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Study and Development of Novel Techniques for PHY-Layer Optimization of Smart Terminals in the Context of Next-Generation Mobile Communications

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Abstract

Future mobile broadband communications working over wireless channels are required to provide high performance services in terms of speed, capacity, and quality. A key issue to be considered is the design of multi-standard and multi-modal ad-hoc network architectures, capable of self-configuring in an adaptive and optimal way with respect to channel conditions and traffic load. In the context of 4G-wireless communications, the implementation of efficient baseband receivers characterized by affordable computational load is a crucial point in the development of transmission systems exploiting diversity in different domains. This thesis proposes some novel multi-user detection techniques based on different criterions (i.e., MMSE, ML, and MBER) particularly suited for multi-carrier CDMA systems, both in the single- and multi-antenna cases. Moreover, it considers the use of evolutionary strategies (such as GA and PSO) to channel estimation purposes in MIMO multi-carrier scenarios. Simulation results evidenced that the proposed PHY-layer optimization techniques always outperform state of the art schemes by spending an affordable computational burden.

Particular attention has been used on the software implementation of the formulated algorithms, in order to obtain a modular software architecture that can be used in an adaptive and optimized reconfigurable scenario.

Keywords

multi-user detection (MUD), channel estimation, adaptive algorithm, minimum bit error rate (MBER), MIMO STBC MC-CDMA

Ai miei genitori,
Alfonso e Teresa.

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Leandro D'Orazio

Contents

List of Tables

List of Figures

List of Abbreviations and Acronyms

1G	First Generation Wireless Communication System
2G	Second Generation Wireless Communication System
3G	Third Generation Wireless Communication System
3GPP	3G-Partnership Project
4G	Fourth Generation Wireless Communication System
ACO	Ant Colony Optimization
AFSA	Artificial Fish Swarm Algorithm
AMPS	Advanced Mobile Phone System
ASF	Antenna Subarray Formation
AWGN	Additive White Gaussian Noise
BA	Bees Algorithm
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
CFO	Carrier Frequency Offset
CG	Conjugate Gradient
CI	Carrier Interferometry

CIR	Channel Impulse Response
CSI	Channel State Information
DD	Decision-Directed
DS-CDMA	Direct-Sequence Code-Division Multiple Access
DS-SS	Direct-Sequence Spread Spectrum
DSP	Digital Signal Processor
DVB	Digital Video Broadcasting
EDGE	Enhanced Data Rates for Global Evolution
EGC	Equal Gain Combining
EM	Expectation Maximization
ETACS	Extended Total Access Communications System
FFT	Fast Fourier Transform
FOMA	Freedom of Mobile Multimedia Access
GA	Genetic Algorithm
GPRS	General Packet Radio Service
GSM	Global System for Mobile communications
HDTV	High-Definition TeleVision
I-FFT	Inverse Fast Fourier Transform
IMT-2000	International Mobile Telecommunications programme
IS	Interim Standard
ISI	Inter-Symbol Interference

ITU	International Telecommunication Union
JDC	Japan Digital Cellular
LMS	Least Mean Square
LS	Least Squares
MAI	Multi-Access Interference
MBER	Minimum Bit Error Rate
MC-CDMA	Multi-Carrier Code-Division Multiple Access
MC-SS	Multi-Carrier Spread Spectrum
MCBER	Minimum Conditional Bit Error Rate
MIMO	Multiple Input Multiple Output
MJBER	Minimum Joint Bit Error Rate
ML	Maximum-Likelihood
MM	Majorize (Minorize) - Minimization (Maximization)
MMS	Multimedia Messaging Service
MMSE	Minimum Mean Square Error
MRC	Maximal Ratio Combining
MSE	Mean Square Error
MUD	Multi-User Detection
NLMS	Normalized Least Mean Square
NMT450	Nordic Mobile Telephone
NN	Neural Network

NRZ	Non-Return-to-Zero
NTT	Nippon Telephone and Telegraph
OFDM	Orthogonal Frequency Division Multiplexing
ORC	Orthogonality Restoring Combining
OVSF	Orthogonal Variable Spreading Factor
PAPR	Peak-to-Average Power Ratio
pcPIC	Per-Carrier Parallel Interference Cancellation
PDF	Probability Density Function
PIC	Parallel Interference Cancellation
PSO	Particle Swarm Optimization
QAM	Quadrature Amplitude Modulation
QE	Quantum Evolution
QoS	Quality of Service
R&D	Research and Development
RAx	3GPP Rural Area channel model
RF	Radio Frequency
RLS	Recursive Least Square
RT	Reconfigurable Terminal
SDMA	Space Division Multiple Access
SDR	Software Defined Radio
SIC	Serial Interference Cancellation

SIMO	Single Input Multiple Output
SINR	Signal-to-Interference-plus-Noise-Ratio
SISO	Single Input Single Output
SNR	Signal-to-Noise Ratio
ST	Space-Time
STBC	Space Time Block Code
STTC	Space Time Trellis Code
SVD	Singular Value Decomposition
TACS	Total Access Communications System
UMTS	Universal Mobile Telecommunications System
VSL	Variable-Spreading-Length
WCDMA	Wideband Code Division Multiple Access
WLAN	Wireless Local Area Networks
WWRF	Wireless World Research Forum
ZF	Zero Forcing

Chapter 1

Introduction

Wireless communication is one of the most active areas of research over the past and the current decades. A variety of services have been offered in such a context, starting from Voice, continuing to Data and now to Multimedia. Significant reductions in cost and time can also be achieved using wireless solutions, providing even several benefits to the users in terms of mobility and flexibility in the placement of terminals. In fact, wireless mobile systems have begun to permeate all areas of our daily life and are therefore required to provide high-speed, high-capacity and high-quality services with performances closer to those afforded by wireline systems. This evolution has been made possible by academic and industrial Research and Development (R&D) labs with the implementation of three generations of cellular systems ([1]).

The first-generation (1G) was analog-based. It used analog modulations and sent information as a continuously varying waveform. The widespread commercial deployment of 1G systems started in the 1979s in Tokyo, Japan by Nippon Telephone and Telegraph (NTT). This was followed in Europe in 1981 by the Nordic Mobile Telephone (NMT450) system developed by Ericsson for Scandinavia, in 1982 by the Total Access Communications System (TACS) for the United Kingdom and in 1985 by the Extended Total Access Communications System (ETACS) for the other european countries. Those systems were not interoperable, given that the operating frequency was different in almost each country. The situation was different in the United States, where only a single analog cellular standard called Advanced Mobile Phone System (AMPS) has been developed by Ameritech in 1983. These systems suffered from low user capacity and had voice quality issues ([2, 3, 4]).

The second generation (2G) cellular systems use digital modulation schemes, source coding, and error correction coding techniques. These advances helped improve user capacity, voice quality, and spectrum efficiency. The spreading of 2G systems started with the european Global System for Mobile communications (GSM) in 1990 ([5]) and continued with North American TDMA Systems (IS-54, IS-136) in 1992 and 1996, North American Spread Spectrum System (IS-95) in 1993 ([6]) and Japan Digital Cellular (JDC) in 1992 ([7]). GSM became the more widely used system throughout the world, providing an upgraded transmission technology with a single, unified standard in Europe. These systems were able to perfectly provide basic services (e.g., voice and low bit-rate data), but when demands for a variety of wideband services increased (e.g., high speed Internet access and video/high quality images transmission), the evolution toward third generation (3G) started. The first step in this direction has been commonly accepted as the second and one-half generation (2.5G), with the development of new technologies always based on the classical GSM (e.g., General Packet Radio Service (GPRS) and Enhanced Data Rates for Global Evolution (EDGE)).

The real 3G mobile systems have been developed to offer both low- and high-bandwidth services like telephony (voice, video, fax, etc.), Internet access (e-mail, web browsing, videoconferencing, e-commerce, etc.), and multimedia (playing music, viewing videos, films, television, etc.), at any time and from anywhere through a single device. The first 3G system was introduced in October 2001 in Japan by NTT DoCoMo under the name FOMA (Freedom of Mobile Multimedia Access) ([8]). It is based on the Wideband Code Division Multiple Access (WCDMA) transmission protocol, which has been recognized by the International Telecommunication Union (ITU) as the most promising candidate for the international 3G standard under the International Mobile Telecommunications programme, IMT-2000. It is able to offer wideband services, such as wireless Internet services (with peak rate of 384 Kbps) and video transmissions (with data rate up to 2Mbps).

At the present time, it is predicted that the current 3G technology and its first evolutions (commonly recognized as the third and one-half generation (3.5G)) will tend to be congested in few years. The research community and the telecommunications industry are therefore working to identify possible solutions for the fourth generation (4G) of wireless communications. It should be able to meet needs of future high-performance applications like wireless broadband access, Multimedia Messaging Service (MMS), video chat, mobile TV, High-Definition TeleVision (HDTV) content, and Digital Video Broadcasting (DVB). It requires an extension of the 3G capacity by an order of magnitude. The 4G tendency is to integrate mobile communications standards (specified by IMT) and Wireless Local Area Networks (WLAN). The resulting technology will be therefore based on a fully IP-based integrated system. The goal is to have data rates in the range 50-100 Mbps in cellular networks and around 1 Gbps in the WLAN environment, with premium quality and high security.

The 4G working group (the Wireless World Research Forum (WWRF), launched on August 2001 by the founding members Alcatel, Ericsson, Motorola, Nokia, and Siemens) has defined the following as objectives of the 4G wireless communication standard ([9, 10, 11, 12, 13]):

- a spectral efficient system
- high network capacity: more simultaneous users per cell
- a nominal data rate of 100 Mbps while the client physically moves at high speeds relative to the station, and 1 Gbps while client and station are in relatively fixed positions as defined by the ITU-R
- a data rate of at least 100 Mbps between any two points in the world
- smooth handoff across heterogeneous networks

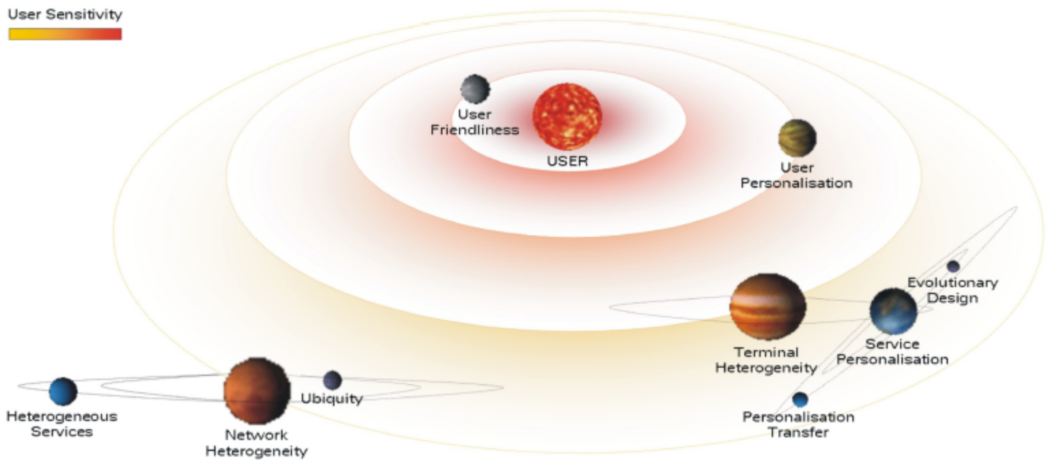


Figure 1.1: The user-centric system presented in [14]

- seamless connectivity and global roaming across multiple networks
- high quality of service for next generation multimedia support
- interoperability with existing wireless standards
- an all IP, packet switched network.

An innovative vision of 4G systems has been provided by Frattasi *et al.* in [14]. As depicted in Fig. 1.1, the user is located in the center of the system and the different key features defining 4G rotate around him on orbits with a distance dependent on a user-sensitivity scale. Therefore, the further the planet is from the center of the system the less the user is sensitive to it. The user-centric system demonstrates that it is mandatory in the design of 4G to focus on the upper layers (max user-sensitivity) before improving or developing the lower ones. Without user friendliness, for example, the user cannot exploit his device and access to other features, such as user personalization.

The research community has already generated several enabling technologies for 4G, e.g., adaptive coding and modulation, iterative (turbo) decoding algorithms, space-time coding, multiple antennas and Multiple Input Multiple Output (MIMO) channels, multi-carrier modulation, multi-user detection, and ultra wideband radio.

The road to the fourth generation is pictorially summarized in Fig. 1.2 ([9]).

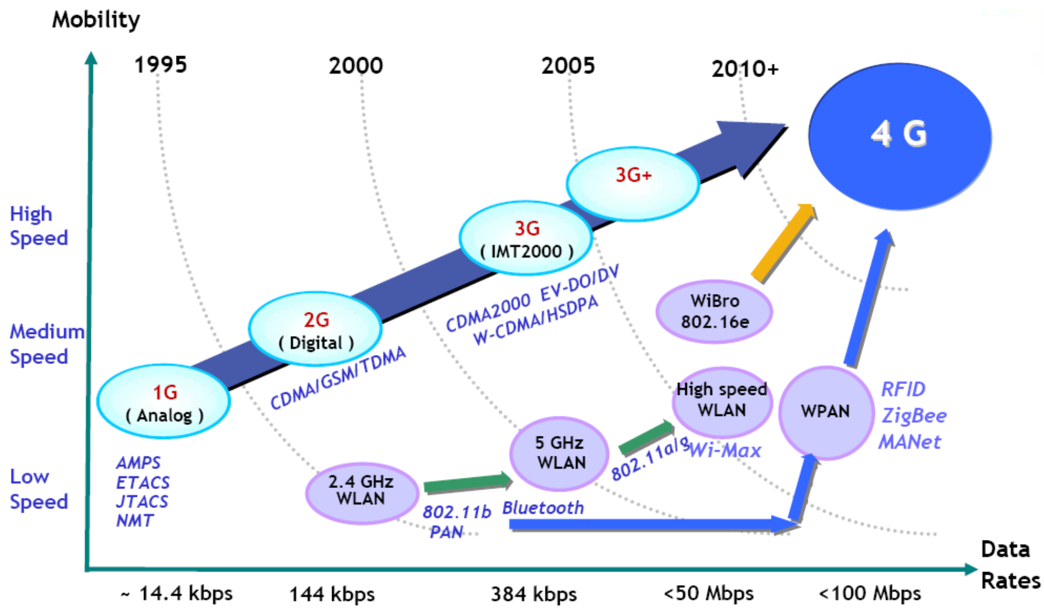


Figure 1.2: Evolution of wireless communication systems

The subject of this thesis is inserted in such a framework, considering the study and development of novel techniques for physical layer optimization of diversity based smart terminals in the context of next-generation wireless communications.

1.1 The Motivations

In order to implement reliable wireless communication networks, it is necessary to consider the hostile physical properties of the wireless channel in the form of rapid time variation, fading, multipath propagation, and co-channel interference. Countermeasures should be employed in order to combat these impairments and to achieve high-speed communications, high-quality communications and/or high-capacity communications.

A widely considered solution consists of the use of diversity in the frequency, time, and space domains.

Frequency diversity can be obtained by transmitting the information-bearing signal by means of several carriers that are spaced sufficiently apart from each other to provide independently fading versions of the signals. This may be accomplished by choosing a frequency spacing equal or larger than the coherence bandwidth of the channel.

The most common techniques actually used to exploit the frequency diversity are based on multi-carrier modulation: Orthogonal Frequency Division Multiplexing (OFDM) and Multi-Carrier Code-Division Multiple Access (MC-CDMA) ([15]).

In MC-CDMA, a user sends simultaneously his data stream over N subcarriers. Multiple users are supported by allowing each user to transmit over the same N subcarriers at the same time by using a unique spreading sequence (typically +1/-1 values) to separate the various users at the receiver.

Time diversity can be obtained by transmitting the information-bearing signal in different time slots, with the interval between successive time slots being equal to or grater than the coherence time of the channel.

The transmission technique that exploits this "natural" diversity in the time domain is Direct-Sequence Code-Division Multiple Access (DS-CDMA) with a Rake receiver ([15]).

In DS-CDMA, each symbol of the data stream of each user is modulated by a known and unique spreading sequence. By using a Rake receiver, it is possible to demodulate each path of the composite multipath signal. In this way, all of the energy provided by the channel will be extracted.

Space diversity can be obtained by using multiple transmit or receive antennas, or both, with the spacing between adjacent antennas being chosen so as to ensure the independence of possible fading events occurring in the channel. The advantage of having N_{Tx} and N_{Rx} multiple antennas at the transmitter and the receiver respectively is to transform the original wireless fading channels into MIMO wireless fading channels ([16]). It has been shown ([17]) that the link capacity can be increased by $m = \min(N_{Tx}, N_{Rx})$ times relative to single-antenna wireless links, because there are m spatial channels created as a result of the multiple antennas and the scattering environment surrounding the transmitter and the receiver. Hence, independent information streams can be delivered on the m parallel spatial channels to realize the increased transmission bit rate (called spatial multiplexing) or one can deliver the same information bits over multiple spatial channels to exploit the

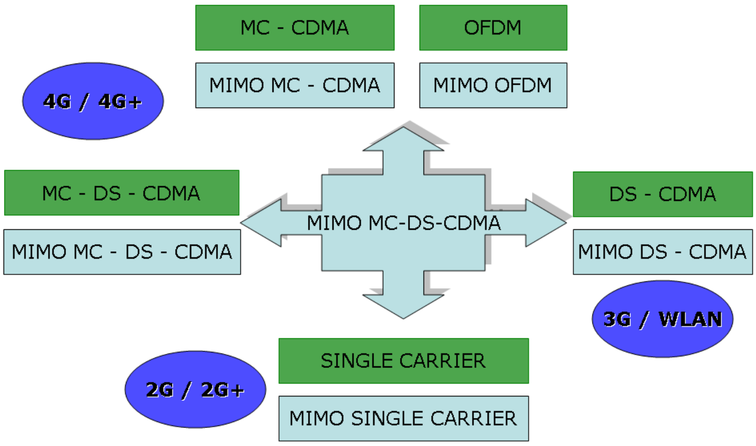


Figure 1.3: Wireless communications techniques overview

spatial diversity so as to enhance the reliability of the transmission.

The three types of diversity obtainable in multipath fading channels (frequency, time, and space diversity) can be exploited separately or jointly. In the first case, the aforementioned techniques are used, i.e., MC-CDMA or OFDM (frequency), DS-CDMA (time), and MIMO systems (space). In the second case, these basic techniques are partially or entirely combined to obtain new, more efficient, and more reliable transmission techniques. In Fig. 1.3, it is possible to find a summary of the obtainable techniques.

It is evident that the most general case is represented by MIMO-MC-DS-CDMA and all the other cases can be obtained by removing one or more “degrees of freedom” from this one. Some of these transmission techniques have been already used as standard for the second and third generations of mobile communications systems and the others are currently considered as possible solutions for the future generations. That is the reason why these techniques and several aspects concerning them have been widely analyzed in the literature.

1.2 The Problems and the Innovative Solutions

In the context of 4G wireless communications systems, the optimization of the radio link is a key issue to be faced. This thesis work jointly considers the diversity in space, time, and frequency domain, in order to provide performances very close to the single-user bound in multipath fading channels. In particular, new strategies for the joint optimization of antenna arrays and baseband receiver sections have been developed. From an algorithmic point of view, the novelty of the considered approach relies on the joint solution of the beamforming problem and the efficient reception for wireless systems equipped with antenna arrays. Usually, the problem of the antenna arrays optimization and the problem of the baseband reception are separately considered in the current literature using different algorithms. On the contrary, the proposed methodology aims to found an integrated approach able not only to maximize the Signal-to-Interference-plus-Noise-Ratio (SINR) at the antenna arrays output but even to minimize simultaneously the Bit Error Rate (BER) at the output of the baseband receiver (both for single carrier and multi-carrier modulations).

This approach is completely different from the traditional Minimum Mean Square Error (MMSE) criterion: the receiver aims to minimize directly the BER rather than the Mean Square Error (MSE) ([18]). Using this kind of approach, it is possible to integrate the space, time, and frequency diversities obtained, e.g., by using smart antennas, Direct-Sequence Spread Spectrum (DS-SS) modulation, and multi-carrier modulations (both OFDM and MC-CDMA). In this way, it is possible to mitigate the effects of the multipath propagation and to reject interference: both RF co-channel interference coming from other transmitters and baseband interferences (i.e., intersymbol interference, clipping noise, interchannel interference of OFDM systems, and multi-user interference in CDMA systems). In this work, considering that MBER approach has not been yet considered in MIMO MC-CDMA systems, it will be introduced into the multi-user detection of Space Time Block Coded (STBC) MIMO MC-CDMA signals.

The Multi-User Detection (MUD) problem has been even handled by considering the conventional MMSE criterion. Despite its intrinsic sub-optimality, it is often preferred in practical applications of MC-CDMA due to its reduced computational load and because it can easily support adaptive implementations based on Least Mean Square (LMS) or Recursive Least Square (RLS) optimization algorithms ([19]). These approaches are very efficient from a computational point of view. However, their performances and convergence rates are strongly influenced by the choice of the updating parameters. This drawback makes them more suitable for static channels rather than for time varying fading channels ([20]). In this work, the application of evolutionary methodologies for optimization like Genetic Algorithms (GAs) has been considered to implement a semi-adaptive MMSE MUD reception in MC-CDMA systems transmitting information over multipath fading channels. Their use has been also investigated in order to implement a computationally tractable Maximum Likelihood (ML) MUD detector for synchronous multi-rate MC-CDMA systems. GAs, an evolutionary computing method, are commonly recognized in the literature as valuable optimization tools. They are characterized by robustness, adaptation capability and reduced sensitivity to parameter setting ([21]). This technique was pioneered by Holland in the 60's and 70's and his work is comprehensively presented in [22], while useful practical details of genetic algorithms are available in [23, 24].

The GAs have been even used for the Channel Impulse Response (CIR) estimation, in conjunction with another evolutionary strategy, the Particle Swarm Optimization (PSO) algorithm. The PSO is a stochastic evolutionary computation technique developed by Kennedy and Eberhart in 1995 ([25]), inspired by social behavior of bird flocking or fish schooling.
In real systems, the fading channel coefficients are not known to the receiver. They are explicitly estimated by the receiver and the estimate is used as if it were the exact Channel State Information (CSI), even if it is only a mathematical estimation of what is truly happening in nature. In such a context, GA- and PSO-assisted MMSE estimate of the channel matrix has been considered, in particular for diversity based 4G-systems.

Both the proposed multi-user detection and channel estimation techniques have been implemented by taking into account their possible application in fully reconfigurable terminals capable of adapting their transmission layer to a "change of status" of the network. Therefore, they have been developed by considering adaptive design issues such as modularity and re-usability of software modules, in order to obtain an adaptive and optimized PHY-layer reconfigurability.

1.3 Research Contributions

Some parts of this thesis have been already published in international publications. In particular, the GA-assisted MUD approach described in section 3.1 has been presented in one conference paper and one journal paper:

- C. Sacchi, L. D'Orazio, M. Donelli, R. Fedrizzi, and F. G. B. De Natale, "A genetic algorithm-assisted semi-adaptive MMSE multi-user detection for MC-CDMA mobile communication systems," in *Proc. of PIMRC 2006 Conf.*, Sept. 2006.
- C. Sacchi, M. Donelli, L. D'Orazio, R. Fedrizzi, and F. G. B. De Natale, "Genetic algorithm-based MMSE receiver for MC-CDMA systems transmitting over time-varying mobile channels," *Electronics Letters*, vol. 43, no. 3, pp. 172–173, Feb. 2007.

The adaptive MBER receiver for STBC MIMO MC-CDMA mobile communication systems proposed in section 3.3 has been presented in one conference paper:

- L. D'Orazio, C. Sacchi, R. Fedrizzi, and F. G. B. De Natale, "An adaptive minimum-BER approach for multi-user detection in STBC-MIMO MC-CDMA systems," in *Proc. of GLOBECOM 2007 Conf.*, Nov. 2007, pp. 3427–3431.

The results obtained by using the channel estimation technique presented in section 4.1 have been published in one conference paper:

- L. D'Orazio, C. Sacchi, M. Donelli, and F. G. B. De Natale, "MMSE multi-user detection with GA-assisted channel estimation for STBC-MIMO MC-CDMA mobile communication systems," in *Proc. of ISSSTA 2008 Conf.*, Aug. 2008, pp. 182–187.

Other research contributions not presented in this dissertation are two conference papers:

- L. D'Orazio, C. Sacchi, F. Granelli, and F. G. B. De Natale, "Situation-aware radio resource management for multi-rate MC-CDMA wireless networks targeted at multimedia data exchanges in local areas," in *Proc. of ACM MOBIMEDIA 2006 Conf.*, Sept. 2006.

- L. D'Orazio, C. Sacchi, and F. G. B. De Natale, "Multicarrier CDMA for data transmission over HF channels: application to "digital divide" reduction," in *Proc. of Aerospace 2007 Conf.*, March 2007.

1.4 Structure of the Thesis

This thesis consists of seven chapters. The outline of each chapter is as follows.

Chapter 1, the present chapter, gives an overview of the motivations, the dealed problems and the proposed solutions. Moreover, it contains outline and research contributions of this dissertation.

Chapter 2 reviews the state of the art of multiple access interference avoidance/cancellation techniques for CDMA systems and overviews channel estimation techniques particularly used in multi-carrier and multiple antenna scenarios.

Chapter 3 and Chapter 4 introduce the proposed MUD techniques and consider the use of evolutionary strategies to channel estimation purposes, respectively.

Chapter 5 takes into account the possibility to use the presented algorithms in an adaptive and optimized reconfigurable system, given their modular implementation.

Chapter 6 presents the experimental results obtained for the proposed techniques.

Chapter 7 concludes the dissertation summarizing the obtained results and introducing suggestions for future works.

Chapter 2

State of the Art

At first, a review of multiple access interference avoidance/cancellation techniques for CDMA systems is provided, considering both Single- and Multiple-User approaches. The second part of the chapter is dedicated to summarize the mostly used channel estimation techniques, in particular for multi-carrier and multiple antenna scenarios.

2.1 Multi-Access Interference Mitigation Techniques for CDMA systems

The trend to deal with more and more simultaneous users tends to allow users to transmit simultaneously on the same frequency band, either using Single Input Single Output (SISO) or MIMO systems. It is well known that the capacity of a communication system is strongly limited by Multi-Access Interference (MAI). In wireless communication channels, the intentional non-orthogonal signaling (e.g., caused in CDMA systems by the cross-correlation between spreading codes of active users) or the non-ideal channel effects (e.g., due to multipath propagation) can lead to lose the orthogonality between multiple users' signals.

In this sub-section, an overview of various MAI reduction techniques will be provided (following the classification reported in Fig. 2.1, [26]).

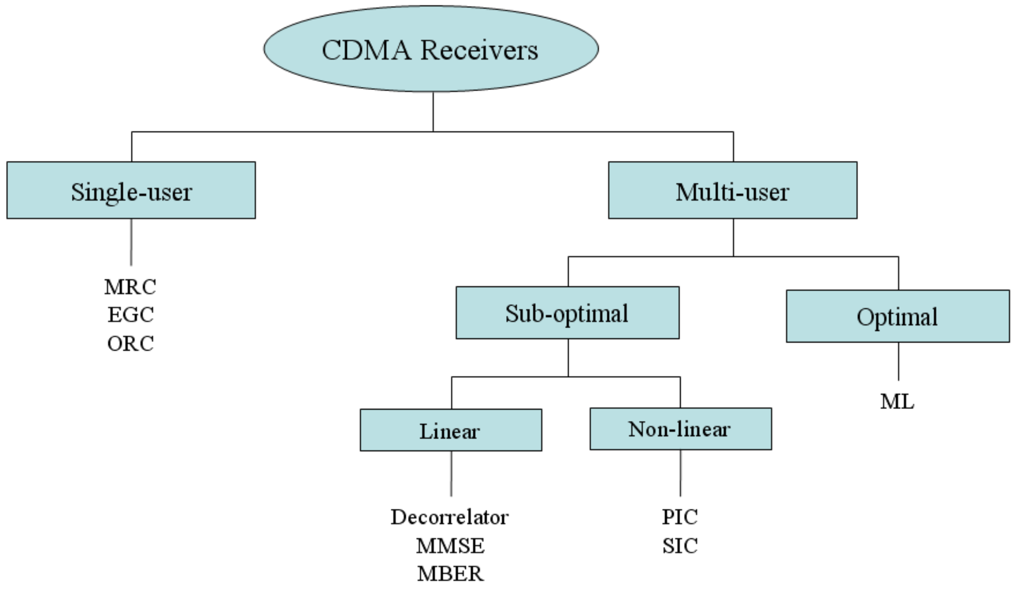


Figure 2.1: Classification of various CDMA receiver techniques

2.1.1 Single-User Detection

The first approach to deal with the MAI problem has been the simple use of the traditional Single-User Detection receivers, where MAI is treated as noise and no use of information regarding the interference created by other users is done ([27]). The Maximal Ratio Combining (MRC) detector consists of a filter matched to the channel's transfer function. It is able to maximize the Signal-to-Noise Ratio (SNR) at the receiver output by reducing the attenuation and eliminating the phase rotation induced by the multipath reflections ([20, 28]). This operation could further compromise the users' orthogonality. In order to mitigate this behaviour, the Equal Gain Combining (EGC) detector corrects only the phase rotation without handle the magnitude, and the Orthogonality Restoring Combining (ORC) or Zero Forcing (ZF) detector attempts to eliminate the channel effect by inverting its effects ([28, 29]).

These single-user techniques have been widely used in the second generation CDMA system like IS-95 and are still implemented in mobile devices since knowledge of the parameters of the interfering users (e.g., spreading code, phase, amplitude, position,...) is often not possible. However, when an increase in the users' number occurs or when the multiple users' signals are characterized by widely varying power level disparities, users equipped with single-user detectors may lose communication. This phenomenon is known as the near-far effect and it can be alleviated by using power control schemes ([30]).

2.1.2 Multi-User Detection

The natural evolution of the research has been to take into account all the available information at the receiver in order to improve the CDMA receivers' performance by reducing or cancelling the MAI. The resulting multi-user detectors are generally characterized by a very high complexity but they offer a huge capacity improvement over the conventional single-user detectors ([31]). These methods are actually practical only at the base-station, where all the information is readily available and there are no power consumption constraints.

The optimum multi-user receiver has been presented by Verdu in [32]. The sequence of symbols is selected by jointly considering the matched filter outputs of all users. Therefore, the resulting K-user Maximum-Likelihood (ML) sequence detector consists of a bank of single-user matched filters followed by a Viterbi algorithm whose complexity per binary decision is $\mathcal{O}\left(2^K\right)$. It offers excellent performance gains over conventional systems but it is too complicated for practical application, given that its complexity grows exponentially with the number of active users (see Fig. 2.2, [32]).

Thus, numerous sub-optimal approaches with acceptable complexity have been proposed in the literature. Excellent reviews of them can be found in [33, 34, 35, 36, 37, 38]. In general, they can be classified into two categories: linear and non-linear detectors.

In the linear multi-user detectors, the soft outputs of the conventional filters are linearly transformed to reduce the access interference and provide better performance. The most used are the decorrelating ([39]), the Minimum Mean Square Error (MMSE) ([40, 41]) and the Minimum Bit Error Rate (MBER) ([18]) detector.
The decorrelating detector linearly transforms the outputs of the conventional matched filter receiver by applying the inverse of the correlation matrix of user spreading codes.

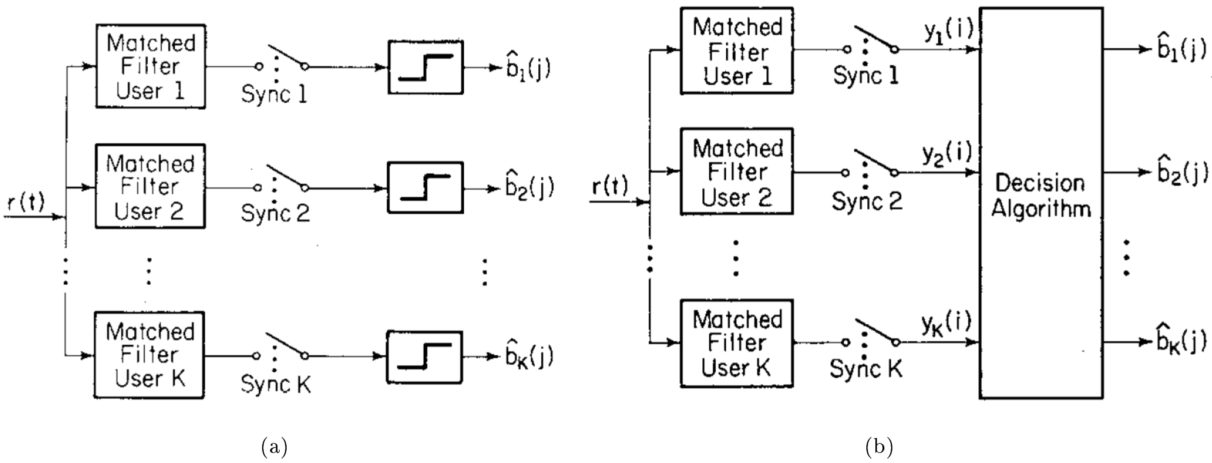


Figure 2.2: Conventional (a) and optimum (b) K-user detector

It has some interesting advantages over the conventional detector, e.g., the received signal power does not have to be estimated or controlled and the near-far effect is strongly reduced ([37]). The disadvantages are the noise enhancement and the impossibility to eliminate any Inter-Symbol Interference (ISI) caused by channel dynamics. The computational complexity is $\mathcal{O}(K^3)$, due to the correlation matrix inversion.
The MMSE detector applies a linear transformation to the output of the conventional detector of a matched filter bank to minimize the square difference between the transmitted symbol sequence and the estimated symbol sequence. The MBER detector aims to directly minimize the BER in output at the decoder.
A deeper dive into the last two approaches will be taken in the follow of the dissertation.

In non-linear multi-user detectors (also called subtractive or interference cancellation detectors), the interfering signals are estimated and then removed from the received signal before detection. The interference cancellation can be carried out either successively (Serial Interference Cancellation, SIC) ([42, 43]) or in parallel (Parallel Interference Cancellation, PIC) ([44, 45]).

Generally speaking, interference cancellers are much simpler than linear multi-user detectors but are inferior in terms of performance ([46, 47, 48]). Therefore, the core of this thesis has been focused on the study and development of novel linear MUD techniques for

CDMA systems. In particular, the application to MC-CDMA systems of detectors based on the MMSE and MBER principles has been considered, both in the SISO and in the MIMO scenario.

The choice of these particular systems has been done in order to remain in the context of the diversity-based 4G-wireless communication devices presented in the former Chapter 1. MC-CDMA transmission techniques can jointly exploit the advantages of multi-carrier OFDM and single-carrier Spread Spectrum DS-CDMA techniques ([15]). As previously enounced, the basic MUD techniques for MC-CDMA are ML, MMSE and MBER detection. For each of them, several modifications have been proposed in the literature in order to increase the performance and reduce the computational complexity.

Unconventional mathematical tools have been recently used to implement near-optimum ML MUD algorithms characterized by a reduced computational load with respect to the Verdu's work [32] (polynomially growing with the number of active users instead of exponentially). In [49] and in [50], a Genetic Algorithm (GA) and a Neural Network (NN) MUD receiver have been presented, respectively. Brunel used in [51] a low-complexity optimum lattice decoder (the sphere decoder) to jointly detect all users. Its complexity is a polynomial function of the number of users and is independent of the modulation size. Thus, it allows optimum performance even for full-loaded systems using large modulations, but only for low noise received signals.
Neither of the above techniques take into account the presence of Carrier Frequency Offsets (CFOs). It tends to destroy the orthogonality among users, greatly degrading the performance of MC-CDMA systems. Such a situation has been considered in [52], where a low computational load ML MUD receiver based on the use of Carrier Interferometry (CI) codes ([53]) has been presented. It exploits the sparsity of the cross-correlation matrix of CI codes to obtain a complexity that grows exponentially with the channel multipath length instead of the number of active users.

The MMSE MUD techniques offer a polynomial complexity but are even able to easily support adaptive implementations ([54]). Two approaches based on the LMS and on the

RLS algorithm have been presented in [19] and another one based on the Normalized Least Mean Square (NLMS) in [55]. They are very efficient from a computational point of view but their performances and convergence rates are strongly influenced by the choice of the LMS/RLS updating parameters. A possible solution to this behaviour has been proposed in [19], consisting in the calculation of the receiver weights deriving from the explicit solution of the MMSE equation ([15]) by using an estimation of the channel matrix obtained through LMS/RLS methodologies. Such an approach can achieve better performance than fully adaptive MMSE solutions as well as increased robustness to the selection of the adaptation parameters. On the other hand, it may always suffer from the same drawbacks of deterministic gradient based algorithms.
A more reliable solution in the presence of uncertainties about channel estimation and equalization has been described in [56], where a supplementary GA-based MUD stage has been inserted after a classical MMSE MUD stage, driven by a blind channel identification algorithm. Another blind linear MMSE detector and channel estimator is shown in [57]. It is based on the RLS updating of the correlation matrix, and the channel can be estimated blindly by solving the minimum eigenvector of a data sub-matrix. A new pilot-based channel estimation scheme has been used in [58] to drive a PIC stage with MMSE filtering.

The MBER criterion has been applied in several works to DS-CDMA systems. Chen *et al.* proposed in [59] a LMS-style stochastic gradient adaptive algorithm based on the approach of kernel density estimation for approximating the BER from training data. A modified version of the same adaptive algorithm is shown in [60]. It is based on the Gradient-Newton algorithm and can speed up the convergence of the multi-user receiver, requiring shorter training data.
A linear adaptive MBER MUD approach is proposed in [61] for asynchronous MC-CDMA systems. It employs an adaptive stochastic gradient algorithm based on the estimation of kernel density function. Instead to use its estimation, the true Probability Density Function (PDF) is directly considered in [62, 63, 64]. A modified version of the same algorithm is presented in [65]. It describes a Minimum Conditional BER (MCBER)

receiver that minimizes the conditional probability of error for reducing the complexity of the detector.

The flow of multimedia traffic through wireless networks is constantly increasing, both in local and in metropolitan areas. Multimedia traffic is characterized by heterogeneous data rates typical of the different streamed media. In this framework, efficient techniques for multi-user and multi-rate data transmission should be investigated. In the case of frequency-selective wireless channels and time-frequency diversity-based transmission techniques, the usual tradeoff between data rate and robustness against channel effects becomes more evident. In a multi-rate context, the diversity gain of higher-data rate transmitters may be reduced with respect to lower-data rate ones. This typically happens in the 3G WCDMA PHY-layer standard of Universal Mobile Telecommunications System (UMTS) (based on DS-CDMA), where variable spreading factors [66] are attributed to various user classes in order to arrange multi-rate services ranging from 15 Kbps to 960 Kbps.
Multi-rate transmission can be fairly managed also by 4G MC-CDMA schemes by attributing to different user classes a different number of subcarriers and variable-length orthogonal spreading codes [67]. The usual tradeoff between diversity gain and data rate turns on a lower number of subcarriers attributed to the "fastest" users that will be penalized with respect to "slowest" users in terms of channel degradation and MAI. In such a perspective, multi-rate MC-CDMA performances could be substantially improved by the adoption of multi-user detection.

All the above techniques are referred to SISO scenario, just considering the diversity in the frequency domain. Recent trends in R&D about mobile communication systems are going towards the joint exploitation of diversity concept in different domains (space, time, and frequency). In particular, there is an increasing interest concerning the integration of MIMO techniques aimed at exploiting diversity in the space domain with digital transmission techniques aimed at exploiting diversity in time and frequency.

The key feature of MIMO techniques is to provide a potential increase of the channel

capacity without an expansion of the Radio Frequency (RF) bandwidth ([68]). Adaptive antenna arrays have been already used in wireless communication systems since late 1960s. Applebaum's paper [69] presented a method for adaptively optimizing the SINR in the presence of any type of noise environment (background noise and jamming signals).
This work was the starting point for "intelligent" or "self-configured" and highly efficient systems: adaptive or smart antennas ([70]). They are aimed at separating a desired signal from interfering ones by controlling the radiation pattern of the array by adjusting the array weights so that a certain optimization criterion is met.
The conventional beamformers are based on the MMSE approach. Several beamforming algorithms based on it have been proposed in the literature (e.g., LMS and RLS algorithms [71], genetic algorithms based solutions [72]). Another usable approach is the MBER one ([73]). A solution based on this approach and on the use of genetic algorithms has been proposed in [74]. A comparison between different MBER-based beamforming algorithms is reported in [75].

The core idea in MIMO system is Space-Time (ST) signal processing in which the time dimension is complemented with the spatial dimension inherent to the use of multiple spatially-distributed antennas ([68, 76, 77]). Commonly used ST coding schemes are ST Trellis Codes (STTC) and STBC.
An example of conceptually simple, computationally efficient and mathematically elegant STBC scheme has been proposed by Alamouti in [78]. Substantially Alamouti's coding is an orthogonal ST block code, where two successive symbols are encoded in an orthogonal 2×2 matrix. The columns of the matrix are transmitted in successive symbol periods, but the upper and the lower symbols in a given column are sent simultaneously through the first and the second transmit antenna respectively. Alamouti's scheme originally considered two transmit antennas and one receive antenna. However, Alamouti demonstrated that the same scheme can be easily generalized to two transmit antennas and a generic number of receive antennas and successively Tarokh *et al.* described in [79] the possibility to use even an arbitrary number of transmit antennas.

Closed form expressions for the average BER have been derived in [80] for STBC systems with generic number of transmit and receive antennas, transmitting data over MIMO correlated Nakagami-m fading channels.

The promising results yielded by MIMO and STBC techniques and the increasing importance of spread-spectrum and multi-carrier modulations in next-generation cellular systems design have recently suggested to researchers to profitably combine diversity in different domains. Examples of space-time-frequency coding schemes have been shown by Petre *et al.* in [81] for MIMO DS-CDMA, by Bizzarri *et al.* in [82] for MIMO OFDM, and, finally, a thorough overview of MIMO MC-CDMA implementations has been proposed by Juntti *et al.* in [16].
In this last work, STBC MIMO MC-CDMA systems have been regarded among the most promising technologies for future cellular standards. They can jointly exploit diversity in different domains in order to counteract multipath fading effects and, therefore, to provide performances very close to the single-user bound.

The MUD problem in STBC MC-CDMA systems has been already dealt. The advantages taken by MMSE MUD in MAI cancellation are well evidenced in [83], both over Rayleigh and MIMO METRA ([84]) channels. In [85, 86, 87], effective schemes employing blind or semi-blind channel estimation techniques have been discussed. More advanced techniques have been recently presented in [88] and [89], where a GA-based MUD detector and a turbo iterative receiver for the downlink of STBC MC-CDMA systems are described, respectively.

Recent trends of R&D in diversity combining and MUD are moving from MMSE approaches to MBER approaches. In such a framework, recent literature has shown that BER cost function might be more suitable for MUD tasks than MSE one.
A combination of MMSE and MBER criterion has been presented in [76] to obtain a multi-stage linear receiver for MIMO multiplexing systems.
A first adaptive MCBER detector for asynchronous DS-CDMA systems with multiple receive antennas is described in [90]. Its extension to general MIMO scenario is proposed in

[91] with the presentation of another receiver which aims to minimize the joint probability of error for all users (MJBER).

The Space Division Multiple Access (SDMA) MIMO OFDM scenario has been considered in [92] and [93, 94]. The former presents a traditional adaptive Conjugate Gradient (CG) algorithm for arriving at the minimum solution of the BER cost function. It offers good performance but its convergence is sensitive to the choice of the algorithm's parameters (e.g., the initialization value and the step-size parameter). The latter uses a GA to overcome these problems. The MBER MUD's weight vectors are directly determined by the GA with a lower complexity than the CG algorithm.

An adaptive space-time equalisation ([68]) assisted MBER MUD scheme for Single Input Multiple Output (SIMO) systems is described in [95] and its evolution using decision feedback in [96, 97]. An iterative version of the same approach is shown in [98]. It is particularly suitable in the over-loaded scenarios.

Recently, a joint generalized scheme of antenna combination (using a modified version of the Antenna Subarray Formation (ASF) scheme presented by Karamalis *et al.* in [99]) and symbol detection based on the MBER criterion has been proposed in [100]. The two issues are jointly considered by solving the highly non-linear decision statistic through a PSO algorithm.

2.2 Channel Estimation Methods

All the previously presented detection techniques require the knowledge of the channel impulse response, which can be provided by a separate channel estimator. For wireless systems, channel estimation can be difficult and computationally intensive, in particular for those using multiple sub-bands and multiple antennas. In fact, its function is to estimate the amplitude and phase shift caused by the multipath propagation for every sub-band and for every transmit/receive antenna pair.

The channel estimation techniques can be classified in *pilot-assisted*, *decision-directed* and *blind*, according to the available information about the transmitted signal.

An extensive overview of channel estimation techniques employed in OFDM systems has been presented in [101], both for SISO and MIMO scenario. In the following subsections, given that estimation of the wireless channel is a very broad topic (e.g., more than 200 references are reported in [101]), a particular emphasis will be placed on the methods developed for multi-carrier and multiple antenna systems. Furthermore, considering that two MMSE channel estimation techniques based on GA and PSO will be presented in this thesis, the application of evolutionary strategies to channel estimation issues will be also considered.

2.2.1 Pilot-Assisted

Pilot-assisted methods use a subset of the available subcarriers to transmit training sequences known to the receiver. The desired frequency domain channel transfer function is directly estimated over the pilots and an interpolation method is then used to obtain the remaining values. The most important issues are the optimum choice of training sequences, their placement, their dimension and the used interpolation method.

The importance of the pilot pattern choice has been evidenced in [102], by comparing in terms of BER several positioning of the pilot symbols, both in time and frequency. The number and placement of pilots in the time-frequency grid has been extensively studied in [103, 104, 105, 106, 107, 108, 109, 110], and their references. It represents an important topic, affecting not only the quality of CIR evaluation but the transmission rate as well.

The most considered interpolation methods are the polynomial interpolation (linear, quadratic, and cubic) ([111, 112, 113, 114]) and the Fast Fourier Transform (FFT) interpolation ([115, 116]). In [111] and [117], the effectiveness of the linear interpolation in terms of system complexity, processing delay and estimation accuracy has been shown. A novel linear interpolator for OFDM systems has been presented in [118] by Doukas and Kalivas. Its performance in terms of MSE and BER have been expressed as a function of the number and distance of the pilots, and of the channel parameters.

In [119], two channel estimation techniques for a MC-CDMA system transmitting over a standard UMTS channel model are compared. One considers transmitting pilot and data symbols in the same OFDM symbol and performing interpolation in frequency between pilot symbols. The other involves transmitting pilot and data symbols in separate OFDM symbols and interpolating in time (see Fig. 2.3 (a) and (b), respectively, [119]).

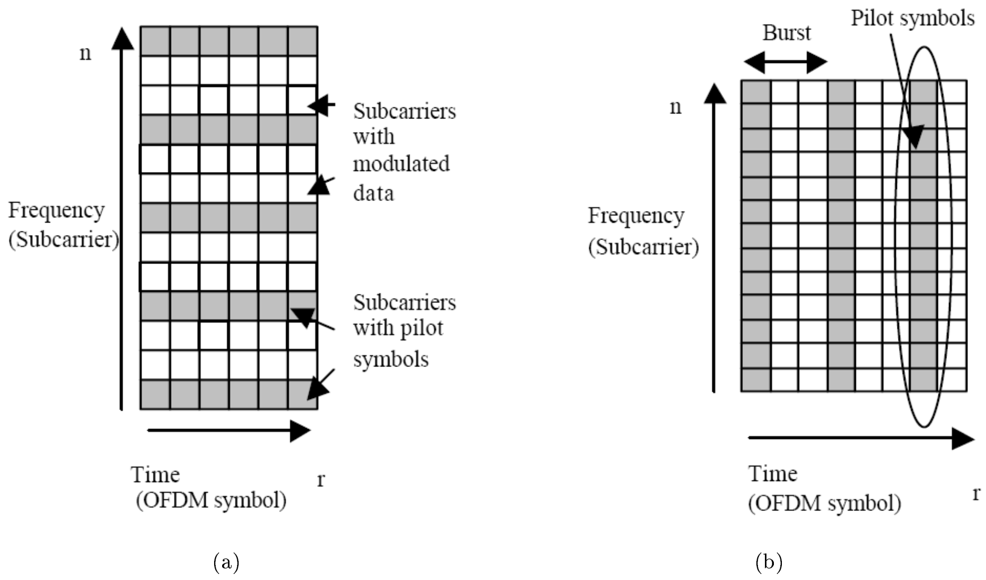


Figure 2.3: Arrangement of pilot symbols

Bastug *et al.* proposed in [120] a three-step dedicated channel estimation procedure which exploits all the existing pilot sequences as well as the structured dynamics of the channel in WCDMA receivers. The method starts with block-wise dedicated and common channel Least Squares (LS) estimates of the channels associated with dedicated and common pilots. Afterward, the initial LS estimates are optimally combined to obtain an improved unbiased MMSE estimate of the dedicated channel, and, finally, it is further refined via Kalman filtering by exploiting the channel temporal correlation.

A robust pilot-based OFDM channel estimator based on the combination of low-pass filtering and delay-subspace projection has been presented in [121].

MMSE-based frequency domain channel estimation is proposed in [122, 123, 124] for multiple-transmit antenna-assisted OFDM scenario.

Expectation Maximization (EM) based pilot-assisted channel transfer function estimation approaches have been shown in [125] and [126] for MIMO OFDM systems. Their generalization in the context of the Majorize (Minorize) - Minimization (Maximization) (MM) algorithm has been presented in [127].

In [128], a PSO-assisted frequency offsets and channel gains estimation algorithm for MIMO systems is described. The evolutionary strategy is used to obtain a first estimate of the frequency offsets (assuming that a training sequence is available). Then channel gains are estimated by ML estimator.

GAs are used in [129] to estimate low Peak-to-Average Power Ratio (PAPR) near-optimum training sequences for channel estimation in an OFDM system. It is shown that such training sequences are able to improve channel estimation and BER performance in a coherent system with a large number of sub-channels. A similar work has been presented in [130] in the context of multiple antenna aided systems.

2.2.2 Decision-Directed

The Decision-Directed (DD) approaches consider all the subcarriers as pilots. The channel estimation of a previous OFDM symbol is used for the data detection of the current estimation, and therafter the newly detected data is used for the estimation of the current channel. The resulting channel transfer function can be accurate in the absence of symbol errors and in particular for slowly varying fading channels, without signaling overhead.

Regarding the space-time coded OFDM scenario, a least-squares error channel estimator has been presented by Li *et al.* in [131]. It exploits the independence of the transmitted subcarrier symbol sequences to recover the different transmit antennas' channel transfer functions.

Jeon *et al.* considered in [132] a subtraction-based channel estimator for the case with two transmit and two receive antennas. For each specific receive antenna, the interfering signal contributions associated with the remaining transmit antennas are subtracted, resulting in a sort of frequency domain PIC-assisted DD channel estimation.

A similar subtraction-based approach has been applied in the time domain in [133], with

a further deepening in [134]. It can be considered as a simplification of [131]. Another reduced-complexity version of the method proposed in [131] has been described in [135]. It returns to consider the channel's correlation in the frequency direction instead of that in the time direction followed in the works of Li.
Gong and Letaief described in [136] a MMSE-assisted DD channel estimator as an extension of the least-squares based approach presented in [131]. It is shown to be practical in the context of transmitting consecutive training blocks.
A robust and efficient EM-based estimation algorithm is considered in [137]. It partitions the problem of estimating a multi-input channel into independent channel estimations for each transmit-receive antenna pair. Another EM-based method has been described in [138] for MIMO STBC OFDM systems. It separates the superimposed received signals into their signal components and estimates the channel parameters of each signal component separately.
Wiener and Kalman channel estimation and tracking algorithms have been described in [139, 140] and [141, 142], respectively. A comparison of LMS and RLS channel estimation techniques has been provided in [143], showing the superiority of the latter over the former.

A novel channel estimation method which optimally combines the decision-directed and the previously described pilot-assisted framework has been shown in [144].

2.2.3 Blind

Blind methods do not require any training sequence to be transmitted but exploit the spatial or temporal structure of the channel or, alternatively, properties of the transmitted signal such as constant magnitude.

Bolcskei *et al.* proposed in [145] a blind channel identification and equalization algorithm for OFDM-based MIMO systems using non-redundant antenna precoding and second-order cyclostationary statistics. Non-redundant linear block precoding has been used extensively in such a context ([146]).

In [147], a method based on Singular Value Decomposition (SVD) accompanied by a simple block precoding scheme is described. Its advantage is that it does not require a decoder at the receiver side, but the coding rate decreases with the number of transmitting antennas. An improved version of the same method has been presented in [148]. It holds the advantages of the previously described scheme without sacrificing the coding rate for any number of transmitting antennas (provided that the numbers of transmitting and receiving antennas are equal).
The traditional subspace based methods have been developed in [149] in the general context of digital communications. They can not be directly applied in MIMO-OFDM scenario if the number of antennas at the receiver is smaller than or equal to the number of antennas at the transmitter. Some solutions to this so-called multi-dimensional ambiguity ([150]) have been proposed in [151, 152, 153, 154].
Coherent processing across the subcarriers has been used in [155] to estimate the channel in the time domain. It estimates the channel parameters in the time domain jointly for all subcarriers instead of doing this in the frequency domain independently for each subcarrier.
A blind strategy addressed to the 2×1 Alamouti system is described in [156]. It estimates the channel parameters by computing the eigenvectors of a matrix containing 4th-order cumulant matrices of the observations. A similar work was presented in [157].

Several other techniques have been recently published in the context of STBC systems, both OFDM (e.g., [158, 159, 160, 161, 162]) and MC-CDMA (e.g., [163, 164, 165, 166, 167]).

A blind PSO-based MIMO channel identification technique has been presented in [168]. It uses particle swarm algorithm to estimate the outputs of channel equalizer, and put the estimation to the inverse filter algorithm. Therefore, it exploits the signal space diversity information and the signal time diversity information.
A modified PSO algorithm based on Lotka-Volterra competition equation has been proposed in [169]. It is applied to determine the impulse response of a SIMO system in a

blind way and outperforms the original PSO.

Joint blind channel estimation and symbol detection schemes using GAs are described in [170] and [171]. The former is a single-user receiver divided into a two-layer optimization loop: the unknown channel model is obtained through a micro genetic algorithm (μ–GA, [172]) and then a set of Viterbi algorithms (one for each member of the channel population) is used to provide the maximum likelihood sequence estimation of the transmitted data sequence.

The latter is always based on the ML decision rule and proposes a multi-user detector that jointly performs the channel estimation and the symbol detection using the same GAs simultaneously.

In the context of SDMA multi-user MIMO OFDM scenario, Jiang *et al.* proposed in [173, 174] a GA-assisted iterative joint channel estimation and multi-user detection approach. It is able to provide a robust performance when the number of users is higher than the number of receiving antennas (the so-called "overloaded" scenario). In such a situation, the limitations of conventional detection and channel estimation techniques are well known ([175]).

Chapter 3

Novel Multi-User Detection Techniques for Multi-Carrier CDMA Systems

This Chapter is aimed at describing some novel Multi-User Detection techniques particularly suited for multi-carrier CDMA scenarios from an algorithmic point of view. Some common guidelines followed for their implementation will be provided in Chapter 5.

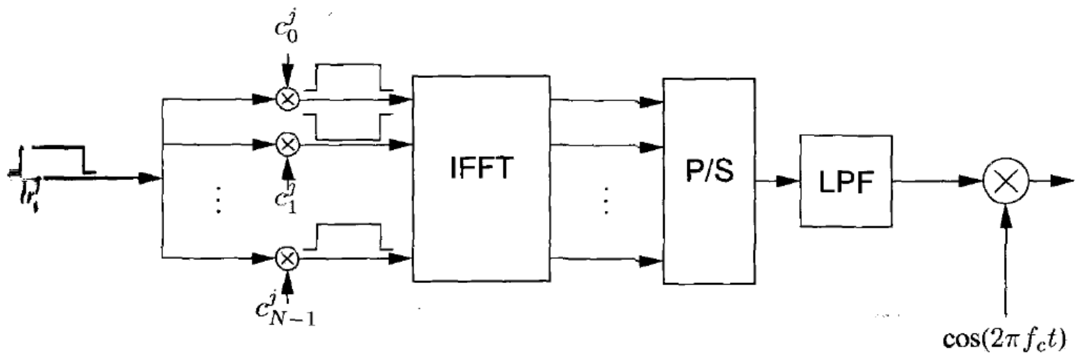
At first, a GA-assisted MUD approach based on the MMSE criterion is described. Then, a GA-assisted Maximum-Likelihood MUD receiver for multi-rate MC-CDMA systems will be proposed. Both are developed for single-antenna MC-CDMA systems. Finally, the description of two MUD techniques based on the MBER approach will be provided for the multi-antenna STBC MC-CDMA context.

3.1 A Genetic Algorithm-Based Semi-Adaptive MMSE Receiver for MC-CDMA Mobile Transmission Systems

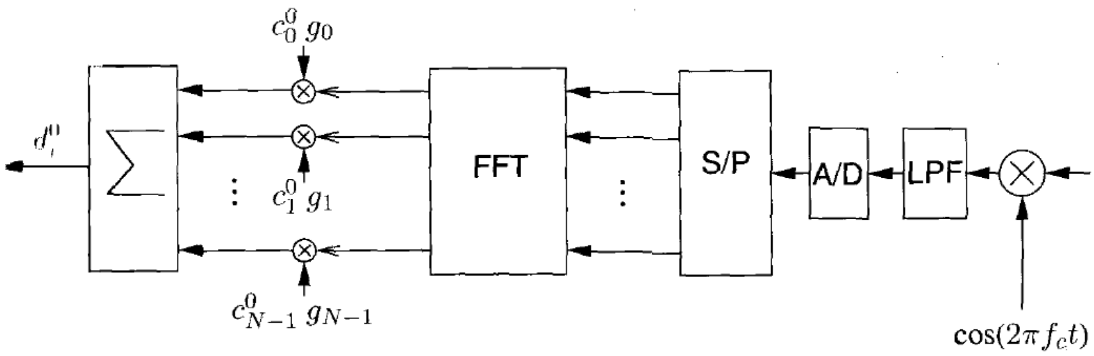
In this section, a GA-assisted MUD approach is described for semi-adaptive per-carrier MC-CDMA systems transmitting over time-varying multipath fading channels. At first, the description of the MC-CDMA received signal model is provided. Then, the GA-assisted MMSE MUD algorithm is detailed.

3.1.1 MC-CDMA Signal Model

The MC-CDMA transmitter applies the spreading sequences in the frequency domain. Each chip of the spreading code is mapped to an individual subcarrier, which maintains a data rate identical to the original input data rate ([15]). A block diagram of the MC-CDMA system is reported in Fig. 3.1 ([26]).



(a) Transmitter side



(b) Receiver side

Figure 3.1: Block diagram of the MC-CDMA system

The complex baseband equivalent multi-user signal of a synchronous downlink MC-CDMA system can be represented as:

$$x(t) = A \sum_{i=-\infty}^{+\infty} \sum_{n=0}^{N-1} \sum_{k=1}^{K} c_n^k a_i^k e^{j\left(\frac{2\pi n t}{T}\right)} p(t - iT) \tag{3.1}$$

where:

- A is the transmitted signal amplitude

- N is the number of subcarriers
- K is the number of active users
- c_n^k represents the n-th chip of the spreading sequence of the k-th user (Hadamard-Walsh sequences of length N have been employed)
- a_i^k is the message symbol transmitted by the k-th user during the i-th signalling period of duration T
- $p(t)$ is a Non-Return-to-Zero (NRZ) rectangular signalling pulse shifted in time given by:

$$p(t) \triangleq \begin{cases} 1 & \text{for } 0 \leq t \leq T \\ 0 & \text{otherwise.} \end{cases} \tag{3.2}$$

Let's suppose to employ a Binary Phase Shift Keying (BPSK) modulation (i.e., $a_i^k \in \{-1, +1\}$), so that each transmitted symbol corresponds to a single bit.

The signal expressed in Eq. 3.1 is transmitted over a Rayleigh multipath-fading channel, characterized by a delay spread T_m and a Doppler spread B_d. The transmission data rate is chosen in order to assure flat fading over each single subcarrier (i.e., $T \gg T_m$) and the signal amplitude A is equal to 1.

Under such hypothesis, the received MC-CDMA signal can be expressed as follows:

$$y(t) = \sum_{i=-\infty}^{+\infty} \sum_{n=0}^{N-1} \sum_{k=1}^{K} h_n(t)\, c_n^k a_i^k e^{j\left(\frac{2\pi n t}{T}\right)} p(t - iT) + \eta(t) \tag{3.3}$$

where $h_n(t)$ is the complex time-varying channel coefficient related to subcarrier n, and $\eta(t)$ is the Additive White Gaussian Noise (AWGN). $h_n(t)$ is a complex Gaussian process with Rayleigh-distributed envelope and uniformly-distributed phase. The samples of $\eta(t)$ are independent and identically-distributed in Gaussian way, with zero mean and variance σ_η^2.

The received signal is then processed by a coherent FFT-based OFDM demux block, low-pass filtered by a bank of integrators, and finally sampled at sampling rate equal to

$1/T$. The sample obtained from the subcarrier n during the i-th signalling interval is given by:

$$y_n(i) = h_n(i) \sum_{k=1}^{K} c_n^k a_i^k + \eta_n(i) \tag{3.4}$$

The received signal energy scattered in the frequency domain is then combined by multiplying each sample $y_n(i)$ by a specific gain. The resulting decision variable is given by:

$$\lambda^k(i) = \sum_{n=0}^{N-1} w_n(i) y_n(i) \tag{3.5}$$

3.1.2 The Proposed GA-Assisted MMSE MUD Receiver Structure

The choice of the diversity-combining weights can be done according to the various techniques proposed in the previous Chapter 2 (i.e., EGC, MRC, ORC,...). In particular, a per-carrier MMSE multi-user detector has been considered in this part of the work ([19]).

The corresponding optimization criterion is to find an N-element weight vector $\mathbf{w}^{Opt.}(i) = \left[w_0^{Opt.}(i), \ldots, w_{N-1}^{Opt.}(i)\right]$ that minimizes the mean square error between the equalized received signal and the noise-less pattern we would have on each subcarrier at the receiver. Such a problem can be formalized as follows:

$$w_n^{Opt.}(i) = \arg\min_{w_n(i)} E\left\{\left|\left(\sum_{k=1}^{K} c_n^k a_i^k\right) - w_n(i) y_n(i)\right|^2\right\} \tag{3.6}$$

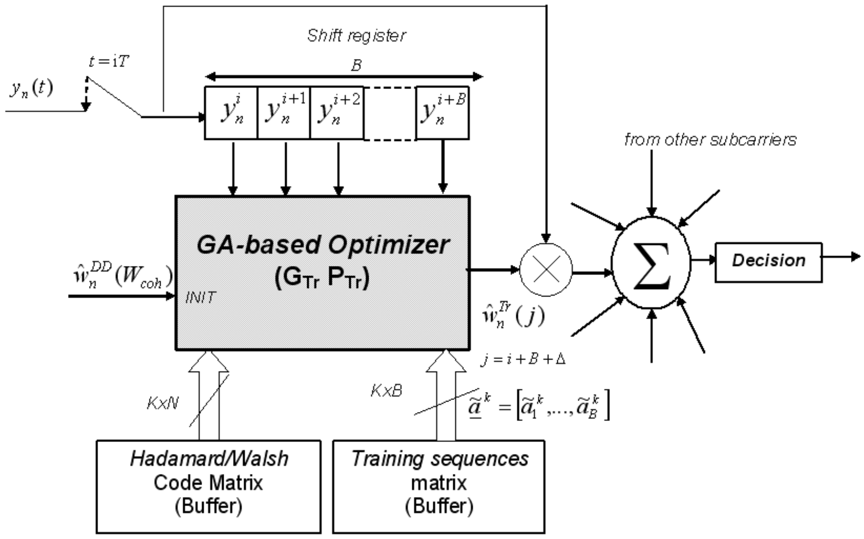
where $E\{\cdot\}$ represents the mathematical expectation operator. The explicit solution to Eq. 3.6 is the following ([15, 19]):

$$w_n^{Opt.}(i) = \frac{h_n^*(i)}{|h_n^*(i)|^2 + 2\sigma_\eta^2/KE_c} \tag{3.7}$$

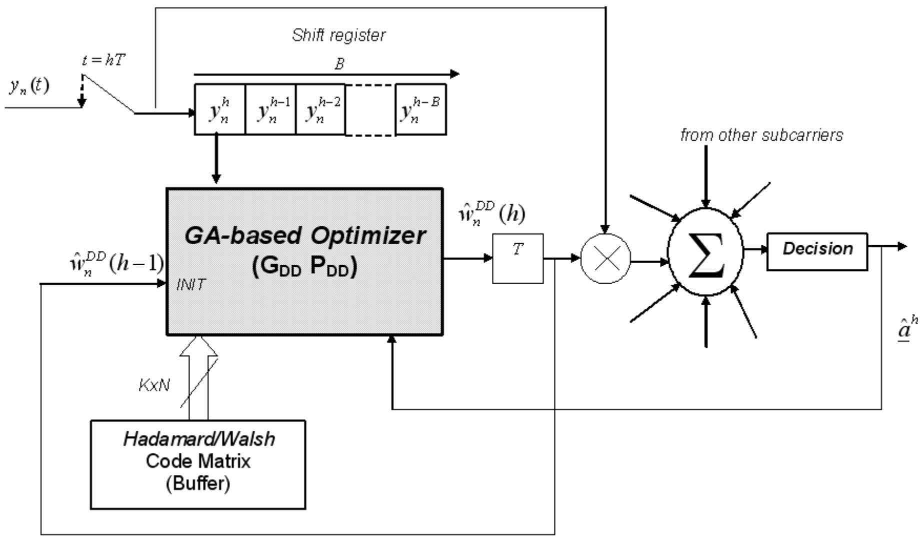
where E_c is the energy per chip and the superscript operator * is the complex conjugate operator.

The use of the ideal weights expressed in Eq. 3.7 requires the exact knowledge of the N-element channel vector $\mathbf{h}(i) = [h_0(i), \ldots, h_{N-1}(i)]$. If it is not available, the real $\mathbf{h}(i)$ could be replaced by its estimation $\hat{\mathbf{h}}(i)$, obtained by using one of the channel estimation techniques described in section 2.2 of the previous Chapter 2. Nevertheless, such an operation would increase the computational complexity of the receiver.

To avoid this additional task, a semi-adaptive GA-assisted MMSE MUD strategy has been analyzed. It is articulated into two different steps:



(a) Training-aided step



(b) Decision-Directed step

Figure 3.2: Block diagram of the GA-assisted MMSE MUD receiver

1. *Training-aided* step: in this period, a binary training sequence $\tilde{\mathbf{a}}^k = \left[\tilde{a}_1^k, \ldots, \tilde{a}_B^k\right]$

of B bits is transmitted for each user k. The task of GA is to compute for each subcarrier the weight $\hat{w}_n^{Tr}(i)$ that minimizes the following metric:

$$\Lambda\left(\hat{w}_n(i)\right) = \frac{1}{B}\sum_{i=1}^{B}\left|\left(\sum_{k=1}^{K} c_n^k \tilde{a}_i^k\right) - \hat{w}_n(i)\, y_n(i)\right|^2 \tag{3.8}$$

The GA-based computation of the optimal weights is performed after having buffered B samples of the received signal $y_n(i)$ (see Fig. 3.2 (a)). The ensamble average of Eq. 3.6 has been replaced in Eq. 3.8 by the sample average made on the entire duration of the training sequence. The GA convergence would be seriously affected by noise effects (particularly at low SNR) if such an average operation would not be performed. This approximation is correct if the channel can be modeled as an ergodic stochastic process. It can be shown that the GA-based estimation of the MMSE weights is unbiased if the following relation is valid for each subcarrier:

$$\frac{1}{B}\sum_{i=1}^{B}\left(\sum_{k=1}^{K} c_n^k \tilde{a}_i^k\right)^2 = K \tag{3.9}$$

It happens when the training sequences of the users are orthogonal. If they are obtained from Hadamard-Walsh matrices, some limitations are imposed to the system. In particular, the training sequences' length has to be equal to a power of two and greater than the number of users (i.e., $B > K$).

The GA works with a selected parameterisation in terms of generation number G_{Tr}, population size P_{Tr}, crossover and mutation probabilities α_{Tr} and γ_{Tr}, respectively. This training step is repeated with a period approximately equal to the coherence time of the channel.

2. *Decision-directed* step: during a coherence period, the stochastic values assumed by the channel coefficients acting over each subcarrier are strongly correlated. Therefore, the time variations of the channel impulse response are reasonably small and a decision-directed updating step can proceed (see Fig. 3.2 (b)). It is performed by the GA, working with a different parameterisation and a different fitness function. The updating procedure is carried on symbol after symbol and it is initialised by

the solution computed during the training-aided step (i.e., $\hat{\mathbf{w}}^{Tr}(i)$). During each symbol period, a single generation of individuals is produced. The new population is stochastically generated in Gaussian way starting from the solution computed at the previous signalling period $\hat{\mathbf{w}}^{DD}(i-1)$ and imposing to the Gaussian generator an updating standard deviation σ_{up}. Such a system parameter is linked to the Doppler spread and to the SNR. An explicit mathematical link is very difficult to be obtained. It should be increased as Doppler spread and SNR increase. Experimental trials pointed out that a good choice for this parameter is:

$$\sigma_{up} \simeq \max_{i,n} \left\{ \left| w_n^{Opt.}(i) - w_n^{Opt.}(i-1) \right| \right\} \tag{3.10}$$

Among the new population, it is chosen the individual that minimizes the following metric:

$$\Omega\left(\hat{w}_n(i)\right) = \left| \left(\sum_{k=1}^{K} c_n^k \hat{a}_i^k \right) - \hat{w}_n(i)\, y_n(i) \right|^2 \tag{3.11}$$

Given that only one generation runs, crossover and mutation operators do not work in such a step (i.e., the values of crossover and mutation probabilities are $\alpha_{DD} = 0$ and $\gamma_{DD} = 0$, respectively). The generation number G_{DD} is equal to one and the population size P_{DD} has to be chosen. The estimated data symbol $\hat{a}_i^k$ is used to calculate the fitness function $\Omega\left(\hat{w}_n(i)\right)$.

This updating procedure is “light”, but it is reasonable because only small variations of the channel amplitude and phase are to be tracked during the coherence period. Moreover, in such a way, the effect of possible symbol errors on weight estimation are conveniently reduced.

These two steps are opportunely combined to obtain the whole GA-based MMSE MUD procedure. It can be summarized as follows:

i) At time $t = 0$ the GA-based procedure is initialised by a constant-value population $\hat{\mathbf{w}}(0) = [1, \ldots, 1]$.

ii) The *Training-aided* step begins. The B-bit known training sequence is transmitted, B samples of the received signal are stored, and the weights vector $\hat{\mathbf{w}}^{Tr}$

is computed by minimizing the per-carrier cost function of Eq. 3.8. The GA parameters (G_{Tr}, P_{Tr}, α_{Tr}, γ_{Tr}) are opportunely chosen.

iii) The *Training-aided* step ends with the computation of the receiver weights at the time $t = BT + \varepsilon T$ (ε is the execution time of the GA-based optimisation procedure expressed in number of bit periods). Now, the GA switches to the *Decision-directed* modality and its parameters are reassigned as follows: $G_{DD} = 1$, $\alpha_{DD} = 0$, and $\gamma_{DD} = 0$. The population size P_{DD} has to be chosen.

iv) The *Decision-directed* updating step ends at the time $t = BT + \varepsilon T + W_{coh}T$, where W_{coh} is the coherence time-window of the channel. The GA is re-initialised with the weights computed at the end of the coherence time-window and re-parameterised in order to start again with the *Training-aided* step of ii).

3.2 Genetic Algorithm-Assisted Maximum-Likelihood Multi-User Detection for Multi-Rate MC-CDMA Systems

In this section, the application of GAs to multi-rate MC-CDMA multi-user detection is proposed and discussed in order to obtain a near-optimum solution to the ML MUD problem, reached by spending a reasonable computational effort. The claimed objective is, in particular, to maintain the computational burden of a polynomial order with respect to system parameters. At first, the description of the multi-rate Variable-Spreading-Length (VSL) MC-CDMA received signal model is provided. Then, the GA-assisted ML MUD algorithm is detailed.

3.2.1 Multi-Rate VSL MC-CDMA Transmission

Let us consider the multi-rate multi-user MC-CDMA transmission concept illustrated in [67] known as VSL access. A fixed amount of bandwidth is allocated for downlink transmission. A fixed number of subcarriers N (being N an integer power of 2 in order to simplify the FFT implementation of the VSL transceiver) is available. The transmitting user population is subdivided into "user classes", each one transmitting a digital data stream over a subset of N_m subcarriers, whose cardinality is an integer fractional value of N and depends on the channel bitrate r_m. More in details, M bitrate classes can be defined by the rule: $r_m = 2^{(M-m)} \cdot r$ (with $m = 1, \ldots, M$), where $r = 1/T$ is the bitrate of the "slowest" user class (i.e., class M), also named *basic data-rate* of the system. The data stream of a user of class m is converted into m parallel outputs. Symbols at each output are copied over $N_m = N/2^{(M-m)}$ branches and then respectively being multiplied by the corresponding bit of spreading codes whose length is N_m. A block diagram of the corresponding transmitter scheme is depicted in Fig. 3.3 ([67]).

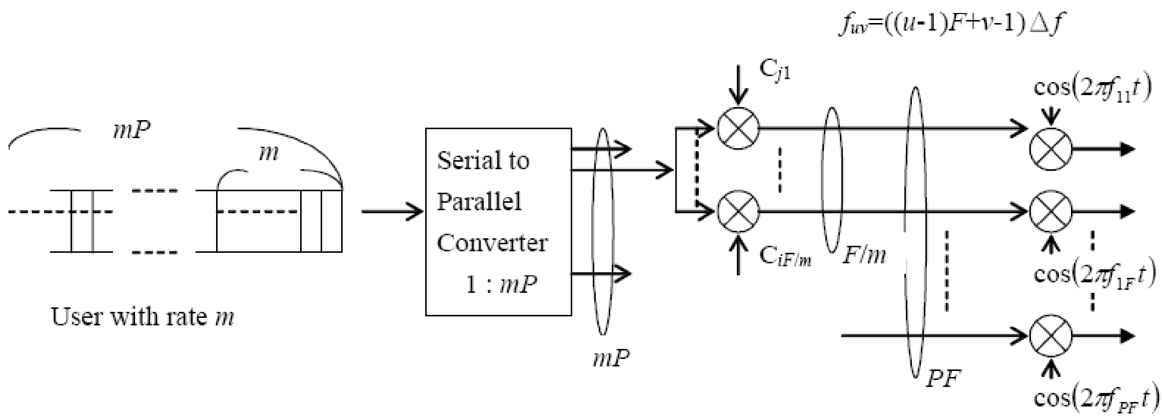


Figure 3.3: Illustration of VSL accessed multi-rate MC-CDMA

The baseband transmitted signal of the u-th user with rate r_m, namely $x_u^{(m)}(t)$, is given as follows:

$$x_u^{(m)}(t) = \sum_{i=1}^{m} A_u^{(m)} D_{u,i}^{(m)} \sum_{n=0}^{N_m-1} c_{u,n}^{(m)} \exp\left\{2\pi \jmath \left[(i-1)\frac{N}{2^{(M-m)}} + n\right]\frac{t}{T}\right\} \tag{3.12}$$

where $0 \le t \le T$, $D_{u,i}^{(m)}$ is the i-th binary BPSK data symbol, $c_{u,n}^{(m)}$ is the n-th chip of the assigned spreading code, and $A_u^{(m)}$ is the user's u transmitted amplitude. According to [67] and in order to simplify the mathematical formalization of the received signal, it is possible to regard a user with rate r_m as $2^{(M-m)}$ effective users at rate r. The decomposition in frequency domain, corresponding spreading codes and spectrum allocation for effective users are pictorially described in Fig. 3.4.

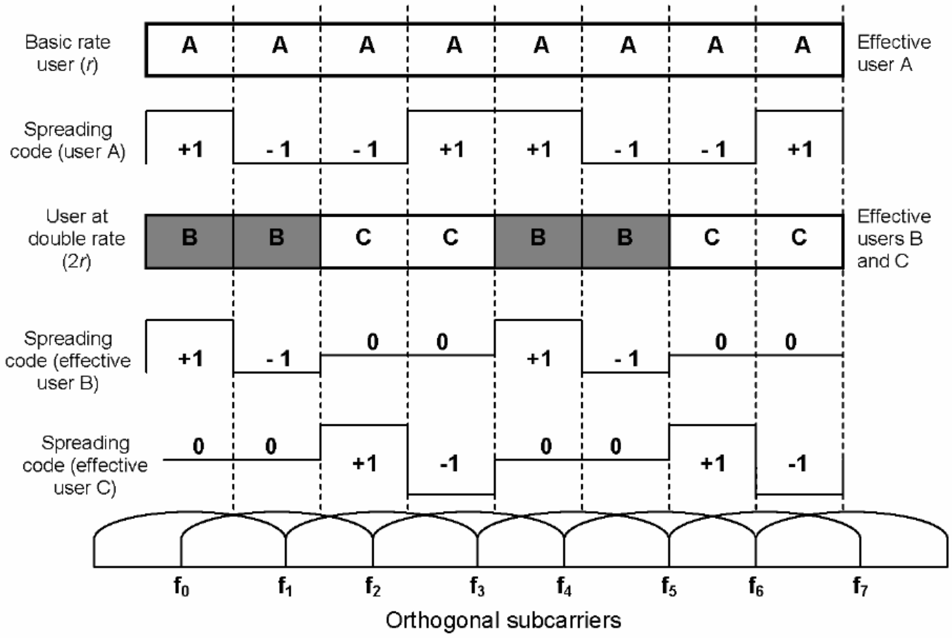


Figure 3.4: Pictorial illustration of the concept of effective users in VSL MC-CDMA multi-rate access

If U_m denotes the number of users transmitting at rate r_m, the total number of effective users in the system is given by:

$$U = \sum_{m=1}^{M} 2^{(M-m)} U_m \tag{3.13}$$

As the users are transmitting at different bit-rate, it is possible to evaluate the received signal after the duration of $2^{(M-m)}$ symbols of a user with rate r_m. This is given by:

$$y(t) = \sum_{u=1}^{U} \sum_{i=1}^{m} A_u D_{u,i} \sum_{n=0}^{N-1} h_{i,n} c_{u,n} \exp\left\{ 2\pi\jmath \left[(i-1) N + n \right] \frac{t}{T} \right\} + z(t) \tag{3.14}$$

being $h_{i,n}$ the channel gain of the (i,n)-th subcarrier with normalized squared amplitude expectation, i.e., $E\left\{ |h_{i,n}|^2 \right\} = 1$, and $z(t)$ the AWGN with power spectral density N_0.

The received signal $y(t)$ is therefore down-converted and the resulting contribution can be expressed in matrix notation:

$$\mathbf{Y} = \mathbf{H}\boldsymbol{\Psi}\bar{\mathbf{I}}\mathbf{D} + \mathbf{Z} \tag{3.15}$$

where $\bar{\mathbf{I}}$ is a $U \cdot N \times N$ matrix, obtained by replicating the $U \times U$ identity matrix $\mathbf{I}$, $\mathbf{H}$ is the $N \times U \cdot N$ channel matrix, and $\boldsymbol{\Psi}$ is the $U \cdot N \times U \cdot N$ diagonal signature matrix of the effective user, as defined in [67]. In VLS access, the matrix $\mathbf{\Psi}$ contains elements of the Orthogonal Variable Spreading Factor (OVSF) sequence matrix described in [67], completed by zeros in correspondence of spreading codes assigned to users transmitting at higher rates. This implies that symbols coming from "fastest" users involve a reduced amount of MAI.

3.2.2 The Proposed GA-Based Multi-User Detection for Multi-Rate VSL MC-CDMA

The optimal MUD in multi-rate MC-CDMA VSL systems is based on the ML criterion ([67]). ML MUD is implemented by minimizing, with respect to the symbols transmitted by the effective users $\hat{\mathbf{D}}$, the absolute squared error between the received signal and the reconstructed noise-less pattern, that is:

$$\hat{\mathbf{D}}^{Opt.} = \arg\min_{\mathbf{D}} \left\{ \left(\mathbf{Y} - \mathbf{H}\mathbf{\Psi}\bar{\mathbf{I}}\mathbf{D}\right)^H \left(\mathbf{Y} - \mathbf{H}\mathbf{\Psi}\bar{\mathbf{I}}\mathbf{D}\right) \right\} \tag{3.16}$$

where the superscript operator ^{H} denotes the Hermitian transpose. The channel matrix $\mathbf{H}$ is supposed here to be completely known. Also, the OVSF code matrix, and therefore $\mathbf{\Psi}$, are assumed to be known by the receiver. Under such hypothesis, the ML-based computation of $\hat{\mathbf{D}}^{Opt.}$ is theoretically feasible. The price to be paid is a computational load exponentially growing with the number of the effective users U. The effective users' number increases with: a) the number of user classes M, and b) the number of orthogonal subcarriers N. Fig. 3.4 clearly evidences that the number of effective users is higher than the number of real users. So, the computational burden of theoretical ML detection in the multi-rate case can reach huge amounts that might not be supported by commercial signal processing hardware products.

In the proposed approach, the metric of Eq. 3.16 is regarded as the fitness of the GA. In Fig. 3.5, the flowchart of the proposed GA-assisted ML MUD detection algorithm is depicted. The initial population consists of P_{pop} individuals obtained starting from the solution $\hat{\mathbf{D}}^0$ obtained by the hard decision made at the output of a single-user EGC receiver stage. In particular, it has been choose to select other individuals as those ones

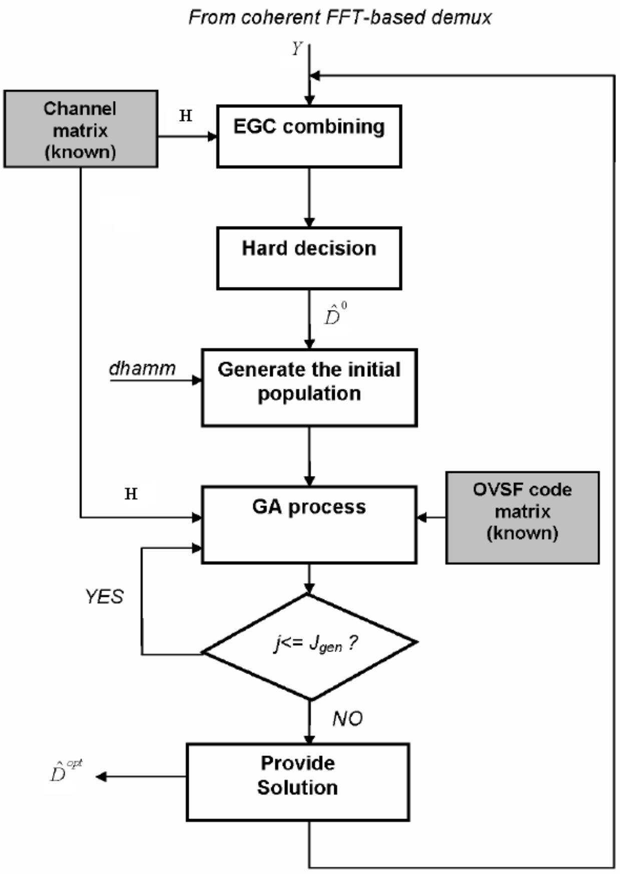


Figure 3.5: Flowchart of the proposed GA-assisted ML MUD algorithm

that differ from $\hat{\mathbf{D}}^0$ by a Hamming distance lower or equal to a maximum given value *dhamm*. The number of the individuals belonging to the so-generated population can be obtained as: $P_{pop} = \sum_{p=0}^{dhamm} \binom{U}{P}$. Such a criterion has been considered in order to provide a good choice of the initial population without spending a relevant computational effort. In [49], the initial population is generated by a stochastic mutation of the hard decision made on the output of a MRC stage. Such a choice might be not very suitable in the presence of high level of MAI. In fact, it is known by literature that MRC is the optimal combining methodology in the single-user case, but its performances rapidly deteriorate when the number of simultaneous users increases (see, e.g., results shown in [15] that evidenced a worst behaviour of MRC with respect to EGC in case of increasing level of MAI). The initialization strategy proposed in this work is very similar to the one considered in [56], where the initial population was generated among the elements differing by *dhamm* from an initial solution obtained by a MMSE MUD stage. Such a last choice may theoretically perform better than the one here proposed. But, from a more practical viewpoint, the MMSE MUD implementation would involve the inversion of a big $N \times N$ matrix $\left(\mathbf{H}\mathbf{\Psi}\bar{\mathbf{I}}\mathbf{\Psi}^H\mathbf{H}^H + N_0\mathbf{I}\right)$ that might be not a trivial task. EGC combining is very simple in case of perfect knowledge of the channel matrix and would not significantly affect the computational burden of the entire receiver chain. After the initialization, a fitness value is associated to the P_{pop} individuals by computing the metric of Eq. 3.16. At each generation, GA stochastic operators are applied in order to evolve the population. Selection is performed by analyzing two individuals and choosing the one with the best value of the fitness. Crossover is applied on solutions belonging to the search space with an assigned probability α. The crossover strategy adopted here is the uniform crossover, in which an individual is created by randomly choosing the i-th bit of the new generated solution among the i-th bit present in one of the two selected parents. The mutation operator is applied by change a bit of the selected individual with an assigned probability γ. Furthermore, elitism has been used in order to maintain the best individual from the generation j to the next generation $j+1$. The population generation terminates when a satisfactory solution has been produced or when a fixed number of iterations J_{gen} has been completed.

3.3 An Adaptive MBER Receiver for Space-Time Block-Coded MIMO MC-CDMA Mobile Communication Systems

The potential advantages of implementing linear MBER MUD in STBC MC-CDMA context can be easily explained. STBC MC-CDMA is a transmission methodology where diversity is obtained both in space and in frequency domain. The diversity gain, increased with respect to the conventional SISO case, is obtained at the price of an increased system complexity. The exploitation of the "full potential" of STBC MC-CDMA techniques can be obtained only by means of optimized multi-user detection approaches. In such a perspective, the investigation of MBER strategies can be regarded as a step-ahead towards the computationally-affordable signal detection optimization also in the STBC MC-CDMA case. The application of MBER reception to MIMO MC-CDMA is not straightforward and has to be investigated by carefully taking into account tight requirementes in terms of ease of implementation and reduced computational effort.

This section describes an adaptive multi-user receiver based on a Minimum-BER approach for synchronous STBC MIMO MC-CDMA systems transmitting data over time-varying multipath fading channels. The practical implementation of the proposed MBER receiver relies on an adaptive LMS algorithm, periodically aided by a training sequence and working in decision-directed modality during a coherence time window of the channel. The presented algorithm relies on the estimation of the probability density function of the decision variables obtained by using the Parzen's windows methodology.

At first, the description of the STBC MIMO MC-CDMA system is provided. Then, the LMS-based MBER MUD algorithm is detailed.

3.3.1 System Description

In this work, a synchronous multi-user STBC MC-CDMA system equipped with $N_{Tx} = 2$ transmit antennas and $N_{Rx} = 2$ receive antennas has been considered (see Fig. 3.6). Let us denote with K the number of mobile users and with N the number of orthogonal subcarriers. Let $\{a_k(i)\}_{i=0,1,\dots}$ be the original information sequence of user k. From the transmitter side, the space-time block coding technique proposed by Alamouti in [78] has been adopted. Therefore, two consecutive symbols of the generic user k (i.e., $a_k(i)$ and $a_k(i+1)$) are mapped to the transmit antennas according to the code matrix given by:

$$\Phi_k(i) = \frac{1}{\sqrt{2}} \begin{bmatrix} a_k(i) & -a_k(i+1)^* \\ a_k(i+1) & a_k(i)^* \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} a_1^k & -a_2^{k*} \\ a_2^k & a_1^{k*} \end{bmatrix} \tag{3.17}$$

with $i = 0, 2, \dots$ and $k = 1, 2, \dots, K$. Without loss of generality, two consecutive symbols of the generic user k (i.e., $a_k(i)$ and $a_k(i+1)$) are mapped to the variables a_1^k and a_2^k,

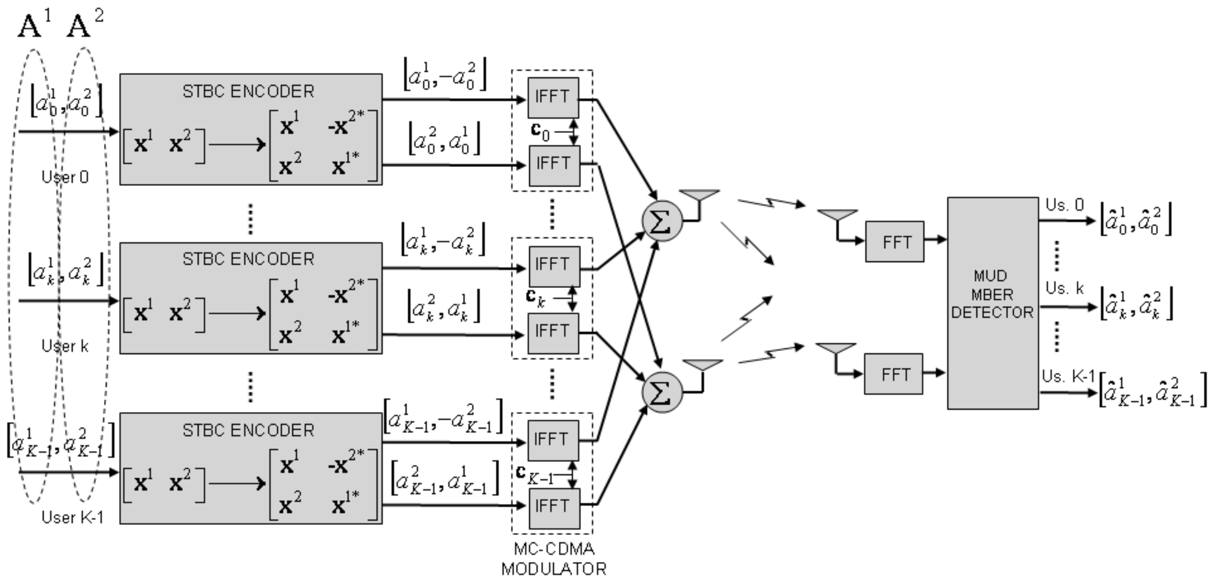


Figure 3.6: The considered STBC MC-CDMA system (2x2)

respectively. This mapping will be useful in order to make more readable the mathematical formulation exposed in the following. The two columns of $\Phi_k(i)$ are transmitted during two consecutive time slots (i and $i+1$). The first element of each matrix column is sent by the first transmit antenna and the second element by the second antenna, respectively.

Adopting a more agile matrix notation, the received signal can be conveniently written in this form:

$$\begin{bmatrix} \mathbf{y}_j(i) \\ \mathbf{y}_j^*(i+1) \end{bmatrix} = \begin{bmatrix} \mathbf{H}_{1j} & \mathbf{H}_{2j} \\ \mathbf{H}_{2j}^* & -\mathbf{H}_{1j}^* \end{bmatrix} \begin{bmatrix} \mathbf{C} & 0 \\ 0 & \mathbf{C} \end{bmatrix} \begin{bmatrix} \mathbf{a}(i) \\ \mathbf{a}(i+1) \end{bmatrix} + \begin{bmatrix} \mathbf{n}_j(i) \\ \mathbf{n}_j^*(i+1) \end{bmatrix} \tag{3.18}$$

where:

- $\mathbf{y}_j(i) = [y_{j,1}(i), \ldots, y_{j,N}(i)]^T$ is the vector of received signals related to the j-th receive antenna element ($j \in \{1,2\}$) during the i-th signaling period ($i = 0, 2, \ldots$) ($[\cdot]^T$ denotes the matrix transposition)

- $\mathbf{H}_{uj}$ is the diagonal channel matrix $diag(h_{u,j,1}, \ldots, h_{u,j,N})$ where $h_{u,j,n}$ ($u \in \{1,2\}$) is the channel coefficient associated with the path associated to the u-th transmit antenna and to the j-th receive antenna over the n-th subcarrier. Let us suppose that the fading over the different antenna elements is uncorrelated. Such a hypothesis has been commonly done in literature about STBC MIMO systems (see, e.g., [78, 85, 176]). Moreover, it is supposed that the channel matrix is time-invariant during a single block duration

- $\mathbf{C} = [\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_K]$ is the spreading code matrix of size $N \times K$ where the column vector $\mathbf{c}_k = [c_{k,1}, \ldots, c_{k,N}]^T$ is the spreading code employed by the user k
- $\mathbf{a}(i) = [a_1(i), \ldots, a_K(i)]^T$ and $\mathbf{a}(i+1) = [a_1(i+1), \ldots, a_K(i+1)]^T$ are the vectors of symbols transmitted by the K users in a STBC block
- $\mathbf{n}_j(i) = [\eta_{j,1}(i), \ldots, \eta_{j,N}(i)]^T$ is the AWGN vector with $\eta_{j,n}(i)$ representing the noise term at subcarrier n, at the j-th receive antenna element during the i-th signaling period, with zero mean and variance σ_η^2.

By jointly considering the two receive antennas, the matrix formulation can be rewritten as follows:

$$\mathbf{Y} = \hat{\mathbf{H}}\hat{\mathbf{C}}\mathbf{A} + \mathbf{N} \tag{3.19}$$

Such a last formulation has been obtained by defining the involved terms as follows: $\mathbf{Y} \triangleq \left[\mathbf{y}_1^T(i) \mid \mathbf{y}_1^H(i+1) \mid \mathbf{y}_2^T(i) \mid \mathbf{y}_2^H(i+1)\right]^T$ (where the operator $\mid$ represents the matrix vertical concatenation), $\hat{\mathbf{C}} = \begin{bmatrix} \mathbf{C} & 0 \\ 0 & \mathbf{C} \end{bmatrix}$, $\mathbf{A} \triangleq \left[\mathbf{a}^T(i) \mid \ \mathbf{a}^T(i+1)\right]^T$ and $\mathbf{N} \triangleq \left[\mathbf{n}_1^T(i) \mid \mathbf{n}_1^H(i+1) \mid \mathbf{n}_2^T(i) \mid \mathbf{n}_2^H(i+1)\right]^T$.

Under such hypothesis, the $2N_{Rx}N \times N_{Tx}N$ channel matrix can be defined as follows:

$$\hat{\mathbf{H}} = \begin{bmatrix} \mathbf{H}_{11} & \mathbf{H}_{21} \\ \mathbf{H}_{21}^* & -\mathbf{H}_{11}^* \\ \mathbf{H}_{12} & \mathbf{H}_{22} \\ \mathbf{H}_{22}^* & -\mathbf{H}_{12}^* \end{bmatrix} \tag{3.20}$$

In the next sub-section, the novel adaptive multi-user detection algorithm based on the LMS implementation of the MBER criterion will be exposed in details.

3.3.2 The Adaptive MBER Multi-User Detection Algorithm for STBC MIMO MC-CDMA Mobile Transmission Systems

Let's start from the formulation of the decision variable for a generalized per-user linear detector. The decision variable of the generic k-th user can be expressed in the usual form:

$$\lambda_s^k = \mathbf{w}_{k,s}^H \mathbf{Y} \qquad \text{with} \quad s \in \{1, 2\} \tag{3.21}$$

where s is the index of the symbol in the block (a_s^k) and $\mathbf{w}_{k,s}$ the receiver weight vector. The resulting decision variables λ_1^k and λ_2^k are employed to estimate the symbols belonging to the k-th user block, i.e., a_1^k and a_2^k, respectively.

Practically, the MBER receiver should compute the optimal weight vector $\mathbf{w}_{k,s}^{Opt.}$ that minimizes the error probability in a transmitted block of symbols P_e^k. Without losing generality, the use of a BPSK modulation with binary antipodal signals has been considered (therefore $a_s^k \in \{-1, 1\}$). The choice of BPSK can be motivated by usual robustness requirements typical of wireless mobile environment. The formulation of the proposed algorithm for multi-level PSK (or Quadrature Amplitude Modulation, QAM) modulations is straightforward.

Under such hypothesis, the formulation adopted in [59] can be used to define the so-called *signed decision variable* Λ_s^k (with $s \in \{1, 2\}$ and $k = 1, 2, \ldots, K$) as follows:

$$\Lambda_s^k = a_s^k \left\{\mathbf{w}_{k,s}^H \mathbf{Y}\right\} = a_s^k \left\{\mathbf{w}_{k,s}^H \hat{\mathbf{H}}\hat{\mathbf{C}}\mathbf{A}\right\} + a_s^k \left\{\mathbf{w}_{k,s}^H \mathbf{N}\right\} \tag{3.22}$$

where $a_s^k \left\{\mathbf{w}_{k,s}^H \mathbf{N}\right\}$ is Gaussian with zero mean and variance $\sigma_\eta^2 \mathbf{w}_{k,s}^H \mathbf{w}_{k,s}$. By defining $\mathbf{A}^{(j)} = \left[a_1^{1,(j)}, \ldots, a_1^{K,(j)} \mid a_2^{1,(j)}, \ldots, a_2^{K,(j)}\right]^T$ as one of the 2^{2K} possible combination of transmitted (equiprobable) data symbols, the value of the possible noise-free signal can take the value only in the set defined by:

$$\mathbf{\Omega}^{(j)} = \mathbf{w}_{k,s}^H \hat{\mathbf{H}}\hat{\mathbf{C}}\mathbf{A}^{(j)} \qquad \text{with} \quad j = 1, \ldots, 2^{2K} \tag{3.23}$$

As shown in [59] the Probability Density Function (PDF) of the random variable Λ_s^k can be written as:

$$f_{\Lambda_s^k}(x) = \frac{1}{2^{2K}\sqrt{2\pi}\sigma_\eta\sqrt{\mathbf{w}_{k,s}^H\mathbf{w}_{k,s}}}\sum_{j=1}^{2^{2K}}\exp\left\{-\frac{\left[x-a_s^{k(j)}\left(\mathbf{w}_{k,s}^H\hat{\mathbf{H}}\hat{\mathbf{C}}\mathbf{A}^{(j)}\right)\right]^2}{2\sigma_\eta^2\mathbf{w}_{k,s}^H\mathbf{w}_{k,s}}\right\} \tag{3.24}$$

Considering that an error in demodulating the user k occurs whenever $\Lambda_1^k < 0$ and/or $\Lambda_2^k < 0$ and considering that the two random variables Λ_1^k and Λ_2^k are independent, the probability of having symbol error in the block of the generic k-th user (in the usual case of two symbols per user block) can be formally written as follows:

$$P_e^k = \Pr\left\{\Lambda_1^k > 0\right\}\cdot\Pr\left\{\Lambda_2^k < 0\right\} + \Pr\left\{\Lambda_1^k < 0\right\}\cdot\Pr\left\{\Lambda_2^k > 0\right\} + \\ + \Pr\left\{\Lambda_1^k < 0\right\}\cdot\Pr\left\{\Lambda_2^k < 0\right\} \tag{3.25}$$

being $\Pr\left\{\Lambda_s^k < 0\right\}$ the probability of error in demodulating the symbol a_s^k and $\Pr\left\{\Lambda_s^k > 0\right\}$ the probability of correct demodulation for the symbol a_s^k (with $s \in \{1,2\}$). The sum of the first two terms of Eq. 3.25 actually computes the average probability of having a single symbol error in the block. The last term of Eq. 3.25 accounts the average probability of having two symbol errors in the block.

The computation of the probability of error of Eq. 3.25, and therefore its minimization, would be theoretically feasible. But, such an operation involves a not tractable computational burden of exponential order with respect to the users' number K. In order to overcome such a problem, the estimation of $f_{\Lambda_s^k}(x)$ based on the Parzen's windows methodology ([177]) has been considered.

In particular, the real PDF of Eq. 3.24 can be approximated with a kernel density estimate based on a block of M samples. The estimated PDF is given as follows:

$$\tilde{f}_{\Lambda_s^k}(x) = \sum_{m=1}^{M}\frac{1}{M\sqrt{2\pi}\rho_\eta\sqrt{\mathbf{w}_{k,s}^H(m)\,\mathbf{w}_{k,s}(m)}}\cdot \\ \cdot\exp\left\{-\frac{\left[x-a_s^k\left(\mathbf{w}_{k,s}^H(m)\,\mathbf{Y}(m)\right)\right]^2}{2\rho_\eta^2\mathbf{w}_{k,s}^H(m)\,\mathbf{w}_{k,s}(m)}\right\} \tag{3.26}$$

where ρ_η is the standard deviation of the PDF estimate. Such a quantity is directly linked with the noise standard deviation, but it cannot be computed in a closed-form. Only a lower bound of it is provided as:

$$\rho_\eta = \left(\frac{4}{3M}\right)^{\frac{1}{5}} \sigma_\eta \tag{3.27}$$

being M the total number of symbols considered for the estimate ([177]). ρ_η has to be considered as a free parameter to be set.

As noted in [18], this density estimate method requires a block of observed data bits and high memory demand at the receiver side. Therefore, it is not suitable for adaptive implementation. To obtain a really sample-by-sample adaptive algorithm, the following single data-point kernel estimation of the PDF of Eq. 3.24 has to be used:

$$\hat{f}_{\Lambda_s^k}(x) = \frac{1}{\sqrt{2\pi}\rho_\eta\sqrt{\mathbf{w}_{k,s}^H \mathbf{w}_{k,s}}} \exp\left\{-\frac{\left[x - a_s^k\left(\mathbf{w}_{k,s}^H \mathbf{Y}\right)\right]^2}{2\rho_\eta^2 \mathbf{w}_{k,s}^H \mathbf{w}_{k,s}}\right\} \tag{3.28}$$

By using the estimated PDF of Eq. 3.28, it is possible to derive a closed-form expression of the probability of error of Eq. 3.25:

$$\begin{aligned} P_e^k = {} & Q\left(\frac{a_1^k\left(\mathbf{w}_{k,1}^H \mathbf{Y}\right)}{\rho_\eta\sqrt{\mathbf{w}_{k,1}^H \mathbf{w}_{k,1}}}\right) + Q\left(\frac{a_2^k\left(\mathbf{w}_{k,2}^H \mathbf{Y}\right)}{\rho_\eta\sqrt{\mathbf{w}_{k,2}^H \mathbf{w}_{k,2}}}\right) + \\ & - Q\left(\frac{a_1^k\left(\mathbf{w}_{k,1}^H \mathbf{Y}\right)}{\rho_\eta\sqrt{\mathbf{w}_{k,1}^H \mathbf{w}_{k,1}}}\right) \cdot Q\left(\frac{a_2^k\left(\mathbf{w}_{k,2}^H \mathbf{Y}\right)}{\rho_\eta\sqrt{\mathbf{w}_{k,2}^H \mathbf{w}_{k,2}}}\right) \end{aligned} \tag{3.29}$$

where $Q(x)$ is the conventional Gaussian error function.

As shown in [18], Eq. 3.29 represents a one-sample or instantaneous estimate of the real probability of error expressed in Eq. 3.25.

Assuming the same probability of error for the two symbols of the STBC block, the third term in Eq. 3.29 is negligible with respect to the first two ones. In such a way, the bit error probability per block, which is the cost function of the analyzed problem, can be rewritten as:

$$P_e^k \simeq Q\left(\frac{a_1^k\left(\mathbf{w}_{k,1}^H \mathbf{Y}\right)}{\rho_\eta\sqrt{\mathbf{w}_{k,1}^H \mathbf{w}_{k,1}}}\right) + Q\left(\frac{a_2^k\left(\mathbf{w}_{k,2}^H \mathbf{Y}\right)}{\rho_\eta\sqrt{\mathbf{w}_{k,2}^H \mathbf{w}_{k,2}}}\right) \tag{3.30}$$

The gradient of the cost function of Eq. 3.30 with respect to the weights' vectors $\mathbf{w}_{k,1}$

and $\mathbf{w}_{k,2}$ can be computed as follows:

$$\nabla P_e^k = \begin{cases} \frac{1}{\sqrt{2\pi}\rho_\eta}\left(\frac{\mathbf{w}_{k,1}^H\mathbf{w}_{k,1}-\mathbf{w}_{k,1}^H\mathbf{w}_{k,1}\mathbf{I}}{\left(\mathbf{w}_{k,1}^H\mathbf{w}_{k,1}\right)^{3/2}}\right)\exp\left\{-\frac{\left(\mathbf{w}_{k,1}^H\mathbf{Y}\right)^2}{2\rho_\eta^2\mathbf{w}_{k,1}^H\mathbf{w}_{k,1}}\right\}\cdot a_1^k\mathbf{Y} \\ \frac{1}{\sqrt{2\pi}\rho_\eta}\left(\frac{\mathbf{w}_{k,2}^H\mathbf{w}_{k,2}-\mathbf{w}_{k,2}^H\mathbf{w}_{k,2}\mathbf{I}}{\left(\mathbf{w}_{k,2}^H\mathbf{w}_{k,2}\right)^{3/2}}\right)\exp\left\{-\frac{\left(\mathbf{w}_{k,2}^H\mathbf{Y}\right)^2}{2\rho_\eta^2\mathbf{w}_{k,2}^H\mathbf{w}_{k,2}}\right\}\cdot a_2^k\mathbf{Y} \end{cases} \tag{3.31}$$

being $\mathbf{I}$ the $N \times N$ identity matrix. It is possible to see in Eq. 3.31 that the amplitude of the weight vector has no effect on the BER in the block (as already noted in [59]). For this reason, it is useful to normalize the weight vector as follows:

$$\mathbf{w}_{k,s}^{'} = \frac{\mathbf{w}_{k,s}}{\sqrt{\mathbf{w}_{k,s}^H\mathbf{w}_{k,s}}} \tag{3.32}$$

Thanks to this simplification, the gradient vector can be rewritten in the more tractable form:

$$\nabla P_e^k = \begin{cases} \frac{1}{\sqrt{2\pi}\rho_\eta}\left(\mathbf{w}_{k,1}^H\mathbf{w}_{k,1}-\mathbf{I}\right)\exp\left\{-\frac{\left(\mathbf{w}_{k,1}^H\mathbf{Y}\right)^2}{2\rho_\eta^2}\right\}\cdot a_1^k\mathbf{Y} \\ \frac{1}{\sqrt{2\pi}\rho_\eta}\left(\mathbf{w}_{k,2}^H\mathbf{w}_{k,2}-\mathbf{I}\right)\exp\left\{-\frac{\left(\mathbf{w}_{k,2}^H\mathbf{Y}\right)^2}{2\rho_\eta^2}\right\}\cdot a_2^k\mathbf{Y} \end{cases} \tag{3.33}$$

Following the concept of the LMS adaptive optimization ([20, 178]), it is possible to formulate an adaptive gradient descent algorithm for the MBER problem discussed above in the following manner:

$$\begin{cases} \hat{\mathbf{w}}_{k,1}^{Opt.}(i+1) = & \hat{\mathbf{w}}_{k,1}^{Opt.}(i) - \mu\frac{\tilde{a}_1^k(i)}{\sqrt{2\pi}\rho_\eta}\exp\left\{-\frac{\left(\left(\hat{\mathbf{w}}_{k,1}^{Opt.}(i)\right)^H\mathbf{Y}(i)\right)^2}{2\rho_\eta^2}\right\}\cdot \\ & \cdot\left(\hat{\mathbf{w}}_{k,1}^{Opt.}(i)\left(\hat{\mathbf{w}}_{k,1}^{Opt.}(i)\right)^H\mathbf{Y}(i)-\mathbf{Y}(i)\right) \\ \hat{\mathbf{w}}_{k,2}^{Opt.}(i+1) = & \hat{\mathbf{w}}_{k,2}^{Opt.}(i) - \mu\frac{\tilde{a}_2^k(i)}{\sqrt{2\pi}\rho_\eta}\exp\left\{-\frac{\left(\left(\hat{\mathbf{w}}_{k,2}^{Opt.}(i)\right)^H\mathbf{Y}(i)\right)^2}{2\rho_\eta^2}\right\}\cdot \\ & \cdot\left(\hat{\mathbf{w}}_{k,21}^{Opt.}(i)\left(\hat{\mathbf{w}}_{k,2}^{Opt.}(i)\right)^H\mathbf{Y}(i)-\mathbf{Y}(i)\right) \end{cases} \tag{3.34}$$

being μ the step-size parameter and ρ_η the already mentioned standard deviation of the PDF estimation obtained by Parzen's windows. Also ρ_η is considered as a parameter. It is possible to note in Eq. 3.34 the presence of the data symbols of the k-th user block. The superscript notation $\tilde{}$ points out that an adaptive decision-directed LMS approach is considered. It is known that decision-directed LMS updating can be affected by slow convergence ([178]). In order to solve this problem and to speed up the convergence of the algorithm, a training-assisted adaptive procedure has been adopted. Practically, a short, known, training sequence is periodically transmitted in order to provide a faster convergence of the LMS procedure to the wanted solution. The period of transmission of the training sequence approximately equals the coherence time of the channel. The decision-directed updating procedure starts at the end of the training phase and goes on till the end of the coherence time window. In this case, the known training sequence is replaced by the decision made on the received symbol at the previous LMS updating step.

3.4 A Linear Multi-User Detector for STBC MIMO MC-CDMA Systems Based on the Adaptive Implementation of the Minimum-Conditional BER Criterion

In this section, a linear multi-user detector is described for MIMO MC-CDMA systems with Alamouti's space-time block coding, inspired by the concept of Minimum Conditional Bit Error Rate (MCBER). The MCBER combiner has been implemented in adaptive way by using LMS optimization.

At first, the description of the considered system model is provided. Then, the theoretical MCBER MUD criterion is explained.

3.4.1 System Model

In the present dealing, a synchronous multi-user MIMO MC-CDMA system based on Alamouti's Space-Time Block Coding ([78]) has been considered. Two transmitting antennas and a single receiving antenna are employed. The extension to scenarios characterized by an increased number of transmitting and receiving antennas is straightforward. A block scheme of the considered STBC MC-CDMA transmission system is drawn in Fig. 3.7.

Two consecutive data symbols of the generic user k ($k = 0, \ldots, K-1$) (i.e., a_k^1 and

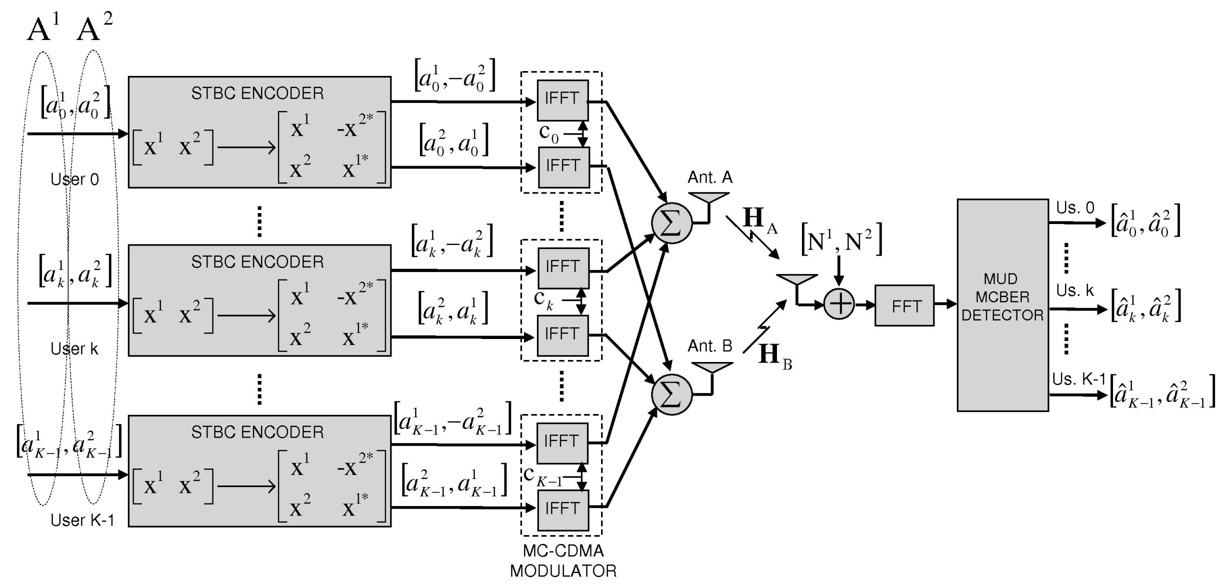


Figure 3.7: The considered STBC MC-CDMA system (2x1)

a_k^2) are mapped to two transmitting antennas according to the code matrix Φ_k, whose elements are given by:

$$\Phi_k = \frac{1}{\sqrt{2}} \begin{bmatrix} a_k^1 & -a_k^{2*} \\ a_k^2 & a_k^{1*} \end{bmatrix} \tag{3.35}$$

This matrix represents the Alamouti's STBC block. Alamouti's scheme exhibits some clear advantages. The classical antenna diversity approach considers the utilization of multiple antennas at the receiver side and a single antenna at the transmitter side. As result, the receiver becomes larger and more expensive. This is the reason why since many years antenna diversity has been exploited only by base stations in the uplink ([78]). Essentially, Alamouti's STBC scheme makes available a space diversity gain also for mobile terminals (therefore in the downlink) only by exploiting transmit diversity. The most economic and advantageous Alamouti's configurations consider two transmit antennas (installed at base station or access point) and a single antenna mounted at the receiver side. This is the configuration considered in this part of the work, where the focus is on the development of cost-effective mobile terminals.

The encoder outputs are transmitted during two consecutive transmission periods (i.e.,

T_1 and T_2). During the first transmission period T_1, two generic BPSK symbols a_k^1 and a_k^2 are sent to two separate Inverse Fast Fourier Transform (I-FFT) based multi-carrier spreading blocks using a unique Hadamard-Walsh sequence $\mathbf{c}_k \triangleq \{c_k(n) : n = 0, \ldots, N-1\}$, where N is the length of the I-FFT and therefore the number of subcarriers employed for spreading. Finally, the RF converted Multi-Carrier Spread Spectrum (MC-SS) signals are simultaneously transmitted by antenna A and antenna B, respectively. In the same way, during the successive transmission period T_2, the symbol $-a_k^{2*}$ is transmitted by antenna A and the symbol a_k^{1*} is transmitted by antenna B, respectively.
In order to make the notation more compact in the multi-user case, it is possible to define two vectors of symbols: $\mathbf{A}^1 \triangleq \left[a_0^1, a_1^1, \ldots, a_{K-1}^1\right]^T$ and $\mathbf{A}^2 \triangleq \left[a_0^2, a_1^2, \ldots, a_{K-1}^2\right]^T$, and the orthonormal code matrix $\mathbf{C}$ as:

$$\mathbf{C} = \begin{bmatrix} c_0(0) & c_1(0) & \cdots & c_{K-1}(0) \\ c_0(1) & c_1(1) & \cdots & c_{K-1}(1) \\ \vdots & \vdots & \ddots & \vdots \\ c_0(N-1) & c_1(N-1) & \cdots\cdots & c_{K-1}(N-1) \end{bmatrix} \tag{3.36}$$

The received signal samples acquired at two consecutive symbol periods after the FFT-based coherent demultiplexing can be expressed as follows:

$$\begin{cases} \mathbf{Y}^1 = \mathbf{H}_A \mathbf{C} \mathbf{A}^1 + \mathbf{H}_B \mathbf{C} \mathbf{A}^2 + \mathbf{N}^1 \\ \mathbf{Y}^2 = -\mathbf{H}_A \mathbf{C} \left(\mathbf{A}^2\right)^* + \mathbf{H}_B \mathbf{C} \left(\mathbf{A}^1\right)^* + \mathbf{N}^2 \end{cases} \tag{3.37}$$

where $\mathbf{Y}^1$ and $\mathbf{Y}^2$ are $N \times 1$ vectors, $\mathbf{N}^j = [\eta_0, \eta_1, \ldots, \eta_{N-1}]^T$ (with $j \in \{1, 2\}$) is the AWGN vector (all vector components are independent and identically distributed with zero mean and variance σ^2), and $\mathbf{H}_{ant} = diag\left(h_0^{ant},\ h_1^{ant}, \ldots, h_{N-1}^{ant}\right)$ (with $ant \in \{A, B\}$) is the $N \times N$ diagonal channel matrix, where h_n^{ant} is the complex channel coefficient related to subcarrier n and to the transmit antenna ant. Let us suppose that fading is flat over each subcarrier and almost time-invariant during two consecutive transmission period (i.e., the coherence time is much greater than the symbol period).

3.4.2 Minimum Conditional BER Decision Criterion

In this sub-section, an analytical expression for the error probability of a STBC MC-CDMA system using generic linear combining at the receiver side will be derived. Then, this expression will be used to formulate the LMS implementation of the MCBER detector, starting from the formulation of the ideal MBER criterion.

A generic linear multiuser detector generates two decision variables based on the linear combination of the received signal samples. Thus, the decision variables for the user k, denoted by $\lambda_{k,1}$ and $\lambda_{k,2}$, can be expressed as follows:

$$\begin{cases} \lambda_{k,1} = \mathbf{w}_k^{1*}\mathbf{Y}^1 + \mathbf{w}_k^2\mathbf{Y}^{2*} \\ \lambda_{k,2} = \mathbf{w}_k^{2*}\mathbf{Y}^1 - \mathbf{w}_k^1\mathbf{Y}^{2*} \end{cases} \tag{3.38}$$

where $\mathbf{w}_k^1 = [w_k^1(0), w_k^1(1), \ldots, w_k^1(N-1)]$ and $\mathbf{w}_k^2 = [w_k^2(0), w_k^2(1), \ldots, w_k^2(N-1)]$ are the vectors of receiver gains employed by the generic k-th user in order to recombine the baseband output of the FFT-based demodulation stage. The two bits contained in a single STBC block (corresponding to the BPSK symbols a_k^1 and a_k^2) can be estimated by observing the real part of $\lambda_{k,1}$ and $\lambda_{k,2}$, respectively. In this work, the employment of a digital BPSK modulation with real antipodal symbols has been considered. The choice of BPSK has been motivated by the fact that such a modulation allows to write an exact analytical expression of the BER at the output of the linear MUD combiner. Other modulations, like M-PSK and M-QAM require approximations that can sound very complex from a mathematical viewpoint or can be quite imprecise (in fact, the BPSK choice is common in literature about MBER and MCBER detection. It is employed, for instance, in [65, 91, 179]).

Under such hypothesis and substituting Eq. 3.37 in Eq. 3.38, it is possible to write the real parts of $\lambda_{k,1}$ and $\lambda_{k,2}$ as follows:

$$\begin{cases} \Re\{\lambda_{k,1}\} = & \Re\left\{ (\mathbf{w}_k^1)^* \mathbf{H}_A \mathbf{C}\mathbf{A}^1 + (\mathbf{w}_k^1)^* \mathbf{H}_B \mathbf{C}\mathbf{A}^2 + (\mathbf{w}_k^1)^* \mathbf{N}^1 + \right. \\ & \left. - \mathbf{w}_k^2 \mathbf{H}_A^* \mathbf{C}\mathbf{A}^2 + \mathbf{w}_k^2 \mathbf{H}_B^* \mathbf{C}\mathbf{A}^1 + \mathbf{w}_k^2 (\mathbf{N}^2)^* \right\} \\ \Re\{\lambda_{k,2}\} = & \Re\left\{ (\mathbf{w}_k^2)^* \mathbf{H}_A \mathbf{C}\mathbf{A}^1 + (\mathbf{w}_k^2)^* \mathbf{H}_B \mathbf{C}\mathbf{A}^2 + (\mathbf{w}_k^2)^* \mathbf{N}^1 + \right. \\ & \left. + \mathbf{w}_k^1 \mathbf{H}_A^* \mathbf{C}\mathbf{A}^2 - \mathbf{w}_k^1 \mathbf{H}_B^* \mathbf{C}\mathbf{A}^1 - \mathbf{w}_k^1 (\mathbf{N}^2)^* \right\} \end{cases} \tag{3.39}$$

Conditioned on the transmitted bit vectors $\mathbf{A}^1$ and $\mathbf{A}^2$, the random variables $\Re\{\lambda_{k,1}\}$ and $\Re\{\lambda_{k,2}\}$ are Gaussian-distributed with mean values:

$$\begin{cases} \mu_{k,1} = \Re\left((\mathbf{w}_k^1)^* \mathbf{H}_A \mathbf{C}\mathbf{A}^1 + (\mathbf{w}_k^1)^* \mathbf{H}_B \mathbf{C}\mathbf{A}^2 - \mathbf{w}_k^2 \mathbf{H}_A^* \mathbf{C}\mathbf{A}^2 + \mathbf{w}_k^2 \mathbf{H}_B^* \mathbf{C}\mathbf{A}^1 \right) \\ \mu_{k,2} = \Re\left((\mathbf{w}_k^2)^* \mathbf{H}_A \mathbf{C}\mathbf{A}^1 + (\mathbf{w}_k^2)^* \mathbf{H}_B \mathbf{C}\mathbf{A}^2 + \mathbf{w}_k^1 \mathbf{H}_A^* \mathbf{C}\mathbf{A}^2 - \mathbf{w}_k^1 \mathbf{H}_B^* \mathbf{C}\mathbf{A}^1 \right) \end{cases} \tag{3.40}$$

and variances:

$$\begin{cases} \sigma_{k,1}^2 = \sigma^2 \left(\|\mathbf{w}_k^1\|^2 + \|\mathbf{w}_k^2\|^2 \right) \\ \sigma_{k,2}^2 = \sigma^2 \left(\|\mathbf{w}_k^1\|^2 + \|\mathbf{w}_k^2\|^2 \right) \end{cases} \tag{3.41}$$

respectively. To make the derivation of the probability of error easier, it is possible to refer to the so-called sign-adjusted decision variables ([179]) defined as follows: $\lambda_{k,1}^s \triangleq a_k^1 \Re\{\lambda_{k,1}\}$ and $\lambda_{k,2}^s \triangleq a_k^2 \Re\{\lambda_{k,2}\}$. These new decision variables, conditioned on the transmitted bit vectors $\mathbf{A}^1$ and $\mathbf{A}^2$, are Gaussian-distributed as well with mean values $a_k^1 \mu_{k,1}$ and $a_k^2 \mu_{k,2}$ and variances $\sigma_{k,1}^2$ and $\sigma_{k,2}^2$, respectively. Thus, the probability to have an error in a STBC block, conditioned on $\mathbf{A}^1$ and $\mathbf{A}^2$, can be written as follows:

$$P_{e/\mathbf{A}^1,\mathbf{A}^2} = \Pr\left\{\lambda_{k,1}^s < 0, \lambda_{k,2}^s > 0\right\} + \Pr\left\{\lambda_{k,1}^s > 0, \lambda_{k,2}^s < 0\right\} + \\ + \Pr\left\{\lambda_{k,1}^s < 0, \lambda_{k,2}^s < 0\right\} \tag{3.42}$$

and, considering that $\lambda_{k,1}^s$ and $\lambda_{k,2}^s$ are independent, Eq. 3.42 reduces to:

$$P_{e/\mathbf{A}^1,\mathbf{A}^2} = \Pr\left\{\lambda_{k,1}^s < 0\right\} \cdot \Pr\left\{\lambda_{k,2}^s > 0\right\} + \Pr\left\{\lambda_{k,1}^s > 0\right\} \cdot \Pr\left\{\lambda_{k,2}^s < 0\right\} + \\ + \Pr\left\{\lambda_{k,1}^s < 0\right\} \cdot \Pr\left\{\lambda_{k,2}^s < 0\right\} \tag{3.43}$$

Using the former considerations and the standard Q function, it can be shown that:

$$\begin{array}{ll} \Pr\left\{\lambda_{k,1}^{s} < 0\right\} = Q\left(\frac{\lambda_{k,1}^{s}}{\sigma_{k,1}}\right) & \Pr\left\{\lambda_{k,1}^{s} > 0\right\} = 1 - Q\left(\frac{\lambda_{k,1}^{s}}{\sigma_{k,1}}\right) \\ \Pr\left\{\lambda_{k,21}^{s} < 0\right\} = Q\left(\frac{\lambda_{k,2}^{s}}{\sigma_{k,2}}\right) & \Pr\left\{\lambda_{k,21}^{s} > 0\right\} = 1 - Q\left(\frac{\lambda_{k,2}^{s}}{\sigma_{k,2}}\right) \end{array} \tag{3.44}$$

Using the above, Eq. 3.43 can be rewritten as:

$$P_{e/\mathbf{A}^1,\mathbf{A}^2} = Q\left(\frac{\lambda_{k,1}^{s}}{\sigma_{k,1}}\right) + Q\left(\frac{\lambda_{k,2}^{s}}{\sigma_{k,2}}\right) - Q\left(\frac{\lambda_{k,1}^{s}}{\sigma_{k,1}}\right) \cdot Q\left(\frac{\lambda_{k,2}^{s}}{\sigma_{k,2}}\right) \tag{3.45}$$

Assuming that the two symbols contained in a STBC block have the same probability of error, the third term in Eq. 3.45 is negligible with respect to the first two ones. Thus, an approximation of Eq. 3.45 is given by:

$$P_{e/\mathbf{A}^1,\mathbf{A}^2} \simeq \hat{P}_{e/\mathbf{A}^1,\mathbf{A}^2} = Q\left(\frac{\lambda_{k,1}^{s}}{\sigma_{k,1}}\right) + Q\left(\frac{\lambda_{k,2}^{s}}{\sigma_{k,2}}\right) \tag{3.46}$$

By considering that the 2^{2K} possible transmitted bit vectors are independent and equiprobable, the average probability of error for the k-th user can be written as:

$$\hat{P}_e^{AV}\left(\mathbf{w}_k^1, \mathbf{w}_k^2\right) = \frac{1}{2^{2K}} \sum_{\forall \mathbf{A}^1} \sum_{\forall \mathbf{A}^2} \hat{P}_{e/\mathbf{A}^1,\mathbf{A}^2} \tag{3.47}$$

The couple of receiver gains vectors $(\mathbf{w}_k^1, \mathbf{w}_k^2)$ minimizing the average probability of error shown in Eq. 3.47 practically implement the ideal MBER detection criterion for the considered STBC MC-CDMA system. In [61], it is pointed out that no closed-form expression for MBER solution can be found. For this reason, a numerical solution has to be investigated. A possible solution is to exploit the LMS algorithm based on the concept of gradient descent ([178, 180]). LMS updating of the filter weights is done iteratively along the negative gradient of the error probability surface, along both directions $\mathbf{w}_k^1$ and $\mathbf{w}_k^2$. The updating rule at i-th iteration is given by:

$$\begin{cases} \mathbf{w}_k^1(i+1) = \mathbf{w}_k^1(i) - \rho \cdot \nabla_1 \left(\hat{P}_e^{AV}\left(\mathbf{w}_k^1, \mathbf{w}_k^2\right)\right)(i) \\ \mathbf{w}_k^2(i+1) = \mathbf{w}_k^2(i) - \rho \cdot \nabla_2 \left(\hat{P}_e^{AV}\left(\mathbf{w}_k^1, \mathbf{w}_k^2\right)\right)(i) \end{cases} \tag{3.48}$$

where ρ is the step-size parameter and ∇_1 and ∇_2 represent the gradient along the two directions $\mathbf{w}_k^1$ and $\mathbf{w}_k^2$, respectively. For the first iteration (namely: $i = 0$), the following initialization has been chosen: $\mathbf{w}_k^1(0) = \mathbf{w}_k^2(0) = \mathbf{c}_k$. This is a reasonable choice, commonly done in the literature dealing with adaptive detection of MC-CDMA signals (see, e.g., [61] and [181]). The two gradient involved in Eq. 3.48 can be expressed as follows:

$$\begin{cases} \nabla_1\left(\hat{P}_e^{AV}\left(\mathbf{w}_k^1,\mathbf{w}_k^2\right)\right) = -\frac{2}{\sqrt{2}}\frac{1}{2^{2K}}\sum_{\forall\mathbf{A}^1}\sum_{\forall\mathbf{A}^2}\Bigg\{ \\ \quad \exp\left\{-\frac{\mu_{k,1}^2}{2\sigma_{k,1}^2}\right\}\frac{a_k^1}{\sigma_{k,1}}\left[\mathbf{H}_A\mathbf{C}\mathbf{A}^1 + \mathbf{H}_B\mathbf{C}\mathbf{A}^2 - \mu_{k,1}\frac{\mathbf{w}_k^1}{\left\|\mathbf{w}_k^1\right\|^2+\left\|\mathbf{w}_k^2\right\|^2}\right] + \\ \quad +\exp\left\{-\frac{\mu_{k,2}^2}{2\sigma_{k,2}^2}\right\}\frac{a_k^2}{\sigma_{k,2}}\left[\mathbf{H}_A\mathbf{C}\mathbf{A}^2 - \mathbf{H}_B\mathbf{C}\mathbf{A}^1 - \mu_{k,2}\frac{\mathbf{w}_k^1}{\left\|\mathbf{w}_k^1\right\|^2+\left\|\mathbf{w}_k^2\right\|^2}\right]\Bigg\} \\ \nabla_2\left(\hat{P}_e^{AV}\left(\mathbf{w}_k^1,\mathbf{w}_k^2\right)\right) = -\frac{2}{\sqrt{2}}\frac{1}{2^{2K}}\sum_{\forall\mathbf{A}^1}\sum_{\forall\mathbf{A}^2}\Bigg\{ \\ \quad \exp\left\{-\frac{\mu_{k,1}^2}{2\sigma_{k,1}^2}\right\}\frac{a_k^1}{\sigma_{k,1}}\left[\mathbf{H}_B\mathbf{C}\mathbf{A}^1 - \mathbf{H}_A\mathbf{C}\mathbf{A}^2 - \mu_{k,1}\frac{\mathbf{w}_k^2}{\left\|\mathbf{w}_k^1\right\|^2+\left\|\mathbf{w}_k^2\right\|^2}\right] + \\ \quad +\exp\left\{-\frac{\mu_{k,2}^2}{2\sigma_{k,2}^2}\right\}\frac{a_k^2}{\sigma_{k,2}}\left[\mathbf{H}_B\mathbf{C}\mathbf{A}^2 + \mathbf{H}_A\mathbf{C}\mathbf{A}^1 - \mu_{k,2}\frac{\mathbf{w}_k^2}{\left\|\mathbf{w}_k^1\right\|^2+\left\|\mathbf{w}_k^2\right\|^2}\right]\Bigg\} \end{cases} \tag{3.49}$$

Thus, the LMS implementation of the MBER detector for the considered STBC MC-CDMA system is given by combining the updating rule of Eq. 3.48 and the gradient expressions of Eq. 3.49.

The computational complexity of this detector is exponential in the number of users $\mathcal{O}\left(2^{2K}\right)$, so its practical application becomes unfeasible as K increases. However, the computational burden of the MBER criterion can be reduced by minimizing the *conditional probability of error* instead of the average probability of error ([65, 91]). The conditional probability of error can be expressed as follows:

$$\hat{P}_e^{COND}\left(\mathbf{w}_k^1,\mathbf{w}_k^2\right) = \frac{1}{2^2}\sum_{\forall a_k^1}\sum_{\forall a_k^2}\hat{P}_{e/a_k^1,a_k^2} \tag{3.50}$$

The BER is conditioned in Eq. 3.50 to the symbols transmitted by the user of interest in its own STBC block and averaged with respect to all possible combinations of these symbols. In the considered case, the Alamouti's block is 2x2-sized; therefore the number of possible symbol combinations is $2^2 = 4$. Dua *et al.* claim in [91] that the MCBER adaptive MUD has a convergence rate comparable to MBER MUD with a minor degradation in terms of bit error rate and affordable computational burden linearly increasing with users' number. For this reason, the MCBER criterion can be regarded as an effective and feasible solution also for multi-user detection in STBC MIMO MC-CDMA systems. The LMS implementation of the MCBER detector can be obtained straightforwardly by using the same updating rule of Eq. 3.48 combined with the following new gradient expressions:

$$\begin{cases} \nabla_1 \left(\hat{P}_e^{COND} \left(\mathbf{w}_k^1, \mathbf{w}_k^2 \right) \right) = -\frac{2}{\sqrt{2}} \frac{1}{2^2} \sum_{\forall a_k^1} \sum_{\forall a_k^2} \Bigg\{ \\ \qquad \exp\left\{ -\frac{\mu_{k,1}^2}{2\sigma_{k,1}^2} \right\} \frac{a_k^1}{\sigma_{k,1}} \left[\mathbf{H}_A \mathbf{C} \tilde{\mathbf{A}}^1 + \mathbf{H}_B \mathbf{C} \tilde{\mathbf{A}}^2 - \mu_{k,1} \frac{\mathbf{w}_k^1}{\left\| \mathbf{w}_k^1 \right\|^2 + \left\| \mathbf{w}_k^2 \right\|^2} \right] + \\ \qquad + \exp\left\{ -\frac{\mu_{k,2}^2}{2\sigma_{k,2}^2} \right\} \frac{a_k^2}{\sigma_{k,2}} \left[\mathbf{H}_A \mathbf{C} \tilde{\mathbf{A}}^2 - \mathbf{H}_B \mathbf{C} \tilde{\mathbf{A}}^1 - \mu_{k,2} \frac{\mathbf{w}_k^1}{\left\| \mathbf{w}_k^1 \right\|^2 + \left\| \mathbf{w}_k^2 \right\|^2} \right] \Bigg\} \\ \nabla_2 \left(\hat{P}_e^{COND} \left(\mathbf{w}_k^1, \mathbf{w}_k^2 \right) \right) = -\frac{2}{\sqrt{2}} \frac{1}{2^2} \sum_{\forall a_k^1} \sum_{\forall a_k^2} \Bigg\{ \\ \qquad \exp\left\{ -\frac{\mu_{k,1}^2}{2\sigma_{k,1}^2} \right\} \frac{a_k^1}{\sigma_{k,1}} \left[\mathbf{H}_B \mathbf{C} \tilde{\mathbf{A}}^1 - \mathbf{H}_A \mathbf{C} \tilde{\mathbf{A}}^2 - \mu_{k,1} \frac{\mathbf{w}_k^2}{\left\| \mathbf{w}_k^1 \right\|^2 + \left\| \mathbf{w}_k^2 \right\|^2} \right] + \\ \qquad + \exp\left\{ -\frac{\mu_{k,2}^2}{2\sigma_{k,2}^2} \right\} \frac{a_k^2}{\sigma_{k,2}} \left[\mathbf{H}_B \mathbf{C} \tilde{\mathbf{A}}^2 + \mathbf{H}_A \mathbf{C} \tilde{\mathbf{A}}^1 - \mu_{k,2} \frac{\mathbf{w}_k^2}{\left\| \mathbf{w}_k^1 \right\|^2 + \left\| \mathbf{w}_k^2 \right\|^2} \right] \Bigg\} \end{cases} \tag{3.51}$$

In this way, the statistical mean is just computed over data symbols of the user of interest. As far as data symbols transmitted by users $\bar{k} = 0, \ldots, K-1$ (with $\bar{k} \neq k$) are concerned, it is possible to define the vectors $\tilde{\mathbf{A}}^j \triangleq \left[\tilde{a}_0^j, \ldots, a_k^j, \ldots, \tilde{a}_{K-1}^j \right]$ (with $j \in \{1, 2\}$) in which the element $\tilde{a}_{\bar{k}}^j$ is the symbol decision performed by user $\bar{k}$. The choice of exploiting the symbol decisions taken by users $\bar{k} \neq k$ has been considered in order to improve the convergence of the adaptive optimization algorithm (as noted in [65]). If $\tilde{a}_{\bar{k}}^j$ symbols are chosen randomly, their effect can average out in the end significantly decreasing the convergence rate of the LMS algorithm.

Chapter 4

Application of Evolutionary Strategies to Channel Estimation in MIMO Multi-Carrier Scenarios

This Chapter takes into account the use of evolutionary strategies to channel estimation purposes. In particular, the application of Genetic Algorithms and Particle Swarm Optimization techniques will be considered in the context of multi-carrier and multi-antenna systems, both in the single- and multi-user cases.

4.1 Genetic Algorithm-Assisted Channel Estimation for STBC MIMO MC-CDMA Systems

The next sub-section is aimed at investigating the terminology and the basic functioning idea of GAs. Then, a description of the GA-assisted channel estimation techniques will be provided.

4.1.1 Basics of GAs

Genetic algorithms have a 20-years history of successful applications in telecommunications, signal processing and electromagnetic fields due to some basic features, useful to solve complex problems with reasonable computational effort ([21]):

1. the convergence to the optimal solution is theoretically guaranteed (provided that a proper parameterisation of the GA procedure is set), avoiding that solution be trapped in local minima;

2. the GA-based procedure can dynamically adapt itself to time-varying system conditions, because a new population of individuals is computed at each new generation.

Standard GA implementations represent feasible solutions as a set of individuals (called *population*). The cost function to be minimized (or maximized) is called *fitness function*. At each iteration (namely: *generation*), the genetic operators of *crossover* and *mutation* are applied on selected *chromosomes* with probability α and γ respectively, in order to generate new solutions belonging to the search space. The population generation terminates when a satisfactory solution has been produced or when a fixed number of generations has been completed.

A more detailed description can be found in [21, 22, 23, 24].

4.1.2 The Proposed GA-Assisted Channel Estimation

In this sub-section, an MMSE channel estimation targeted to MIMO STBC systems is considered. In particular, the MMSE approach proposed in [182] has been modified for the STBC MIMO MC-CDMA system with Alamouti's coding previously described in sub-section 3.4.1.

In such a context, the target of the GA is to minimize with respect to the estimated channel matrices the following MSE metric:

$$J\left(\mathbf{H}_A, \mathbf{H}_B\right) = \left\|\mathbf{Y}^1 - \hat{\mathbf{H}}_A\mathbf{C}\mathbf{A}^1 - \hat{\mathbf{H}}_B\mathbf{C}\mathbf{A}^2\right\|^2 + \\ + \left\|\mathbf{Y}^2 + \hat{\mathbf{H}}_A\mathbf{C}\left(\mathbf{A}^2\right)^* - \hat{\mathbf{H}}_B\mathbf{C}\left(\mathbf{A}^1\right)^*\right\|^2 \qquad (4.1)$$

This is not a trivial task from a computational point of view. As described in Chapter 2, state of the art methodologies for channel estimation in STBC systems are substantially based on the insertion of training sequences and on the inversion of signal covariance matrices. The application of such methodologies to the case of multi-user STBC MC-CDMA systems would require the inversion of big covariance matrices, growing more and more with the users' number K. In order to avoid such kind of operations, several techniques have been proposed in the literature (see section 2.2 for a detailed description). However, some are conceptually complex and computationally hard, and others are strongly influenced by the choice of the distinguishing parameters.

In order to obtain an adaptive and robust channel estimation technique, a GA-assisted MMSE strategy has been implemented. It follows a strategy similar to the one described in section 3.1 for the linear MUD in the single-carrier MC-CDMA case. It is articulated into two steps:

1. *Training-aided* step: during this step, an L bit-length binary training sequence $\breve{\mathbf{a}}_k = \left[\breve{a}_k^1, \ldots, \breve{a}_k^L\right]$ is transmitted in form of header for each user k. The bits of the training sequence are organized in $L/2$ consecutive pairs, each one corresponding to a pair of symbols transmitted in two consecutive signaling periods. In such a way, the vectors of known bits $\breve{\mathbf{A}}^1 = \left\{\breve{a}_k^{2j-1} : k = 1, \ldots, K \ \wedge \ j = 1, \ldots, L/2\right\}$ and $\breve{\mathbf{A}}^2 = \left\{\breve{a}_k^{2j} : k = 1, \ldots, K \ \wedge \ j = 1, \ldots, L/2\right\}$ are employed to compute the MSE metric (j is the index of the signaling period). The training step is repeated with a period approximately equal to the coherence time of the channel. The GA optimizer computes at each signaling period the estimated channel matrices using a selected parameterisation in terms of generation number G_{Tr}, population size P_{Tr}, crossover and mutation probabilities α_{Tr} and γ_{Tr}, respectively. The footer Tr means that the GA parameterisation is related to the training step.

2. *Decision-directed* adaptive step: the outputs of the training step are the channel matrices $\left(\hat{\mathbf{H}}_A\right)^{Tr}$ and $\left(\hat{\mathbf{H}}_B\right)^{Tr}$ obtained by a GA-based optimizer parameterised in such a way to "learn" the channel in reliable way. During a coherence time period, the stochastic values of the channel coefficients acting over each subcarrier are strongly correlated. By this, a decision-directed adaptive updating step should be reasonably

forecast. In the present dealing, the decision-directed updating step is performed by the GA, working with a different parameterisation. The GA-based updating procedure is initialized by the solution computed during the training-aided step, i.e., $\left(\hat{\mathbf{H}}_A\right)^{Tr}$ and $\left(\hat{\mathbf{H}}_B\right)^{Tr}$. During a symbol period a single iteration is performed by the GA and a single generation of individuals is produced. The symbols employed in this step to fill the data vectors $\mathbf{A}^1$ and $\mathbf{A}^2$ are the estimated symbols decided at the previous signaling period. In particular, we have: $\tilde{\mathbf{A}}^1(j) = \{\tilde{a}_k^1(j-1) : k = 1, \ldots, K\}$ and $\tilde{\mathbf{A}}^2(j) = \{\tilde{a}_k^2(j-1) : k = 1, \ldots, K\}$. In such a step, crossover and mutation operators do not work, because only a GA generation runs. This updating procedure is "light", but this is reasonable because only small variations of the channel amplitude and phase are to be tracked during the coherence period. Moreover, in such a way, the effects of possible symbol errors on channel estimation are conveniently reduced.

In order to make clearer the proposed approach, the whole GA-assisted channel estimation procedure can be summarized as follows:

i) At time $t = 0$ the GA-based procedure is initialized by a constant-value population. In particular, the identity matrices have been chosen for initialization.

ii) The *Training-aided* step begins. The L-bit known training sequence is transmitted and the estimated channel matrices are computed by minimizing the cost function of Eq. 4.1. The GA parameters (G_{Tr}, P_{Tr}, α_{Tr}, γ_{Tr}) are opportunely chosen.

iii) The *Training-aided* step ends with the computation of the channel matrices at the time $t = LT + \varepsilon T$ (ε is the execution time of the GA-based optimization procedure expressed in number of bit periods T). Now, the GA switches to the *Decision-directed* adaptive modality.

iv) At the beginning of the adaptive step, the GA is initialized with the channel matrices computed at the end of ii), and the GA parameters are reassigned as follows: generation number $G_{DD} = 1$, population size P_{DD}, crossover probability $\alpha_{DD} = 0$ and mutation probability $\gamma_{DD} = 0$. The footer DD means that the GA parameterisation is related now to the *Decision-directed* adaptive step. The GA procedure produces a single population of individuals that are quite close to the one chosen during the previous signaling interval. Such kind of population is stochastically generated in Gaussian way, imposing to the Gaussian generator an updating standard deviation σ_{up} that actually is a system parameter. Such a parameter is linked to the Doppler spread and to the signal-to-noise ratio. An explicit mathematical link is very difficult to be obtained, but, as thumb rule, it is possible to say that it needs to be increased as SNR and Doppler spread increase.

v) The *Decision-directed* updating step ends at the time $t = LT + \varepsilon T + W_{coh}T$, where W_{coh} is the coherence time-window of the channel (expressed in number of bits). The GA is re-initialized with the channel matrices computed at the end of the coherence time-window, and re-parameterised in order to start again with the *Training-aided* step ii).

4.2 Particle Swarm Optimization-Assisted Channel Estimation for STBC MIMO OFDM Systems

In this section, the terminology and the basic functioning idea of PSO is provided ([183, 184]). Then, its application to channel estimation will be considered.

4.2.1 Overview of PSO

The Particle Swarm Optimization algorithm is a biologically-inspired stochastic optimization technique developed by Eberhart and Kennedy in 1995 ([25]), motivated by social behaviour of bird flocking or fish schooling. It shares many similarities with evolutionary computation techniques, in particular with GAs. The PSO algorithm is initialized with a *population* of solutions (randomly or opportunely chosen) and searches the global optimum of a real-valued function (*fitness function*) defined in a given space (*search space*) by updating *generations* (even called *epochs*). However, unlike GA, PSO has no evolution operators such as mutation and crossover. The potential solutions (called *particles*) fly through the problem space by following the current optimum particle.

From the metaphorical point of view, this algorithm can be summarized as follows. The individuals of a society hold an opinion that is part of a "belief space" (the search space). Individuals share this opinion and may modify it by considering three aspects:

- the knowledge of the environment (its fitness value)
- the individual's previous history of states (its memory)
- the previous history of states of the individual's neighborhood.

The definition of neighborhood configures the "social network" of the individuals. Several neighborhood topologies exist (e.g., full, ring, star) depending on whether an individual interacts with all, some, or only one of the rest of the population. Following certain rules of interaction, the individuals in the population adapt their scheme of belief to the ones that are more successful among their social network. Over the time, a culture arises, in which the individuals hold opinions that are closely related.

The "continuous" version of the PSO algorithm uses a real-valued multidimensional space as belief space. The position x_{id} of the i-th particle in dimension d of that space is determined by

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \tag{4.2}$$

The velocity v_{id} of the particle determines its movement. It can be calculated as follows:

$$v_{id}^{t+1} = w \cdot v_{id}^{t} + c_1 \cdot \psi_1 \cdot \left(p_{id}^{t} - x_{id}^{t}\right) + c_2 \cdot \psi_2 \cdot \left(p_{gd}^{t} - x_{id}^{t}\right) \tag{4.3}$$

where:

- v_{id}^{t} is the component in dimension d of the i-th particle velocity in iteration t

- x_{id}^t is the component in dimension d of the i-th particle position in iteration t
- c_1 and c_2 are constant weight factors
- p_i is the best position achieved so long by particle i
- p_g is the best position found by the neighbors of particle i
- ψ_1 and ψ_2 are random factors in the $[0, 1]$ interval
- w is the inertia weight.

A constraint (v_{max}) is imposed on v_{id}^t to ensure convergence. Its value is usually kept within the interval $[-x_{id}^{max}, x_{id}^{max}]$, being x_{id}^{max} the maximum value for the particle position. A large inertia weight (w) favors global search, while a small inertia weight favors local search. If inertia is used, it is sometimes decreased linearly during the iteration of the algorithm, starting at an initial value close to 1.

The PSO algorithm requires tuning of some parameters: the individual and sociality weights (c_1,c_2) and the inertia factor (w). Both theoretical and empirical studies are available to help in selection of proper values ([185, 186, 187, 188, 189, 190, 191]).

From the described procedure, it is clearer that PSO shares many common points with GA. Both algorithms start with a certain population, both have fitness values to evaluate the population. Both update the population and search for the optimum with random techniques.

However, PSO does not have genetic operators like crossover and mutation. Particle update themselves with the internal velocity. They also have memory, which is also important to the algorithm. Compared with GAs, the information sharing mechanism in PSO is significantly different. In GAs, chromosomes share information with each other. So the whole population moves like a one group towards an optimal area. In PSO, only the global (or local) best individual gives out the information to others. It is a one-way information sharing mechanism. The evolution only looks for the best solution. Compared with GA, all the particles tend to converge to the best solution quickly even in the local version in most cases ([192]). The computational complexity of PSO is comparable with GA, but its performance is usually much better than GA ([193]).

4.2.2 The Proposed PSO-Assisted Channel Estimation

In this sub-section, an MMSE channel estimation technique is described. The basic functioning is similar to the one described in the previous section. The main differences are the application to STBC MIMO OFDM systems (instead of STBC MIMO MC-CDMA systems) and the use of the PSO algorithm (instead of the GA) for optimization purposes.

In such a context, the traditional received single-user OFDM signal samples acquired at two consecutive symbol periods after the FFT-based coherent demultiplexing could be expressed as follows:

$$\begin{cases} \mathbf{Y}^1 = \mathbf{H}_A \mathbf{A}^1 + \mathbf{H}_B \mathbf{A}^2 + \mathbf{N}^1 \\ \mathbf{Y}^2 = -\mathbf{H}_A \left(\mathbf{A}^2\right)^* + \mathbf{H}_B \left(\mathbf{A}^1\right)^* + \mathbf{N}^2 \end{cases} \tag{4.4}$$

where $\mathbf{Y}^1$ and $\mathbf{Y}^2$ are $N \times 1$ vectors, $\mathbf{A}^j$ (with $j \in \{1, 2\}$) are the vectors containing the user BPSK symbols, $\mathbf{N}^j = [\eta_0, \eta_1, \ldots, \eta_{N-1}]^T$ (with $j \in \{1, 2\}$) is the AWGN vector (all vector components are independent and identically distributed with zero mean and variance σ^2), and $\mathbf{H}_{ant} = diag\left(h_0^{ant}, h_1^{ant}, \ldots, h_{N-1}^{ant}\right)$ (with $ant \in \{A, B\}$) is the $N \times N$ diagonal channel matrix, where h_n^{ant} is the complex channel coefficient related to subcarrier n and to the transmit antenna ant.

The usual hypothesis is that fading is flat over each subcarrier and almost time-invariant during two consecutive transmission period (i.e., the coherence time is much greater than the symbol period). Nevertheless, the effect of time-varying frequency selectivity cannot be neglected in such systems as clearly stated in [194]. In fact, the introduction of STBC into OFDM systems is not so straightforward. The length of the symbol period is much longer than that of a single-carrier system with the same data-rate. Therefore, a fading process slow enough to be considered block-fading in a single carrier system might not be so in a system with an OFDM architecture. Such a problem can be solved by considering the OFDM channel non quasi-static over the space-time blocks:

$\mathbf{H}_{ant}$ remains constant during the first transmission interval of the block $(\mathbf{H}_{ant}(t))$ but changes to $\mathbf{H}_{ant}(t+1)$ at the next one. Therefore, the received signals at time t and $t+1$ become:

$$\begin{cases} \mathbf{Y}(t) = \mathbf{Y}^1 = \mathbf{H}_A(t)\,\mathbf{A}^1 + \mathbf{H}_B(t)\,\mathbf{A}^2 + \mathbf{N}^1 \\ \mathbf{Y}(t+1) = \mathbf{Y}^2 = -\mathbf{H}_A(t+1)\,(\mathbf{A}^2)^* + \mathbf{H}_B(t+1)\,(\mathbf{A}^1)^* + \mathbf{N}^2 \end{cases} \tag{4.5}$$

By using such notation, it is possible to write the traditional MSE metric presented in [131] as follows:

$$\begin{aligned} J\left(\mathbf{H}_A(t), \mathbf{H}_B(t), \mathbf{H}_A(t+1), \mathbf{H}_B(t+1)\right) = \\ \left\| \mathbf{Y}^1 - \hat{\mathbf{H}}_A(t)\,\mathbf{A}^1 - \hat{\mathbf{H}}_B(t)\,\mathbf{A}^2 \right\|^2 + \\ + \left\| \mathbf{Y}^2 + \hat{\mathbf{H}}_A(t+1)\left(\mathbf{A}^2\right)^* - \hat{\mathbf{H}}_B(t+1)\left(\mathbf{A}^1\right)^* \right\|^2 \end{aligned} \tag{4.6}$$

The target of the PSO is to minimize it with respect to the estimated channel matrices. The followed strategy is the same proposed in sub-section 4.1.2. Therefore, it is articulated into two steps exactly following the already described sequence. Obviously, the characterizing parameters are those typical of the PSO algorithm.

Chapter 5

Adaptive and Optimized PHY-Layer Reconfigurability

The implementation of the previously described multi-user detection and channel estimation techniques has been done by taking into account some basic design issues typical of Software Defined Radio (SDR) systems, such as modularity and re-usability of developed software modules ([195]). In such a way, they could be used in the design and the implementation of "full smart" reconfigurable terminals (RTs) capable of adapting their transmission layer to a "change of status" of the network, meaning with the term "status" the location and situation information, together with the identification of the transmission modes available, the typology of the transceiver, the computational capability, and power consumption constraints. The reconfiguration action can belong to two main categories:

- a change of transmission modality (vertical handover)
- a reconfiguration of the parameters of the operating transmission modality in order to optimize adaptively the Quality of Service (QoS) with respect to a situation modification (e.g., an increase of traffic or interference load, a change of channel propagation conditions, etc.).

Such a concept is well depicted in Fig. 5.1. The channel state information (known in

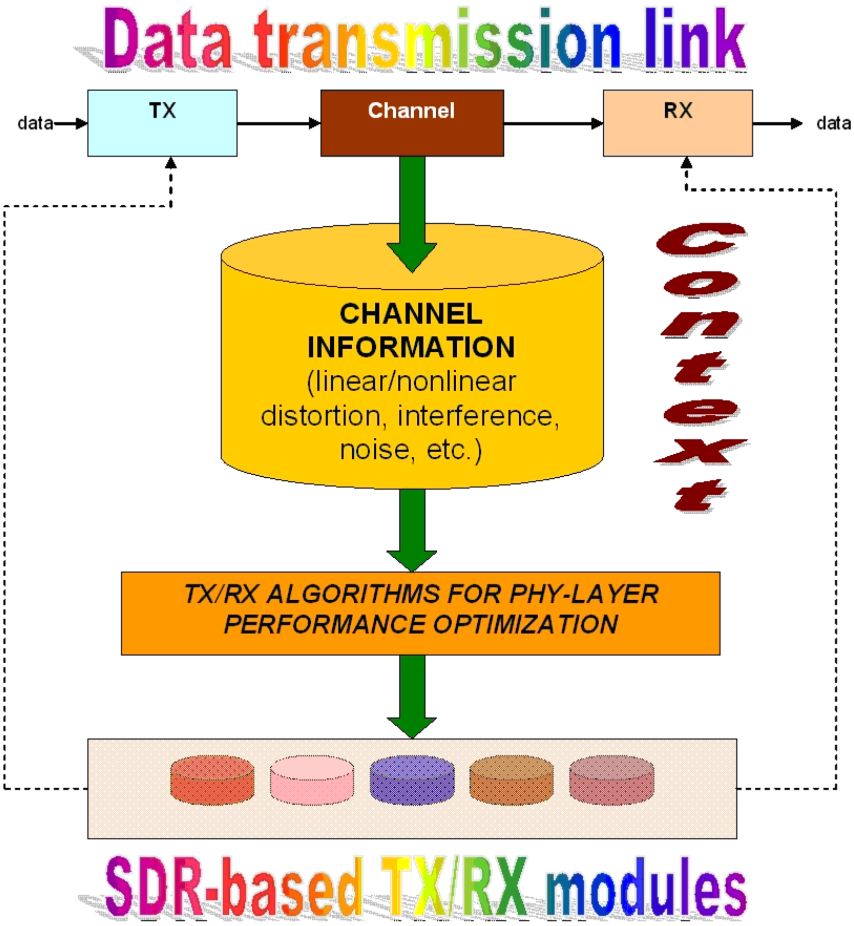


Figure 5.1: PHY-layer reconfigurability

the case of non-linear distorsions due to amplifiers or estimated in the multipath fading case) can be used to chose and parameterise a set of SDR transceiver modules, aimed at dynamically configure the PHY-layer in order to adapt itself to network situation. After that, the modules are loaded in the transmitting and receiving devices. The different PHY-layer configurations should be also able to provide the best performances in terms of bit error rate.

The SDR-based implementation should guarantee the due degree of flexibility and reconfigurability to the user terminal and to the entire network. The considered approach is completely different from the state of the art idea of embedding in a “black box” some co-existing standard terminals provided with some switching protocol (even working on the basis of location/situation aware information). A RT should be capable of taking in charge a generic wireless transmission mode provided by means of dynamically linked SDR libraries containing the executable code of the overall protocol stack elements managed at terminal level. The word "generic" means that the transmission mode should be both standard, and non-standard (e.g., customized techniques for point-to-point connections), or related to future on-going standards (e.g., OFDM and MC-CDMA regarded as key transmission techniques for new generation WLAN and cellular networks). But, in any case, the design and the implementation of the SDR-based RT will be performed in adaptive and optimized way. Generally speaking, the RT should be regarded as a "full smart terminal" provided with extended adaptive reconfigurability managed both at RF, and baseband level. In the standard transmission case, this means that, while retaining the basic feature e.g. of UMTS, S-UMTS or IEEE 802.11 signals, the degrees of freedom allowed to each transmission configuration will be exploited in order to optimize system performances. As an example, UMTS standard could profitably exploit joint space and time diversity provided by antenna arrays and rake receivers using co-ordinates adaptive array optimization strategies, channel equalization, and multi-user detection algorithms (examples in literature have been already proposed for DS-CDMA systems ([196])). MIMO systems represent other feasible examples of such capabilities ([197]). This is possible now because smart antennas allow an effective software tuning of the radiation pattern depending on channel conditions and interference load (also when bursts of interfering signals are coming to the antenna with stochastic time of arrivals ([72])), and SDR procedure can actually work up to the IF stage ([198]). This can lead to the dynamic and adaptive optimization of the RT for the generic transmission mode selected (see Fig. 5.2), starting from the physical layer level.

When a switching from a wireless connection (standard or not standard) to another one is issued by the network manager (and physically managed by a proper middleware layer as shown in Fig. 5.2), a new "software-radio" library containing the executable procedures implementing the new physical layer functionalities will be downloaded replacing

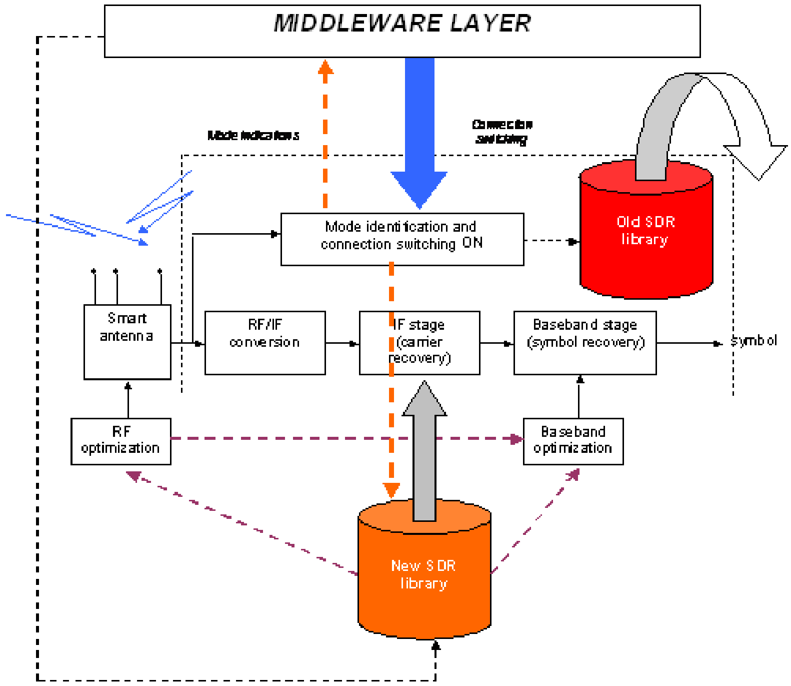
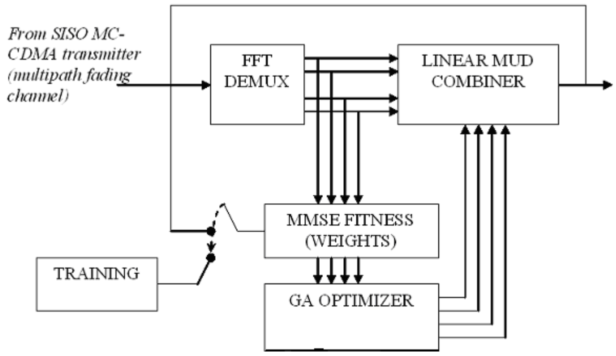


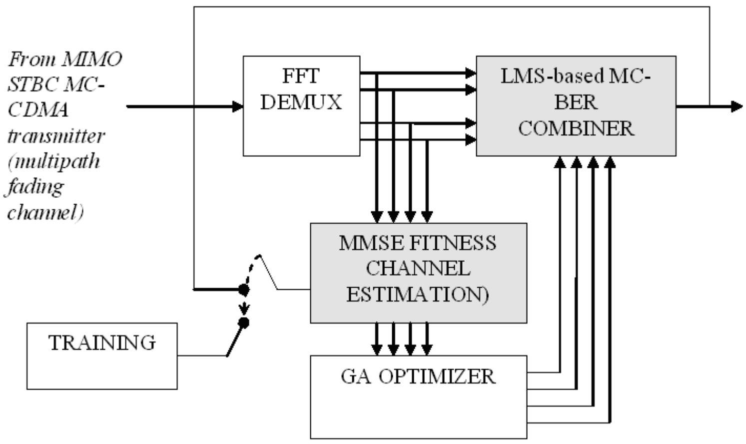
Figure 5.2: General overview of the reconfigurable architecture

the old one. Of course, this task is not trivial, because the dynamic reconfiguration of the mobile terminal should be optimized with respect to the channel conditions, bandwidth and power resources available, interference load, transmission modalities, etc. ("status" of the network) in order to provide the best QoS to the connecting user. So, mobile terminals should be provided with an augmented flexibility of the physical layer. The set of SDR algorithms loaded and executed by a DSP (Digital Signal Processor) architecture (for example) should dynamically adapt itself to the conditions of the new communication environment. In such a sense, it is possible to say that the reconfigurability of the terminal should be both "adaptive" and "optimized" with respect to the wireless context. In such a way, thanks to SDR solutions, situation/location awareness can be translated into adaptive and optimized reconfigurability of the mobile terminal directly managed at physical layer level.

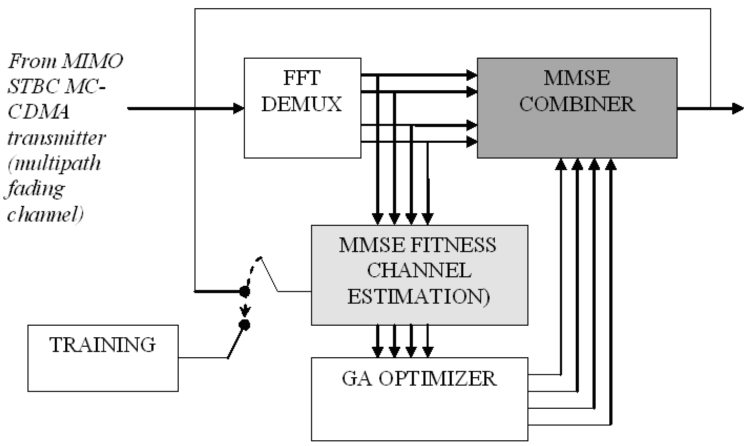
Such concepts have been taken into account during the software implementation phase. The result is an "object oriented" vision that allows to use the software modules as ba-



(a)



(b)



(c)

Figure 5.3: Examples of basic blocks' organization

sic elements to build more complex transceiver architectures. Some examples of such a concept are reported in Fig. 5.3 (a), (b), and (c). It is interesting to note that the same blocks (opportunely parameterised) are used to build the different communication systems described in section 3.1, 3.3 and 4.1, respectively.

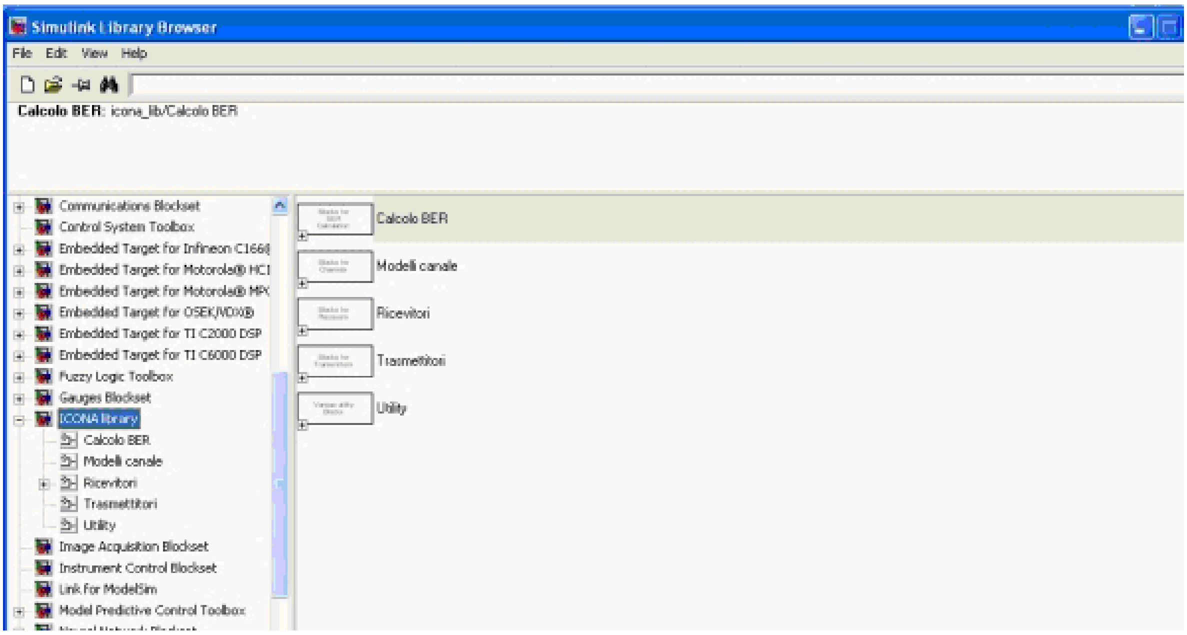


Figure 5.4: Basic blocks of the Simulink library

Simulators have been implemented in Matlab-Simulink environment ([199]). Their modularity allowed to create a library which contains all the basic blocks (see Fig. 5.4). They have been also combined in order to obtain the innovative algorithms presented throughout this thesis (see Fig. 5.5 for a general overview, and Fig. 5.6 for the MCBER receiver example).

Some receivers of the library have been emulated on a DSP module. In particular, the DSK 320C6416T module of Digital Spectrum ([200]) has been used (see Fig. 5.7). It is equipped with a 1.1 GHz CPU. The emulation of the MCBER algorithm provided the same results obtained through software simulations, confirming the effectiveness of the hardware implementation.

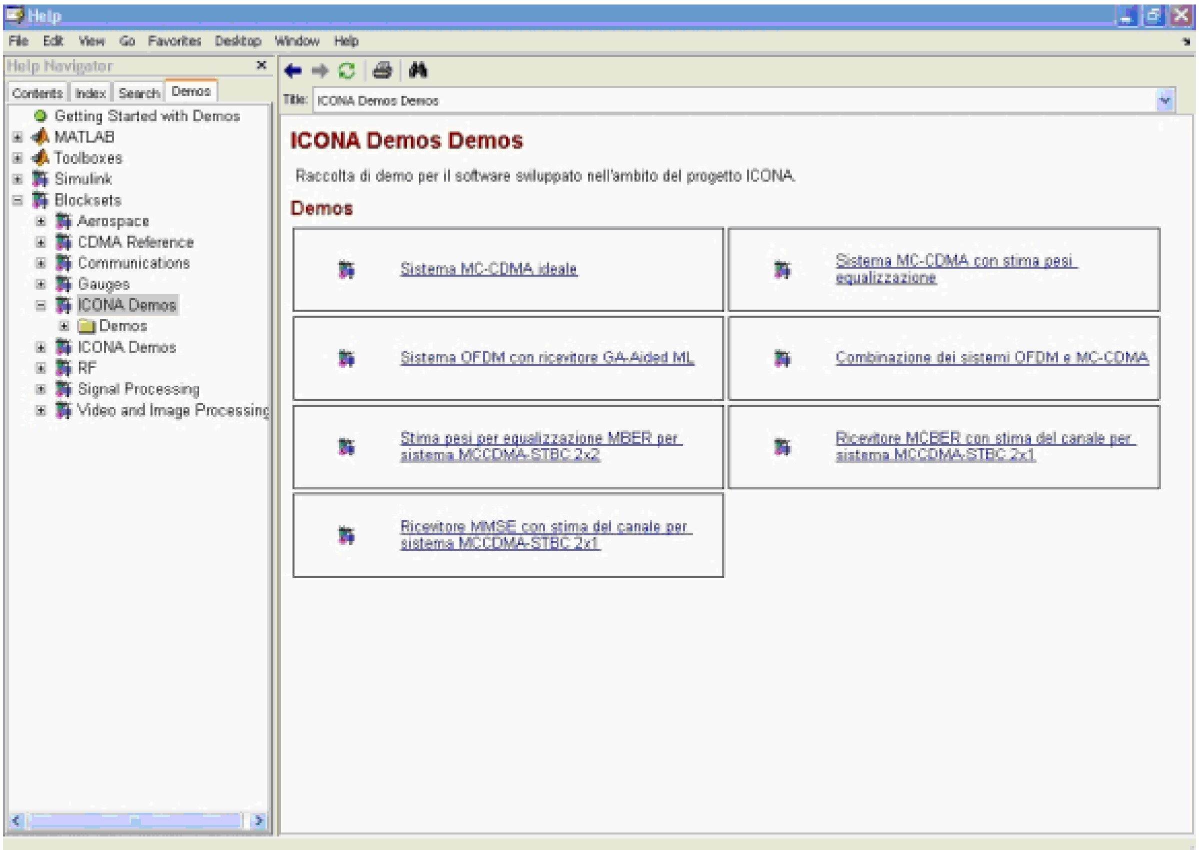
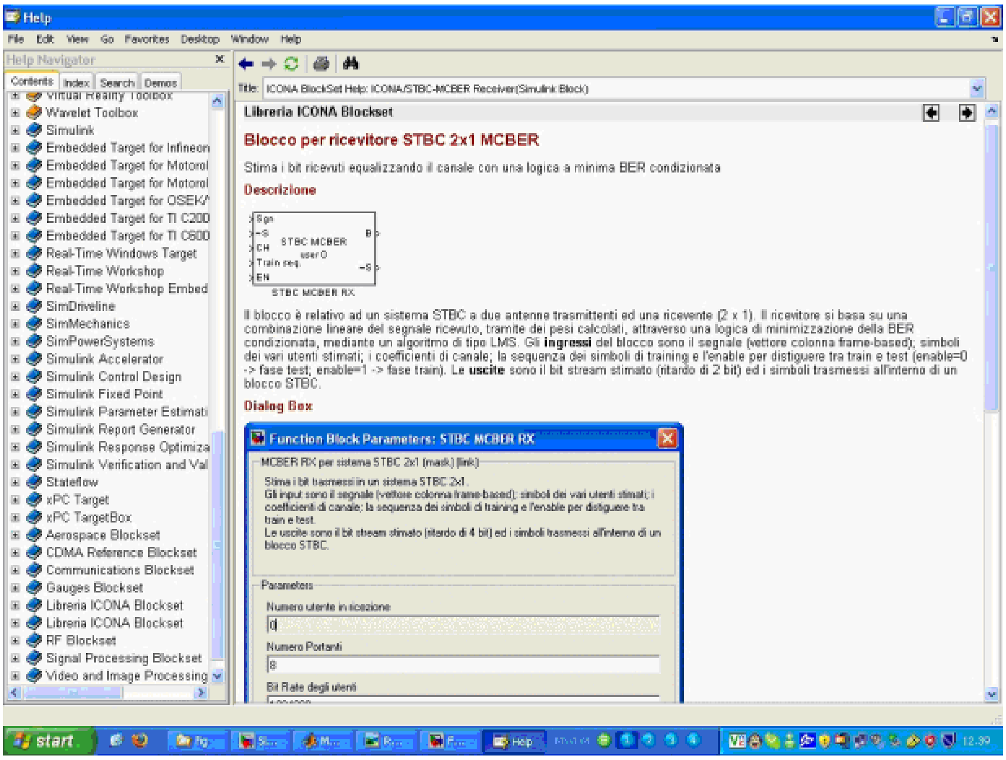
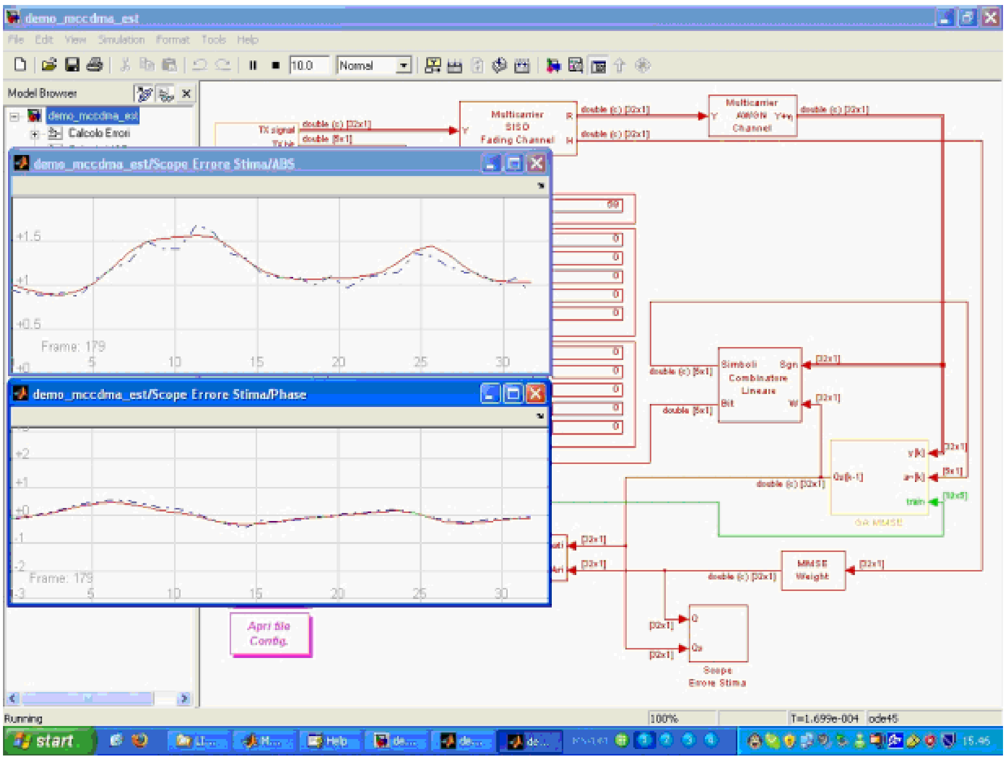


Figure 5.5: Innovative algorithms implemented in the Simulink library



(a)



(b)

Figure 5.6: MCBER algorithm implemented in the Simulink library

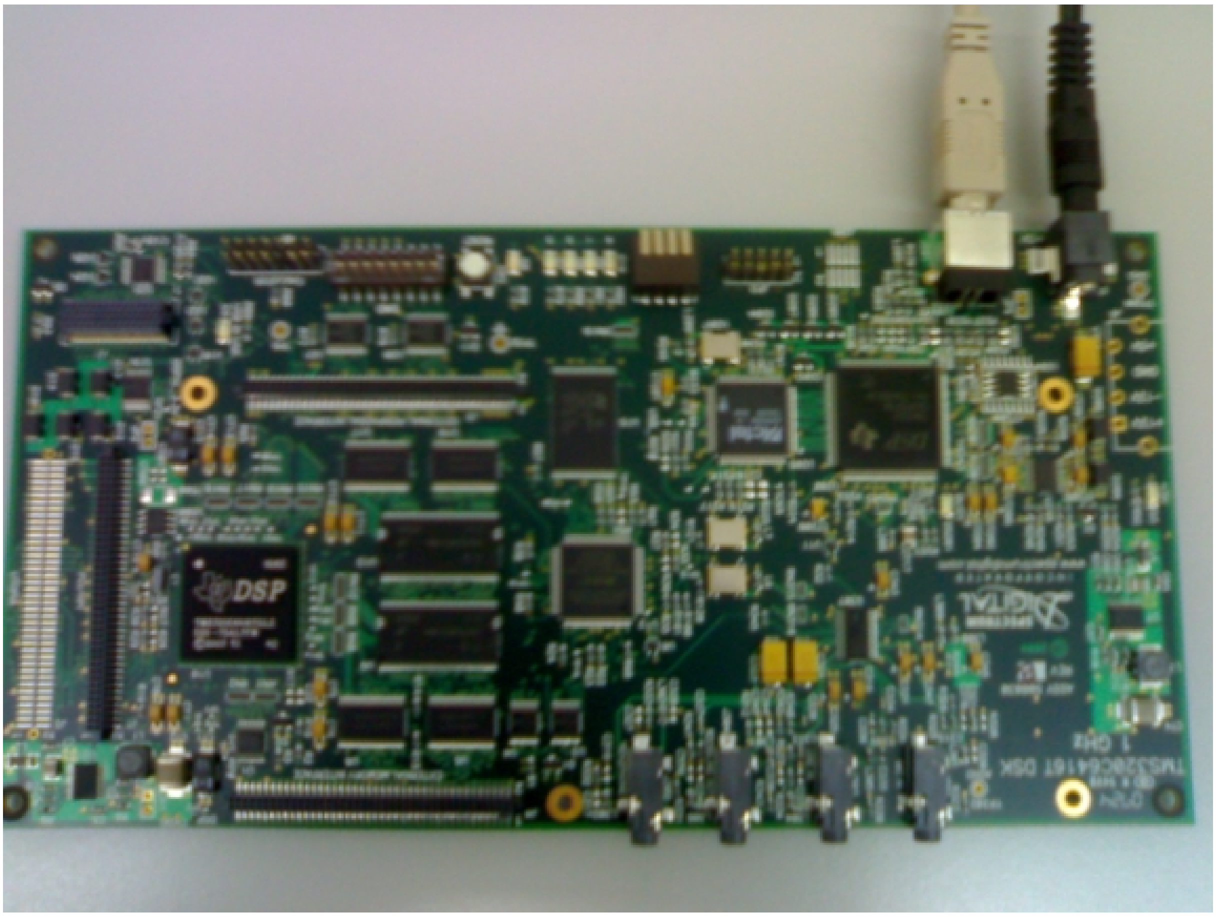


Figure 5.7: Digital Spectrum DSP module

Chapter 6

Experimental Results

This Chapter is aimed at providing experimental results regarding the MUD techniques and the channel estimation strategies previously described.

6.1 GA-Assisted MMSE MUD Receiver for MC-CDMA Systems

The effectiveness of the semi-adaptive GA-assisted per-carrier MMSE MUD detector presented in section 3.1 has been tested by means of intensive simulations. Its performances have been measured in terms of BER over a urban multipath channel with a transmission data rate r_b equal to 1024 Kbps. The corresponding tapped delay line channel model is summarized in Tab. 6.1.

The features of the channel in terms of coherence bandwidth, Doppler spread, coherence time and Rice factor are summarized in Tab. 6.2.

Tap Number	Delay [μs]	Amplitude [dB]
1	0.1	-4
2	0.2	-8
3	0.3	-12
4	0.4	-16
5	0.5	-20

Table 6.1: Channel model (urban)

Channel	Coherence bandwidth [MHz]	Doppler spread [Hz]	Coherence time [μs]-([bit])	Rice factor (linear)
urban	2.1	100	1.8 - (1843)	1

Table 6.2: Parameters of the considered channel

The goodness of the proposed algorithm has been tested considering the insertion of the training phase at the beginning of each coherence time of the channel. The length of the training and decision-directed phases has been chosen through a preliminary series of simulations. The same procedure has been followed to obtain the GA parameters for the two steps characterizing the algorithm. The resulting parameterisation that seems to satisfy the tradeoffs in terms of algorithmic efficiency and computational sustainability is the following:

- *Training-aided* step: generation number $G_{Tr} = 10$, population size $P_{Tr} = 10$, crossover probability $\alpha_{Tr} = 0.9$, mutation probability $\gamma_{Tr} = 0.01$
- *Decision-directed* step: generation number $G_{DD} = 1$, population size $P_{DD} = 10$, crossover probability $\alpha_{DD} = 0$, mutation probability $\gamma_{DD} = 0$
- Training sequence length $B = 32$ bit
- Coherence window length $W_{coh} = 1700$ bit (according to the Jake's model for Rayleigh channels [201]).

The proposed MMSE MUD receiver has been compared with the following state of the art algorithms:

i) LMS per-carrier MMSE MUD shown in [19]. The weight-updating rule of the LMS receiver is given as follows:

$$\hat{w}_n^{LMS}(i+1) = \hat{w}_n^{LMS}(i) + \mu \left\{ \sum_{k=1}^{K} c_n^k a_i^k - \hat{w}_n^{LMS}(i)\, y_n(i) \right\} (y_n(i))^* \tag{6.1}$$

where μ is the *step-size* parameter.

ii) RLS per-carrier MMSE MUD shown in [19]. The weight-updating rules of the RLS receiver are given as follows:

$$\hat{w}_n^{RLS}(i+1) = \hat{w}_n^{RLS}(i) + \left\{ \sum_{k=1}^{K} c_n^k a_i^k - \hat{w}_n^{LMS}(i)\, y_n(i) \right\} (V_n(i))^* \tag{6.2}$$

$$V_n(i) = \frac{P_n(i)\, y_n(i)}{\lambda + (y_n(i))^* P_n(i)\, y_n(i)} \tag{6.3}$$

$$P_n(i+1) = \lambda^{-1} \{1 - V_n(i)\, (y_n(i))^*\} (y_n(i))^* P_n(i) \tag{6.4}$$

where λ is the so-called *forgetting factor*.

iii) The ideal MMSE MUD with optimum solution computed as in Eq. 3.7. It represents a “lower bound” of the achievable performance.

The LMS and RLS algorithms have been modified in order to work in semi-adaptive modality with the periodic transmission of a B-bit length training sequence. The step-size parameter has been also reduced from the training to the decision-directed step in order to force a fast convergence to the optimum weights during the former and to reduce the impact of symbol errors in the latter. Its values reported in the following are referred to the training-aided modality. In the decision-directed modality, their values have been reduced to a magnitude order less.

Simulation results in terms of BER are reported in Fig. 6.1 and 6.2. BER results versus SNR are plotted for a fixed number of users ($K = 9$) in Fig. 6.1. BER performances of the proposed GA-assisted MMSE MUD receiver are almost coincident with ones yielded by ideal MMSE MUD requiring perfect knowledge of channel gains for all SNR values. Moreover, it clearly outperforms both adaptive MMSE receivers based on deterministic algorithms. Both LMS and RLS performances are strongly influenced by the choice of the parameters μ and λ. Two curves related to the LMS are drawn with different step sizes values (0.01 and 0.05). The resulting performances are really different. The sensitivity to the parameter λ is very strong also for RLS (small variation of the parameter can significantly worse performance). Nevertheless, RLS can approach ideal MMSE in case of few transmitting users and relatively slow fading channels, as stated in [19].

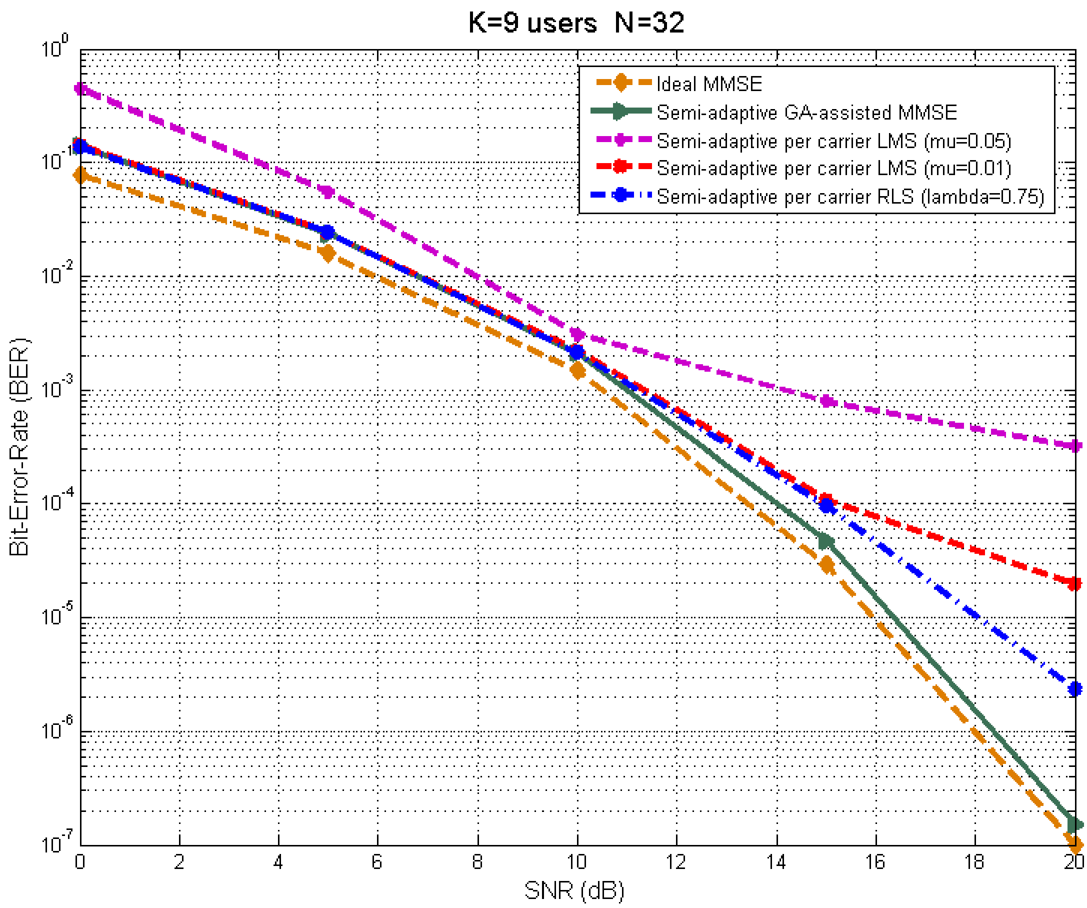


Figure 6.1: BER vs SNR for the simulated MC-CDMA receivers (with $K = 9$ users)

In Fig. 6.2, BER results versus users' number are reported for a fixed SNR value of 20 dB. It is worth noting that the performances of the proposed algorithm are very close to those offered by ideal MMSE for whatever number of users. Adaptive algorithms offer instead performances substantially degrading for larger values of K. Such results confirm the sub-optimality of steepest descent algorithms when the number of users increases.

A comparison between the tracking properties of the considered algorithms can be done by observing Fig. 6.3, where the amplitude and the phase of the estimated receiver weight are shown for subcarrier 8, with $K = 30$, $N = 32$, and SNR $= 20$ dB. The proposed technique (grey thick line) provides a good tracking of the ideal MMSE weight (dash-dotted black line). The noisy spikes are due to the fitness computation performed in the

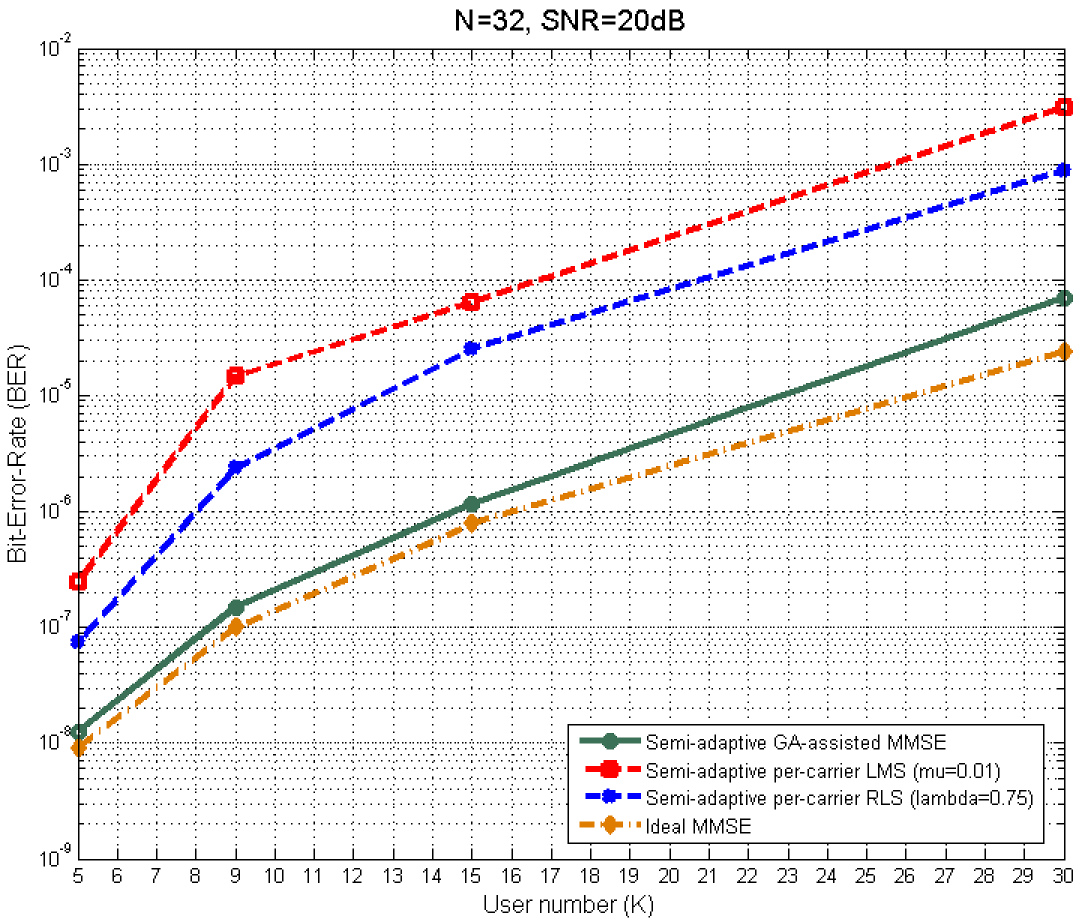


Figure 6.2: BER vs K for the simulated MC-CDMA receivers (SNR = 20 dB)

decision-directed step without any kind of averaging. LMS-based weight estimation (solid black line) exhibits problems due to lag error ([178]) when the fast channel variations occur.

From the computational point of view, the proposed algorithm requires a number of elementary operations equal to $B \cdot K \cdot N \cdot G_{Tr} \cdot P_{Tr}$ during the training-aided step (see [21] for a detailed analysis of the GA computational complexity). During the decision-directed step, the computational burden of the GA is reduced to $K \cdot N \cdot P_{DD}$ elementary operations.

The complexity of the LMS receiver is proportional to $K \cdot N$, but it is generally less performing than GA-based MMSE MUD and is strongly influenced by the step-size pa-

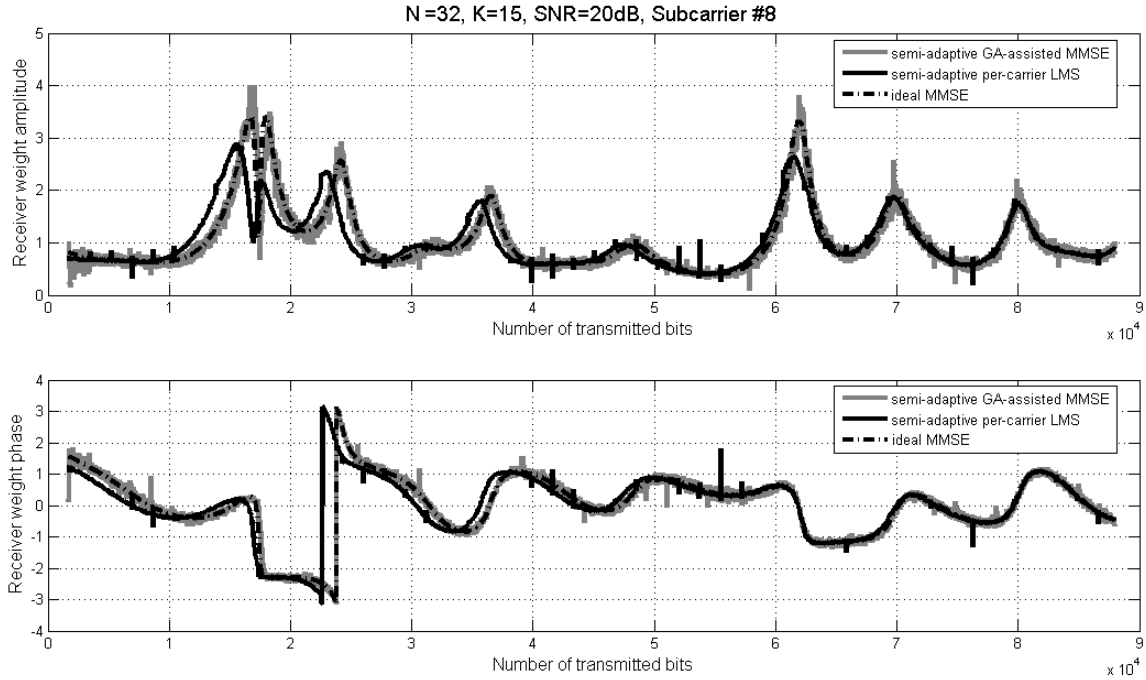


Figure 6.3: Receiver weight estimated by the considered algorithms for subcarrier #8 ($N = 32$, $K = 15$, SNR = 20 dB)

rameter setting. The RLS detector offers better performances but the computational requirement is comparable with the proposed algorithm.

The choice of the GA parameters has been done through devoted simulation trials. It has been shown that for a generation number higher than 10, the normalized mean squared error between the estimated weights and the optimum weights does not decrease. Such a behaviour perfectly follows the remarks reported in [202]: it is often better to use larger populations with less number of generations than small populations accompanied by greater time for search. This observation also justifies the choice to use just one generation in the decision-directed step.

Finally, concerning the setting of the updating standard deviation σ_{up} during the decision-directed step, it has been observed that a unique value of σ_{up} made on the basis of Eq. 3.10 for high SNR (e.g., 15-20 dB) can effectively perform also for higher SNR (e.g., 30 dB) and lower SNR (e.g., 10 dB). For very low SNR (e.g., 0-5 dB), the Gaussian noise

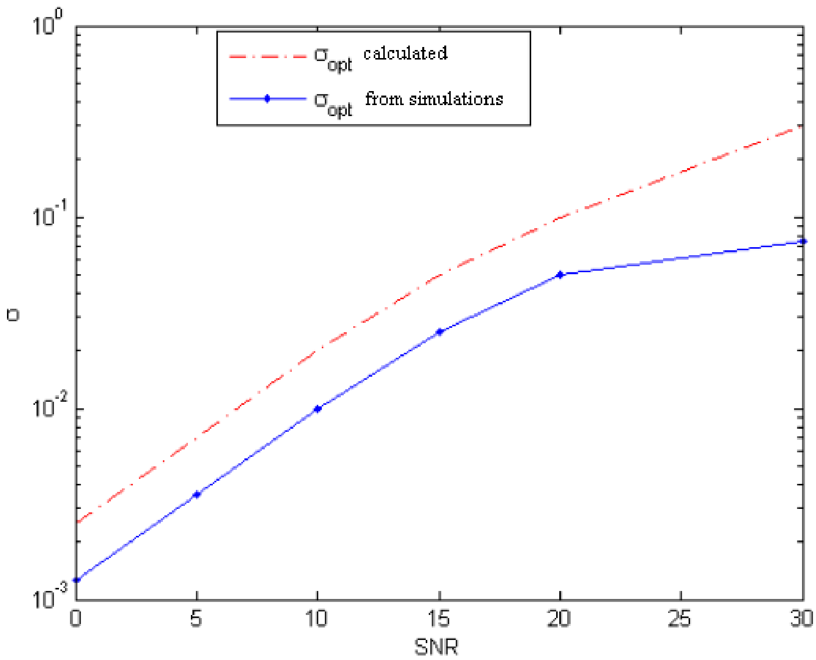


Figure 6.4: GA updating standard deviation

is clearly predominant and the updating standard deviation should be lowered. Such a behaviour is clearly reported in Fig. 6.4, where the best value of σ_{up} obtained through simulations (solid blue line) and the value of σ_{up} obtained by using Eq. 3.10 (dash-dotted red line) are plotted for each SNR value.

6.2 GA-Assisted ML MUD Receiver for Multi-Rate VSL MC-CDMA Systems

In order to assess the GA-based MUD algorithm proposed in section 3.2, some selected simulation trials have been performed by using an equivalent baseband simulator of a multi-rate MC-CDMA downlink transmission system. In order to define more realistic simulation trials, the multipath fading channel modelling and parameterisation has been performed through some experimental data reported in [203] and related to 1.95 GHz 3GPP (3G-Partnership Project) transmission scenarios. In particular, a 4-paths Rayleigh fading channel related to an urban vehicular scenario has been simulated by using a tapped delay line with coherence bandwidth equal to 1.25 MHz and Doppler spread equal to 125 Hz. The users' amplitudes A_u have been chosen in order to maintain the per-bit signal-to-noise ratio E_b/N_0 equal for all user classes ([67]). The simulated multi-rate MC-CDMA configuration employs $N = 16$ orthogonal subcarriers in order to allow $M = 3$ user classes to transmit at data rates equal to 1024 Kbps (class 1), 512 Kbps (class 2), and 256 Kbps (class 3). The effective processing gains of the different user classes are: $N_1 = 4$, $N_2 = 8$, and $N_3 = 16$, respectively. The maximum user load allowed by the OVSF spreading code attribution has been considered, i.e., $U = 16$ effective users corresponding to $U_1 = 1$ user of class 1, $U_2 = 2$ users of class 2, $U_3 = 8$ users of class 3.

As far as the parameterisation of the GA optimizer is concerned, crossover probability α and mutation probability γ equal to 0.9 and 0.01 have been selected, respectively. This setting is reasonable because α is the index of the "evolutionary capability" of the GA, whereas a high value of γ would turn the GA into a kind of random search ([202]). In the absence of specific analytical selection criteria, the generation number J_{gen} and the population size P_{pop} (depending on the parameter $dhamm$, as mentioned in section 3.2) have been chosen by means of preliminary experimental trials explicitly devoted to. The heuristic selection criteria enunciated in [202] have been considered in these simulations:

a) the population size should be sufficiently large in order to have a conveniently-dimensioned space search

b) the number of generations should be appropriately assigned in dependence of the population size.

In fact, in case of large population, too strict limit for the search time can force algorithm to stop without having enough time to realize its search possibility. The test was performed considering E_b/N_0 equal to 15 dB. As final results of such preliminary simulation trials, a reasonable choice of the GA parameterisation has been derived keeping into account the usual tradeoff between computational complexity and achieved performances. In particular, the following parameters have been selected: $J_{gen} = 10$ and $dhamm = 2$, corresponding to a value of $P_{pop} = 137$.

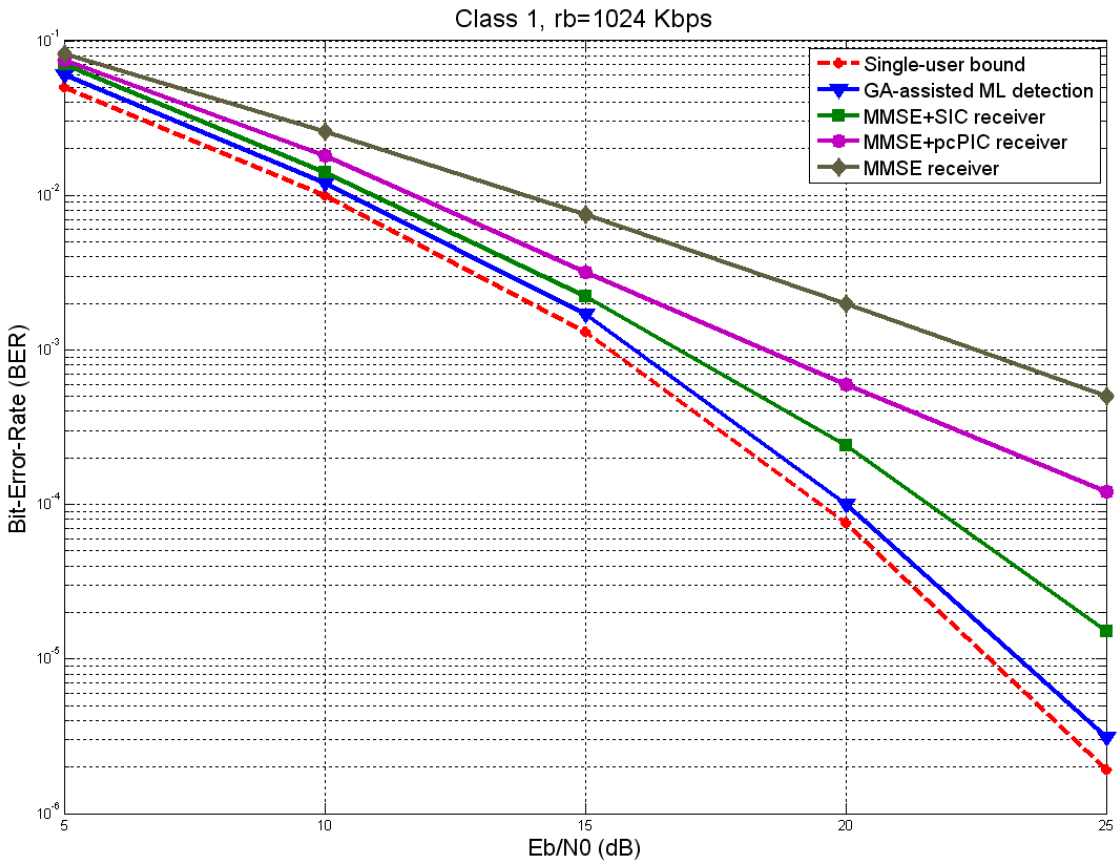


Figure 6.5: BER results vs E_b/N_0 provided by the different MUD algorithms assessed (GA-assisted ML MUD, MMSE-SIC, MMSE-pcPIC, MMSE) and by the single-user bound: user class #1 ($N_1 = 4$, $r_{b1} = 1024$ Kbps), urban 3GPP vehicular channel, $J_{gen} = 10$, $dhamm = 2$

In Fig. 6.5, 6.6, and 6.7, curves drawing the average BER results versus E_b/N_0 achieved by the proposed GA-assisted ML detection are shown for users belonging to class 1, class 2, and class 3, respectively. These are compared with corresponding results yielded by the following MC-CDMA detection schemes (the ideal knowledge of the channel state information has been supposed in all the simulations performed):

i) Single-stage per-user linear MMSE MUD ([15, 67]).

ii) Two-stage detection scheme proposed in [204] (and, similarly, in [205]), consisting of a per-user linear MMSE stage followed by a Per-Carrier Parallel Interfer-

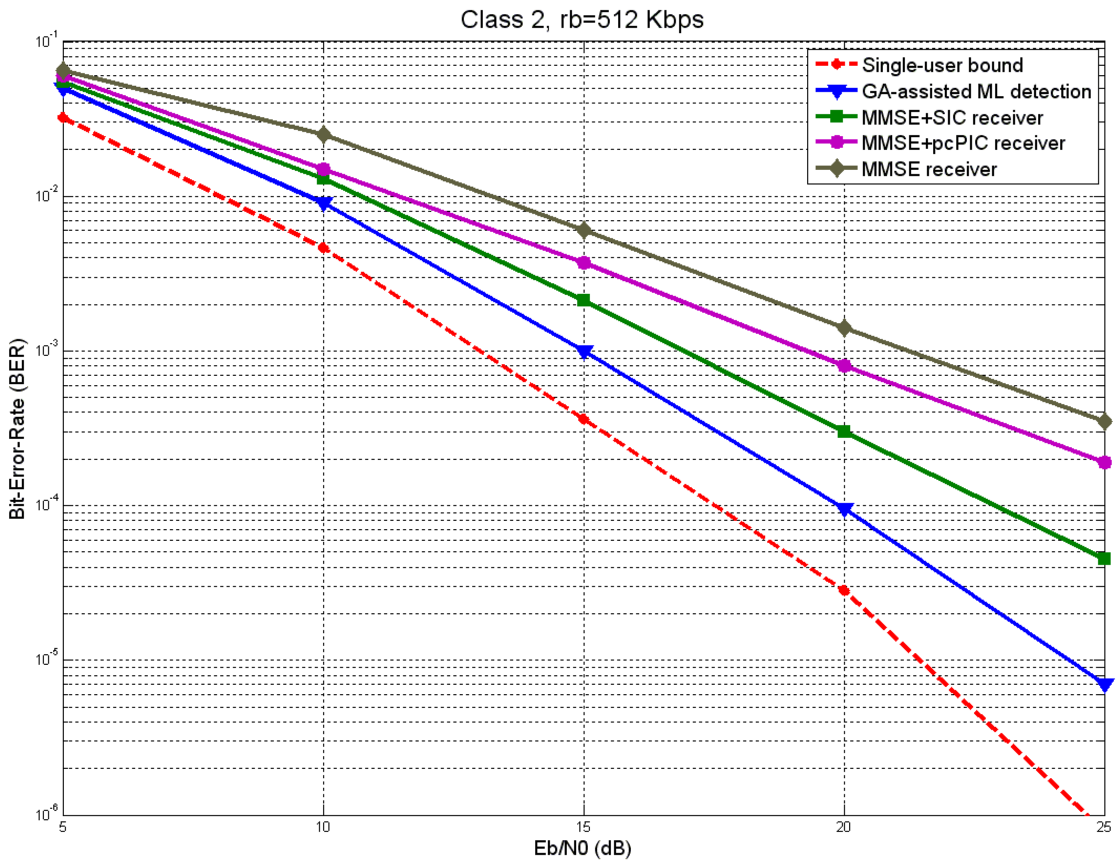


Figure 6.6: BER results vs E_b/N_0 provided by the different MUD algorithms assessed (GA-assisted ML MUD, MMSE-SIC, MMSE-pcPIC, MMSE) and by the single-user bound: user class #2 ($N_2 = 8$, $r_{b2} = 512$ Kbps), urban 3GPP vehicular channel, $J_{gen} = 10$, $dhamm = 2$

ence Cancellation (pcPIC) stage. The N contributions provided as output by the pcPIC stage are then combined by using the MRC criterion.

iii) Linear MMSE receiver followed by a SIC stage, as described in [206] and [207]. The MMSE SIC is based on a per-user successive decoding with an arbitrary, but fixed order. In the multi-rate VSL MC-CDMA context, it is reasonable to assume that users are received starting from the slower to arrive to the faster.

iv) Curves of the single-user bound achieved for the different users classes. The single-user bound has been derived by simulating a single-user MC-CDMA system (therefore interference-free) using a number of subcarriers equal to effective

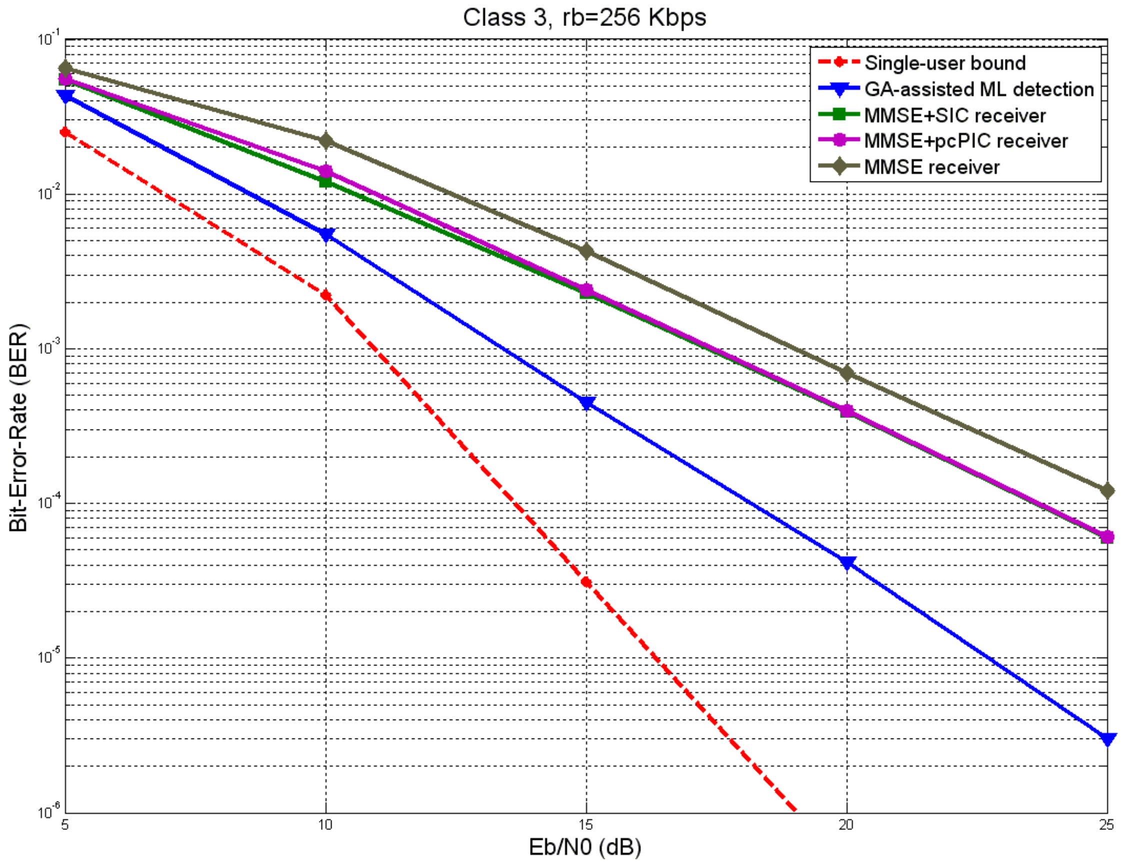


Figure 6.7: BER results vs E_b/N_0 provided by the different MUD algorithms assessed (GA-assisted ML MUD, MMSE-SIC, MMSE-pcPIC, MMSE) and by the single-user bound: user class #3 ($N_3 = 16$, $r_{b3} = 256$ Kbps), urban 3GPP vehicular channel, $J_{gen} = 10$, $dhamm = 2$

processing gain of the intended class ($N_1 = 4$ for the class 1, $N_2 = 8$ for the class 2 and $N_3 = 16$ for the class 3). The output of the coherent FFT demux is then combined on the basis of the MRC criterion that is the optimal (ML-based) criterion in the case of single-user transmission.

It is possible to note that the GA-assisted ML MUD performs better than sub-optimum MMSE, MMSE-pcPIC, and MMSE-SIC MUD algorithms for all the considered user classes. In particular, the proximity of the related BER curve to the single-user bound is dramatically evident in Fig. 6.5. As the users' data rate decreases and, therefore, the processing gain increases, the single-user bound tends to depart from all sub-optimal algorithms. This is not unexpected, because the single-user bound drawn in Fig. 6.5-6.7 is actually a lower bound also on theoretically-optimal ML MUD, as stated in [67]. However, by observing BER curves of Fig. 6.6 and Fig. 6.7, it is possible to note that the performance improvement yielded by GA-assisted ML MUD even becomes more relevant. It is worth noting that that BER performances of MMSE-pcPIC and MMSE-SIC algorithms drawn in Fig. 6.7 for user class 3 are almost coincident. This is due to the successive cancellation order followed in the simulations.

MUD Algorithm Assessed	Order of Computational Complexity	# of Elementary Operations Needed to Compute the Problem Solutions	# of Elementary Operations Needed to Compute the Problem Solutions Normalized with Respect to Theoretical ML MUD
GA-assisted ML detection	$N + P_{pop} + (\alpha + \gamma)\, J_{gen} P_{pop}$	$1.4 \cdot 10^3$ ($J_{gen} = 10$, $P_{pop} = 137$, $\alpha = 0.9$, $\gamma = 0.01$)	$2.1 \cdot 10^{-2}$
MMSE [15]	$U \cdot N$	$2.56 \cdot 10^2$	$3.9 \cdot 10^{-3}$
MMSE-pcPIC [204]	$U^2 \cdot N$	$4.1 \cdot 10^3$	$6.25 \cdot 10^{-2}$
MMSE-SIC [206, 207]	$U^2 \cdot N$	$4.1 \cdot 10^3$	$6.25 \cdot 10^{-2}$

Table 6.3: Analysis of computational complexity of the different MUD algorithms assessed

As far as computational issues are concerned, Tab. 6.3 shows the order of computational complexity for each MUD algorithm assessed (second column), the number of elementary operations required by each algorithm to derive a sub-optimal solution to the considered problem (third column), and finally in the fourth column, the number of elementary operations normalized with respect to the corresponding value required by the theoretical ML MUD exploring the full search space (equal to 2^U). The reader can note that the computational burden of the proposed GA-assisted ML MUD increases only by less than one order of magnitude with respect to that one required by MMSE MUD and is slightly reduced with respect to MMSE-pcPIC and MMSE-SIC. In the last column of Tab. 6.3, the noticeable reduction of computational effort with respect to theoretical ML MUD is clearly shown. If the number of effective users U increased, such a computational saving would be even more glaring.

6.3 Adaptive MBER MUD Detector for STBC MIMO MC-CDMA Systems

The adaptive MBER MUD algorithm for STBC MIMO MC-CDMA systems presented in section 3.3 has been tested by means of intensive simulations. The following parameters have been fixed: number of subcarriers $N = 8$, transmission data rate $r_b = 1024$ Kbps, Hadamard-Walsh sequences for CDMA spreading (such a choice is suggested by some widely-cited references about MC-CDMA like [15]).
The simulated mobile transmission channel has been modeled according to the guidelines issued by the 3GPP standardization group in [208]. In particular, the Rural Area channel model (identified by the acronym RAx) has been used. Its tapped delay line model is summarized in Tab. 6.4.

Tap Number	Delay [μs]	Amplitude [dB]
1	0	0
2	0.1	-4
3	0.2	-8
4	0.3	-12
5	0.4	-16
6	0.5	-20

Table 6.4: Channel model (RAx)

The corresponding coherence bandwidth is around 2 MHz and the considered Doppler spread is equal to 100 Hz.

A known sequence of 32 bits has been adopted for the periodic training-aided modality. The adopted training sequence is a pseudo-random binary vector taken by the Hadamard-Walsh set. The training period has been chosen equal to the coherence time of the channel (approximately equal to the inverse of the maximum Doppler shift; therefore 10 msec or, equivalently, 10240 bit periods).

In order to compare the proposed MBER algorithm with state of the art approaches, the following receivers have been considered:

i) The EGC receiver shown in [176]. Such receiver assumes the perfect knowledge of the CSI. In this case, the EGC receiver coherently recombines diversity branches without amplitude weighting. It is the typical single-user receiver, clearly sub-optimum in the multi-user case.

ii) The LMS adaptive implementation of the linear MMSE MUD receiver shown in [85] and [176]. The same updating strategy used for the LMS-based MBER receiver (i.e., periodic training and decision-directed updating within a channel coherence window) has been adopted also for the MMSE adaptive receiver. The weight updating rule for adaptive MMSE is therefore given as follows:

$$\begin{cases} \hat{w}_{1,n}^{LMS}(i+1) = \hat{w}_{1,n}^{LMS}(i) + \xi \left\{ \tilde{a}_1^k(i) - \hat{w}_{1,n}^{LMS}(i)\,\mathbf{Y}(i) \right\} \mathbf{Y}^H(i) \\ \hat{w}_{2,n}^{LMS}(i+1) = \hat{w}_{2,n}^{LMS}(i) + \xi \left\{ \tilde{a}_2^k(i) - \hat{w}_{2,n}^{LMS}(i)\,\mathbf{Y}(i) \right\} \mathbf{Y}^H(i) \end{cases} \tag{6.5}$$

being ξ the step-size parameter of the LMS procedure.

iii) The MRC reception of the single-user MAI-free signal ([176]), obtained assuming the ideal CSI knowledge, has been adopted as "single-user bound" for the tested performances (it is known from [15] that MRC reception is theoretically optimum for single-user MC-CDMA systems).

Simulation results in terms of BER have been shown in Fig. 6.8 ($K = 2$ users, namely "light load"), Fig. 6.9 ($K = 4$ users, namely "half load"), and Fig. 6.10 ($K = 7$ users, namely "full load").

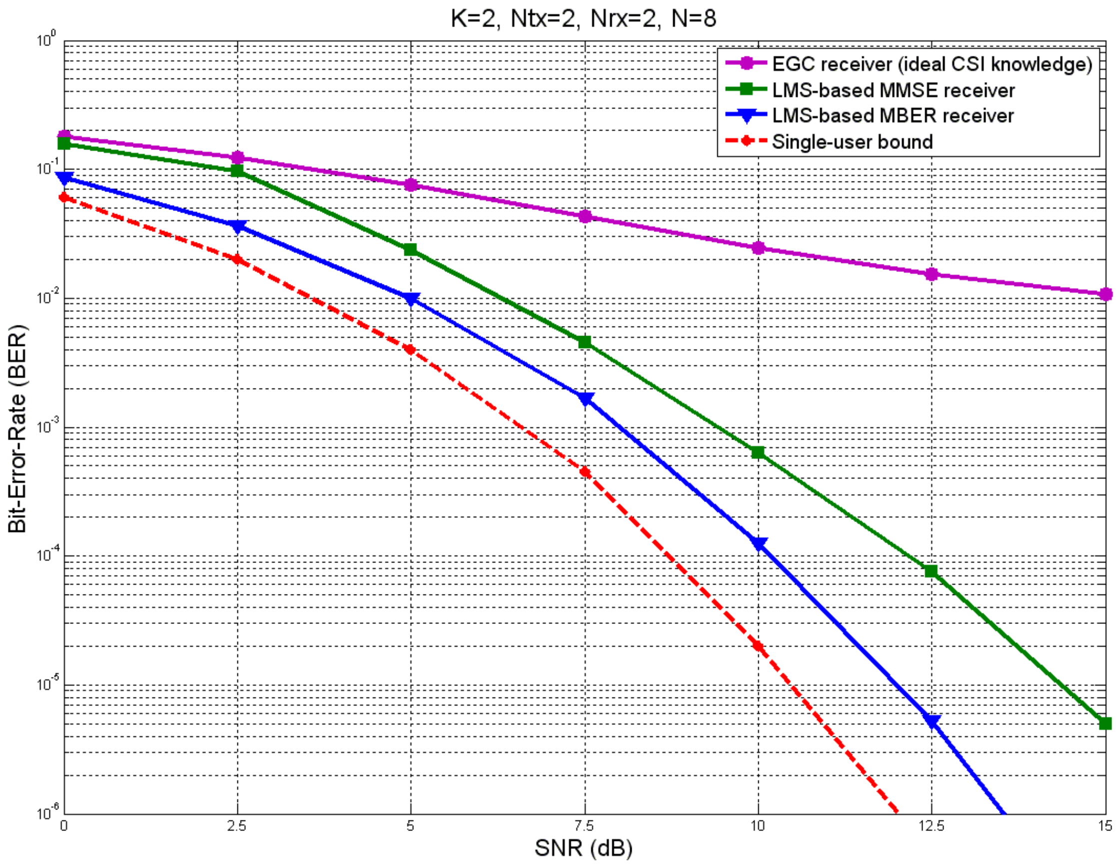


Figure 6.8: BER results vs SNR provided by the different signal detection algorithms assessed (with $K = 2$ users, $N = 8$ subcarriers, $N_{Tx} = N_{Rx} = 2$ antenna elements)

The numerical values of the parameters controlling the weight updating (μ, ρ_η, and ξ) have been experimentally chosen in order to achieve the best results in terms of BER both for the LMS-based MBER MUD and MMSE MUD. The sensitivity to parameterisation is a well-known limitation of deterministic gradient adaptive optimization approaches ([178]). Experimental trials evidenced that the parameter ρ_η is directly linked with transmission SNR (as clearly understandable by Eq. 3.27). On the other hand, step-size parameters μ and ξ are more depending on the users number K and subcarriers' number N. In particular, it has been observed that the step-size should be decreased for increasing values of K and N. Moreover, the parameterisation has been differentiated in the training-aided modality with respect to the decision-directed updating modality. In fact,

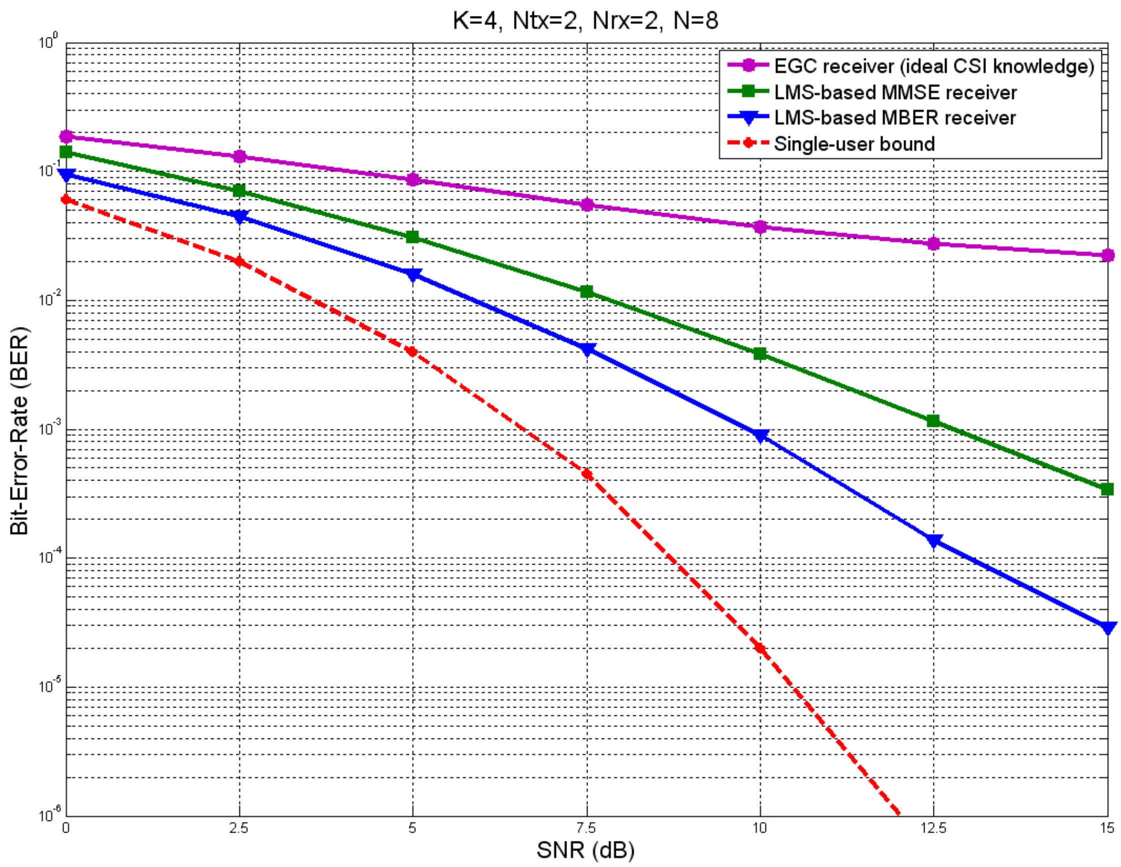


Figure 6.9: BER results vs SNR provided by the different signal detection algorithms assessed (with $K = 4$ users, $N = 8$ subcarriers, $N_{Tx} = N_{Rx} = 2$ antenna elements)

the training phase should ensure a fast convergence of the weights to the optimal value, exploiting a sequence of known bits. On the other hand, the decision-directed phase is only devoted to track the small variations of the channel impulse response in the presence of noisy symbol decisions. In order to avoid the recursive computation of a noisy gradient, the step size is consistently decreased during decision-directed updating with respect to the training phase.

As far as BER results are concerned, one can note from Fig. 6.8 and Fig. 6.9 that when the user load is "light" ($K = 2$) or "half" ($K = 4$) the BER curve provided by the MBER MUD receiver is quite close to the single-user bound, clearly outperforming EGC and LMS-based MMSE MUD. Poor BER performances provided by EGC receiver

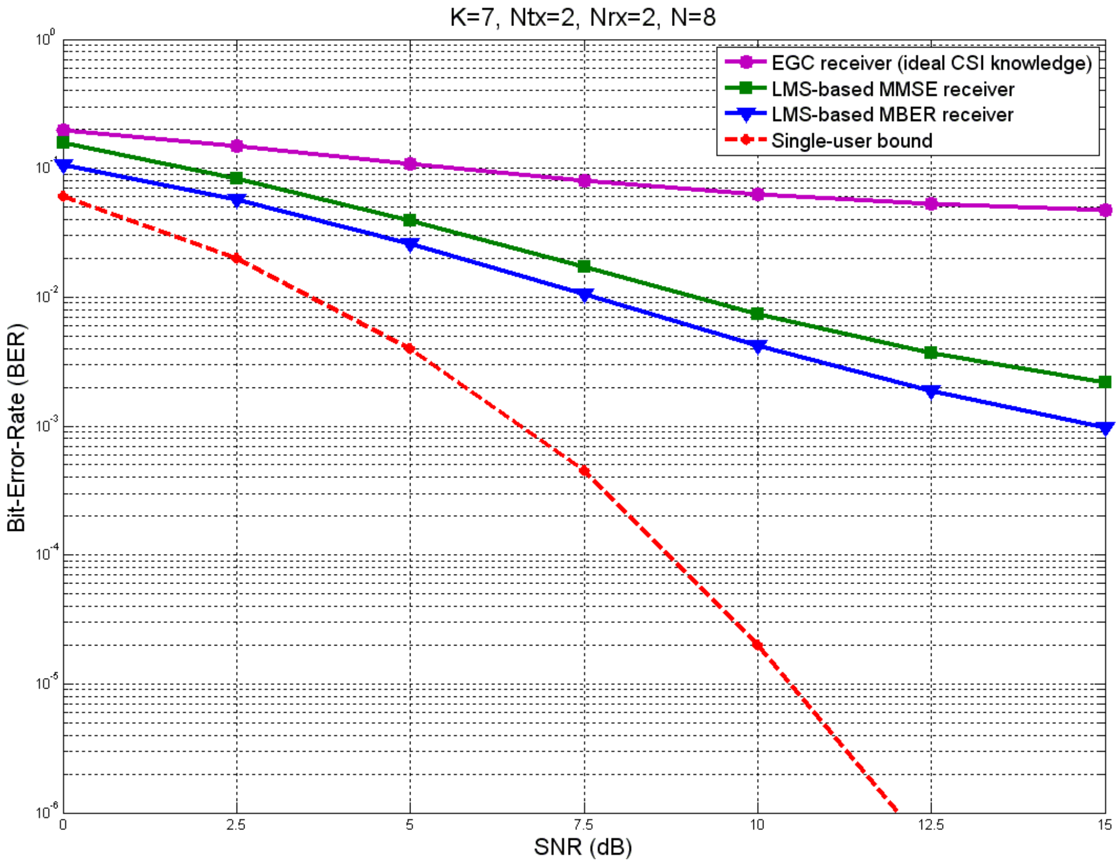


Figure 6.10: BER results vs SNR provided by the different signal detection algorithms assessed (with $K = 7$ users, $N = 8$ subcarriers, $N_{Tx} = N_{Rx} = 2$ antenna elements)

confirm, in all the tested cases, the unsuitability of single-user detection in the presence of multi-user transmission and frequency-selective channel distortions. On the other hand, as the number of users approaches the maximum allowable value (see Fig. 6.10, related to the "full load" case with $K = 7$), the MBER MUD approach still provides better results than MMSE one. Nevertheless, the two curves are closer one with respect to another than in Fig. 6.8 and Fig. 6.9. Moreover, they are farer from the single-user bound.
Such kind of behavior has been already noted by Chen in [59] for the MBER MUD applied to the DS-CDMA case and can be motivated by statistical reasons. As users' number K increases, the global detection noise (including AWGN and multi-user interference) is getting more and more Gaussian-distributed and, therefore, optimizing the receiver with

respect to the MMSE provides very close results to optimizing on BER. Moreover, the single-user bound curve depicted in Fig. 6.8-6.10 is a lower bound also on theoretically optimum ML detection as it does not take into account the presence of the multi-user interference. In case of increasing number of users, it is getting more and more difficult for a linear receiver to approach the single-user bound.

As far as computational issues are concerned, it is worth noting that the theoretical ML detection is characterized by an unaffordable computational order $\mathcal{O}\left(2^K\right)$ that is exponentially-growing with the users' number K. The same problem occurs when the theoretical MBER criterion is considered, as mentioned in sub-section 3.3.2. On the contrary, the proposed LMS-based MBER MUD receiver represents a step ahead with respect to state of the art linear combining receivers, however obtained with an affordable computational effort. In fact, analyzing the different terms of Eq. 3.34, one can note that the computational order of the adaptive LMS-based MBER MUD is $\mathcal{O}\left(K\right)$, therefore linear with respect to the users number. The same computational order characterizes both the LMS-based MMSE MUD and the single-user EGC combiner. Considering that the adaptive LMS-based MBER MUD always outperforms in terms of measured BER both EGC and LMS-based MMSE, the advantages of the proposed detection scheme are evident at a first glance.

6.4 Adaptive MCBER MUD Detector for STBC MIMO MC-CDMA Systems with GA-Assisted MMSE Channel Estimation

The performances of the LMS-based MCBER detector presented in section 3.4 have been evaluated by means of intensive simulation trials in a Rayleigh fading channel fixing the following parameters: number of subcarriers $N = 8$, transmission data rate $r_b = 1024$ Kbps, coherence bandwidth of the channel 2.1 MHz, Doppler spread of the channel 100 Hz. Two test cases have been considered: the most theoretical case related to the MCBER detector exploiting the ideal CSI knowledge and the more realistic case related to the MCBER detector supported by the GA-assisted channel estimation described in section 4.1 (a block diagram of the resulting transceiver scheme is depicted in Fig. 6.11).

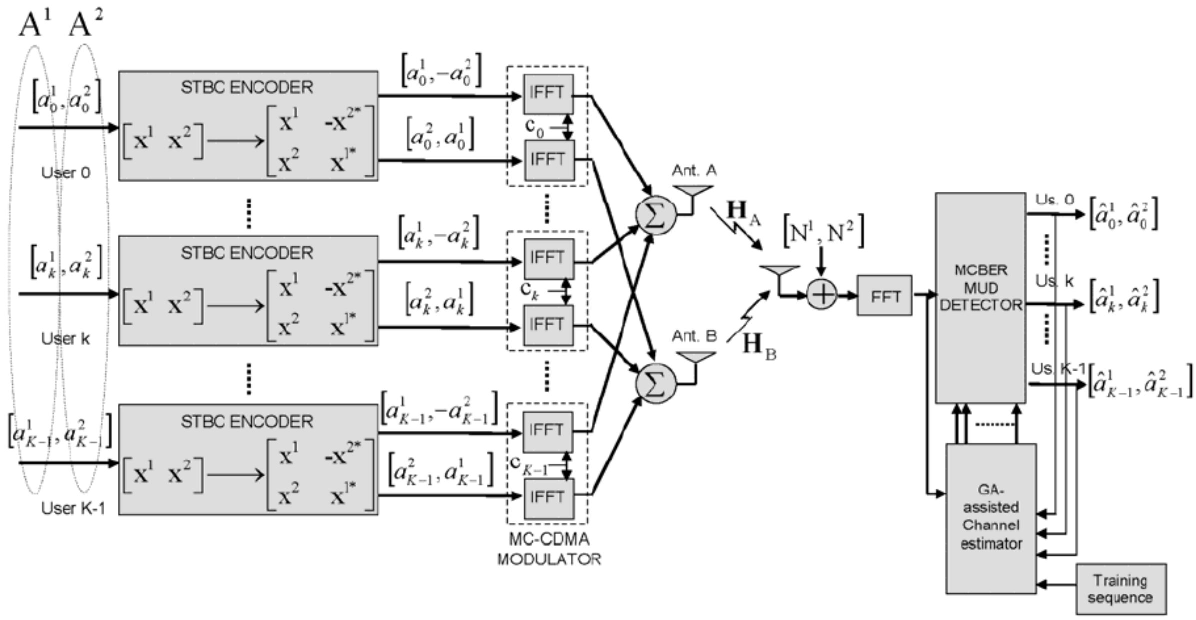


Figure 6.11: Block diagram of the STBC MIMO MC-CDMA system with GA-assisted channel estimation

In such a way, it is possible to test the effectiveness of the channel estimation strategy adopted together with the impact of non-ideal channel estimation on MCBER performances.

In order to verify the effectiveness of the proposed approach, other state of the art receivers have been considered for comparison, namely:

i) The ideal MMSE MUD receiver exploiting ideal CSI knowledge ([85, 176]).

ii) The MMSE MUD receiver supported by the GA-assisted channel estimation.

iii) The LMS adaptive implementation of MMSE receiver shown in [176] and [181].

iv) The single-user EGC receiver considered in [176].

As lower bound, the BER curve obtained by MRC detection in the single-user case has been considered (i.e., the optimal single-user detection, supposing the absence of multi-user interference). The GA optimizer has been parameterised as follows:

- *Training-aided* step: generation number $G_{Tr} = 30$, population size $P_{Tr} = 30$, crossover probability $\alpha_{Tr} = 0.9$, mutation probability $\gamma_{Tr} = 0.01$
- *Decision-directed* step: generation number $G_{DD} = 1$, population size $P_{DD} = 10$, crossover probability $\alpha_{DD} = 0$, mutation probability $\gamma_{DD} = 0$
- Training sequence length $B = 32$ bit
- Coherence window length $W_{coh} = 1800$ bit (according to the Jake's model for Rayleigh channels [201]). Therefore the overhead due to the insertion of the training sequence equals to less than 1.8%.

Three different scenarios including $K = 2$, $K = 4$, and $K = 6$ users have been considered. The corresponding BER curves vs SNR are shown for all the tested receivers in Fig. 6.12, Fig. 6.13, and Fig. 6.14, respectively.

It can be seen that in all scenarios the proposed LMS-based MCBER detector with and without ideal CSI knowledge clearly outperforms both EGC detector and LMS-based MMSE adaptive detector that exhibit a nasty error floor as the number of users increases. Moreover, the proposed MCBER detector exploiting ideal CSI knowledge yields performances that are better than those ones of ideal MMSE detector. Such a last improvement is clearly evident for $K = 2$ and $K = 4$ users, whereas it becomes slighter for $K = 6$ users. In general, for an increasing number of users, BER curves related to ideal MMSE and MCBER tend to become closer to each other and more distant with respect to the single-user bound. Such behaviour is not unexpected. As number of users K increases, the global detection noise (including AWGN and multi-user interference) is getting more and more Gaussian-distributed and, therefore, optimizing the receiver with respect to the MMSE provides very close results to optimizing on BER. Moreover, the single-user bound curve depicted in Fig. 6.12-6.14 is a lower bound also on theoretically optimum ML detection

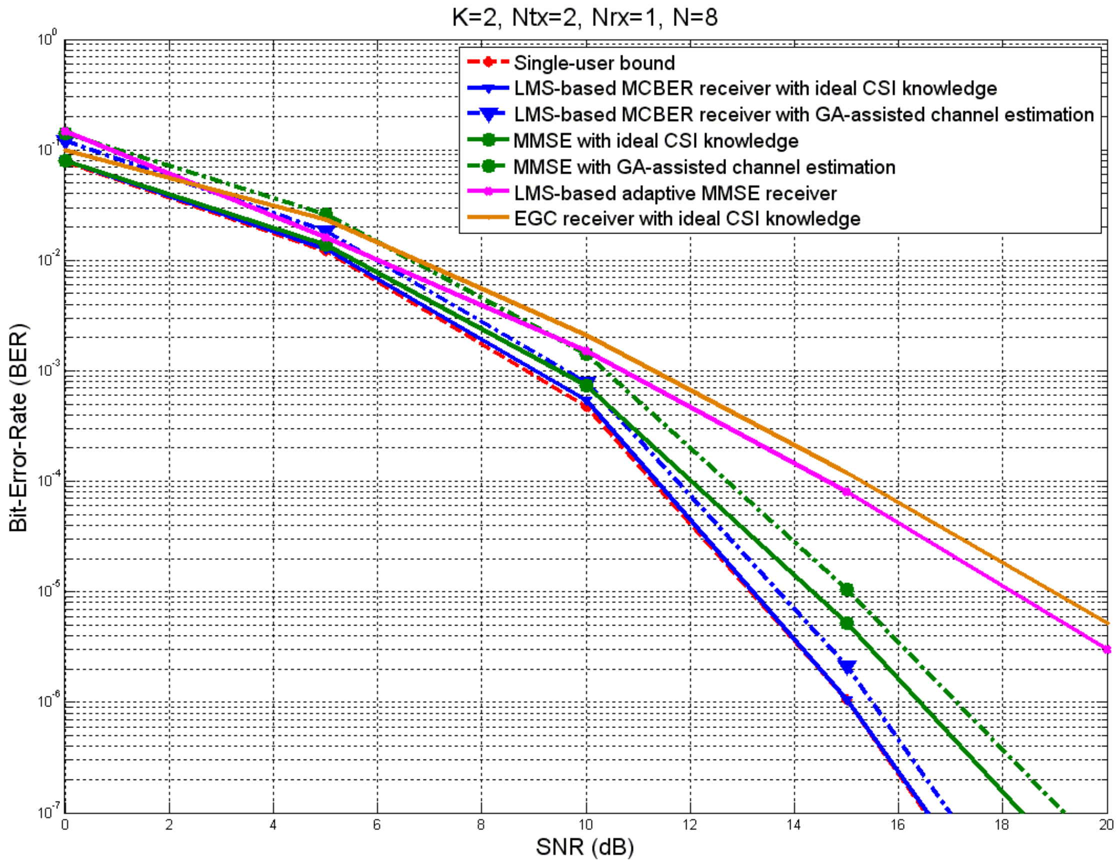


Figure 6.12: BER performance yielded by LMS-based MCBER and ideal MMSE (with ideal CSI knowledge and GA-assisted channel estimation), LMS-based MMSE multi-user detectors and EGC receiver (with ideal CSI knowledge) for $N = 8$ subcarriers and $K = 2$ users

as it does not take into account the presence of the multi-user interference. In case of increasing number of users, it is getting more and more difficult for a linear receiver to approach the single-user bound.

Focusing the attention on the effectiveness of the proposed GA-assisted channel estimation methodology, it is possible to see from Fig. 6.12-6.14 that the MCBER detector supported by non-ideal channel estimation performs very close to MCBER detector exploiting the ideal channel knowledge for $K = 2$ and $K = 4$ users. The effects of non-ideal channel estimation are more evident for higher number of users ($K = 6$) and therefore in the presence of higher level of multiuser interference.

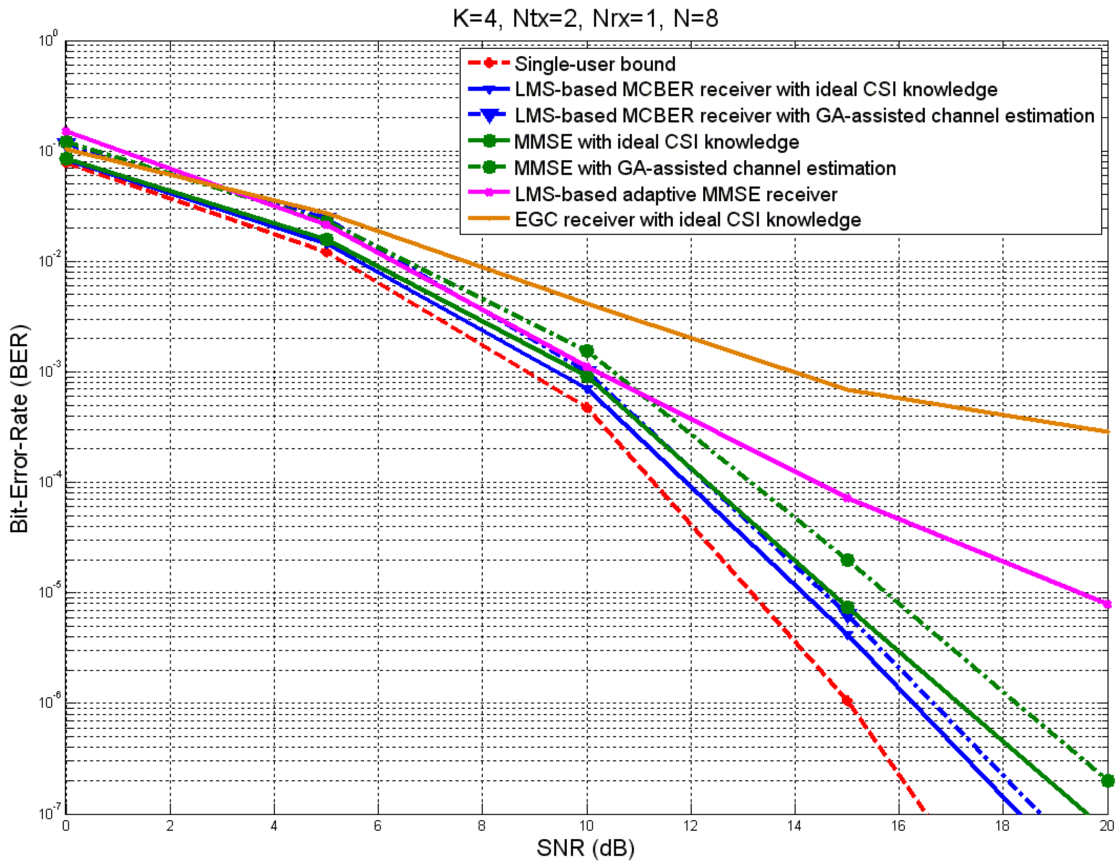


Figure 6.13: BER performance yielded by LMS-based MCBER and ideal MMSE (with ideal CSI knowledge and GA-assisted channel estimation), LMS-based MMSE multi-user detectors and EGC receiver (with ideal CSI knowledge) for $N = 8$ subcarriers and $K = 4$ users

The most relevant fact able at confirming the correctness of the conducted analysis is that the proposed MCBER detector always outperforms MMSE MUD when working together in the same conditions of "channel knowledge".

The effectiveness of the GA-assisted channel estimator has been tested in terms of error variance in the worst case of interference load (i.e., $K = 6$). The results shown in Fig. 6.15 highlight that such a variance, computed on the overall channel coefficients, is decreasing with SNR and exhibits satisfactory values (e.g., lower than 10^{-2} for SNR > 10 dB). Such results can be regarded as a further confirmation of the goodness of the proposed GA-assisted channel estimation approach.

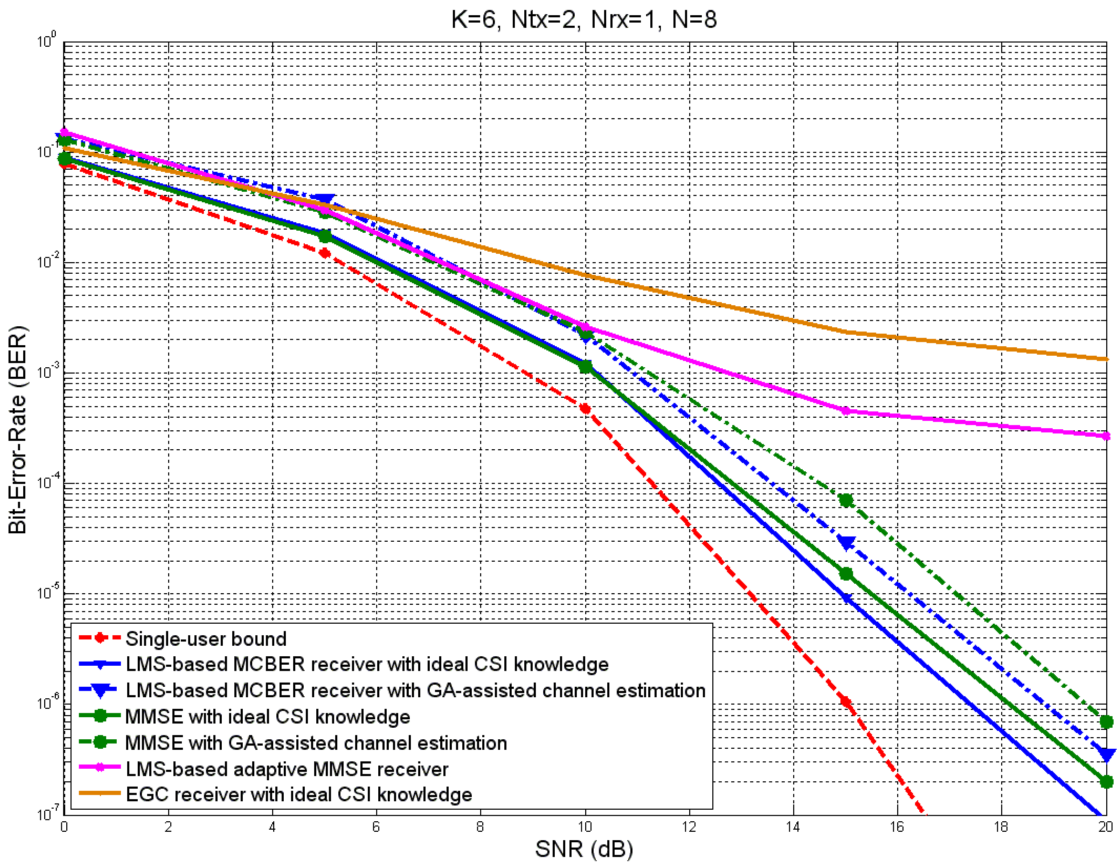


Figure 6.14: BER performance yielded by LMS-based MCBER and ideal MMSE (with ideal CSI knowledge and GA-assisted channel estimation), LMS-based MMSE multi-user detectors and EGC receiver (with ideal CSI knowledge) for $N = 8$ subcarriers and $K = 6$ users

As far as computational issues are concerned, current literature claims that MCBER criterion has a computational order which is linear with the number of users ([91]). The computational effort is therefore reduced with respect to the ideal MMSE detector which is $\mathcal{O}(K^3)$ ([65, 85, 176, 209]) and it is comparable with the LMS-based adaptive implementation of MMSE (which is linear again). The reduction of the computational complexity is one of the main advantages yielded by the proposed approach. In fact, the MCBER criterion is theoretically closer to optimality than MMSE and simulation results shown in Fig. 6.12-6.14 confirm this claim. Moreover, the developed adaptive MCBER MUD algorithm is also less demanding from a computational viewpoint than ideal MMSE, although

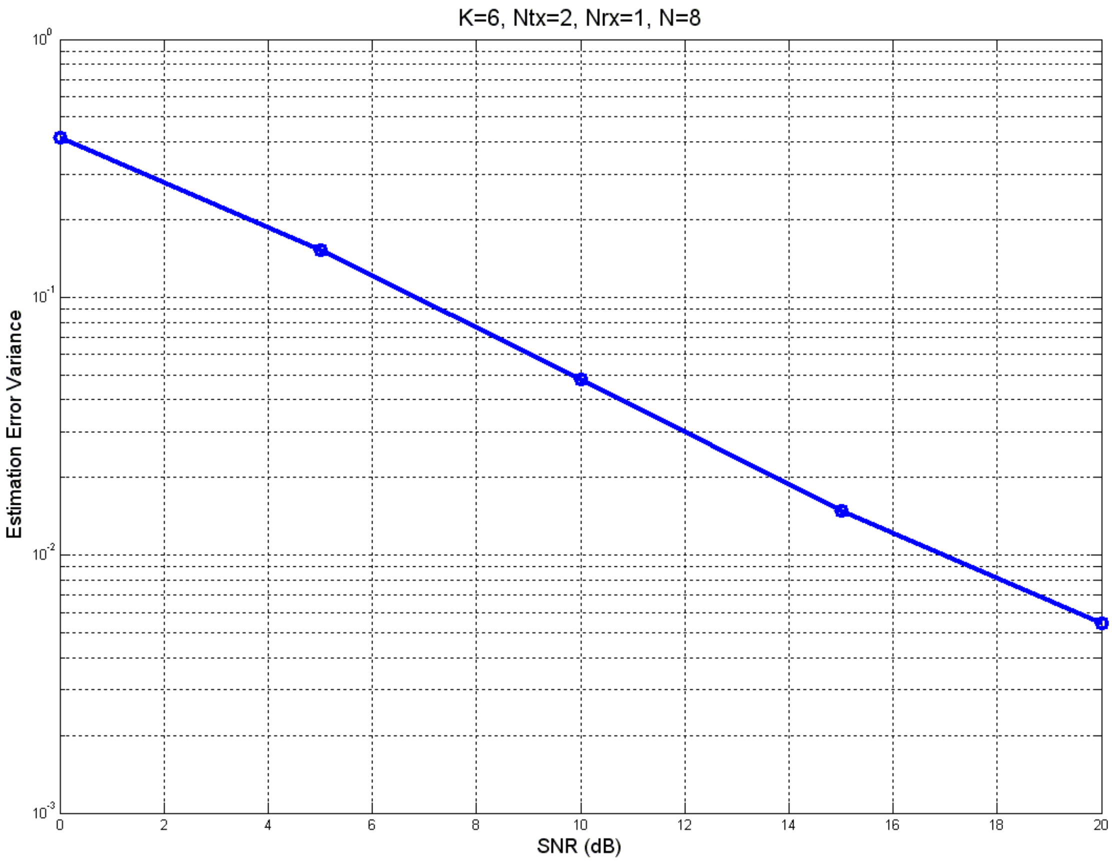


Figure 6.15: Variance of the channel estimation error measured for $K = 6$ users, $N = 8$ subcarriers, $N_{Tx} = 2$ and $N_{Rx} = 1$ antenna elements

requiring the same knowledge of the channel state information.

About computational complexity of the GA-assisted MMSE channel estimator, it is possible to say that GA requires a number of elementary operations to derive a solution that is equal to $\nu_{op} = (\alpha + \gamma) \cdot G \cdot P$ (see, e.g., [21]). Thus, $B \cdot K \cdot N \cdot G_{Tr} \cdot P_{Tr}$ elementary operations are required during the training-aided step. Their execution time is equal to εT, where $\varepsilon > 1$. The value assigned to ε mainly depends on the computational power of the signal-processing device employed. During the decision-directed step, the computational burden of the GA is reduced to $K \cdot N \cdot P_{DD}$ elementary operations to be executed during a signalling period T. Such a computational requirement is comparable with that one involved by state of the art STBC channel estimation algorithms (see, e.g., [85, 182, 210, 211]).

To conclude this section, some notes about algorithmic parameterisation are now provided. The step-size parameter λ of both LMS-based algorithms (MMSE and MCBER) has been chosen empirically for each scenario in order to minimize the overall BER over the various SNR values. From the parameters selection phase, it has been noted that LMS-based MCBER detector is characterized by a reduced sensitivity to parameterisation with respect to state of the art LMS-based MMSE MUD. Indeed, fixing the number of users K, the step-size λ is substantially invariant with respect to SNR values. On the other hand, LMS-based MMSE multi-user detector would require a different value of λ for each SNR in order to provide satisfactory BER performances.

As far as the parameterisation of the GA-based optimizer is concerned, it is possible to say that formal methodologies targeted to find an optimal parameterisation of genetic procedures are not available. In literature, there are only some interesting heuristic analysis like the one proposed by Tsoi in [202]. So GA parameters have been selected by means of explicitly-devoted simulation trials, performed by keeping into account the major guidelines pointed out in [202] that basically are these two ones:

a) the population size should be sufficiently large in order to have a conveniently-dimensioned space search

b) the number of generations should be appropriately assigned in dependence of the population size.

In fact, in case of large population, too strict limit for the search time can force algorithm to stop without having enough time to realize its search possibility. At the end of the simulation trials devoted to parameterisation, numerical values for generation number, population size, crossover, and mutation probabilities have been found in order to assure the best tradeoff between achieved results and computational load. In particular, an intermediate SNR equal to 15 dB has been assumed as reference value, and the best parameterisation has been derived by simulations for this value. Then, it has been observed by other simulations that the GA parameterisation chosen for the reference SNR is "very close to the best" also for higher and lower SNR values. It confirms the reduced sensitivity to parameterisation of GA procedures.

6.5 MMSE PSO-Assisted Channel Estimator for STBC MIMO OFDM Systems

The goodness of the PSO-assisted channel estimation technique described in section 4.2 have been tested through intensive simulation trials in a Rayleigh fading channel fixing the following parameters: number of subcarriers $N = 32$ and $N = 64$, transmission data rate $r_b = 1024$ Kbps, coherence bandwidth of the channel 2.1 MHz, Doppler spread of the channel 10 Hz.

Its performances have been compared with those one offered by the GA-assisted channel estimation technique proposed in section 4.1 and the traditional LMS and RLS steepest descent algorithms presented in [143]. The GA-based algorithm has been opportunely modified to operate in STBC MIMO OFDM systems, instead of STBC MIMO MC-CDMA systems. Such a modification can be easily done by considering the fitness function expressed in Eq. 4.6 (instead of the one reported in Eq. 4.1). The rest of the algorithm remains unchanged.

The effectiveness of the proposed approach has been tested by considering the MRC receiver proposed in [194] with different CSI knowledges (i.e., ideal, LMS-assisted, RLS-assisted, GA-assisted, and PSO-assisted). Abreu *et al.* noticed that the estimates obtained with the conventional linear decoder for Alamouti's scheme are no longer orthogonal in the presence of a non-quasi-stationary fading process. Such a situation leads to have error floors at higher SNR values (as already noticed in [212, 213, 214, 215, 216]). The solution proposed by Abreu *et al.* was to use the following combiner:

$$\begin{cases} \hat{\mathbf{A}}^1 = \left(\mathbf{H}_A\left(t\right)\right)^* \mathbf{Y}^1 + \mathbf{H}_B\left(t+1\right)\left(\mathbf{Y}^2\right)^* \\ \hat{\mathbf{A}}^2 = \left(\mathbf{H}_B\left(t\right)\right)^* \mathbf{Y}^1 - \mathbf{H}_A\left(t+1\right)\left(\mathbf{Y}^2\right)^* \end{cases} \tag{6.6}$$

instead of the conventional one represented by:

$$\begin{cases} \hat{\mathbf{A}}^1 = \left(\mathbf{H}_A\left(t\right)\right)^* \mathbf{Y}^1 + \mathbf{H}_B\left(t\right)\left(\mathbf{Y}^2\right)^* \\ \hat{\mathbf{A}}^2 = \left(\mathbf{H}_B\left(t\right)\right)^* \mathbf{Y}^1 - \mathbf{H}_A\left(t\right)\left(\mathbf{Y}^2\right)^* \end{cases} \tag{6.7}$$

The PSO optimizer has been parameterised as follows:

- *Training-aided* step: epoch number $E_{Tr} = 30$, population size $P_{Tr} = 30$
- *Decision-directed* step: epoch number $E_{DD} = 10$, population size $P_{DD} = 10$
- Inertia weight w linearly decreasing from 0.9 to 0.5
- Maximum particle velocity $v_{max} = 0.01$
- Individual and sociality weights $c_1 = c_2 = 1.6$
- Training sequence length $B = 32$ bit
- Coherence window length $W_{coh} = 1800$ bit (according to the Jake's model for Rayleigh channels [201]).

The GA optimizer has been parameterised as follows:

- *Training-aided* step: generation number $G_{Tr} = 30$, population size $P_{Tr} = 30$, crossover probability $\alpha_{Tr} = 0.99$, mutation probability $\gamma_{Tr} = 0.09$
- *Decision-directed* step: generation number $G_{DD} = 10$, population size $P_{DD} = 10$, crossover probability $\alpha_{DD} = 0.99$, mutation probability $\gamma_{DD} = 0.09$
- Training sequence length $B = 32$ bit
- Coherence window length $W_{coh} = 1800$ bit (according to the Jake's model for Rayleigh channels [201]).

LMS and RLS updating parameters have been chosen through devoted simulation trials. Simulation results in terms of BER are reported in Fig. 6.16 and Fig. 6.17 for the case with 32 and 64 subcarriers, respectively.

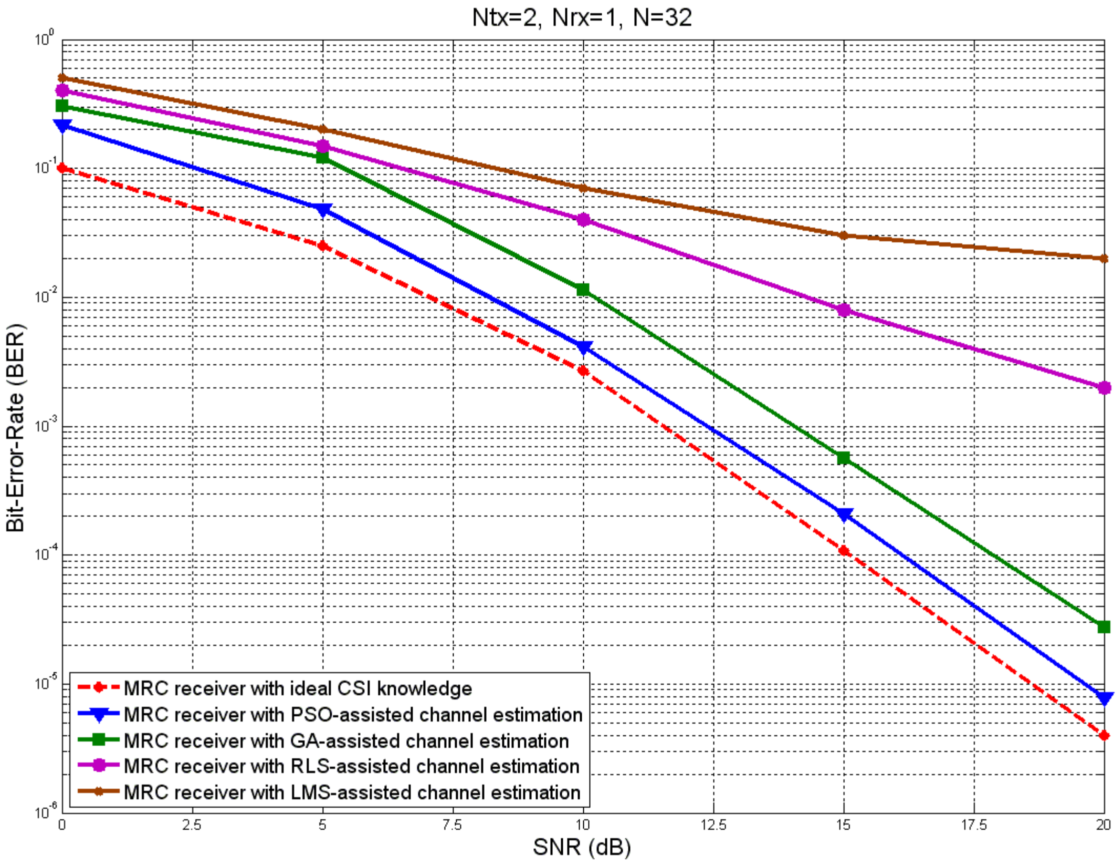


Figure 6.16: BER performance yielded by MRC detector of Eq. 6.6 (with ideal CSI knowledge, LMS-assisted, RLS-assisted, GA-assisted, and PSO-assisted channel estimation) for $N = 32$ subcarriers

It can be seen that in both scenarios the proposed GA- and PSO-based receivers clearly outperforms both LMS and RLS steepest descent algorithms that exhibit a nasty error floor as the SNR increases. Both MRC receivers assisted by channel estimation techniques based on evolutionary strategies perform really close to the one with ideal CSI knowledge. The best performances are provided by the detector with the PSO-assisted channel estimator. It confirm the superiority of the PSO algorithm with respect to GA in this application (as already described in subsection 4.2.1).

The same behaviour has been observed in terms of error variance in the case with 32 subcarriers. The results shown in Fig. 6.18 highlight that such a variance, computed on the overall channel coefficients, is decreasing with SNR and it is lower for the PSO-assisted

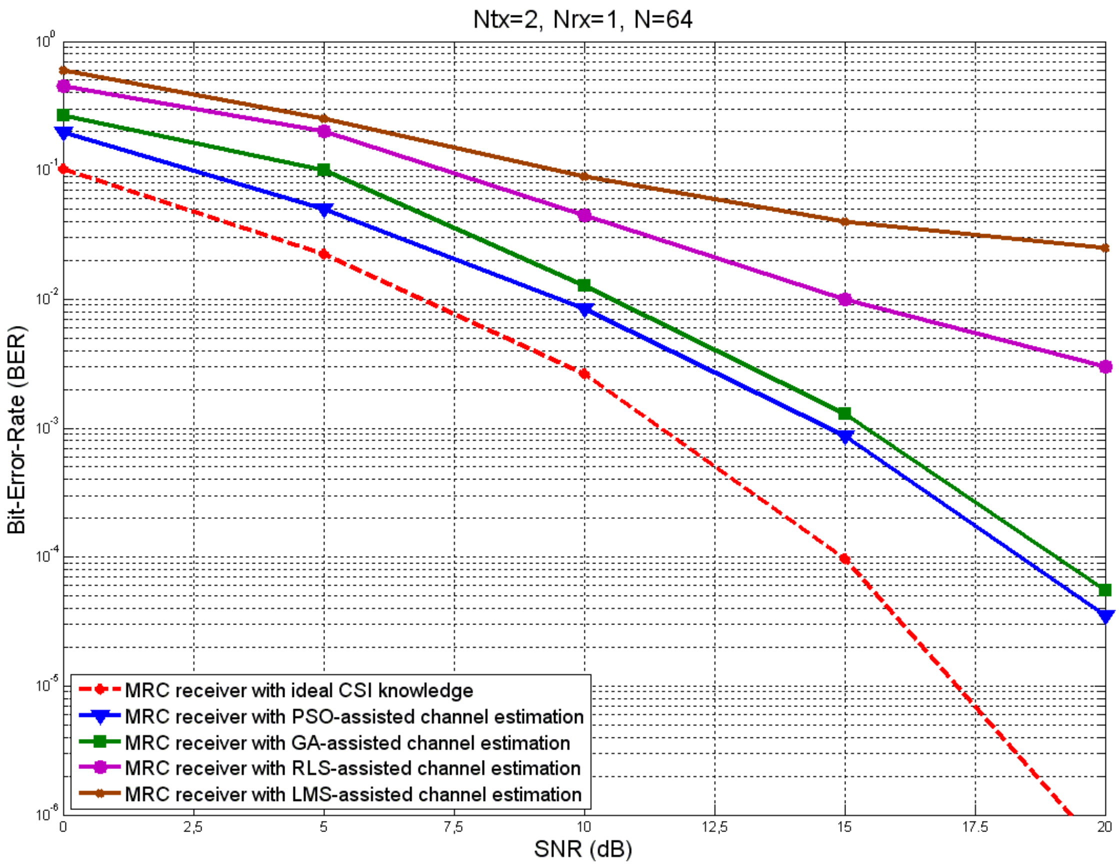


Figure 6.17: BER performance yielded by MRC detector of Eq. 6.6 (with ideal CSI knowledge, LMS-assisted, RLS-assisted, GA-assisted, and PSO-assisted channel estimation) for $N = 64$ subcarriers

channel estimator.

The computational order of PSO is $\mathcal{O}(E \cdot G)$ and it is therefore comparable with that of GA, which is $\mathcal{O}(P \cdot G)$ ([193]).

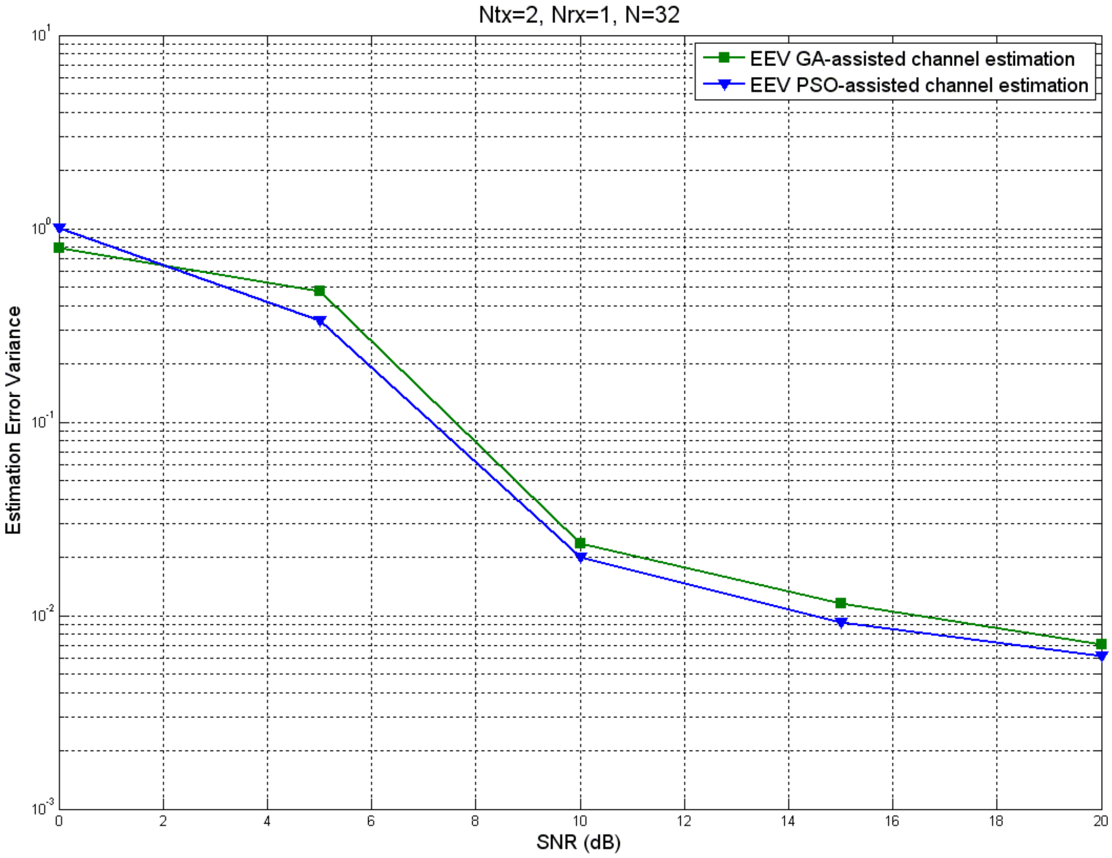


Figure 6.18: Variance of the channel estimation error measured for $N = 32$ subcarriers, $N_{Tx} = 2$ and $N_{Rx} = 1$ antenna elements, both for the GA-assisted and the PSO-assisted channel estimator

Chapter 7

Conclusions and Future Works

In this Chapter, the methods and results presented in this thesis are reviewed and several lines for future research are suggested. The main targets have been the study and development of novel techniques for physical layer optimization of diversity based smart terminals in the context of next-generation wireless communications. In particular, novel multi-user detection techniques for multi-carrier CDMA systems and the application of evolutionary strategies to channel estimation in MIMO multi-carrier scenarios have been considered. All the formulated algorithms have been implemented in a modular software architecture, in order to use them in an adaptive and optimized reconfigurable scenario.

Section 3.1 has formulated a novel semi-adaptive GA-based approach for MMSE MUD in MC-CDMA systems transmitting information over time-varying fading channels. The proposed algorithm evidenced some advantages with respect to other state of the art solutions. First, it does not require any channel estimation but just a short training sequence periodically transmitted. Then, simulation results achieved in terms of BER evidenced a near-ideal behaviour of the proposed algorithm, outperforming LMS- and RLS-based approaches especially when the impact of MAI becomes predominant in limiting transmission capacity.

Future works could introduce an average operation in the computation of the fitness function also in the decision-directed step, in order to better counteract noise effects. Other intensive simulation trials should be done in presence of time varying channels characterized by very fast multipath fading.

Section 3.2 proposed the use of GAs in the context of the multi-user detection of multi-rate variable-spreading-length MC-CDMA signals transmitted over mobile downlink channels. Results shown evidenced a promising quasi-optimal behaviour of the proposed GA-based MUD algorithm, provided that GA parameters are carefully tuned. The performance improvement achieved with respect to state of the art interference cancellation schemes is clearly demonstrated. Such relevant results have been achieved by spending an affordable computational burden.
Future works could concern with some relevant aspects not faced in the present work, like, e.g., effects of non-ideal channel estimation, effects of system non-linearities, joint GA-based channel estimations and symbol detection, etc.

Section 3.3 presented a novel adaptive LMS-based MBER multi-user detection approach for MIMO STBC MC-CDMA systems transmitting information over time-varying multipath fading channels. The proposed algorithm evidenced some advantages in terms of improved BER performances with respect to state of the art receivers that rely on the mean squared error minimization (MMSE) and on single-user diversity combining (EGC). Experimental results evidenced that, in the case of full user load, BER curves of LMS-based MMSE and LMS-based MBER become closer than in other test cases. This can be justified by the statistical properties of global detection noise that becomes more and more Gaussian as the users' number increases.
Future research works should be devoted to the exploitation of more efficient optimization strategies based on the stochastic gradient (e.g., genetic algorithms, particle swarm optimization). Considering again steepest descent-based optimization methodologies, the application of RLS to MBER reception should be investigated as well. In this case, the definition and the recursive computation of the Kalman gain vector do not appear as trivial as in the MMSE case and, for this reason, might be an interesting subject of future works.

Section 3.4 investigated a multi-user detection strategy inspired to the concept of conditional BER minimization for MIMO MC-CDMA systems using Alamouti's space-time block coding. In the perspective of a real receiver deployment, an adaptive LMS-based implementation of the MCBER detector has been proposed supported by the robust and computationally-affordable MMSE channel estimation assisted by a genetic optimizer described in section 4.1. The proposed MCBER approach always allows improving BER performances with respect to other state of the art linear detectors working with the same degree of channel knowledge. It is worth noting that the performance improvement with respect to MMSE MUD strategies is achieved by spending a reduced computational effort, linearly increasing with the number of users. Numerical results evidenced that BER curves of MCBER and ideal MMSE are getting closer as the number of users approaches the maximum allowable value. This behaviour is intrinsic to the linear multi-user detection and fully motivated by the nature of the MCBER criterion adopted.
Future research activities might concern the utilization of non-conventional optimization strategies (e.g., GA, PSO, etc.) to provide a numerical solution to the MCBER problem instead of the proposed LMS-based solution.

Section 4.2 described a PSO-based MMSE channel estimation technique for STBC MIMO OFDM systems. Its performances have been compared with those ones offered by a similar GA-assisted channel estimation technique in terms of BER and computational complexity. Obtained results showed the superiority of the PSO algorithm with respect to GA even with lower computational complexity.
Future works could consider the application of the proposed technique over faster multipath fading channels. Another interesting aspect would be the test of other evolutionary strategies in the same context (such as Ant Colony Optimization (ACO, [217, 218]), Quantum Evolution (QE, [219]), Bees Algorithm (BA, [220]), and Artificial Fish Swarm Algorithm (AFSA, [221])).

Chapter 5 gave an overall view of the developed software modules in terms of modularity and reusability. Future works could consider the implementation of the whole set of proposed algorithms on the same DSP device. The resulting SDR library should be able to automatically adapt the functioning of the reconfigurable terminal to the network situation.

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