steady state is reached and t_a is the time taken for an iteration to be carried out. It is assumed that the time taking for each of the iterations is the same. However, learning rate does not tell an accurate story about the learning process of an individual user. This is because training samples contribute differently to the final optimal value [124] therefore, the learning efficiency is examined as shown below:

$$LE = \frac{L_{UC}}{L_{TC}} \tag{6.18}$$

Useful learning cost (L_{UC}) is defined as the number of trials carried out while trying the offered bid value that eventually becomes the optimal bidding price while the total learning cost (L_{TC}) is the total number of trials before convergence. This chapter has examined 3 potential learning models that can be used given an auction based DSA network. The scenario is now formulated and subsequently examined.

6.4 Simulation Scenario

Assume that the traffic model is developed and driven by a Poisson process. This means that the length of the file and the interarrival time are exponentially distributed. To evaluate the performance of the proposed learning algorithms, an auction scenario using a multi-winner first price sealed bid auction with a reserve price is modelled. This is done in an uplink scenario with one WSP and N in the system. It is assumed that the users are connection oriented while using the WINNER II B2 propagation model as detailed in [89] for the propagation loss. All the channels in the system are assumed to be identical and no channel has a better quality than the other. However, users may experience different fading and path loss depending on the location of the transmitting users. Hence, each of the users in the same location, experiencing the same fading and path loss perceives the quality of the channels to be the same. N_{USA} out of the N possible users in the system request the use of the channel by submitting a bid during every bidding periods ($b_1, b_2, b_3 \dots . b_{N_{USA}}$). The bids are picked from the traffic load bin as explained earlier. The value of N_{USA} varies depending on the traffic load in the system. The initial bidding value is chosen randomly from the possible bidding values in the bins. Based on the bids submitted by the N_{USA} bidders, N_{WU} winners emerge at any bidding period t. The number of winners that emerge is dependent of the number of available channels in the system therefore N_{WU}=N_{AC}. Such winners are allocated the channel after the auction process as shown in the flow chart in figure 6.1. However not all the users allocated the channels are able to transmit because of the reserve price and the channel quality as explained in chapter 5. The number of users that are able to transmit after the auction and allocation period is represented as N_{UT}. The users that are allocated the channels at time t use the channel for a fixed period of time depending on the transmitting characteristics of the users. This is based on the TSB as explained in chapter 2 before releasing the channel. Throughout this chapter only 4 users are picked randomly among all the users in the system to be the learning users, while the others are not learning.

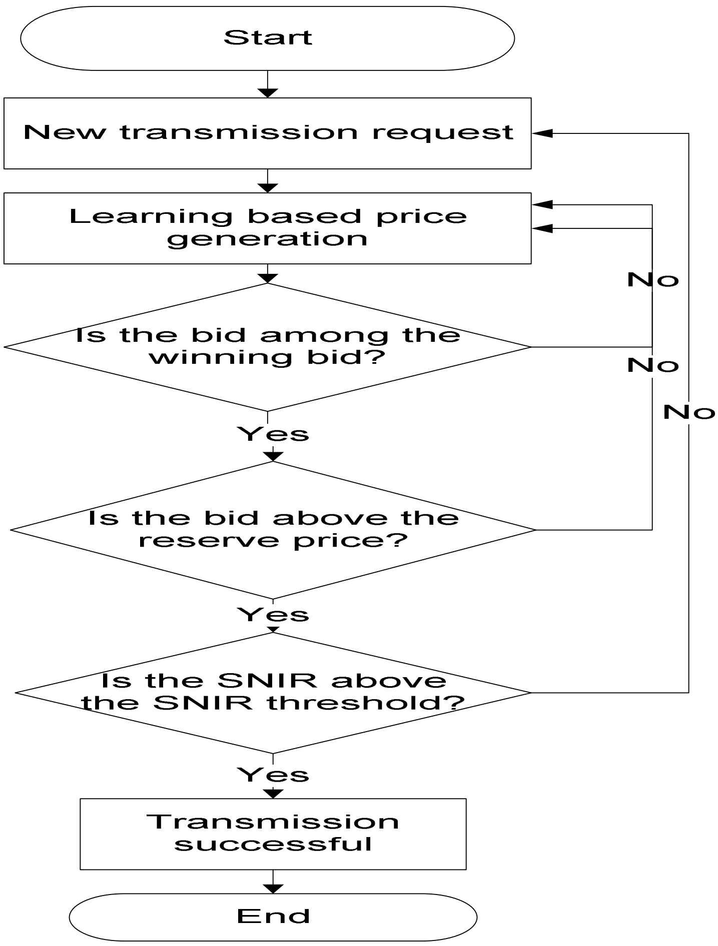

Figure 6.1. Learning Based Auction Process

The relationships that exist between the users in the system (N), users seeking the spectrum (N_{USA}) and the allocated users (N_{WU}) is as shown below and the total number of channels in the system (N_{TC}) and the number of available channels(N_{AC}).

$$N_{WU} \subseteq N_{USA} \subseteq N \tag{6.19}$$

$$N_{AC} \subseteq N_{TC} \tag{6.20}$$

During the allocation process, the winning users are allocated the channels provided the offered bid is above the reserve price and the SNIR of each of the winning bidders is above the set threshold $SNIR_{threshold}$. The other parameters used are as specified in table 3.1.

6.5 Evaluation of Learning in an Auction Process

This section examines the scenarios where learning can be adopted and the implications of the learning process converging at a sub-optimal point. This is done in terms of the energy and delay characteristics of the system. The weight associated with each offered bid examined has a wide range of values. Hence the weights are normalised as shown below:

$$W_n = \frac{W_p^y}{N_{\tau_a}} \tag{6.21}$$

Where $\boldsymbol{W_n}$ is the normalised final weight, $\boldsymbol{W_p^y}$ is the weight for the $\boldsymbol{y^{th}}$value in traffic load bin $\boldsymbol{P}$ and $\boldsymbol{N_{\tau_a}}$ is the total number of events or iteration for a particular offered value for the entire exploration period. Before discussing the results, one important concept relating to the understanding of the results is explained.

6.5.1 Learning Convergence

The learning process should lead to a convergence point as defined below:

Definition 1: The learning process is said to have converged if a user works out the optimal bidding price.

In this work, the optimal bidding price must obey rules 1 and 2 as stated below

Rule 1: The converged bidding price is the least price that gives the highest reward weight.

Rule 2: The convergence bidding price must optimise the utility value of the user, allowing the learning user to consume the least possible energy and the least possible delay in the system.

To prove the above rules, the different scenarios are examined and some assumptions are relaxed in order to understand the effects of such assumption on the performance of the system. The scenarios are modelled with the assumption that the auctioneer knows the optimal bidding price. This means that after the bids are submitted and analysed the auctioneer is aware of the price unit that gives the best utility performance. This assumption is reasonable because in a real world auction scenario, the auctioneer has the knowledge of the optimal bidding price after analysing the submitted bids. This is because the auctioneer collects all the bids from all the sources and determines the winner. However, the users do not have this knowledge hence, the need for learning the optimal bidding price.

It is a difficult task to show the performance of each of the bidding values and there is no point showing the values below the reserve price since such values can never be accepted by the auctioneer in the model. Hence the weight of some of the bid values after a number of iterations is shown in table 6.3 Based on the results in table 6.3, the optimal value that allows the bidder to win at least 50% of the time is above 49 price units.

Table 6.3: The number of times a bid value is used successful by a learning bidder

No of Events / Bid Value	50	100	200	300	400	500

47	0	0	0	0	0	0
48	0	0	0	0	0	0
49	4	12	19	49	71	96
50	27	57	113	184	255	343
51	39	78	155	240	323	401
52	41	92	189	286	356	463

The table shows that the reserve price is above 48 price units at a traffic load of 4 Erlangs. No user can win with any price below 49 price units. Therefore in the remaining results in the sub section, only values above 49 price units are explored. In other results, a similar range is examined depending on the traffic load in the system.

Before going into the modelling scenario, the importance of introducing equation 6.6 in the learning process is examined along with the convergence when more than one value has the same learning weight is determined. It can be seen that because the users want to win with the least possible amount, the utility equation allows the learning process to converge at the lowest price that ensures the least amount of energy is consumed by the system. If the price utility function is not taken into consideration there might be more than one convergence point after the exploration period, then from rule 1, the convergence value is the least value. This must be achieved before the learning process converges. The proof of this is quite simple. This is because for a bidding price to converge to the optimal bidding price, it must win the auction process most of the time. Hence, if a value wins the auction process, then any value above such value must also win assuming it was offered by a bidder in the same system. It can be seen from table 6.4 which shows the learning weight at a traffic load of 3 Erlangs that when the utility function is not taking into consideration that more than one bid value give the same weight value (i.e. 50-55 bid values). If this occurs from rule 1, the least offered price is the best bidding price however, to avoid this from happening, the utility function as defined in 6.6 is used so that the bid value that performs best can be easily identified.

Table 6.4 Weight of possible bidding values in traffic load bin

Bid Value	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**	**53**	**54**	**55**
Weight	27	32	35	39	48	90	90	90	90	90	90

From the above table, the converged bidding price is 50 price units based on rules 1 and 2. The reason for having the same weight after 50 price units is because any value above 49 price units the learning bidder wins all the time. It can also be seen from the above table that if the utility is not taken into consideration, it is difficult to have an optimal (single) value with the highest reward weight. This helps to show how the convergence in this work is defined and why equation 6.6 was introduced.

In order to show the consequences of the learning process converging at a non-optimal and the optimal point on the delay and energy consumption of the system, the total energy consumption and average delay per file sent for such convergence points are examined. Figure 6.2 shows the total energy consumed by only the learning users in the system if the learning process converge between 48 price units and 51 price units for a traffic load of between 1 and 4 Erlangs. It can be seen that below 4 Erlangs, all offered bids consume a similar amount of energy.

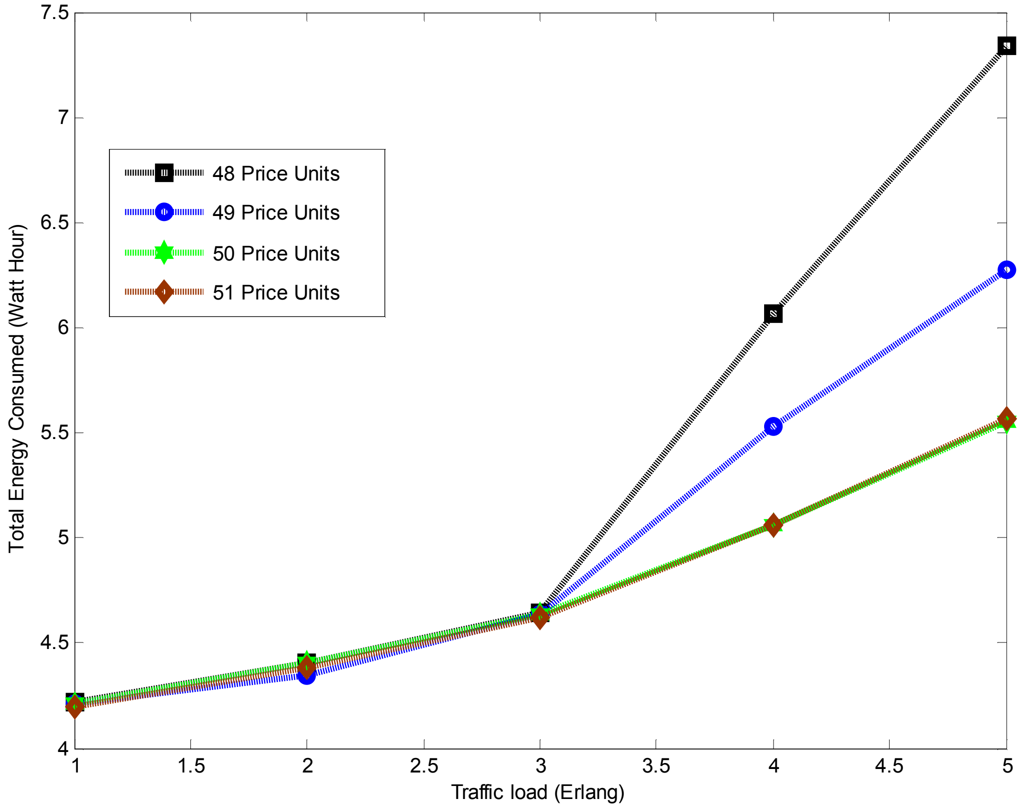

Figure 6.2. Energy consumed per file sent for different offered bid

This is because at lower traffic loads, such values (48 to 52 price units) are always higher than the bid offered by the non-learning users therefore, the exploiting users always win the auction process. However, at traffic load of 4 Erlangs, the offered bid of 48 or 49 price units gives higher energy consumed compared to offered bid of 50 and 51 price units. This is because with a traffic load of 4 Erlangs the offered bid of 48 and 49 price units are sometimes lower or the same as the bids of the non-learning bidders. Therefore, the non-learning bidders sometimes win the auction process at the expense of the learning users. The offered bid of 50 and 51 price units gives the lowest and the same amount of energy consumption per file sent at traffic load of 4 Erlangs because the exploiting users are able to win the bid using those values all the time. This again shows that at traffic load of 4 Erlangs the optimal price is above 49 price units.

Furthermore, the implications of the exploitation of such values on the delay experienced by the learning users in the system are examined in order to understand the effects. Figure 6.3 shows the average delay against traffic load for different offered bid values between 48 and 51 price units. It can be seen that below 4 Erlangs the energy consumption is the same for all offered bids and at 4 Erlangs the delay is almost the same for 50 and 51 price units. This is due to the reasons as explained earlier for figure 6.2.

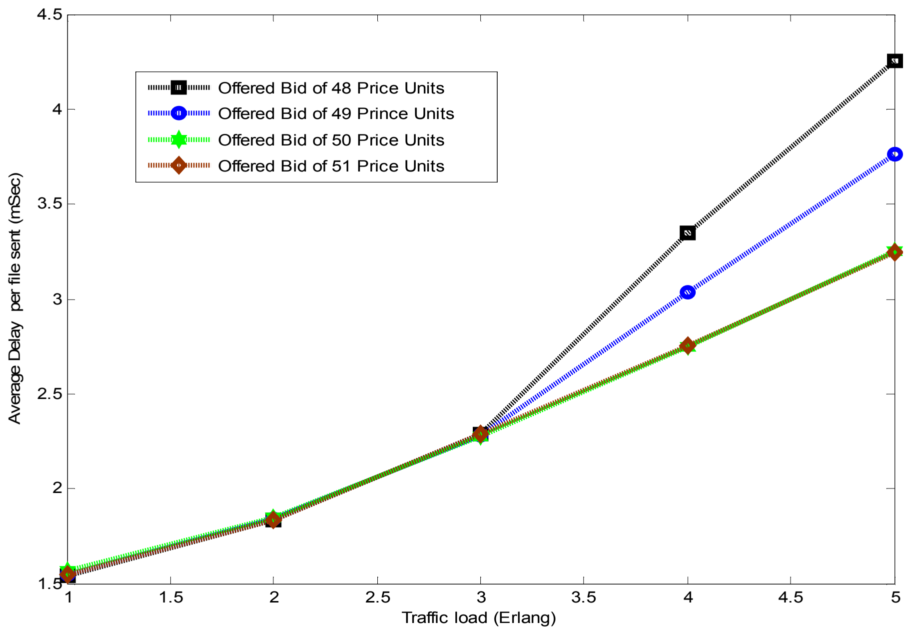

Figure 6.3. Delay per file sent for different offered bid

Furthermore, 50 and 51 price units also gives the least amount of delay because the learning bidder wins all the time if they offer either 50 or 51 price units as their offered bid. From figures 6.2 and 6.3, it can be seen that the best offered bid that guarantees a bidder winning at 4 Erlangs of traffic load is either 50 price units or above. However in terms of the utility (using equation (6.5)), it can be seen from figure 6.4 that 50 price units offer a better utility to the user.

Another important parameter to show is the utility of the users when the learning process converges at the optimal and non-optimal point in order to understand how satisfied the users are during the auction process. Figure 6.4 shows the utility obtained by the learning users when exploiting 50 and 51 price units respectively. Only the two offered bid prices are examined because they give the least possible consumed energy and delay as shown in figures 6.2 and 6.3 respectively. At an offered traffic level below 3 Erlangs, the utility obtained by exploiting 50 and 51 price units is very low because the exploiting users are winning the bids but they pay too much for the spectrum.

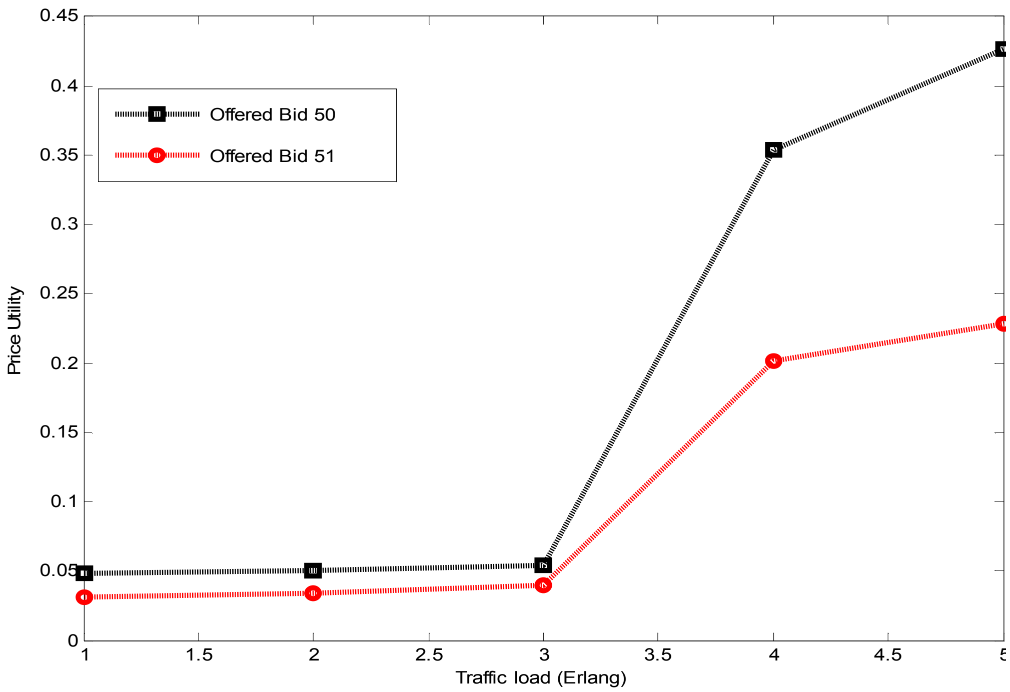

Figure 6.4. Utility obtained using 50 and 51 price units

This might lead to a situation known as 'the winners curse', which is defined as a situation where a bidding user exceeds the intrinsic value of the item purchased. At an offered traffic load of 4 Erlangs and above, the utility of the exploiting users improves because the bids offered by the non-learning users are relatively close to what is offered by the exploiting users. As expected, the offered bid of 50 price units gives a better utility compared to 51 price units.

The above results have demonstrated that by using the proposed scheme the learning process can only be said to have converged if a price units of 50 gives the highest weight during the learning process. From the definition of the convergence in this scenario it can be seen that 50 price units is the convergence bidding price. This is because the convergence bidding price must use the least consumed energy, deliver the least delay and achieve the best utility as stated in rule 2.

6.5.2 Evaluation of Different Models of Learning

In order to examine how fast each of the learning models converges, the three learning models are examined and compared in this section. The price utility is taking into consideration and the traffic load bin as explained is used in modelling this section. Figures 6.5 (a-d) - 6.7(a-d) show the weight of each of the offered bids after 100, 260, 400 500 iterations for figures (a), (b), (c) and (d) respectively when using linear reinforcement learning, Q learning and Bayesian learning respectively. First, it can be seen from the all the above scenarios that at 500 events, the converged price gave the highest reward weight. This is because the price utility was taken into consideration by assuming that the users want to win with the least possible value. It can also be seen that it takes about 400, 250 and 100 iterations for the learning process to converge using reinforcement learning, Q learning and Bayesian learning respectively. This shows that Bayesian learning converges fastest among the three learning methods. This is because Bayesian learning incorporates prior knowledge and this aids the learning process to converge faster than the other two methods examined.

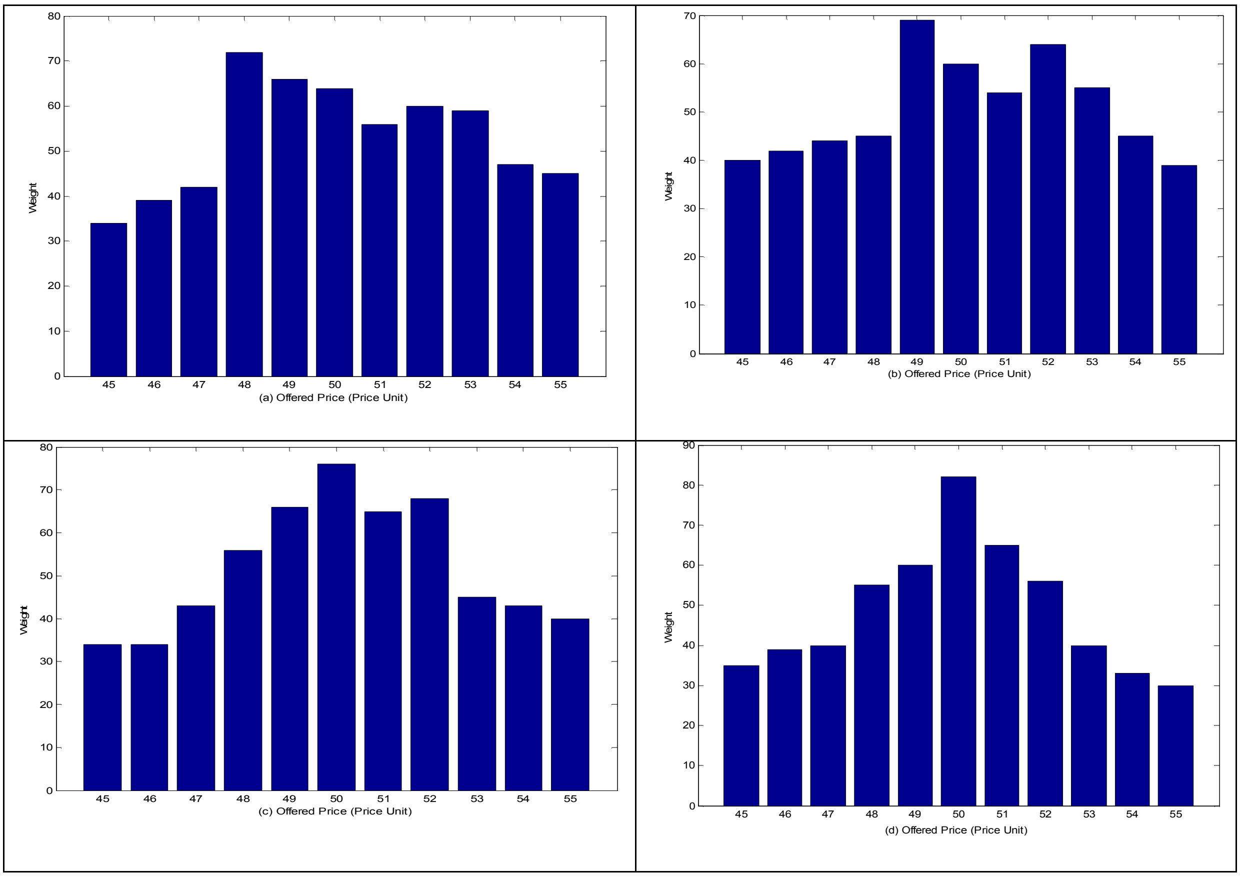

Figure 6.5. Linear Reinforcement learning for (a) 100 (b) 260 (c) 400 (d) 500 Events

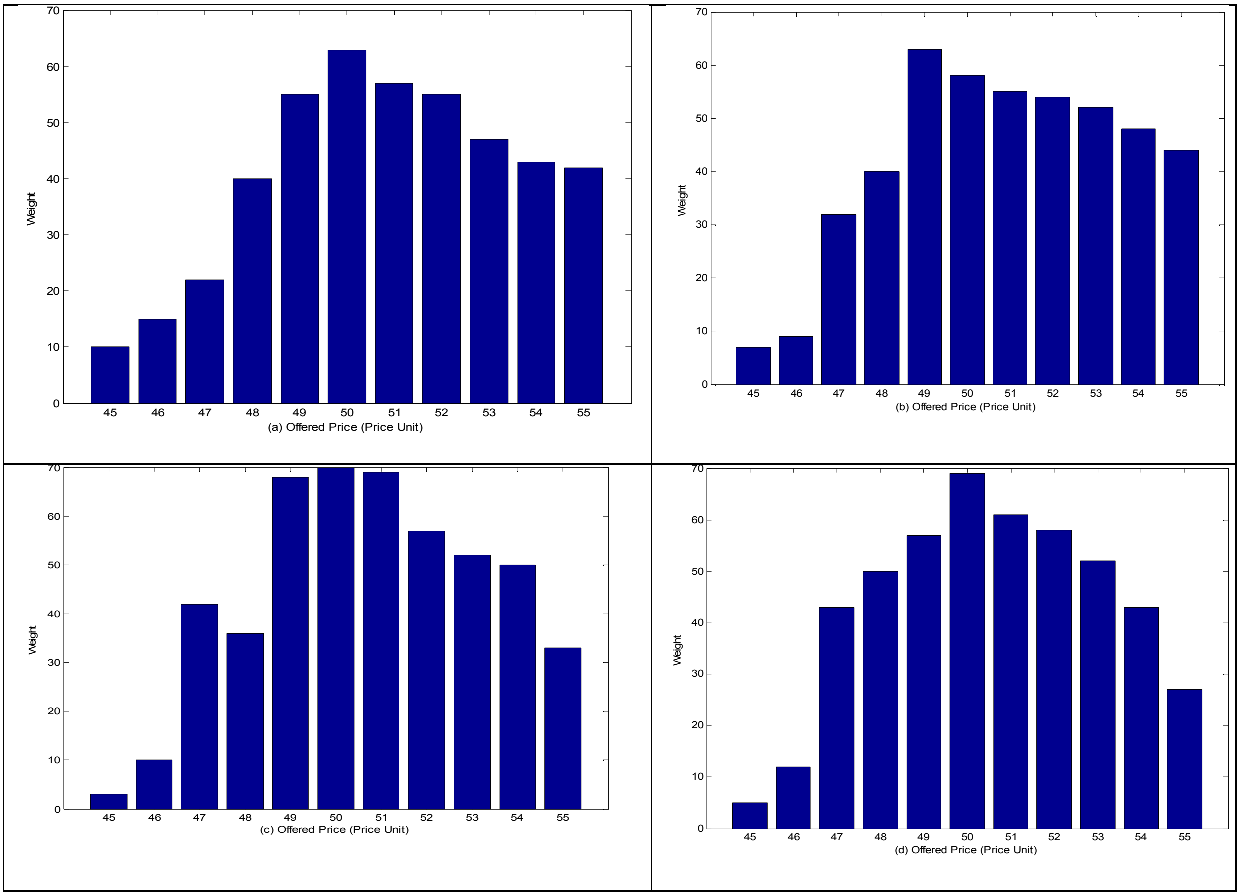

Figure 6.6. Q Learning for (a) 100 Events (b) 260 Events (c) 400 Events (d) 500 Events

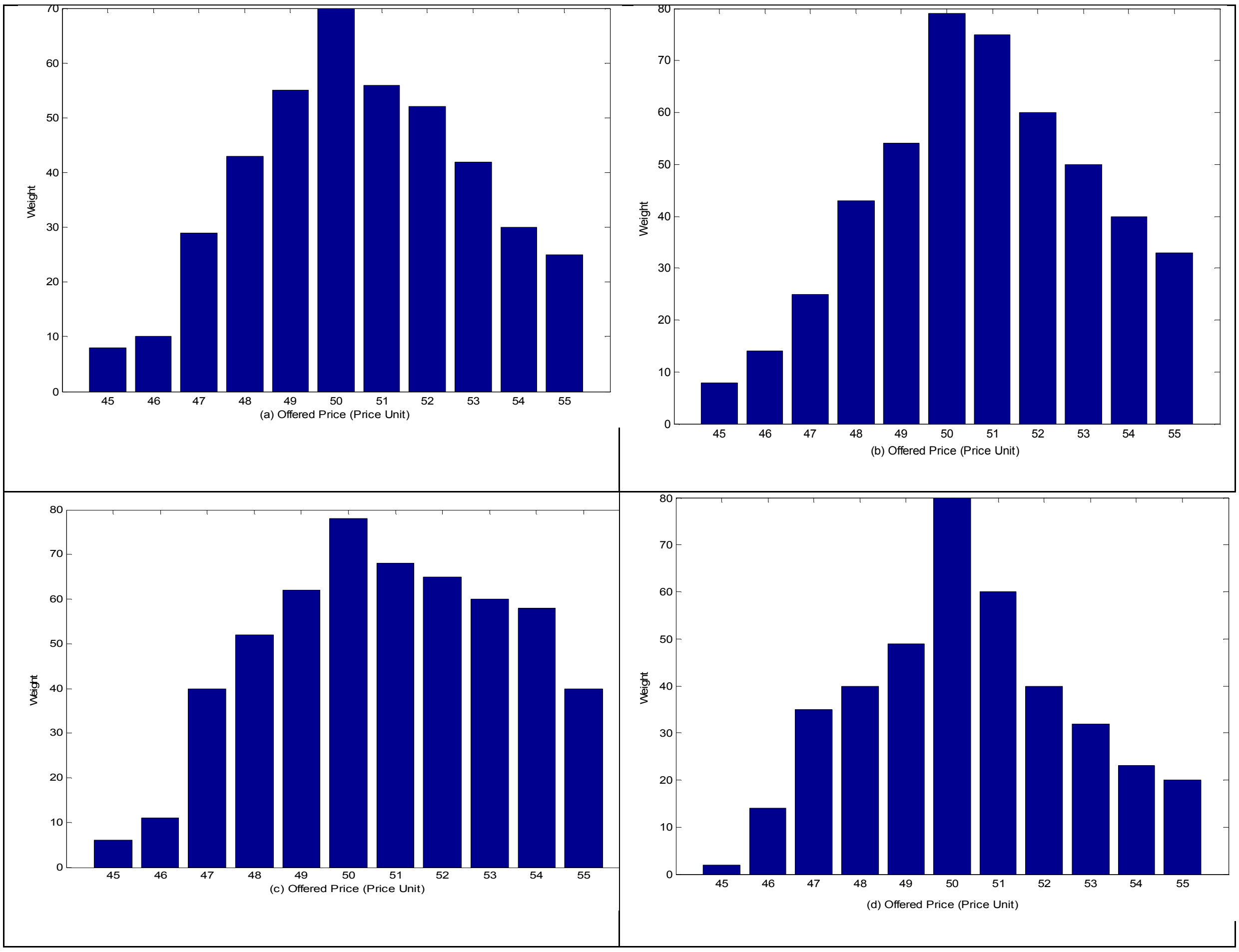

Figure 6.7. Bayesian learning for (a) 100 (b) 260 (c) 400 (d) 500 Events

After demonstrating that the Bayesian learning model converges fastest of the 3 methods, it is important to show the performance of the three learning models in terms of the energy consumed and the delay. This is to examine if the Bayesian learning method also helps with other performance metrics of the proposed system.

Figure 6.8 shows the average energy consumed using different learning methods and that of the non-learning user. It is worth pointing out that the moving average is used in generating the results in this chapter. This figure also shows that Bayesian learning which converges fastest compared to the other two learning methods gives the least consumed energy after convergence. It can be seen that for a learning user, as the number of events increases, the average energy consumed per file sent decreases. This is as a result of the learning process moving closer to the optimal point during the exploration process. As the number of events increases, the user learns the optimal bid until a steady state is reached. For the non-learning bidder the average energy consumed at steady state is higher when compared with the learning users. This is because the user does not learn the optimal value, rather the user wants to maximise utility.

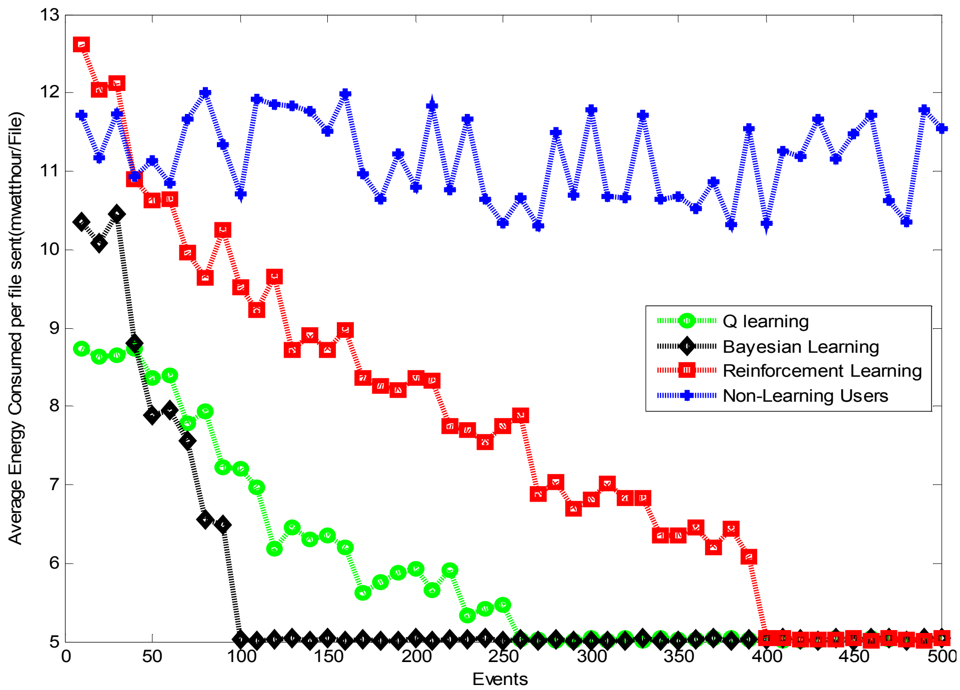

Figure 6.8. Average energy consumed for linear reinforcement learning Q Learning, Bayesian learning and non-learning bidders

Another important parameter in any wireless network is the delay. Hence the delay experienced during the exploration process is examined. Figure 6.9 shows the average delay per file sent in the system for the different learning methods and the non-learning users. The average used is the moving average. It can be seen that the average delay reduces as the number of events decreases for the learning users. This is because as the learning progresses the users learns to bid above the reserve price and reduces the probability of a file being rejected as a result of price. Just like in the energy graph, Bayesian learning reaches a steady state faster than Q learning and linear reinforcement because of the prior probability that has been incorporated. This shows that Bayesian learning helps in reducing the delay in the system during the learning process.

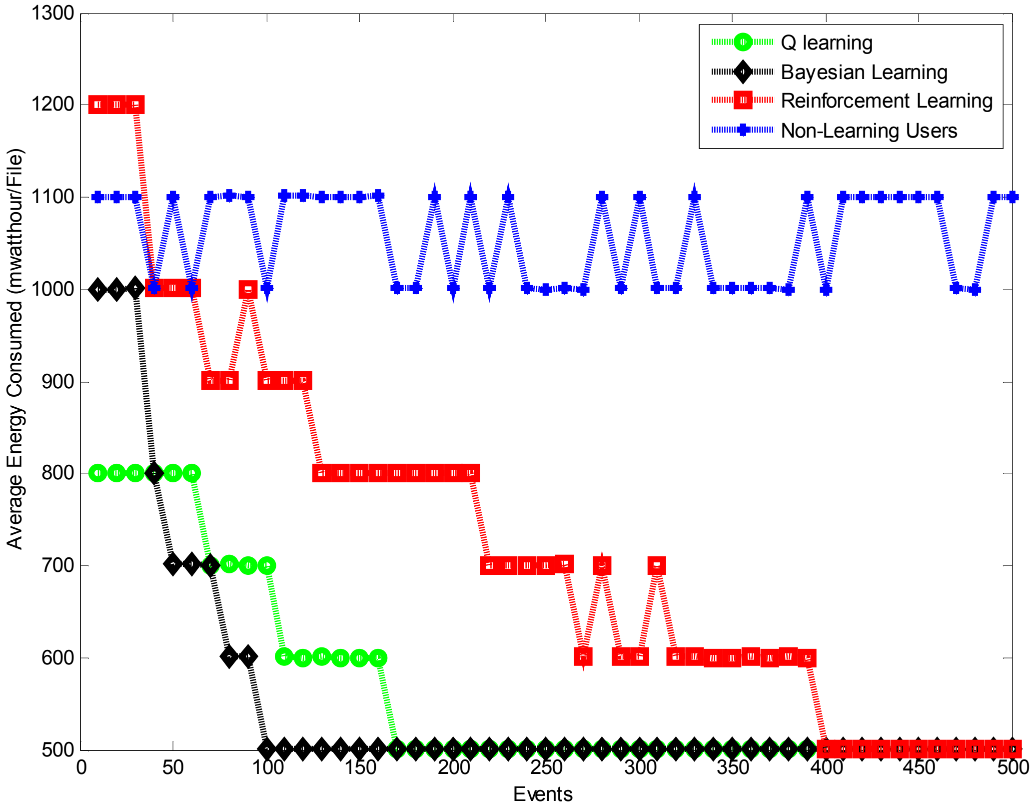

Figure 6.9. Average delay for reinforcement learning Q Learning, linear Bayesian learning and non-learning bidders

6.5.3 Learning Rate and Learning Efficiency

So far the performance of the system using modelling techniques has been shown. The three learning models using the learning rate and learning efficiency equations as explained earlier are now examined. These metrics are also important because they demonstrate how effective and how fast the models converge. The results are shown below

Table 6.5 Learning rate and efficiency of different learning schemes

Learning Model	Learning Rate	Learning Efficiency

Linear Reinforcement Learning	0.0011	0.24323
Q Learning	0.0016	0.2645
Bayesian Learning	0.005	0.27536

In terms of the learning rate as calculated for all the three models it can be seen that Bayesian learning performs best, since it takes the shortest time to converge. However, all the 3 models give approximately the same value in terms of the learning efficiency. This is because all the three models eventually converge at the optimal point and the useful learning increases as the total learning increases. This shows that all the three learning models can be used but Bayesian learning converges faster followed by Q learning and then reinforcement learning.

6.6 Conclusions

This chapter examined the concept of bid learning in an auction based dynamic spectrum access network. It showed how users can employ bid learning to learn the bid of their competitors so as to be able to place better bids using reinforcement learning, Q learning and Bayesian learning. Different learning methods were explored and the chapter showed that Bayesian learning performs best in terms of low energy consumption and low delay compared to the other learning models such as Q learning and reinforcement.

Chapter 7

A Game Based Energy Sensitive Spectrum Auction and Bid Learning Process for Dynamic Spectrum Access

Contents

7.1 Introduction

This chapter examines the concept of a game based model in combination with an auction process to characterise the interactions that exist between the different competing elements in an auction based DSA network. The use of these two concepts to model a DSA network can also be found in [73, 125-127]. A typical game deals with several entities or players that take decisions to maximise their utility. The action/decision taken by the players in a formulated game determines their utility and subsequently the Nash Equilibrium (NE) [72]. In chapter 6, the advantages of bid learning in terms of energy and delay reduction was formulated. This chapter uses a game model to examine how all the players in a heterogeneous wireless network can choose to learn different parameters about each other during an auction process, with the aim of minimising the energy consumed. It also seek to establish how a Nash Equilibrium can be achieved when all the players are learning and see the effects if the players decide to deviate from the Nash Equilibrium.

This chapter is organised as follows: Section 7.2 defines some of the new and important models used in this chapter. Section 7.3 defines the utility function adopted. Section 7.4 shows a modelling scenario where the different competing players can learn different parameters about each other using some of the obtained results. Section 7.5 defines the game model. In section 7.6 the models from chapters 4-7 are compared in order to show the improvements made. Section 7.7 gives the conclusions.

7.2 System Model and Parameters

The wireless users are divided into two groups, the HPU and the LPU. The three types of entity (WSP, HPU and LPU) form the players in the game model. The word "users" is used to refer to either the HPU or the LPU but not the WSP.

7.2.1 The Energy Model

The energy model used here is as explained in chapter 3. A user (i) whose bid is rejected because the offered price is below the reserve price $(b_i < r)$, or the bid is lower in comparison to that of the highest N_{AC} bidders is effectively wasting energy.

7.2.2 The Reserve Price

The reserve price used in this chapter is slightly different from the other chapters. Now a fixed reserve price is assumed provided the WSP is not learning. This is done so that the impact of having a reserve price can be observed during the formulated game. However, when the WSP is learning, the WSP formulates a dynamic reserve price for each of the users as explained and used in chapters 4-6. Hence, when the WSP is learning, the reserve price is dependent on the traffic load in the system. The idea behind this assumption is that the WSP can only observe or change the reserve price provided the WSP is able to observe the bids of the users, the traffic load and the available resource in the system, and then use such information to learn the appropriate value for the reserve price. This assumption is reasonable because without learning the parameters, the reserve price might be set too high or low, leading to congestion or underutilization. Hence, it is formulated as shown below:

$$r = \begin{cases} r \propto Traffic\ load, & When\ WSP\ is\ Learning \\ fixed, & \text{When WSP is not learning} \end{cases} \tag{7.1}$$

7.2.3 The Users Bid

In an auction process, the bid of a user is important as it determines if the user wins or loses at the end of the process. To simplify the bid generation process, a concept called the Offered Bid Bin (OBB) is introduced. The OBB is like a lottery/raffle basket containing different bid values. A bidder dips into the bin (depending on the belief of the user) and picks a bid value. It is assumed that A_{bs} bins are available in the system and they are arranged in an ascending order. Each bin contains a specified range of continuous values ($OBB_1 < OBB_2 < OBB_3 \dots OBB_{A_{bs}}$). This means that a bid picked from OBB_2 is greater than a bid from a bid picked from $OBB_1 (b_i^{OBB_1} < b_i^{OBB_2} < b_i^{OBB_3} \dots \dots b_i^{OBB_{A_{bs}}})$. Where $b_i^{OBB_{A_{bs}}}$ is the bid value picked by user i from $OBB_{A_{bs}}$.

A user intending to seek access to the radio spectrum picks a bid from any of the bins depending on the user's belief regarding the values of the bids submitted by other users in the system. It is quite similar to the traffic load bin used in chapter 6. However, unlike in chapter 6 where the bids are assumed to be a discreet value, here the values are real numbers within the given monotonically increasing range function, which are assigned to the specific OBB. A continuous distribution is used rather than a discrete distribution in order to avoid all the learning users from picking the exact same value as sometimes occurs in chapter 6. Another difference is that the bins in the OBB are not associated with the traffic load. The OBB is formulated as explained because the assumption in chapter 6 that a user knows the system's traffic load might not always be true, as such information is available mainly to the WSP.

7.2.4 The Users Belief

As stated earlier, the offered bid of a user depends on the belief of the user regarding the bids of others. This sub-section describes how a user selects the belief during the auction process. Two beliefs models are proposed, the greedy (non-learning) and the learning model.

7.2.4.1 The Greedy or Non-learning Model

A user using the greedy model is assumed to be myopic and only intends to maximise its utility by bidding a low value. Such a user is known as extremely price sensitive bidder [128]. The bidder does not mind wasting energy by losing the auction process. Hence, it is assumed here that such a user is not learning the bid of the others or the reserve price.

7.2.4.2 The Learning Model

Learning about the optimal bidding price can be useful to control the traffic load in the system especially when the system is congested in addition to the reduction in consumed energy and delay as demonstrated in chapter 6. Users that use the learning model are assumed to be interested in always winning or not wasting energy hence, such players learn different parameters (as shown in figure 7.1 and explained below) in order not to lose the auction process.

LPU Learning

A LPU receives a form of subsidy using the green payment equation as explained in chapter 4, (while the HPU are taxed using the same green payment equation). It is assumed that the LPU are provided with the information about the previous bids of the HPU in additional to the incentive received from the WSP. This information is used by the LPU as the prior information during the learning process. The WSP provides such information only to the LPU because as shown in chapter 4 the WSP prefers the LPU transmitting rather than the HPU. This is because in a small cell scenario with channel reuse the utility of the WSP can only be maximised if all channels in all cells are allocated. This can only be done if the interference in the system is kept low as explained and shown in section 5.3.2.

HPU Learning

A HPU can only learn about the bids of the LPU based on an estimated prior knowledge while using the Bayesian learning model [64]. In this chapter, the HPU learn to understand when the LPU are not transmitting in order to increase their chances of winning the auction process.

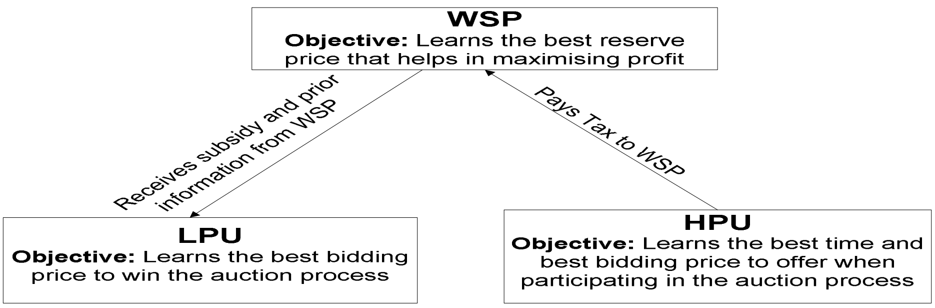

Figure 7.1: Summary of the learning process

WSP Learning

The information available to the WSP is the bids submitted by the users. The aim of the WSP is to maximise revenue. Therefore, the WSP learns the user's reservation price. The reservation price is determined by the user's budget (as explained in chapter 2). If the reserve price is higher than the user's reservation price then no user is able to pay hence, the spectrum is not utilised. On the other hand if there is congestion in the system the WSP can increase the reserve price in order to prevent more users attempting to transmit. Therefore, the maximum possible price that a user can pay plays an active role in determining the best value of the reserve price. The chapter adopts the Bayesian bid learning method because it gives a better performance as shown in chapter 6. However, Bayesian learning requires a prior probability distribution and hence, the Dirichlet distribution is introduced.

7.2.5 The Dirichlet Distribution

The Dirichlet distribution is a continuous multivariate probability distribution which can be used in Bayesian learning [129, 130]. It is used because it allows a prior probability to be derived in a multi-agent scenario such as an auction process [64]. The distribution is a discrete probability parameterised by a set of non-negative hyper parameters used as a generalization form for the beta distribution. The distribution is usually referred to as a conjugate prior. This is because a Dirichlet prior gives a Dirichlet posterior. Suppose an event X_i has been observed a number of times represented as $\alpha_i - 1$, where $i = 1 \ldots. J, J$ represents the number of possible outcomes. Such outcomes can be the possible offered bid values that a user can bid $(b_1, b_2 \ldots. b_j)$. This can be shown as a Dirichlet distribution,

$$F(x_1 \ldots. x_{K-1}; \alpha_1 \ldots. \alpha_k = \frac{1}{B(\alpha)} \prod_{i=1}^{J} x_i^{\alpha_i - 1} \tag{7.2}$$

Where $B(\alpha)$ is a normalization factor expressed as a gamma factor as shown below:

$$B(\alpha) = \frac{\prod_{i=1}^{j} \Gamma(\alpha_i)}{\Gamma(\sum_{i=1}^{j} \alpha_i} \tag{7.3}$$

$$\alpha = (\alpha_1 \ldots \ldots \alpha_j)$$

The above equation is well defined only when the elements in α are non-negative. The non-negative (α) is known as the hyper parameter.

Using the Dirichlet distribution to generate the prior is quite useful. It allows for the prior distribution to have a lesser influence on the posterior distribution as the learning progresses. It also allows the agent to update the bid distribution relatively easily by updating the parameters $(B(\alpha))$. In an auction scenario if a learning user fails to win, the user can update the Dirchlet parameter by setting $B(\alpha)$ to the new value in the next round. The update distribution is then used to improve the learning in the next round.

7.3 The Utility Function

A utility function measures the payoff of the players. In this chapter, it is defined for each set of players using a power utility function because of its rapidly increasing nature. It is as used and explained previously in chapter 6. All the players are assumed to be rational and they seek to maximize their utility. The utility function of the users is divided into four parts: the utility based on the bid value (U_B), the utility based on the OBB (U_{OBB}), the utility based on the energy consumed per file sent (U_E) and the utility based on the green payments (U_R). These four factors are taken into consideration because they are regarded as the important measures of the satisfaction of the users in relation to the system performance.

7.2.1 Utility in Terms of the OBB

The higher the OBB a user picks a bid from, the lower the utility of the user in terms of the OBB. This means that a user that picks a bid from OBB_1 has a higher utility value in terms of the OBB compared to a user that picks a bid from OBB_2 or higher ($U\left(OBB_{A_{bs}}\right) < U\left(OBB_{A_{bs}-1}\right) \ldots., U(OBB_2) < U(OBB_1)$). This is because the users are price sensitive and the users aim is to win with the least possible amount. This assumption is quite strict because even though a losing bidder needs to increase the offered bid, the probability of winning the user's utility value in terms of OBB drops using the equation below. The assumption is however reasonable because the users aim to win with the least possible amount.

$$U_{OBB} = 2^{\frac{OBB_i}{OBB_{A_{bs}+1}}} - 1 \tag{7.4}$$

Where OBB_i is the bin where user i picks a bid and $OBB_{A_{bs}}$ is the bin containing the maximum possible bids. The bin ($OBB_{A_{bs}}$) that contains the set of maximum possible bid values has the least utility. $OBB_{A_{bs}+1}$ is used as the denominator in order to avoid a user picking a bid from $OBB_{A_{bs}}$ and having a utility of zero.

7.2.2 Utility in Terms of the Actual Offered Bid

The utility in terms of the actual offered bid allows us to differentiate between users picking a low value of the bid to those picking a high value from the same OBB. As an illustration, a user offering a bid of 5.55 picked from OBB_5 has a lower utility compared to a user picking 5.95 from the same bin. The utility is formulated as shown below, where set $\boldsymbol{N_{WU}}$ represents the winning bids in a bidding round

$$\boldsymbol{N_{WU}} = \{b_1, b_2, b_3 \dots b_{N_{WU}}\} \tag{7.5}$$

$$\delta = \begin{cases} (\max(\boldsymbol{N_{WU}}) - \min(\boldsymbol{N_{WU}}) & for\ b_i < \max(\boldsymbol{N_{WU}}) \\ \max \boldsymbol{N_{WU}} + d_k - \min(\boldsymbol{N_{WU}}) & for\ b_i = \max(\boldsymbol{N_{WU}}) \end{cases}$$

(7.6)

$$U_B = \begin{cases} 2^{\frac{Max(N_{WU})-b_i}{\delta}} - 1 & If\ a\ bidder\ wins \\ 0 & otherwise \end{cases} \tag{7.7}$$

b_i is the bid of any user i. If a bidder is not among the winning bidders, the utility of such a user is zero. The lower part of equation 7.6 contains a fixed value d_k which is specified in the parameters table. This is used for the user with the maximum bid to prevent a user from having a utility function value of zero. The value of d_k is picked to be quite small so that it does not affect the utility of the highest bidder.

7.2.3 Utility in Terms of Energy Consumed During the Bidding Process

From the energy model, the more efficient a user is in terms of offering a bid that is accepted by the WSP, the more energy efficient the user is. A user whose bid is never rejected is considered to be more energy efficient compared to a user whose bid is sometimes/often rejected. This is because a user can only participate in the bidding process when in the ON state as explained earlier in chapter 3. It is measured as shown below:

$$U_E = 2^{\left(\frac{N_{FS}}{N_{FG}}\right)} - 1 \tag{7.8}$$

Where N_{FS} is the number of times a user has sent a file successfully, N_{FG} is the number of times a user i has attempted to send a file but the users bid was rejected as a result of price. A rejected bid as a result of other factors (apart from price) is not considered as part of F_i.

7.2.4 Utility in Terms of the Green Payments

The utility in terms of the green payments is set to determine the satisfaction of the user depending on the value of the received green subsidy. The higher the amount of green payments subsidy received, the higher the utility of a user in terms of the green payment. However, it is assumed that a user paying a tax has a utility value of zero in terms of the green payment. This is done in order to allow for the simplification of this work rather than having a negative utility.

$$U_R = \begin{cases} 2^{\frac{R_i}{R_{max}}} - 1 & for\ Green\ Subsidy \\ 0 & For\ Green\ tax \end{cases} \tag{7.9}$$

R_i is the green payment tax/subsidy for user i respectively, R_{max} is the maximum subsidy.

7.2.5 The Overall Utility of the User

The overall utility of each of the user can vary between 0 and 1 as shown below:

$$U = \frac{\frac{U_R+U_{OBB}}{\omega}+U_B+U_E}{2+\frac{2}{\omega}} \tag{7.10}$$

Where ω can vary between 1 and 2. This is done in order to vary the impact of U_R and U_{OBB} on the utility value. ω is specified in the parameters table 7.1. It is introduced to reduce the weight associated to the utility in terms of the green payments and the OBB because it is assumed that they have less impact on the general utility of the users in this model. The components of the utility function that has less impact depend on the on the service offered by the system. This is because the satisfactions derived by users vary with the offered service. The peak point in figure 7.2 might be difficult to achieve because a user might prefer one factor more than the others, depending on the application in use. It can be as shown below.

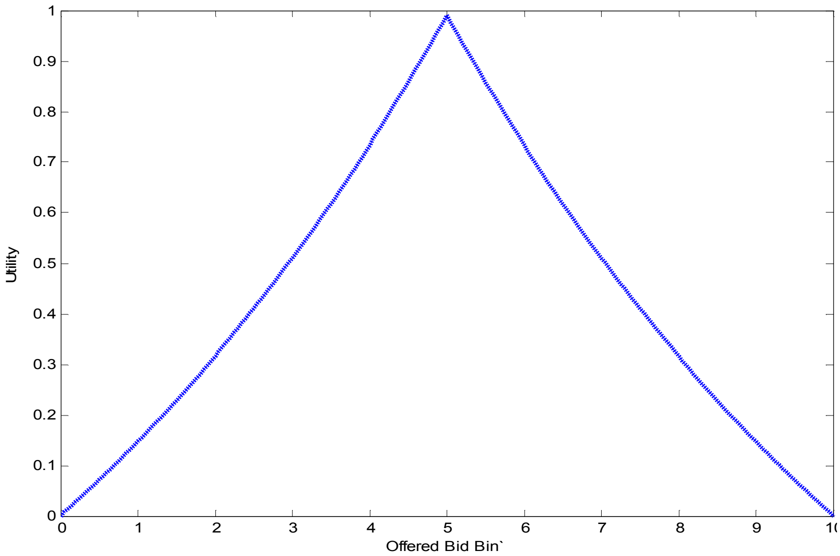

Figure 7.2. Illustration of the Utility Function

Another important player in the game model in this chapter is the WSP. Therefore the utility of the WSP is also considered.

7.2.6 Utility of the WSP

The utility of the WSP is based on the total revenue obtained. It is as shown below:

$$u_i(t)=2^{\frac{N_{CAU}(t)}{N_{TC}(t)}}-1 \tag{7.11}$$

Where $N_{CAU}(t)$ is the total number of channels that was available and used up till time t and $N_{TC}(t)$ is the total number of channels that was available in the system up till time t. This utility is related to the revenue because if a channel is not occupied, the WSP is losing some revenue.

7.4 The Modelling Scenario

A cognitive network with users seeking access to the spectrum in an opportunistic manner is modelled, where N_{USA} out of the possible N users in the system are competing for N_{AC} unlicensed channels (where N_{AC} is the number of available channels). A multi-channel scenario ($N_{AC} > 1$) is modelled using an uplink scenario. Users that require the use of the spectrum submit a bid based on their belief using the OBB. Two types of beliefs are used in this chapter as explained earlier. The bid of each user is either taxed or subsidized using the concept of green payments as used in chapters 4 and 5. The channel is allocated to the highest bidder(s) represented as N_{WU} using the first price sealed bid auction with a reserve price. The transmit power of the user depends on the group in which the user belongs as explained in chapter 4. All users in the same group transmit at the power level. The WINNER II B2 propagation model is used as detailed in [89]. The remaining parameters used in the simulations are as given in table 7.1 in addition to the ones in table 3.1.

Table 7.1 Parameters used

Parameters	**Value**
A_{bs}	12
d_k	0.001
ω	1

The truncated Shannon equation is used to model the transmission rates of each of the users as detailed in [86]. The Dirichlet distribution is used in generating the prior and the posterior distribution for the learning players and the flow chart is as shown below shown.

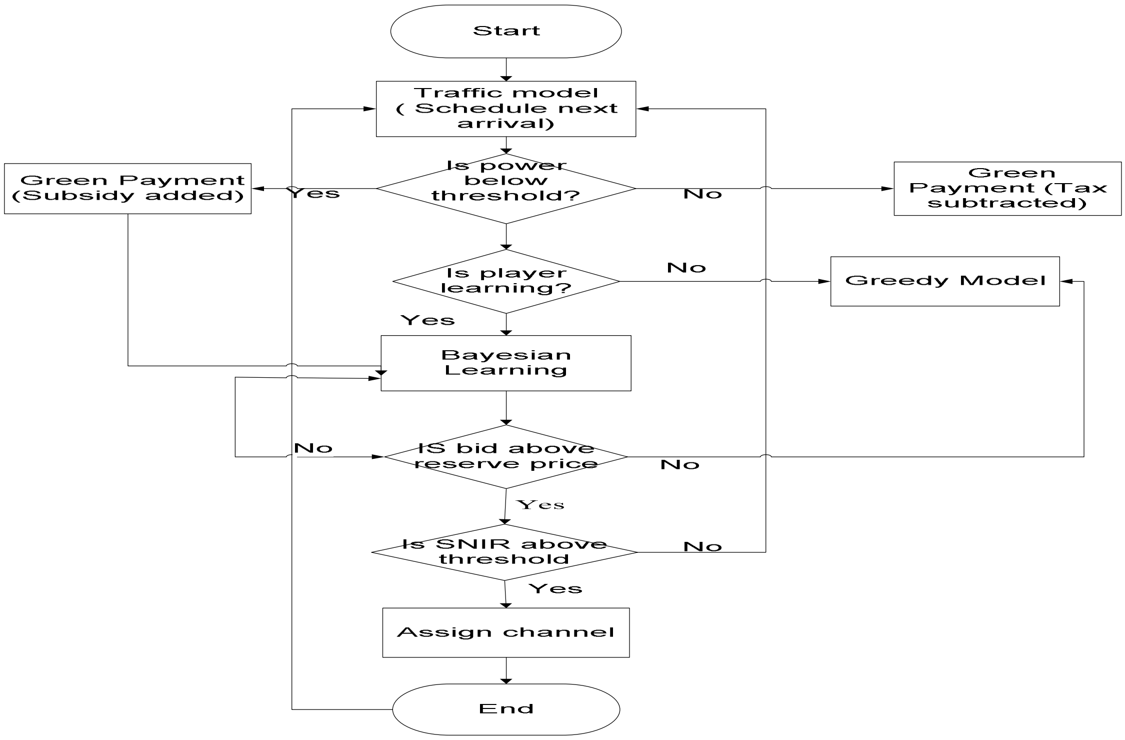

Figure 7.3. System Flow Chart

The algorithm for the learning process is summarised below:

1. Treat the unknown parameter (Probability of the bids) as a uniform random variable
2. Assume the prior distribution for the unknown parameter
3. Update the distribution of the parameter based on data $(B(\alpha))$
4. Compute the hyper parameter (α)
5. Finally compute prior probability and the posterior probabilities $P(B|A)$

For the LPU the prior distribution in step 2 is provided by the WSP. The users compute the posterior probability for all the possible value of OBB. The user picks a random bid from the distribution of the OBB with the highest $P(A|B)$. This is repeated until a steady state is reached. During the iterations, the utility obtained is repeated for a number of times before another OBB is examined.

7.4.1 Efficient Exploration Based on Transfer Learning

In order to understand the effects of transfer learning on the time taken for the learning process to converge, the models with and without the transfer learning are considered. Figure 7.4 shows the energy consumed by the system when the traffic load is 4 Erlangs. In this model, all the users in each of the two groups are allowed to learn individually as they arrive in the system. The players are not allowed to share information about what they have learnt. This led to the long learning period compared to figure 7.5 where the users are allowed to transfer what they have learnt to others provided they belong to the same group.

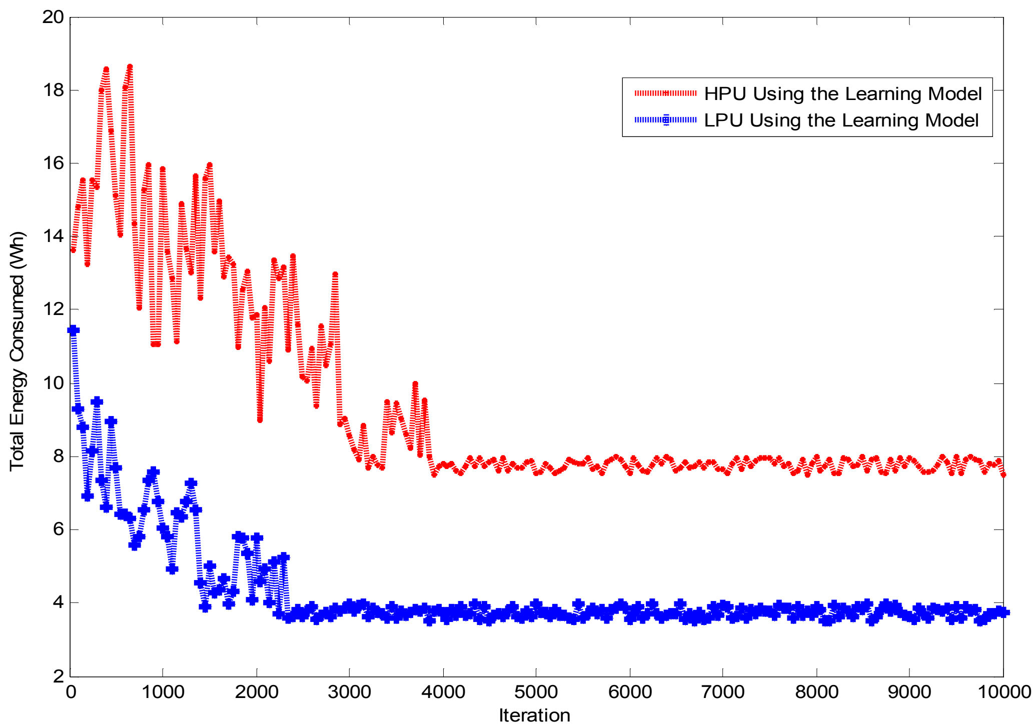

Figure 7.4. Energy consumed per file sent against number of iteration using the individual learning scheme

The longer learning period in figure 7.4 is because the learning process converges after all the learning users in the system have completed their learning process individually rather than having a sort of information exchange as done in figure 7.5.

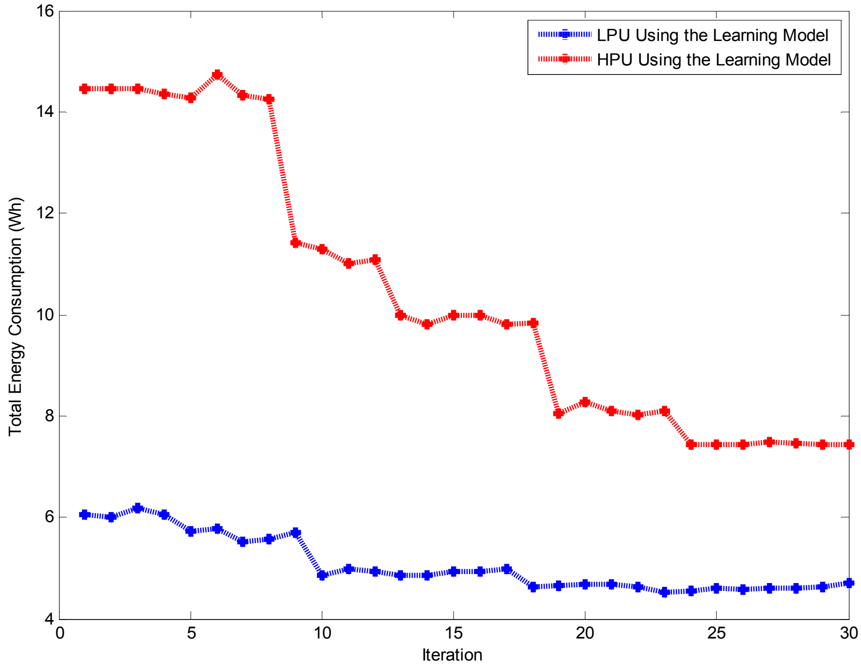

Figure 7.5. Energy consumed per file using transfer learning between users in the same group

Hence, in order to reduce the exploration period transfer learning is introduced, where the players in the same group can share information regarding the reserve price, the traffic load in the system and the optimal bidding price. The Bayesian learning model used in this work also incorporates a form of transfer learning due to the prior knowledge involved. However, the users in this model went further by processing the prior information collectively. Transfer learning is used in the remaining results in this chapter

7.4.2 Performance Analysis

In order to understand the reasons behind the game formulation, a scenario where only the WSP and one of the user group is learning while the other players are using the greedy model is examined. This is done mainly because of two reasons. First, it enables the understanding of the behaviour of each of the players. Second, it helps in examining if the players can learn different parameters about each other. The result obtained is the average for each of the players. As an example the utility function obtained in the results is calculated as shown below:

$$U = \frac{\sum_{1}^{N_{USA}} U_i}{N_{USA}} \tag{7.12}$$

Figure 7.6(a) shows the offered price against the number of iterations by the LPU and the HPU when the LPU are learning and the HPU are using the greedy model. Figure 7.6 (b) shows the offered price against the number of iterations for the two user groups for the converse case where the HPU are learning and the LPU are using the greedy model. Here, an iteration is the same as a bidding round as defined in chapter 2. It can be seen that as the number iterations increase, the offered bid also increases for both the HPU and the LPU with the use of learning. However, the average price is the same throughout either when the LPU or HPU are adopting the greedy model. This is because the learning users explore all the different OBB starting from the least OBB that gives the highest probability while using the Bayes formula as explained earlier. This continues until the user discovers the OBB that gives the highest utility value. As the learning progress, the probability attached to each OBB is updated. The distribution used in the prior probability is also updated. The reason for the learning process of the LPU taking fewer iterations (this might not be obvious with figure 7.6 but it is obvious with figure 7.7) is because they obtain prior knowledge from the WSP as stated earlier. Therefore, the OBB with lower values give a lower probability value when Bayes formula is applied and they are not exploited. However, the HPU does not get such prior information from the WSP and therefore, all the OBB are assigned the same prior probability at the beginning of the learning process. From figure 7.6 (b) it can be seen that the peak price paid by the HPU is about 25 price units. However, this is not the same as the price obtained at steady state (after 36 iterations). This is because the user exploited a higher offered traffic bin but the utility of the user fell hence, the user moves back by exploiting the bin that gives the highest utility to complete the learning process.

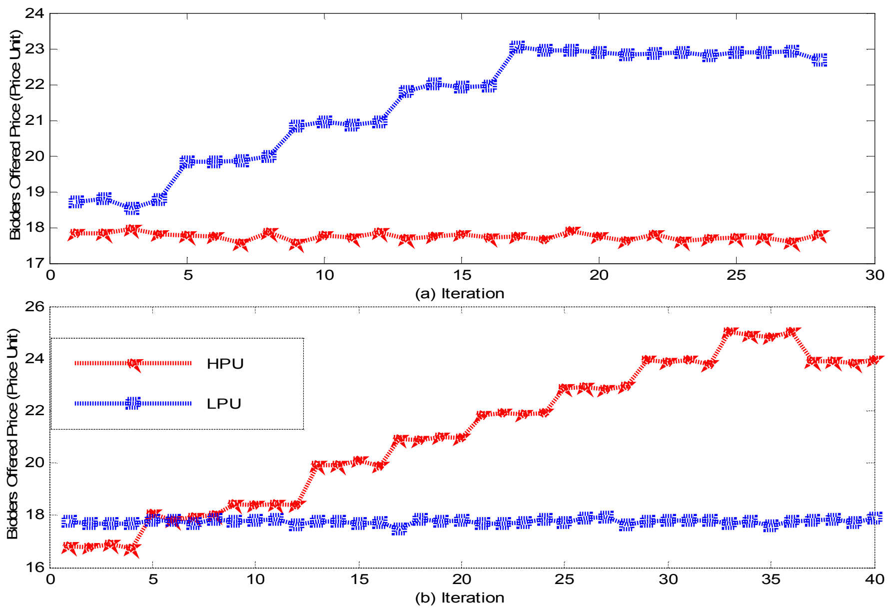

Figure 7.6.(a) The offered bid for LPU learning (b) The Offered bid for HPU learning

Another important parameter that is considered is the utility function. Figure 7.7 shows the average utility function obtained by the LPU and the HPU when the LPU are learning and the HPU are adopting the greedy model at a traffic load of 4 Erlangs. As the number of iteration increases, the utility obtained by the LPU increases until after about 20 iterations when the utility falls, then increases again on the 24th iteration. The fall in the utility is because at the 21st iteration, the learning users (LPU) explore a higher price from a higher OBB. This gives a lower value of utility. This is because as the value of the OBB increases the utility of the user in terms of OBB decreases. However, from the general utility equation given in equation 7.10, it can be seen that the U_E is added to U_{OBB} therefore, a high value of one (either U_E or U_{OBB}) and a low value of the other gives a lower combined utility to the user. This is also true even when the other components in the utility equation are considered. The utility equation shows that the maximum utility that any user can obtain is when the utility from all components is high. Therefore, after 20 iterations when the learning LPU increases its price as seen from figure 7.6 the utility drops. This is because at that point the utility in terms of the consumed energy is at the maximum value and utility in terms of OBB reduces thus the general utility obtained falls. When the utility drops after exploring a new OBB, the learning user moves back and exploit the OBB that gives the highest utility At this point the learning process is completed. Figure 7.7 (b) shows the average utility obtained against traffic load in Erlangs when the LPU are learning and the HPU are using the greedy model. The result shows that as the traffic load increases, the maximum utility obtained by the two group's decreases. This is because at low traffic loads the HPU and the LPU can avoid each other since the traffic in the system is low. Hence, the players in the two user groups can transmit, but as the traffic load increases the gap between the utility obtained by the two groups widens out. This is because the HPU are forced out of the system to accommodate the LPU. As the traffic in the system approaches 4 Erlangs (which is the maximum that can be accommodated) more HPU are refused access. Hence, the learning process makes more difference.

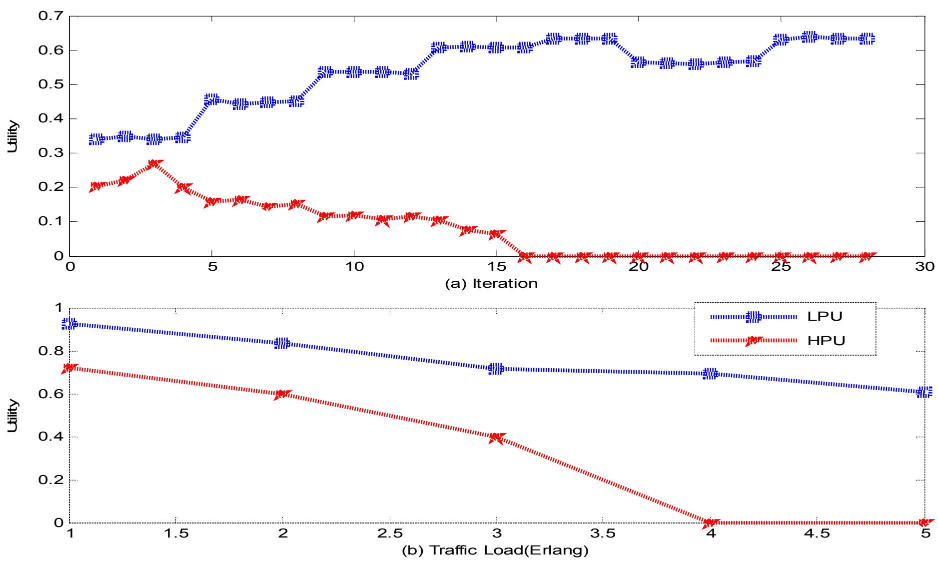

Figure 7.7. The utility obtained when the LPU are learning

Figure 7.8(a) shows the utility obtained against the number of iterations when the HPU are learning and the LPU are using the greedy model at a traffic load of 4 Erlangs. The result obtained is similar after the initial zero utility to the result obtained in figure 7.7. However, the learning process takes longer. This is because at the beginning of the learning process the HPU does not have any prior knowledge. Hence, an equal probability is attached initially to all the possible values in all the OBB. Therefore, the HPU takes a longer time to learn the optimal bid values and the OBB that gives the highest value of utility. At the start of the iteration, the HPU explores the OBB with values less than the reserve price and hence the reason for the initial zero utility. The reason for the rise then sudden fall after the 28th iteration is the same as explained for the LPU. Figure 7.8(b) shows the average utility obtained by the LPU and the HPU against the traffic load. It can be seen that at low traffic loads the difference between the utility obtained by the learning HPU and the non-learning LPU is not greatly significant compared to values at higher offered traffic. This is because at lower traffic loads the green payments subsidy is applied to the bids of the LPU to encourage them. Another reason for this observation is that at low traffic loads most of the users intending to transmit are able to do so because there are more free channels. However, as the traffic load increases, the number of users is significantly more than the number of available channels. This shows that even when the LPU obtain a form of subsidy from the green payments and the HPU are taxed, the learning users still have an edge over the greedy users.

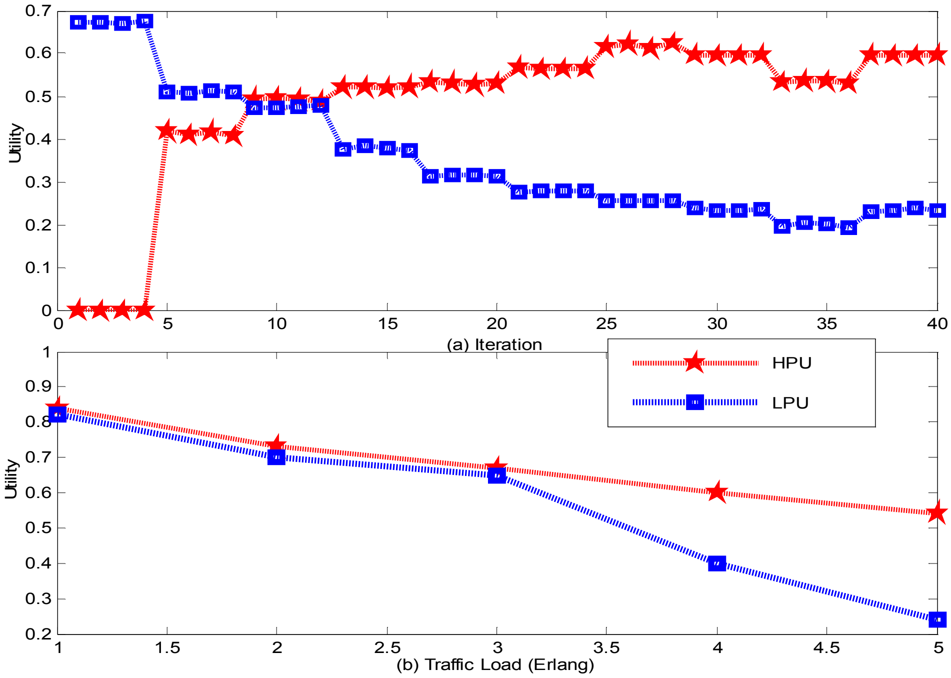

Figure 7.8 The utility obtained when the HPU are learning

Figure 7.9 (a) shows the obtained average energy consumed per file sent when the LPU are using the learning model and the HPU are using the greedy model at a traffic load of 4 Erlangs. It can be seen that as the learning progresses for the LPU, there is a slightly drop in the amount of energy consumed by the LPU players in the system compared to that of the HPU in figure 7.9 (b). This is because at the beginning of the process, the LPU does not explore the OBB whose values are lower when compared to what is provided by the WSP in terms of the offered bid of the HPU because of the prior knowledge. The average energy for the HPU after the 18th iteration is zero because at that point no HPU are allowed into the system. Hence, it is not because the HPU are not consuming energy at that point but they are not able to send any file so the average energy per file sent is zero.

Energy consumption is one of the important parameters considered in this thesis hence the energy consumed using the game model is examined. Figure 7.9(b) shows the average energy consumed per file sent when the HPU are learning and the LPU are using the greedy model.

It can be seen that the average energy consumed by the HPU is initially zero. The reason for this is because at that point the HPU explore the OBB whose bid values are less than the reserve price and since no user can win a bid if the offered bid is less than the reserve price, the bids of all the HPU are rejected and no file is sent. Hence, the have average energy per file sent is zero. As the learning process progresses the HPU are able to send files and the average energy consumed begins to drop. It is worth pointing out that at the highest OBB which gives a lower utility value to the LPU reduces with the number of iterations unlike that of the HPU. This is due to the green payments offering a subsidy to the LPU. With higher OBB, more HPU are able to get in at the expense of the LPU but because the gain due to U_E is not as significant due to the loss, as a result of reduced utility due to U_{OBB} the utility of the HPU drops. It can also be seen from the same figure that that average energy consumed by the LPU is increasing but it is still lower compared to that of the HPU because of the varying transmit power that each of the user is using in order to obtained the desired bit rate.

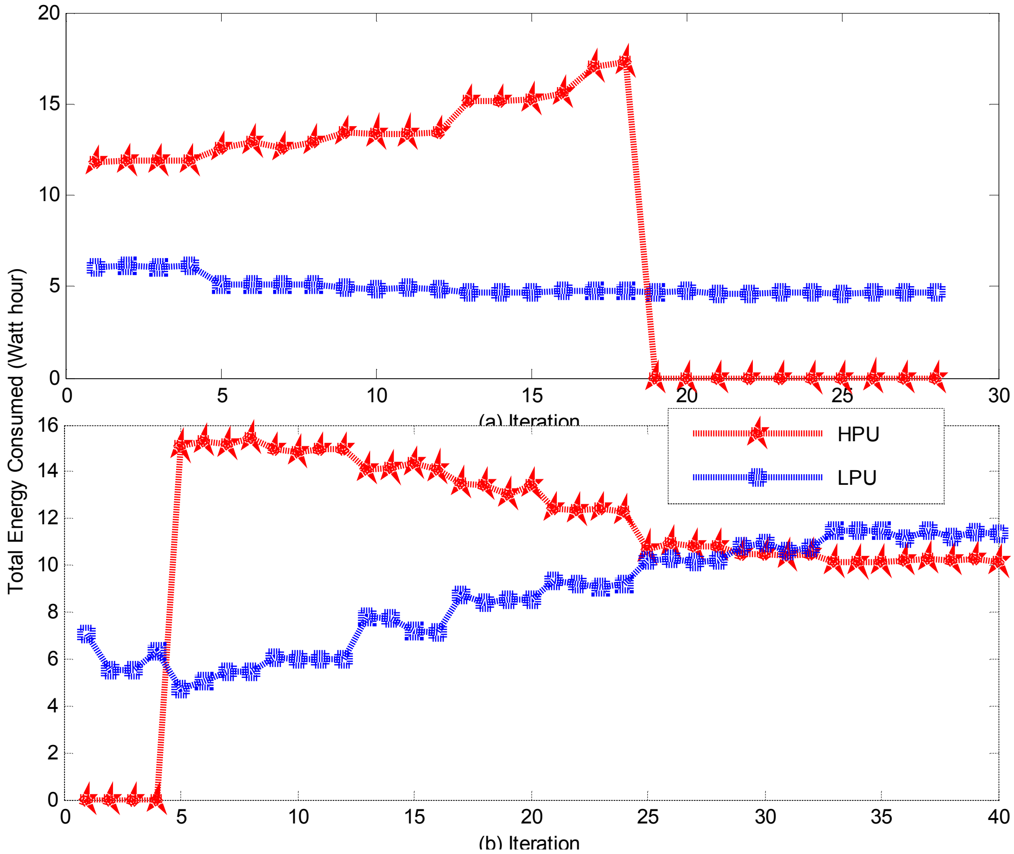

Figure 7.9. (a)Energy consumption for LPU learning (b) Energy consumption for HPU learning

Figure 7.10 (a) shows the utility obtained by the by the WSP against iteration at a traffic load of 4 Erlangs when either of the two user group is learning or adopting the greedy model. The WSP has a better utility when the LPU are learning compared to when the HPU are learning. This is because when the HPU are learning, the interference caused by the HPU is significantly more than when the LPU are learning. Therefore, it forces some of the winning users to abort their transmission because their SNIR falls below the SNIR threshold. This result also shows the reason why the WSP prefers the LPU in the system compared to the HPU hence, the subsidy and the prior information. The Utility of the WSP also increases as either the LPU or HPU are learning because as the learning results in more channels being used out of the total.

Figure 7.10(b) shows the utility obtained by the WSP against the traffic load. The utility of the WSP increases with the traffic load because at lower traffic loads not all the available channels are in use all the time, but as the traffic load increases, an increasing number of channels are in use. Given the utility equation for the WSP, the greater the numbers of channels in use the higher the utility of the WSP. This is because the aim of the WSP is not to have a channel idle when it can be in use. This also increases the revenue obtained by the WSP.

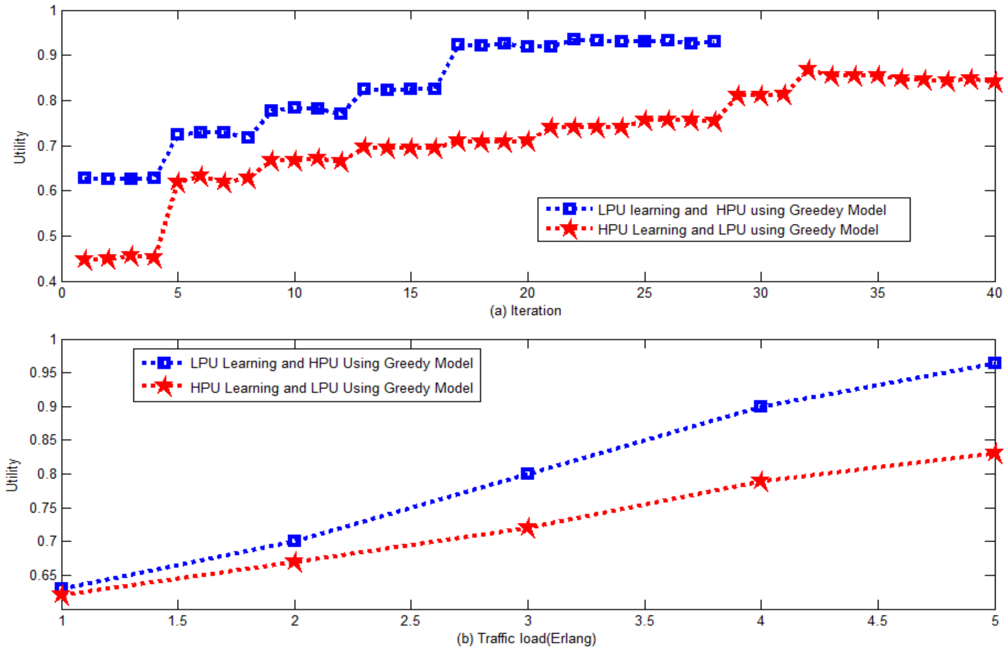

Figure 7.10. The Utility of the WSP

From the above obtained results (figure 7.6 to 7.10), it can be seen that due to the prior information obtained, the LPU does not have a problem by offering a bid below the reserve price. This is because the prior knowledge can only suggest a bid above the reserve price. However, the HPU has this problem because from the initial iteration all the OBB are assigned a uniform prior probability since no prior information is obtained from the WSP. If the HPU does not learn the reserve price and only offer bids below the reserve price, the HPU are wasting energy by switching into the transmuting mode and denied access as a result of reserve price. Furthermore, it is better for the HPU to learn the traffic load in the system and choose to stay out. This means they do not attempt to transmit when the traffic load in the system is high given the fact that at high traffic loads the HPU might never be successful at the expense of the LPU. This is obvious from the green payments model. This might be harsh to the HPU but the reality is that both the LPU and HPU are opportunistic users in the system hence, it is in the system best interest for them not to cause significant interference to the primary user should be primary user decided to transmit. In view of above and due to the peculiar nature of bid learning as explained earlier, a learning process is modified to allow the two user groups to learn simultaneously in the game model so that the energy consumed can be minimised.

7.5 The Game Model

This chapter has so far demonstrated that each player can learn different parameters about each other by showing how and what each player can learn. The game model is now used to examine the utility of the learning users compared to the non-learning users. This section also investigates if a player can increase their utility by unilaterally changing from the learning model to the non-learning model or the other way round. The already formulated utility functions in section 7.3 are used.

A game model is used to study the allocation of the spectrum in order to obtain a satisfactory and a fair energy efficient auction based mechanism. As formulated earlier, this chapter assumes a game which can be represented as a tuple $\boldsymbol{G}= [\boldsymbol{P}, \boldsymbol{A}, \boldsymbol{U}]$. Where $\boldsymbol{P}$ represents the set of players in the game, $\boldsymbol{A}$ represents the set of actions that is available to the players and U is the payoff or the utility obtained by taking an action. The players are represented as $\boldsymbol{P}= [G_{HPU}, G_{LPU}, W]$. Where, G_{HPU} represents the HPU, G_{LPU} represents the LPU and W

represents the WSP. Two actions are available to the players to either learn or use the greedy/non-learning approach $\boldsymbol{A} = [A^l, A^g]$. Each of the players aim is to maximise the obtained utility by bidding using the bid value that offers the maximum possible utility. The utility of the WSP depends on the revenue received as explained in section 7.3 of this chapter. The players in the same group form a coalition. In this coalition, they share information such as the optimal OBB with each other. Therefore, a transfer learning scenario as explained earlier is assumed. The aim of the game is to examine how a Nash Equilibrium can be achieved.

Each group of players can choose different actions (A^l or A^g) but the players in the same group can only choose or use the same action in an auction round. This means that if the G_{LPU} decides to learn, all the users in the group are learning. If G_{LPU} is not learning then no user in that group can decide to learn. This is the same for G_{HPU} and the WSP.

In the game formulation, a player belonging to G_{LPU} learns the optimal bid value by learning based on the prior probability provided by the WSP using Bayesian learning or adopting the greedy model. Each G_{HPU} can decide not to use the greedy model by learning the likelihood of being among the highest bidder and stays out if the likelihood is low. Depending on the value of the likelihood, the number of HPU that should attempt to bid during the next bidding round is determined. The equation of the likelihood is formulated such that the number of HPU attempting depends on the available channels and the offered bid of the users. This prevents a situation where the users are attempting to access the channels with either a low value of offered bid or when few channels are available in the system. This is because in such scenarios, it is most likely that the channels would be allocated to the LPU who are also attempting during the same bidding round. The formulation is as shown below:

$$P_r(i) = (\frac{b_i - b_m}{V_{max} - b_m})^{N_{USA} - N_{AC}} \qquad N_{USA} > N_{AC} \tag{7.14}$$

Where b_m is the value of the reserve price if known to the user otherwise it is the minimum possible bid by user i based on the budget of the user. V_{max} is the maximum possible valuation for a user per file and b_i is the bid for user i. The probability is calculated for all the HPU users. If the probability is high for all the HPU attempting to transmit, then they are allowed, but if it is low, only a fraction are allowed as shown in equation (7.16). The users allowed are picked in descending order of the probability. The numbers allowed depend on the arriving users and the numbers of channels available. This is because at low traffic loads more HPU can be allowed, the numbers allowed decrease as the traffic load increase. It is as shown below:

$$N^{a}_{USA_{HPU}}(t) = P_r N^{ar}_{USA_{HPU}}(t) \tag{7.15}$$

Where $N^{ar}_{USA_{HPU}}(t)$ is the total number of HPU who arrived and wants to transmit during a transmission period t, $N^{a}_{USA_{HPU}}$ is the number of arriving HPU that are allowed to attempt to transmit after multiplying by the probability and P_r here is probability calculated from equation (7.14). This shows that the higher the likelihood, the higher the number of HPU allowed into the system. However, using the equation to determine the number of users allowed is not optimal. Therefore, the HPU varies the probability (P_r) in equation 7.14 and learns the optimal value for each traffic load provided P_r is positive initially. The equation is used in generating the prior probability and it serves as basis for the learning process. The HPU users use Bayesian learning to learn the optimal number of users to be admitted into the system by exploring different numbers starting from the minimum provided by equation 7.14. Furthermore, the WSP also learns the traffic load which is used to fix the reserve price. When the system is congested (at traffic load of 4 Erlangs and above) the reserve price is fixed in such a manner that only bids from the highest OBB can be above the reserve price. Therefore, the HPU paying the green tax are denied complete access to the spectrum. In this model it is assumed that that WSP is also learning the traffic load in this system using that Bayesian learning model in order to fix the appropriate reserve price. Below are the summary of the assumptions:

- Players are rational and are seeking the best action which they understand to be the actions that maximise their utility
- All the players who are users (G_{HPU}, G_{LPU}) have the same budget (B) per file and no user can spend above his budget under any condition
- A participating user in each group submits a bid $(b_1, b_2, b_3 \ldots . b_{N_{USA}})$ where N_{USA} is the number of users submitting a bid.
- All users in the same group pick the bid value using the same OBB provided they are bidding in the same bidding round.
- All the players can either chose to learn or adopt the greedy approach.

7.5.1 Performance Analysis

Examining the performance of the system using the modelling scenario, figure 7.11 shows the utility obtained by the HPU and the LPU against iteration at 3 Erlangs. In the game formulation, the LPU learn the OBB that gives them the highest utility while the HPU learn the traffic load in the system. A traffic load of 3 Erlangs is used in the game formulation because at 4 Erlangs the HPU are never allowed to transmit in the system as explained earlier. Therefore, no results can be obtained for the HPU.

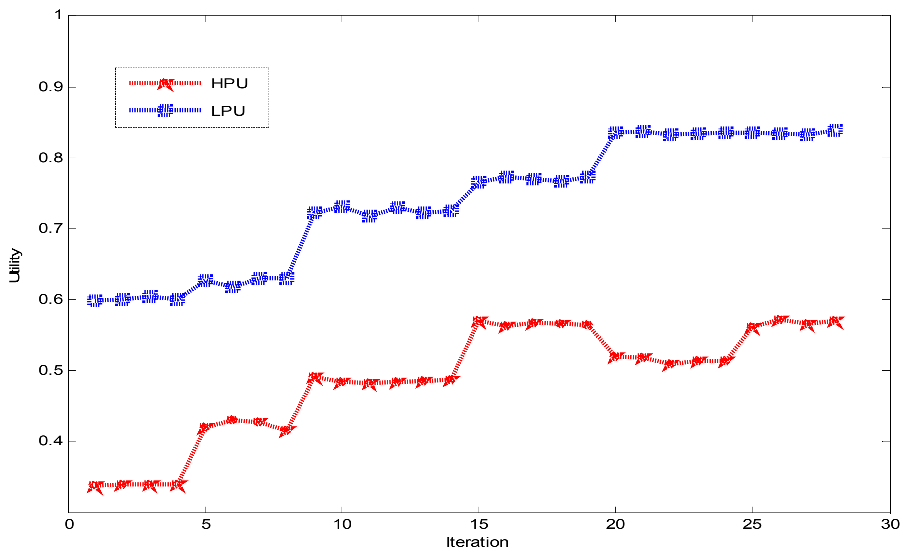

Figure 7.11. Utility of HPU and LPU when both are learning.

The utility obtained by either the LPU or the HPU increases as the learning progresses. However, at the 20th iteration the utility of the HPU decreases because the HPU are exploring the possibility of allowing more HPU to attempt to transmit but such users are unable to transmit therefore the utility in terms of U_E reduces. It is worth pointing out that throughout the game formulations it was assumed that the HPU has learnt the best OBB to use and is only picking bids from the best OBB. Therefore, U_{OBB} for the HPU is constant. The utilities obtained by the LPU are more than that of the HPU because the LPU are giving more priority to transmit compared to the HPU because of the green payments. The above figure showed the utility of each user that is learning. The results if one of the players is deviating from the learning process is now showed in order to examine the effects of such user deviating.

Figure 7.12 (a) shows the average utility obtained by all the users in the system when all the 3 players are learning and the average utility when one of the three players is deviating from the learning model. The average for one deviation is shown because on the average, the utility graph of any player deviating looks similar. Hence, the three utilities are summed together and the average is used. It can be seen that if one of the players is deviating, the utility is lower compared to when all the users are learning. This is because if any of the players is not learning, energy is wasted and the utility obtained is lower. Figure 7.12(b) shows utility obtained by the system (all three learning) against traffic load. As the traffic load increases, the utility obtained reduces. This is because increasing the traffic load increases the number of arriving users in the system and reduces the utility that each of the users can obtain.

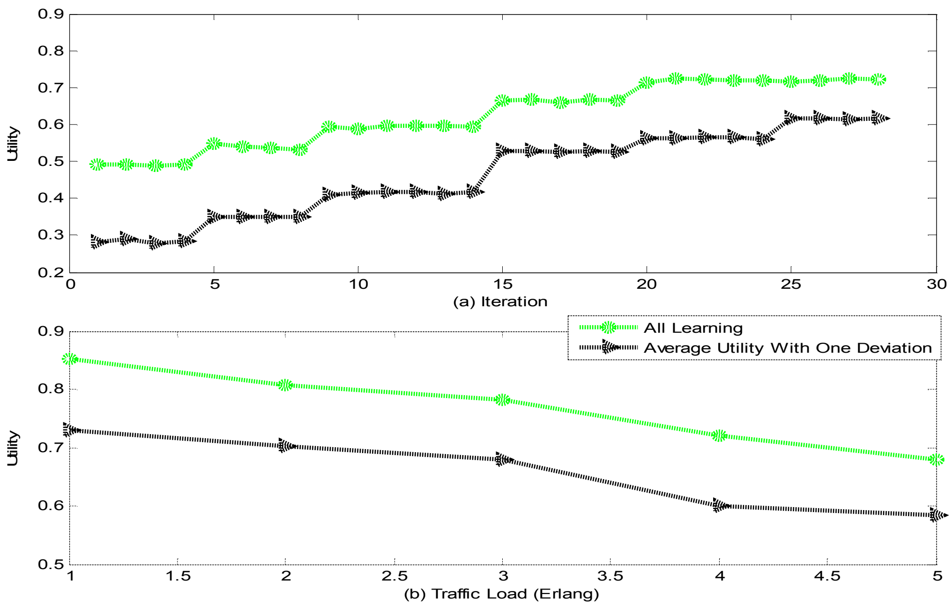

Figure 7.12 Utility for all the 3 players learning and utility for one player deviating

Figure 7.13 (a) shows the average energy consumed by the system when the LPU and the HPU are learning. The LPU consumes less energy compared to the HPU. This should be expected because of the difference in their transmit powers. As the learning progress, the energy consumed is reducing. This is because the users are learning to use either the optimal bidding price to find out the appropriate number of users to be introduced into the system depending on the traffic load in the system.

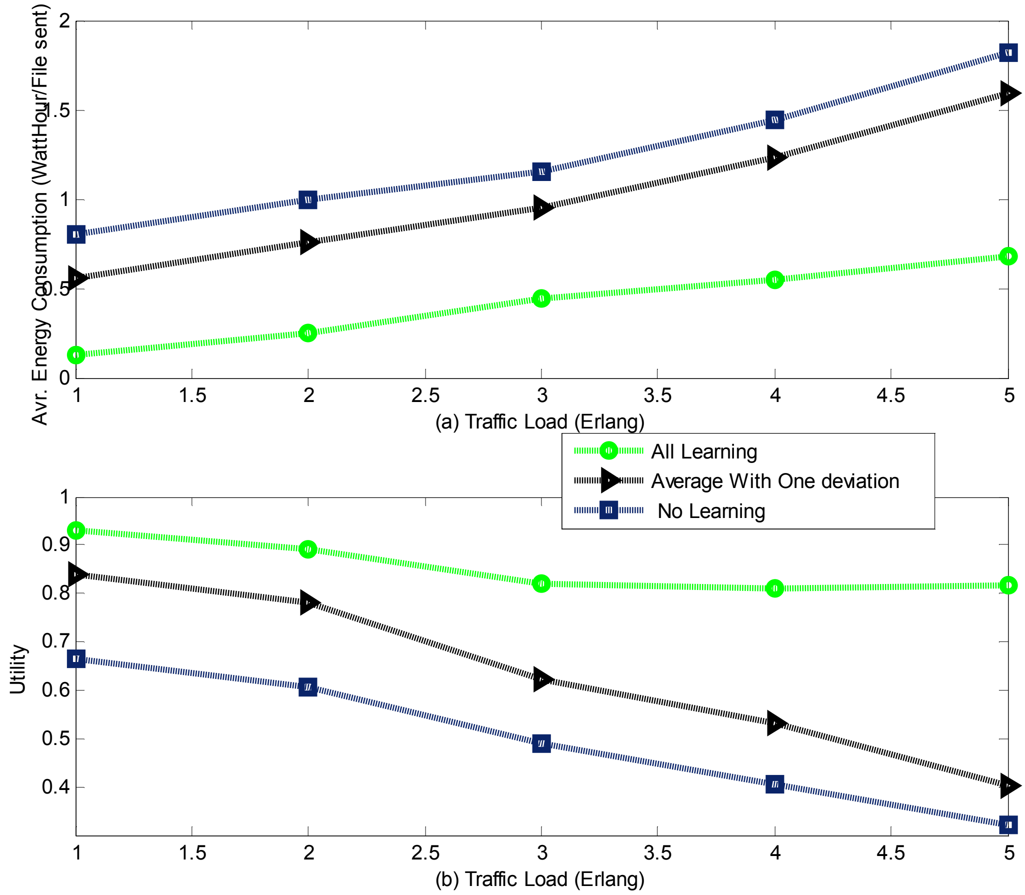

Figure 7.13. The Average energy consumed by LPU and HPU (b) The Average energy consumed by all learning and average with one of the players deviating

While figure 7.13 (b) shows the total energy consumed by the system (both HPU and the LPU) when all the users are learning and the average energy when one of the user is deviating from the learning model. It can be seen that the average energy consumed with one deviation is significantly higher. This is because when one of the players is not learning, the energy consumption level of the players is increased compared to when all the three players are learning. The learning process gets better for the learning players as the number of iteration increases and the amount of energy consumed reduces until the best utility is obtained.

Figure 7.14 (a) shows the average energy consumed per file sent against traffic load with all three players are learning, the average with one of the users deviating from the learning model and when none of the players are learning. It can be seen that as the traffic load increases, the energy consumption increases for all the scenarios. This is because as the traffic load increases the collision and activity in the system increases. When all the three players are learning the average energy consumption is lower and the reason is the same as explained for figure 7.13. It can be seen that using the proposed model an average of 40% of energy is saved compared to when none of the users are learning.

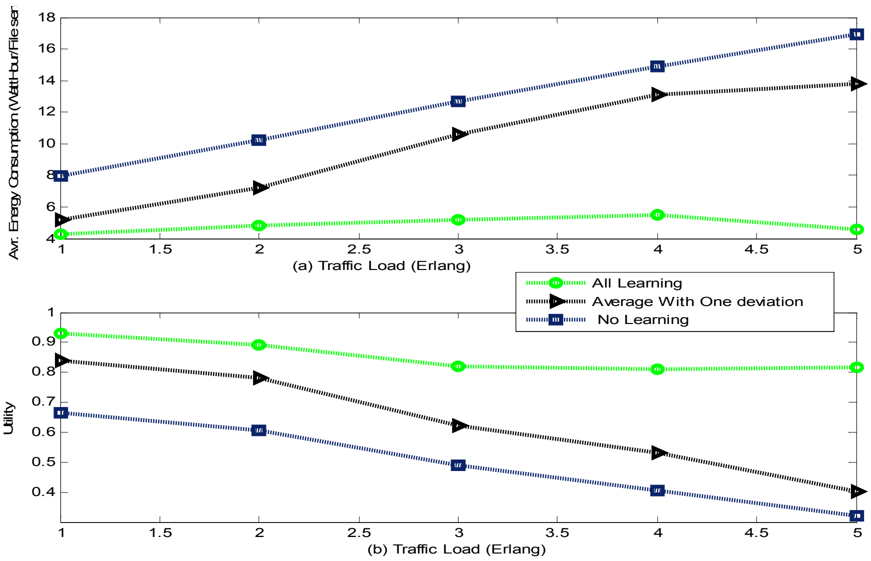

Figure 7.14(a) Energy Consumption (b) Utility in terms of energy consumption

Figure 14 (b) shows the utility obtained in terms of energy consumption (U_E) against traffic load. It can be seen that the average utility falls with the traffic load because as the traffic load increases the activity in the system increases and more collision occurs in the system. As expected when all the three players are learning, the average utility is significantly more than when a user is deviating especially as the traffic load increases. At lower traffic load, the users can avoid each other by transmitting on different channels, making the values closer at lower traffic loads compared to higher traffic loads. It can also be seen that with the proposed model there is an average of 20% increases in utility compared to when the learning process is not used.

Delay is one of the important parameters that determine the functionality of a wireless network. This is because different applications have different tolerance level for delay. Hence the delay experience by the players is also examined. Figure 7.15 shows the delay against the traffic load when all the players are learning, when one of the players is deviating and when all the players are deviating. The delay increases as the traffic load increases for all the 3 scenarios because as the traffic load increases, the number of users entering the system also increase, thereby, increasing the delay. It can be seen that the delay in the system is lower when all the players are learning compared to when one player is deviating or all are deviating. There is an average of 33% reduction in delay using the proposed model for all traffic loads that was considered.

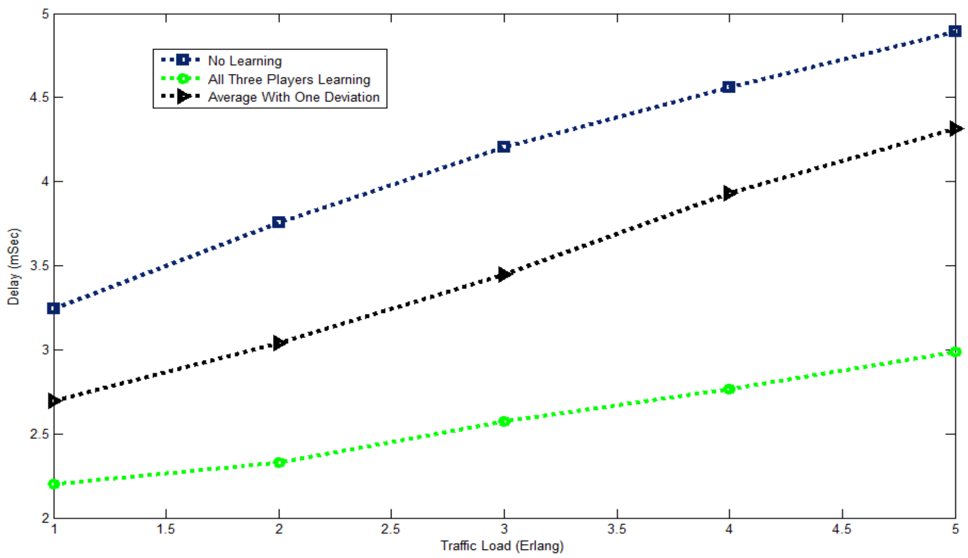

Figure 7.15. The system delay with all three scenarios

Another important performance metric in a wireless communication network is the blocking probability. Hence the blocking probability is examined to see if there is an improvement in the blocking probability of the system with the players learning. Figure 7.16 shows the blocking probability of the system when all the three players are learning and the average blocking when one of the players is deviating from the learning model against the traffic load in the system. It can be seen that as the traffic load increases, the blocking also increases. This is because there is an increase in the system's collision. Blocking due to price and insufficient resources is considered here (such as unavailability of transiting channel or when the SNIR of a transmitting user falls below the SNIR threshold). This result shows that learning reduces the blocking experienced by the users. Hence, the performance parameters are better with learning. From the results, the scheme helps with congestion control by reducing the blocking experience by the users. This is because the reserve price is used to prevent the HPU at high traffic loads.

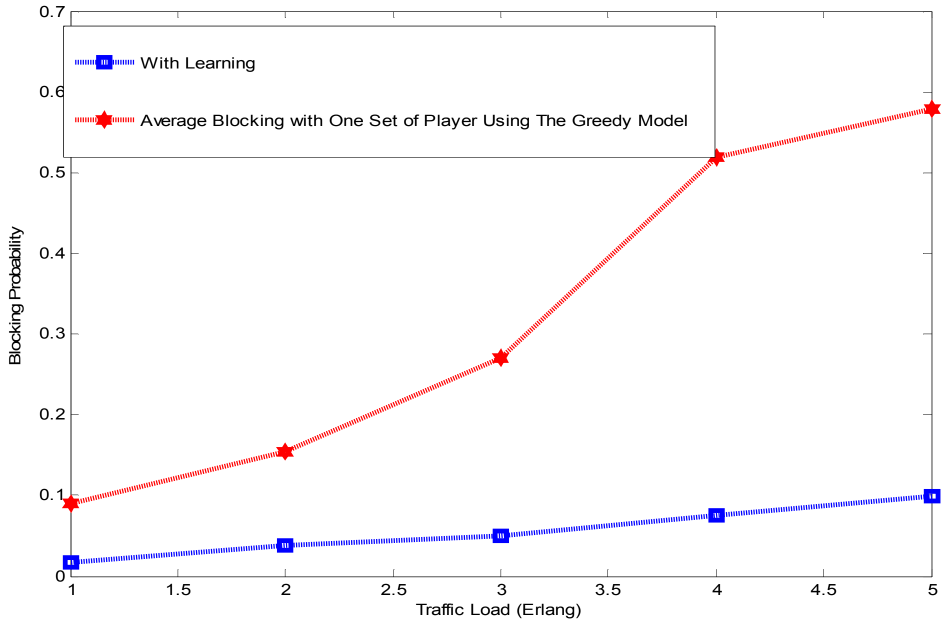

Figure 7.16. The blocking probability for all three players learning and the average with one of the three players deviating from learning.

All the three players are contributing one way or the other to the performance of the system, hence the effects of the WSP not learning is examined. Figure 7.17(a) shows the utility obtained by the WSP when learning and when using the greedy model. As expected, the utility obtained when learning is significantly higher than when not learning. This is because when the WSP is not learning, the reserve price in the system is not set to reflect the present situation. Hence, the learning process does converge at a non-optimal value. This shows that it is important for the WSP to learn and use the reserve price to control the admission process. Figure 7.17(b) shows the average utility obtained when the WSP and one of the users is not learning, when the WSP is learning but the other two players are not. For all three scenarios the utility obtained by the WSP increases. This is because as the traffic load increases, more of the available channels are in use. It can also be seen that the utility obtained at all traffic loads is significantly lower compared to when all three are learning. The results also show that the greater the number of players not learning, the lower the overall utility.

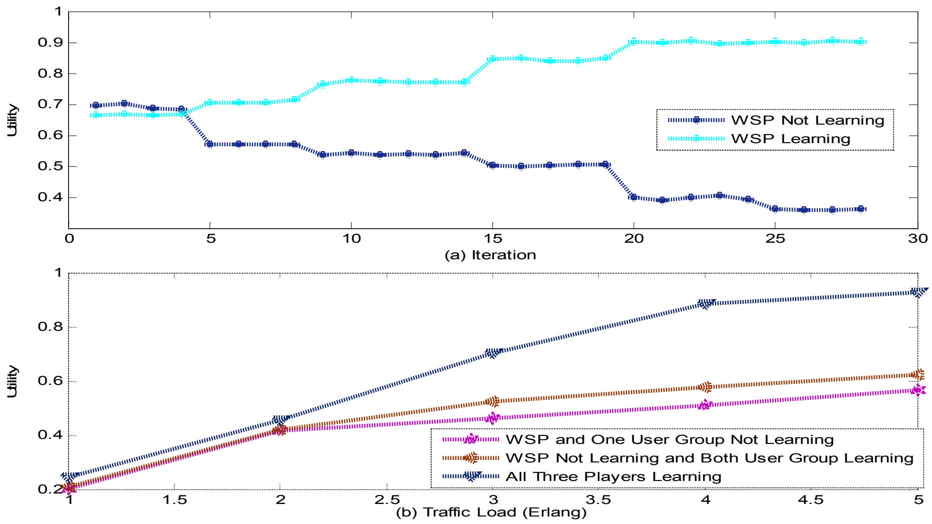

Figure 7.17(a) Utility against traffic load (a) WSP is learning at 3 Erlangs and WSP not learning (b) WSP and one of the users is not learning

Figures 7.11 to 7.17 shows that none of the players are better off or are having a higher utility value by deviating from the learning model. This shows that learning by all the three players forms a Nash Equilibrium for the proposed game model giving the definition of Nash equilibrium in [70].

7.6 The comparisons of the results obtained using the different models

So far from chapters 4 to 7 different models have been proposed given an auction model for DSA. An auction model with green payment and reserve price was proposed in chapter 4. However, there was a need to improve on the model in order to reduce two important parameters: The energy consumed and the delay. In this section, the proposed models are compared (where applicable) in order to show if gains were made. The best scheme in each chapter is used in carrying out the comparison.

The energy consumed by the system is one of the important parameters examined throughout this thesis. Hence the energy consumed using just the green payment and the reserve price alone as proposed in chapter 4 is compared with the green payment with multiple bidding process with the knowledge of the reserve price as proposed in chapter 5 and with the learning model proposed in chapters 6 and 7. Figure 7.8 shows the energy consumed by the three models examined. It can be seen that the model with learning consumed the least amount of energy compared with the other process. This is because with the learning model the users learn the appropriate bid price that is above the reserve price before attempting to participate in the auction process. Significant savings (about 60% on the average) is made using the MBP compared to just only the green payment. This is because using the MBP allows the users to use most of the available channels simultaneously.

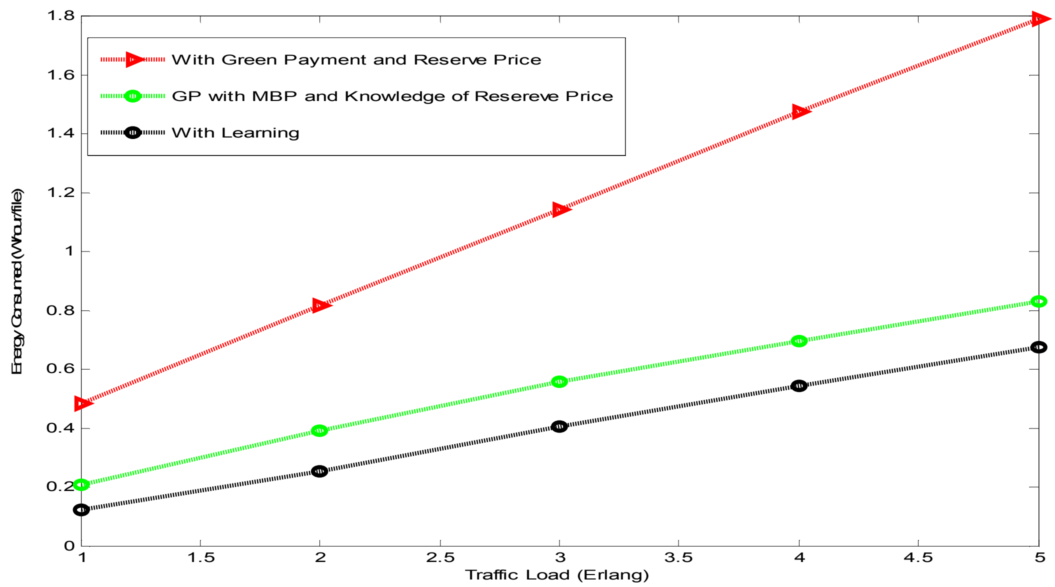

Figure 7.18. Energy consumed by the system with green payment alone, MBP with the green payment and with learning

Another important parameter considered in this thesis is the delay experienced by the users when using all the proposed models. Hence the delays are also compared across all the models from chapters 4-7. Figure 7.19 shows the delay experienced by the users across all the three proposed models. The results obtained in terms of delay are similar to those obtained in figure 7.18 (the energy consumed). The reasons behind this result are the same as the explained reasons with the energy consumption in figure 7.18.

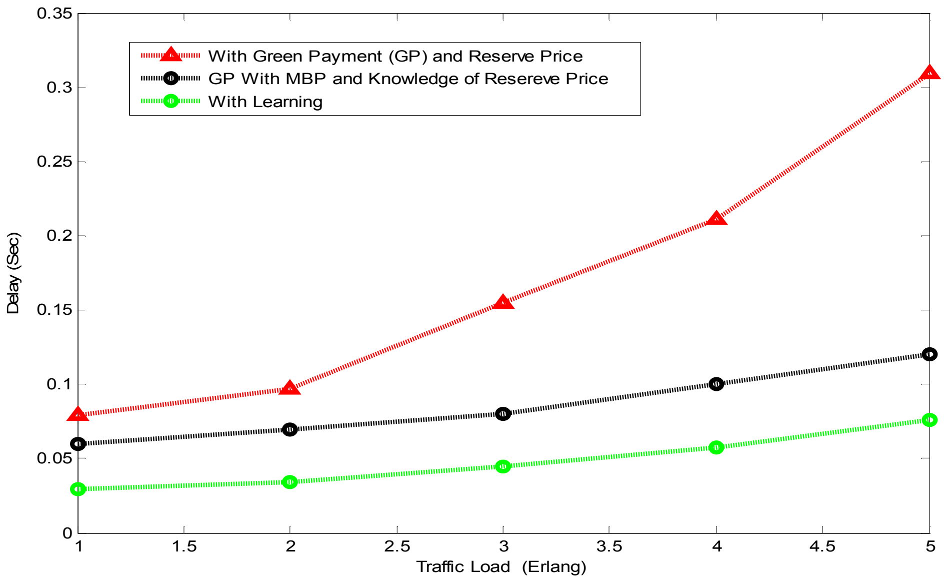

Figure 7.19. Delay experienced with green payment alone, MBP with the green payment and with learning

The models proposed so far aim to use the price paid by the users to regulate the use of the radio spectrum. However, it not possible to compare the revenue obtained by the WSP across all the 4 modelling chapters. This is because the price model used in chapters 4 and 5 are significantly different from those used chapters 6 and 7. The pricing model used in chapter 6 also different from that of chapter 7. Hence it is only possible to compare the revenue obtained by the WSP from chapters 4 and 5. Figure 7.20 shows the average revenue obtained by the WSP using the green payment and reserve price and the MBP with the green payments and reserve price. The average revenue obtained using the two models are the same. This is because the same price generation model is used in the two models.

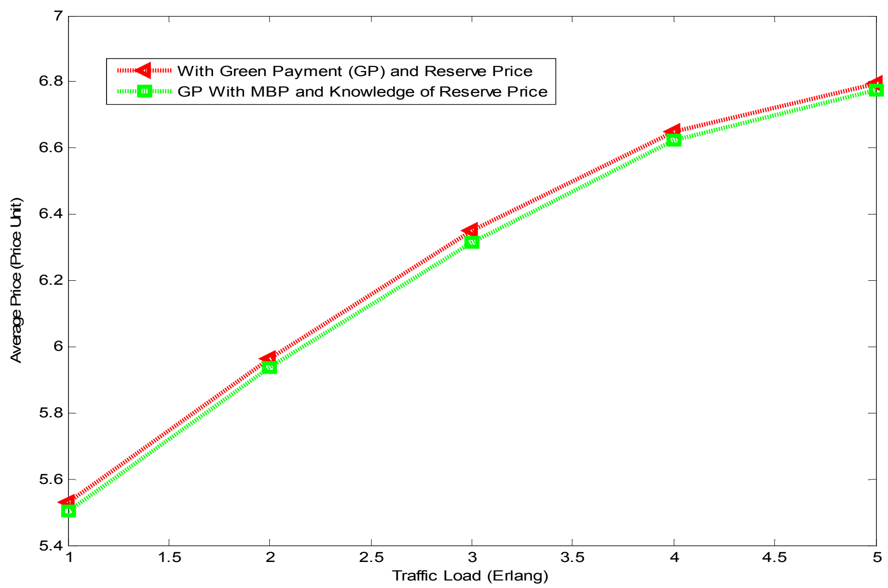

Figure 7.20. Average revenue per file sent using the green payment with reserve price alone and in combination with the MBP

7.7 Conclusions

This chapter developed a learning scenario where all the users in the system can learn simultaneously. Different parameters were learnt by each of the users in the game model. Utility functions which were explicitly dependent on four parameters which determine the satisfaction received by the users was proposed. The utility function was based on the bid price, the green payments and the energy consumed by the user during the auction process. First, a situation where one of the players is learning and the others are using the greedy approach was modelled after then a scenario where all the users are learning simultaneously was examined. The results showed that none of the players are be better off by adopting the greedy model compared to the learning model. This is based on the utility function obtained when the two models were compared. The results also showed that the energy consumed by the system is lower when all the users are learning the different parameters about each other compared to when of the player group is using the greedy model. Finally, the results across all the four modelling chapters are also compared and the learning model performs significantly better than the other models in terms of the delay and the energy consumed per file sent.

Chapter 8.

Future Work

Contents

8.1 Introduction

This thesis showed how dynamic spectrum pricing can be implemented for a cognitive radio based network. In particular, it showed how the price paid by wireless users can be used as an incentive for an efficient use of the radio spectrum using the concept of the green payments. A number of improvements to the existing schemes are needed in order to implement the proposed schemes. There is a need to modify the auction process from file based auction process to either a time or session based auction process. This is due to the overhead involved in carrying out a file based auction process in practice. However, such change does not affect the fundamental results in this work. It only affects the periodicity of the auction process. Some of the other improvements that can be done are discussed below.

8.2 Future Improvements

8.2.1 Users Bid and Budget

In most parts of this thesis, two assumptions regarding the users bid were made. First, it is assumed that all the users have the same budget and the budget is unlimited. In reality, these assumptions might not always be true. There is a need in future to examine the effects of the users having different budgets on the performance of the auction scheme. There is also a need to examine scenarios how the budget affects the bid learning process. Examining such a scenario can help to improve the learning process carried out in chapter 6.

8.2.2 Examine the Effects of the Auction Process on the Primary Users

The effects of the auction process carried out for the secondary users on the primary user should also be examined. Throughout this thesis the effects of the secondary users on the primary users was not directly examined. This is necessary as part of the future work. This is because in the proposed scheme, the primary and secondary users may coexist. The presence of the secondary users using an auction process may have some effects on the primary users.

8.2.3 Multiple Wireless Service Providers and Other Methods of Calculating the Green Payment

The implementation of dynamic spectrum management is expected to allow the coexistence of multiple wireless service providers. These providers are expected to provide secondary access to users who require the use of the radio spectrum as proposed in [131]. However, throughout this thesis it was assume that the presence of only one service provider. The presence of multiple service providers might have some effects on the reserve price put in place by all the service providers. The service providers might also be competing with one another to attract more users. This might have some significant effects on the revenue of the service providers and the fund for the green payment subsidy. A solution to this might be to make the pot of funds that pay for the subsidy to come from a different source. This consideration might also have some effects on how the green payment is calculated.

8.2.4 Negotiation of Transmit Power after the Allocation of the Radio Spectrum

Throughout this thesis the presence of just two types of users was assumed, the LPU and the HPU. In the real world with the presence of millions of different types of devices for different tasks, it might be difficult to strictly categorise the users into two categories. The use of fuzzy logic might be considered to help in categorising the users. Furthermore, in this thesis the LPU are always transmitting using a low power and this is the same for the HPU who transmit using a high power. This means that a scenario in which users are ready to negotiate their transmit power was not considered. This should allow such users to benefit from the subsidy handed out. This work also considered a scenario where the LPU are ready to pay the tax by switching from being a low powered user to a high powered user because of the application in demand. Hence, the future work could examine how this can be done.

8.2.5 Examination of Different Pricing Models

This thesis mainly examined the first price spectrum auction model. It is quite important to examine different pricing models to establish the application of the revenue equivalence theorem to the wireless radio auction model. The revenue equivalence theorem states that any auction mechanism should result in the same outcome in terms of revenue provided the items are allocated to the same bidders. This should also include an extensive comparison between auction based pricing schemes and non-auction based models.

8.2.6 Examination of Different Energy Models

Throughout this thesis, the energy model adopted assumes that users intending to use the radio spectrum indicate their interest by submitting a bid. Each user was assumed to be consuming some form of energy by participating in the auction process. The amount of energy consumed by each user in the same group during the bidding process is assumed to be the same. This assumption shaped some of the results. In as much as the assumption is reasonable, there is a need to examine how each user is switched on and off during the auction process. It was assumed that the transmitters are able to transmit immediately after they are switched on and switched off immediately when they are not transmitting or bidding.

However, in potential scenarios this is not always true. Most electronic devices need some time after switching on to become active and establish the necessary connections and this is also necessary when an electronic device is switched off. This is because some tail back time is needed before a device is up and ready to transmit or be powered off completely.

8.3 Conclusions

This chapter has provided an overview of the future work that can be carried out in order to improve some of the proposed approaches used in this thesis. The future work is based on how the proposed scheme can be improved. Some of the improvements include the introduction of multiple wireless service providers in order to understand how DSA scheme can actually be implemented. The chapter has also proposed to examine in future the effects of the proposed scheme on the primary users who are the licensed owners of the radio spectrum because they are not considered directly in this thesis.

Chapter 9

Summary and Conclusions

Contents

This thesis has investigated issues associated with the application of an auction in allocating the radio spectrum for a short period of time. It also investigated the effects of an auction process on the performance of the wireless system and the energy consumed during the auction process. A periodic auction process where users are allocated the spectrum based on their bids is examined. The concept of green payments was introduced to allow the use of price to encourage the efficient use of the radio spectrum for a small cells scenario. It was found out that this unique concept of green payments helps in improving the performance of the auction based DSA network. The use of the multiple bidding process and an admittance threshold which further helped in reducing the delay and the energy consumed by the wireless network is introduced. The concept of bid learning and game model was also introduced making the proposed system to be more efficient in terms of the energy consumed and the utility of the users.

Chapter 1 presented a general introduction to this thesis. Chapter 2 provided a comprehensive literature review on the research topic as an aid to the understanding of the subsequent chapters. The review chapter focused mainly on dynamic spectrum access, cognitive radio and spectrum pricing and machine learning.

Chapter introduced the simulation tools and performance measures used in this thesis. The chapter also explained the simulation methodology and techniques adopted in the later chapters. Before arriving at a specific technique or methodology, some other methods with their advantages and disadvantages were examined. This work adopted the use of MATLAB simulation tool to model the proposed auction based scenario. Delay, blocking and dropping probabilities were also explained. The different propagation models were also considered before arriving at the WINNER II model which was used throughout this thesis.

Chapter 4 put forward the concept of green payments to aid energy efficiency in dynamic spectrum allocation. First, the chapter established the user model and the auction model as used in modelling the chapters. The optimal bidding and transmission period was defined and derived. It was established that the optimal bidding period must be less than the transmission period but long enough to allow enough users to submit their bid in order for an auction process to take place. The effect of the green payments on the performance of the proposed network was also examined.

Chapter 5 served as the mathematical formulation using the concept of utility functions to model the proposed scenario. It examined the effects of having the reserve price either as public or private knowledge in an auction based spectrum assignment scheme. Furthermore, the chapter introduced the concept of a congestion charge and the probability of being among the highest bidders. The use of the probability does not eradicate the prospect of a bidder losing but it reduces the number of users losing the auction. Therefore it reduces the energy consumed compared to a scenario where the probability is not used. Blocking due to insufficient resources and blocking due to price were also analysed in this chapter. Utility functions were used to model the behaviour of the users and the system. Single bidding and multiple bidding processes were also formulated and examined and it was discovered that the multiple bidding process helps in reducing the amount of energy consumed during the auction process. The performance metrics of the system showed that the concept of green payments with the probability of being among the highest bidders also helped in reducing the energy consumed in the auction based scheme. It also helped in reducing the system delay and blocking probability.

Chapter 6 examined the use of learning to aid the bidding process. This is important because in the previous chapters, a situation where some channels are available but they were not allocated (because the offered bids were below the reserve price) often occurred. This led to a situation where the throughput of the system is sometimes lower. This also led to the use of multiple bidding process in chapter 5. Hence, the concept of artificial intelligence with the use of linear reinforcement learning, Q learning and Bayesian learning were investigated. The chapter also showed that Bayesian learning provides better learning rate compared to the others.

Chapter 7 proposed a game model where the users and the service provider are the players in the game. It examined the existence of Nash Equilibrium in the proposed game. The game provided a situation where all the users in the system can learn different parameters about each other. It showed how the LPU can learn the best bid price to win the auction process while the HPU are learning the best time to participate in the auction process. This was done in order to provide a much better performance for the proposed system in terms of delay and consumed energy. It adopted the use of Bayesian learning with the introduction of the Dirichlet distribution. The concept of utility function was also examined to determine the suitability of the outcome of the game. The chapter also compared the models from chapters 4 to 7 and it showed that the learning model performs significantly better than the other models.

Chapter 8 proposed some future work. The future work showed how the current work can be improved in order for it to be implemented in the nearest future.

9.1 Summary of Original Contributions

A significant part of this thesis uses the concept of green payments. This was done to encourage the efficient use of the radio spectrum by the secondary or opportunistic users who are seeking short term access to the radio spectrum. The proposed scheme allows for secondary users to transmit in a manner that they avoid significant interference with the primary users who are assumed to be present but excluded by the database. The main aim of this work is to use price to regulate the radio spectrum in order to grant short term access to the secondary users. This thesis formulated some novel ideas in order to contribute to the ongoing work in the research area. Some of the contributions have been published and a list of publications is also provided after this chapter. However, this section summarises some of the novel contributions.

9.2.1 The Concept of a Green Payment

The introduction of the concept of the green payment during the auction process is perhaps the most significant contribution in this work. Although the use of an incentive to discourage selfish users from using the radio spectrum has previously been proposed in [132]. The scheme only discourages collusion. The author used the concept of game theory by designing a collusion resistant reserve price scheme. In this work, the green payment is used to allow for an efficient use of the radio spectrum given an auction based dynamic spectrum access scenario, where users are seeking short term access to the radio spectrum. The green payment serves as a form of incentive for users to transmit using a low power in order to reduce the interference to other secondary users and the primary users in the system. The primary users are assumed to be present but excluded by the database. This is important because the cell structure of most future wireless networks are based on smaller cells. This is because of the need to increase the carrying capacity of the wireless system given the increase in demand for the use of the spectrum and the perceived scarcity of the radio spectrum. The use of small cell allows for better frequency reuse in a wireless network. The concept of green payments as used in this work helped in improving the energy efficiency level of the system, reduce the system delay and make the proposed auction based dynamic spectrum assignment scheme to be more efficient. The concept of green payments is used throughout this thesis and it was published in the paper at the ICT conference in Casablanca.

9.2.2 The Concept of Congestion Charge

The concept of congestion charge was introduced in chapter 5. Generally, short term spectrum allocations have been proposed as a means of preventing congestion in the system [133]. However, this work went further by introducing the congestion charge. The congestion charge was introduced in addition to the green payments in order to further penalise non-power efficient users as the system is becoming congested. In this work, the congestion charge reflects the importance of controlling congestion in the system especially with the ever increasing demand of the radio spectrum. A scheme similar to congestion pricing was used in [134], where demands exceeds capacity. This was done in a scheme with two providers competing for the use of the spectrum. However, the work used the congestion charge to encourage efficient use of the radio spectrum.

9.2.3 Learning Based Auction Model

Artificial intelligence or learning based schemes have been widely used in wireless communications especially reinforcement learning with its modifications. However, to date, no publication that uses artificial intelligence to learn the appropriate bidding price in a centralised system for a dynamic spectrum access scheme was found. The learning based scheme was implemented in order to ensure a reduction in the number of bidders to have their bid rejected. This is because the higher the number of rejected bids the higher the energy wasted. Therefore, in a bid to reduce the amount of consumed energy in an auction based system, the learning based schemes were introduced. Using the learning based schemes improved the performance of the system significantly compared to schemes without the learning as shown in the results. The work related to this was published by IEEE at the Consumer Communications and Networking Conference (CCNC) in Las Vegas.

9.2.4 Energy Efficient Bid Learning

There is a lots of research work regarding dynamic spectrum access and some of the proposed models are using an auction process to allocate the radio spectrum. Energy efficiency is currently dominating discussions about the future wireless communications system. However, during this research [135] was the only publication where energy efficiency, dynamic spectrum assignment and learning was considered together. In the paper, the author modelled the licensed channel using a Finite State Markov Channel (FSMC) and CR users select a preferred channel. The author also used game theory and learning to model the interaction among the users. However, there was no auction process or bid learning in the paper. Hence, the concept of bid learning is novel in this thesis. Energy efficiency bid learning processes ware considered in chapter 4, 5 and 6 and form the basis of most of the publications throughout this research work.

9.2.5 Effect of using an Auction Process in Short Term Allocation the Radio Spectrum on Delay and Throughput Performance of a Wireless Network

Throughout this work, an auction process is used in allocating the radio spectrum for short term use. It also studied the effect of using an auction process on the performance of the system. As mentioned earlier, the use of an auction in allocating the radio spectrum for short term use is not novel. However, throughout this research, the papers that were found only considered economic issues such as the revenue generated by the system, utility of the users or the social welfare among others. None of the papers actually considered the effect of the auction process on the performance of the system such as system delay, throughput. Hence, the study of such performance metric is novel to this thesis. In the study of the performance of the system, it was discovered that the impact of a sealed bid first price auction on the performance of the wireless system. The study of such effects is considered important because those metrics determines to a large extent the applications that the system can offer to the users seeking a wide range of applications.

List of Symbols

Δ_i	Delay of user i
Δ_{max}	Maximum allowable delay by the system
h_t	Holding time
R	Green payment
ψ^{HPU}	SNR of HPU
ψ^{LPU}	SNR of LPU
ψ_i	SNR of user i
ψ_j	SNR of the set threshold
A^G	Greedy action
A_{bs}	Number of available offered traffic bins
A^l	Learning action
A_s	Available action during learning process
B_T	Total budget
B_r	Bit rate
C_f	Congestion factor
C_r	Price constant
D_i	Data rate of user i
D_{max}	Maximum allowable data rate
E_i	Energy consumed by user i
E_t	Total energy consumed
F_s	File size
G_{ii}	Gain of user i
G_{ij}	Gain of the interfering users

HPU	High Powered Users
L_P	Traffic load bin
LPU	Low Powered Users
MBP	Multiple Bidding Process
N	Total number of users in the system
N_{AC}	Number of available channels for transmission
$N_{CAU}(t)$	Total number of available channels that has been used up to time t
N_{FAP}	Number of filed attempted transmission due to insufficient Price
N_{FAR}	Number of filed attempted transmission due to insufficient resources
N_{FG}	Number of files generated
N_{FS}	Number of files sent
N_{TC}	Total number of transmission channels in the system
N_{USA}	Number of users seeking access
N_{WU}	Number of winning users
N_b	Number of blocked activations
$P(A)$	Probability of A occurring
$P(A\|B)$	Probability of A occurring given that event B has already occurred
$P(B\|A)$	Probability of B occurring given that event A has already occurred
$P(B)$	Probability of B occurring
$P_{r_{Threshshold}}$	Probability threshold
P_D	Power consumed by the user device
P_j	Transmit power of interfering users
$P_{rN_{AC}}$	Probability of being among the highest N_{AC} bidders
P_r	Probability
RL	Reinforcement Learning

R_W	Reward weight during learning process
R_{tot}	Total green payment
R_{tsp}	Total subsidy paid
R_{ttp}	Total tax paid
S	Shannon equation bound
SBP	Single Bidding Process
$SNIR$	Signal to Noise and Interference Ratio
$SNIR_{max}$	Maximum possible signal to Noise and interference Ratio
$SNIR_{threshold}$	Signal to Noise and interference ratio Threshold
S_s	Learning State
T	Transmitting period
T_L	Traffic load in the system
T_r	Transmission rate
T_r	Transmission rate
U_{B_p}	Utility in terms of blocking due to price
U_Δ	Utility in terms of delay
U_B	Utility in terms of bidding value
U_D	Utility in terms of data rate
U_E	Utility in terms of energy
U_G	General utility function
U_{OBB}	Utility in terms of offered bid bin
U_P	Utility in terms of price
U_R	Utility in terms of green payment
U_a	Utility in terms of admission process
U_n	Utility of the nth user
U_{sw}	Utility of social welfare

V_i	Bid valuation of user i
V_{max}	Maximum bid valuation of any bidding users
V_{min}	Minimum bid valuation of any bidding users
W	Weight of an action during the learning process
W_P^y	Total reward or weight of the y^{th} value in traffic load bin p
W_R	Winning ratio
$b_i^{OBB_{A_{bs}}}$	Offered bid value picked by user i from $OBB_{A_{bs}}$
b_i	Bid of user i
b_t	Bid of any user at time t
b_{t-1}	Bid of any use at time $t-1$
i	Any user in the system
r_{Est}	Estimated value of the reserve price
t	Auction period
t_{FG}	The Time a file is generated
t_{FS}	The time a file is sent
t_s	Time of transmissions in seconds
$\boldsymbol{A}$	Action set
$\boldsymbol{G_{HPU}}$	HPU group
$\boldsymbol{G_{LPU}}$	LPU group
γ_s	Discount factor during learning process
θ	The absolute value of the linear difference between the SNR value of a user i (ψ_i) and the value of the SNR of a set threshold (ψ_j).
LRL	Linear Reinforcement Learning
OBB	Offered Bid Bins
P	Transmit power

Thr	Throughput
r	Reserve price
$\boldsymbol{P}$	Player set
α	Shannon equation rate reduction factor
τ	Number of iterations
$\tau(t)$	Total number of iterations up to time t

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