Adaptive Signal Combining and Detection in Cooperative Wireless Networks

by

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Thesis

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DECLARATION

I certify that this work has not been accepted in substance for any degree, and is not concurrently being submitted for any degree other than that of Doctor of Philosophy (PhD) being studied at the University of Greenwich. I also declare that this work is the result of my own investigations except where otherwise identified by references and that I have not plagiarised the work of others.

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ABSTRACT

In this research adaptive algorithms were developed for multiuser detection and signal combining in cooperative wireless networks. Some of the key contributions and works of this research thesis are: *1.* A computationally simple Adaptive Minimum Mean Square Error Multiuser Detection scheme was proposed to eliminate multiple access interference in uplink communication of an asynchronous cooperative CDMA wireless network, where users cooperate in a relaying mode while they exchange data and channel information with the destination node. The proposed scheme provides better interference resistance than optimum multiuser detection Maximum Likelihood Sequence Estimation in cooperative wireless networks. The performance was examined under Amplify-and-Forward and Decode-and-Forward cooperative protocols in flat fading Rayleigh wireless channels. *2.* Adaptive signal combining was proposed for cooperative wireless networks and its performance was analysed by using Least Mean Square and Recursive Least Square algorithms. The other classical non-adaptive techniques Maximal Ratio Combining and Wiener were also examined. It was also shown that adaptive signal combining achieves Wiener's solution in cooperative wireless networks with added benefit of computational simplicity over classical combining schemes. *3.* Weighted Least Square Error Method of signal combining was proposed for wireless signal combining, where estimates of inverse of the channel noise variance was used as weight of the combiner. The proposed method was a receiver with noise estimation filters at each received branch for the

noise estimation. The reciprocal of the estimate of the channels noise variance were used as weights of combiner to achieve Wiener's solution of signal combining. The proposed algorithm was used in cooperative, non cooperative wireless networks and multiple antennas system. It was also shown that un weighted least square error method is equivalent to equal gain combining scheme. The performance of the proposed mathematical algorithms were examined with computer simulations in various wireless channel models.

ABBREVIATIONS

AMUD	Adaptive Multiuser Detection
A-MMSE-MUD	Adaptive Minimum Mean Square Error Multiuser Dectection
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
CDMA	Code Division Multiple Access
i.i.d	Independent Identically Distributed
LMS	Least Mean Square
RLS	Recursive Least Square
MAI	Multiple Access Interference
MF	Matched Filter
MIMO	Multiple Input Multiple Output
RS-MIMO	Random Signature Multiple Input Multiple Output
MLSE	Maximum Likelihood Sequence Estimator
MMSE	Minimum Mean Square Error
MSE	Mean Square Error

MUD	Multiuser Detection
OFDMA	Orthogonal frequency Division Multiplexing Acess
SINR	Signal to Interference Noise Ratio
SISO	Single Input Single Output
SNR	Signal to Noise Ratio
STBC	Space-Time Block Coding
ZMCSCG	Zero Mean Circular Symmetric Complex Gaussian

NOTATIONS

$S_1, S_2, ..., S_K$	Users/Sources
$R_1, R_2, ..., R_L$	Users/Relays
$x(n)$	BPSK data symbols transmitted by sources
P_{S_k}	Power transmitted by k^{th} source S_k
$\mathbf{s}_k(t)$	Spreading waveform(signature)of S_k
$\mathbf{y}_I(t)$	Received signal at receiver for Phase I
τ_k	Transmission delay of the k^{th} user
$\mathbf{h}$	Complex time invariable channels co-efficient
$\mathbf{v}(t)$	Additive White Gaussian noise of channels
$\mathbf{y}_{II}(t)$	Received signal at receiver for Phase II
$\hat{\mathbf{X}}_\ell(n)$	Detected symbol matrix at ℓ^{th} relay
$\mathbf{t}_\ell(n)$	Re-encoded symbol matrix at ℓ^{th} relay
$\mathbf{y}(n)$	Received signal at input of filters of network node
γ	Amplification factor for Amplify-and-Forward protocol
T_c	Chip interval
$\mathbf{a}$	m dimensional complex valued weight vector
$\mathbf{a}_{opt}$	m dimensional complex valued optimum weight vector
$E(.)$	Probabilistic expectation
$J_{\mathbf{a}}$	Minimum mean square error
$e(n)$	Error between the reference signal and the output of adaptive filter
$\mathbf{e}_m(n)$	Error signal vector

$\mathbf{H}$	Channel's Matrix
$\mathbf{z}$	Cross-correlation matrix vector
$\mathbf{R}$	Correlation matrix
∇	Gradient
μ	Step size constant of least mean square algorithm
$\mathbf{y}_m(n)$	Received baseband signal at m^{th} antenna
I	Interference
n	Time interval
$\varrho(m,m)$	Coefficient of Correlation Matrix

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LIST OF PUBLICATIONS

List of publications during the PhD research programme:

Conference Publications

1. Athar Qureshi, Triantafyllos Kanakis, Charan Litchfield and Predrag Rapajic, *"Adaptive MMSE Multiuser Detection (A-MMSE-MUD) in Asynchronous Co-operative CDMA Networks"* , Softcom 2010, Croatia, 23 Sept., 2010.

2. Athar Qureshi, Triantafyllos Kanakis and Predrag Rapajic, *"Adaptive Combining of Signals with Unequal Noise Variances"*, CimSim 2010, Bali, Indonasia, 28 Sept., 2010.

3. Athar Qureshi, Triantafyllos Kanakis and Predrag Rapajic, *"Interference Resistance of Adaptive Multiuser Detection in Asynchronous Detect and Forward Relaying CDMA Networks"*, BCFIC 2011, Riga, Latvia , 16 Feb., 2011.

4. Titus Eneh, Predrag Rapajic, Kwashie Anang and Athar Qureshi, *"Information Capacity of the Communications Systems with Adaptive MMSE Receivers"*, ICFIT 2010, Changsha, China, 14 Dec., 2010.

Journal Publications

1. Athar Qureshi, Triantafyllos Kanakis and Predrag Rapajic, *"Adaptive Combining for Unequal Channel Noise Variances for Wireless Communication Networks"*, vol. 11, IJSSST, UK, Oct., 2010.

2. Athar Qureshi, Ramkumar Balasubramanyam and Predrag Rapajic, *"Signal Combining by Weighted Least Square Error Method for Wireless Communication Networks"*, vol. 11, IJSSST, UK, Oct., 2010.

Chapter 1

INTRODUCTION

1.1 Multiuser Detection in Cooperative Wireless Networks

The evolution of wireless starts in the days when Nicola Tesla demonstrates the transmission of electrical energy in free space with an experiment controlling a model submarine. Later, Marconi used radio waves for transatlantic analogue transmission, from Great Britain to the east coast of Canada in 1902. Gradually, developments have been made in the field of wireless technology, and it transformed from analogue to digital wireless communication. The information theory was formulated by Shannon who proposed his famous information capacity formula in [1], which is still a fundamental principle in designing communication systems. Various systems have been proposed to improve the information capacity, so that data can be sent to the destination and detect with least communication errors within a specific available bandwidth spectrum. Multiple input multiple output antenna (MIMO) system was one of the schemes, which was applied to the wireless systems to improve the system capacity. MIMO was presented by Telatar in [2][3], where he had derived his popular mathematical formulas for the information capacities of MIMO channels and described computational methods to examine performance in Gaussian and Rayleigh MIMO channels. Some of the other information capacity analyses derived from the fundamental principles of Shannon and Telatar were presented in [4-8]. In last few decades the demands of wireless technology for commercial purposes were increased exponentially. Communication related industries had played important role by actively financing and participating in research and development. In the process of evolution and expansion of various communication applications, new wireless standards are developed. Figure 1.1 [9], shows the trends in the usage of spectrum, future predictions and demands. Today's wireless systems challenges are to meet the unprecedented demand for wireless technology of various engineering applications. Most of the wireless applications operations are under strict limitation of bandwidth by the government authorities and wireless communication standardising organizations. It is therefore, required to fully exploit the available and precious bandwidth resources by developing methods of error free wireless communication. More precisely, there is a need to design systems to improve information capacity of the wireless systems to fully utilize available frequency bandwidth spectrum.

Various techniques were developed by the researchers to improve information capacity. One of them is cooperative wireless networks, which are next generation wireless networks that emerged on the principle of virtual MIMO networks, where methods were employed in distributed antenna systems to improve information capacity of the wireless networks. In cooperative wireless networks each node of the network acts as an antenna element of virtual MIMO to transfer data to other nodes. They are cost effective systems that utilise the benefit of spatial diversity. They enhance degrees of freedom to improve the bit error rate performance (BER). A commonly used cooperative wireless networks is shown in figure 1.2 and figure 1.3, where users in a cluster transmit data signals to the relays of another cluster for onward transmission towards destination. At relays cluster usually adaptive beamforming, transmit beamforming and space time block code signalling techniques have been used to improve reliability, quality and speed of the network. In the last few decades various advances in signal processing techniques for MIMO system are implemented successfully, where multiple transmit and receive antennas on transreceivers of wireless networks are used. MIMO considerably improves the system's reliability and throughput, consequently the information capacity of the wireless networks is increased. These techniques are very effective to improve the weaker communication link, which is due to a strict power control to reduce interference in wireless networks. However, due to size, cost and hardware constraints, the use of MIMO techniques in cooperative networks may not always be feasible, particularly in small wireless/mobile devices due to antenna correlation among multiple antennas. This has created interest to develop many-to-many or cluster-to-cluster communication, which involves single antenna network nodes that cooperatively transmit and receive by forming virtual antenna arrays. This method is broadly named as cooperative communication. The idea is to make these virtual multiple antenna arrays to mimic as MIMO systems therefore, most of the theoretical principles of MIMO are equally applicable to these systems and hence derive better performance. Multiplexing, detection, channel coding, modulation scheme and spatial diversity are other important techniques that are usually designed and implemented in these networks to improve the information capacity of the wireless networks.

Signal Multiplexing is a technique to provide communication access over the specific channels to multiple users. Among multiplexing techniques, code division multiple access (CDMA) is the backbone of existing third generation (3G) wireless and mobile systems. It allows multiple users to share limited time and bandwidth resources. Signal detection in CDMA systems is very important to achieve high speed communication with reasonable information capacity performance. By using various multiuser detection schemes we can detect the signals in non cooperative (2G)(3G)(4G) and cooperative wireless networks (5G). The multiuser detection (MUD) schemes were well investigated in past literature, some of the popular techniques were presented in [10-22] for non cooperative CDMA wireless networks. Adaptive Minimum Mean Square Multiuser Detection (A-MMSE-MUD) in cooperative wireless networks is one of the focus areas of this research Thesis. The pioneer research work in modern cooperative wireless networks was presented by Cover and Elgamal, where they investigated the information theoretic study on the relay channels under additive white Gaussian channel noise [23]. They described the channel capacity lower bounds of physically degraded relay channels for different random coding schemes.

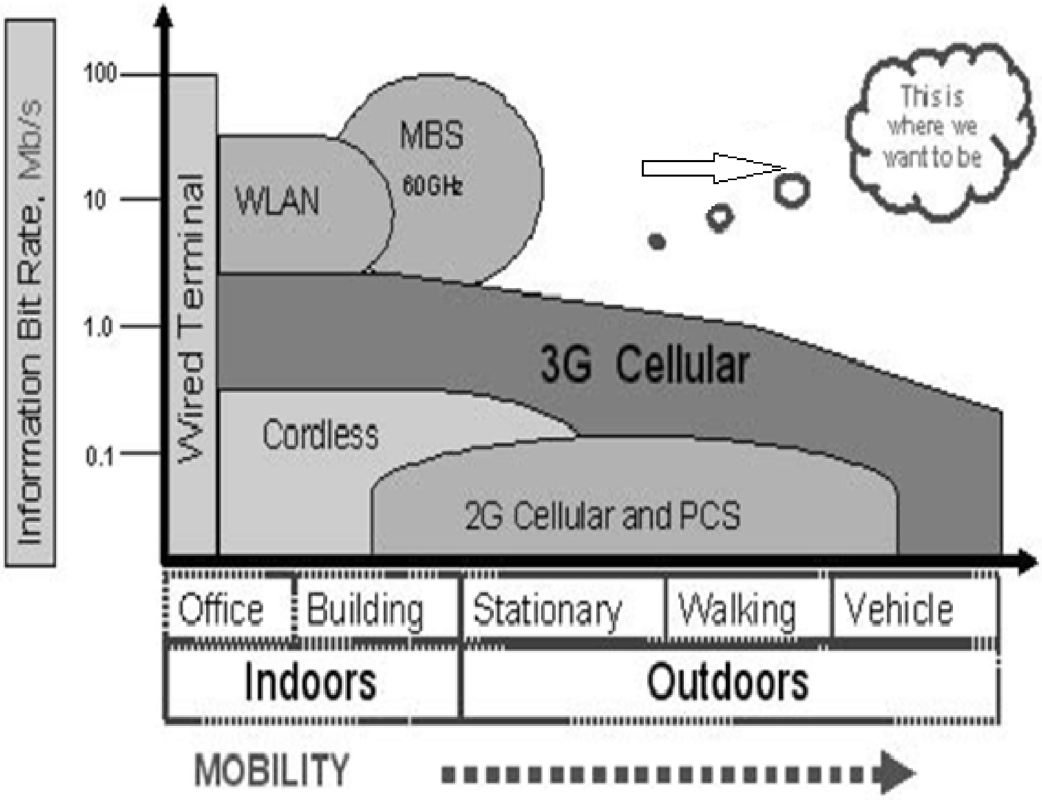

Figure 1.1: Wireless radio spectrum usage trends:

- Figure shows the trends in Wireless Technology. Researchers are investigating the various methods to improve performance up to 100 Mb/sec data communication rate for all types of wireless users. Present systems provide only the data communication rate of 5 Mb/sec, for stationary and walking wireless users. And this data communication rate is even lower as 1 Mb/sec for wireless users in moving vehicles.

The multiuser detection schemes with different protocols in cooperative CDMA wireless networks were presented in [23-35]. Some of the other literature related to the different aspects including system description, implementation aspects, performance analyses and multi-hop cooperative communication were discussed in [36-52]. Some of the important research theses related to cooperative wireless networks were presented in [53-55], where various cooperative protocols, strategies, signal power and modulation schemes were proposed. Existing multiuser detection schemes for cooperative and non cooperative wireless networks are; match filter, decorrelator, minimum mean square error, optimum technique maximum likelihood sequence estimation and relay assisted decorrelator [56][57].

Extensive literature review revealed that adaptive implementation in cooperative wireless networks is overlooked and therefore, adaptive multiuser detection by using MMSE for cooperative CDMA wireless networks is one of the key areas of this research thesis. In this research adaptive multiuser detection is proposed by using A-MMSE-MUD in cooperative wireless networks, which uses the bank of adaptive filter to detect the signals. Whereas, in other MUD techniques, usually fractionally spaced linear transversal bank of filters are used to detect the signals. The aim of this research work is to develop a simple, low complexity, efficient and reliable adaptive algorithm for detection in cooperative CDMA wireless networks. CDMA multiuser detection (MUD) receivers are supposed to be capable of estimating the system parameters by a coordinated training routine from the transmitter. The communication parameters to be estimated are signal delay, signal phase, signal amplitude, CDMA signatures, multi-path channel profile and the number of users. Moreover, CDMA MUD are useful to mitigate multi access interference (MAI) in non-cooperative and cooperative CDMA networks. Different cooperative network models were used in past literature. The popular previous research works in cooperative communication was assuming that there is a single source in the network and others are relays, or considering orthogonality of spreading codes from multiple sources that transmits over an orthogonal channel. In this research, a realistic scenario is considered, where each relay may cooperate with multiple users simultaneously with approximately orthogonal spreading codes. However, keeping the orthogonality is very complex in classical multiuser detection schemes, but CDMA wireless with proposed A-MMSE-MUD has the capability to overcome the problem of non orthogonality of spreading codes. The research of A-MMSE-MUD is performed in a network where messages received from multiple sources are amplified by existing signal processing techniques or decoded by using purposed A-MMSE-MUD at the relays and are jointly processed by adaptive MMSE filter before being retransmitted to the base station. At base station the A-MMSE MUD performed after combining the beams of direct transmission of signals and the beams of the signals from relays. Network model of the proposed network is same as shown in the figure 1.2. In A-MMSE-MUD receiver, bank of MF for maximum likelihood computation is replaced by a bank of adaptive MMSE filters by using LMS or RLS algorithm. It is in contrast to the conventional approach for the detecting the signals, to use a matched filter for each user's signal by ignoring the cross-correlation among user's transmission. The parameters of the adaptive filters continuously adjusted by receiving the training sequences from the transmitter to adjust the parameter of filters for matching the desired signal at specific period of time. Some of the strategies presented in past literature are based on relaying techniques are amplify-and-forward (AF), decode-and-forward (DF), coded cooperation, quantize and forward etc.. In this research work the focus is remained on the use of AF and DF scheme where relay decode or amplify before forwarding to destination node. An overview of these protocols is presented in the next chapter.

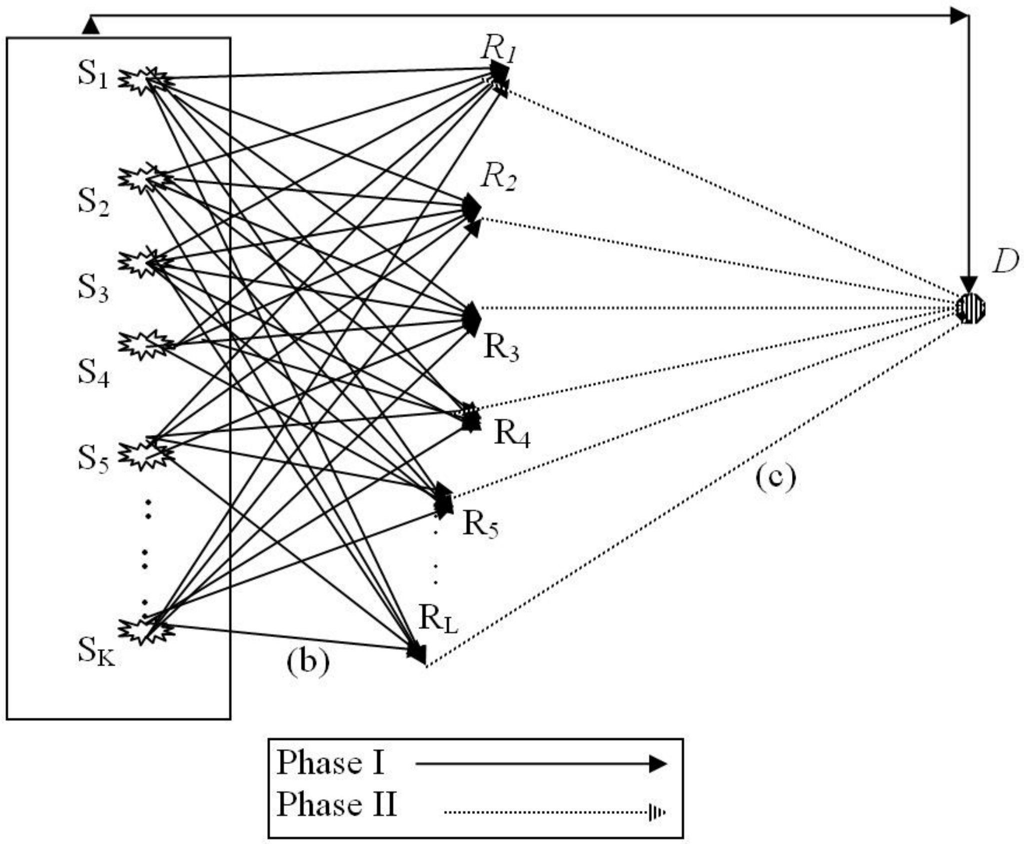

Figure 1.2: General model of cooperative wireless network:

- Multiple users cluster $S_1, S_2, ..., S_K$ transmit the signals directly to destination in (Phase I), and via relays $R_1, R_2, ..., R_L$ to the destination D in (Phase II) through wireless Rayleigh channel. On destination node two beams are combined and signal detection are performed.

1.2 Signal Combining in Cooperative Wireless Networks

In past literature, extensive research work were performed on signal combining algorithms. The detailed literature related to the adaptive systems were presented in [58-92]. In the previous research work, classical schemes of adaptive equalisation and combining were discussed in [58-61]. In particular, B.Widrow [62] and Jack H Winters in [64] presented signal combining in various wireless channels, where they had shown that the BER performance of LMS and RLS algorithms arbitrarily close to the Wiener solution (optimum solution). Later adaptive combining was presented for various applications in [64-86]. Most of the research work for the theory of adaptive filters are summarised in the books of S Haykin [87] and Ali H Sayed [88]. In the previous known research work, it was assumed that channel noise variance is Gaussian with zero mean and unit variance. Which is very un realistic situation in practical implementation, therefore, the assumption made throughout this research work is un equal channel noise variance. Further, it is assumed that the reception of the signals is at low signal to noise ratio regions. Because, wireless communications usually operate under low signal to noise/interference ratio(SNIR). The level of the noise/interference is usually very high in practical wireless system, if it is compared with received signal's power. The typical received power is as low as -125 dBm at base station of 2G/3G Nokia Siemens mobile communication system. Adaptive algorithms for signal combining are a powerful tool to perform in such an environment. A typical structure of an adaptive combining system is shown in figure 1.3.

Signal combining is very important aspect of the communication. It is very important to obtain full benefit of the space diversity by selecting suitable combining technique. As mentioned earlier, to increase the information capacity, we have to efficiently utilize available bandwidth resources by various techniques. One of the techniques, that fully utilize the available bandwidth resources is receive diversity, which can be fully achieved with signal combining. Space diversity provides an attractive method for the bit error rate (BER) performance improvement in wireless communication networks. For example, the typical Nokia Smart antenna system for (2G)(3G)(4G) mobile communication provides improvement in wireless channel information capacity by 50 percent. Receive spatial diversity can be achieved with the use of multiple antennas by receiving different versions of the transmitted signal. In other words, various received signal sequences are subjected to different level of statistical corruption that may be additive and/or multiplicative due to thermal noise/impulsive noise (Gaussian noise due to multiple electronic circuitry) and signal fading. In this research, it is considered that the corruptions of received signals are due to random additive Gaussian distribution of noise. It is also considered that the corruption can be multiplicative channel distortion due to multipath propagation, Doppler's phase shift, diffraction and interference etc. Moreover, in modern wireless systems we are using multiple input and multiple output antenna systems, cooperative wireless networks, orthogonal frequency division multiplexing access schemes, higher modulation schemes other than binary phase shift keying. We also experience the poor quality of signal due to fast moving vehicles and dense urban city environments. All these factors somehow cause channel interference in the received signal. The channel interference itself can be statistically treated as additive Gaussian thermal noise. It means these all factor increase the effects of Gaussian channel noise variance and signal usually received at very low signal to noise ratio at destination node or base station.

In wireless Communication, transmit and receive diversity is important to achieve optimum channel information capacity, for this purpose, MIMO antenna system is a useful technique where sets of antenna arrays achieve space diversity. Cooperative wireless networks not only utilize the benefit of MIMO space diversity in distributed manner using relays but also by an un-distributed manner with use of multiple antenna at destination node or base station, which provides an attractive method for the bit error rate (BER) performance improvement in wireless networks. Moreover, there is also great current research interests on the topic of multiple antennas at mobile station. Transmitted wireless signals disperse in space due to wireless communication channel environments and propagate in the form of multiple version of same signal. Receiving multiple versions of the same original transmit signal, in other words, received signal sequences are subjected to different statistical corruption that may be additive and/or multiplicative due to thermal noise/impulsive noise, signal fading and interference, as mentioned earlier. In cooperative communication, each node (Source/Mobile Station and Destination/Base Station) of the system act like an antenna element of a virtual MIMO system, this is very useful to achieve the required diversity and optimum capacity of channels at low cost. These relays serve as virtual MIMO antenna elements to form beams of transmission through direct transmission and indirect transmission from the relays. At destination node two beams impinge on multiple antennas, where signal combining is performed to acquire the full benefit of diversity. Hence, the information capacity of wireless network improved considerably. Cooperative communication is a promising technique that can overcome the problem of fading by combining multiple replicas of the transmitted signal for mobile communication systems. Moreover, signal combining is not only an important aspect of cooperative communication but also essential in of other data communication systems, like: satellite communication, optical fibre communication and radar.

An advanced wireless/mobile network operates in a licensed band, consisting of a wireless receiver with MIMO system, transmitting and receiving digital information over a wireless Rayleigh channel. The mobile station communicate with each other through a trans-receiver, which is responsible for maintaining a wireless connection. In general, a wireless trans-receiver ensures that the communicating mobile devices are always connected with sufficient power in an uplink and downlink device, so that the information exchange is uninterrupted. But as we increase the power of a system, inter cell interference also increases particularly in uplink communication. In the down link, if we increased the power, the intra cell interference cause signal distortion. Therefore, typical commonly used Nokia equipment only operated at about 50 percent of the transmitting power (40 Watt). Strict power control has been used in practical systems to reduce interference which causes low receive power compared to channel noise at receiver. On destination node multiple antennas receive the signals through various communication paths and combined by using one of the available signal combining methods. However, the levels of noise/interference on various receive components are different, especially in the case of wireless communication. The effect of these unequal noise variance more prominent in signals that operate under low to noise ratio in wireless systems. The strength of the signal envelopes varies as they reaches the wireless receiver where unequal noise of the channels are added to the signals from the communication channel. The signal strength depends upon the travel distance to the receiver, the interference experienced in the multipath channels, Gaussian noise and the Doppler shift of the signal envelope. All these factors cause signals to reach the receiver at different instants of time, that also make the communication asynchronous. The usefulness of the information symbols at the receiver depends on how much of transmitted data is recovered based on a receiver combining and detection algorithms. Usually combiner performance is evaluated in a Gaussian, flat fading Rayleigh and frequency selective Rayleigh wireless communication channels. In non adaptive algorithms, MRC and its driven form are used and practically implemented in most the present mobile communication systems. For the adaptive implementation of signal combining, two adaptive algorithms on a linear transversal filter commonly have been used in past literature and for practical application: least mean square (LMS) and recursive least square algorithm (RLS). Many researchers proposed a different derived forms of these algorithms in the past literature to improve the performance and most of the work on the problem of unequal channel noise variance was never addressed by the researchers. And it is commonly considered that the communication channels are with Additive White Gaussian Noise (ADWGN) with zero mean and unit variance. Therefore, environment un equal channel noise variance is assumed throughout this research.

The benefit of adaptive implementation is computational simplicity, which is less than maximal ratio combining and optimum combining (Wiener). Specifically, the LMS adaptive algorithm is simplest in computational complexity. This research reveals that the performance of combining of signal fully depend upon the correct noise estimation, therefore, respective channel noise variances are used for the proposed algorithm weighted least square (WLS) error method of signal combining. Based on the result of variance dependence on accurate signal combining, the literature has been reviewed and it is discovered that WLS error method uses the factor of noise variance for estimation in different practical applications. The least square methods (LSM) were commonly used in past and useful techniques of estimation. There are many reasons which make it favourite for various estimation techniques. First, the common estimators like adaptive filter, MMSE and Wiener can be implemented within this framework. Second, using squares makes LSM computation simple and mathematically tractable, because the Pythagorean Theorem shows that when the mean square error is independent of an estimated quantity, one can add the square of error and square of the estimated quantity. Third, the mathematical derivatives, eigen decomposition and singular value decomposition have been well investigated from about a century ago. LSM probably is one of the oldest techniques of advanced estimation theory, and even its advent is dated back to Greek mathematics, the first modern scientist who used this method was probably Galileo. The modern approach was first reported in 1805 by the French mathematician Legendre. Gauss was another famous German mathematician who competed with Legendre's work and published a research work, in which he mentioned that he has discovered LSM and used it as early as 1795 in estimating the orbit of an asteroid. The use of LSM in a modern statistical framework can be traced to Galton in 1886, who used it in his work on the heritability of size, which laid down the foundations of correlation and named it as 'regression analysis'. Two scientists that had presented a brilliant work in statistics, were Pearson and Fisher. They used and developed it in different contexts in factor analysis for Pearson and experimental design. Nowadays, the LSM is widely used to estimate the numerical values of the parameters to fit a function to a set of data and to characterize the statistical properties of estimates. It exists with several variations. Its simpler version is called ordinary least squares (OLS). Throughout this thesis, it is named as un weighted least squares error method. More accurate version of OLS is called weighted least squares (WLS), which often performs better than un weighted least squares because it uses variance factors of error for each observation. The other suboptimum variations of the least square methods are alternating least squares and partial least squares. WLS has been used for fitting the curves in econometrics [93-100] and for mathematics [101-105]. Some researchers used this method for focusing of the beam [105][106] in various applications without knowing the importance, upper bound of the system performance and its application for signal combining. Weighted Least Squares Image Matching based tracking algorithm was given [107]. In [108][109], researchers had proposed a simple recursive solution to passive tracking of manoeuvring targets using time difference of arrival measurements. The FIR and IIR filter design on the basis of this method were given in the literature [110-123]. During the research investigation, it is observed that WLS error method of signal combining never used previously for signal combining. Therefore, a research related to WLS error method of signal combining is carried out in the context of unequal channel noise variance. Chapter-6 of this research thesis presents WLS error method of signal combining and the investigation of its performance upper bound in various wireless channel models. It is also shown that for the better combining of signal WLS error method is superior than all other signal combining methods. It is computationally simple and only require the estimates of channel noise variance at each branch of the combiner.

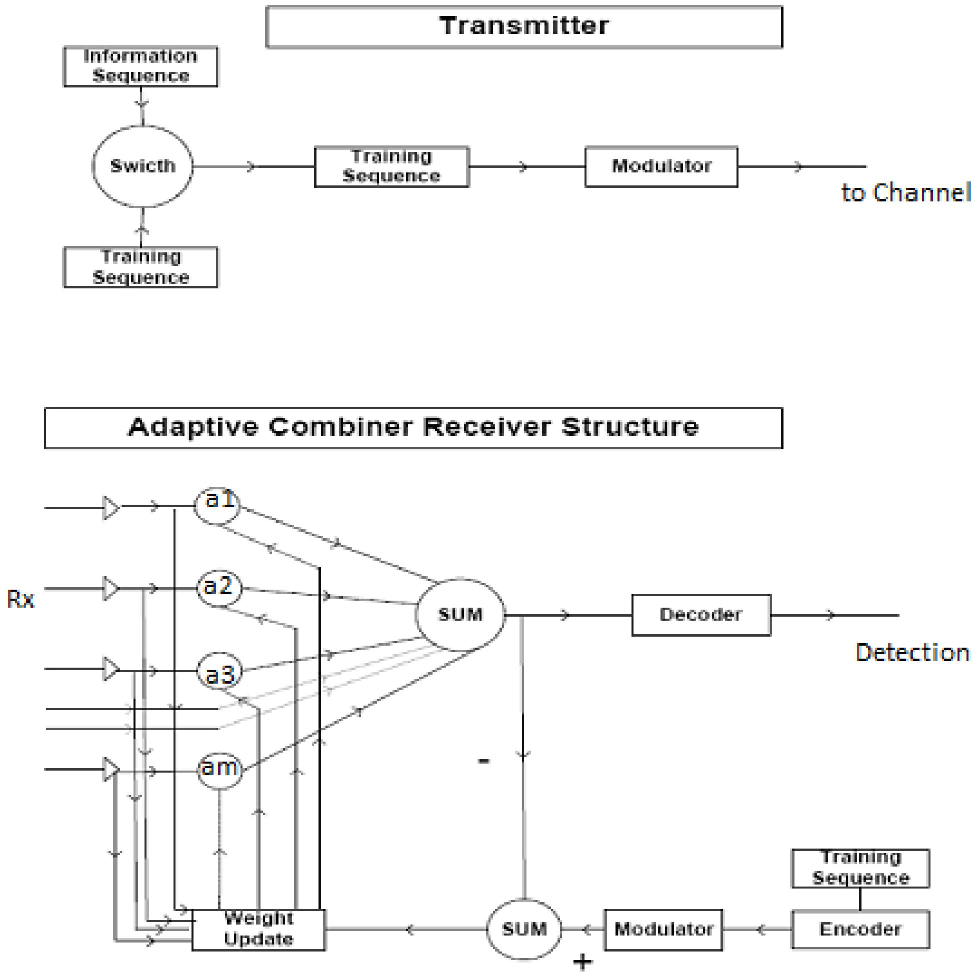

Figure 1.3: Existing (classical) system of transmitter and adaptive combiner:

- Transmitter sends modulated information signals through wireless channel, where signals disperse into multiple paths.
- Receiver collect the disperse energy of the signals with multiple antennas and combine them by using different adaptive algorithms.
- Classical systems assume that the Gaussian channel noise is with zero mean and unit variance.

1.3 Problem Statement

The importance of research and development is vital for the progress of science and engineering. The growth of wireless communication technologies has been exceptional in the last decade and it is predicted that the demand for these technologies will increase dramatically in coming years. Therefore, it is required to broaden the vision of wireless engineering by developing advance techniques at all layers of the wireless network, particularly at physical layer of wireless networks, where accurate and correct algorithms must be used. A little improvement in performance at the physical layer dramatically improves overall output of the wireless networks. To meet increasing demand, many efforts have been made in past research literature by using various techniques, as mentioned in the start of this chapter. The aim of the all schemes is to reduce the communication bit error rate, so that information capacity can be fully achieved during the communication. The computational complexity is also very important factor in designing algorithms for signal processing. The complexity further increases in cooperative wireless networks, particulary when network size grows and feasibility of implementation becomes very difficult. Most of the proposed signal combining and multiuser detection schemes presented in past literature are too complex to implement in cooperative wireless networks. Therefore, it is required to present combining and multiuser detection that are not only effective in all conditions of a communication channel but also computationally simple. Moreover, most of the performed work by the researchers was designed for synchronous systems, whereas in reality, signal arrived on antenna device incoherent in time and space. Therefore, it is required to design systems which can effectively combine and detect in the asynchronous communication systems.

Another important problem in wireless systems is the unequal channel noise variance, which exist in cooperative and non-cooperative wireless networks. During the detailed literature review it is observed that this problem is never addressed properly and overlooked, particularly when combining the signals were performed. Therefore, it is also required to develop algorithms (adaptive or non adaptive) for detection and combining of the signals, according to their respective channel noise variance. There were many technique previously used in past literature and practically implemented in a multi cellular environment both in cooperative and non cooperative wireless networks, but still there is a need of developing cooperative wireless networks with adaptive signal combining and detection. Adaptive signal combining, weighted least square method and A-MMSE-MUD in cooperative wireless networks are some possible research directions that can combine and detect the received signals to provide diversity and remove multiple access interference (MAI) in cooperative wireless networks. The outcomes of this research would bring optimization in existing wireless communication systems (2G and 3G). Also, they would be useful for next generation (4G and 5G) of wireless networks.

1.4 Key Contribution of the Thesis

In this research a number of innovative contribution are presented, some of the important contributions of this thesis are as follows:

- In this research A-MUD technique adaptive minimum mean square multiuser detection (A-MMSE MUD) is developed in cooperative networks, which is used for non cooperative wireless networks in past literature and wireless systems. The presented scheme is a computationally simple mathematical algorithm for signal detection which reduces the complexity, whereas previous versions proposed by other researchers are computationally complex and not feasible for practical implementation in cooperative wireless networks. Basically, an asynchronous cooperative CDMA wireless network uplink transmission with A-MMSE-MUD is developed and analysed. Two protocols of cooperative communication wireless networks are used, (i) Amplify-and-Forward (AF) at relays of the network and A-MMSE-MUD at destination (ii) A-MMSE-MUD at the relays and destination in a Decode-and-Forward (DF) operation. Two performance measures: System's information capacity and bit error rate (BER) are used to assess the improvement in communication system. The comparison of the information capacity and BER performance of the proposed detection method with other multiuser detection schemes under the same conditions are presented and basically: AF strategy is used at the relays and A-MMSE-MUD at the destination, in an asynchronous cooperative communication networks. The system's BER performance, in terms of improved SNR is better by several dB at the BER 10^{-3} to 10^{-5} . The information capacity benefit is about 1.5 bit/sec/Hz, from 5dB to 30dB SNRs. These results provide significant improvement in comparison to existing multiuser detection techniques in such wireless networks. This research has also dealt with a realistic scenario of asynchronous transmission in uplink of CDMA wireless communication system, whereas, most of the previous work was for a synchronous system. The developed A-MMSE-MUD can provide high speed communication by fully utilizing existing bandwidth spectrum. This technology can be used for next generation(4G and 5G) wireless networks. The analysis and results were published as peer referenced conference papers [123][124].

- In second major contribution of this research thesis, adaptive signal combining with LMS and RLS algorithms in cooperative wireless networks in presence of equal and unequal noise variance is presented. It is shown that significant gain can be achieved by using the adaptive algorithm with additional benefit of computational simplicity. The direct consequence of this gain is improvement in information capacity and BER improvement in comparison to conventional methods of signal combining. The information capacity and BER benefit is more significant when there is a difference of signal to noise ratio of combining signals which is very common in cooperative communication wireless networks. Adaptive LMS and RLS algorithm are used and their performance analysed with computer simulation in different wireless channels in terms of ensemble average mean square error and BER. It is expected that this research result will be used to provide ultra high speed communication facilities in the 4G and 5G wireless devices [125][126].

- In the third major contribution, an innovative Weighted Least Square Method of signal combining for wireless communication is proposed and analysed, which can be used for cooperative and noncooperative wireless networks. The algorithm of the proposed method of signal combining was used for target tracking and curve fitting in previous research literature and related practical implementations. The proposed method has better performance than all other signal combining schemes and applicable in the realistic wireless networks, where we have unequal channel noise variance. It is the simplest in computational complexity and achieved the Wiener's solution (optimum) performance of signal combining. Whereas the maximal ratio combining is unable to provide the required performance, due to unequal channel noise variance presence in the receiver systems. A mathematical algorithm is developed for the proposed method and computer simulations are used to verify the performance in various channel models. The research work were also published as peer referenced journal paper [127].

1.5 Thesis Outline

This thesis constituted of the following parts: Chapter-1 describes a brief introduction, chapter-2 represents some of the fundamental cooperative diversity concepts, cooperative protocols and methods. Chapter-3 presents an adaptive multiuser detection technique by using A-MMSE-MUD in cooperative wireless networks. The mathematical derivation and computer simulation performance of Information Capacity/BER is also presented in chapter-3. Chapter-4 presents interference resistance of the A-MMSE-MUD scheme in cooperative relaying networks and its computer simulation performance. Chapter-5 presents the performance of various classical combining schemes including adaptive signal combining in cooperative wireless networks. Chapter-6 presents weighted least square algorithm for signal combining, which is equally useful for cooperative and non cooperative wireless networks. Chapter-7 summarises the conclusions and points to the areas for possible future research. In appendices the developed system's MATLAB code are given.

Chapter 2

COOPERATIVE DIVERSITY

2.1 Relaying Methods in Cooperative Wireless Networks

The relaying methods are the most important aspects of cooperative wireless networks. In relaying methods every node of the wireless network supports to forward communication data towards destination nodes by using the antenna of the relays. The function of the relays is to remove the channel distortion, noise effects and reconstruction of the signal by amplification or by decoding before further transmission. In this section, commonly used methods for relaying in cooperative wireless networks are described that commonly available in previous literature. As mentioned earlier, combining and detection are two fundamental techniques to improve the performance but there are some other factors that also affects the system performance. One of these factors is the use of relaying protocols at relays to obtain full benefit of diversity. Many relaying protocols/methods are used for cooperation in past literature, but here only two of them are described as they have been used throughout this research. They were wildly analysed and used by previous researches. All of the relaying method are complex and increase computational complexity. Therefore, we have to select them carefully when implementing in cooperative wireless networks with common multiuser detection techniques. With the use adaptive combining and detection schemes, we can fully obtain the benefit of the relaying scheme to improve communication performance. Typical cooperative relaying network model is shown in figure 1.4.

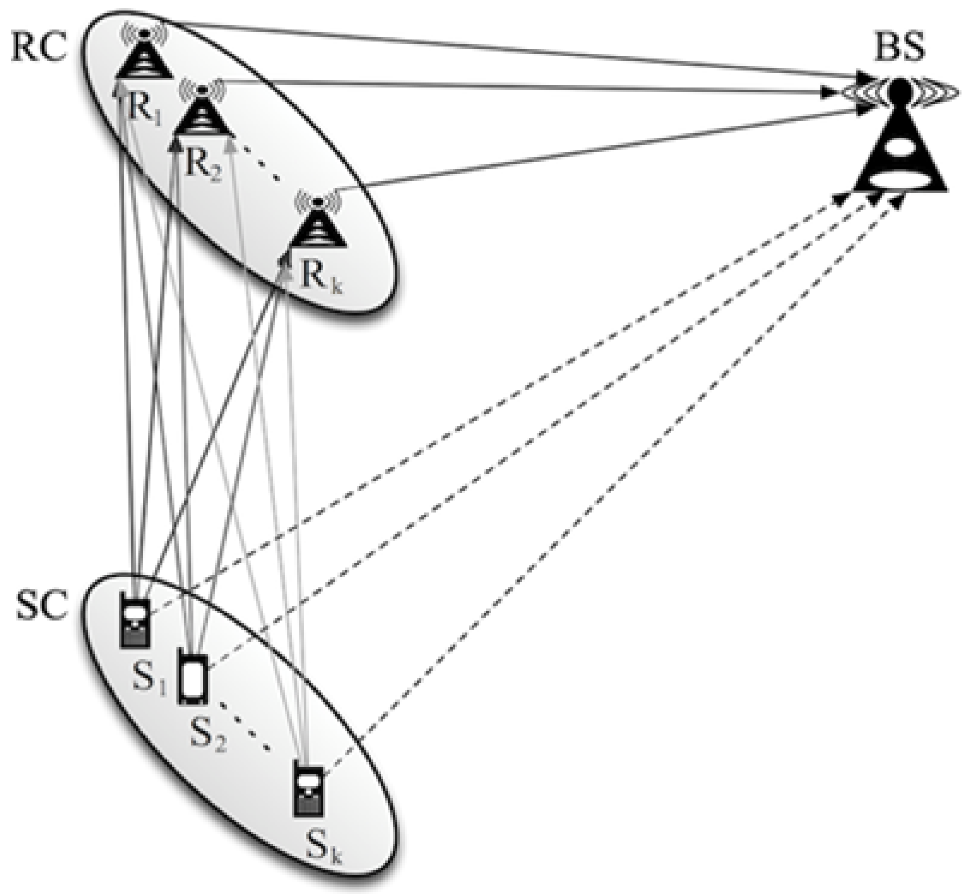

Figure 2.1: A cooperative relaying wireless network model:

- Source cluster of wireless users transmit signals to relays cluster for onward transmission to the destination node. There is also a direct transmission of the signals from source cluster to the destination.

2.1.1 Decode-and-forward (DF) Protocol

In DF relaying method/protocol, a cooperating node (relay) first decodes signals received from a source and then relay/retransmit them. The receiver at the destination node receive the signal beam from multiple relays (relays link) and a signal beam directly from sources (direct link) to combine and detect. This type of cooperative protocol is ideally useful when the channels from source to relays are Gaussian, which is most probable in urban cellular mobile and wireless line of sight communication. For other channel environments, it is greatly possible that cooperating node decode symbols with too many errors, resulting in error propagation at 'sources to relays' link. Perfect regeneration at the relays may require retransmission of symbols, the use of forward error correction or other error correction algorithms depends upon the quality of the channels between the source-to-relay links and selection of new relay cluster by sources. This protocol is not suitable for delay limited networks. In this method, which is also used in this research, a single mobile user transmits data symbols to multiple relaying nodes to obtain the benefit of virtual multiple antenna system. And then decoding is performed at relays. The number of errors in received symbols are completely dependent upon the channel quality.

2.1.2 Amplify and Forward (AF)Protocol

In this relaying method/protocol each cooperating node receives the signals transmitted by the source nodes and transmits the same envelope of signal with an amplification of the signal by using advance signal processing techniques instead of decoding. Signals in their noisy form are amplified to compensate for the attenuation suffered between the source-to-relay links and retransmitted with unequal noise variance. The destination requires knowledge of the channel state between source-to-relay links to correctly decode the symbols sent from the source, which is coordinated by typical training sequence (pilots) from the transmitter. If the adaptive implementation is performed then the channel state information is not required at transmitter or receiver. This relaying method required complex signal processing such as sampling, amplifying and retransmitting analogue values, which has been successfully performed by various advanced signal processing methods. This protocol avoids error propagation and retransmission at relays, but produces unequal noise amplification in signals. This protocol is also used in this research.

2.2 Signalling Techniques in Cooperative Wireless Networks

In this section some of the most common signalling techniques available in previous literature are described, which have been used at relays of cooperative wireless networks. Signalling technique is also an important factor for the quality of the communication in wireless networks, particularly, when we use non adaptive systems for detection and combining. These techniques have been used for MIMO and commonly available in past literature. In this research transmit beamforming is used for non adaptive detection techniques for performance comparison with adaptive techniques due to its common use in previous literature and simplicity of implementation. For proposed A-MMSE-MUD, channel estimation is coordinated by a training sequence. Therefore, the signalling is performed by training sequence and it does not require any other method for signalling at relays. Based on fundamental relaying methods/protocols (AF and DF), architectures (multiple sources and multiple relays) and signalling strategies (STBC and transmit beamforming) most of the research on cooperative communication has been focused on the performance improvements over traditional methods of multi-hop communication in the asymptotic regime.

2.2.1 Distributed Space-Time Coding

This type of signalling is similar to the space-time block coding (STBC) technique commonly used in MIMO antenna systems. In this scheme cooperative nodes encode the signal using STBC, such that each node transmits a column of the block code. Extensive research work has been performed in previous literature to explore the benefit of these coding schemes [128-134]. The advantage of using space-time coding is to fully obtain the benefit of spatial diversity available in cooperative wireless network in a bandwidth efficient manner by sending signals in sequences of particular code (called space time block code). This processing is usually performed on the high cost of computational complexity of systems and complexity grows with network size growth. Many authors in the past also presented the derived form of this type of transmission strategy by fundamentally following the same principles. Early techniques were consisted of scalar coded methods like repetition diversity over orthogonal frequency bands and bandwidth conserving schemes such as time shifting and phase sweeping diversity. Later developments in this area saw the emergence of vector coding for multi-antenna systems presented by Alamouti [134] on the simplest block codes that achieve full diversity and were relatively computationally simple. In general this type of coding is very useful not only for MIMO systems but also for cooperative wireless networks (virtual MIMO). However, it increases the wireless network's complexity, particularly when wireless network size grows with the increase of cooperative nodes. The practical implementation of this system is not feasible for cooperative wireless networks (5G), as recently reported in [135][29], where channel estimation base cooperation was preferred for practical implementation. In this research adaptive signalling is used, which is one of the method of channel estimation base cooperation, which provide the same performance as STBC signalling, while computational complexity of proposed adaptive processing is much lesser than STBC signalling.

2.2.2 Distributed Transmit Beamforming

Distributed transmit beamforming scheme has been used for wireless sensor networks. In transmit beamforming, the channel state information is assumed to be available at the transmitter. It use the routine training signals during the transmission. This scheme is particularly useful to increase average SNR at receiver in the environments, where spatial diversity gains are limited, for example air-to-ground communication. However, to implement beamforming in cooperative wireless network, a continuous feedback of channel state information (CSI) at each of the cooperating nodes is required. In practice, obtaining channel state information on relays is extremely complex. Therefore, an adaptive version of transmit beamforming [136] is a better approach, where channel estimation performed by a training sequence. We can use adaptive beamforming at the transmitter to produce the same performance as classical technique of beamforming. Another option is to use adaptive combining at the receiver of destination node. Therefore, throughout this research adaptive combining is used, which does not require any channel state information and signaling technique at relays . This research has also observed that adaptive signal combining is better than received MRC. Therefore, one can easily predict that adaptive beamforming at the relays is better than transmit beamforming. This topic of research is beyond the scope of this work, but it can be explored in future research.

2.3 Channel Models

Following are some of the channel models that have been used in past research for non-cooperative and cooperative wireless networks. This research has used them to examine the performance of various the presently available and the proposed algorithms.

2.3.1 Gaussian Channel

In this channel model the fading of the communication signal at the receiver is only caused by Gaussian distribution of noise, which is due to various factors including air/atmosphere, receiver and transmitter circuits. This noise causes additive impairment in the received signal. Most of the previous works assume this noise was equal in all channels with zero mean and unit variance, but in reality it is unequal and different at each receive branch of a multiple antenna system. Therefore, it is more realistic to assume unequal noise variance for additive white Gaussian noise. In previous section the sources of Gaussian noise were discussed in detail. Chapter 6 of this research particularly addressed a realistic scenario of unequal channel noise variance, where signal combining and detection at low signal to noise (SNR) region are examined. In this research the channel model for the fading of the signal-symbol at the receiver is taken as Gaussian distribution. The discrete Gaussian channel model is used to describe the fundamental information capacity of a digital wireless system. The transmitted communication signal is assumed to fade across the entire frequency spectrum, linearly. Since the interference is assumed to span across the bandwidth of the entire spectrum in use for the communication channel, the receiver is assumed to recover base-band information, leaving only unequal AWGN in channels. The pass band analysis resulted in a complex variable, but at base band however, only the one sided real component of the power spectrum is considered to save energy to meet the energy or power constraint. This is the most common limitation on the input of energy or power. In a coded system over a Gaussian channel, a symbol is assumed to have an average power constraint. In a Gaussian channel the additive noise is caused by variety of factors, but by the central limit theorem, the cumulative effect of a large number of small random effects will be approximately normal, thus a Gaussian assumption is valid. In cooperative wireless networks the Gaussian channel can be established with any two communicating line of sight nodes. The whole network management by using protocols on all layers of cooperative transmission is to ensure availability of the maximum number of Gaussian (line of sight) channels within the networks. Wireless channels are usually Gaussian in short range, line of sight and satellite communication. The cellular mobile phone systems in dense urban areas have a great probability of obtaining a Gaussian channel from neighbouring mobile phones for relaying. Wireless sensors systems can be embedded in a sensing environment on the same principle to obtain Gaussian channels. The degradation in performance of a system is usually due to multipath propagation which can be removed by setting proper network protocols at all layers of cooperative wireless networks to obtain communication through Gaussian channels. The choice of protocol for cooperative wireless network is very important to obtain Gaussian channel for the communication.

2.3.2 Flat Fading Raleigh Channel

Wireless signals propagate through extremely unfavourable random channels, which does not allow the simple AWGN channel assumption. Therefore, we have to analyse the system performance in a Rayleigh channel before the practical implementation of the system. A Gaussian channel with zero mean and unit variance provides us with the theoretical achievable upper bound of the information capacity. The research aim is to design systems that obtain the performance close to the upper bound. Radio signals propagate by means of reflection, diffraction, and scattering, which result in three effects: attenuation, large-scale shadowing, and small-scale fading. It is assumed that all three effects are independent of each other. Signal attenuation depends upon the distance between the transmitter and the receiver. It is inversely proportional to distance, which can be predicted by a deterministic model. Large-scale shadowing of a signal is mainly caused by multiple reflections and/or diffractions of the signal during transmission. These characteristics can be modelled as a log-normal distribution. Multiple versions of a transmitted signal with different delays, such that it has time and location varying property, cause small-size fading. One of the type of channel with the fading phenomenon is due to multi-path time delay spread called a flat fading channel. In which the period of the transmitted signal is greater than the multi-path delay spread. In simple terms channel can be termed as flat fading when multi path channel has only one tap. And the convolution operation reduces to a simple multiplication due to this assumption. The received wireless signal power varies significantly in a flat fading channel, it is very important to accurately capture the distribution of the channel gain in designing a wireless system. The most common used signal amplitude distribution in flat fading channels is the Rayleigh distribution, which is used to test various presented and proposed systems of this research.

2.4 MIMO System Capacity

The capacity of a digital communication system is defined by its ability to reliably transfer digital information bits over the communication channel. It is known as the Shannon-Hartley theorem of information capacity. In Gaussian channels, it was shown that information capacity **C** is represented by the following equation:

$$\mathbf{C} = \mathbf{B}\log_2(1 + \frac{\mathbf{S}}{\mathbf{N}}) \tag{2.1}$$

Where **B** is the bandwidth of the communication channel, the signal **S** and noise powers **N** measured in watts. It can be observed from the above definition that the upper bound of digital information capacity is intrinsically tied to the communication channel over which reliable information transmission is being attempted. The signal and noise associated with a received information bit cannot be separated and hence is referred to as the signal to noise ratio (SNR). The channel capacity is defined as the upper bound on the amount of information can be transmitted over communication channel. The popular formula for the Shannon capacity expressed in bps/Hz is given by:

$$\mathbf{C} = \log_2(1 + \rho \cdot |H|^2) \tag{2.2}$$

Where $|H|^2$ is the normalized channel power transfer characteristic. Here ρ represents SNR. From this formula it is obvious that for high SNRs a 3 dB increase in ρ gives another bit/cycle capacity. Information capacity of a system is a very important measure in designing wireless communication systems. Using multiple antennas at the transmitter and the receiver is one of the techniques which improve information capacity dramatically. The information capacity formula for a MIMO channel with random signatures establishes a missing link between the classical Shannon channel capacity formula for a point to point communication system and the cellular mobile communications scenario. In addition to Telatar and other research work, the random signature MIMO (RS-MIMO) channel capacity analysis was presented in [137], where a set of implicit system design rules could be drawn leading to the cellular mobile system design achieving Shannon capacity of the point to point communication. If the number of independent antennas in the receiver are m, then the capacity is increased m times in comparison with a single antenna system even in the presence of mutual interference. A study of the multi-antenna system, specifically the adaptive antenna array systems provides useful insights into capacity achieving MIMO systems compared to other MIMO systems, such as beamforming or multi-sector receive antenna systems. Therefore, the use of MIMO is justified by adaptive antenna array systems in wireless communication systems. To examine the performance, simulated Bit Error Rate (BER) performance usually computed, which can be measured by applying hard decision decoding to the received data stream at the output of the various types of filters. The capacity performance in computer simulation of the system in terms of the output minimum mean square error (MMSE) is given by the following equation [19].

$$\mathbf{C} = \frac{1}{2} \log \frac{1}{\epsilon_0} \tag{2.3}$$

The fundamental relationship between information capacity and MMSE forms a base-line in understanding the context of MMSE estimation. The information capacity of an MMSE receiver with output is given by the above equation where ϵ_o is the output MMSE and information capacity **C** is the maximum data rate achievable with an increasingly small probability of error. To examine the information capacity in term of MMSE estimate, the analyses and computer simulations were presented for the performance of various filters in [138], the detail of the presented analysis are beyond the scope of this research thesis.

Chapter 3

ADAPTIVE MINIMUM MEAN SQUARE ERROR MULTIUSER DETECTION IN COOPERATIVE CDMA WIRELESS NETWORKS

3.1 Introduction

Multiplexing techniques provide multiusers to share the resources of channels in time and frequency domain. Wireless and mobile Code division multiplexing access (CDMA) systems are most popular schemes among existing 2G and 3G wireless/mobile systems. 3G wireless systems are based on CDMA technology. Propagating CDMA signals face various destructive factors during the transmission. Fading is one of the problems, which occurs in the communication due to multipath propagation of waves and severe signal attenuation. MIMO antenna configuration has been used for decades to overcome fading problems by sending multiple versions of the original signal. As it was described in previous chapter that cooperative communication wireless network is a virtual MIMO scheme. In that scheme each node of the wireless network acts as an antenna element of a virtual MIMO system. Cooperative Wireless systems basically use three fundamental ideas (i) use relays (single or multiple hop) to provide spatial diversity to overcome fading environment, (ii) set a protocol at relay to sends information to a specific node of network and form a virtual MIMO antenna array, where each user act as an element of antenna array and (iii) on destination node use of multiple antennas to combine signal beams received from different paths. This chapter presents the research work of cooperative CDMA wireless network with A-MMSE-MUD algorithm, which was examined with two cooperative protocols DF and AF. CDMA Multiuser detection (MUD) techniques can deal with the de-modulation of digitally modulated signals in the presence of multiuser access (MAI) interference. Early MUD schemes was presented for non cooperative CDMA networks by [10-12] [19] and later for cooperative communication wireless networks in [22][24][56] MUDs to mitigate MAI. A-MMSE-MUD was proposed in [19][20][28] for non cooperative. The motivation of this research is to develop a cooperative CDMA wireless network by using A-MMSE-MUD to eliminate MAI, when cooperative protocols AF and DF are applied.

A-MMSE-MUD receivers are very capable of estimating and detecting the system parameters such as signal delay/timing, signal phase, signal amplitude, signatures, multi-path channel profile and the number of users. In CDMA system, usual training routine is operated by the transmitter for estimation and detection. For low numbers of users, classical detection schemes using matched filters are very effective but as the CDMA wireless networks size grows the performance decreased exponentially, whereas the performance of the A-MMSE-MUD technique is linear and its computational complexity increase with the increase of the user, linearly. The linear performance of A-MMSE-MUD means that the performance of the scheme decreases linearly with the increasing the number of wireless/mobile users in CDMA systems. It was also found that A-MMSE-MUD technique is also useful in interference mitigating aspects, which will be covered in next chapters. The cooperative schemes are shown and analysed in this research are:

- A simple A-MUD technique A-MMSE-MUD is developed and its simulation performance is examined for eliminating MAI in a cooperative wireless CDMA network.

- An AF strategy is used at the relays and A-MMSE-MUD detection at the destination node in an asynchronous cooperative wireless CDMA network. This system's BER performance is about 10^{-3} at a SNR of $10dB$ while the channel information capacity performance is nearly $4bits/s/Hz$ at the same SNR. This system's BER performance is about 10^{-5} at a SNR of $20dB$ while the channel information capacity performance is nearly $8bits/s/Hz$ at the same SNR.

- An A-MMSE-MUD DF strategy is used at the relays and an A-MMSE-MUD decode at the destination, in an asynchronous cooperative wireless network. This system's BER performance is about 10^{-4} at a SNR of $10dB$ while the channel information capacity performance is nearly $6bits/s/Hz$ at the same SNR. This system's BER performance is about 10^{-5} at a SNR region of $17dB$

while the channel information capacity performance is nearly $9bits/s/Hz$ at the same SNR.

The rest of the chapter is organized as follows: The presented model for a cooperative wireless CDMA system used in the research is given in section 3.2. Proposed A-MMSE-MUD for the networks is in section 3.3. Performed computer simulation experiments and performance comparisons are shown in section 3.4. Finally, concluding remarks for the research are described in section 3.5.

3.2 System Model

To understand about the performed research work of A-MMSE-MUD techniques in cooperative wireless, consider a wireless network where K wireless/mobile users, denoted by $S_1, S_2, ..., S_K$, serve as sources and L wireless/mobile users, denoted by $R_1, R_2, ..., R_L$ serve as relays. All sources broadcast data to the relays, where further processing is performed by amplification to boost the signal power or MUD is performed to detect the signal. Relays further transmit signals to the destination node or base station for MUD as shown in figure 3.2. A typical cooperation strategy is modelled with two orthogonal phases, to avoid interference between the two phases [57].

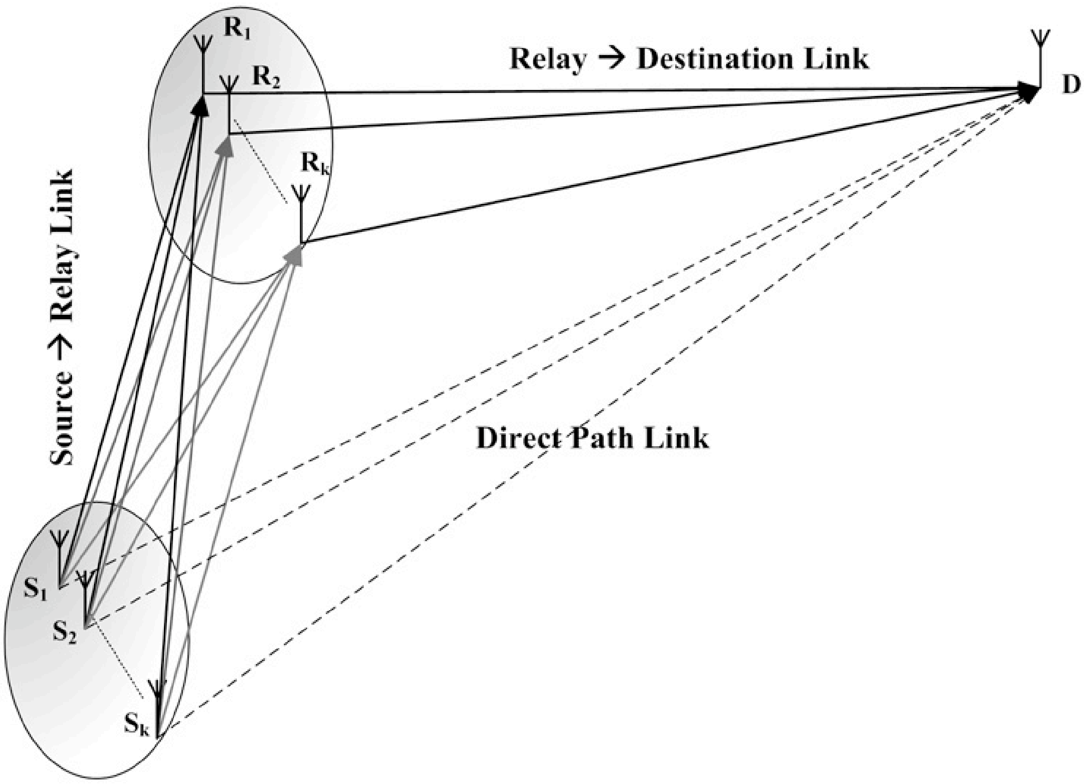

Figure 3.1: General system model of a presented cooperative wireless CDMA network:

- Source cluster $S_1, S_2, ..., S_K$ transmit data to relay cluster $R_1, R_2, ..., R_L$. Relay cluster further transmits the same data to the destination D. Source cluster also transmits directly to the destination. On the destination two beams from Relay Link and Direct Path Link are combined. And further signal detection is performed by A-MMSE-MUD.

3.2.1 Phase I (a): Transmission from Sources to Destination

In Phase $'Direct - Path - Link'$ I (a), each source 'K' transmits a message with N data symbols to the destination 'D'. Let $\mathbf{x}(n) = [x_1(n), x_2(n)..., x_K(n)]^\dagger$ be the BPSK data symbols transmitted by sources $S_1, S_2, ..., S_K$ during the n^{th} symbol period, where $x_k(n) = \{-1, 1\}$ for k^{th} user and:

$$\begin{aligned}\mathcal{E}[\mathbf{x}(n)\mathbf{x}(p)^\dagger] &= \mathbf{I}_{(K\times K)}, \quad if\ n = p \\ &= \mathbf{O}_{(K\times K)}, \quad otherwise\end{aligned}$$

Here p is time interval other than n. **I** represents the identity matrix and **O** represents null matrix of the order of $K \times K$. Let P_{S_k} be the power transmitted by k^{th}source S_k and let $\mathbf{s}_k(t)$ be the spreading waveform(signature) of S_k. Under the asynchronous CDMA signal assumption, the CDMA signal received at the destination node in the presence of additive white Gaussian noise may be expressed as

$$\mathbf{y}_I(t) = \sum_{n=1}^{N}\sum_{k=1}^{K} \mathbf{h}_{S_kD}(\sqrt{P_{S_k}})x_k(n)\mathbf{s}_k(t - nT - \tau_k) + \mathbf{v}_I(t) \tag{3.1}$$

Where T is symbol period, $\mathbf{h}_{S_kD}$ is the complex channel co-efficient from S_k to D and τ_k is the transmission delay of the k^{th} user. This research has assumed a block fading environment, where channels coefficient remain constant for N-symbol block and are independent and identically distributed (i.i.d) from block to block. The channels coefficient $\mathbf{h}_{S_kD}$ is assumed to be zero mean circularly symmetric complex Gaussian (ZMCSCG) and variance $\sigma^2_{S_kD}$, i.e., $\mathbf{h}_{S_kD} \sim \mathcal{CN}(0, \sigma^2_{S_kD})$, and is assumed to be independent among sources. And $\mathbf{v}_I(t)$ is the additive white Gaussian noise (AWGN) with distribution $\mathcal{CN}(\mathbf{O}_{K\times 1}, \sigma_v^2\mathbf{R})$. If s is the spreading gain, the spreading gain waveform for $\mathbf{s}_k$ is given by:

$$\mathbf{s}_k(t) = 1/\sqrt{s}\sum_{i=1}^{s} \mathbf{c}_k(t)\psi(t - iT_c), k = 1, 2..., K \tag{3.2}$$

where $\mathbf{c}_k(i)$ is the i^{th} element of the ± 1 spreading sequence assigned to S_k, and $\psi(t)$ is the normalized chip wave form with unit energy and duration $T_c = T/s$. Here T is the symbol duration.

The digital baseband signal received by first branch of signal combiner (Direct Link) of the destination node, is given by $\mathbf{y}_I(n)$. On the destination node, proposed A-MMSE-MUD is used to detect data symbols. The detail of A-MMSE-MUD is described in section 3.3. This research has proposed to use K adaptive MMSE filters instead of matched filters to detect the received signals. The A-MMSE-MUD used on each node of the wireless CDMA network. Also matched filter, decorrelator, MMSE and relay assisted decorrelator are examined by the computer simulation for the comparison.

3.2.2 Phase I (b) Transmission from Sources to Relays

Each source broadcasts the message with N data symbols to the relays $R_1, R_2, ..., R_L$ is called $'Source-Relay-Link'$. The signal is also observed at the adaptive MMSE or filters bank at ℓ^{th} relay during the n^{th} symbol period. It is given by

$$\mathbf{y}_{I'}(t) = \sum_{n=1}^{N}\sum_{k=1}^{K}\mathbf{h}_{S_kR_\ell}(\sqrt{P_{S_k}})x_k(n)\mathbf{s}_k(t-nT-\tau_{k\ell}) + \mathbf{v}_{I'}(t) \tag{3.3}$$

Where T is symbol period, $\mathbf{h}_{S_kR_\ell}$ is the complex channel co-efficient from S_k to R_ℓ and $\tau_{k\ell}$ is the transmission delay assumed for the k^{th} user at the ℓ^{th} relay. The channel coefficient $\mathbf{h}_{S_kR_\ell}$ is assumed to be ZMCSCG and variance $\sigma^2_{S_kR_\ell}$, i:e, $\mathbf{h}_{S_kR_\ell}$ $\sim \mathcal{CN}(0, \sigma^2_{S_kR_\ell})$, and is assumed to be independent among sources. And $\mathbf{v}_{I'}(t)$ is AWGN with distribution $\mathcal{CN}(\mathbf{O}_{K\times 1}, \sigma_v^2\mathbf{R})$. The digital baseband signal received at relay node is given by $\mathbf{y}_{I'}(n)$, where A-MMSE-MUD performed. The detected symbols are given by $\hat{\mathbf{x}}_\ell(n)$. Symbols are transmitted again towards destination node with same spreading sequence. On destination node proposed A-MMSE-MUD is used to detect data symbols. The detail of A-MMSE-MUD is describe in section 3.3. Where, this research proposed to use K adaptive MMSE filters instead of matched filters to detect the received signals. The MUD techniques; A-MMSE-MUD, matched filter, decorrelator, MMSE and relay assisted decorrelator examined by the computer simulation for the comparison.

3.2.3 Phase II Transmission from Relays to Destination

In this phase (Relay Destination Link), ℓ^{th} relays forward the detected data symbols with the same spreading sequence of respective sources to the destination by transmit beamforming at relays. Let us assume that the detected symbols $\hat{\mathbf{x}}_\ell(n)$ in the previous section may be re-encoded into a symbol matrix

$$f(\hat{\mathbf{x}}_\ell) = \mathbf{t}_\ell(n) \tag{3.4}$$

Where f represents the function which is the use of signalling/coding scheme at relay as discuss in chapter 1. This research has used transmit beamforming for the match filter, decorrelator, MMSE and relay assisted decorrelator and a routine training sequence signalling for the A-MMSE-MUD. This research also assumed for the scheme that each relay transmits with the same spreading codes of users in time n:

$$\mathbf{t}_\ell(n) = [t_{\ell,1}(n), t_{\ell,2}(n)..., t_{\ell,K}(n)]^\dagger \tag{3.5}$$

The term in above equation is the symbol vector transmitted by R_ℓ during the n^{th} symbol period. One of the advantages of the A-MMSE-MUD technique is that it does not require the any signalling technique at relays like transmit beamforming or distributed space time block coding [56], the function of signalling being performed by a training sequence for the bank of adaptive filter at receiver. Therefore, the proposed system provides significant simplicity in a wireless network. Here $\mathbf{t}_\ell(n)$ entirely depends on the detected symbols. $\hat{\mathbf{x}}_\ell(n)$ are detected symbols re-encoded and further sent towards the destination as $\mathbf{t}_\ell(n)$. The observation signal on second branch (Relay Link) of combiner is given by:

$$\mathbf{y}_{II}(t) = \sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{\ell=1}^{L}\mathbf{h}_{R_\ell D}(\sqrt{P_{R_\ell}})t_{\ell,k}(n)\mathbf{s}_k(t-nT-\tau_\ell)+\mathbf{v}_{II}(t) \tag{3.6}$$

Where T is the symbol period, $\mathbf{h}_{R_\ell D}$ is the complex channel coefficient from R_ℓ to D and τ_ℓ is the transmission delay of the ℓ^{th} relay. The channel coefficient $\mathbf{h}_{R_\ell D}$ is assumed to be ZMCSCG and variance $\sigma^2_{R_\ell D}$, i.e., $\mathbf{h}_{R_\ell D} \sim \mathcal{CN}(0, \sigma^2_{R_\ell D})$, and is assumed to be independent among relays. $\mathbf{v}_{II}(t)$ is the AWGN with distribution $\mathcal{CN}(\mathbf{O}_{K\times 1}, \sigma_v^2\mathbf{R})$. The received digital signal for the indirect transmission is denoted by $\mathbf{y}_{II}(n)$. After the signal combining on the destination node, the signal obtained after combining at the input of decision device by adaptive filters during the n^{th} symbol period is given in section 3.3. For amplify and forward, amplification is performed at each relay to forward the received signals for MUD at the destination. Therefore, the observation signal of equation 3.7 is multiplied by amplification factor Amplify-and-Forward protocol γ, which is given in following by Laneman [24] in his famous research work:

$$\gamma \le \sqrt{\frac{P_{S_k}}{\mathbf{h}_{S_k R_\ell}P_{S_k}+\mathbf{v}_{I'}(t)}} \tag{3.7}$$

Thus the transmission equation from relays to destination in the case of AF is given by:

$$\mathbf{y}_{II}(t) = \gamma\mathbf{y}_{I'}(t) = \gamma[\sum_{n=1}^{N}\sum_{k=1}^{K}\mathbf{h}_{S_k R_\ell}(\sqrt{P_{S_k}})x_k(n)\mathbf{s}_k(t-nT-\tau_k)+\mathbf{v}_{I'}(t)] \tag{3.8}$$

The direct received signal beam $\mathbf{y}_I(t)$ and received beam through relays $\mathbf{y}_{II}(t)$ are combined before detection at the destination by different combining techniques. In coming chapter 5 and chapter 6 of this research thesis describes about the used and proposed various methods of signal combining.

3.3 A-MMSE-MUD in Cooperative Communication Networks

A simple mathematical algorithm is also developed which provide very very low computational complexity to detect receive data by A-MMSE-MUD. Different types of signal processing mathematical analyses were presented for channel pre-coding in [56], where a whitening filters at relays are used but with very high and nonlinear computational complexity.

In A-MMSE-MUD research investigation bank of matched filters are replaced by A-MMSE filters for channel estimation and detection. The research has adopted an alternative approach instead of the conventional approach for the detecting the signal by using a matched filter for each signal by ignoring the correlation between signals of different users. In single user detection every matched filters receiver is equivalent to an A-MMSE receiver [20][19], but for the multiple user bank of matched filters performance degrades non linearly. The term linear means that, when the mobile users increase the performance of detection degrade in a linear curve. To understand A-MMSE-MUD consider $\mathbf{y}_I(t)$ or $\mathbf{y}_{II}(t)$ is received analogue symbol of duration T at the input of a receiver on any B^{th} node (relay or destination) and $\mathbf{y}_I(n)$ or $\mathbf{y}_{II}(n)$ digital form of the signal from the output of analogue to digital convertor. Consider $\mathbf{y}(n)$ to be the received digital signal at any node of the network in respective received digital output of the symbol from the output in chip interval T_c. In a wireless communication environment, non-orthogonal transmitted signals from independent users arrive asynchronously at the receivers [28]. The delay causes further increase in non orthogonality of the spreading codes and the correlation due to non-orthogonality of spreading sequences further increases at receiver. The coefficient of correlation matrix $\mathbf{R}$ is given by:

$$\mathcal{E}[\mathbf{y}(n)\mathbf{y}^*(n)] = \varrho(s, s)$$

The digital output for the n^{th} symbol period on relays or destination nodes is given by:

$$\mathbf{y}(n) = \mathbf{Rh}x(n) + \mathbf{v}(n) \tag{3.9}$$

Here **R** correlation matrix is given by:

$$\mathbf{R} = \begin{pmatrix} \varrho(1,1) & \varrho(1,2) & ... & \varrho(1,s) \\ \varrho(2,1) & \varrho(2,2) & ... & \varrho(2,s) \\ ... & ... & ... & ... \\ \varrho(s,1) & \varrho(s,2) & ... & \varrho(s,s) \end{pmatrix} \tag{3.10}$$

The received signal at each node received by bank of MF or adaptive filters for multiuser detection, therefore:

$$\mathbf{y}(n) = \hat{\mathbf{x}}(n) = [\hat{x}_1(n), \hat{x}_2(n)..., \hat{x}_K(n)]^\dagger \tag{3.11}$$

Is the received signal matrix as given by $\mathbf{y}(n) = [y_1(n), y_2(n), ...y_K(n)]$. The matrix **R** is Hermitian and can be uniquely defined by specifying the values of the correlation co-efficient $\varrho(s,s)$. The error between the reference signal(training sequence at receiver $x(n)$ and the output of n^{th} symbol of an adaptive filter at the bank of adaptive filter is given by:

$$e(n) = (x(n) - \hat{x}(n)) \tag{3.12}$$

where $\hat{x}(n)$ is the signal estimated at the receiver and is given by

$$\hat{x}(n) = \mathbf{a}^H(n) \cdot \mathbf{y}(n) \tag{3.13}$$

Here $\mathbf{a}^H(n)$is α dimensional complex valued weight vector of n^{th} symbol.

$$\mathbf{a}(n) = [a_1, a_2......., a_s](n) \tag{3.14}$$

The superscript s represent the tap of filter, which is equal to spreading gain. During the adaptation mode the weight parameters are adjusted such that mean square error $J_{\mathbf{a}}$ is minimized in n^{th} symbol time. For simplicity, n is with every term but this research are not mentioning it in the following equations for sake of simplicity. Mean square error is given by:

$$J_{\mathbf{a}} = E[e \cdot e^*] \tag{3.15}$$

$$J_{\mathbf{a}} = E[(x - \mathbf{a}^H \cdot \mathbf{y})][(x - \mathbf{a}^H \cdot \mathbf{y})^*] \tag{3.16}$$

$$J_{\mathbf{a}} = E[x \cdot x^*] + \mathbf{a}^H E[\mathbf{y} \cdot \mathbf{y}^H]\mathbf{a} - \mathbf{a}^H E[\mathbf{y} \cdot x^*] - E[x \cdot \mathbf{y}^H]\mathbf{a} \tag{3.17}$$

The first term $E[x \cdot x^*]$ in above equation, represents the variance of the desired signal. The expectation $E[\mathbf{y} \cdot \mathbf{y}^H]$ represents the $s \times s$ correlation matrix $\mathbf{R}$, earlier mentioned in equation 3.10. Let the third term is given by $\mathbf{z} = E[\mathbf{y} \cdot x^*]$. It is the $s \times 1$ cross-correlation matrix vector between the received components and the reference sequence. And the forth term is given by $E[x \cdot \mathbf{y}^H] = \mathbf{z}^H$

Where $\mathbf{z}^H = [z_1^*, z_2^*, ...z_N^*]$. The coefficients z_i are given by $z_i = E[\mathbf{y}_(n) \cdot x^*_{(n)}]$. For stationary input and reference signals the surface obtained by plotting the mean square error $J_{\mathbf{a}}$ versus the weight coefficient has a fixed shape and curvature i^{th} a unique minimum point. The adaptive process seeks that minimum point, where the weight vector is optimal. Differentiating the mean squared error function $J_{\mathbf{a}}$ with respect to each coefficient of the weight vector a yields the gradient ∇.

$$\nabla = \partial J_{\mathbf{a}} / \partial \mathbf{a} = \begin{pmatrix} \partial J_{\mathbf{a}} / \partial a_1 \\ \partial J_{\mathbf{a}} / \partial a_2 \\ \cdots\cdots \\ \partial J_{\mathbf{a}} / \partial a_s \end{pmatrix} \tag{3.18}$$

Differentiating the mean squared error function $J_{\mathbf{a}}$ with respect to each coefficient of the weight vector $\mathbf{a}$ yields the gradient ∇. The optimal weight vector $\mathbf{a}_{opt}$ can be determined by setting the gradient ∇ equal to zero:

$$\nabla = -2\mathbf{z} + 2\mathbf{R} \cdot \mathbf{a} = 0 \tag{3.19}$$

Where 0 is an m by 1 null vector at the minimum point of the error surface, the A-MMSE-MUD is optimum in the mean squared error sense, and the equation can be simplified in the form

$$\mathbf{R} \cdot \mathbf{a}_{opt} = \mathbf{z} \tag{3.20}$$

Which is a Wiener-Hopf or normal equation, where the vector representing the estimation error is normal to the vector output of the filter. One possible solution of this equation is matrix inversion as follows:

$$\mathbf{a}_{opt} = \mathbf{R}^{-1} \cdot \mathbf{z} \tag{3.21}$$

Another simple solution that does not require matrix inversion or explicit calculations of the correlation coefficient is the steepest decent method (SDM). The SDM is a recursive procedure which can be used to calculate the optimal weight vector $\mathbf{a}_{opt}$. Let $\mathbf{a}$ and ∇ denote the values of the weight vector and the gradient vector within the n^{th} symbol period, respectively. Then succeeding values of the weight vector are obtained by the recursive relation. After each symbol period number n the weight of the filter is updated until the optimum coefficient is obtained. After obtaining the optimum coefficient adaptive filter hard decision decoding applied. The criterion for applying hard decision decoding is usually by setting a threshold on mean square error or on cross-correlation value. The updated co-efficient of adaptive filter is given by:

$$\mathbf{a}(n+1) = \mathbf{a}(n) - \mu \cdot \nabla \tag{3.22}$$

Where μ is step size constant that controls stability and the rate of adaptation. If $'\nabla'$ express in terms of instantaneous estimates $\hat{\mathbf{z}} = \mathbf{y} \cdot x^*$ and $\hat{\mathbf{R}} = \mathbf{y} \cdot \mathbf{y}^H$ Then the equation can be simplified as the LMS algorithm:

$$\mathbf{a}(n+1) = \mathbf{a}(n) + 2\mu.\mathbf{y}(n) \cdot x^*(n) - \mathbf{y}(n)^H \cdot \mathbf{a}(n) \tag{3.23}$$

which can be expressed in term of $e(n)$ as,

$$\mathbf{a}(n+1) = \mathbf{a}(n) + 2\mu \cdot \mathbf{y}(n) \cdot e(n) \tag{3.24}$$

Where $n = 1, 2, 3$........

This equation tells about the updated weight vector, which is computed from the current weight vector by adding the input vector scaled by the complex conjugate value of the error and by μ which control the size of correction. This is the process that obtains the approximate optimum weight of the filter. The signal at the input of the decision device after minimization of error through n^{th} adaptive filters during the n^{th} symbol period is given for any phase denoted by $\hat{x}(n)$. The received symbol vector in time n is given by:

$$\hat{\mathbf{x}}(n) = [\hat{x}_1(n), \hat{x}_2(n)....., \hat{x}_K(n)] \tag{3.25}$$

3.4 Performance Comparison and Numerical Simulations

3.4.1 Simulation Conditions

In first simulation results in figure 3.2 for non cooperative CDMA wireless network, four users sends 200 training BPSK data and 10^5 data bits through flat fading Rayleigh channels to the destination, where bank of adaptive filters used for A-MMSE-MUD and bank of match filters are used for matched filter multiuser detection (MF-MUD). Basically, LMS algorithm are used for the adaptive filter. However, any adaptive algorithm can be used. The simulation experiments of the A-MMSE-MUD and MF-MUD carried out by using MATLAB programing. The BER results are averaged through 200 channel realizations.

In other computer simulation experiments in figure 3.3, the simulations are aimed at determining the BER performance of A-MMSE-MUD for DF and AF schemes in multi-user Rayleigh flat fading environment against various SNRS. MF-MUD and Channel Pre-coding are performed at relays and MF-MUD performed at destination in one the case of decode-and-forward scheme. The mathematical formu-

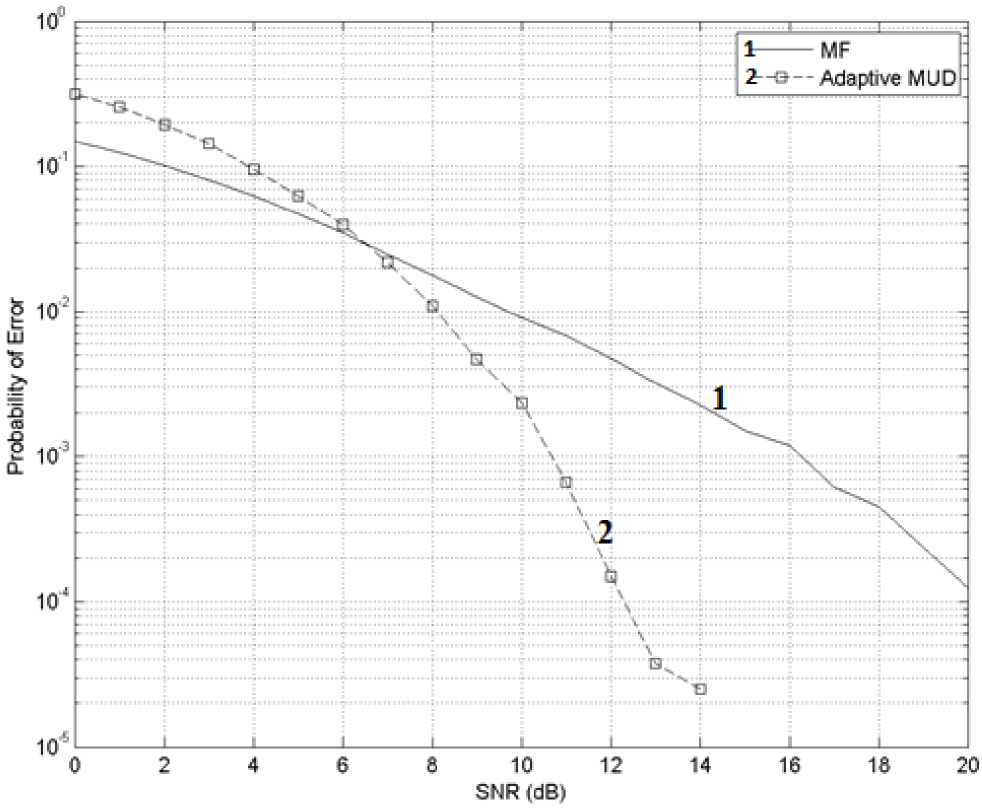

Figure 3.2: BER performance for four sources non cooperative communication:

1. Non Cooperative Wireless System with Multiuser Detection using a Matched Filter.

2. Non Cooperative Wireless System with A-MMSE-MUD using an Adaptive Filter.

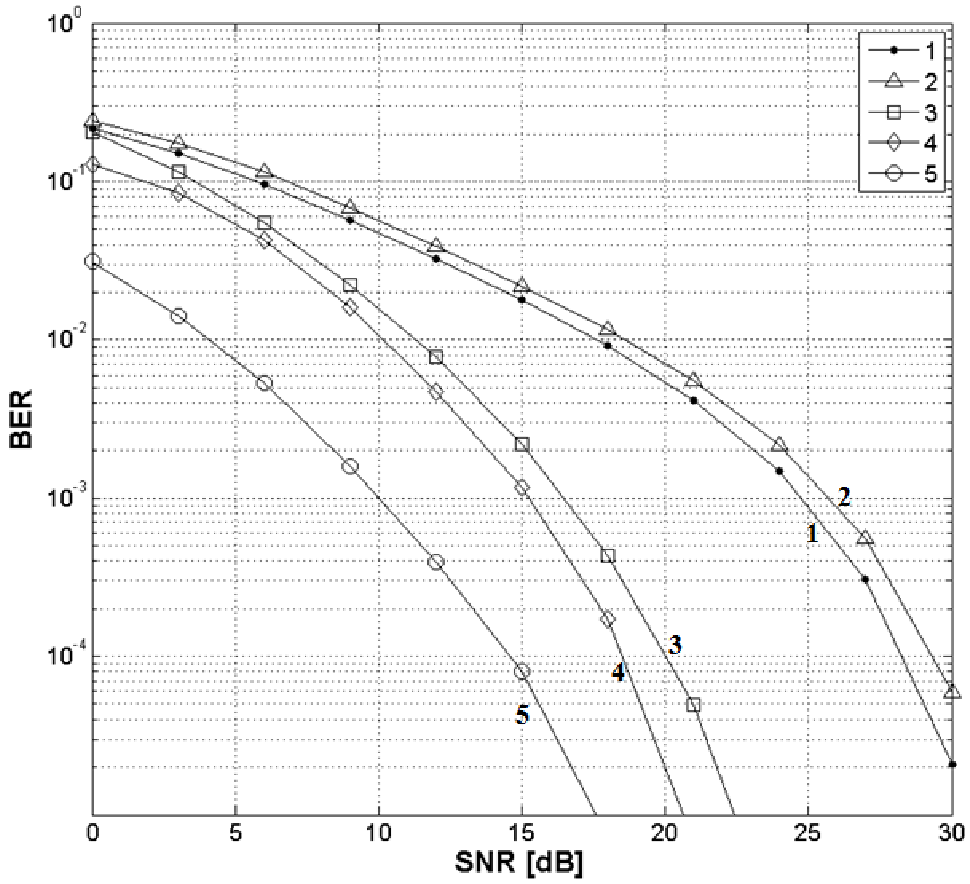

Figure 3.3: BER performance for four sources and four relays:

1. Two Cooperative Nodes; Precoding at Relay and MF at Destination.
2. Two Cooperative Nodes; AF at Relay and MF at Destination.
3. Two Cooperative Nodes; MF at Relay and Destination Node.
4. Two Cooperative Nodes; AF at A-MMSE-MUD at Destination.
5. Two Cooperative Nodes; A-MMSE-MUD at Relay and Destination Node.

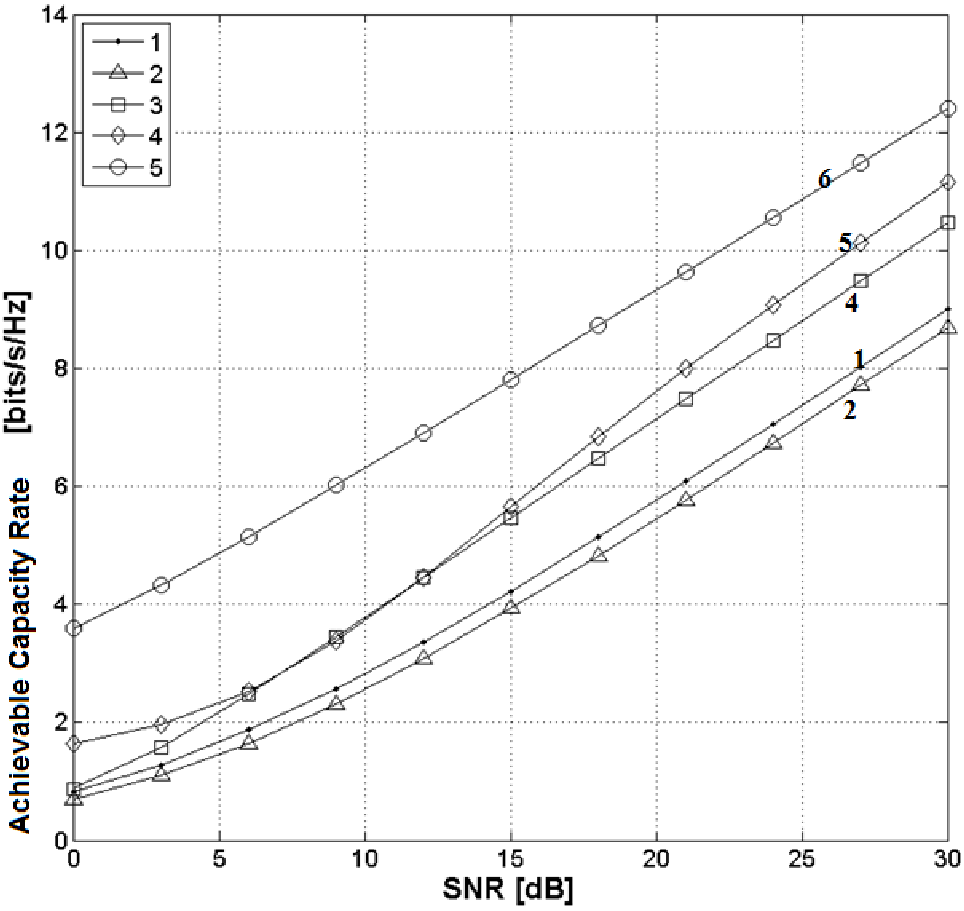

Figure 3.4: Information Capacity achievable rate for four sources and four relays:

1. Two Cooperative Nodes; Precoding at Relay and MF at Destination.
2. Two Cooperative Nodes; AF at Relay and MF at Destination.
3. Two Cooperative Nodes; MF at Relay and Destination Node.
4. Two Cooperative Nodes; AF at A-MMSE-MUD at Destination.
5. Two Cooperative Nodes; A-MMSE-MUD at Relay and Destination Node.

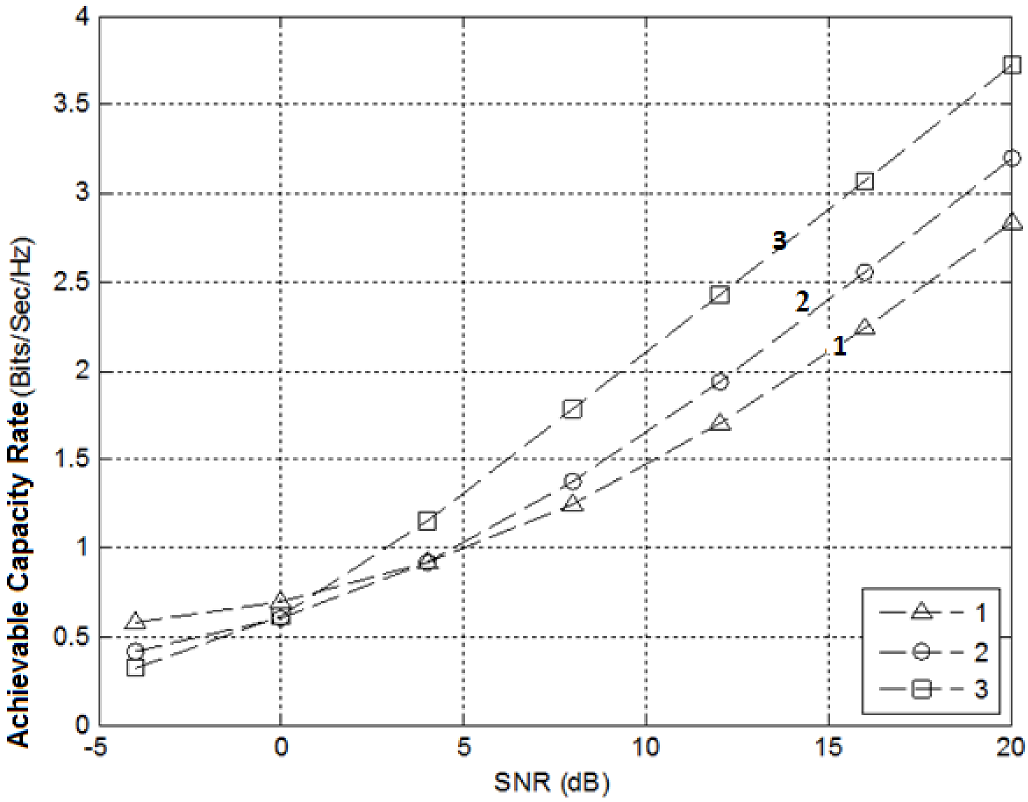

Figure 3.5: Information Capacity achievable rate for two users and two relays:

1. Two Cooperative Nodes; MF at Relay and Destination Node.
2. Two Cooperative Nodes; AF at Relays and A-MMSE-MUD at Destination.
3. Two Cooperative Nodes; DF by A-MMSE-MUD at Relays and Destination.

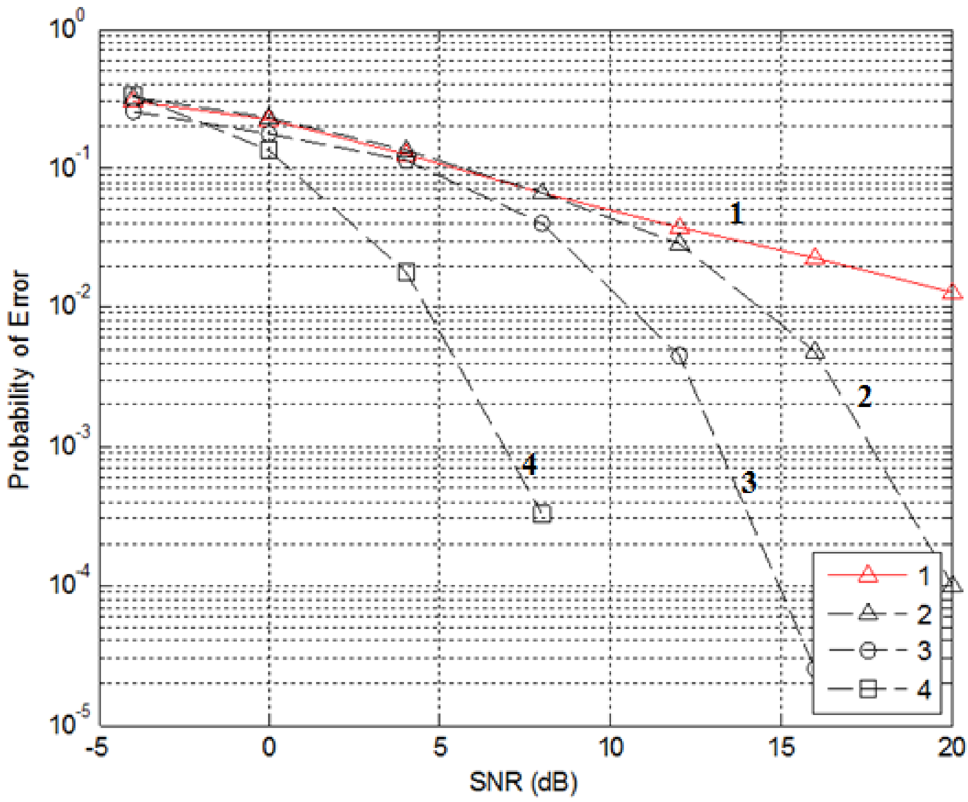

Figure 3.6: BER performance for two users and two relays:

1. Two Cooperative Nodes; AF at Relays MF at Destination.
2. Two Cooperative Nodes; DF at Relays by MF and MF at Destination.
3. Two Cooperative Nodes; AF at Relays and A-MMSE-MUD at Destination.
4. Two Cooperative Nodes; DF by A-MMSE-MUD at Relays and Destination.

las are used for Channel Pre-coding from [56]. It is considered that communication is established among four source users and four relays cooperative MIMO system through flat fading Rayleigh channels, where the relays decode or amplify the signals of multiple users. The transmitted 10^5 randomly generated bits and the BER results are averaged through 200 channel realizations. 200 bits of BPSK signal are used for the training of adaptive filters at relays and destination. Transmit beamforming is used at relays to send data bits to destination. The following conditions exist in all simulations of cooperative wireless network; a) un-coded coherent BPSK is used for modulation, b) non Cooperative CDMA wireless network is considered with four users and a destination node and Cooperative CDMA wireless network is consider with two/four users and two/four relays, c) independent fading characteristics are on each channel and it is assumed that channels are un-correlated, d) the training sequences are generated independently using uniformly distributed pseudo-random number generators, e) the noise on each channel is additive Gaussian random variable with zero mean and a variance σ, f) these simulations use bank of adaptive transversal finite impulse response filters for the A-MMSE-MUD and also uses LMS algorithm for minimization of error, g) spreading gain is 16 both at relay and destination, h) it is assumed that channel state information not available at relays or destination for A-MMSE-MUD, i) equal gain combining is used for combining the direct path link and relay destination link transmission. The used MATLAB codes are given in Appendix I.

In figure 3.4 Shannon capacity formula is used to obtained the Information capacity results, where the capacity performance in simulation of the system is taken in terms of the output minimum mean square error (MMSE) is given by equation 2.1. The simulation graph is ploted against various SNRs. The MATLAB code for this experiment is used in same manner as mentioned above. In figure 3.5 information capacity examined with respect to various SNRs for 2 users and 2 relays by using equation 2.1. Whereas, in figure 3.6 BER is calculated against various SNRs for 2 users and 2 relays.

3.4.2 Simulation Results

Figure 3.2 shows the BER performance of Classical MF-MUD and A-MMSE-MUD, BER performance for four users. It is clearly seen that the performance of A-MMSE-MUD significantly better than the performance of MF-MUD. Figure 3.3 demonstrates the capacity performance results of a two sources and two relays cooperative system, where the bank of matched filters approach in contrast to the A-MMSE-MUD approach is simulated. It is observed that the A-MMSE-MUD at relay and destination achieves a channel information capacity of about 8 bits/s/Hz at 15dB of signal to noise ratio (SNR), whereas amplify and forward matched filtering and matched filtering with precoding approach provided 4 bits/s/Hz at the same SNR. It is clearly observed that amplify and forward with A-MMSE-MUD at the destination node and decode and forward and matched filtering have the same performance on different SNR. Therefore, A-MMSE-MUD is a effective technique, even the amplification being performed at relays.

This research obtained consistent results for the capacity of the system, demonstrated in figure 3.4, where the BER performance results of two sources and two relays cooperative systems are analyzed. The bank of matched filters approach is in contrast to the A-MMSE-MUD, which clearly shows the non linear performance. It is observed that the A-MMSE-MUD at relay and destination approach achieves BER performance of about 10^{-4} at 15dB of SNR, where as amplify and forward matched filtering and matched filtering with precoding approach provide 10^{-2} at the same SNR. It is observed that amplify and forward with A-MMSE-MUD at destination node and decode and forward and matched filtering have the same performance on different SNR. Therefore, A-MMSE-MUD is the best technique when amplification is perform at relays. Figure 3.4 only presents BER performance of the classical match filtering and adaptive multiuser detection in the cooperative communication wireless network.

3.5 Conclusions

This chapter presented a decentralized approach of asynchronous cooperative CDMA wireless networks with an A-MMSE-MUD technique to eliminate MAI. Two protocols of cooperative communication, AF and DF are examined in use with A-MMSE-MUD. The computer experiments show that DF outperform all other schemes to mitigate the MAI on each node of the wireless network, whereas Amplify and Forward in use with A-MMSE-MUD performance is better than other multiuser detection schemes, even amplification has been performed on relay nodes. With presented A-MMSE-MUD we can improve the performance of cooperative CDMA wireless networks considerably. Further investigation is required for the interference mitigation of proposed schemes which will be presented in the next chapter.

3.6 Summary

Asynchronous cooperative CDMA wireless network uplink transmission was examined in this chapter, where users cooperate in a relaying mode while they exchange data and channel information with the base station to achieve diversity gains. MAI occurs at both the relays and destination due to asynchronous transmission and non orthogonality of the spreading waveforms. In order to deal MAI, A-MMSE-MUD was used by a bank of linear adaptive filters. Two protocols of cooperative communication wireless networks were used, (i) amplify and forward at relays and A-MMSE-MUD at destination, (ii) A-MMSE-MUD at the relays and destination in a decode and forward operation. This research compared the result with other multiuser detection schemes under the same conditions in a cooperative CDMA wireless network and found that the amplify and forward scheme in use of A-MMSE-MUD removes the MAI even amplification was performed on the relays nodes. Whereas, decode and forward scheme outperform all other multiuser detection scheme. Simulation experiments has shown that both schemes amplify and forward and decode and forward with A-MMSE-MUD provide significant improvement in the bit error rate and capacity performance of the cooperative communication CDMA networks.

Chapter 4

INTERFERENCE RESISTANCE OF ADAPTIVE MULTIUSER DETECTION IN COOPERATIVE CDMA WIRELESS NETWORKS

4.1 Introduction

CDMA wireless networks are playing a central role in modern wireless and mobile communication systems, since they allow multiple users to share limited time and bandwidth resources. In case of severe signal attenuation and fast channel variation commonly known as fading, BER increases and channel information capacity drops significantly. Signal interference caused by external sources and co-channel users is another deteriorating factor in communication performance. To overcome fading problems multiple copies of the original signal is transmitted by MIMO configuration. As mentioned in previous chapter, the main principle in cooperative CDMA wireless networks is the benefit utilization from each node (relay) of the wireless network. Cooperative systems are cost effective and utilize the benefit of space diversity by enhanced degrees of freedom. Several methods to tackle the interference problems in various multiuser detection schemes were proposed in past literature. MF technique is an optimum technique when single user communication is performed through Gaussian channel but as the number of users grows and multiplexing access is used in communication, the performance of MF degrade exponentially, which is undesirable for the use in wireless CDMA networks. Multiplexing schemes were formulated for interference cancelation independent of whether the channels were line-of-sight or fading. In cooperative communication, due to further complexity of the system, MF nearly failed to perform, hence, not feasible to implement. MLSE is an optimum multiuser detection technique which provides the best performance of multiuser detection but as the number of users increases in wireless network the complexity and cost of processing also increases. Moreover, it also need channel state information, therefore, it is not always viable to implement. A-MMSE-MUD is a technique, where the computational complexity increases linearly with the increase of users. It does not require the channel state information. It is also very effective in interference mitigation. Various performance analyses have been presented in past literature for cooperative relaying networks but interference tolerance (resistance) analysis are required to analyse in cooperative CDMA wireless networks. Therefore, the main purpose of this chapter is to investigate interference resistance of A-MMSE-MUD [20] for the DF relaying operation within a cooperative CDMA wireless network. Apart from the channel estimation and detection responsibility, A-MMSE-MUD is being used for the mitigation of MAI. A-MMSE-MUD receivers are capable of estimating the system parameters such as signal delay, signal phase, signal amplitude, CDMA signatures, multi-path channel profile and the number of users in a CDMA system by using a training routine coordinated by the transmitter. This chapter shows that A-MMSE-MUD achieved a BER performance arbitrarily close to that of an MLSE filter but with linear computational complexity. A-MMSE-MUD provides robustness and mobility in time variable frequency selective multi-path fading channel, improves the BER performance and therefore, enhances channel information capacity of a multi-cellular environment. The main principles were used in the system shown in this chapter drawn from [22-24], where each node of the system acts as a relay part of a cooperative network. In practical implementation of wireless networks, strict signal power control are used to avoid unnecessary interference in the networks. However, reducing power of the signals increase the bit error rate. Therefore, it is required to develop a multiuser detection scheme which provide interference resistance capabilities. By using various multiuser detection schemes, we can detect the signals on a base station from MAI. In the previous chapter A-MMSE-MUD was used in cooperative CDMA wireless networks. Cooperative systems are cost effective, utilise the benefit of space diversity by enhanced degrees of freedom and provide small bit error rate. Detailed literature related to the performance of cooperative wireless networks was mentioned earlier in the chapter 1 and chapter 2.

A-MUD schemes were presented and used from many years [19] [20].Various performance analyses were presented in past literature for cooperative relaying networks with multiuser detection techniques: BER, information capacity, outage probability and interference tolerance analysis for cooperative communication wireless networks. The main purpose of this chapter is to investigate interference resistance (tolerance) of A-MMSE-MUD for the DF relaying operation within a cooperative CDMA wireless network. Apart from the channel estimation and detection responsibility, A-MMSE-MUD has been used for the mitigation of Multiple Access Interference (MAI). A-MMSE-MUD receivers are capable of estimating system parameters such as signal delay, signal phase, signal amplitude, CDMA signatures, multi-path channel profile and the number of users in a CDMA system by making use of a training routine coordinated by the transmitter. A-MMSE-MUD provides robustness and mobility in a time variable frequency selective multi-path fading channel, improves the BER performance and therefore, enhances channel information capacity in a multi-cellular environment. This chapter shows with mathematical analysis and computer simulation that A-MMSE-MUD achieves a BER performance arbitrarily close to MLSE MUD with an added benefit of linear computational complexity in cooperative CDMA wireless networks. The comparison of the performance of MF and A-MMSE-MUD in cooperative CDMA wireless network are also presented. For the A-MMSE-MUD implementation, fractionally space linear transversal bank of filters are used in this research. Wireless relaying with A-MMSE-MUD scheme used in the research:

- operates under partial or no knowledge of the channel state information (CSI) at any stage of the communication.
- capable of mitigating MAI.
- fully capable of operating in both synchronous and asynchronous transmissions.
- provides performance of about 10^{-3} at a SNR of $22dB$, while the channel information capacity performance of the system is nearly $27 bits/s/Hz$ at the

same SNR.

- provides interference resistance (tolerance/mitigation) better than MLSE multiuser detection (theoretical upper bound of Multiuser detection), when number of users are increased.

- provides interference resistance better than MF multiuser detection, when number of users are increased.

The rest of the chapter is organized as follows: The general system model is shown in section 4.2. The simulation system model is described in detail in section 4.3 and the simulation results are shown and discussed in section 4.4. Earlier, the A-MMSE-MUD scheme used at relays and base station is analytically presented in section 3.3. Finally, concluding remarks are given in section 4.5.

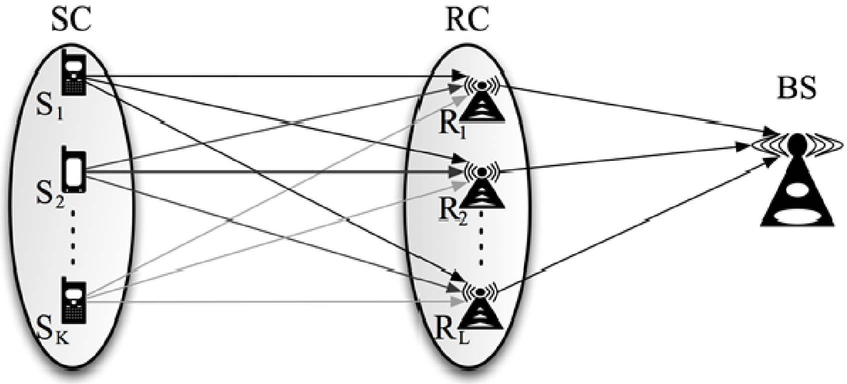

Figure 4.1: A cooperative relaying CDMA wireless network:

- Here mobile users cluster send signals to relays cluster. On relay cluster A-MMSE-MUD is used. Relay cluster transmit the detected data to destination node/base station, where A-MMSE-MUD is used.

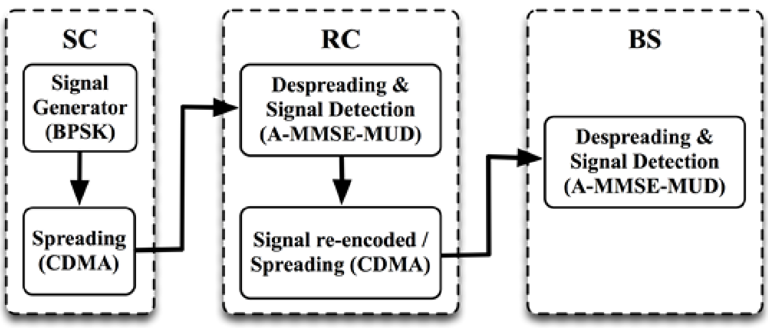

Figure 4.2: Protocol flow diagram of the cooperative relaying CDMA networks:

- BPSK signal send to relay through Rayleigh wireless channel. At relays A-MMSE-MUD used to detect data. The data is further transmitted to destination, where A-MMSE-MUD used to detect data.

4.2 System Model

In a similar manner to the previous chapter and as presented in [22][56], let us consider again that K users are denoted by $S_1, S_2, ..., S_K$, serving as source communication terminals located in the Source Cluster (SC) and L relaying communication nodes are denoted by $R_1, R_2, ..., R_L$ located in the Relaying Cluster (RC) as shown in figure 4.1. The nodes in relay cluster can be mobile users or fixed relays. The source communication nodes transmit data packets to all the relays in the RC and are then forwarded to the Base Station (BS). A-MMSE-MUD is used at the RC and the BS for signal detection.

4.2.1 Protocol Description

The concept demonstrated in this chapter is shown in figure 4.2. Individual data signal packets are generated by the transmitting communication terminals in the SC. Data is spread by unique CDMA spreading signature codes, that individually allocated to each communication terminal of the SC. Data signal is then fed into a flat fading Rayleigh wireless channel, which is affected by additive Gaussian noise. This phase of communication is described in details in the subsection 4.2.2.

The communication terminals at the RC receive packets from all transmitting communication nodes and by means of A-MMSE-MUD, they are Despread and Detect. Each of the relay of wireless communication nodes will re-encode and spread data before they forward it to BS. The wireless channel is assumed here as a flat fading Rayleigh channel affected by additive Gaussian noise. This type of the communication is described in details in subsection 4.2.3. BS uses A-MMSE-MUD to Despread and Detect the incoming signals from all relay nodes. By using A-MMSE-MUD technique, BS remains tolerant to MAI, while it is capable in asynchronous reception at wireless communication terminals. Also the constant hand-off operation provided by A-MMSE-MUD enables the mobility. The signal detection is mathematically shown in section 3.3.

4.2.2 Phase I: Source Cluster to Relay Cluster Operation

Each source of the 'K' transmits communication terminals propagates a M-long data symbol to all communication nodes of the RC. Let $\mathbf{x}(n) = [x_1(n), x_2(n), ..., x_K(n)]^\dagger$ be the BPSK data symbols transmitted by sources $S_1, S_2, ..., S_K$ during the n^{th} symbol period, where $x_k(n) = \{-1, 1\}$ and:

$$\mathcal{E}[\mathbf{x}(n)\mathbf{x}[p]^\dagger] = \mathbf{I}_{(K\times K)}, \quad if\ n = p$$

$$= \mathbf{O}_{(K\times K)}, \quad otherwise$$

Where **I** represents an identity matrix and **O** represents a null matrix of $K \times K$ matrix dimensions. Each communication terminal (S_k) in the SC propagates with a transmit signal power of P_{S_k} while $\mathbf{s}_k(t)$ is the spreading waveform (signature) of S_k. The spreading gain of spreading waveform $\mathbf{s}_k$ of the CDMA system is given by:

$$\mathbf{s}_k(t) = 1/\sqrt{s}\sum_{n=1}^{s}\mathbf{c}_k(n)\psi(t - nT_c), k = 1, 2..., K \tag{4.1}$$

where $\mathbf{c}_k[n]$ is the n^{th} element of the ± 1 spreading sequence assigned to S_k, and $\psi(t)$. Under the asynchronous CDMA signal assumption, the signal received at the relay cluster in the presence of additive white Gaussian noise (AWGN)$\mathbf{v}_I(t)$ is expressed as:

$$\mathbf{y}_I(t) = \sum_{n=1}^{N}\sum_{k=1}^{K}\mathbf{h}_{S_kR_\ell}(\sqrt{P_{S_k}})x_k(n)\mathbf{s}_k(t - nT - \tau_k) + \mathbf{v}_I(t) \tag{4.2}$$

where T is symbol period, τ_k is the transmission delay assumed for the k^{th} user at ℓ^{th} relay. It is assumed that there is a block fading environment, where channel coefficients ($\mathbf{h}_{S_kR_\ell}$) are time invariable, independent and identically distributed (i.i.d). The channel coefficients $\mathbf{h}_{S_kR_\ell}$ are assumed to be Zero Mean $(\mu_{S_k} = 0)$ Circularly Symmetric Complex Gaussian (ZMCSCG) with variance $\sigma^2_{S_kR_\ell}$ random variables , i:e, $\mathbf{h}_{S_k R_\ell} \sim \mathcal{CN}(0, \sigma^2_{S_k R_\ell})$, and is assumed to be independent among sources. The digital signal obtained at the input of decision device after error minimization by using the A-MMSE-MUD filter during the n^{th} symbol period is denoted as $\mathbf{y}_I(n)$. Further operation and analysis are demonstrated in section 4.3.

4.2.3 Phase II: Relay Cluster to Base Station Operation

In this phase all relays detect and forward the incoming data signals by the use of the same spreading sequence signatures of the respective communication terminals of the SC. It is assumed that the symbols detected $(\hat{\mathbf{x}}_\ell)$ in *Phase I* may be encoded into a single symbol matrix of dimensions $K \times N$:

$$t_\ell(n) = [t_{\ell,1}(n), t_{\ell,2}(n)..., t_{\ell,K}(n)]^\dagger \tag{4.3}$$

It is the transmit symbol vector by the ℓ^{th} relay communication node (R_ℓ) of the n^{th} symbol, $\mathbf{t}_\ell(n)$ depends on the detected symbol $\hat{\mathbf{X}}_\ell$. The symbol fed into the bank of adaptive filters is given by:

$$\mathbf{y}_{II}(t) = \sum_{m=1}^{N} \sum_{k=1}^{K} \sum_{\ell=1}^{L} \mathbf{h}_{S_\ell D}(\sqrt{P_{R_\ell}}) t_{\ell,k}(n) \mathbf{s}_k(t - mT - \tau_\ell) + \mathbf{v}_{II}(t) \tag{4.4}$$

Where T is symbol period, $\tau\ell$ is the transmission delay assumed for the ℓ^{th} user at the BS. It is assumed that there is a block fading environment where channel coefficients ($\mathbf{h}_{R_\ell BS}$) are time invariable, independent and identically distributed (i.i.d). The channel coefficients $\mathbf{h}_{R_\ell BS})$ are assumed to be ZMCSCG with variance $\sigma^2_{R_\ell BS}$ random variable, i.e, $\mathbf{h}_{R_\ell BS} \sim \mathcal{CN}(0, \sigma^2_{R_\ell BS})$, and is assumed to be independent among sources.

4.3 Adaptive Multiuser Detection for the Relaying Communication Networks

Matched Filters with Maximum Likelihood computation were commonly used in past literature [22][23][24]. In A-MMSE-MUD the bank of MF is replaced by a bank of Adaptive MMSE matched filters as shown in [20]. In MF multiuser detection approach, a sufficient knowledge of the channel statistics at the BS terminal is achieved by neglecting the correlation between signals originated by different transmit communication terminals. The main cause of correlation is non-orthogonality of spreading codes of CDMA wireless systems. This orthogonality further destroyed by asynchronous communication, where signal arrived at different instants at receiver. Therefore, the performance of MF dropped significantly with the increase of users and correlation of the signals. The A-MMSE multiuser detection use the parameters of adaptive filters that continuously changed by received training sequences from the transmitter to adjust the adaptive filters for matching the desired signal. After the training operation, the adaptive filter operates in decision directed mode. Therefore, in a single user environment every matched filter receiver plays the role of an Adaptive MMSE (A-MMSE). A-MMSE filter minimizes the error by the adaptive algorithms. This research used LMS algorithm which is actually the steepest decent algorithm (SDM) to minimize the mean square error of the incoming signals. It used a fractionally spaced adaptive linear transversal filter for A-MMSE-MUD, which is insensitive to the time differences in the signal arrival of different users, thus the receiver timing recovery is extremely simplified. The adaptive filter is in contrast to the multiuser receiver where the observation vector is not the output from the bank of matched filters, but the sampled signal itself. Adaptive multiuser technique also provides a tool to obtain instantaneous estimates of the channels. In past research of [29], cooperative communication was presented with a protocol based on channel estimation, which was realistic approach in cooperative communication. This research has also adopted the same approach.

Let $\mathbf{y}_n(t)$ be the general form of n^{th} received analogue signal of symbol duration T at the input of the analogue to digital convertor. And $\mathbf{y}(n)$ is the received digital output of respective symbol from the output of the convertor device. In multi-cellular environment SC communication nodes transmit information independently. Therefore, non-orthogonal transmitted signals from independent users arrive asynchronously at the receivers as shown in [28] where, the delay can not neglected. Due to non orthogonality and the latency of the spreading codes signal correlation exists among the communication terminals of the RC and BS respectively. The digital output of the n^{th} symbol period on RC or BS is given by:

$$\mathbf{y}(n) = \mathbf{Rh}x(n) + \mathbf{v}(n) + I \tag{4.5}$$

Here I represents interference caused by MAI and external source interference. The MSE between the reference signal and the output of the n^{th} symbol of the adaptive filter is given in previous chapter under section 3.3, which leads to derivation of A-MMSE-MUD. The error is given by following equation:

$$e(n) = (x(n) - \hat{x}(n)) \tag{4.6}$$

4.4 Simulation System Model

Uncoded coherent BPSK modulated signals are transmitted with normalized powers (unit energy) over a flat fading Rayleigh communication channels composed of two user terminals at the SC and two relays terminal at RC. Communication channels follow independent fading characteristics on each channel with unequal and independent ZMCSCG. MLSE, MF and A-MMSE-MUD approaches are spread by a spreading factor of 16, for the performance examinations. The length of training sequence is 500 bits as the data sequence is 10^5. The term SNR used in this thesis indicates the signal to thermal noise power ratio. The CDMA independent and uniformly distributed pseudo-random training sequences send from each user of SC to RC and from RC to destination node for MLSE and A-MMSE MUD. After the channel estimation the CDMA data sequence send and the BER calculated against the various SNR. A plot is drawn between SNR and BER with computer simulation. Interference is also added to the signal at destination node as given in the equation 4.5. The interference is of same length as training sequence of data signal. The experiments carried out with two and three interferer as shown in figure 4.3 and figure 4.4. In second experiment MF and A-MMSE-MUD used for MUD with four users and four relays at SC and RC respectively. And 3 and 5 interferer added in the received signals at destination node as shown in figure 4. LMS algorithm used for the convergence of adaptive filters for A-MMSE-MUD at relays and destination. MF and MLSE algorithm is used for MLSE MUD. It is assumed, that the channel noise is additive Gaussian Noise with zero mean and with unit variance. The information capacity performance in simulation of system in terms of the output minimum mean square error (MMSE) is obtained by well known equation of capacity in equation 4.3. The used computer simulation code are presented in Appendix I.

4.5 Simulation Resutls

Figure 4.3 demonstrates the information capacity performance results of the upper bound MLSE with a bank of matched filters approach. Whereas, A-MMSE-MUD approach use bank of adaptive filters with LMS algorithm. It is shown that MLSE approach achieves a channel capacity of about 39 bits/s/Hz at 30dB of SNR when the A-MMSE-MUD technique achieves a 38 bits/s/Hz at the same SNR. It is clearly shown that the MLSE bank of matched filters approach outperforms A-MMSE-MUD approach in a perfect MAI free environment. However, in the presence of a single channel interferer, MLSE approach saturates at about 22 dB of SNR at a channel information capacity of about 19 bits/s/Hz to 30 dB of SNR. For the same SNR, in the presence of a channel interferer, A-MMSE-MUD approach achieves a channel capacity of about 36 bits/s/Hz. Figure 4.4 shows the BER performance results of MLSE bank of matched filters approach in contrast to the proposed A-MMSE-MUD technique. It is shown that in a MAI free operation the theoretical upper bound MLSE technique achieves a BER or 10^{-3} at a SNR of about 19dB while in the presence of channel interference the same performance is achieved at a SNR of 30dB. In other words, the SNR loss due to channel interference is almost 11dB. On the other hand in a MAI free operation, the A-MMSE-MUD approaches a BER of 10^{-5} at a SNR of 24dB while in the presence of channel interference it achieves the same BER at a SNR of 27dB. In other words the SNR loss due to MAI is about 3dB.

Figure 4.5 and figure 4.6 show the performance of MF and A-MMSE multiuser detection with three and five interferers respectively. This research analysed the performance of direct transmission with MF and A-MMSE. And MF and A-MMSE with relays cooperation. The results confirm the better performance of A-MMSE with relaying cooperation. In figure 4.5, the proposed scheme provides 10^{-3} BER at 18 dB SNR, that is 7 dB gain with respect to the performance without cooperation, while the performance of MF remained in the range of 10^{-1} to $10^{-1.5}$ even with cooperation. In figure 4.6, the proposed scheme provide 10^{-3} BER at 21 dB SNR, that is significant gain with respect to the performance without cooperation, while the performance of MF remained in the range of 10^{-1} to $10^{-1.2}$ even with a cooperation.

4.6 Conclusions

This chapter presents an asynchronous uplink relaying communication CDMA network where A-MMSE-MUD is utilized to eliminate MAI, enable asynchronous operation, secure mobility and while all this happens when computational complexity remains linear. The technique demonstrated in this paper achieves a channel spectral

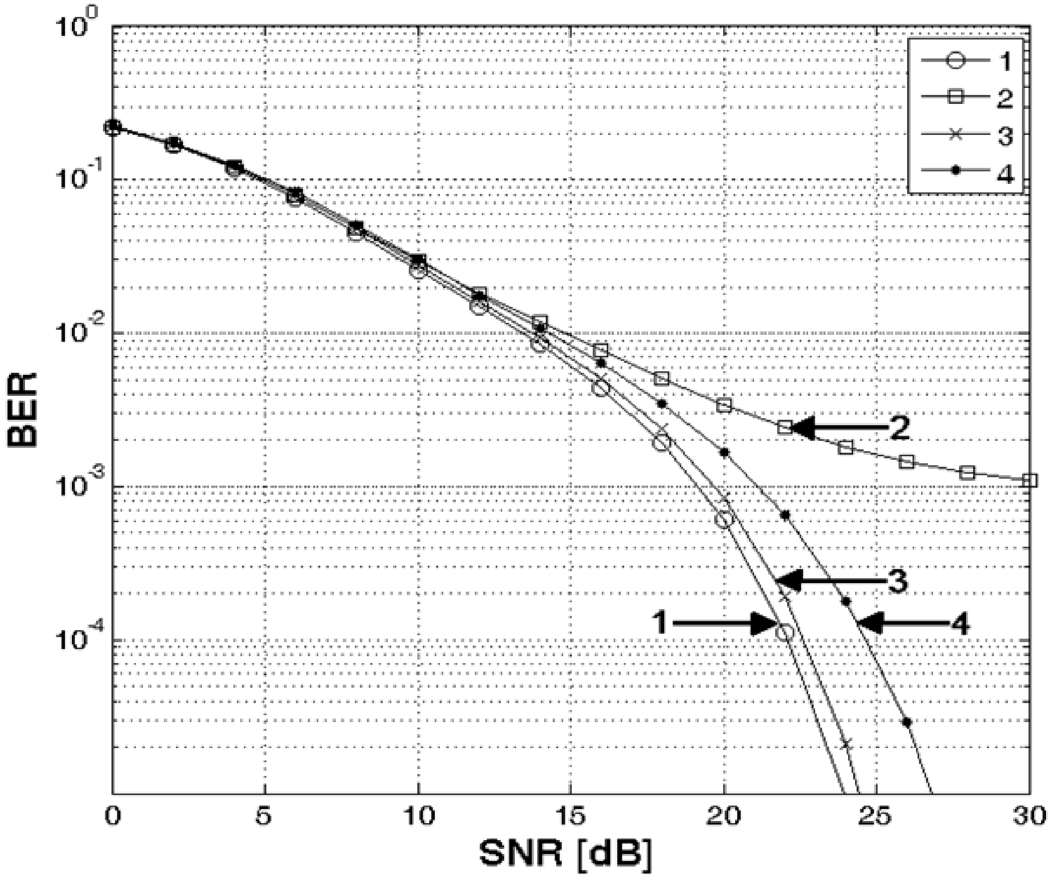

Figure 4.3: BER performance for for two users in SC without interferers and with two interferers:

1. MLSE Approach - No MAI
2. MLSE Approach - Single Channel Interferer
3. A-MMSE-MUD Approach - No MAI
4. A-MMSE-MUD Approach - Single Channel Interferer

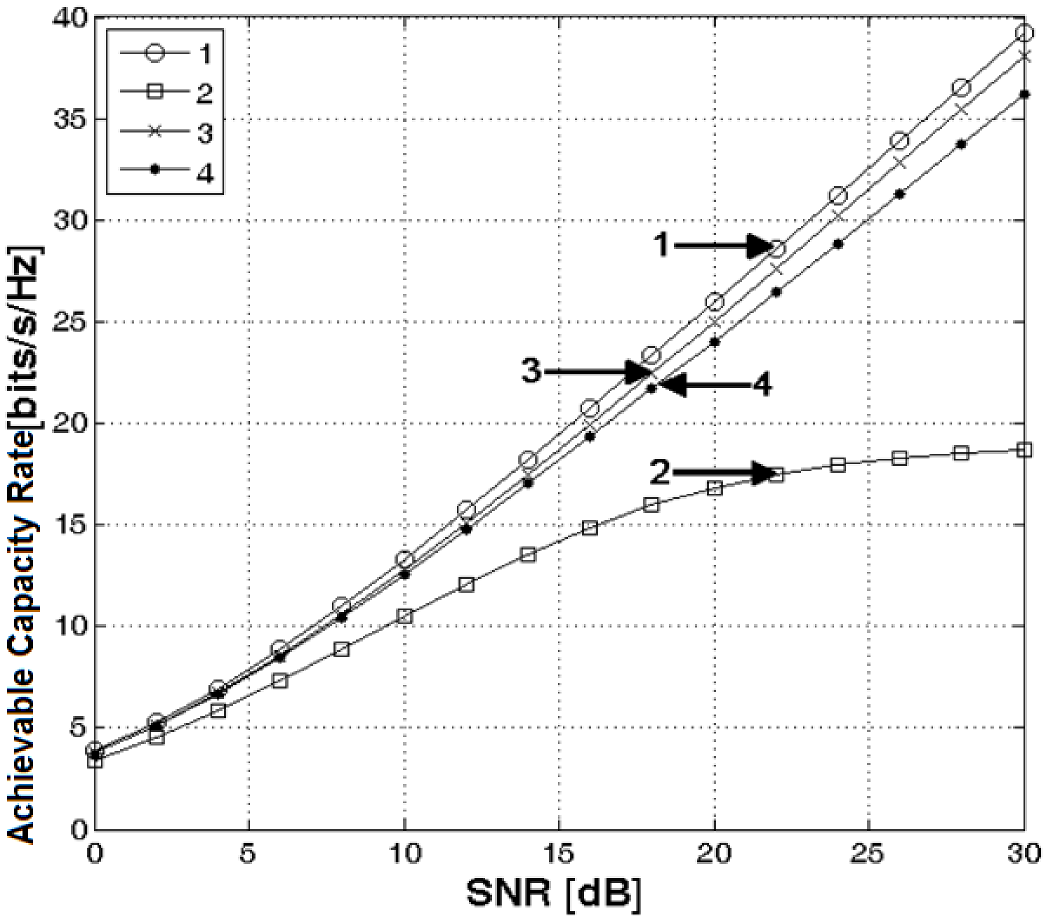

Figure 4.4: Achievable Information Capacity Rate for two users in SC without and with two interferers:

1. MLSE Approach - No MAI
2. MLSE Approach - Single Channel Interferer
3. A-MMSE-MUD Approach - No MAI
4. A-MMSE-MUD Approach - Single Channel Interferer

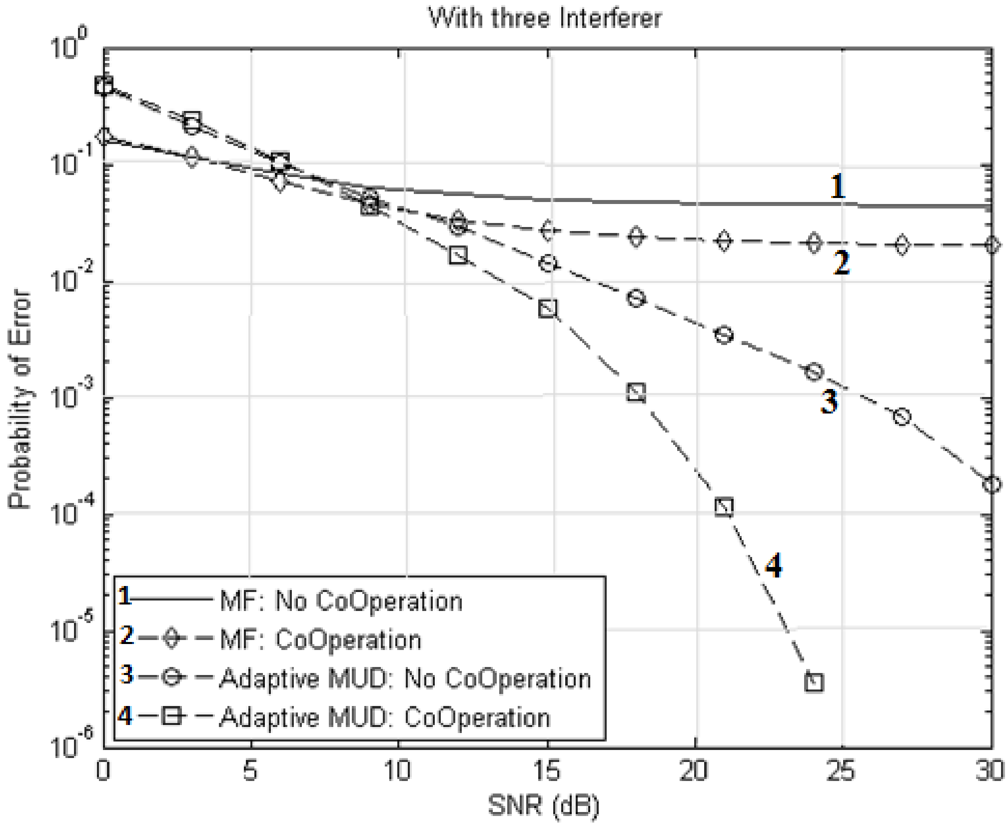

Figure 4.5: Probability of bit error for four users with three interferers:

1. MF No Cooperation
2. MF With Cooperation
3. A-MMSE-MUD: No Cooperation
4. A-MMSE-MUD: With Cooperation

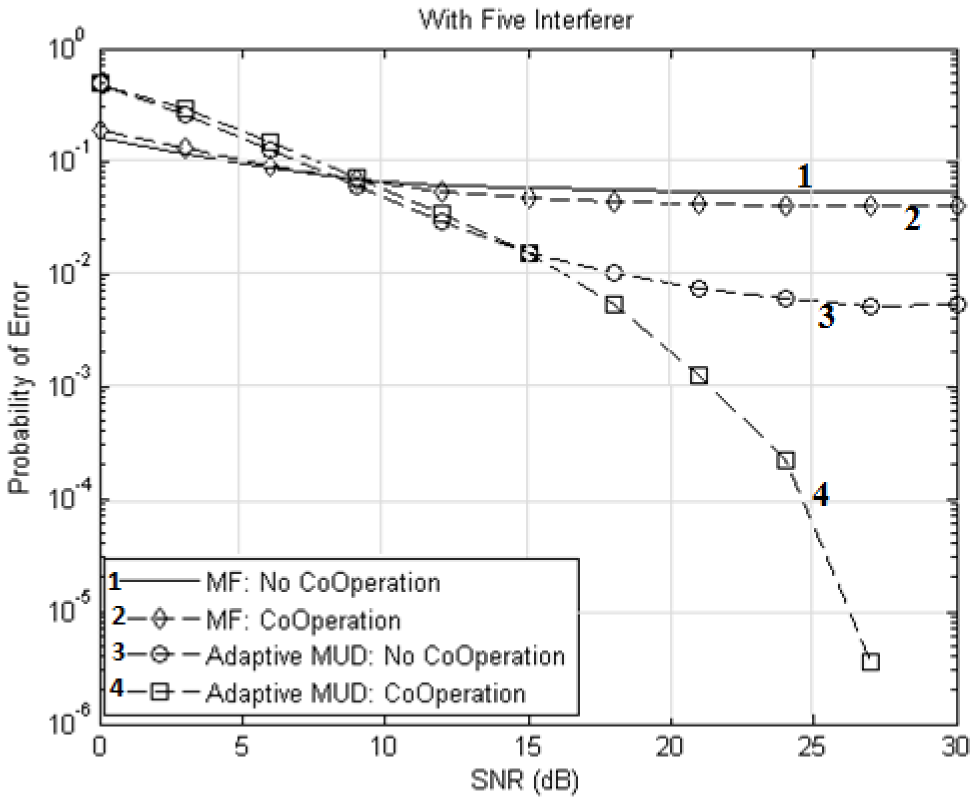

Figure 4.6: Probability of Bit Error for four users with five interferers:

1. MF No Cooperation
2. MF With Cooperation
3. A-MMSE-MUD: No Cooperation
4. A-MMSE-MUD: With Cooperation

efficiency arbitrarily close to the theoretical upper bound in a MAI free operation. In the presence of channel interference it achieves almost same information capacity performance as without interference. It is shown that in the presence of interference the proposed technique achieves a channel information capacity of about 38 bits/s/Hz at a SNR of 30 dB. In a similar manner to information capacity results, BER results show that the A-MMSE-MUD Detect and Forward relaying technique remain tolerant to channel interference while the MAI free operation achieves a BER performance arbitrarily close to the theoretical upper bound (MLSE). It is necessary to point out the fact that MLSE results make the assumption of full channel state information at every communication terminal. Whereas, the proposed A-MMSE-MUD for cooperative CDMA does not require any channel state information at transmitter or receiver.

4.7 Summary

The uplink of an asynchronous DF CDMA wireless network interference tolerance was investigated in this chapter, where relays and base station use A-MMSE-MUD to detect incoming signals. Relays exchange data and channel information with the base station to achieve diversity gains. Due to non orthogonality of random spreading waveforms, Multiple Access Interference occurs, at both the relays and base station. In order to mitigate Multiple Access Interference, A-MMSE-MUD was used by fractionally spaced linear transversal bank of filters.

It was shown that A-MMSE-MUD enables asynchronous cooperative communications and extremely effective in mitigating channel interference. It was also shown that the BER and Capacity performance of the scheme were arbitrarily close to non linear MLSE theoretical upper bound results in a channel interference free operation. However, in the presence of channel interference, the scheme outperforms the theoretical upper bound approach by nearly 9 dB at a BER of 10^{-3} and by 17 bits/s/Hz in information capacity at a SNR of 30dB. The figure 4.7 chart shows various MUD techniques in cooperative CDMA wireless networks. A-MMSE-MUD presented in cooperative CDMA wireless networks of chapter 3 and chapter 4 is claimed as contribution of this thesis.

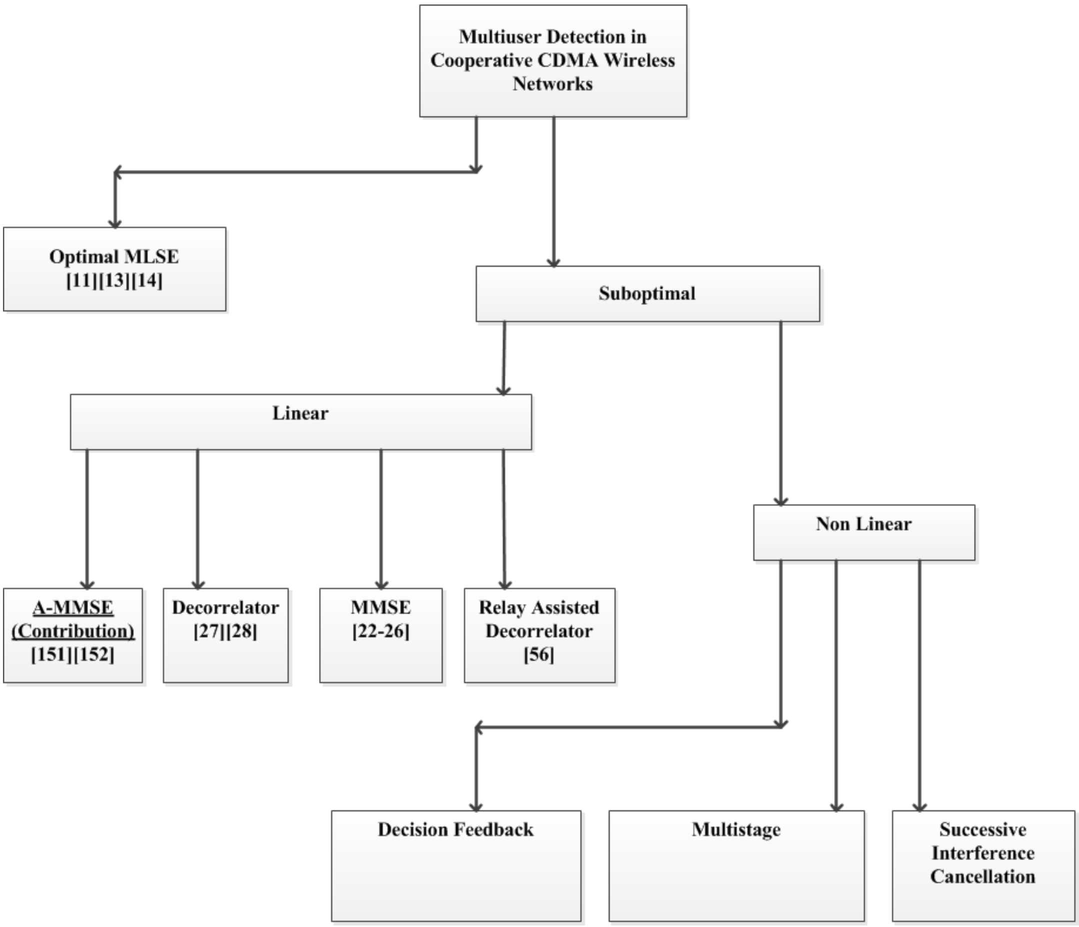

Figure 4.7: Multiuser detection algorithms in cooperative CDMA wireless networks:

- MUD in Cooperative CDMA Wireless Networks classified as Optimal MLSE and Suboptimal algorithms. The Optimal MLSE algorithm is very complex, where Viterbi decoding has been used. Viterbi decoding requires large computations and practically not feasible for practical situation of CDMA wireless detection. However, it provides the theoretical upper bound for the multiuser detection. Therefore, Suboptimal algorithms has been used in all practical situations. The Suboptimal algorithms further classified into Linear and Non Linear categories. Linear algorithm having the computational complexity directly proportional to the number of user, whereas, in non Linear algorithm the computational complexity increase exponentially with the increase of the number of user. The research contribution A-MMSE-MUD falls in linear algorithm category.

Chapter 5

ADAPTIVE SIGNAL COMBINING IN COOPERATIVE WIRELESS NETWORKS

5.1 Introduction

When discussing reception of signals we use the resources of antenna arrays or distributed virtual MIMO systems (called cooperative wireless networks), to provide service multiple users simultaneously. Diversity combining devotes the entire resources of the arrays and virtual MIMO systems to service multiple users in fading channels. Specifically, diversity schemes enhance reliability by minimizing the channel fluctuations due to fading by sending multiple replicas of identical data over multiple channels. The central idea in diversity is to send the same data signals at multiple antennas with reasonable separation to each other. The statistical probability of all these signal version being in a deep fade becomes lower. Multiple antenna arrays at destination nodes and distributed virtual MIMO systems, therefore, provide maximum benefit when the fading is independent from element to element. Usually independent fading would arise in a moderately dense and highly dense urban environment, where the several multipath components add up very differently at each element through different relays. Classically, it is observed that fading has three components: path loss, large-scale and small-scale fading. Over fairly long periods the first two components are approximately invariant and can deal with using strict power control. Diversity combining is particularly use to tackle small scale fading. Therefore, this research work has used slow, flat and Rayleigh fading as channel model for the signal fluctuations.

The Rayleigh channel model assumes that the fading remains independent from one element to the next and identically distributed. Each element, therefore, acts as an independent sample of the random Rayleigh fading process and each antenna of the array receives unique copy of the transmitted signal. The goal of combining is to increase the SNR and reduce the BER. Various methods were used in previous research for signal combining purpose with that aim. If we have m elements in the receiving antenna array, m independent copies of the same signal impinge on the antenna array. It is unlikely that all m elements are of received copies communicate through deep fades. At least one copy will have reasonable power and able to adequately process the signal. Antenna diversity is also known as space diversity. It is one of the many wireless diversity schemes that uses MIMO systems to increase communication channel information capacity in order to improve the quality and reliability of a wireless link.

There are two types of signal distortion in wireless networks; additive and multiplicative. The causes of these distortion are Gaussian noise and flat fades or frequency selective fades (depending upon the channel environment). Cooperative communication is a promising technique that can overcome this weakness by reducing the fading effects by combining multiple replicas of the transmitted signal. Cooperative communication networks presented and explained in previous chapters. Usually two cooperative protocols incorporated at relays: amplify-and-forward (AF) and decode-and-forward (DF) [25] with a maximal ratio combining (MRC) scheme at destination. The cooperative relays strategies were explained in past literature by [56][29], where they implicitly or explicitly describe the importance of channel estimation to get benefit from cooperation. Throughout this research the concepts of this research literature have been used. This research used AF and DF relaying protocols at relays for forwarding data with adaptive signal combining at the destination [62]. Most of the relaying schemes currently known, assume a DF relaying scheme under the assumption of a theoretical perfect decoding scheme applied in the relays. This research has used the same assumption with an additional assumption of a Gaussian channel from source to relays to examine the maximum benefit of cooperation. Usually, two adaptive algorithms on linear transversal filter have been used for signal combining: Least mean square (LMS) and recursive least square algorithm (RLS). These presented scheme, does not require channel estimate, rather it requires signal itself after channel equalization. Consequently, it reduces the computational complexity for signal combining. This chapter deals with the signal combining in cooperative wireless networks.

In past literature, extensive work is performed on adaptive algorithms for channel equalization, noise cancellation and signal combining. The brief literature review of the past research was already discussed in chapter 1. The benefit of adaptive implementation is computational complexity which is less than MRC and optimum combining (Wiener). Particularly the LMS adaptive algorithm is simplest in computational complexity. In recent research publications [125][126], a Newton's recursive formula base LMS algorithm is proposed for adaptive signal combining, which is effective for Gaussian channels with unequal noise. RLS and LMS algorithms presented and used for some applications were presented in [138-142]. The contributions of this chapters are as follows:

- This chapter presents the cooperative wireless networks with adaptive signal combining on destination node with LMS, MRC, Wiener and RLS algorithms.
- The computer simulation results in a wireless flat fading Rayleigh channel has shown the performance of the proposed adaptive LMS algorithm provide 10^{-3} BER at 10dB and 10^{-5} BER at 20dB with both AF and DF protocols equal to MRC and optimum combining.
- A cooperative channel model is proposed for wireless network, where source to relays node communicate in Gaussian channel and relays to destination node in Rayleigh channel.

The rest of the chapter is divided into the following sections; section 5.2 presents the cooperative wireless network model, section 5.3 presents optimum combining (Wiener) and section 5.4 is related to MRC technique. Section 5.5 deals with presented adaptive signal combining with classical LMS and classical RLS algorithm in a cooperative wireless network. Section 5.6 presents computer simulation results and section 5.7 is for the conclusions.

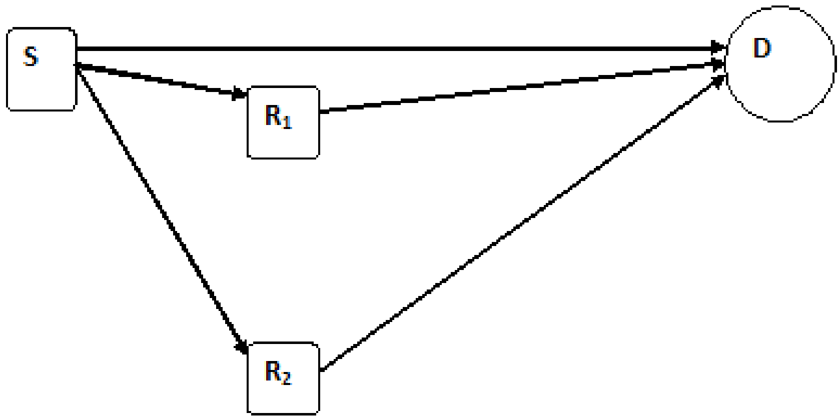

Figure 5.1: A cooperative wireless network with one source, two relays and a destination node:

1. Source node S transmits signal to relays and destination node. The channel from source to relay is taken as the Gaussian channel and from source to destination node as the flat fading Rayleigh channel.

2. Relay nodes R_1, R_2 transmit signal to destination node through Rayleigh channels. On relays transmit beamforming signalling is used for non adaptive methods of signal combining. And training sequence signalling is used for adaptive signal combining.

3. On destination node D, adaptive signal combining is used.

5.2 Cooperative Wireless Networks Model

Figure 5.1 shows the used cooperative wireless system model. Cooperative wireless network's communication is divided into two phases to avoid interference. A training sequence is operated to setup and maintain the connection between source-relays and source-destination links to adaptively adjust the weights of adaptive filters. In past literature a commonly used assumption of perfect error correction at relays was used with DF protocol. This research has taken the same assumption with a further addition that 'for AF protocol, there are Gaussian channels from source to relays communication'. The mentioned assumption is very realistic particularly for a dense urban network and line of sight communication. The related literature was described in previous chapters, where usually cooperative communication in time, frequency or code domain consists of the following phases:

- In phase 1, a source sends information to relays from the Gaussian channels. And source sends information to destination through Rayleigh channels.
- In phase 2, the relays forward the information to destination after using relaying cooperative protocols AF or DF from the Rayleigh channels.

The signals received at the combiner after analogue to digital conversion for source to destination communication is given by:

$$y_I(n) = h_1.x(n) + v_1(n) \tag{5.1}$$

Communication from source to relays can be written as:

$$y_{I'}(n) = h_0.x(n) + v_0(n) \tag{5.2}$$

DF protocol relays to destination communication is given by:

$$y_{II}(n) = h_2.x(n) + v_2(n) \tag{5.3}$$

For AF protocol, relays to destination communication of above equation becomes:

$$y_{II}(n) = h_2.y_0(n) + v_2(n) \tag{5.4}$$

From above equations:

$$y_{II}(n) = [h_2.h_0].x(n) + [v_0(n) + v_2(n)] \tag{5.5}$$

For the AF protocol, Gaussian channel is assumed between source node to relay nodes with zero mean and unit variance, therefore one can assume $h_0 = 1$. At relays signal amplification performed, hence, the signal received at the destination after channel equalization is:

$$y_{II}(n) = \gamma.x(n) + \frac{[\gamma v_0(n) + v_2(n)]}{h_2} \tag{5.6}$$

The term on the right side of the equation is noise of relay assisted received signal at destination, which is given by:

$$A = \frac{[\gamma v_0(n) + v_2(n)]}{h_2} \tag{5.7}$$

Whereas, the signal and noise received by direct transmission after equalization:

$$B = \frac{v_1(n)}{h_1} \tag{5.8}$$

Therefore, in coming sections this research will analyses an innovative method of signal combining with unequal noise variance. The signal power transmitted from the relay nodes is same as power of the source node. Power analyses of the cooperative network is beyond the scope of this research, it is commonly available in past literature, particularly in [57].

5.3 Optimum Combining (Wiener) for Single Channel Noise Variance

The symbols received after combining are given by:

$$\hat{x}(n) = \mathbf{a}_m^H(n)\mathbf{y}_m(n) \tag{5.9}$$

where $\mathbf{a}_m^H(n)$ is M-dimensional complex value weight vector is given by:

$$\mathbf{a}_m^H(n) = [a_1, a_2.....a_m] \tag{5.10}$$

$\mathbf{y}_m(n)$ is received complex valued vector, which is given by:

$$\mathbf{y}_m^H(n) = [y_1(n), y_2(n).....y_m(n))] \tag{5.11}$$

And the channel noise in each receive signal is given by following matrix:

$$\mathbf{v}_m(n) = [v_1(n), v_2(n).....v_m(n))] \tag{5.12}$$

This research assumed that above mentioned vectors remain constant for whole block of transmitted data. If the two beam of signals adaptively combine (direct and relay assisted), then error $e(n)$ between the reference signal and the output of adaptive filter is for the n^{th} symbol is given by:

$$e(n) = (x(n) - \hat{x}(n)) \tag{5.13}$$

Here $x(n)$is a digital reference training sequence known at receiver filter. From equation 5.9 and equation 5.15, we can get:

$$e(n) = (x(n) - \mathbf{a}_m^H(n) \cdot \mathbf{y}_m(n)) \tag{5.14}$$

The mean square error (MSE) is given as:

$$J(a_m(n)) = \mathcal{E}[e(n).e^*(n)] \tag{5.15}$$

From equation 5.16 and equation 5.17:

$$J(a_m(n)) = \mathcal{E}[(x(n) - \mathbf{a}_m^H(n).\mathbf{y}_m(n))(x(n) - \mathbf{a}_m^H(n).\mathbf{y}_m(n))^*] \tag{5.16}$$

Let **z** is the expectation m by 1 cross-correlation matrix vector between the received components and the reference sequence, and the expectation:

$$J(c_m(n)) = \mathcal{E}[x(n).\mathbf{y}_m(n)^H] = \mathbf{z}^H \tag{5.17}$$

And $[\mathbf{a}_m(n)]_{opt}$ is the optimal weight vector, then:

$$\mathbf{R}[\mathbf{a}_m(n)]_{opt} = \mathbf{z} \tag{5.18}$$

The above equation is the Wiener equation or the normal equation (optimum combining) [64][76]. One possible solution of this equation is matrix inversion of correlation matrix **R**, mathematically:

$$[\mathbf{a}_m(n)]_{opt} = \mathbf{R}^{-1}\mathbf{z} \tag{5.19}$$

For mxm receive antenna system, the correlation matrix of received signal is given by:

$$\mathbf{R} = E[\mathbf{y}_m(n)\mathbf{y}_m^H(n)] = \begin{bmatrix} \varrho(1,1) & \varrho(1,2) & ..... & \varrho(1,m) \\ \varrho(2,1) & \varrho(2,2) & ..... & \varrho(2,m) \\ .... & .... & ...... & .... \\ \varrho(m,1) & \varrho(m,2) & ..... & \varrho(m,m) \end{bmatrix} \tag{5.20}$$

The matrix **R** is Hermitian and can be uniquely defined by specifying the values of the correlation coefficients $\varrho(1,1), \varrho(1,2), ..., \varrho(1,m)$. Where $\varrho(i,j) = \varrho^*(j,i)$. The above matrix equation was mentioned for signal combining by S A Hanna in [76]. The inverse of the matrix can be used to find Wiener's solution of the signal combining.

5.4 Maximal Ratio Combining (MRC)

Transmit signal at a particular time instant undergoes through the airlink. The receive chain can be modeled by a complex multiplicative distortion consist of a magnitude response and a phase response. The channel between the transmit antenna and the first receive antenna is denoted by h_1 and between the transmit antenna and the second receive antenna is denoted by h_2 where,

$$h_1 = \alpha_1 e^{j\theta_1} \tag{5.21}$$

$$h_2 = \alpha_2 e^{j\theta_2} \tag{5.22}$$

The received signal for two antenna system is given by:

$$y_1(n) = h_1 x(n) + v_1(n) \tag{5.23}$$

$$y_2(n) = h_2 x(n) + v_2(n) \tag{5.24}$$

Classical MRC for two received signals $y_1(n)$ and $y_2(n)$ is given by well known equation of MRC equalization:

$$\hat{x}(n) = \frac{h_1^*(n).y_1(n) + h_2^*(n).y_2(n)}{h_1^*(n).h_1(n) + h_2^*(n).h_2(n)} \tag{5.25}$$

Here $(.)_m^*(n)$ represent a complex conjugate. The above mentioned formula is being used for MRC simulation results in this thesis. MRC weigh the received signal with considering the equal channel noise variance in $y_1(n)$ and $y_2(n)$. Actually, MRC only combine the signal according to signal power.

5.5 Adaptive Signal Combining in Cooperative Wireless Networks

Classical adaptive signal combining shown in figure 1.3 and figure 5.1 represents the classical m-branch adaptive signal combining system, where m is the number of antennas of the receiver communication terminal. The benefit of an adaptive receiver over MRC and Wiener's combining is that the computational complexity of adaptive combining is lesser than MRC. Used adaptive combining schemes are also near far resistant, therefore, it does not require strict power control. Let the base band received signal vector is $\mathbf{y}_m(n)$. Adaptive filter combines by adaptive algorithm with a step size regulated by the signal received power in case of classical normalize least mean square error (NLMS) and according to signal to noise ratio with a proposed WLS algorithm, where inverse of variance of noise multiplied with signal itself [125][126], which will be discussed in following chapter. A training operation coordinated by the transmitter was been used to adjust the m^{th} weighing coefficient $\mathbf{a}_m$ of the adaptive combiner. The reference signal at receiver in a time interval n is denoted by $x(n)$, whereas $\hat{x}(n)$ is combined signal. The term $(.)^*$ represents a complex conjugate.

5.5.1 Classical Least Mean Square Algorithm (LMS) for Equal Channel Noise Variance

In this section classical least means square (LMS) algorithm is described. It was developed by Bernard Widrow in the 1960s. This algorithm is very successful and wildly used for various signal processing applications; signal combining, channel equalization, multiuser detection, signal combining and artificial intelligence etc. Its popularity is due to computational simplicity, ease of implementation and good convergence properties. The purpose of using the LMS algorithm is to build the MMSE weights for the given environment. The LMS algorithm adaptively produces weights that minimize the mean-squared error between a desired signal and the arrays output. In the MMSE combining we need information of the communication parameters by using training signals to determine the optimal weights. We can also say that it weighs to steer the reception in the direction of the desired signal power and minimize reception from the noise/interfering or undesirable signals. But classical LMS only observe the power of signal and neglect the presence of channel noise. This situation severely effects the reception performance. The WLS error method of signal combining will be proposed in next chapter, which is the solution of the problem with a slight disadvantage of computational complexity. Different version of the LMS algorithm were presented in [139][140]. And just as in the MMSE weighting case, the required information is the desired signal's direction and power. The direction is specified via the desired signal's steering vector and the signal power. Note that these parameters can vary with time, as the environment is assumed to be changing. The directions and power can be determined using various direction finding algorithms, which analyze the received signals at each antenna in order to estimate the directions and power. The LMS algorithm requires an estimate of the autocorrelation matrix in order to obtain weights that minimise the mean square error (MSE). The LMS algorithm estimates the autocorrelation matrix using only the current received signal at each antenna. The weights are updated iteratively, at discrete instances of time. The estimate of the autocorrelation matrix at time n, written with a bar overhead. The adaptive weights are mentioned as $\mathbf{a}_m(n)$, where n is an index that specifies time. The LMS weighting algorithm simply updates the weights by a small amount in the direction of the negative gradient of the MSE function. By moving in the direction of the negative gradient, the overall MSE is decreased at each time step. In this manner, the weights iteratively approach to the optimal values that minimise the MSE. Moreover, since the adaptive algorithm is continuously updating, as the environment changes the weights adapt as well. The adaptive algorithms are in contrast to Wiener's solution, where solution does not require matrix inversion. Explicit calculation of the correlation co-efficient is the steepest decent method (SDM). The SDM is recursive procedure that can be used to calculate the optimal weight vector $[\mathbf{a}_m(n)]_{opt}$. Let $\mathbf{a}_m(n)$ and $\nabla_m(n)$ denote the values of the weight vector and the gradient vector, respectively. Then succeeding values of the weight vector can be obtained by the recursive relation. After obtaining the optimum weight vector, adaptive filter operates in decision directed mode. Therefore:

$$\mathbf{a}_m(n+1) = \mathbf{a}_m(n) - \mu\nabla_m(n) \tag{5.26}$$

Where μ is the step size constant that controls stability and the rate of adaptation. Putting the value of $\nabla_m(n)$ in above equation:

$$\mathbf{a}_m(n+1) = \mathbf{a}_m(n) - \mu(-2\mathbf{z} + 2\mathbf{R}\mathbf{a}_m(n)) \tag{5.27}$$

Further simplification yields:

$$\mathbf{a}_m(n+1) = \mathbf{a}_m(n) + \mu(2\mathbf{z} - 2\mathbf{R}\mathbf{a}_m(n)) \tag{5.28}$$

If we express $\mu \cdot \nabla_m(n)$ in terms of instantaneous estimates:

$$\mu \cdot \mathbf{z} = \mathbf{y}_m(n) \cdot x^*(n) \tag{5.29}$$

And:

$$\mathbf{R} = \mathbf{y}_m(n) \cdot \mathbf{y}_m(n)^H \tag{5.30}$$

Then the equation can be simplified as:

$$\mathbf{a}_m(n+1) = \mathbf{a}_m(n) + 2\mu\mathbf{y}_m(n) \cdot (x^*(n) - \mathbf{y}_m^H(n) \cdot \mathbf{a}_m(n)) \tag{5.31}$$

Here n represents the iteration number/symbol number/time. Which can be expressed in terms of $e^*(n)$ as:

$$\mathbf{a}_m(n+1) = \mathbf{a}_m(n) + 2\mu \cdot \mathbf{y}_m(n) \cdot e^*(n) \tag{5.32}$$

The term $2\mu \cdot \mathbf{y}_m(n) \cdot e^*(n)$ is called the correction factor. The term μ controls the size of correction. It is usually selected by multiplying the number of taps and the signal power. Therefore, in classical adaptive combining using LMS algorithm the adaptive filter converge according to power of signal. For two receive antennas:

$$a_1(n+1) = a_1(n) + 2\mu \cdot y_1(n) \cdot e^*(n) \tag{5.33}$$

$$a_2(n+1) = a_2(n) + 2\mu \cdot y_2(n) \cdot e^*(n) \tag{5.34}$$

5.5.2 Recursive Least Square Algorithm (RLS)

Several adaptive algorithms have expanded upon ideas used in the original LMS algorithm. Most of these algorithms seek to produce improved convergence properties at the expense of increased computational complexity. The RLS algorithm seeks to minimize the MSE just as in the LMS algorithm. However, it uses a more sophisticated updates to find the optimal weights that is based on the matrix inversion lemma. Adaptive solution does not require matrix inversion. Some of the relevant literature of RLS algorithm other than the books mentioned in the chapter 1. Basically for RLS algorithm, Newton's Recursive Method with regularization is employed in step size therefore Newton's Method is replaced by

$$\mathbf{a}_m(n+1) = \mathbf{a}_m(n) + \mu[\epsilon_0 \mathbf{I} \cdot \mathbf{R}]^{-1}(2\mathbf{z} - 2\mathbf{R} \cdot \mathbf{a}_m(n)) \tag{5.35}$$

Where ϵ_0 is a constant called the iteration dependent regularization parameter and **I** is an identity matrix of the same dimension as **R**. By instantaneous approximation of the above equation and setting parameter of RLS algorithm for initialization. Following are the sets of equations for RLS algorithm applied for signal combining. The λ forgetting factor is taken as $\lambda = 0.99$; Initially set $P_1(n-1), P_2(n-1) = 0.3$ for two receive signals. These are defined as complex matrices approximately equal to the inverse of the covariance matrix. The terms ϕ_1 and ϕ_2 are gain terms applied to the weight update, and are a function of λ.

$$\hat{x}(n) = (y_1(n)(a_1(n)) + (y_2(n)(a_2(n)) \tag{5.36}$$

$$e(n) = (x(n) - \hat{x}(n)) \tag{5.37}$$

$$\phi_1(n) = \lambda\phi_1(n-1) + y_1^*(n) \cdot y_1(n) \tag{5.38}$$

$$\phi_2(n) = \lambda\phi_2(n-1) + y_2^*(n) \cdot y_2(n) \tag{5.39}$$

$$P_1(n) = \phi_1^{-1}(n) \tag{5.40}$$

$$= \frac{\lambda^{-1}(P_1(n-1) - ((\lambda^{-1}P_1^*(n-1)y_1^*(n) \cdot y_1(n)P_1(n-1))}{(1+\lambda^{-1}.y_1(n)P_1(n-1)y_1^*(n)))} \tag{5.41}$$

$$P_2(n) = \phi_2^{-1}(n) \tag{5.42}$$

$$= \frac{\lambda^{-1}(P_2(n-1) - ((\lambda^{-1}P_2^*(n-1)y_2^*(n) \cdot y_2(n)P_2(n-1))}{(1+\lambda^{-1}y_2(n)P_2(n-1).y_2^*(n)))} \tag{5.43}$$

$$a_1(n) = a_1(n-1) + (P_1(n)(a_1^*(n))(e(n))) \tag{5.44}$$

$$a_2(n) = a_2(n-1) + (P_2(n)(y_2^*(n))(e(n))) \tag{5.45}$$

Same set of equations are used for computer simulation in following section. The matrix form of the equation 5.43 and equation 5.44 is:

$$\mathbf{a}_m(n) = \mathbf{a}_m(n-1) + (\mathbf{P}_m(n)(\mathbf{y}_m^*(n))(e(n))) \tag{5.46}$$

5.6 Performance Comparison and Numerical Simulations

For the BER analysis, this research has simulated a cooperative communication wireless network with an adaptive combiner at the destination node shown in figure 5.1 and figure 5.2. In figure 5.2, the base band signal after channel equalization is fed into the combiner on the destination node of the cooperative communication wireless network. A single source transmits BPSK data to two relay nodes where either AF or DF protocol is employed. The following conditions are present in all simulations: a) 120 training binary bits are sent and 200000 bits of un-coded coherent BPSK data signal are sent through a Rayleigh channel from source to destination and than relays to destination. At relays hard decision decoding was performed for decode-and-forward (DF) protocol and amplification performed for amplify-and-forward (AF) scheme. For AF it is assumed that sources can find line of sight communication with relays nodes and therefore, transmission from source to relays is through a Gaussian channel with zero mean and variance one. And for the decode and forward, computer simulation has the classical assumption of perfect error correction. It is also assumed that with a suitable error correction scheme and channel selection, the BER is negligible at relays. b) LMS and RLS algorithms are used at the adaptive combiner on the destination for signal combining. This research also used MRC and Optimum combining scheme at receiver for comparison of simulation results. It is also assumed the channels between source and destination and from relays to destination are wireless flat fading Rayleigh c) these computer simulations are taken SNR on the x-axis and received signal BER on y-axis of plot. The used MATLAB code is given in Appendix II.

Figure 5.3 shows the performance of AF operation of cooperative networks. The performance of the proposed system in a wireless flat fading Rayleigh channel shows that the used technique provides about 10^{-3} BER at 10dB and 10^{-5} BER at 20dB, with both DF protocols equal to MRC and optimum combining. Figure 5.4, shows the performance of the DF protocol cooperative network in all wireless flat fading Raleigh channels. The performance of proposed adaptive combining in these channel environment is about 10^{-3} BER at 10dB and 10^{-5} BER at 20dB with both DF protocols equal to MRC and optimum combining.

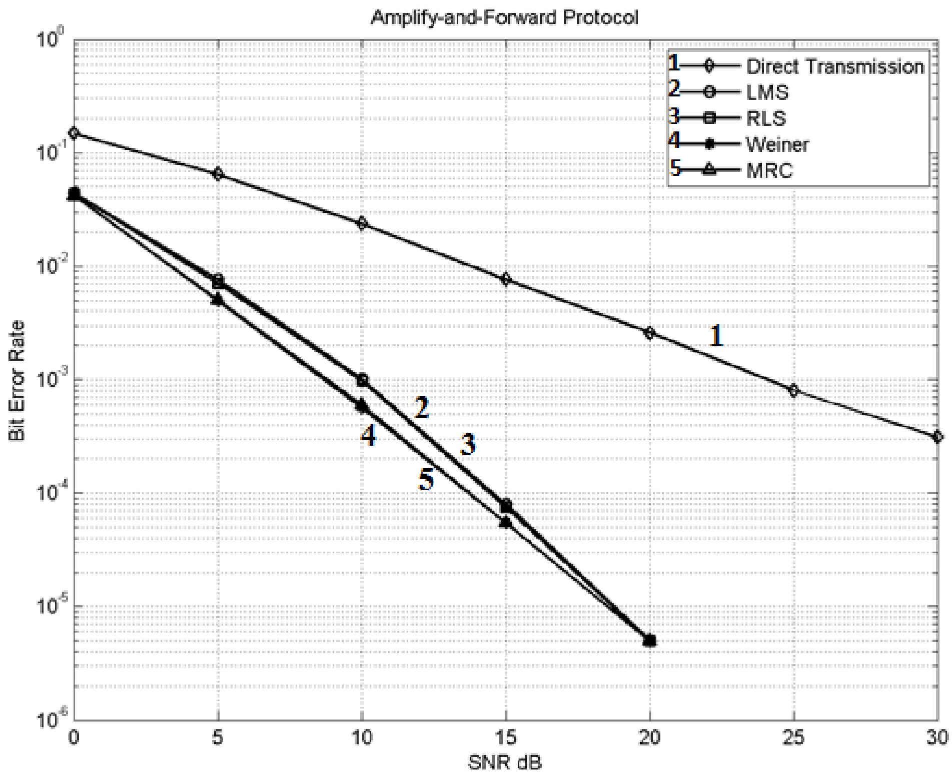

Figure 5.2: BER performance for AF in wireless flat fading Rayleigh channels:

1. 1x1 BPSK Bench Mark (Direct transmission).
2. Classical LMS Algorithm.
3. Classical RLS Algorithm.
4. Optimum Combining (Wiener).
5. Maximal Ratio Combining (MRC).

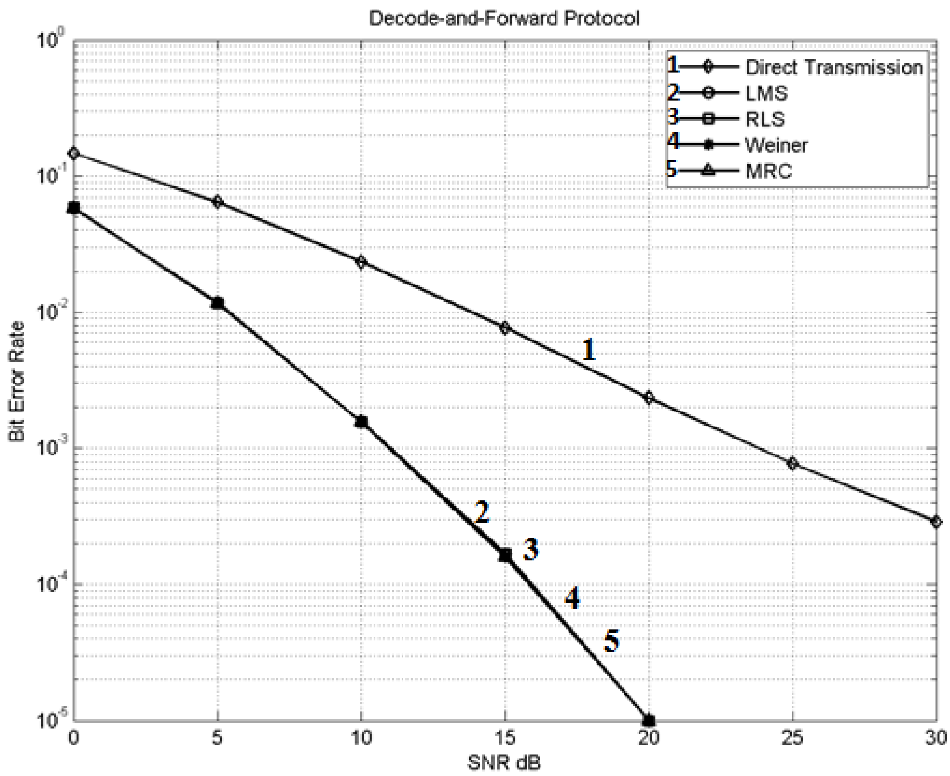

Figure 5.3: BER performance for DF in wireless flat fading Rayleigh channels:

1. 1x1 BPSK Bench Mark (Direct transmission).
2. Classical LMS Algorithm.
3. Classical RLS Algorithm.
4. Optimum Combining (Wiener).
5. Maximal Ratio Combining (MRC).

5.7 Conclusions

The classical adaptive signal combining schemes with using LMS and RLS algorithms is used for cooperative wireless communication. It is observed that both algorithms provide same performance as of Wiener's and MRC combining schemes. The LMS algorithm has benefit of computational simplicity over other schemes. The combining schemes are tested for cooperative wireless networks with the assumption of zero mean and unit variance Gaussian channel noise. However, optimum adaptive algorithms are required to develop for cooperative wireless networks to address the problem of unequal channel noise variance. A cooperative channel model is also introduced, when AF cooperative protocol is used. In the used channel model, it is assumed that source nodes and relays nodes communicate in Gaussian channels. Whereas, the communication from source to destination and relays to destination are through wireless flat fading Raleigh channels.

5.8 Summary

The uplink of a cooperative wireless network was examined, where users cooperate by relaying each other's messages to the base station. Direct transmission and relays assisted transmission beams were combined by using multiple antennas at destination node. The combining of the beams were performed by using LMS and RLS algorithms to maximize received SNR. The used system weighs the direct transmission and relay assisted beams and provide equal performance to MRC and optimum combining (Wiener). Two cooperative protocols AF and DF were employed with adaptive signal combining in flat fading Rayleigh wireless communication channels. For single a source node, two relays nodes and a destination node with two receive antennas, the used combining schemes provide 10^{-3} at 10 dB SNR and 10^{-5} at 20 dB SNR.

Chapter 6

SIGNAL COMBINING BY WEIGHTED LEAST SQUARE ERROR METHOD FOR WIRELESS NETWORKS

6.1 Introduction

In chapter 1, a brief literature review of Least square method (LSM) was presented. LSM was commonly used in various applications; target tracking, medical diagnosis and computing estimations of parameters and fitting data. It is one of the oldest techniques of modern statistics. It was first published in 1805 by the French mathematician Legendre. After the publication of Legendres memoir, Gauss, the famous German mathematician, published another memoir (in 1809) in which he mentioned that he had previously discovered this method and used it as early as 1795. A somewhat bitter anteriority dispute was followed (a bit reminiscent of the Leibniz-Newton controversy about the invention of calculus), however, this did not diminish the popularity of this technique. Galton used it (in 1886) in his work on the heritability of size which laid down the foundations of correlation and (also gave the name) regression analysis. Both Pearson and Fisher, who did so much in the early development of statistics, used and developed it in different contexts (factor analysis for Pearson and experimental design for Fisher). Nowadays, the least square method is widely used to find or estimate the numerical values of the parameters to fit a function to a set of data and to characterize the statistical properties of estimates. It exists with several variations: its simpler version is called ordinary least squares (OLS) or un-weighted least squares, a more sophisticated version is called weighted least squares (WLS), which often performs better than OLS because it can modulate the importance of each observation in the final solution. In wireless communication networks combining of received signals at the destination node/base station or mobile phone with multiple antennas is vital. The need for signal combining is increased further with the advancement of optical fibre communication systems, MIMO, satellite communication systems and next generation cooperative communication wireless networks. In cooperative wireless networks each node cooperates in transmitting information to other nodes, as discussed in previous chapters. Many authors have presented the equalization of channels and combining of the signals. Various techniques were used in past literature for combining of received signals with multiple antennas, they were mentioned in the previous chapters. In chapter 5, adaptive signal combining [125] [126] were presented for cooperative wireless networks, where the need of channel noise variance based algorithm was discovered. The consequence of the research of chapter 5 leads this research to develop a combining method called weighted least square error for signal combining.

This research proposes to use a well known method of weighted least square (WLS) error method for signal combining. The method was used commonly in estimation theory for target tracking, econometrics and medical diagnosis [97-100][109]. The theory of weighted least square method has been well investigated in past literature, the complex details of the mathematical theory for least squares methods are beyond the scope of this research. This research restricts the work towards WLS error of signal combining use, implementation and analysis of the performance. This research analyses and shows the performance of WLS error method of signal combining by computer simulation. In particular, the performance measure of ensemble average mean square error [59] and bit error rate (BER) are examined. From mathematical analysis and computer simulation, it is observed that an un-weighted least square error method is equivalent to equal gain combining. And a weighted least square combining scheme provides performance very close to optimum signal combining (Wiener Solution). This research has also shown with mathematical analyses and computer simulation that with the classical assumption of zero mean unit variance, WLS method of combining, equal gain combining, adaptive combining with LMS and RLS algorithm and optimum combining provide equal performance. And it is shown that the computational complexity of WLS error method is lowest in the unequal channel noise variance conditions. And the used scheme provides performance close to optimum combining (Wiener solution), even in the realistic situation of unequal noise variances at multiple receive branches of the antennas. In this research work it is assumed that both channels and noise are uncorrelated, independent and identically distributed. The least squares criterion has important statistical interpretations. If appropriate probabilistic assumptions about underlying error distributions are made, least squares produces what is known as the maximum-likelihood estimate of the parameters. Even if the probabilistic assumptions are not satisfied, years of experience have shown that least squares produces useful results. The computational techniques for linear least squares problems make use of orthogonal matrix factorizations. To use the weighted least square error method of signal combining, the proposed system couples the adaptive filter on each antenna element to estimate the noise variance of the channels and then the inverse of these estimate are used as weights of combiner. However, one can also use other filters instead of an adaptive filter for noise estimation. The original contributions claimed in this chapter are as follows:

- A signal combining method of weighted least square error method is proposed for wireless communication networks.
- It is shown by mathematical analysis and computer simulations that un-weighted least square error actually the method of equal gain combining.
- The performance of the proposed method achieves Wiener solution with unequal/different channels noise variance.
- Computer simulated Bit Error Rate (BER) performance is presented for the system. It is about 10^{-3} bits at 8 dB SNR and about 10^{-4} at 16 dB SNR in a wireless Rayleigh channel with two receive antennas.

The rest of the chapter is divided into following sections: Section 6.2 describes the system model and optimum signal combining (Wiener). Section 6.3 presents classical MRC, section 6.4 presents the WLS error method to find the Wiener solution for signal combining, section 6.5 describes performance comparisons and numerical simulations and finally section 6.6 is reserved for the conclusions.

6.2 System Model and Optimum Signal Combining (Wiener)

Figure 6.1 represents the baseband representation of the presented m-branch combiner. It is considered that at any given time, a signal $\mathbf{s}(t)$ is sent from the transmitter. The time invariable channels $\mathbf{h}_m$ including the effects of the transmit chain, the air-link, and the receive chain may be modelled by a complex multiplicative distortion composed of a magnitude response and a phase response. In the presented system model, the channels between the transmit antenna and the receive antennas are assumed to be wireless flat fading Rayleigh with Gaussian noise $\mathbf{v}_m(t)$ of variance σ_m. Receive signals arriving from the m^{th} antenna were frequency down converted by the down converter (DC) fed to the low pass filter (LPF), digitalized by the analogue to digital convertor (ADC) and further sent to the filter $\mathbf{f}_m$. Decision and error (D and E) devices provides interface between the noise estimation filters and weights of combiner. A noise estimation filter can be an adaptive or non adaptive. However, in this research adaptive filters are used for noise estimation. The noise (error) are due to the multipath propagation of signals that cause interference, additive Gaussian noise and signal interference which are estimated by the usual training routine. The inverse of the channel noise variance are used as weights of the combiner. Then the weights of the combiner multiplied with each respective signal to combine signals according to SNR. Let $\mathbf{y}_m(t)$ be the general form of the m^{th} received analogue signal in symbol duration T. And let $\mathbf{y}_m(n)$ is digital output of respective symbol from the output of ADC in time T. Figure 6.1 represents baseband representation of the presented m-branch combiner. At a given time t, a signal $\mathbf{s}(t)$ is sent from the transmitter by using multiple antennas. The channels h_m including the effects of the transmit chain, the air-link, and the receive chain may be modelled by a complex multiplicative distortion composed of a magnitude response and a phase response. The channels between the transmit antenna and the receive antennas are taken to be Gaussian, flat fading Rayleigh and frequency selective Rayleigh channels with Gaussian noise $\mathbf{v}_m$ of variance σ_m, for computer simulation experiments. For the Gaussian channels, we can take $\mathbf{h}_m = 1$ (Identity column matrix), since noise channel distortion are only due to Gaussian noise with respective channel variance σ_m . Receive signals arriving from m^{th} antennas are frequency down converted by the down converter (DC), fed to low pass filter (LPF) and digitalized by the analogue to digital convertor (ADC) and further sent to the filters $\mathbf{f}_m$ for noise estimation. In the presented system and computer experiments, these filters were taken as adaptive filters for the noise estimation, however any noise estimation filter can be used. The decision and error (D and E) device provides interface between the noise estimation filter and weight of combiner. The noise is the channel's distortion noise, channel's interference and additive Gaussian noise termed as error computed by the usual training sequences. The inverse of channels noise variance are used as weights of the combiner. The weights are kept constant for the whole block of received data until the next training starts. The weights of combiner multiplied with each signal for the singal combining according to SNR. The estimate of symbols $\hat{x}(n)$ after combining is given by:

$$\hat{x}(n) = \mathbf{a}_m^H(n)\mathbf{y}_m(n) \tag{6.1}$$

The mathematical derivation of the above equation is presented in chapter 5 which leads us to the following Wiener's equation:

$$[\mathbf{a}_m(n)]_{opt} = \mathbf{R}^{-1}\mathbf{z} \tag{6.2}$$

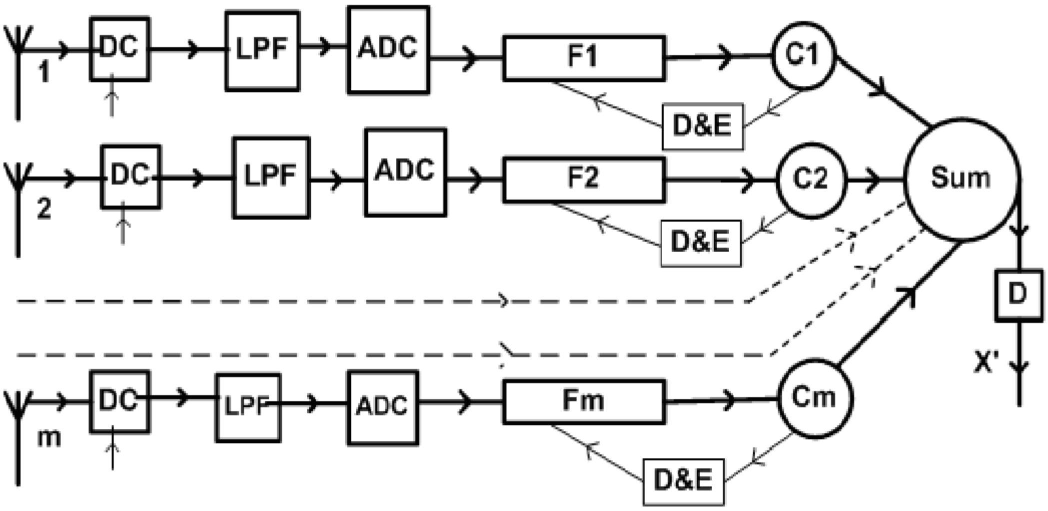

Figure 6.1: Signal Combiner Receiver Structure for Weighted Least Square Error Method:

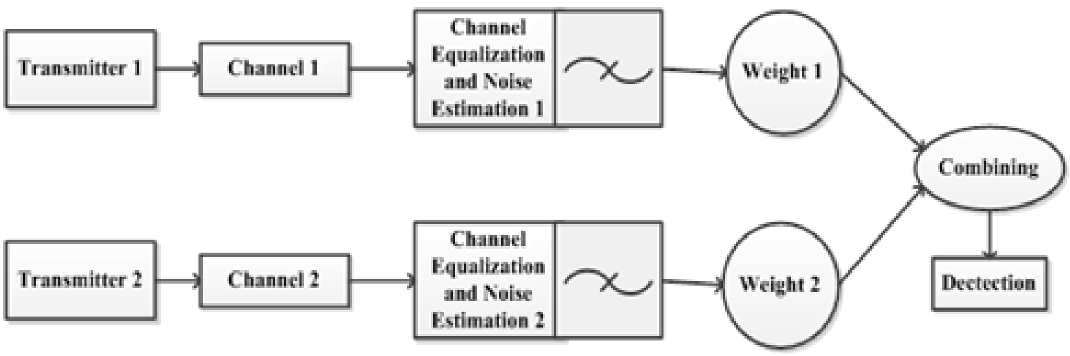

Figure 6.2: Simulation model for Weighted Least Square Error Method of Signal combining:

6.3 Un Weighted Least Square Error Method of Signal Combining

The Least square error method is a concept of fitting the curve to obtain the best estimate of the line, to acquire the best solution. Consider the received signals vector $\mathbf{y}_m(n)$. The average error vector for the length of training sequence is $\mathbf{e}_m$ between the reference signal and the output of filter is for a m^{th} symbol is given by:

$$\mathbf{e}_m = [e_1, e_2.....e_m] \tag{6.3}$$

$$\mathbf{e}_m = (\mathbf{x}(n) - \mathbf{y}_m(n)) \tag{6.4}$$

In these anlyses, time invariable channel is assumed and variation of channel noise remained constant for the duration of training and subsequent data transmission. If there are two receive antennas than the following set of equation evaluate the errors:

$$e_1 = (x(n) - y_1(n)) \tag{6.5}$$

$$e_2 = (x(n) - y_2(n)) \tag{6.6}$$

Here $x(n)$ is reference sequence (training) matrix with all entries equal to $x(n)$. Consider the m number of filters for noise estimation. This research used adaptive filters for that purpose. The least square error e^2 is given by:

$$e^2 = \mathbf{e}_m^T \cdot \mathbf{e}_m = e_1^2 + e_2^2.....e_m^2 \tag{6.7}$$

And for two antennas:

$$e^2 = \begin{pmatrix} e_1 & e_2 \end{pmatrix}^T \cdot \begin{pmatrix} e_1 & e_2 \end{pmatrix} = e_1^2 + e_2^2 \tag{6.8}$$

In above equation, the weighing coefficients of the right side of above equation are unity. The sum of the errors of all signals does not provide minimum error because it is equally weighing all the errors with unit channel noise variance. The above equation clearly indicates that the equal gain combining is equivalent to un-weighted least square error combining. In the above equation the un-weighted least square method is weighing equally (unit) to all of the errors signal to minimize the error. These weights are multiplied with respective signals to obtain equal gain combining. It provides optimum combining performance with classical assumption of zero mean and unit variance. In reality to minimize the error, we have to weigh the signals according to the quality of the signals, particularly when unequal channel noise variances are at the receive branches. Therefore, the weighted least square error method is required. The weights of the least square error method are used as weighing coefficients to combine signals as they weigh to minimize the error.

6.4 Weighted Least Square Error Method of Signal Combining

In practice received signals have different level of corruption, therefore, the error weighing equally does not provide least square error when channel noise variance are unequal. To minimize least square error e^2 by the theory of WLS estimation, one has to multiply each signal's square of error e_m^2 to its respective inverse of channel noise variance to obtain the WLS error. With WLS estimation method equation (6.8) becomes:

$$e^2 = \mathbf{e}_m^T \cdot \mathbf{e}_m = a_1 \cdot e_1^2 + a_2 \cdot e_2^2 + ...a_m e_m^2 \tag{6.9}$$

Where $\mathbf{a}_m$ represents the respective weight to minimize the error. The value of $\mathbf{a}_m$, according to WLS estimation theory is the noise variance of respective channels. We can write the above equation as a proposed weighted equation presented for three branches of the combiner receiver:

$$e^2 = \epsilon_m^T \epsilon_m == \frac{1}{\sigma_1^2} \times e_1^2 + \frac{1}{\sigma_2^2} \times e_2^2 + ...\frac{1}{\sigma_m^2} \times e_m^2 \tag{6.10}$$

The $\mathbf{a}_m$ matrix provides unequal weights for minimizing error in the WLS error method and can be used for optimum signal combining. These weights are used for signal combining according to the level of error (noise) of signal. Detailed mathematical derivation for WLS error is given in related literature that were mentioned earlier.

6.5 Performance Comparison and Numerical Simulations

6.5.1 Simulation Model

The simulation model is shown in Figure 6.2. The simulations are aimed at determining the convergence of error of two combined signals under Gaussian noise with unequal noise variances in Gaussian, Rayleigh flat fading and frequency selective wireless channels. The single source transmits signals through multipath communication channel towards destination, where multiple antennas are used for the reception of the signal. The received power is normalized at each antenna of the destination and error is computed between the received signal and the reference sequence available at destination. The error computed at each antenna. The reciprocal of the error variance is considered as channel noise variance and used as a weight of the each antenna element. After multiply each signal with reciprocal of channel noise variance, the summation is taken, which is termed as combined signal. The errors are computed and ensemble average mean square error curve plotted by using MATLAB simulations. Different channel noise variance are taken in the simulation for WLS error method. For equal gain combining or un-weighted least square error method, the unit noise variance is taken. Then, BER curve plotted against various SNR in the various channel environment. The following conditions exist in all simulations; a) Un-coded coherent BPSK is used for modulation and experiments have taken the transmit power as variable b) Independent fading characteristics are present on each channel when a flat fading Rayleigh channels are used and it is assumed that path losses are negligible c) The training sequences are generated independently with using uniformly distributed pseudo-random number generators d) Different levels of noise variance n(t) are taken on each channel with zero mean $N(0, \sigma)$ e) The simulations use adaptive transversal finite impulse response filters on each branch for channel equalization and noise estimation f) Least mean square algorithm is used to estimate error for noise estimation. The MATLAB computer simulation steps and codes are given in Appendix III.

6.5.2 Results

In figure 6.3 computer simulation clearly shows the difference of ensemble average mean square error curves for two methods, un-weighted and WLS combining in Gaussian communication channels. This research has kept the unequal channel noise variance for the computer simulations. As expected from mathematical theory, there is significant difference in error curves of un-weighed (equal gain combining) and WLS error for signal combining. In first simulation, the WLS error method provides about a 4dB gain in minimizing the error. Because, un-weighted equally weighted the signals with unit variance. The reason for better performance of WLS error method is the use of inverse of channel noise variance in each branch of combiner. Figure 6.4 represent BER performance for combining of two signals in Gaussian channels with unequal noise variance. In this specific example when 4dB power is received at each branch of the combiner receiver. The presented simulated BER performance is in a Gaussian channels with different/unequal channel noise variance of 1.43 and 9.04 respectively and the signal received on the first branch is:

$$10log_{10}(\frac{4}{1.43}) = 4.46dB \tag{6.11}$$

And on second branch is:

$$10log_{10}(\frac{4}{9.04}) = -3.5dB \tag{6.12}$$

This research aimed to determine the performance of MRC, Optimum (Wiener) and weighted least square error combining for comparison in the same channel conditions. The proposed scheme and optimum scheme (Wiener) only produce few errors with used inverse of channel noise variance. It is important to note here that in the computer simulation, signal power is considered on x-axis, instead of SNR. The MRC scheme is unable to achieve optimum performance, due to channel noise. From the figure, it is clear that the proposed scheme provide very few errors for all transmit power from 2.2 dB to 4dB and it is expected that beyond 4dB, we would get consistent results. It is also important to note that the MRC has linear performance improvement from 10^{-2} to 10^{-4} bits, but still far behind from optimum. In figure 6.5, this research simulated the BER performance in a wireless flat fading Rayleigh channel with different channel noise variance 1.43 and 9.04. This research found the performance of MRC, Optimum(Wiener) and WLS error combining. The proposed scheme and optimum scheme almost produced the same performance. The performance of the presented scheme is only 0.4 dB less than that the performance of the optimum combining for all SNRs. Whereas, the MRC method of signal combining is lagging behind 4dB to 6dB to the optimum combining performance. In figure 6.6 this research carried out the computer simulations for two received signals. In these experiment BER performance is measured in a wireless frequency selective Rayleigh channel with channel impairment (tap) of 0.5 and 0.3 respectively. Results show that the optimum combining failed to combine in such a situation. It is again important to observe that MRC provides inferior performance than the proposed method and at 6dB the proposed system provide almost zero BER. Both adaptive and non adaptive implementation of WLS can be implemented, however, in the simulation work of this research, adaptive filters are used on each branch of combiner for noise estimation.

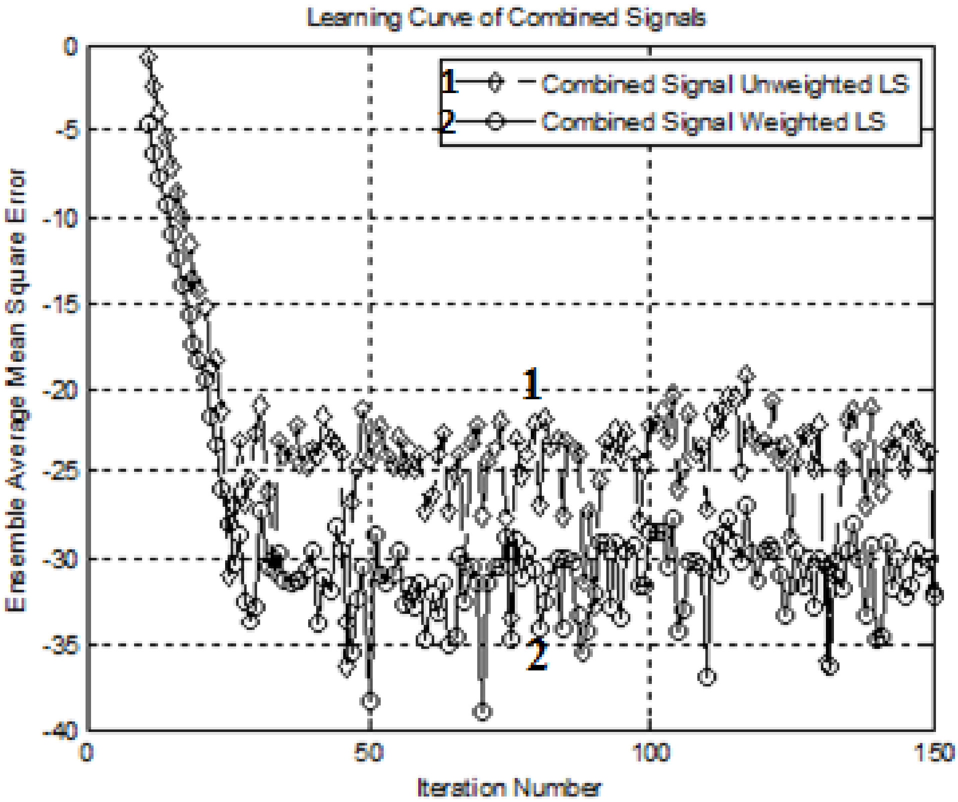

Figure 6.3: Learning curves for Un-Weighted and Weighted Least Square Error Method of Signal Combining:

1. Un-weighted least square error combining or Equal Gain combining.
2. Weighted Least Square Error Combining equivalent to Wiener combining .

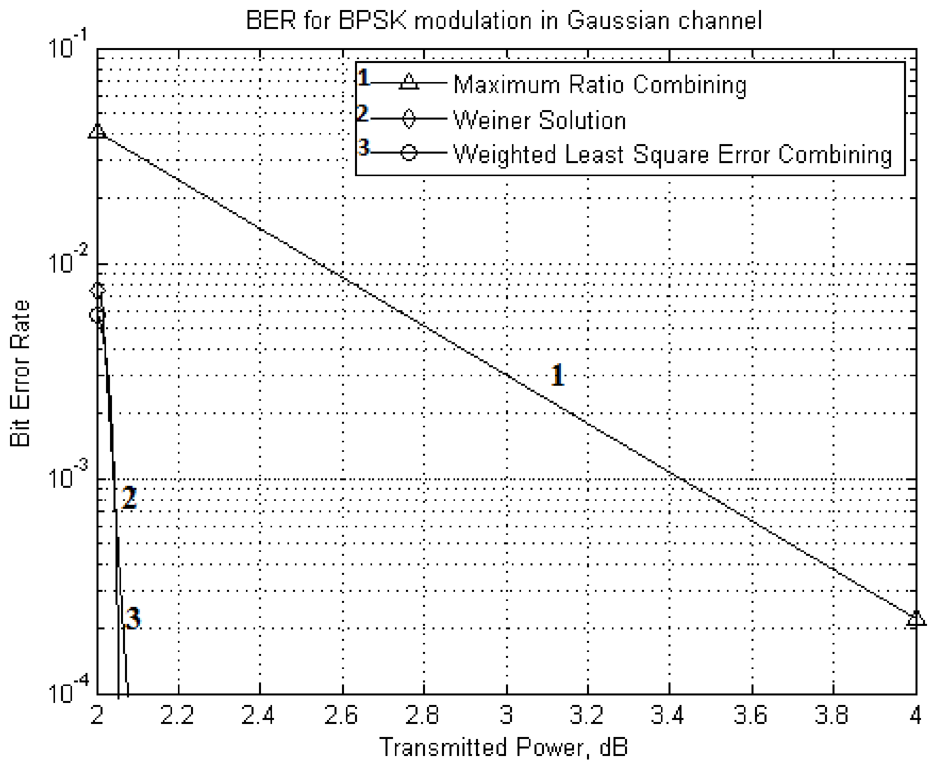

Figure 6.4: BER performance for two users in Gaussian channels:

1. Maximal Ratio Combining.
2. Optimum Signal Combining or Wiener Solution.
3. Proposed Weighted Least Square Error Method of Signal Combining.

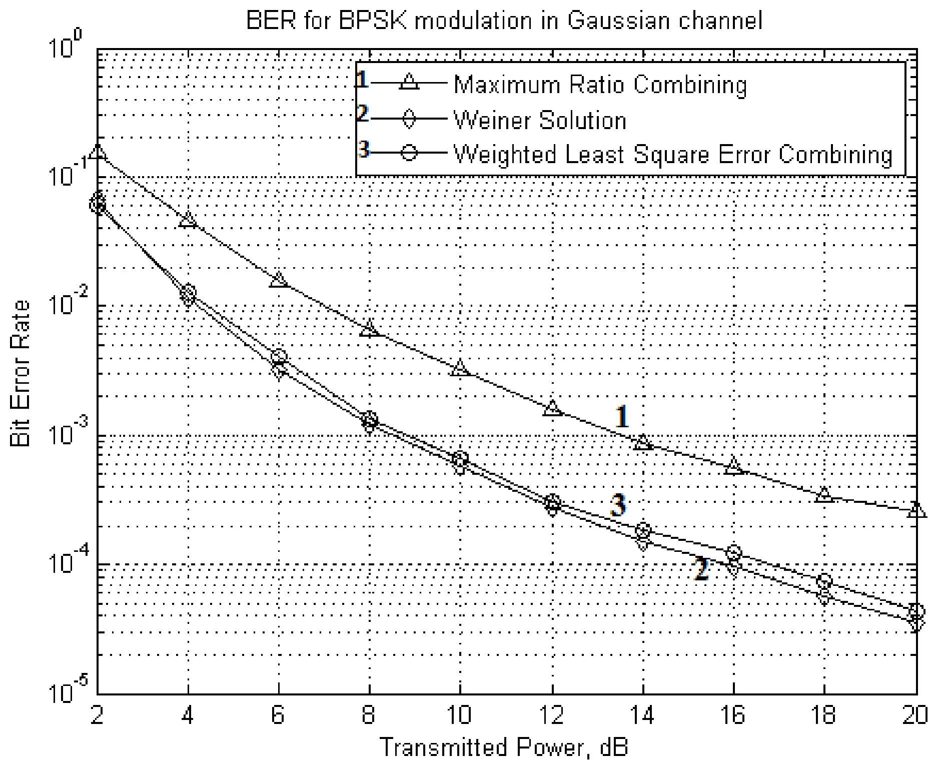

Figure 6.5: BER performance for two users in Flat Fading Rayleigh channel:

1. Maximal Ratio Combining.
2. Optimum Signal Combining or Wiener Solution.
3. Proposed Weighted Least Square Error Method of Signal Combining.

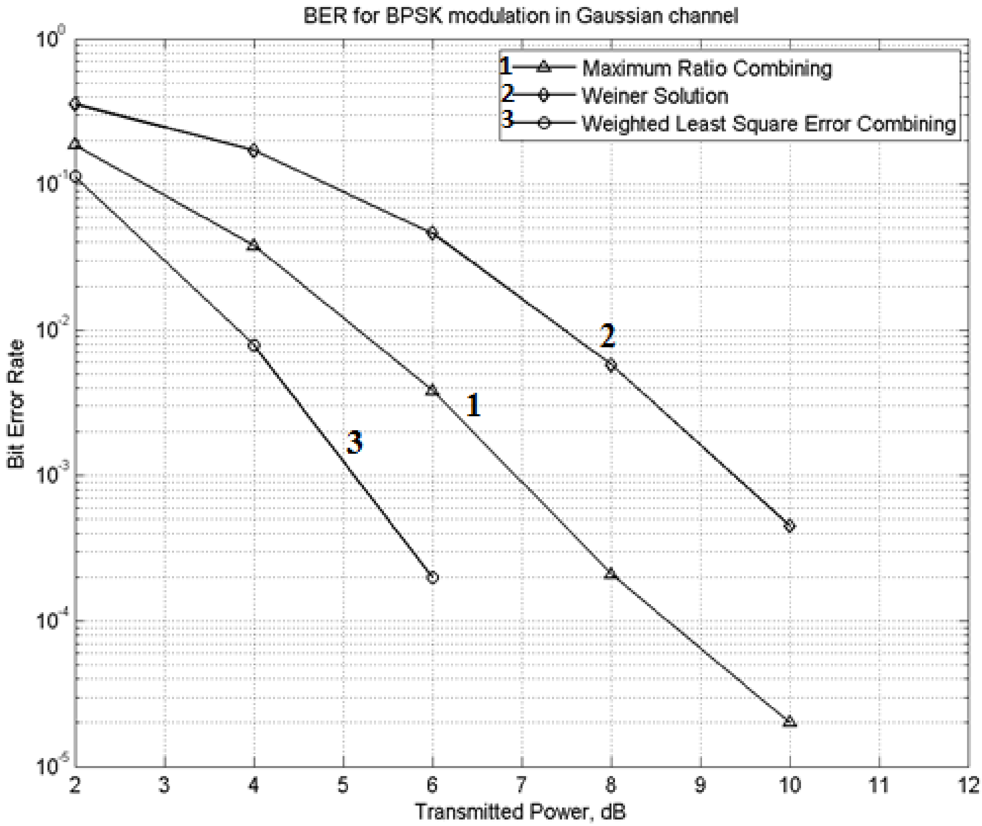

Figure 6.6: BER performance for two users in frequency selective Rayleigh fading channel:

1. Maximal Ratio Combining.
2. Optimum Signal Combining or Wiener Solution.
3. Proposed Weighted Least Square Error Method of Signal Combining.

6.6 Conclusions

Weighted least square error method of signal combining is proposed. The method is linear and it is the simplest among all other combining schemes, where only error (channel noise) estimation is required to obtain near optimum performance of signal combining. The performance of the proposed system depends upon the accuracy of channel noise estimation. The presented technique is computationally simple and particularly useful when we have un equal channel noise variance. It is also found that un-weighted least square error method of signal combining is equivalent to equal gain combining. This research shows that to design optimum signal combiner, we only require to design an optimum channel noise estimator. Existing multiple antenna combiners, Maximal Ratio Combiner or its modified forms was also examined for the performance comparisons. Computer simulation results were presented to shows the performance of the existing and proposed methods of signal combining. Further investigation is needed to find the performance of weighted least square error signal combining with correlated noise.

6.7 Summary

This chapter was about a weighted least square error method of signal combining for wireless communication. The method had been commonly used for target tracking and in econometrics, applied mathematics and medical diagnosis. The system presented for signal combining by weighted least square error was a combiner with filters at each received branch for the error estimation (noise). The inverse of the channels noise variance was used as the weights of the combiner to achieve Wiener's solution. The presented scheme of signal combining was particularly useful when

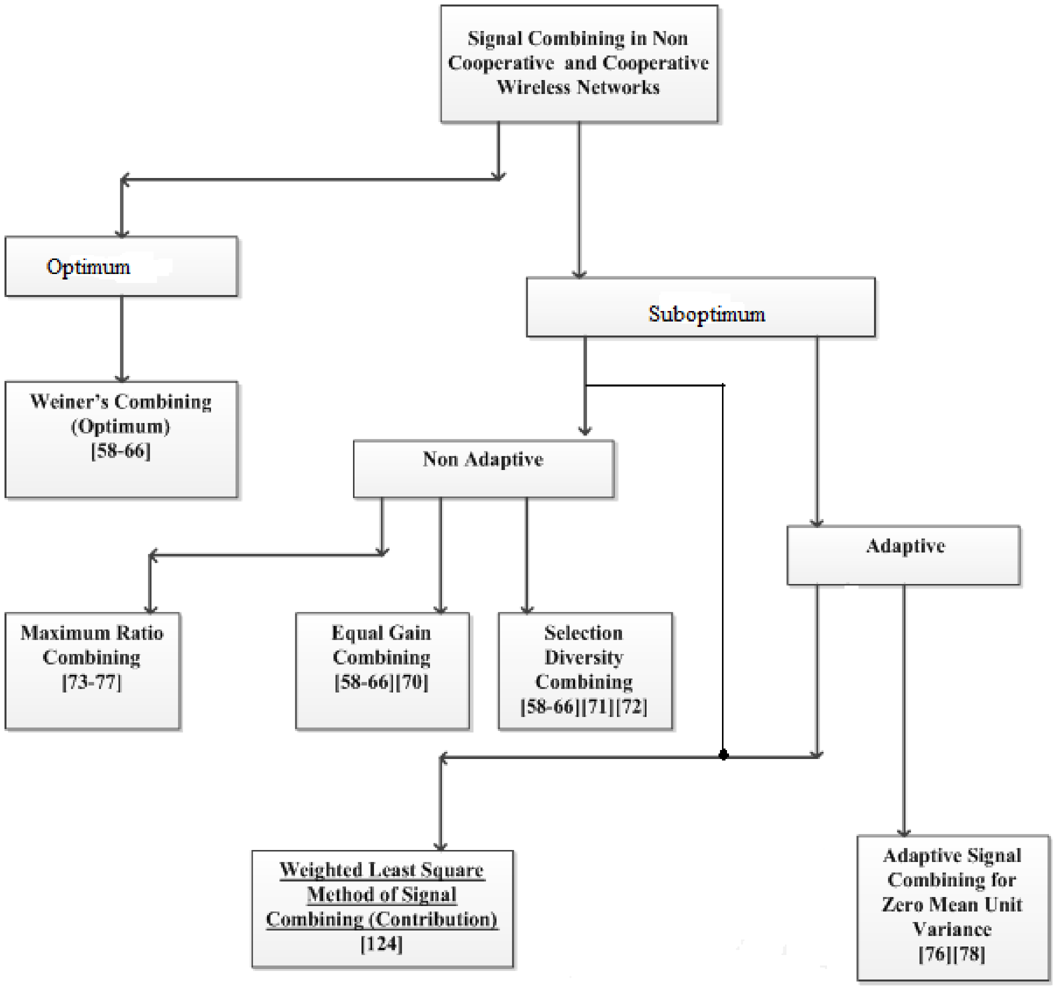

Figure 6.7: Signal combining in non cooperative and cooperative wireless networks:

- Signal combining can be classified into two categories, i:e Optimum and Sub-optimum. Optimum combining is Weiner's combining. In suboptimum categories generally adaptive and non adaptive algorithm are commonly used in various applications. Proposed WLS method of signal combining can be implemented by using adaptive and non adaptive filters.

wireless communication are subjected to unequal noise variance which is very common in present wireless communication systems. The performance of the scheme was shown by computer simulation in Gaussian, flat fading Rayleigh and frequency selective Rayleigh wireless communication channels. The computer simulation performance of the system was about 10^{-3} bits at 8 dB SNR and about 10^{-4} at 16 dB SNR in a wireless flat fading Rayleigh channel with two receive antennas. Figure 6.7 shows the research contributions of chapter 5 and chapter 6.

Chapter 7

CONCLUSIONS

7.1 Conclusions

Optimum adaptive signal combining and detection methods were developed for cooperative wireless networks. This research also discussed the specific limitations of existing techniques designed for cooperative systems. More specifically, the focus of this thesis was the A-MMSE-MUD techniques for multiuser detection. Explicitly, it was pointed out that in the open literature there was a paucity of use of A-MMSE-MUD in cooperative wireless networks, which are capable of supporting a higher number of users. A-MMSE-MUD has emerged as a promising solution for future high rate cooperative communication networks. A historical review of the 20-years of A-MMSE-MUD and cooperative communication literature revealed the need for channel estimation/signal detection. More specifically, the milestones in the history of A-MMSE-MUD and cooperative communication wireless networks were presented in the literature, where the key events and contributions across several decades were summarized, where some of the the associated contributions found in the literature were outlined and acknowledged.

Furthermore, an overview of the advances in combining techniques was provided, followed by the introduction of adaptive signal combining for wireless networks (both cooperative and non-cooperative). This research proposed an optimum adaptive signal combining method for wireless signals based upon Newton's recursive formula base least mean square algorithm, where this research proposed to include the multiplicative factor of inverse of channel noise variance in the step sizes of LMS algorithm. This research used mathematical algorithms for the adaptive signal combining in cooperative wireless networks and analyzed the ensemble average mean square error performance and bit error rate performance of the method, when this research used unequal step sizes at each branch of combiner to maximise signal to noise ratio. The used method achieve gains in MSE and BER performance. Hence, it was shown that optimum adaptive combiner converge according to the SNR. The dependence of LMS algorithm was found upon the factor of inverse of variance, which revealed the importance of noise estimation at each branch for signal combining. Also an innovative method of weighted least square error of signal combining was proposed. The mathematical algorithm derived for the proposed method. The various computer simulations performed to examine the performance in term of MSE and BER in different wireless communication channel. It was observed that proposed weighted least square error method of signal combining was optimum and computationally simpler than all other existing methods of signal combining.

There are a variety of fruitful areas for future research on cooperative diversity and related topics. Many issues were mentioned in earlier chapters, but some of the larger and more important ones here.

- Radio and network implementation of proposed A-MMSE-MUD, adaptive signal combining with unequal channel noise variance and signal combining with weighted least square method are required.

- There is a need to analyze the performance of A-MMSE-MUD multi hop of cooperative wireless networks.

- It would be interesting to use higher modulation schemes other than BPSK in cooperative wireless networks and to use the adaptive decision feed back equalizer for signal detection.

- Cross layer designs for the cooperative wireless networks are required to design with the use of proposed adaptive systems.

- Further exploration in the context of cooperative diversity are to investigate the performance of adaptive signal combining with unequal noise variance and weighted least square error method of signal combining in the context of correlated MIMO system. There is a need to address the issue of antenna correlation, particularly in mobile device.

- There is also need to analyze the performance upper bound of the proposed signal combining methods, when we increase the number of antenna elements.

- Research results revealed the importance of noise estimation for signal combining. Instead of developing various version adaptive algorithms for signal combining, it will be more effective to develop accurate noise estimators for achieving optimum signal combining.

- This research can be further extended to the development of adaptive multiuser detection for MIMO systems.

Chapter 8

APPENDICES

8.1 Appendix I: MATLAB Codes for Adaptive MMSE Multiuser Detection in Cooperative Wireless Networks

clear;

Initialisation

CAverage = 100; AVERAGE = 100; peMFCnorelay = 0;

peAMUDCnorelay = 0; MSECnorelay = 0; peMFCampfwd = 0;

peAMUDCampfwd = 0; MSECampfwd = 0; peMFCdetfwd = 0;

peAMUDCdetfwd= 0; MSECdetfwd = 0; peMFCdetfwd2 = 0;

peAMUDCdetfwd2 = 0; MSECdetfwd2 = 0; CAMUDnorelay = 0;

CAMUDampfwd = 0; CAMUDdetfwd = 0; CAMUDdetfwd2 =0;

TRain = 6000; Training length.

SNR = 0:4:20; SNR in dB. Np = 100000; Number of symbols.

Nrelay = 4; Number of relay terminals

K = 4; Number of Users

G = 32; Spreading Factor

UserDelays = round(10*rand(1,K));

Asynchronous Transmission

GroupRelayDelay = 4;

User time delays in chips:Mobile-BS

Nscalerly = sqrt(2exp(1-Pexp)); exp represents exponent. Keep noise same for relays, but now set the rms variable for improved SNR (Shorter distance).

Mx = max(UserDelays);

FilExpand = 3; Assume Length of Despreading 3 times longer than spreading factor FG = FilExpand*G;

L = FilExpand-1; Parameter for determining number of symbols to prevent overflow in asynchronous detection.

Delay = ceil(FilExpand/2);

Parameter for detection delay in asynchronous detection.

Es = 1; Assume Unit Energy Per User

Nvar = 10*log10(mean(Es)) - SNR;

Noise variance for adjusting different SNR's.

nvar = sqrt(G)*sqrt(10.exp(Nvar/10));

Convert to linear Units and scale by Spreading Gain.

for chann = 1:CAverage

peMFnorelay = 0; peAMUDnorelay = 0; MSEnorelay = 0;

peMFampfwd = 0; peAMUDampfwd = 0; MSEampfwd = 0;

peAMUDdetfwd = 0; MSEdetfwd = 0;

MENorly = 0; MEAmpFWD = 0; MEDetFWD = 0;

hmiso1 = (1/sqrt(2))*(randn(1,K)+ sqrt(-1)*randn(1,K));

Fading Channel MISO 1

Hmiso1 = diag(hmiso1); Mobile to Base Station

Hmimo = (1/sqrt(2))*(randn(Nrelay,K)+ sqrt(-1)*randn(Nrelay,K));

Mobile to Relay

hmiso2 = (1/sqrt(2))*(randn(1,Nrelay) + sqrt(-1)*randn(1,Nrelay));

Fading Channel MIMO, Relay to Base station

Hmiso2 = diag(hmiso2);

Normalization, i.e. hmiso = hmiso/norm(hmiso)

for av = 1:AVERAGE

for n = 1:K

b(n,:) = (sign(randn(1,Np))+1)/2; Binary Sequence.

bbpsk(n,:) = 2*(b(n,:) - 0.5); BPSK Modulation.

btx(n,:) = sqrt(Es)*bbpsk(n,:); Transmit signal.

S(:,n) = sign(randn(G,1));

Generate Random Spreading Sequence Mobile - Relay

Srly(:,n) = sign(randn(G,1));

Generate Random Spreading Sequence

Relay - BS, Same spreading sequence

end

SRx = [flipud(S);zeros((FilExpand-1)*G,K)];

Opposite Spreading Sequences to Despread

SRxrly = [flipud(Srly);zeros((FilExpand-1)*G,K)];

TrMat = [];

Generate Spreading Sequences for all users: Mobile - BS

for k = 1:K

for n = 1:Np

st(:,1+G*(n-1):n*G) = S(:,k).'*btx(k,n);

Generate Spreaded Sequences for all users: Mobile - BS

end

TxSequence = [zeros(1,UserDelays(:,k)),st,zeros(1,Mx - UserDelays(:,k))];

TrMat = [TrMat;TxSequence];

end

TXMob2BS = Hmiso1*TrMat;

if K greater than 1 (Use mathematical sign)

RxMob2BS = sum(TXMob2BS);

Received signal at one antenna of BaseStation without noise.

else RxMob2BS = TXMob2BS;

end

RxMob2Rly = Hmimo*(sqrt(1/2)*TrMat);

for g = 1:length(SNR)

nmbs = nvar(:,g)*(randn(1,length(RxMob2BS))

```
+ sqrt(-1)*randn(1,length(RxMob2BS)));
nmrly = Nscalerly*nvar(:,g)*(randn(Nrelay,length(RxMob2Rly))
+ sqrt(-1)*randn(Nrelay,length(RxMob2Rly)));
Noise variance at receiver
RTMob2BS = RxMob2BS + nmbs;
Received Sequence Mobile - BS.
RTMob2Rly = RxMob2Rly + nmrly;
Matrix of received multiuser sequences at each relay element.
Xaf = zeros(Nrelay);
for a = 1:Nrelay; exp represents power
Xaf(a,a) = sqrt((1/Nrelay)*(1/(((1/K)*sum(abs(Hmimo(a,:)).exp2))
+ ((2/(K*Es))*((Nscalerly*nvar(:,g))exp2)))));
Xdf(a,a) = sqrt((1/Nrelay)*(1/(((1/K)*sum(abs(Hmimo(a,:)).exp2))
+ ((2/(G*K*Es))*((Nscalerly*nvar(:,g))exp2)))));
end
Xaf = sqrt((1/Nrelay)*(1/((1
+((2/(K*Es))*((Nscalerly*nvar(:,g))exp2)))));
Xdf = sqrt((1/Nrelay)*(1/((1 +
((2/(G*K*Es))*((Nscalerly*nvar(:,g))exp2)))));
RTMob2RlyAMPFWD = Xaf*RTMob2Rly;
for m = 1:Nrelay
D = [];AMUD And Forward: Soft Approach
for k = 1:K
RxRECFWD = RTMob2Rly(m,1+UserDelays(:,k):(Np*G) + UserDelays(:,k));
Normalize RxRDECFWD for AMUD Purpose.
v = sqrt(sum(abs(RxRDECFWD).exp2)/length(RxRDECFWD));
RxRDECFWD = (sqrt(K)/v)*RxRDECFWD;
XRdecfwd = zeros(FG,Np-L);
```

Matrix for storing all received samples.

for a = 1:Np-L

XRdecfwd(:,a) = RxRDECFWD(:,FG+(a-1)*G:-1:1+G*(a-1)).’;

end

t = zeros(FG,1);

for f = 1:TRain

if f less than TRain/2

mu = 0.0001;

else mu = 0.0001;

end

e = bbpsk(k,Delay+f-1)- t’*XRdecfwd(:,f);

t = t + 2*mu*conj(e)*XRdecfwd(:,f);

end

E(k,:) = t’*XRdecfwd;

if Delay greater than 1

F(k,:) = [bbpsk(k,1:Delay-1),E(k,:),bbpsk(k,1+Np-(Delay-1):Np)];

Packet in lost BPSK Training symbols.

else F(k,:) = E(k,:);

end

for a = 1:Np

stseq(:,1+G*(a-1):a*G) = Srly(:,k).’*F(k,a);

end

TSeq = stseq; Assume each relay transmits users synchronously.

D =[D;TSeq];

end

if K greater than 1

RTRly(m,:) = [zeros(1,Mx+GroupRelayDelay*G),sum(D)];

Sum All Components at each Relay.

```
else RTRly(m,:) = [zeros(1,Mx+GroupRelayDelay*G),D];
end
D = zeros(K,length(XRdecfwd));
end
RTMob2RlyDECFWD = Xdf*RTRly;
TrMatAMPFORWARD = RTMob2RlyAMPFWD;
TrMatDECFORWARD = RTMob2RlyDECFWD;
TXRely2BSAMPFwd =(conj(Hmiso2)*Hmiso2)*TrMatAMPFORWARD;
Transmit beamforming based on Channel Weights. Assumed perfect CSI.
TXRely2BSDECFwd = (conj(Hmiso2)*Hmiso2)*TrMatDECFORWARD;
RxNoRelay = RTMob2BS;
if Nrelay greater than 1
RxAMPFWD = sum(TXRely2BSAMPFwd) + (sqrt(1/2))*RxMob2BS
+ (Nscalerly*nmbs);
RxDECFWD = sum(TXRely2BSDECFwd)
+ [(sqrt(1/2))*RxMob2BS,zeros(1,GroupRelayDelay*G)]
+ [(Nscalerly*nmbs),(Nscalerly*nmbs(:,1:GroupRelayDelay*G))];
else
RxAMPFWD = TXRely2BSAMPFwd
+ (sqrt(1/2))*RxMob2BS + (Nscalerly*nmbs);
RxDECFWD = TXRely2BSDECFwd
+ [(sqrt(1/2))*RxMob2BS,zeros(1,GroupRelayDelay*G)]
+ [(Nscalerly*nmbs),(Nscalerly*nmbs(:,1:GroupRelayDelay*G))];
end
vrxnorly = sqrt(sum(abs(RxNoRelay).exp2)/length(RxNoRelay));
RxNoRelay = (sqrt(K)/vrxnorly)*RxNoRelay;
Normalizing signal energies for detection.
vrxafwd = sqrt(sum(abs(RxAMPFWD).exp2)/length(RxAMPFWD));
```

```
RxAMPFWD = (sqrt(K)/vrxafwd)*RxAMPFWD;
vrxdfwd = sqrt(sum(abs(RxDECFWD).exp2)/length(RxDECFWD));
RxDECFWD = (sqrt(K)/vrxdfwd)*RxDECFWD;
RxSequenceDECFWD
= RxDECFWD(:,1+Mx+GroupRelayDelay*G:length(RxDECFWD));
for k = 1:K
RxSequenceNoRelay
= RxNoRelay(:,1+UserDelays(:,k):(Np*G) + UserDelays(:,k));
RxSequenceAMPFWD
= RxAMPFWD(:,1+UserDelays(:,k):(Np*G) + UserDelays(:,k));
Xnorelay = zeros(FG,Np-L);
Xampfwd = zeros(FG,Np-L);
Xdecfwd = zeros(FG,Np-L);
for a = 1:Np-L
Xnorelay(:,a) = RxSequenceNoRelay(:,FG+(a-1)*G:-1:1+G*(a-1)).';
Xampfwd(:,a) = RxSequenceAMPFWD(:,FG+(a-1)*G:-1:1+G*(a-1)).';
Xdecfwd(:,a) = RxSequenceDECFWD(:,FG+(a-1)*G:-1:1+G*(a-1)).';
end Despread with MF.
dMFnorelay(k,:) = conj(hmiso1(:,k))*(1/G)*SRx(:,k).'*Xnorelay;
dMFampfwd(k,:) = (1/G)*SRx(:,k).'*Xampfwd;Despread = MF.
FOR BPSK - Sign Detection
DHatMFnorelay(k,:) = sign(real(dMFnorelay(k,:)));
FOR BPSK - Sign Detector
DHatMFampfwd(k,:) = sign(real(dMFampfwd(k,:)));
BHatMFnorelay(k,:) = ((DHatMFnorelay(k,:)+1)/2);
pemfnorelay(k,g) = sum(xor(b(k,FilExpand:length(b)),BHatMFnorelay(k,:)))
/length(BHatMFnorelay);
BHatMFampfwd(k,:) = ((DHatMFampfwd(k,:)+1)/2);
```

```
pemfampfwd(k,g) = sum(xor(b(k,FilExpand:length(b)),BHatMFampfwd(k,:)))
/length(BHatMFampfwd);
if pemfampfwd(k,g) greater than 0.5
pemfampfwd(k,g) = 1 - pemfampfwd(k,g);
end
wnorelay = zeros(FG,1);
Adaptive MUD coefficients.
wampfwd = zeros(FG,1);
wdecfwd = zeros(FG,1);
for f = 1:TRain
if f less than TRain/2
mu = 0.0005;
else mu = 0.0001;
end
enorelay(:,f) = bbpsk(k,Delay+f-1)- wnorelay'*Xnorelay(:,f);
eampfwd(:,f) = bbpsk(k,Delay+f-1)- wampfwd'*Xampfwd(:,f);
edecfwd(:,f) = bbpsk(k,Delay+f-1)- wdecfwd'*Xdecfwd(:,f);
wnorelay = wnorelay + 2*mu*conj(enorelay(:,f))*Xnorelay(:,f);
wampfwd = wampfwd + 2*mu*conj(eampfwd(:,f))*Xampfwd(:,f);
wdecfwd = wdecfwd + 2*mu*conj(edecfwd(:,f))*Xdecfwd(:,f);
end
dMUDnorelay(k,:) = wnorelay'*Xnorelay;
dMUDampfwd(k,:) = wampfwd'*Xampfwd;
dMUDdetfwd(k,:) = wdecfwd'*Xdecfwd;
MseNoRLY(k,g) = mean(abs(bbpsk(k,Delay:length(b)-(Delay-1))
- dMUDnorelay(k,:)).exp2);
MseAmpFWD(k,g) = mean(abs(bbpsk(k,Delay:length(b)-(Delay-1))
- dMUDampfwd(k,:)).exp2);
```

```
MseDetFWD(k,g) = mean(abs(bbpsk(k,Delay:length(b)-(Delay-1))
- dMUDdetfwd(k,:)).exp2);
BPSK - Sign Detector
DHatMUDnorelay(k,:) = sign(real(dMUDnorelay(k,:)));
BPSK - Sign Detector
DHatMUDampfwd(k,:) = sign(real(dMUDampfwd(k,:)));
DHatMUDdetfwd(k,:) = sign(real(dMUDdetfwd(k,:)));
BHatMUDnorelay(k,:) = ((DHatMUDnorelay(k,:)+1)/2);
peamudnorelay(k,g) = sum(xor(b(k,Delay:length(b)
-(Delay-1)),BHatMUDnorelay(k,:)))
/length(BHatMUDnorelay);
BHatMUDampfwd(k,:) = ((DHatMUDampfwd(k,:)+1)/2);
peamudampfwd(k,g) = sum(xor(b(k,Delay:length(b)-(Delay-1))
,BHatMUDampfwd(k,:))) /length(BHatMUDampfwd);
BHatMUDdetfwd(k,:) = ((DHatMUDdetfwd(k,:)+1)/2);
peamuddetfwd(k,g) = sum(xor(b(k,Delay:length(b)-(Delay-1))
,BHatMUDdetfwd(k,:)))
/length(BHatMUDdetfwd);
end
end
if K = 1
pemfnorelay = sum(pemfnorelay)/K;
pemfampfwd = sum(pemfampfwd)/K;
peamudnorelay = sum(peamudnorelay)/K;
peamudampfwd = sum(peamudampfwd)/K;
peamuddetfwd = sum(peamuddetfwd)/K;
end
peMFnorelay = peMFnorelay + pemfnorelay;
```

```
peMFampfwd = peMFampfwd + pemfampfwd;
peAMUDnorelay = peAMUDnorelay + peamudnorelay;
peAMUDampfwd = peAMUDampfwd + peamudampfwd;
peAMUDdetfwd = peAMUDdetfwd + peamuddetfwd;
MENorly = MENorly + MseNoRLY;
MEAmpFWD = MEAmpFWD + MseAmpFWD;
MEDetFWD = MEDetFWD + MseDetFWD;
MSEnorelay = MSEnorelay + abs(enorelay).exp2;
MSEampfwd = MSEampfwd + abs(eampfwd).exp2;
MSEdetfwd = MSEdetfwd + abs(edecfwd).exp2;
end
peMFCnorelay = peMFCnorelay + (peMFnorelay/AVERAGE);
peMFCampfwd = peMFCampfwd + (peMFampfwd/AVERAGE);
peAMUDCnorelay = peAMUDCnorelay + (peAMUDnorelay/AVERAGE);
peAMUDCampfwd = peAMUDCampfwd + (peAMUDampfwd/AVERAGE);
peAMUDCdetfwd = peAMUDCdetfwd + (peAMUDdetfwd/AVERAGE);
MENorlyC = MENorly/AVERAGE;
MEAmpFWDC = MEAmpFWD/AVERAGE;
MEDetFWDC = MEDetFWD/AVERAGE;
CAMUDnorelay = CAMUDnorelay + 0.5*log2(2./MENorlyC);
CAMUDampfwd = CAMUDampfwd + 0.5*log2(sqrt(2)./MEAmpFWDC);
CAMUDdetfwd = CAMUDdetfwd + 0.5*log2(sqrt(2)./MEDetFWDC);
MSECnorelay = MSECnorelay + (MSEnorelay/AVERAGE);
MSECampfwd = MSECampfwd + (MSEampfwd/AVERAGE);
MSECdetfwd = MSECdetfwd + (MSEdetfwd/AVERAGE);
end
peMFC1 = peMFCnorelay/CAverage;
peMFC2 =peMFCampfwd/CAverage; peAMUDC1
```

```
= peAMUDCnorelay/CAverage;
peAMUDC2 = peAMUDCampfwd/CAverage; peAMUDC3 =
peAMUDCdetfwd/CAverage;
CAMUDnorelay = CAMUDnorelay/CAverage;
CAMUDampfwd = CAMUDampfwd/CAverage;
CAMUDdetfwd = CAMUDdetfwd/CAverage;
if K greater than 1
C1 = sum(CAMUDnorelay)/K;
C2 = sum(CAMUDampfwd)/K;
C3 = sum(CAMUDdetfwd)/K;
else C1 = CAMUDnorelay;
C2 = CAMUDampfwd;
C3 = CAMUDdetfwd;
end
MSEC1 = MSECnorelay/CAverage; MSEC2 = MSECampfwd/CAverage;
MSEC3 = MSECdetfwd/CAverage;
figure
semilogy(SNR,peMFC1,'-r exp')
hold
semilogy(SNR,peAMUDC1,'–k exp')
semilogy(SNR,peAMUDC2,'–ko')
semilogy(SNR,peAMUDC3,'–ks') grid xlabel('SNR (dB)')
ylabel('Probability of Error') yy=legend('1', '2', '3', '4', 4);
figure plot(SNR,C1,'–k exp')
hold
plot(SNR,C2,'–ko')
plot(SNR,C3,'–ks')
grid
```

xlabel('SNR (dB)')

ylabel('Capacity (Bits/Sec/Hz)')

yy=legend('1', '2', '3', 4);

figure

plot(MSEC1,'k')

plot(MSEC2,'k')

figure plot(MSEC3,'k')

8.2 Appendix II: MATLAB Codes for Adaptive Signal combining in Cooperative Wireless Networks

clear

N = 10exp4; Number of bits or symbols

rand('state',100); Initializing the rand() function

randn('state',200);

Initializing the randn() function from source to relay

We assume channel is gaussian from relay to destination it

is flat fading Rayleigh with one tap for the direct transmission.

it is flat fading Rayleigh with one tap same as in relay to

destination transmission

ip = rand(1,N)greater than 0.5;

generating 0,1 with equal probability

s = 2*ip-1; BPSK modulation 0 -greater than -1; 1 - greater than 0

n = 1/sqrt(2)*[randn(1,N) + j*randn(1,N)];

white gaussian noise, 0dB variance

EbN0dB = [0:20]; multiple Eb/N0 values

h=1; flat fading Rayleigh channel with one tap for ii =

1:length(EbN0dB)

h1=1; for the relay channel gaussian h2=1; for the relay channel

is gaussian because it is line of sight mobile device that

receive the data.

y = s*h+ 10exp(-EbN0dB(ii)/20)*n;

Additive white Gaussian noise of direct transmission

y=y./h; E1=y-s;

y11 = s*h1+ 10exp(-EbN0dB(ii)/20)*n;

y21 = s*h2 + 10exp(-EbN0dB(ii)/20)*n;

Additive white Gaussian noise of sources to relays

r1=s*h+s*h+10exp(-EbN0dB(ii)/20)*n

Relays to destination

Decode and forward scheme.

r1=r1./(h); Equalisation

V1= sqrt(sum(abs(y11).exp2)/length(y11));

V2=sqrt(sum(abs(y21).exp2)/length(y21));

r2=(sqrt(2)/V1)*y11*h+(sqrt(2)/V2)*y21*h+10exp(-EbN0dB(ii)/20)*n

Relay to Destination

Amplify and forward scheme.

r2=r2./(h); Equalisation

ipHat1 = real(r1)greater than 0; Decode and forward scheme

ipHatA = real(r2)greater than 0; Amplify and forward scheme

ipHat = real(y) greater than 0; Direct transmission

ipHatsr1 = real(y11)greater than 0;

Computing errors for relay transmission. source to relay 1

ipHatsr2 = real(y21)greater than 0; source to relay 2

Decode and forward error computation

nErrsr1(ii) = size(find([ip- ipHatsr1]),2);

```
nErrsr2(ii)=size(find([ip- ipHatsr2]),2);
nErrsrT(ii)=nErrsr1(ii)+nErrsr2(ii);
nErr1(ii) = size(find([ip- ipHat1]),2);Counting the errors.
Relays to Destination, decode and forward error computation
nErrsrGT(ii) =nErrsrT(ii)+nErr1(ii)
nErrA(ii) = size(find([ip- ipHatA]),2); Amplify and forward
nErr(ii) = size(find([ip- ipHat]),2); Important direct transmission
Information capacity
C1=1/2*log(1/mean(E1)); end simBer = nErr/N;
simBerA = nErrA/N; simulated BER, Amplify and forward
simBer1 = nErrsrGT/N; simulated BER, Decode and Forward
theoryBer = 0.5*erfc(sqrt(10.exp(EbN0dB/10)));
figure(1)
semilogy(EbN0dB,theoryBer,'b.-');
hold on
semilogy(EbN0dB,simBer,'–kd');
hold on
semilogy(EbN0dB,simBerA,'–ks');
hold on
grid on
semilogy(EbN0dB,simBer1,'-ko');
hold on
legend('Direct transmission','Amplify and forward',
'Decode and forward Relay Transmission');
figure(2)
semilogy(C1,EbN0dB,'-ko')
```

8.3 Appendix III: MATLAB Codes for WLS Error Method of Signal combining

WLS Error Method of Signal combining, BER Results.

```
clc;
clear all
Initialisation
nErrMRCT=0;
n00ErrT=0;
n1ErrT=0;
nErrT=0;
n2ErrT=0;
n3ErrT=0;
n4ErrT=0;
n4bErrT=0;
EbN0dB = [2:2:20];
q=2.0; for av=1:1
for ii = 1:length(EbN0dB)
numPoints = 10
No=10exp5; numb=(numPoints+No); training+data
sig2 =EbN0dB(ii)*sign(randn(No,1));
sig1=EbN0dB(ii)*ones(numPoints,1); Training
s=[sig1;sig2];training and decision directed mode
X = s;
x1=X; signal no 1
h1 =.5;
Flat fading Rayleigh Channel with variance 0.5
N1 =-1.2*1/sqrt(2)*(randn(numb,1) + i*randn(numb,1));
```

d1 = h1.*x1+ N1; [hints: 10*log10(0.1)=-5.23; SNR=0+5.23=5.23]

Signal channel convolution, plus noise

D1=d1.*conj(h1); Mu1 =0.5;

ip00Hat1 = real(X)greater than 0 ; hard decision decoding

ip00Hat = real(D1)greater than 0

n00Err(ii) = size(find([ip00Hat1- ip00Hat]),1); No of Error

d1 = h1.*x1+ N1; [hints: 10*log10(0.1)=-5.23; SNR=0+5.23=5.23]

D1=d1.*conj(h1); Equalisation

x = X; Signal no 2

h =0.3; Channel 2

N = -3*1/sqrt(2)*(randn(numb,1) + i*randn(numb,1));

Normalized to 0db

d = h.*x + N; [hints: 10*log10(0.6)=-2.22; SNR=0+2.22=2.22]

D=d.*conj(h); meu=0.0000005 meu1=0.0000005

W=0; W1=0; Adaptive Combiner with filtering

MRC=(D1+D)./(h1.*conj(h1)+h.*conj(h));

ip1Hat1 = real(X)greater than =0 ;

ip1HatMRC = real(MRC) greater than 0;

nErrMRC(ii) = size(find([ip1HatMRC-ip1Hat1]),1);

D1=D1/sqrt(sum(D1.exp2))

D=D/sqrt(sum(D.exp2));

CRX1=xcorr(s,D1); CRX2=xcorr(s,D); Wiener Combining

wt=var(CRX2)*1/var(N.*conj(h));

wt1=var(CRX1)*1/var(N1.*conj(h1));

SyR4=((D1)*(wt1)+((D)*(wt))); ip4Hat1 = real(X)greater than 0;

ip4Hat = real(SyR4) greater than 0;

n4Err(ii) = size(find([ip4Hat- ip4Hat1]),1);

wtb=((1/(var((N./h)))));

```
wt1b=(1/(var((N1./h1)))); SyR4b=((D1)*(wt1b)+((D)*(wtb)));
ip4bHat1 = real(X)greater than 0;
ip4bHat = real(SyR4b)greater than 0;
n4bErr(ii) = size(find([ip4bHat- ip4bHat1]),1);
end
n00ErrT=n00ErrT+n00Err; Match filter
nErrMRCT=nErrMRCT+nErrMRC ; MRC
n4ErrT=n4ErrT+n4Err; Wiener
n4bErrT=n4bErrT+n4bErr; Weighted
end
n00ErrT=n00ErrT./av;
n1ErrT=n1ErrT./av;
nErrMRCTav=nErrMRCT./av; mrc
n3ErrT=n3ErrT./av;[unweighted]
n4ErrT=n4ErrT./av;
n4bErrT=n4bErrT./av;
simBer = n00ErrT./numb; BER
simBer2 = n1ErrT./numb;
simBerMRC = nErrMRCTav./numb; MRC
simBer4 = n3ErrT./numb;
simBer5 = n4ErrT./numb;
simBer5b = n4bErrT./numb;
EbN0Lin = 10.exp(EbN0dB/10);
theoryBernRx1 = 0.5.*(1-1*(1+1./EbN0Lin).exp(-0.5)); p = 1/2 -
1/2*(1+1./EbN0Lin).exp(-1/2); theoryBernRx2 = p.exp2.*(1+2*(1-p));
figure(2)
semilogy(EbN0dB,simBerMRC,'-k exp','LineWidth',1.2);
MRC
```

hold on

semilogy(EbN0dB,simBer5,’-kd’,’LineWidth’,1.2); MRC

hold on

semilogy(EbN0dB,simBer5b,’-ko’,’LineWidth’,1.2); Weighted

hold on

legend(’Maximum Ratio Combining’,’Weiner Solution’,

’Weighted Least Square Error Combining’);

xlabel(’Transmitted Power, dB’);

ylabel(’Bit Error Rate’);

title(’BER for BPSK modulation in Gaussian channel’);

grid on

WLS Error Method of Signal Combining, MSE Results.

clear all

err=0; seperr=0; seperr2=0; error2=0; err1=0; ERRR1=0;

ERROR=0; ERR1=0; seperr2=0; seperr=0; E=0; E1=0; ERR1nf=0; for

av=1:400 numPoints = 150;

numTaps = 10; channel order

Mu1 = 0.015; iteration step size

s=ones(numPoints,1);

X = s

x1=X; signal no 1

choose channel to be random uniform

h1 =1/sqrt(2)*(randn(numTaps, 1) + i*randn(numTaps, 1));

N1 =1/sqrt(2)*(randn(numPoints,1) + i*randn(numPoints,1));

d1 = filter(h1, 1, x1) +0.3* N1;

d1 = d1/max(d1);

initialize variables

w1 = []; y1 = []; in1 = [];

```
e1 = [];
w1 = zeros(numTaps+1,1) + i*zeros(numTaps+1,1); Weights
LMS Adaptation
for n = numTaps+1 : numPoints
select part of training input
in1 = x1(n : -1 : n-numTaps) ;
y1(n) = w1'*in1;
e1(n) = d1(n)-y1(n);
e12(n) = (d1(n)-y1(n))exp2;
w1 = w1 + Mu1*( real(e1(n)*conj(in1)) - i*imag(e1(n)*conj(in1)) );
end
Mu = 0.015; Iteration step size
x = X; Signal no 2
h = 1/sqrt(2)*(randn(numTaps, 1) + i*randn(numTaps, 1));
N = 1/sqrt(2)*(randn(numPoints,1) + i*randn(numPoints,1));
d = filter(h, 1, x) + 0.9*N;
d = d/max(d)
w = []; y = []; in = [];
e = [];
w = zeros(numTaps+1,1) + i*zeros(numTaps+1,1);
LMS Adaptation
for n = numTaps+1 : numPoints
select part of training input
in = x(n : -1 : n-numTaps) ;
y(n) = w'*in;
compute error
e(n) = d(n)-y(n);
e2(n) = (d(n)-y(n))exp2
```

```
w = w + Mu*( real(e(n)*conj(in)) - i*imag(e(n)*conj(in)) );
end
y1=y1/max(y1);
y=y/max(y);
sepErr = ((e12))*(1/(var((e1))));WLS weight1
sepErr2=((e2))*(1/(var((e)))); WLS weight2
Error1 = ((e1).exp2)+((e).exp2); Un-weighted LS
Error2 = ((((e1).exp2)*(1/(var((e1))))+((e).exp2)*;
exp represents exponent
(1/(var((e))))))/((1/(var((e1)))+(1/(var((e1)))))); Weighted LS
err1 = err1+e12;
err = err+e2;
seperr=seperr+sepErr;
seperr2=seperr2+sepErr2;
error2=seperr+seperr2;
ERROR=ERROR+Error1;Un-weighted LS
E=E+Error2; Weighted LS
end error=err1./av; Averaging
seperr=seperr./av;
seperr2=seperr2./av;
err1=err1./av; Equaliser of branch 1
err=err./av; Equaliser of branch 2
error2=seperr./av; Weighted LS
ERROR=ERROR/av; Un-weighted LS
E=E/av;
figure(1)
plot(10*log10(abs(ERROR)),'–kd','LineWidth',1.2);Un-weighted LS
hold on
```

```
plot(10*log10(abs(E)),’-ko’,’LineWidth’,1.2); WLS
hold on
title([’ Learning Curve of Combined Signals ’]);
xlabel(’Iteration Number’);
ylabel(’Ensemble Average Mean Square Error ’);
legend(’Combined Signal Unweighted LS’,’Combined Signal Weighted LS’);
grid on
hold on
```

Chapter 9

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