New Schemes of MUD for Synchronous DS-CDMA and its Overloaded Systems

By

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DEDICATED TO

HOLY PROPHET (P. B. U. H.)

THE GREATEST SOCIAL REFORMER

&

MY DEARLY LOVED FATHER (LATE),

PRAISEWORTHY MOTHER,

LOVING SPOUSE AND KIDS

Abstract

The demand for better techniques in the field of multiuser detection for CDMA and WCDMA systems has grown especially in the last decade. This is due to the exponential growth in the number of subscribers and high data rate requirements due to multimedia and wireless internet services. However, there are many formidable limiting factors on the way to achieving this objective. One of the most challenging issue is the multiple access interference (MAI) in multiuser detection (MUD). Another issue is the computational complexity of the multiuser detector, which grows exponentially with the number of users for maximum likelihood detector (MLD). This will prohibit the use of MLD as multiuser detector unless its computational complexity is decreased substantially. These two major issues have been addressed in this dissertation.

The problem of MAI has been tackled in a simple manner in this dissertation by using the concept of an additional redundant user, named as 'Pseudo-user', for DS-CDMA systems. In this proposed scheme, the matched filters followed by minor linear processing have resulted in the removal of MAI completely. This scheme is theoretically independent of the number of users. However, this has been achieved at the expense of a minor percentage loss in bandwidth and noise enhancement. The percentage loss of bandwidth can be decreased by increasing the number of users.

The complexity issue of MLD has been addressed by using particle swarm optimization (PSO) technique. Two soft versions of PSO have been proposed. The results achieved are almost optimal, but at a much lower computational complexity as compared to that of conventional approach for MLD.

The above two schemes, i.e. the pseudo-user scheme and PSO scheme along with multicarrier modulation, have been applied to WCDMA overloaded systems in order to assert their practical applicability. The proposed schemes were tried on two types of channels ─ simple additive white Gaussian noise (AWGN) channel and slowly flat fading channel. The results have been compared with some standard techniques as well as recently reported techniques in the literature.

List of Publications and Submissions

1. **M. A. S. Choudhry**, A. Naveed, and I. M. Qureshi, "Pseudo-user Concept for Parallel Interference Cancellation in DS-CDMA System," *IEE Electronics Letters*, vol.42, issue 12, p. 707-709, June 8, 2006.
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7. M Zubair, **M. A. S. Choudhry**, A. Naveed, and I. M. Qureshi, "Multiuser

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(Muhammad Aamer Saleem Choudhry)

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List of Abbreviations

1G	First Generation
2G	Second Generation
AMPS	Advanced Mobile Phone Systems
AWGN	Additive white Gaussian Noise
BEPD	Binary Evolutionary Programming Detector
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
BPSOD	Binary Particle Swarm Optimization Detector
CDMA	Code Division Multiple Access
DS	Direct Sequence
EA	Evolutionary Algorithm
EM	Expectation-Maximization
EP	Evolutionary Programming
ES	Evolutionary Strategies
FDMA	Frequency Division Multiple Access
FH	Frequency Hopping
GA	Genetic Algorithm
GD	Gradient Descent

GP	Genetic Programming
GSM	Global System for Mobile Communications
HIC	Hybrid Interference Cancellation
HPIC	Hard Parallel Interference Cancellation
HPSO	Hard Particle Swarm Optimization
ISI	Inter-Symbol Interference
LMMSE	Linear Minimum Mean Square Error
LPIC	Linear Parallel Interference Cancellation
MAI	Multiple Access Interference
MBER	Minimum Bit Error Rate
MC-CDMA	Multi-Carrier Code Division Multiple Access
MLD	Maximum Likelihood Detector
MMSE	Minimum Mean Square Error
MOO	Multi-Objective Optimization
MOPSO	Multiple Objective Particle Swarm Optimization
MSE	Mean Square Error
MUD	Multiuser Detection
OFDM	Orthogonal Frequency Division Multiplexing
PAES	Pareto Archive Evolution Strategy
PCS	Personal Communications Services
PIC	Parallel Interference Cancellation
PN	Pseudo-Noise
PPIC	Partial Parallel Interference Cancellation

PSO	Particle Swarm Optimization
PU-PIC	Pseudo-User Parallel Interference Cancellation
RBF	Radial Basis Function
SCG	Scaled Conjugant Gradient
SC-PIC	Soft Cancellation Parallel Interference Cancellation
SDMA	Space Division Multiple Access
SFFR	Slowly Flat Fading Rayleigh
SIC	Successive Interference Cancellation
SNR	Signal to Noise Ratio
SPSO	Soft Particle Swarm Optimization
SPSO1	Soft Particle Swarm Optimization Version 1
SPSO2	Soft Particle Swarm Optimization Version 2
SUMF	Single User Matched Filter
TDMA	Time Division Multiple Access
WCDMA	Wide-Band Code Division Multiple Access

Chapter 1

INTRODUCTION

1.1 Multiple Access Techniques

Multiple access techniques are involved when multiple users access the communication channel simultaneously. Basic wireless multiple access techniques are frequency division multiple access (FDMA), time division multiple access (TDMA) [1], space division multiple access (SDMA) [2, 3], and code division multiple access (CDMA) [4, 5]. In FDMA, available frequency bandwidth is divided into sub-bands, where each user has a dedicated frequency sub-band for its transmission. First generation (1G) mobile phone systems, advanced mobile phone systems (AMPS), use FDMA for multiple access technique. In case of TDMA the time is divided into slots and each time slot is dedicated to a specific user for its communication. TDMA is used as a multiple access technique for the second generation (2G) mobile communication systems, known as global system of mobile (GSM) [6]. In SDMA the spatial dimension can be utilized for partitioning the users. As the terminology suggests the users are spatially separated from each other. SDMA techniques are invoked for reducing the multiple access interference. In CDMA, all of the available bandwidth and time resources are allocated to all users simultaneously. The users are given distinct codes rather than distinct frequency bands, as in FDMA, or time slots, as in TDMA.

1.2 CDMA Systems

CDMA is based on spread spectrum techniques [7], where each user transmits his signal using a bandwidth much larger than the data rate. This expansion in bandwidth results in frequency diversity, which is advantageous with respect to the frequency selectivity of the mobile radio channel. CDMA also has the advantages of voice activity, privacy, soft capacity limit, soft hand-off capability, and above all the greater uplink capacity [8]. All these technological merits make CDMA as the multiple access technology for next-generation wireless services [9].

CDMA has two major spreading schemes, namely, direct sequence CDMA (DS-CDMA) and frequency hopping CDMA (FH-CDMA). In DS-CDMA, each user is assigned a unique code used as spreading sequence. In FH-CDMA, each user transmits data on a narrow-band frequency slot, which changes according to a pre-assigned pattern, unique to each user. In this dissertation, only DS-CDMA is studied which is deemed to be more suitable for mobile communications. Hence, hereafter CDMA will imply DS-CDMA unless otherwise stated. CDMA can also be divided into short-code and long-code CDMA depending on the period of spreading codes. If the period equals a symbol interval, i.e., the spreading code remains the same symbol by symbol, it is called short-code CDMA, otherwise, it is called long-code CDMA. In long-code CDMA, the spreading code is generated by shift registers and has a period several times longer than a symbol interval. Therefore the statistical properties of spreading codes resemble those of random generated chips. Hence it is also called random-code CDMA.

The choice of a suitable spreading code is very important for attaining good performance in the CDMA communication systems. Traditional spreading sequences, such as *m*-

sequences, Gold codes and Kasami codes [5] exhibit non-zero off-peak auto- and cross-correlations, which results in a high MAI for asynchronous as well as synchronous uplink transmissions [5]. Another family of spreading codes is constituted by orthogonal Walsh codes [5]. They retain their orthogonality only in case of perfectly synchronous transmission, while exhibiting non-zero off-peak auto- and cross-correlations in asynchronous scenarios. Consequently, these imperfect correlation properties limit their achievable performance in asynchronous scenarios. Hence traditional CDMA cellular systems are interference limited and suffer from the ‘near-far’ effects, unless complex and power hungry interference canceller or multiuser detectors (MUD) [5] are employed to combat these adverse effects.

In recent past there has been an ever increasing demand in the capacity which is either due to increase in the number of subscribers, or high data rate requirement of multimedia and wireless internet services. Therefore wideband code division multiple access (WCDMA) has gained tremendous attention [10]-[16]. The multiuser detectors (MUD) for these systems are major research issue. However, the capacity, and hence the data rate of wireless communication are limited due to the obvious reasons of frequency selectivity and time varying nature of the multi-path wireless channel. The other formidable limiting factors for the capacity of the wireless system, especially when the system becomes overloaded, are MAI and computational complexity of MUD. The solution to these limiting factors is the main focus of the dissertation.

1.3 Contributions of Dissertation

The following are the major contributions of this dissertation.

A novel concept of pseudo-user has been introduced in parallel interference cancellation (PIC) detector which we may call pseudo-user PIC (PU-PIC) detector. Ideally it removes MAI completely without any complex computations, but at the expense of a little loss in bandwidth and very little enhancement in the noise.

Maximum likelihood detector (MLD) is not practically used due to its computational complexity, which is of the order of 2^K where K is the number of users. However, it is optimum in the sense of bit error rate (BER). In this dissertation two soft versions of particle swarm optimization (PSO) algorithm have been introduced to recast the complexity problem of MLD. Therefore, near optimum results are achieved with very low computational complexity.

To solve the problem of system overloading, two receivers are also proposed in this dissertation. In the first receiver, the PU-PIC detector along with multicarrier modulation is used to overcome the problem of system overloading. In the second receiver, the combination of proposed PSO algorithm and multicarrier modulation has been used. Thus, the problem of system overloading is efficiently handled with near optimum results.

All above proposed receivers are checked for two different channels to confirm their validity. First one is additive white Gaussian noise (AWGN) channel and the second one is multipath slowly flat fading Rayleigh (SFFR) channel.

1.4 Organization of Dissertation

The dissertation is organized as follows:

Chapter 2 starts with the historical background of multiuser detection. The CDMA signal and channel model are presented next. Fundamental multiuser detectors and their working are also described in this chapter.

Chapter 3 contains the idea of Pseudo-User PIC (PU-PIC) detector which removes MAI with very little computations. PU-PIC detector detects the bits of all users in parallel with the help of the data of a pseudo-user which is already known to all the receivers. Simulation results show that in equal power scenario, the performance of proposed PU-PIC detector is very attractive with very low computations.

Chapter 4 addresses the computational complexity of MLD. PSO based MUD has been performed to recast the computational complexity of optimum MLD and it has given very attractive results. Two soft versions of PSO are proposed in this chapter.

Chapter 5 presents the multiuser detectors for overloaded WCDMA system. In this chapter there are two contributions. The first one is a combination of multicarrier modulation and PU-PIC detector to solve the problem of overloaded system. The second one is the combination of soft version of PSO and multicarrier modulation for an overloaded system.

Chapter 6 concludes the dissertation and gives proposals for the future work.

Chapter 2

MULTIUSER DETECTION

2.1 Introduction

In this chapter, a brief history of multiuser detection is presented first. After that the CDMA signal and channel model are given. Then some working concepts of different multiuser detectors along with the optimum maximum likelihood detectors are given. A brief explanation of the sub-optimal detectors like, conventional single user detector, decorrelating detector and minimum mean square error detector, is also given. Then the interference cancellation techniques like, successive interference cancellation and parallel interference cancellation have been described. Finally the multiuser detection using genetic algorithms and neural networks has also been covered.

2.2 Background

In conventional single-user detection, hard decisions are made simply according to the matched filter outputs. By assigning mutually orthogonal codes to all users, each of them may achieve interference free single-user performance. It is, however, not possible to maintain the orthogonality at the receiver in a mobile environment, and thus MAI appears. It is well known that the MAI can severely degrade the bit error rate (BER) performance of a CDMA system. The conventional detector also suffers from a ubiquitous near-far problem in practice, which means when the received signal energies are very dissimilar; the signal component from a weak user may be buried in the MAI from a stronger user, even if the signature waveforms have very low cross-correlations [10]. Rigid power control is required to ensure that all user signals arrive at about the same power at the receiver. However, the near-far problem is not an inherent weak point of CDMA system. Rather, it is the inability of the conventional single-user receiver to exploit the structure of the MAI. They treat MAI as Gaussian noise which is a kind of loss of information, that may in turn, result in severe performance loss.

The optimum multiuser detector was proposed by Verdu [17] in 1986, known as optimum maximum likelihood detector (MLD). Unfortunately, this detector is too complex for practical CDMA systems, especially when the number of users is large. Therefore, over the last decade, researchers have focused on finding the solutions of MUD [17]-[31], which are feasible to implement in terms of computational complexity and may be suboptimal. The most fundamental group of multiuser detectors is linear multiuser detector, which applies a linear mapping to the soft output of the conventional detector to reduce the MAI observed by each user. The important types of linear detectors are the decorrelating or zero-forcing detector and the minimum mean square error (MMSE) detector [18]. In [19], Wei *et al.* proposed tree-search based multiuser detectors such as the M-algorithm and T-algorithm. For asynchronous CDMA multiuser detection subject to frequency offset was proposed in [20]. In the same year, the adaptive minimum bit error ratio (AMBER) linear multiuser detector was proposed and investigated in [21]. In 2002, Poor and Tanda proposed multiuser detector for flat fading non-Gaussian channels [22]. Joint multiuser detection and channel estimation based on expectation-maximization was proposed in 2003 [23]. In the following year Das and

Varanasi designed optimum noncoherent multiuser decision feedback detector [24]. Recently a non-linear multiuser detector for Rayleigh fading channel has been proposed bt Leong *et al.* [25]. MMSE-based multiuser detection using distributed antennas has been proposed in [26]. Minimum variance and minimum bit error rate multiuser detectors have been also proposed [27-29]. Hanzo *et al.* investigated the uplink performance of large area synchronized CDMA (LAS-CDMA) in [30]. In [31], an objective-function-based multiuser detector was proposed. This detector was based on a multistage approach, which, at every stage, updated one and only one bit corresponding to the largest gain calculated from a given objective function.

For practical implementation the interference cancellation schemes have been a subject of maximum attention. The interference cancellation based multiuser detectors typically achieve an attractive performance versus complexity trade-off [32]. These techniques rely on simple processing elements constructed around the matched filter concept. Interference cancellation techniques comprise parallel interference cancellation (PIC) [33], successive interference cancellation (SIC) [34] and hybrid interference cancellation (HIC) [35]. Different improvements in multiuser detectors based on interference cancellation were proposed [36-46]. In [36], to support a high-user load, a PIC assisted multiuser detector was proposed. Iterative multiuser detectors invoking antenna arrays were investigated in [37]. Honig *et al.* proposed adaptive iterative multiuser decision feedback detection [38]. A fuzzy-based adaptive partial PIC was proposed and investigated by Wen and Huang in [39]. To enhance the performance of PIC, an optimal two-stage decoupled partial PIC was proposed in [40]. Reed *et al.* [41] proposed iterative MUD using turbo coding. Outputs from the matched filters were processed using turbo iterative decoding [42][43]. The complexity of the iterative turbo detector is of the order of $O(2^K)$. For reducing the complexity, PIC-based iterative multiuser detectors were proposed [44]-[46].

Blind multiuser detection, in which receiver does not have the knowledge of signature waveforms, has also been investigated in the literature [47-53]. The blind multiuser detector was first proposed by Honig *et al*. [47]. Wang and Poor introduced subspace algorithm based linear blind multiuser detectors in [48]. Later Wang and Poor extended their work [49] for dispersive asynchronous CDMA systems. This work was enhanced for group-blind multiuser detection for uplink CDMA in [50][51]. In [52], blind iterative multiuser detectors were investigated in the context of unknown interferers. Ricci *et al*. proposed blind multiuser detector based on multi-rate or multi-code CDMA systems [53]. A transmitter optimization for blind and group-blind multiuser detection was proposed in [54]. Li *et al*. proposed multiuser detectors based on sequential expectation-maximization (EM) algorithm in [55]. A nonlinear group-blind multiuser detector was proposed by Spasojevic *et al*. [56].

Genetic Algorithm (GA) based MUD has also been investigated in the literature. Juntti *et al*. [57] proposed iterative hybrid GA based search scheme first time in 1997. In the recent years Yen and Hanzo [58]-[62] have done a lot of work on the performance of GA-based MUD. In [59] Yen and Hanzo achieved near optimum bit error rate (BER) performance for dispersive Rayleigh fading channel with very low complexity. They also proposed GA assisted multiuser detectors based on a truncated window and designed for asynchronous DS-CDMA communicating over multipath fading channels [62]. Yen and Hanzo [63] proposed GA based blind multiuser detector.

In contrast to single-carrier CDMA, multicarrier CDMA (MC-CDMA) exploits the advantages of multicarrier modulation. MC-CDMA systems have also been investigated in the recent years [64]-[76]. Computationally complex MLD for MC-CDMA was proposed by Schnell and Kaiser [71]. To address the complexity of MLD, a LMMSE detector was proposed by Miller and Rainbolt [72] for MC-CDMA systems. In [73] subspace based MMSE multiuser detection and channel estimation was carried out blindly for MC-CDMA systems. The conventional MMSE receiver required exact timing estimation. An error in timing estimation inflicts intersymbol interference (ISI) and inter-subcarrier interference, both of which severely degrade the performance of the detector. To avoid timing estimation problem Zhong *et al*. [74] proposed partial sampling MMSE multiuser detector for MC-CDMA, which requires no timing estimation. An iterative semi-blind multiuser detector for turbo-coded MC-CDMA systems has been proposed recently by Kafle and Sesay [75]. The iterative receiver was capable of blindly suppressing the unknown interference. Zhang *et al*. [76] proposed a simple blind adaptive decorrelating detector for asynchronous MC-CDMA systems over Rayleigh fading channels. This detector did not require channel estimation and was derived by making use of the cross-correlation matrix between the consecutively received signals.

Problem of overloading arises when the number of users, K, in the system exceeds the total number of available spreading sequences. Number of techniques has been investigated to solve the problem of overloading [77]-[85]. Kapur and Varanasi [84] proposed a detector for overloaded CDMA systems. In this dissertation multiuser detection for overloaded MC-CDMA systems has also been investigated.

2.3 CDMA Signal and Channel Model

Low pass equivalent model for a K user synchronous CDMA system is depicted in figure 2.1. Each user is assigned a signature waveform of duration T_b, where T_b is the symbol interval. A signature waveform of k^{th} user may be expressed as

$$g_k(t) = \sum_{n=0}^{L-1} a_n p(t - nT_c), \qquad 0 \le t \le T_b \tag{2.3.1}$$

where $a_n, 0 \le n \le L-1$ is a pseudo-noise (PN) code sequence consisting of L chips that can take values from the alphabet $\{+1, -1\}$, $p(t)$ is a pulse of duration T_c, where T_c is the chip interval, and $T_b = LT_c$. Without loss of generality, we assume that all K signature waveforms have unit energy, i.e.

$$\int_0^{T_b} g_k^2(t)dt = 1 \tag{2.3.2}$$

We shall assume the synchronous transmission throughout the thesis. The cross-correlation in two signature waveforms is defined as

$$\rho_{jk} = \int_0^{T_b} g_j(t) g_k(t) dt \tag{2.3.3}$$

For simplicity, we assume that binary antipodal signals are used to transmit the information from each user. As the transmission is synchronous, we consider the interval and the signal corresponding to the transmission of only one bit.

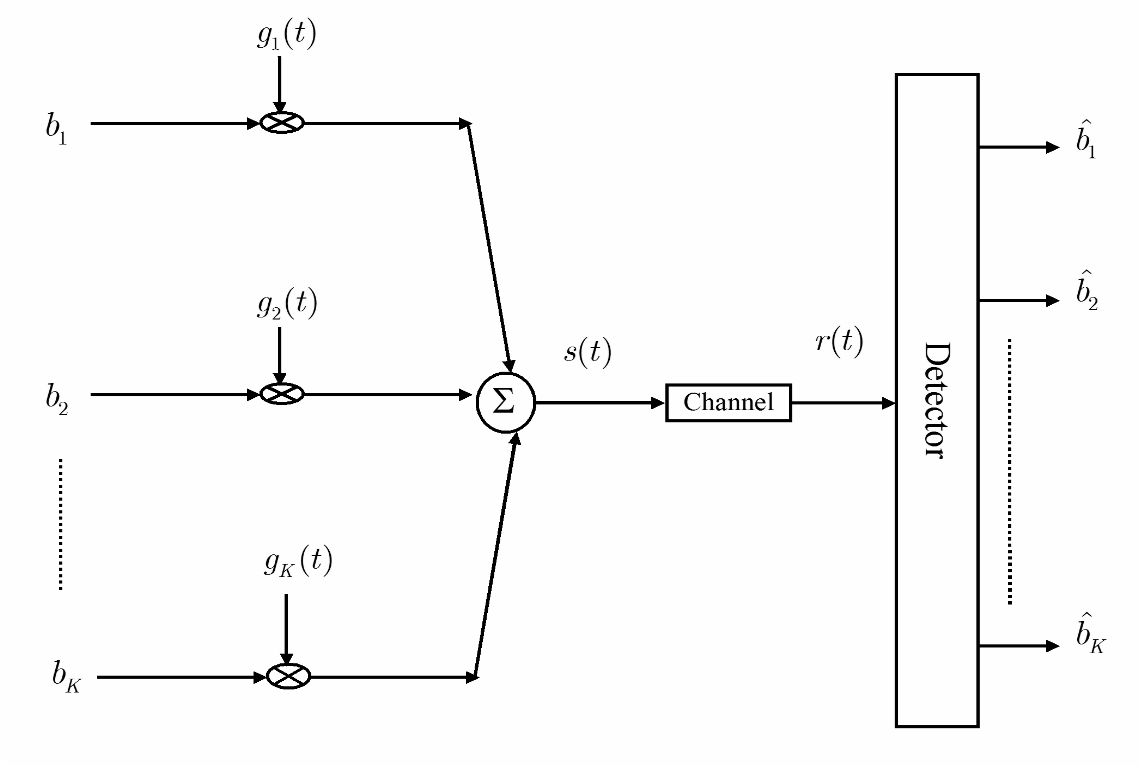


Fig. 2.1 Low-pass equivalent model for a synchronous CDMA system.

The equivalent low-pass of the composite transmitted signal for K users may be expressed as

$$s(t) = \sum_{k=1}^{K} A_k b_k g_k(t) \tag{2.3.4}$$

where A_k, b_k, and $g_k(t)$ are the transmitted amplitude, data bit and signature waveform, respectively, of k^{th} user.

The received signal from additive white Gaussian noise (AWGN) channel is given as

$$r(t) = s(t) + n(t) \tag{2.3.5}$$

The received signal from fading channel is given as

$$r(t) = h(t)s(t) + n(t) \tag{2.3.6}$$

where $h(t)$ is complex fading coefficient and $n(t)$ is the noise with power spectral density $N_0/2$.

2.4 Multiuser Detectors

In this section, a brief introduction of various multi-user detectors is presented. We shall see that the optimum maximum likelihood detector (MLD) has a computational complexity that grows exponentially with the number of users. Such a high complexity motivates to devise suboptimum detectors having lower computational cost. All suboptimum detectors proposed in the literature have some advantages and disadvantages. Therefore, the area of multiuser detection is always an open field for researchers.

2.4.1 Optimum Maximum Likelihood Detector (MLD)

The optimum MLD is defined as the detector that selects the most probable sequence of bits $\{b_k(n), 1 \le n \le N, 1 \le k \le K\}$ given the received signal $r(t)$ observed over the time interval $0 \le t \le T_b$ for synchronous transmission. In synchronous transmission, each user produces exactly one symbol which interferes with the desired symbol.

Hence $r(t)$ may be expressed as

$$r(t) = \sum_{k=1}^{K} A_k b_k g_k(t) + n(t) \qquad 0 \le t \le T_b \tag{2.4.1}$$

In case of the optimum MLD, the log-likelihood function is computed as

$$\Lambda(\mathbf{b}) = \int_0^{T_b} \left[r(t) - \sum_{k=1}^{K} A_k b_k g_k(t) \right]^2 dt \tag{2.4.2}$$

and the information sequence $\{b_k, 1 \le k \le K\}$ that minimizes $\Lambda(\mathbf{b})$ is selected . If we expand the integral in (2.4.2), it becomes:

$$\Lambda(\mathbf{b}) = \int_0^{T_b} r^2(t)dt - 2\sum_{k=1}^{K} A_k b_k \int_0^{T_b} r(t) g_k(t)dt + \sum_{j=1}^{K}\sum_{k=1}^{K} A_j A_k b_j b_k \int_0^{T_b} g_j(t) g_k(t)dt \qquad (2.4.3)$$

It can be observed that the integral involving $r^2(t)$ is common to all possible sequences $\{b_k\}$ and hence is of no relevance in determining the transmitted sequence. Therefore, it may be neglected. Thus instead of minimizing (2.4.3), one should maximize the following correlation metric

$$C(\mathbf{r},\mathbf{b}) = 2\sum_{k=1}^{K} A_k b_k r_k - \sum_{j=1}^{K}\sum_{k=1}^{K} A_j A_k b_j b_k \rho_{jk} \qquad (2.4.4)$$

where r_k represents the cross correlation of the received signal with each of the K signature sequences, given as

$$r_k = \int_0^{T_b} r(t) g_k(t)dt \qquad 1 \le k \le K \qquad (2.4.5)$$

The correlation metric given in (2.4.4) can be written in vector form as

$$C(\mathbf{r},\mathbf{b}) = 2\mathbf{b}^T\mathbf{r} - \mathbf{b}^T\mathbf{R}\mathbf{b} \qquad (2.4.6)$$

where

$$\mathbf{r} = [r_1, r_2, \ldots, r_K]^T \qquad (2.4.7)$$

and

$$\mathbf{b} = [A_1 b_1, A_2 b_2, \ldots, A_K b_K]^T \qquad (2.4.8)$$

and $\mathbf{R}$ is the correlation matrix given as

$$\mathbf{R} = \begin{pmatrix} \rho_{11} & \cdots & \rho_{1K} \\ \vdots & \ddots & \vdots \\ \rho_{K1} & \cdots & \rho_{KK} \end{pmatrix} \qquad (2.4.9)$$

where ρ_{jk} is as given in (2.3.3). It can be observed that the optimum detector must have knowledge of the received signal energies to compute the correlation metrics.

The optimum receiver for synchronous transmission consists of a bank of K correlators or matched filters followed by a detector as shown in figure 2.2. It computes the 2^K correlation metrics given by (2.4.6) corresponding to the 2^K possible transmitted information sequences. Then, the detector selects the sequence corresponding to the largest correlation metric.

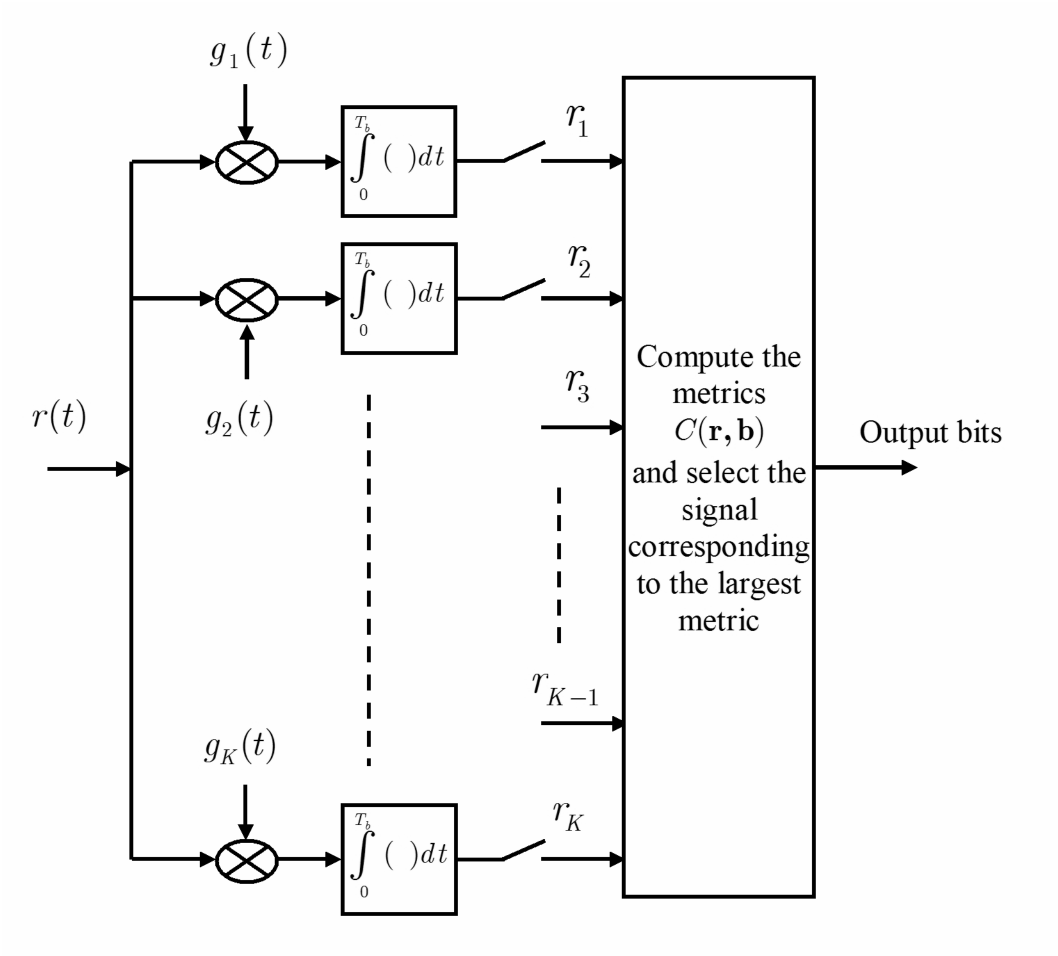


Fig. 2.2 Optimum multiuser Receiver for Synchronous CDMA Transmission

2.4.2 Sub-Optimum Detectors

The exhaustive search in optimum MLD clearly makes it impractical for a high number of users. Hence, despite the optimum performance, owing to its excessive complexity the employment of the optimum MLD becomes impractical for real-time implementation. Therefore, numerous reduced-complexity suboptimum multi-user detectors have been proposed in the literature [33][57].

2.4.2.1 Conventional Single User Detector

In conventional single user detection, the receiver for each user consists of a demodulator that correlates the received signal with the signature sequence of the user. The correlator output then passes to the detector, which makes a decision based on the single correlator output. Thus, the conventional detector neglects the presence of the other users of the channel or, equivalently, assumes that the aggregate noise plus interference is white and Gaussian.

Considering the synchronous transmission, the output of the matched filter for the k^{th} user in the interval $0 \le t \le T_b$ is given as

$$\begin{aligned} r_k &= \int_0^{T_b} r(t) g_k(t) dt \\ &= A_k b_k + \sum_{\substack{j=1 \\ j \neq k}}^{K} A_j b_j \rho_{jk} + n_k \end{aligned} \tag{2.4.10}$$

The final bit decision is given as

$$\hat{b}_k = \operatorname{sgn}\left[r_k \right] \tag{2.4.11}$$

where the noise component n_k is given as

$$n_k = \int_0^{T_b} n(t) g_k(t) dt \tag{2.4.12}$$

Since $n(t)$ is white Gaussian noise with power spectral density $\frac{N_0}{2}$, the variance of n_k is

$$E\left[n_k^2\right] = \frac{1}{2} N_0 \int_0^{T_b} g_k^2(t) dt = \frac{1}{2} N_0 \tag{2.4.13}$$

Clearly, if the signature sequences are orthogonal, the interference from the other users given by the middle term in (2.4.10) vanishes and the conventional single user detector is optimum. On the other hand, if one or more of the signature sequences are not orthogonal to the user signature sequence, the interference from the other users will become excessive, especially, when the power levels of the received signals of one or more of the other users is sufficiently large than the power level of the k^{th} user. This situation is generally called the near-far problem in multi-user communications, and requires some type of power control for conventional detection.

2.4.2.2 Decorrelating Detector

Conventional detector has a complexity that grows linearly with the number of users, but its vulnerability to the near-far problem requires some type of power control. Decorrelating detector [85] is another type of detector that also has a linear computational complexity but does not exhibit the vulnerability to other-user interference. In synchronous transmission, the received signal vector $\mathbf{r}$ that represents the output of the K matched filters is

$$\mathbf{r} = \mathbf{Rb} + \mathbf{n} \tag{2.4.14}$$

where $\mathbf{b}$ and $\mathbf{R}$ are given as in (2.4.8) and (2.4.9) respectively. The noise vector with elements $\mathbf{n} = [n_1, n_2, \ldots, n_K]$ has a covariance given as

$$E[\mathbf{nn}^T] = \frac{N_0}{2}\mathbf{R} \tag{2.4.15}$$

The decorrelating detector selects the vector $\mathbf{b}$ that minimizes the following likelihood function

$$\Lambda(\mathbf{b}) = (\mathbf{r} - \mathbf{Rb})^T \mathbf{R}^{-1} (\mathbf{r} - \mathbf{Rb}) \tag{2.4.16}$$

The result of this minimization yields

$$\mathbf{b^o} = \mathbf{R}^{-1}\mathbf{r} \tag{2.4.17}$$

Then, the detected symbols are obtained by taking the sign of each element of $\mathbf{b^o}$ i.e.

$$\hat{\mathbf{b}} = \operatorname{sgn}(\mathbf{b^o}) \tag{2.4.18}$$

Since the estimate $\mathbf{b^o}$ is obtained by performing a linear transformation on the vector of correlator outputs, the computational complexity is linear in $K \times K$. The advantages of decorrelating detector are that it provides substantial performance improvement over the conventional single-user detector, and also it does not have to estimate the received signal amplitude. Moreover, it exhibits a significantly lower complexity than the optimum MLD and exhibits near-far resistance.

However, a disadvantage of this detector is that it enhances the noise. More explicitly, the power of the noise at the output of the decorrelating detector is always higher than that of the original noise. Another disadvantage of the decorrelating detector is that the complexity of inverting the correlation matrix is high, in particular when the number of users is high.

2.4.2.3 Linear Minimum Mean Square Error (LMMSE) Detector

Minimum mean square error detector seeks for the linear transformation $\mathbf{b}^0 = \mathbf{Ar}$, where the matrix $\mathbf{A}$ is to be determined so as to minimize the mean square error (MSE) [18]

$$\begin{aligned} J(\mathbf{b}) &= E\left[\left(\mathbf{b}-\mathbf{b}^0\right)^T\left(\mathbf{b}-\mathbf{b}^0\right)\right] \\ &= E\left[\left(\mathbf{b}-\mathbf{Ar}\right)^T\left(\mathbf{b}-\mathbf{Ar}\right)\right] \end{aligned} \tag{2.4.19}$$

where the expectation is with respect to the data vector $\mathbf{b}$ and the additive noise $\mathbf{n}$. Using principle of orthogonality the optimum matrix $\mathbf{A}$ may be found by forcing the error $\left(\mathbf{b}-\mathbf{Ar}\right)$ to be orthogonal to the data vector $\mathbf{r}$. Thus,

$$\begin{aligned} &E\left[\left(\mathbf{b}-\mathbf{Ar}\right)\mathbf{r}^T\right] = 0 \\ &E\left(\mathbf{br}^T\right) - \mathbf{A}E\left(\mathbf{rr}^T\right) = 0 \end{aligned} \tag{2.4.20}$$

For synchronous transmission, we have

$$E(\mathbf{br}^T) = E(\mathbf{bb}^T)\mathbf{R}^T = \mathbf{DR}^T \tag{2.4.21}$$

and

$$\begin{aligned} E(\mathbf{rr}^T) &= E\left[(\mathbf{Rb}+\mathbf{n})(\mathbf{Rb}+\mathbf{n})^T\right] \\ &= \mathbf{RDR}^T + \frac{N_0}{2}\mathbf{R}^T \end{aligned} \tag{2.4.22}$$

where $\mathbf{D}$ is a diagonal matrix with diagonal elements $A_k,\ 1 \le k \le K$. By substituting (2.4.21) and (2.4.22) into (2.4.20) and solving for $\mathbf{A}$, we obtain

$$\mathbf{A}^o = \left(\mathbf{R} + \frac{N_0}{2}\mathbf{D}^{-1}\right)^{-1} \tag{2.4.23}$$

Then
$$\mathbf{b}^o = \mathbf{A}^o\mathbf{r} \tag{2.4.24}$$

and
$$\hat{\mathbf{b}} = \mathrm{sgn}(\mathbf{b}^o) \tag{2.4.25}$$

The LMMSE detector balances the desire to completely eliminate the MAI with the desire of avoiding the background noise enhancement. Since it takes the effects of the background noise into account, the LMMSE detector generally provides a better performance than the decorrelating detector. A big disadvantage of this detector is that unlike the decorrelating detector, it requires the estimation of the K users received signal amplitudes. Furthermore, like the decorrelating detector, the LMMSE detector also has to invoke matrix inversion.

2.4.3 Interference Cancellation Schemes

For practical implementation the interference cancellation schemes have been subject of most attention. These schemes rely on simple processing elements constructed around the matched filter. In one of the earliest articles on this subject, Varanasi and Aazhang proposed a parallel multi-stage structure [33]. The detector selects in each stage the most likely transmitted symbol for each user in parallel assuming that the decisions made for all the other users in the previous stage are correct. That is why it is termed as parallel interference cancellation (PIC) in the literature. SIC differs from PIC in that it adopts serial instead of parallel approach. HIC belongs to the family of group detectors [50], in which users are divided into groups and detection is performed parallel within a group but serial among the groups. Performance-wise SIC is superior to PIC. However, the computational complexity of PIC is less than SIC.

2.4.3.1 Successive Interference Cancellation

The received signal in DS-CDMA system is given as

$$r(t) = \sum_{k=1}^{K} A_k b_k g_k(t) + n(t) \qquad (2.4.26)$$

In successive interference cancellation (SIC) all the K users have been ranked according to their received signal power, with the lowest power user being labelled as first user and the highest power user labelled as K^{th} user, that is

$$|A_1|^2 \leq |A_2|^2 \leq \ldots \leq |A_K|^2$$

After power ranking, the received composite signal is processed by the matched filter of the user with strongest power for the sake of obtaining the initial data estimates.

$$\hat{b}_K = \operatorname{sgn}\left(\int_0^{T_b} r(t) g_K(t) dt \right) \qquad (2.4.27)$$

Then make decisions for the other $K-1$ bits, $b_K, b_{K-1}, \ldots, b_1$, according to the descending signal strength order as

$$\hat{b}_k = \operatorname{sgn}\left(\int_0^{T_b} \left(r(t) - \sum_{j=k+1}^{K} A_j b_j g_j(t) \right) g_k(t) dt \right) \qquad (2.4.28)$$

After the first iteration estimates, $\hat{b}_1, \hat{b}_2, \ldots, \hat{b}_K$ for all K bits are available. Now start a second iteration and replace the old estimate of $\hat{b}_K$ with the new one given as

$$b_K^{(new)} = \operatorname{sgn}\left(\int_0^{T_b} \left(r(t) - \sum_{j=1}^{K-1} A_j b_j g_j(t) \right) g_K(t) dt \right) \qquad (2.4.29)$$

Thereby using the information available all other bit decisions obtained in the first iteration. The decisions for the other $K-1$ bits according to the descending signal strength order as

$$\hat{b}_k^{(new)} = \text{sgn}\left(\int_0^{T_b}\left(r(t) - \sum_{j=1}^{k-1} A_j \hat{b}_j g_j(t) - \sum_{j=k+1}^{K} A_j \hat{b}_j^{(new)} g_j(t)\right) g_k(t)dt\right) \quad (2.4.30)$$

The general structure of SIC detector is shown in figure 2.3.

The SIC detector imposes only modest additional complexity and has the potential of providing a significant performance improvement over the conventional single-user detector. It does, however, pose a couple of implementation difficulties. Firstly, one additional bit delay is imposed by each cancellation stage. Thus, a trade-off has to be made between the number of users and the amount of tolerable delay. Secondly, all users must be ranked according to their received signal power, which must be updated after each cancellation stage.

A trade-off must be found between the precision of power ranking and the acceptable processing complexity. Initial estimates for SIC detector is also very crucial. That is if the initial data estimate of k^{th} user is unreliable, then even if the timing, power and phase estimates are perfect, bit estimation will be still wrong, the interference imposed on the remaining users indexed from $(k+1)$ to K will be enhanced, rather than reduced.

Thus, certain minimum performance threshold must be exceeded by the matched filter based conventional detector for the SIC to achieve a further performance improvement.

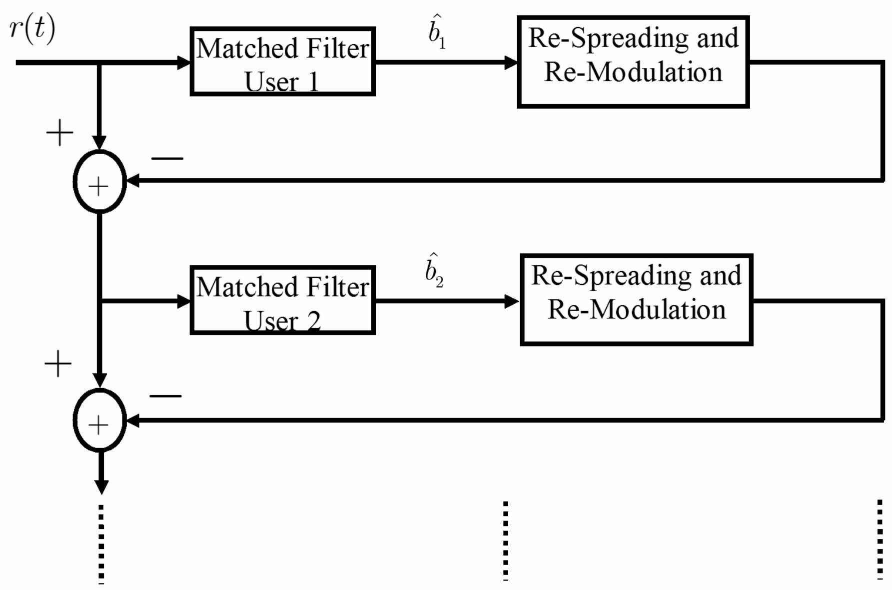


Fig. 2.3 Schematic diagram of SIC Detector

2.4.3.2 Parallel Interference Cancellation

In case of an efficient power control, all signal powers are of the same order. Therefore, there is no reason for one of these signals to be privileged. In this case parallel interference cancellation (PIC) detector can be applied. In contrast with the SIC based multi-user detector, the PIC aided detector estimates and subtract the MAI imposed by all interfering users from the signal of the desired user in parallel. The received signal in DS-CDMA system is given in (2.3.5). In the first iteration of PIC detector, the single user matched filter (SUMF) receiver outputs for all the users are calculated in parallel to obtain the estimates as given below

$$\hat{b}_k = \operatorname{sgn}\left(\int_0^{T_b} r(t) g_k(t) dt \right) \tag{2.4.31}$$

For $k = 1, 2, \ldots, K$. After this first iteration, estimates $\hat{b}_1, \hat{b}_2, \ldots, \hat{b}_K$ for all K bits are available. In second iteration, replace the old estimates $\hat{b}_k$ by the new one

$$b_k^{(new)} = \operatorname{sgn}\left(\int_0^{T_b} \left(r(t) - \sum_{\substack{j=1 \\ j \neq k}}^{K} A_j b_j g_j(t) \right) g_k(t) dt \right) \tag{2.4.32}$$

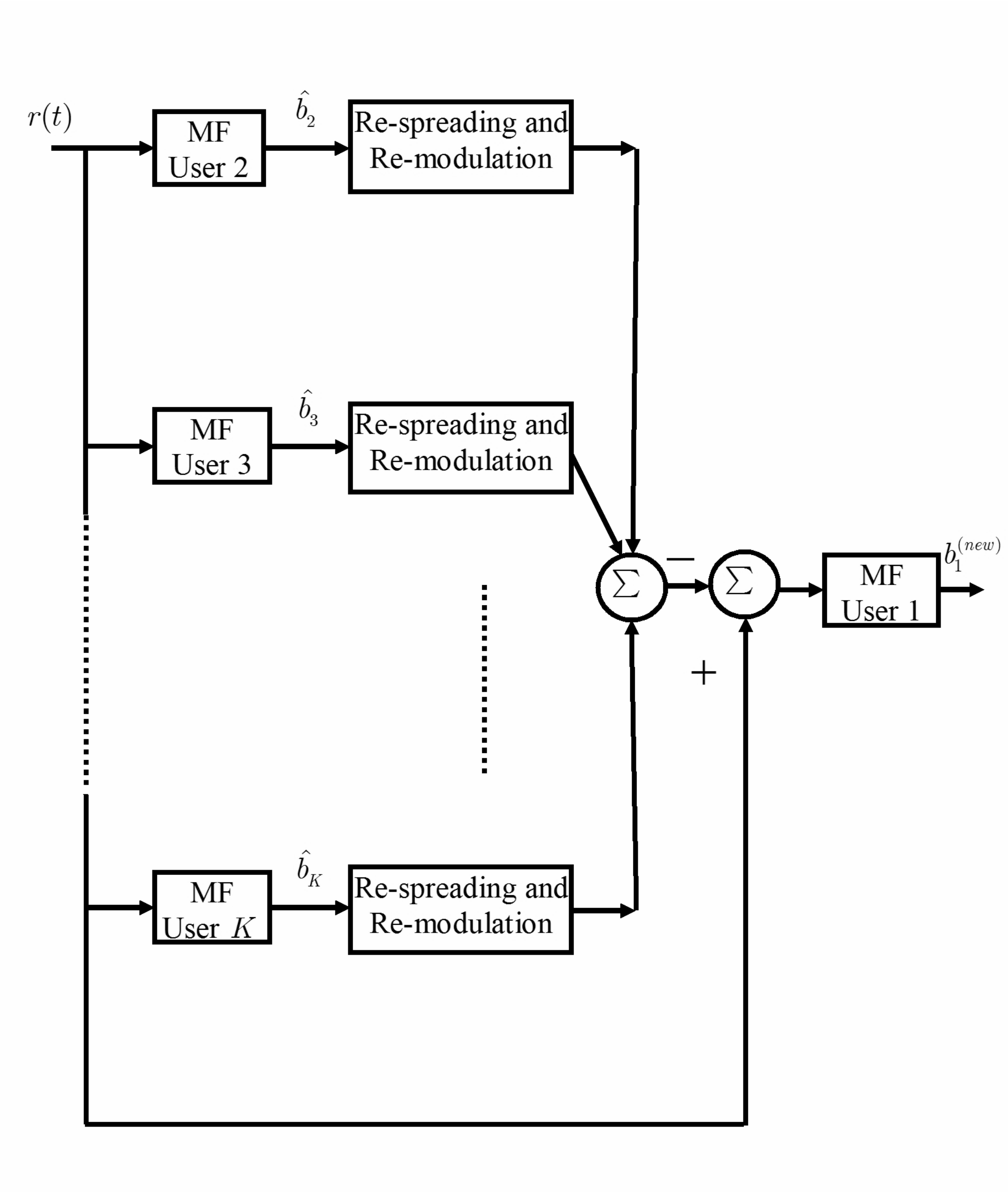


Fig. 2.4 Schematic diagram of one stage PIC Detector

Again this is done in parallel. It is obvious that this method needs a reliable first SUMF estimates for most users. It will fail if most users have a power level far below the level of one more high power level users. Desired user signal can be refined in multiple stages. In each cancellation stage, the signal of each user is reconstructed by invoking the data estimates from the previous cancellation stage. Then, for each user, the reconstructed signals of all the other users are subtracted from the received composite signal and the resultant signal is processed by the matched filter receiver in order to obtain a new set of data for each of the K users to be used in the next interference cancellation stage. The reconstruction, cancellation and re-estimation operations are repeated as many times as the complexity of system is affordable. The advantage of PIC over SIC is that it does not require the power estimation of all users to be updated after each cancellation stage, and that all the users have the same processing delay. Figure 2.4 shows schematic of PIC receiver for user 1.

2.4.4 Multiuser Detection Using Evolutionary Techniques

2.4.4.1 GA-Based Multiuser Detection

Optimum MLD is capable of achieving a near single user performance by maximizing the likelihood function given in (2.4.6). In other words, the multi-user detector will achieve the optimum single user performance, if it carries out an exhaustive search over the entire search space of the vector $\mathbf{b}$. Unfortunately, the associated complexity is excessive, even in case of the non-dispersive synchronous scenario of supporting K BPSK users, which is of the order of $O(2^K)$. Hence genetic algorithms have been proposed for reducing the associated complexity [5].

Let us assume that the current bit of interest is the i^{th} bit of all of the K synchronous users. GA commences their search for the optimum solution at the first generation with an initial population of P possible solutions, each consisting of K antipodal bits. A fitness value is associated with each K-bit candidate solution, which is computed by substituting the corresponding elements of each individual in to (2.4.6) . Based on the evaluated fitness, a new population of P individuals is created for the next generation through a series of genetic processes to be defined in the next chapter. These processes are repeated, until the final generation individuals are generated. In most cases, the GA is capable of approaching the optimum MLD performance at a fraction of its complexity while some time it may not converge to global optimum. Another disadvantage of GA is its slow convergence.

2.4.4.2 Multiuser Detection using Neural Networks

Neural Network approach is another nonlinear multiuser detection technique [86]-[93]. The neural network receiver was made first by Azhang, Paris and Orsak [86]. They demonstrated by applying a complicated training method called assisted back propagation, where the number of neurons increases exponentially with the number of the nodes. The performance of multilayer perceptron is close to that of the optimum receiver. The receiver proposed in [87] uses a radial basis function (RBF) neural network that becomes too complex under the multipath environment. The energy function of a Hopfield network is identical to the likelihood function encountered in multiuser detection. Therefore, some researchers have used the Hopfield neural network for multiuser detection [88]-[91]. A neural network based decision feedback scheme for interference suppression was investigated in [92]. A compact neural network [93], an annealed neural network [94], a modified Kennedy-Chua neural network which is based on the Hopfield model [95] was used for multiuser detection. The robust version of the linear decorrelating detector with three layer recurrent neural network was proposed in [96]. Shayesteh and Amindavar analyzed the performance of a two-layer perceptron neural network using back propagation training algorithm as the multiuser detector of CDMA signals in AWGN and fading channels [97]. Since neural network approach for multiuser detection is simple for AWGN channel, it become complex under multipath environment. It is also a nonlinear technique, which may stuck in local minimum.

Chapter 3

MUD USING PSEUDO-USER CONCEPT

3.1 Introduction

In this chapter a simple and efficient method to remove MAI completely is presented. The given method is based on the concept of pseudo user [98]. The word 'pseudo user' is utilized here due to the reason, that the data of this user is already known to the receiver. The proposed scheme completely removes MAI in the synchronous CDMA system, which is not possible with the other existing schemes. The computational complexity of the proposed algorithm is negligible in comparison to the optimal and even sub-optimal detectors. The probability of bit error in the proposed algorithm for AWGN channel is comparable to that of binary orthogonal single user case. Moreover, it is almost independent of the number of users. The proposed PU-PIC detector is checked for AWGN channel and SFFR channel.

3.2 System Model

The proposed system is slightly different from the standard synchronous CDMA system given in equation (2.3.4) and figure 2.1. In this scheme, apart from the data of K users, there is an additional pseudo-user, whose data bit b_P and signature waveform $g_P(t)$ are known to all the users. Transmitter of the proposed system is shown in figure 3.1.

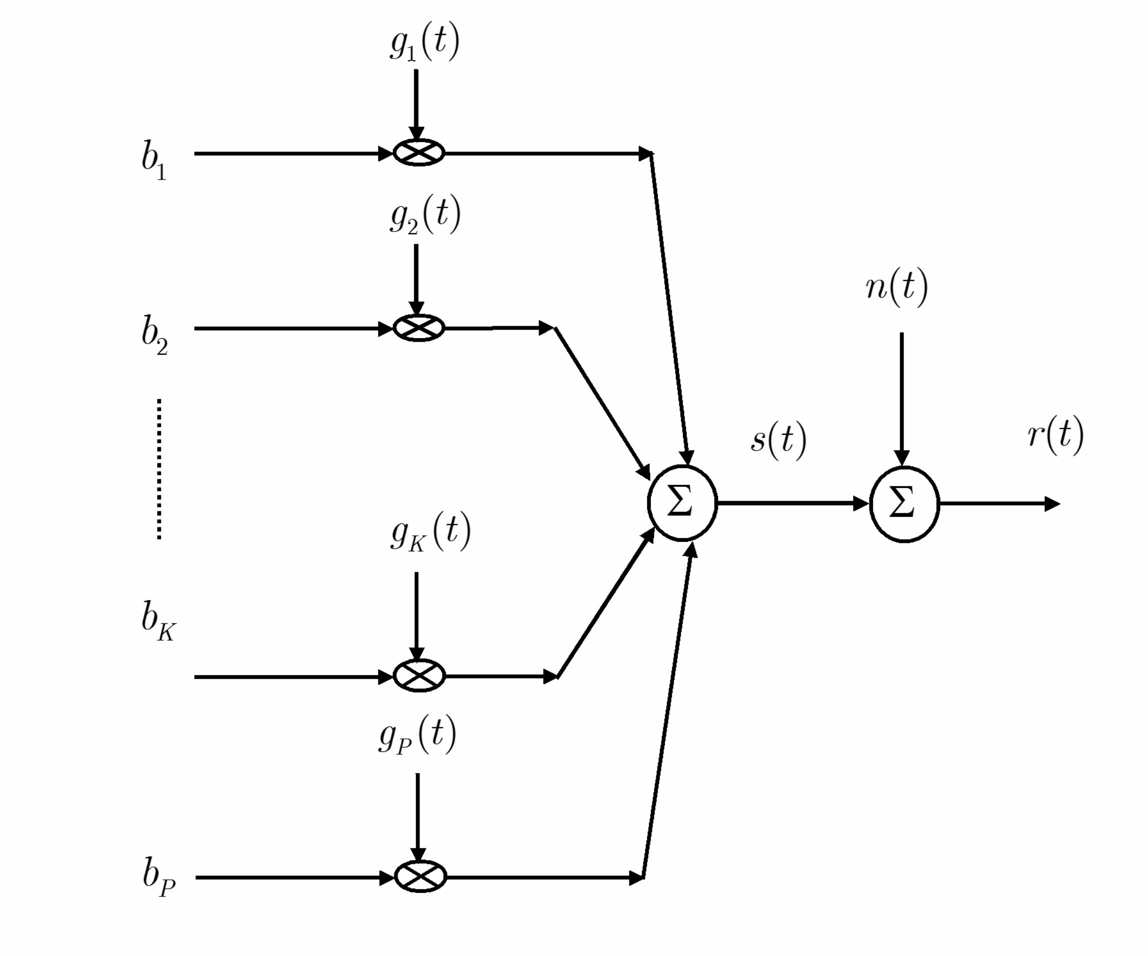


Fig. 3.1 Proposed Transmitter of PU-PIC System

Thus the transmitted signal is given as

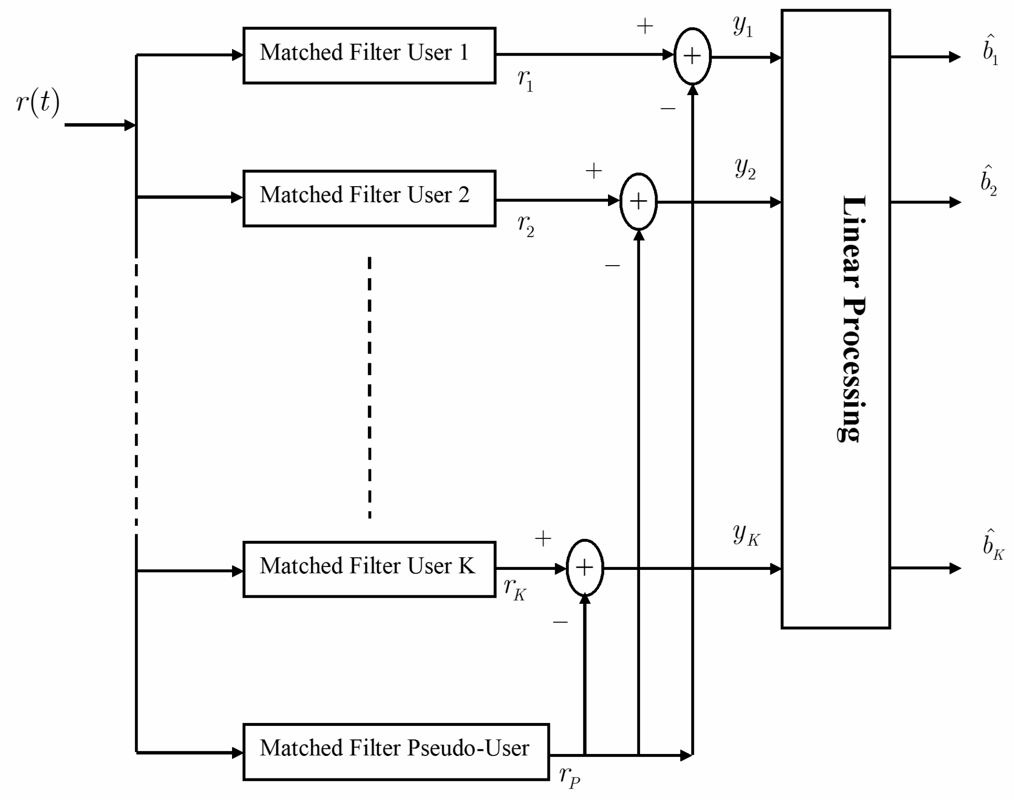
$$s(t) = \sum_{k=1}^{K} A_k b_k g_k(t) + A_P b_P g_P(t) \tag{3.2.1}$$

where A_k, A_P, b_k, b_P, and $g_k(t)$, $g_P(t)$ are the transmitted amplitudes, data bit, and the spreading waveforms of k^{th} user and pseudo-user, respectively. The composite signal of K users along with that of pseudo-user is then transmitted over AWGN channel. The composite received signal is thus given as

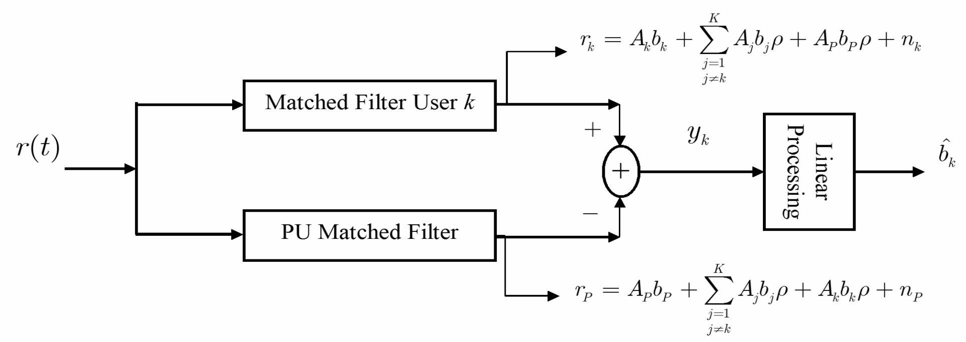
$$r(t) = \sum_{k=1}^{K} A_k b_k g_k(t) + A_P b_P g_P(t) + n(t) \tag{3.2.2}$$

3.3 Proposed PU-PIC Detector for AWGN Channel

The proposed receiver for PU-PIC detector is shown in figure 3.2.



(a)



(b)

Fig. 3.2 (a) Receiver Structure for K users (b) Pseudo-user detector for k^{th} user

Receiver of each user consists of two matched filters, one matched to its own signature waveform, g_k, and the other matched to the signature waveform of the pseudo-user, g_P. In the first stage, the outputs of both matched filters of the k^{th} user are given as

$$r_k = A_k b_k + \sum_{\substack{j=1 \\ j\neq k}}^{K} A_j b_j \rho + A_P b_P \rho + n_k \tag{3.3.1}$$

$$r_P = A_P b_P + \sum_{\substack{j=1 \\ j\neq k}}^{K} A_j b_j \rho + A_k b_k \rho + n_P \tag{3.3.2}$$

where

$$n_i = \int_0^{T_b} n(t) g_i(t) dt$$

and we have assumed $\rho_{jk} = \rho \quad \forall \quad j,k$ as required for the application of PU-PIC detector. n_k and n_P are zero mean noise components with variance given as

$$\begin{aligned} E\left[n_i^2\right] &= E\left[\int_t \int_\tau n(t)n(\tau)g_i(t)g_i(\tau)dtd\tau\right] \\ &= \int_t \int_\tau g_i(t)g_i(\tau)E\left[n(t)n(\tau)\right]dtd\tau \\ &= \int_t \int_\tau g_i(t)g_i(\tau)\frac{N_0}{2}\delta(t-\tau)dtd\tau \\ &= \frac{N_0}{2}\int_t g_i^2(t)dt \\ &= \frac{N_0}{2} \end{aligned} \tag{3.3.3}$$

The correlation between these noise components is given by

$$
\begin{aligned}
E\left[n_k n_P\right] &= E\left[\int_t \int_\tau n(t) g_k(t) n(\tau) g_P(\tau) dt d\tau\right] \\
&= \int_t \int_\tau g_k(t) g_P(\tau) E\left[n(t) n(\tau)\right] dt d\tau \\
&= \int_t \int_\tau g_k(t) g_P(\tau) \frac{N_0}{2} \delta(t-\tau) dt d\tau \\
&= \frac{N_0}{2} \int_t g_k(t) g_P(t) dt \\
&= \frac{\rho N_0}{2}
\end{aligned}
\tag{3.3.4}
$$

The difference of the two outputs of the equations (3.3.1) and (3.3.2) is given as

$$
\begin{aligned}
y_k &= r_k - r_P \\
&= A_k b_k + \sum_{\substack{j-1 \\ j \neq k}}^{K} A_j b_j \rho + A_P b_P \rho + n_k - A_P b_P - \sum_{\substack{j-1 \\ j \neq k}}^{K} A_j b_j \rho - n_P \\
&= A_k b_k + A_P b_P \rho + n_k - A_P b_P - A_k b_k \rho - n_P \\
&= A_k b_k (1-\rho) - A_P b_P (1-\rho) + n_k - n_P
\end{aligned}
\tag{3.3.5}
$$

Since data of pseudo-user is known, the second term in the above equation can be removed. The estimate of the k^{th} user bit is given as

$$
\begin{aligned}
\hat{b}_k &= \operatorname{sgn}\left[\frac{y_k + A_P b_P (1-\rho)}{(1-\rho)}\right] \\
&= \operatorname{sgn}\left[A_k b_k + \eta_k\right]
\end{aligned}
\tag{3.3.6}
$$

where the additive noise, η_k , is given as

$$
\eta_k = \frac{(n_k - n_P)}{(1-\rho)} \tag{3.3.7}
$$

As can be seen, the MAI has been completely removed. The noise η_k has zero mean and variance σ_η^2 given as

$$
\begin{aligned}
E\left[\eta_k^2\right] &= E\left[\frac{\left(n_k - n_P\right)^2}{\left(1-\rho\right)^2}\right] \\
\sigma_n^2 &= \frac{1}{\left(1-\rho\right)^2}\left\{E\left[n_k^2\right] + E\left[n_P^2\right] - 2E\left[n_k n_P\right]\right\} \\
&= \frac{1}{\left(1-\rho\right)^2}\left\{\frac{N_0}{2} + \frac{N_0}{2} - 2\frac{N_0}{2}\int_0^{T_b} g_k(t) g_P(t) dt\right\} \\
&= \frac{1}{\left(1-\rho\right)^2}\left\{N_0 - N_0\rho\right\} \\
&= \frac{N_0}{\left(1-\rho\right)}
\end{aligned}
\tag{3.3.8}
$$

The bit error probability of the proposed scheme comes out to be

$$
P_b = Q\left(\sqrt{\gamma_b(1-\rho)}\right) \tag{3.3.9}
$$

where $\gamma_b = E_b/N_0$ and $E_b = A_k^2$

This probability of error is exactly equal to that of binary orthogonal case for $\rho = 0$ and equal to that of binary PAM for $\rho = -1$. Though the conditions are restrictive i.e. spreading codes with same cross-correlation throughout, yet the result is quite interesting.

3.4 Performance of PU-PIC Detector in AWGN Channel

In this section, we provide a comparison of newly proposed scheme with some already existing algorithms of MUD. In simulations the spreading codes with normalized cross-correlations $\rho = 0.2258$ has been used. Figure 3.3, shows that proposed detector is not only better than the single user conventional detector but it also outperforms the decorrelating and LMMSE detectors. Comparison of proposed PU-PIC detector with other PIC detectors, such as linear PIC (LPIC), hard PIC (HPIC), soft cancellation PIC (SC-PIC) and partial PIC (PPIC) is given in figure 3.4.

Clearly the performance of PU-PIC is superior to the other competitors. Figure 3.5 indicates the performance of proposed PU-PIC detector for different system loads.

The proposed scheme for MUD in synchronous DS-CDMA completely removes MAI with negligible computation, but under a restrictive assumption, i.e. the cross-correlation between all signature waveforms is constant. Obviously its applicability will be limited to those codes which exhibit this property. Its superior performance costs a small percentage of the bandwidth for pseudo-user, but this cost becomes negligible when the number of users is large.

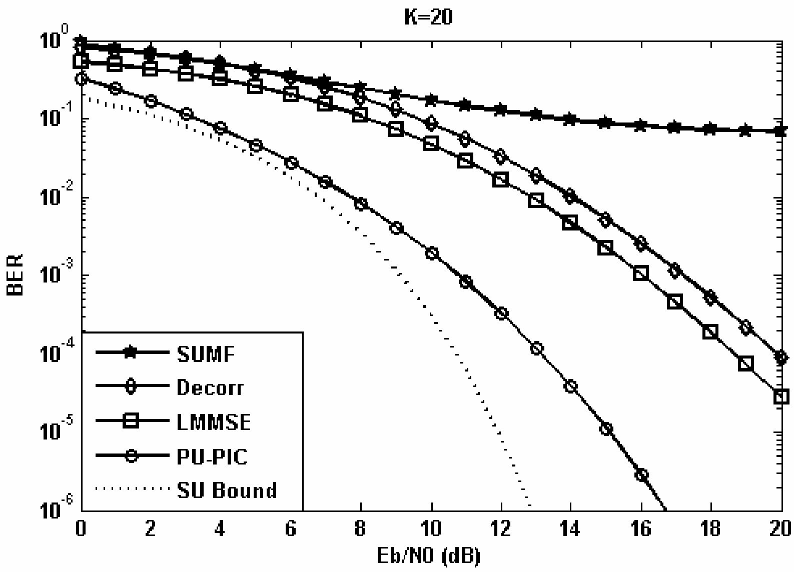


Fig. 3.3 Performance comparison of PU-PIC detector with other sub-optimal detectors for $K = 20$. Gold codes with constant cross-correlation 0.2258 are used to spread data.

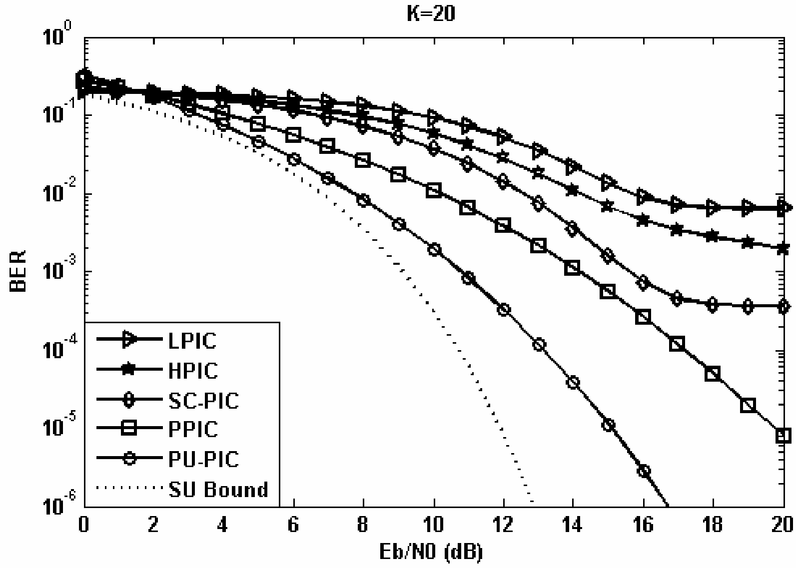


Fig. 3.4 Performance Comparison of PU-PIC detector with some other PIC detectors for K=20. Gold codes with constant cross-correlation 0.2258 are used to spread data.

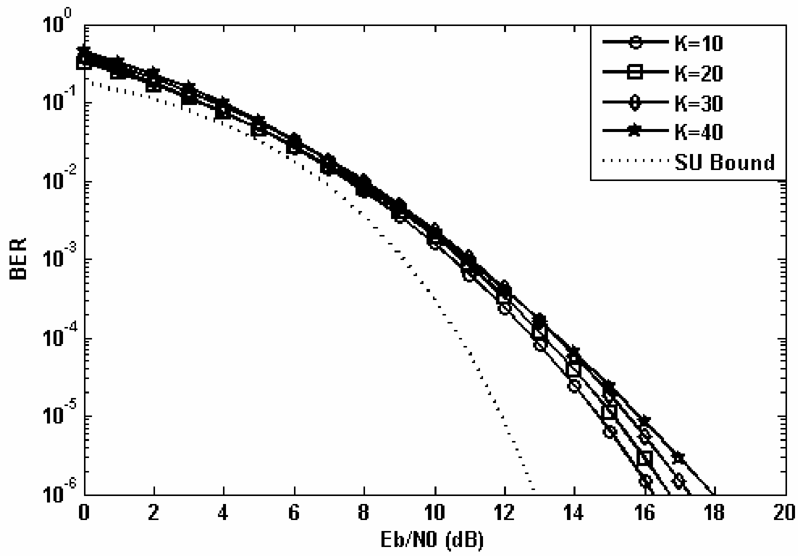


Fig. 3.5 Performance of proposed PU-PIC detector for 10, 20, 30 and 40 users. Gold codes of length 31 with cross-correlation 0.2258 are used to spread data.

Another problem is the noise enhancement as in decorrelating detector, but with one big difference. While in decorrelating detector the noise enhancement increases with the number of users [99], in the proposed scheme, the noise enhancement is only due to the pseudo-user, and does not increase with the increase in the number of users.

3.5 Proposed PU-PIC Detector for Multipath SFFR Channel

Consider a K user synchronous CDMA system, where the transmitted signal is given in (3.2.1). The composite signal of K users along with that of pseudo-user is then transmitted over SFFR channel. The composite received signal is thus given as

$$r(t) = h(t)s(t) + n(t) \tag{3.5.1}$$

where $h(t)$ is complex channel fade coefficient. It is given as

$$h(t) = \alpha(t)e^{j\varphi(t)} \tag{3.5.2}$$

where $\alpha(t)$ is Rayleigh distributed channel gain and $\varphi(t)$ is the phase shift uniformly distributed between 0 to 2π. As the channel is assumed to be SFFR, therefore $h(t)$ may be regarded as a constant during at least one signaling interval. i.e.

$$h(t) = \alpha_k e^{j\varphi_k} \tag{3.5.3}$$

The figure 3.6 represents channel behavior of one of the systems employing PU-PIC detector. Each channel is independent SFFR channel in a down-link application.

The proposed PU-PIC receiver for each user consists of two matched filters. One matched to its own signature waveform and the other one matched to the signature waveform of pseudo-user as shown in figure 3.2. The outputs of both matched filters are given as

$$r_k = A_k b_k h_k + \sum_{\substack{j=1 \\ j\neq k}}^{K} A_j b_j h_k \rho + A_P b_P h_k \rho + n_k \tag{3.5.4}$$

and

$$r_P = A_P b_P h_k + \sum_{\substack{j=1 \\ j\neq k}}^{K} A_j b_j h_k \rho + A_k b_k h_k \rho + n_P \qquad (3.5.5)$$

where we have assumed $\rho_{jk} = \rho \;\; \forall \;\; j,k$ and n_k, n_P along with their properties are given in, (3.3.3) and (3.3.4).

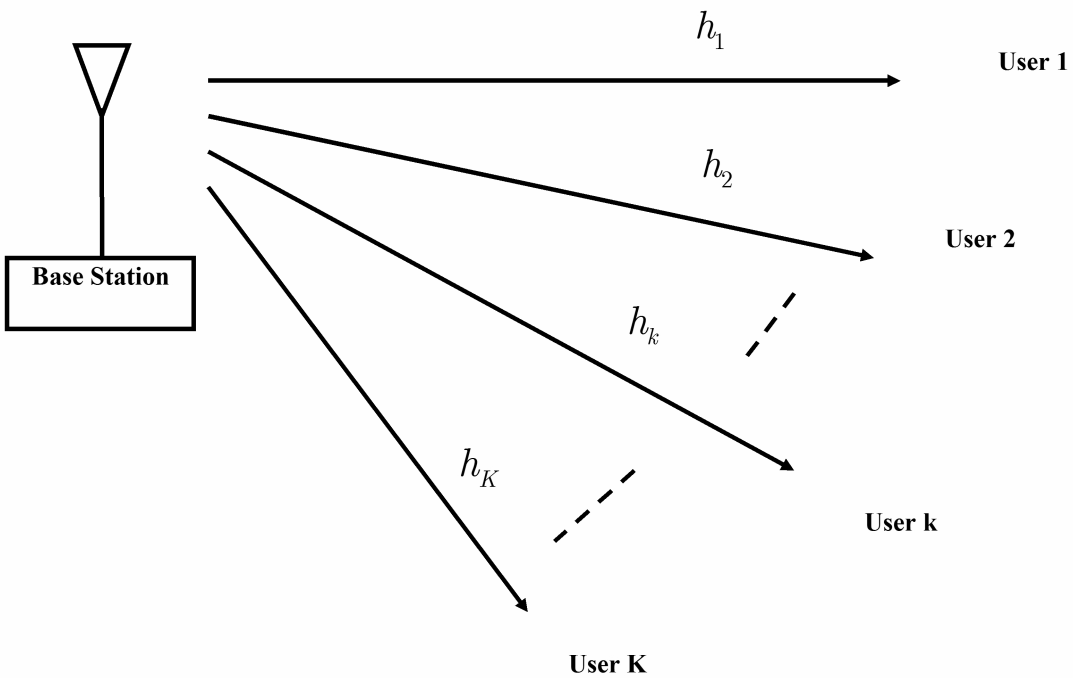


Fig. 3.6 Channel behavior of frequency non-selective channel

The difference of the outputs of both matched filters is then given as

$$\begin{aligned} y_k &= A_k b_k h_k + A_P b_P h_k \rho + n_k - A_P b_P h_k - A_k b_k h_k \rho - n_P \\ &= A_k b_k h_k (1-\rho) - A_P b_P h_k (1-\rho) + n_k - n_P \end{aligned} \qquad (3.5.6)$$

The estimate of the k^{th} user bit is given as

$$\begin{aligned}\hat{b}_k &= \mathrm{sgn}\left[\mathrm{Re}\left\{\frac{h_k^* y_k + A_P b_P \left|h_k\right|^2 (1-\rho)}{(1-\rho)}\right\}\right] \\ &= \mathrm{sgn}\left[\mathrm{Re}\left\{A_k b_k \left|h_k\right|^2 + \frac{h_k^*(n_k - n_P)}{(1-\rho)}\right\}\right]\end{aligned} \tag{3.5.7}$$

3.6 Performance of PU-PIC Detector in SFFR Channel

The performance of PU-PIC detector in SFFR channel is shown in figures 3.7, 3.8 and 3.9. In these simulations Gold codes of constant correlation 0.2258 with chip length of 31 are used for spreading purpose. Figure 3.7 shows the performance of PU-PIC detector against standard sub-optimal detectors, like single user matched filter (SUMF), decorrelating detector and linear minimum mean square error (LMMSE) detector. It is clear from figure 3.7 that the performance of PU-PIC detector is better than that of sub-optimal detectors. Comparison of PU-PIC with other PIC detectors is given in figure 3.8. PU-PIC gives better BER compared to other PIC detectors. Independence of PU-PIC of the number of users is shown in figure 3.9. The difference between the performance of single user bound and the PU-PIC detector is due to the noise enhancement in the proposed detector, which degrades its performance.

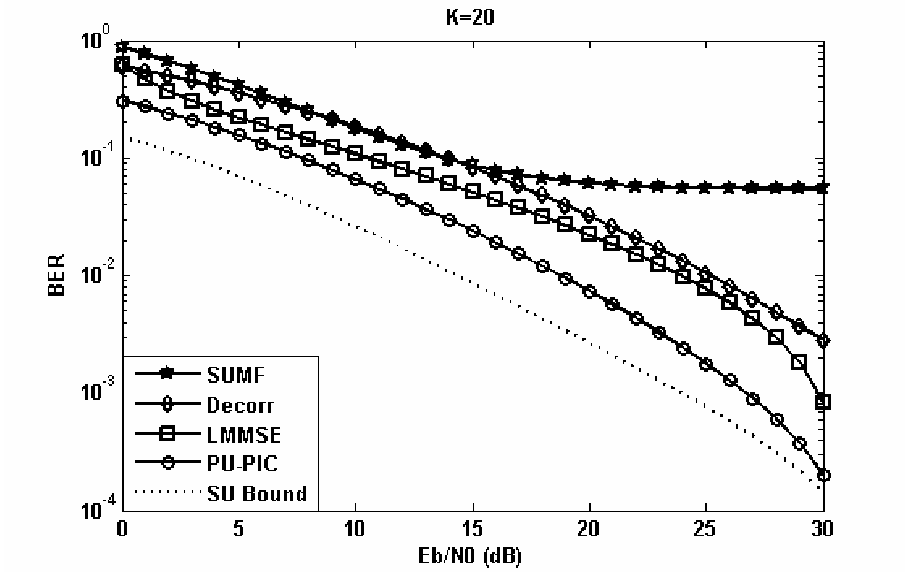


Fig. 3.7 Performance comparison of PU-PIC detector with other sub-optimal detectors for $K = 20$ in fading channel. Gold codes with constant cross-correlation 0.2258 are used to spread data.

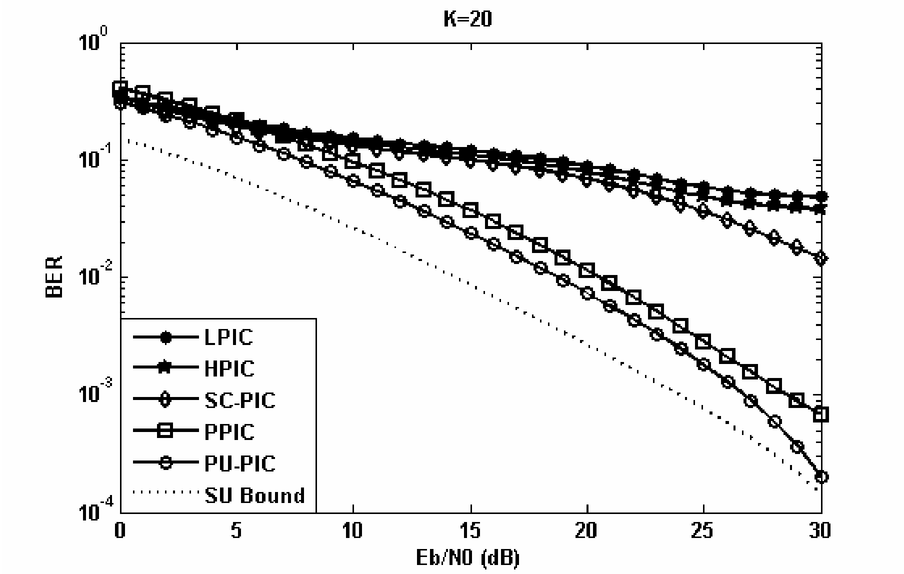


Fig. 3.8 Performance comparison of PU-PIC detector with some other PIC detectors for flat fading channel where $K = 20$. Gold codes with constant cross-correlation 0.2258 for spreading the data.

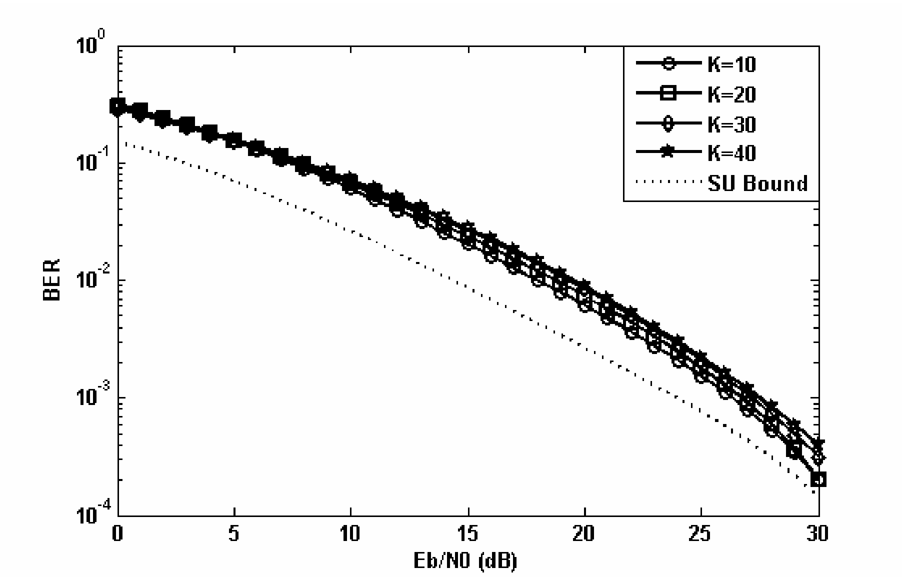


Fig. 3.9 Performance of proposed PU-PIC detector in fading channel for 10, 20, 30 and 40 users. Gold codes of length 31 with cross-correlation 0.2258 are used for spreading the data.

Chapter 4

PSO-BASED MULTIUSER DETECTION

4.1 Introduction

In the preceding chapters, we have discussed the complexity problem of the optimum MLD [17]. The computational complexity of MLD grows exponentially with the number of users. Suboptimum detectors, which include the decorrelating detector [85] and the linear minimum mean square error detector (LMMSE) [18] are simple, but require matrix inversion. In case of interference cancellation schemes the successive interference cancellation (SIC) [34], cancels out the interferences successively, but is computationally heavy. Parallel interference cancellation (PIC) [33], removes all the interferences simultaneously, making it computationally light, however, performance-wise it is inferior to SIC. Some alternative emerging approaches for MUD are based on genetic algorithm (GA) [57]-[65] and neural network [86]-[97]. Similarly Kennedy and Eberhart [99] developed an entirely new kind of social intelligence model, named, particle swarm optimization (PSO) to be recast as an optimization, learning, and problem solving method. PSO accomplish the same goal as GA and EP but with faster convergence and less computation.

In this chapter we have proposed two versions of soft PSO for MUD. The use of PSO lowers the search space to save a big amount of computation, which cannot be avoided while using the optimum MLD. PSO can be used to solve a wide range of different optimization problems [101]-[103]. The PSO is simpler and faster than GA, which makes it a good candidate for MUD [104]. We have used PSO algorithm with soft decisions in contrast with the original PSO algorithm [100], which is hard decisions-based. Soft decisions further enhance the performance of the PSO algorithm. We have proposed two variants of PSO algorithm, which are discussed in the subsequent sections.

4.2 Introduction to PSO

The objective of optimization is to search for the values of a set of parameters that optimize a given objective function subject to certain constraints [105][106]. A choice of values for the set of parameters that satisfy all constraints is called a feasible solution. The set of values that give the best solution is called optimal solutions [105]. Evolutionary algorithms have been successfully applied to the above problems to find out approximate solutions [107]. Detailed discussion about optimization can be found in [108][109] and [110]. Evolutionary algorithms (EAs) are general-purpose stochastic search methods simulating natural selection and evolution in the biological world. Other optimization methods are Hill-Climbing and Simulated Annealing. EAs differ from other optimization methods, in a way that EAs maintain a population of potential (or candidate) solutions instead of just a single solution [111][112].

Generally, the working of all EAs is same. In all EAs, a population of individuals is initialized where each individual represents a potential solution to the problem at hand. A fitness function is used to evaluate the quality of each solution. In each iteration, a new population is formed by using a selection process. In selection process, the probability of selecting the individual having greater fitness is more. Individuals are altered using evolutionary operators. This procedure is repeated until convergence is reached. The best solution found is expected to be a near-optimum solution [113]. The two most frequently used evolutionary operators are mutation and crossover:

1. **Mutation** modifies an individual inverting the value of a binary digit in the case of binary representations, or by adding (or subtracting) a small number to (or from) selected values in the case of floating point representations [113]. Mutation is performed to avoid being trapped in a local optimum.
2. **Crossover** generates new individuals by combining the fractions from two (or more) individuals [113]. The main objective of crossover is to explore new areas in the search space [111].

Four major evolutionary techniques have been used in the literature:

1. **Genetic Programming (GP)** [114] which is used to search for the individual with highest fitness to solve a specific problem. Individuals are represented as trees and the focus is on genotypic evaluation.
2. **Evolutionary Programming (EP)** [115] which is generally used to optimize real-valued continuous functions. EP uses selection and mutation operators instead of using the crossover operator. The focus is on phenotypic evaluation and not on genotypic evaluation.
3. **Evolutionary Strategies (ES)** [116] which is used to optimize real- valued continuous functions. ES uses selection, crossover and mutation operators. ES optimizes both the population and the optimization process, by evolving strategy parameters.
4. **Genetic Algorithms (GA)** [117] which is generally used to optimize general combinatorial problems [107]. The GA is a commonly used algorithm and has been used for comparison purposes in this dissertation. The focus in GA is on genetic

evolution using both mutation and crossover, although the original GAs developed by Holland [118] used only crossover.

EAs have successfully been applied to a wide variety of optimization problems, for example: image processing, pattern recognition, scheduling, engineering design. etc. [107][117], where as GAs are especially been used for multiuser detection [57]-[65].

The particle swarm optimization (PSO) algorithm, originally introduced by Kennedy and Eberhart [100], is modeled after the social behavior of birds in a flock. PSO is a population based search process where individuals, referred to as particles, are grouped into a swarm. Each particle in the swarm represents a candidate solution to an optimization problem. In a PSO system, each particle is "flown" through the multidimensional search space, adjusting its position in search space according to its own experience and that of neighboring particles. A particle therefore makes use of the best position encountered by itself and that of its neighbors to position itself toward an optimal solution. The performance of each particle (i.e. the distance of a particle to the global optimum) is measured using a predefined fitness function which encapsulates the characteristics of the optimization problem. Several authors have suggested diversity improvement and convergence acceleration additions to the PSO. The algorithm's convergence behavior has also been extensively analyzed [106][119][120][121]. The rest of this section presents a general mathematical model for continuous as well as discrete PSO algorithm.

4.2.1 Mathematical Model for Continuous PSO Algorithm

Each particle in a swarm maintains the information about the following three parameters:

(a) x_i : The current position of the i^{th} particle in the search space;

(b) v_i : Current velocity of i^{th} particle;

(c) y_i : The personal best position of i^{th} particle discovered so far.

The personal best position associated with a particle i is a position that yielded the highest fitness value for the particle so far. f denotes the fitness function, and $f(x_i)$ the fitness of i^{th} particle.

Particle positions may be initialized randomly within the search space. Particle velocities are initialized to be within the value range $[-V_{\max}, V_{\max}]$.

The personal best of a particle at a time step t is updated as:

$$y_i(t+1) = \begin{cases} y_i(t) & if\ f(x_i(t+1)) \geq f(y_i(t)) \\ x_i(t+1) & if\ f(x_i(t+1)) < f(y_i(t)) \end{cases} \quad (4.2.1)$$

Two main approaches exist for PSO, named as local best (lbest) and global best (gbest), where the difference is in the neighborhood topology used to exchange experience among particles. For the gbest model, the best particle is determined from the entire swarm, and all other particles flock towards this particle. If the position of the best particle is denoted by the vector $\hat{\mathbf{y}}$, then

$$\hat{\mathbf{y}}(t) = \arg \min_{1 \leq i \leq s} f(\mathbf{y}_i(t)) \quad (4.2.2)$$

where s is the total number of particles in the swarm. For the lbest model, a swarm is divided into overlapping neighborhoods of particles. For each neighborhood N_j, a best particle position is designated by $\hat{\mathbf{y}}_j$. This best particle is referred to as the neighborhood best particle, defined as

$$N_j = \{\mathbf{y}_{i-l}(t), \mathbf{y}_{i-l+1}(t), \ldots \mathbf{y}_{i-1}(t), \mathbf{y}_i(t), \mathbf{y}_{i+1}(t), \ldots \mathbf{y}_{i+l-1}(t), \mathbf{y}_{i+l}(t)\} \quad (4.2.3)$$

$$\hat{\mathbf{y}}_j(t+1) \in N_j \left| f(\hat{\mathbf{y}}_j(t+1)) = \min\{f(\mathbf{y}_i)\}, \forall \mathbf{y}_i \in N_j \right. \tag{4.2.4}$$

Neighborhoods are usually determined using particles indices, although topological neighborhoods have also been used [122]-[125]. The gbest PSO is a special case of lbest with $l = s$, where l is the number of particles per neighborhood. For each iteration of a gbest PSO, the j^{th}-dimension of the i^{th} particle, velocity vector, $\mathbf{v}_i$ and its position vector $\mathbf{x}_i$ is updated as follows:

$$v_{i,j}(t+1) = v_{i,j}(t) + c_1 r_{1,j}(t)(y_{i,j}(t) - x_{i,j}(t)) + c_2 r_{2,j}(t)(\hat{y}_j(t) - x_{i,j}(t)) \tag{4.2.5}$$

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \tag{4.2.6}$$

where c_1 and c_2 are the acceleration constants and $r_{1,j}(t), r_{2,j}(t) \sim U(0,1)$. For each iteration of the lbest PSO, the velocity update for particle i is defined as:

$$v_{i,j}(t+1) = v_{i,j}(t) + c_1 r_{1,j}(t)(y_{i,j}(t) - x_{i,j}(t)) + c_2 r_{2,j}(t)(\hat{y}_{i,j}(t) - x_{i,j}(t)) \tag{4.2.7}$$

Upper and lower bounds are specified on $\mathbf{v}_i$, to avoid too rapid movement of particles in the search space; that is, $v_{i,j}$ is clamped to the range $[-V_{\max}, V_{\max}]$.

4.2.2 Mathematical Model for Discrete PSO Algorithm

The generalized mathematical model for discrete PSO algorithm has the following steps.

1. Initialize a population of all K particles in the swarm to random positions within the search space with binary strings.
2. Initialize velocities for each position in a particle for whole population.
3. Initialize particle personal best positions as the current positions of the particles.
4. Calculate the fitness for each particle by using a fitness function.

5. Initialize the global best position with the particle having the highest fitness.
6. Repeat until convergence or maximum number of iterations
    a) Update the fitness of each particle i using the fitness function and the current position of the particle.
    b) Update personal best position of each particle.
    c) Update the global best particle position.
    d) Update the velocity vector for each particle as follows

    $$v_{im}(n) = v_{im}(n-1) + \varphi_1(p_{im} - b_{im}(n-1)) + \varphi_2(p_{gm} - b_{im}(n-1))$$

    where $v_{im}(n)$ is the velocity of m^{th} position of i^{th} particle in n^{th} iteration. b_{im} is the m^{th} position of i^{th} particle. p_{im} is the local best of i^{th} particle and p_{gm} is the global best particle. φ_1 and φ_2 are the weights for personal and global intelligence respectively.

    e) Apply the bounds on velocity vectors as follows

    $$\begin{array}{c} if \;\; v_{im} > V_{\max}, \\ v_{im} = V_{\max} \end{array} \quad \text{and} \quad \begin{array}{c} if \;\; v_{im} < -V_{\max}, \\ v_{im} = -V_{\max} \end{array}$$

    where $V_{\max}$ is constant representing the maximum velocity.

    f) Update each position of all the particles as follows

    $$if(rand() < S(v_{im})), \quad then \quad b_{im} = 1 \quad else \quad b_{im} = -1$$

    where $$S(v_{im}) = \frac{1}{1 + \exp(-v_{im})} \tag{4.2.8}$$

4.2.3 Applications of PSO

This section describes a number of application areas where the PSO approach was used to solve specific problems. The basic form of the algorithm was same, only the definition of particle was different according to the requirement of the problem. This section provides a flavor of the extensive number of applications mentioned in literature.

4.2.3.1 Training of Neural Networks

Supervised neural network training has been the area of extensive research and several techniques such as gradient descent (GD) and scaled conjugant gradient (SCG) have been developed to train them [112][126].

In the pioneer work on PSO algorithm, Kennedy and Eberhart reported positive results when using it to train feed-forward networks [100]. They tested their neural networks on the *XOR* problem, as well as the well-known Fisher iris data [127]. They informally remarked that networks trained with the PSO had slightly better generalization. Eberhart and Hu used PSO to train a neural network in the medical environment [128]. The goal of the network was to distinguish between patients suffering from tremors. Tremors are a medical condition that describe uncontrollable limb movement. Apart from learning neural network weights, Eberhart and Hu used the PSO algorithm to learn the slopes of the sigmoidal transfer functions employed in the neural network's neurons.

4.2.3.2 Multi Objective Optimization

Recently, particle swarms have been applied to multi-objective optimization (MOO) problems. Performing MOO with evolutionary algorithms is a vast area of research. The interested readers may consult the references provided herein [129]-[131].

The multiple objective particle swarm optimization (MOPSO) algorithm, introduced by Coello Coello and Lechuga [131], uses an approach motivated by the Pareto Archive Evolution Strategy (PAES) [130]. As described above, the goal of MOO techniques is to locate non-dominated solutions in the search space. MOPSO maintains a global repository of 'flight experience' where each particle is allowed to save the located non-dominated solutions after each iteration.

4.2.3.3 Multiuser Detection

In the recent years PSO algorithm has also been used for MUD along with evolutionary programming and genetic algorithms [132]-[135]. In [132], Zhen-su Lu and Shi Yan proposed two algorithms for MUD. The first one is Binary evolutionary programming detector (BEPD) and the second one is Binary PSO detector (BPSOD). Both algorithms have used the basic concept of PSO [100], without any important amendment. A modified PSO algorithm for space time block coded DS-CDMA systems has been proposed in [133]. In [134] Liu and Xiao also proposed a multiuser detector using PSO algorithm. Zubair *et al.* [135] have combined radial basis functions with PSO to solve the problem of multiuser detection and gave very attractive results.

4.3 PSO-Based MUD for AWGN Channel

Consider a K-users synchronous CDMA system, in which the received signal is given by (2.3.5). In case of conventional single user matched filter (SUMF) detector, received signal $r(t)$ is initially passed through a filter matched to the user signature waveform given as (2.4.10). Then the decision for the information bits is based on the signs of the outputs from the matched filters, given as

$$\hat{b}_k = \mathrm{sgn}(r_k) \qquad (4.3.1)$$

According to optimum MLD, $\mathbf{b} = [b_1, b_2, \ldots, b_K]$ is selected which minimizes (2.4.3), or maximizes the correlation metric given in (2.4.6). This is a search over $M = 2^K$ possible combinations of the components of $\mathbf{b} = [b_1 \; b_2 \ldots b_K]$, that clearly indicates the computational complexity. That is why, practically it is never used. Practically suboptimum detectors have been used instead, to reduce the computational cost that grows linearly with the number of users in this case. PSO is another option which reduces the search space and hence computational cost tremendously. Figure 4.1 shows the schematic of next proposed PSO-Based multiuser detector.

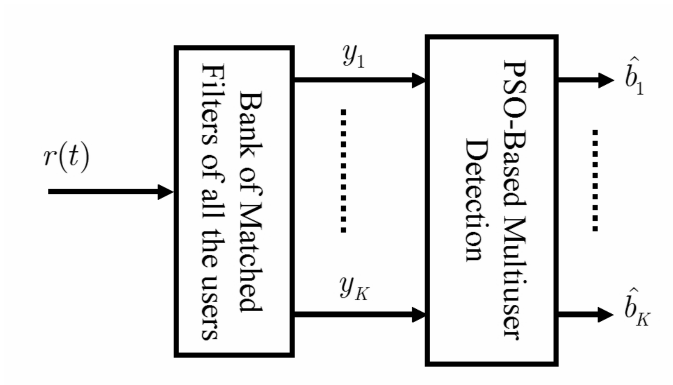


Fig. 4.1 Schematic of the PSO-Based MUD employed in a synchronous DS-CDMA system

4.3.1 Hard PSO for Multiuser Detection

PSO assumes that each possible solution is a particle in a swarm. Any i^{th} particle, or solution, is written as

$$\mathbf{b}_i = [b_{i1} \; b_{i2} \; \ldots b_{im} \ldots b_{iK}] \qquad (4.3.2)$$

where K is the total number of users b_{im} is the position of the i^{th} particle and m^{th} user. Corresponding to each position, we have a particle velocity v_{im}. The spirit of PSO is to use personal, as well as, collective intelligence. Thus each particle keeps the record of its position that has given best performance so far. It is denoted by

$$\mathbf{p}_i = [p_{i1} \ p_{i2} \ \cdots p_{im} \cdots p_{iK}] \quad (4.3.3)$$

Similarly the swarm also keeps the record of the position for global best performer given by

$$\mathbf{p}_g = [p_{g1} \ p_{g2} \cdots p_{gm} \cdots p_{gK}] \quad (4.3.4)$$

The following steps are followed for conventional or hard PSO (HPSO) for MUD

Step1: The output of conventional detector, which is a hard decision on matched filter output, is taken as input particle $\mathbf{b}_1$. The rest of the population is generated by perturbing $\mathbf{b}_1$, where perturbation means flipping sign of any one position of $\mathbf{b}_1$ selected randomly. Thus we get a population of N particles

Step2: Using (2.4.6) as fitness function, we evaluate the fitness of each particle. Then we find the best performer $\mathbf{p}_g$ of the population. Also looking at the history of each particle we record their corresponding local best positions $\mathbf{p}_i$.

Step 3: Rest of the algorithm has followed the steps 2 to 6 as given in the mathematical model for discrete PSO algorithm in section 4.2.2.

In all the above cases the decision on b_s is hard (± 1) starting from matched filters and all the way through PSO. Now we propose two modified version of PSO with soft decisions and call it as soft PSO version1 and soft PSO version2.

4.3.2 Proposed Variants of PSO for Multiuser Detection

4.3.2.1 Soft PSO Version1 (SPSO1)

In this case the logical steps are exactly the same as for HPSO however, following changes has been introduced.

a) We do not use the hard output of SUMF as the input particle for PSO which is given as (4.3.1). Instead a soft decision is given as

$$\hat{b}_k = \tanh(r_k) \quad k = 1, 2, \ldots, K \tag{4.3.5}$$

Figure 4.2 shows the behavior of $\tanh()$

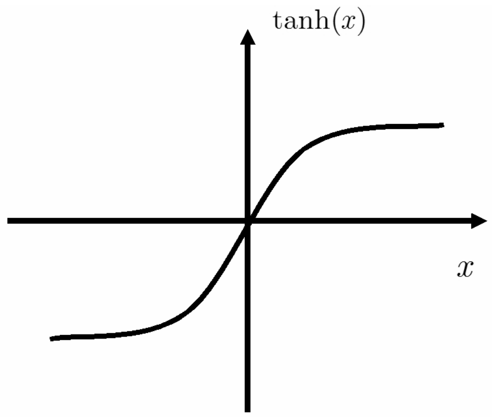


Fig. 4.2 Behavior of $\tanh()$ function

Thus $\hat{b}_k \in [-1, 1]$ and it is no more a hard decision in which $\hat{b}_k \in \{1, -1\}$. First particle is constructed with $\hat{b}_k \in$ [-1,1] , $k = 1, 2, \ldots, K$. All other particles are formed by perturbed the first particle i.e. change the sign of a randomly chosen bit.

b) The statement given in step 3 for HPSO is a hard decision on b_{im}. We change it into a soft decision.

$$if(rand() > S(v_{im})),\quad then\ b_{im} = -1 + S(v_{im}),\quad else\ b_{im} = S(v_{im})$$

However, in the last cycle, the decision taken is a hard decision.

4.3.2.2 Soft PSO Version2 (SPSO2)

Following are the changes made for SPSO2

(i). In SPSO2, the velocity update equation is given as

$$v_{im}(n) = v_{im}(n-1) + \varphi_1(1-\beta)(p_{im} - b_{im}(n-1)) + \varphi_2\beta(p_{gm} - b_{im}(n-1)) \tag{4.3.6}$$

where $0 \le \beta \le 1$, since we want to avoid the local minima trap in the early stages, we will like to move the particles more close to p_{im}, that is, more importance should be given to local intelligence in the beginning and global intelligence at the end. To achieve this β is given a smaller value i.e. 0.1, initially and then it is increased continuously to the value 0.9 up to the end.

(ii). For continuous case we have the following statement

$$b_{im}(t+1) = b_{im}(t) + v_{im}(t+1) \tag{4.3.7}$$

For discrete case its equivalent is given as:

$$if(rand() < S(v_{im})),\quad then\quad b_{im} = 1\quad else\quad b_{im} = -1$$

Since we are considering soft decision PSO, therefore, we may use (4.3.7) with a modification such that b_{im} does not cross the limits of ± 1. Hence we propose the following expression for updated b_{im} given as follows.

$$b_{im}(n+1) = b_{im}(n) + 2\tanh(\gamma v_{im}),\qquad 0 \le \gamma \le 1 \tag{4.3.8}$$

It is clear from the above equation that whenever v_{im} is large, the value of b_{im} increases softly to give an ultimate decision of +1 and vice versa.

4.3.3 Simulation Results and Discussion

Simulations have been performed and results are taken for the system containing different number of users. Each user in the system is assigned 31 bit Gold sequence for spreading the data. The performance of SPSO1 and SPSO2 has been checked first of all against suboptimal schemes, such as SUMF detector, decorrelating detector and LMMSE detector and results are given in figure 4.3 that confirm the better performance of SPSO1 and SPSO2 algorithms over suboptimal detectors. The performance of SPSO1 and SPSO2 has also been checked against HPSO and GA algorithms with different system load. We have used population size, $P = 10$ and executed the algorithm for 20 iterations, $Y = 20$ for the system containing 10 users. Performance comparison of SPSO1, SPSO2, HPSO and GA for 10 users system is given in fig. 2.4. Performance of proposed SPSO1 and SPSO2 is better than HPSO and GA. In fig. 2.5, $P = 20$ and $Y = 30$ have been used to optimize the SPSO1, SPSO2, HPSO and GA algorithms with system load, $K = 20$. Once again SPSO1 has defeated all other algorithms. $P = 50$ and $Y = 30$ have been used for the system accommodating 30 users and results are given in fig. 2.6. for the system containing 40 users, we have used $P = 80$ and $Y = 40$ to optimize the SPSO1, SPSO2, HPSO, and GA algorithms. It can be seen from fig. 4.4 to fig. 4.7, that performance-wise SPSO1 and SPSO2 gave better results than HPSO and GA with much less computational complexity then MLD.

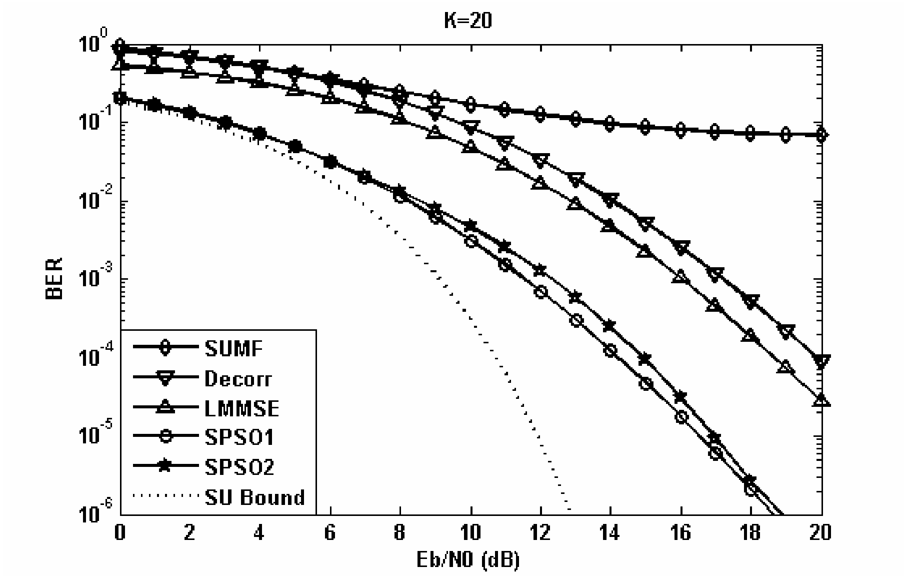


Fig. 4.3 Performance of SPSO1 and SPSO2 against sub-optimal detectors for AWGN channel where the number of users in the system is 20.

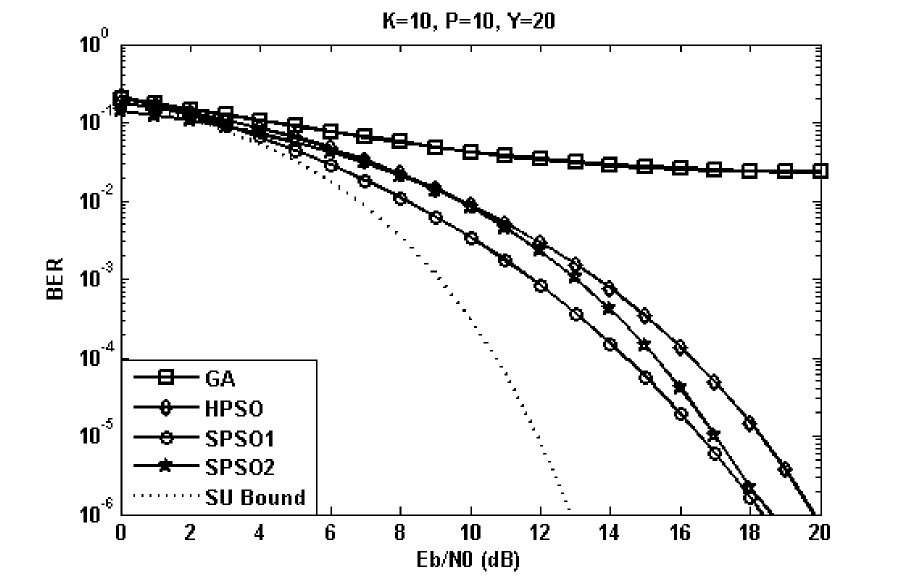


Fig. 4.4 Performance Comparison of SPSO1 and SPSO2 with GA and HPSO for AWGN channel. Single user bound is also given. Number of users, $K = 10$

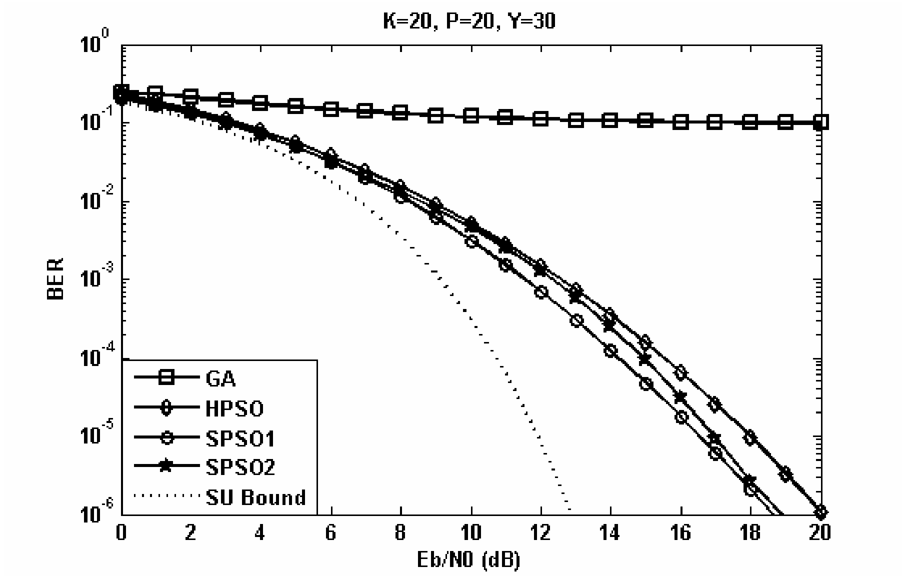


Fig. 4.5 Performance Comparison of SPSO1 and SPSO2 with GA and HPSO for AWGN channel. Single user bound is also given. Number of users, $K = 20$

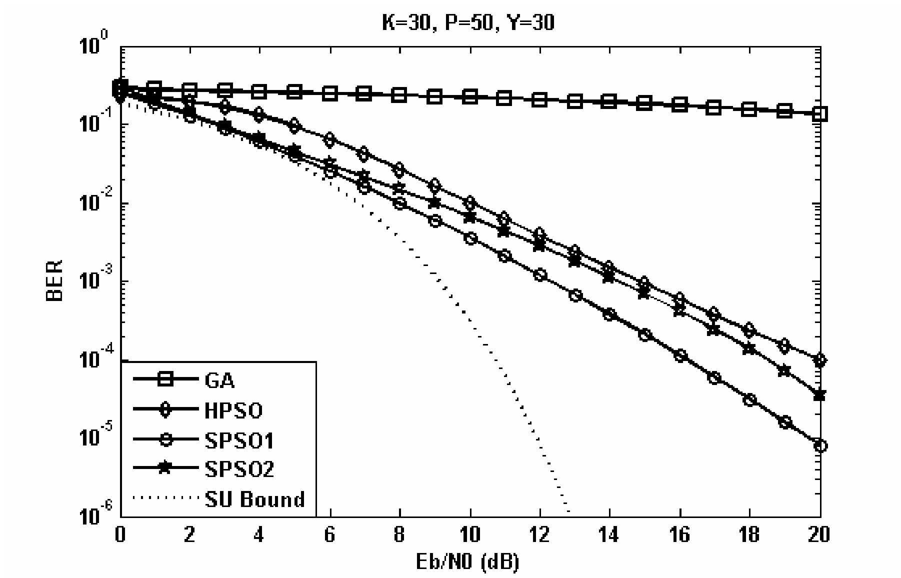


Fig. 4.6 Performance Comparison of SPSO1 and SPSO2 with GA and HPSO for AWGN channel. Single user bound is also given. Number of users, $K = 30$

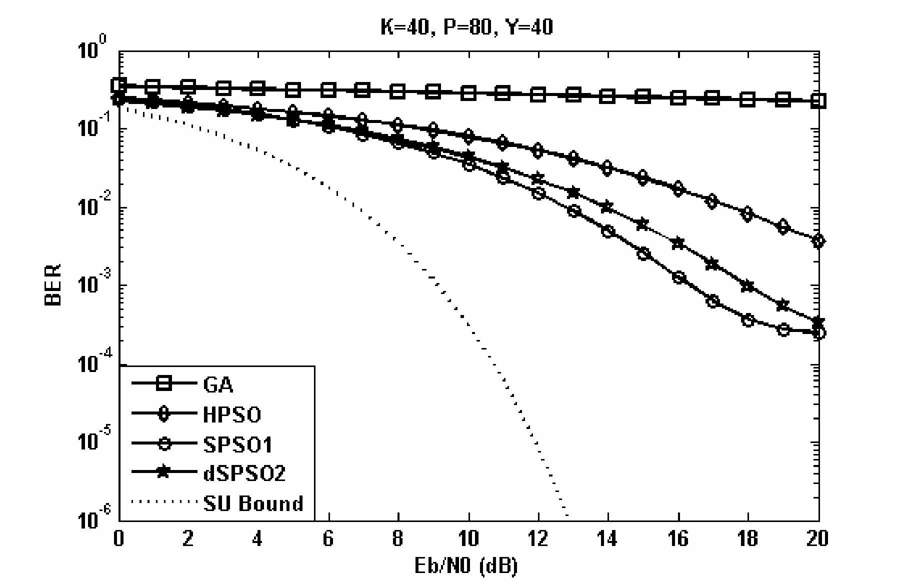


Fig. 4.7 Performance Comparison of SPSO1 and SPSO2 with GA and HPSO for AWGN channel. Single user bound is also given. Number of users, $K = 40$

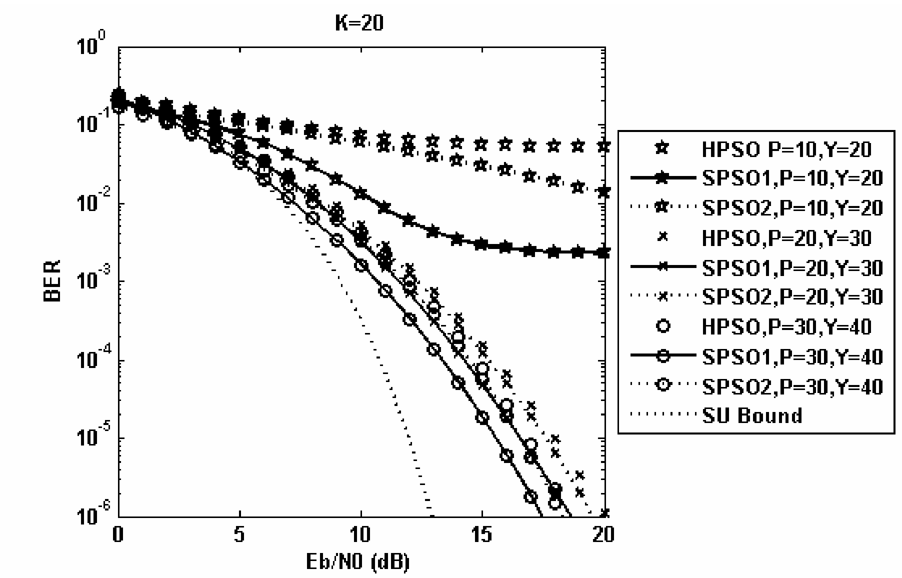


Fig. 4.8 BER performance of SPSO1 and SPSO2 for different Complexities for AWGN channel

The results of fig. 2.7 for $K = 40$ are not much attractive, but if we notice the computational complexity i.e. PY=3200, which is very much less than the computational complexity of MLD i.e. 2^{40}. By increasing the number of particles and/or number of iterations, we can get better results. The improvement in the BER with a small increase in the computational complexity is shown in fig. 4.8. Both SPSO1 and SPSO2 have improved their performance with increasing computational complexity.

4.4 PSO-Based MUD for Multipath SFFR Channel

Consider a K users DS-CDMA system in which the signal of each user is assumed to propagate over an independent SFFR channel. The fading envelop of each path is statistically independent for all the users. Hence the single coefficient channel impulse response of the k^{th} user can be expressed as $\alpha_k e^{j\varphi_k}$, where the amplitude α_k is a Rayleigh distributed random variable, while the phase φ_k is uniformly distributed between $[0, 2\pi]$. Hence the received signal can be expressed as

$$r(t) = \sum_{k=1}^{K} A_k b_k g_k(t) \alpha_k e^{j\varphi_k} + n(t) \qquad (4.4.1)$$

The output vector $\mathbf{r}$ of the bank of matched filters can be formulated as

$$\mathbf{r} = \mathbf{RHb} + \mathbf{n} \qquad (4.4.2)$$

where $\mathbf{b}$ and $\mathbf{R}$ are given in (2.4.8) and (2.4.9) respectively, and

$$\mathbf{H} = diag\left[\alpha_1 e^{j\varphi_1}, \alpha_2 e^{j\varphi_2}, \ldots, \alpha_K e^{j\varphi_K}\right]$$

$$\mathbf{n} = \left[n_1, n_2, \ldots, n_K\right]^T$$

According to [135], the optimum ML detector detects the data bits as follows

$$\hat{\mathbf{b}} = \arg\left\{\max_{\mathbf{b}}\left[\Lambda(\mathbf{b})\right]\right\} \tag{4.4.3}$$

Where

$$\Lambda(\mathbf{b}) = 2\,\mathrm{Re}\left[\mathbf{b}^T\mathbf{H}^*\mathbf{r}\right] - \mathbf{b}^T\mathbf{HRH}^*\mathbf{b} \tag{4.4.4}$$

where $(\cdot)^T$ and $(\cdot)^*$ are the transpose and conjugate operators respectively.

This is an exhaustive search of 2^K possibilities, which is impractical. We have used our proposed SPSO1 algorithm with (4.4.4) as cost function. Hereafter SPSO will imply on SPSO1 unless otherwise stated.

4.4.1 Simulation Results and Discussion

Simulations have been performed for the systems containing 10, 20, 30, and 40 users. Each user in the system is assigned 31 bit Gold sequence to spread the data. We have used the computational complexities (P=10, Y=20), (P=20, Y=30), (P=50, Y=30) and (P=80, Y=40) to optimize the SPSO, HPSO, and GA algorithms for 10, 20, 30 and 40 users respectively. Performance comparison of the proposed SPSO-based multiuser detector against other standard suboptimal multiuser detectors is shown in fig. 4.9. The BER for SPSO has been obtained with the computational complexity PY=600, which is a fraction of the computational complexity of MLD, which is 2^{20}. As we can observe, BER of SPSO is very close to single user bound. BER comparison of SPSO, HPSO and GA for $K = 10$ are given in fig. 4.10 with computational complexity PY=200. BER comparison of SPSO, HPSO and GA for $K = 20$ is plotted in figure 4.11. Similarly fig. 4.12 and fig. 4.13 are presented the performance comparison of SPSO with GA and HPSO for $K = 30$ and 40 respectively. It can be seen from these figures that the SPSO not only outperform the GA, but are also better than HPSO. The computational complexity for SPSO is much less than that of MLD. The reason behind using the different computational complexity for different system loads is that PSO algorithm required a minimum number of particles and number of iterations to converge for fix number of users. In figure 4.14, BER of SPSO for different computational complexities has been plotted for $K = 20$. It can be seen from fig. 4.14 that for SPSO the computational complexity PY=20x30=600 is even giving very attractive results that are very close to single user bound.

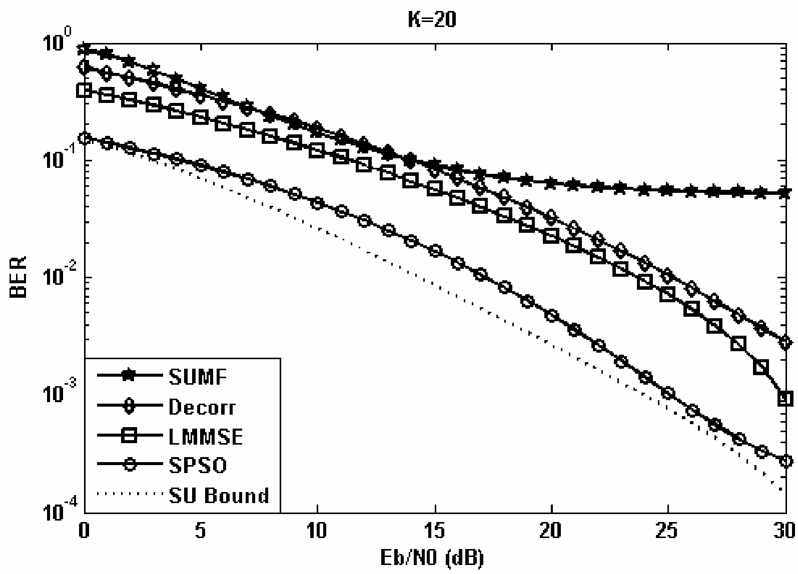


Fig. 4.9 BER Performance of SPSO for $K = 20$ against sub-optimal detectors for SFFR channel.

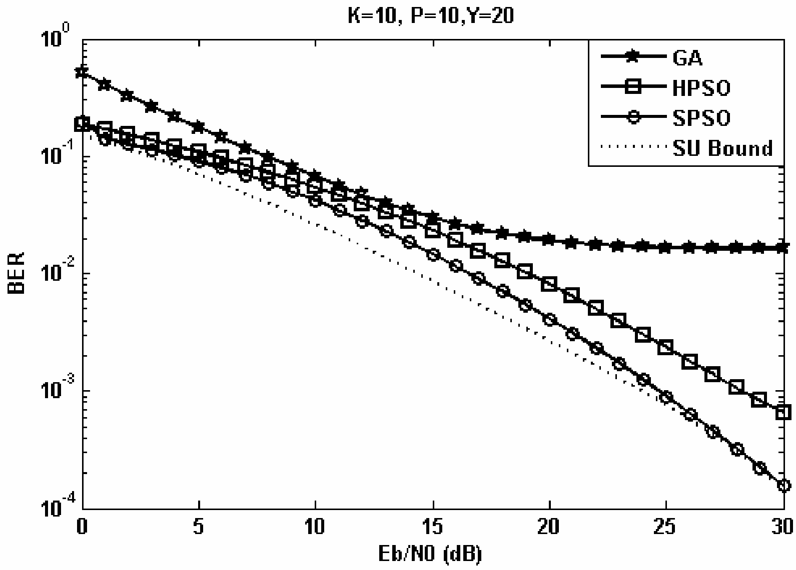


Fig. 4.10 Performance comparison of SPSO with GA and HPSO for SFFR channel. Single user bound is also given. Number of users, $K = 10$

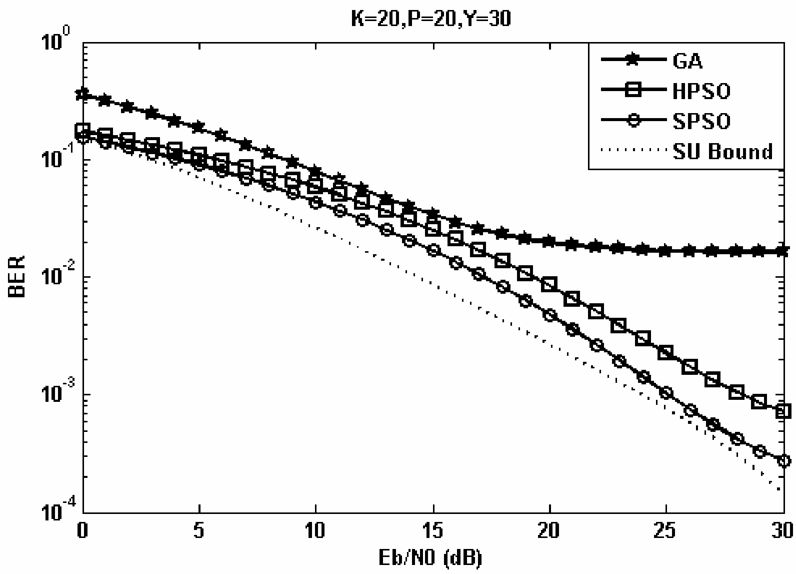


Fig. 4.11 Performance Comparison of SPSO with GA and HPSO for SFFR channel. Single user bound is also given. Number of users, $K = 20$

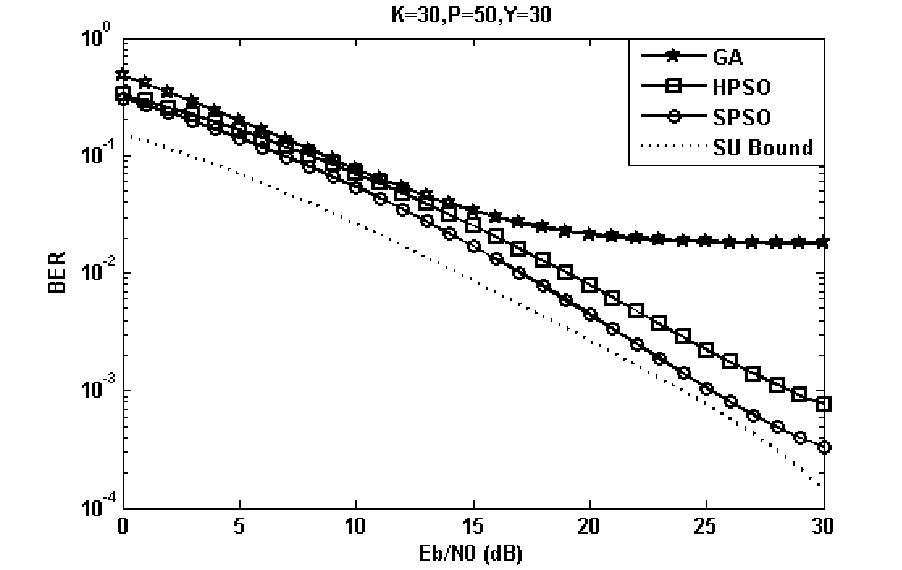


Fig. 4.12 Performance Comparison of SPSO with GA and HPSO for SFFR channel. Single user bound is also given. Number of users, $K = 30$

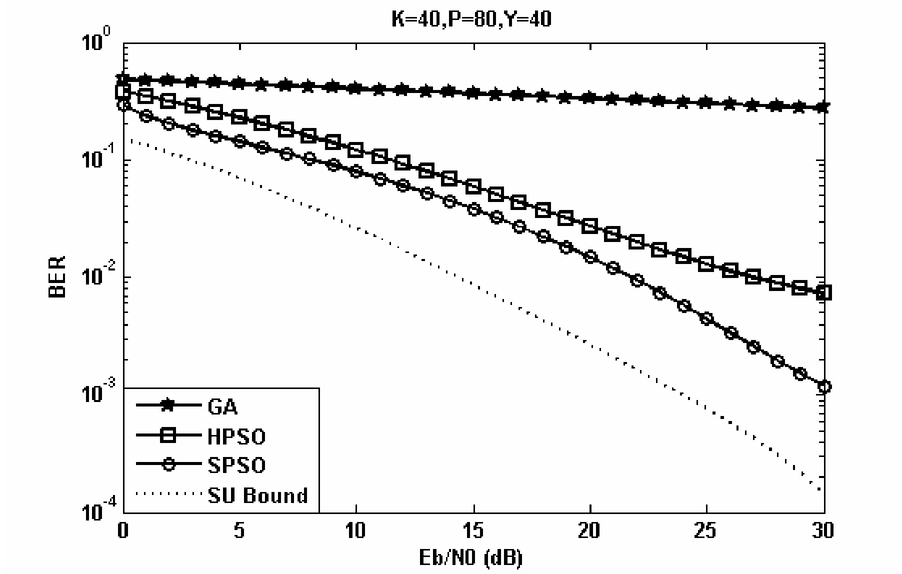


Fig. 4.13 Performance Comparison of SPSO with GA and HPSO for SFFR channel. Single user bound is also given. Number of users, $K = 40$

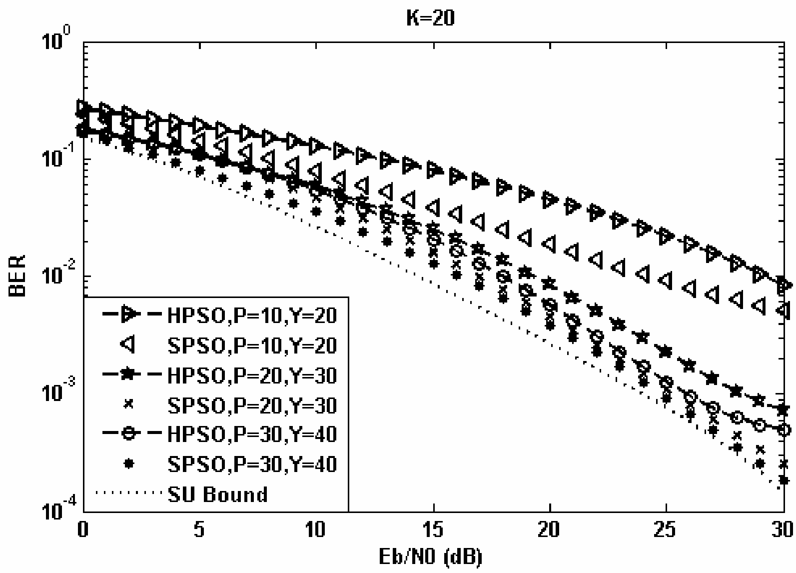


Fig. 4.14 BER performance of SPSO and HPSO for different Complexities for SFFR channel for $K = 20$ users CDMA system.

Chapter 5

MUD FOR OVERLOADED CDMA SYSTEMS

5.1 Introduction

This chapter deals with the overloaded systems. In CDMA system, the problem of overloading arises when the number of users is larger than the number of available spreading sequences. In this situation the users are divided equally in groups. Each user in a group is given a unique spreading code. The set of spreading codes used by one group is reused by the other groups as well. The composite signal of each group is sent on a different carrier i.e. M groups are sent on M different carriers equally spaced in frequency domain. The composite signal of each group can be easily separated on the receiver side due to M demodulators at different respective frequencies. Once the composite signal of each group is separated one may use either PU-PIC detector or PSO-based detector to extract the data of users within that group. One can also find the set of spreading codes in a group that have same cross-correlation to use the PU-PIC detector. However, if such codes are not available then the PSO-based detector is the only choice. It is important to mention that PU-PIC detector can be used for downlink as well as for synchronous MUD whereas PSO-based detector can only be used for synchronous MUD.

5.2 Overloaded System with PU-PIC Detector in AWGN Channel

Consider a communication system with N number of users that are arranged in M groups each having $K+1$ users (i.e. $N = M(K+1)$). The $(K+1)^{th}$ user of each group is the Pseudo-user, whose data is already known to the receiver. Fig. 5.1 shows the transmission of $K+1$ users of m^{th} group.

The data of each user in this group is spread by a unique code. Composite signal of each group is then multiplied with a carrier that is orthogonal to the carriers of other groups. Modulated signals of all groups are then combined and transmitted over an AWGN channel.

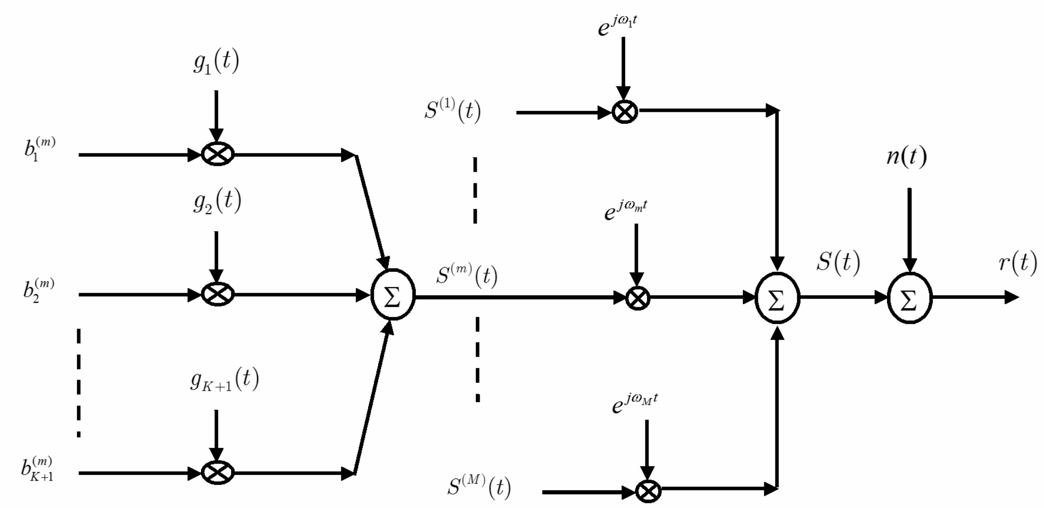


Fig. 5.1 Proposed Transmitter for the overloaded CDMA system

The composite signal of m^{th} group is given by

$$S^{(m)}(t) = \sum_{k=1}^{K+1} A_k^{(m)} b_k^{(m)} g_k(t) \tag{5.2.1}$$

where $A_k^{(m)}$, $b_k^{(m)} \in \{1,-1\}$ are the amplitude and data bit, respectively, for the k^{th} user of m^{th} group and $g_k(t)$ is the signature waveform for k^{th} user which is given as

$$g_k(t) = \sum_{i=0}^{L-1} a_{ki} p(t - iT_c) \qquad (5.2.2)$$

where a_{ki} is the i^{th} chip of the k^{th} user spreading code. $p(t)$ is a pulse having width T_c, where the bit interval $T_b = LT_c$.

The composite signal of all the groups is given as

$$S(t) = \sum_{i=1}^{M} S^{(i)}(t) e^{j\omega_i t} \qquad (5.2.3)$$

5.2.1 Proposed Pseudo-user Assisted Multiuser Detector

Fig. 5.2 shows the proposed receiver structure. The received signal is given as

$$r(t) = S(t) + n(t) \qquad (5.2.4)$$

where $S(t)$ is given by (5.2.3) and $n(t)$ is zero mean AWGN. Detection of each group is accomplished by multiplying the received signal with the respective carrier of that particular group. Detection of the noisy composite signal of m^{th} group is given as

$$\hat{S}^{(m)}(t) = S^{(m)}(t) + n^{(m)}(t) \qquad (5.2.5)$$

where $n^{(m)}(t)$ is the low pass equivalent of noise

Matched filter detector is then used to get the initial estimate of individual user's bits. The output of the bank of matched filter for m^{th} group is given as

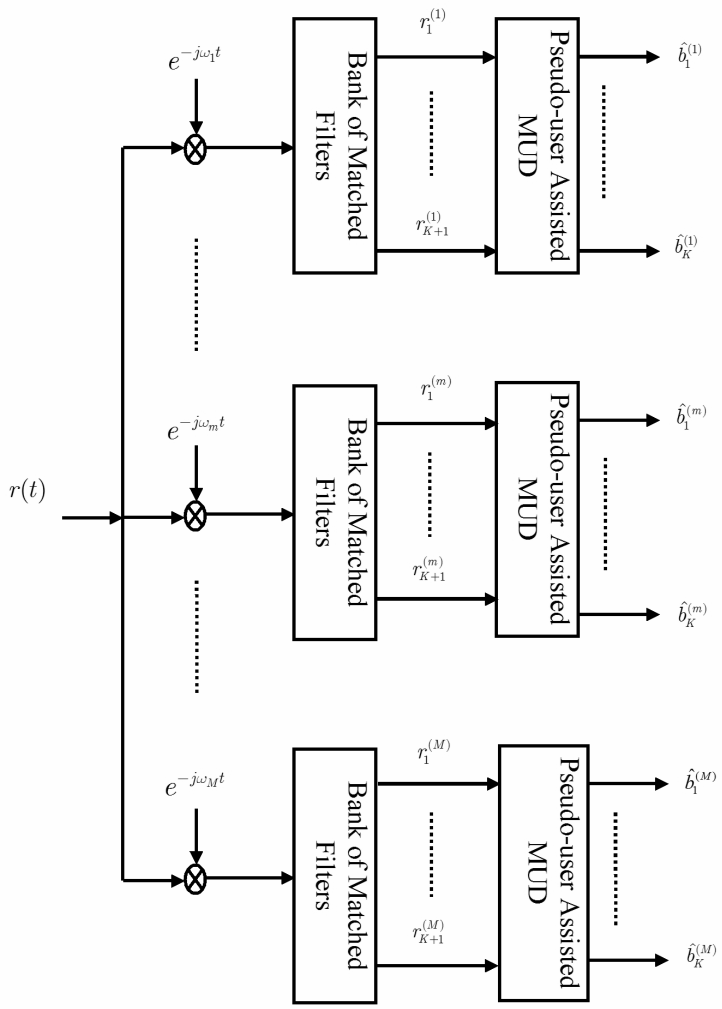


Fig. 5.2 Block diagram of Proposed Pseudo-user assisted multiuser detector for overloaded CDMA system.

$$
\begin{aligned}
r_k^{(m)} &= \int_0^{T_b} \hat{S}^{(m)}(t) g_k(t) dt \qquad for\ k = 1 \cdots (K+1) \\
&= \int_0^{T_b} \left[S^{(m)}(t) + n^{(m)}(t) \right] g_k(t) dt \\
&= \int_0^{T_b} \left[\sum_{i=1}^{K+1} A_i^{(m)} b_i^{(m)} g_i(t) + n^{(m)}(t) \right] g_k(t) dt \\
&= A_k^{(m)} b_k^{(m)} + \sum_{\substack{j=1 \\ j \neq k}}^{K+1} A_j^{(m)} b_j^{(m)} \rho + n_k
\end{aligned}
\tag{5.2.6}
$$

where $$n_k = \int_0^{T_b} n^{(m)}(t) g_k(t) dt \tag{5.2.7}$$

First term in (5.2.6) is the data of k^{th} user of m^{th} group, second term is MAI and the third term is the noise component. There are different algorithms, proposed in literature, to separate the data bits of individual users such as matched filter detector, MMSE detector, decorrelating detector, SIC and PIC etc. However, the performance of PU-PIC detector and PSO-based detector has been proved to be superior to these classical detectors. Therefore we shall use them for detection purposes.

When the cross-correlation between the signature waveforms of different users in a group is same, the PU-PIC detector is a better choice as compared to the PSO-based detector. Thus in this section we have used PU-PIC detector for the final detection of individual bits. We have already observed that each receiver in this case consists of two matched filters, one is matched with its own signature waveform and the other matched with the signature waveform of the pseudo-user i.e. $(K+1)^{th}$ user. The output of the pseudo-user is given as

$$\begin{aligned} r_{K+1}^{(m)} &= \int_0^{T_b} \hat{S}^{(m)}(t) g_{K+1}(t) dt \\ &= A_{K+1}^{(m)} b_{K+1}^{(m)} + \sum_{j=1}^{K} A_j^{(m)} b_j^{(m)} \rho + n_{K+1} \end{aligned} \tag{5.2.8}$$

The difference of (5.2.6) and (5.2.8) is given as.

$$\begin{aligned} y_k^{(m)} &= r_k^{(m)} - r_{K+1}^{(m)} \\ &= A_k^{(m)} b_k^{(m)} (1-\rho) + A_{K+1}^{(m)} b_{K+1}^{(m)} (\rho - 1) + n_k^{(m)} - n_{K+1}^{(m)} \\ &= A_k^{(m)} b_k^{(m)} (1-\rho) - A_{K+1}^{(m)} b_{K+1}^{(m)} (1-\rho) + n_k^{(m)} - n_{K+1}^{(m)} \end{aligned} \tag{5.2.9}$$

By using the information of pseudo-user we get the estimate of the k^{th} user data bit of m^{th} group, given as

$$\hat{b}_k^{(m)} = \mathrm{sgn}\left(A_k^{(m)} b_k^{(m)} + \eta_k\right) \tag{5.2.10}$$

where, the additive noise $\eta_k = (n_k^{(m)} - n_{K+1}^{(m)}) \big/ (1-\rho)$ is zero mean and variance σ_η^2 which is given previously in chapter 3, is given as

$$\sigma_\eta^2 = \frac{N_0}{(1-\rho)} \tag{5.2.11}$$

It can be seen, that the major portion of MAI has been removed.

The theoretical bit error probability of the proposed scheme is same as given by (3.3.9), which was originally derived for a simple system and is given as

$$P_b = Q\left(\sqrt{\gamma_b (1-\rho)}\right) \tag{5.2.12}$$

5.2.2 Simulation Results and Discussion for PU-PIC Detector

The proposed algorithm is simulated and its performance is shown in fig. 5.3 to fig. 5.5. In these simulations, we have used 31 chip length Gold codes to spread the data of individual user. Gold codes have three values of cross-correlations among the code words [99]. We have extracted a particular subset in which all the codes have same cross-correlation which is 0.2258. Same Gold codes are used for other groups. The advantage of this technique is that we can accommodate any number of users with limited number of spreading codes.

BER of proposed scheme for the systems having different number of groups is plotted in fig. 5.3. The number of users in each group is same. It can be seen that performance in this scenario, where each group has 8 users, is comparable for 2, 5, 10, 20, 30, and 40 groups. In all the cases the BER decreases exponentially for SNR greater than 10 dB. It is due to the fact that the interference is avoided among the groups by using orthogonal carriers, so that the BER becomes almost independent of the number of groups. Therefore by increasing the number of groups we can accommodate as much users as we need to resolve the problem of overloading. Fig. 5.4 shows the performance of the variable size group with 4, 8, 16, and 32 users. It is clear from the figure that the performance of the proposed detector is better for smaller group sizes, which is also the requirement of proposed detector, i.e. the signature waveforms having same cross-correlation. In Figure 5.5, the comparison of proposed detector with other suboptimal detectors is presented. The superior performance of the proposed detector over the previous classical work is obvious. The above results prove the applicability of the proposed detector for overloaded system.

We have considered multicarrier modulated CDMA system in which users are divided equally into groups. In each group we have introduced a pseudo-user whose information is known to all the receivers of that group. Although by doing this, the spectral efficiency is decreased, but the amount of computation is amazingly small, which is an interesting feature of this proposal. Moreover, simulation results show that the performance scheme is almost independent of the number of groups, unlike most of the other schemes in the literature. However, the proposed scheme is not independent of the number of users per group. It deteriorates as the number of users per group increases. A small drawback in the proposed detector is the noise enhancement. However, unlike the decorrelating detector, it does not involve the noise linked with all the users. It involves only the user noise and the corresponding pseudo-user noise.

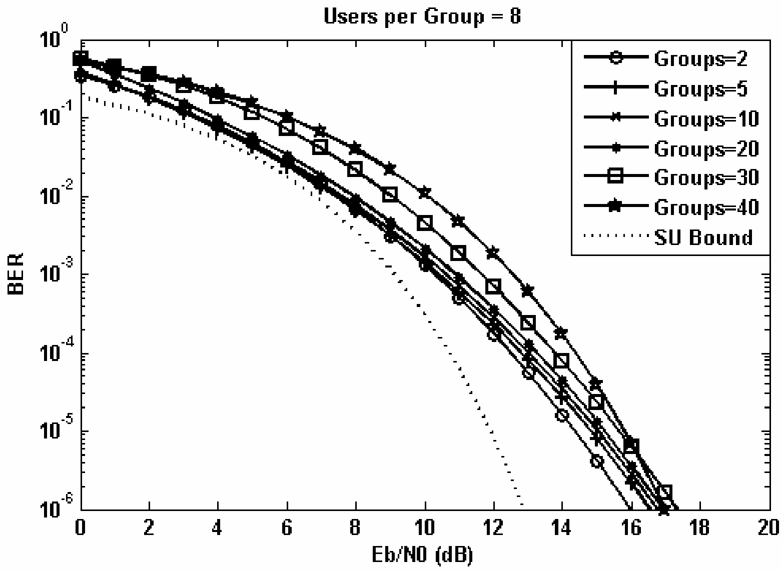


Fig. 5.3 BER performance of different groups containing 8 users in AWGN channel. 31 chip long 8 Gold codes are used with cross-correlation 0.2258 to spread the data of all users in each group.

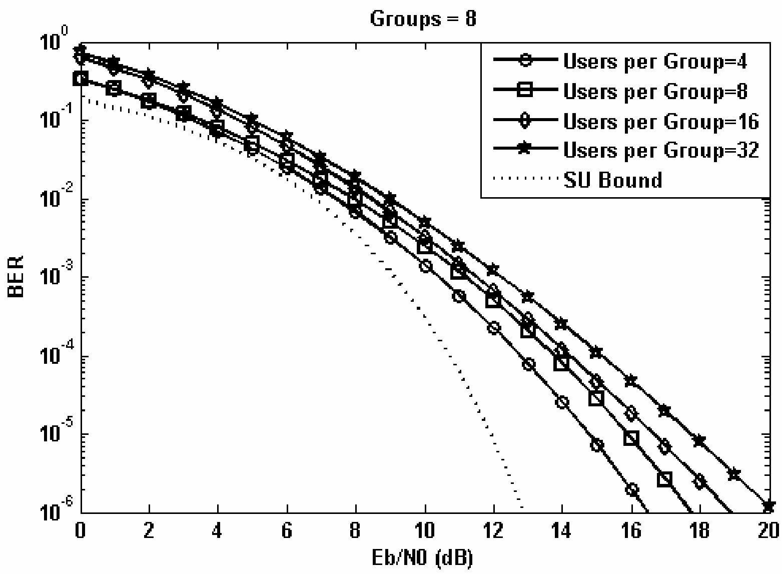


Fig. 5.4 BER performance against E_b/N_0 keeping number of groups constant (8 groups) in AWGN channel. The changing parameter is number of users per group. 31 chip long Gold codes are used for spreading the data.

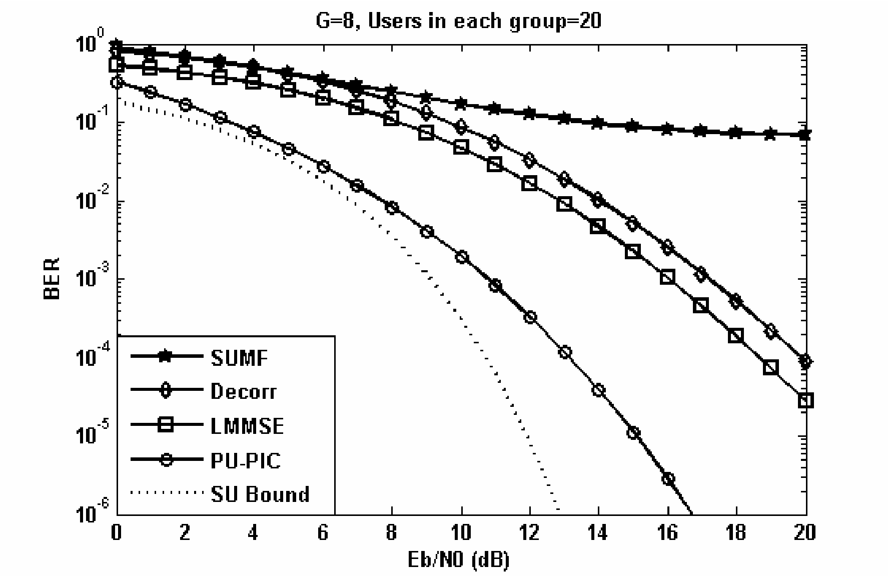


Fig. 5.5 Comparison of the proposed PU-PIC detector with other suboptimal detectors for $K = 160$ divided equally into 8 groups in AWGN channel. 31 chip long Gold codes with constant cross-correlation 0.2258 are used to spread the data.

5.2.3 PSO-Based Multiuser Detection for AWGN Channel

The multiuser detection for the same overloaded system as shown in figure 5.1 has also been accomplished with the help of PSO. The proposed receiver is same as in figure 5.2 except that the PU-PIC detector has been replaced with PSO-based detector, as shown in figure 5.6. As given in (5.2.5) the received signal of m^{th} group is given as

$$\hat{S}^{(m)}(t) = S^{(m)}(t) + n^{(m)}(t) \tag{5.2.13}$$

where $n^{(m)}(t)$ is the low pass equivalent of noise and $S^{(m)}(t)$ is the transmitted signal of m^{th} group given by,

$$S^{(m)}(t) = \sum_{k=1}^{K} A_k^{(m)} b_k^{(m)} g_k(t), \quad 0 \le t \le T_b \tag{5.2.14}$$

where $A_k^{(m)}$, $b_k^{(m)} \in \{1, -1\}$ are the amplitude and data bit for the k^{th} user of m^{th} group and $g_k(t)$, the signature waveform for k^{th} user.

The optimum maximum-likelihood receiver computes the log-likelihood function

$$\Lambda(\mathbf{b}) = \int_0^T \left[\hat{S}^{(m)}(t) - \sum_{k=1}^{K} A_k^{(m)} b_k^{(m)} g_k(t)\right]^2 dt \qquad (5.2.15)$$

Select $\mathbf{b}_K = [b_1 \ \ b_2 \ \dots \ b_K]^T$, that minimizes (5.2.15), or maximizes the following correlation metric form

$$C(\hat{\mathbf{S}}_K^{(m)}, \mathbf{b}_K^{(m)}) = 2\sum_{k=1}^{K} A_k^{(m)} b_k^{(m)} \hat{S}_k^{(m)} - \sum_{j=1}^{K}\sum_{k=1}^{K} A_j^{(m)} A_k^{(m)} b_j^{(m)} b_k^{(m)} \rho_{jk} \qquad (5.2.16)$$

where

$$\hat{S}_k^{(m)} = \int_0^T \hat{S}^{(m)}(t) g_k(t) dt \qquad 1 \le k \le K \qquad (5.2.17)$$

In vector form, it can be written as

$$C(\hat{\mathbf{S}}_K^{(m)}, \mathbf{b}_K^{(m)}) = 2\mathbf{b}_K^{(m)^T} \hat{\mathbf{S}}_K^{(m)} - \mathbf{b}_K^{(m)^T} \mathbf{R} \mathbf{b}_K^{(m)} \qquad (5.2.18)$$

where T is the transpose operator, $\mathbf{R}$ is same as in (2.4.9), and

$$\hat{\mathbf{S}}_K^{(m)} = \left[\hat{S}_1^{(m)}, \hat{S}_2^{(m)}, \dots, \hat{S}_K^{(m)}\right] \qquad (5.2.19)$$

$$\mathbf{b}_K^{(m)} = \left[b_1^{(m)}, b_2^{(m)}, \dots, b_K^{(m)}\right]^T \qquad (5.2.20)$$

For convenience we have taken $A_k^{(m)} = 1, \forall k, m$. Optimum multi-user detector searches for the data vector based on ML estimator given as

$$\hat{\mathbf{b}}^{(m)} = \arg\left\{\max_{\forall b \in \{1,-1\}} \left[C\left(\hat{\mathbf{S}}_K^{(m)}, \mathbf{b}_K^{(m)}\right)\right]\right\} \qquad (5.2.21)$$

For each group this is a search over $M = 2^K$ possible combinations of the components of $\mathbf{b}^{(m)} = \left[b_1^{(m)}, b_2^{(m)}, \dots, b_K^{(m)}\right]$. Due to the computational cost, it is not practically viable.

PSO has been considered here as a better option because it reduces the search space and hence computational cost significantly. We have used our proposed SPSO algorithms for multiuser detection in each group. The logical steps of SPSO are same as mentioned in section 4.4. Since all the groups are independent, hence computations can be performed in parallel. Thus an overloaded system becomes a problem of simple multiuser detection.

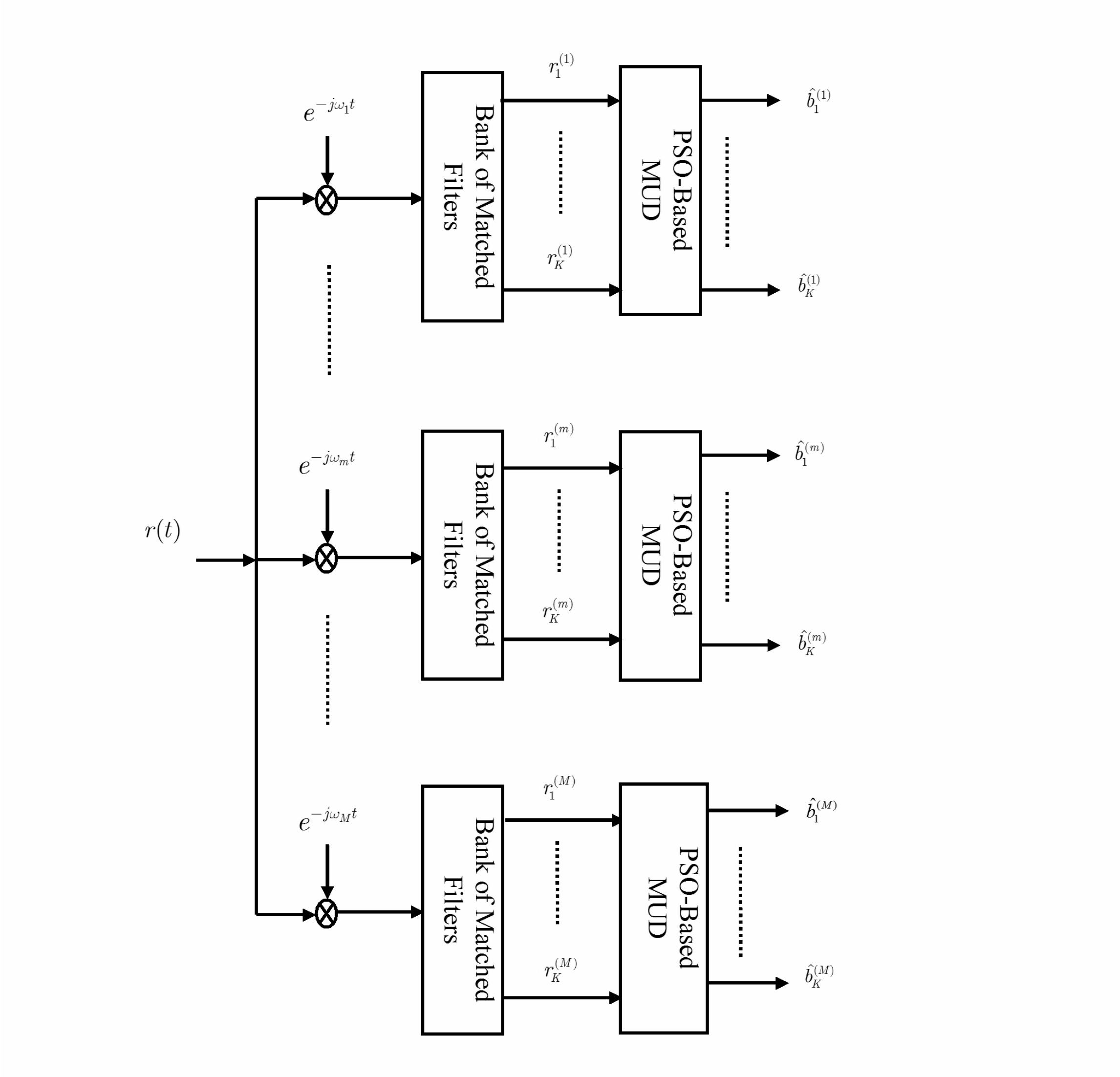


Fig. 5.6 Block diagram of Proposed PSO-based multiuser detector for overloaded CDMA system.

5.2.4 Simulation Results and Discussion for PSO-Based MUD

The performance of the proposed scheme is shown in figures 5.7-5.10. BER at different number of groups having same number of users is plotted in figure 5.7. It can be seen that the bit error rate (BER) performance in this scenario where each group has 10 users is almost same for 2, 5, 10, 20, and 30 groups and BER follows the single user bound SNR less than 10 dB, especially when the number of users is small. It is due to the fact that interference is avoided between the groups by using orthogonal carriers for all the groups, so the BER is almost independent of the number of groups. Therefore, by increasing the number of groups, we can accommodate as many users as we need, to resolve the problem of overloading. Figure 5.8 shows the performance of the variable size group with 10, 20, 30, and 40 users. It is clear that the performance of the proposed PSO-based detector is better for smaller group sizes.

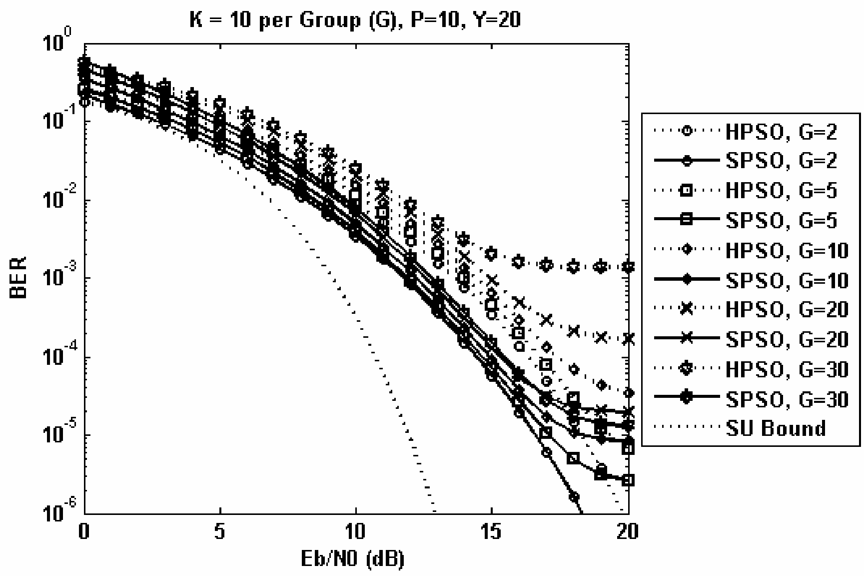


Fig. 5.7 BER performance with different groups each contains 10 users for AWGN channel. 31 chips long Gold codes are used to spread the data of users of each group.

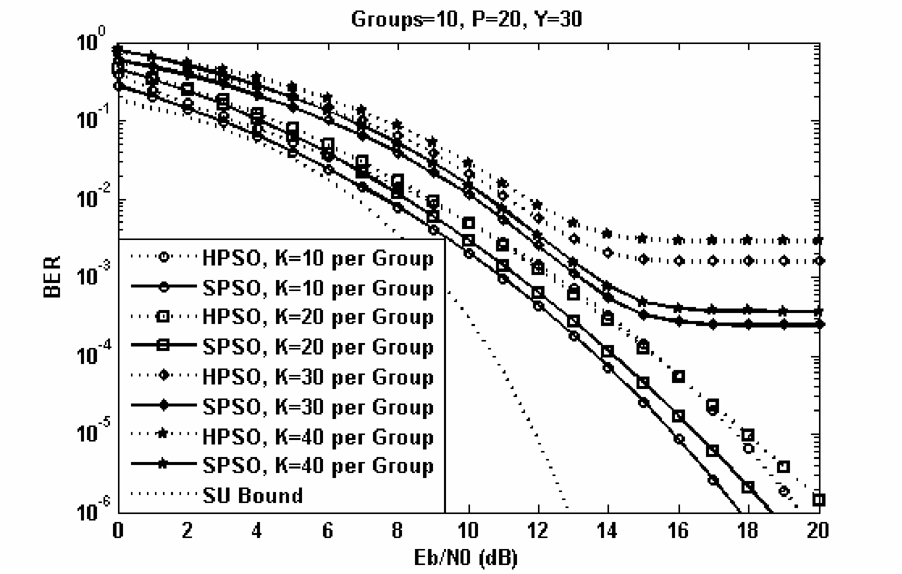


Fig. 5.8 BER performance against E_b/N_0 keeping number of groups constant (10 groups) for AWGN channel. The changing parameter is number of users per group. 31 chip long Gold codes are used for spreading the data.

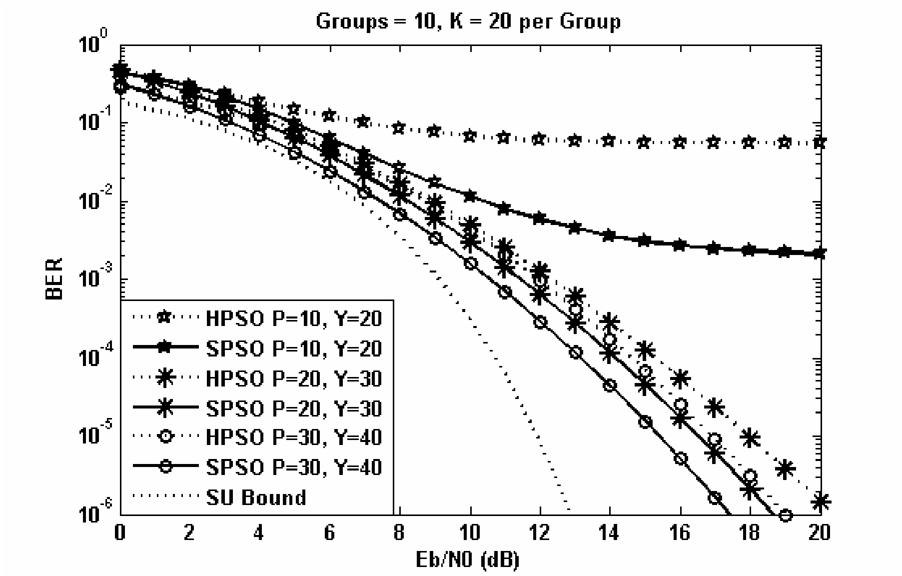


Fig. 5.9 BER performance of HPSO and SPSO at different Complexities for AWGN channel

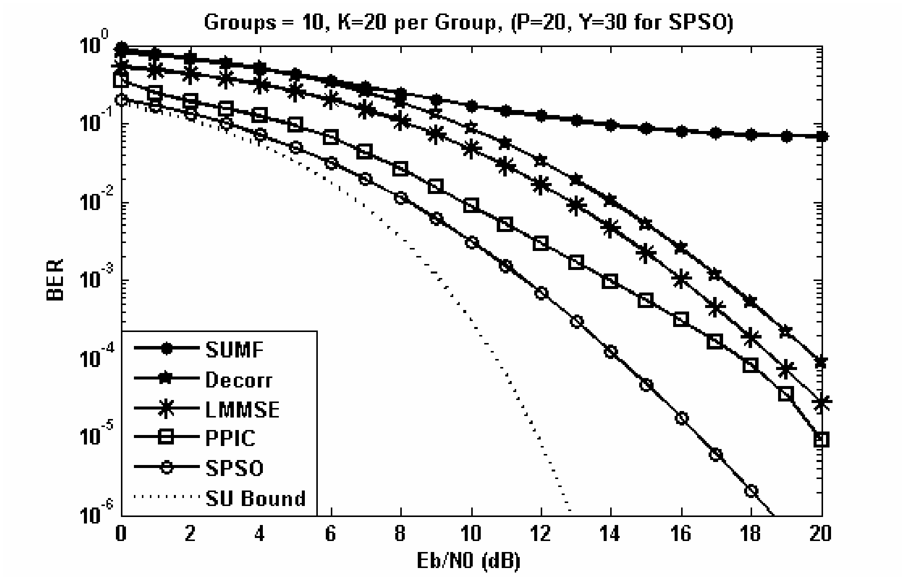


Fig. 5.10 Performance comparison of the proposed SPSO-based detector with other suboptimal detectors for $K = 200$ divided equally into 10 groups in AWGN channel. 31 chips long Gold codes are used to spread the data.

In Figure 5.9, the comparison of HPSO and SPSO is given at different computational complexities. Proposed SPSO is showing better results than HPSO, especially when given, reasonable number of iterations (PY=30x40=1200). Figure 5.10 gives the BER comparison of the proposed detector with other suboptimal detectors. All the results prove the applicability of the proposed detector for the overloaded system.

5.3 Overloaded System in Multipath SFFR Channel

In this section PU-PIC and PSO-based detectors are being presented for SFFR channel. Their performance has been evaluated and a comparison with the other detectors is also presented.

5.3.1 Proposed PU-PIC Multiuser Detector in SFFR Channel

The outputs of the k^{th} user and pseudo-user matched filters are given as

$$r_k^{(m)} = A_k^{(m)} b_k^{(m)} h_k + \sum_{\substack{j=1 \\ j \neq k}}^{K} A_j^{(m)} b_j^{(m)} h_k \rho + A_P^{(m)} b_P^{(m)} h_k \rho + n_k^{(m)} \tag{5.3.1}$$

$$r_P^{(m)} = A_P^{(m)} b_P^{(m)} h_k + \sum_{\substack{j=1 \\ j \neq k}}^{K} A_j^{(m)} b_j^{(m)} h_k \rho + A_k^{(m)} b_k^{(m)} h_k \rho + n_P^{(m)} \tag{5.3.2}$$

where we have assumed $\rho_{jk} = \rho \ \forall \ j,k$ and $n_k^{(m)}$, $n_P^{(m)}$ are same as given in, (3.3.3) and (3.3.4). Again the difference of the outputs of two matched filters is given as

$$\begin{aligned} y_k^{(m)} &= A_k^{(m)} b_k^{(m)} h_k + A_P^{(m)} b_P^{(m)} h_k \rho + n_k^{(m)} - A_P^{(m)} b_P^{(m)} h_k - A_k^{(m)} b_k^{(m)} h_k \rho - n_P^{(m)} \\ &= A_k^{(m)} b_k^{(m)} h_k^{(m)} (1-\rho) - A_P^{(m)} b_P^{(m)} h_k (1-\rho) + n_k^{(m)} - n_P^{(m)} \end{aligned} \tag{5.3.3}$$

The k^{th} user and the pseudo-user signals are coming from the same channel simultaneously, therefore (5.3.3) can be written as

$$y_k^{(m)} = A_k^{(m)} b_k^{(m)} h_k (1-\rho) - A_P^{(m)} b_P^{(m)} h_k (1-\rho) + n_k^{(m)} - n_P^{(m)} \tag{5.3.4}$$

The bit decision of k^{th} user of m^{th} group is given as

$$\begin{aligned} \hat{b}_k^{(m)} &= \operatorname{sgn}\left[\operatorname{Re}\left\{\frac{h_k^* y_k^{(m)} + A_P^{(m)} b_P^{(m)} \left|h_k\right|^2 (1-\rho)}{(1-\rho)}\right\}\right] \\ &= \operatorname{sgn}\left[\operatorname{Re}\left\{A_k^{(m)} b_k^{(m)} \left|h_k\right|^2 + \frac{h_k^*(n_k - n_P)}{(1-\rho)}\right\}\right] \end{aligned} \tag{5.3.5}$$

5.3.2 Simulation Results and Discussion of PU-PIC Detector

In this case the simulation pattern which is given in section 5.2.2 has been repeated with the difference of the communication channel. The results in figures 5.11 to 5.13 are taken for SFFR channel. It can be seen that the proposed PU-PIC detector is equally good for this channel. Independence of the PU-PIC detector to the number of groups and number of users can be observed clearly in figure 5.11 and 5.12. The BER comparison of PU-

PIC with other suboptimal detectors is given in figure 5.13. Clearly the PU-PIC detector outperforms the other suboptimal detectors.

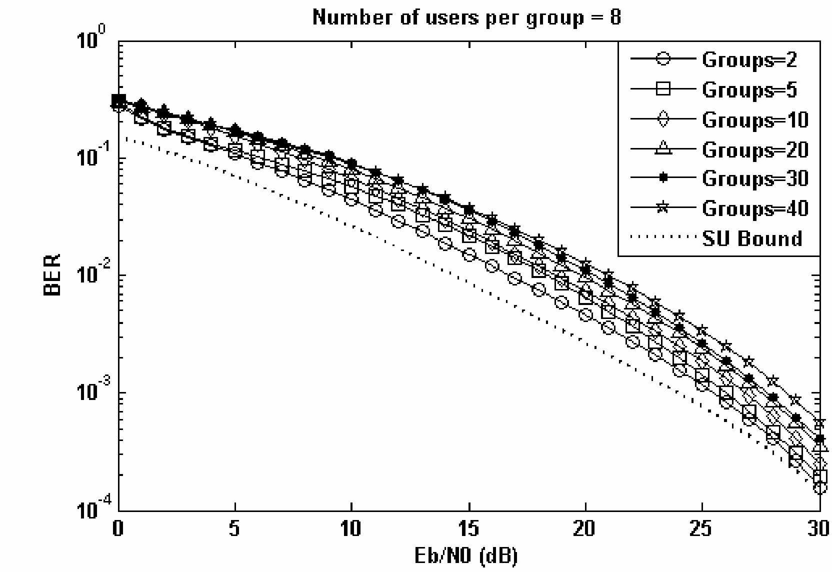


Fig. 5.11 BER performance of PU-PIC detector for different groups containing 8 users in SFFR channel. 31 chips long 8 Gold codes are used with cross-correlation 0.2258 to spread the data of users of each group.

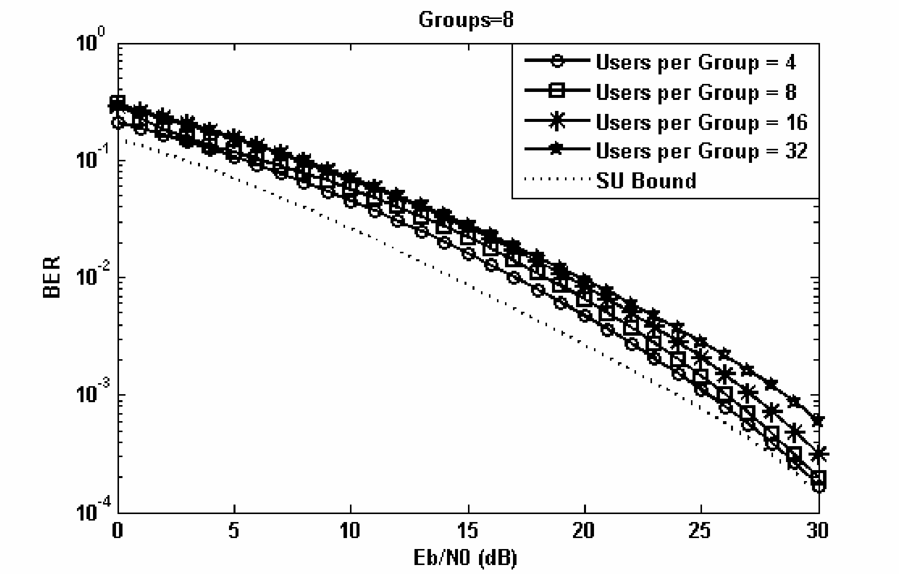


Fig. 5.12 BER performance of PU-PIC detector against E_b/N_0 keeping number of groups constant (8 groups) in SFFR channel. The changing parameter is number of users per group. 31 chips long Gold codes are used for spreading the data

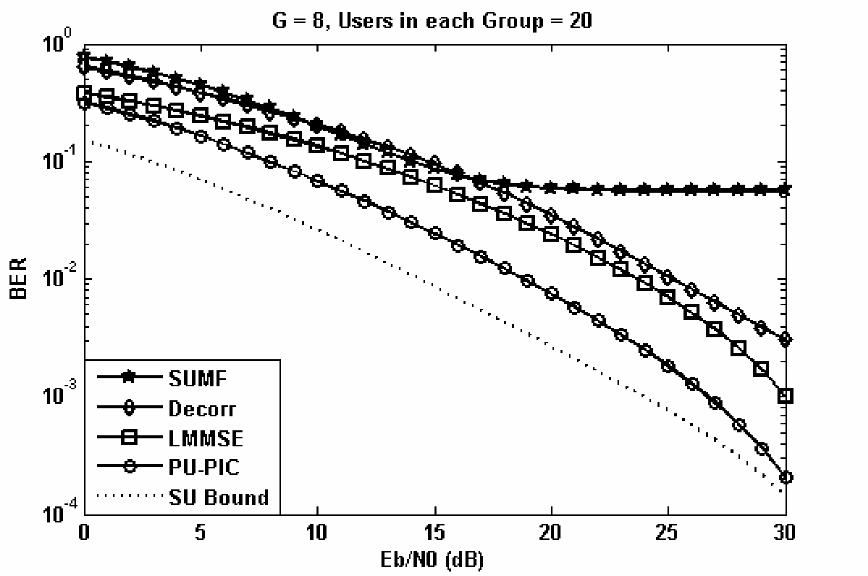


Fig. 5.13 BER performance of the proposed PU-PIC detector against other suboptimal detectors for $K = 160$ divided equally into 8 groups in SFFR channel. 31 chips long Gold codes with constant cross-correlation 0.2258 are used to spread the data.

5.3.3 PSO-Based Multiuser Detection in SFFR Channel

Consider a K users DS-CDMA system in which the signal of each user is assumed to be propagated over an independent SFFR channel. The fading envelop of each path is statistically independent for all the users. Hence the single coefficient channel impulse response of the k^{th} user can be expressed as $\alpha_k e^{j\varphi_k}$, where the amplitude α_k is a Rayleigh distributed random variable, while the phase φ_k is uniformly distributed between $[0, 2\pi]$. Hence the received signal can be expressed as

$$r^{(m)}(t) = \sum_{k=1}^{K} A_k^{(m)} b_k^{(m)} g_k(t) \alpha_k^{(m)} e^{j\varphi_k^{(m)}} + n^{(m)}(t) \tag{5.3.6}$$

The output vector $\mathbf{y}^{(m)}$ of the bank of matched filters for m^{th} group can be formulated as

$$\mathbf{r}^{(m)} = \mathbf{R}\mathbf{H}^{(m)}\mathbf{A}^{(m)}\mathbf{b}^{(m)} + \mathbf{n}^{(m)} \tag{5.3.7}$$

where $\mathbf{R}$ is as given in (2.4.9), and

$$\mathbf{H}^{(m)} = diag\left[\alpha_1^{(m)} e^{j\varphi_1^{(m)}}, \alpha_2^{(m)} e^{j\varphi_2^{(m)}}, \ldots, \alpha_K^{(m)} e^{j\varphi_K^{(m)}}\right]$$

$$\mathbf{A}^{(m)} = diag\left[A_1^{(m)}, A_2^{(m)}, \ldots, A_K^{(m)}\right]$$

$$\mathbf{b}^{(m)} = \left[b_1^{(m)}, b_2^{(m)}, \ldots, b_K^{(m)}\right]^T$$

and

$$\mathbf{n}^{(m)} = \left[n_1^{(m)}, n_2^{(m)}, \ldots, n_K^{(m)}\right]$$

According to [67] and [145], the optimum MLD detects the data bits as follows

$$\hat{\mathbf{b}}^{(m)} = \arg\left\{\max_{\mathbf{b}^{(m)}}\left[\Lambda(\mathbf{b}^{(m)})\right]\right\} \tag{5.3.8}$$

where

$$\Lambda(\mathbf{b}^{(m)}) = 2\,\mathrm{Re}\left[(\mathbf{b}^{(m)})^T (\mathbf{H}^{(m)})^* \mathbf{y}^{(m)}\right] - (\mathbf{b}^{(m)})^T \mathbf{H}^{(m)} \mathbf{R} (\mathbf{H}^{(m)})^* \mathbf{b}^{(m)} \tag{5.3.9}$$

where $(.)^T$ and $(.)^*$ are the transpose and conjugate operators.

This procedure involves an exhaustive search over 2^K vectors, which is impractical. Another viable option is PSO, which basically lowers the computational cost of optimum MLD. We have used our proposed SPSO algorithm, explained in section 4.3.2.1. The results hence obtained are quite attractive with much less computations as compared to optimum MLD. The cost function used for SPSO is given by (5.3.9).

5.3.4 Simulation Results and Discussion for PSO-Based MUD

The performance of the proposed multiuser detector while communicating on SFFR channel is shown in figures 5.14 to 5.17. BER for different number of groups containing same number of users is plotted in figure 5.14. It can be seen that the performance in this scenario i.e. each group has 10 users, is almost same for 2, 5, 10, 20, and 30 groups and BER follows the single user bound. This is due to the reason that the interference between the groups has been avoided by using orthogonal carriers. Therefore, the BER is almost independent of the number of groups. By increasing the number of groups we can accommodate as many users as desired to resolve the problem of overloading. Figure 5.15 shows the performance with the variable group sizes i.e. groups having 10, 20, 30, and 40 users each. The superior performance of the proposed PSO-based algorithm is evident in the fig. 5.14 and fig. 5.15. In fig. 5.16, the comparison of HPSO and SPSO is given for different computational complexities. Proposed SPSO show better results especially when the number of iterations are reasonable (PY=30x40=1200), which are 2^{20} in case of optimum MLD. Figure 5.17 provides the BER comparison of proposed detector with other suboptimal detectors. The better performance of the proposed PSO-based detector over other suboptimal detectors is clear. These results are sufficient to prove the applicability of the proposed detector for overloaded systems.

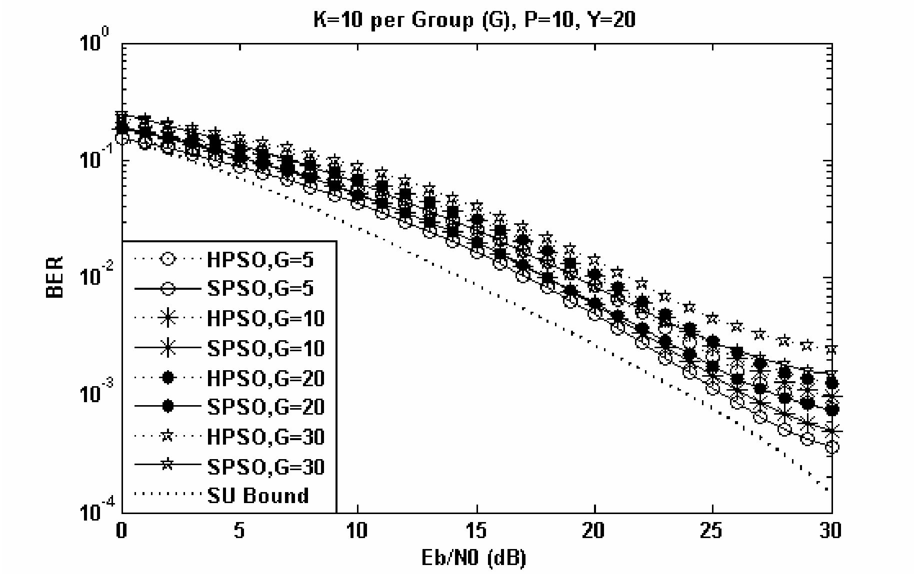


Fig. 5.14 BER performance of PSO-based detector for different groups containing 10 users in SFFR channel. 31 chips long Gold codes are used to spread the data of users of each group.

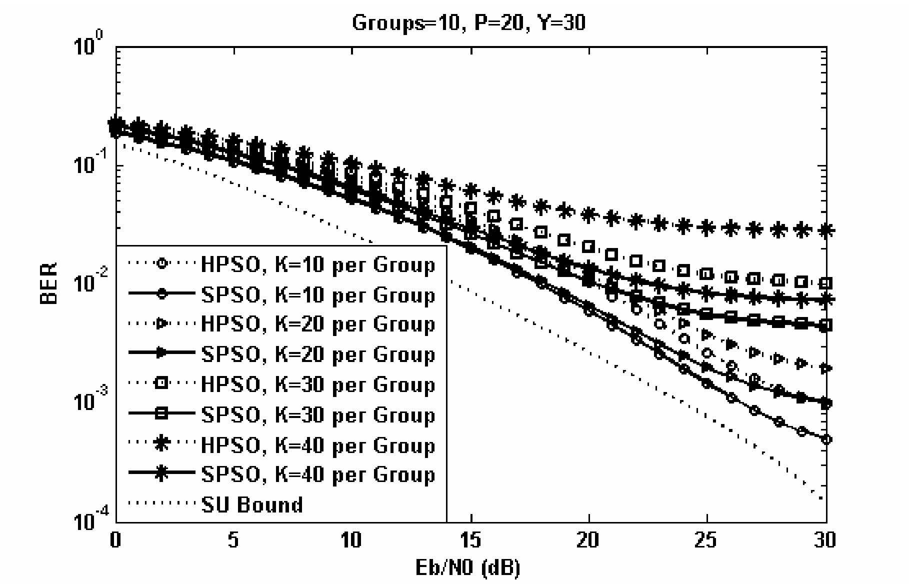


Fig. 5.15 BER performance of PSO-based detector against E_b/N_0 keeping number of groups constant (10 groups) in SFFR channel. The changing parameter is number of users per group. 31 chip long Gold codes are used for spreading the data.

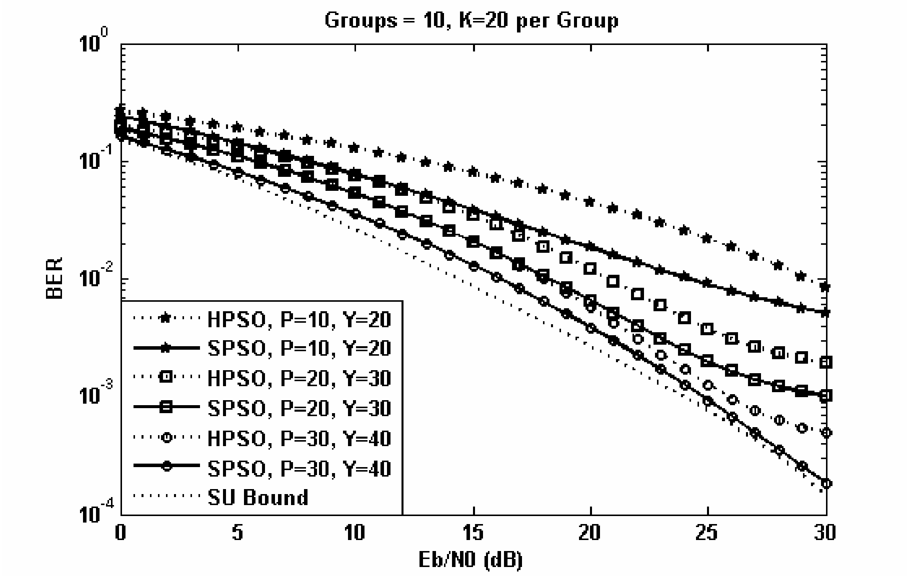


Fig. 5.16 BER performance of HPSO and SPSO for different Complexities in SFFR channel

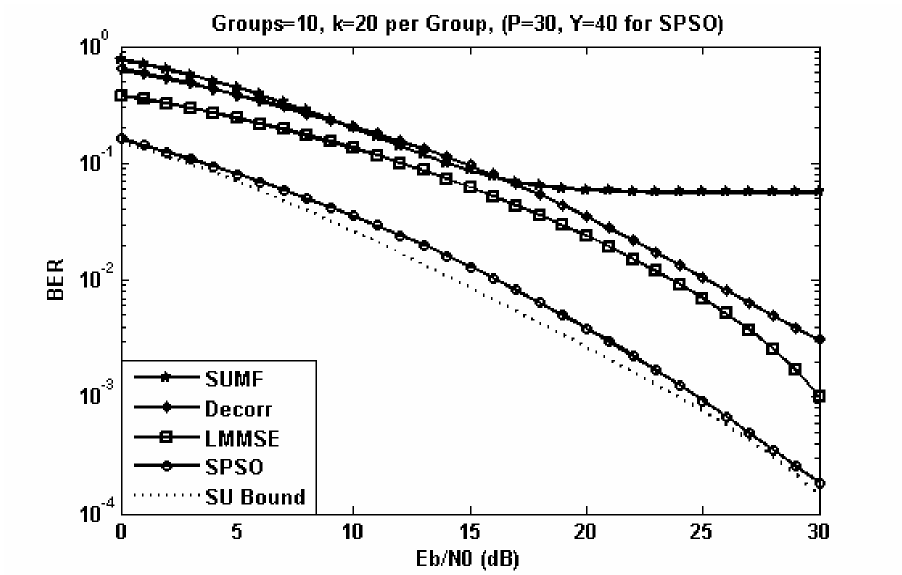


Fig. 5.17 BER performance of the proposed SPSO-based detector against other suboptimal detectors for $K = 200$ divided equally into 10 groups in SFFR channel. 31 chips long Gold codes are used to spread the data.

Chapter 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

This dissertation is concerned with the multiuser detection in CDMA systems. Different approaches for multiuser detection are devised for CDMA systems. There are two major issues addressed in this dissertation in designing a receiver for CDMA systems. The first one is related to multiple access interference. The other issue is the receiver complexity of optimum MLD that grows exponentially with the number of users. We have presented a novel approach to reduce the effect of MAI. Proposed PU-PIC detector is very simple and removes MAI very elegantly. There are two drawbacks in the PU-PIC detector. Firstly it enhances noise, but the noise enhancement is only due to pseudo-user signal in contrast with the decorrelating detector. Noise components of other users cancel out at least theoretically. Secondly, some bandwidth is wasted due to the redundant information of pseudo-user. By increasing the number of users in the system, this bandwidth loss can be minimized. Therefore PU-PIC detector is suitable for downlink applications.

We have also addressed the computational complexity of the optimum MLD that grows exponentially with the number of users. PSO algorithm gave very attractive results with very less number of computations as compared to MLD. The main advantage of PSO is its fast convergence. We found that for a fix number of particles there is some fix number of iterations even if we increase the size of particles i.e. increase the number of users, the number of iterations almost remains same. PSO-based multiuser detector detect the data of all users simultaneously, therefore it is suitable for synchronous uplink communication and for base station to base station link. Moreover, its utility will be justified compared to that of PU-PIC detector where spreading codes does not have constant cross-correlation.

Due to the increasing demand of wireless applications, number of subscribers is increasing day by day. When the number of users exceeds the number of available spreading sequences, the system becomes overload. In chapter 5, we tried to solve the problem of overloading. We divided the total users of the system into groups. Each group contained the number of users not more than the available signatures. Same set of signatures has been used for all the groups. Composite data for each group is modulated through orthogonal carriers. After detecting each group through orthogonal carrier, we proposed two different detectors for detecting the individual user bits. PU-PIC detector and SPO-based detector work with the same spirit as we mentioned previously. Both detectors have been checked for simple AWGN channel and SFFR channel. Both detectors have shown promising performance not only for simple systems but also for overloaded systems.

6.2 Future Work

In this dissertation, we have proposed different multiuser detection techniques for synchronous CDMA communication systems. However, the field of CDMA communication systems still has many areas to be investigated. Wireless communication systems are assumed asynchronous mostly. Hence, designing of a multiuser detector for asynchronous CDMA is a very attractive problem that will be addressed in near future.

In the current dissertation we have investigated our proposed multiuser detectors for simple AWGN and SFFR channel. The work will be further enhanced to frequency selective and fast fading Rayleigh channels. In this current work we exploit the multicarrier modulation to solve the problem of system overloading. In order to increase the capacity of wireless channel, our future research will focus on the combination of orthogonal frequency division multiplexing (OFDM) and CDMA. The proposed scheme of this dissertation will also be tested on Rician and Nakagami fading channels.

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Certificate

It is certified that the research work contained in this dissertation has been carried out under the supervision of Dr. Ijaz Mansoor Qureshi, at Muhammad Ali Jinnah University, Islamabad Campus. It is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

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