Non-Linear Fuzzy Receivers for DS-CDMA Communication System

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Abstract

Direct sequence-code division multiple access (DS-CDMA) technique is used in cellular systems where users in the cell are separated from each other with their unique spreading codes. In recent times DS-CDMA has been used extensively. These systems suffers from multiple access interference (MAI) due to other users transmitting in the cell, channel inter symbol interference (ISI) due to multipath nature of channels in presence of additive white Gaussian noise (AWGN).

This thesis presents an investigation on design of fuzzy based receivers for DS-CDMA system. Fuzzy based receiver has been proposed to work as chip level based (CLB) receivers and also multi user detection (MUD) receivers. It is seen that fuzzy receiver is capable of providing performance close to optimal radial basis function (RBF) receivers and provide considerable computational complexity reduction.

Extensive simulation studies demonstrate the performance of the fuzzy receivers and the performance have been compared with RAKE receiver, matched filter (MF) receiver, minimum mean square error (MMSE) receiver and RBF receiver.

Declaration of Originality

This thesis was composed entirely by myself. The work reported herein was conducted exclusively by myself in the Department of Electronics and Instrumentation Engineering at National Institute of Technology, Rourkela. The software written to perform the simulations was written by myself with the following exceptions:-

- The routines used to generate random numbers, Gaussian noise, to allocate and deallocate memory dynamically in C++ were obtained from *Numerical Recipes in C* [1].

Sharmistha Panda
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July 9, 2004

Certificate

This is to certify that the work in this thesis entitled "Non-Linear Fuzzy Receivers for DS-CDMA Communication System" by Ms. Sharmistha Panda has been carried out under my supervision in partial fulfillment of the requirements for the degree of Masters of Technology in Electronics and Instrumentation Engineering during session 2002-2004 in the Department of Electronics and Instrumentation Engineering, National Institute of Technology, Rourkela, and this work has not been submitted elsewhere for a degree.

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July 9, 2004

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Acronyms and abbreviations

ANN	artificial neural network
ANFF	adaptive neuro fuzzy filters
AWGN	additive white Gaussian noise
BER	bit error ratio
BPSK	binary phase shift keying
BS	base station
CCI	co-channel interference
CDMA	code division multiple access
CLB	chip level based
COG	centre of gravity
DFE	decision feedback equalizer
DRBF	direct radial basis function
DS	direct sequence
DSMA	direct sequence multiple access
FAF	fuzzy adaptive filter
FBF	fuzzy basis function
FDMA	frequency division multiple access
FEC	forward error correction
FHMA	frequency hopped multiple access
FIR	finite impulse response
GSM	global system for mobile communication
HDTV	high definition television
ISI	inter symbol interference
LMS	least mean square
LOS	line of sight
LP	linear programming
LPI	low probability of interception
MAI	multiple access interference
MFs	matched filters

MLP	multi layer perceptron
MMSE	minimum mean square error
MSC	mobile switching centre
MUD	multi user detection
NZ	non-zero
PCS	personal communication system
PG	processing gain
PPB	preprocssing based
PN	pseudonoise
PNN	probabilistic neural network
PSD	power spectral density
PSTN	public switched telephone network
RBF	radial basis function
RBFN	radial basis function network
RF	radio frequeccy
RLS	recursive least square
SDMA	space division multiple access
SNR	signal to noise ratio
SRK	square root kalman
SS	spread spectrum
SSMA	spread spectrum multiple access
TDMA	time division multiple access
THMA	time hopped multiple access
w.r.t	with respect to

Nomenclature

Symbols	**Description**
a_i	real valued input
$a_i(k)$	real world crisp input
$\underline{a}$	$(a_1, \ldots, a_n) \in I_U$ real valued input vector
b	element of O_V
$b(k)$	crisp output
b^l	system output due to rule $R^{(l)}$
$b(\underline{a})$	output of the real valued input vector
C_c	capacity of the communication channel
C_d	minimum distance between cells which broadcast on the same frequency
$C_{i,n}$	spreading sequence of i^{th} user at chip time n
$\mathbf{c}_j$	j^{th} RBF centre
$c_{j,n}$	n^{th} component of the j^{th} RBF centre
E_b	energy per data bit
E_b/N_o	signal to Gaussian noise ratio
$e(k)$	error signal at time index k
F_i^l	fuzzy set F corresponding to rule l and input a_i
f	frequency
f_{bit}	data bit frequency
f_{chip}	chip frequency
$f(x)$	Arbitrary function f with variable x
G^l	fuzzy inference corresponding to rule l
G_P	processing gain in decibel = $10 \log_{10} g_P$
g_i^-	minimum value of fuzzy filter input a_i
g_i^+	maximum value of fuzzy filter input a_i
g_P	processing gain in linear version= W_{SS}/W_D
$h(t)$	impulse response of a channel

$H(z)$	z-transform for channel impulse response $h(t)$
I_U	input universe of discourse
i	arbitrary variable
j	arbitrary variable
k	arbitrary variable
l	arbitrary variable
L	chip length
m	equaliser order
M_i	number of membership functions for input i in a fuzzy filter
n	arbitrary value
N_c	number of fuzzy IF $\ldots$ THEN $\ldots$ rules in a fuzzy filter
N_o	single sided Gaussian noise power spectral density
O_V	output universe of discourse
$\frac{P}{N}$	signal to noise ratio
p_i^l	real valued parameter
$\mathbb{R}$	1-dimensional space in $\mathbb{R}$
$\mathbb{R}^i$	i-dimensional space in $\mathbb{R}$
r_c	cell radius
$R^{(l)}$	a fuzzy rule l
$S_D(f)$	power spectral density of data signal
$S_{SS}(f)$	power spectral density of the spread spectrum signal
$s(kL+n)$	transmitted signal at time index n
T	time
T_{bit}	period of one data bit
T_{chip}	period of one data chip
$t(k)$	output of the RBF network
U	number of simultaneously transmitting users the system
w_j	weight j of a filter/ RBF centre/ neuron / equaliser
W	channel bandwidth in Hz
W_{SS}	bandwidth of the data signal
W_D	bandwidth of the spread spectrum signal
$x_i(k)$	k^{th} input data of user i
$\hat{x}_i(k)$	k^{th} estimated bit of the desired user i

$\tilde{\mathbf{x}}(k)$	preprocessor output $= [\tilde{x}_1(k), \ldots, \tilde{x}_U(k)]^T$ at time index k
$y(kL+n)$	channel output at time n
$\mathbf{y}(k)$	vector notation of $y(kL+n)$ for $1 \leq n \leq L$
δ_i^j	centre j corresponding to input i for a fuzzy filter
$\eta(kL+n)$	AWGN at time index n
φ_j	j^{th} center output
ϱ	learning rate for weights in a fuzzy filter
σ	centre spread parameter
ω^l	overall truth value of the premise of rule $R^{(l)}$
σ_i^j	spread parameter for fuzzy centre δ_i^j
ψ_i^j	membership function j for input i
$\mathbf{\Psi}$	fuzzy basis function
$\vartheta_l(k)$	weight corresponding to rule l of the fuzzy adaptive filter
$\otimes$	convolution
$\mu_{F_i^l}$	membership function of fuzzy set F_i^l
$\|.\|$	Euclidean distance

Chapter 1
Introduction

1.1 Introduction

The aim of the personal communication system (PCS) is to provide communication services in any form from any place at any time through any medium and without any delay by using one pocket-sized unit at minimum cost with acceptable quality and security through the use of a single personal telecommunication reference number [2]. Communication is often called the market of future. However consumer needs and wishes cannot be satisfied if the required technology is not available at a reasonable price. As the society tends towards mobility, technology tends towards portability.

Now days most of the people are familiar with a number of mobile radio communication equipment used in day to day life. Remote controllers for home entertainment equipment, cordless telephones, pagers and cellular telephones are examples of such mobile radio communication system. Generally the term mobile is used to specify any radio terminal that can be moved during operation or in other words radio terminal that can be attached to a high speed mobile platform [3]. However, the cost, complexity, performance, and the type of service offered by each of these mobile systems are vastly different. This has lead to variety of research in this field. The growing demand for capacity in the wireless communication system is the driving force behind improving established network and the development of a new worldwide mobile standard.

1.2 Mobile communication

The limitation imposed on communication by the channel bandwidth and the signal to noise ratio (SNR) is defined by Shannon equation [4]

$$C_c = W \log_2 \left(1 + \frac{P}{N}\right) \tag{1.1}$$

where C_c is the capacity of the communication channel measured in bits/sec, W is the bandwidth in Hz and P/N is the SNR. This relationship between capacity and bandwidth has led to an increased demand, and hence an increased scarcity of the resources. In mobile communication system, the available frequency spectrum is limited and hence it must be exploited efficiently. In order to do so mobile communication uses techniques based on multiuser communication, where the aim is to accommodate as many transmitting users as possible using a certain frequency band. This can be achieved by multiple access techniques. Mobile commu-

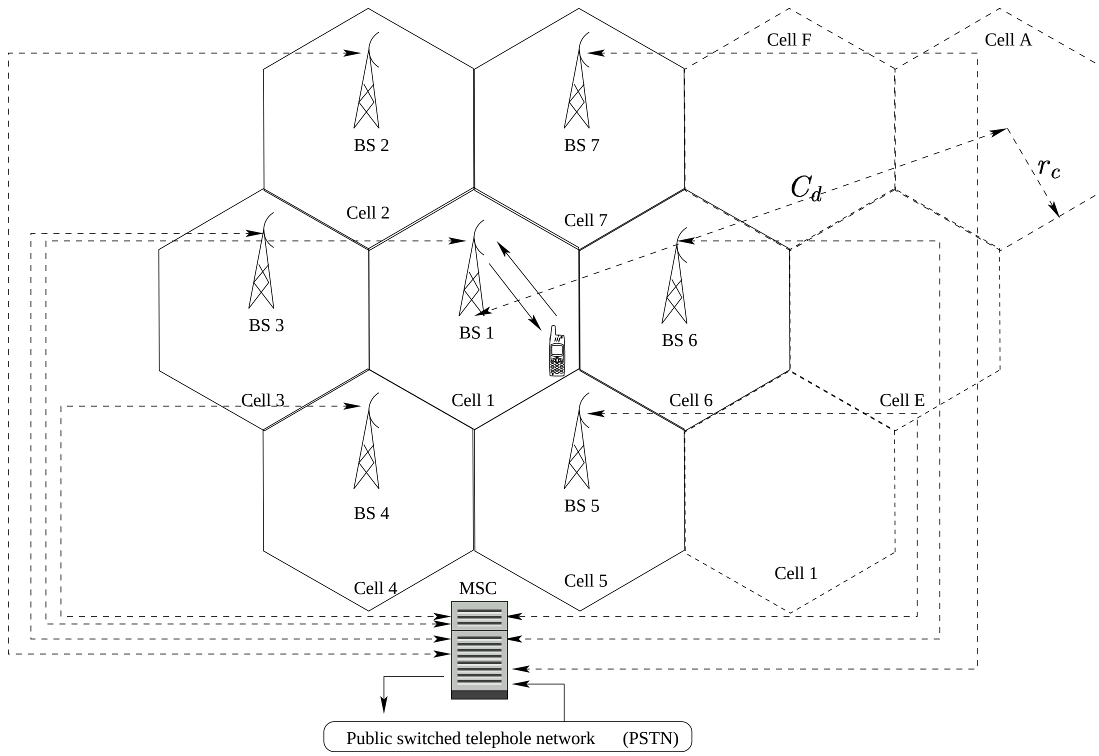


Figure 1.1: *Cellular communication system*

nication is analogous to cellular communication. It can be thought of as terrestrial network of cells [5], depicted as hexagons because it covers the largest area and a fewest number of cells can cover the geographic region. Here the investigations are carried out in a single cell with U simultaneously transmitting users for the downlink scenario. Each hexagon cell covers a certain region and has a base station in its centre, to which all the users in the cells are linked [6]. The base stations are connected to mobile switching centre (MSC). MSC is responsible for connecting all mobiles to the public switched telephone network (PSTN) in the cellular system as shown in Figure 1.1.

1.3 Multiple access techniques

The main task of the communication system designer is to make the best use of the system resources. The challenge is to make the most efficient use of the RF bandwidth. Frequency division multiple access (FDMA), Time division multiple access (TDMA) and Code division multiple access (CDMA) are the three major access techniques, used to share the available bandwidth in a mobile communication system to provide group of users in one RF channel. CDMA technique is a wideband[1] system and it comes under spread spectrum multiple access technique. Figure 1.2(a) shows the working of FDMA, in which every user communicate over an individual channel over the whole period of time. FDMA is often referred to as the first generation system. In TDMA system, more then one user can share the same channel at the same time as shown in Figure 1.2(b). This multiple access method is used in the global system for mobiles (GSM) system, which was the first digital cellular standard for voice communications and is termed as the second generation system.

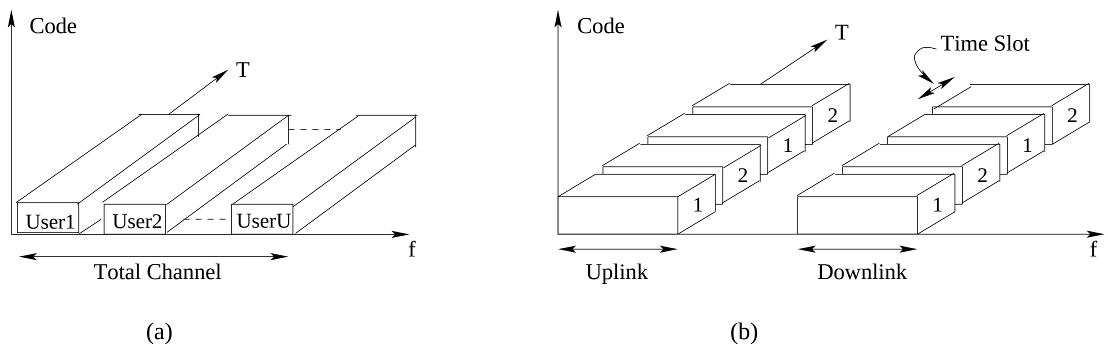


Figure 1.2: *Working of FDMA and TDMA system*

1.4 Spread spectrum multiple access (SSMA)

SSMA uses signal, which have a transmission bandwidth that is several order magnitude higher then the minimum required RF bandwidth [7]. pseudonoise (PN) sequence converts a narrow band signal to a wideband noise like signal before transmission. SSMA also provides immunity to multipath interference and robust multipath access capability [3]. There are three types of SSMA techniques. Frequency hopped multiple access (FHMA), Time Hopped Multiple Ac-

[1]transmission bandwidth of single channel is much large then the coherence bandwidth of the channel

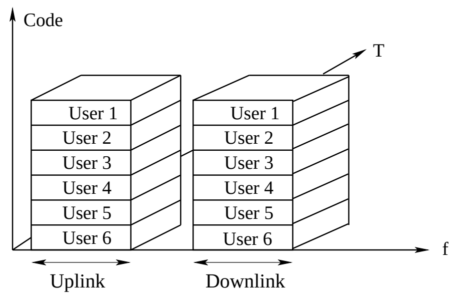


Figure 1.3: *Working of CDMA system*

cess (THMA) and Direct sequences multiple access (DSMA) or Code division multiple access (CDMA).

1.5 Code division multiple access (CDMA)

In CDMA systems, a narrow band message signal is convolved with a very large bandwidth signal called the spreading sequence. The spread signal is a PN code sequence that has a chip rate which is much greater the data rate of the message. All users in the CDMA system use the same carrier frequency and transmit simultaneously. Each user has its own spreading code called PN code word [8], which are approximately orthogonal to each other. All other code words appear as noise due to decorrelation. For detection of message signal, the receiver needs to know the code word used by the transmitter. It is believed that the capacity of the CDMA system is much greater then that of established TDMA system, which makes CDMA a candidate for third generation systems [9, 10]. The Figure 1.3 shows the working of CDMA system. In CDMA system all users share a common channel in time and frequency. All users transmit continuously over the full channel bandwidth. the users are separated only in space.

1.6 Literature review

The simplest DS-CDMA receivers are based on matched filters (MFs) [11] for a non-dispersive channel and RAKE receivers for multipath channels. The multiple access interference (MAI) performance of matched filter/ RAKE receivers can be enhanced by applying cancellation at the expense of increased receiver complexity. There are many receiver designs based on linear equalizer structure. For example those based on MMSE equalizer [12]. It has been shown that the DS-CDMA can be a pattern recognition problem [13] in multi dimentional space. DS-

CDMA receivers have been designed using Volterra series expansion, processing the received signal at chip rate. Comparatively less complex multiuser detection (MUD) receivers using radial basis function network (RBFN) have also been used for this work which processes the signal at symbol rate [14, 15]. Then another receiver is proposed based on linear programming (LP) [16]. A hybrid receiver [17] was also proposed which combined LP and RBFN. This structure has lower complexity then the full RBF and possesses good performance. Recent finding shows that space division multiple access(SDMA)-recurrent networks provides better performance as compared to linear square root kalman (SRK) algorithm based techniques. Hybrid CDMA-SDMA exhibits a very good potential for increase in the capacity and the performance of mobile communication system [18]. Modified decision-based network which improves the MUD detector performance has been discussed in [19]. Improvement in performance can be achieved by using chip-level decision feedback equalizer (DFE) as compared to other adaptive chip-level linear equalizer. The number of users can be increased by using adaptive chip-level DFE with satisfactory performance [20].

1.7 Object of the work

The work proposed here intends to develop non-linear receivers for DS-CDMA using fuzzy and neuro fuzzy technique. Fuzzy filters [21] are nonlinear filters that can be incorporate linguistic information in the form of IF ... THEN ... fuzzy rules. Fuzzy filters have been used for equalization. Review of the fuzzy-based nonlinear channel equalization has also been provided in [22]. This non-linear receiver minimizes the probability of error when deciding on a data bit. It has already been shown that RBF equalizers have superior performance then the linear equalizers in multipath channel and that an RBF filter has superior performance to an MMSE filter in a non-dispersive multipath CDMA system. Fuzzy receiver provides considerable implementational advantages over RBF receiver [22]. Additionally fuzzy receiver provides an efficient method for co-channel interference (CCI) suppression [23]. Fuzzy receivers has also been used in mobile communication applications. Considering close relationship between RBF and fuzzy system it is thought that fuzzy system can provide efficient receiver architecture for DS-CDMA downlink scenario.

In this work it is proposed to carry out the following studies.

- Implementation of Fuzzy filter for the DS-CDMA downlink receiver.

- Investigate implementational issues related to fuzzy receivers for DS-CDMA system.

1.8 Layout of the thesis

This thesis is organized into six chapters. Current chapter is a brief introduction into mobile communication system and ends with the thesis layout Figure 1.4. Following this introduction, Chapter 2 provides a more detail discuss on DS-CDMA system. Chapter 3 discusses the fundamentals of fuzzy logic system and design of fuzzy filters. In Chapter 4 fuzzy implementation of chip level based (CLB) receivers and its is compared with the established linear and direct radial basis (DRBF) receiver. Following this multiuser detection (MUD) receivers with reduced computational complexity has been discussed in Chapter 5. Finally Chapter 6 provides concluding remarks and future work.

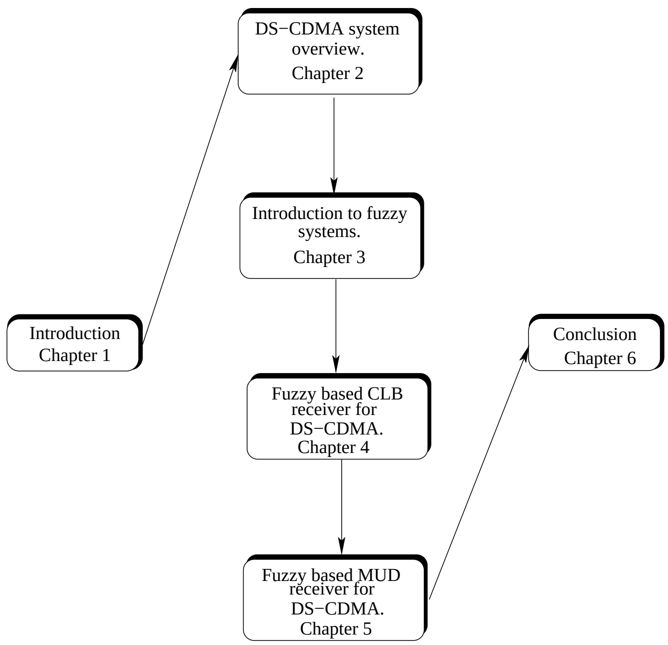


Figure 1.4: *Layout of the thesis*

Chapter 2
DS-CDMA System and Overview

2.1 Introduction

In this section the principle of spread spectrum and its application in multiple access is discussed. Multiple access schemes are used to allow many mobile users to share simultaneously a finite amount of radio channels in a fixed radio spectrum. The sharing of the spectrum is required to achieve high capacity by simultaneously allocating the available bandwidth to multiple users.

Following this introduction, spread spectrum (SS) communication technique is discussed in the section 2.2. The application of this SS technique to produce a multiple access system is described in the section 2.3. The section 2.4 deals with the construction of a simplified form of a baseband signal to be transmitted, while section 2.5 considers the effects of multipath channel on this signal. Section 2.6 discusses the simplest receiver structure using matched filter (MF). Principle structure of multiuser detector is described in section 2.7. While generation of Gold sequence is discussed in section 2.8 and the chapter ends with the concluding remark.

2.2 Spread spectrum communication techniques

SS is the technique in which an already modulated signal is modulated for the second time in such a way as to produce a waveform which interfere in a barely noticeable way with any other wave operating in the same frequency band [24]. This feature is called low probability of interception (LPI). To allocate each user a specific signature, or spreading sequence and to use this sequence to expand the bandwidth, or to spread the spectrum of the signal to be transmitted, is known as the SS multiple access technique. Both transmitter and the receiver know this spreading sequence. It is also independent of the data bits [25]. All the sequences are randomly distributed, and there is no correlation between any two sequences. Let the sequence of data bits $x_i(k)$ have the period T_{bit} and the spreading sequence of length L, generally called chips to distinguish them from the data bits have the frequency f_{chip} where $f_{chip} \gg (1/T_{bit})$.

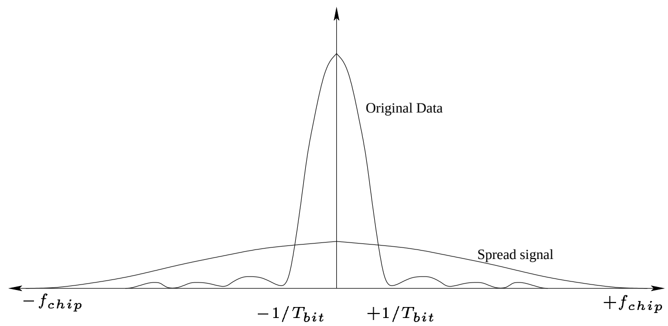


Figure 2.1: *Spread spectrum concept in frequency domain*

In other words it is assumed that $f_{chip} \gg f_{bit}$. From the above assumption it can be seen that the transmitted data is random and independent, the power spectral density (PSD) of the original unspread signal is given by [26].

$$S_D(f) = T_{bit}\left(\frac{sin\pi f T_{bit}}{\pi f T_{bit}}\right) \tag{2.1}$$

And assuming that spreading sequence is *pseudorandom* in nature, the PSD of the spreaded signal is given by

$$S_{SS}(f) = \frac{1}{f_{chip}}\left(\frac{sin\pi f/f_{chip}}{\pi f/f_{chip}}\right) \tag{2.2}$$

The relationship between the above spectral densities is sketched in the Figure.2.1. It may be seen that the effect of narrow-band interference[1] or white noise[2] which interferes with the signal between transmission and reception is reduced due this inverse despreading operation. The enhancement in performance due to the bandwidth expansion at the transmitter and contraction process at the reception is termed as processing gain (PG) g_P. The processing gain is represented as the ratio of bandwidth associated with the spreaded signal W_{SS} and that of the data signal W_D.

$$g_P = \frac{W_{SS}}{W_D} = \frac{T_{bit}}{T_{chip}} \tag{2.3}$$

The processing gain L, is the length of the spreading sequence, expressed in decibel form as

$$G_P = 10\log_{10}(g_P) \tag{2.4}$$

[1]the interference is from other existing communication systems
[2]the noise is due to fi nite power over a wide range of frequencies e.g. thermal noise

The SS signal is largely tolerant to external interfering factors, there will be degradation in performance as the number of SS signals in the same cell increases. The work presented here will focus only on inter-cell[3], with intra-cell[4] interference being modeled by encompassing its effects into the overall background noise level. To make a good comparison, the background noise is expressed in terms of a modified form of signal to noise ratio (SNR), it takes account the processing gain.

$$\frac{E_b}{N_0} = 10log_{10}\left(\frac{g_P}{2\sigma^2}\right) \tag{2.5}$$

Where E_b/N_0 is the signal to Gaussian noise ratio, and σ^2 is the Gaussian noise variance.

2.3 Basic principles of DS-CDMA system

This section focuses on mobile communication system based on SS, particularly DS-CDMA. The SS signal is obtained from convolving the current data bit and the spreading sequence.

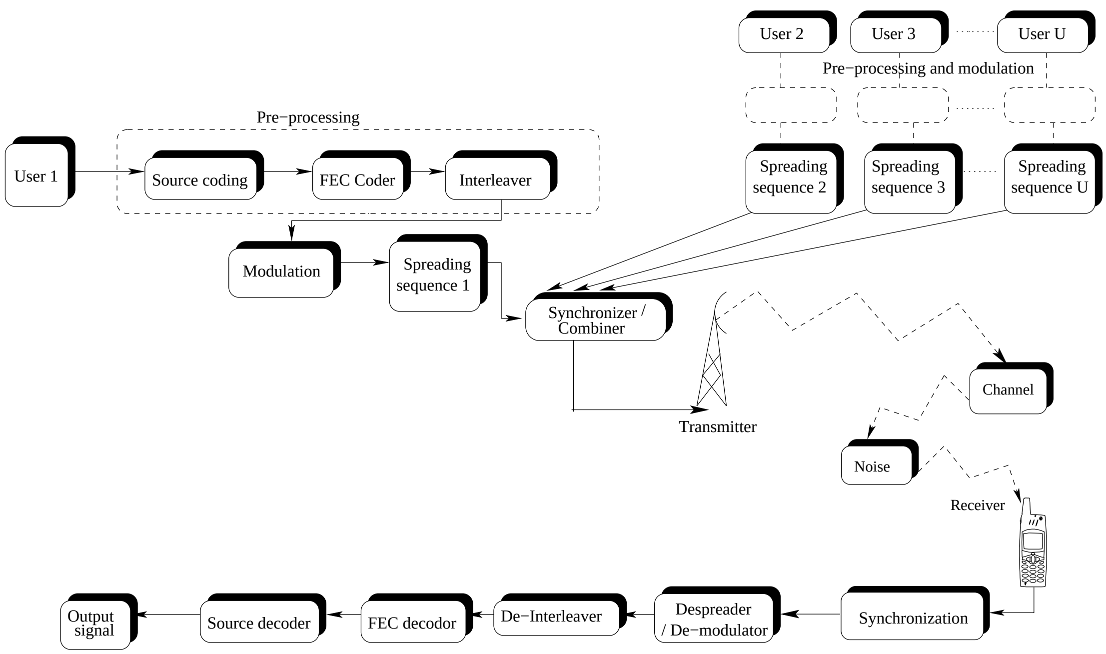


Figure 2.2: *Block diagram for general DS-CDMA communication system*

Transition of a single user system to a multiple access system is achieved by allocating each

[3]interference from other users in the same cell
[4]leakage from adjoining cells

user a unique spreading sequence. The basic elements of a DS-CDMA communication system is shown in the Figure 2.2. The input signal is first pre-processed by incorporating source coding and forward error correction (FEC), before the interleaving stage is applied to separate adjacent bits in an effort to provide some protection from a fading channel producing a block of errors. Binary phase shift keying (BPSK) modulation is applied before performing the bandwidth expansion using user-specific spreading sequence. Other users encoded and spreaded signal is then combined synchronously to form the transmitted signal. At the receiver the signal is despreaded and demodulation operations are performed. The requited data may be estimated by decoding the resultant data.

2.4 DS-CDMA Transmitter principle

The simplest model for a transmitter for downlink of a DS-CDMA system is shown in the Figure 2.3. The transmitted signal, $s(kL+n)$ at time $t = nT_{bit}$ is constructed by coherently summing the spreading sequence of each user, $C_{i,n}$ by that user's data bit $x_i(k)$ over all active users, to give

$$s(kL+n) = \sum_{i=1}^{U} C_{i,n} x_i(k) \tag{2.6}$$

where $1 \leq i \leq U$, $1 \leq n \leq L$ and k is the time index of the user transmitted bit. In the uplink case the process is same except that the users transmit their signal independent of each other and are no longer synchronized. This is modeled by inserting user-specific time delay on the resulting spread signal corresponding to each user.

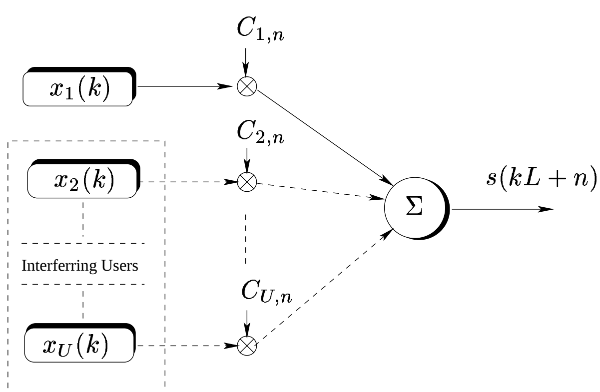


Figure 2.3: *Simplified synchronous DS-CDMA downlink transmitters for U active users*

2.5 Multipath channel background

The received signal consist of direct line of site (LOS) components and a few non-LOS components. The received signal consists of a combination of individual reflected signals from the obstacles, like buildings etc, between the transmitter and the receiver and those arrives at various delay, depending on the length of each RF paths [27]. This situation is called multipath channel. These can be time varying, due to the motion of the receiver with respect to the transmitter. This process is represented in Figure.2.4, where the mobile receives a LOS component and three reflected components. In addition the signal is corrupted by additive white Gaussian noise.

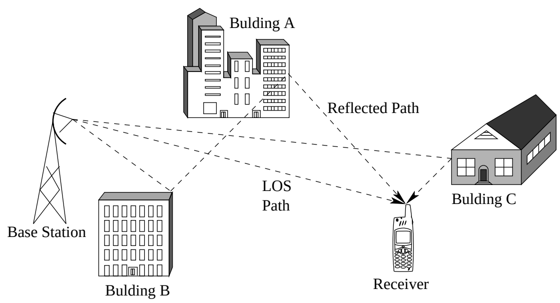


Figure 2.4: *Example of multipath, the received signal consist of many reflections and delayed versions of the transmitted signal*

2.5.1 Channel effects

Channel performance is described as the range of frequency over which the channel effects remain same and is called the coherence bandwidth, denoted as f_0, and the time duration over which the channel response is invariant which is called the coherence time, denoted as T_0. These parameters can be calculated [27] from the two dual functions, the multipath intensity profile $S(\tau)$ and, the Doppler power spectral density $S(\nu)$, which are the measure of the received signal power as the function of delay time τ and the Doppler shift ν respectively.

2.6 DS-CDMA Receiver principles

The work of the receiver is to recover the data $x_i(k)$ from the spectrum of the received signal vector $y(kL + n)$. This is done by multiplying the received signal with the used spreading sequence, which is generated locally by the receiver. The received signal, consisting of L chips is passed to the block of delay elements, where z^{-1} represents a delay of one chip, until the complete L chip signal has been read. These values are then passed to multiplier block in parallel, which forms the scalar product of $y(kL+n)$ and the tap weight vector $\omega_n \in C_{i,L}$ where L is the number of tap weights. This is shown in Figure 2.5 for $L = 7$. This finite impulse response (FIR) filter block produces a soft output $\tilde{x}_i(k)$, which is then passed through the decision block to give a hard estimate, $\hat{x}_i(k)$ of the original data bit $x_i(k)$.

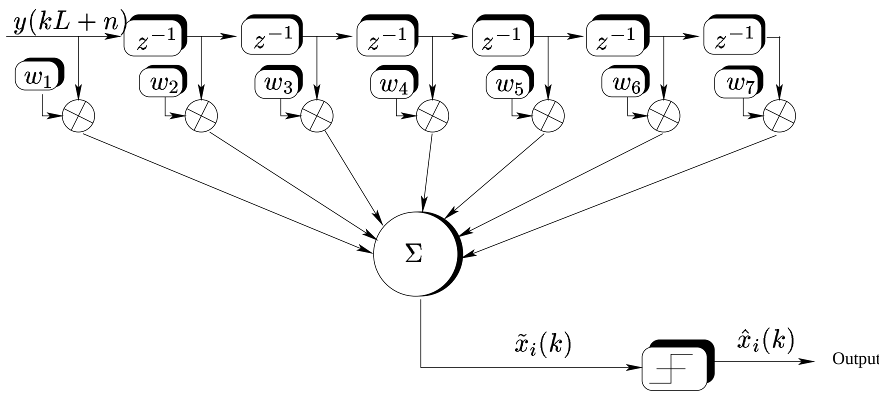


Figure 2.5: *DS-CDMA correlator receiver with 7 tap weights*

This is the structure of simplest receiver, commonly known as MF receiver with L tap weights $w_n : 1 \leq n \leq L$, matched to the original spreading sequence of the desired user. In practice, synchronization of the chip level signal is a highly non-trivial process [25]. The performance of this receiver has been shown to degrade considerably as the number of simultaneously transmitting users increases [28]. Hence improving the capacity of SS systems is achieved either by reducing the total interference[5] by enhancing the single user detection methods or by making use of multiple access interference (MAI) through improved interference cancellation or multiuser detection technique (MUD). The next section discusses the basic principle of MUD technique.

2.7 Principle of MUD technique

Instead of canceling the interference from the other users, the MUD operates by treating the MAI as additional information, which is used to obtain a better estimate of the desired data [29]. The basis principle of the MUD technique is shown in the Figure 2.6. The preprocessing

[5]combination of multiple access interference and background noise

block receives the signal $y(kL+n)$ at chip rate. $y(kL+n)$ is then passed through the bank of MFs in non-dispersive channel or else RAKE receivers in case of channel ISI, which calculates a set of soft decisions $\tilde{\mathbf{x}}(k) = [\tilde{x}_1(k), \tilde{x}_2(k), \ldots, \tilde{x}_U(k)]$. The signal $y(kL+n)$ is down sampled by L. The vector $\tilde{\mathbf{x}}(k)$ contains sufficient statistics for the detection of $\hat{x}_i(k)$, then the individual soft decision $\tilde{x}_i(k)$.

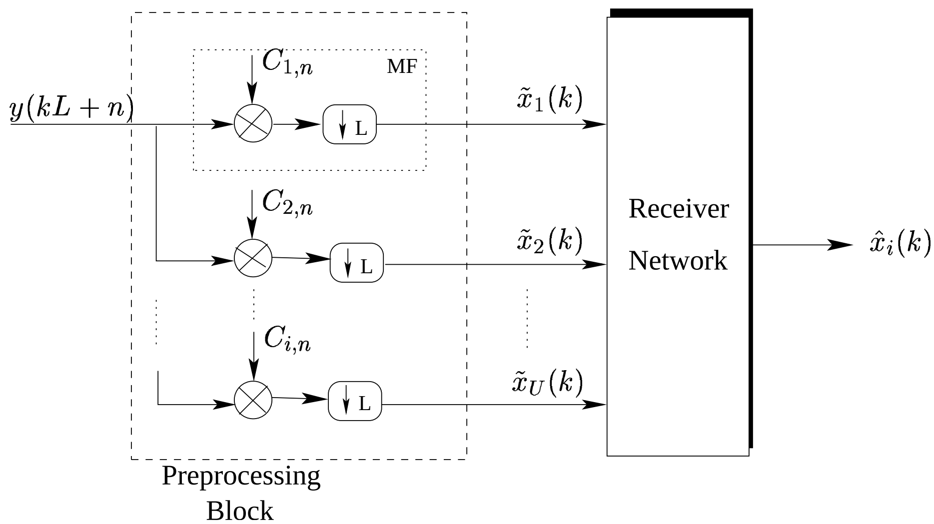


Figure 2.6: *Principle of MUD*

The receiver network, which processes the signal at bit rate may be implemented using RBF, fuzzy technique etc as discussed in chapter 5. The main disadvantage of MUD technique is the complexity of the receiver increases in an exponential manner. Hence base station is the most suitable place to carry out this operation where sufficient resources are available.

2.8 Pseudo-random sequences: Gold sequence

The spreading sequence used in DS-CDMA system are generally pseudorandom in nature. Gold sequences offer a reasonable choice of spreading sequences for DS-CDMA systems, hence used in the later chapter. To achieve increased capacity, at an expense of altering the correlation properties, a pair of m-sequences may be used to generate a set of Gold sequence [8], which have the property that the cross-correlation is always equal to -1, when the phase offset is zero. Non-zero (NZ) phase offset produces a correlation value from one of the three possible values. To generate 31 chip Gold sequence, a pair of specially selected m-sequences (where $m = 5$), and performing the modulo-2 sum of the two sequences for each of the $L = 2^m - 1$

cyclically shifted version of one sequence relative to the other sequence. Thus L Gold sequence is generated as illustrated in Figure.2.7. The other types of spreading sequences used in DS-CDMA system are pseudonoise (PN) sequences [30], orthogonal sequences: Walsh sequences, convolutional coding [28] etc.

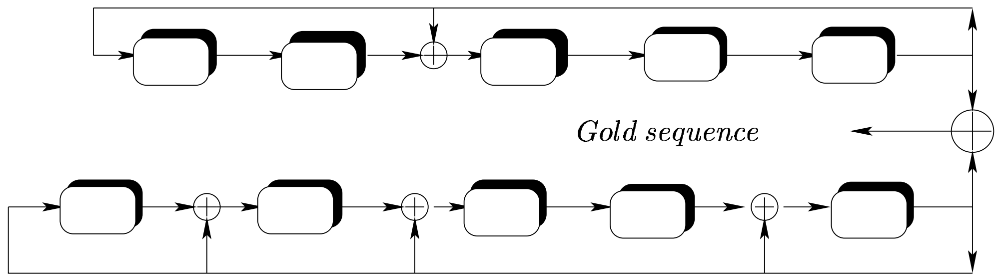


Figure 2.7: *Generation of Gold sequences of length 31*

2.9 Conclusion

This chapter reviewed the basic principles of SS communications and described the implementational aspects of DS-CDMA. The simplified transmitter structure for downlink scenario has been outlined, the model for communication channel is introduced. Simplest chip level processed MF receiver and MUD technique has been discussed in brief. Process of generation of 31 chip Gold sequence was described at the end.

Chapter 3
Introduction to Fuzzy Systems

3.1 Introduction

Fuzzy logic system have long excelled at delivering promising results from imprecise or ambiguous information, and fuzzy logic emulates the ability to reason and make use of approximate data to find precise solutions. Its primary use has been in pattern recognition, pattern classifications, control, image processing, embedded controllers etc. Now fuzzy logic is entering the mainstream with a wide range of desktop applications. The largest commercial uses for fuzzy logic are as controllers for tasks such as managing temperatures and energy efficiency in heating and cooling devices and regulating timing and fuel flow in automobile engines. Controllers also are used to make constant operating adjustments to subway trains, home appliances, cameras, and elevators. Fuzzy logic provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. Fuzzy logic's approach to control problems mimics how a person would make decisions, only much faster. This chapter provides an introduction to fuzzy logic system.

Following this introduction section 3.2 discusses about the fuzzy logic system and section 3.3 provides a classification of fuzzy logic system. The next section 3.4 outlines a brief introduction to fuzzy and neuro fuzzy filters. In section 3.5 the design of a fuzzy adaptive filter is discussed which is trained with LMS algorithm. This section also shows computational advantages of fuzzy logic system. The chapter ends with the concluding remarks.

3.2 What is a fuzzy logic system ?

There are two important information sources in engineering stream, one is sensors, which provides numerical measurements of variables, and second is the human experts who provides linguistic instructions and descriptions about the system. The information from the sensors are called numerical information and the information from the human experts are called linguistic information. Numerical information is represented by numbers, for example–$1.03, 0.56$, and so on, whereas linguistic information is represented by words like small, large, low, very low, very large, and so forth. Conventional engineering approaches can only make use of numerical informations. Due to much of human knowledge is represented in linguistic terms, incorporating it into engineering systems in a systematic and efficient manner is most important.

There are at least three reasons why linguistic informations are usually represented in fuzzy terms. Those are:

- It is more convenient and efficient way to communicate our knowledge in fuzzy terms. That is understandable, because if we use only crisp terms, then we must first have precise definitions of these crisp terms. This will result in a chain of definitions, which is a very inefficient and inconvenient procedure which clearly does not happen in our day to day life.
- Our knowledge about many problem is fuzzy. For example, when we learn a new theory, we often find that we understand *something* about the theory, for example, its motivation, basic ideas, advantages disadvantages, and so on, but we are not sure about some of the details. Now if we are asked to introduce the theory to another person, then that person can only get a fuzzy picture of the theory. But the point is that although the picture is not clear, it may serve the purpose quite well and may be sufficient for a higher-level manager.
- The last point is that the real time systems are very complex to describe in crisp terms. For example, our knowledge about a complex chemical process can be represented in fuzzy terms, for example, "*if the temperature is high, then the reaction is intense*" another example is the working of a washing machine. The point here is that even if the linguistic information is not precise, it provides sufficient information about the system. We should make use of this information in a scientific way.

3.3 Classification of fuzzy logic system

Fuzzy systems or fuzzy logic[1] system is the name for systems which have a direct relationship with fuzzy concepts (like fuzzy sets, linguistic variables) and fuzzy logic [31–33]. The most

[1] In the literature it is also commonly referred to as fuzzy logic controller

popular fuzzy logic systems may be classified into three types: pure fuzzy logic system, Takagi and Sugeno's fuzzy system, and fuzzy logic system with fuzzifier and defuzzifier. Each of these are described in following subsections.

3.3.1 Pure fuzzy logic systems

The basic configuration of a pure fuzzy logic system is shown in the Figure 3.1 where the fuzzy rule base consists of a collection of fuzzy IF $\ldots$ THEN $\ldots$ rules, and the fuzzy inference engine uses these fuzzy IF $\ldots$ THEN $\ldots$ rules to determine a mapping from fuzzy sets in the input universe of discourse $I_U \subset R^n$ to fuzzy sets in the output universe of discourse $O_V \subset R$ based on fuzzy logic principles. The fuzzy IF $\ldots$ THEN $\ldots$ rules are of the following form:

$$R^{(l)} : \text{IF} \quad a_1 \text{ is } F_1^l \quad \text{and} \quad ... \quad \text{and} \quad a_n \text{ is } F_n^l \quad \text{THEN} \quad b \text{ is } G^l \tag{3.1}$$

where F_i^l and G^l are fuzzy sets, $\underline{a} = (a_1, \ldots, a_n)^T \in I_U$ and $b \in O_V$ are the input and the output linguistic variables, respectively, and $l = 1, 2, \ldots, M$. Each fuzzy IF $\ldots$ THEN $\ldots$ rule of (3.1) defines fuzzy set $F_1^l \times \ldots \times F_n^l \rightarrow G^l$ in the product space $I_U \times O_V$. The pure fuzzy

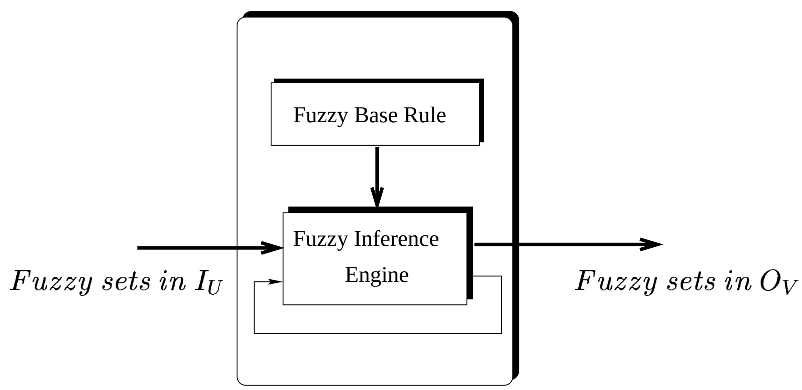


Figure 3.1: *Configuration of a pure fuzzy logic system*

logic system constitutes the essential part of the fuzzy logic systems. The main disadvantages of the pure fuzzy logic system is that its inputs and output are fuzzy sets, whereas in most of the engineering systems the inputs and outputs of the system are real-valued data and these have to converted to fuzzy type data for use in pure fuzzy logic system.

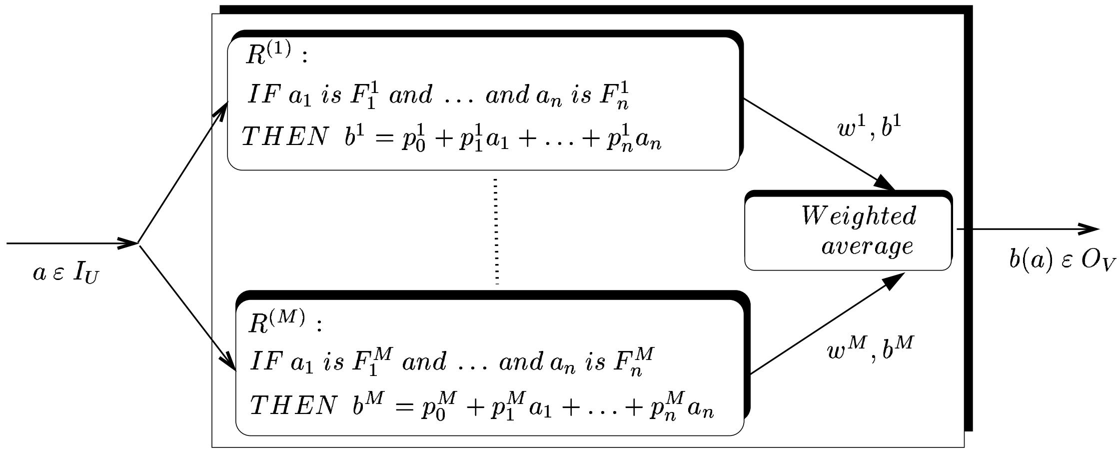


Figure 3.2: *Basic configuration of a Takagi and Sugeno's fuzzy system*

3.3.2 Takagi and Sugeno's fuzzy system

To overcome the disadvantages of the pure fuzzy system, Takagi and Sugeno [34] proposed another fuzzy logic system whose inputs and outputs are real-valued. Instead of considering the fuzzy IF ... THEN ... rules in the form of (3.1), Takagi and Sugeno proposed the following IF ... THEN ... rules:

$$\begin{aligned} R^{(l)} : \text{IF} \quad a_1 \text{ is } F_1^l \quad \text{and} \quad \ldots \quad \text{and} \quad a_n \text{ is } F_n^l, \\ \text{THEN} \quad b^l \ = \ p_0^l + p_1^l a_1 + \ldots + p_n^l a_n \end{aligned} \tag{3.2}$$

where F_i^l are fuzzy sets, p_i^l are real-valued parameters, b^l is the system output due to rule $R^{(l)}$, and $l = 1, 2, \ldots, M$. In this rules the IF part if fuzzy and the THEN part is crisp– the output is the linear combination of input variables. For a real-valued input vector $\underline{a} = (a_1, \ldots, a_n)^T$, the output $b(\underline{a})$ of Takagi and Sugeno's fuzzy system is a weighted average of the $b^{l\prime}s$:

$$b(\underline{a}) = \frac{\sum_{l=1}^{M} \omega^l b^l}{\sum_{l=1}^{M} \omega^l} \tag{3.3}$$

where the weight ω^l implies the overall truth value of the premise of rule $R^{(l)}$ for the input and is calculated as:

$$\omega^l = \prod_{i=1}^{n} \mu_{F_i^l}(a_i) \tag{3.4}$$

The configuration of Takagi and Sugeno's fuzzy system is shown in Figure.3.2. The advantages

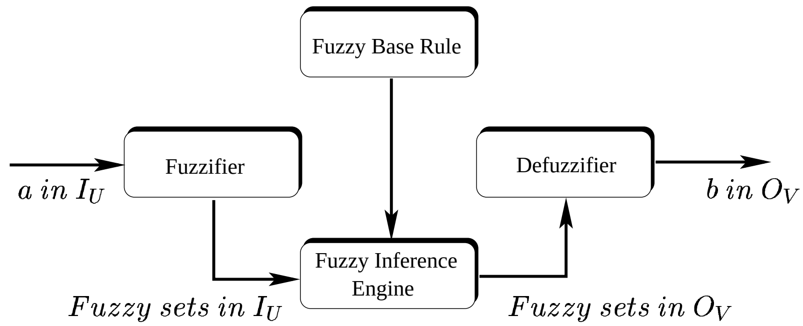


Figure 3.3: *Basic configuration fuzzy system with fuzzifier and defuzzifier*

of this fuzzy logic system is that it provides a compact system equation (3.3). The weak point of this fuzzy logic system is that the THEN part of the rule is not fuzzy; thus, it does not provide a natural frame work to incorporate fuzzy rule for human expert.

3.3.3 Fuzzy logic system with fuzzifier and defuzzifier

In order to use the pure fuzzy logic system shown in Figure.3.1 in engineering systems where, inputs and outputs are real-valued variables, the most straight forward way is to add a fuzzifier to the input and a defuzzifier to the output of the pure fuzzy logic system. This is shown in Figure 3.3. The fuzzifier maps crisp points in I_U to fuzzy sets in I_U, and the defuzzifier maps fuzzy sets in O_V to crisp points in O_V. The advantages of a fuzzy logic system with fuzzifier and defuzzifier is it's inputs and outputs are real-valued variables. Second, it provides a natural framework to incorporate fuzzy IF ... THEN ... rules for the human experts. Third, there is much freedom in the choices of fuzzifier, fuzzy inference engine, and defuzzifier, so that we can choose the most suitable fuzzy logic system for a particular problem. The next section discusses the fuzzy and neuro fuzzy filters using fuzzifier and defuzzifier.

3.4 Fuzzy and neuro fuzzy filters

The Figure 3.3 in section 3.3.3 shows a general fuzzy logic system with a fuzzifier and a defuzzifier. Referring to the previous section, Figure 3.4 shows a typical fuzzy logic system with adaptive algorithm. The fuzzifier converts the real world crisp input sample $a_i(k)$ to a fuzzy output F_i^l described by the membership function ψ_i^l. This provides the degree to which the input scalar $a_i(k)$ belongs to the fuzzy set F_i^l. The inference engine provides the relationship between the fuzzy input in terms of membership functions and the fuzzy output of the controller using a set of IF ... THEN ... rules derived from the rule base. The rule l in the fuzzy rule base can be defined as

$$R^{(l)} : \text{IF} \quad a_1 \text{ is } F_1^l \quad \text{and} \quad ... \quad \text{and} \quad a_n \text{ is } F_n^l \quad \text{THEN} \quad b \text{ is } G^l \tag{3.5}$$

The defuzzifier converts the inferences G^l to provide the crisp output $b(k)$. Generally in a fuzzy system the rule base is generated in advance with expert knowledge of the system under consideration. However, recently [35] online learning properties have been introduced which provide scope for training. This feature in fuzzy systems is achieved with the adaptation and learning block that uses the available information in the system. The available linguistic rules can also be applied in the adaptation algorithm. This is shown in Figure 3.4. These types of systems are also called adaptive neuro fuzzy filters (ANFF) [36] and they possesses the ability to incorporate training like neural networks and can also use rule bases from human experts as in fuzzy systems. The adaptive fuzzy systems have been applied to a variety of engineering applications [37] such as medical diagnostics, image processing, pattern classification [38, 39], clustering [40] control applications [41] and time series forecasting [42] etc.

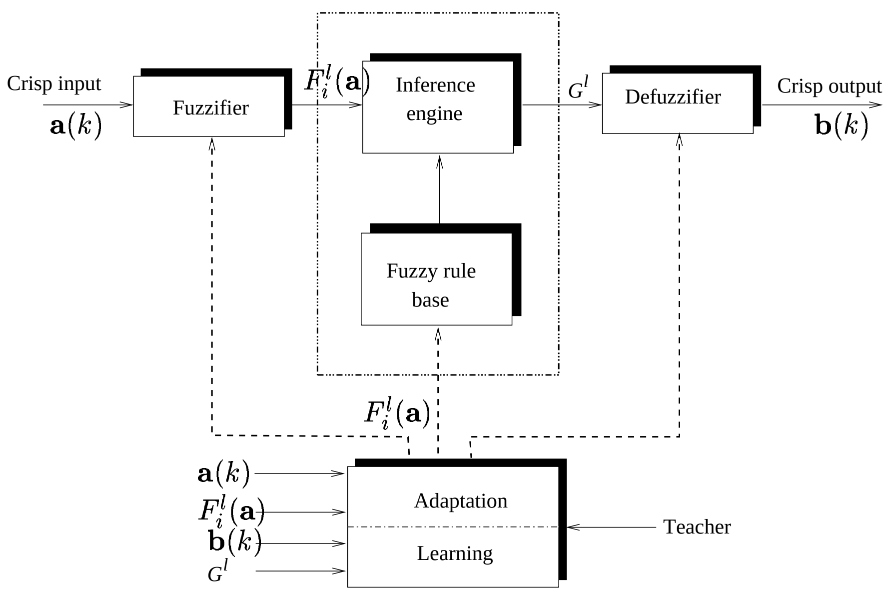


Figure 3.4: *A typical fuzzy logic system*

Wang et. al. [21] presented fuzzy basis functions (FBF) and used a combination of these functions for universal approximation and later on used them as a fuzzy filter [31] for channel equalization. Gan [43, 44] proposed fuzzy techniques for the adjustment of the step size in the LMS algorithm and a similar technique was used [45] for step size adjustment of LMS algorithm for equalization of high definition television (HDTV) systems. Lin and Juang [36, 46] developed the ANFFs and used it for noise reduction. This ANFF constructs its rule base in a dynamic way with the training samples. These ANFF provide scope to design nonlinear filters that are computationally simple and can accept linguistic variables from expert systems. The fuzzy filter used in the work reported here is discussed in the next section.

3.5 Fuzzy adaptive filter

The fuzzy adaptive filter (FAF) was originally proposed by Wang and Mendel [31]. Fuzzy filters are nonlinear filters that can incorporate fuzzy IF $\ldots$ THEN $\ldots$ rules from a human expert system. Wang and Mendel had proposed two types of fuzzy filters [31], the RLS fuzzy filter and the LMS fuzzy filter. The fuzzy filter used in this thesis has a structure similar to the RLS filter proposed in [31] and the equalizer is trained with the LMS algorithm. The filter considered here maps a real input vector $\mathbb{R}^m \to \mathbb{R}$ with the function

$$f_{faf}\{\mathbf{a}(k)\} : I_U \subset \mathbb{R}^m \to \mathbb{R} \tag{3.6}$$

where, $\mathbf{a}(k) = [a_1(k),\ a_2(k),\ \ldots,\ a_i(k),\ \ldots,\ a_m(k)]^T$, $a_i(k) \in I_U \equiv [g_i^-, g_i^+]$ is the input to the fuzzy filter and g_i^-, g_i^+ are the minimum and maximum limits for the input scalars $a_i(k)$. Here $f_{faf}\{\mathbf{a}(k)\}$ is the FAF output, corresponding to the filter input $\mathbf{a}(i)$. The filter minimizes the sum squared error performance index such that

$$e(k) = \sum_{i=0}^{k} \left[b(i) - f_{faf}\{\mathbf{a}(i)\}\right]^2 \tag{3.7}$$

where $b(i)$ is the desired filter output corresponding to the filter input $\mathbf{a}(i)$ and $e(k)$ is the sum of the error squares that needs to be minimized.

3.5.1 Filter design

A fuzzy filter with an input vector of length m and a scalar output is shown in Figure 3.5. Each element of the filter input is fuzzified with a Gaussian membership function. The membership

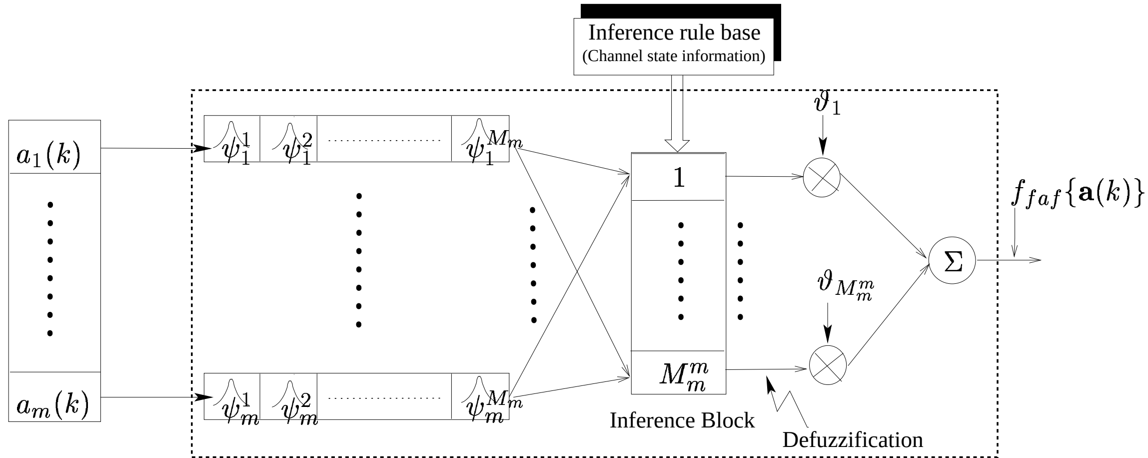


Figure 3.5: *Structure of an adaptive fuzzy filter*

function for the inputs can be represented as

$$\psi_i^j(k) = \exp\left\{-\frac{1}{2}\left(\frac{a_i(k)-\delta_i^j}{\sigma_i^j}\right)^2\right\} \tag{3.8}$$

where δ_i^j and σ_i^j are the jth centre and spread parameters respectively corresponding to input scalar a_i, $1 \le i \le m$ such that the input space $a_i \in I_U \equiv [g_i^-, g_i^+]$ is completely covered. These parameters once selected remain fixed and the input a_i is associated with the membership functions $\psi_i^1,\ \psi_i^2,\ \ldots,\ \psi_i^{M_i}$, so that the filter is characterized by a total of $\sum_{i=1}^m M_i$ membership functions. The filter consists of fuzzy IF $\ldots$ THEN $\ldots$ rules of the form

$R^{(1,1\ldots,1)}$: IF a_1 is F_1^1 a_2 is F_2^1 $\ldots$ a_m is F_m^1 THEN b is $\psi_1^1\psi_2^1\ldots\psi_m^1$

$\ldots$

$R^{(1,1,\ldots,M_m)}$: IF a_1 is F_1^1 a_2 is F_2^1 $\ldots$ a_m is $F_m^{M_m}$ THEN b is $\psi_1^1\psi_2^1\ldots\psi_m^{M_m}$

$\ldots$

$R^{i1,i2,\ldots,im}$: IF a_1 is F_1^{i1} a_2 is F_2^{i2} $\ldots$ a_m is F_m^{im} THEN b is $\psi_1^{i1}\psi_2^{i2}\ldots\psi_m^{im}$

$\ldots$

$R^{M_1,M_2,\ldots,M_m}$: IF a_1 is $F_1^{M_1}$ a_2 is $F_2^{M_2}$ $\ldots$ a_m is $F_m^{M_m}$ THEN b is $\psi_1^{M_1}\psi_2^{M_2}\ldots\psi_m^{M_m}$

where each of the terms $i1,\ i2,\ \ldots, im$ are single indices each ranging from 1 to M_i respectively. The filter considered here finds the following nonlinear function of the membership functions ψ_i^j so that,

$$f_{faf}\{\mathbf{a}(k)\} = \sum_{i1=1}^{M_1}\sum_{i2=1}^{M_2}\ldots\sum_{im=1}^{M_m}\vartheta_l(k)^{(i1,i2,\ldots,im)}\left\{\psi_1^{i1}(k)\,\psi_2^{i2}(k)\ \ldots\ \psi_m^{im}(k)\right\} \tag{3.9}$$

where $\vartheta(k)^{(i1,\, i2,\, \ldots,\, im)}$ is the weight associated with the fuzzy IF ... THEN ... rule $R^{i1,\, i2,\, \ldots,\, im}$.

The weight parameter $\vartheta(k)^{(i1,i2,\ldots,im)}$ is updated during the adaptation procedure so as to minimize the desired cost function in (3.7). Using the LMS algorithm to update the filter parameter $\vartheta k^{(i1,i2,\ldots,im)}$,

$$\vartheta(k+1)^{(i1,i2,\ldots,im)} = \vartheta(k)^{(i1,i2,\ldots,im)} + \varrho\left[b(k) - f_{faf}\{\mathbf{a}(k)\}\right] \boldsymbol{\Psi}\{\mathbf{a}(k)\}^{(i1,i2,\ldots,im)} \tag{3.10}$$

where,

$$\boldsymbol{\Psi}\{\mathbf{a}(k)\}^{(i1,i2,\ldots,im)} = \psi_1^{i1}\, \psi_2^{i2}\, \ldots\, \psi_m^{im} \tag{3.11}$$

Here, $\boldsymbol{\Psi}(\mathbf{a})^{(i1,i2,\ldots,im)}$ is the input to the filter weight $\vartheta^{(i1,i2,\ldots,im)}$, ϱ is the learning rate and $j1,\, j2,\, \ldots,\, jm$ constitute single indices. The filter function in (3.9) finds a weighted sum of all possible combinations of the products of the membership functions, taking one from each input. Here it can be seen that the term $\boldsymbol{\Psi}\{\mathbf{a}(k)\}^{(i1,i2,\ldots,im)}$ is a FBF [21] with singleton fuzzifier, Gaussian membership function, product inference and centre of gravity (COG) defuzzifier. A combination of these basis functions can be used for universal approximation [21]. With the use of different types of membership functions, inference rules and defuzzification processes a variety of fuzzy filters can be designed to optimize any arbitrary function. Each of the FBF's works as a fuzzy rule and the FAF consist of fuzzy rules.

$$N_c = \prod_{i=1}^{m} M_i \tag{3.12}$$

It is well established in neural literature [47, 48] that the Gaussian RBF is good at characterizing local properties and that the neural networks with sigmoid nonlinearities are good at characterizing global properties. The fuzzy filter designed in this section will have the capabilities to optimize both local and global properties. The relationship of the FBF with other form of basis functions like RBF and PNN have been discussed in [49, 50]. The filter proposed can also be trained with RLS algorithm [31]. This fuzzy filter designed above can be termed as the neuro fuzzy filter since the interference can be designed with the rule base and the defuzzifier weights are at the output layer can be trained like neural networks

3.6 Conclusion

This chapter discussed the basics of a fuzzy logic system. The capability of fuzzy logic systems to incorporate linguistic information in a natural systematic way is the advantage of the fuzzy logic system over other types of universal approximators like polynomials, neural networks and so on. By specifying the fuzzy logic principles used in the fuzzy logic systems, and other factors like fuzzifier and defuzzifier, a particular fuzzy logic system can approximate any nonlinear function to arbitrary accuracy. This issue is further discussed in the next chapter.

Chapter 4
Fuzzy based CLB receiver for DS-CDMA system

4.1 Introduction

In this chapter new type of chip level based (CLB) receivers for DS-CDMA system are presented. These fuzzy based CLB receivers are the fuzzy implementation of the RBF receiver with reduced complexity. Performance of these receivers are compared with traditional receivers such as matched filters (MFs) and direct RBF (DRBF) also commonly known as CLB RBF receiver.

Following this introduction, section 4.2 provides an overview of CLB receiver and its RBF implementation. The fuzzy implementation of the DRBF CDMA receiver is presented section 4.3 followed by computational issues related to the fuzzy receivers. Extensive simulation results have been presented in the section 4.5. The chapter ends with a concluding remark

4.2 Overview of the CLB RBF receiver

In order to process the received signal $y(kL+n)$ without looking at the particular receiver design (which is described later in this chapter), Figure 4.1 show a conventional single user receiver known as CLB receivers. This receiver processes the received signal $y(kL+n)$ at chip rate giving output at symbol rate.

Figure 4.1: *Chip rate based receiver*

System model for the transmission in the DS-CDMA considered here is presented in Figure 4.2. It shows the downlink scenario, where the mobile unit receives signal $y(kL+n)$ from the base station. The information bits corresponds to one of U users are denoted as $x_i(k)$. $x_i(k)$ takes the values $+1/-1$ with equal probability and k denotes the time index of user transmitted symbols. The information bits transmitted by each user are then convolved with each of their mutually orthogonal spreading sequences $C_{i,n}$, where $1 \leq i \leq U$ (number of users active) and $1 \leq n \leq L$ (spreading sequence length).

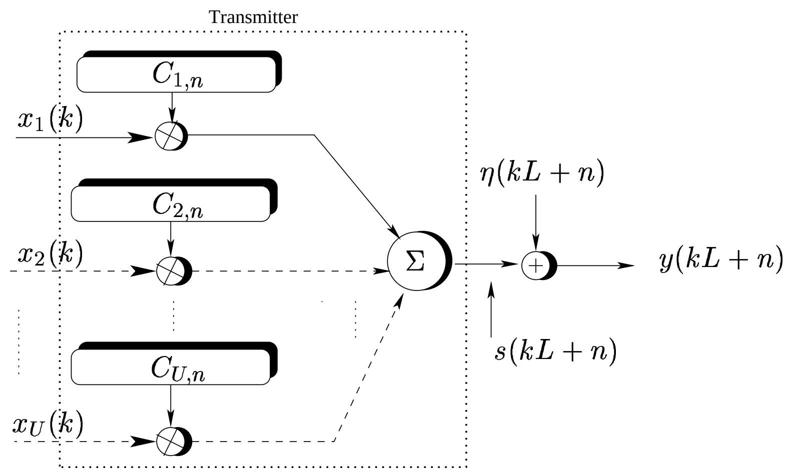


Figure 4.2: *Conventional synchronous DS-CDMA downlink transmitter for U transmitting users*

Gold codes [8], convolutional codes [28], Pseudonoise (PN) codes [30] are some of the coding techniques used. The spreaded signal from each user are then combined to form

$$s(kL+n) = \sum_{i=1}^{U} x_i(k) C_{i,n} \tag{4.1}$$

which is then transmitted through the non-dispersive channel. Channel adds AWGN to the signal. With this the received signal $y(kL+n)$ can be represented as

$$y(kL+n) = \sum_{i=1}^{U} x_i(k) C_{i,n} + \eta(kL+n) \tag{4.2}$$

at the point where bit k, chip n is received. $\eta(kL+n)$ is the noise component at chip rate. In the AWGN case there is no need to consider n outside the range $1 \leq n \leq L$ as outside this time the signal will contain no information relating to data bit k.

The job of the receiver is to estimate the transmitted signal $x_i(k)$ of the desired user using the information content in the $y(kL+n)$. As the input signal is processed at chip rate n, it is called chip rate based receiver (CLB). The structure of CLB receiver using RBF is shown in Figure 4.3. The input to the RBF network is given by $y(kL+n)$. $y(kL+n)$ can be represented as

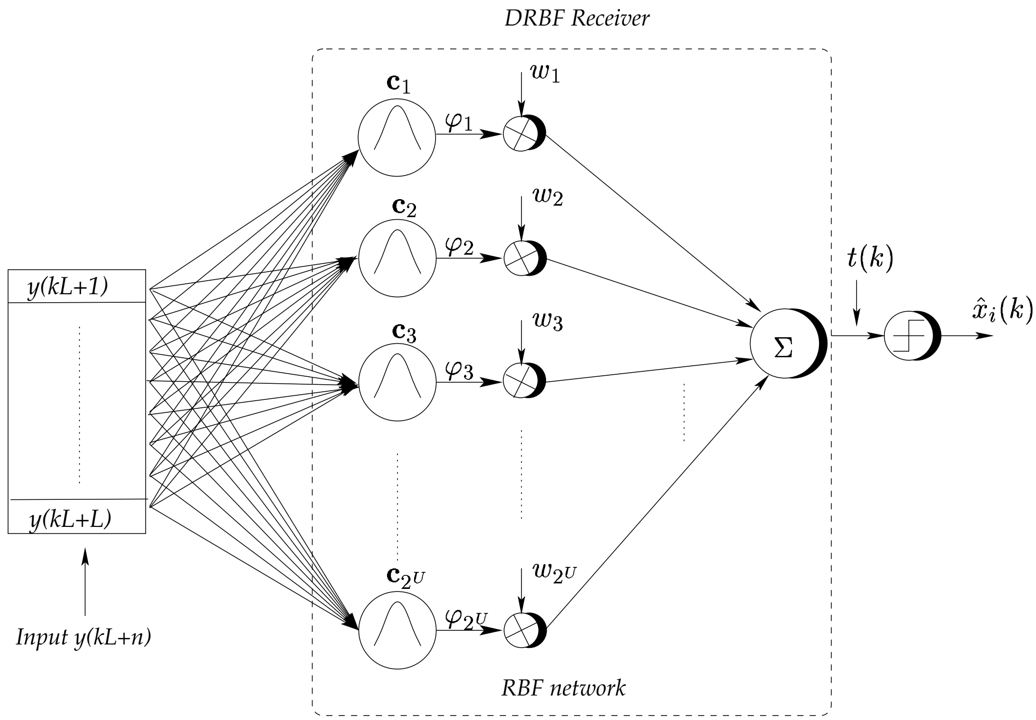


Figure 4.3: *The structure of the CLB RBF receiver*

vector $\mathbf{y}(k) = [y(kL+1), y(kL+2), \ldots, y(kL+L)]$ for $1 \leq n \leq L$. The output of the RBF network is given by

$$t(k) = \sum_{j=1}^{2^U} w_j \exp\left(\frac{-\|\mathbf{y}(k) - \mathbf{c}_j\|^2}{2\sigma^2}\right) \tag{4.3}$$

The right side of (4.3) represents the RBF decision function. The RBF has 2^U centres of dimension L, σ is the centre spread parameter and w_j denotes the weight associated with each centre. The RBF output $t(k)$ is passed through a hard limiter to provide $\hat{x}_i(k)$, estimated value of the transmitted symbol of the desired user $x_i(k)$. An increment in number of users increases the number of RBF centre by two times. The larger number of centres associated with this DRBF receivers prompted us to use fuzzy based receivers for this application. This RBF receiver provides the optimal performance for CDMA system [51]. The computational complexity issues associated with these RBF receivers have been widely investigated and a number of near optimal solutions using neural networks [19], recurrent networks [18], Viterbi [52] has been investigated.

4.3 Fuzzy implementation of the CLB RBF receiver

In order to propose a fuzzy based DS-CDMA receiver we used a fuzzy filter discussed in chapter 3. The close relationship of this filter with RBF was reported by [22]. This fuzzy implemented RBF DS-CDMA receiver is presented in Figure 4.4. The output of the channel $y(kL+n)$ as

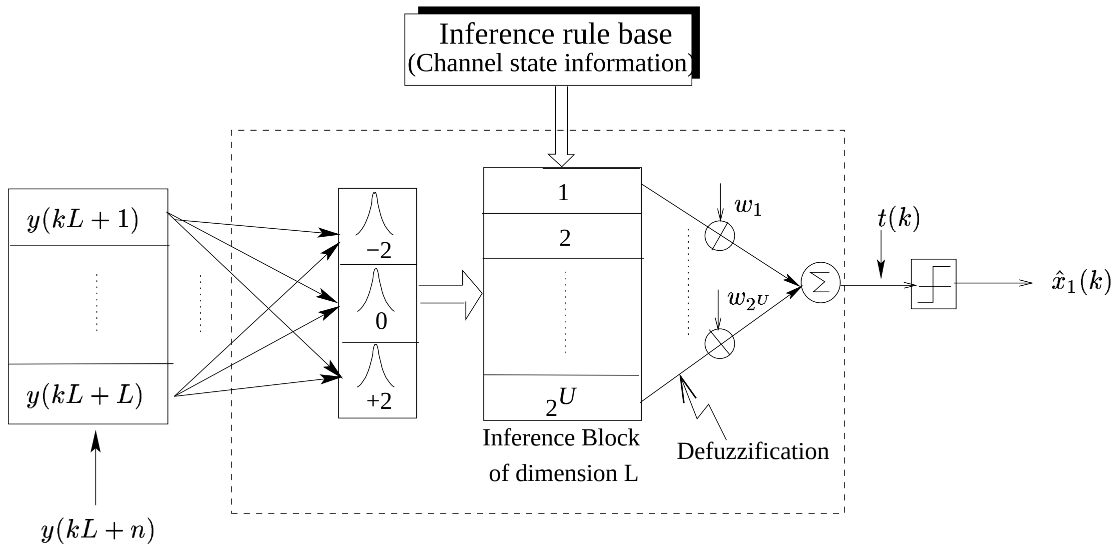


Figure 4.4: *Fuzzy implementation of RBF receiver*

shown in Figure 4.3, feeds the fuzzy filter. The fuzzy filter consists of a fuzzifier with Gaussian membership function. The centres of the membership function are located at points as shown in the Table 5.1, which are derived from noise free received signal states for number of users active in the system. This is presented in Table 5.1 variation in number of users from 1 to 7. The fuzzifier convert the crisp received data from the channel into fuzzy variables. The order of the input to the fuzzifier is L. With this, there are a total of $(U+1)\times L$ fuzzy inputs corresponding to each set of crisp input of order L. The rule base consists of combining one of each membership function from each of the input scalars. With this there are 2^U rules in the rule base, which are generated by combining all possible fuzzifier output taking one from each input scalar of the input vector. The inference rule used here is product inference. The inference block provides 2^U outputs generated with product rule. The defuzzification is achieved with COG defuzzifier. It provides a weighted sum of it's input from inference block with it's set of weights. The receiver so designed is presented in Figure 4.4. This receiver can be considered as an alternative implementation of RBF receiver [53]. The RBF decision function in (4.3) discussed in the previous section can also be represented as

$$t(k) = \sum_{j=1}^{2^U} w_j \left\{ \prod_{n=1}^{L} \exp\left(\frac{-\|y(kL+n) - c_{j,n}\|^2}{2\sigma^2} \right) \right\} \tag{4.4}$$

where $c_{j,n}$ constitute the n^{th} component of the RBF centre and RBF input. The inner product of $exp(.)$ of vector has been replaced by product of $exp(.)$ of scalar terms of the vector. The system shown in the (4.4) is represented by the fuzzy system shown in the Figure 4.4. There are 2^U rules in the rule base. the product inference block of dimension L provides 2^U outputs generated with product rule. The defuzzifier provides a weighted sum of it's inputs from inference block with it's set of weights. The weights associated with the defuzzifier can be optimized with adaptive algorithm during the training process with the training data. Figure 4.4 shows the receiver structure of the receiver when $U = 2$ users are active in the system. This proposed receiver (Fuzzy1) can be considered as an alternative implementation of RBF receiver [22]. The Fuzzy1 receiver can be trained with LMS algorithm as described in the section 3.5 or algorithms like RLS [31].

U	*Possible centre positions*
1	$+1/-1$
2	$+2/0/-2$
3	$+3/+1/-1/-3$
4	$+4/+2/0/-2/-4$
5	$+5/+3+1/-1/-3/-5$
6	$+6/+4/+2/0/-2/-4/-6$
7	$+7/+5/+3/+1/-1/-3/-5/-7$
8	$+8/+6/+4/+2/0/-2/-4/-6/-8$

Table 4.1: *Centre locations of the fuzzifier of Fuzzy1 and Fuzzy2 CLB receiver*

The fuzzy decision function shown in (4.4) can be further simplified as

$$t(k) = \sum_{j=1}^{2^U} w_j \left\{ \min_{n=1}^{L} \left\{ \exp\left(\frac{-\|y(kL+n) - c_{j,n}\|^2}{2\sigma^2} \right) \right\} \right\} \tag{4.5}$$

Here the $\prod_{n=1}^{L}$ rule has been replaced by $\min_{n=1}^{L}$ rule which helps further reduction in computational complexity. In this case the input to the fuzzy filter is $y(kL+n)$. This fuzzy filter consists of fuzzifier with Gaussian membership function as shown in Figure 4.4. The centres of the membership function are located at points as shown in the Table 5.1, depending upon the number of users simultaneously transmitting in the system.There are 2^U rules in the rule base.

the minimum inference block of dimension L provides 2^U outputs generated with minimum rule. The defuzzifier provides a weighted sum of it's inputs from minimum inference block with it's set of weights. The weights associated with the defuzzifier can be optimized with adaptive algorithm like LMS during the training process with the training data. This proposed receiver can be considered as an alternative implementation of RBF receiver. And here it is termed as the Fuzzy2 filter, where the filter function defined in (4.5). (4.4) is termed as the Fuzzy1 filter. The Fuzzy1 uses product inference where as Fuzzy2 provides minimum inference.

4.4 Computational complexity issues

In this section, we discuss the computational complexity requirements for implementing the fuzzy DS-CDMA CLB receiver. The fuzzy receiver complexity is compared with RBF receiver. The computational complexity for the Fuzzy1, Fuzzy2 and CLB RBF receiver is presented in Table 4.2. The table presents the general computational complexity associated with the three types of receivers. Again complexity for cases with 2 and 7 users are also discussed in particular.

U	*Technique*	*Centres/ Rule*	*Multiplication.*	*Addition/ Subtraction/ Comparison*	$exp(.)$
	RBF	2^U	$2^U \times L + 2^U$	$2^U \times (L-1) + 2^U$	2^U
	Fuzzy1	2^U	$2^U \times (L-1)$ $+2^U + L \times (U+1)$	$L \times (U+1) + 2^U$	$(U+1) \times L$
	Fuzzy2	2^U	$2^U + L \times (U+1)$	$(U+1) \times L$ $2^U + (L-1) \times 2^U$	$(U+1) \times L$
2	RBF	4	32	28	4
	Fuzzy1	4	49	25	21
	Fuzzy2	4	25	49	21
7	RBF	128	1024	896	128
	Fuzzy1	128	952	184	56
	Fuzzy2	128	184	952	56

Table 4.2: *Computational complexity for CLB receivers using RBF, Fuzzy1 and Fuzzy2*

From the table it is seen that, when 2 users are active, the RBF receiver will have $2^U = 4$ centres each with a dimensionality of $L = 7$. The Fuzzy1 and Fuzzy2 receivers will have $(U+1)$ membership function and $2^U = 4$ product and minimum inference rules respectively.

When the number of users increased to 7, the number of RBF centres increases to 128 same as the number of inference rules in the Fuzzy1 and Fuzzy2 CLB receivers. From the table it can be seen that, the fuzzy based CLB receivers provide RBF implementation of CLB receiver with considerable computational complexity reduction in terms of multiplication, addition and $exp(.)$ calculations. Additionally the computational complexity reduction achieved with the fuzzy receiver increases with respect to RBF receiver with increase in number of active users in the system. The Fuzzy2 receiver reduces the multiplications considerably.

4.5 Simulation results

In order to validate the proposed fuzzy CLB receivers for DS-CDMA applications, extensive simulation studies were conducted. The results obtained were compared with the CLB receiver using RBF network and simple linear receiver like MF. All the simulation studies were conducted on a $P - IV$@1.9GHz PC with 512MB of RAM with Redhat 9.0 operating system. GNU C++ compiler is used to test the simulations. During the training period the receiver parameters were optimized/ trained with 1000 random samples and the parameters so obtained were averaged over 50 experiments. The parameters of the receiver were fixed after the training phase. The receiver weights were trained using gradient search algorithm like LMS.

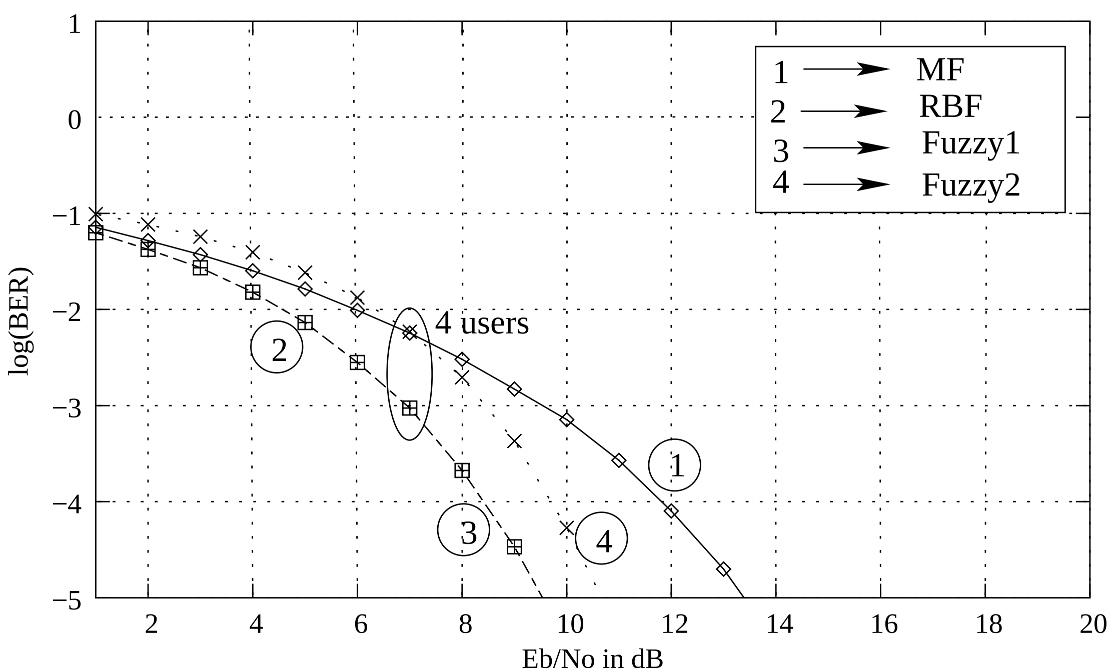


Figure 4.5: *BER performance for varying E_b/N_o with 4 users being active in the system*

Bit error rate (BER) was considered as the performance index. Monte Carlo simulation were conducted to estimate the BER performance of the fuzzy CLB receivers and the performance was compared with CLB RBF and linear MF receivers. In all the experiments randomly generated $+1/-1$ samples were transmitted for each user. These samples were spread using Gold sequence of length 7 corresponding to each of the users. This restricted the maximum permissible user's in the system to 7. After spreading, the sequences were added and transmitted through the non-dispersive channel. The channel corrupted the transmitted signal with AWGN. The channel output was fed to the various receiver structures. A total of 10^7 bits were transmitted by each user and a minimum of 1000 errors were recorded. The tests were conducted for different levels of E_b/N_o. Additionally tests were also conducted by varying number of active users in the system for fixed value of E_b/N_o.

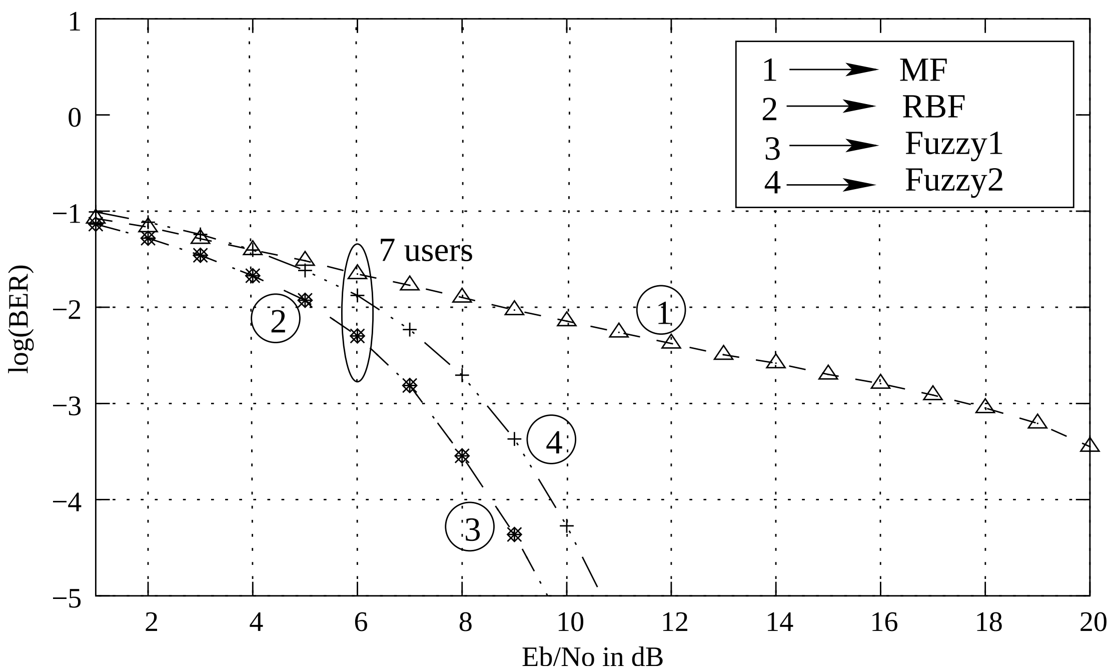


Figure 4.6: *BER performance for varying E_b/N_o with 7 users being active in the system*

In the first test we considered a non-dispersive channel. BER performance of the four type of receivers with 4 and 7 users active in the system is shown in the Figure 4.5 and Figure 4.6 respectively for various values of E_b/N_o in the channel. From the simulation studies it is seen that performance degradation of the MF at a BER of 10^{-5} is about 4dB as compared to the RBF/Fuzzy1 CLB receiver and about 2.5dB as compared to the Fuzzy2 CLB receiver. Similarly from the Figure 4.6 it is seen that performance degradation of the MF at a BER of 10^{-3} is about 10dB as compared to the RBF/Fuzzy1 CLB receiver and about 7.5dB as compared to the Fuzzy2 CLB receiver. Here it is seen that when number of users are 7, The MF receiver performance does not improve considerably with increase in E_b/N_o. The performance degradation of the MF is high $w.r.t$ to increase of active users U in the system as compared to RBF/ Fuzzy1/ Fuzzy2 CLB receiver.

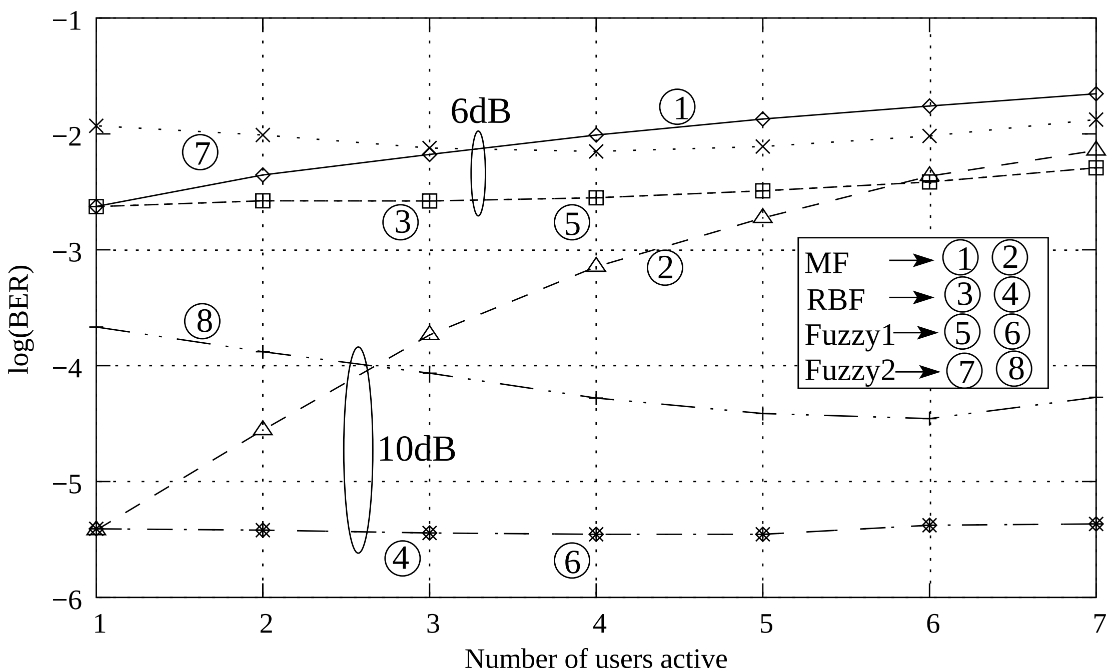


Figure 4.7: *Performance of chip-level receivers in AWGN, 7-chip spreading sequence, with varying number of users active in the system*

Subsequently the BER performance of the receivers were studied for E_b/N_o values of 6dB and 10dB at the channel output against change in loading in form of number of users being active in the system. The results were plotted in Figure 4.7. From this it can be seen that Fuzzy1 receiver performs exactly same as the optimal DRBF receiver. The performance of the proposed Fuzzy2 receiver is in between MF and the optimal RBF receiver for all loading conditions. Here the number of active users varied from 1 to 7. From the graph it is seen that for a fixed value of BER when E_b/N_o at the channel output improves, more number of users can be accommodated in the system. The simulation studies show that the proposed Fuzzy1 receiver is an implementation of optimal RBF receiver and provides the same performance for a reduced computational complexity. Where as the proposed Fuzzy2 receiver provides performance in between MF and RBF receiver with reduced computational complexity compared to RBF receiver. This provides a performance tradeoff for complexity.

4.6 Conclusion

In this chapter RBF based CLB receiver has been implemented with fuzzy system. The fuzzy receivers proposed uses Gaussian membership function, product/ minimum inference and centre of gravity (COG) defuzzifier. The Fuzzy1 receiver with product inference provides computational complexity reduction over the optimal RBF receiver and it provides a performance exactly same as the RBF receiver. The proposed Fuzzy2 receiver with minimum inference provides further reduction in computational complexity over the optimal DRBF receiver outperforms the conventional MF but the performance is poor as compared to the optimal DRBF.

Chapter 5
Fuzzy implementation of the RBF MUD receiver for DS-CDMA

5.1 Introduction

Multiuser Detection deals with the demodulation of mutually interfering digital streams of information. Cellular telephony, satellite communication, high-speed data transmission lines, digital radio/ television broadcasting, fixed wireless local loops, and multi track magnetic recording are some of the communication systems that are affected by multiple access interference (MAI). The superposition of transmitted signals may originate from non-ideal characteristics of the transmission medium, or it may be an integral part of the multiplexing method as in the case of DS-CDMA. Multiuser Detection exploits the considerable structure of the MAI interference in order to increase the efficiency with which channel resources are employed. The principle of working of MUD receiver for DS-CDMA was introduced in 2.7.

Considering DS-CDMA a non-linear classification problem, it has been shown that the non-linear receivers always outperform the conventional linear receivers [13]. Existing non-linear receivers based on artificial neural network (ANN) [54], radial basis function (RBF) [55], polynomial series networks [56], recurrent networks [57] can approximate the decision boundary well and possess superior performance, but at an expense of higher computational complexity and larger training time. Therefore possesses considerable difficulty in implementation.

Since the optimal decision boundary in DS-CDMA is non-linear [55], this problem was solved adaptively by employing the use of a non-linear radial basis function (RBF) network [14, 15], with excellent performance achieved at an expense of increased computational complexity. Its complexity in terms of number of center calculation grows exponentially with increase in number of users. Thus optimal MUD receiver structure with reduced complexity is investigated here, which cancels the effect of corruption of the transmitted signal by the communication channel and background noise. In equalization applications fuzzy receivers provides considerable computational complexity reduction with respect to the RBF receivers and provides exactly the same bit error rate (BER) performance as the RBF receiver.

Following this introduction, DS-CDMA system model is discussed in the section 5.2. The next section 5.3 provides discussion on adaptive fuzzy implementation of MUD receiver for DS-CDMA. The performance of the proposed receivers with other standard receivers is discussed. In the section 5.4 computational complexity reduction issues are analyzed. Then simulation studies validates the proposed receivers. The last section provides the concluding remarks.

5.2 DS-CDMA system consideration

The system model considered here presented in Figure 5.1 and earlier discussed in the section 4.2. It shows the downlink scenario where the mobile unit receives signal $y(kL+n)$ from the base station. The information bits corresponding to one of U users is denoted as $x_i(k)$ takes the values $+1/-1$ with equal probability. k denotes the time index of user transmitted symbols. The information bits transmitted by each user are convolved with each of the mutually orthogonal spreading sequence $C_{i,n}$ where $1 \leq i \leq U$ (number of users active) and $1 \leq n \leq L$ (spreading sequence length).

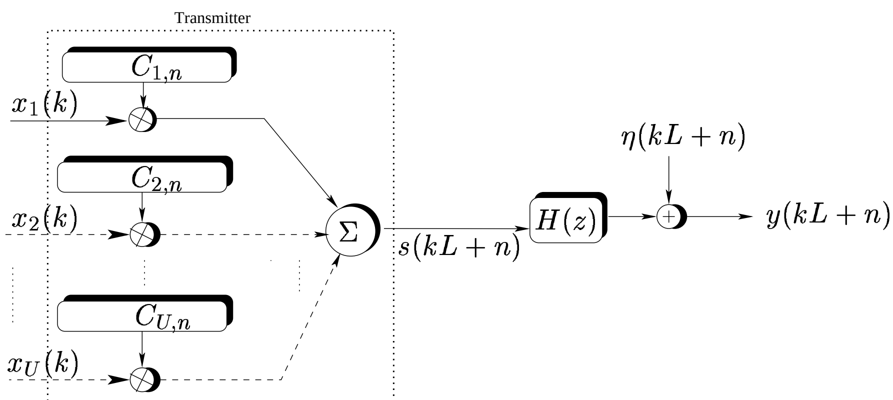


Figure 5.1: *Conventional synchronous DS-CDMA downlink transmitter*

Gold codes, convolutional codes, Pseudo-noise (PN) are the some of the coding techniques used. With this the bandwidth of $x_i(k)$ is enhanced. the processing gain of the system is defined as $PG = \frac{W}{B}$ where, W denotes the spreaded signal bandwidth and B id the unspreaded signal bandwidth. The spreaded signal from each of the user are combined to form

$$s(kL+n) = \sum_{i=1}^{U} x_i(k) C_{i,n} \tag{5.1}$$

which is transmitted through the channel $H(z)$. The channel corrupts the signal with inter

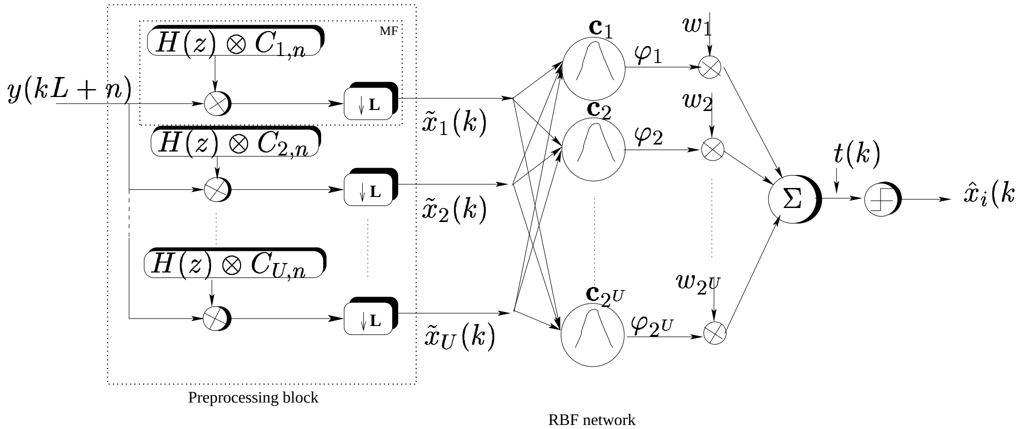


Figure 5.2: *RBF receiver with preprocessing stage*

symbol interference (ISI) and effects of fading. Additive white Gaussian noise (AWGN) also gets added to the signal. With this the received signal $y(kL+n)$ can be represented as

$$y(kL+n) = H(z) \otimes s(kL+n) + \eta(kL+n) \tag{5.2}$$

where $\otimes$ denotes the convolution and $\eta(kL+n)$ is the AWGN component at the chip rate. The job of the receiver is to estimate $x_i(k)$ of the desired user using the information content in $y(kL+n)$. The receiver receives the input signal at chip rate n and processes the signal at sample rate k. This type of receiver are called multiuser detection (MUD) receiver. The structure of MUD receiver using RBF is shown in Figure 5.2. To combat the effect of MAI and channel ISI, the received signal $y(kL+n)$ is fed to a preprocessor block. If there are U simultaneously transmitting users in the system then the preprocessing stage consists of a bank of U MFs and in presence of channel ISI this filter is replaced by RAKE receivers [11]. The performance of a MUD receiver has seen to be better then a linear receiver since the linear receivers does not have any process of removing MAI. The preprocessing block is shown in Figure 5.2, at the front end of the RBF receiver. The synchronized received signal $y(kL+n)$ of length L, is mapped to signal $\tilde{\mathbf{x}}(k) = [\tilde{x}_1(k), \ldots, \tilde{x}_U(k)]^T$ of length U. This preprocessor output is fed to the RBF network. This reduces the dimension of a DS-CDMA receiver's input vector from L to U. The preprocessing based (PPB) RBF receiver process signal vector $\tilde{\mathbf{x}}(k)$ and outputs the estimated value of the k^{th} bit of the desired user $\hat{x}_i(k)$. The output of the RBF network is presented as

$$t(k) = \sum_{j=1}^{2^U} w_j \exp\left(\frac{-\|\tilde{\mathbf{x}}(k) - \mathbf{c}_j\|^2}{2\sigma^2}\right) \tag{5.3}$$

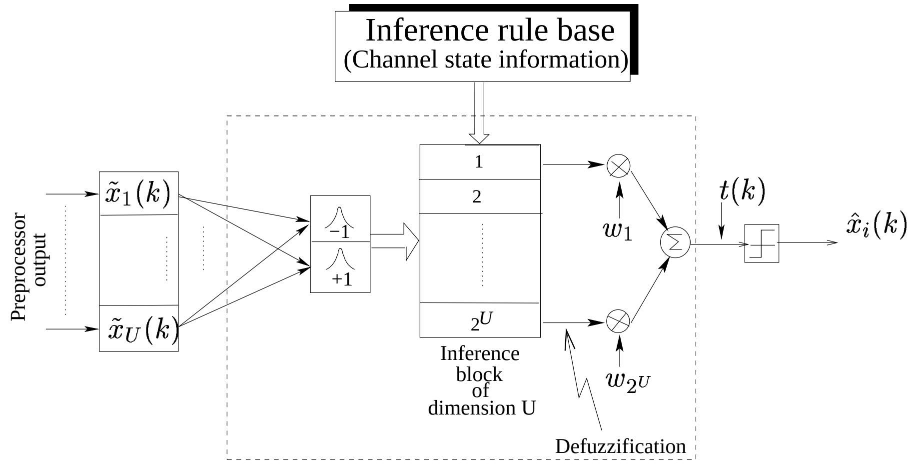


Figure 5.3: *Fuzzy implementation of RBF receiver*

where RBF has 2^U centres of dimension U, σ is the centre spread parameter and w_j denotes the weight associated with each centre. The RBF output $t(k)$ is passed through a hard limiter to provide $\hat{x}_i(k)$, estimated value of the transmitted symbol of the desired user $x_i(k)$. As the number of transmitting users increases, the computational complexity of the RBF receiver also increases in terms of number of centres. Without reducing the RBF technique's performance, fuzzy provides considerable implementational advantages over RBF as shown in Figure 5.3.

5.3 Fuzzy Filter for DS-CDMA Multi User Detection Receiver

In the previous section RBF MUD receiver was discussed. This receiver was presented in Figure 5.2. The RBF receiver decision function in (5.3) can be modified by taking product of exponential scalar terms instead of taking the exponential of a vector euclidean distance. Hence (5.2) can be represented as

$$t(k) = \sum_{j=1}^{2^U} w_j \left\{ \prod_{i=1}^{U} \exp\left(\frac{-\|\tilde{x}_i(k) - c_{j,i}\|^2}{2\sigma^2} \right) \right\} \tag{5.4}$$

where $1 \leq i \leq U$ constitute the i^{th} components of the RBF centre and RBF input. The inner product of $exp(.)$ of vector has been replaced by product of $exp(.)$ of scalar terms of the vector. The function presented in (5.4) can be presented as the fuzzy system as shown in Figure 5.3. The output of the preprocessing block constituting the bank of MFs shown in Figure 5.2, feeds the fuzzy filer. The fuzzy filter consists of fuzzifier with Gaussian membership function. The centres of the membership function are located at -1 and $+1$. These fuzzifiers convert the crisp data from the preprocessor into fuzzy variables. The order of the input vector to the fuzzifier is U and the input from each of these U inputs is fed to the fuzzifier. With this, there are a total of $2U$ fuzzy inputs corresponding to each set of crisp input of order U. The rule base consists of combining one of each membership function from each of the input scalars. With this there are 2^U rules in the rule base, which are generated by combining all possible fuzzifier output taking one from each input scalar of the input vector. The inference rule used here is product inference. The inference block provides 2^U outputs generated with product rule. The defuzzification is achieved with center of gravity defuzzifier. It provides a weighted sum of it's input from inference block with it's set of weights. The receiver so designed is presented in Figure.5.3. This receiver (Fuzzy1 MUD) can be considered as an alternative implementation of RBF MUD receiver widely discussed in literature [53].

An example is considered to describe the detail design of the fuzzy receiver discussed here. If the number of users in the scenario discussed here is $U = 2$, there will be $2U = 4$ fuzzified inputs to the inference engine from a total of 2 input scalars constituting the input vector. The number of rule base is $2^U = 4$ and the output defuzzifier combines these 4 inference outputs with suitable weights. If the number of active user increases to 6 the number of fuzzy inputs will be $2U = 12$ and number of inference rule will be $2^U = 64$.

Considering each of the exponential terms to be < 1, their product results in an rule output < 1. Hence we can replace the product rule here by minimum inference to reduce computational complexity at the cost of some errors. The decision function is shown in (4.4).

$$t(k) = \sum_{j=1}^{2^U} w_i \left\{ \min_{i=1}^{U} \left\{ \exp\left(\frac{-\|\tilde{x}_i(k) - c_{j,i}\|^2}{2\sigma^2} \right) \right\} \right\} \tag{5.5}$$

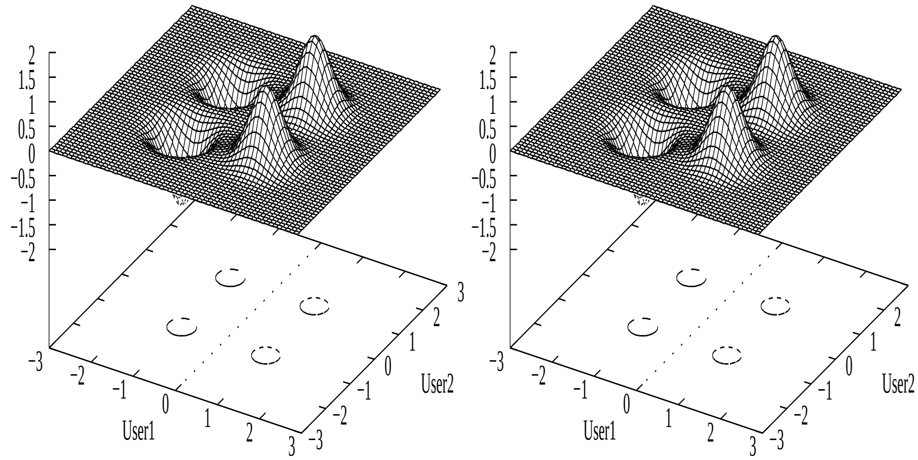
In this case the input to the fuzzy filter is $\tilde{\mathbf{x}}(k)$. This fuzzy filter consists of fuzzifier with Gaussian membership function as in Figure 5.3. The centres of the membership function are located at $+1/-1$. There are 2^U rules in the rule base. The minimum inference block of dimension U provides 2^U outputs generated with minimum rule. The defuzzifier provides a weighted sum of it's inputs from minimum inference block with it's set of weights. The weights associated with the defuzzifier can be optimized with adaptive algorithm like LMS during the training process with the training data. This proposed receiver is termed as Fuzzy2 MUD receiver in this thesis and is considered as an alternative implementation of RBF/Fuzzy1 receiver.

U	*Tech-que*	*Centres/ Rule*	*Multiplication.*	*Addition/ Subtraction/ Comparison*	$exp(.)$
	RBF	2^U	$2^U \times U + 2^U$	$2^U \times (U-1) + 2^U$	2^U
	Fuzzy1	2^U	$2^U \times (U-1)$ $+2^U + 2 \times U$	$2 \times U + 2^U$	$2 \times U$
	Fuzzy2	2^U	$2 \times U + 2^U$	$2 \times U + 2^U$ $+(U-1) \times 2^U$	$2 \times U$
2	RBF	4	12	8	4
	Fuzzy1	4	12	8	4
	Fuzzy2	4	8	12	4
7	RBF	128	1024	896	128
	Fuzzy1	128	910	142	14
	Fuzzy2	128	142	910	14

Table 5.1: *Computational complexity for CLB receivers using RBF, Fuzzy1 and Fuzzy2*

5.4 Computational complexity issues

In this section, we discuss the computational complexity requirement for implementing the fuzzy DS-CDMA MUD receivers. We also compare fuzzy receivers complexity with RBF receiver. The computational complexity for the Fuzzy1 MUD, Fuzzy2 MUD and RBF MUD receiver have been presented in Table.5.1. The table shows the computational complexity requirement of the receiver in general and for $U = 2$ and $U = 7$ users in particular are active in the system. When 2 users are active the RBF MUD receiver has $2^2 = 4$ centres each with a dimensionality of 2. The fuzzy receiver will use $2U = 4$ membership functions and $2^U = 4$ inference rules. When the number of user increases to 7, the number of RBF centres increases to 128 so as the number of inference rules in the fuzzy filter. From the table it can be seen that, the fuzzy based MUD receivers provides the RBF implementation of MUD receiver with considerable computational complexity reduction in terms of multiplication, addition and $\exp(.)$ calculations. Additionally the computational complexity reduction achieved with the fuzzy receiver increases with respect to RBF receiver with increase in number of active users in the system. It is also seen that the Fuzzy2 receiver minimizes the need of multiplication considerably and replaces them with comparison operations. The Fuzzy receivers provide considerable complexity reduction in terms of $exp(.)$ calculation.

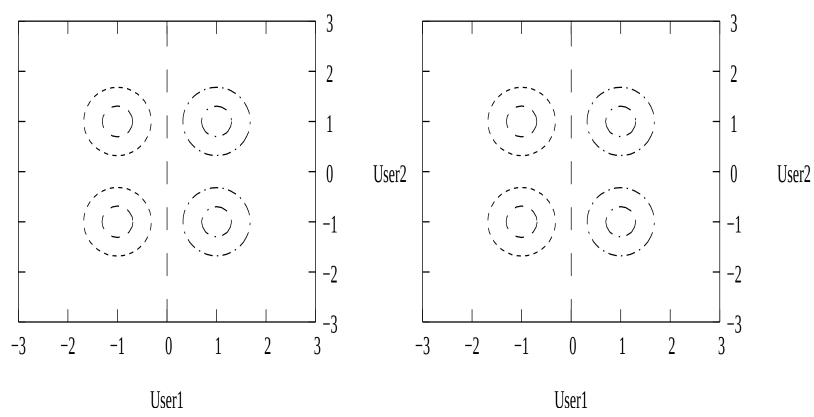


(a) RBF Receiver　　**(b)** Fuzzy1 Receiver

Figure 5.4: *Surface plot of RBF and Fuzzy1 MUD receiver at* $E_b/N_o = 7dB$ *for the channel* $0.3482 + 0.8704z^{-1} + 0.3482z^{-2}$

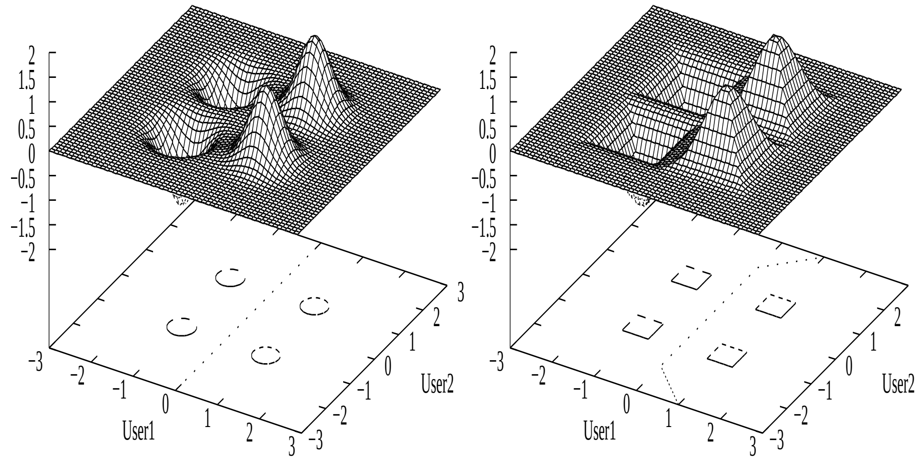
5.5 Simulation results

Extensive simulation studies were conducted to validate the proposed fuzzy MUD receivers for DS-CDMA application. The results obtained were compared with MUD receivers using RBF network and simple linear MMSE receiver using LMS training. During the training period the receiver parameters were optimized/ trained with 1000 random samples and the parameters so obtained were averaged over 50 experiments. The parameters of the receiver were fixed after



(a) RBF Receiver　　**(b)** Fuzzy1 Receiver

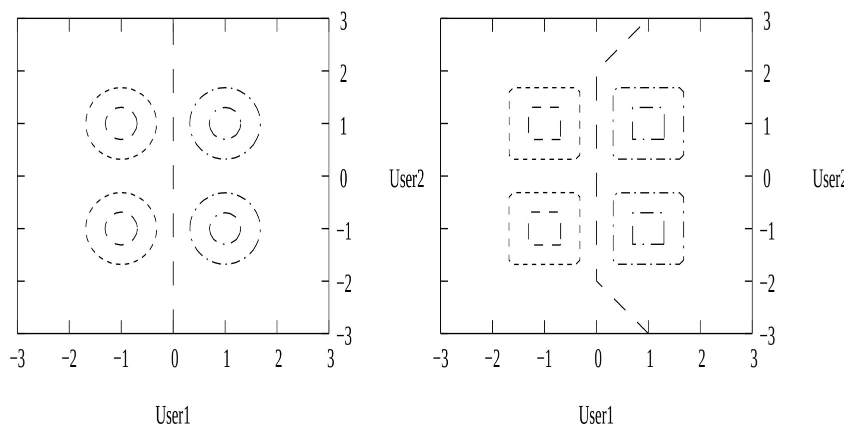
Figure 5.5: *Decision boundary of RBF and Fuzzy1 MUD receiver at* $E_b/N_o = 7dB$ *for the channel* $0.3482 + 0.8704z^{-1} + 0.3482z^{-2}$



(a) RBF Receiver **(b)** Fuzzy2 Receiver

Figure 5.6: *Surface plot of RBF and Fuzzy2 MUD receivers at* $E_b/N_o = 7dB$ *for the channel* $0.3482 + 0.8704z^{-1} + 0.3482z^{-2}$

the training phase. All the receiver parameters were trained with the same set of training samples. The RBF and Fuzzy1 MUD receiver decision function surface along with their decision boundaries with 2 active users is plotted in Figure 5.4 and Figure 5.5 respectively. From this it can be seen that Fuzzy1 MUD receiver provides a decision boundary exactly same as the RBF MUD receiver.



(a) RBF Receiver **(b)** Fuzzy2 Receiver

Figure 5.7: *Decision boundary of RBF and Fuzzy2 MUD receiver at* $E_b/N_o = 7dB$ *for the channel* $0.3482 + 0.8704z^{-1} + 0.3482z^{-2}$

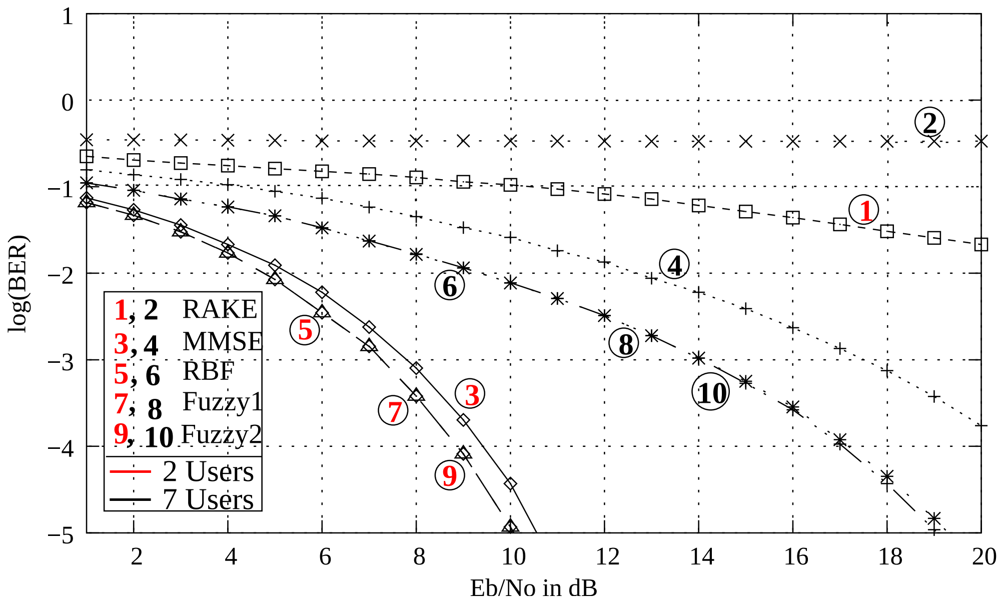


Figure 5.8: *Performance of bit-level receivers in AWGN, 7-chip spreading sequence,with varying E_b/N_o, channel considered is* $0.5 + 1.0z^{-1}$

The surface plot of decision function given in (5.5) is plotted in Figure 5.6 and Figure 5.7 respectively shows the decision boundary with 2 active users in the system. From the figures the difference between the decision boundary of RBF MUD and Fuzzy2 MUD receiver can be visualized. From all the figures it is seen that the fuzzy receiver is able to provide a decision boundary which closely resembles the RBF receiver decision boundary. The channel considered is $0.3482 + 0.8704z^{-1} + 0.3482z^{-2}$ at a noise level of $E_b/N_o = 7$dB. The x and y axis represents the user transmitted data varying between $+3$ to -3. The $z-$axis represents the MUD receiver output.

In the next phase of simulation studies, bit error rate (BER) was used as the performance index. Monte Carlo simulations were conducted to estimate the the BER performance of the fuzzy receivers and were compared with RBF MUD receiver and the conventional linear receivers. In all the experiments, randomly generated $+1/-1$ samples were transmitted for each user. These samples were spread with Gold sequence of length 7 corresponding to each of the users. The maximum permissible users in the system was limited to 7 due to length 7 Gold sequence. After spreading, the sequences were added and transmitted through the channel. The channel corrupted the transmitted signal with inter symbol interference (ISI) and AWGN. The channel output was fed to the preprocessor consists of a bank of MFs, which provides the input to the RBF/ fuzzy receivers. A total of 10^7 bits were transmitted by each user and a minimum 1000

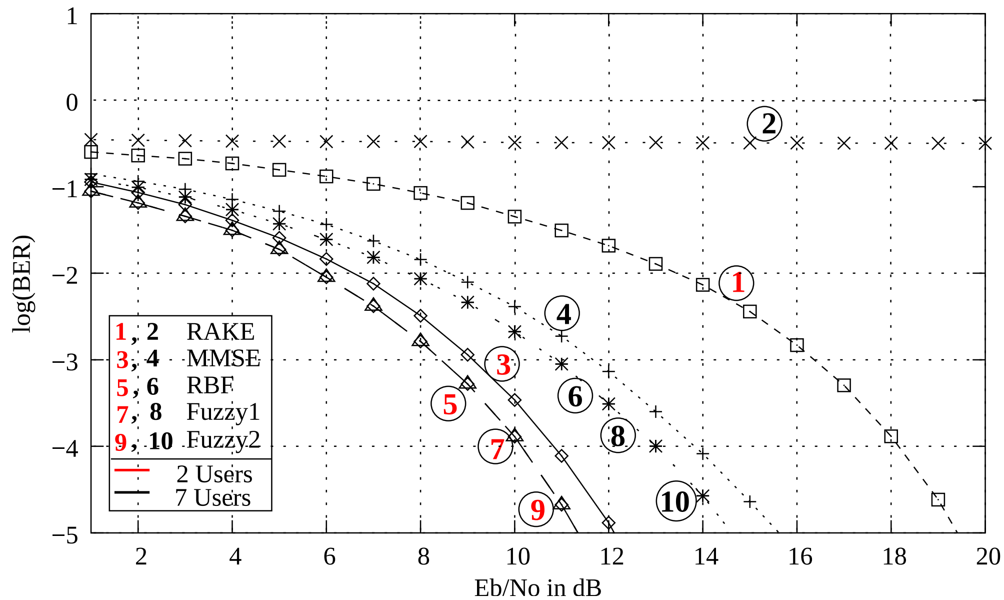


Figure 5.9: *Performance of bit-level receivers in AWGN, 7-chip spreading sequence,with varying E_b/N_o, channel considered is* $0.407 - 0.815z^{-1} - 0.407z^{-2}$

errors were recorded. The test were conducted for different levels of E_b/N_o and varying number of users active in the cell. In the first test, the channel was characterized by its transfer function $H(z) = 0.5 + 1.0z^{-1}$. This is a nonminimum phase channel with zero located outside the unit circle. The BER performance of the five types of the receivers viz RAKE receiver, MMSE receiver with LMS training, RBF MUD receiver, Fuzzy1 and Fuzzy2 MUD receiver with 2 users and 7 users active in the system is shown in the Figure 5.8. From the BER performance it can be seen that the Fuzzy1 MUD provides a performance which is exactly same as the RBF receiver and Fuzzy2 MUD receiver provides a performance which closely resembles RBF receiver. When the active users in the system is 2 the performance of the MMSE receiver is comparable to that of the RBF receiver. But the performance of the RAKE receiver is worse even the number of active users in the system is less. From the simulation studies it is seen that performance degradation of the MMSE receiver at a BER of 10^{-3} is 3.5dB as compared to the RBF/ Fuzzy1/ Fuzzy2 MUD receiver when $U = 7$ active users are simultaneously transmitting in the system. When $U = 2$ users are active this performance loss is about 0.5dB at BER of 10^{-5}. With 7 active users RAKE receivers nearly fails to provide acceptable performance even at very high E_b/N_o. Similar results were obtained for the channels $0.407 - 0.815z^{-1} - 0.407z^{-2}$. This is a mixed phase channel with one zero inside and one zero outside the unit circle. In this case the performance degradation of the MMSE receiver at a BER of 10^{-5} is 0.5dB to 1dB as compared to RBF/ Fuzzy1/ Fuzzy2 MUD receiver. This is shown in the

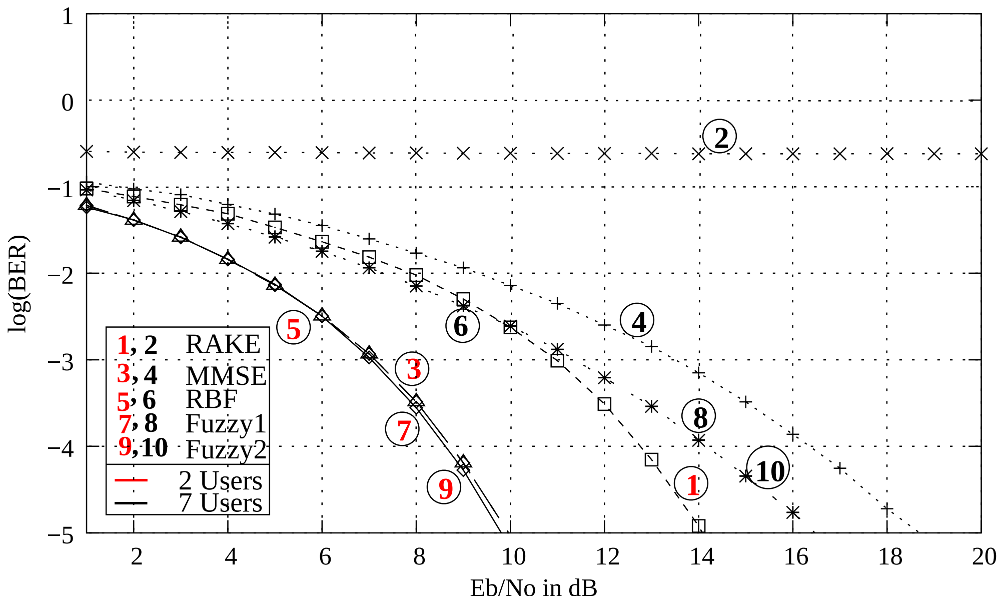


Figure 5.10: *Performance of bit-level receivers in AWGN, 7-chip spreading sequence,with varying E_b/N_o, channel considered is* $1.0 + 0.5z^{-1} + 0.2z^{-2}$

Figure 5.9. Additionally the RAKE receiver performance is very low. Figure 5.10 shows the performance of the receivers, when channel considered is $1.0 + 0.5z^{-1} + 0.2z^{-2}$. This is a minimum phase channel with zeros inside the unit circle. In this case the performance of the MMSE receiver as compared to RBF/ Fuzzy1/ Fuzzy2 MUD receiver is indistinguishable when $U = 2$ users active in the system. The performance loss of the RAKE receiver is 4dB at BER of 10^{-5}. The performance of the MMSE receiver is 2.5dB below then that of the RBF/ Fuzzy1/ Fuzzy2 MUD receiver when BER is kept at 10^{-5} for all the receivers when 7 users are active in the system. When the users increases the performance of the RAKE receiver is indifferent irrespective of the high value of E_b/N_o at the channel input.

The performance of the receivers corresponding to the channel $0.3482+0.8704z^{-1}+0.3482z^{-2}$ is shown in the Figure 5.11. This channel is a mixed phase channel with one zero inside and one zero outside the unit circle. When the active users in the channel is 2, MMSE receiver performance is about 2dB below then the RBF/ Fuzzy1/ Fuzzy2 MUD receivers at a BER value of 10^{-5}. The performance of the RAKE receiver is worse irrespective of the users active and the value of E_b/N_o at the channel input. The performance of the MMSE and the RAKE receiver saturates for higher value of U as shown in the Figure 5.11. In this case it is seen that the performance degradation of the MMSE receiver at BER of 10^{-2} is 8dB as compared to the RBF/ Fuzzy1/ Fuzzy2 MUD receiver when $U = 7$ active users are simultaneously transmitting.

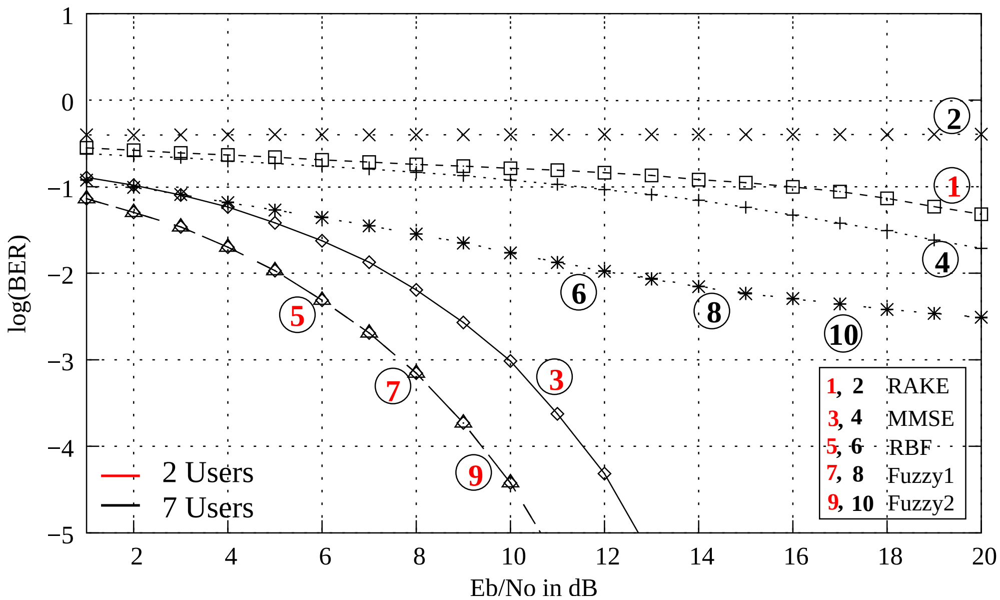


Figure 5.11: *Performance of bit-level receivers in AWGN, 7-chip spreading sequence,with varying E_b/N_o, channel considered is* $0.3482 + 0.8704z^{-1} + 0.3482z^{-2}$

Subsequently the BER performance of the receivers were studied for fixed E_b/N_o values of 2dB and 10dB, at the channel output against varying loading conditions by changing the numbers of active users from 1 and 7 users being active in the system. First the channel considered was $0.5 + 1.0z^{-1}$. These results were plotted in the Figure 5.12. Here the number of active users varied from 1 to 7.

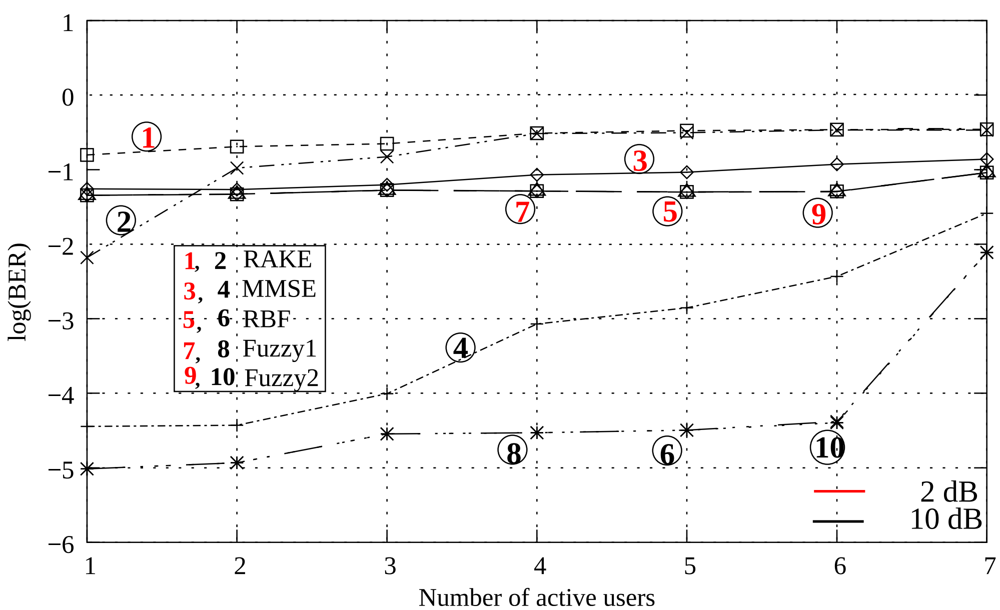


Figure 5.12: *Performance of bit-level receivers in AWGN, 7-chip spreading sequence,with varying number of users U, channel considered is* $0.5 + 1.0z^{-1}$

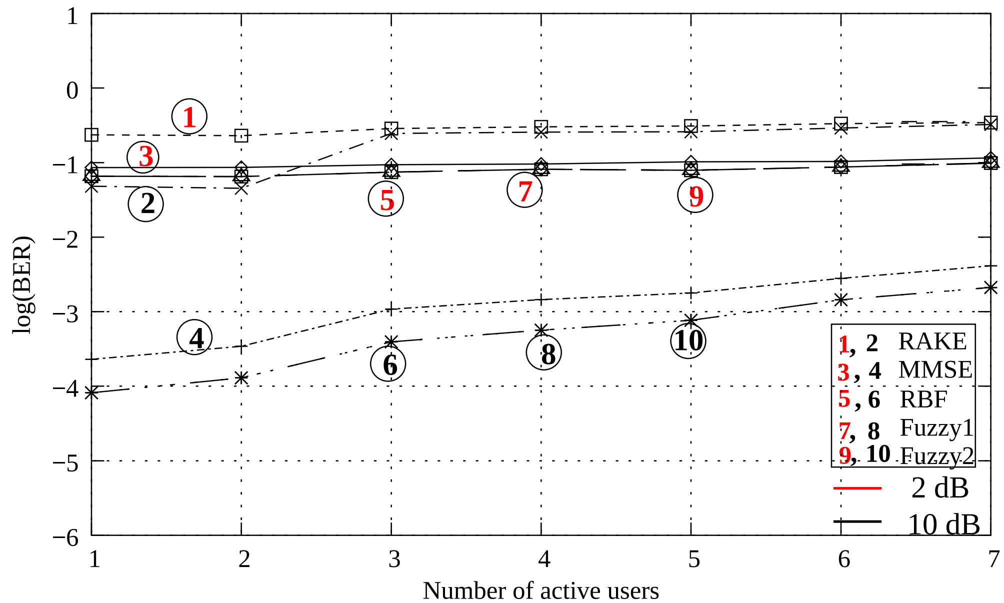


Figure 5.13: *Performance of bit-level receivers in AWGN, 7-chip spreading sequence,with varying number of users U, channel considered is* $0.407 - 0.815z^{-1} - 0.407z^{-2}$

From this graph it can be seen that for a fixed value of BER when E_b/N_o at the channel output increases, more number of users can be accommodated in the system using RBF/ Fuzzy1/ Fuzzy2 MUD receiver, keeping the system performance same.

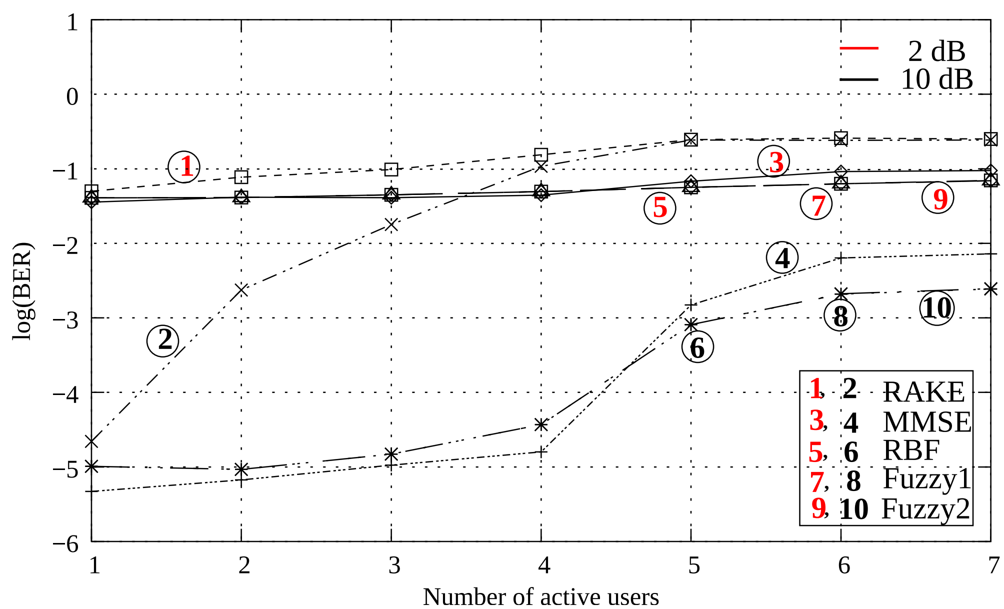


Figure 5.14: *Performance of bit-level receivers in AWGN, 7-chip spreading sequence,with varying number of users U, channel considered is* $1.0 + 0.5z^{-1} + 0.2z^{-2}$

For example, when BER= 10^{-4}, RBF/ Fuzzy1/ Fuzzy2 MUD receiver can accommodate 6 users where as MMSE receiver can accommodate only 3 users for a E_b/N_o value of 10dB is shown in the Figure 5.12. Figure 5.13 shows the BER performance of the receivers for varying values of active users in the system when the channel impulse response is $0.407 - 0.815z^{-1} - 0.407z^{-2}$. The graphs were plotted for the E_b/N_o values of 2dB and 10dB. Active users in the system is varied from 1 to 7. Form the figure it is seen that RBF/ Fuzzy1/ Fuzzy2 MUD receiver can accommodate more number of users as compared to MMSE or RAKE receiver when the performance is kept at 10^{-3} for a E_b/N_o value of 10dB. Similar results were obtained from the channels viz $H(z) = 1.0 + 0.5z^{-1} + 0.2z^{-2}$ and $H(z) = 0.3482 + 0.8704z^{-1} + 0.3482z^{-2}$, and results were plotted in Figure 5.14 and Figure 5.15. respectively.

The extensive simulation studies conducted have demonstrated that the Fuzzy1 and Fuzzy2 MUD receivers provide nearly optimal RBF receiver performance and they outperform the linear MMSE and RAKE receiver performance.

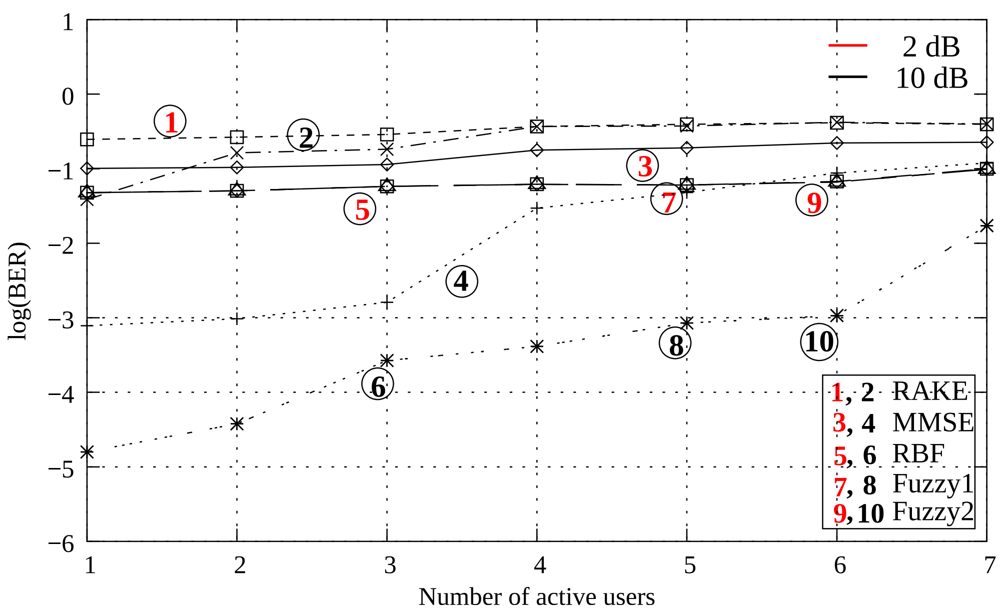


Figure 5.15: *Performance of bit-level receivers in AWGN, 7-chip spreading sequence,with varying number of users* U, *channel considered is* $0.3482 + 0.8704z^{-1} + 0.3482z^{-2}$

5.6 Conclusion

In this chapter non-linear receiver structures using RBF multiuser detection has been implemented with fuzzy system. Two fuzzy methods of constructing the receiver has been considered, and the performance of these receivers has been simulated and shown to outperform conventional linear receivers like MMSE and RAKE receivers. Both types of fuzzy receivers have been shown which provide computational complexity reduction over the RBF MUD receiver. First is the Fuzzy1 MUD receiver with Gaussian membership function as the fuzzifier, product inference engine and center of gravity (COG) defuzzifier provides performance exactly same as RBF MUD receiver with lower computational complexity. The simulation results show that the performance of this proposed Fuzzy1 MUD receiver is exactly same as that of the optimal RBF MUD receiver. Second is the more simplified Fuzzy2 MUD receiver structure. Fuzzy2 MUD receiver consists of Gaussian membership function fuzzifier, minimum inference engine and COG defuzzifier. The proposed Fuzzy2 MUD receiver with minimum inference provides further reduction in computational complexity over the Fuzzy1 MUD receiver. Simulation results demonstrate the performance of the Fuzzy2 MUD receiver. Performance of this proposed receiver is same as that of the RBF/Fuzzy1 MUD receiver.

Chapter 6
Conclusion

6.1 Introduction

The research carried out in this thesis primarily discusses fuzzy system based non-linear receiver structure for DS-CDMA communication system. Fuzzy implementation of CLB and MUD RBF receiver has been presented and the computational advantages of fuzzy receiver has been compared with the conventional receivers like MMSE, MF and RAKE etc. This chapter summarizes the work reported in this thesis, specifying the limitations of the study and provides some indications for future work.

Following this introduction section 6.2 lists the achievements from the work. Section 6.3 provides the limitations and section 6.4 presents indications toward future work.

6.2 Achievement of the thesis

The work presented in this thesis can be seen as made up of two distinct parts. The First part presents the development of CLB fuzzy receivers for AWGN channel[1], secondly, MUD fuzzy receivers have been developed to mitigate the effects of MAI in presence of channel ISI and AWGN[2].

Chapter 4 of this thesis presented new fuzzy implementation of CLB RBF receiver. It is seen that RBF receivers uses estimates of noise free signal vectors to estimate the centres. Fuzzy can also be implemented using RBF with scalar centres. Subsequently, the design of the fuzzy receivers using FAF is presented . Fuzzy receivers designed with FAF were based on LMS fuzzy filters. The computational complexity associated with the RBF receivers makes them difficult for practical implementation as the number of centres increases exponentially with the increase on active transmitting users in the system. Fuzzy implemented RBF CLB receiver

[1]this part is discussed in the chapter 4
[2]this topic is discussed in the chapter 5

reported here uses Gaussian membership function, product/ minimum inference in the form of IF ... THEN ... rules and a COG defuzzifier. The use of fuzzy system in implementing RBF CLB receiver provides flexibility in the design. With use of different forms of inference rules like product or minimum rule and defuzzification processes other forms of near optimal or optimal receivers can be designed. Some of the major contributions of this chapter are summarized here. Fuzzy CLB receivers

- are computationally more efficient then optimal RBF receivers, from the implementational point of view;
- have an ability to use different forms of inference rules, defuzzification processes providing alternate scheme to facilitate compromise between receiver performance and computational complexity;
- provide a performance which is close to RBF receiver.

Chapter 5 of the thesis presented the development of fuzzy MUD receiver to mitigate the effects of MAI from the other users transmitting in the same cell and channel ISI. In presence of MAI, the performance of the linear receivers like RAKE receiver, MMSE receiver drops drastically irrespective of the higher values of E_b/N_o. Linear receiver does not have any process to remove the effects of interference from other users. MUD receiver considers the information contained in MAI as additional information for the detection of the intended data. MUD receiver processes the received signal at bit rate. Hence the dimension of the centre reduces from L to U. MUD receiver with RBF implementation provides optimal performance. The main disadvantage of this receiver is the computational complexity increases in an exponential manner as the number of transmitting users increases. Hence difficult for practical implementation. These computational issues prompted the design of new fuzzy receivers. Fuzzy MUD receives are the fuzzy implementation of the RBF receiver. Two types of fuzzy receivers have been proposed. First one is Fuzzy1 MUD receiver with Gaussian membership fuzzifier where scalar centres are located at $+1/-1$, product inference rule and COG defuzzifier. This Fuzzy MUD receiver provides exactly the same performance a that of optimal RBF MUD receiver. Second is the Fuzzy2 MUD receiver with Gaussian membership function, minimum instead of product inference rule and COG defuzzifier. Performance of Fuzzy2 MUD receiver is nearly same as that of the RBF MUD receiver. The major contribution from this chapter are listed below. The fuzzy MUD receivers:

- provide better performance as compared to linear receivers like RAKE receiver, MMSE receiver. The fuzzy MUD receiver is computationally more efficient then the RBF MUD receivers from the implementational view point.
- can implement different forms of inference rules, defuzzification processes to provide alternate near optimal MUD receivers.

6.3 Limitations of the work

Following are the limitations of the work reported in this thesis:

- The channel model used in the simulation was a stationary channel. In practice the channel suffers from fading in addition to multipath components.
- The work reported in this thesis investigates the receiver in the downlink scenario only. The receiver in the uplink scenario suffers from near-far effect in addition to difficulty in synchronization.
- The studies reported here in used Gold code for spreading. Performance of other coding techniques have not been investigated.

6.4 Scope for further research

From the limitations of the work it can be seen that the work reported in this thesis can be extended for the following:

- **Non stationary channel:-** Where the channel can be additionally affected by Rayleigh fading and Doppler's fading
- The receiver design for uplink scenario to take care of near-far effect and synchronization can also be considered.
- Performance of fuzzy receiver with different type of spreading code.

Excluding this, further work can also be taken up for fuzzy implementation of antenna array receivers for uplink scenario.

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