Chapter 3

MIMO and Channel Parameter Estimation with its Performance Comparison

3.1 Performance Comparison of Conventional and Massive MIMO – An Introduction

The fundamental problem with wireless or remote communication is the degradation of signal quality and is disturbed before it reaches the receiver, and it can affect the transmission quality. MIMO technology is a resolution to this kind of issues. This aids in improving the wireless access in various applications like Wi- MAX, Wi-Fi, and others. In 4G and Long-Term Evolution (LTE) it is used to improve high-speed data transfer efficiency. The transmitters and receivers in MIMO systems both have multiple antennas, allowing the symbol to pass through numerous pathways between transmitter and receiver. As a result, MIMO model have higher maximum throughput and link reliability. Orthogonal Frequency Division Multiplexing (OFDM) is a major platform which allows MIMO. In older systems, data symbols were delivered over a wider bandwidth, which made it hard to retrieve lost information. OFDM, on the other hand, sends data symbols in parallel over a longer period on a narrow band frequency spectrum. The ability of the receiver to pull each symbol separately is of greater advantage. Since each symbol is sent for a longer duration, even if any symbol has degenerated, the best symbol has a much better chance of being pulled in. This advantage that MIMO offers leads to increased hardware complexity.

Massive MIMO is another option for dealing with this issue. It achieves asymptotic orthogonality by employing huge antennas in the base station (BS) that compensates for interfering at the user terminal (UT).

Massive MIMO is a MIMO system with a large quantity of antennas at the base station (BS), ranging from hundreds to thousands, that serves a set of UT. The massive MIMO scenario is given in Figure 3.1. SNR, increased gain, capacity, coverage, latency, and data rates are all advantages of using a huge number of antennas. Massive MIMO has a basic concept that may collect entire benefits of conventional MIMO on a larger range. It contributes to the creation of a secure, reliable, and efficient broadband network. The channel information is required to gather supplied by additional antenna elements, which allows for reliable communication. As a result, channel state information (CSI) and channel parameter estimation are required at the BS in order to acquire channel knowledge.

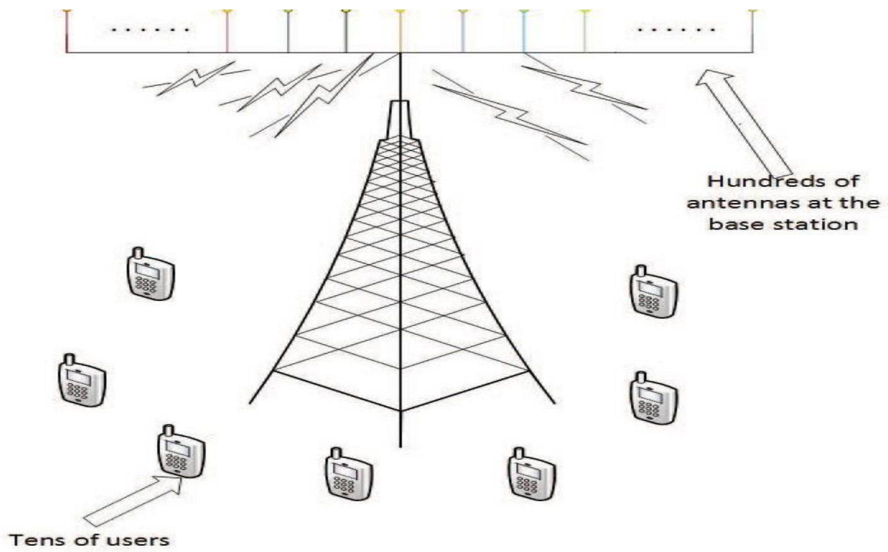

Figure 3.1: Massive MIMO scenario

Pilot data must exchange to calculate the BS, UT and CSI, which is a time- consuming process in FDD mode. The downlink and uplink streams in FDD mode must use different bands of frequency. In order to attain CSI, these two steps should be followed: first, sending data for training to each client by BS; second, the users are required to calculate the parameters and communicate the calculated CSI to the Base Station. As a result, antennas numbers at transmitter end determines the CSI time, which in this case is a large number. To conquer this can be preferably to use the TDD method, which relies on the reciprocity of the channel for estimation [36]. The data transmission in TDD systems, the uplink and downlink is made in an appropriate way. The pilot sequence is transmitted in the uplink stream every coherence time interval. Instead of transmitters, the number of users determines the number of pilot sequences that are required in order to estimate the channel size.

Two major works are underway in this chapter. For conventional and massive MIMO, the efficiency of training-based channel estimation (TBCE) and blind channel estimation (BCE) strategies for estimating channel parameters is first examined. The performances of the two methodologies are evaluated with respect to SNR and BER. Second, the performance of Compressed Sensing in MMSE channel estimation is compared to that of Conventional LS and MMSE.

The remaining part of the Chapter is divided into two sections. The performance of Conventional and Massive MIMO is compared in Section 3.1, and the Compressed Sensing of MMSE Channel Estimation with Conventional LS and MMSE are discussed in Section 3.2. The methodology for implementing the work is described in Subsection 3.1.1 of Section 3.1. The channel estimation techniques TBCE and BCE are the focus of Subsection 3.1.2. Subsection 3.1.3 illustrates the simulation results for large MIMO and traditional or normal MIMO approaches using TBCE and BCE, respectively. Subsection 3.1.4 gives the summary about the work. Under Section 3.2, the Subsection 3.2.1 discusses about channel estimation techniques, followed by compression sensing with MMSE in Subsection 3.2.2. Simulation results for LS and MMSE methods are given under Subsection 3.2.3. Finally, the summary of conventional LS, MMSE and CS MMSE works are discussed in Subsection 3.2.4.

3.1.1 Implementation Methodology

The simulation tool MATLAB is used to carry out the implementation. As illustrated in the block diagram in 3.2, channel estimation is conducted as below:

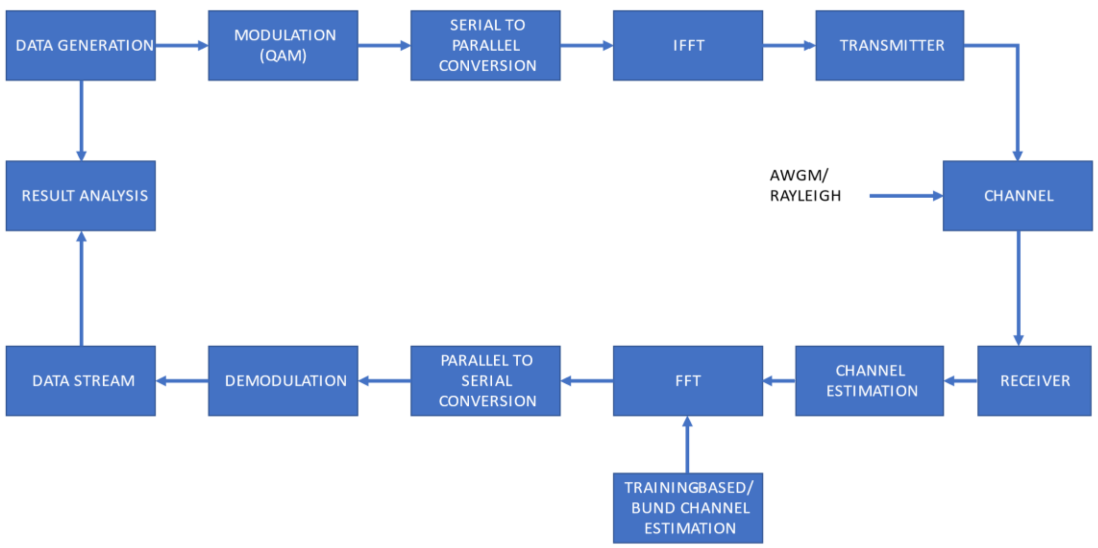

Figure 3.2: Implementation Methodology

At the BS serving ten users, channel estimation for massive MIMO and traditional 2 x 2 MIMO is done using one hundred antennas. The execution makes use of the OFDM technique, in which the bits are first, produced serially and then modified using QAM. Modulated data is transformed into a set of parallel data to produce OFDM signals. After serial to parallel conversion, Inverse Fast Fourier Transforms (IFFT) is employed to produce the N subcarriers for OFDM symbols. The OFDM symbols produced are further disseminated over a sizable number of transmitters, which can number hundreds in a large-scale MIMO situation and two in a typical MIMO case after the data has also undergone IFFT processing. The receiver receives these signals after they have travelled over the channel.

3.1.2 Channel Estimation

In wireless technology, channel estimation is essential. Real-time channel changes include natural variances, high rises, impediments, and other factors that scatter the signal over time. Suppose the channel model seems to have a Rayleigh model based on such effects. An additive white Gaussian noise channel model is used to estimate the channel's size and is given by

$$y = Hx + n \tag{3.1}$$

where H is a matrix representation of the Rayleigh model, including all channel parameters associated with the path of each and every channel. In the above equation, N denotes an AWGN channel that is normally a matrix. SNR regulates the amount of noise variance in this scenario. The information transmitted is contained in the signal component x . In certain techniques, such as the BCE and TBCE, the received signal is used to estimate the channel.

3.1.2.1 Training-Based Channel Estimation

A technique employed for TBCE to trained/pilot sequences that are named as the transmitter and receiver. Training sequence is to be sent before the data containing the valuable information is sent. These trained sequences are used by the receiver in estimation and minimization of the channel effects. Using the MMSE estimator, the error brought on by channel noise is reduced at the receiver. In this paper, the authors present the results of their work on two types of multi-input multiple-output MIMO. These are known as 2 x 2 MIMO and 2 x 4 MIMO used with MSME estimator [85]. The performance of massive MIMO is then compared to that of traditional 2 x 2 MIMO using the SNR-BER plot. Because the massive MIMO is operating in Time division Duplexing mode, Pilot sequences are communicated in the uplink stream.

Due to this, the quantity of pilot symbols are employed based on fewer users than the number of transmit antennas is possible by taking into account the exact number of transmitting and receiving antennas. In this proposed work, both transmitting (M) and receiving (L) antennas are taken as (i) 2 for conventional MIMO (ii) 100 and 10 for massive MIMO. For every path among the transmitter and the receiver, a channel matrix H is constructed, yielding $M\ X\ L$ matrix. The signal component y obtained by the channel matrix H is obtained by taking into account the consumer symbol and the noise vector N . Channel approximation is done with the generated symbol y .

The transmitted symbol x is estimated by multiplying the received symbol, y by the weight, w. The BER is then determined by comparing the estimated symbol $\hat{x}$ to the transmitted symbol x. The findings demonstrate that the huge that is Massive MIMO system has a superior bit error rate when compared to traditional systems.

Table 3.1: Performance graphs of BER VS SNR for the two modulation schemes in training based estimates of the channel

SNR(dB)	Conventional MIMO (BER)		Massive MIMO	
	QPSK	16-QAM	QPSK	16-QAM
0	1.126	1.56	1.23	1.855
5	0.849	1.297	0.073	0.123
10	0.512	0.879	0.001	0.002
15	0.246	0.463	0	0
20	0.104	0.204	0	0
25	0.036	0.046	0	0

3.1.2.2 Blind Channel Estimation

In BCE, the determination of the Eigen values and vectors as derived from the received symbols is required in BCE before channel estimation can start. The orthogonal unitary matrix, the estimating channel parameters, must be calculated. The orthogonal unitary matrix must be calculated to estimate the channel parameters. The orthogonal unitary matrix must be calculated at the receiver for a blind channel. As a result, altering an obtained symbol's numerical is necessary to find the unitary matrix.

To determine the unitary matrix, the statistical independence of the received symbol has to be exploited. To maximize the statistical independence, the kurtosis function is used which is defined as follows:

$$K[y] = E[|y^4|] - 2(E[y^2])^2 - E[yy]E[y^*y^*] \quad (3.2)$$

By maximizing the kurtosis function, which is the cost function, it is possible to determine the unitary matrix.

$$j(W) = \sum_{k=1}^{n} K[y_k] \quad (3.3)$$

To obtain the unitary matrix, the cost function has to be minimized which is done initially by creating a random matrix Wand operating a cost function. This is made orthogonal by taking the gradient of the cost function, which is defined as:

$$\delta_w = \frac{\partial(j(W))}{\partial W^*} \quad (3.4)$$

3.1.3 Simulation Results for Conventional and Massive MIMO

The results of a 2 x 2 MIMO (Conventional MIMO system) and a 100 x 10 MIMO system are compared in this work (Massive MIMO systems). The modulation techniques used for the symbols are 16-QAM and QPSK. The BER of a QPSK modulation method is greater than those of 16-QAM since the spacing among text locations is larger in a QPSK system than in a 16-QAM arrangement. This is shown in Tables 3.1 and 3.2. Figures 3.3, 3.4, 3.5, 3.6 and 3.7 shows TBCE and BCE simulation outcomes.

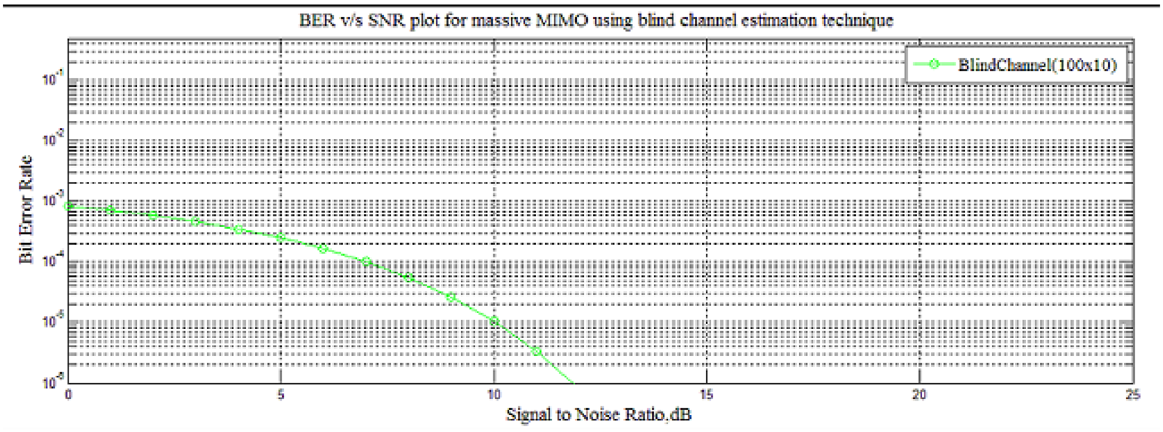

Figure 3.3: Plot of Bit Error Rate Versus Signal to Noise ratio for blind channel in Massive MIMO environment

Table 3.2: Performance graphs of BER VS SNR for two modulation schemes in blind parameter estimates of the channel

SNR(dB)	Conventional MIMO (BER)		Massive MIMO	
	QPSK	16-QAM	QPSK	16-QAM
0	0.319	0.557	0.003	0.011
5	0.042	0.168	0.001	0.003
10	0.002	0.007	0	0.001
15	0	0.001	0	0
20	0	0	0	0
25	0	0	0	0

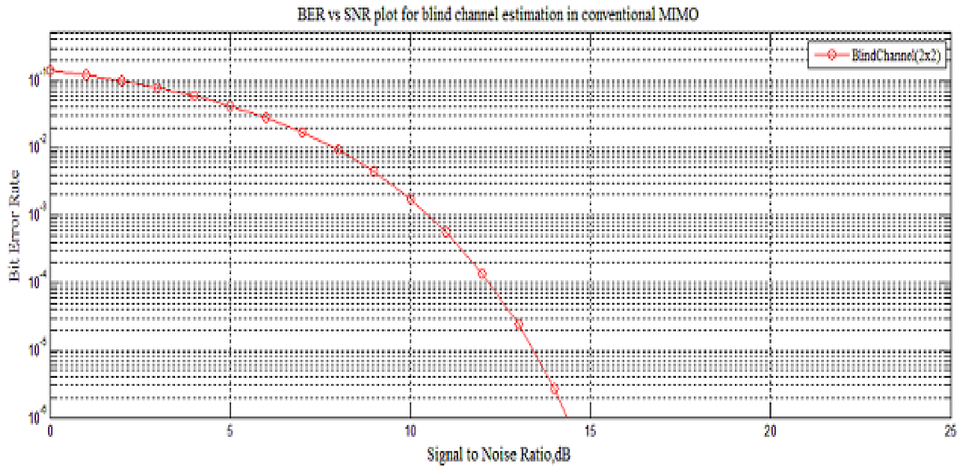

Figure 3.4: Performance Analysis of Conventional MIMO with blind channel

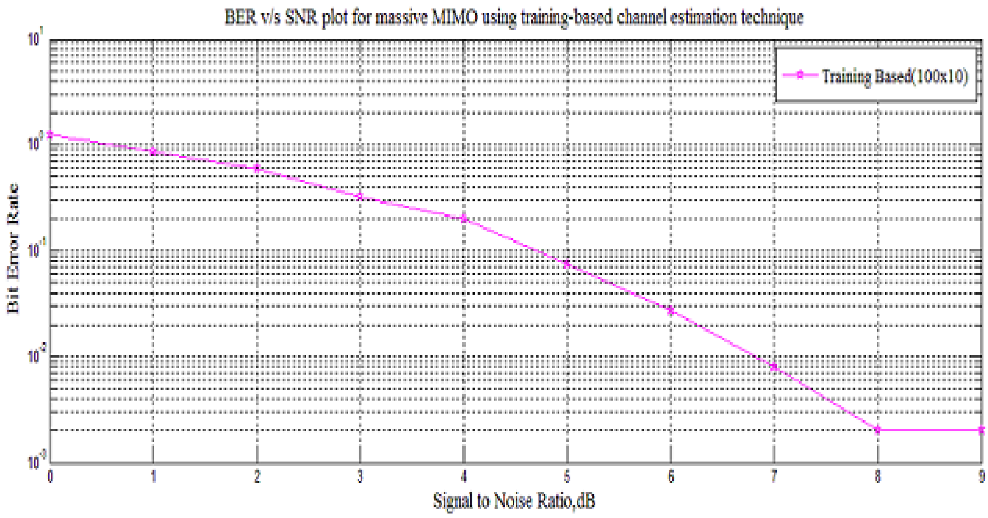

Figure 3.5: Performance Analysis of Massive MIMO with the effect of training Based channel

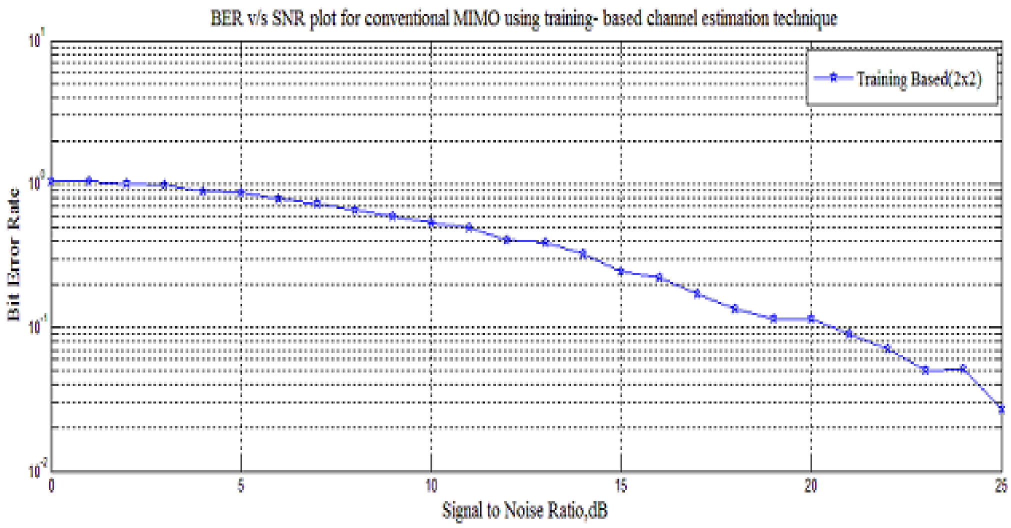

Figure 3.6: Performance Analysis of Conventional MIMO with the effect of training Based channel (2 x 2)

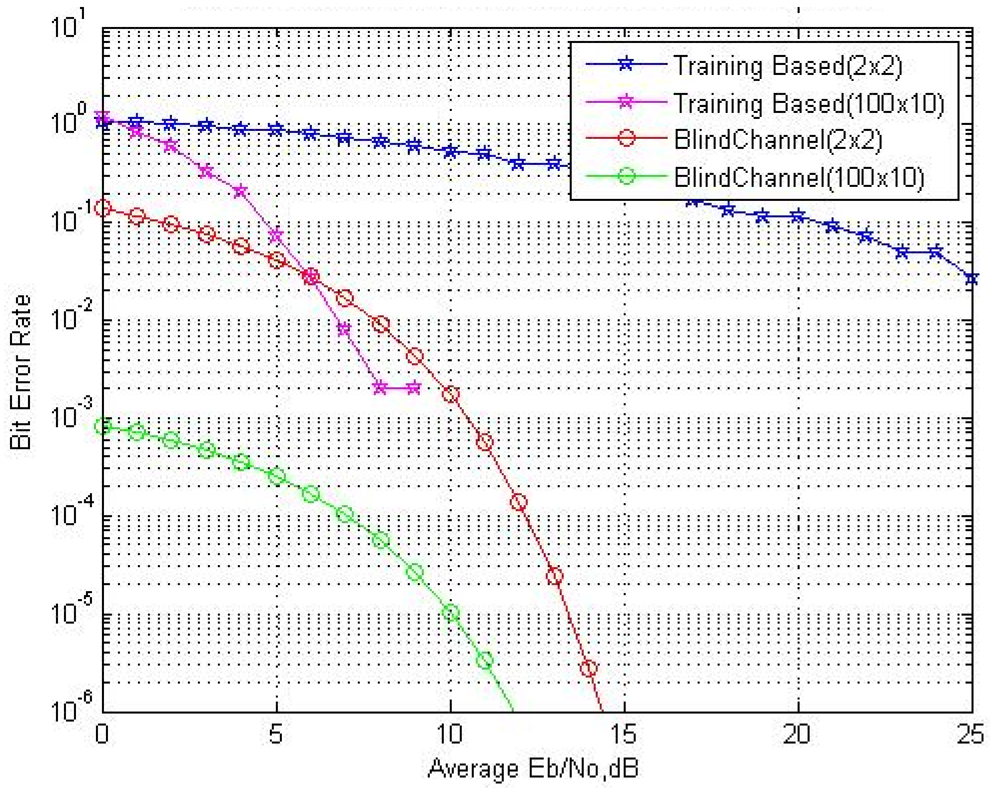

Figure 3.7: Comparative Analysis of Conventional and Massive MIMO

3.1.4 Summary of Conventional and Massive MIMO

The performance of 2 x 2 and massive MIMO is compared using channel estimation. The BCE and TBCE approaches also use this method. In the communication industry, decreasing the BER is very important to ensure that the system is reliable. With massive MIMO, the BER becomes more obvious. This is because the technology has a higher BER count which provides an upper hand compared to training-based methods.

3.2 Estimation of Compressed Sensing MMSE Channels using Conventional LS and MMSE

In wireless communication systems, multiple-input multiple-output (MIMO) orthogonal frequency division multiplexing (OFDM) technology is evolving. Due to the increasing number of wireless systems and the advancements in the technology, the need for channel estimation has become more important. This work shows how this process can be performed in order to reap the benefits of massive MIMO systems. We present a compressed sensing (CS) method based on priority that examines the channel with few dominating taps, i.e., the sparse aspect of the channel is exploited, to get channel parameters. Priority is given to the user with the greatest need in this method, where all user equipments (UE) are not of equal importance. When the number of UEs exceeds the number of available channels, UEs are rated based on some heuristics. The proposed method for channel estimation, which is a compressed sensing technique, performed better than the traditional methods when it comes to the performance of the channel estimation. In terms of its BER and SNR, the proposed method outperforms the traditional methods.

3.2.1 Channel Estimation

In wireless communication, estimation of the channel is of vital importance. In real scenario, the channel changes over time, usually when the transmitter or the receiver is moving at a vehicular speed which is the case in mobile communication [86]. So it is essential to acquire the channel state information (CSI) in a timely approach. In this work, estimation of the channel is done by the sequence of training which are well known mutually to transmitter as well as receiver. Recognized bits of training together with their corresponding samples received are utilized by receiver, for the purpose of assessing the channel.

3.2.1.1 Least Square Method

In this method of Least Square estimation, it assesses the $h[m]$ system by limiting the error of square among detected signal and estimated signal. LSE mainly minimizes the square distance between the received signal and original signal. This method is known by its low complexity, because they do not need the statistic information of channel. System is modeled in matrix form as

$$y = Xh \tag{3.2}$$

In equation 3.2, error signal produced is as follows

$$e = y^* - y \tag{3.3}$$

In equation 3.3, expected output is represented by y^*

$$s = (y^* - Xh) * \ (y^* - Xh)^T \tag{3.4}$$

Equation 3.4 is simplified by equating for zero, and then finally the following is obtained

$$h^* = (x^T x)^{-1} x^T y \tag{3.5}$$

Above equation 3.5 written as below, by considering x to be invertible matrix

$$H_{LS} = X^{-1} * y \tag{3.6}$$

3.2.1.2 Minimum Mean Square Error

The goal of the MMSE estimator used in estimating the channel's size is to reduce the mean square error. This method is mainly done by having the necessary knowledge about the channel statistics [87].If X is considered for transmitting in channel h , and then MSE Z is given as

$$Z = mean(Y^* - Y)^2 = E(Y^* - Y)^2 \tag{3.7}$$

Z Indicates mean square error, E represents value expected.

To get the equations in order to find the channel response, theory of correlation as well as expected value has been utilized. Estimated channel h_{mmse} is obtained by the below formula

$$h_{mmse} = f^*\left(r_{gy}^* \, r_{yy}^{-1} y\right) \tag{3.8}$$

$f -$ Noise matrix, $r_{yy}^{-1} y -$ Auto covariance matrix, $r_{gy} - g, y$ Cross covariance matrix

3.2.2 Compressed Sensing with MMSE

Compressed sensing (CS) is a new technique that has been developed recently. It has seen as a beneficial signal acquiring framework for signals portrayed as insufficient or compressible in time or frequency. One way of utilization of the CS technique is in channel estimation. If the channel drives response takes after sparse spreading, by applying the CS strategy along these lines, the training sequence length can be abridged compared with earlier estimation systems. Recent measurements show that the deficient or sparse lacking assumption is sensible with packed channels. In recent times the survey on compacted identifying based systems has drawn a lot of contemplation and concerning results can be found by simulations.

When the transmitter sends the signal, and if the number of transmitters is more than the existing channels, pilot symbols corresponding to a particular transmitter will be considered based on weight factors and they will be compressed using Fast Fourier transform to get the coefficients. After insertion of coefficients, they will be transmitted to the receiver, where it is reconstructed using Inverse Fast Fourier transform and later the channel is estimated using MMSE.

Compressed sensing for channel estimation relies on the assumption that channels can indeed be represented compactly in some basis, and thus fewer samples are required to learn the channel than what was traditionally thought. Compressed sensing (CS) theory tells us that the number of samples needed is ideally proportional to the amount of information in the signal.

Transmitter sends the source signal and when the number of transmitter is more than the available channels, the pilots to be used for compressed sensing must be decided based on some heuristics. In this solution, calculation of priority is done based on demand that is estimated at transmitter and its importance commercially. With the transmitter selected based on this priority, the pilot signals corresponding to that transmitter alone is chosen and compressed using fast Fourier transform to get the coefficients. The coefficients are then inserted and transmitted as signal to the receiver end. At the receiver end pilot is reconstructed using Inverse Fast Fourier transform and then used for Channel Estimation using Minimum mean Square. By this way the channel is given in proportionate to demand and its commercial priority of senders.

The commercial importance is indicated by rating the transmitter from one to five and then assigning five with highest priority and one to lowest priority.
The demand is estimated using moving aggressive model.

$$\begin{aligned} MA_i &= \alpha T_i + (1-\alpha) MA_{i-1} \qquad \text{When } T_i \neq 0 \\ &= (1-\alpha) MA_{i-1} \qquad \text{Otherwise} \end{aligned} \tag{3.9}$$

With the estimated demand and the commercial priority, overall rating is calculated by using equation

$$R = W_1 * CR + W_2 * MA_i \tag{3.10}$$

Where R is the overall rating and CR is the commercial rating, W_1 and W_2 are coefficients for degree of importance, the value choosed in such a way that $W_1 + W_2 = 1$.Once the R is calculated for each transmitter, it is ordered and the ordered list is used for pilot construction

Assuming N subcarriers, frequency response of impulse response is given as,

$$H_{i,j} = \left[H_{i,j}(0), H_{i,j}(1) \dots H_{i,j}(N-1)\right]^T \qquad (3.11)$$

By considering frequency response that has been estimated, where demodulation reference signal are inserted, composite channel frequency response is given by,

$$G_{n,m}^{MMSE} = \frac{R_{est}E_{DMRS}^{T}}{N} * \left(\frac{R_{est}E_{DMRS}^{T}E_{DMRS}}{N} + \sigma^2 I\right)^{-1} G_{n,m} \qquad (3.12)$$

This method is considered as MMSE based compressed sensing (CS MMSE). MMSE is used even though it is complex, because of noise and intercarrier interference of LS method. But matrix inversion at each iteration is required in MMSE, so the CS MMSE is used where the inverse is calculated only once.

3.2.3 Simulation results for LS and MMSE

MATLAB is used as a simulation tool and number of error bits is calculated by considering the bits that has been distorted due to noise over channel. Number of error bits over total bits that has been transmitted gives the measure of bit error rate. Figure 3.8 shows the comparison of bit error rate graph. From the graph it is inferred that compressed sensing based MMSE provides better result compared to conventional LS. Figure 3.9 shows same scenario, from analyzing the curve it infers that compressed sensing based MMSE provides better result compared to conventional MMSE,

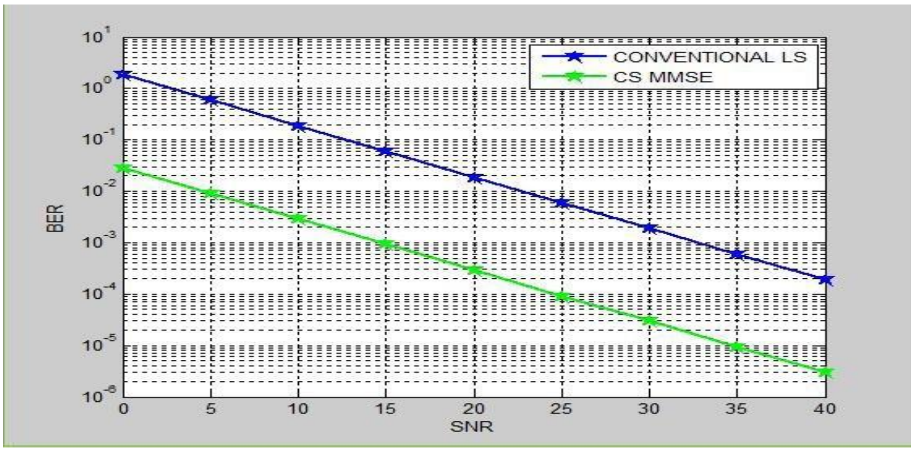

Figure 3.8: BER comparison graph (LS and CS MMSE)

Here normalized energy per bit (E_b/N_0) variations are defined upto 40 dB due to which in the graphs, SNR variations are shown upto 40 dB.

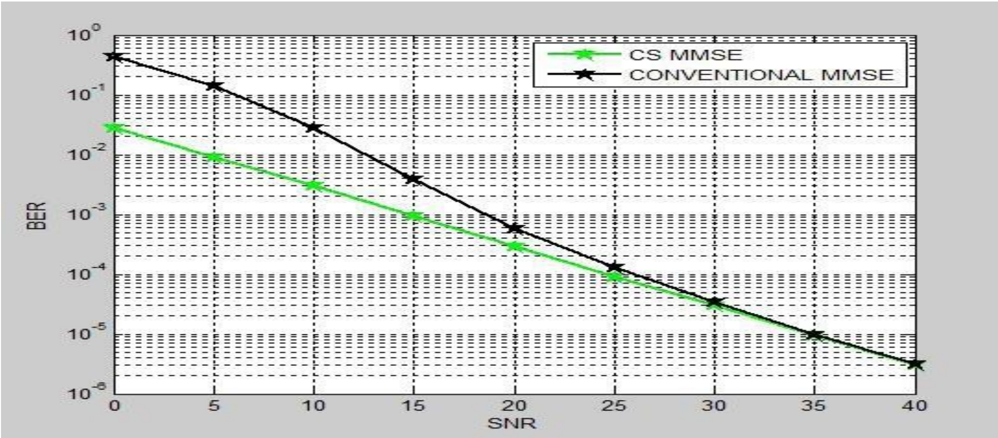

Figure 3.9: BER comparison graph (Conventional MMSE and CS MMSE)

When the transmitter sends the signal, and if the number of transmitters is more than the existing channels, pilot symbols corresponding to a particular transmitter will be considered based on weight factors and they will be compressed using Fast Fourier transform to get the coefficients. After insertion of coefficients, they will be transmitted to the receiver, where it is reconstructed using Inverse Fast Fourier transform and later the channel is estimated using MMSE.BER performance shows better improvement at the high SNR values.

Figure 3.10 shows the same scenario but it includes Comparison of all the three methods such as conventional least square method, compressed sensing MMSE and conventional MMSE. Table 3.3 shows comparison of bit error rate for all the algorithms.

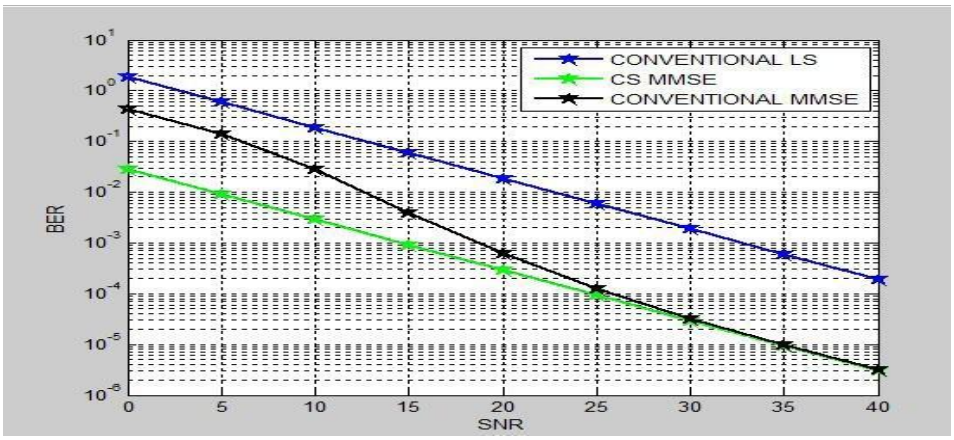

Figure 3.10: BER Comparison graph (Conventional LS, MMSE and CS MMSE)

Table 3.3: BER Comparison values for Conventional LS, MMSE and CS MMSE

SNR(dB)	BER (CONVENTIONAL LS)	BER (CONVENTIONAL MMSE)	BER (CS MMSE)
0	1.5848	0.3162	0.0251
5	0.3981	0.1	0.01
10	0.1584	0.0251	0.0025
15	0.0398	0.0031	0.0001

3.2.4 Summary of Conventional LS, MMSE and CS MMSE

The presented work on compressed sensing based channel estimation is designed and compared with the conventional techniques like least square and minimum mean square error performance of OFDM based system. Based on the performance curve, it has been shown that the BER curve from compressed sensing method MMSE reduces the Bit error rate significantly than LS and MMSE. In addition, it has been shown that the method can also suppress the demodulation reference signal by using the minimum mean square and least square methods.