Adaptive Radio Resource Management Schemes for the Downlink of the OFDMA-based Wireless Communication Systems

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This thesis is submitted in fulfilment of the academic requirements
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As the candidate's supervisor, I have approved this dissertation for submission.

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Declaration

I declare that this thesis is my own work. Where collaboration with other people has taken place, or material generated by other researchers is included, the parties and/or materials are indicated in the acknowledgements or are explicitly stated with references as appropriate.

This work is being submitted for the Master of Science in Electrical Engineering at the University of Cape Town. It has not been submitted to any other university for any other degree or examination.

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Bernard Nyakundi Isaac 31/03/2014

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Dedication

To my loving wife Irene and our boys: Gerald, Ibrahim and Enock

Abstract

Due to its superior characteristics that make it suitable for high speed mobile wireless systems OFDMA has been adopted by next generation broadband wireless standards including Worldwide Interoperability for Microwave Access (WiMAX) and Long Term Evolution – Advanced (LTE-A).

Intelligent and adaptive Radio Resource Management (RRM) schemes are a fundamental tool in the design of wireless systems to be able to fully and efficiently utilize the available scarce resources and be able to meet the user data rates and QoS requirements. Previous works were only concerned with maximizing system efficiency and thus used opportunistic algorithms that allocate resources to users with the best opportunities to optimize system capacity. Thus, only those users with good channel conditions were considered for resource allocation and users in bad channel conditions were left out to starve of resources.

The main objective of our study is to design adaptive radio resource allocation (RRA) algorithms that distribute the scarce resources more fairly among network users while efficiently using the resources to maximize system throughput.

Four scheduling algorithms have been formulated and analysed based on fairness, throughputs and delay. This was done for users demanding different services and QoS requirements. Two of the scheduling algorithms, Maximum Sum Rate (MSR) and Round Robin (RR) are used respectively, as references to analyze throughput and fairness among network users. The other two algorithms are Proportional Fair Scheduling (PFS) and Margin Adaptive Scheduling Scheme (MASS). While exploiting the idea of multiuser diversity, the PFS algorithm, balances the system efficiency in resource usage and fairness in resource distribution among users. MASS on the other hand, allocates as minimal transmit power as possible to a user to be able to transmit at a particular minimum rate while maintaining QoS for a given service.

In order to analyze and compare the different RRA algorithms developed in this dissertation, link-level analysis was carried out using the Matlab analytical tool. Based on the results obtained, it is shown that the proposed RRA algorithms facilitate a fairer distribution of system resources between users than the system maximization technique.

Acknowledgements

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May our good Lord abundantly bless all of you and your families!

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Abbreviations

RRM	Radio Resource Management
RRA	Radio Resource Allocation or Assignment
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	OFDM-based Frequency Division Multiple Access
TDMA	Time Division Multiplexing Access
FDMA	Frequency Division Multiplexing Access
ISI	Inter-symbol Interference
ICI	Inter-channel Interference
SNR	Signal-to-Noise Ratio
SINR	Signal-to-Interference-plus-Noise Ratio
CQI	Channel Quality Indicator
NLOS	Non-line of Sight
LOS	Line of Sight
BER	Bit Error Rate
WIMAX	Worldwide Interoperability for Microwave Access
LTE-A	Long Term Evolution - Advanced
DFT	Discrete Fourier Transform
IDFT	Inverse Discrete Fourier Transform
FFT	Fast Fourier Transform
IFFT	Inverse Fast Fourier Transform
QoS	Quality of Service
IMT-A	International Mobile Telecommunications - Advanced
ITU	International Telecommunications Union
1G	1^{st} Generation Analog Mobile Communication Systems
2G	2^{nd} Generation Digital Mobile Communication Systems
3G	3^{rd} Generation Digital Mobile Communication Systems
4G	4^{th} Generation Digital Mobile Communication Systems

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Chapter 1

1 Introduction

1.1 Motivation

The next generation wireless communication systems is expected to support the ever changing requirements and expectations of both the users and mobile network operators. Users are demanding even higher data rates and reliable communication every passing day and operators want to maximize their revenue base [1]. This then calls for development and implementation of efficient radio resource management (RRM) schemes that will share the limited and scarce resources more efficiently and fairly while supporting the large number of users with different QoS requirements [2].

Orthogonal frequency division multiple access (OFDMA) technology is one of the preferred high performance physical layer air interfaces for next generation broadband wireless communication systems. Indeed, it has been adopted by several 4G standards including WiMAX [3] and LTE-A [4].

Efficient RRM techniques are crucial in utilizing the resources and flexibilities offered by OFDMA access technology. Previous work used opportunistic policies to maximize the system efficiency through allocating the resources to only those users who maximize the system capacity. Although they optimized system efficiency, a downside of opportunistic schemes was that they were unfair to users who could not maximize efficiency; those with poor channel conditions.

Therefore, RRM schemes that balances the trade-off between fair resource sharing and efficient resource utilization amongst network users irrespective of their channel conditions is crucial. The objective of our work is to design and implement adaptive RRM schemes that balance the trade-off between fair sharing of resources and efficient utilization of scarce radio resources amongst network users.

The allocation of resources can follow different criteria, for example, users with the best channel quality can be assigned the resources to maximize utilization. Here, channel quality is used as an efficient indicator of resource allocation. In [5], opportunistic RRA algorithms were proposed which maximizes efficiency in the usage of resources, by adaptively allocating resources to only those users who present the highest efficiency indicator.

When the resources have different efficiency indicators to different users (multiuser diversity), the balance between efficiency and fairness appears naturally. Therefore, if opportunistic RRA schemes are used in exploring these diversities, unfair situations in the resource utilization will arise. It is apparent from the foregoing discussion that a basic balance between user fairness and resource efficiency must be considered.

For the time-varying and frequency-varying wireless channel, a significant challenge is posed especially on efficient resource usage and fair distribution of resources to the network users. Thus, optimal radio resource allocation (RRA) techniques that always provide maximum efficiency and fairness in wireless networks is still an open problem. The performance of the algorithms presented in this work was investigated using performance metrics that included: system throughput, fairness and delay.

1.2 Background information

The demand for reliable wireless communication has persisted for a long time and is expected to go on for a long time in future especially due to the ever-changing requirements and expectations of both the network users and operators. This has caused major evolutions of wireless voice and data communication systems. From the 1G system that supported analog voice communication to 2G digital voice networks, to 3G that supports multimedia data and now 4G that support a wide range of telecommunication services such as advanced mobile services etc. All this networks have different characteristics that offer different services to satisfy their user requirements. These developments however, have introduced new challenges in the way limited and scarce radio resources (subcarriers, timeslots, power and rates, etc), are to be efficiently utilized and fairly shared among network users. A number of works [1], [6] have rightfully shown that resource management can be used to significantly increase the performance of a wireless network leading to customer satisfaction and increase in operator revenue.

To address the difficult problem of resource allocation, adaptive radio resource management techniques have been proposed by previous research works [2], [7]. Also to address the need to support high data rates demanded by network users, OFDMA access technology has been widely adopted by the 4G technologies as their preferred air interface. Indeed, OFDMA is considered as a strong candidate for the next generation wireless systems [8]. As such our work will focus on resource management in OFDMA systems. OFDMA technology will be briefly described in the next section.

Adaptive resource allocation techniques are broadly grouped either as margin adaptive (MA) or rate adaptive (RA). In MA allocation, the system endeavors to allocate as minimal power as possible to a subcarrier to support a fixed user data rate and maintain a given bit error rate (BER). In RA optimization problem the objective is to maximize the user's data rate, given a transmit power constraint.

Previous research efforts in OFDMA resource allocation problem has mainly focused on maximizing the utilization of the system resources. This is well accomplished by use of opportunistic resource allocation algorithms whose main objective is to maximize system efficiency. Jang and Lee [5] developed a RRM scheme that exclusively assigns a subcarrier to a user with the highest channel gain on that subcarrier in an OFDM symbol which maximizes the system sum rate. But this scheme starves those users with low channel gains of resources, especially those at the cell edge, making it unfair. This problem of unfairness was addressed by Rhee and Cioffi [9] who designed an RRM algorithm that allocates resources in such a way as to make all users achieve same data rates. But this technique fails to address the different QoS requirements of users in real systems, which may need different rates to support different levels of service and thus call for different fairness considerations.

Kivanc *et al*., [10] proposed an MA-based class of low computational algorithms that minimizes power consumption with BER and data rate constraints for different types of services. Wong *et al*., [11] formulated a power minimization problem with a minimum user data rate constraint using integer programming and continuous relaxation-based suboptimal solution methods. They showed that their method outperformed the fixed allocation techniques – time division multiplexing access (TDMA) and frequency division multiplexing access (FDMA). However, these techniques still starved users of resources on the periphery.

From the preceding discussion it is evident that for wireless communication systems, efficiency and fairness are important issues in resource assignment. By dividing the total system throughput by its total bandwidth, system spectral efficiency is obtained. Throughput is therefore, defined as the data rate per unit bandwidth. This implies that the user's achieved data rate is disregarded and only the total system data rate is taken into account. Therefore, while the system attains the highest spectral efficiency by assigning resources to users in good channel conditions, it becomes unfair to users in poor channel conditions as they are starved of resources. Indication on how equally the resources are distributed between users, on the other hand, gives the system fairness. In wireless resource allocation, there is always a trade-off between system fairness in resource distribution and efficiency in resource usage.

In our work, the balance between fairness in the resource distribution and efficiency in the resource usage is used as a background RRM problem that inspires the RRA algorithms proposed in this dissertation.

In the following section, we present an overview of OFDMA access technology which explains the reasons why we were motivated to choose OFDMA in this work.

1.3 Overview of OFDMA

Currently, the IEEE 802.16 [3] and 3GPP LTE-A [4] are the only two standards accepted by ITU as compliant with 4G requirements set by IMT-A. Both standards use Orthogonal Frequency Division Multiplexing (OFDM) technology as their air interface and OFDM-based Orthogonal Frequency Division Multiple Access (OFDMA) as their multiple access technique in the downlink direction. OFDM and OFDMA were chosen due to their important properties that are suitable in high speed mobile communication wireless systems [8], [12]. OFDM splits a wideband channel into multiple parallel narrowband subcarriers each carrying a stream of low data rates. Two main advantages are extracted from this setup: one, because each subcarrier will perceive an almost flat frequency response, the system becomes resistant to frequency selective fading generated by multipath propagation; and two, the sum of parallel low data rates streams of each of the subcarriers will lead to a high data rate transmission if the system bandwidth is large enough. In addition, implementing demodulators at the mobile terminal to receive an OFDM signal only requires a Fast Fourier Transform which has a reasonable computational complexity.

OFDMA is an extension of OFDM. While OFDM only allows one user to access the air interface at a time over the OFDM symbol, OFDMA allocates a group of orthogonal subcarriers to different users so they can access the air interface simultaneously, Figure 1.1 [12]. Thus OFDMA exploits the multiuser diversity well. This is because users perceive the channel differently from each other on every subcarrier. With intelligent allocation mechanisms, users can be allocated subcarriers that have high channel gains on them. This way the system will be able to maximize some performance metrics. Figure 1.1 shows a train of OFDM symbols along both time and frequency domains in a situation where three users (A, B, and C) would like to access the air interface. As illustrated OFDMA, assigns different subcarriers to different users at a time. Two methods are used for assigning subcarriers namely; distributed and contiguous.

The block diagram for the downlink of a typical OFDMA system is shown in Figure 1.2 [2]. With limited resources i.e., bandwidth and power, the BS communicates with multiple users in the downlink of an OFDMA system. At the BS, a combined subcarrier, power and bit assignment algorithm is applied to determine the number of subcarriers to assign to a user, the power to be allocated to every subcarrier and the number of bits to be transmitted within every subcarrier.

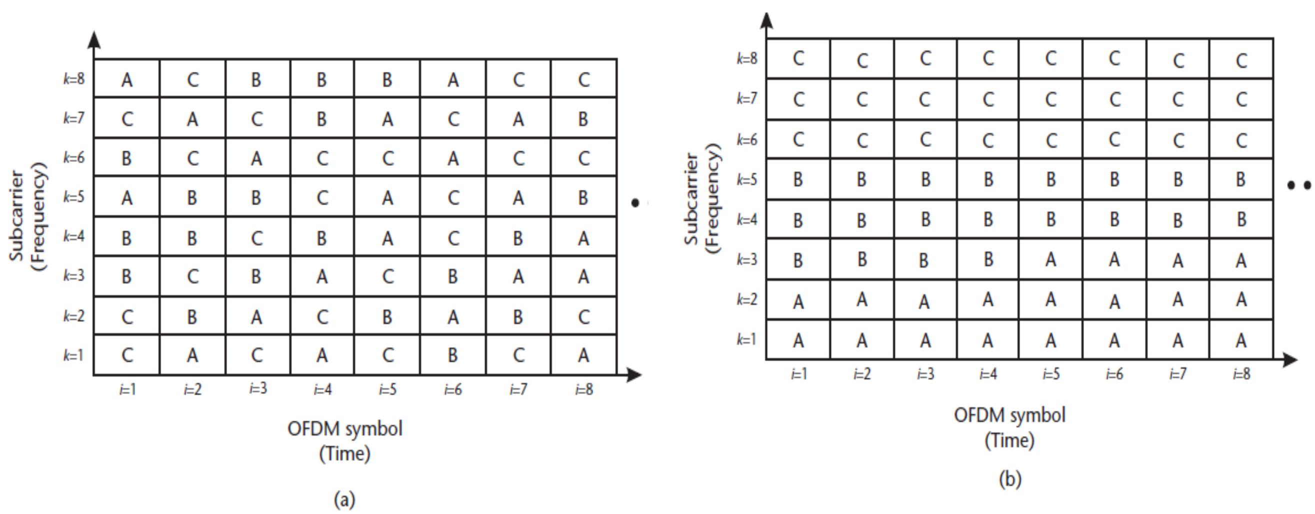


Figure 1.1 Multiple users using OFDMA (a) Distributed subcarriers (b) Contiguous subcarriers

The transmitter makes these decisions based on the channel information feedback by the users. This way the transmitter, through intelligent RRM techniques can attempt to maximize resource utilization. Depending on the number of bits allocated as well as the modulation scheme chosen, power to be assigned to every subcarrier is determined. The frequency domain complex symbols from the modulators are then transformed by the IFFT into time domain. Along with the added cyclic prefix (CP), the complex symbols are converted into analogue signals which are then up-converted by the Transmit Filter/RF and transmitted over the air. To eliminate ISI between adjacent OFDM symbols, the cyclic prefix is chosen larger than the delay spread. Furthermore, to maintain orthogonality among subcarriers, cyclic prefix must be appropriately sized [13]. After the subcarrier and bit allocation is performed, the BS communicates this information to the MTs through a separate control channel and therefore, the users only need to decode information meant for them.

OFDMA has the following advantages:

- ✓ ISI and multipath fading are effectively combated by using cyclic prefix symbols;
- ✓ Each subcarrier's modulation and coding can be adjusted easily;
- ✓ It has simple equalization;
- ✓ OFDMA uses IDFT/DFT (and more efficient IFFT/FFT) thus enabling low-complexity modulator implementation;
- ✓ OFDMA offers high spectral efficiency;
- ✓ Through distributed carriers, OFDMA can benefit from frequency diversity to improve performance;
- ✓ With the use of contiguous subcarriers OFDMA could use multiuser diversity to enhance performance

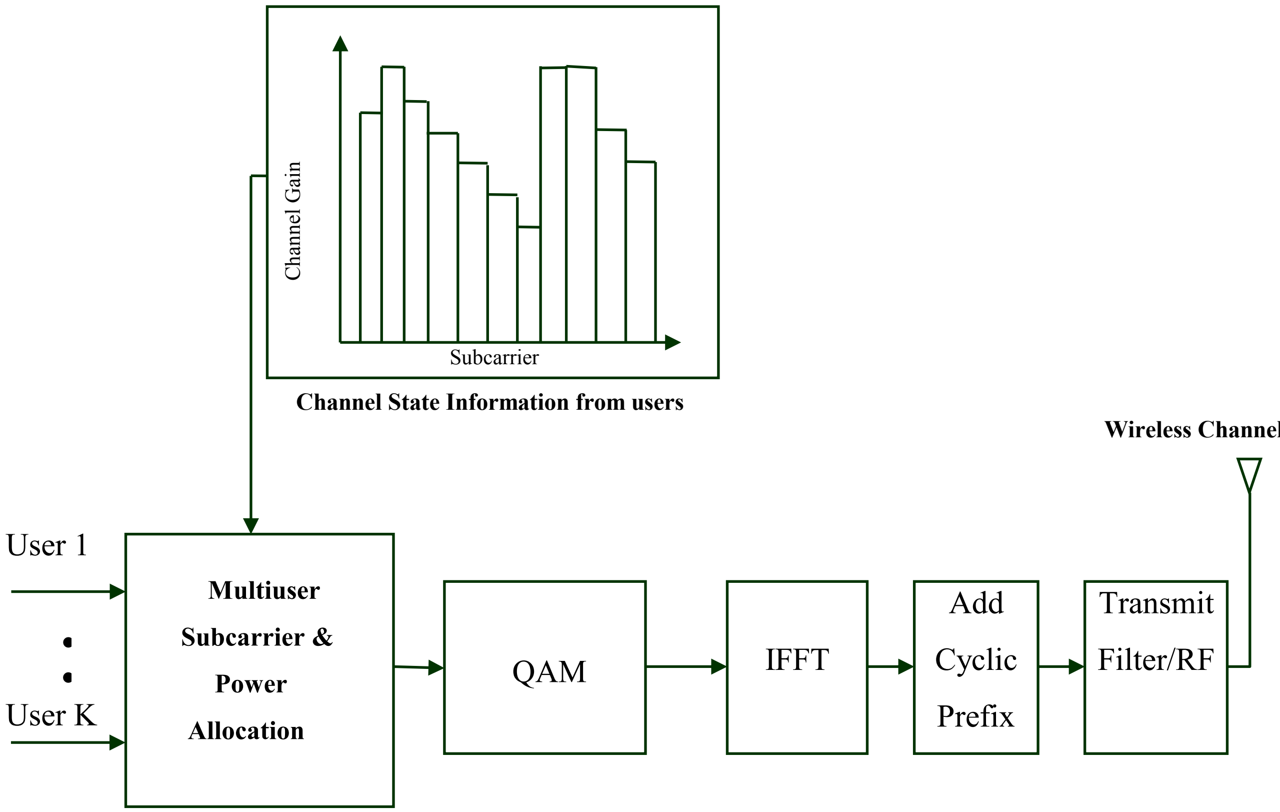


Figure 1.2 An OFDMA Transmitter Block Diagram with Adaptive Resources Allocator.

1.4 Objectives of the Dissertation

By carefully formulating adaptive RRM schemes that are aligned with the requirements of next generation wireless broadband networks, the vision of providing services in all places to many more users while satisfying their QoS requirements can be achieved. The research statement is thus stated:

Adaptive RRM is a technique that can be used in OFDMA wireless communication systems to help bridge the gap between fairness and efficiency, which results in more users being served in a network.

In verifying the stated research statement, the following objectives will be considered:

1. Study the performance of adaptive RRM in opportunistic systems whose objective is to maximize efficiency in terms of fairness, throughputs and delay in OFDMA systems.
2. Study the performance of adaptive RRM in systems whose goal is to balance the contradictory objectives between fairness and efficiency based on throughput, fairness and delay in OFDMA systems.
3. Compare the performance parameters of opportunistic systems, systems that balance efficiency and fairness, and systems that support fairness only in OFDMA systems.

1.5 Research Questions

This study seeks to evaluate the different adaptive RRA algorithms in the downlink of the OFDMA wireless system supporting heterogeneous services. Our focus is based on the observation that most previous studies have concentrated on opportunistic RRM schemes that endeavour to optimize system capacity without taking into consideration fair distribution of resources among network users.

The study will address the following research questions.

1. What is the relationship between system throughput maximization and fair distribution of resource allocation involving network users in the downlink of OFDMA systems supporting heterogeneous services?
2. How do the different radio resource allocation (RRA) schemes compare in satisfying user expectations with different quality of service provisions in OFDMA systems?
3. How do the varying link conditions affect user resource allocation in the downlink of an OFDMA system?

1.6 Research Methodology

In order to carry out the study and be able to meet the research objectives, different research methodologies have been used in this work including:

1. **Literature review**: A compilation of the RRM policies found in literature has been carried out, in order to strengthen the knowledge base of the research subject. This has made it possible for the formulations and proposal of RRA schemes that have been implemented in the MATLAB 7.9.0 (R2009b) analytical tool environment. At the same time, it has led to the determination of the models that are the basis for our analysis.

2. **The algorithm design methodology** was used to come up with the different codes for the RRA schemes used in OFDMA systems for resource assignment.
3. **The RRA algorithms analysis**: The codes for the different RRA algorithms developed were analysed using the MATLAB 7.9.0 (R2009b) analytical tool. This process determined that the codes developed performed as envisioned in the mathematical models.
4. **Performance analysis**: This method was used to evaluate and compare the different RRA schemes based on different performance metrics that included system throughputs, fairness and delay. From the results obtained, conclusions have been drawn and future work pointed out.

1.7 Scope of Dissertation

The scope of this research is limited to developing adaptive radio resource allocation (RRA) algorithms that balance the trade-off between fair distribution of resources and efficient allocation of the resources among network users. Two algorithms proportional fair scheduling (PFS) and margin adaptive scheduling scheme (MASS) will be compared and analyzed with maximum sum rate (MSR) and round robin (RR) algorithms that are considered as references.

Many versions of RRA algorithms do exist. But this work is only based on the four RRA algorithms above.

Many performance parameters are available in literature for comparing and analyzing RRA algorithms. However, for our purpose we only use fairness based on [14], throughput and delay as performance parameters to compare and analyze the RRM algorithms developed.

The channel models described in the appendix are only used to generate the channel responses of users in the four algorithms during subcarrier assignment. Indeed, various channel models exists. However, this project has only focused on Jakes and filtered Gaussian models to model the Rayleigh fading.

Although other analytical evaluation tools are available and could be used in the performance analysis of the algorithms developed, our algorithms were developed and analyzed using MATLAB 7.9.0 (R2009b) analytical tool.

1.8 Dissertation Outline

The rest of this dissertation is organized as follows:

Chapter two presents the framework of resource management for OFDMA wireless systems. Some of the topics discussed include: resource management challenges and the available resources and diversities in OFDMA systems; the RRM techniques and common optimization tools for solving RRM problems.

In chapter three, scheduling and resource allocation techniques in OFDMA systems are described. A description of two resource allocation classes: margin adaptive and rate adaptive are provided. The process of choosing the analytical tool to use for performance analysis of our work is done. Also the description of the m-file scripts developed in our work is given.

Chapter four focuses on modelling of adaptive RRA algorithms in the downlink of OFDMA systems. The system model used in this study and the channel characteristics assumed in the analysis of the algorithms is described. Algorithms for the different RRM schemes are developed. Three performance parameters including fairness, throughput and delay are discussed.

In Chapter five, the Matlab function codes developed based on the formulations derived in chapter 4 were run and the results obtained are analysed and discussed. The link-level setup and parameters used in the analysis are provided while the performance evaluations of the developed algorithms are presented.

Chapter six provides the concluding remarks on the findings of the study and gives recommendations for future work.

The appendix discusses the channel models; filtered Gaussian noise model and Jakes model, used in modelling the Rayleigh fading that was considered in this work.

Chapter 2

2 Radio Resource Management for OFDMA Wireless Systems

2.1 Introduction

The scarcity of radio resources is a major concern in the wireless communication systems. Therefore, radio resource management policies that efficiently utilize the scarce resources are critical. This chapter presents the resource management for OFDMA wireless systems. The chapter begins in section 2.2 which presents an overview of the challenges encountered in the process of managing resources in a wireless network. The resources and diversities available in OFDMA wireless network are described in section 2.3 and 2.4 respectively. Section 2.5 explains the different RRM techniques used in OFDMA systems. The most common optimization tools used to solve RRM problems for OFDMA systems are presented in section 2.6. Section 2.7 reviews different RRM architectures one can encounter in OFDMA systems and the chapter summary is provided in section 2.8.

2.2 Resource management challenges

The wireless revolution has been witnessed averagely every decade starting from 2G system in early 1990. This has brought into existence an unimaginable increase in the number of mobile subscribers, and a large number of applications that have evolved from voice only to multimedia to advanced mobile services being supported currently by 4G systems. Future networks are expected to support even a large number of multimedia and other converged applications. These developments require new ways of managing the networks to be able to flexibly and efficiently utilize the scarce radio resources and fairly share them amongst network users while guaranteeing their QoS requirements.

The network operator can improve their network performance by either using network planning or through static reconfiguration of the existing network parameters or through use of adaptive resource techniques.

Radio resource management techniques are used in the utilization of the radio resources of the air interface of a given cellular network and are decisive in guaranteeing of QoS requirements for different service classes. They are also used as means for maximizing system capacity and providing acceptable fairness in the resource distribution among network users.

This work looks at adaptive resource management techniques that will enhance the performance of the network by efficiently utilizing the available resources in the network. The next section looks at the resources available in OFDMA system and the ways RRM policies can be used to manage and utilize them optimally.

2.3 Radio resources in OFDMA system

RRM policies can take advantage of the different resources available in OFDMA to improve the performance of the wireless system. Therefore, through intelligent management of these resources, users' QoS requirements are met and network operators' revenue is increased. Different radio resources are available in OFDMA for sharing among the network users and are summarized below:

2.3.1 Frequency Subcarrier

When the wireless channel varies significantly between the different users, frequency domain adaptation achieves high performance gains. Consequently, frequency domain adaptation becomes an important component for efficient utilization of system bandwidth. An RRM scheme in OFDMA system has the capability of dynamically assigning users with subcarriers depending on the channel gains leading to high performance.

2.3.2 Time Slot

The wireless channel capacity is continuously varying in time and RRM in OFDMA exploits these variations in time domain by scheduling users depending on their channel state at a particular time. This adaptation was found to substantially increase spectral efficiency as was observed with the 3GPP High Speed Downlink Packet Access (HSDPA) system.

2.3.3 Modulation and Coding Schemes (MCS)

Adaptive modulation and coding enables a robust and spectrally efficient transmission over the time-varying channel and if implemented carefully, can allow the transmitter to send high data rates over the subcarriers with good channel conditions. RRM in OFDMA uses this technique over a multiple of OFDM symbols. The adaptive modification of the modulation and coding strategies is referred to as link adaptation. The details of modulation and coding are however ignored as our interest is on the performance analysis of RRM techniques.

2.3.4 Transmission Power

The transmit power per subcarrier can be adapted in order to increase the spectral efficiency in the frequency-selective wireless channel. For higher spectral efficiency, frequency areas with low attenuation relative to other frequencies could receive more transmit-power. Transmit power can be changed accordingly depending on the subcarrier states and the number of bits it is carrying.

2.4 Diversity Techniques

One of the techniques used to overcome fading in a wireless communication system is diversity which enables the receiver to receive multiple copies of the transmitted signal, increasing the SNR and decreasing the probability of error [15]. Based on how the user perceives the channel at given times, RRM schemes can take advantage of this diversities and allocate users resources to substantially increase the performance of the system, for example, allocating subcarriers to users with good channel gains.

2.4.1 Frequency diversity

In distributed subcarrier scheme, the subcarrier allocator pseudo randomly distributes subcarriers across the band. From a user's perspective, such a distribution of subcarriers offers frequency diversity as some of the subcarriers allocated to the user will experience fades while others will not. Frequency diversity plays a greater role in mobile communication because of multipath fading effects. When a mobile terminal is moved from one location to another, it experiences different channel responses due to multipath effects as Figure 2.1 illustrates [12]. As users move from location X to location Y, the allocated subcarriers experience different channel responses. RRM schemes developed in this work use distributed subcarrier method in allocating subcarriers to users.

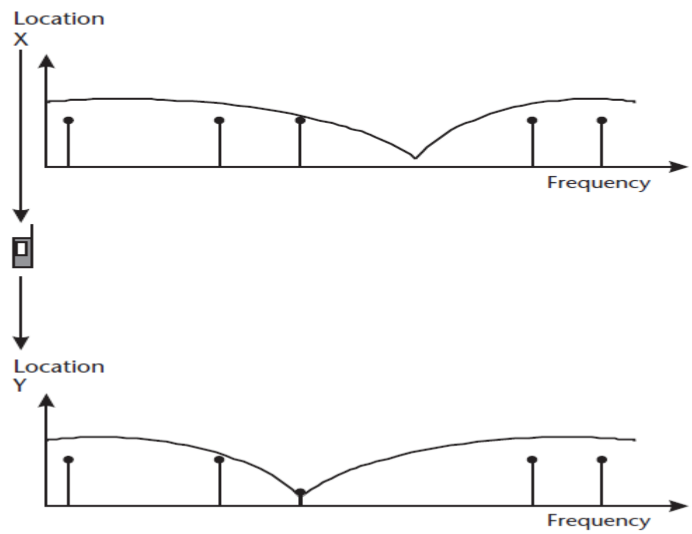


Figure 2.1 A block diagram depicting a mobile terminal experiencing different channel responses: At location X, subcarriers is not degraded by the channel response. At location Y, a subcarrier is experiencing deep fade.

2.4.2 Time diversity

Time diversity arises when a message signal is transmitted over different time slots whose separation is equal to or greater than the coherence time of the channel.

2.4.3 Antenna diversity

Antenna diversity enables the transmission and reception of signals through several antennas which are sufficiently spaced apart. When a system uses more than one transmit and or receive antennas, reliability is improved and the quality of the wireless link is enhanced. RRM techniques can intelligently use the antenna diversity to increase performance, although this is not implemented as it is out of the scope of the work.

2.4.4 Multiuser diversity

Different users located at different places experience different channel responses and this creates what is called a multiuser diversity. Through contiguous subcarrier allocation to different users, multiuser diversity is achieved. Note that depending on the users' channel response, the base station can allocate a set of contiguous subcarriers to a user who has the best experience on that channel, Figure 2.2 [12]. OFDMA systems have the capability of assigning subcarriers to users based on their SINRs and therefore, the BS can allocate a contiguous set of subcarriers to a user with high SINR experience. This diversity is widely used in our work.

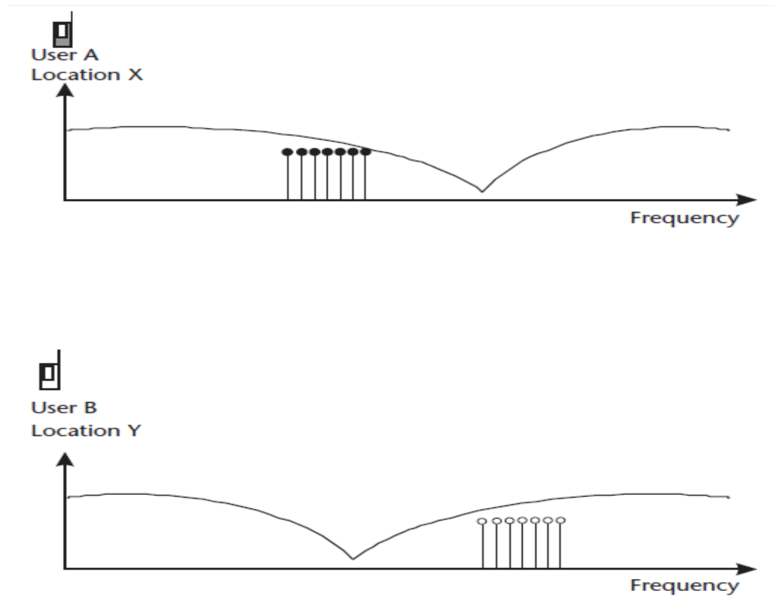


Figure 2.2 A block diagram showing multiuser diversity: At location X, user A's subcarriers are experiencing a good channel response (away from the null). At location Y, user B's subcarriers are also experiencing a good channel response (away from the null).

2.5 RRM Techniques for OFDMA Systems

In OFDMA cellular systems, allocation of resources corresponds to a multi-dimensional problem in time, frequency and spatial domains. Therefore, an intelligent resource allocation strategy is seen as key to significantly improve the performance of OFDMA systems and to fully exploit the different kinds of diversity offered by the system.

From the preceding explanation, it is evident that intelligent and efficient RRM techniques are essential to provide considerable gains in coverage, capacity and QoS for OFDMA broadband wireless networks. From a business point of view, improved coverage, capacity and QoS represent better investment returns and better services. And from the subscribers' perspective, this will lead to better services, high fairness and enhanced QoS levels with widespread availability at possibly lower prices.

This then calls for innovative RRM strategies that efficiently utilizes and distributes resources to users in an OFDMA system. The diversities present in the wireless network should be exploited by RRM schemes developed. This will ensure efficient utilization of the resources available in the network while guaranteeing user fairness and QoS requirements. There are many RRA algorithms available for OFDMA cellular systems and it is not the objectives of this dissertation to present an exhaustive list of such techniques, although, brief overview of some is presented below:

2.5.1 Dynamic Subcarrier Allocation (DSA)

Depending on the radio resource allocation policy in use [16] and the multiuser diversity, subcarriers can be adaptively assigned to different users to take advantage of the different channel gains experienced by subcarriers as observed from different users.

2.5.2 Adaptive Power Allocation (APA)

A subcarrier may experience different channel gain depending on which frequency it is related to (frequency diversity), for which user it is allocated (multiuser diversity), and when it is allocated (time diversity). Considering this, it may be advantageous to adaptively assign each subcarrier different power levels [17].

2.5.3 Adaptive Modulation and Coding (AMC)

It is also known as bit loading [18]. By exploiting frequency and time diversities, AMC can allocate the best MCS to each subcarrier according to the link conditions i.e., SNR.

In this dissertation, DSA and equal power allocation (EPA) is used. Although, APA introduces considerable performance improvement in the low SNR regions as compared to EPA, its performance gain is negligible in the high SNR regions [5], [19].

2.6 Optimization Tools

There are many RRM problems in OFDMA-based cellular networks. Some possible objectives of RRM techniques include: capacity maximization, optimized coverage, minimum power consumption, enhanced QoS, high fairness, proportional fairness, etc. Most of these RRM approaches can be formulated as RRA optimization problems, with an objective function that must be minimized or maximized with optimization constraints that correspond to physical restrictions of the network.

Optimization tools differ in the way they solve the presented problems and thus some factors to consider in choosing the optimization tools to use include: formulation of the optimization problem itself, the nature of variables involved, the possibility of linearization of the objective function and the possibility of relaxation of the optimization constraints. In any case, even for the same RRM problems, different RRA policies arise depending on the optimization formulation used.

Furthermore, some suboptimal approaches are used when the optimum solution of the optimization problem is too difficult to solve. Listed below are two of the most common approaches found in literature [16], [17]:

2.6.1 Relaxation of Constraints

The idea is to relax some optimization constraints in order to make the problem tractable. An example is to relax the integer constraints on subcarrier or bit assignments, and allow multiple users to share one resource element. By doing this, the problem may become a linear programming problem that can be solved efficiently. However, after solving the relaxed problem, one must revert back to the integer solution as from the network's point of view, only integer solutions are feasible.

2.6.2 Problem splitting

Using this approach complex optimization problems are split into several simpler steps. Through these simpler steps, a suboptimal solution that is close to the optimal can be obtained. This approach is used widely in the RRA schemes proposed in this dissertation.

Some common optimization tools present in literature for OFDMA systems include:

2.6.3 Heuristics

This is an experience-based technique for solving optimization problems and is used to find suboptimal solutions with the hope that they are close to optimum with much less complexity than other conventional combinatorial optimization techniques. This tool has been used by many works in the literature.

2.6.4 Utility Theory

Originally, this theory was conceived for applications in economics [20], but found attention of researchers working in communication area. By quantitatively formulating the relations between user experience and various network performance metrics, utility functions are able to capture the satisfaction level of users for a given resource assignment.

2.6.5 Branch and Bound (BnB)

It is an approach that has been developed for solving combinatorial optimization problems [21] and it combines enumeration of all possible solutions by means of "branches" and the process of "pruning" some of them.
Some of the optimization tools used to solve specific RRA problems includes:

2.6.6 Convex Optimization

It's a common tool used to propose RRA techniques for OFDMA systems. Example is the Lagrangian's method of multipliers [22]. The Lagrangian was used to solve the well known finite tones water pouring problem analytically [23]. Another example is the Simplex method for solving a class of optimization problems known as linear programming which was applied in [24] to solve a linear programming problem in OFDMA multi-cell system.

2.6.7 Hungarian Method

Is a classic tool for solving the assignment problem [25] in a special class of transportation problems. Works in [26] have used the Hungarian method as an optimization tool towards the RRM in OFDMA systems.

2.6.8 Game Theory

Models situations or games in which the success of an individual in making choices depends on the choices of others. In [27], a distributive non-cooperative game is proposed to perform subcarrier assignment, power control, and adaptive modulation for multi-cell OFDMA networks.

2.7 RRM Architectures in OFDMA System

While reviewing the current state about RRM for OFDMA macro cell networks, two distinct scenarios were observed: single cell and multi cell. The single cell is characterized by the presence of one transmitter (BS) and multiple receivers (MTs). For single cell case, SNR was used as a quality measure for the users. On the other hand, multi cell scenario consists of multiple transmitters (BSs) and multiple receivers (MTs). Here SINR is the quality measure for the different users, as inter-cell interference between multiple cells is available and must be taken into account.

Depending on where resource allocation is performed, RRM can be classified as either centralized or distributed or hierarchical.

2.7.1 Centralized Resources Management

In centralized RRM schemes, a central entity such as an RRM server connects to all BSs and knows all the channel quality indicators (CQI) of all users in all the subcarriers available in the system. The allocation of resources is executed by the central entity. Some of the resources that need distribution through the central entity include subcarriers, power applied to each subcarrier and MCSs used in each subcarrier. Although, the centralized scheme can be used as a benchmark for performance evaluation, it has the disadvantage of exhibiting high computational overhead due to the requirement to send the assignment information. Authors in [28] consider the centralized approach.

2.7.2 Distributed Resources Management

High signaling overhead is a characteristic of the centralized RRM scheme. To reduce the high signaling overhead, distributed schemes were naturally devised. In distributed schemes, no central entity is responsible for receiving all the measurement reports from the users and BSs. Neither, is there a central entity to distribute resources to MTs and BSs. Rather, several distributed systems share the responsibility of resource allocation. In [29], the authors formulated distributed RRA algorithms for OFDMA systems.

2.7.3 Hierarchical Resources Management

In hierarchical RRM scheme, different entities are involved in resource allocation. The different entities, such as RRM server and the BSs, are placed in different levels of the hierarchy and share the resource allocation tasks based on its level. Hierarchical RRM algorithms, studied in [30], offers a good trade-off between the centralized and distributed schemes.

In this dissertation the evaluation of the proposed RRA techniques will be carried out in a single cell scenario where all resource allocation information needed by the RRM techniques reside in the BS.

This has been necessitated by the fact that, the trend in the next generation mobile communication network require that the RRM techniques should be executed in the BSs and not in the radio network controllers anymore, as was the case for the Third Generation (3G) systems.

Chapter 3 of this dissertation will explore the different works found in literature that consider single cell scenarios.

2.8 Chapter Summary

In this chapter, the RRM challenges encountered in the design of resource management schemes have been presented. The available radio resources and diversities in OFDMA-based wireless systems and ways to efficiently utilize them have been discussed. Different RRM optimization tools that are used to solve RRM problems that exist in OFDMA networks have also been described. Also discussed in this chapter are the different RRM architectures available for the design of different RRA algorithms depending on the resource allocation strategy chosen.

It is evident from this chapter that scheduling and resource allocation techniques (generally referred to as Radio Resource Management (RRM) techniques) are key to efficient utilization of the scarce radio resources of the air interface of a given wireless network. Therefore, there is need to explore the different scheduling and resource allocation in OFDMA-based wireless networks that can be used to intelligently and efficiently allocate the scarce resources to allow for best delivery of QoS to users at minimum cost. This leads us to Chapter 3, where different scheduling and resource allocation techniques found in literature will be discussed.

Chapter 3

3 A Survey of Scheduling and Resource Allocation in OFDMA Wireless Networks

3.1 Introduction

In this chapter, we provide a review of some of the key developments that have taken place recently in multiuser OFDMA wireless systems. Section 3.2 discusses the related work in scheduling and resource allocation optimization problems. Section 3.3 discusses different analytical tools and why Matlab was chosen as a tool to analyse our work. This section also describes the m-file scripts developed in our work. The concluding remarks for this chapter is given in section 3.4

3.2 Related Work

3.2.1 Scheduling Algorithms in OFDMA Wireless Systems

The aim of a resource-scheduling algorithm is to assign the resource units and transmission powers for each sub-frame in order to optimize a function of a set of performance metrics, for example maximize throughput, minimize delay, improve spectral efficiency or reduce outage probability.

Scheduling and resource allocation functionalities in terms of inputs and outputs are graphically represented in Figure 3.1. In reference to Figure 3.1, scheduling decisions depends on specific objectives pursued with the strategy to be considered that then decides the best methods and tools that are used to carry out the scheduling and resource allocation functions.

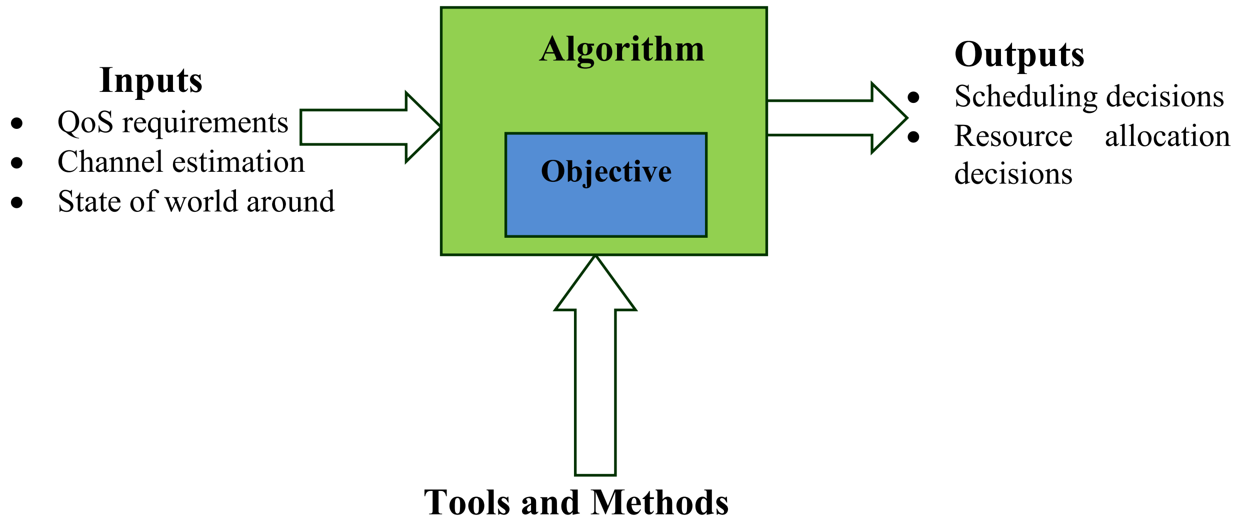


Figure 3.1 Graphical representation of scheduling algorithm design.

Scheduling complexity has increased over the last couple of years, due to wireless systems becoming more and more complex. In order to reduce complexity, some works in the literature [31], proposed a problem splitting technique that breaks the scheduling procedure into several simpler steps. As indicated in Figure 3.1 scheduling depends on the channel estimates feedback by the users to be able to make informed decisions so as to schedule the users during times that there can best utilize the system resources. That way, a scheduler algorithm can ensure all users are served fairly and that the efficient utilization of resources is not compromised.

3.2.2 Network Design and Management Paradigm Shift

Wireless communication network designers were faced with particular challenges on how to utilize more efficiently the group of available radio resources especially with the convergence of mobile and internet-based data access services. Whereas network planning had a fundamental role since until 2nd generation mobile communication systems (2G) that only supported voice, RRM was not crucial then. Therefore, the “divide and conquer" was the conventional approach used for such a system.

However, due to the ever-increasing requirements for high data rates, 3rd generation mobile communication systems entered the market. Thus, due to increased requirements for high spectral efficiency, an aggressive spectral reuse by the system designers ensured. Despite the gains obtained by spectral reuse in addition to power control and dynamic resource allocation, increased interference in the network was experienced.

Additionally, resource planning and power control in multi-cell networks were traditionally designed to reach a target SINR for all interfering terminals simultaneously. For connection oriented voice calls, this SINR balancing act insured the worst-case outage probability scenario [32].

Modern and future networks are expected to support and manage different QoS requirements in the presence of mixed traffic composed of possibly Real Time (RT) and Non-Real Time (NRT) applications. The concept of a specific operating point is less relevant and network-planning phase has no sense without radio resource management (RRM). The inherent frequency-selective and time-varying nature of the wireless channel should be taken into account.

Scheduling algorithms, while fulfilling QoS requirements, should also utilize system resources optimally and at the same time, maintain fairness among network users located in the system. Besides, Adaptive Modulation and Coding (AMC) schemes typically feature in current systems aiming at maximizing the sum network capacity that appears as an important performance parameter. The inadequacy of the divide and conquer approach used in network-wide performance optimization is apparent owing to the issues abovementioned.

Therefore, the utilization of the ever-changing channel by the use of opportunistic scheduling [33], was the first idea explored by researchers dealing with wireless scheduling problem. System capacity maximization is the objective of such a scheme. By taking advantage of multiuser diversit, opportunistic algorithm can allocate subcarriers to the user(s) with highest channel responses on the subcarriers. This maximises system capacity, although it becomes unfair to users who experience poor channel conditions, as they will be starved of resources for a long time. Nevertheless, to take advantage of these gains, link adaptation strategies must be used when channel conditions are favourable for transmission.

In order to integrate QoS constraints into opportunistic algorithms, some works were carried out and the trade-off between multiuser diversity and user satisfaction was explored [34]. Other works [9] considered the problem of fairness. Here, the authors studied the max-min fairness based RRM problem, where the same data rate was assumed for all users. Authors in [35] proposed an allocation process that maximized packet throughputs subject to some outage probabilities. Most of these scheduling techniques studied in the past either scheduled users to maximize efficiency or to maximize fairness. Our work will focus on obtaining a trade-off between fairness and efficiency.

3.2.3 Resource Allocation in OFDMA Wireless Networks

Recently, resource allocation problem in OFDMA wireless networks has been an active area of research. The problem includes allocation of time slots, assigning subcarriers, and allocating power to different users. Among the works found in literature that considered the problem of resource allocation, two main optimization approaches were found:

- **Margin Adaptive (MA):** MA's goal is to allocate as minimal power to subcarriers as possible while guaranteeing the user rate requirements and bit error rate [11], [10]. This technique is more suitable for applications such as voice that have fixed rate requirements.
- **Rate Adaptive (RA):** RA's main goal is to maximize an objective function based on instantaneous user rates within every transmission time interval (TTI), subject to a constraint on the BS overall transmit power . This technique is best suited for NRT services such as IP-based and bursty data.

Margin Adaptive Resource Allocation

In order to solve the MA problem, the method of relaxation of constraints was first employed and presented in [11], where the integer constraints of the subcarrier assignment were relaxed. A suboptimum solution to this optimization problem was suggested where the user with the highest share of the subcarrier was allocated that subcarrier. Subsequently, power was distributed between the subcarriers using the power-loading algorithm. This ensured the fulfilment of the rate requirements of the mobile terminals with minimum power assignment. With this simplification, however, the solution obtained gave a lower bound estimation of the minimum transmit power, although the work showed that the suboptimal solution obtained was very close to optimum. The work in [11], although too complex, formed the initial work in MA optimization problem which was subsequently used as a benchmark for other works in this area.

The authors in [35] proposed a real-time heuristics algorithm where they split the problem into two steps: initially subcarrier assignment was obtained through a constructive algorithm which is based on ordered lists of subcarriers; in the second phase, an iterative swapping of the subcarriers among network players is performed on the initial assignment with the aim of minimizing the objective function. Through experiments, it was verified that, the performance obtained was close to the one provided by the optimal allocation in [11] though with low complexity.

In [10] the combination of problem splitting and heuristics to solve the MA problem was used. First the number of subcarriers every MT will receiver is determined using a greedy algorithm. Second, the specific subcarrier assignment is done. Simulation results indicated that the power requirements of the proposed algorithm slightly exceeded those of [11] even as the central processing unit run times were less than a factor of 100. The authors of [24] and [36] also employed the combination of problem splitting approach and heuristics based optimization.

Rate Adaptive Resource Allocation

In rate adaptive approach, there are a number of techniques used that depend on the objective function and the considered constraints. Authors in [5] proposed an integer programming problem whose objective was formulated to maximize the instantaneous total cell rate. A computationally efficient greedy algorithm was proposed, which allocates subcarriers to a user with the best channel conditions. Power is then distributed with respect to the objective function using a power-loading algorithm.

Another variant of the rate adaptive approach tries to maximize a lower bound of all terminals' instantaneous rates, which introduces a fairness component into the RRA problem [1]. An efficient algorithm that applied the problem splitting approach in [37] first solved this rate adaptive variant. In the first step, the combined power and subcarrier assignment based on the average channel gain is solved. The so-called assignment problem is solved in the second step, where the best subcarrier/MT pair is determined. The Hungarian method [25] was proposed in solving the assignment problem by the authors of [37] and then adaptively allocate power to the MTs to distribute amongst the subcarriers. In [38], a multiuser OFDM adaptive resource allocation method referred to as proportional rate was proposed. The problem splitting approach was used to solve the problem with the aim of reducing complexity. Therefore, subcarrier assignment and power allocation were performed sequentially. Lastly, a procedure is derived for optimal power allocation.

Authors in [9] and [39], proposed rate adaptive works that could be solved by using the heuristics only. For example, the authors in [9] apart from using the problem splitting and integer relaxation methods propose a heuristic algorithm that assigns subcarriers with equal power. They claimed that most of the time the subcarriers assigned to users are in good conditions and thus equal power distribution will not reduce system performance so much. This idea is also used in our work where equal power allocation to subcarriers is assumed. Otherwise, authors in [17] showed that equal power distribution for a wireless point-to-point connection reach almost the same performance as adaptive power allocation. Considering the frequency selective nature of the users' channel, authors in [39] proposed a heuristic scheme that jointly performs subcarrier and power assignment.

To cope with complex rate adaptive optimization problem, some works have proposed to use more than one optimization approach. For example, authors in [40] have proposed a combined problem splitting and integer relaxation approaches in obtaining the solution for the rate adaptive optimization problem. The optimal subcarrier and bit allocation problems, which were formulated in [40] as nonlinear optimizations, were solved by integer programming by converting the nonlinear problem into linear. A sub-optimum approach that performs, separately, bit loading and subcarrier allocation was proposed based on this.

Form the foregoing discussion, it is apparent that, for a wireless channel that is time-varying and frequency-selective, a major challenge is posed especially on efficient resource usage and fair distribution of resources to the network users. Thus, an optimum RRA scheme that maximizes efficiency and promises to share resources more fairly remains an open research problem.

In this dissertation, our focus will be on studying the effects of a mixed service scenario on system capacity and fairness using different RRA algorithms on the downlink of an OFDMA wireless system. Therefore, we evaluate and compare the performance of both the margin adaptive and the rate adaptive algorithms with respect to instantaneous rates and long term averages.

The summaries of margin adaptive and rate adaptive schemes are given respectively in Tables 3.1 and 3.2 [7].

Table 3.1 Margin Adaptive Schemes

Scheme	Performance	Complexity	Overhead	CSI	Fairness
Wong and Cheng [11]	in terms of average SNR/bit and number of users supported, outperforms OFDM-TDMA and OFDM-FDMA with fixed resource allocation	$O(NL_{iter} >> K, N)$	Ignored	Perfect	Ignored
Kivanc and Liu [10]	slightly degraded from [11], but it's performance is better than OFDM-TDMA with fixed resource allocation, in terms of transmit power/bit/s, but	*O(KN)*	Ignored	Perfect	Ignored
Zhang and Letaief [41]	in terms of average SNR/bit and number of users supported, outperforms OFDM-TDMA with fixed resource allocation	$O(NL_{iter} >> K, N)$	Ignored	Perfect	PF
Wang *et al.* [42]	in terms of spectral efficiency, simulation results shown to match theoretical ones	Not applicable	Considered	Perfect	Ignored
Han *et al.* [27]	in terms of achievable rate and required transmit power outperforms classical water-filling	*O(NlogN)*	Ignored	Perfect	Ignored
Xiaowen and Jinkang [43]	in terms of average SNR/bit and number of users supported, outperforms OFDM-TDMA with fixed resource allocation	Not applicable	Ignored	Perfect	Ignored

Table 3.2 Rate Adaptive schemes summary

Scheme	Performance	Complexity	Overhead	CSI	Fairness
Rhee and Cioffi [9]	in terms of achievable rate, outperforms OFDM-TDMA, with fixed resource allocation	Not applicable	Ignored	Perfect	Ignored
Shen *et al.* [38]	in terms of achievable rate, outperforms OFDM-TDMA, with fixed resource allocation	Not applicable	Ignored	Perfect	PF
Jang and Lee [5]	in terms of achievable rate, outperforms [8] and OFDM-FDMA, with fixed resource allocation	Not applicable	Ignored	Perfect	Ignored
Yin and Liu [37]	in terms of achievable rate, outperforms OFDM-TDMA, with fixed resource allocation	$O(N^4)$	Ignored	Perfect	Ignored
Kim *et al.* [44]	Required transmit power comparable to [8]; Achievable rate higher than [Rhee]'s	$O(N^2)$, for suboptimal solution $O(N^4)$, for optimal solution	Ignored	Perfect	Ignored
Tang and Zhang [45]	Analytic results were compared with simulations results. Statistical delay bound derived	Not applicable	Ignored	Perfect	PF

3.3 Methodology

This section describes the different analytical tools and why Matlab was chosen for analysing the performance of the link level algorithms proposed in this work. It also presents the m-file scripts developed in this work.

3.3.1 Analytical tools

Many analytical tools are available that can be used in analysing link level OFDMA algorithms developed in this work. Some of the tools are described and an explanation given on why Matlab was proposed as the tool to be used in analysing the algorithms developed.

GNU Octave

Is a high-level programming language that is intended for numerical computations. Usually used with Linux operating systems. GNU octave uses a language that is compatible with Matlab. We use Windows OS and thus not handy to use it although needed more time to learn it also.

Mathematica

Mathematica is a proprietary analytical tool. Mathematica has many features that include data and matrix manipulation, combinatorial problems tools, support local and global constrained and unconstrained optimization. Have not used it before and this meant putting more effort and time in learning it and thus end up with less time to work on our project, and thus was not chosen.

Labview

Labview is a proprietary tool that supports both textual and graphical programming approaches. Labview stands for Laboratory virtual instruments engineering works. It is a system design platform and development environment for visual programming language. Mostly used for data acquisitions, instrument control and industrial automation. As visual language needed to be learned and also haven't used labview before, meant more time could have been spend learning how to use labview. Therefore, was not used for those reasons.

Matlab

Matlab is a powerful numerical computing environment for handling engineering and scientific calculations. Matlab is proprietary software that stands for Matrix Laboratory and was primarily developed to support numerical computing. Additional tools and packages such as optimization toolbox and Simulink are embedded into it. It is widely used in the academia and industry for performance analysis. Matlab has become the natural choice for numerical analysis due to its wide acceptance and easy to understand manipulations. MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and Fortran. Most of the functions that we required to implement our analytical model are available in Matlab. Also had prior knowledge of Matlab and thus did not waste a lot time learning [46].

Based on the above discussions we found Matlab more appealing to use in our work. More so, it has most of the functionalities that we required for performance analysis of the analytical algorithms developed.

3.3.2 M-file scripts

Matlab scripts were developed based on the equations given in Chapter 4 for the different algorithms. Below is a description of the functions of different m-files scripts developed. The results obtained are presented in Chapter 5.

Channel modelling functions

Two different scripts, filtered Gaussian model and Jakes model, were developed. The two models were used to model a Rayleigh fading. Filtered Gaussian model is a function that creates a fading signal from in-phase and quadrature Gaussian noise sources. Applying the appropriate filtering provides the Doppler spectrum. Jakes model function models a mobile channel behaviour according to Clarks' assumption by summing a set of complex sinusoids.

Scheduling algorithm function

This function computes different channel responses, one per user and time slot. Thereafter, the scheduler scheme is computed according to four different algorithms, MSR, RR, PFS and MASS.

Fairness function

This function computes fairness according to [14] for four different scheduling algorithms: PFS, RR, MASS and MSR. Fairness F lies between $0 < F < 1$. If $F = 1$, then all users in the system consume exactly their fair share of resources. If $F = 0$, then one user consumes all resources allocated. Graphs of fairness versus number of users for different scenarios for the four algorithms are plotted.

Throughput function

This function computes the system throughput for different set of users according to different algorithms PFS, RR, MASS and MSR. It then plots graphs showing throughput versus number of users in three different scenarios for the four different algorithms.

Throughput and fairness versus t_τ parameter

This function computes the system fairness and system capacity versus t_τ parameter according to three different algorithms, PFS, MSR and RR. Graphs showing throughput versus t_τ parameter and fairness versus t_τ parameter for the three algorithms were plotted.

Delay function

This function computes the probability that a user *k* is transmitting less than R_{min} bits per unit time. Graphs showing the outage probability versus delay are plotted. Outage probability in this context means the probability that a user *k* is transmitting less that R_{min} bits/time.

3.4 Chapter Summary

In this chapter, a review of scheduling and resource allocation strategies in literature and in particular for OFDMA systems has been carried out. The methodology that was used in developing the algorithms proposed in this dissertation is described. From the preceding discussions, numerous issues were identified, notably in scheduling and resource allocation in OFDMA systems. This then points us to Chapter 4 where different adaptive resource allocation techniques are developed to study the effects of a mixed service scenario on system capacity and fairness using different RRA algorithms on the downlink of an OFDMA wireless system.

Chapter 4

4 Adaptive RRA Schemes in the Downlink of OFDMA Systems

4.1 Introduction

From radio resource allocation (RRA) perspective, three main strategies can be used to maximize the performance of OFDMA wireless systems [7]: subcarrier allocation, power loading, and bit loading. Resource allocation optimizes the performance of OFDMA systems by intelligently allocating subcarriers to users who can use them more efficiently within OFDM symbol duration. Modulation type (number of bits) and the power to be assigned to every subcarrier are performed by the bit loading and power assignment optimization modules, respectively. Therefore, in designing efficient OFDMA systems, optimization, as discussed in section 2.6, is an important mathematical tool. A resource allocation process is said to be adaptive if its allocation is based on channel state information (CSI) feedback by users to the BS.

This chapter presents a set of specific adaptive RRA algorithms in the downlink of an OFDMA-based wireless communication systems operating in different scenarios. The chapter begins in section 4.2, where the system model to be used in this work is presented, with the channel characteristics to be assumed also described. Section 4.3 gives the general RRA problem formulation to be considered in this work. The four different RRA algorithms: RR, MSR, PFS and MASS which forms the main objectives of this work are discussed in section 4.4. The performance metrics to be used to evaluate and compare the algorithms are described in section 4.5 and finally the chapter summary is provided in section 4.6.

4.2 System Model

The considered downlink of an OFDMA system is presented. The propagation channel is assumed to be frequency selective Rayleigh fading channel that remains static within an OFDM symbol i.e., is quasi static. We also assume that perfect channel state information is available at both the base station (BS) and the mobile terminals (MTs).

The problem of resource allocation in the downlink of the multiuser OFDMA system with K users and C subcarriers is to determine the elements of matrix $S = [s_{k,c}]_{K,C}$ specifying which subcarrier to assign to which user and vector $p = [p_{k,c}]_{K,C}$ specifying how much power to allocate to each subcarrier, as shown in Figure 4.1 [2].

Authors in [5] showed that the throughput of a multiuser OFDM is optimized when a subcarrier is assigned to a single user with the highest channel gain on the subcarrier among the users. Thereafter, power is distributed by the water-filling method [47] between the subcarriers. Based on this theorem, the elements of matrix S is determined by restricting a subcarrier to be used by a single user only. In this work, to obtain the elements of vector ***p***, equal power allocation algorithm, which distributes power equally to all subcarriers, is considered. With equal power allocation, we can make valid conclusions on the comparison between the different resource allocation algorithms. In the forward link of a multiuser multicarrier system, such as OFDMA system, only one total power constraint exists.

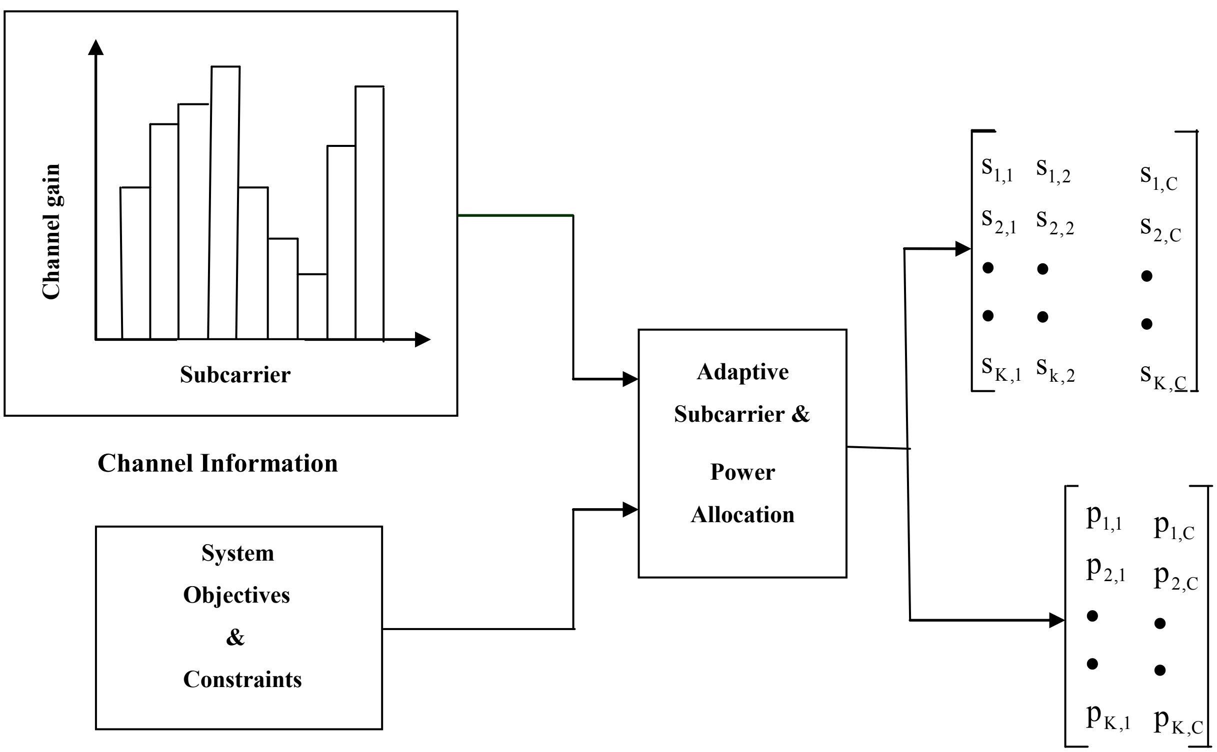


Figure 4.1 Summary of the problem of resource allocation in OFDMA systems

In formulating the optimization problem of resource assignment, it is assumed that the system has *K* active users all the time, with QoS requirements that differ based on bit error probability and data rate. Also, they always have some data to transmit, when scheduled for transmission [2].

4.3 Adaptive Radio Resource Allocation Problem Formulation in OFDMA Wireless Systems

Consider an OFDMA system scenario with *K* users, a total system bandwidth of *W* Hz subdivided into *C* subcarriers. The data rate of the k^{th} user at subcarrier *c* in time slot *t*, $R_{k,c}(t)$ in bits/sec, is expressed as [2]:

$$R_{k,c}(t) = \frac{W}{C}\sum_{c=1}^{C} s_{k,c}(t)\log_2\left(1+\chi_{k,c}(t)\right) \tag{4.1}$$

where $s_{k,c}(t)$ is a binary allocation variable, that is 0 if subcarrier *c* is not allocated to user *k* at time slot *t* and 1 if subcarrier *c* is assigned to user *k* at time slot *t*. $\chi_{k,c}(t)$ is the signal-to-noise ratio (SNR) of user *k* on subcarrier *n* at time slot *t* and is expressed as:

$$\chi_{k,c}(t) = p_{k,c}(t)H_{k,c}(t) = \frac{p_{k,c}(t)\left|h_{k,c}(t)\right|^2}{N_0\frac{W}{C}} \tag{4.2}$$

where $p_{k,c}(t)$ is the power assigned to user *k* in subcarrier *c* at time slot *t*. $H_{k,c}(t)$ and $h_{k,c}(t)$ gives the channel-to-noise ratio and channel gain of user *k* in subcarrier *c* at time slot *t*, respectively. N_0 is the power spectral density of AWGN and $N_0\frac{W}{C}$ is the noise power on each subcarrier.

The optimization problem of adaptive radio resource allocation could be formulated with two possible objectives depending if it is rate adaptive (RA) method or margin adaptive (MA) formulation that is being used, and followed by a variety of constraints. The general problem formulation of the subcarrier and power assignment in an OFDMA system is given as [2], [7]:

Objective: For RA optimization problem

$$\max_{s_{k,c}(t),p_{k,c}(t)} R_T = \frac{W}{C}\sum_{k=1}^{K}\sum_{c=1}^{C} s_{k,c}(t)\log_2\left(1+\frac{p_{k,c|}(t)\,|\,h_{k,c}(t)\,|^2}{N_O\frac{W}{C}}\right)$$

Or: For MA optimization problem

$$\min_{s_{k,c}(t),p_{k,c}(t)} P_T = \sum_{k=1}^{K}\sum_{c=1}^{C} s_{k,c}(t)p_{k,c}(t)$$

Subject to:

C1: $s_{k,c}(t) \in \{0,1\}, \forall_{k,c}$ (4.3)

C2: $\sum_{k=1}^{K} s_{k,c}(t) = 1, \forall_c$

C3: $p_{k,c}(t) \geq 0, \forall_{k,c}$

C4: $\sum_{k=1}^{K}\sum_{c=1}^{C} s_{k,c}(t)p_{k,c}(t) \leq P_T$

C5: User rate requirements

where R_T is the total system capacity and P_T is the total transmitter (BS) power.

Constraints C1 and C2 restricts allocation of a subcarrier to a single user only. C3 ensures that negative power is not assigned to a subcarrier and C4 is the total transmits power constraint. Fixed or variable data rate requirements of the users are determined by constraint C5.

4.4 Adaptive Radio Resource Allocation Algorithms

The problem posed by (4.3) is computationally intractable as it involves both binary variables $s_{k,c}(t)$ and continuous variables $p_{k,c}(t)$. The non-linear constraints in (4.3) increase the difficulty in finding an optimum result as the feasible set is not convex.

Therefore most of the works have been focusing on designing suboptimal algorithms with lower computational complexity but still attain near optimal results. Many algorithms [10], [48] and [9], make the optimization problem in (4.3) convex and easy to solve by relaxing the integer constraint on the assignment variable. Thus, $s_{k,c}(t)$ becomes a sharing factor of user *k* to subcarrier *c* at time slot *t*. Although this simplification is made, it must be noted that in most real time application scenarios, a subcarrier is actually allocated or not allocated to a user.

In this section we will focus on the RRA problem and the different classes of algorithms most commonly applied to formulate and solve the problem identified in section (4.3).

4.4.1 Round Robin (RR) Scheduling Scheme

Round Robin (RR) assigns time slices to each MT in equal portions and in order, handling all MTs as having the same priority and thus RR turns out to be one of the simplest scheduling algorithms. RR scheduling is also starvation-free.

Although RR algorithm allows all users sharing a common channel to transmit or receive on a regular basis, hardly does it provide very good services to the MTs due to its low efficiency in resource utilization. This is so because, RR does not consider the different channel conditions experienced by the users i.e. multiuser diversity and thus could be allocating subcarriers to users that are in fading state most of the times [49]. The algorithm used for RR is shown in **Algorithm 1.** For the RR scheduler, **Algorithm 1** was developed and implemented in MATLAB 7.9.0 (R2009b) analytical tool. The results are presented in Chapter 5.

Algorithm 1 Resource Allocation Procedure in RR Scheduler

1. **for** all users **do**
2. **for** all time slots **do**
3. **if** the number of time slots is not exceeded **do**
4. Allocate all subcarriers in that time slot to user k
5. **end if**
6. **end for**
7. **end for**

4.4.2 Maximum Sum Rate (MSR) Scheduling Scheme

Maximum sum rate is a scheduling algorithm that typically maximizes the system sum data rate. It exploits the fact that different users experience different channel gains and hence will experience good channel conditions at different times and frequencies. Maximum sum rate allocates the channel at every given instant only to the user with the highest channel gain. Authors of [5] and [9], proved that if subcarriers are allocated to users with highest channel gain on it and power is distributed using water-filling, the system throughput increases tremendously. However, a maximum sum rate resource allocation scheme does not ensure fairness and QoS to users with low channel gains.

The mathematical formulation of maximum sum rate scheduling scheme is given by [1], [5], [9], and [7]:

Objective:

$$\max_{s_{k,c}(t),p_{k,c}(t)} \sum_{k=1}^{K}\sum_{c=1}^{C}\Psi(\chi_{k,c}(t),P_e)s_{k,c}(t)$$

Such that

$$\text{C1: } \sum_{k=1}^{K} s_{k,c}(t) \le 1, \forall_c \tag{4.4}$$

$$\text{C2: } \sum_{c=1}^{C} p_{k,c}(t) = P_T$$

$$\text{C3: } p_{k,c}(t) \ge 0, \forall_c$$

where $\Psi(\chi_{k,c}(t),P_e)$ is a rate-power function that relates data rate per subcarrier to a SNR $\chi_{k,c}(t)$ as defined in (4.2) for user *k* on subcarrier *c* at time slot *t* and bit error probability P_e [7]. Although it is possible to share subcarriers among users, subcarriers are assumed to be assigned to only a single user and constraint C1 ensures this. Constraints C2 ensures the total BS power is not exceeded while constraint C3 prevents negative power allocation. In the multiuser radio resource formulation, another additional constraint usually imposed is to ensure that the data rate of each user is above or equal to some required minimum, that is

$$R_{k,c}(t) \cong \Psi\left(\chi_{k,c}(t),P_e\right) \ge R_k^{min}, \forall_k, \forall_c \in A_k^{'} \tag{4.5}$$

where a minimum rate required by user *k,* is R_k^{min} and the set of subcarriers allocated to user *k* is $A_k^{'}$. For example, the definition of the function $\Psi(\cdot)$ is given in [5] as:

$$\Psi(\chi_{k,c}(t),P_e) = \frac{W}{C}\log_2\left(1+\frac{\chi_{k,c}}{\Gamma}\right) \tag{4.6}$$

where the SNR gap Γ is expressed as:

$$\Gamma = \frac{-\ln\left(5P_e\right)}{1.5} \tag{4.7}$$

The problem in (4.4) is not convex and thus, its computational complexity renders it impractical in real systems. The authors in [37] propose a two-step approach in solving (4.4). The number of subcarriers to be assigned to each user is determined and the power to be assigned to each subcarrier is evaluated in the first step. For details, refer to Algorithm 2. In the second step, bit loading and subcarrier assignment (using the Hungarian method) is performed.

Algorithm 2 Resource allocation for MSR algorithm **[37]**

Need:

$C_k \geq 0$ and $p_c \geq 0$, where C_k is the number of subcarriers assigned to user k. Every user k demands a rate of $R_{k,c}$, and has a channel gain of h_k averaged over all the user's allocated subcarriers.

1. For every user $k \in \{1,2,3,\cdots,K\}$, set $C_k = 1$
2. Compute $C_a = \sum_{\forall_k} C_k$.
3. Power requirements for each user is calculated as: $p_k = \frac{C_k}{h_k}\Psi^{-1}\left(\frac{R_k}{C_k}\right)$
4. Total power transmit requirements is calculated as: $P_a = \sum_{\forall_k} p_k$
5. **while** $P_a \geq \frac{C_a}{C} P_T$ **do**
6. Let $G_k = \left[\frac{C_k}{h_k}\Psi^{-1}\left(\frac{R_k}{C_k}\right) - \frac{(C_k+1)}{h_k}\Psi^{-1}\left(\frac{R_k}{C_k+1}\right)\right]$
7. Select $\hat{k} = \arg\min_k G_k$.
8. Update $C_{\hat{k}} = C_{\hat{k}} + 1$ and $P_{\hat{k}} = P_{\hat{k}} - G_{\hat{k}}$.
9. **end while**

In our work, MSR is used as a reference to compare the proposed PFS and MASS algorithms in terms of throughput, fairness and delay in the endeavour to insure all network players are satisfied, and that their QoS requirements are met at the end. Algorithm 1 was implemented in MATLAB 7.9.0 (R2009b) environment and its results are presented in Chapter 5.

4.4.3 Proportional Fair Scheduling (PFS) Scheme

In a practical system, to realize the idea of multiuser diversity, one is straight away faced with two issues: delay and fairness. The MSR strategy maximizes not only system capacity, but also the throughput of individual users when circumstances are ideal and users' have same fading statistics. However, the statistics are not symmetrical in practical systems: some users are in a rich scattering environment while others have no scatters around them; some users are closer to the BS with high SNR averages while others are in poor channel conditions or far away from the BS with low SNR averages; other users are stationary and some are moving. Besides, maximizing the average throughputs is not the only long-term strategy. There are latency requirements in practice, in which case, the performance metrics of interest is the average throughputs over a delay time scale. Being able to exploit the multiuser diversity gain inherent in such a system, while addressing these issues is challenging.

To meet these challenges, a simple scheduling algorithm, *Proportional Fair Scheduling* (PFS), has been designed in an OFDMA wireless system. In this system, users feedback their channel state information to the BS in terms of a requested data rate $R_{k,c}(t)$, which is the current data rate that can be supported on subcarrier *c* and time slot *t* of the k^{th} user.

In a past window of length t_τ, PFS keeps track of the long-term average throughput $T_{k,c}(t)$ and schedules user k^* with the largest

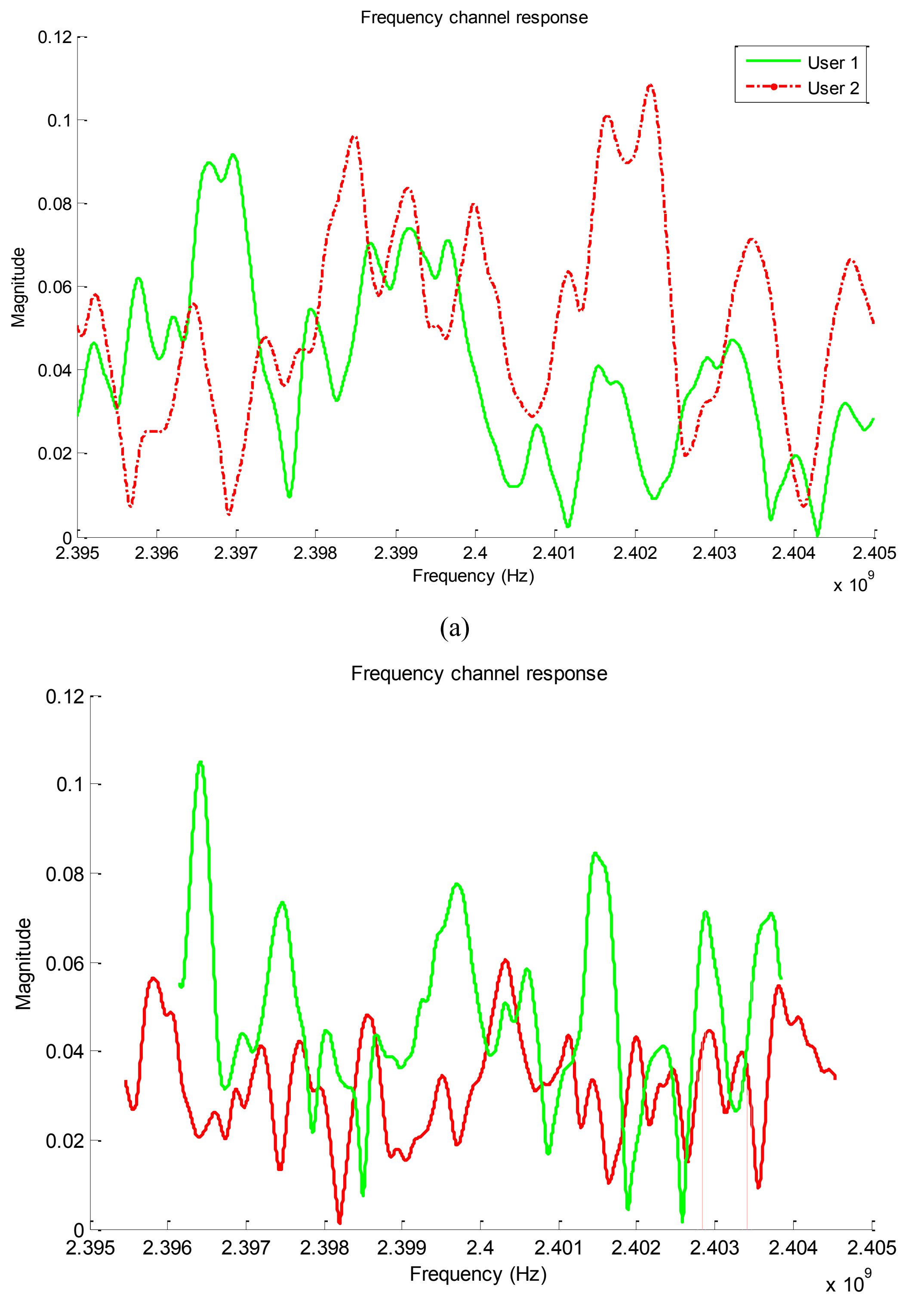
$$\frac{R_{k,c}(t)}{T_{k,c}(t)} \tag{4.8}$$

in time slot *t* among all the active system users, where $R_{k,c}(t) = \log(1 + SNR_{k,c}(t))$ is the viable rate of user *k* in time slot *t*. Using an exponentially weighted low-pass filter, the long-term average throughput $T_{k,c}(t)$ can be updated as [50]:

$$T_{k,c}(t+1) = \begin{cases} (1 - \frac{1}{t_\tau})T_{k,c}(t) + \frac{1}{t_c} R_{k,c}(t), k = k^* \\ (1 - \frac{1}{t_\tau})T_{k,c}(t), k \neq k^* \end{cases} \tag{4.9}$$

This dissertation, takes subcarriers independently of each other in the implementation of the PFS algorithm in an OFDMA system. Therefore, we compute which user has the largest value given by equation 4.8 at each subcarrier and time slot in order to assign this subcarrier to that particular user. Also, we have to update the users' average throughput by equation 4.9 at each subcarrier and time slot. Transmission power is equally distributed among subcarriers using equal power allocation algorithm which is the one considered in this work.

By inspecting Figure 4.3, one gets an intuitive understanding of how this algorithm operates. The frequency channel response of two users is plotted as a function in two different fading statistics scenarios, equal and unequal. The two users have identical fading statistics as plotted in Figure 4.3 (a). If the scheduling time scale t_τ is much larger than the correlation time scale of the fading dynamics, then by symmetry the throughput of every user converges to the same value. As a result, the scheduling algorithm reduces to picking always the user with the highest requested rate. The scheduling algorithm becomes totally fair in the long term as every user is served when her channel is good. In Figure 4.3 (b), although both channels fluctuate due to multipath fading perhaps because of different distances from the BS, the channel for one of the user is much stronger than the other user's on average. It would be highly unfair for the system to always pick the user with statistically stronger channel conditions as this means all resources will be assigned to the user and leaving the weak user out. Contrary to this, under the proposed scheduling algorithm, users compete for resources not directly based on their requested data rates but only after their respective average throughputs have been normalized. When a user's instantaneous channel quality is high relative to its own average channel condition over the time scale t_τ, the algorithm schedules the user. If a sufficient number of active users are available in the system, the benefit of multiuser diversity can still be exploited. This is because, channels of different users fluctuate independently and with many users, there is a high likelihood of finding a user whose channel is near its peak.



(a)

(b)

Figure 4.3 Frequency channel response (a) equal users (b) unequal users

The Parameter t_τ

The parameter t_τ is coupled to the latency time scale of the application and through this time scale, peaks are defined. The throughput is averaged over a longer period, if the latency time scale is large. Therefore, the scheduler can afford to wait longer before scheduling a user when its channel hits a really high peak [51].

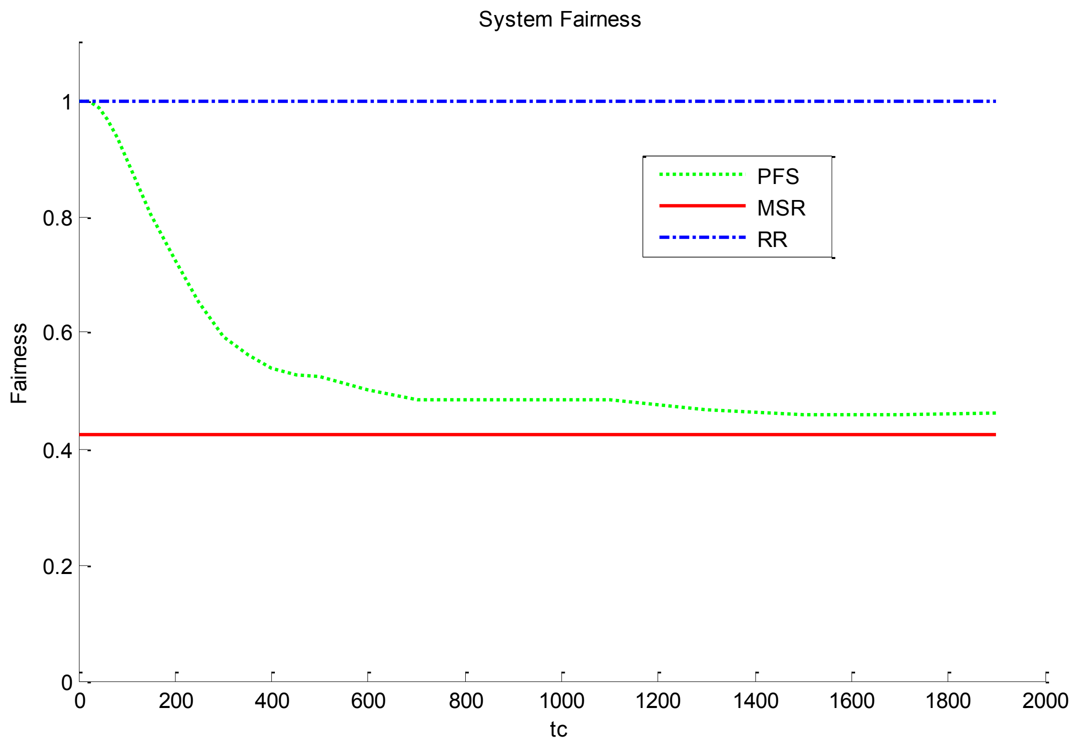
The larger value of t_τ parameter is infinity. In this situation the resource assignment according to PFS algorithm is decided solely by instantaneous SNR, leading to maximum system throughput and poor fairness characteristics. Conversely, the lower value of t_τ is one, in which case scheduling becomes fair. Therefore, t_τ means the trade-off between fairness and throughput. In Figure 4.4 (a), the system fairness is showed versus t_τ parameter according to three different algorithms, PFS, RR and MSR. When fairness parameter is one, every user share the same amount of resources, and when fairness parameter is zero, only one user consumes all resources. Fairness according to RR and MSR algorithms remains constant and represents fairness boundaries as there are independent of t_τ parameter. MSR algorithm represents the least fairness and RR algorithm represents the largest fairness. As illustrated in Figure 4.4 (a) if t_τ tends to 1, there is an increase in fairness and PFS behaviour tends to RR behaviour, but if t_τ tends to infinity, fairness reduces and PFS behaviour tends to MSR behaviour.

On the other hand, in Figure 4.4 (b) throughput versus t_τ parameter is shown. As stated above, MSR and RR algorithms are independent of t_τ parameter and represent behaviour's boundaries. RR algorithm represents the smallest throughput and MSR algorithm represents the largest throughput. As one can see in Figure 4.4 (b) if, t_τ tends to 1, there is a reduction in throughput and PFS behaviour tends to RR behaviour. Alternatively, if t_τ tends to infinity, there is an increase in throughput and PFS behaviour tends to MSR behaviour.

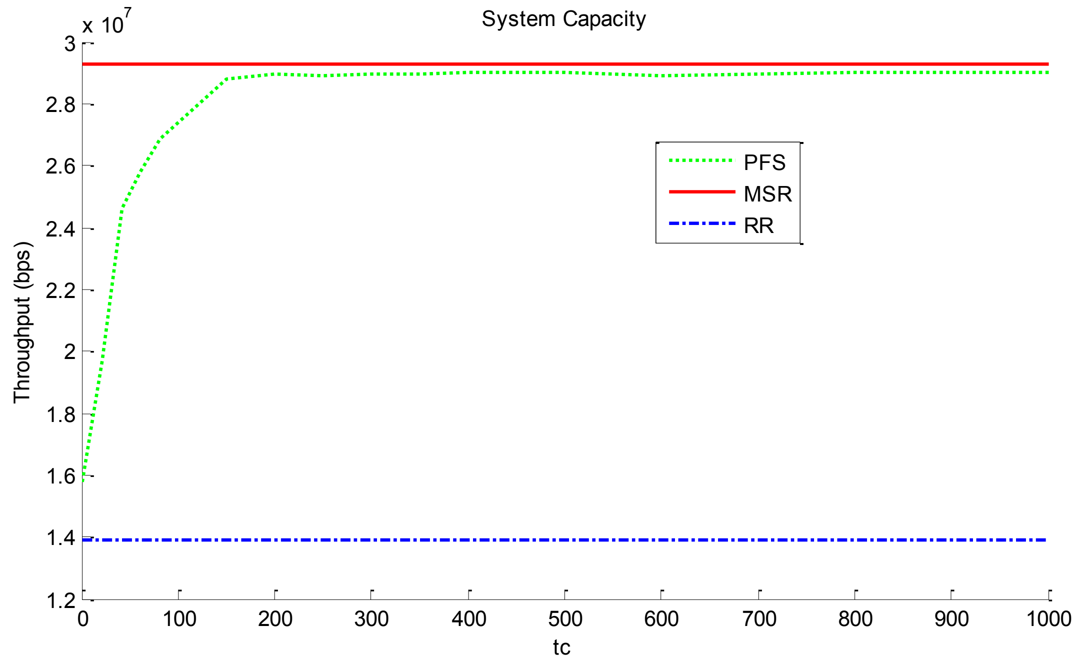
The system parameters used in analysing this scenario for this explanation is given in Table 4.1.

Table 4.1 System parameters used to test the behaviour of PFS, RR and MSR versus t_τ parameter

Time slots	100
Number of subcarriers simulated	16
t_τ	1-2000
Number of users	4
Mobile speed (km/h)	3



(a)



(b)

Figure 4.4 PFS, RR and MSR behaviour versus t_τ parameter (a) fairness (b) throughput

For PFS scheme, **Algorithm 3** was developed and implemented in MATLAB 7.9.0 (R2009b) environment and the analytical results are presented in Chapter 5.

Algorithm 3 Resource Allocation in PFS Scheme

1. Initialize the average throughputs $T_{k,c}(t)$ to some value.
2. **for** all users **do**
3. Calculate $R_{k,c}(t)$ according to equation 4.1
4. **for** all timeslots **do**
5. **for** all subcarriers **do**
6. Calculate $\frac{R_{k,c}(t)}{T_{k,c}(t)}$
7. **if** $\frac{R_{k,c}(t)}{T_{k,c}(t)}$ is maximum **do**
8. Schedule the user

9. Update $T_{k,c}(t)$ according to equation (4.9)
10. **end if**
11. **end for**
12. **end for**
13. **end for**

4.4.4 Margin Adaptive Scheduling Scheme (MASS)

Given a set of user data rates with fixed QoS requirements, the algorithms of this group can be formulated. In this case, allocation of as minimum power level as possible to each subcarrier *c* such that the data rate is equal or greater than some fixed value R_k, is the MASS's optimization goal.

A minimum data rate R_k^{min} (for a given BER) for each user in the downlink of an OFDMA system is assumed. This leads to a determination of the number of bits to apportion to each subcarrier for that user and the modulation/coding scheme to be used in every subcarrier. In general, the optimization problem of MASS is formulated as follows: [2], [7], [10].

Objective

$$\min_{s_{k,c}(t),p_{k,c}(t)} \sum_{k=1}^{K}\sum_{c=1}^{C} s_{k,c}(t)p_{k,c}(t)$$

Subject to:

$$\begin{aligned}
&\text{C1: } s_{k,c}(t) \in \{0,1\}, \forall_{k,c} \\
&\text{C2: } \sum_{k=1}^{K} s_{k,c}(t) = 1, \forall_{c} \\
&\text{C3: } p_{k,c}(t) \geq 0, \forall_{k,c} \\
&\text{C4: } \sum_{k=1}^{K}\sum_{c=1}^{C} s_{k,c}(t)p_{k,c}(t) \leq P_T \\
&\text{C5: } \sum_{n=1}^{C} \Psi(\chi_{k,c}(t),P_e)s_{k,c}(t) \geq R_k^{min}, \forall_{k}
\end{aligned} \tag{4.10}$$

with C5 indicating the rate requirements.

This problem was first addressed by Wong *et al*. [11], where the optimization problem was formulated as [11], [7]:

$$\min_{s_{k,c}(t), c_{k,c}(t)} \sum_{k=1}^{K}\sum_{c=1}^{C} \frac{g_k(m_{k,c}(t))}{|h_{k,n}(t)|^2} s_{k,c}(t)$$

$$\text{s.t. } \sum_{c=1}^{C} s_{k,c}(t) m_{k,c}(t) \geq R_k^{min}, \forall_k \qquad (4.11)$$

$$\sum_{k=1}^{K} s_{k,c}(t) = 1, \forall_c$$

where $g_k(m_{k,c}(t))$ is user *k's* required power (in joules/symbol) in subcarrier *c* at time slot *t* for reliable reception of $m_{k,c}(t)$ bits/second.

$g_k(m_{k,c}(t))$ therefore, depends on the selected modulation/coding scheme. The optimization problem given by equation (4.11) can become convex and thus tractable, by relaxing $s_{k,c}(t)$ and $m_{k,c}(t)$ to assume real values in [0, 1] and [0, M] respectively. This work served as a reference for further works that followed, although the complexity involved in solving for optimal solutions in this case was still too high to be implemented in practical systems.

MASS Algorithm

Kivanc and Liu [10] proposed a suite of more computationally efficient algorithms for suboptimal power-and-subcarrier allocation following reference [11]. This algorithm divides the problem of joint allocation into two steps. The number of subcarriers to be assigned to each user based on the user's rate requirements and average SNR is determined in the first step. When every user experiences a flat-fading channel, the algorithm is shown to find the distribution of subcarriers that minimizes the total power required. The results are very close to the optimal solutions provided in [11] though their computational complexity was much lower than [11]. In the second step based on CSI, a set of subcarriers is allocated to every user.

In line with reference [10], we have developed two algorithms that allocate subcarriers adaptively to users. Fixed power is used at the BS in order to make relevant comparisons with the other algorithms. Therefore, equal power distribution algorithm is used that simply assigns all subcarriers an equal amount of the total transmit power.

Consider a system with *K* users and *C* subcarriers and that to satisfy rate requirements, every user *k* must transmit at least R_k^{min} bits per unit time. A user can transmit at most R_{max} bits per unit time and subcarrier, so R_{max} is the maximum subcarrier response value that the user reaches. Let $r_{k,c}(t)$ be the transmission rate for user *k* on subcarrier *c* at time slot *t* and $H_{k,c}(t)$ be the channel gain.

The aim is to find a subcarrier assignment, which enables every user to satisfy its rate requirements. The problem is split into two steps namely:

1. Resource Assignment that allocates subcarriers to every user based on rate requirements and average channel gain of the user. Authors in [10] refer to this algorithm as BABS (Bandwidth Assignment Based on SNR).
2. Subcarrier Assignment, which use the result of the resource assignment stage and channel information to allocate the subcarriers to the users. Authors in [10] refer to this algorithm as RCG (Rate Craving Greedy) algorithm.

Solving these sub-problems separately, gives a good solution that is close to optimal but that guarantees for every user a certain level of service.

Resource Assignment Algorithm

Resource assignment algorithm uses the rate requirements and the average SNR to determine the number of subcarriers to assign to every user.

Assume that a subcarrier *c* for user *k* at time slot *t* experiences a channel gain of $H_k(t) = \sum_{c=1}^{C-1} \left|H_{k,c}(t)\right|^2 / C$. Let user *k* be assigned x_k subcarriers. The optimal rate-power allocation, when the gain on every subcarrier is the same is to transmit $\frac{R_k^{min}}{x_k}$ bits on every subcarrier, resulting in total transmission power of [10]:

$$\frac{x_k f\left(R_k^{min} / x_k\right)}{H_k(t)}. \tag{4.12}$$

The purpose is to find a set of x_k subcarriers $k = 1,...,K$ which satisfy [52]:

$$\min \sum_{k=0}^{K} \frac{x_k}{H_k(t)} f\left(\frac{R_k^{min}}{x_k}\right)$$

$$\text{s.t.} \sum_{k=0}^{K} x_k = C \tag{4.13}$$

$$x_k \in \left\{\left\lceil \frac{R_k^{min}}{R_{max}} \right\rceil,....,C\right\}, \forall_k .$$

A greedy descent algorithm was suggested to find the optimal distribution of subcarriers between users with the assumptions of the flat channel. The algorithm is shown in Algorithm 4.

Algorithm 4 Bandwidth assignment based on SNR [10]

1. Let the maximum rate (bits/unit time) a subcarrier can transmit to be R_{max}. In addition, let the minimum rate required by user *k* be defined as R_k^{min}.
2. Compute the number of subcarriers to assign to each user: $x_k = \left\lceil \frac{R_k^{min}}{R_{max}} \right\rceil, \forall_k$.
3. **while** $\sum_{k=1}^{K} x_k > C$ **do**
4. Search for $\tilde{k} = \arg\min_{\forall_k} x_k$
5. Set $C_{\tilde{k}} = 0$
6. **end while**
7. Over all subcarriers, computer the average channel gain for user *k*: $H_k(t)\cdot$
8. **while** $\sum_{k=}^{K} x_k < C$ **do**
9. When one more subcarrier is allocated to user *k*, calculate the difference in transmission power: $\Delta p_k = \frac{x_k+1}{H_k(t)} f\left(\frac{R_k^{min}}{x_k+1}\right) - \frac{x_k}{H_k(t)} f\left(\frac{R_k^{min}}{x_k}\right), \forall_k \cdot$
10. Search for $\hat{k} = \arg\min_{\forall_k} \Delta p_k$
11. Set $x_{\hat{k}} = x_{\hat{k}} + 1\cdot$
12. **end while**

Subcarrier Assignment Algorithm

Once the number of subcarriers is determined, step two involves assigning specific subcarriers to different users. Since different users perceive different channels, the problem is still difficult to solve. The starting point for RCG algorithm is to estimate the users' transmission rate on every subcarrier and then maximize the total transmission rate. For the model used in analysis, the rate is given by $r_{k,c}(t) = \frac{W}{C}\log_2\left(1 + SNR_{k,c}(t)\right)$, based on Shannon's capacity.

The implemented subcarrier allocation algorithm works as follow: At first each user gets x_k subcarriers according to their rate requirements, if the sum of the whole subcarriers allocated does not fit within the available bandwidth, we have to:

1. Remove subcarriers from users who are demanding few subcarriers.
2. Add subcarriers to users demanding more subcarriers but so far allocated few subcarriers according to the SNR.

A simplified algorithm to carry out the steps above is given in **Algorithm 5** [10]

Algorithm 5 Subcarrier allocation algorithm for MASS

Certify

$r_{k,c}(t)$ is the approximate communication rate of user k on subcarrier *c,* x_k is the number of assigned subcarriers to every user.

1. Set $C_k = \{\ \}, \forall_k \cdot$
2. **for** each subcarrier *c* **do**
3. Search for user with highest rate i.e., $\hat{k} = \arg\max_{\forall_k} r_{k,c}(t)$
4. Update $C_{\hat{k}} = C_k U\{c\}$
5. **end for**
6. **for** all k users, if $|C_k| > x_k$ **do**
7. **while** $|C_k| > x_k$ **do**
8. Search for $\hat{j} = \arg\min_{\forall_j \forall_k}(-r_{k,c}(t) + r_{j,c}(t))$
9. Search for $\hat{c} = \arg\min_{\forall_C}\left(-r_{k,c}(t) + r_{\hat{j},c}(t)\right)$
10. Set $C_k = C_k \setminus \{\hat{c}\}$
11. Set $C_{\hat{j}} = C_{\hat{j}} U\{\hat{c}\}$

12. **end while**

13. **end for**

In section 4.5, the performance parameters that will be used to evaluate and compare the RRA algorithms described and developed using MATLAB 7.9.0 (R2009b) simulator will be discussed. Equipped with the algorithms developed in this section and the following discussion of the performance parameters that include system fairness, throughputs and delay, we shall simulate the results in Chapter 5 and make the necessary conclusions.

4.5 Performance Parameters

Performance parameters are system metrics used to determine the performance of a system in a given environment. The performance parameters discussed in this dissertation include system throughputs, system fairness and delay.

4.5.1 System Throughputs or Capacity

One of the most important properties of information system, throughput, will be discussed in this section. Considerable interest in specifying the performance of wireless networks is always a requirement within the industry due to the growing demand for wireless communication systems. Throughput is a measure of how much information can be transmitted and received per unit time with a negligible probability of error. It is generally considered within a framework that maximizes the system performance [53], [54].

To ensure sufficient coverage and network functionality (capacity, interference, etc.), a careful design and deployment procedure should be carried out. The actual data throughput or data being transmitted, for a wireless networking gear is often just a fraction of the theoretical maximum signalling rate. Research conducted in [55] showed that when access points or clients are located near an interfering transmitter or when frequency planning is not conducted carefully the user throughput performance changes drastically. A number of other important environmental and product-specific factors, including: transmitter and receiver separation distance, transmission power levels, obstacles such as buildings, radio frequency interference, and signal propagation can limit the data throughputs. As a result, although the wireless networking products are capable of a *C* bps signalling rate, the practical data throughput rate is more likely to be much less.

Capacity of the Channel

At the input of a communication system, discrete source symbols are mapped into a sequence of channel symbols that are then transmitted through a wireless channel that is random by nature. As the signal travels through the wireless media, the channel adds random noise to the channel symbols.

Channel throughput is a measure of how much information can be transmitted and received with a negligible probability of error. Through simplification, if we assume that the channel can support at most *C* bits per time slot, where C is the channel capacity according to Shannon-Hartley Theorem, then a measure of the channel potential can be determined.

Shannon-Hartley Theorem

The Shannon–Hartley theorem, in information theory, is an application of the noisy channel coding theorem to the typical case of a continuous-time analog communications channel subject to Gaussian noise. The result establishes the maximum amount of error-free digital information that is transmittable over the communication link with a given bandwidth in the existence of the noise interference [53], [56]. The theoretical maximum information transfer rate of the channel is referred to as the Shannon limit or Shannon capacity of a communications channel [53].

Subject to Gaussian noise, the Shannon–Hartley theorem establishes the capacity of a channel for a finite bandwidth continuous-time channel. If such a thing as an infinite-bandwidth, noise-free analog channel existed, we could transmit unlimited amounts of error-free data over the channel per unit of time. But both bandwidth and noise-interference limitations are characteristics that are found in practical signals. Fortunately, a cap on maximum information transfer is not imposed by bandwidth limitations alone. This is because in a well thought-experiment model the signal to be transmitted can take on an infinite number of different voltage levels on each cycle, with each slightly different level being assigned a different bit sequence [56]. However, it's found that there is a limit to the amount of information that can be transferred, even when clever multi-level encoding techniques are used, if both noise and bandwidth limitations are combined. Taking into account all possible multi-level and multi-phase encoding schemes, the theorem shows that the theoretical maximum data rate C with arbitrarily low BER for a given average signal power that can be sent through an analog communication channel subject to AWGN interference is given by [53]:

$$C = W\log_2\left(1+\frac{P_{av}}{WN_0}\right) \tag{4.14}$$

where W is the bandwidth of the channel in hertz, P_{av} is the average transmitted power, and C is the channel capacity in bits per second.

The capacity of a channel is defined as the maximum information rate that can be used causing negligible probability of errors at the output. Equation (4.14) is taken as the information rate of the channel in the analysis.

Outage Probability

Outage capacity is one more measure of channel capacity that is commonly used. Depending on the channel instantaneous response, capacity is treated as a random variable although in our analysis we assume that it remains constant during the transmission of a finite-length coded block of information [54]. If the channel capacity falls below the outage capacity, there is no possibility that the transmitted block of information can be decoded with no errors, whichever coding scheme is employed. The upper bound of the probability that the data rate is below an outage capacity (C_{outage}) can be mathematically expressed as [53]:

$$F\{C \le C_{outage}\} = p \tag{4.15}$$

And the lower bound, representing the probability that $C_{outage}$is less than the channel capacity is given by [53]:

$$F\{C \ge C_{outage}\} = 1 - p \tag{4.16}$$

4.5.2 System Fairness

One of the most important properties in a wireless communication environment where scarce system resources are being shared by users is fairness. Appropriate performance measures are required in order to evaluate and find the best performing scheduling discipline. For best effort users the major concern for the scheduling discipline is to maximize the total throughput for users as there are served a fair amount of the throughput.

Definition

Fairness is a desirable property of the wireless network as it offers protection between users. This implies that the traffic flow of another user cannot be affected by the traffic flow of an ill-behaving user.

In general, based on whether or not a system meets certain criteria (usually in terms of throughput or delay), the system may be said to be fair or unfair. For example, a scheduling algorithm may be said to be fair if all users receives a throughput of more than *X* bits/sec and unfair otherwise. Another example might be that a system is said to be unfair if the probability of any user experiencing a delay less than τ is greater than *p;* if the probability is less than *p* the system is fair. The rationale behind the proposed definitions is to see if a value for the "fairness" of a system or scheduling algorithm can be defined in a similar manner to how Shannon defined a value for the "information" of a source. The fairness value should also make sense from both a semantic and a mathematical sense. Shannon's definition was based on probabilities of events. In comparison, the proposed fairness measures are based on proportions of allocated resources [14]. In order to evaluate fairness, we propose two set of users, equal and unequal weighted users.

Equal Weighted Users

Depending on the circumstances under which the definition is applied a "resources" in question will be defined. Probable examples include time, or slots each user is allocated, the amount of bandwidth allocated, the number of bits or packets sent to users. The proportion for each user would then be the number or amount of packets, bandwidth, slots, etc. allocated to that user, relative to the total allocated to all the users in the system.

For a random variable or process *X*, the self-information of the event $X = x_i$ is:

$$I(x_i) = \log \frac{1}{P(x_i)} = -\log P(x_i) \tag{4.17}$$

where $P(x_i)$ is the probability of the event $X = x_i$.

Using proportions instead of probabilities, a measure for fairness can be defined in a similar manner. When all *K* users of a system are considered equal, the definition for the "*self-fairness*" of a given user is expressed as [14]:

$$\mathrm{F_i} = \frac{-\log \mathrm{p_i}}{-\log(1/\mathrm{K})} = -\frac{\log \mathrm{p_i}}{\log \mathrm{K}} \tag{4.18}$$

where p_i, is the amount of resources allocated to user i, and the $\log K$ term is a normalization factor. The reciprocal of the self-fairness, gives the ***"****self-unfairness*" of a user in the system.

Average Fairness

Given the self-information of the N possible events of the process X, the average self-information in the process X can be found by [14]:

$$H(X) = \sum_{k=1}^{N} \frac{P(x_k)}{I(x_k)} = -\sum_{k=1}^{N} P(x_k) \log P(x_k) \tag{4.19}$$

Similarly, the proposed definition for the "average fairness" of a system of *K* users is [14]:

$$\overline{F} = \sum_{k=1}^{K} p_k F_k = -\sum_{k=1}^{K} p_k \frac{\log p_k}{\log K} \tag{4.20}$$

Comments

Some interesting properties are yielded by above definitions [14]:

1. The value of self-fairness and self-unfairness will be unity, when a user consumes exactly its fair share of resources (i.e. a proportion of 1/K).
2. If a user consumes increasingly more resources than the other users, the user becomes more unfair and thus the self-unfairness increases and the self-fairness decreases.
3. On the contrary, the self-unfairness decreases and the self-fairness increases if a user consume fewer resources in favor of other system users.
4. All the other users in the system will see the greedy user to be less fair (or more unfair) if in the limit a single user consumes all the available resources. Logically, therefore self-fairness and self-unfairness for the user will be infinity and zero respectively.
5. If a user gives up all its deserved resources in favor of other users, then that user becomes the fairest which is reflected by the resulting values of zero and infinity for the self-unfairness and self-fairness, respectively.
6. With a system of *K* users, the value for the average fairness of the system is between 0 and 1 inclusive. Moreover, when all users in the system consume exactly their fair share of the resources (i.e., $p_1 = p_2 = ... = p_K = 1/K$) the maximum value of unity is achieved. In the limit when one user consumes all the allocated resources while the other *K-1* users are starved the minimum of zero occurs.

7. Similarly, the average unfairness ranges between 1 and infinity, with the lower and upper extreme values occurring under the same conditions as the maximum and minimum values respectively for the average fairness. That is, a value of unity will result only if all users consume their fair share of resources, and infinity will result if a single user consumes all the allocated resources.

Unequal Weighted Users

When individual users have different weightings (for example, to achieve different levels of QoS) the above definitions can be extended to the more general case of unequal weighted users. The authors in [57] argue that for a system with *K* users and a set of backlogged flows *D(t)* during the time interval $[t_1,t_2]$ a queuing system is fair if:

$$\forall_j, i \in D(t_1, t_2), \left| \frac{M_j(t_1, t_2)}{r_j} - \frac{M_i(t_1, t_2)}{r_i} \right| = 0 \tag{4.21}$$

where M_i, is the capacity granted to flow i (i.e. the resources assigned to flow i), and r_i is user i's weighting. Consequently, the proportion of resources assigned to user i that is considered to be fair, can be shown to be given by:

$$P_{fair,i} = \frac{r_i}{r_T} \tag{4.22}$$

where r_T is the sum of all users' weightings. The formula for the weighted self-fairness of a user can be deduced from the above proportion, and is given by:

$$F_i = \frac{\log p_i}{\log r_i / r_T} \tag{4.23}$$

The reciprocal of equation (4.23) gives the weighted self-unfairness of a user.

Weighted Average fairness

It would be attractive to define the weighted average fairness as $\sum_{k=1}^{K} p_k F_k$ as in the case of equal weighted users. However, it is impossible to make this definition and still maintain the properties discussed before. Instead, the system average weighted fairness is given by [14]:

$$\overline{F} = \frac{r_T \sum_{k=1}^{N} C_k p_k F_k}{\sum_{k=1}^{K} C_k r_k} \tag{4.24}$$

where the normalization constant C_k, is given by:

$$C_k = \frac{1 + \frac{1}{\ln(r_1/r_T)}}{1 + \frac{1}{\ln(r_k/r_T)}} \tag{4.25}$$

The purpose of C_k is to guarantee that the maximum value of the weighted average fairness is unity (as in the case of equally weighted users), and that the maximum occurs when a user consumes exactly her fair share of the resources [14].

Comments

Some interesting properties are yielded by the above definitions:

1. The weighted definitions share all the same properties as the equal weighted definitions. The only difference is that the value of 1 occurs for weighted self fairness, self-unfairness, average fairness, and average unfairness when *k = 1,2,….,K,* instead of $p_k = 1/K$ as before.
2. An implicit time scale in the proportions exists, that is, over a certain period of time the proportions of resource allocation would be measured. The proposed measures can be used to examine both the short-term fairness and the long-term fairness of systems since the period used can be arbitrary, [58].

4.5.3 Delay Constraints

In practical system, a deadline associated with every packet generated by an application exists. The packet would be dropped, if the system cannot allocate enough resources to serve the packet before the deadline. To preserve some given packet dropped probabilities, different applications have different delay requirements that the system should guaranteed. Because of resource limitation, error characteristic and mobility, it is more challenging to provide QoS guarantees in the wireless network compared to the wired network.

For different services, scheduling the available bandwidth is a non-trivial task. Some applications, e.g. voice, require a relatively small amount of bandwidth with less strict delay requirements, whereas some others, e.g. video, require a huge amount of bandwidth and are very delay sensitive [59]. These applications should all be satisfied if the system has enough resources to support and sustain QoS of every application.

A packet can be dropped in a wireless environment, mainly because of the following reasons: poor wireless channel quality; collision of the packets from different applications; or not enough resources for sending a critical packet. Using different scheduling algorithms, our objective is to evaluate the probability of a user transmitting below R_{min}, which is related to the packet-dropping rate.

4.6 Chapter Summary

The system model for the adaptive RRA schemes in the downlink of OFDMA systems has been presented and analyzed. Also developed was the general problem formulation which led to development of specific algorithms for the different RRA schemes. The performance parameters to be used to evaluate the performance of the RRA algorithms have also been discussed.

In the following chapter, results based on the derived equations and algorithms will be presented and the performance metrics will then be used to compare the different algorithms in different scenarios.

Chapter 5

5 Results and Analysis

5.1 Introduction

The performance results obtained using the algorithms developed and equations obtained in chapter 4 are presented in this chapter.

This chapter begins in section 5.2 where the system parameters used to run the Matlab codes are presented. Section 5.3 presents the performance evaluation of the different algorithms using the performance metrics discussed in section 4.5. Graphs for the system fairness versus number of users, system capacity versus users and outage probability versus delay are presented. Section 5.4 concludes the chapter.

5.2 System Parameters

Appropriate performance measures for comparing the different RRA schemes are required in order to evaluate and find the scheduling policy with the best performance. In this work, system throughputs, system fairness, and delay constraints performance metrics (as discussed in section 4.5), were used to evaluate and compare the different scheduling policies discussed in section 4.4. Functions performing different roles were developed and implemented in MATLAB 7.9.0 (R2009b) analytical tool which was used in ascertaining our research statement and thus research objectives.

Users with different channel response averages in three different scenarios were considered:

1. All users are transmitting voice, with constant rate of 16 Kb/time slot.
2. All users are transmitting video with constant rate, 64 Kb/time slot.
3. Mix scenario where 50% of users transmitting data, while 40% of the users transmitting voice and the remaining 10% of users transmitting video. Data traffic is assumed to be exponentially distributed with a mean of 40kbps [10].

The parameters used in analyzing the performance of the algorithms are given in Table 1.

Table 5.1 System Parameters

Parameters	Value
Maximum BS transmission power	1W
Carrier frequency	2.4 GHz
Number of subcarriers	16
Number of timeslots	100
Scheduling time scale - t_c	1 - 2000
Number of users	5 - 25
Rates (kbps)	16, 64, exp(40)
Mobile speed	3km/h
Video deadline (timeslots)	2
Data deadline (timeslots)	4
Voice deadline (timeslots)	1

5.3 Performance Evaluation

This section presents the performance evaluation of the different codes developed in Matlab. The equations and algorithms discussed in section 4.4 were used to develop the codes implemented in Matlab and the performance metrics described in section 4.5 are used to evaluate and compare the schemes.

5.3.1 System Fairness

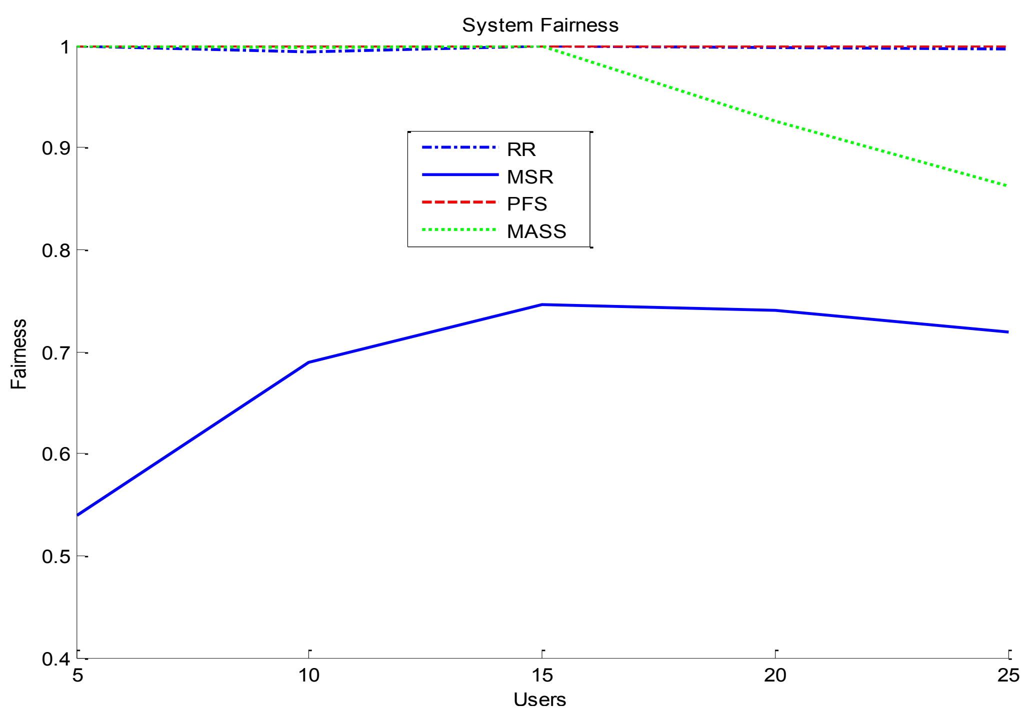
In wireless networks, fairness is a desirable property as it offers protection between users and therefore, traffic flow of an ill-behaving user cannot affect the traffic flow of other users.
Our analysis aims to examine the performance of suboptimal algorithms, PFS and MASS and compare with RR and MSR algorithms based on fairness on distribution of resources according to [14]. The results presented in this section are obtained for all the RRA algorithms discussed in section 4.5.

Figures 5.1 (a), (b) and (c) show the graphs of system fairness versus users with different channel response average in three different scenarios.

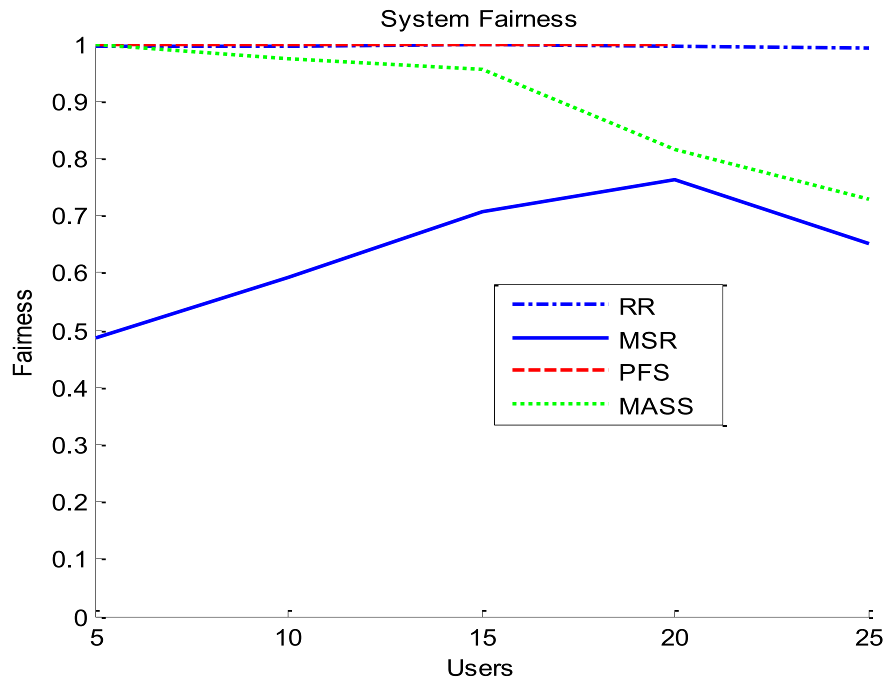
MSR policy is the un-fairest algorithm because it allocates the system resource to users who have the strongest channel response, while starving users with poor channel response. Subsequently the achieved fairness results by this algorithm are the lowest of all the analysed algorithms.

Compared to MSR scheduler, PFS scheduler is independent from rate requirements, so the results achieved in these three different scenarios are more or less the same. As shown in Figure 5.1, PFS algorithm has good fairness behaviour because as we saw in section 4.5, with a low t_τ parameter this algorithm maintains index fairness without involving system throughput.

On the other hand, MASS algorithm allocates subcarriers to users according to users' rate requirements and channel response. In Figure 5.1, it can be seen that, the larger the number of users in the system, the lower the MASS' fairness index, but there are differences among them. In scenario A, Figure 5.1 (a), MASS maintains total fairness until the number of users in the system is more than 15. In scenario B, Figure 5.1 (b), MASS maintains total fairness until five users. The reason for this behaviour is because when there are enough subcarriers to satisfy users' rate requirements MASS allocates the same amount of resources among users. But when there are fewer subcarriers, MASS algorithm allocates subcarriers to users with higher demands until satisfying their rate requirements. Then, MASS distributes any remaining subcarriers among users. Users who are demanding video service need more subcarriers than users who are demanding voice service, so when there are not enough subcarriers, users who are transmitting voice have to wait. In scenario C, Figure 5.1 (c), an intermediate situation in a mixed scenario is plotted.



(a)



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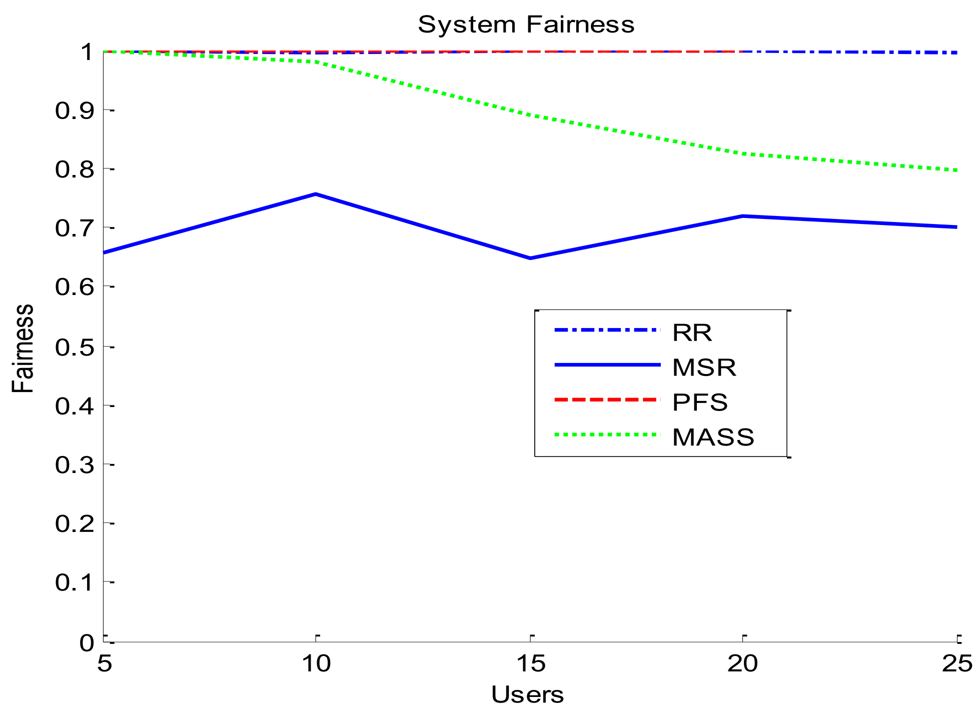


(c)

Figure 5.1 System fairness versus users with different channel response average in different scenarios: (a) scenario A, (b) scenario B, (c) scenario C

5.3.2 System Throughput

In this section, system throughput criteria will be used to compare the algorithms. Because MSR algorithm achieves the highest throughputs, it will be used as reference on system capacity. The most interesting concept is that in order to attain the highest capacity, only one user should transmit at any given time over the allocated subcarrier. This user has the strongest signal at that particular time instant, relative to the average received powers of all the users [5].

To compute system throughput, at first the scheduler scheme is assumed to know the subcarriers over which the user is transmitting. This is because each channel is divided into 16 subcarriers and there are more users than the number of subcarriers. After that, the channel capacity is computed at each subcarrier according to equation 4.14. Finally, the mean value for all time slots simulated is computed.

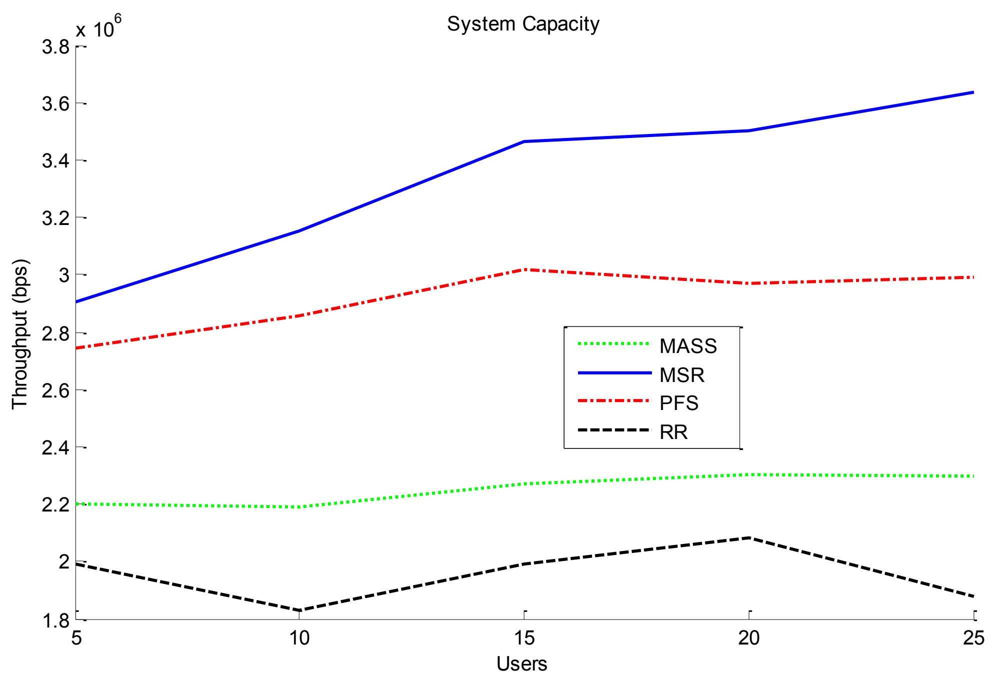
Figures 5.2 (a), (b) and (c) shows the plots for system throughputs versus number of users for different RRA algorithms in different scenarios. As can be deduced from the plots, the system capacity achieved by RR policy reaches the lowest value. This is because RR algorithm does not take into account multiuser diversity and allocates all subcarriers to one user at every time slot independently of users' channel response and rate requirements. The value reached remains relatively constant with different set of users.

According to system throughputs, MSR algorithm reaches the best result because this algorithm allocates system resources to users with the strongest channel and thus, it maximizes the system throughput. The larger the number of users in the system, the larger the system throughput because finding a channel stronger is much more probable when there are many more network users. This is verified by all the graphs in Figure 5.2.

These two algorithms represent the system throughput's boundaries. PFS algorithm exploits the fact that the propagation channel between the BS and MSs is independent of each other, giving rise to multiuser diversity. Thus, PFS algorithm has a good behaviour because it reaches a good level of system throughput without comprising fairness. In this case, users compete for resources not directly based on their SNRs but only after their respective average throughputs have been normalised. As discussed in section 4.4, the larger the users in the system the larger the system throughput, because getting a user with high channel response is much more probable. But the value reached with this policy is lower than the value obtained by MSR policy because PFS endeavours to balance the trade-off between fairness in resource distribution among users and system efficiency.

Up to now, the different scheduler policies discussed are independently of which scenario is considered because these algorithms allocate resources without taking into account users' rate requirements directly.

In Figure 5.2, when the users' numbers increase in the system, the system throughput of MASS algorithm is not as good as the system throughput achieved with MSR and PFS algorithms. When the scheduler scheme is computed by MASS algorithm, the system throughput remains relatively constant or decreases when the number of users increases. The reason for this behaviour is because of the procedure used by MASS. At first MASS algorithm computes the number of subcarriers every user gets based on rate requirements. Afterwards, MASS algorithm allocates subcarriers to users based on channel state information. Therefore, this policy only takes into account multiuser diversity after allocating subcarriers to users depending on their rate requirements.



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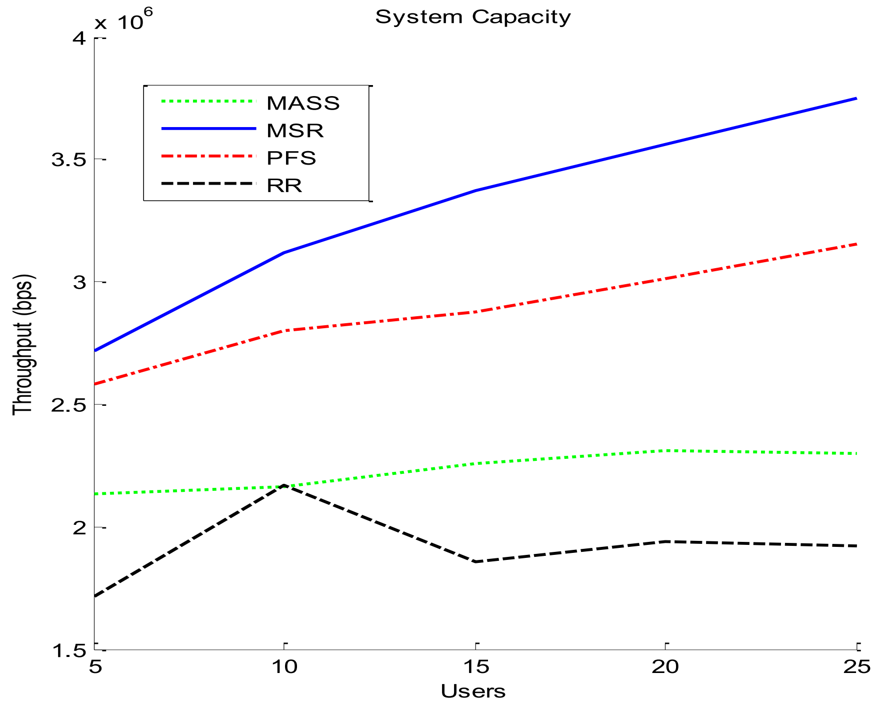

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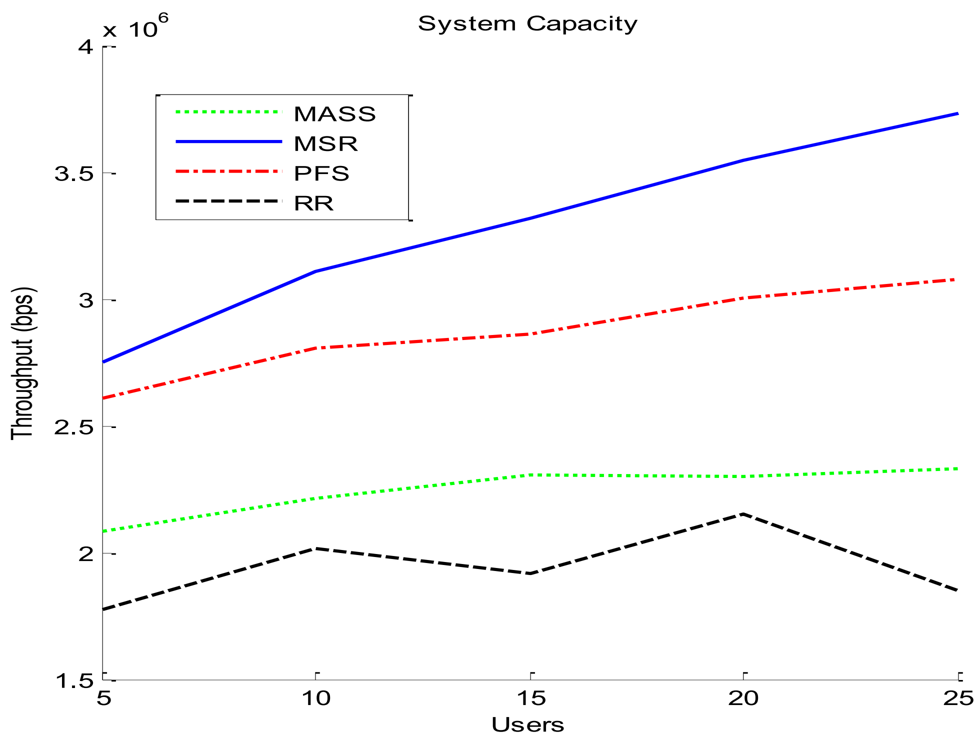


(c)

Figure 5.2 System capacity versus users in different scenarios: (a) scenario A, (b) scenario B, (c) scenario C

5.3.3 Delay Constraints

In this section we simulate different scenarios and evaluate the probability of a user transmitting less than a requested rate $R_{\min}$ based on the service requested for.

The analytical results are shown in Figures 5.3 - 5.8. Every subcarrier can reach about 25Kb per time slot as the channel is divided into 16 subcarriers. A minimum of three subcarriers will be required to satisfy QoS requirements for video users, if one time slot is taken as a deadline of video packets and at least a transmission rate of 64KB per time slot. Under these circumstances, the system could offer service to five users with zero packets dropping probability. These results give a measure of the number of users this system can serve with zero probability of packet dropping or alternatively, the users' satisfaction level.

If we suppose that all users are transmitting data, and that to achieve QoS, one user cannot be more than 4 time slots without transmitting, then the probability of a user transmitting less than $\mathrm{R}_{\min}$ indicates the packet dropping probability and thus rate at which QoS requirements are not met. In Figures 5.3 - 5.8, different analytical results are presented according to different scheduling policies simulated in different scenarios. If we allocate the system resources using RR algorithm, the packet deadline should be in such a way as to be equal to the number of users. Otherwise, as can be seen from the results, if the number of users exceeds the packet deadline, some users will wait for much too long and their packets will be dropped because of high delay times. This is because, RR algorithm allocates all subcarriers to one user at each time slot and this amount of data is enough to satisfy the data requirements, so the delay in time slots, according to this algorithm, is equal to the number of users in the system.

The larger the number of users in the system, the larger the delay, so if we want to reach QoS, our system will only accept so many users as the delay restriction. In the results, RR algorithm has a linear behaviour. It means that at each time slot, each user gets subcarriers enough to satisfy demanded data service.

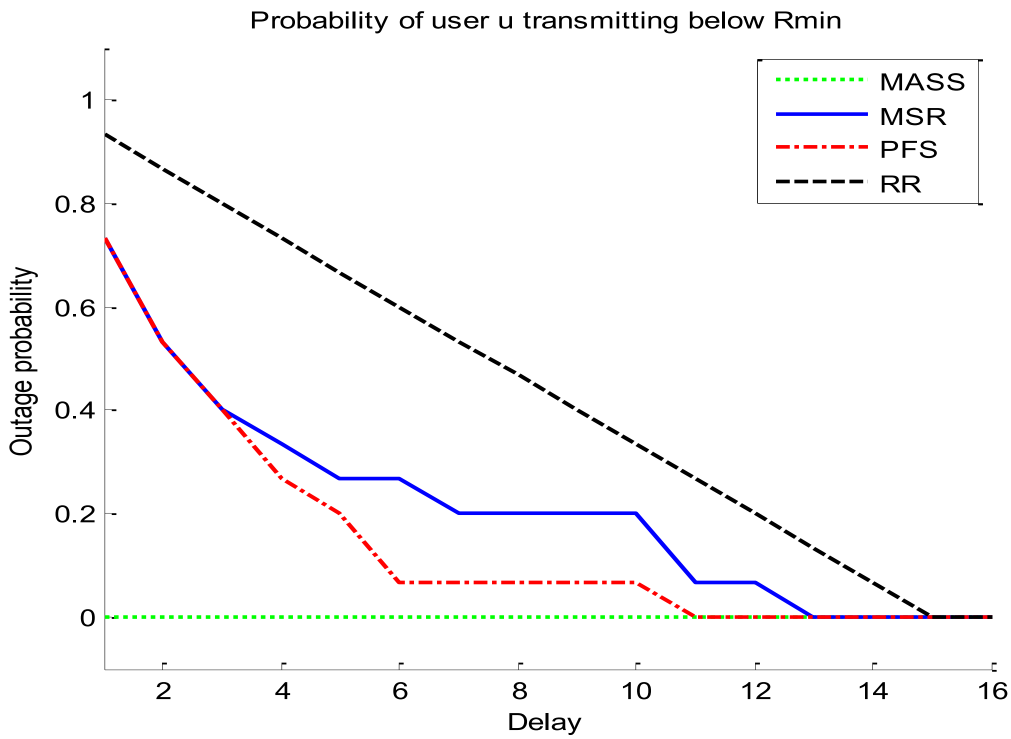
If we allocate the system resources using MASS algorithm, we can see that when there are enough subcarriers to satisfy demanded services by users, the algorithm reaches zero delay, and hence, MASS algorithm satisfies users' QoS requirements. For example when there are 15 or less users transmitting voice (see Figure 5.3 (a)) there are subcarriers enough to serve users without waiting.

But the larger the number of users in the system, satisfying data requirements for all users is more difficult, because MASS algorithm allocates more subcarriers to users who are demanding more data rates. Therefore, the larger the number of users, the higher the probability that one user does not get subcarriers enough to transmit because the system resources are limited. In all Figures 5.5 and 5.8, MASS algorithm does not reach zero probability because at least there is one user who does not get enough subcarriers to support transmission. This scenario takes place when the number of subcarriers is fewer than the number of users. For example, in Figure 5.5, there is one user demanding 100kbps and other demanding 2kbps, according to MASS algorithm, the scheduler allocates enough subcarriers to satisfy the user who is demanding more resources, and because of limited resources in the system, the user who is demanding 2kbps gets no subcarrier(s). Subsequently, from this analysed scenario, it is shown that MASS algorithm is not fair enough.

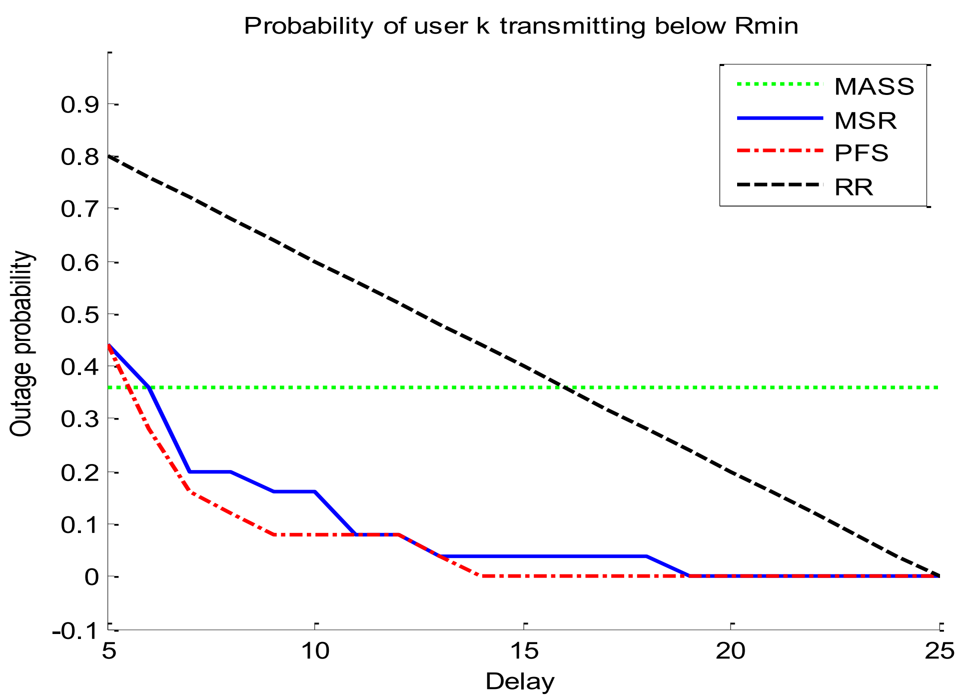
When the number of users is more than the number of subcarriers, in this case all scenario C's for Figures 5.3 - 5.8, according to delay requirements, PFS algorithm has the best behaviour. PFS reaches zero probability faster than the other algorithms. This is because all users are served in all time slots simulated and the subcarriers allocated to users are enough to satisfy data requirements. The larger the number of users in the system, the larger the delay, so if we want to carry out QoS, we have to limit the number of users. In Figure 5.3 and Figure 5.6, we can see that the users are transmitting voice and the delay restriction for this service is two time slots, so if we want to reach QoS, we have to restrict the number of users to at least five.

MSR algorithm allocates subcarriers to users who attain the highest SNR at each time slot. Consequently, when all users have the same channel response average and there are enough resources for all users, MSR will distribute the resources equally and all users will be able to meet their data rate requirements. For example when users are transmitting voice, in Figure 5.3, we can see that the delay is not much more than the delay according to PFS algorithm. Therefore, we can say that MSR algorithm achieves good results compared with PFS algorithm in scenarios where all users have the same channel response average. But when there are users with channel responses stronger than others, Figure 5.6 - 5.8, for example when these users are nearer to BS than others, the whole system resources are allocated to theses users. Thus, there are users who never get subcarriers to transmit. In this case, the probability that one user is transmitting less than $R_{\min}$ increase when number of users increases and remains constant in time because users with weak channels will not get subcarriers.

Also from Figure 5.3 and Figure 5.4, algorithms reach zero packet dropping probability when users are transmitting video later than when users are transmitting voice. This occurs because video service demands more resources than voice services. Consequently, to satisfy all users demanding video services is harder. These cause longer delay times and thus high packet dropping probabilities.

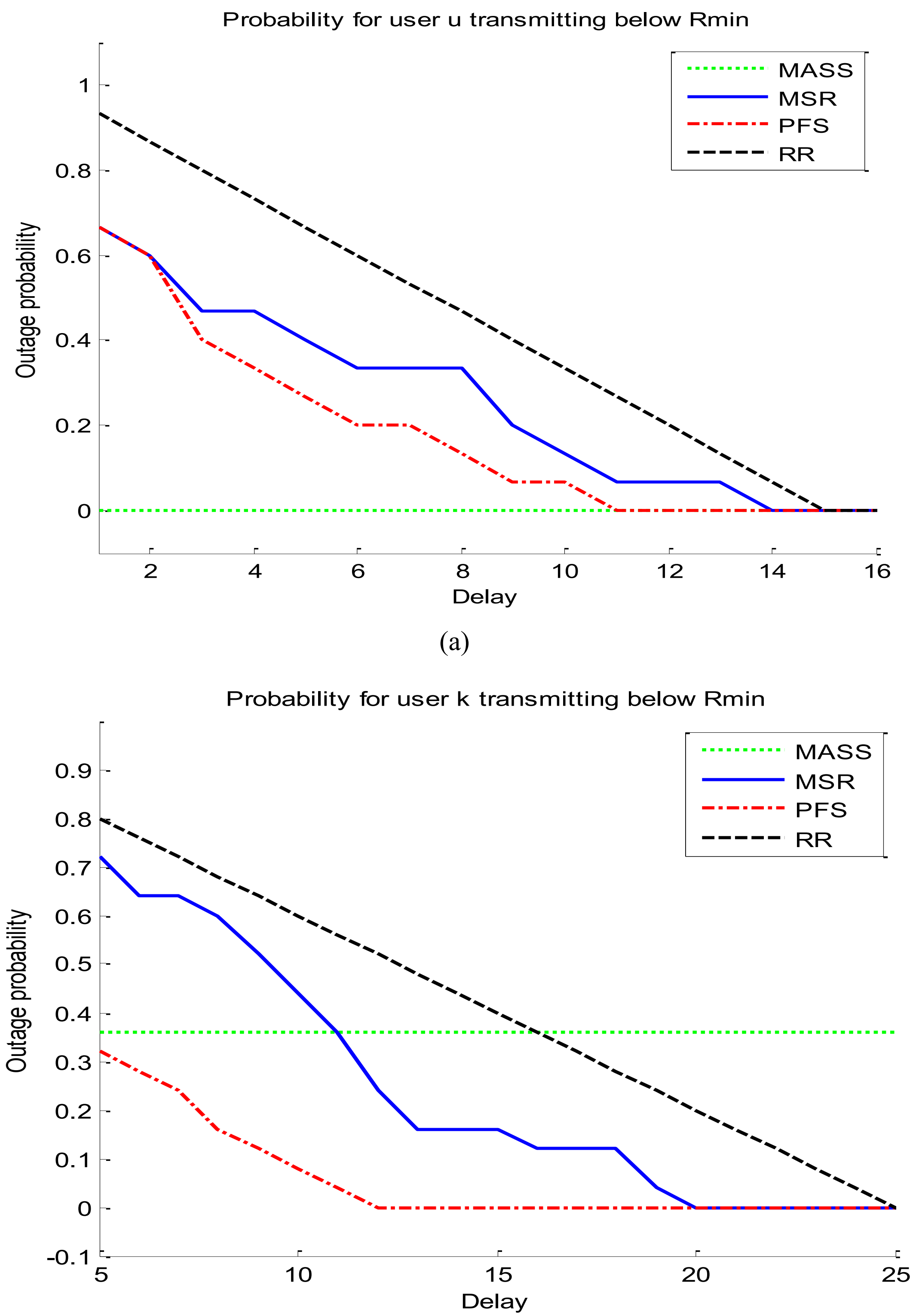


(a)



(b)

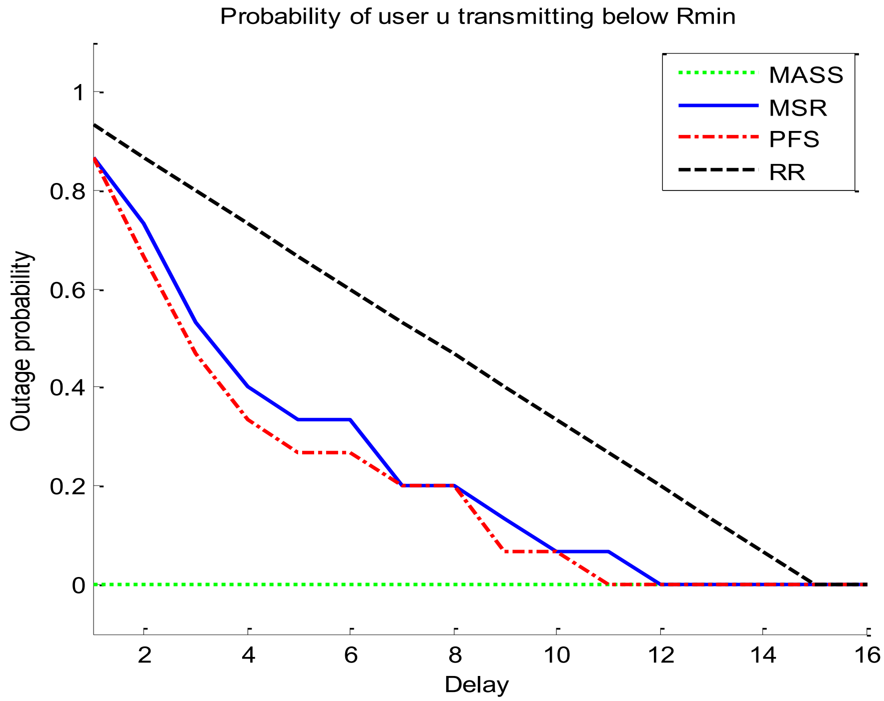
Figure 5.3 Probability of a user transmitting below R_{min} in scenario A with equal channel response (a) 15 users, (b) 25 users



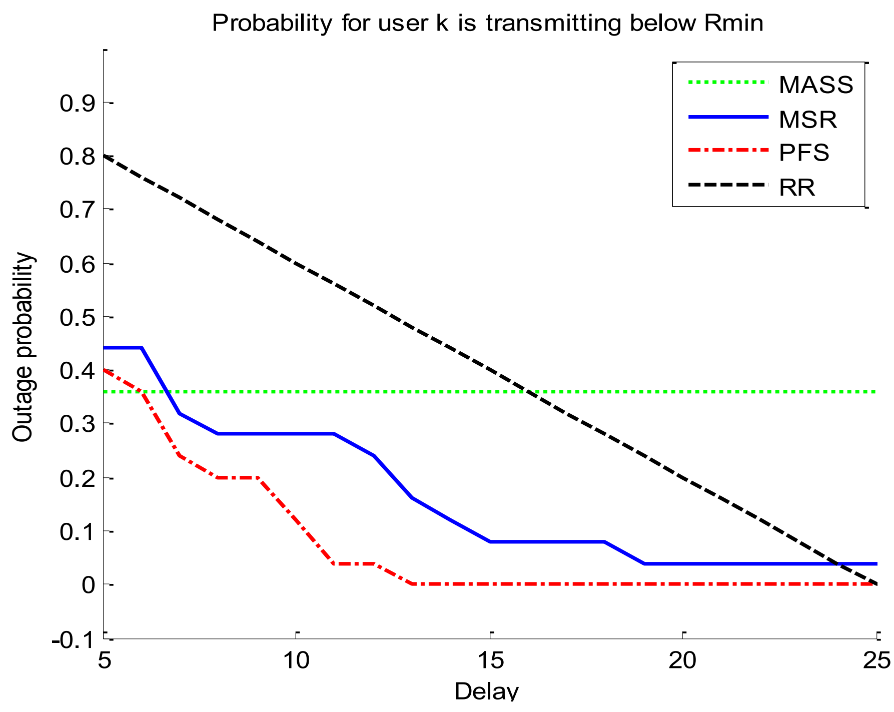
(a)

(b)

Figure 5.4 Probability of a user transmitting below R_{min} in scenario B with equal channel response average (a) 15 users, (b) 25 users

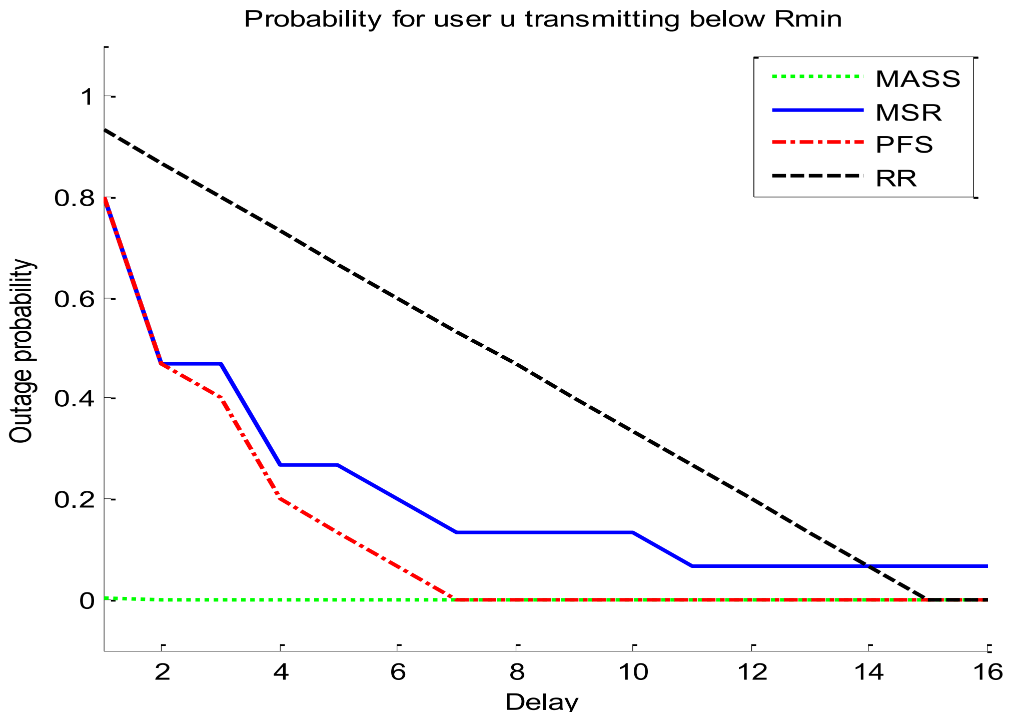


(a)

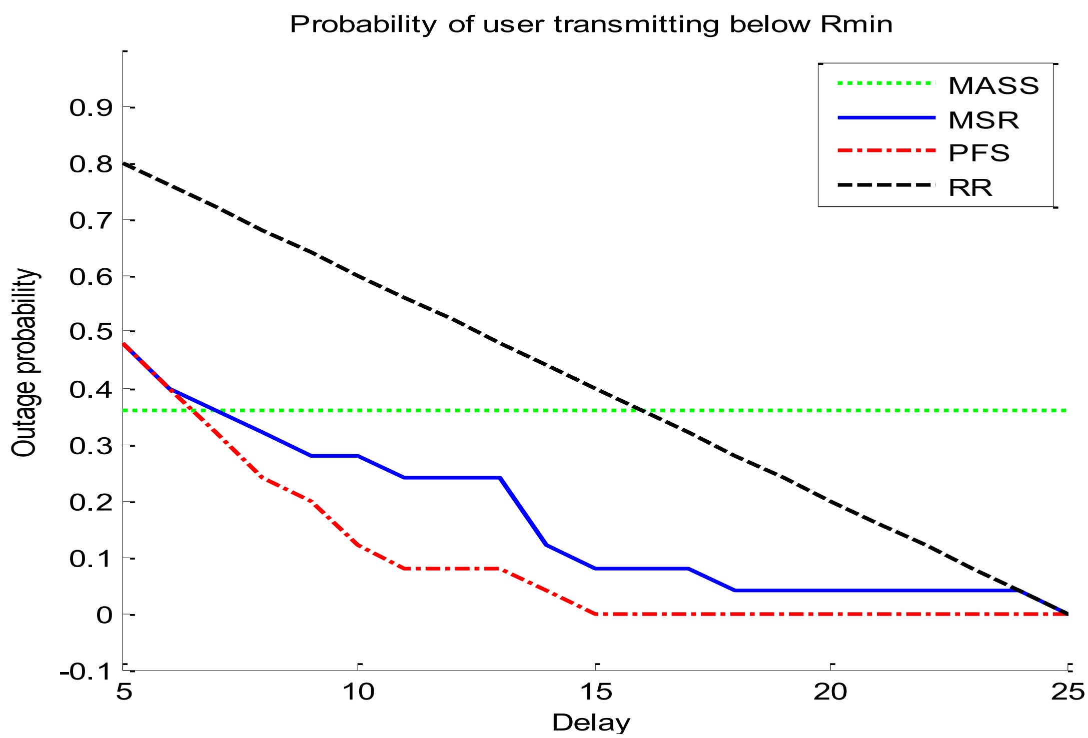


(b)

Figure 5.5 Probability of a user transmitting below R_{min} in scenario C with equal channel response average (a) 15 users, (b) 25 users

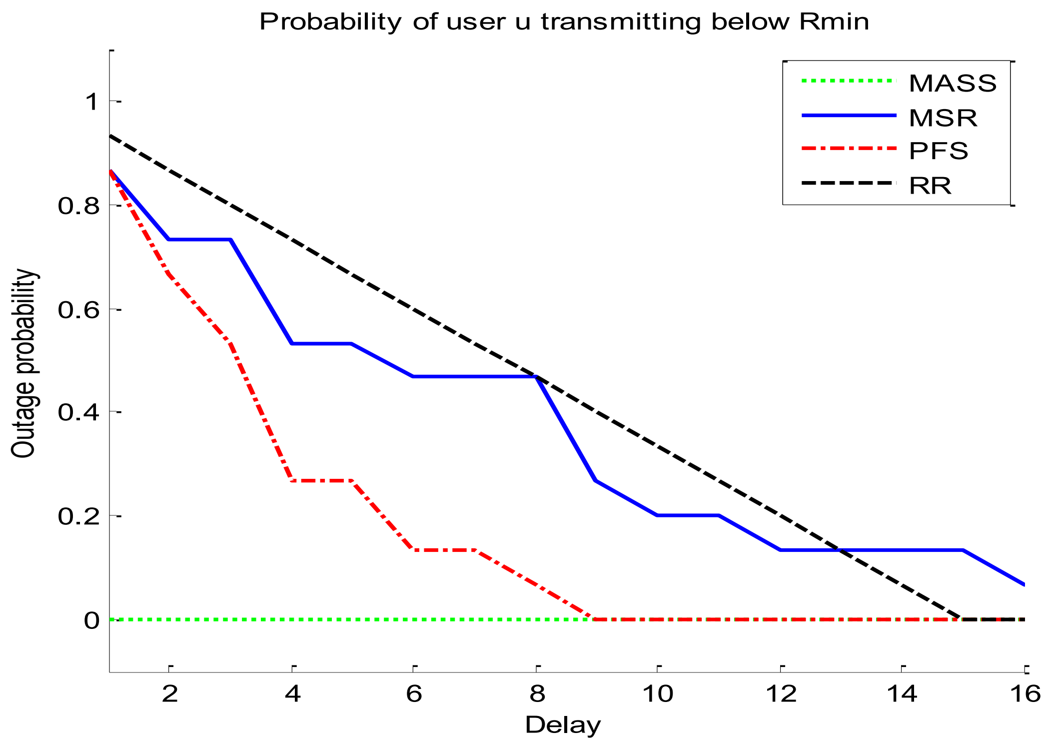


(a)

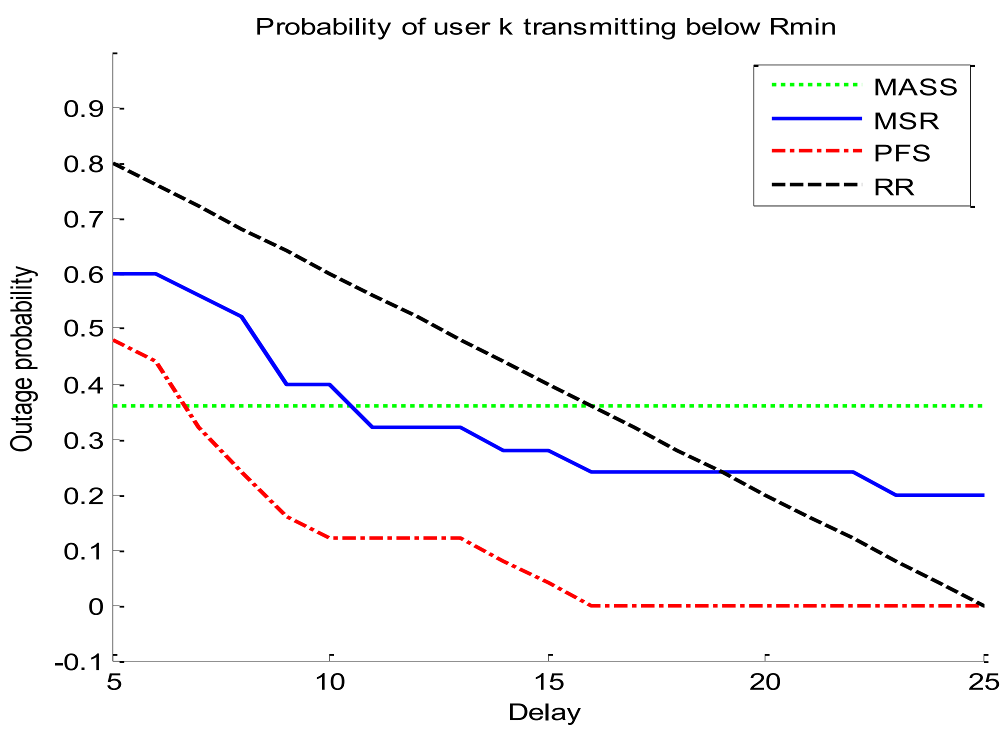


(b)

Figure 5.6 Probability of a user transmitting below R_{min} in scenario A with unequal channel response average (a) 15 users, (b) 25 users

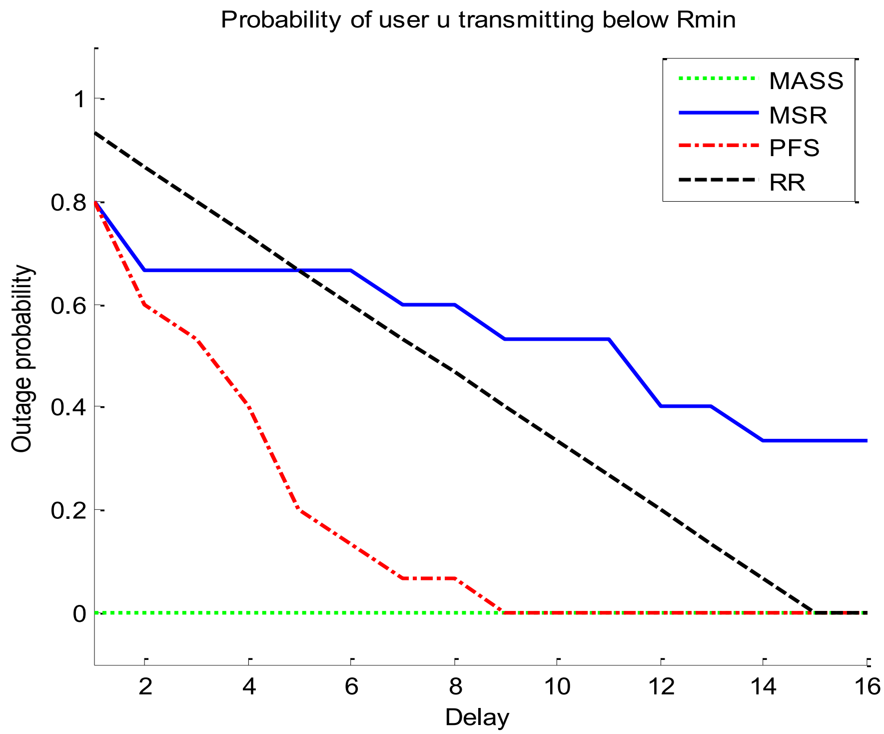


(a)

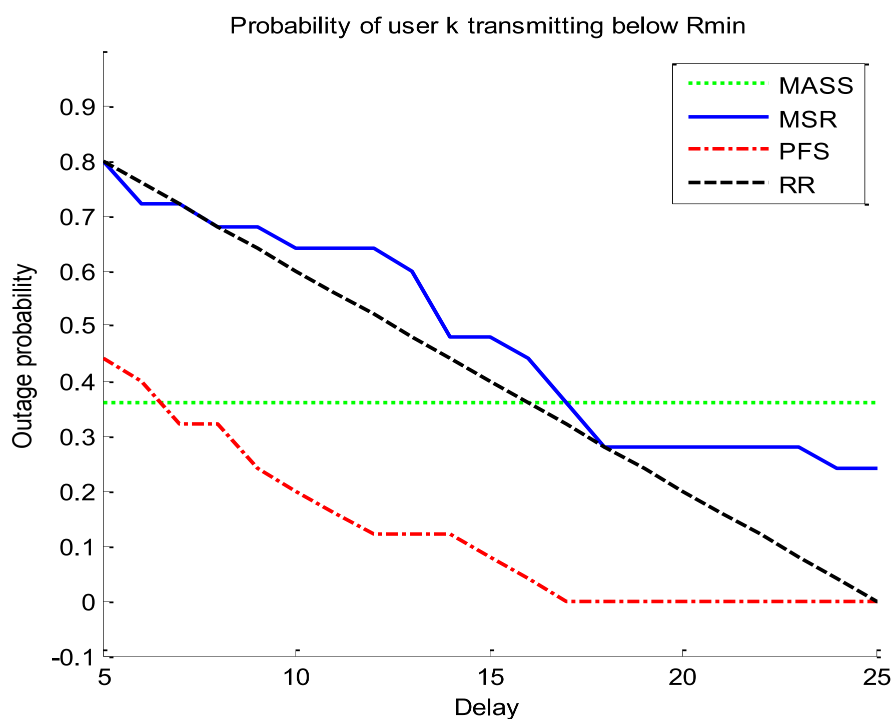


(b)

Figure 5.7 Probability of a user transmitting below R_{min} in scenario B with unequal channel response average (a) 15 users, (b) 25 users



(a)



(b)

Figure 5.8 Probability of a user transmitting below R_{min} in scenario C with unequal channel response average (a) 15 users, (b) 25 users

5.4 Chapter Summary

The performance evaluation for the different RRA algorithms under different scenarios supporting heterogeneous services has been presented. The performance comparison was done based on system throughputs Vs number of users, system fairness Vs number of users and Outage probability Vs delay.

Based on this results, it is concluded that a relationship do exist between system efficiency (capacity) in resource usage and fairness in resource distribution. When the system's sole goal is to maximize efficiency (MSR algorithm), then fairness takes the back seat. But when both system efficiency and fairness are taken into account, (PFS algorithm), a compromise between efficiency and fairness in resource distribution brings down the system capacity. These ensure that all users are served with the minimum resources that promise to maintain given QoS requirements for all the users. On the other hand, MASS exhibited a situation of minimum power consumption and rate requirements while maintaining QoS for the users although this algorithm performs below MSR and PFS and not fair compared with PFS algorithm. It is also concluded that fairness alone (RR) without taking into account the channel responses of users and rate requirements is very inefficient and wastes resources unnecessarily.

In the next chapter, the concluding remarks are presented and future works that can be done to enhance this work is presented.

Chapter 6

6 Conclusions and Future Work

6.1 Introduction

This chapter presents the concluding remarks of the work that was carried out and also discusses some of the work that can be done in future to enhance the work already carried out.

6.2 Conclusions

The convergence of mobile and internet data has complicated the management of the scarce resources to be shared among network users. High efficient air interfaces that can support high data rates with high flexibilities are required. OFDMA is one of the preferred high performance physical layer air interfaces for next generation broadband wireless communication systems. Indeed, it has been adopted by several 4G standards including WiMAX and LTE-A.

However, efficient RRM techniques are crucial in utilizing the resources and flexibilities offered by the access technologies and in particular OFDMA. Previous work used opportunistic policies to maximize the system efficiency through allocating the resources to only those users who maximize the system capacity. Although it optimized system efficiency, a downside of opportunistic schemes was that it was unfair to users who could not maximize system efficiency; users with poor channel conditions.

This then calls for RRM schemes that can balance the trade-off between fairness in resource distribution and efficiency in resource usage. The objective of our study was to design adaptive RRM schemes that balances the trade-off between efficiency in resource usage and fairness in resource distribution among network users.

Two RRA algorithms, MSR and RR, were used as references to compare with PFS and MASS algorithms. This is because MSR achieves the maximum system throughput but is totally unfair and RR is totally fair, but it does not take into account the idea of multiuser diversity, so it does not reach good system throughputs. PFS and MASS on the other hand, work towards balancing the trade-off between system efficiency and fairness among network users.

MASS and PFS algorithms exploit the idea of multiuser diversity, but they work differently. PFS algorithm does not take into account rate requirements directly. It works by tracking the average throughput of each user in a past window of length t_τ and allocates subcarriers to user *k* at time slot *t* with the largest $R_{k,c}(t)/T_{k,c}(t)$. This algorithm treats subcarriers independently of each other.

MASS computes the number of subcarriers each user requires in two steps: in the first step, it allocates subcarriers according to rate requirements and average user SNR and endeavors to assign as minimal power to the subcarriers as possible to support a given rate on that subcarrier. In the second step, based on estimated rate of transmission and channel response, subcarriers are removed from users demanding lower rates and assigned to users who demand high rates. This means that when there are users demanding services with very different data rates, users who are transmitting less data never get subcarriers enough and these users will not be served. Therefore, MASS works well in environments where users are demanding same services and when there are enough resources.

It was demonstrated that PFS policy with a low t_τ parameter, reaches better results on fairness, system throughput and delay than MASS policy in mixed service scenario. Also, the results showed that MSR outperforms PFS and MASS algorithms when it comes to supported throughputs. When compared with RR algorithm both PFS and MASS outperforms RR algorithms on throughputs supported although, RR shows better fairness compared to MASS. PFS closely compares with RR in terms of fairness. Therefore, PFS generally finds a compromise between system efficiency and fairness as it serves as many network users as possible while maintaining their QoS requirements.

Having analyzed the performance of the adaptive RRM techniques based on fairness, throughput and delay, the research statement may then be verified. The research statement can be restated thus: adaptive RRM is a technique that can be used in OFDMA wireless communication systems to bridge the gap between efficiency and fairness, which could lead to more users being served in a network. From the results, we observe that PFS was able to balance between efficiency and fairness by allocating resources to all users irrespective of their channel states. Although this reduced the efficiency of the system, more users were served i.e., fairness was introduced while the QoS of the users were met. Even so, Figure 5.2 shows that PFS throughputs were comparable to those of MSR algorithm whose only objective was to maximize efficiency although few users were served. Therefore, adaptive RRM techniques can indeed be used to bridge the gap between system efficiency and fairness among network users in a wireless system.

6.3 Future Work

The study carried out the performance analysis based on the assumptions that ideal CSI was available at both the transmitter and receiver and that no delay was experienced during feedback from the transmitter. In practical systems, ideal CSI is not available both at the transmitter and receiver and also there are delays experienced during feedback of the CSI from receiver to transmitter. An interesting study will be to look at these issues and carry out performance analysis on estimated CSI values with delay constraints on the feedback control channel.

Other areas that can be explored include the trade-offs between the contradicting resource allocations objectives such as fairness versus coverage, performance versus complexity, fairness versus QoS etc., and finding a compromise between them.

Cross-layer design and MIMO systems are other areas that can extend this work

6.4 Chapter Summary

The concluding remarks of the research has been presented, where conclusions based on the performance of the proposed algorithms; PFS and MASS, has been compared to MSR and RR algorithms. We were able to verify the research statement which states: adaptive RRM is a technique that can be used in OFDMA wireless communication systems to bridge the gap between efficiency and fairness, which could lead to more users being served in a network. Based on our results and analysis, adaptive RRM policy is indeed a technique that can be employed in wireless communication to help bridge the gap that exists between fair distribution of resources and efficiency in resource usage among network users.

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Appendix

In this appendix, we present the link-level small-scale fading channel models used in modelling the channel that was considered in the formulation of the radio resource allocation algorithms proposed in this dissertation. The appendix starts in section A.1 where the propagation models used in modelling the small-scale fading that follows the Rayleigh distribution is presented. Section A.2 presents the graphs that were obtained by the modelled channels.

A.1 Channel Models

The statistical characterization of multipath channels does not in itself provide a constructive way of emulating the channel. For this purpose we need to synthesize a generative model.

There is need to generate a random process with a specific envelope fading density function and a specific Doppler spectrum in order to simulate a narrowband channel. A group of narrowband simulators with different gains connected together through a tapped delay line results into a wideband simulator. Passing the random variable through a filter with a specific spectral shape, resembling the Doppler spectrum of the channel, generates a random variable with the distribution function of envelope fading. Another way to form the specific spectrum is through generating a series of oscillators with different frequencies and adding their outputs.

A variety of fading channels [60], [53] have extensively been simulated using the first approach. Simulation of mobile radio channel, using the Clarke's assumption of isotropic scattering [59] is based on the second approach. In this work, both approaches have been used to model the characteristics of the envelope fading. The envelope fading considered is Rayleigh fading. Therefore, the link between the transmitter and receiver will be considered to be having no direct LOS.

A.1.1 Filtered Gaussian Model

To simulate a fading radio channel between the transmitter and receiver, a widely used approach is constructing the fading signal through the in-phase and quadrature Gaussian noise sources [60]. As the complex Gaussian noise process envelop has a Rayleigh PDF, a Rayleigh fading will be accurately simulated at the output of the simulator. With this approach, the

Doppler spectrum of the channel of interest can be provided by using an appropriate filtering on Gaussian noise sources. Figure A.1 illustrates a simple method used to simulate Rayleigh fading as a radio frequency signal using a filtered Gaussian noise process, at each tap line [61].

If a multipath channel is composed of a group of resolvable distinct components that originate as reflections or scattering from smaller structures, e.g., houses, small hills, etc., it is called a discrete multipath channel. The model in its most general form has, in addition to variable tap gains, variable delays and variable number of taps. The low pass equivalent impulse response of a discrete multipath channel is given as [60], [53]:

$$\bar{h}(\tau,t)=\sum_{k=1}^{K}\bar{g}_k(\tau_k(t),t)\delta(\tau-\tau_k(t)) \tag{A.1}$$

For many channels it can be assumed as a reasonable approximation that the number of discrete components is constant and the delay values vary very slowly and can also be assumed constant. The model then simplifies to [60], [53]:

$$\bar{h}(\tau,t)=\sum_{k=1}^{K}\bar{g}_k(t)\delta(\tau-\tau_k) \tag{A.2}$$

where $\bar{g}_k(t)$ and τ_k are the complex tap attenuation and tap delay respectively. Different tap attenuations will be simulated according to different scenarios.

The number of taps needed by the band-limited model is usually small. We will determine the number of taps by estimating the band-limited power delay profile (PDP) that determines the maximum delay power spread T_m at which the magnitude of the delay spread is still relevant.

In this analysis, the signal components at the receiver which falls below 20 dB of the strongest component will not be considered.

In Figure A.1, the generation of the tap-gain process for the discrete multipath channel model starts with a set of K independent complex processes (*$W_i(t)$, i=1,2,3...K)*, where the magnitude is a complex Gaussian variable with zero-mean and unit variance, and the phase is distributed uniformly between 0 and 2π.

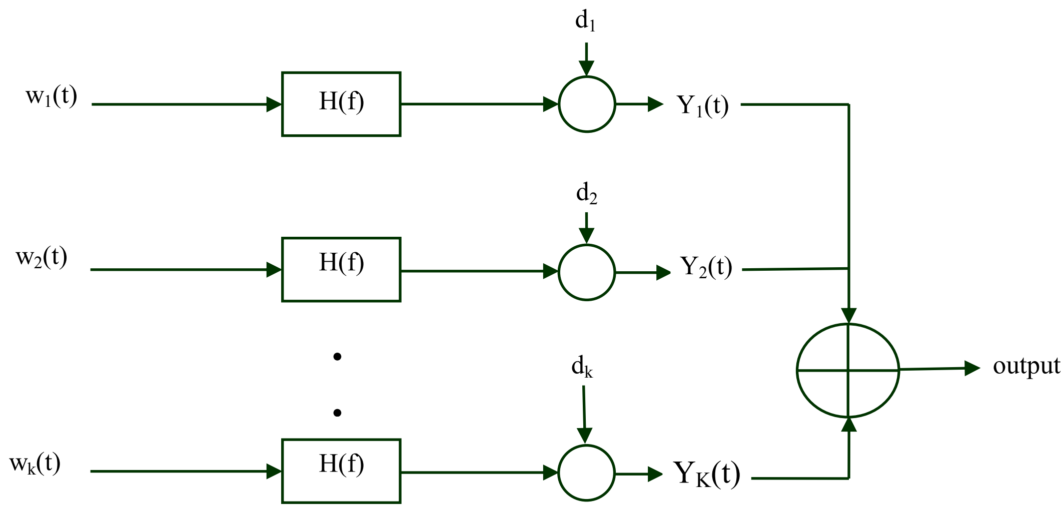


Figure A.1 Tap delay line model

This process is filtered to produce the appropriate Doppler spectrum (H(f)), then scaled to produce the desired amplitude of the discrete channel (d_i, $i = 1,2,3....,k$). Finally all taps have to be added to model the multipath channel.

A.1.2 Jakes Model

Another different way of RF modeling through complex filtered Gaussian noise is by summing up a group of complex sinusoids to approximate the Rayleigh fading process. For the PDF of the resulting envelope to provide an accurate approximation to the Rayleigh PDF the sinusoid numbers in the group is made sufficiently large. The sinusoids are weighted to produce a good approximation of the preferred Doppler spectrum channel when this modeling method is used. Jakes [62] suggested one such technique.

Jakes [62] showed that by summing a relatively small number of sinusoids with frequencies and relative phases of the sinusoids set according to specific formulations, a good approximation of the theoretical Doppler spectrum for the isotropic scattering mobile radio channel can be made. The ideal isotropic continuum of arriving scatter components is approximated by *N* plane waves arriving at uniformly azimuthal angles using the model described by Jakes. The model defines another integer $N_o = 1/2\{(N/2) - 1\}$ and restricts *N/2* to be an odd integer.

This leads to an analytical model having one complex frequency oscillator with frequency $\omega_m = 2\pi f_m$ plus a summation of N_0 complex lower-frequency oscillators with frequencies equal to the Doppler shifts $\omega_m \cos\theta_n$, where θ_n is the arrival angle for the n^{th} plane wave and $n = 1,2,....,N_o$ [62]. As part of initialization, the initial phase for each oscillator is chosen appropriately. The complex envelope T(t) of the fading signal can be expressed as [62]:

$$T(t) = \frac{E_o}{\sqrt{2N_o + 1}}\left(x_c + jx_s\right) \tag{A.3}$$

where

$$x_c(t) = 2\sum_{n=1}^{N_o} \cos\phi_n \cos\omega_n t + \sqrt{2}\cos\phi_N \cos\omega_m t \tag{A.3.1}$$

$$x_s(t) = 2\sum_{n=1}^{N_o} \sin\phi_n \cos\omega_n t + \sqrt{2}\sin\phi_N \cos\omega_m t \tag{A.3.2}$$

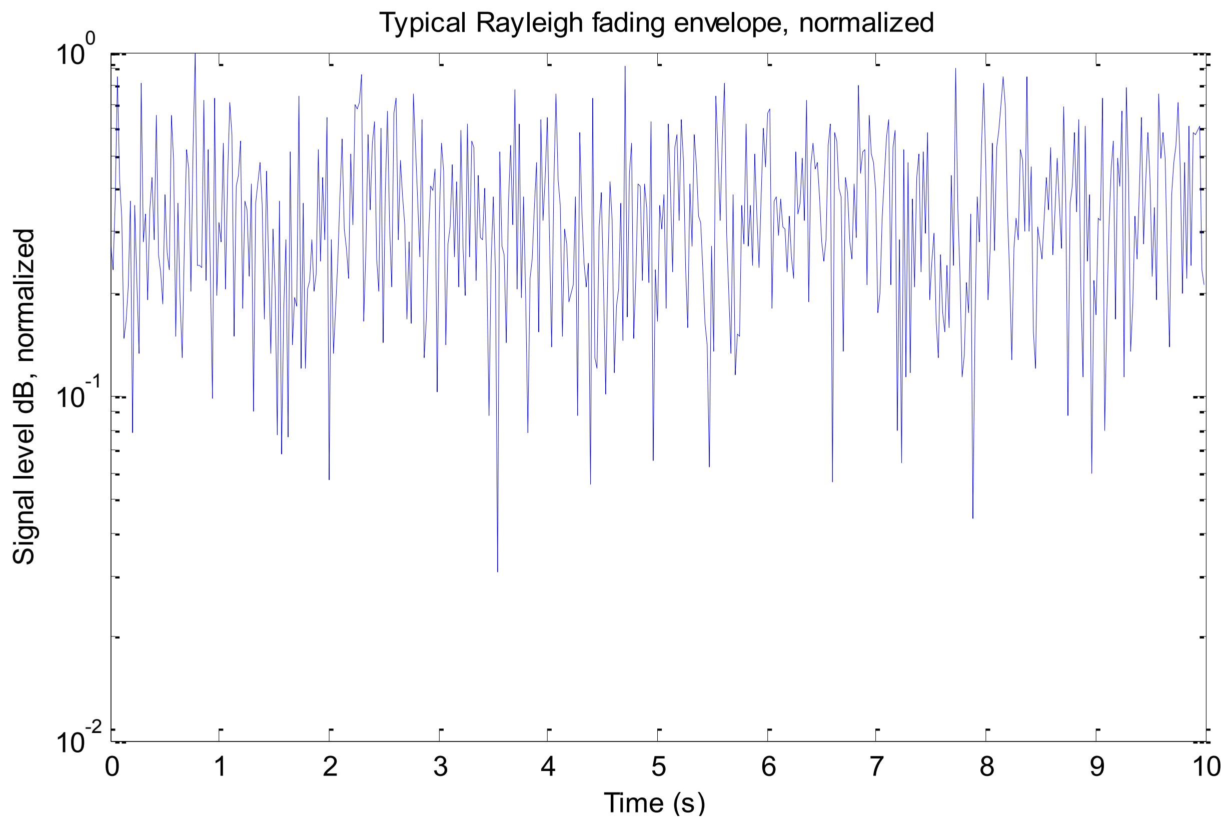
where $\omega_n = \omega_m \cos(2\pi n/N)$, $n = 1,2,...,N_o$. ϕ_n and ϕ_N are the initial phases of the n^{th} Doppler-shifted and maximum Doppler frequency sinusoids respectively. $x_c(t)$ is the in-phase quantity while $x_s(t)$ is the quadrature quantity.

This method can be used, if the Doppler shift components' initial phases (ϕ_N and ϕ_n), are chosen to make the phase of the resulting fading process produce a distribution that is as near to uniform as is feasible. In our work, $\phi_N = 0$ and $\phi_n = \pi n/(N_o + 1)$, were used, where $n = 1,2,...,N_o$ [62]. The envelope $|T(t)|$ is approximately Rayleigh, if the Doppler-shifted sinusoids numbers are selected to be large enough such that, T(t) gives better estimate to a complex Gaussian process. For the ideal case of Rayleigh fading [62], Jakes suggested that $N_0 = 8$ provides an acceptable accurate approximation.

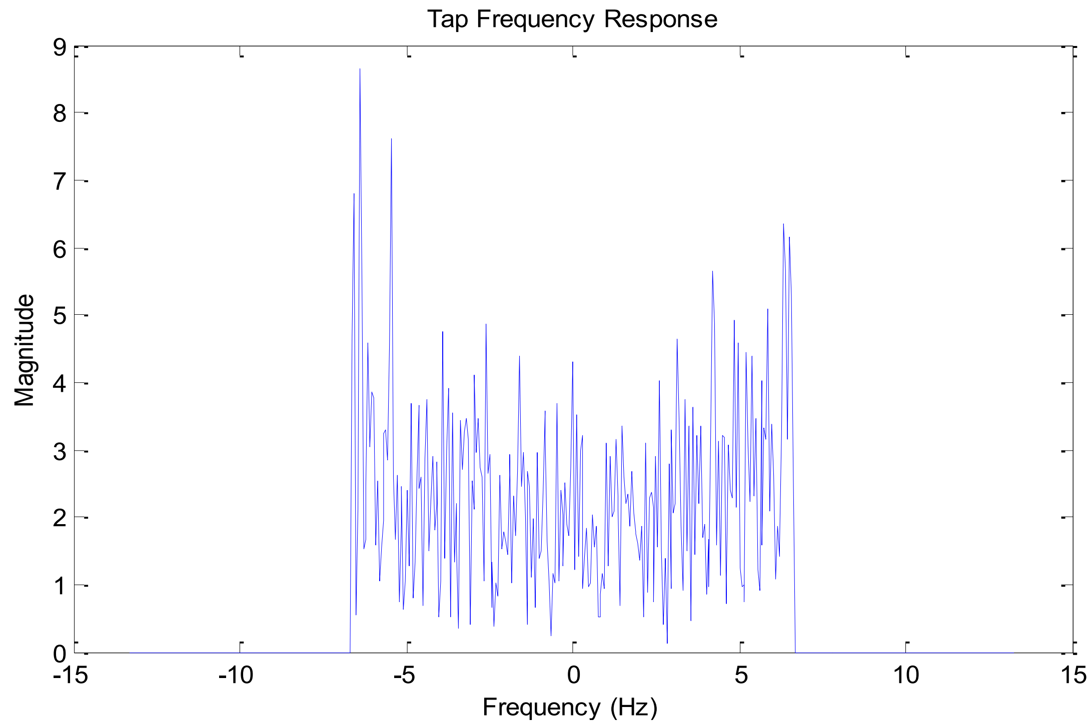
A.2 Generated Results for the Modeled Channels

A.2.1 Filtered Gaussian Noise Model

As discussed in section A.1, fading radio channel can be constructed through the in-phase and quadrature Gaussian noise sources. In Figure A.2 (a) typical Rayleigh fading envelope of a radio channel has been simulated and plotted. As shown, the signal has many fades and peaks. Fades corresponds to destructive interference between taps arriving from different paths, while peaks correspond to constructive combination of the taps signals. In Figure A.2 (b) the Doppler power spectrum is plotted. In Figure A.2 (c), an estimate of PDP which simulates an urban environment has been plotted. And finally, in Figure A.2 (d) the frequency channel response has been plotted.

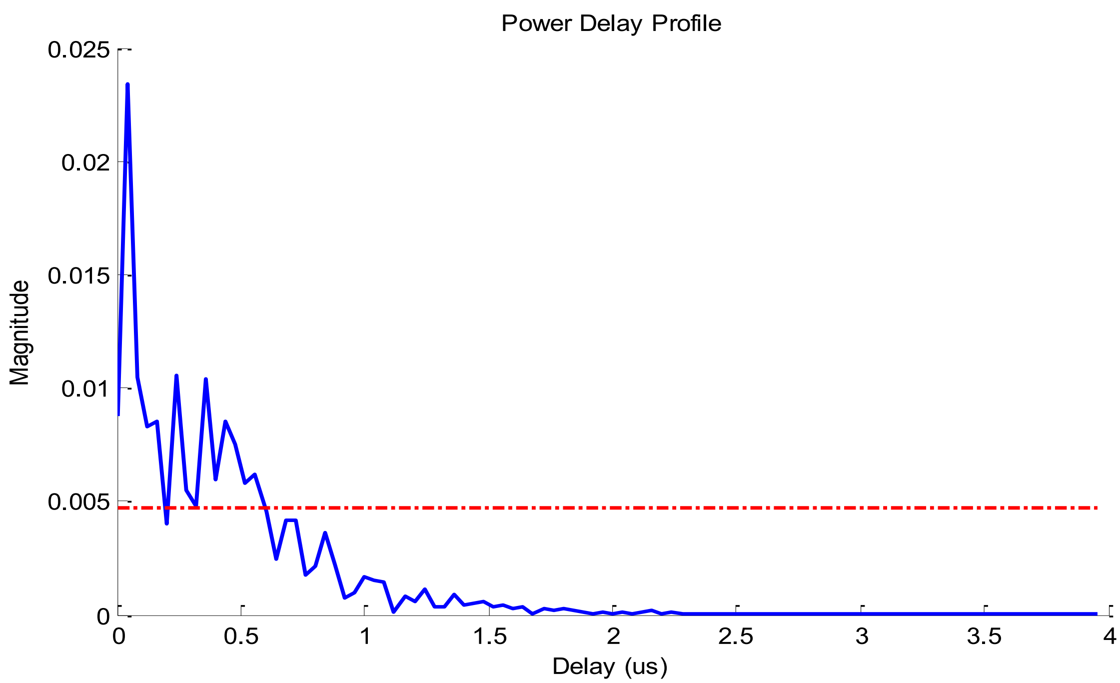


(a)



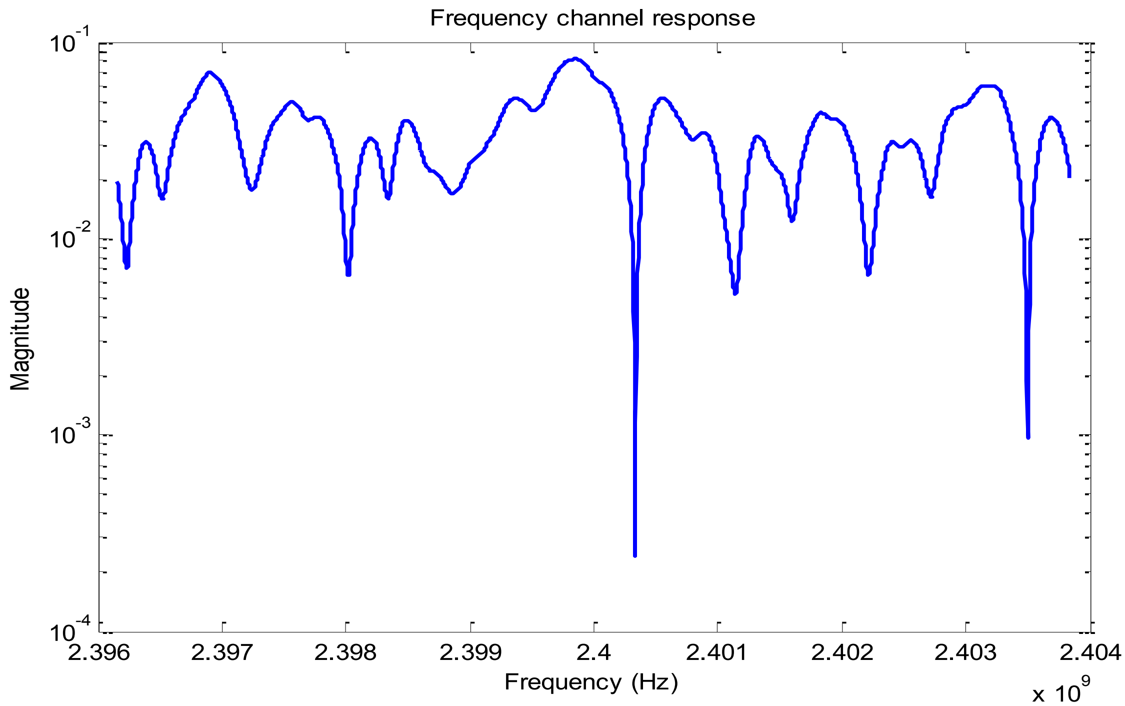
Tap Frequency Response
Magnitude
9
8
7
6
5
4
3
2
1
0
-15
-10
-5
0
5
10
15
Frequency (Hz)

(b)



Power Delay Profile
Magnitude
0.025
0.02
0.015
0.01
0.005
0
0
0.5
1
1.5
2
2.5
3
3.5
4
Delay (us)

(c)

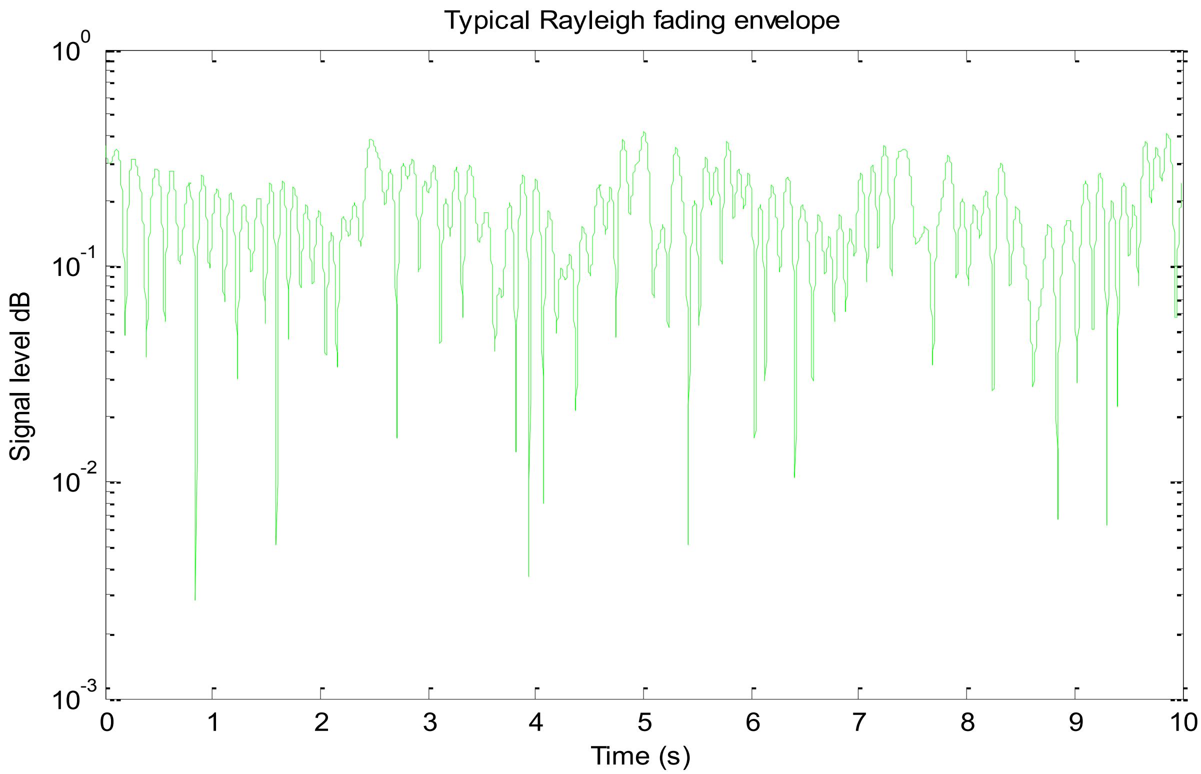


(d)

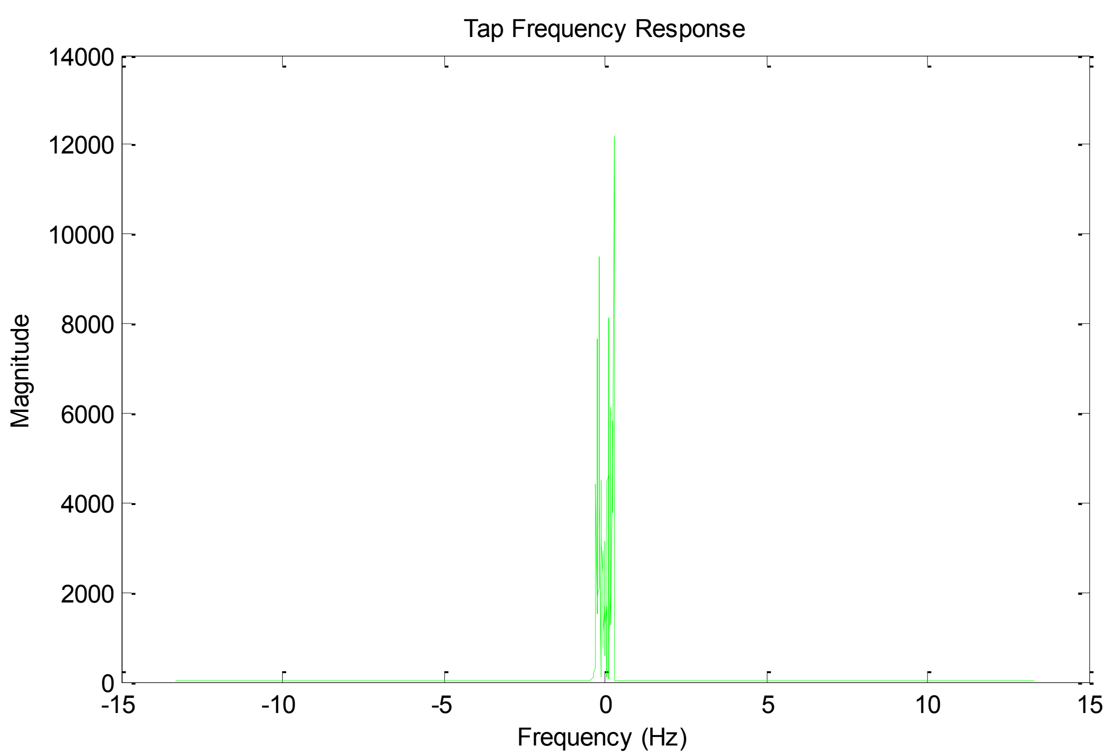
Figure A.2 Filtered Gaussian Noise models for mobile radio channel (a) fading envelop, (b) Doppler power spectrum, (c) estimate PDP, (d) frequency channel response

A.2.2 Jakes Model

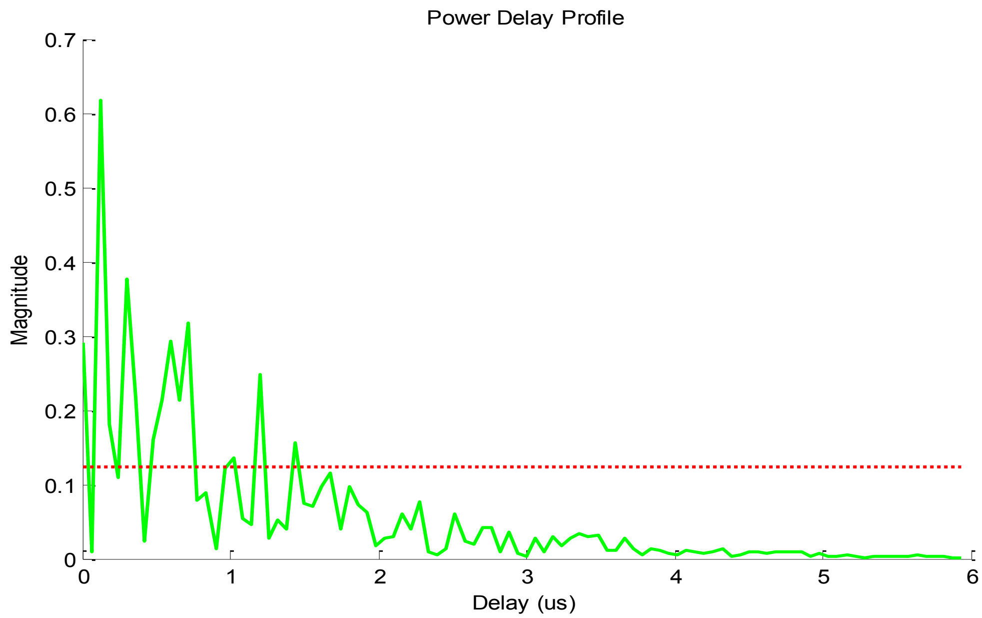
As discussed in section A.1.2, fading radio channel can be constructed by summing a set of complex sinusoids. Typical Rayleigh fading envelope of a radio channel has been simulated and plotted and is shown in Figure A.3 (a). Here, the signal is shown to consist of many fades and peaks which correspond to destructive interference between taps arriving from different paths and constructive combination of the taps signals, respectively. In Figure A.3 (b) the Doppler power spectrum is plotted and is shown to be narrow. This is because the Doppler frequency is small when the user is walking. In Figure A.3 (c), an estimate of PDP which simulates an urban environment has been plotted. Figure A.3 (d), finally plots the frequency channel response.


Typical Rayleigh fading envelope
Signal level dB
Time (s)
10^0
10^-1
10^-2
10^-3
0
1
2
3
4
5
6
7
8
9
10

(a)


Tap Frequency Response
Magnitude
Frequency (Hz)
14000
12000
10000
8000
6000
4000
2000
0
-15
-10
-5
0
5
10
15

(b)



(c)

(d)

Figure A.3 The Jakes model for a mobile channel when the user is walking (3km/h), (a) fading envelop, (b) Doppler power spectrum, (c) PDP estimate, (d) frequency channel response.