Adaptive Modulation and Resource Allocation in wireless Communication Systems

MS

By

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MS Electronic Engineering

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بسم الله الرحمن الرحيم

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This dissertation is submitted to I.I.U. in partial fulfillment of the requirements for the degree of

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Certificate of Approval

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To My Parents and Teachers

Abstract

A wireless system features a centralized basestation communicating to a number of users physically scattered around the basestation. The purpose of resource allocation at the basestation is to intelligently allocate the limited resources, e.g. total transmit power and available frequency bandwidth, among users to meet users' service requirements. Channel-aware adaptive resource allocation has been shown to achieve higher system performance than static resource allocation, and is becoming more critical in current and future wireless communication systems as the user data rate requirements increase. Adaptive resource allocation in a multichannel downlink system is more challenging because of the additional degree of freedom for resources, but offers the potential to provide higher user data rates. Multiple channels can be created in the frequency domain using multiple carrier frequencies, multicarrier modulation (MCM), or in the spatial domain with multiple transmit and receive antennas. This dissertation aims to study the system performance, in multiuser multicarrier systems with adaptive resource allocation, and adaptive modulation.

This thesis proposes that the adaptive modulation is applied to SISO system as well as MIMO system on a subcarrier by subcarrier basis, as a method for combating the effects of frequency selective fading. Each subcarrier in the OFDM system transmits a different amount of data based on the Signal to Noise Ratio (SNR) for that subcarrier. The channel performance is tracked on a regular basis using the bi-directional nature of the link to ensure that both the transmitter and receiver know what modulation scheme is currently being used on each subcarrier. we will show that BER performance of SISO fixed system, SISO Adaptive and MIMO adaptive system, and see that MIMO adaptive system will increase the system efficiency in terms of BER.

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List of Acronyms

AMPS	Advanced Mobile Phone Systems
AWGN	Additive White Gaussian Noise
BC	Broadcast Channel
BER	Bit Error Rate
CDMA	Code Division Multiple Access
CP	Cyclic Prefix
CSI	Channel State Information
DMT	Discrete Multi-Tone
DSL	Digital Subscriber Line
EDGE	Enhanced Data rates for GSM Evolution
E-TACS	European Total Access Communication System
FDD	Frequency Division Duplex
FDMA	Frequency Division Multiple Access
GPRS	General Packet Radio Service
GSM	Global System for Mobile
GSO	Gram-Schmidt Orthogonalization
HDR	High Data Rate
IFFT	Inverse Fast Fourier Transform
LAN	Local Area Network
MA	Margin Adaptive
MAC	Multiple Access Channel
MCM	Multicarrier Modulation
MIMO	Multiple-input multiple-output
MISO	Multiple-input single-output
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
OSM	Optimal Spectrum Management
QAM	Quadrature Amplitude Modulation
RA	Rate Adaptive
RHS	Right Hand Side
RxAS	Receive Antenna Selection

SDMA	Spatial Division Multiple Access
SNR	Signal-to-noise Ratio
SVD	Singular Value Decomposition
TDD	Time Division Duplex
TDMA	Time Division Multiple Access
V-BLAST	Vertical Bell Laboratories Layered Space-Time
WCDMA	Wideband Code Division Multiple Access
ZF	Zero Forcing

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Chapter 1

Introduction

In 1970s the concept of cellular wireless communication was introduced, and from the last decades it becomes the most successful Wireless application being used by billions of subscribers today. Wireless system use the radio frequency for communication and radio signals strength weakens with distance, so the limited frequency bandwidth can be reused to cover wide area and increase the user capacity.

There are three generations of cellular systems till now; in 1980s the United States adopts FM technology by using frequency division multiple access (FDMA). It is known as advanced mobile phone systems (AMPS). And in Europe there was similar analog cellular system, named as European Total Access Communication System (ETACS). This was first generation of cellular systems. In 1990s the existing analog technology of cellular system was converted to digital system, so this was the beginning of second generation. This 2G technologies have provided much higher communication capacity at an even lower cost. In United State IS-136, IS-95 and in Europe Global System for Mobile (GSM) were major standards of 2G. The demand of high data rate in 2G has improved the cellular system to 2.5G standards with some enhancement in 2G standards e.g. General Packet Radio Service (GPRS) and Enhanced Data rates for GSM Evolution (EDGE) for GSM, IS-136 high speed (IS-136HS) for IS-136, and IS-95 high data rate (IS-95 HDR) for IS-95 [4]. The third and current generation of cellular systems includes wideband code division multiple access (WCDMA) and CDMA2000 [2]. The WCDMA frequency division duplex (FDD) and time division duplex (TDD) standards have been adopted in Europe and China, respectively, while CDMA2000 has been deployed in Korean and America. With different spreading factors and modulation methods, WCDMA and CDMA2000 can support transmission rate up to several mega-bits per second. The next generation of wireless cellular systems is envisioned to be multicarrier-based for its efficient bandwidth usage [6].

1.1 Spectrum Sharing Technologies

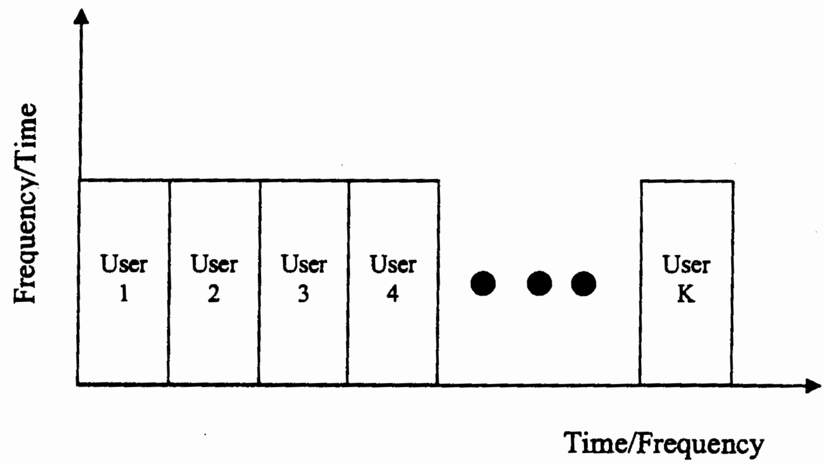

Figure 1.1 TDMA and FDMA

Time division multiple access (TDMA), frequency division multiple access (FDMA), code division multiple access (CDMA), and spatial division multiple access (SDMA) are spectrum sharing technologies. The limited spectrum resources are shared among multiple users for successful communication so it is called multi-user communication system.

TDMA divides the transmit time into a serial number of time slots. One user is allowed to transmit in a time slot over the entire bandwidth. Similarly, FDMA creates multiple subbands in the frequency domain. A user may be able to occupy a subband throughout the whole transmission period. Figure 1.1 shows the basic idea of TDMA and FDMA. TDMA and FDMA were widely employed in earlier generations of cellular systems.

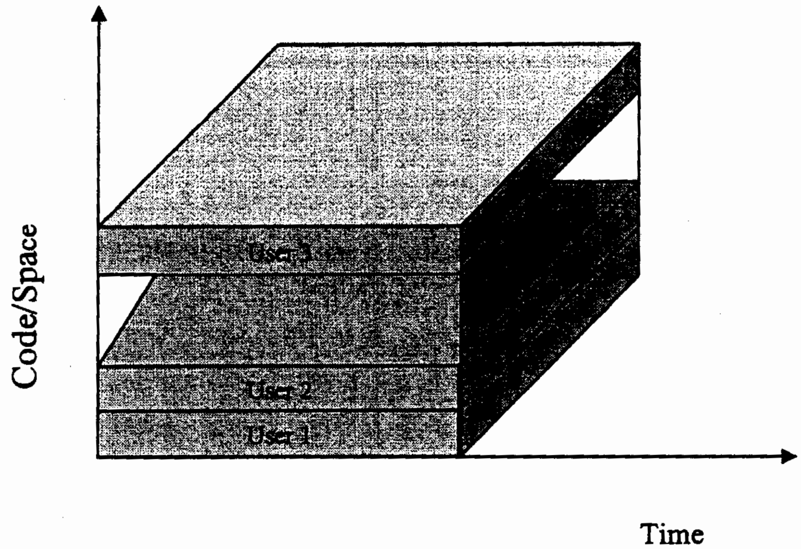

Figure 1.2 CDMA and SDMA

In CDMA users are separated in code domain Instead of time or frequency domain ,and multiple users shares same bandwidth at the same time without interfering the other users because each user is allocated a specific code. In SDMA we use multiple antennas at transmitter and receiver end to separate users in the spatial domain, in SDMA users also share the same bandwidth simultaneously. The basic idea of CDMA and SDMA is shown in Figure 1.2.

Multiple access technologies can also be used in combination. For example, WCDMA TDD employs CDMA with TDMA, where the transmission time is divided into a number of time slots and within each time slot, multiple users employ CDMA to access the whole bandwidth. Further, FDMA is used in almost all cellular systems.

1.2 Resource Allocation in Wireless Communication Systems

In wireless communication system a centralized basestation needs to communicate to multiple users, with limited resources, e.g. total transmit power and available frequency bandwidth. The users can be separated in the time, frequency, code, or spatial domain, the basestation allocates the resources among users. Earlier generations of wireless systems adopted static resource allocations such as time or frequency division multiple access, where the basestation takes turns to serve one user in a designated time slot or frequency band, irrespective of the user channels. The wireless channel is, however, time-varying and frequency selective. The channels experienced by different users are largely independent because of users' different locations. The basestation should allocate the limited resources among users by taking the user channel conditions into consideration and enhance the system performance. Further, adaptive resource allocation in a Multichannel downlink system is more challenging because of the additional degree of freedom for resources. Multiple channels can be created in frequency domain using multiple carrier frequencies, multicarrier modulation (MCM) or in spatial domain with multiple transmit and receive antennas. MCM and MIMO are two promising technologies that have been adopted in various standards. Adaptive resource allocation in multiuser Multichannel wireless systems has drawn significant attention recently.

1.2.1 Multicarrier Modulation

Multicarrier modulation efficiently utilizes the bandwidth to enable high speed transmission for wireless [1] [2] and wireline [3] communication systems. As the data rate requirements get higher and higher, the transmission bandwidth increases significantly. The wireless channel exhibits multipath property in the time domain, or equivalently selectivity [4] in the frequency domain. Successful transmission over a frequency selective channel is more challenging than a narrowband frequency flat channel, as inter-symbol interference degrades the system performance. Advanced signal processing techniques, such as equalization [5], have been proposed to combat the channel dispersion. Multicarrier modulation divides the whole bandwidth into a number of parallel subchannels. As long as the number of subchannels is sufficiently large, the frequency response in each subchannel is close to be flat, as shown in Figure 1.3. Hence equalization per subchannel is much easier to perform.

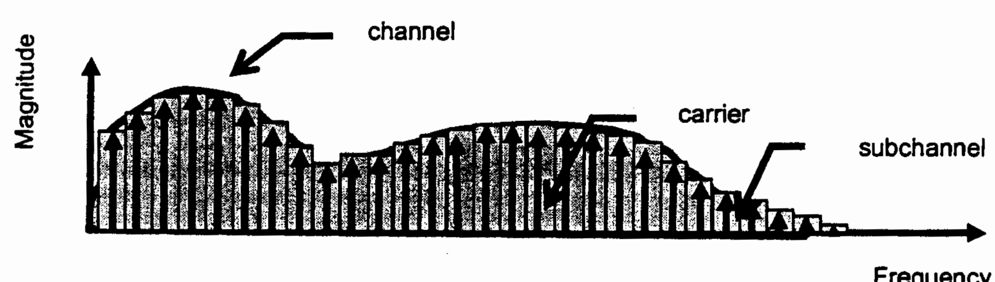

Figure 1.3 Multicarrier Modulation

1.2.2 Multiple Antenna Systems

Multiple-input-multiple-output (MIMO) antenna communication systems have been an intensive research area in the last decade. MIMO systems fully utilize the spatial dimension to improve the transmission reliability and/or the system throughput. A point-to-point narrowband MIMO system is shown in Figure 1.5. In contrast to conventional single antenna systems, the wireless MIMO channel between the communication pair can be represented as a matrix.

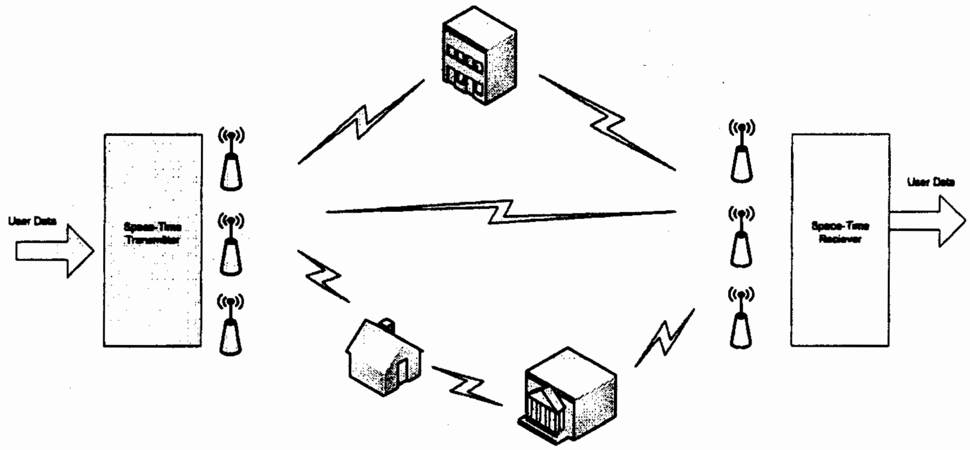

Figure 1.4 A Point to Point MIMO System

Some physical and non-physical models can be found in [6], and MIMO channel model is widely adopted in literature for system performance evaluations. Since wireless channel is time-varying, the signal reception is very poor when the channel is in deep fading. To overcome channel fading problem we use diversity in the communication link. The idea of using multiple receiver antennas to exploit the spatial diversity was proposed decades ago [7]. With optimal combining of the received signals from multiple antennas, the transmission reliability can be significantly improved. In the spatial domain, multi-antenna systems can even suppress co-channel interference [8] [9]. Later, researchers found that if multiple antennas are both equipped at the transmitter and receiver, then a number of parallel channels can be established to increase the spectral efficiency [10] [11] [12]. It was proven in [11] that for point-to-point Raleigh fading channels, the MIMO channel capacity scales linearly with the minimum number of transmit and receive antennas in high SNR regime. The results in [11] theoretically show the potential of MIMO systems in spectral efficiency enhancement. The researchers in Bell Laboratories showed that the V-BLAST (Vertical Bell Laboratories Layered Space-Time) architecture [13] [14] can provide a spectral efficiency of tens of bits per second per Hertz. In summary, MIMO technologies provide the diversity and multiplexing opportunities to improve the communication reliability and spectral efficiency [15]. A theoretical study on the tradeoff between diversity and multiplexing of MIMO systems was presented in [16], and a practical algorithm on the switching between diversity and multiplexing was proposed in [17].

1.3 Assumptions in the Dissertation

- *Perfect channel station information of all users available at the basestation*

  User channel state information is crucial for exploiting multiuser diversity in multiuser wireless communication systems. In this dissertation, I assume users perfectly estimate and feedback their channel information to the basestation. Limited feedback technique [18] [19] or channel prediction [20] [21] can be used to reduced the amount of feedback overhead. The throughput of multiuser systems with imperfect channel state information is still an intensive on-going research area [22].

- *Continuous Shannon channel capacity formula as user throughput measure*

  The Shannon capacity, which is a continuous function, is used as the user throughput in this dissertation. In practical systems, user data rates assume discrete values due to different modulation and coding schemes. The continuous Shannon capacity formula, however, simplifies the analysis of adaptive resource allocation and provides an upper bound on the achievable throughput. A signal-to-noise ratio gap can be included in the Shannon capacity formula to model the signal-to-noise ratio degradation [23] [24]. This gap is widely used in digital subscriber line standards, e.g. [25] [26].

- *Single cell environment*

  In this dissertation, only resource allocation in a single cell is considered. Hence, other-cell interference is not modeled. For users at the cell edges, Other cell interference is not negligible as it greatly impacts the user channel-to-interference-plus-noise ratio. To schedule users in cell edges or in soft handover, either basestation coordination or static frequency planning is required. Several researchers have already discussed resource allocation in multi-cell environment or with inter-user interference, e.g. [27] [28]. Generally, resource allocation in a multi-cell scenario is much more complicated than single cell. The resource allocation algorithms discussed in this dissertation can be applied to users for whom other-cell interference does not dominate the amount of additive white Gaussian noise.

- *Infinitely backlogged user queues*

  The goal of resource allocation discussed in this dissertation is to maximize the throughput given various constraints. The user queues are assumed to be infinitely backlogged. In other words, when one user is scheduled for transmission, he/she always has some information data to transmit. Although the amount of user data is limited in practice, there is always a subset of users who require an opportunity to communicate. Hence, the resource allocation algorithms presented in this dissertation can be applied to those active users.

1.4 Contributions of the Thesis

All the previous research work in adaptive resource allocation involves the adaptation of subchannels and power only, but the modulation scheme remains fixed. This thesis proposes that the adaptive modulation is applied on a subcarrier by subcarrier basis, as a method for combating the effects of frequency selective fading. Each subcarrier in the OFDM system transmits a different amount of data based on the Signal to Noise Ratio (SNR) for that subcarrier. The channel performance is tracked on a regular basis using the bi-directional nature of the link to ensure that both the transmitter and receiver know what modulation scheme is currently being used on each subcarrier. Finally the comparison of Adaptive modulation with fixed modulation is presented to show the performance of both schemes in terms of BER and SNR.

1.5 Organization of the Dissertation

This thesis presents a study of resource allocation for **OFDM** systems. The ultimate aim of this work is to maximize the system spectrum/power efficiency, satisfy each user's **QoS** requirements, and ensure a fair resource allocation.

After presenting preliminary knowledge in Chapter 2, we present in Chapter 3 an adaptive resource allocation methodology for downlink transmission of cellular OFDM systems. In Chapter 3 an optimization frame work for adaptive resource allocation in multiuser OFDM systems. Since the optimal solution to the constrained fairness problem is extremely computationally complex to obtain, so the optimal problem is divided into suboptimal algorithm that separates subchannel allocation and power allocation. So subchannel allocation is first performed by assuming an equal power distribution. An optimal power allocation algorithm then maximizes the sum capacity while maintaining proportional fairness. This suboptimal technique will reduce the complexity from exponential to linear in the number of subchannels. Adaptive modulation is a method for obtaining a high spectral efficiency in a fading environment. The work presented in chapter 3 uses fixed modulation, I have extended it to use adaptive modulation.

The chapter 4 outlines applying adaptive modulation to OFDM systems in a single user environment. The analysis and simulation is considered in two stages. The first stage involves the application of a variable-rate variable-power MQAM technique for a Single-Input Single-Output (SISO) OFDM system. This is compared with the performance of fixed OFDM transmission where a constant rate is applied to each subcarrier. The second stage applies adaptive modulation to a general MIMO system by making use of the Singular Value Decomposition to separate the MIMO channel into parallel subchannels. The simulation results show that the adaptive algorithm employed to SISO/OFDM and MIMO/OFDM system outperforms the SISO system having fixed-rate variable-power. Further, we found that MIMO in general leads to better BER performance.

In chapter 5, the future enhancements and new ideas for research are presented. It also provides a conclusion of this work.

Chapter 2

Channel Characteristics

The wireless channel places fundamental limitations on the performance of wireless communication systems. Unlike the wireline channel, the wireless channel can vary from line-of-sight (LOS) to one that is severely obstructed by buildings, mountains, etc. Due to multiple propagation paths, the received signals consist of multiple delayed and attenuated copies of the transmitted signal. In addition, the wireless channel is time variant due to the motion of the mobile users or the surroundings.

Wireless channels can be categorized into two groups: "Large Scale Fading" and "Small Scale Fading". Traditional propagation models estimate the mean power received at given distances from the transmitter. For large distances (in the order of kilometers), large scale propagation models are used. Small-scale fading describes rapid fluctuations in amplitude, phase, or multipath delay of a radio signal over a short period of time or a short travel distance. It is caused by interference between the multipath waves.

2.1 Small-Scale Multipath fading

In this section, we will describe the characteristics of the wireless channels subject to multipath fading. The three most important effects of the small-scale fading are [34-36]

- Rapid changes in signal strength over a small travel distance or time interval;
- Random frequency modulation due to varying Doppler shifts on different multipath signals; and
- Time dispersion caused by multipath propagation delays.

Assume that $s_b(t)$ is the baseband signal to be transmitted and f_c is the carrier frequency. The corresponding RF signal transmitted over the wireless channel can be written as

$$S(t) = Re\left[s_b(t)e^{j2\pi f_c t}\right] \tag{2.1}$$

Let $\rho_l(t)$ and $\tau_l(t)$ denote the amplitude and the propagation delay for the l-th path. Then, the received bandpass signal is given by

$$\begin{aligned} r(t) &= \sum_l \rho_l(t) s\left(t-\tau_l(t)\right) \\ &= \mathrm{Re}\left\{\left[\sum_l \rho_l(t) e^{-j2\pi f_c(t)\tau_l(t)} s_b\left(t-\tau_l(t)\right)\right] e^{j2\pi f_c t}\right\} \end{aligned} \tag{2.2}$$

where the additive white Gaussian noise (AWGN) is ignored for simplicity. It is apparent from Equation. (2.2) that the equivalent baseband signal is

$$r_b(t) = \sum \rho_l(t) e^{-j2\pi f_c(t)\tau_l(t)} s_b\left(t-\tau_l(t)\right) \tag{2.3}$$

It can be concluded from (2.3) that the multipath channel can be regarded as a time-variant FIR system. We have

$$r_b(t) = s_b(t) \otimes h(t,\tau) \tag{2.4}$$

where

$$h(t,\tau)=\sum_{l}\rho_l(t)e^{-j2\pi f_c(t)\tau_l(t)}\delta\left(\tau-\tau_l(t)\right) \quad (2.5)$$

$h(t,\tau)$ is the impulse response of the channel at time t to an impulse input applied at time t – τ. In most wireless communication systems, the total number of multipath is usually very large. According to the central limit theorem [35], the time-variant impulse response $h(t,\tau)$ may be modeled as a complex-valued Gaussian random process in the t variable.

The modulated symbol duration is much greater than the largest path delay then all the paths cannot be resolved. In this case, all the frequencies in the transmitted signal bandwidth will go through almost the same random attenuation and phase shift. This is known as flat fading and the channel impulse response is expressed as

$$h(t,\tau)=\alpha(t)e^{j\varphi(t)}\delta(t) \quad (2.6)$$

When the propagation delay is larger than the symbol duration, the frequency components in the transmitted signal will go through different attenuations and phase shift along the different path delays. This is called frequency-selective fading. In such a channel, some of the multipath can be resolved and the channel can be expressed as

$$h(t,\tau)=\sum_{l=1}^{L}\alpha_l(t)e^{j\phi_l(t)}\delta\left(\tau-\tau_l(t)\right) \quad (2.7)$$

where L is the number of resolvable paths. In (2.6) and (2.7), $\alpha_l(t)$ is the channel gain and $\phi_l(t)$ is the channel phase shift. When there is no LOS, $\alpha_l(t)$ will be Rayleigh distributed with,

$$f_a(\alpha)=\frac{\alpha}{\sigma^2}e^{\frac{a^2}{2\sigma^2}} \quad (2.8)$$

where $2\sigma^2$ is the time average power of the received signal.

When there is a direct path (case of LOS), $\alpha_l(t)$ will be of Rician distribution with

$$f_a(\alpha)=\frac{\alpha}{\sigma^2}e^{-\frac{\alpha^2+A_d^2}{2\sigma^2}}I_o\left(\frac{\alpha A_d}{\sigma^2}\right) \tag{2.9}$$

where A_d is the amplitude of the dominant path and $I_o(\,)$ is the modified Bessel function of the first kind and zero-order. When $A_d \rightarrow 0$, the Rician distribution degenerates to a Rayleigh distribution. Delay spread and coherence bandwidth is the parameters that describe the time dispersive nature of the channel in a local area. The *mean excess delay* is the first moment of the power delay profile and is defined to be

$$\bar{\tau}=\frac{\sum_l \alpha_l^2\tau_l}{\sum_l \alpha_l^2} \tag{2.10}$$

The rms (root mean squared) delay spread is the square root of the second central moment of the power delay profile and is defined to be

$$\sigma_\tau=\sqrt{\overline{\tau^2}-\left(\bar{\tau}\right)^2} \tag{2.11}$$

where $$\overline{\tau^2}=\frac{\sum_l \alpha_l^2\tau_l^2}{\sum_l \alpha_l^2} \tag{2.12}$$

The coherent bandwidth is a range of frequencies over which two frequency components have strong potential for amplitude correlation. If the coherence bandwidth is defined as the bandwidth over which the frequency correlation function is above 0.9, then the coherence bandwidth is approximately [37]

$$B_c \approx \frac{1}{50\sigma_\tau} \tag{2.13}$$

Likewise, Doppler spread and coherence time are parameters which describe the time varying nature of the channel in a small-scale region. If we assume that the channel is wide sense stationary, the Doppler power spectrum $D(f)$ of a mobile channel for an omni-directional mobile antenna and the received plane wave with uniformly distributed arrival angle can be given by

$$D(f)=\frac{a}{\pi f_d\sqrt{1-\left(\frac{f-f_c}{f_d}\right)^2}} \tag{2.14}$$

where a is a constant and f_d is the maximum Doppler spread, which is given by

$$f_d=\frac{v}{c}f_c \tag{2.15}$$

where v is the velocity at which a mobile is moving and c is the velocity of light. Coherence time T_c is a statistical measurement of the time duration over which the channel impulse response is essentially invariant, and quantifies the similarity of the channel response at different times. The Doppler spread and coherence time are inversely proportional to each other, i.e.

$$T_c\approx\frac{1}{f_d} \tag{2.16}$$

2.2 Categories of Small-Scale Fading

The relation between signal parameters (i.e., the bandwidth, symbol period, etc.) and channel parameters (i.e., the rms delay spread, the Doppler spread, etc.), small-scale fading can be categorized based on two aspects: multipath delay spread and Doppler spread. Multipath delay spread leads to time dispersion and frequency-selective fading; so based on this, small-scale fading can be categorized into flat fading and frequency-selective fading. The multipath delay spread is a channel parameter in time domain, while the phenomenon that the channel is flat or frequency selective corresponds to the frequency domain. Thus, the time domain parameter, multipath delay spread, influences the channel characteristic in frequency domain.

Doppler spread leads to frequency dispersion and time-selective fading, so in terms of this, small-scale fading can be categorized into fast fading and slow fading. The Doppler spread is a channel parameter in frequency domain, while the phenomenon that the channel changes fast or slow belongs to time domain. Similarly, the frequency domain parameter, the Doppler spread *Ds*, influences the channel characteristic in time domain. Knowing these relationships will help us in designing the system.

Table 2.1 gives the categories of small-scale fading. If the coherence bandwidth *Bc* of the channel is much larger than the bandwidth of the transmitted signal, the received signal undergoes flat fading. In contrast, if the coherence bandwidth of the channel is smaller than the bandwidth of the transmitted signal *Bs*, the received signal suffers from frequency-selective fading. When this happens, the received signal is distorted and Inter Symbol Interference (ISI) is induced. What is more, it is much more complex to model frequency-selective fading channels than flat fading channels since each multipath has to be modeled and the channel needs to be modeled as a linear filter. Therefore, it is preferable to deal with a flat fading channel for signal transmission. However, since we can not change the multipath delay spread and coherence bandwidth of the channel, we can only try to design the symbol period and signal bandwidth such that flat fading of the channel results for the transmitted signal. Hence, given the delay spread, to improve the performance of the transmission, we choose such a value for the symbol period in the adaptive modulation algorithm that we get a flat fading channel instead of a frequency-selective one.

Table 2.1 Categories of Small Scale Fading

Categorization basis	**Fading types**	**condition**
Multipath delay spread	Flat fading	$B_S \langle\langle B_C$
	Frequency-selective fading	$B_S \rangle B_C$
Doppler spread	Fast fading	$T_S \rangle T_C$
	Slow fading	$T_S \langle\langle T_C$

Based on the Doppler spread, the channel can be classified as fast fading or slow fading. If the channel impulse response (in time domain) changes quickly within the symbol period *Ts*, i.e., if the coherence time *Tc* of the channel is smaller than the symbol period of the transmitted signal, the channel creates fast fading on the received signal. This will result in signal distortion. If the channel impulse response changes at a much slower rate than the transmitted baseband signal, the channel creates slow fading on the received signal. The channel behaves static all over certain symbol periods. It is easy to see that a slow fading channel is preferable as it results in a more stable transmission quality. But the Doppler spread is not determined by the system's design. However, we can try to design the symbol period and signal bandwidth to give slow fading on the transmitted signal. Therefore, given the Doppler spread, we choose such a value for the signal bandwidth/subcarrier bandwidth in the adaptive modulation algorithm that we get a slow fading channel instead of a fast fading one, as it results in better performance.

2.3 Orthogonal Frequency Division Multiplexing

OFDM has long been considered as a very promising solution for supporting high-data-rate transmission in future broadband wireless communication systems. The basic idea of OFDM is to divide the available spectrum into several *subcarriers* so that the information symbols are transmitted in parallel on the subcarriers over the wireless channel. This allows us to design a system supporting high data rates while maintaining symbol durations much longer than the channel's delay spread. By doing so, each subcarrier experiences almost a flat fading, and the detrimental effects of the multipath channels are reduced to a multiplication of each subcarrier by a complex transfer factor. A schematic diagram of an OFDM system is shown in Figure 2.1.

High-data-rate communications are limited not only by noise but often more significantly by the intersymbol interference (ISI) due to the time dispersive nature of the wireless channels. Generally, the effects of ISI are negligible as long as the delay spread is significantly shorter than the duration of one transmitted symbol. This implies that the symbol rate of communication systems is practically limited by the channel's memory. For high rate transmission where symbol rates exceeding this limit are to be transmitted over the channel, mechanisms must be implemented in order to combat the effects of ISI [38].

Data to be transmitted are first arranged in parallel for each subcarrier and modulated independently. The complex numbers X_k which represent the signal constellation of each subcarrier are transformed into the time domain by performing a Inverse Fast Fourier Transform (IFFT). Assuming that we have N subcarriers, the output of the IFFT which consists of N samples x_n is

$$x_n = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k e^{j2\pi \frac{kn}{N}} \tag{2.17}$$

In order to ensure that the received time-domain OFDM symbol is demodulated from the channel's steady-state response, each time-domain OFDM symbol is extended by the so-called cyclic extension or guard interval of N_g samples duration, as shown in Figure 2.2. If the cyclic prefix is longer than the impulse response of the channel, the inter-OFDM symbol interference due to the channel memory is completely eliminated.

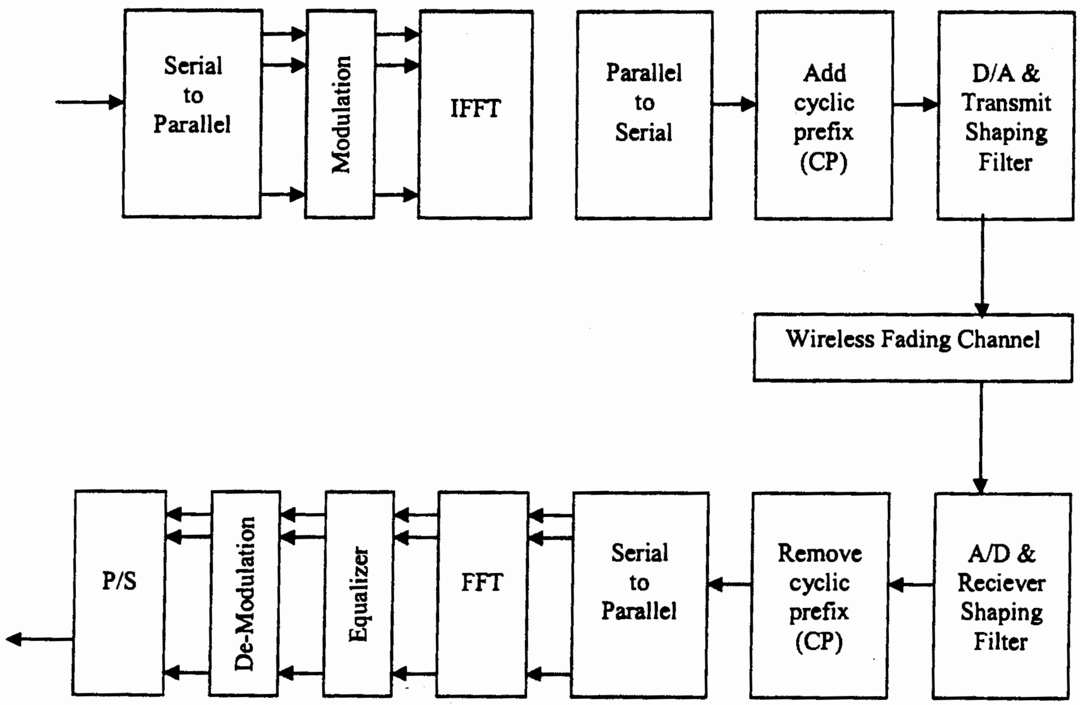

Figure 2.1 OFDM system model

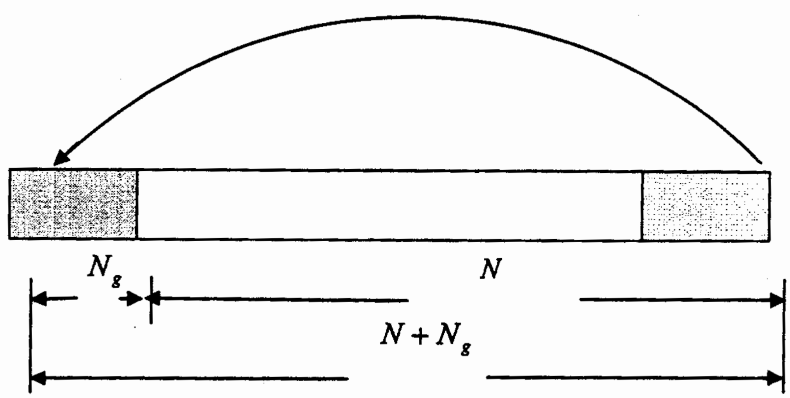

Figure 2.2 The cyclic prefix of an OFDM symbol

After removing the cyclic prefix at the receiver, we retrieve the complex number by Fast Fourier Transform (FFT). As we have inserted a cyclic prefix, the received signal is the result of a circular convolution between x_n and the channel response h. The result of the FFT on the received signal is then merely a product of X_k and H_k, the frequency response of the channel on each subcarrier. By including the channel noise, we have

$$\hat{X}_k = H_k X_k + \eta_k \tag{2.18}$$

where η_k is the additive white noise in the frequency domain. In addition, the frequency response of the channel at t can be calculated as

$$H(f,t) = \int_{-\infty}^{+\infty} h(t,\tau) e^{-j2\pi f\tau} d\tau = \sum a_l(t) e^{-j2\pi f\tau_l(t)} \tag{2.19}$$

and H_k is obtained by substituting f with the frequency of the k^{th} subcarrier.

2.4 Multiple Input Multiple Output Antenna System

2.4.1 MIMO Structure

MIMO systems are one of the most popular areas that have drawn enormous attention in recent years [39, 40, 41-44]. In such systems, multiple antennas are deployed at both the transmitter and receiver to exploit the spatial dimension freedom and combat the harmful effects in mobile radio communication and therefore improve the system performance. Besides the performance enhancement, deploying multiple antennas can bring a huge increase in the system capacity, which is one of the most critical issues for current wireless communication services.

The block diagram of a MIMO system is shown in Figure 2.3. At the transmitter side, the input data stream is demultiplexed into J parallel substreams. Each substream is transmitted over all transmit antennas in the same frequency band with different transmit antenna weights. At the receiver, the multiple antennas can separate the substreams and give an estimation of the original data stream.

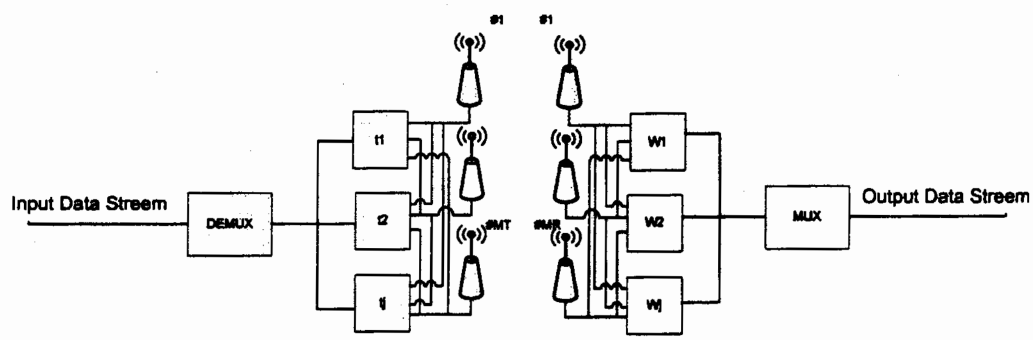

Figure 2.3 Block diagram of MIMO systems

2.4.2 MIMO Multiplexing using Singular Value Decomposition

It was proved in [40] that SVD based space-time vector coding (STVC) allows the collection of the signal power in space and is a theoretical means to achieve high capacity for MIMO systems. By SVD, the M_R and M_T channel matrix can be decomposed into

$$\mathbf{H} = \mathbf{U}\mathbf{S}\mathbf{V}^H = \sum_{j=1}^{rank(\mathbf{H})} \mathbf{u}_j s_j \mathbf{v}_j{}^H \tag{2.26}$$

where

$$\mathbf{U} = \left[\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_{M_R}\right]$$

denotes the left singular vectors and

$$\mathbf{V} = \left[\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_{M_T}\right]$$

represents the right singular vectors. $s_1, s_2, \ldots, s_{rank(H)}$ are singular values, and are arranged in a descending order, without loss of generality. It was pointed out in [40] that by configuring the transmit antenna weights using right singular vectors **v** and receive antenna weights using right singular vectors **u**, up to $rank(\mathrm{H})$ parallel channels are constructed.

2.5 Adaptive Modulation

The basic idea of adaptive modulation is to take advantage of the variation of the fading channel. Instead of maintaining a fixed transmit rate at a given time, adaptive modulation adjust the transmit rate and power according to the channel situation. In other words, a higher transmission rate should be used when the channel is under a good condition and vice versa. Lots of algorithms have been proposed to use adaptive modulation in the time domain to exploit the time-variant channel capacity [45-51]. They gave impressive result in increasing the transmission rate or improving the system performance.

The notion of adaptive modulation in the context of OFDM was proposed as early as 1989 by Kalet [52], which was further developed by Chow *et al* [53] and was refined for duplex wireless links, for example in [54]. The basic idea of such algorithms is to apply high modulation levels on the subcarriers with favorable channel conditions to improve the spectral efficiency, while transmitting few bits on the subcarriers in deep fades to avoid bit errors.

In order to allocate appropriate modulation modes to the subcarriers, three allocation criterions were investigated in the literature. They are the fixed-threshold controlled algorithm, upper bound BER algorithm, and fixed-throughput adaptation algorithm [38]. In these criterions, transmission modes are adapted in order to maximize the data rate given a fixed long-term or instantaneous **BER**, or to minimize the bit errors given a fixed data rate.

Chapter 3

Resource Allocation in OFDM Systems

3.1 Introduction

Orthogonal frequency division multiplexing (OFDM) is a promising technique for the next generation of wireless communication systems [55] [56]. OFDM divides the available bandwidth into N orthogonal subchannels. By adding a cyclic prefix (CP) to each OFDM symbol, the channel appears to be circular if the CP length is longer than the channel length. Multiuser OFDM adds multiple access to OFDM by allowing a number of users to share an OFDM symbol. Two classes of resource allocation schemes exist: fixed resource allocation [57] and dynamic resource allocation [58] [59] [60 [61]. Fixed resource allocation schemes, such as time division multiple access (TDMA) and frequency division multiple access (FDMA), assign an independent dimension, e.g. time slot or subchannel, to each user. Due to the time-varying nature of the wireless channel, dynamic resource allocation makes full use of multiuser diversity to achieve higher performance.

Two classes of optimization techniques have been proposed in the dynamic multiuser OFDM literature: margin adaptive (MA) [61] and rate adaptive (RA) [58] [60]. The margin adaptive objective is to achieve the minimum overall transmit power given the constraints on the users' data rate or bit error rate (BER). The rate adaptive objective is to maximize each user's error-free capacity with a total transmit power constraint. These optimization problems are nonlinear and hence computationally intensive to solve. In [59], the nonlinear optimization problems were transformed into a linear optimization problem with integer variables. The optimal solution can be achieved by integer programming. However, even with integer programming, the complexity increases exponentially with the number of constraints and variables.

Two rate adaptive optimization problems have been proposed by researchers. Recently, Jang and Lee proposed the rate maximization problem [58]. In [58], they proved that the sum capacity is maximized when each subchannel is assigned to the user with the best subchannel gain and power is then distributed by the water-filling algorithm. However, fairness is not considered in [58]. When the path loss differences among users are large, it is possible that the users with higher average channel gains will be allocated most of the resources, i.e. subchannels and power, for a significant portion of time. The users with lower average channel gains may be unable to receive any data, since most of the time the subchannels will be assigned to users with higher channel gains. In [60], Rhee and Cioffi studied the *max-min* problem, where by maximizing the worst user's capacity; it is assured that all users achieve a similar data rate. However, the *max-min* optimization problem can only provide maximum fairness among the users. In most wireless systems of interest, different users require different data rates, which may be accommodated by allowing users to subscribe to different levels of service.

In this chapter, we formulate another optimization problem that balances the tradeoff between capacity and fairness. The objective function is still the sum capacity, but proportional user data rates are assured by imposing a set of nonlinear constraints into the optimization problem. Hence the proportionality in this chapter compares the user data rates to the set of system parameters instead of another feasible set of user data rates as in the networking area. Further, while large channel fluctuations are intentionally created with "dumb" antennas for long-term proportional fairness resource allocation in [62], the algorithm presented in this chapter maintains proportional rates among users for each channel realization, which ensures the rates of different users to be proportional in any time scale of interest.

3.2 System Model

A multiuser OFDM system is shown in Figure 3.1. In the basestation, all channel information is sent to the subchannel and power allocation algorithm through feedback channels from all mobile users. The resource allocation scheme made by the algorithm is forwarded to the OFDM transmitter. The transmitter then selects different numbers of subchannel for different users. The resource allocation scheme is updated as fast as the channel information is collected.

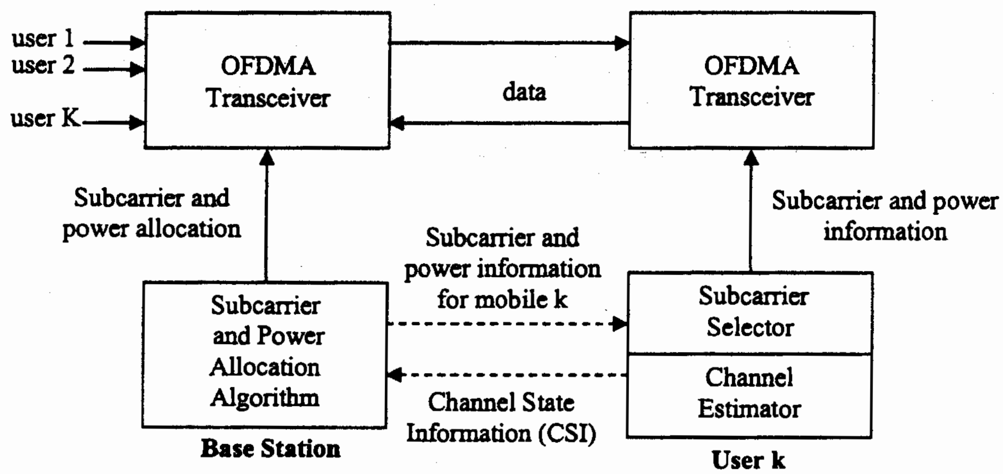

Figure 3.1 Multiuser OFDM System Block Diagram

In this chapter, perfect instantaneous channel information is assumed to be available at the basestation and only the broadcast scenario is studied. It is also assumed that the subchannel and power allocation information is sent to each user by a separate channel. Throughout this dissertation, it is assumed a total of K users in the system sharing N subchannels; with total transmit power constraint p_{total}. The objective is to optimize the subchannel and power allocation in order to achieve the highest sum error-free capacity under the total power constraint. The equally weighted sum capacity is adopted as the objective function, but the idea of proportional fairness is introduced into the system by adding a set of nonlinear constraints. The benefit of the proportional fairness is that the capacity ratios among users can be explicitly controlled to meet each user's target data rate, given sufficient total available transmit power. Mathematically, the optimization problem considered in this chapter is formulated as

$$\operatorname*{Max}_{p_{k,n},\rho_{k,n}} \sum_{k=1}^{K} \sum_{n=1}^{N} \frac{\rho_{k,n}}{N} \log_2 \left(1 + \frac{p_{k,n} h_{k,n}^{\;2}}{N_o \frac{B}{N}} \right) \tag{3.1}$$

Subject to:

$$\sum_{k=1}^{K}\sum_{n=1}^{N} p_{k,n} \le p_{total}$$

$$p_{k,n} \ge 0 \text{ for all } k, n$$

$$\rho_{k,n} = \{0,1\} \text{ for all } k, n$$

$$\sum_{k=1}^{K} \rho_{k,n} = 1 \text{ for all } k, n$$

$$R_1 : R_2 : \ldots : R_K = \gamma_1 : \gamma_2 : \ldots : \gamma_K$$

where K is the total number of users; N is the total number of subchannels; N_o is the power spectral density of additive white Gaussian noise; B and P_{total} are the total available bandwidth and power, respectively; $p_{k,n}$ is the power allocated for user k in the subchannel n; $h_{k,n}$ is the channel gain for user k in subchannel n; $\rho_{k,n}$ can only be the value of either 1 or 0, indicating whether subchannel n is used by user k or not. The fourth constraint shows that each subchannel can only be used by one user. The capacity for user k, denoted as R_k, is defined as

$$R_k = \sum_{n=1}^{N} \frac{\rho_{k,n}}{N} \log_2 \left(1 + \frac{p_{k,n} h_{k,n}{}^2}{N_o \frac{B}{N}} \right) \tag{3.2}$$

Finally $\{\gamma_i\}^K_{i=1}$ is a set of predetermined values which are used to ensure proportional fairness among users. The fairness index is defined as

$$F = \frac{\left(\sum_{k=1}^{K} \gamma_k \right)^2}{K \sum_{k=1}^{K} \gamma_k{}^2} \tag{3.3}$$

with the maximum value of 1 to be the greatest fairness case in which all users would achieve the same data rate. When all γ_k terms are equal, the objective function in (3.1) is similar to the objective function of the *max-min* problem [60], since maximizing the sum capacity while making all R_k terms equal is equivalent to maximizing the worst user's capacity. Hence, [60] is a special case of the constrained-fairness problem.

3.3 Optimal Subchannel Allocation and Power Distribution

The optimization problem in (3.1) is generally very hard to solve. It involves both continuous variables $p_{k,n}$ and binary variables $\rho_{k,n}$. Such an optimization problem is called a mixed binary integer programming problem. Furthermore, the nonlinear constraints in (3.1) increase the difficulty in finding the optimal solution because the feasible set is not convex.

In a system with K users and N subchannels, there are K^N possible sub-channel allocations, since it is assumed that no subchannel can be used by more than one user. For a certain subchannel allocation, an optimal power distribution can be used to maximize the sum capacity, while maintaining proportional fairness. The optimal power distribution method is derived in the next section. The maximum capacity over all K^N subchannel allocation schemes is the global maximum and the corresponding subchannel allocation and power distribution is the optimal resource allocation scheme. However, it is prohibitive to find the global optimizer in terms of computational complexity. A suboptimal algorithm is derived in this chapter to reduce the complexity significantly while still delivering performance close to the global optimum. Furthermore, it is computationally complex to find the optimal solution. For these reasons, we use a suboptimal technique in the next section.

3.4 Suboptimal Subchannel Allocation and Power Distribution

Ideally, subchannels and power should be allocated jointly to achieve the optimal solution in (3.1). However, this poses a prohibitive computational burden at the basestation in order to reach the optimal allocation. Furthermore, the basestation has to rapidly compute the optimal subchannel and power allocation as the wireless channel changes. Hence low-complexity suboptimal algorithms are preferred for cost-effective and delay-sensitive implementations. Separating the subchannel and power allocation is a way to reduce the complexity because the number of variables in the objective function is almost reduced by half. Section 3.4.1 discusses a subchannel allocation scheme. Section 3.4.2 presents the optimal power distribution given a certain subchannel allocation.

3.4.1 Suboptimal Subchannel Allocation

In this section, a suboptimal subchannel algorithm based on [60] is proposed. In the suboptimal subchannel allocation algorithm, equal power distribution is assumed across all subchannels. The channel-to-noise ratio for user k in subchannel n is defined as $H_{k,n} = h_{k,n}^2 / N_o \frac{B}{N}$ and Ω_k is the set of subchannels assigned to user k. The algorithm can be described as

1) Initialization

Set $R_k = 0$, $\Omega_k = \phi$ for $k = 1,2,...,K$ and $A = \{1,2,...,N\}$

2) For k = 1 to K

(a) Find n satisfying $|H_{k,n}| \geq |H_{k,j}|$ for all $j \in A$

(b) Let $\Omega_k = \Omega_k \cup \{n\}$, $A = A - \{n\}$ and update R_k according to (3.2)

3) While $A \neq 0$

(a) Find k satisfying $R_k / \gamma_k \leq R_i / \gamma_i$ for all i $1 \leq i \leq K$

(b) For the found k, find n satisfying $|H_{k,n}| \geq |H_{k,j}|$ for all $j \in A$

(c) For the found k and n, Let $\Omega_k = \Omega_k \cup \{n\}$, $A = A - \{n\}$ and update R_k According to (3.2)

The principle of the suboptimal subchannel algorithm is for each user to use the subchannels with high channel-to-noise ratio as much as possible. At each iteration, the user with the lowest proportional capacity has the option to pick which subchannel to use. The subchannel allocation algorithm is suboptimal because equal power distribution in all subchannels is assumed. After subchannel allocation, only coarse proportional fairness is achieved. The goal of maximizing the sum capacity while maintaining proportional fairness is achieved by the power allocation in the next section.

3.4.2 Optimal Power Distribution for a Fixed Subchannel Allocation

To a certain determined subchannel allocation, the optimization problem is formulated as

$$\underset{p_{k,n}}{\mathrm{Max}}\sum_{k=1}^{K}\sum_{n\in\Omega_k}\frac{1}{N}\log_2\left(1+\frac{p_{k,n}{h_{k,n}}^2}{N_o\frac{B}{N}}\right) \tag{3.4}$$

subject to: $\sum_{k=1}^{K}\sum_{n\in\Omega_k} p_{k,n} \le p_{total}$

$p_{k,n} \ge 0$ for all k, n

Ω_k are disjoint for all k

$\Omega_1 \cup \Omega_2 \cup \ldots \cup \Omega_k \subseteq \{1,2,\ldots N\}$

$R_1 : R_2 : \ldots : R_K = \gamma_1 : \gamma_2 : \ldots : \gamma_K$

where Ω_k is the set of subchannels for user k, and Ω_k and Ω_l are mutually exclusive when $k \ne l$. The optimization problem in (3.4) is equivalent to finding the maximum of the following cost function. where $\{\lambda_i\}^K{}_{i=1}$ are the Lagrangian multipliers. After differentiating (3.5) with respect to $p_{k,n}$ and setting each derivative to 0, it can be obtained that

$$L=\sum_{k=1}^{K}\sum_{n\in\Omega_k}\frac{1}{N}\log_2\left(1+p_{k,n}H_{k,n}\right)+\lambda_1\left(\sum_{k=1}^{K}\sum_{n\in\Omega_k}p_{k,n}-p_{total}\right)$$
$$+\sum_{k=2}^{K}\lambda_k\left(\sum_{n\in\Omega_k}\frac{1}{N}\log_2\left(1+p_{1,n}\right)\right)-\frac{\gamma_1}{\gamma_k}\sum_{n\in\Omega_k}\frac{1}{N}\log_2\left(1+p_{k,n}H_{k,n}\right) \tag{3.5}$$

$$\frac{\partial L}{\partial p_{1,n}}=\frac{1}{N\ln 2}\frac{H_{1,n}}{1+H_{1,n}p_{1,n}}+\lambda_1+\sum_{k=2}^{K}\lambda_k\frac{1}{N\ln 2}\frac{H_{1,n}}{1+H_{1,n}p_{1,n}}=0 \tag{3.6}$$

$$\frac{\partial L}{\partial p_{k,n}}=\frac{1}{N\ln 2}\frac{H_{k,n}}{1+H_{k,n}p_{k,n}}+\lambda_1-\lambda_k\frac{\gamma_1}{\gamma_k}\frac{1}{N\ln 2}\frac{H_{k,n}}{1+H_{k,n}p_{k,n}}=0 \tag{3.7}$$

For $k = 1,2,3\ldots,K$ and $n \in \Omega_k$.

Power Distribution for a Single User

In this section, the optimal power distribution strategy for a single user k is derived. From either (3.6) or (3.7), it can obtained that

$$\frac{H_{k,m}}{1+H_{k,m}p_{k,m}}=\frac{H_{k,n}}{1+H_{k,n}p_{k,n}} \tag{3.8}$$

for $m,n \in \Omega_k$ and k=1,2,...,K Without loss of generality, we assume that $H_{k,1} \leq H_{k,2} ... \leq H_{k,N_k}$ for k=1,2,...,K and N_k is number of subchannels in Ω_k. Thus, (3.8) can be rewritten as

$$p_{k,n} = p_{k,1} + \frac{H_{k,n} - H_{k,1}}{H_{k,n} H_{k,1}} \tag{3.9}$$

for $n = 1,2,...,N_k$ and k=1,2,...,K . Equation (2.10) shows that the power distribution for a single user *k* on subchannel *n*. More power will be put into the subchannels with higher channel-to-noise ratio. This is the water-filling algorithm [63] in frequency domain. By defining $P_{k,tot}$ as the total power allocated for user *k* and using (3.9), $P_{k,tot}$ can be expressed as

$$p_{k,tot} = \sum_{n=1}^{N_k} p_{k,n} = N_k p_{k,1} + \sum_{n=2}^{N_k} \frac{H_{k,n} - H_{k,1}}{H_{k,n} H_{k,1}} \tag{3.10}$$

for k=1,2,...,K .

Power Distribution among Users

Once the set $\{P_{k,tot}\}^K{}_{k=1}$ is known, power allocation can be determined by (3.9) and (3.11). The total power constraint and capacity ratio constraints in (3.4) are used to obtain $\{P_{k,tot}\}^K{}_{k=1}$ with (3.8) and (3.10), the capacity ratio constraints can be expressed as

$$\frac{1}{\gamma_1} \cdot \frac{N_1}{N} \left(\log_2 \left(1 + H_{1,1} \frac{p_{1,tot} - V_1}{N_1} \right) + \log_2 W_1 \right)$$
$$= \frac{1}{\gamma_1} \cdot \frac{N_k}{N} \left(\log_2 \left(1 + H_{k,1} \frac{p_{k,tot} - V_k}{N_k} \right) + \log_2 W_k \right) \tag{3.11}$$

for k=2,3,...,K where V_k and W_k are defined as

$$V_k = \sum_{n=2}^{N_k} \frac{H_{k,n} - H_{k,1}}{H_{k,n} H_{k,1}} \tag{3.12}$$

and

$$W_k = \left(\prod_{n=2}^{N_k} \frac{H_{k,n}}{H_{k,1}} \right)^{\frac{1}{N_k}} \tag{3.13}$$

for k=1,2,...,K

Adding the total power constraints

$$\sum_{k=1}^{K} P_{k,tot} = P_{total} \tag{3.14}$$

There are K variables $\{P_{k,tot}\}^K{}_{k=1}$ in the set of K equations in (3.11) and (3.14). Solving the set of functions provides the optimal power allocation scheme. The equations are, in general, nonlinear. Iterative methods, such as the Newton-Raphson or Quasi-Newton methods, can be used to obtain the solution, with a certain amount of computational effort. In the Newton-Raphson method, the computational complexity primarily comes from finding the update direction.

In High Channel-to-Noise Ratio Case, the linear condition rarely happens and the set of equations remains nonlinear, which requires considerably more computation to solve. However, if the channel-to-noise ratio is high, approximations can be made to simplify the problem. First consider (3.12), in which V_k could be relatively small compared to $P_{k,tot}$ if the channel-to-noise ratios are high. Furthermore, if adaptive subchannel allocation is used, the best subchannels will be chosen and they have relatively small channel gain differences among them. Thus, the first approximation is $V_k = 0$. Second, assuming that the basestation could provide a large amount of power and the channel-to-noise ratio is high, the term $H_{k,1}P_{k,tot} / N_k$ is much larger than 1. With the above two approximations, (3.11) can be rearranged and simplified to be

$$\left(\frac{H_{1,1}W_1}{N_1} \right)^{\frac{N_1}{\gamma_1}} \left(P_{1,tot}\right)^{\frac{N_1}{\gamma_1}} = \left(\frac{H_{k,1}W_k}{N_k} \right)^{\frac{N_k}{\gamma_k}} \left(P_{k,tot}\right)^{\frac{N_k}{\gamma_k}} \tag{3.15}$$

where k=1,2,...,K , Substituting (3.15) into (3.14), a single equation with the variable can $P_{1,tot}$ can be derived as

$$\sum_{k=1}^{K} c_k \left(p_{1,tot}\right)^{d_k} - P_{total} = 0 \tag{3.16}$$

where

$$c_k = \begin{cases} 1 & \text{if k=1} \\ \dfrac{\left(\dfrac{H_{1,1}W_1}{N_1}\right)^{\frac{N_1\gamma_k}{N_k\gamma_1}}}{\dfrac{H_{k,1}W_k}{N_k}} & \text{if k=2,3,...,K} \end{cases} \tag{3.17}$$

and

$$d_k = \begin{cases} 1 & \text{if k=1} \\ \dfrac{N_1\gamma_k}{N_k\gamma_1} & \text{if k=2,3,...,K} \end{cases} \tag{3.18}$$

Numerical algorithms, such as Newton's root-finding method [64] or the false position method [64], can be applied to find the zero of (3.16).

3.4.3 Existence of Power Allocation Scheme

Solution to Single User Power Allocation

For a certain user *k*, there is no power allocation if $V_k > P_{k,tot}$. This situation could happen when a subchannel is allocated to a user who does not have a high channel gain in that subchannel. The greedy water-filling algorithm would rather stop using this subchannel. In case this situation happens, the set of Ω_k, as well as the corresponding values of N_k, V_k and W_k, need to be updated and the power allocation algorithm presented in 3.4.2 should be executed again, as shown in Figure.3.2.

Solution to Multiuser Power Allocation

In case that the channel-to-noise ratio is high, there is one and only one solution to (3.16) since every item in the summation monotonically increases and (3.16) achieves different signs at $P_{1,tot} = 0$ and $P_{k,tot} = \text{Ptotal}$. A numerical algorithm can be used to find the solution to (3.16). The complexity of finding the solution will primarily rely on the choice of the numerical algorithm and the precision required in the results.

After $P_{1,tot}$ is found $\{P_{k,tot}\}^{K}{}_{k=2}$ can be calculated using (3.15). Then the overall power allocation scheme can be determined by (3.9) and (3.10). In general, it can be proved that there must be an optimal subchannel and power allocation scheme that satisfies the proportional fairness constraints and the total power constraint. Furthermore, the optimal scheme must utilize all available power. Several facts lead to the above conclusion. First, to a certain user, the capacity of the user is maximized if water-filling algorithm is adopted.

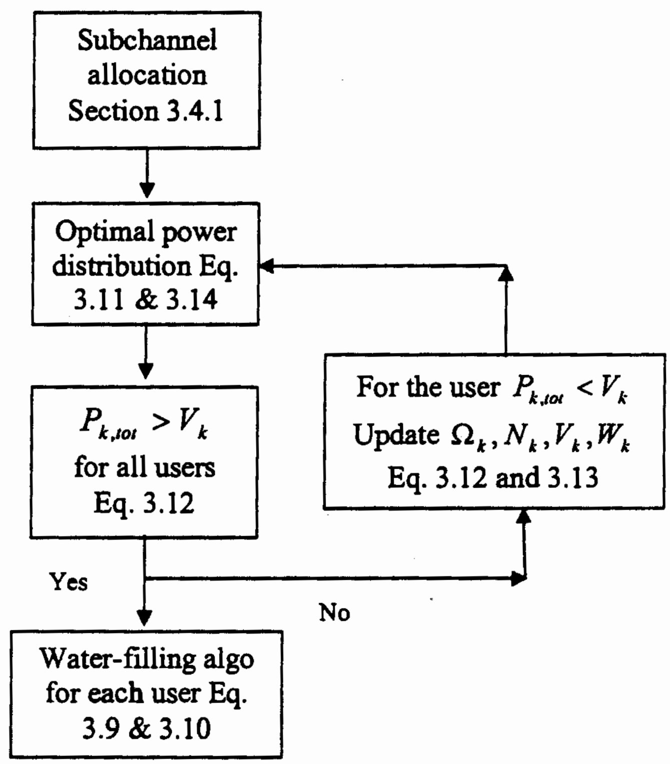

Figure 3.2 Resource Allocation Algorithm

Furthermore, the capacity function is continuous with respect to the total available power to that user. In other words, $R_k(P_{k,tot})$ is continuous with $P_{k,tot}$ Second, if the optimal allocation scheme does not use all available transmit power, there is always a way to redistribute the unused power among users while maintaining the capacity ratio constraints, since $R_k(P_{k,tot})$ is continuous with $P_{k,tot}$ for all *k*. Thus, the sum capacity is further increased. If the Newton-Raphson method returns a non-feasible

$P_{k,tot}$, the set Ω_k and the associated N_k, V_k and W_k would need to be updated. The Newton-Raphson method should be performed until all $P_{k,tot} > V_k$

3.5 Numerical Results

In this section, simulation results are presented to show the performance of the adaptive resource allocation algorithm. The tradeoff between sum capacity and the fairness constraints is also illustrated.

In all simulations presented in this section, the wireless channel is modeled as a frequency-selective channel. It is assumed that the power delay profile is exponentially decaying with $\left[1, \frac{1}{e}, \frac{1}{e^2}\right]$. The total available bandwidth and transmit power are 1 MHz and 1 W, respectively.

3.5.1 Comparison with Maximum Fairness

The objective in [60] is to maximize the minimum user's capacity. By setting, the objective of the optimization problem in (3.1) is identical to the one in [60], since the worst user's capacity is maximized when all users have the same capacity and the sum capacity is maximized. Hence, the problem in [60] is a special case of the framework presented in this chapter. In this section of simulations, the worst user's capacity is compared. In [60], a suboptimal algorithm is proposed to achieve near-optimal capacity using adaptive subchannel allocation, but an equal power distribution is assumed. When the number of users increases, the equal power distribution does not equalize every user's capacity. By transferring power from the users with high capacity to the users with low capacity, the worst user's capacity could be even increased. For the purpose of comparison, I use the suboptimal algorithm in [60], which is a special case of the subchannel allocation algorithm in 3.4.1, to allocate the subchannels first and then apply the optimal power allocation scheme proposed in 3.4.2. Both of these adaptive schemes are compared with the fixed time division multiple access (TDMA) resource allocation scheme.

The wireless channel is modeled as before, and the total transmit power available at the basestation is 1 W. The power spectral density of additive white Gaussian noise is -80 dBW/Hz, and the total bandwidth is 1 MHz, which is divided into 64 subchannels. The maximum path loss difference is 40 dB, and the user locations are assumed to be uniformly distributed.

Figure 3.3 shows the capacity vs. number of users in the OFDM system. Adaptive resource allocation can achieve significant capacity gain over non-adaptive TDMA. Also the adaptive scheme with optimal power allocation achieves even higher capacity than the scheme with equal power distribution. Notice that this capacity gain is purely from the optimal power allocation algorithm, since both adaptive resource allocation algorithms adopt the same subchannel allocation. Further, Figure 3.3 and Figure 3.4 shows that the capacity gain over TDMA increases when the number of users increases. In a system of 16 users, the adaptive scheme with the proposed optimal power allocation achieves 17% more capacity gain than the scheme with equal power distribution, when compared to fixed TDMA.

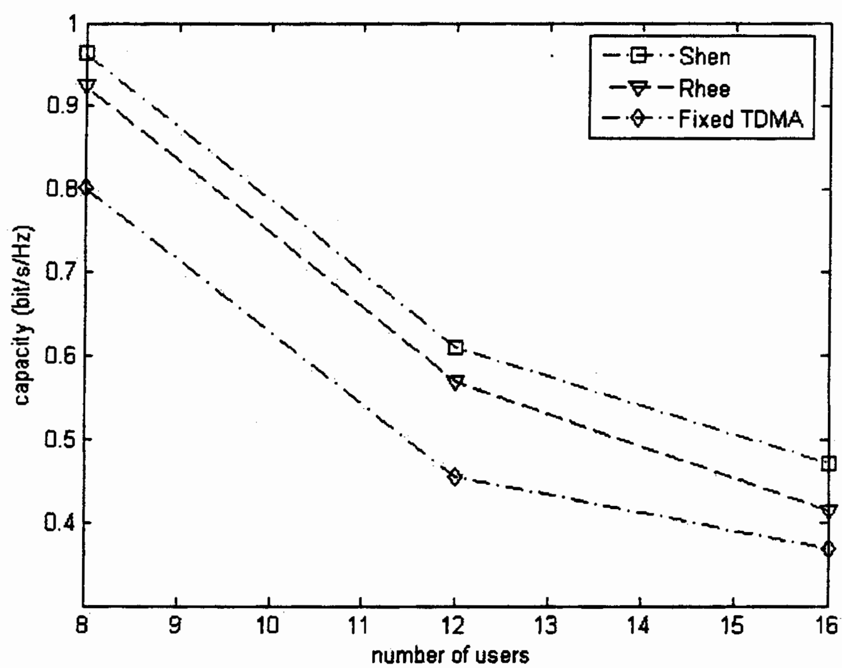

Figure 3.3 Minimum user's capacity vs. number of users.

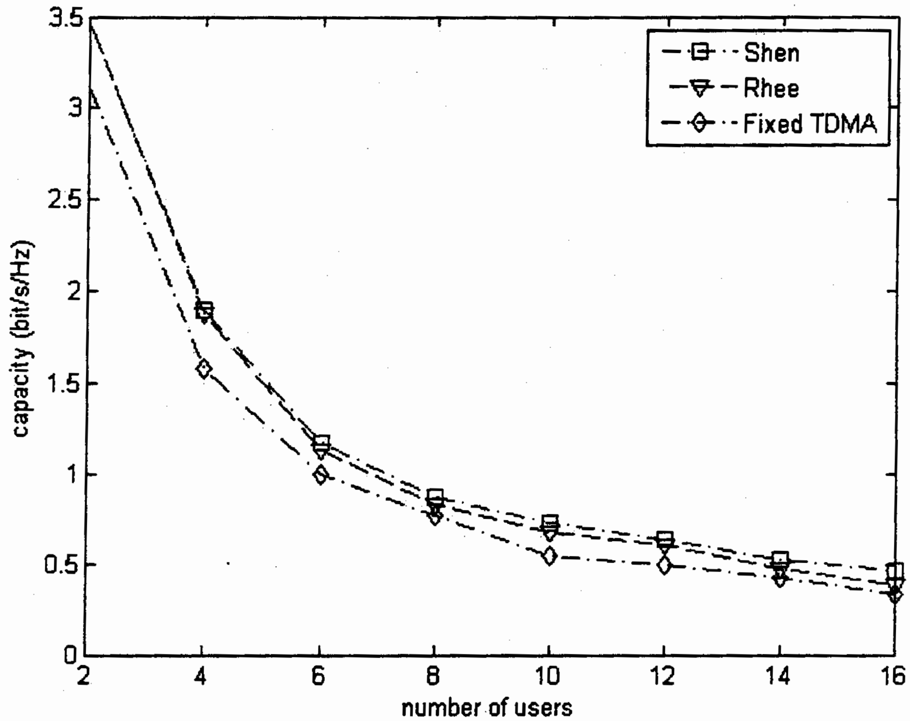

Figure 3.4 Minimum user's capacity vs. number of users.

Chapter 4

Adaptive Modulation

4.1 Introduction

In previous chapters we have discuss that to make full use of available bandwidth we can create sub channels, the basic idea is to split high data rate stream into several low data rate sequences and to modulate them separately. This technique is called as Multi-Carrier Modulation (MCM). To avoid Inter-Symbol Interference (ISI) we need only a simple equalizer at receiver end. The most famous type of MCM is Orthogonal Frequency Division Multiplexing (OFDM), OFDM is extension of Frequency Division Multiplexing (FDM). In FDM parallel sub channels have overlapped spectrum, but in OFDM, the parallel sub channels are orthogonal so they can be recovered at the receiver end without any problem.

Adaptive modulation technique is used with OFDM to enhance the performance of MCM system. For the implementation of adaptive modulation we require the perfect channel state information at transmitter end, so transmitter can set the adaptive parameters like modulation and coding scheme according to channel condition but knowledge of channel condition at transmitter end is a difficult task.

The work presented in this chapter is related to the study and development of methods to produce optimal transmitter adaptations in a multi-user OFDM system. In single-user OFDM systems, where all the available sub channels are used by a single transmitter-receiver pair, as well as for MIMO system.

4.2 Adaptive Modulation Techniques

4.2.1 How to Improve the Link Performance

In adaptive modulation, the modulation parameters are set according to Channel State Information (CSI), so we save our recourses of transmit power and coding scheme. In adaptive modulation strategy we can increase the data rate of decrease the transmit power according to channel condition, If channel is bad we save our recourses and if channel is good condition we use higher modulation scheme and average transmit power. And as soon as channel condition changed, the modulation scheme will also change accordingly.

Channel estimation is a big is issue, and we will not discuss it in detail here. For the time being, we need the transmitter have a perfect knowledge of the CSI in order to settle its constellation size and transmitted power. Moreover this transmitter configuration must be available at the receiver with perfect synchronization such that the demodulation of the transmitted symbols can be carried out without problems. For a single carrier system we will refer to the system model depicted in figure 4.1 that has been presented in [65] jointly with an in-depth analysis on the tradeoffs in adapting all combinations of different modulation parameters. A more advanced and realistic model is presented in [66] with a proposal of adaptive modulation for fading channels. We will consider a group of parallel blocks like the ones in Figure 4.1 provided that the subchannels are independent and they are processed in parallel. To clarify the used notation, it must be noticed that $r[i]$ represents the data sequence to be transmitted, $x[i]$ is the waveform sent to the channel, and $g[i]$ and $n[i]$ are the squared value of the instantaneous channel gain and the noise sequence respectively. $s[i]$ denotes the transmit power. At the receiver a channel estimator produces an estimate of the channel state that is used both at the transmitter and the receiver for both the adaptation and demodulation processes. It is assumed that the return path for the CSI is perfect (instantaneous and error free).

The proposed model in Figure 4.1 implicitly proposes a time adaptation of the system, i.e. the time- varying channel makes the transmitter change its parameters accordingly. However, this is not the only kind of adaptation that can be done in a digital communications system. A frequency adaptation and a time-frequency adaptation are also possible in a MCM system.

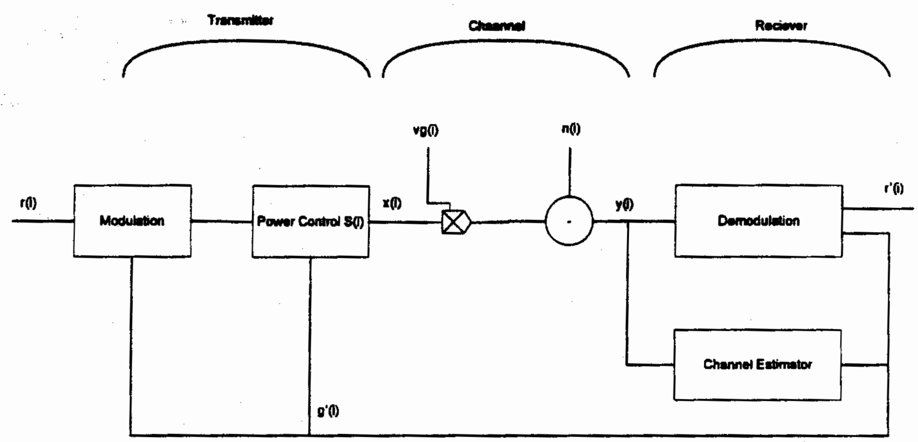

Figure 4.1 System Model for a Single-Carrier Adaptive-Modulation Scheme

As soon as the broadband channel presents a multipath structure and the transmitter or the receiver are not static at their location, a situation that is typical in many wireless fading channels, each $g[j]$ with $j = \{1, 2, ..., N\}$ has a different value. This fact makes that each subchannel be adapted individually to obtain the desired performance enhancement. Of course, the price to pay is a larger overall system complexity placing high demands on the channel estimators, the feedback-channel requirements and the resource allocation algorithms to optimally decide the transmitter parameters.

4.2.2 Objective of Adaptive Modulation

The task in wireless communications consists mainly of two aspects: the transmission Quality of Service (QoS) and the throughput. Adaptive modulation is created for the same purpose. The main goal of adaptive modulation is to find a software solution for a flexible, compatible and multiple application system with small volume, for example, via software radio. The advantage of adaptive modulation is that it can realize higher transmission QoS and higher throughput by efficient usage of the channel situation. Therefore, in our work on adaptive modulation we will concentrate on the following:

- To get higher transmission QoS;
- To get higher throughput (bit rate and frequency spectrum efficiency).

In our work, we use BER to represent QoS.

4.2.3 Adaptive Modulation Categories

There are two categories of adaptive modulation: slow adaptive modulation and fast adaptive modulation, which are defined by how often the transmission settings are updated. In slow adaptive modulation, transmission parameters are assigned when the user connects to the system and they remain constant throughout the transmission. In this case the parameter settings are based on the channel situation at the moment the user starts communications every time. If the channel does not vary fast, this can improve the transmission quality and throughput. In fast adaptive modulation, the parameters are controlled slot by slot based on the instantaneous channel conditions, and thus the transmitter can adjust to fading channel conditions for each slot or for a few slots [67]. Although fast adaptive modulation is effective in improving transmission quality, the average bit rate is subject to the channel conditions. Therefore, the scheme is more suitable to support data transmission rather than for constant bit rate services, such as voice transmission [68]. We study the fast adaptive modulation algorithm in our work.

4.2.4 Advantages of Adaptive Modulation

Intelligent radio communications that include not only adaptive reception techniques, such as the adaptive equalizer, but also adaptive transmission control techniques, is a new and attractive concept for future wireless personal multimedia communication systems. This is because it has high potential to achieve high quality and a high transmission bit rate with high flexibility under traffic and propagation path conditions that vary in time and space. The adaptive modulation technique is one of the effective intelligent radio communication techniques, [68]. Mobile radio links are subject to severe multipath fading, which may severely degrade the link Carrier to Noise Ratio (CNR) and consequently increase the BER. Fading compensation such as an increased link budget margin or interleaving with channel coding is typically required to improve link performance. However, these techniques are designed relative to worst-case channel conditions, resulting in poor utilization of the full channel capacity for a good percentage of the time (i.e., under shallow fading conditions). Adapting certain parameters of the transmitted signal with the fading channel leads to better utilization of the channel spectrum, [70].

Adaptive modulation provides a higher average link spectral efficiency by taking advantage of the time varying nature of wireless channels: they transmit at high speeds under favorable channel conditions and respond to channel degradation through a smooth reduction of their data throughput. Adaptive modulation realizes higher throughput and higher quality transmission in land mobile communications than fixed modulation level systems by making some modulation parameters variable according to the instantaneous situation of the channel.

4.2.5 Disadvantages and Limits of Adaptive Modulation Systems

Adaptive modulation looks like an ideal technique that can solve a lot of problems in transmission systems and make these systems more efficient. But is it easy to realize? From the analysis given before, it can be seen that the answer is no. Adaptive modulation is a non-trivial task in practice, because to realize it, one needs to solve the following problems:

- Accurate SNR measurements at the receiver are required;
- The interference may change more quickly than the feedback round trip;
- The fading channel may vary between channel estimation and data transmission;

Therefore, the support of other techniques is needed to make adaptive modulation systems function satisfactorily.

4.2.6 Resource Allocation for the Single-User Scenario

System Description

The single-user scheme is the one where all the available subcarriers in an OFDM system are dedicated to only one transmitter-receiver pair which is assigned to one user or service. Following the description of the basic OFDM system shown in the previous section, we assume that the cyclic prefix is longer than the channel impulse response. Then, each OFDM subcarrier faces an independent, flat-fading, narrowband channel, the overall OFDM system drawn in Figures 2.1 and 2.2 can be modeled with a simpler block diagram as in figure 4.2

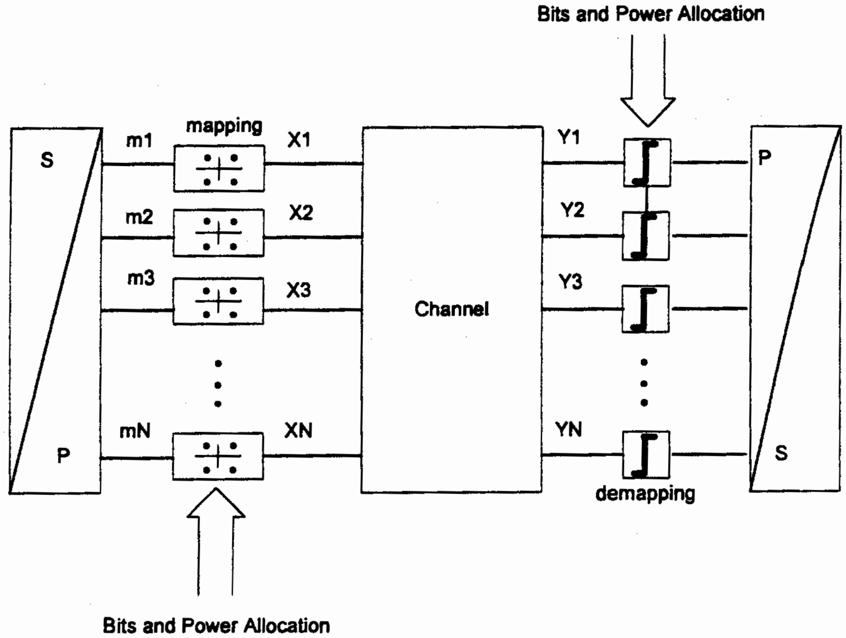

Figure 4.2 Single-User OFDM system

X_n represents the complex symbol that has been allocated to the sub-carrier n (mapped according to the bit and power allocation algorithm). H_n are the channel coefficients (i.i.d. Rayleigh distributed), n_n is the noise sequence effecting the sub-carrier n (with variance $s_n^{\ 2} = E\left|n_n[k]^2\right|$and Y_n is the received symbol from the sub-channel n.

4.3 Chow's algorithm

This algorithm originally developed for DMT in ADSL systems is described in the famous paper from [71]. In some literature, it is presented as the first sub-optimal solution to the bit loading problem in multicarrier systems with benefits concerning implementation issues. Strategy of minimizing the transmit power for a given bit rate is used to generate the transmitter configuration.

4.4 Campello's algorithm

Campello proposed in his paper [72] an optimal and efficient algorithm to implement in practice, the way of doing the adaptation is quite different from Chow's algorithm with lower number of operations (faster implementation). As before, the optimization criterion is to distribute the minimum transmit power among the subcarriers for a given bit rate.

4.5 Adaptive Modulation Algorithm

This section demonstrates OFDM with adaptive modulation applied to Multiple-Input Multiple-Output (MIMO) systems. We apply an optimization algorithm to obtain a bit and power allocation for each subcarrier assuming instantaneous channel knowledge. The analysis and simulation is considered in two stages. The first stage involves the application of a variable-rate variable-power MQAM technique for a Single-Input Single-Output (SISO) OFDM system. This is compared with the performance of fixed OFDM transmission where a constant rate is applied to each subcarrier. The second stage applies adaptive modulation to a general MIMO system by making use of the Singular Value Decomposition to separate the MIMO channel into parallel subchannels. For a two-input antenna, two-output antenna system, the performance is compared with the performance of a system using selection diversity at the transmitter and maximal ratio combining at the receiver.

4.5.1 Adaptive Loading and MIMO

Adaptive modulation is an important technique that yields increased data rates over non-adaptive uncoded schemes. An inherent assumption in channel adaptation is some form of channel knowledge at both the transmitter and the receiver. Given this knowledge, both the transmitter and receiver can have an agreed upon modulation scheme for increased performance. In this section, we consider adaptive bit and power allocation schemes [73], [74]. Namely, we presuppose a desired number of bits to be transmitted by a single OFDM symbol (consisting of N subchannels), and we load these bits onto the subchannels in such a way that minimum power is allocated to the entire transmission. In addition to adaptive modulation, MIMO is a useful technology with significant data rate improvements of SISO systems. Further to adaptive modulation applied to SISO/OFDM systems, this paper seeks to explore adaptive modulation combined with MIMO/OFDM. A key concept employed here is that every matrix channel can be decomposed into a set of parallel subchannels over which data can be transmitted independently, given appropriate precoding and shaping transformations at the transmitter and receiver, respectively.

4.5.2 Channel Model

Throughout this work, the channel is assumed to be a Rayleigh fading channel, corresponding to a rich scattering environment with time variation characterized by the fade time. In the MIMO case, the channel is a matrix channel with equation

$$\mathbf{y}_n = \sum \mathbf{H}_i \mathbf{x}_{n-l} + \mathbf{n}_n \tag{4.1}$$

where, in general, the values $\mathbf{y}_k, \mathbf{x}_k$, $\mathbf{n}_k$ can be vectors, and $\mathbf{H}_k$ can be a matrix. Thus, the delay spread of the channel is L symbol periods. An exponentially-decaying profile of channel taps is modeled by fixing the powers of all the elements in each random matrix $\mathbf{H}_k$ to a constant $\mathrm{E_i}$. These coefficients $\mathrm{E_i}$ form a decaying geometric progression in the variable i. During a coherence time interval, all matrices $\mathbf{H}_k$ are constant, and when the channel decorrelates, they are all drawn newly according to their respective pdf's. Further, for simplicity it is assumed that the channel decorrelates at the end of an **OFDM** symbol transmission.

4.5.3 Modulation and Demodulation

A modulator transforms a set of bits into a complex number corresponding to an element of a signal constellation. In this paper, given the adaptive algorithm, the modulator has as input a set of bits and power value, so that the output of the modulator is a constellation symbol corresponding to the number of bits on the input, appropriately scaled to have a desired power. The modulator is taken to have only a finite number of rates available, which means that only a finite number of constellations are available for the modulation. Specifically these constellations are drawn from the set of constellations having number of symbols equal to an even power of 2. Further, in order to provide robustness against bit errors, Gray-coded constellations are employed for each modulation order available. This Gray coding ensures that if a symbol error occurs, where the decoder selects an adjacent symbol to that which the transmitter intended to be decoded, there is only a single bit error resulting.

Many demodulation techniques can be employed, including maximum-likelihood, MMSE, and zero-forcing. For our work, in order to simplify the demodulator, demodulation is performed using a zero-forcing approach, given knowledge of the individual at-fading channel gain for each subchannel.

4.6 Adaptive Loading

The advantage of **OFDM** is that each subchannel is relatively narrowband and is assumed to have flat-fading. However, it is entirely possible that a given subchannel has a low gain, resulting in a large **BER**. Thus, it is desireable to take advantage of subchannels having relatively good performance; this is the motivation for adaptive modulation. In the context of time-varying channels, there is a decorrelation time associated with each frequency-selective channel instance. Thus, a new adaptation must be implemented each time the channel decorrelates. The optimal adaptive transmission scheme, which achieves the Shannon capacity for a fixed transmits power, is the waterfilling distribution of power over the frequency selective channel. However, while the waterfilling distribution will indeed yield the optimal solution, it is difficult to compute, and it tacitly assumes infinite granularity in the constellation size, which is not practically realizable.

The adaptive loading technique employed in this paper is an efficient technique to achieve power and rate optimization based on knowledge of the subchannel gains [73], [71]. Only six different square MQAM signal constellations are used; this scheme is expected to perform with efficiency very close to those using unrestricted constellations. In the discrete bit loading algorithm of [73], we are given a set of N increasing convex functions $\mathrm{p}_n(b)$ that represent the amount of power necessary to transmit b bits on subchannel n at the desired probability of error using a given coding scheme. We will assume $\mathrm{p}_n(b)=0$. The allocation problem which will be using can be formulated as:

Power Minimization Problem

$$\min \sum_{n=1}^{N} p_n(b_n) \tag{4.2}$$

$$\text{Subject to} \sum_{n=1}^{N} b_n = B$$

$$b_n \in Z, b_n \geq 0, n = 1,2,\ldots,N.$$

To initialize the bit allocation, the scheme of [71] is employed. The procedure is summarized as follows:

Algorithm Initialization

1) Compute the subchannel signal to noise ratios
2) Compute the number of bits for the ith subchannel based on the formula

$$\hat{b}(i) = \log_2(1 + SNR(i)/GAP) \tag{4.3}$$

3) Round the value of $\hat{b}(i)$ down to $b(i)$.

4) Restrict $b(i)$ to take values 0,1,2,4,6 or 8 (correspond to available modulation orders).

5) Compute the power for the ith subchannel based on the number of bits initially assigned to it using the formula

$$p_i(b(i)) = (2^{b(i)} - 1)/GNR(i), whereGNR(i) = SNR(i)/GAP \tag{4.3}$$

6) Form a table of power increments for each subchannel. For the ith subchannel

$$\Delta p_i(b) = p_i(b) - p_i(b-1) = \frac{2^{b-1}}{GNR} \tag{4.4}$$

Consider the k^{th} channel. Given the channel gain and noise PSD, the power increment table will provide the incremental energies required for the subchannel to transition from supporting 0 bits to 1 bit, from 1 bit to 2 bits, from 2 bits to 3 bits and so on. Since we require our system to have a maximum of 8 bits, the power increment required to go from 8 bits to 9 bits is set to a very high value. Also, we require the subchannel to have only 0, 1, 2, 4, 6 or 8 bits. Thus, odd numbers of bits are not supported. In order to take care of this, the power increment table has to be changed using a clever averaging technique. It is best described by an example

Suppose the power increment required for supporting an additional bit from 2 bits in the nth subchannel is 30 units and that required for supporting an additional bit from 3 bits is 40 units. Then, reassign the power increment values to the same value, namely, the average of the two. In this case, that value is 35 units. This assures us that if a subchannel is allocated a single bit for going from 2 bits to 3 bits, then in the next iteration the same minimum amount of additional power required to support another bit will imply that the same subchannel will be allocated the next bit as well. The same averaging procedure is repeated for all other possible bit transitions. The only exception that might arise is when the algorithm terminates, not having assigned the final bit to even out the total number of bits on that subchannel. In order to resolve this issue, we used an algorithm proposed in [73], (the function ResolveTheLastBit), which will be discussed in the detail later in the section.

Note that we have introduced a new term, GAP. This parameter is in effect a tuning parameter. Different values for GAP yield different $\frac{E_b}{N_o}$ ratios for a given desired number of bits B to transmit. This is because the GAP directly impacts the power table value calculations. Thus, tuning the GAP allows us to characterize the BER performance of the system. Given the initial bit allocation, the following algorithm optimizes the bit allocation [73]:

Algorithm

Input:

b, initial bit allocation

B, the total number of bits to be allocated

Output:

b, the optimized bit allocation

Algorithm:

$B' \leftarrow 0$

for n = 1 to N

$B' \leftarrow B' + b(n)$

$while(B' \neq B)$

$if(B' > B)$

$n = \arg\max_{1 \le j \le N} \Delta p_j(b_j)$

$B \leftarrow B - 1$

$b(n) \leftarrow b(n) - 1$

else

$m = \arg\max_{1 \le j \le N} \Delta p_j(b_j + 1)$

$B \leftarrow B + 1$

$b(n) \leftarrow b(n) + 1$

Finally, in order to deal with a single violated bit constraint, we employ the following algorithm [73]:

Algorithm ResolveTheLastBit

1) Check that the input bit allocation contains at most one violation of the bit constraint

2) If there is a single violation, (say it is in subchannel v), find the bit from the current bit allocation having the largest incremental power that can be used to fill up subchannel v. Let

$$P_1 = \Delta p_v(b(v)) - \Delta p_i(b(i)) \tag{4.5}$$

3) Find the bit that will cost the least to increment in the other subchannels which have been allocated either 0 or 1 bit only. The reason we have this constraint is that all the other subchannels will have 2, 4, 6 or 8 bits and allocating a single bit to them will violate the bit constraint. Let

$$P_2 = \Delta p_j(b(j)) - \Delta p_{vi}(b(v)) \tag{4.6}$$

4) Perform the change corresponding to the smallest of P1 and P2.

Given these three algorithms, we have a complete characterization of the bit loading procedure for a given frequency selective channel.

4.7 MIMO/OFDM Systems

4.7.1 MIMO

MIMO systems are defined as point-to-point communication links with multiple antennas at both the transmitter and receiver. The use of multiple antennas at both transmitter and receiver provides enhanced performance over diversity systems where either the transmitter or receiver, but not both, have multiple antennas. This technique can significantly increase the data rates of wireless systems without increasing transmits power or bandwidth. The cost of this increased rate is the added cost of deploying multiple antennas, the space requirement of these extra antennas and the added complexity required for multi-dimensional signal processing.

A great deal of research work has been devoted to the area of combining this spatial scheme with OFDM systems. This system combines the advantages of both techniques in providing simultaneously increased data rate and elimination of the effects of delay spread. Power control for subchannels on MIMO/OFDM system can be crucial in enhancing the spectral and power efficiency. Without any interference, the best power control to optimize the transmission is the waterfilling solution. But as discussed before, it is not practically feasible and we have employed the above adaptive loading algorithm to characterize the practical performance of MIMO/OFDM system with a single antenna OFDM system.

4.7.2 Analysis of MIMO/OFDM Systems

Consider a MIMO system employing t transmits antennas and r receives antennas. For each tone, the MIMO channel response can be represented by a matrix of size $m \times n$ where the matrix element $h_{j,k}$ represents the channel gain from transmit antenna k to receive antenna j. If we consider the case of perfect channel state information at the transmitter and receiver, we can decompose the MIMO channel on each tone into parallel non-interfering SISO channels using the singular value decomposition (SVD). Let the instantaneous channel matrix on the ith tone have singular value decomposition (SVD)

$$\mathbf{H}_i = \mathbf{U}_i \mathbf{S}_i \mathbf{V}_i^* \tag{4.7}$$

where $\mathbf{u}_i$ and $\mathbf{v}_i$ are unitary matrices, and $\mathbf{s}_i$ is the diagonal matrix of singular values of $\mathbf{H}_i$. Note that the operator $(.)^*$ is the conjugate transpose operator. Now, if we use a transmit precoding filter of $\mathbf{v}_i$ and a receiver shaping filter of $\mathbf{u}_i$, the equivalent MIMO channel between the IFFT and FFT blocks decomposes into parallel subchannels. Note that the number of such subchannels is exactly equal to the number of nonzero singular values of $\mathbf{H}_i$. Denote this number by $c(i)$.

4.7.3 Adaptive Modulation for MIMO/OFDM

Given the decomposition outlined above, the adaptively modulated MIMO/OFDM system requires that each subchannel have the corresponding precoder and shaping matrix applied to it. Thus, we obtain M effective subchannels, where

$$M = \sum_{i=1}^{N} c(i) \tag{4.8}$$

In other words, the MIMO/OFDM adaptive modulation problem decomposes into a bit loading over all the nonzero singular values of all the subchannels. Thus, the problem will be larger than in the SISO case, but the decomposition has allowed us to proceed without any changes to the optimization algorithm.

4.8 Simulation Results

4.8.1 Assumptions and Simulation Details

Throughout the simulation, the entire system is only considered as a discrete-time system. This simplifies the model somewhat, in that pulse-shaping and matched-filtering are eliminated from consideration. However, these system attributes are relatively simple to incorporate, and do not lead to significant insights beyond those observed with the discrete-time system.

Both a SISO and MIMO simulator were built, and the MIMO simulator was updated to have the SISO system occurs as a special case. The following parameters were held constant throughout the simulation:

Table 4.1 Simulation Parameters

Number of subcarriers	64
OFDM symbol time	64 symbol periods
Guard time	16 symbol periods
MQAM available	0, 1, 2, 4, 6, 8
Power delay profile	$\left[1, 1/e, 1/e^2\right]$
Noise variance	1×10^{-3}
BER	10^{-3}

4.8.2 Results

Given the above parameters, simulations were conducted with 100 Monte Carlo iterations for each case.

4.8.2.1 Bit Allocation

To demonstrate the bit allocation, an instance of the channel was generated and the optimal bit allocation found. Figure 4.3 shows the channel frequency response, the allocation of bits to each subchannel, and the corresponding power on each subchannel. As expected, the subchannels experiencing very poor channel instances had few or zero bits allocated to them. Also, it is interesting to note that the finite number of MQAM constellations available means that the rate remains fixed over some intervals where the gain does not vary too widely.

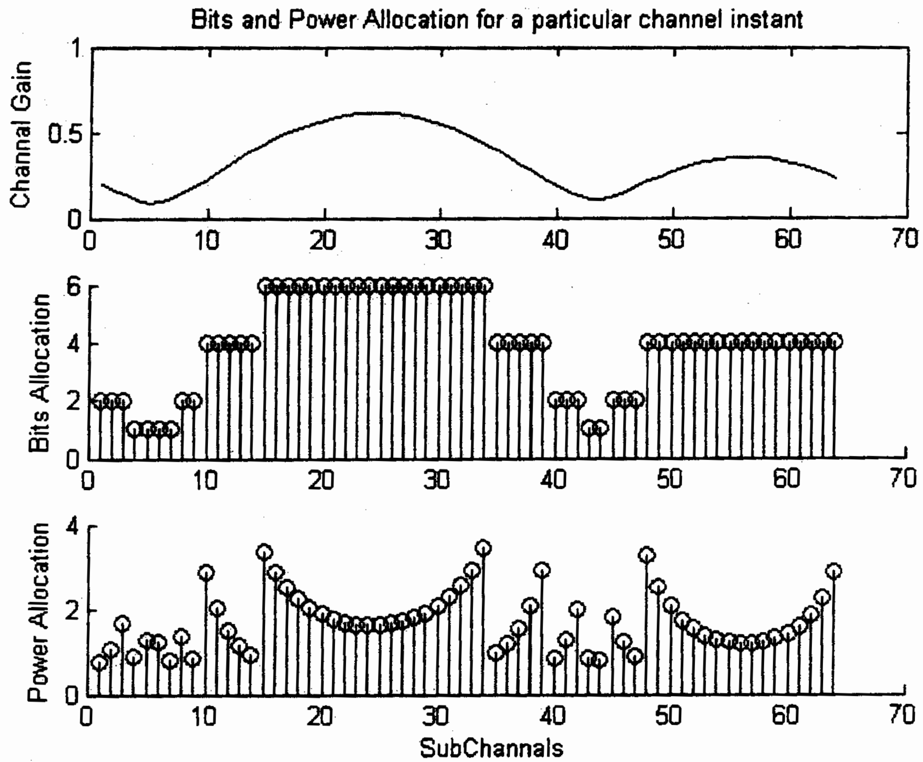

Figure 4.3 Power and Bit Allocation for a Channel Instance

4.8.2.2 BER performance

For comparison purposes, the fixed-rate SISO simulator was implemented, where the total number of bits per tone was fixed for all tones, and variable power optimization was applied. The BER performance of the adaptive SISO, adaptive MIMO, and fixed-rate SISO are in Figure 4.4. In all simulations the MIMO system was held as a 2×2 link. Note that increased averaging (more Monte Carlo iterations) would surely smooth out the BER curves. Clearly, at any given BER the fixed-rate SISO system will be outperformed by the adaptive SISO system, which in turn will be outperformed by the adaptive MIMO system. For all three systems, the total number of bits per OFDM symbol were always held constant, to ensure fair comparison.

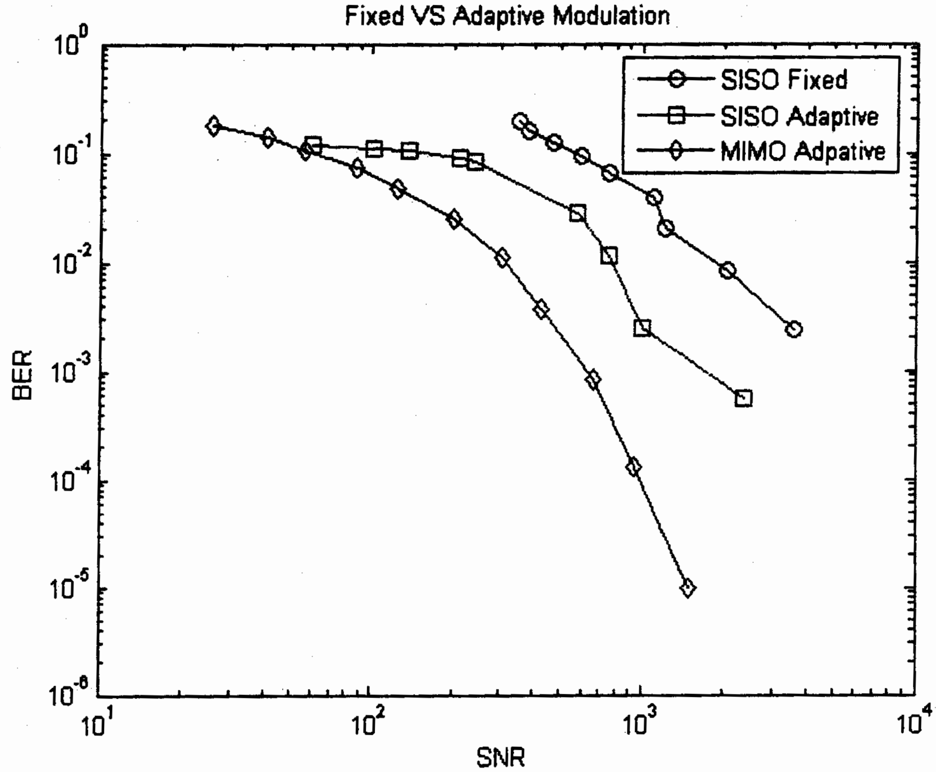

Figure 4.4 BER curves for various schemes

The performance of proposed adaptive resource-allocation scheme is investigated with the assumption that mobile station MS is equipped with two antennas and Base station BS is equipped with four antennas. For comparing performance of proposed algorithm with the conventional MIMO/OFDM system with SDMA and FDMA with adaptive and without adaptive modulation we assume 64 sub channels and 2 users in the system, from Figure 4.5 it can be seen that when we compare with conventional nonadaptive SDMA system with MF or MMSE receivers, the proposed algorithm achieves the significant diversity gain and power gain. There is about 12dB performance improvement over the MMSE system for BER of10^{-2}. The proposed system also shows great improvement in power efficiency with comparison of nonadaptive FDMA and adaptive FDMA system.

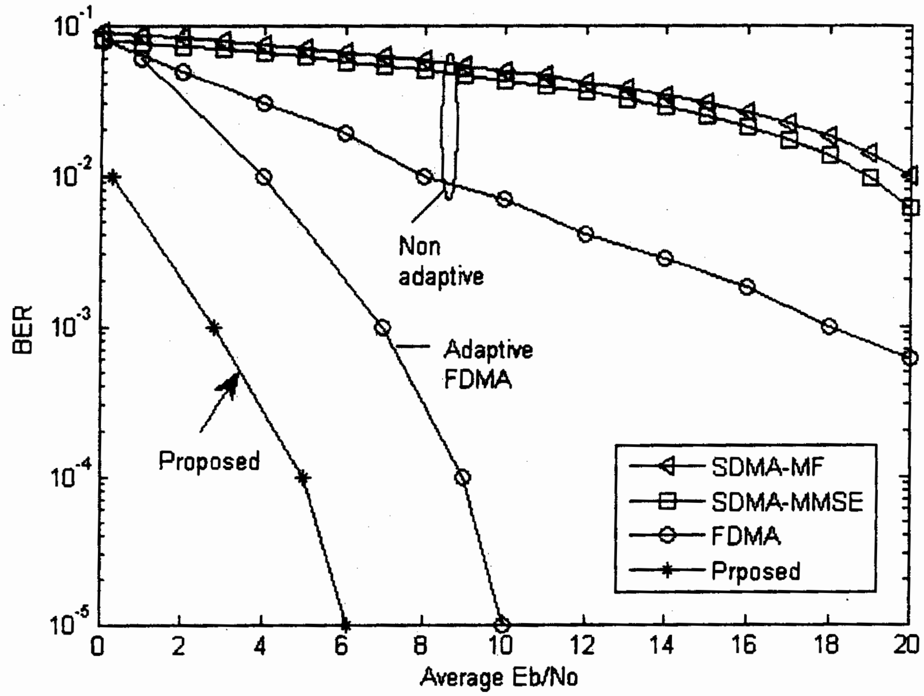

Figure 4.5 Performance comparisons between the proposed algorithm and the conventional SDMA and FDMA System

The performance of proposed algorithm when there are two, four six users is shown in Figure 4.6. To ensure a fair comparison, the total number of bits transmitted during an OFDM symbols is fixed at 256 bits per symbol. It can be seen that power efficiency is improves when there are more users in the system. This is because more users provide a large number of independent channels, which can be interpreted as multiuser diversity. Figure 4.6 also indicates that proposed algorithms can operate at very low SNM when there are sufficient users in the system.

The effect of the spatial correlation is investigated in Figure 4.7 where transmit power is plotted as a function of correlation when there are two users and target BER is 10^{-2}. For comparison, the performance of the static allocation is also plotted. It can be seen that proposed algorithm achieves higher power efficiency when the correlation is low since frequency is reused and each user is allocated small number of sub channels. In this case more transmit power is needed to ensure QoS.

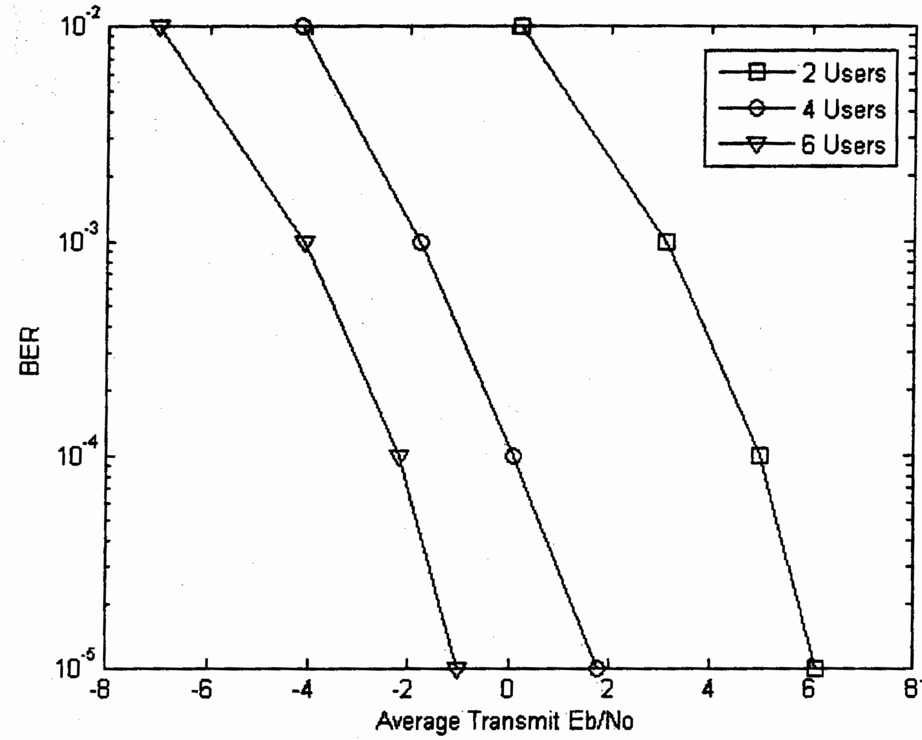

Figure 4.6 Performance of Proposed Adaptive scheme for K = 2, 4, 6, respectively

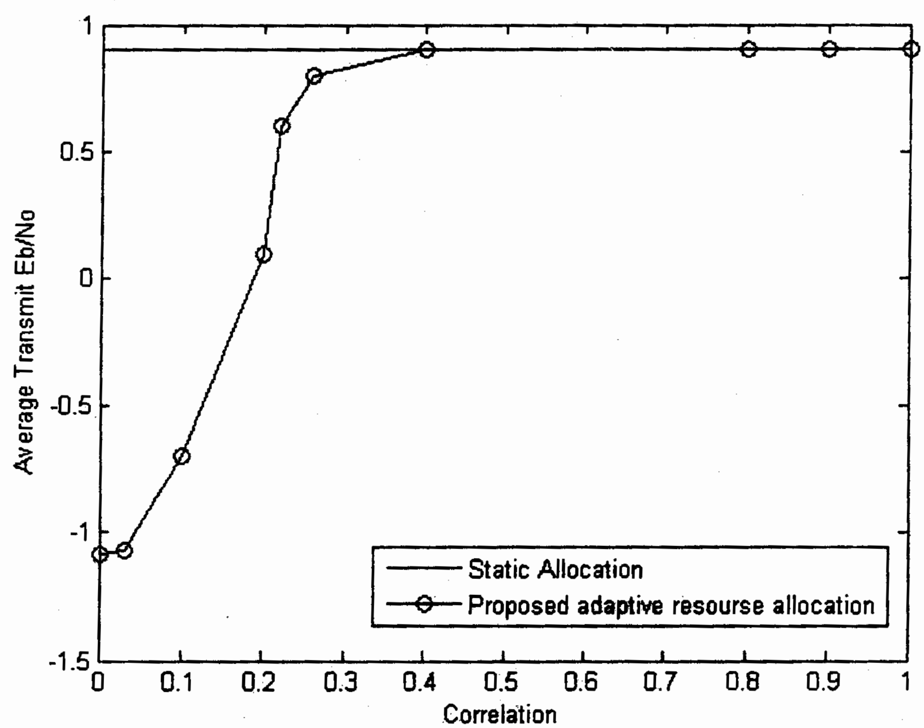

Figure 4.7 Performance of Proposed Adaptive scheme versus correlation when BER = 10^{-2}

Now we have divided all the users into groups according to their mutual correlation. Specifically, we set a threshold r. The users with a correlation higher than r are considered as highly correlated and are classified into one group, the intergroup interference can be assumed as cancelled perfectly, the users within one group are very likely to cause intragroup interference since their correlation is high. We investigate in Figure 4.8 that how the threshold value r effects the system performance. 2 users and four users system is simulated and it can be seen that when r is too large, the required transmit power is increased, this is because with a large threshold value, highly correlated users are likely to share the same sub channels, and detector fails to cancel the interference between them. When the r is too low, most of users should transmit on separate sub channel, so a large number of transmit power is needed to achieve given data rate for every users. It also shows that the system performance is similar within range of r = 0.3 to r = 0.7.

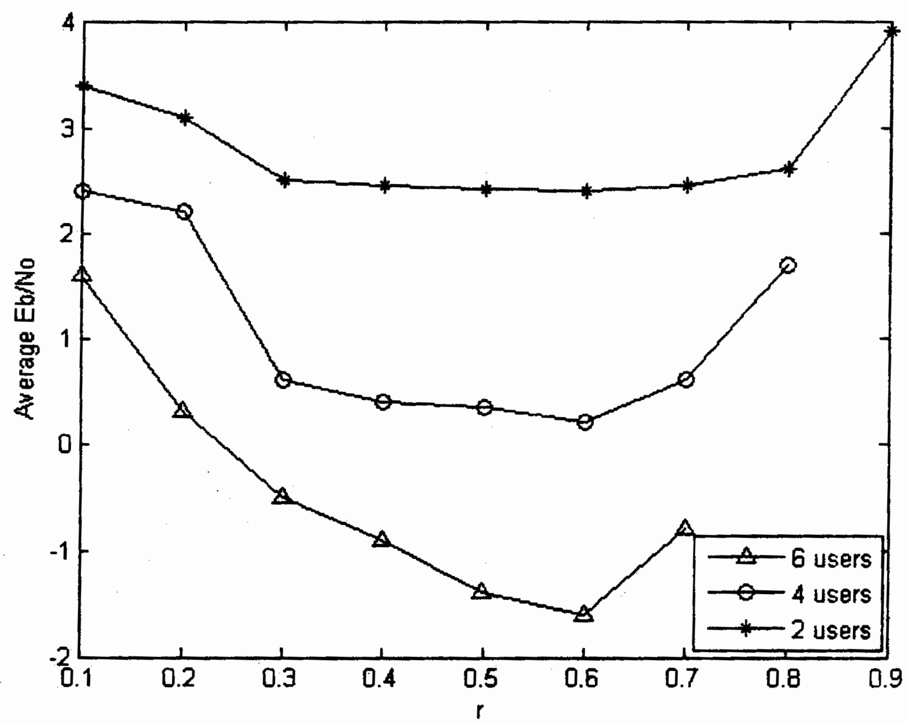

Figure 4.8 Average received SNR to achieve a BER = 10^{-3} for different values of r.

In Figure 4.9 we investigate the multiuser diversity improvement with an increasing number of users. Assume that the ratio of the number of receive antennas to number of users is fixed to be two. The total data rate is same as 256 bits per OFDM symbol duration and the correlation threshold is 0.6. It can be seen from figure that the overall power efficiency is improves as number of users increases. This is because an increasing number of users provide a large number of independent channels, which can be interpreted as multiuser diversity. Hence the algorithm has more freedom to improve the overall power efficiency.

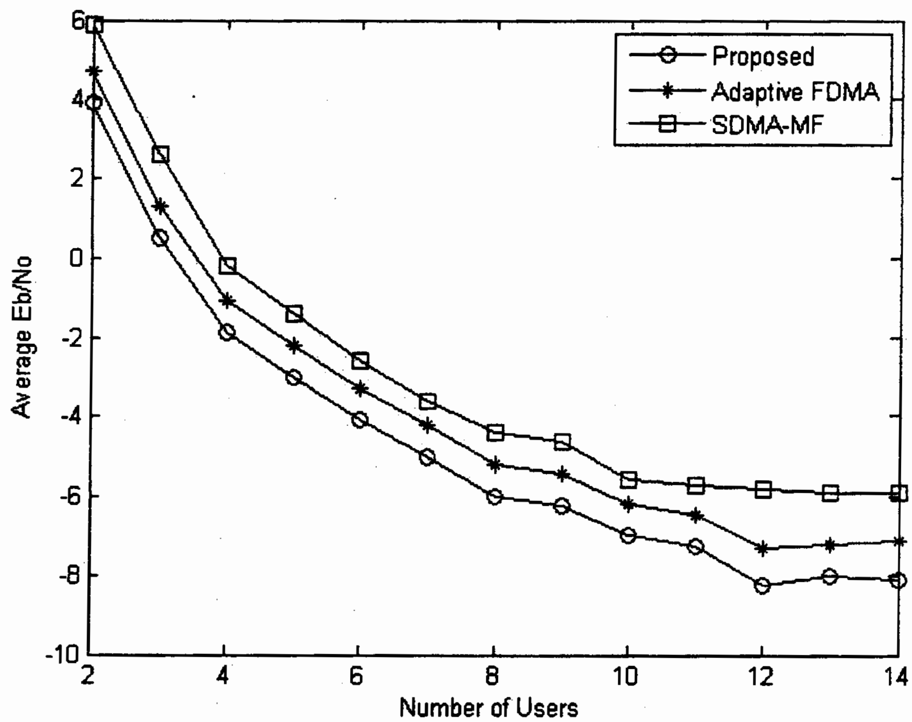

Figure 4.9 Power consumption verses the number of users in the system r = 0.6.

The system throughput which is define as the total number of successfully transmitted packets in a time unit is investigated in Figure 4.10 with and without adaptive recourse allocation. It can be seen that in the low SNR region, the throughput is mainly determined by the transmission power. In the high SNR region where the system is able to transmit more packets than those arrived, the system throughput is decided by amount of input traffic. The figure also shows that the diversity order is significantly improved by using the proposed adaptive algorithm and there is around 5 dB gain when throughput becomes stable.

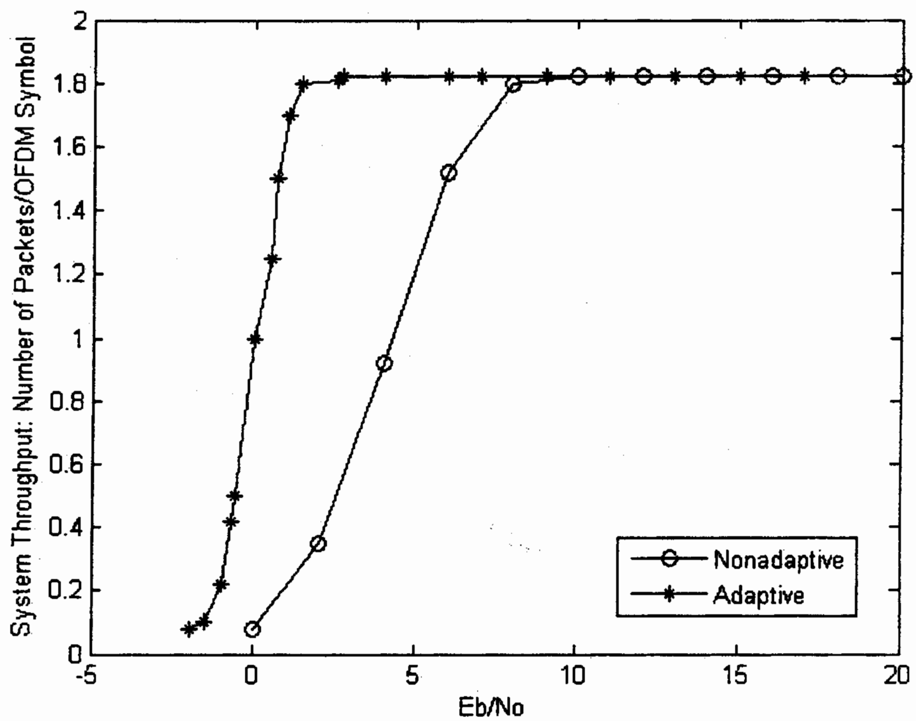

Figure 4.10 System throughput with and without adaptive resource allocation when each frame contains 3 OFDM symbols for data transmission

In Figure 4.11, it is investigated that system throughput is increases when the number of OFDM symbols per frame increases. In addition having more OFDM symbols in a frame leads to lower computational complexity and less overheads.

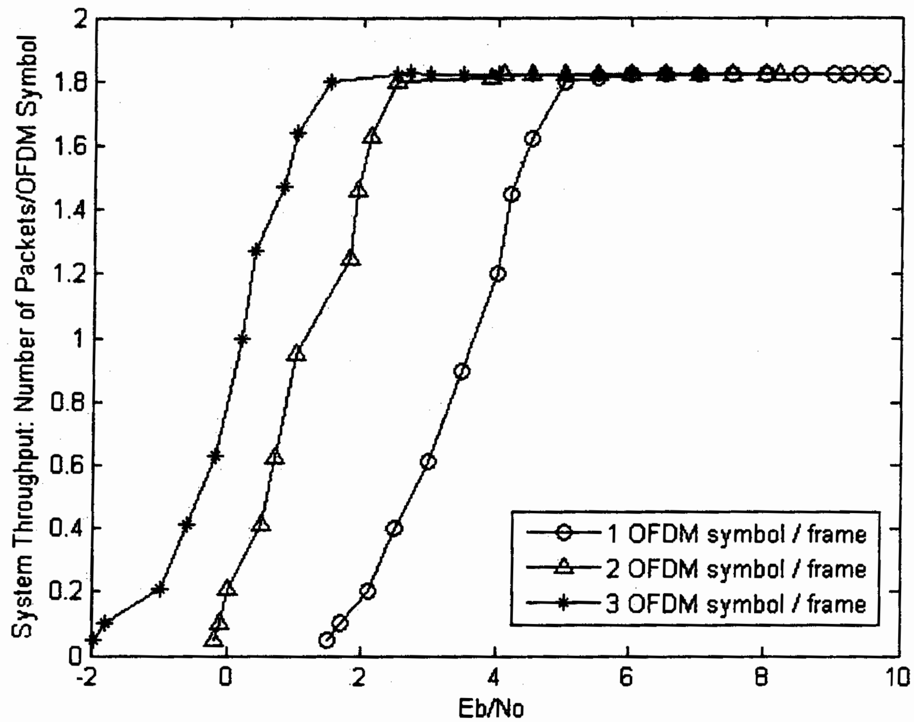

Figure 4.11 System throughput with various number of OFDM symbols per frame

Chapter 5

Conclusions & Future work

5.1 Conclusion

As the data rate requirements increase for media-rich communications, channelaware adaptive resource allocation is becoming more critical to system performance. Enabled by multicarrier modulation and multi-antenna technologies, multiple parallel channels can be created in either the frequency or spatial domain. Compared to single channel systems, resource allocation in multiuser multichannel systems is more challenging because of the additional degree of freedom for resources. In this dissertation, I study the performance of adaptive resource allocation in multiuser multichannel wireless communication systems. We also thoroughly analyzed adaptive optimization algorithms for MIMO/OFDM. We find that the adaptive algorithm employed gives a SISO/OFDM system which outperforms the SISO system having fixed-rate variable-power adaptive modulation. Further, we found that MIMO in general leads to better BER performance.

We conclude that MIMO/OFDM is a very promising technology, and practical adaptive rate and power optimization algorithms serve well to improve performance.

5.2 Future Work

In this section, I propose few future research topics for multicarrier and/or multi antenna wireless systems, potentially for other researchers interested in this area. A very useful extension of this work would be in multiuser MIMO/OFDM systems, and characterizing good rate and power sharing algorithms to achieve good mutual BER performance of all users, such as in [75] and [76].

- *Adaptive Resource Allocation in Multiuser MIMO-OFDM Systems*

  The next generation of cellular systems is likely to be OFDM based with multiple antennas. With OFDM, the wideband is divided into a number of parallel subchannels in the frequency domain. With multiple antennas, multiple users can be supported for simultaneous transmissions in each frequency subchannel. Resource allocation in multiuser MIMO-OFDM systems is likely to be even more challenging because the limited resource shall be optimized in multiple dimensions.

- *Impact of Imperfect Channel State Information for Adaptive Resource Allocation*

  Users' channel state information (CSI) is required at the basestation for adaptive resource allocation in both multiuser OFDM and multiuser MIMO systems. In this dissertation, it is assumed that channel station information is perfectly known at the basestation through a separate feedback channel. The CSI is usually estimated at the receivers and, hence, prone to estimation errors. Moreover, feedback delays may cause outdated CSI used by the adaptive resource allocation algorithm. The impact of imperfect CSI to the system performance with adaptive resource allocation needs further study

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