REAL TIME CHANNEL ESTIMATION FOR MIMO SYSTEMS

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Submitted By

ASHU TANEJA

Roll No. 800961004

Under guidance of

MS. SURBHI SHARMA

Assistant Professor, ECED

ELECTRONICS AND COMMUNICATION ENGINEERING DEPARTMENT

THAPAR UNIVERSITY

PATIALA-147004, INDIA

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CERTIFICATE

I, Ashu Taneja , hereby declare that the work, which is being presented in this thesis, entitled "**Real Time Channel Estimation for MIMO Systems**" is an authentic record of my own work carried out towards the partial fulfilment for the award of degree of M.E (Master of Engineering) at Thapar University, Patiala under the guidance of Ms. Surbhi Sharma, Assistant professor , ECED.

The matter presented in this report has not been submitted in any other University or Institute for the award of any degree.

Ashu Taneja

(Ashu Taneja)
Signature of student

This is certified that the above statement made by the student is correct to the best of my knowledge and belief.

20/6/11

(Ms. Surbhi Sharma)
Assistant Professor, ECED
Thapar University, Patiala.

Countersigned by

Professor & Head
ECED, Thapar University
Patiala-147004

(Dr. S.K. Mohapatra)
Dean of Academic Affairs
Thapar University
Patiala-147004

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ASHU TANEJA

Roll No. 800961004

ABSTRACT

High transmission data rate, spectral efficiency, and reliability are necessary for future wireless communications systems. In a multipath-rich wireless channel, deploying multiple antennas at both the transmitter and receiver achieves high data rate, without increasing the total transmission power or bandwidth. When perfect knowledge of the wireless channel conditions is available at the receiver, the capacity has been shown to grow linearly with the number of antennas. However, the channel conditions must be estimated since perfect channel knowledge is never known *a priori*. In practice, the channel estimation procedure can be aided by transmitting pilot symbols that are known at the receiver. Different channel estimation techniques are used - Least Square (LS), Minimum Mean Square (MMSE), Iterative channel estimation, MAP channel estimation, Channel estimation based on adaptive filtering and so on.

WARP is Wireless Open Access Research Platform.

The WARP board is equipped with the radio nodes which are responsible for the processing of signals to be transmitted and received. The input samples are transmitted through the antenna associated with the transmitting radio node of the WARP FPGA board. These samples are then received by the antenna associated with receiving radio node. The generation of information bits and their modulation along with activation of modules of WARP FPGA such as radio boards, clocks and downloading of signals to be transmitted through the antenna are done through the program running offsite of the WARP FPGA board.

The samples received on the antenna associated with the receiving radio node of the WARP FPGA board along with the transmitted pilots are used to estimate the channel. The SNR vs BER are evaluated using different channel estimation techniques for different modulation techniques. The performance of these channel estimation techniques in real time validates the analysis when compared to that of simulated channel estimation techniques.

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LIST OF ABBREVIATIONS

WARP	Wireless Open Access Research Platform
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
SDR	Software Defined Radio
ASIC	Application Specific Integrated Circuit
CDMA	Code Division Multiple Access
DFT	Discrete Fourier Transform
FDMA	Frequency Division Multiple Access
FIR	Finite Impulse Response
FFT	Fast Fourier Transform
IDFT	Inverse Discrete Fourier Transform
ICI	Inter Carrier Interference
ISI	Inter Symbol Interference
IT	Implicit Training
LSE	Least Square Estimation
MCM	Multicarrier Modulation
MMSE	Minimum Mean Square Estimation
OFDM	Orthogonal Frequency Division Multiplexing
SISO	Single Input Single Output

MIMO	Multiple Input Multiple Output
PSK	Phase Shift Keying
QPSK	Quadrature Phase Shift Keying
SNR	Signal to Noise Ratio
TDMA	Time Division Multiple Access
MAP	Maximum a-posteriori
RSSI	Received Signal Strength Indicator
PLL	Phase Locked Loop
ADC	Analog to Digital Converter
DAC	Digital to Analog Converter
FPGA	Field Programmable Gate Array
MAC	Media Access Control
SER	Symbol Error Rate
MSE	Mean Square Error
RF	Radio Frequency
PROM	Programmable Read Only Memory

CHAPTER 1

INTRODUCTION

1.1 Overview

High transmission data rate, spectral efficiency, and reliability are necessary for future wireless communications systems. Unlike Gaussian channels, wireless channels suffer from attenuation due to multipath in the channel. Multiple copies of a single transmission arrive at the receiver at slightly different times. Without diversity techniques, severe attenuation makes it difficult for the receiver to determine the transmitted signal. Diversity techniques provide potentially less-attenuated replica(s) of the transmitted signal at the receiver. Multiple-Input Multiple-Output (MIMO) antenna systems are a form of spatial diversity [1]. In a multipath-rich wireless channel, deploying multiple antennas, at both the transmitter and receiver, achieves high data rate without increasing the total transmission power or bandwidth. Additionally, the use of multiple antennas at both the transmitter and receiver provides significant increase in capacity .When perfect channel knowledge is available at the receiver, the capacity has been shown to grow linearly with the number of antennas. Most MIMO detection schemes are based on perfect channel knowledge being available at the receiver. However, perfect channel knowledge is never known *a priori*. In practice, the channel estimation procedure is aided by transmitting pilot symbols that are known at the receiver [2]. Pilot symbols reduce spectral efficiency. The system performance depends on the quality of the channel estimate. The quality of the channel estimate is dependent on the number of pilot symbols. To increase spectral efficiency, it is desirable to limit the number of transmitted pilot symbols.

MIMO systems are ideal for rich scattering environments. The channel between any pair of transmit and receive antennas can be modelled as independent identically distributed (i.i.d) complex Gaussian random variables when there are significant number of multipaths in the environment. Possible occurrences of the idealized channel conditions include the class of indoor channels, such as wireless local area networks, fixed wireless networks, and wireless ad-hoc networks.

1.2 Background For Channel Estimation

Fig. 1.1 shows a generic simulation layout for a communication system, which utilizes channel estimation and signal detection operations in equalisation. The digital source is usually protected by channel coding and interleaved against fading phenomenon, after which the binary signal is modulated and transmitted over multipath fading channel. Additive noise is added and the combined signal is received. Due to the multipath channel there is some intersymbol interference (ISI) in the received signal. Therefore a signal detector needs to know channel impulse response (CIR) characteristics to ensure successful equalisation (removal of ISI). Equalization without separate channel estimation (e.g., with linear, decision-feedback, blind equalizers) is also possible, but not discussed in this thesis work. After detection the signal is deinterleaved and channel decoded to extract the original message.

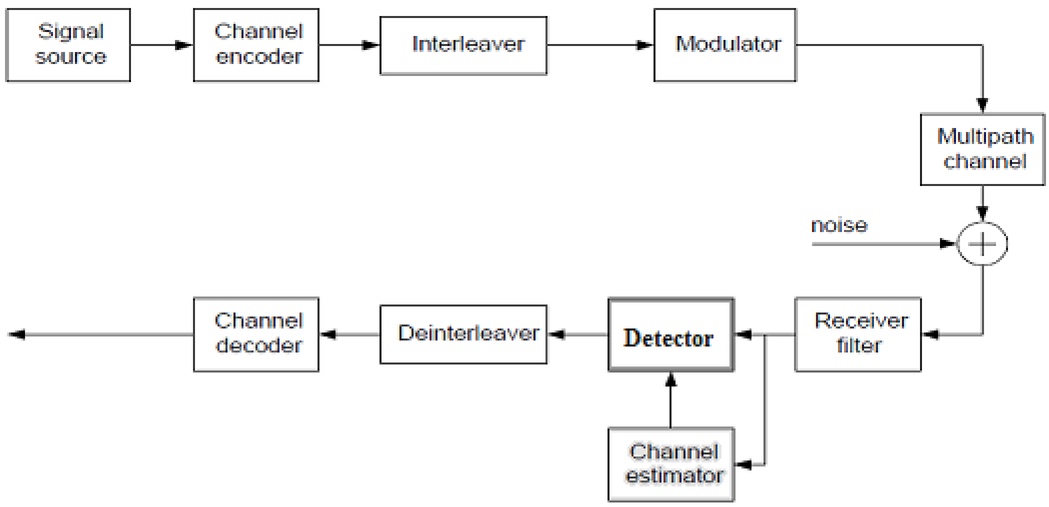


Figure 1.1: Block diagram for a system utilising channel estimator and detection [3].

In this thesis we are mainly interested in the channel estimation part. The channel state information can be obtained through training based, blind and semi blind channel estimation. The blind channel estimation is carried out by evaluating the statistical information of the channel and certain properties of the transmitted signals [4]. Blind Channel Estimation has its advantage in that it has no overhead loss; it is only applicable to slowly time-varying channels due to its need for a long data record. In training based channel estimation algorithms, training symbols or pilot tones that are known *a priori* to the receiver, are multiplexed along with the data stream for channel estimation [5]. Semi-blind channel technique is hybrid of blind and training technique, utilizing pilots and other natural constraints to perform channel estimation.

1.3 Channel Estimation

A *channel* can describe everything from the source to the sink of a radio signal . This includes the physical medium (free space, fiber , waveguides etc.) between the transmitter and the receiver through which the signal propagates. An essential feature of any physical medium is, that the transmitted signal is received at the receiver, corrupted in a variety of ways by frequency and phase-distortion, inter symbol interference and thermal noise.

A *channel model* on the other hand can be thought of as a mathematical representation of the transfer characteristics of this physical medium.

Channel estimation is simply defined as the process of characterizing the effect of the physical channel on the input sequence. If the channel is assumed to be linear, the channel estimate is simply the estimate of the impulse response of the system. It must be stressed once more that channel estimation is only a mathematical representation of what is truly happening. A "good" channel estimate is one where some sort of error minimization criteria is satisfied.

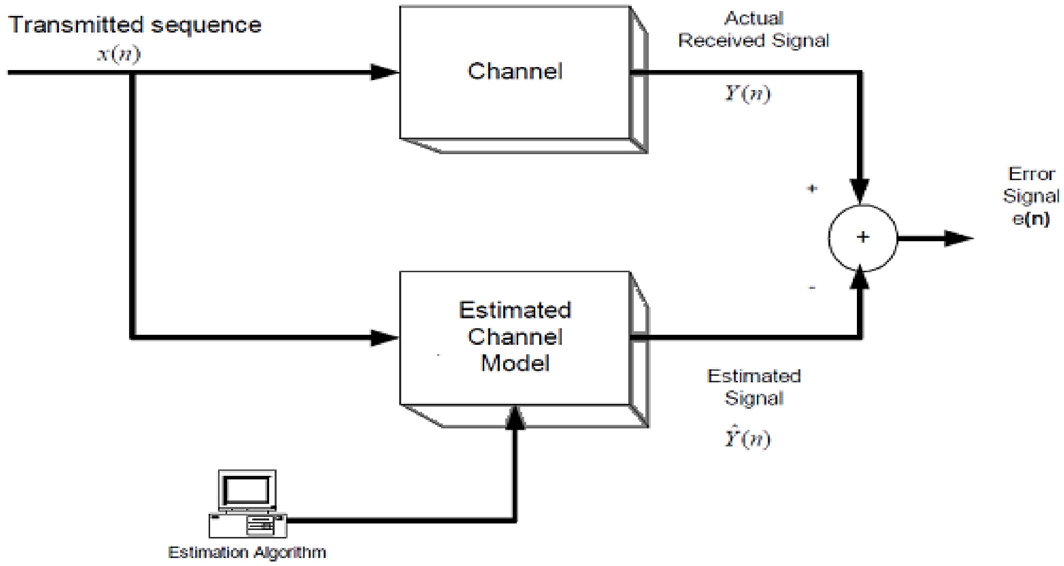


Figure 1.2 : A general Channel Estimation Procedure [3].

In the figure above *e(n)* is the estimation error. The aim of most channel estimation algorithms is to minimize the mean squared error (MMSE), $E[e^2(n)]$ while utilizing as little computational resources as possible in the estimation process.

1.3.1 Need for Channel Estimation

Channel estimation algorithms allow the receiver to approximate the impulse response of the channel and explain the behaviour of the channel. This knowledge of the channel's behaviour is well-utilized in modern radio communications. Adaptive channel equalizers utilize channel estimates to overcome the effects of inter symbol interference. Diversity techniques (for e.g. the IS-95 Rake receiver) utilize the channel estimate to implement a matched filter such that the receiver is optimally matched to the received signal instead of the transmitted one. Maximum likelihood detectors utilize channel estimates to minimize the error probability. One of the most important benefits of channel estimation is that it allows the implementation of coherent demodulation. Coherent demodulation requires the knowledge of the phase of the signal. This can be accomplished by using channel estimation techniques.

In this thesis work , we have used channel estimation to extract the information symbols out of the received signal as most detection schemes require channel information which is not known a-priori. We know that wireless channels suffer from attenuation due to multipath in the channel. Due to the multipath channel there is some intersymbol interference (ISI) in the received signal. Therefore a signal detector needs to know channel impulse response (CIR) characteristics to ensure successful equalisation (removal of ISI) and extraction of information so as to minimise the error between the actual transmitted symbols and the symbols extracted from the received signal using estimated channel information. Hence we go for channel estimation.

1.3.2 Types of Channel Estimations

Training Sequences vs. Blind Methods.

Once a model has been established, its parameters need to be continuously updated (estimated) in order to minimize the error as the channel changes. If the receiver has a-priori knowledge of the information being sent over the channel, it can utilize this knowledge to obtain an accurate estimate of the impulse response of the channel. This method is simply called ***Training sequence based Channel estimation***. It has the advantage of being used in any radio communications system quite easily. Even though this is the most popular method in use today, it still has its drawbacks. One of the obvious drawbacks is that it is wasteful of bandwidth. Precious bits in a frame that might have been otherwise used to transport information are stuffed with training sequences for channel estimation. This method also suffers due to the fact that most communication systems send information lumped frames. It is only after the receipt of the whole frame that the channel estimate can be extracted from the embedded training sequence. For fast fading channels this might not be adequate since the coherence time of the channel might be shorter than the frame time.

Blind methods on the other hand require no training sequences. They utilize certain underlying mathematical information about the kind of data being transmitted [4]. These methods might be bandwidth efficient but still have their own drawbacks. They are notoriously slow to converge (more than 1000 symbols may be required for an FIR channel with 10 coefficients). Their other drawback is that these methods are extremely computationally intensive and hence are impractical to implement in real-time systems. They also do not have the portability of training sequence-based methods. One algorithm that works for a particular system may not work with another due to the fact they send different types of information over the channel.

In this thesis work we will discuss channel estimation techniques based on training sequences or pilot tones.

1.4 Introduction to WARP FPGA XC4VFX100

WARP is Wireless Open Access Research Platform. WARP FPGA board is a platform on which real time implementation can be done. The WARP board is equipped with the radio nodes which are responsible for the processing of signals to be transmitted and received. The input samples are transmitted through the antenna associated with the transmitting radio node of the WARP FPGA board. These samples are then received by the antenna associated with receiving radio node. WARP Lab is a framework which brings together WARP and MATLAB. With WARPLab, we can interact with WARP nodes directly from the MATLAB workspace and signals generated in MATLAB can be transmitted in real-time over-the-air using WARP nodes.

1.4.1 System Model

The user creates in MATLAB the samples to be transmitted. The samples to be transmitted are downloaded to buffers in the nodes assigned as transmitters. The user sends a trigger to transmitter and receiver nodes. Upon reception of this trigger, samples are transmitted over-the-air and captured in real-time. The user reads captured samples from the receiver nodes to the MATLAB workspace. Received samples are processed offline in MATLAB. Downloading of the signals from Host PC containing MATLAB and its transmission and reception is shown in the figure 1.3.

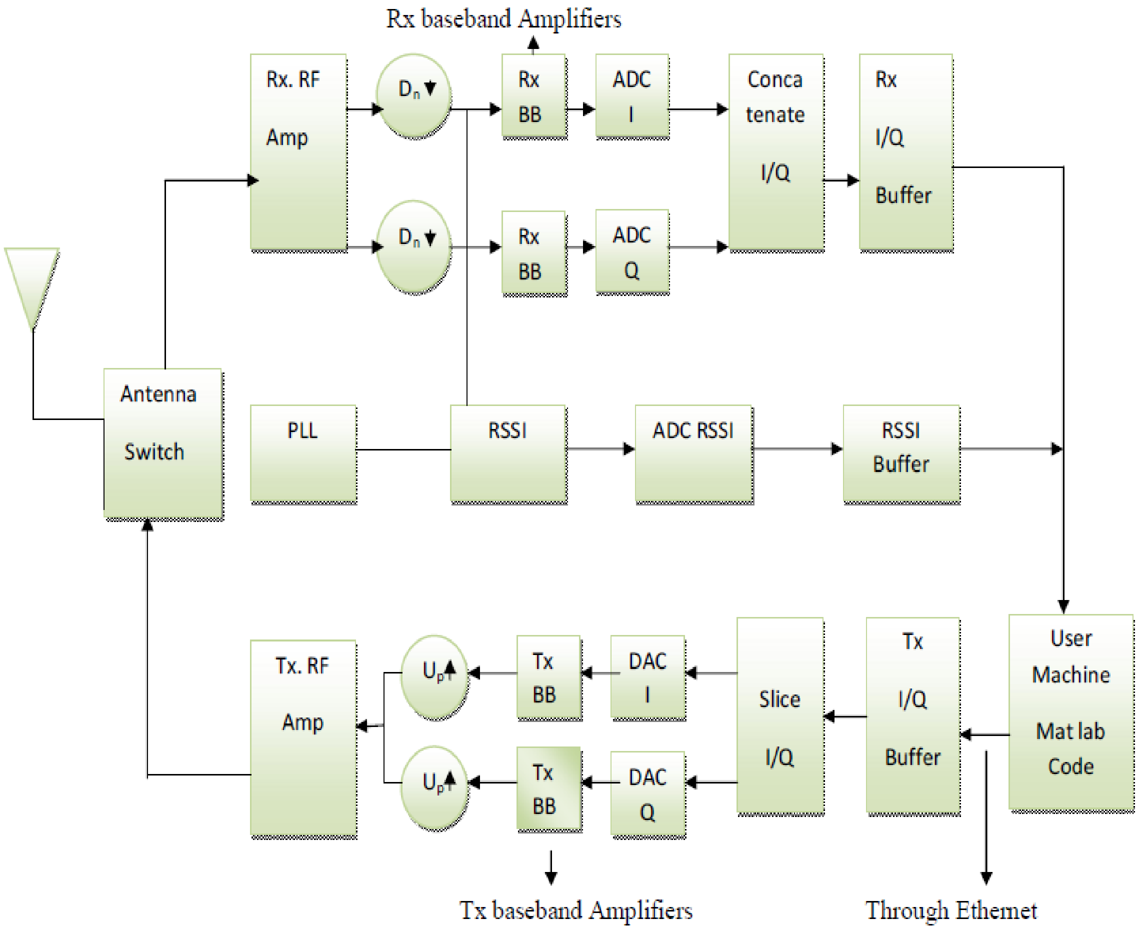


Figure 1.3: System model showing the signal flow and processing [25].

The Host PC and WARP node are two devices between which the interaction takes place. The Host PC includes the main M-Code and its sub modules such as functions. The MATLAB program can be run and associated with WARP board only through Ethernet interface and is shown in figure 1.3. The Ethernet MAC is designed for operation in 10/100/1000 Mb/sec. In full duplex mode the data rate is 100/1000 Mb/sec and in half duplex mode it is 10/100 Mb/sec. It also provides support for frames of any length. Through Ethernet the signals are downloaded on to the radio boards with the help of Radio controller and Radio bridges. The radio bridge is a custom peripheral which provides the external connections for the radio controller core. The radio controller is a custom peripheral designed to utilize the many functions of the radio boards. It contains SPI logic to set the registers in the Radio and DAC chips on the boards and logic to keep track of the control pins for both of the chips. Also provided with the radio controller are drivers that enable the use of the radio controller The Radio bridge which is supporting the radio controller contains very little logic; its only job is to tie the radio controller's ports to whichever daughter card slots contain WARP radio boards. Abstracting these connections to a separate peripheral allows the use of a single radio controller core with arbitrary arrangements of radio boards. WARP FPGA board has a simple circuitry for handling the different issues related to downloading, processing and transmission of signals. The tool used for the accessing the processor is Xilinx ISE IMPACT. This tool is responsible for configuring the upstream and downstream devices using JTAG boundary scan, preparing PROM file, system ACE file, Boundary-scan file and downloading connection cable (Ethernet) and bit stream required for the processing of the signal. The block constitutes Ethernet as the mode for accepting the signal to be transmitted. The I/Q signals entered is buffered using transmitter buffer which is sliced into I and Q form individually. The Digital to Analog converters are given inputs in I/Q form whose amplified outputs are then up converted to increase the frequency. This interpolated RF is then amplified and sends via TX antenna. The signals transmitted are received at the antenna of receiving board where these signals are amplified. The amplified signals are decimated with the help of PLL (phase locked loop) so as to make the received frequency same as that of transmitted baseband signal. The down converted baseband is amplified and then given to analog to digital converters which individually convert the Analog I and Q waveforms into digital domain. Concatenation of I and Q occurs and this combined signal is then buffered to Ethernet. The received signals are now further processed offline so as to obtain the correct signal.

1.5 Objective of Thesis

- Study of MIMO systems and its benefits.
- Study of the WARP FPGA Board.
- Study of Different Channel Estimation Techniques.
- Implementation of various channel estimation techniques on WARP platform.
- Comparison of the simulated channel estimation techniques with their performance in real time.

1.6 Outline of Report

In this report, the performance of different channel estimation techniques is presented in real time with hardware implementation . The remaining of the report is organized as follows:

In chapter 1, Introduction to Channel estimation, Need for channel estimation and Types of channel estimation are discussed.

In chapter 2, Literature survey of channel estimation techniques and WARP FPGA board is briefly presented.

In chapter 3, Description of WARP FPGA board involving its main modules used in the signal processing is presented.

In chapter 4, Different Channel Estimation Techniques based on training sequences or pilots are discussed.

In chapter 5, Simulation results and parameters used in simulating the design code are presented and compared with the real-time results obtained on the Test-Bed.

CHAPTER 2

LITERATURE SURVEY

F.Delestre and Y.Sun [6] propose a new pilot aided channel estimation algorithm for MIMO-OFDM system over frequency selective channel. In this channel estimation algorithm , pilots are first transmitted in order to estimate the channel. Here, as the system is based on OFDM, pilots are sent at the beginning of each OFDM block in order to decode the data in that block. The algorithm can work for any modulation and any number of subcarrier. The comparison has also been done between the ideal MIMO-OFDM scheme where channel is assumed to be known at the receiver and the proposed channel estimation method.

C. Tellambura, Y. J. Guo, and S. K. Barton [7] consider estimating a channel impulse response using a known aperiodic sequence. It is shown that the eigen values of the autocorrelation matrices of a pair of complementary sequences sum to a known constant. For time-domain channel estimation, training sequences can be classified broadly into two : periodic and aperiodic. A figure of merit is proportional to the largest eigen value of the associated autocorrelation matrix. A performance measure has been proposed to assess the quality of binary sequence for CE, using the trace of the inverse of its associated autocorrelation matrix.

Jun Ma, Philip Orlik, Jinyun Zhang and Geoffrey Ye Li [8] discuss a two-hop multi-input-multi-output (MIMO) amplify-and-forward (AF) relay system consisting of a source node (SN), a relay node (RN), and a destination node (DN). There is no direct communication link between the SN and the RN and data are conveyed from the SN to the DN via two orthogonal channels by time-division or frequency-division. Since the simple RN in this system is unaware of the structure of its received signal, the interim channels over the SN-RN and the RN-DN hops, H_1 and H_2, cannot be estimated directly. The interim channels, H_1 and H_2, are estimated based on the amplifying matrix P at the RN and the corresponding overall channel, $H = H_2PH_1$.

Matthias Stege, Marcus Bronzel & Gerhard Fettweis [9] present the impact of channel estimation errors on the performance of STBC for flat fading channels as well as for multipath channels. The performance of STBC and Receive Diversity has been compared. There is a SNR-loss of more than 3dB for STBC compared to receive diversity [10][11]. The difference between the performance with realistic and ideal channel estimates are smaller for receive diversity. STBC is more affected by channel estimation errors. At high SNR an error floor is observed for both STBC and receive diversity & the noise variance of channel estimation is twice as high as for receive diversity which results in additional performance loss.

Jongsoo Choi , Martin Bouchard and Tet Hin Yeap [12] propose an adaptive filtering-based iterative channel estimators with the incorporation of an iterative receiver over a flat-fading MIMO wireless link In an iterative channel estimation method, both pilot symbols and soft (or hard) estimates of the data symbols are used to improve the channel quality in a semi blind manner.Iterative channel estimation is performed using the dedicated pilot symbols located in a preamble and the estimated code symbols fed back from the decoders. At the first iteration, an initial CSI is estimated using only known pilot symbols, where we employ the LS estimation. As the iterations proceed between the SISO detector and the SISO decoders, both the pilot and the estimated code symbols are contributed to the iterative channel estimator.

M.A.Mohammadi, M.Ardabilipour , B.Moussakhani and Z.Mobini [13] propose a method in which optimum training sequences are derived based on calculated MSE for LS channel estimation. Then utilizing these training sequences ,adaptive methods based on LMS and RLS are applied to estimate the channel for a system which emits independent data streams from transmitter antennas. Proposed method is capable of computing all sub-channel coefficients between a receiver antenna and all transmitters.

Hala M. Mahmoud, Allam S. Mousa and Rashid Saleem [14] propose Kalman and Least Square (LS) estimators to estimate the Channel Frequency Response (CFR) at the pilots location, then CFR at data sub channels are obtained by mean of interpolation between estimates at pilot locations. Different types of interpolations have been used such as: low pass interpolation, spline cubic interpolation and linear interpolation. Kalman estimation has better performance than LS estimation.

Xiaodong Cai and Georgios B. Giannakis [15] give a promising pilot symbol assisted channel estimation technique for high rate transmissions over wireless frequency-selective fading channels. They have analysed the symbol error rate (SER) performance of OFDM with M-ary phase-shift keying (M-PSK) modulation over Rayleigh-fading channels, in the presence of channel estimation errors. Both least-squares error (LSE) and minimum mean-square error (MMSE) channel estimators are considered. The number of pilot symbols, the placement of pilot symbols, and the power allocation between pilot and information symbols have also optimised to minimize the performance loss due to channel estimation errors and thereby minimize SER.

Ye (Geoffrey) Li, Nambirajan Seshadri and Sirikiat Ariyavisitakul [16] propose a channel estimation technique for an OFDM system with transmitter diversity using space-time coding. Different channel parameter estimation approaches are developed, which are crucial for the decoding of space-time codes, and the MSE bounds for these estimation approaches are derived. It was evaluated that for an OFDM system with two transmitter antennas and two receiver antennas using space-time coding, permitting 1.475 bits/s/Hz, the required SNR is about 9 dB for 10% WER(word error rate), and 7 dB for 1% BER (bit error rate).

Sebastian Caban, Christian MehlfAuhrer, Robert Langwieser, Arpad L. Scholtz, and Markus Rupp [17] present a flexible testbed developed to examine MIMO algorithms and channel models by transmitting data at 2.45GHz through real, physical channels, supporting simultaneously four transmit and four receive antennas. It investigates the performance of highly sophisticated wireless systems taking into account the imperfections of real-world. Thus, combining the advantages of Matlab and FPGA environment, the MIMO testbed developed allows for rapid verification of baseband algorithms and their critical parts with minimum effort.

Ove Edfors, Magnus Sandell, Jan-Jaap van de Beek, Sarah Kate Wilson and Per Ola BAorjesson [18] present a new approach to low-complexity channel estimation in orthogonal frequency division multiplexing (OFDM) systems. A low rank approximation is applied to a linear minimum mean-squared error (LMMSE) estimator that uses the frequency correlation of the channel. An optimal low-rank estimator is also derived using the singular-value decomposition (SVD).

Meng-Han Hsieh and Che-Ho We [19] propose the channel estimation methods for OFDM systems based on comb-type pilot sub-carrier arrangement. The channel estimation algorithm based on comb-type pilots is divided into pilot signal estimation and channel interpolation. The pilot signal estimation is based on LS or MMSE criteria, together with channel interpolation which is based on piecewise-linear interpolation or piecewise second-order polynomial interpolation. The computational complexity of pilot signal estimation based on MMSE criterion can be reduced by using a simplified LMMSE estimator with low-rank approximation using singular value decomposition.

M. Uysal, N. Al-Dhahir and C. N. Georghiades [20] introduce a space-time block-coded orthogonal frequency-division multiplexing (STBC-OFDM) scheme for frequency-selective fading channels which does not require channel knowledge either at the transmitter or at the receiver. The decoding algorithm is based on generalized maximum-likelihood sequence estimation whose form allows the derivation of a recursive expression. The receiver operates on a number of processors implemented by Viterbi-type algorithms, each assigned to a specific frequency tone in the OFDM scheme.

K. Elangovan and Dr. PLK Priyadarsini [21] propose three techniques to estimate the channel responses namely, Least Mean Square (LMS), Normalized LMS (NLMS) and Recursive Least Square (RLS) algorithm. The fading caused due to multi path delay are cancelled using these three equalization techniques. NLMS has better affect on reducing the BER compared to LMS. In order to have excellent tracking another adaptive equalization algorithm called RLS is adopted.

M.A. Saeed , N. K. Noordin , B.M. Ali , S. Khatun and M. Ismail [22] propose an adaptive time-domain channel estimation and tracking scheme based on recursive least squares (RLS) algorithm for MIMO OFDM-based wireless local area networks (WLANs). The estimated channel impulse response (CIR) is Fourier transformed and zero forcing (ZF) equalization is performed in frequency domain. The optimum channel estimate can be obtained by minimizing the exponentially weighted cost function .The channel estimates are updated recursively upon receiving new training symbols. Synchronized replicas of the training symbols, locally stored at the receiver will act as references. In channels where higher Doppler frequencies are experienced, the performance can be improved by increasing the training rates.

Ivan Cosovic and Gunther Auer [23] establish an analytical framework to dimension the pilot grid for MIMO-OFDM operating in time-variant frequency selective channels. The optimum placement of pilot symbols in terms of overhead and power allocation is identified that maximizes the training-based capacity for MIMO-OFDM schemes without channel knowledge at the transmitter. For pilot-aided channel estimation (PACE) with perfect interpolation, it is shown that the maximum capacity is achieved by placing pilots with maximum equidistant spacing given by the sampling theorem, if pilots are appropriately boosted. Allowing for realizable and possibly suboptimum estimators where interpolation is not perfect, a semi analytical method is presented which finds the best pilot allocation strategy for the particular estimator.

Hailong Cui and Predrag B. Rapajic [24] present the trade off between complexity and performance of four different types of GSM receiver: Conventional training sequence channel estimation receiver, iterative channel estimation feedback from equalizer, iterative channel estimation plus iterative equalization and decoding, and combination of iterative channel estimation and Iterative equalization and decoding. The combination of iterative channel estimation and iterative equalization and decoding has the best trade off among the receivers with iterative processes. It has about 1.3 dB gain over conventional receiver using training sequence estimation only.

Arun P. Kannu and Philip Schniter [26] consider a cyclic-prefixed block based pilot-aided transmission (PAT) over the single-antenna doubly selective channel, where the channel is assumed to obey a complex-exponential basis expansion model. First, a tight lower bound on the mean-squared error (MSE) of pilot-aided channel estimates is derived, along with necessary and sufficient conditions on the pilot/data pattern that achieves this bound. From these conditions, novel minimum-MSE (MMSE) PAT schemes are proposed and upper/lower bounds on their ergodic achievable rates are derived.

Haralambos Pozidis and Athina P. Petropulu [27] propose a novel cross-correlation based framework for the problem of blind equalization in communications. Assumption is made to have access to two observations obtained either by sampling, at the symbol rate, the outputs of two sensors or by oversampling, by a factor of two, the output of a single sensor. In either case, the two observations correspond to the outputs of two channels excited by the same input. The channels are estimated using the theory of signal reconstruction from phase only. The phase used is the phase of the cross spectrum of the observations filtered through their minimum phase equivalent filters.

Ye (Geoffrey) Li [28] present two techniques to improve the performance and reduce the complexity of channel parameter estimation: optimum training-sequence design and simplified channel estimation. The optimal training sequences not only simplify the initial channel estimation, but also attain the best estimation performance. The simplified channel estimation significantly reduces the complexity of the channel estimation at the expense of a negligible performance degradation.

Kala Praveen Bagadi and Prof. Susmita Das [31] compare channel estimation based on both block-type pilot and comb-type arrangements in both SISO and MIMO OFDM based systems. Channel estimation based on comb-type pilot arrangement is achieved by giving the channel estimation methods at the pilot frequencies and the interpolation of the channel at data frequencies. The estimators can be used to efficiently estimate the channel in both OFDM systems given certain knowledge about the channel statistics. The MMSE estimator assumes a priori knowledge of noise variance and channel covariance. The advantage of diversity in MIMO system results in less BER than SISO system. And simulation results show that MMSE estimation for MIMO OFDM provides less MSE than other systems.

CHAPTER 3

WARP FPGA XC4VFX100 DESCRIPTION

WARP is wireless open access research platform. WARP was developed in Rice University in U.S.A. by Murphy Brothers. WARP is being widely used throughout the world for research in wireless domain. Many wireless applications can be run and implemented on WARP-FPGA board such as SISO, MIMO and SIMO. WARP, the Wireless Open-Access Research Platform is a hardware involving FPGA as the main module. WARP board consists of other modules such as Analog board, Clock board, Radio board, User I/O board and Video board [25]. The most important of these is Radio board which is responsible for transmission and reception of signals. To each radio board, antennas are connected with helical radiation pattern. The transmitted signal frequency is 2.4 GHZ. Along with this other hardware modules and I/O ports associated with WARP board are WARP FPGA board memory resources, WARP FPGA board user I/O, WARP FPGA Board Power Supplies, WARP FPGA Board Clocking, Ethernet, WARP Multi gigabit Transceivers. The WARP FPGA board has been shown in the figure 3.1 in operating mode.

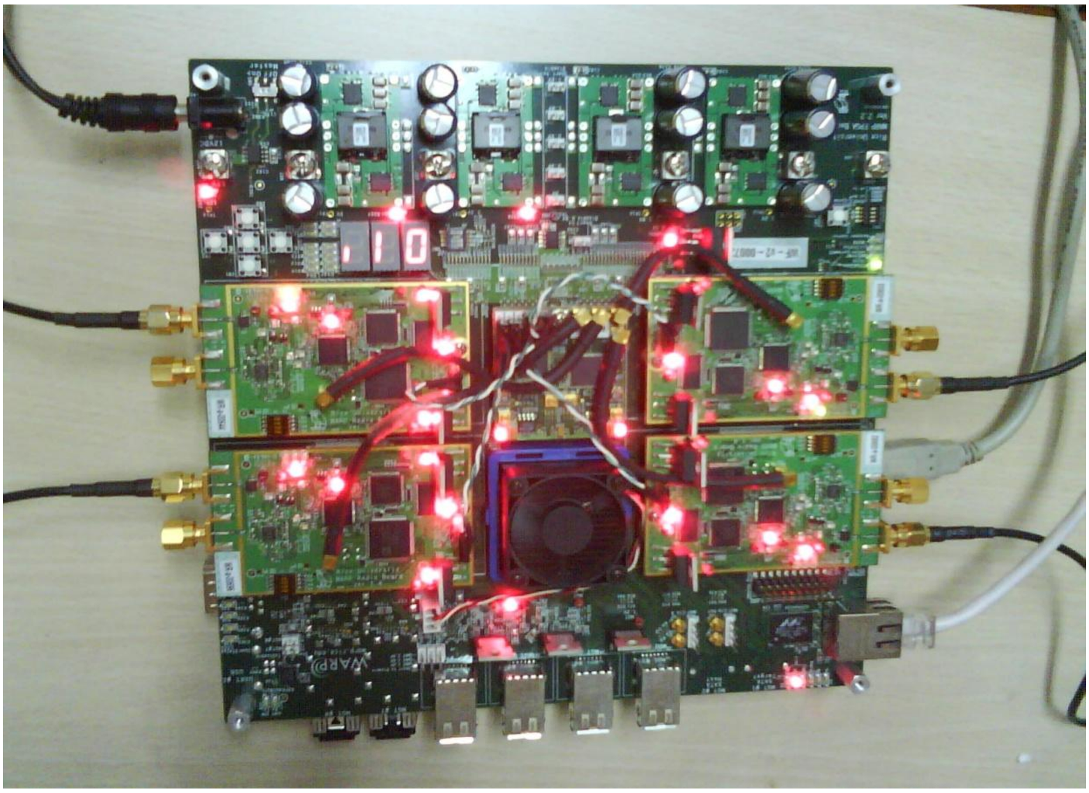


Figure 3.1 : WARP FPGA in operating mode[25].

To use the board firstly generate a vector of samples to be transmitted and send the samples to the WARP board. Then WARP board is prepared for the transmission and reception by connecting accurately the I/O ports. The signals generated for the transmission through MATLAB programming are then downloaded to the buffer of the transmission board and then these signals are processed and transmitted through the antenna associated with that radio board. The boards must be programmed with the WARP Lab bit stream because this bit stream provides storage of RSSI values and the receiver reads these RSSI values. The signals to be transmitted are undergone different modulation techniques separately and are then transmitted through radio board which is one of the modules of WARP board discussed below.

3.1 Modules of WARP FPGA Board

WARP board involves various hardware modules along with I/O interfaces such as WARP FPGA board memory resources, WARP FPGA board user I/O, WARP FPGA Board Power Supplies, WARP FPGA Board Clocking, Ethernet, WARP Multi gigabit Transceivers, etc.

3.1.1 WARP FPGA Daughter Cards

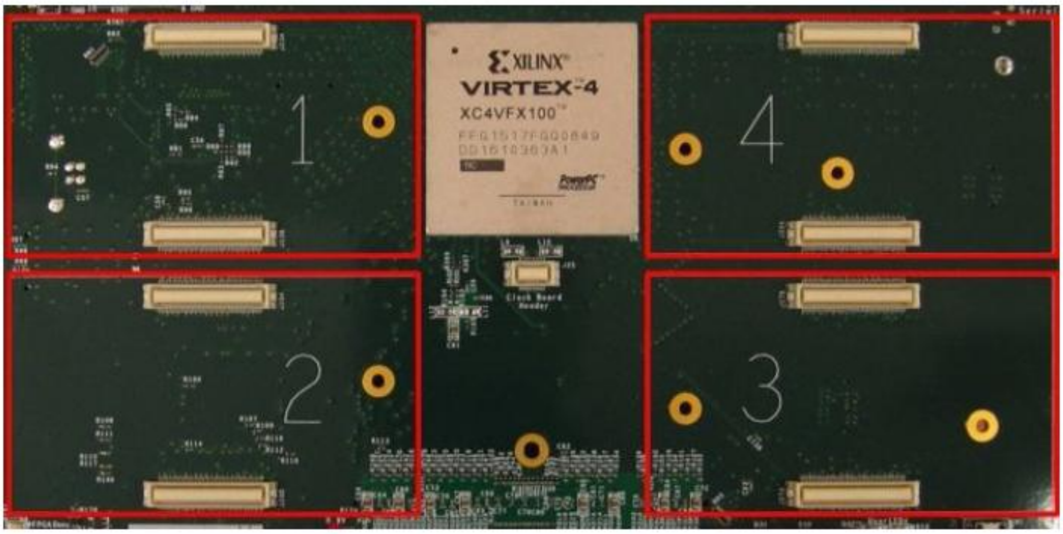


Figure 3.2: WARP FPGA Radio Daughter Card [25].

The WARP FPGA Board has four daughter card slots. One of the Daughter card has been shown in the figure 3.2.The four slots are electrically and mechanically identical. The WARP hardware supports any combination of daughter cards in the four slots.

However, a given FPGA design will require a specific arrangement of daughter cards once synthesized. The four Daughter card slots on the WARP FPGA board are given with 5v supply. A second power plane is also connected to the Daughter card slots and can be driven by an off-board supply via a dedicated 6-pin header on the FPGA board. A Clock is provided which initiates transmission and reception of signals by sending SYNC pulse whenever required.

3.1.2 Ethernet

The FPGA Board has one 10/100/1000 Ethernet device present which is shown in figure 3.3. The design uses the Marvell Gigabit Ethernet PHY which implements all the physical layer functionality and the Virtex-4 FPGA uses one of the hardened Tri-mode Ethernet MAC for the MAC layer.

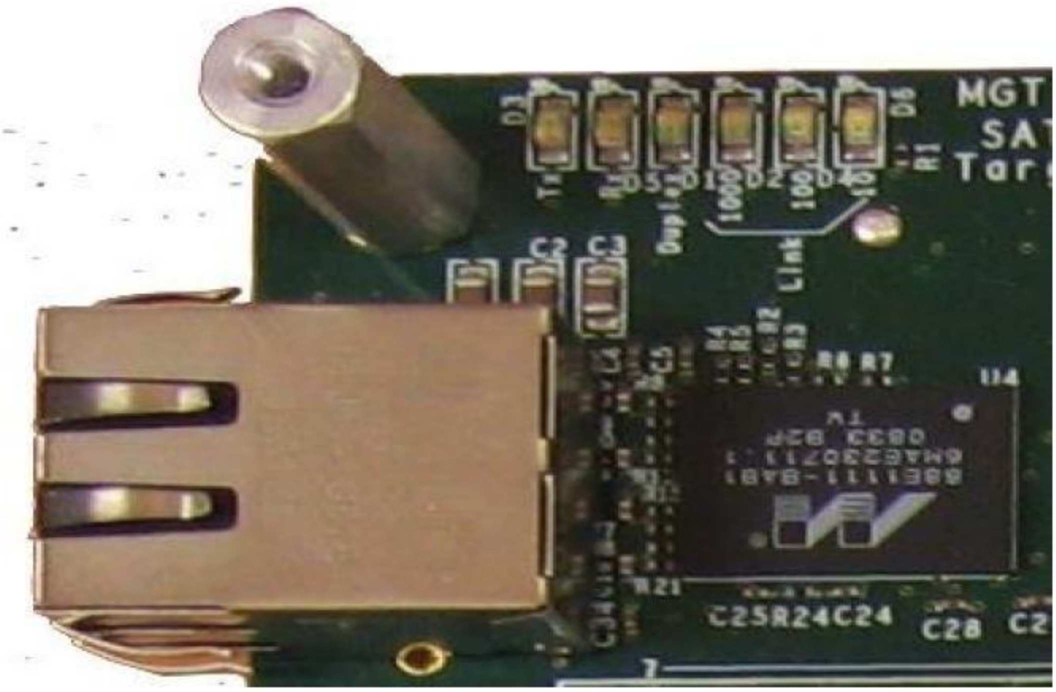


Figure 3.3: Ethernet for Interfacing WARP Board and MATLAB [25].

Physical layer link is shown by LEDs which show the status such as packet transmission, packet reception, duplex link and speed. Maximum Speed of 1Gbps and minimum of 10Mbps can be achieved.

WARP FPGA consists of Multi gigabit transceivers (MGT) as another module. There are ten pairs of MGTs each of which works in full duplex mode and supports data rate of 6.5Gbps. Eight MGT interfaces are there in all which are mapped to the corresponding MGT in FPGA through different connectors known as jumpers. Off board connectors and oscillators are two sources for providing clock to MGT. Further MGT can be given clock externally as an input and also can give clock externally. A global clock is provided on the WARP board to provide clocking to radio boards. WARP also consists of RAM having 6.7 MB of memory in the form of logic slices. A DDR slot is there which is routed to dedicated I/O and clocking resources and supports up to 2GB modules. Further a user I/O is also provided which are intended for debugging custom designs in the hardware. Five FPGA inputs are provided which are connected to external pull down registers such that when a button is pressed logic high occurs and otherwise logic low. WARP FPGA board operates from a single external 12v supply while Radio daughter cards slot supply is 5v supply.

3.2 Specifications of WARP FPGA Board

Figure 3.4 gives the pictorial view of the WARP FPGA board. Using WARPLab framework, radio nodes are interacted directly from the MATLAB workspace and signals generated in MATLAB are transmitted in real-time over-the-air using radio node.

Fig 3.4: Pictorial view of the Test Bed [25].

A. Tx/Rx I/Q Buffers

- Independent Tx/Rx I/Q Buffers.
- Each buffer can store a maximum of 2^{14} samples.
- Buffers persist between triggers.
- Samples are read from Tx I/Q Buffers to I/Q DACs at 40 MHz.
- Samples are written from I/Q ADCs to Rx I/Q buffers at 40MHz.

B. Tx Signal Requirements

- Lowest Frequency: 30 kHz. Radios filter DC.
- Highest Frequency: Depends on the Tx/Rx Low Pas Filter (LPF) Corner Frequency Setting. By default, Tx and Rx LPF are set to nominal mode. Possible Tx/Rx LPF settings are the following.
  Tx LPF corner frequency: Mode 0: Undefined, Mode 1: 12 MHz (Nominal Mode), Mode 2: 18 MHz (Turbo Mode 1), Mode 3: 24 MHz (Turbo Mode2).
  Rx LPF corner frequency: Mode 0: 7.5 MHz, Mode 1: 9.5 MHz (Nominal Mode), Mode 2: 14 MHz (Turbo Mode 1), Mode 3: 18 MHz (Turbo Mode 2).
- 40 MHz sampling frequency.

C. Tx/Rx Amplifiers

- The Tx path applies gain at three amplifiers: Tx Base Band (Tx BB), Tx RF, and Tx RF PA. The Tx RF PA is always fixed at 30 dB gain. The Tx BB and Tx RF amplifiers are adjusted digitally, the range of gains is the following.
  TxBB : In [0,3] applies 1.5 dB/step.
  Tx RF: In [0, 63] applies 0.5 dB/step.
- The Rx path applies gain at two amplifiers: Rx Base Band (Rx BB) and Rx RF. Rx amplifiers are adjusted digitally, the range of gains is the following.
  Rx BB : In [0,31] applies 2dB/step.
  Rx RF: In [1, 3] applies 15 dB/step.

CHAPTER 4

CHANNEL ESTIMATION TECHNIQUES

4.1 Normal LS Channel Estimation For Single Signal

The channel impulse response is estimated based on the known training sequence, which is transmitted in every transmission burst. We assume that the channel conditions remain the same during the transmission of each burst. We will first send the known training sequences. Since receiver has the knowledge about the information being sent ,the channel impulse response can be estimated. This CIR information is is fed back to the transmitter after which it transmits the data symbols .Since we know the CIR we can obtain the information transmitted from the received signal. This is explained mathematically as below:

Consider first a communication system, which is only corrupted by noise as depicted in Fig. below. Digital signal a is transmitted over a fading multipath channel h_L, after which the signal has memory of L symbols. Thermal noise is generated at the receiver and it is modelled by additive white Gaussian noise n, which is sampled at the symbol rate. The demodulation problem here is to detect the transmitted bits a from the received signal y. Besides the received signal the detector needs also the channel estimates $\hat{h}$, which are provided by a specific channel estimator device.

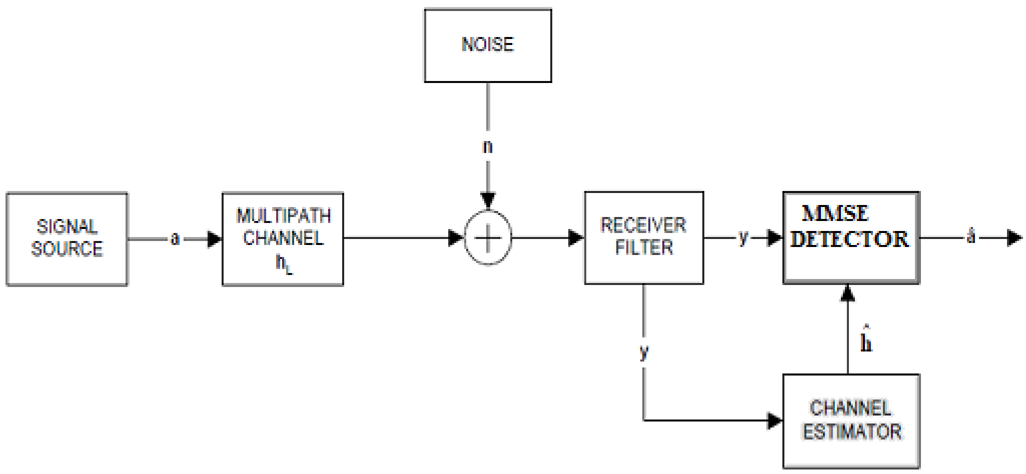


Figure 4.1: Block diagram of a noise-corrupted system [29].

The received signal **y** can be expressed as follows

$$y = Mh + n \tag{4.1}$$

where the complex channel impulse response h of the wanted signal is expressed as

$$h = \begin{bmatrix} h_0 & h_1 \ldots\ldots & h_L \end{bmatrix}^T \tag{4.2}$$

and n denotes the noise samples. Within each transmission burst the transmitter sends a unique training sequence, which is divided into a reference length of P and guard period of L bits, and denoted by

$$m = \begin{bmatrix} m_0 & m_1 \ldots\ldots & m_{P+L-1} \end{bmatrix}^T \tag{4.3}$$

having bipolar elements $m_i \in \{-1,+1\}$. Finally to achieve Eq. (1) the circulant training sequence matrix M is formed as

$$M = \begin{bmatrix} m_L & \cdots & m_1 & m_0 \\ m_{L+1} & \cdots & m_2 & m_1 \\ \vdots & & \vdots & \vdots \\ m_{L+P-1} & \cdots & m_P & m_{P-1} \end{bmatrix} \tag{4.4}$$

The LS channel estimates are found by minimising the following squared error quantity

$$\hat{h} = \arg\min_h \|y - Mh\|^2 = \left(M^H M\right)^{-1} M^H y \tag{4.5}$$

where $(\ )^H$ and $(\ )^{-1}$ denote the Hermitian and inverse matrices, respectively.

4.2 Joint Channel Estimator For 2 Signals

Let us consider now a communication system in the presence of co-channel interference that is shown in Fig.4.2. Two synchronised co-channel signals have independent complex channel impulse responses

$$h_{L,n} = \begin{bmatrix} h_{0,n} \ , & h_{1,n} \ ,\ldots\ldots, & h_{L,n} \end{bmatrix} \tag{4.6}$$

where n =1, 2 and L is the length of the channel memory.

The sum of the co-channel signals and noise n is sampled in the receiver. The joint demodulation problem is to detect the transmitted bit streams a_1 and a_2 of the two users from the received signal y. To assist that joint detection operation the joint channel estimator provides channel estimates $\hat{h}_1$ and $\hat{h}_2$.

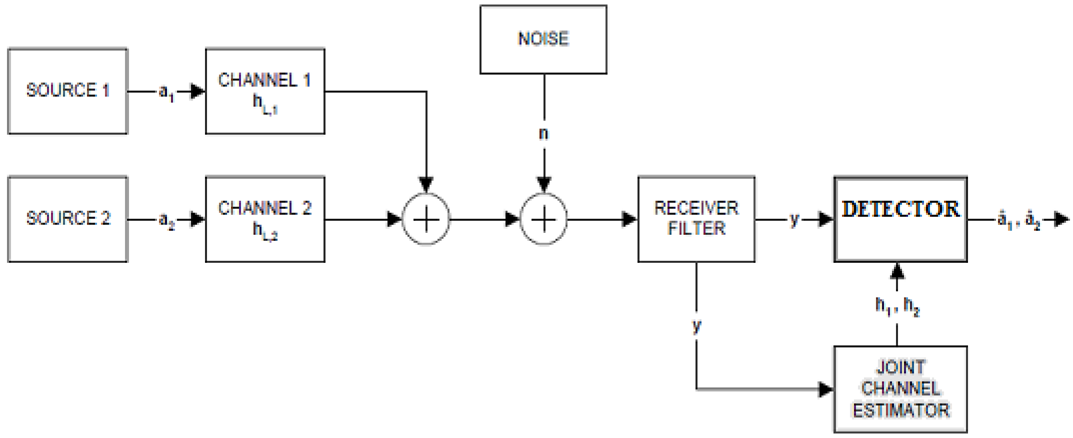


Figure 4.2: Block Diagram of Co-channel signal system [29].

The complex channel impulse responses of the two synchronous co-channel signals are expressed with a vector as follows

$$\tilde{h} = \begin{bmatrix} h_{L,1} \\ h_{L,2} \end{bmatrix} \tag{4.7}$$

containing the channel taps of the individual signals denoted by

$$h_{L,n} = \begin{bmatrix} h_{0,n} \\ h_{1,n} \\ \vdots \\ h_{L,n} \end{bmatrix} \quad ,n = 1,2 \tag{4.8}$$

Hence, $\tilde{h}$ has totally $2*(L+1)$ elements. Both the transmitters send their unique training sequences with a reference length of P and guard period of L bits.

The sequences are denoted by

$$m_n = \begin{bmatrix} m_{0,n} \\ m_{1,n} \\ \vdots \\ m_{P+L-1,n} \end{bmatrix} \quad ,n = 1,2 \tag{4.9}$$

The circulant training sequence is denoted as

$$M_n = \begin{bmatrix} m_{L,n} & \cdots & m_{1,n} & m_{0,n} \\ m_{L+1,n} & \cdots & m_{2,n} & m_{1,n} \\ \vdots & & \vdots & \vdots \\ m_{L+P-1,n} & \cdots & m_{P,n} & m_{P-1,n} \end{bmatrix} \quad ,n = 1,2 \tag{4.10}$$

And they are gathered into one large matrix.

$$\tilde{M} = [M_1 \quad M_2] \tag{4.11}$$

The received signal y is given by

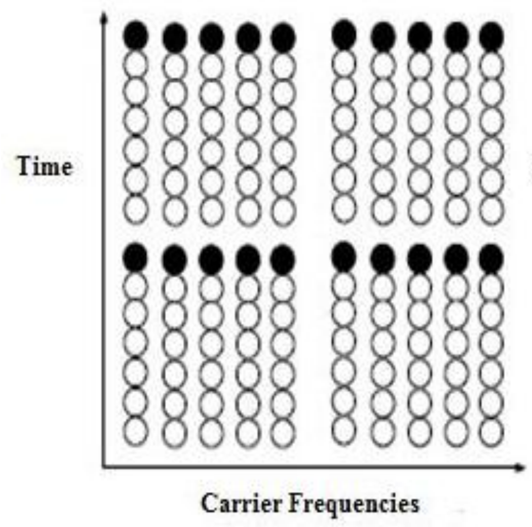
$$y = \tilde{M}\,\tilde{h} + n \tag{4.12}$$

The LS channel estimates can be found simultaneously for the both users by minimising the squared error quantity, which produces in the presence of AWGN the following solution

$$\hat{h} = \arg\min_{h} \left\| y - \tilde{M}\,\tilde{h} \right\|^2 = \left(\tilde{M}^H \tilde{M} \right)^{-1} \tilde{M}^H y \tag{4.13}$$

4.3 Channel Estimation Based on Block-type and Comb-Type Pilot Arrangement

In training based channel estimation algorithms, training symbols or pilot tones that are known to the receiver, are multiplexed along with the data stream for channel estimation [30]. The idea behind these methods is to exploit knowledge of transmitted pilot symbols at the receiver to estimate the channel. For a block fading channel, where the channel is constant over a few OFDM symbols, the pilots are transmitted on all subcarriers in periodic intervals of OFDM blocks. This type of pilot arrangement, depicted in Fig.4.3, is called the block type arrangement. For a fast fading channel, where the channel changes between adjacent OFDM symbols, the pilots are transmitted at all times but with an even spacing on the subcarriers, representing a comb type pilot placement as shown in Fig. 4.4.The channel estimates from the pilot subcarriers are interpolated to estimate the channel at the data subcarriers.



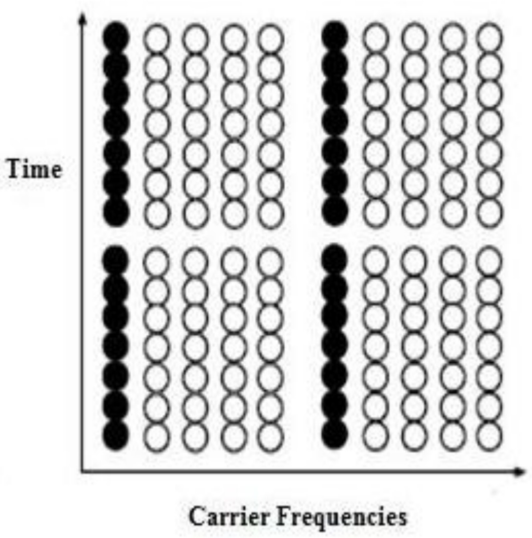


Figure 4.3: Block Type Pilot Placement [31]. Figure 4.4: Comb Type Pilot Placement [31].

4.3.1 Channel Estimation Based on Block Type Pilot Arrangement

In block-type pilot based channel estimation, OFDM channel estimation symbols are transmitted periodically, in which all subcarriers are used as pilots. If the channel is constant during the block, there will be no channel estimation error since the pilots are sent at all carriers. The estimation can be performed by using either LS or MMSE. If inter symbol interference is eliminated by the guard interval, we write in matrix notation

$$\begin{aligned} Y &= XFh \\ &= XH + W \end{aligned} \tag{4.14}$$

where

$$X = diag\{X(0, X(1),........X(N-1)\}$$

$$Y = [Y(0), Y(1),........Y(N-1)]^T$$

$$W = [W(0), W(1),......W(N-1)]^T$$

$$H = [H(0), H(1),......H(N-1)]^T = DFT\{h\}$$

$$F = \begin{bmatrix} W_N^{00} & \cdots & W_N^{0(N-1)} \\ \vdots & \ddots & \vdots \\ W_N^{(N-1)0} & \cdots & W_N^{(N-1)(N-1)} \end{bmatrix} \quad (4.15)$$

is the DFT matrix with

$$W_N^{nk} = \frac{1}{\sqrt{N}} e^{-j2\pi(n/N)k}$$

Minimum Mean Square Error (MMSE) Estimation

The MMSE estimator employs the second-order statistics of the channel conditions to minimize the mean-square error [32].The MSE (mean square error) is expressed as

$$J(e) = E\left[\left(H - \hat{H}\right)^2\right] \quad (4.16)$$

Invoking the well-known orthogonality principle in order to minimize the mean square error,vector $e = H - \hat{H}$ has to be set orthogonal by the MMSE equalizer to the estimators input vector Y.

$$E\left[\left(H - \hat{H}\right)Y^H\right] = 0 \quad (4.17)$$

Suppose R_{hh} , R_{HH} and R_{YY} denote the auto-covariance matrix of h, H and Y respectively and R_{hY} denote the cross covariance matrix between h and Y. Also σ_N^2 denote the noise variance $E\{|W|^2\}$.Assuming that the channel vector h and the noise W are uncorrelated, it is derived that

$$\begin{aligned} R_{hY} &= E\{hY^H\} = R_{hh}F^H X^H \\ R_{YY} &= E\{YY^H\} = XFR_{hh}F^H X^H + \sigma^2 I_N \\ R_{HH} &= E\{HH^H\} = E\{(Fh)(Fh)^H\} = FR_{hh}F^H \end{aligned} \quad (4.18)$$

Assuming R_{hh} (thus R_{HH}) and σ_N^2 are known at the receiver in advance, the MMSE estimator of h is given by

$$\hat{h}_{MMSE} = R_{hY} R_{YY}^{-1} Y^{HH} \quad (4.19)$$

At last, it is calculated

$$\hat{H}_{MMSE} = FR_{hY}R_{YY}^{-1}Y^{HH} \tag{4.20}$$

$$\begin{aligned}\hat{H}_{MMSE} &= F\,\hat{h}_{MMSE} = F[(F^H X^H)^{-1} R_{hh}{}^{-1}\sigma_N^2 + XF]^{-1}\bar{Y} \\ &= FR_{hh}[(F^H X^H XF)^{-1}\sigma_N^2 + R_{hh}]F^{-1}\hat{H}_{LS} \\ &= R_{HH}[R_{HH} + \sigma_N^2 (XX^H)^{-1}]^{-1}\hat{H}_{LS}\end{aligned} \tag{4.21}$$

Least square (LS) channel estimation

We have to minimise

$$\begin{aligned}J &= (Y - XH)^H (Y - XH) \\ &= (Y^H - H^H X^H)(Y - XH) \\ &= (Y^H Y - Y^H HX - H^H X^H Y + H^H X^H XH)\end{aligned} \tag{4.22}$$

For minimisation of J, we have to differentiate it with respect to H

$$\frac{\partial J}{\partial H} = 0$$

which implies

$$\hat{H}_{LS} = X^{-1}Y \tag{4.23}$$

4.3.2 Channel Estimation Based on Comb-Type Pilot Arrangement

In comb-type pilot based channel estimation, the *Np* pilot signals are uniformly inserted into *X(k)* according to the following equation:

$$X(k) = X(mL + l) \quad l = 1,2,....L - 1 \tag{4.24}$$

$$= \begin{cases} X_p(k) & l = 0 \\ \inf .Data & l = 1,2,.....L - 1 \end{cases}$$

where L = No. of subcarriers / Np , m = pilot carrier index.

We define $\{ H_p(k)\ k = 0, 1, \ldots Np \}$ as the frequency response of the channel at pilot sub-carriers.

The estimate of the channel at pilot sub-carriers based on LS estimation is given by:

$$H_p(k) = \frac{Y_p(k)}{X_p(k)} \quad k = 0,1,\ldots\ldots.N_p - 1 \tag{4.25}$$

$Y_p(k)$ and $X_p(k)$ are output and input at the k^{th} pilot sub-carrier respectively.

In comb-type pilot based channel estimation, an efficient interpolation technique is necessary in order to estimate channel at data sub-carriers by using the channel information at pilot sub-carriers [33][34]. In the linear interpolation method the channel estimation at the data-carrier k, $mL < k < (m + 1) L$, using linear interpolation is given as

$$\begin{aligned} H_e(k) &= H_e(mL + l) \quad 0 \le l < L \\ &= \left(H_P(m+1) - H_P(m)\right)\frac{l}{L} + H_P(m) \end{aligned} \tag{4.26}$$

where H_p is channel estimation value at pilot frequency. The low-pass interpolation is performed by inserting zeros into the original sequence and then applying a low pass FIR filter that allows the original data to pass through unchanged and interpolates between such that the mean-square error between the interpolated points and their ideal values is minimized.

4.3.3 Application in SISO OFDM and MIMO OFDM Systems

The channel estimation based on block –type and comb-type pilot arrangement can be used for SISO OFDM systems and MIMO OFDM systems. The SISO-OFDM system employs a single transmitter and a single receiver while MIMO-OFDM system employs multiple transmitters and multiple receivers. The block diagrams for both SISO-OFDM and MIMO-OFDM systems utilising pilot based channel estimation are shown in figure 4.5 and 4.6 respectively.

SISO OFDM Channel Estimation

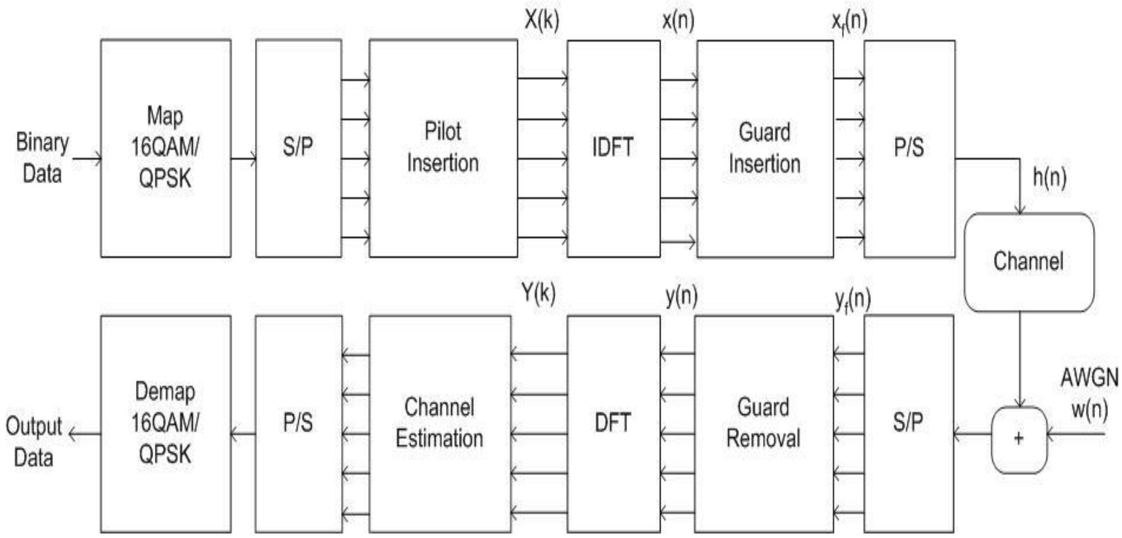


Figure 4.5:   SISO System Block diagram [31] .

For SISO OFDM systems , the channel estimation based on both block –type and comb-type pilot arrangement can be done using LS or MMSE techniques as explained above.

MIMO OFDM Channel Estimation

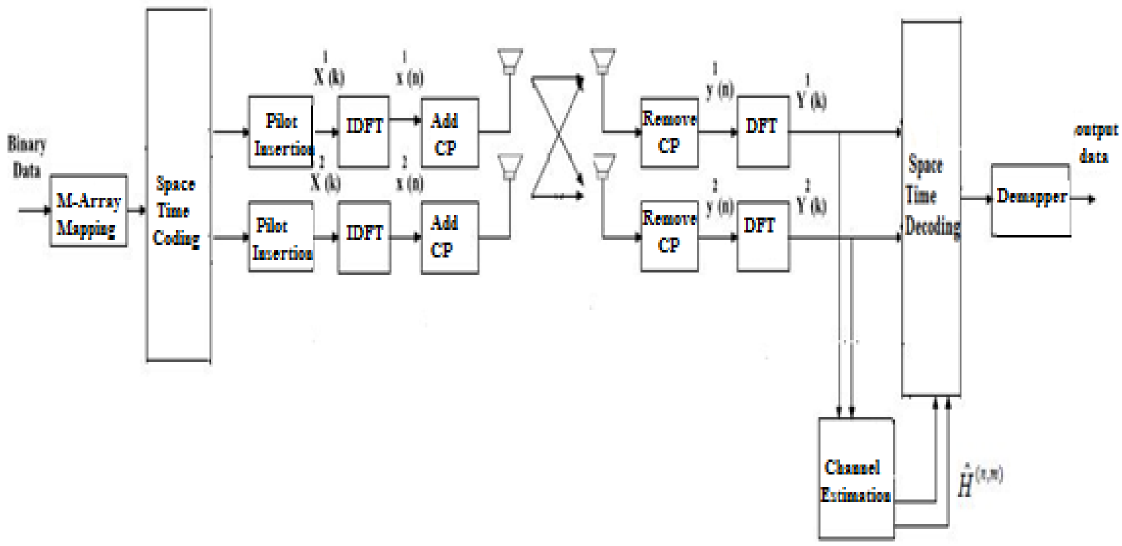


Figure 4.6: MIMO system block diagram [31].

As MIMO systems employ multiple antennas at the transmitter and receiver so channel estimation is performed as given below.

The LS channel estimation for MIMO-OFDM System between n^{th} transmitter and m^{th} receiver antenna is

$$\hat{H}_{LS}^{(n,m)} = \left(X^{(n)}\right)^{-1} Y^{(m)} \tag{4.27}$$

MMSE channel estimation for MIMO-OFDM System between n^{th} transmitter and m^{th} receiver antenna is

$$\hat{H}_{MMSE}^{(n,m)} = F R_{hY} R_{YY}^{-1} Y^{(m)} \tag{4.28}$$

where $$R_{hY} = R_{hh}^{(m,n)} F^{H} \left(X^{(n)}\right)^{H}$$

$$R_{YY} = X^{(n)} F R_{hh}^{(n,m)} F^{H} \left(X^{(n)}\right)^{H} + \sigma^2 I_N$$

where n = 1, 2….N_T, m = 1, 2….N_R and N_T, N_R are the numbers of transmit and receive antennas, respectively, $X^{(n)}$ is an *N X N* diagonal matrix whose diagonal elements correspond to the pilots of the *n*th transmit antenna and $Y^{(m)}$ is N length received vector at receiver antenna *m*.

4.4 Channel Estimation Using SVD (Modified MMSE)

Modified MMSE is used to reduce the complexity. The complexity reduction of the MMSE estimator consists of two separate steps. In the first step we reduce the complexity of this estimator by averaging over the transmitted data *i.e.* we replace the term $(XX^H)^{-1}$ in equ.(4.21) with its expectation $E(XX^H)^{-1}$. Assuming the same signal constellation on all tones and equal probability on all constellation points, we get $E(XX^H)^{-1} = E|1/x_k|^2 I$, where I is the identity matrix. Defining the average signal-to-noise ratio as $SNR = E|x_k|^2/\sigma_N^2$, we obtain a simplified estimator

$$\hat{H}_{MMSE} = R_{HH}\left(R_{HH} + \frac{\beta}{SNR} I\right)^{-1} \hat{H}_{LS} \tag{4.29}$$

where $\beta = E|x_k|^2 E|1/x_k|^2$ is a constant depending on the signal constellation. For example in the case of 16-QAM transmission, β = 17/9. In the second step, the optimal rank reduction of the estimator is obtained using the singular value decomposition (SVD) [35].

We denote the SVD of the channel correlation matrix

$$R_{HH} = U\Lambda U^{H} \tag{4.30}$$

where U is a matrix with orthonormal columns $u_0, u_1, ... u_{N-1}$ and Λ is a diagonal matrix, containing the singular values $\lambda_0 \geq \lambda_1 \geq ...... \geq \lambda_{N-1}$ on its diagonal. This allows the estimator to be written as

$$\hat{H}_{SVD} = U\Delta U^{H}\,\hat{H}_{LS} \tag{4.31}$$

where Δ is a diagonal matrix containing the values δ_k on its diagonal which are given by :

$$\delta_k = \frac{\lambda_k}{\lambda_k + \frac{\beta}{SNR}}, k = 0,1,....., N-1 \tag{4.32}$$

The best rank-*p* approximation of the estimator in (10) then becomes

$$\hat{H}_{SVD,p} = U\begin{bmatrix} \Delta_p & 0 \\ 0 & 0 \end{bmatrix} U^{H}\,\hat{H}_{LS} \tag{4.33}$$

where Δ_p is the upper left $p \times p$ corner of Δ.

4.5 MAP Channel Estimation

Maximum *a posteriori* (MAP) channel estimation is an alternative to Least Squares estimation that yields comparable performance in the Rayleigh fading channel. MAP channel estimation requires knowledge of the training sequence, the channel covariance, and the noise covariance at the receiver [36]. The same system model described for LS estimation applies to MAP estimation. The MAP estimate for the channel matrix maximizes the a posteriori probability density function $p(\mathbf{H}|\ r, X)$ with respect to $\mathbf{H}$.

The map estimate for H satisfies

$$\frac{\partial}{\partial \mathbf{H}} \ln p(\mathbf{H}|r, X)\Big|_{\mathbf{H}=\hat{\mathbf{H}}_{map(X)}} = 0 \tag{4.34}$$

Bayes rule states that

$$p(\mathbf{H}|r, X) = \frac{p(r|\mathbf{H}, X)\,p(\mathbf{H}|X)}{p(r|X)} \tag{4.35}$$

where

$$p(r|\mathbf{H}, X) = \pi^{-L}|R_n|^{-1}\exp\left(-(r - X\mathbf{H})R_n^{-1}(r - X\mathbf{H})\right) \quad (4.36)$$

$$p(\mathbf{H}|X) = \pi^{-NL}|R_{\mathbf{H}}|^{-1}\exp(-\mathbf{H}^H R_{\mathbf{H}}^{-1}\mathbf{H}) \quad (4.37)$$

R_n is the noise covariance and R_h is the channel covariance. For independent Rayleigh fading channels, R_h can be approximated as an identity matrix.

The MAP estimate is

$$\hat{\mathbf{H}}_{map}(X) = (X^H R_n^{-1} X + R_{\mathbf{H}}^{-1})^{-1} X^H R_n^{-1} r \quad (4.38)$$

An *Nt x Nt* matrix inversion is required to find the MAP estimate. The computational complexity for the matrix inversion remains constant as the number of training symbols increases.

4.6 Iterative Channel Estimation

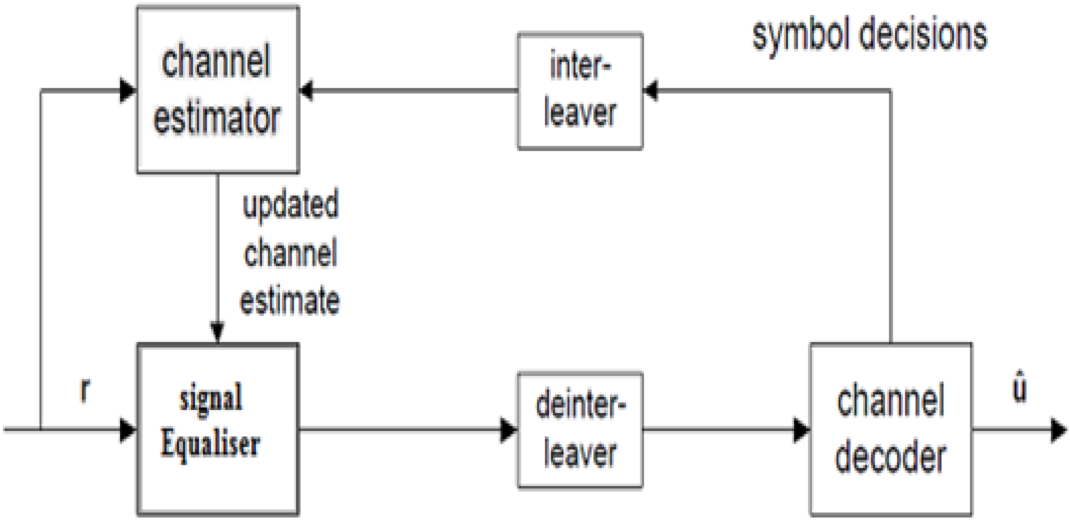


Figure 4.7: Block diagram for iterative channel estimator [29].

A decision-directed adaptive channel estimation method is presented, which diminishes the degradation due to the channel estimation and thereby improves the receiver performance.

The idea in short is to feed back the decoded symbols to the channel estimator and by that means update the earlier channel estimate assuming that the whole burst is now known by the receiver.

First iteration round (conventional)

Let us assume block fading channel (constant during a burst), so the received block is then given as

$$r = Ah + w = \begin{bmatrix} r_{c1} \\ r_m \\ r_{c2} \end{bmatrix} \tag{4.39}$$

where $$A = \begin{bmatrix} A_1 \\ M \\ A_2 \end{bmatrix}$$

where h is the channel impulse response to be estimated. Received sample vectors $\mathbf{r}_{c1}$ and $\mathbf{r}_{c2}$ are corresponding to coded data blocks $\mathbf{c}_1$ and $\mathbf{c}_2$, whereas $\boldsymbol{r}_m$ corresponds to the known training sequence (midamble). Respectively, $\boldsymbol{A}_1$ and $\boldsymbol{A}_2$ contain transmitted data bits and M contains training bits. Conventional channel estimation is based on the training bits using the received midamble samples

$$r_m = Mh + w \tag{4.40}$$

The LS channel estimate in the presence of AWGN is given by

$$\hat{h}_{LS} = (M^H M)^{-1} M^H r_m \tag{4.41}$$

After this we can solve for instance by MLSE detector the coded data $\mathbf{c}$ as follows

$$\hat{c} = \arg\max_c \; p(r|\hat{h}, c) \tag{4.42}$$

In order to improve decision reliability further, the channel decoding operation is performed. Hence, the information bits u are found by

$$\hat{u} = \arg\max_u \; p(\hat{c}|u) \tag{4.43}$$

Further iterations

As the coded data is needed in the feedback to the channel estimator, re-encoding $\mathbf{c_1}$ = E$\hat{u}$ is performed and then an extended training sequence matrix

$$A = [A_1 \quad M \quad A_2]^T$$

is formed using these coded data bits $\mathbf{c_1}$ and the known training bits in the middle. Now the channel estimator knows the whole burst and can re-estimate CIR.

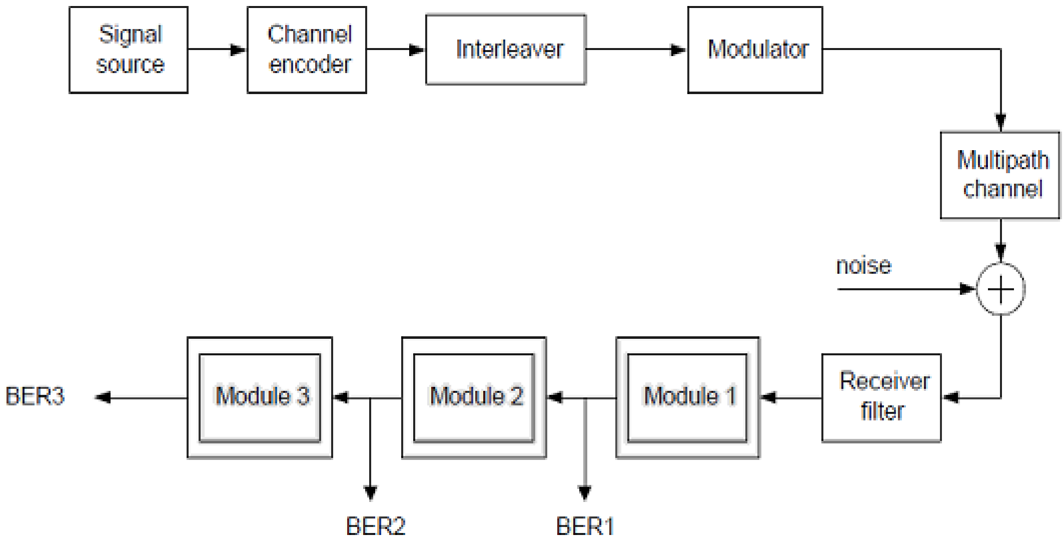
If one-shot LS estimation were performed using the whole burst, the new estimator would be

$$\hat{h}_{LS}^{extend} = (A^H A)^{-1} A^H r \tag{4.44}$$

The matrix inversion requires a lot of computation, which can be avoided by using a simple updating rule, like Least Mean Square (LMS) adaptation

$$\hat{h}_{k+1} = \hat{h}_k - \mu A_k^H (A_k \hat{h}_k - r) \tag{4.45}$$

where $h_{\mathbf{k+1}}$ is the new estimate, A_k is the data matrix containing the known symbols (data+training), **r** is the received sample vector and m is the step size of the iterative algorithm.



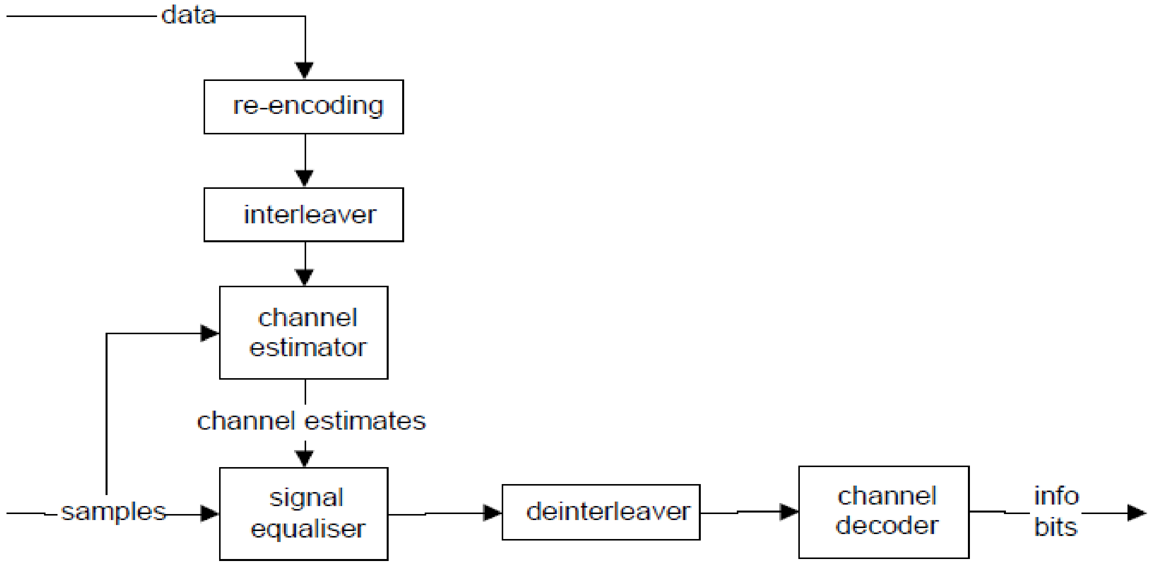


Figure 4.8: A pipelined structure for iterative channel estimation [29].

There are several consecutively placed receiver modules, each of which is describing one iteration round. Hence, the receiver is able to start processing the next radio block although the previous block is still under further iterations. It is also easy to evaluate the receiver performance (BER, BLER etc.) after each module in the simulator, which are corresponding to different iterations [29].

LMS adaptation rule, which is used in this iterative channel estimation scheme, is quite sensitive for the step size parameter m. Therefore one has to be careful, when selecting this parameter value, as a wrong selection may ruin a long simulation due to possible divergence problems. It is better to be sure that the selected parameter value is suitable for the whole SNR range of interest and all possible channel profiles.

4.7 Channel Estimation Based On Adaptive Filtering

An adaptive filter is a filter that self-adjusts its transfer function according to an optimizing algorithm. Because of the complexity of the optimizing algorithms, most adaptive filters are digital filters that perform digital signal processing and adapt their performance based on the input signal. By way of contrast, a non-adaptive filter has static filter coefficients (which collectively form the transfer function).

Recursive Least Square (RLS) Algorithm

The Recursive least squares (RLS) filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals [37-39].

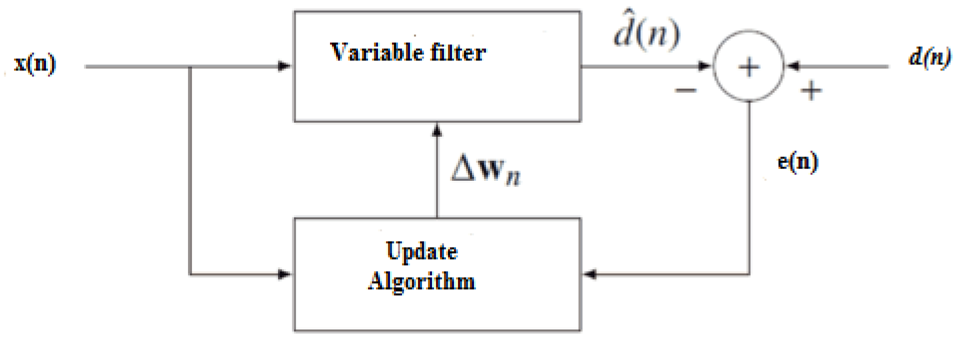


Figure 4.9: Block Diagram for RLS algorithm [38].

The error implicitly depends on the filter coefficients through the estimate $\hat{d}(n)$

$$e(n) = d(n) - \hat{d}(n) \tag{4.46}$$

The cost function C which we desire to minimise, being a function of $e(n)$ is therefore also dependent on the filter coefficients:

$$C(w_n) = \sum_{i=0}^{n} \lambda^{n-i} e^2(i) \tag{4.47}$$

where $0 < \lambda \leq 1$ is the forgetting factor. The cost function is minimized by taking the partial derivatives for all entries k of the coefficient vector w_n and setting the results to zero

$$\frac{\partial C(w_n)}{\partial w_n(k)} = \sum_{i=0}^{n} \lambda^{n-i} e(i) \frac{\partial e(i)}{\partial w_n(k)} = \sum_{i=0}^{n} \lambda^{n-i} e(i) x(i-k) = 0 \tag{4.48}$$

Next, replace $e(n)$ with the definition of the error signal

$$\sum_{i=0}^{n} \lambda^{n-i} \left[d(i) - \sum_{l=0}^{p} w_n(l) x(i-l) \right] x(i-k) = 0 \tag{4.49}$$

Rearranging the equation yields

$$\sum_{l=0}^{p} w_n(l) \left[\sum_{i=0}^{n} \lambda^{n-i} x(i-l) x(i-k) \right] = \sum_{i=0}^{n} \lambda^{n-i} d(i) x(i-k) \tag{4.50}$$

This form can be expressed in terms of matrices

$$R_x(n)w_n = r_{dx}(n) \tag{4.51}$$

where $R_x(n)$ is the weighted sample correlation matrix for $x(n)$, and $r_{dx}(n)$ is the equivalent estimate for the cross-correlation between $d(n)$ and $x(n)$. Based on this expression we find the coefficients which minimize the cost function as

$$w_n = R_x^{-1}(n)r_{dx}(n) \tag{4.52}$$

Least Mean Square (LMS) Algorithm

Least mean squares (LMS) algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal) [40].

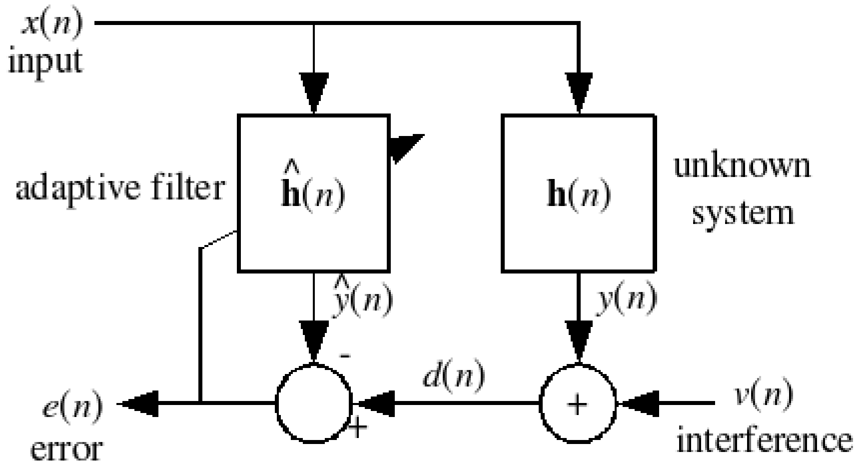


Figure 4.10 : Block diagram for LMS algorithm [39].

An unknown system $h(n)$ is to be identified and the adaptive filter attempts to adapt the filter $\hat{h}(n)$ to make it as close as possible to $h(n)$, while using only observable signals $x(n)$, $d(n)$ and $e(n)$; but $y(n)$, $v(n)$ and $h(n)$ are not directly observable.

$$x(n) = [x(n), x(n-1), ...x(n-p+1)]^T$$

$$h(n) = \lfloor h_0(n), h_1(n), ...h_{p-1}(n) \rfloor$$

$$y(n) = h^H(n)x(n)$$

$$d(n) = y(n) + v(n)$$

$$e(n) = d(n) - \hat{y}(n) = d(n) - \hat{h}^H(n)x(n) \qquad (4.53)$$

The idea behind LMS filters is to use steepest descent to find filter weights $h(n)$ which minimize a cost function. We start by defining the cost function as

$$C(n) = E\left\{|e(n)|^2\right\} \qquad (4.54)$$

where $e(n)$ is the error at the current sample 'n' and $E\{.\}$ denotes the expected value.

This cost function ($C(n)$) is the mean square error, and it is minimized by the LMS. Applying steepest descent means to take the partial derivatives with respect to the individual entries of the filter coefficient (weight) vector

$$\nabla_{\hat{h}^H} C(n) = \nabla_{\hat{h}^H} E\left\{e(n)e^*(n)\right\} = 2E\left\{\nabla_{\hat{h}^H}(e(n)))e^*(n)\right\} \qquad (4.55)$$

where ∇ is the gradient operator.

$$\nabla_{\hat{h}^H} e(n) = \nabla_{\hat{h}^H}(d(n) - \hat{h}^H .x(n)) = -x(n) \qquad (4.56)$$

$$\nabla C(n) = -2E\left\{x(n)e^*(n)\right\}$$

Now, $\nabla C(n)$ is a vector which points towards the steepest ascent of the cost function. To find the minimum of the cost function we need to take a step in the opposite direction of $\nabla C(n)$. To express that in mathematical terms

$$\hat{h}(n+1) = \hat{h}(n) - \frac{\mu}{2}\nabla C(n) = \hat{h}(n) + \mu E\left\{x(n)e^*(n)\right\} \qquad (4.57)$$

where $\frac{\mu}{2}$ is the step size(adaptation constant).

$$\hat{E}\left\{x(n)e^*(n)\right\} = \frac{1}{N}\sum_{i=0}^{N-1} x(n-i)e^*(n-i) \qquad (4.58)$$

where N indicates the number of samples we use for that estimate.

The simplest case is $N = 1$

$$\hat{E}\left\{x(n)e^*(n)\right\} = x(n)e^*(n) \tag{4.59}$$

For that simple case the update algorithm follows as

$$\hat{h}(n+1) = \hat{h}(n) + \mu \; x(n)e^*(n) \tag{4.60}$$

CHAPTER 5

RESULTS AND DISCUSSION

In this chapter, we present the simulation results of communication systems utilizing the channel estimation methods discussed in the previous chapter.

5.1 Performance of SISO-OFDM Systems Using Least Square Channel Estimation Method.

In this simulation work, first the random bits to be transmitted are generated. The pilots are inserted at the pilot locations and data bits at the data locations. These are then modulated using different modulation techniques like BPSK, QPSK, 8-PSK and 4-QAM. After that IDFT is performed and cyclic prefix is added. The guard interval or the length of the cyclic prefix is longer than the maximum delay spread of the channel. They are then transmitted over a frequency-selective fading channel through a single transmitter antenna. Additive noise is added to the received signal. The cyclic prefix is removed from the noise corrupted received signal which is then subject to DFT. Now, since the transmitted pilots and received pilots are known, the channel state information is estimated using Least Square channel estimation technique. The detector at the receiver utilise this estimated channel to obtain the information out of the received signal which is then demodulated to get random bits.

5.1.1 Simulation Results

In this simulation, we have considered an OFDM system with N=32 number of sub-channels and P=4 number of pilots . The total number of data sub-channels is (N-P) =28. The guard interval is taken to be N/4. The frequency selective channel has L=4 zero mean uncorrelated complex Guassian random taps. The pilot interval is 8. Taking number of iterations to be 200, the SNR vs BER plot with SNR values varying from 1 to 10 for a Quasi-static channel is shown in figure 5.1.The comparison has been done for different modulation techniques – BPSK ,QPSK , 8-PSK , 4-QAM. Figure 5.2 gives the BER comparison for an ergodic channel for BPSK, QPSK, 8-PSK and 4-QAM.

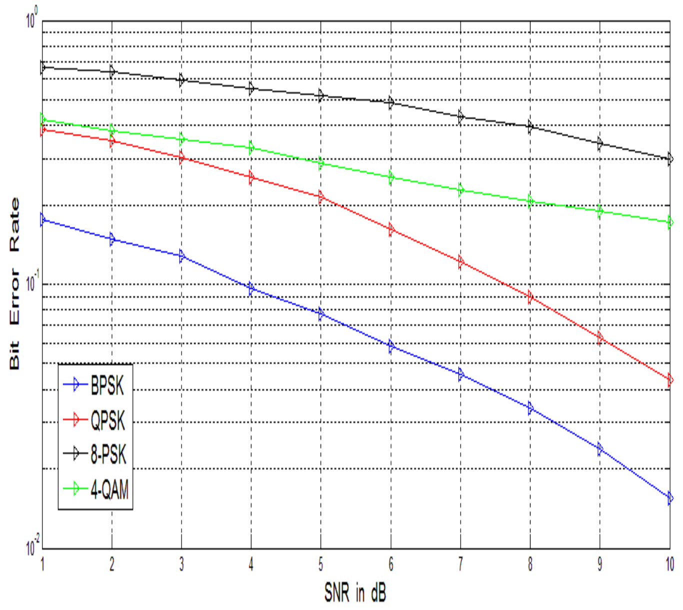


Figure 5.1: Comparison of BERs for BPSK, QPSK , 8-PSK , 4-QAM for a Quasi-static channel.

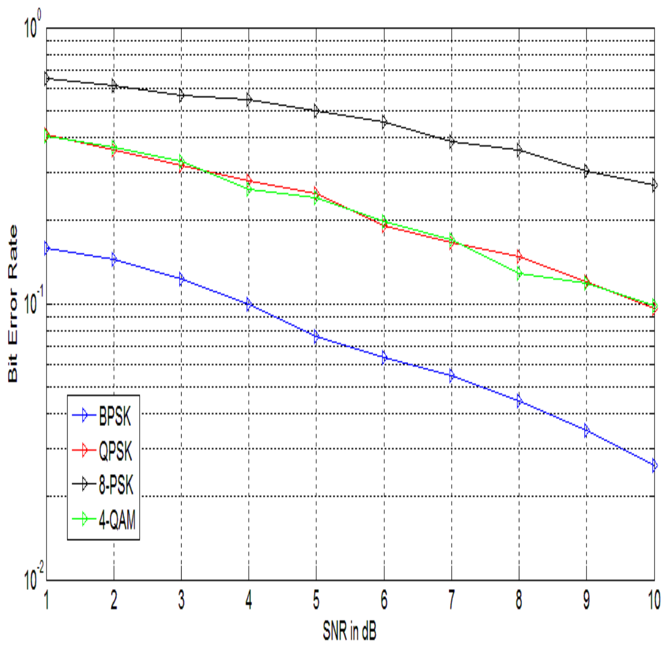


Figure 5.2: Comparison of BERs for BPSK, QPSK, 8-PSK , 4-QAM for an ergodic channel.

The figures 5.3 and 5.4 give the BER comparison between a Rayleigh channel and a Rician channel for BPSK modulation technique and QPSK modulation technique respectively.

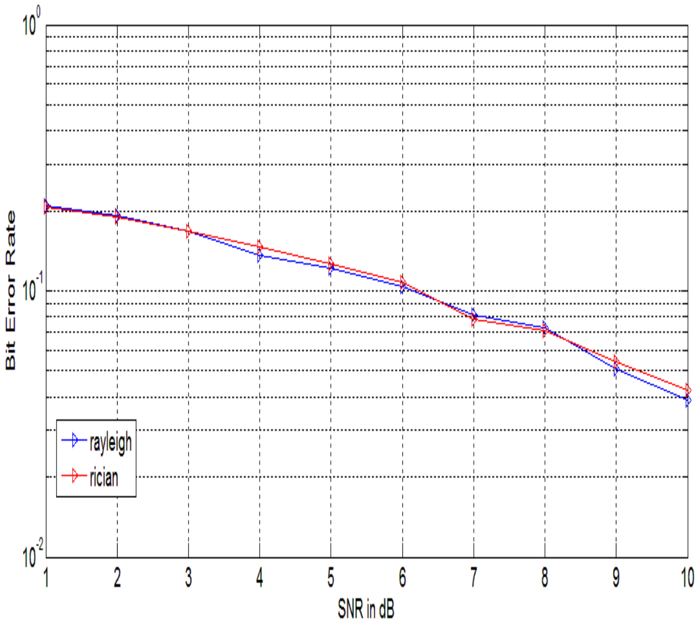


Figure 5.3: BER comparison between a Rayleigh channel and Rician channel for BPSK modulation.

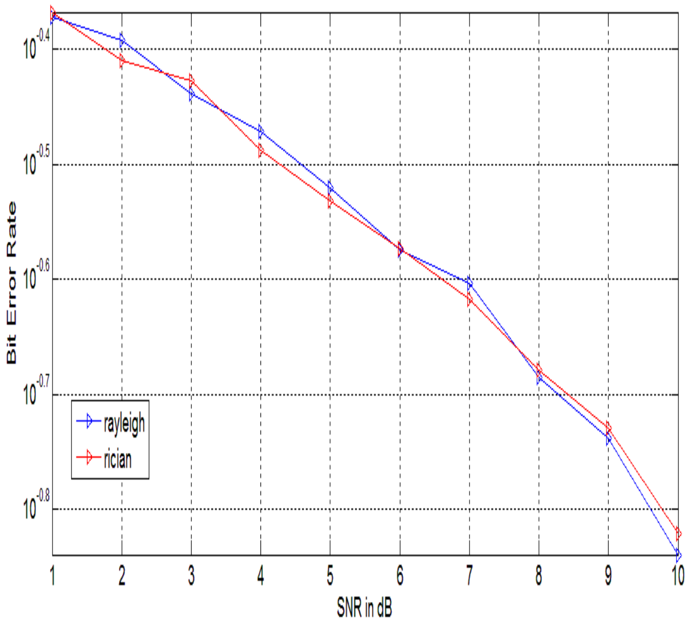


Figure 5.4: BER comparison between a Rayleigh channel and Rician channel for QPSK. modulation.

5.1.2 Results on Test-Bed

While implementing the Least–Square channel estimation method on the Test-Bed, we have taken $N= 2^{12}$ number of sub-channels and P = 64 number of pilots . The total number of data sub-channels is (N-P) = 4032. The mean BER versus the SNR is obtained, which is averaged over 50 OFDM blocks at every SNR value. The SNR is varied from 1 to 5 and the results are shown for different modulation techniques like BPSK ,QPSK,8-PSK and 4-QAM .The results are shown below:

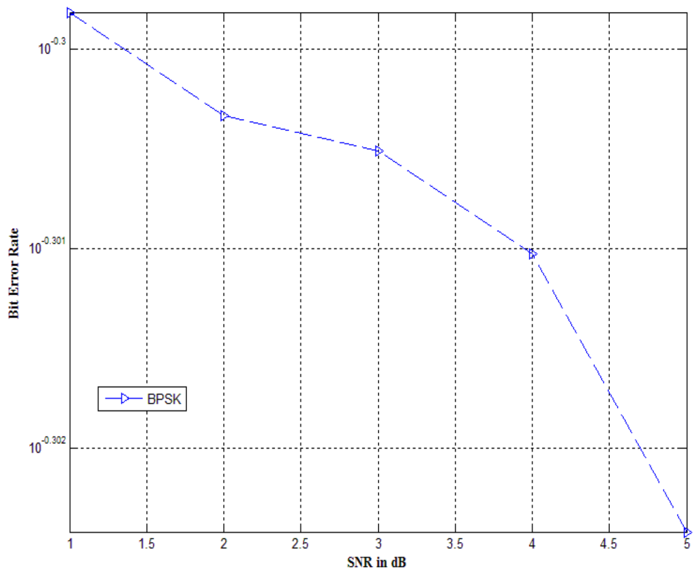


Figure 5.5: BER vs SNR plot for BPSK modulation technique.

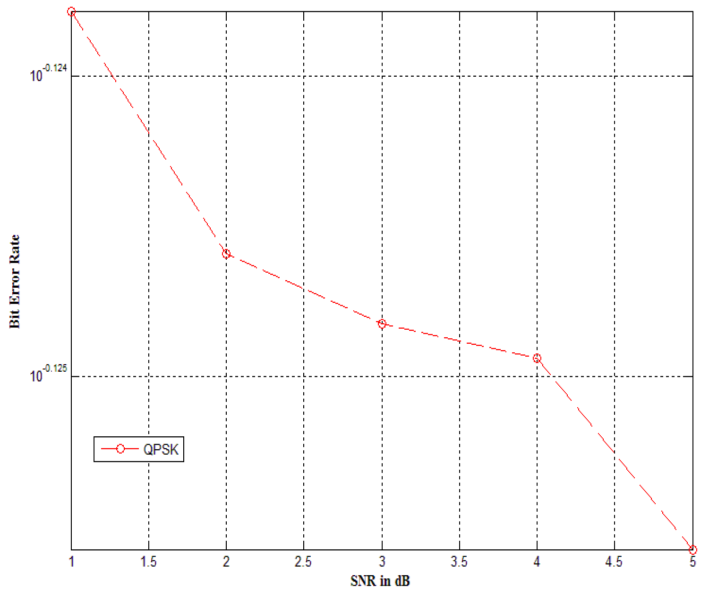


Figure 5.6: BER vs SNR plot for QPSK modulation technique.

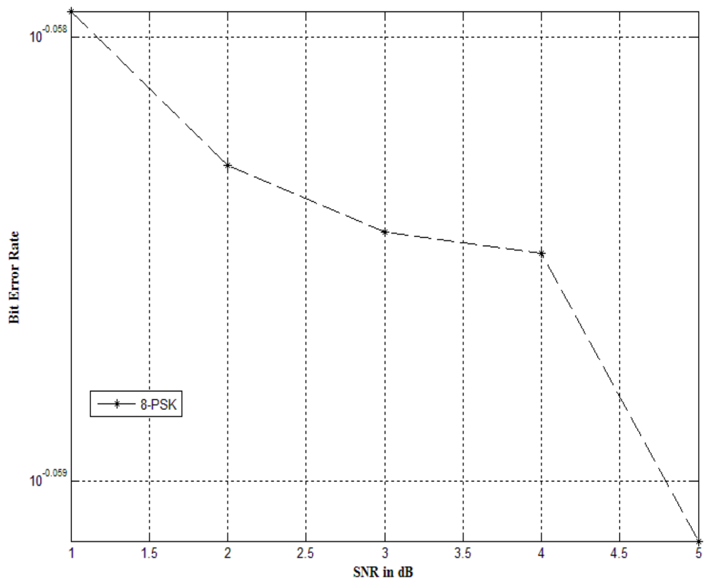


Figure 5.7: BER vs SNR plot for 8-PSK modulation technique.

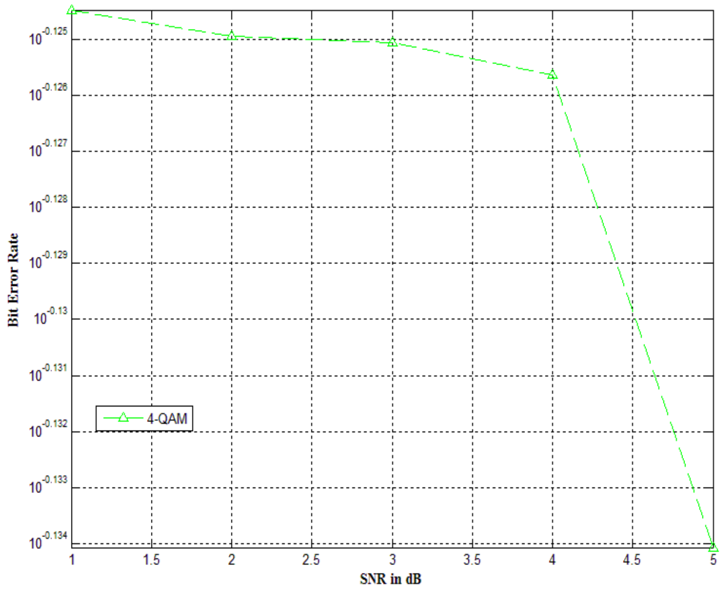


Figure 5.8: BER vs SNR plot for 4-QAM modulation technique.

The following table contains the summary of the results of Least Square channel estimation technique when subjected to different modulations and different channel models.

Table 5.1: SNR vs BER of LS channel estimation method for different modulations.

Modulation Scheme	SNR required at BER 8 x 10^{0}	
	Quasi-static channel	Ergodic channel
BPSK	1	<1
QPSK	5.3	5.9
4-QAM	8.5	5.9
8-PSK	>11	>10

Thus, we have seen that if we apply LS channel estimation technique then the SNR required at BER of 8 x 10^{0} is least for BPSK modulation for both quasi-static channel as well as ergodic channel.

5.2 Comparison of Different Channel Estimation Techniques – Least Square (LS), Minimum Mean Square Error (MMSE), Singular Value Decomposition (SVD).

5.2.1 Simulation Results

To compare the performance of LS , MMSE and SVD channel estimation techniques, we consider an OFDM system with N=32 number of input samples. We assume that the guard intervals are longer than the maximum delay spread of the channel. The channel is assumed to be Rayleigh fading with input sample period 1.0000e-006 and channel filter delay 4. Figure 5.9 and Figure 5.10 shows the mean BER versus the SNR, which is averaged over 1000 OFDM blocks at every SNR value. The comparison has been made for different modulations e.g 16-QAM and 16-PSK.

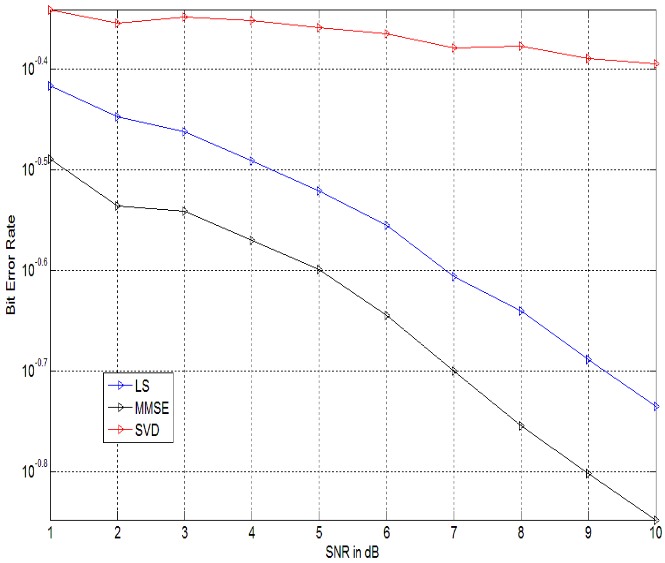


Figure 5.9: Comparison of BERs in Rayleigh fading channel for 16-QAM.

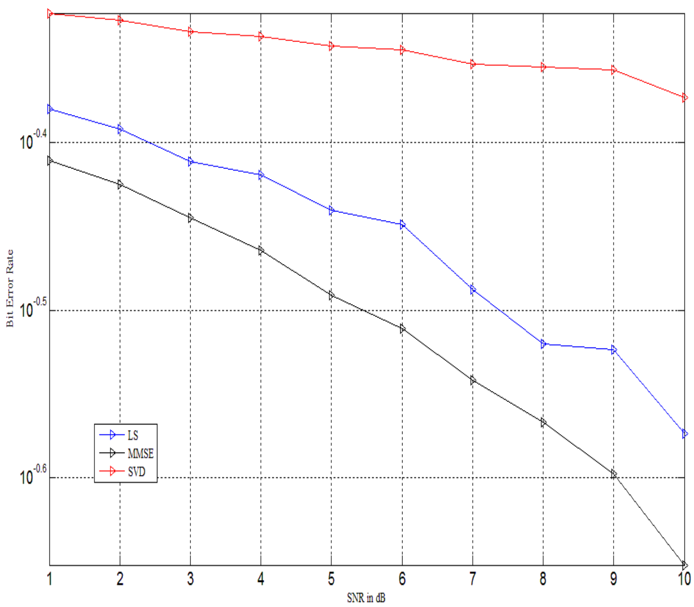


Figure 5.10: Comparison of BERs in Rayleigh fading channel for 16-PSK.

Similarly, figure 5.11 and 5.12 gives the BER vs SNR for a Rician channel for 16-QAM and 16-PSK respectively.

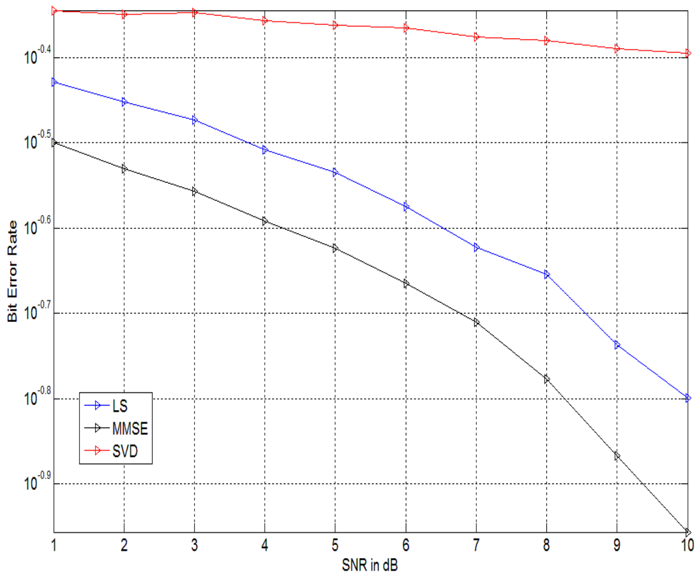


Figure 5.11: Comparison of BERs in Rician fading channel for 16-QAM.

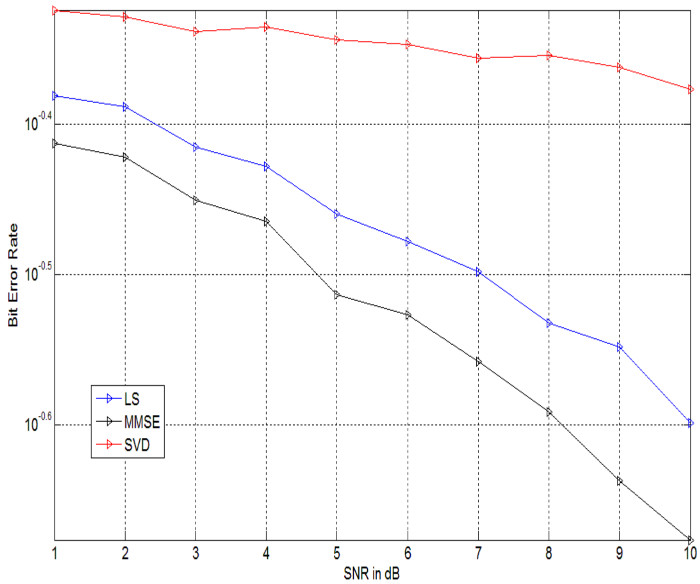


Figure 5.12: Comparison of BERs in Rician fading channel for 16-PSK.

5.2.2 Results on Test-Bed.

Here, we evaluate the BER performance of OFDM system utilising three different channel estimation methods viz LS, MMSE and SVD on Test-Bed.We have taken 512 number of input samples.Taking number of iterations to be 50 and SNR values varying from 1 to 5,the comparison has been shown for 16-QAM and 16-PSK in figure 5.13 and figure 5.14 respectively.

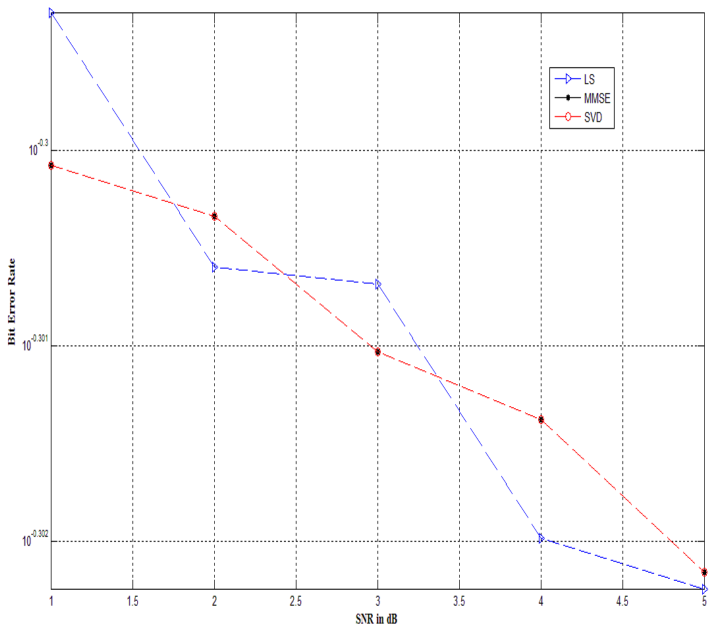


Figure 5.13: Comparison of BERs for 16-QAM.

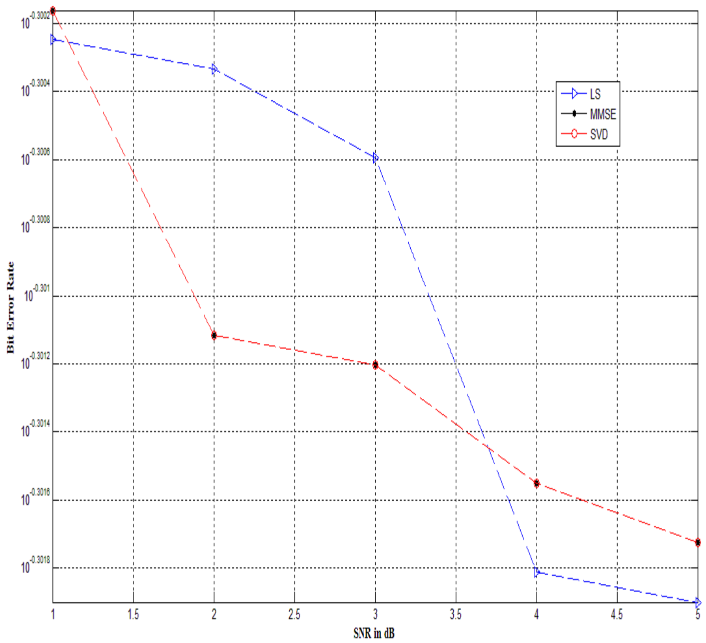


Figure 5.14: Comparison of BERs for 16-PSK.

We have summarised the results in the following tables.

Table 5.2 : SNR vs BER of LS,MMSE and SVD for a Rayleigh channel.

Channel Estimation Technique	SNR required at BER $10^{-0.5}$	
	16-PSK	16-QAM
LS	7.5	4.3
MMSE	5.5	1.3
SVD	>15	>12

Thus, we have seen that for a Rayleigh channel, SNR required at BER of $10^{-0.5}$ is least for MMSE channel estimation technique for 16-QAM modulation.

Table 5.3: SNR vs BER of LS, MMSE and SVD for a Rician channel.

Channel Estimation Technique	SNR required at BER $10^{-0.5}$	
	16-PSK	16-QAM
LS	4.7	3.7
MMSE	7	1
SVD	>10	>10

It is clear from table 5.3 that SNR required at BER $10^{-0.5}$ is least for MMSE channel estimation technique for 16-QAM modulation for a Rician channel too.

5.3 Channel Estimation Method for OFDM System with Alamouti-Based STBC.

In this simulation work, the binary stream is first generated , modulated and mapped to a sequence of complex modulation symbols. The modulated sequence is then passed through a space time block encoder. We use Alamouti based transmitter diversity scheme. STBC operation is performed over the modulated sequence and it is turned into two parallel information streams. To each of these information streams pilots are added and then Inverse Discrete Fourier Transform (IDFT) is performed on each serial data stream. To avoid the effects of intersymbol-interference, a cyclic prefix (CP) is added to output samples. These are then transmitted from two different antennas thereby achieving transmit diversity.The signal that is received is subjected to cyclic prefix removal and DFT. The outputs are sent to the STBC decoder and the estimates of the transmitted OFDM symbols are computed using channel state information provided by the channel estimator.

5.3.1 Simulation Results

The BER performance of STBC-OFDM system based on Alamouti transmitter diversity scheme with adaptive filtering based channel estimation algorithm is being investigated here. Here we consider an OFDM system with N=32 number of subchannels and P=5 number of pilots . The relative length of cyclic prefix is taken to be 1/4. The frequency selective channel is Rayleigh distributed. Taking number of simulation points to be 10000 and iterations to be 100, the BER vs SNR plot with SNR values varying from 1 to 5 for a Rayleigh channel is shown in figure 5.15.The comparison has been made between different modulation techniques – BPSK ,QPSK ,16-QAM.

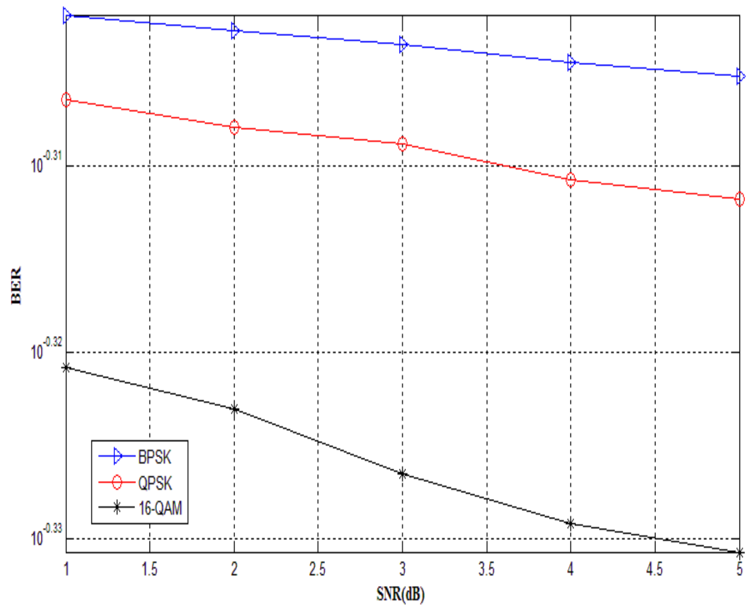


Figure 5.15: Comparison of BERs for BPSK, QPSK and 16-QAM for a Rayleigh fading channel.

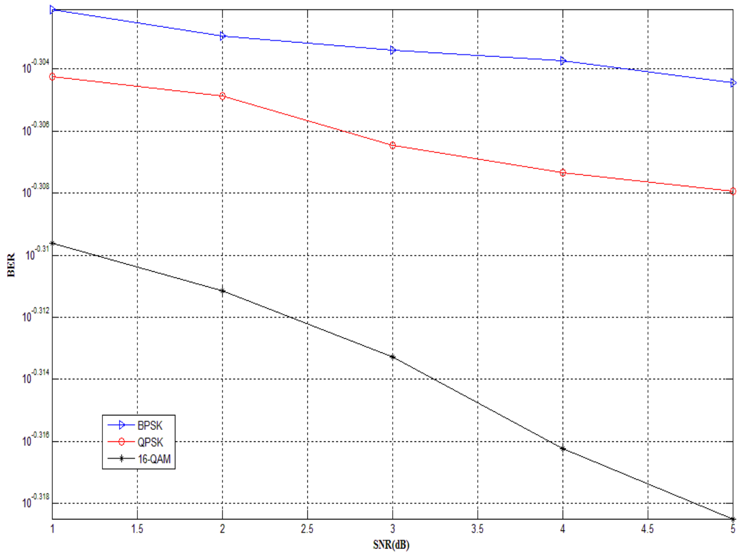


Figure 5.16: Comparison of BERs for BPSK, QPSK and 16-QAM for a Rician fading channel.

In the same way, figure 5.16 gives the BER comparison for a Rician fading channel for BPSK, QPSK and 16-QAM.The figures 5.17 and 5.18 give the MSE of channel estimates for every value of SNR in which a comparison has been made between a Rayleigh channel and a Rician channel for BPSK, QPSK and 16-QAM modulation techniques respectively.

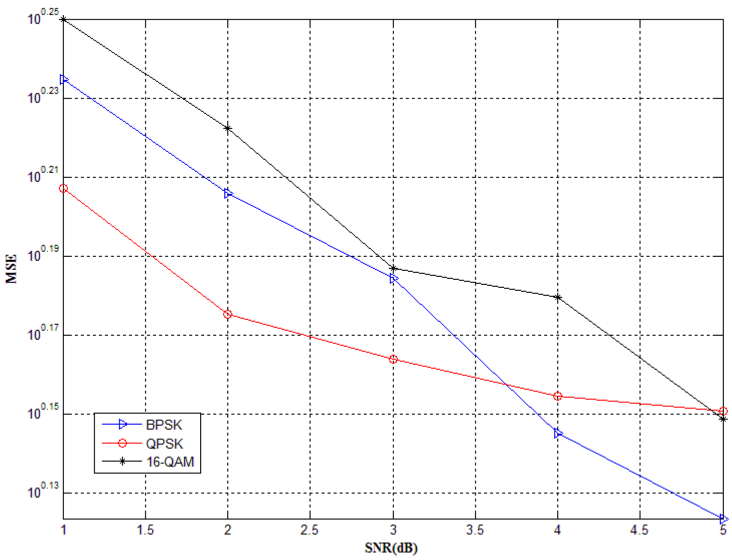


Figure 5.17: Comparison of MSE of channel estimates for BPSK, QPSK and 16-QAM for a Rayleigh channel.

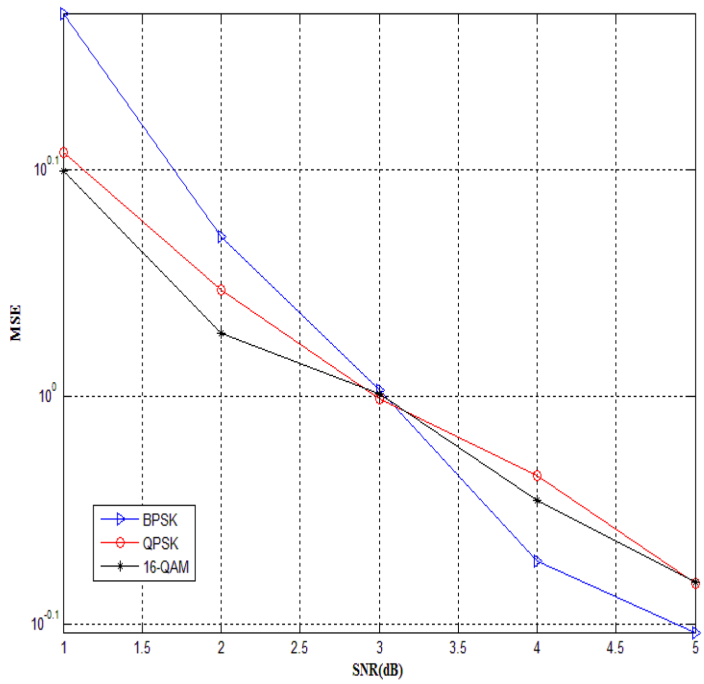


Figure 5.18: Comparison of MSE of channel estimates for BPSK, QPSK and 16-QAM for a Rician channel.

5.3.2 Results on Test-Bed.

The Channel Estimation Algorithm for STBC-OFDM system based on Alamouti transmitter diversity technique is implemented on Test-Bed with number of input samples varying from 3240 for BPSK, 6400 for QPSK and 12560 for 16-QAM respectively. Taking number of iterations to be 100 and SNR values varying from 1 to 5, the BER vs SNR and MSE vs SNR results are given below :

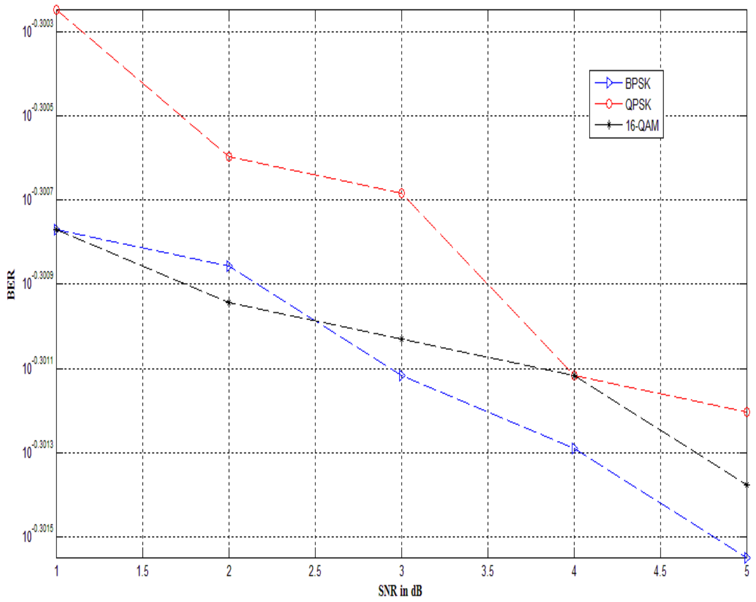


Figure 5.19: Comparison of BER for BPSK, QPSK and 16-QAM .

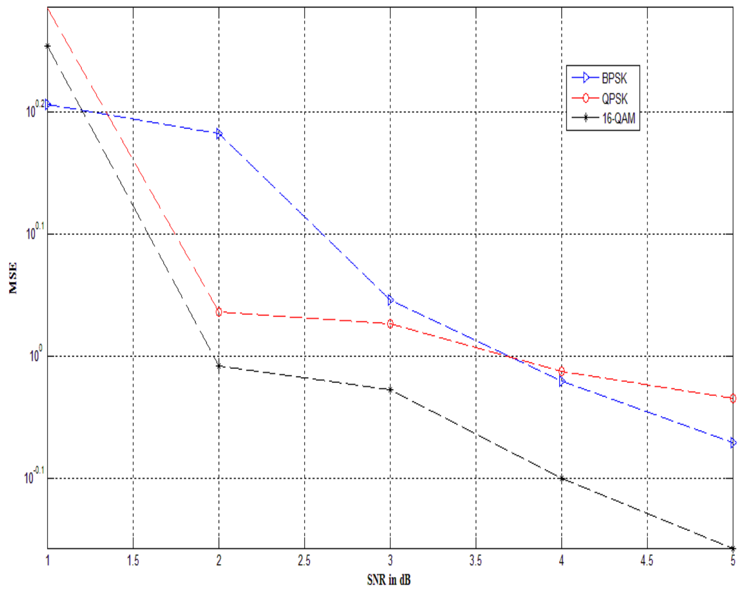


Figure 5.20: Comparison of MSE for BPSK, QPSK and 16-QAM .

The results of STBC-OFDM system utilising channel estimation are summarised in the following table:

Table 5.4: SNR vs BER of an STBC-OFDM system for BPSK,QPSK and 16-QAM for a Rayleigh and a Rician channel.

Modulation Scheme	SNR required at BER $10^{-0.31}$	
	Rayleigh channel	Rician channel
BPSK	>5	>5
QPSK	3.65	>5
16-QAM	<1	1.25

The table shows that SNR required at BER of $10^{-0.31}$ is least in case of Rayleigh channel for 16-QAM modulation.

CONCLUSION

This report presents some approaches that model channel estimation. It is also shown that the estimation is usually based on the known training bits and corresponding received samples. In this report comparison between different channel estimation techniques has been done. Different channel estimation techniques are simulated in MATLAB and the simulated results are compared with the results obtained with WARP FPGA Board in real-time. The samples are transmitted by the antenna associated with the transmitting radio node of the WARP Board and the samples are received on the antenna associated with the receiving radio node of the WARP Board. Firstly, the BER performance of Least Square channel estimation technique is evaluated for BPSK, QPSK 8-PSK and 4-QAM for both quasi-static and ergodic channel. For Quasi-static channel, the SNR required at BER of 8×10^{0} is 1dB for BPSK and it is greater than 11dB for 8-PSK.For ergodic channel the SNR required at BER of 8×10^{0} is less than 1dB for BPSK and it is greater than 10dB for 8-PSK.

Then the Least Square method, Minimum Mean Square method and Singular Value Decomposition method of channel estimation are compared for 16-PSK and 16-QAM modulations for Rayleigh channel and Rician channel. The simulation results show that for Rayleigh channel, the SNR required at BER of $10^{-0.5}$ is 7.5dB for 16-PSK and it is 4.3dB for 16-QAM for the LS method. The MMSE method of channel estimation requires SNR of 5.5dB for 16-PSK and 1.3dB for 16-QAM.And the SVD method requires SNR greater than 15dB for 16-PSK and greater than 12dB for 16-QAM.For Rician channel, the LS method of channel estimation requires SNR of 4.7dB for 16-PSK and 3.7dB for 16-QAM at BER of $10^{-0.5}$ .The MMSE method requires 7dB for 16-PSK and 1dB for 16-QAM.And the SVD method requires more than 10dB for both 16-PSK and 16-QAM.

Lastly, we have applied a channel estimation method on an STBC-OFDM system employing Alamouti based transmitter diversity scheme. The BER performance is evaluated for BPSK,QPSKand16-QAM.The simulation results show that SNR required at BER of $10^{-0.31}$ is less than 1dB for 16-QAM and more than 5dB for BPSK for Rayleigh channel and it is 1.25dB for 16-QAM and more than 5dB for 16-PSK. Thus, the WARP FPGA makes it possible to realize the various channel estimation techniques in real time so that practical performance can be achieved. In future, we can implement various other channel estimation techniques such as Iterative channel estimation, MAP channel estimation and Maximum-likelihood channel estimation on the WARP Board and compare its performance with the simulated results.

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