A MODIFIED CHANNEL ESTIMATION & EQUALIZATION ALGORITHM FOR HIGH SPEED COMMUNICATION SYSYTEM

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ABSTRACT: Orthogonal Frequency Division Multiplexing (OFDM) has recently been applied in wireless communication systems due to its high data rate transmission capability with high bandwidth efficiency and its robustness to multi-path delay. Fading is the one of the major aspect which is considered in the receiver. The main objective is to transmit the data with low bit error with error free transmission. rate in the noisy environment. To cancel the effect of fading, channel estimation and equalization procedure must be done at the receiver before data demodulation. In this paper, Modified iterative – linear minimum mean square error (MI-LMMSE) estimators are suggested and bit error rate (BER) & mean square error (MSE) performance has been analyzed. Channel estimation modified iterative linear minimum mean square error (MI-LMMSE) algorithm is also integrated with CC-OFDM system and presented with modified iterative NLMS algorithm (MI-NLMS) in terms of convergence rates analysis. The performance of proposed algorithms is analyzed in terms of BER, SNR, and MSE.

KEYWORDS: Channel estimation, LMS, NLMS, and Decision directed, BER, SNR, MSE, and OFDM.

1. INTRODUCTION:

A convolution coding based OFDM system with channel equalization & channel estimation is used to reduced bit error rate & overcoming the distortions. In this paper, channel equalization techniques are analyzed to improve the performance of communication system.

In last decades, Orthogonal Frequency Division Multiplexing (OFDM) based communication a system has been identified as one of key transmission techniques for next generation wireless communication systems. The main attractions of OFDM are handling the multi-path interference, and mitigate inter-symbol interference (ISI) causing bit error rates in frequency selective fading environments. Wireless mobile communication systems of the 21st century have to confirm a wide range of multimedia services such as speech, image, and data transmission with different and variable bit rates up to 2 Mbit/s. It is all recognized that there is a great impact of channel coding on the performances of OFDM based wireless communication system to provide high data rates over severe multipath channels [1].

Channel equalization is the process in which the transmitting signal affected by the unwanted signals during transmission process is trying to become noise free. The ISI (Inter Symbol Interference) imposes the main obstacles for achieving increased digital transmission rates with the required accuracy. Traditionally, inter symbol interference problem is resolved by channel equalization. A channel equalizer is an important component of a communication system. The equalizer depends upon the channel characteristics. The adaptive equalizer and the decision device at the receiver compensate the ISI created by the channel. Thus it may be necessary for the channel equalizer to track the time varying channel in order to provide reasonable performance. The main key goal of this adaptive filter based equalizer is to minimize the mean square error of equalized signals before reaching to the receiver [2].

Channel estimation with equalization in OFDM systems is investigated. The main objective of this thesis is to investigate the performance of channel estimation with equalization in OFDM systems. The new algorithms have been proposed for channel estimation & channel equalization in this paper.

2. LITERATURE REVIEW:

Sunho Park et.al: Author's proposed a new decision-directed channel estimation technique dealing with pilot shortage in the MIMO-OFDM systems. The proposed channel estimator uses soft symbol decisions obtained by iterative detection and decoding (IDD) scheme to enhance the quality of channel estimate. Using the soft information from the decoders, the proposed channel estimator selects reliable data tones, subtracts interferences, and performs re-estimation of the channels. From numerical simulations, we show that the proposed channel estimator achieves considerable improvement in system performance over the conventional channel estimators in realistic MIMO-OFDM scenarios [3].

The system model considers imperfect channel estimation, pilot contamination (PC), and multicarrier and multipath channels. Then, a simple H-infinity (H-inf) channel estimation approach is proposed to have good suppression to PC. This approach exploits the space-alternating generalized expectation–maximization (SAGE) iterative process to decompose the multicell multiuser MIMO (MU-MIMO) problem into a series of single-cell single-user single-input single-output (SISO) problems, which reduces the complexity significantly. It is shown from the results that the H-inf has better suppression capability to PC than classical estimation algorithms [4].

3 .CHANNEL ESTIMATION:

Channel estimation is a method to characterize the impact of the physical medium on the input sequence. The key aim of channel estimation is to evaluate the impact of the channel on known or partially known group of transmittances. OFDM systems are specifically equipped for channel estimation. The sub carriers are closely spaced. The channel is estimated on the basis of the training sequence that will be known to both transmitter and receiver. The receiver can employ the known training bits and the respective received samples for estimating the channel.

3.1 LSE channel estimation

LSE estimator reduces the square error between estimation and detection to estimate channel h[m]. In matrix form, the actual output can be written as

y=Xh

and the error is e= is the expected output.

The square error (S) can be defined as [5]

$$\begin{aligned} S &= |e|^2 \\ &= (\overline{y} - y)^2 \\ &= (\overline{y} - y) * (\overline{y} - y)^t \\ &= (\overline{y} - Xh) * (\overline{y} - Xh)^t \end{aligned}$$

where t stands for the complex transpose of matrix. The equation can be minimized by taking its derivative w.r.t *h* and equating it corresponding to zero. The final equation is [5],

$$\overline{h} = (X^t X)^{-1} X^t y$$

where $\overline{h} = hls = X^{-1}y$.

3. 2 MMSE channel estimation

The MMSE estimator minimizes the mean-square error. Mean square error = mean $(y^{-}-y)^2$= $E(^{-}y-y)^2$. Notion of expected value and correlation can be utilized to derive the equations for locating the channel response. The estimated channel is

$$H_{mmse} = F * (R_{gY} * R_{YY}^{-1} * Y).$$

Where,

R_{YY} = X*F*X'*F' + Variance of the noise * Identity matrix.

4. CHANNEL EQUALIZATION:

Channel Equalizer is very much needed not only to mitigate the noise effect or ISI but to provide an optimum signal to the decision device at the receiver so that decision device can take a good decision in favor of original signal. The existing equalizers like decision feedback, zero forcing etc are not preferable over Adaptive algorithm based Equalizers. Unlike normal digital filters most of the Adaptive Filters are able to work in recursive manner which helps to reduce the computational complexity on the basis of particular application. The key goal of working with Adaptive filters is to minimize the MSE as minimum as possible. Figure 1 shows the basic process required for channel equalization using adaptive filter [6].

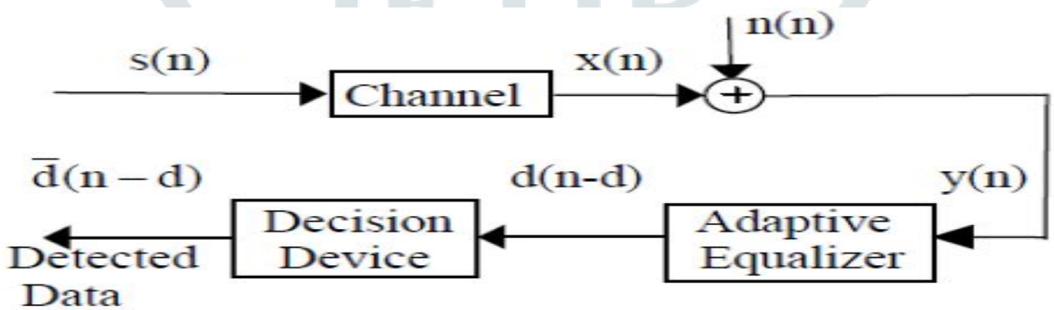


FIG 1: CHANNEL EQUALIZATION

4.1 LMS ALGORITHM: LMS algorithm was first developed by Widrow and Hoff in 1960. The design of this algorithm was stimulated by the Wiener-Hopf equation. By modifying the set of Wiener-Hopf equations with the stochastic gradient approach, a simple adaptive algorithm that can be updated recursively was developed. This algorithm was later on known as the least mean- square (LMS) algorithm. It does not require measurement of correlation functions nor matrix inversion.

Basic idea behind LMS filter is to approach the optimum filter weights by updating filter weights in manner to converge optimum filter weight. Algorithm starts by assuming small weights (zero in most cases) and at each step by gradient of mean square error weights are updated [7].

The process of this algorithm, it send filter input that is specified by x(k) passing through adaptive filter. It give filter output is specified by y(k).

$$y(k) = w(k)^T \ x(k)$$

where $w(k)^T$ is transpose and k is time index. It compares the filter output to the desired signal that is specified by d(k) and gets the error by this equation[8]

$$e(k) = d(k) - y(k)$$

The LMS algorithm try to adjust the adaptive filter coefficient that make e(k) be minimized, it is shown in function mean square error (MSE), it use the error to adjust the next coefficient of adaptive filter by this equation[9]

$$w(k+1) = w(k) + \mu e(k) \times (k)$$

4.2 NORMALIZED LMS (NLMS): The normalized least mean square (NLMS) algorithm has superior convergence properties than the least mean square (LMS) algorithm. However, weight noise effect of the NLMS algorithm is large so that the steady state residue power is larger than that for the LMS algorithm. A generalized NLMS algorithm is developed based upon the pseudo inverse of an estimated covariance matrix. However in practice, an improved LMS method that is Normalized-LMS (NLMS) is used to achieve stable calculation and faster convergence. The NLMS algorithm can be formulated as a natural modification of the LMS algorithm based on stochastic gradient algorithm. The final weight vector can be updated by,

$$w(n+1) = w(n) + \frac{\mu}{a + \|x(n)\|^2} x(n) e^* \qquad \text{.....................(1)}$$

where the NLMS algorithm reduces the step size μ to make the large changes in the update weight vectors. This prevents the update weight vectors from diverging and makes the algorithm more stable and faster converging than when a fixed step size is used. Equation (1) represents the normalized version of LMS (NLMS), because step size is divided by the norm of the input signal to avoid gradient noise amplification due to x (n). Here the gradient estimate is divided by the sum of the squared elements of the data vector [10].

5. PROPOSED METHOD:

Firstly the data input is applied to the FEC i.e. forward error correcting code in which convolutional coding with interleaving is used .A convolutional encoder first encodes the binary input data. Coded bits are sent to interleaving and then the binary values are represented on BPSK modulator. To be able to adjust the signal in the receiver for a possible phase drift, pilot carriers can be inserted. In the Serial to Parallel block, the serial input symbol-stream is transformed into a parallel stream. These parallel symbols are modulated onto the sub carriers by applying the Inverse Fast Fourier Transform. Following the IFFT block, the parallel output is converted back again to serial and guard interval, cyclic prefix of the time domain samples, is appended to eradicate ISI. In the receivers, the guard interval is removed and the opposite processing is carried out to transmitter like time samples are converted by the FFT into complex symbols. In the channel estimation technique Modified iterative LMMSE algorithm is used & in the channel equalization modified iterative NLMS equalizer is used. Demodulated symbols are block deinterleved. These bits are forwarded to Viterbi decoder. Decoded bits are going to be assigned to a specific user and then extracted utilizing the required bit rate information of the user

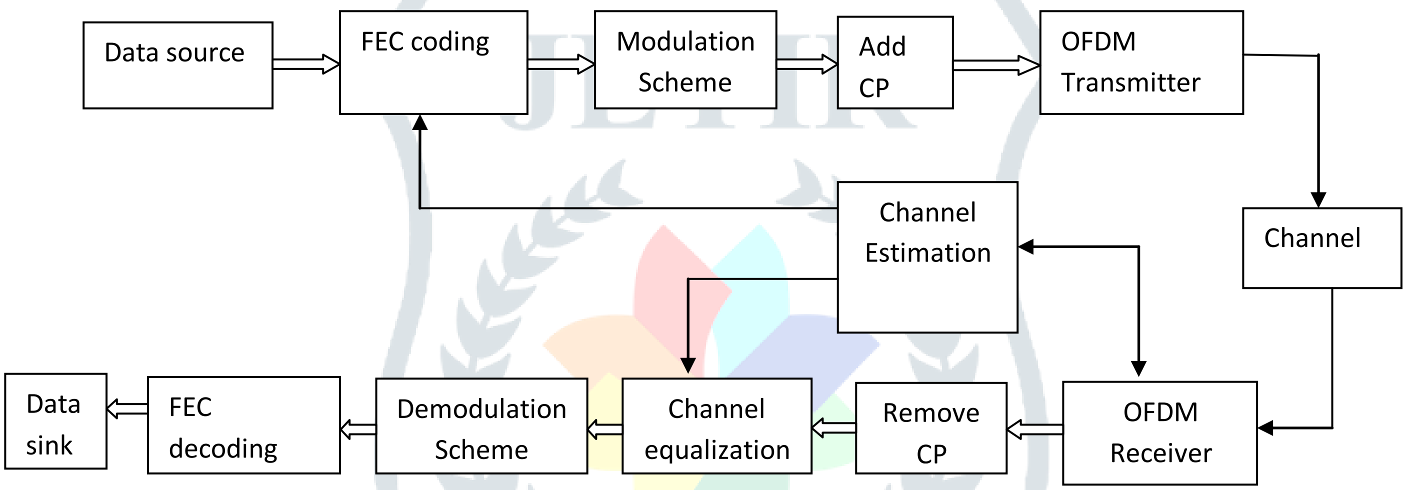


FIG 2: BLOCK DIAGRAM OF PROPOSED METHOD

Algorithm for proposed method:

Step 1: Initialize with parameter of least square (LS) channel estimation.

Step 2: Develop the new modified LS channel estimation.

Step 3: After that iteratively develop the modified iterative LMMSE CE algorithm in which new modified LS is used.

Step 4: along with channel estimation channel equalization technique is develop which is called MI-NLMS.

Step 5: In MI-NLMS Consider weighting window function W. and also initialize it

If w = weighting window function

Step 6: calculate Error function e(i)

E(i)= d(i)- y(i)

Step 7: Updating weighting function

Step 8: convergence plot is obtained.

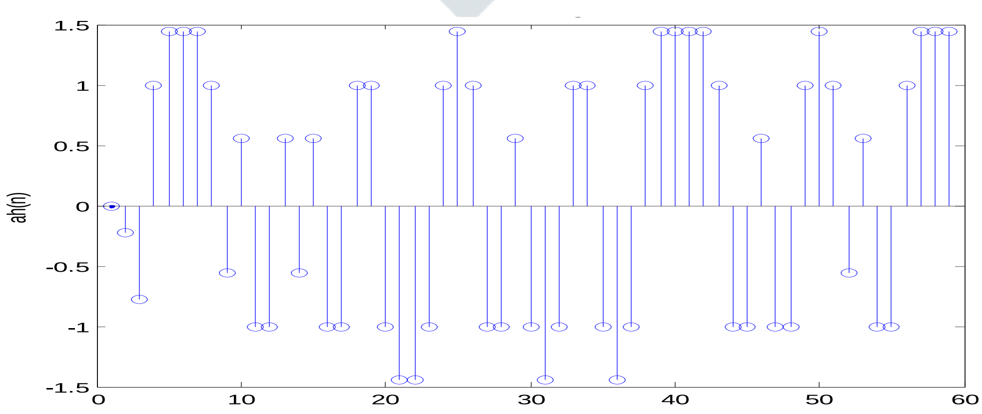
Step 9: Finally Plot the BER v/s SNR, MSE v/s SNR & speed of convergence plot.

6. SIMULATION RESULTS:

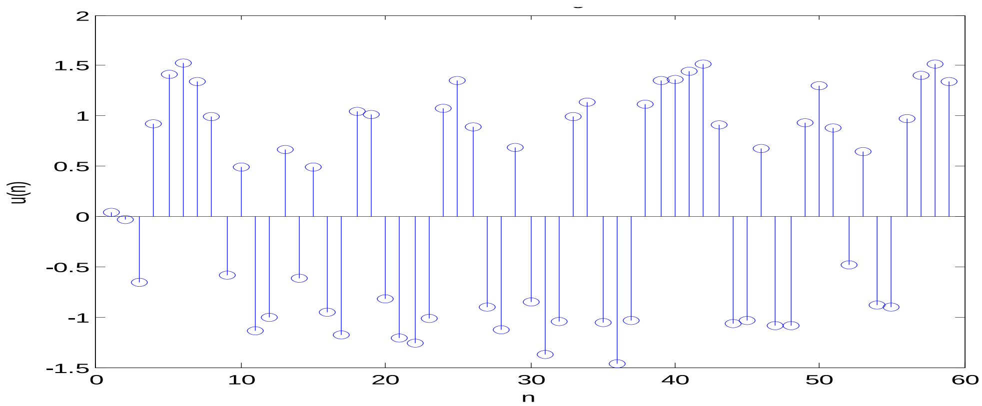
In this section, we compare the performance of the proposed channel estimation with channel equalization technique with the conventional approaches through computer simulations. To confirm the effectiveness of the proposed methods, two metrics, that is, MSE and BER are adopted for performance evaluation. The simulation results of comparison of transmitted signal and received signal are shown in figure (3)

TABLE 1: Simulation Parameters

S.NO.	PARAMETERS	VALUES
1.	FFT Size	64,128, 256
2.	CP	¼
3.	Coding	Convolutional coding
4.	Constraint length	7
5.	SNR	-10 to 15 dB
6.	Modulation	BPSK, 16 QAM, 64 QAM
7.	Code rate	1/2
8.	Channel length	4,8



a) Transmitted message

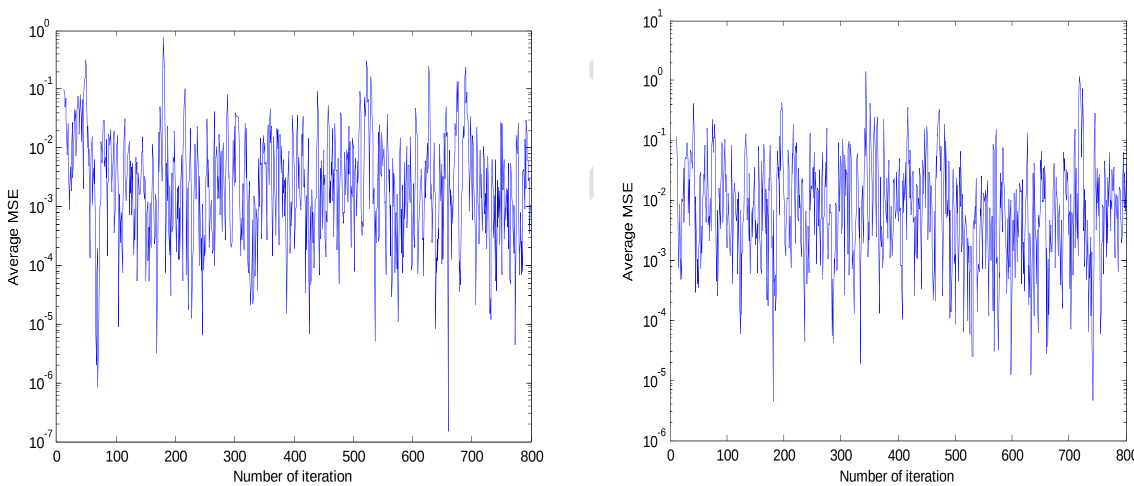


b) Received message

FIG. 3 COMPARISON OF TRANSMITTED AND RECEIVED MESSAGE

6.1. Mean Square Error (MSE) Comparison of proposed algorithm between conventional Algorithm.

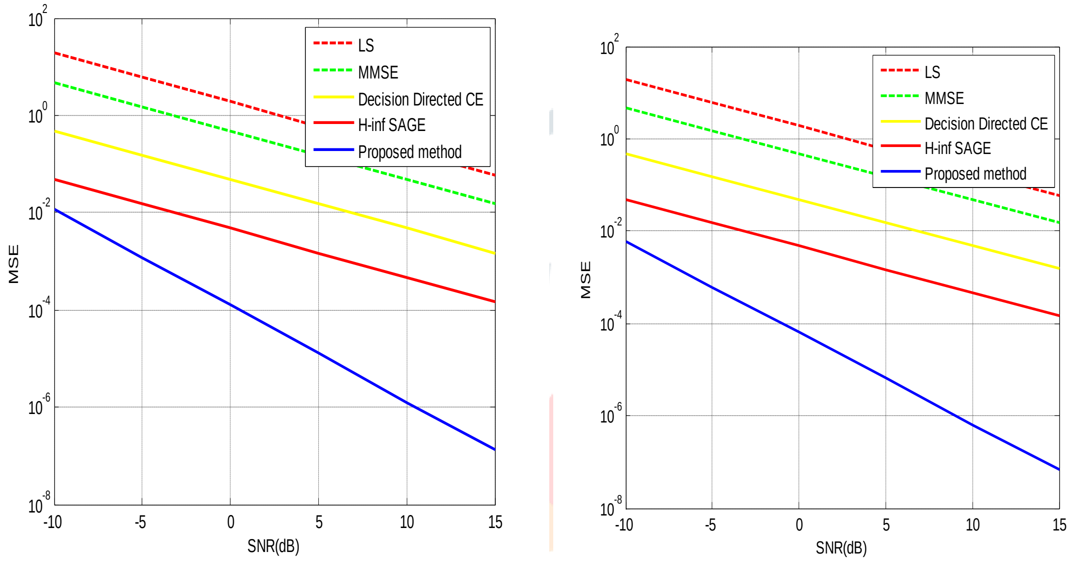
Figure 4 shows the Average MSE v/s number of iteration of proposed algorithm with conventional algorithm by computer simulation, respectively. It is also shows the speed of convergence for different SNR fig 4a. Shows the speed of convergence for SNR = 5Db & fig b shows the speed of convergence for SNR= 10 dB. Fig.8 shows the performance in terms of BER versus Eb/No for uncoded data, BPSK, 16QAM and 64QAM. The figure shows that system performs better in BPSK than other modulation scheme.



a) 5 dB **b) 10 dB**

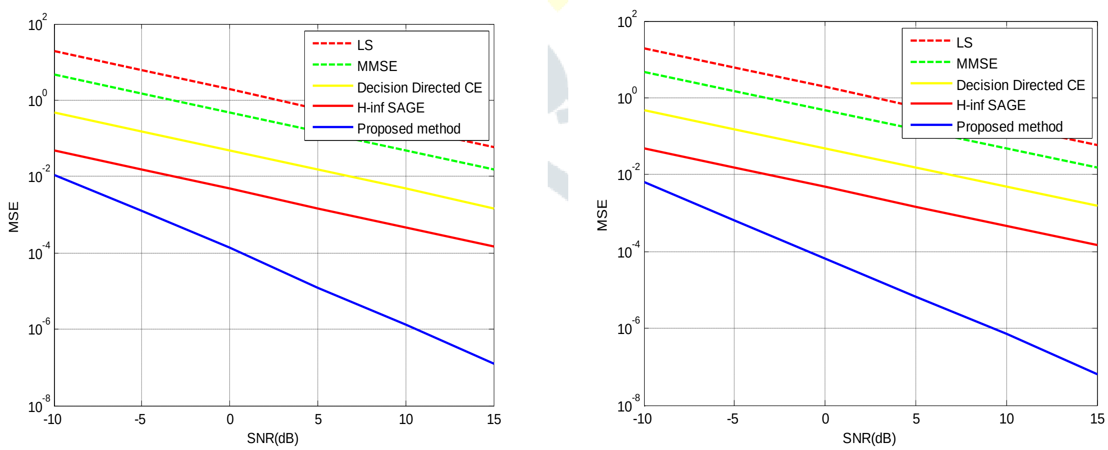
FIG 4: AVERAGE MSE V/S NUMBER OF ITERATION a) for SNR = 5 dB & b) 10 dB.

MSE V/s. SNR characteristics are plotted as shown in Figs. 5 and 6 respectively. It can be observed proposed method gives better output as compared to LS i.e. Least square CE, MMSE , DD-CE, H-inf SAGE algorithm. Fig 5 a shows the MSE Plot V/S SNR for FFT size N= 128, L=4 & fig 5 shows FFT size N= 256, L= 4 similarly fig 6 shows respectively .figure 7 shows the BER v/s Eb/No. plot & shows the low bit error rate of proposed method as compared to other conventional algorithm.



a) N= 128, L= 4 b) N= 256, L= 4

Fig 5: MSE Plot V/S SNR a) N= 128, L=4 & b) N= 256, L= 4



a)N= 128, L =8 b) N= 256, L=8

Fig 6: MSE Plot V/S SNR a) N= 128, L=8 & b) N= 256, L= 8

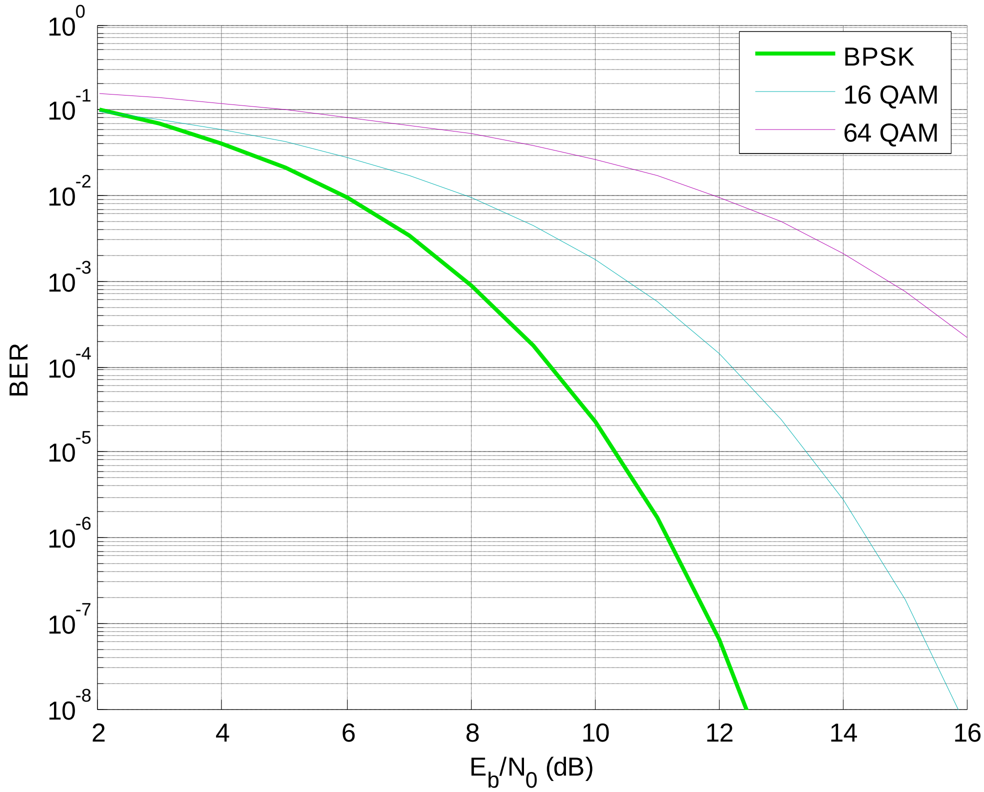


FIG 7: PLOT OF BER V/S EB/NO. FOR DIFFERENT MODULATION TECHNIQUE

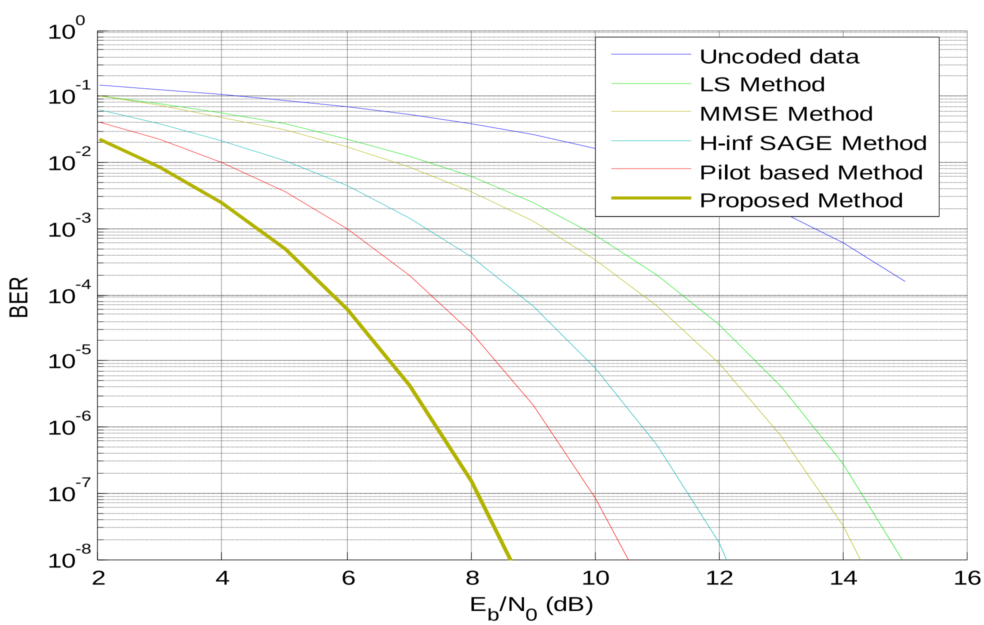


FIG 8: PLOT OF BER V/S EB/NO(DB) OF THE CONVENTIONAL AND PROPOSED METHOD FOR BPSK MODULATION SCHEME

7. CONCLUSION:

In this paper, we introduce a new modified iterative- Linear minimum mean square error (MI- LMMSE) channel estimator's technique with modified iterative NLMS (MI-NLMS) Channel equalization algorithm in the CC-OFDM systems. The performance can be improved by applying FEC codes in contrast to uncoded system. From simulation results it is observed that my proposed algorithm outperforms than that of other conventional algorithm. With the help of my proposed algorithm we transmit the data with low bit error rate with high convergence speed & low error rate in the noisy environment.

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