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BER analysis of using Adaptive Channel Equalization Methods for MC-CDMA Communication System

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Abstract— Our society where communication through modern technology is prominent, seeking high speed voice, video and data in quantities that could not be imagined even a decade ago. The mobility and channel impairments have added more challenges. Multi Carrier Code Division Multiple Access (MC-CDMA) system is an attractive choice for high speed wireless communication as it avoids the problem of Inter Symbol Interference (ISI). The approach of this paper is based on Least Mean Square (LMS), Normalized Least Mean Square (NLMS) and Recursive Least Square (RLS) algorithms are considered as channel equalization method that are proposed and examined to fight for the ISI effect for MC-CDMA system of achieving fast and reliable wireless digital communication. The simulation results of estimated Bit Error Rate (BER) show that the proposed system with Binary Phase Shift Keying (BPSK) modulation with RLS algorithm outperforms as compared to other modulation techniques and channel equalization methods.

Index Terms— channel equalization technique, convolutional coding, Least Mean Square algorithm, multi carrier code division multiple access, Normalized Least Mean Square algorithm, OFDM, Recursive Least Square algorithm.

1 INTRODUCTION

MULTICARRIER (MC) modulation is a highly attractive technique to support multi user access and high data rates. Therefore, a combination of Code Division Multiple Access (CDMA) schemes and Orthogonal Frequency Division Modulation (OFDM) techniques-which is referred to as multicarrier CDMA (MC-CDMA) provides the benefits for future high data rates applications. Several multi access techniques that are supported muticarrier techniques and CDMA system have been proposed [1]-[4]. But high speed transmission in MC-CDMA system mostly suffers from Inter Symbol Interference (ISI) and additive noise.

Wiener and Kalman filters [5] are the most widely used linear filters that require priori information (statistical parameters) where Wiener requires knowledge of signal covariance and Kalman requires knowledge of state-space model signal. Unfortunately the causes of Inter Symbol Interference (ISI) are not stationary [6]. So, adaptive filters perform well in an environment where the relevant statistical parameters are unavailable.

Scientific and engineering disciplines are widely used the adaptive algorithms, both theoretical and applied include topics such as system identification, channel equalization, adaptive control, adaptive filtering for signal processing, and pattern recognition [7]. Medical and other scientific applications are discussed in [8]-[9].

A suitable filter structure and proper adaptive algorithm need to be designed for adaptive channel equalization in MC-CDMA system. The adaptive equalization algorithms recursively determine the filter coefficients in order to eliminate the effects of noise and ISI [10]-[12].

Among the numerous algorithms that can be used for adaptive filtering, the Least Mean Square (LMS) algorithm has got the popularity in adapting filtering is its computational simplicity, making it easier to implement than all other commonly used adaptive algorithms [13]. There are two distinct well known and most frequently applied algorithms Normalized Least Mean Square (NLMS) [14]-[17] and Recursive Least Square (RLS) [18] algorithms for noise cancellation [19]. However, it is obvious that NLMS algorithm has the advantage of low computational complexity. On the other hand, the best adaptive equalization algorithm, RLS which has the weakest point of high computational complexity. Therefore, it is clear that the computational complexity and fast convergence parameters are considered for choosing adaptive algorithm [20].

It was mentioned before that the ISI created by multiple channels is far more destructive compared to channel and/or receiver noise so that efforts are aimed at the goal of eliminating or at least mitigating the distortion caused by ISI. The distortion obviously generates some bit or symbol errors in digital communication systems. The models and approximations formed for multipath wireless channels are based on the equivalent baseband model of the communication system. Furthermore, the transmitted and received signals are shown in discrete-time by their samples at the k^{th} time step [7],

$$s[k] = s\ (kT_s) \quad \text{and} \quad r[k] = r\ (kT_s) \qquad (1)$$

where the channel impulse response (CIR) supports the continuous time symbol duration by T_s. Consequently, the CIR can be written as a discrete-time impulse response h (h_0, h_1, … h_{N_c}-1), k=0, 1, … N_c-1 . Discrete time channel model is shown in Fig.1. It is noteworthy that there are two main as-

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sumptions about CIR, that it can be considered constant relative to equalization time (slow-varying), and causal (the matter of the choice for the time reference).

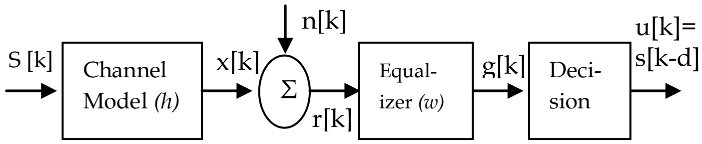

Fig. 1. Discrete time channel model.

The rest of the paper is organized as follows. In Section 2 the mathematical model of adaptive algorithm of LMS, NLMS and RLS will be described. Section 3 presents the BER effect for MC-CDMA system with Binary Phase Shift Keying (BPSK), Differential Binary Phase Shift Keying (DBPSK), Quadrature Phase Shift Keying (QPSK) and Quadrature amplitude modulation (QAM) are considered for bit mapping. Again, the Section 4 shows a comparison of the BER analysis among adaptive channel equalization algorithms and also exhibits the good performance of those algorithms in attenuating the noise. Finally, the Section 5 concludes the paper with some future remarks.

2 Formulation of the Model

In order to attain analytical results for BER performance, the transmitter based on CDMA and OFDM spreads the serial to parallel converted [21] data streams using a given spreading code in the time domain. We consider a transmit signal for usr k is described in Fig.2 and Fig. 3 and transmitted signal $S_k(t)$ of the

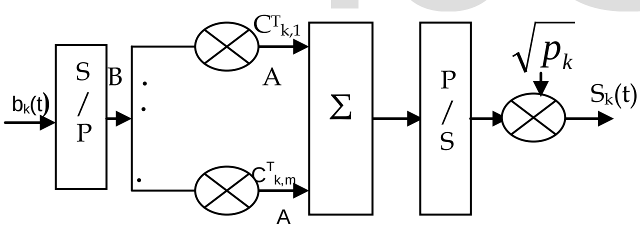

Fig. 2. Baseband signal analysis with spreading code and subcarrier channelizing multiplier.

multicarrier form [22]

$$S_k(t) = \sqrt{p_k}\sum_{n=-\infty}^{\infty}\sum_{m=1}^{M} b_k[n]c_{k,m}[n]e^{jw_ct+w_st}$$

$$= \sqrt{p_k}\sum_{n=-\infty}^{\infty}\sum_{m=1}^{M} b_k[n]c^I_{k,m}[n]\cos(w_ct+w_st) - c^Q_{k,m}[n]\sin(w_ct+w_st) \qquad (2)$$

where

w_c	carrier frequency
w_s	Subcarrier spacing
M	Subcarrier number
M	Number of Subcarriers
$b_k(t)$	data bit of user K at time n
$C_{k,m} = C^I_{k,m} + C^Q_{k,m}$	The complex I and Q spreading sequence for user K on subcarrier m

From Fig. 1, it is assumed that we use the following vector notation. For OFDM vector A of length M carries user data with A= $[a_0, a_1, \ldots, a_{M-1}]^T$. In CDMA, A=CB where $C_{k,m}$ is N by N code matrix and B= $[b_0, b_1, \ldots, b_{M-1}]^T$ represents a frame of user data. The kth column of C represents the "Spreading Code" of user data stream k will be denoted as (C_k [0], C_k [1], …, C_k [N-1]]^T. Walsh-Hadamard matrix [23] is used to define individual communication channels.

It is also observed that frames are created by a Serial to Parallel (S/P) conversion of an incoming data stream, applying the code spreading, a I-FFT and a Parallel to Serial (P/S) conversion with cyclic prefix insertion to avoid interframe interference. Each wave has its particular Doppler frequency offset w_i, path delay T_i and amplitude D_i, each of which is assumed to be constant. That is, we make the common assumption that the time-varying nature of the channel arises from the accumulation of multiple components. Due to motion of the antenna at constant velocity, each component has a linearly increasing phase offset, though all with a different slope. The Doppler offset *2Πfi* lies within the Doppler spread $-2\pi f_\Delta \le w_i \le 2\pi f_\Delta$, $f_\Delta = {vf_c}/{c}$ with the maximum Doppler shift. Here, *v* is the velocity of the mobile antenna and c is the speed of light. The carrier frequency is $2\pi f_c = w_c$ [24].

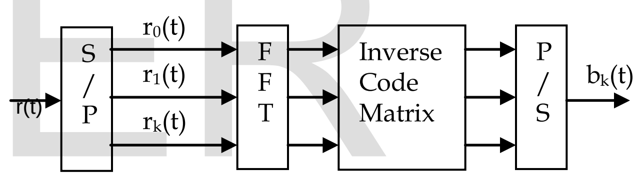

Fig. 3. Baseband signal analysis with spreading code and subcarrier channelizing multiplier.

The received signal *r(t)* consists of the composition of all reflected waves, namely

$$r(t) = \sum_{m=1}^{M}\sum_{i=0}^{I_w-1} b_k[n]c_{k,m}[n]e^{j(w_ct+nw_s+w_i)x(t-T_i)} + n(t) \qquad (3)$$

Here *n(t)* represents the Additive White Gaussian Noise (AWGN) with a double sided power spectral density of $N_0/2$. I_w is the multipath channel contributors appear to then individual Doppler offset w_i.

The output of the antenna array *x(t)* is given by

$$x(t) = s(t)a(\theta_0) + \sum_{m=1}^{M} r_m(t)a(\theta_i) \qquad (4)$$

Where *S(t)* denotes the desired signal arriving at angle θ_0 and $r_m(t)$ denotes the interfering signal arriving at angle of incidence θ_i respectively, θ_i and θ_0 are the vectors of desired and interfering signals. Therefore, it is required to construct the desired signal from the received interfering signals.

As shon in Fig. 4 the antenna array pattern is optimized to have maximum possible gain in the direction of the desired signal and nulls in the directin of the interferers where the

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weight vector will be calculated using LMS, NLMS and RLS algorithm based on the Minimum Squared Error (MSE) criterion.

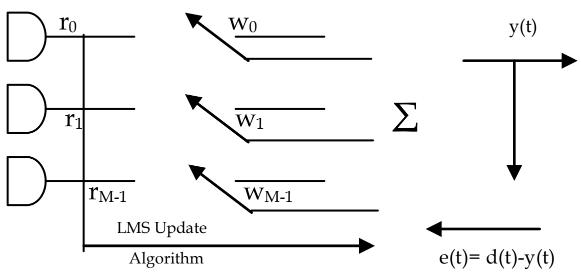

Fig. 4. LMS adaptive Network

2.1 LMS Algorithm

The LMS algorithm uses a gradient based method of steepest decent. This algorithm estimates the gradient vector from the available data. In (2) shows the generic filter vector update equation can be stated as follows [25]

$$h(n+1) = h(n) + \mu X(n) w(n) e(n) \quad (5)$$

Now table 1 shows the explanation of notations to setup the adaptive filtering [13].

TABLE 1
EXPLANATION OF NOTATIONS

h(n)	Length- M column vector of filter coefficients to be adjusted at each time instant n
x(n)	Length, M vector of input signal samples to adaptive filter, [x(n), x(n-1), …, x(n-M+1)]^T
e(n)	Length L vector of error samples. [e(n), e(n-1), …, e(n-L+1)]^T
X(n)	M x L signal matrix whose columns are given by x(n), x(n-1)…., x(n-L+1)
w(n)	L x L symmetric weighting matirix
μ	Step-size

Steepest descent uses a deterministic gradient in a recursive computation of the Weiner filter for stochastic inputs which distinguish the LMS methods. If it were possible to make exact calculation of the value of gradient vector at each iteration n, and if the step size parameter μ is suitable chosen, then steepest descent can easily use the Weiner filter [26] [27].

From Fig.4, it is seen that the basic goal of LMS filter is to find the minimum value of the mean square error, J_{min} by updating the filter weights. The algorithm follows the steps [29]:

1. At begin the initial tap weight vectopr w(0) guess the minimum point of error surface may be located or usually set to the null vector.
2. Then compute the gradient vector, the real and imaginary parts of which one defined as the derivative of the mean squared error J(n).
3. Compute the updated weight vector.
4. Go to Step2 and repeat the process.

In the same way, the updated value of the tap-weight vector at time n+1 is computed by using the simple recursive relation

$$w(n+1) = w(n) + \tfrac{1}{2}\mu[-\nabla J(n)] \quad (6)$$

The factor is used for the purpose of canceling a factor 2 from eq (6). So, the gradient vector is given by

$$\nabla J(n) = \begin{bmatrix} \frac{\partial j(n)}{\partial a_0(n)} + j\frac{\partial j(n)}{\partial b_0(n)} \\ \frac{\partial j(n)}{\partial a_1(n)} + j\frac{\partial j(n)}{\partial b_1(n)} \\ \vdots \quad \vdots \quad \vdots \quad \vdots \\ \frac{\partial j(n)}{\partial a_{M-1}(n)} + j\frac{\partial j(n)}{\partial b_{M-1}(n)} \end{bmatrix}$$

$$= -2P + 2Rw(n) \quad (7)$$

Where $\frac{\partial j(n)}{\partial a_k(n)}$ and $\frac{\partial j(n)}{\partial b_k(n)}$ are the partial derivatives of the cost function J(n) with respect to the real part $a_k(n)$ and the imaginary part $b_k(n)$ of the kth tap-weight $w_k(n)$. In (7) the correlation matrix R and the cross-correlation vector P are known so that we may compute the gradient ∇ j(n) for a given value of tap weight vector W(n). Thus substituting (6) in (7):

$$w(n+1) = w(n) + \mu.[P - Rw(n)], \text{ n=1, 2, …} \quad (8)$$

So, the value of R and P based on the tap-input vector and desired response,

$$\bar{R}(n) = u(n)u^H(n) \quad (9)$$
$$\bar{P}(n) = u(n)d^*(n) \quad (10)$$

Now, the instanteous estimate of the gradient vector is

$$\hat{\nabla} J(n) = -2u(n)d^*(n) + 2u(n)u^H(n)\hat{w}(n) \quad (11)$$

So, substitue (9) and (10) in (8) and calculate the new recursive relaion for updating the tap-weight vector

$$\hat{w}(n+1) = \hat{w}(n) + \mu u(n)[d^*(n) - u^H(n)\hat{w}(n)] \quad (12)$$

Now we may write the final result in the form of three basic relations as follows [30]:

1. Filter output:
$$y(n) = \hat{w}^h(n)u(n) \quad (13)$$
2. Estimation Error:
$$e(n) = d(n) - y(n) \quad (14)$$
3. Tap-weight adaption:
$$\hat{w}(n+1) = \hat{w}(n+1) + \mu u(n)e^*(n) \quad (15)$$

2.2 NLMS Algorithm

In LMS algorithm, the correction $\mu u(n)e^*(n)$ applied to the tap weight vector $\hat{w}(n)$ at iteration n+1 is directly proposional to the tap-input vector u(n). Therefore, when u(n) is large, the LMS algorithm experiences a gradient noise amplification

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problem. To overcome this, normalized LMS algorithm discovered which is companion to the ordinary LMS algorithm. In particular, the correction applied to the tap-weight vectior $\hat{\mathrm{w}}(n)$ at iteration n+1 is "normalized" with respect to the squared Euclidean norm of the tap-input vector u(n) at iteration n, hence the term "normalized". The normalization is such that [30]:

1. The effect of large fluctuations in the power levels of the input signal is compensated at the adaptation level.
2. The effect of large input vector length is compensated, by reducing the step size of the algorithm.

Applying squared Euclidean norm of the tap-input vector u(n) to LMS Tap-weight adaption become

$$\hat{\mathrm{w}}(n+1) = \hat{\mathrm{w}}(n+1) + \frac{\overline{\mu}}{\|U(n)\|^2} u(n) e^*(n) \tag{16}$$

The principal characteristics of the Normalized LMS algorithm are the following:

• The adaptation constant μ is dimensionless, whereas in LMS, the adaptation has the dimensioning of a inverse power.

• Step size

$$\mu(n) = \frac{\overline{\mu}}{\|u(n)\|^2}$$

• The Normalized LMS algorithm is convergent in mean square sense if 0 < $\overline{\mu}$ < 2 [30].

2.3 RLS Algorithm

The Recursive least squares (RLS) is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals. This is in contrast to other algorithms such as the least mean squares (LMS) that aim to reduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS and similar algorithm they are considered stochastic [28].

Initialization of RLS algorithm by setting:

P(0)= $\delta^{-1} I$, $\delta =$ Small positive constant

$\hat{w}(0) = 0$,

RLS algorithm gives the followings [29]:

1. Gain Vector:

$$\mathrm{k(n)} = \frac{\lambda^{-1}\mathrm{P(n\text{-}1)u(n)}}{1+\lambda^{-1}\mathrm{u}^{H}\mathrm{(n)P(n\text{-}1)u(n)}} \tag{17}$$

2. Filter output:

$$y(n-1) = \hat{w}^H(n-1)u(n) \tag{18}$$

3. Estimation Error:

$$\xi(n) = d(n) - y(n-1) \tag{19}$$

4. Tap-weight adaption:

$$\hat{w}(n) = \hat{w}(n-1) + k(n)\xi^*(n) \tag{20}$$

5. Updated Matrix:

$$P(n) = \lambda^{-1}P(n-1) - \lambda^{-1}k(n)u^H(n)P(n-1) \tag{21}$$

After successfully applying three adapting algorithms, the algorithm adjusted the filter coefficients inorder to remove the ISI effect. Now to decorate with k[th] user data, the estimated bits $\hat{b}_k(t)$ are reencoded to form an estimate of the receive signal for that user, Z_k . This is then substracted from the current compsite signal Y_k to form a cleaner signal that can be used to find the bits for user k+1.

For each user k, the composite signal use for detection is described by its subcarriers

$$y_{k,m}(t) = y_{k-1,m}(t) - z_{k-1,m}(t), \; k \geq 2, \; \forall m \tag{22}$$

where $z_{k,m}(t)$ is an estimate of the received signal for user k on subcarrier m, and described by

$$z_{k,m} = \sqrt{P_k}\,\Re\left\{h_{k,m}, c_{k,m}\hat{b}_k e^{j(\omega_m(t-\varsigma_k)+\theta_{k,m})}\right\}$$

We can evaluate, the local-mean power, $P_{k,n}$ which is given as,

$$P_{k,n} = E\left[\beta^2{}_{k,n}\right]\frac{\rho}{N} \tag{23}$$

where the total-mean power of the k-th user is defined to be $P_k = N.P_{k,n}$.

Demodulating each subcarrier includes applying a phase correction, $\hat{\theta}_{0,i}$ and a gain correction factor $d_{0,n} = \beta_{0,n}.a_0[n]$ is multiplied by the n-th subcarrier signal. All the signals at the output of the correlators are combined and can be written as

$$\gamma = \sum_{l=0}^{L-1}\gamma_l \tag{24}$$

where γ_l is the SNR at every branch. The branch number is assumed that equal to the subcarrier number, that is, L=M. The decision variable D_0 of the m-th data bit reference user, and given by

$$D_0 = \frac{1}{T_b}\int_{mT_b}^{(m+1)T_b} r(t).\sum_{l=0}^{L-1} a_0[l].d_{0,l}.\mathrm{Re}[e^{(w_l t+Q_{0,0})}]dt \tag{25}$$

$$= U_s + I_{MAI} + \eta_0$$

The desired signal can be expressed as

$$U_s = \sqrt{\frac{P}{2N}}\sum_{l=0}^{L-1}\beta^2{}_{0,l}.a_0[m] \tag{26}$$

And the second term, I_{MAI}, is the MAI (Multiple access interfaces) contributed from all other users which can be written as

$$I_{MAI} = \sqrt{\frac{P}{2N}}\sum_{k=1}^{K-1}\sum_{n=0}^{L-1} a_k[m].b_k[m].a_0[m].\beta_{k,m} .\beta_{0,n}.\cos(\theta'_{k,n}) \tag{27}$$

where $\theta'_{k,n} = \theta_{0,n} - \theta_{k,n}$

3 Effect on BER for MC-CDMA System

A generalized avarege BER for k-th user using coherent BPSK (binary phase shift keying) modulation scheme is derived in this section. For coherent demodulation in the presence of AWGN, the probability of error condition on the instantaneously SNR can be expressed as

$$P_e(s) = 0.5Q(\sqrt{SNR}) \tag{28}$$

Where the Gaussian Q-function is defined by

$$Q(x) = \int_x^\infty \tfrac{1}{2}\pi e^{(-r^2/2)}dt\,,$$

And the receiver instantaneously SNR, which conditioned on $\gamma_{o,n} = \beta^2{}_{0,n}$, at output of the receiver is calculated as

$$\frac{U^2{}_s}{\sigma^2{}_T} = \frac{\frac{P}{2N}\sum_{n=0}^{N-1}\beta^2{}_{0,n}}{\sigma^2_{I_{MAI}} + \sigma^2\eta_0} \tag{29}$$

Where $\sigma^2_{I_{MAI}}$ is the varience of I_{MAI}, the MAI can be approximated by a Gaussian r.v. with zero mean and the varience, $\sigma^2_{I_{MAI}}$ can be determined as

$$\sigma^2_{I_{MAI}} = E[I^2_{MAI}] = \tfrac{P}{2}(k-1).E[\beta^2_{k,n}]$$
$$.E[\cos^2\bar{\theta}_{k,n}] = \tfrac{P}{4}(k-1)\Omega_{k,n} \tag{30}$$

Where $\Omega_{k,n} = E[\beta^2_{k,n}]$, $E[\cos^2\bar{\theta}_{k,n}] = 1/2$. On the other hand, background noise term η_0 is a random variable with zero mean and the varience can be calculated as

$$\sigma^2_{I_{MAI}} = E[I^2_{MAI}] = \frac{NN_0}{4T_b} \tag{31}$$

By substituting (30) and (31) into (29), which can be obtaind as

$$\frac{U^2}{\sigma^2_T} = \frac{1}{2N}.S_N(\sigma_0)^{-1} \tag{32}$$

Where

$$S_N = \sum_{n=0}^{N-1}\beta^2_{0,n} \Big/ \Omega_{k,n}$$

And

$$\sigma_0 = \frac{NN_0}{4PT_b\Omega_{k,n}} + \frac{k-1}{4} = \frac{N}{4\gamma_0} + \frac{k-1}{4}$$

Where

$$\gamma_0 = PT_b\Omega_{k,n}\big/N_0 = E_b\Omega_{k,n}\big/N_0$$

is the SNR of each bit and $E_b = PT_b$ denotes the bit energy.

The average BER can be expressed as

$$P_e = \tfrac{1}{2}\int_0^\infty Q\left(\sqrt{\frac{2S_N}{\frac{(K-1)d(L,\delta)}{N^2}\Omega'_0 + \frac{N_0}{E_b}}}\right)f_\gamma(x)dx$$
$$= \frac{1}{2\pi}\sum_{l=1}^{L}\sum_{\gamma=1}^{m}\beta_{l_\gamma}\left(\frac{1}{\lambda_l}\right)^\gamma. \tag{33}$$
$$\int_0^{\pi/2}\left[\frac{2}{\left(\frac{(K-1)d(L,\delta)}{N^2}\Omega_0 + \frac{N_0}{E_b}\right)\sin^2\theta} + \frac{1}{\lambda_l}\right]^{-\gamma} d\theta$$

Where λ_l is given in (24), and σ_0 are shown in (32).

4 Numerical Results

In this section we evaluate the BER performance of MC-CDMA system with channel equalization method, investigate the effect of channel equalization technique with different modulation schemes BPSK, DBPSK, QPSK and QAM, and compare the performance of each system. Note that all the BER results in this section were computed from (33). For convenience, the parameters connom in all figures are summarized as follows:

TABLE 2
Simulation Parameters

Parameters	Types/values
Modulation Scheme	QPSK,BPSK,QAM, DPSK
Processing Gain	8
No of Iteration	500
CP length	103
Channel Coding	½ rated convolutional encoding
Delay	7
SNR	1-10 dB
LMS Parameter	μ=0.008
NLMS Parameter	μ=0.008, δ=0.0001
RLS Parameter	λ=.99, δ=0.004
Spreading Code	Walsh-Hadamard

In Fig. 5 shows the filtered output signal of BPSK modulation where considering the SNR value at 3dB and the BER values of RLS is 0.01, NLMS 0.01 and LMS approximately 0.03. The system achieves a gain of 3dB in RLS and NLMS as compared to LMS.

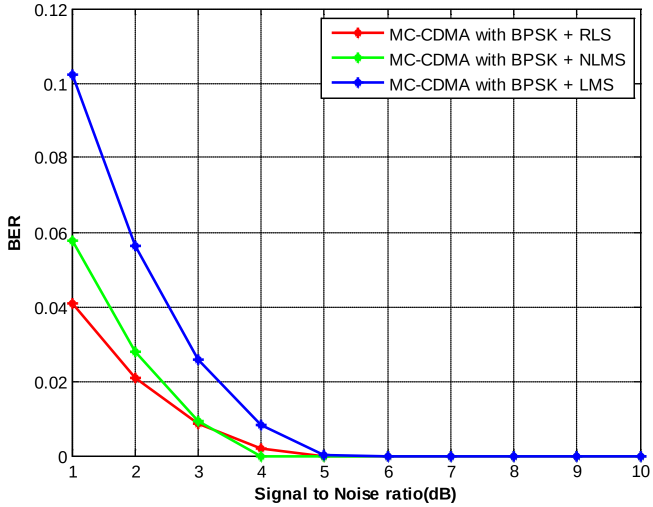

Fig. 5. Comparative analysis of BER vs SNR for MC-CDMA system under implementation of BPSK modulation schemes with LMS, NLMS and RLS channel equalization methods.

In Fig. 6 shows the results of DPSK modulation where considering the SNR value at 3dB and the BER values of RLS is 0.09, NLMS 0.095 and LMS approximately 0.1 which is increasing than using BPSK modulation scheme. Here it is also seen that the system achieves a gain of 1.06 dB in RLS as compared to NLMS and also 1.11dB in RLS as compared to LMS at SNR value of 3dB.

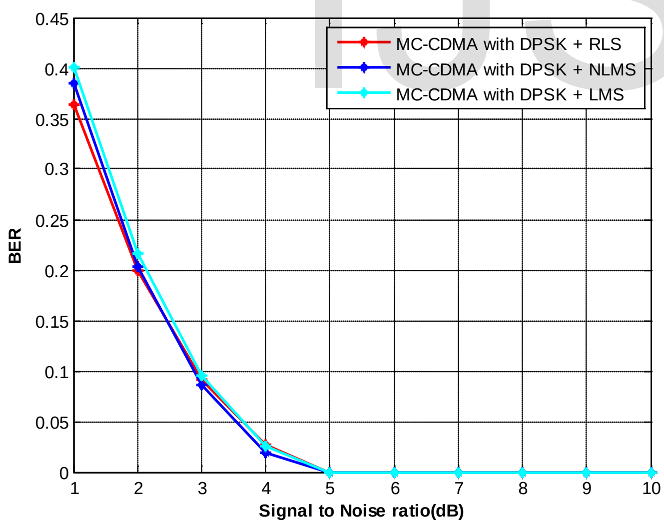

Fig. 6. Comparative analysis of BER vs SNR for MC-CDMA system under implementation of DPSK modulation schemes with LMS, NLMS and RLS channel equalization methods.

In Fig. 7 presented the results of QPSK modulation where at the same SNR value (3dB), the BER perfromance of RLS is 0.23, NLMS 0.25 and LMS approximately 0.27 which shows the bit error rate is increased than using BPSK and DPSK modulation scheme.

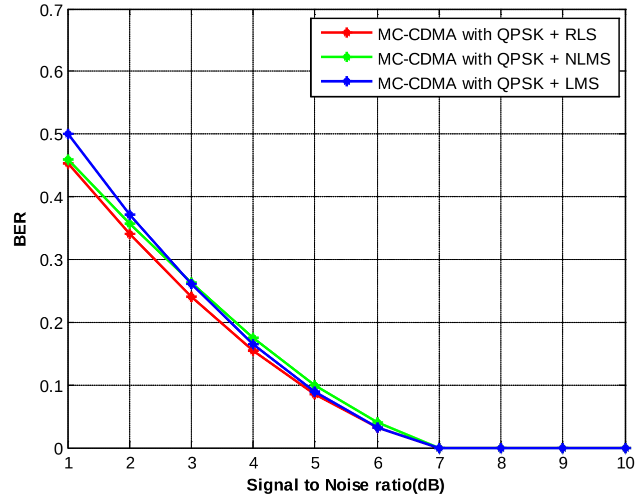

Fig. 7. Comparative analysis of BER vs SNR for MC-CDMA system under implementation of QPSK modulation schemes with LMS, NLMS and RLS channel equalization methods.

In Fig. 8 used to analyze the comparative analysis of BER versus SNR, the BER value of RLS is 0.13, NLMS and LMS is 0.14 at 3dB SNR value respectively.

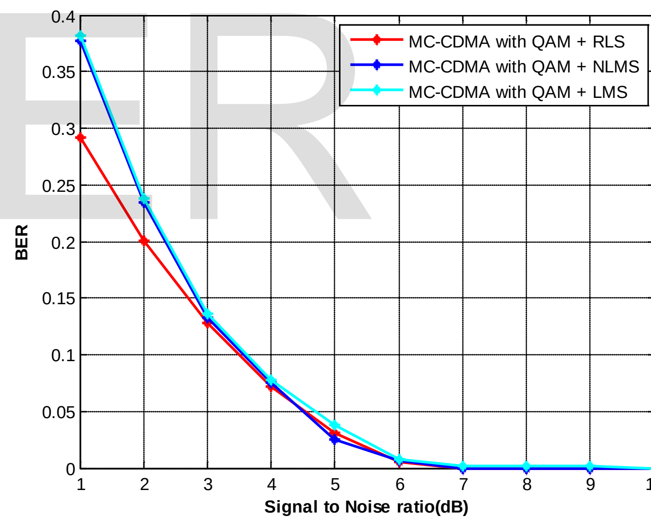

Fig. 8. Comparative analysis of BER vs SNR for MC-CDMA system under implementation of QAM modulation schemes with LMS, NLMS and RLS channel equalization methods.

In Fig. 5 through Fig. 8 shows that RLS provides best result among three equalization techniques with four digital modulation techniques individually. In Figure 5, it is observable that at very low SNR value area, the system performance is comparatively better under deployment of the Recursive Least Square (RLS) channel equalization scheme with BPSK modulation scheme. It is also observable that with increase in SNR values, the bit error rate has reached to zero.

The Bit Error Rate (BER) calculation in four different modulation techniques BPSK, DPSK, QPSK and QAM at SNR value of 3dB with three channel equalization techniques LMS, NLMS and RLS is shown in Fig. 9. It is clear to see this analysis RLS method shows the best performance in every modulation schemes [31].

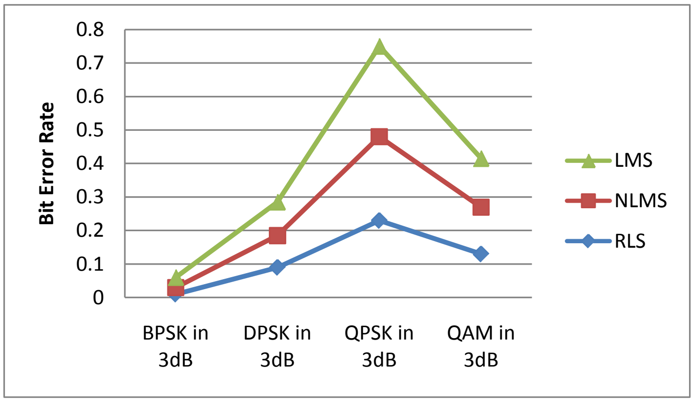

Fig. 9. BER analysis of LMS, NLMS and RLS with four different modulation techniques at SNR value of 3dB

5 Conclusion

In this study, the performance of the MC-CDMA system has been investigated and its analytical BER performance has been derived. A range of system performance results highlights the impact of digital modulations under three channel equalization techniques. A comparison on the adaptive filtering algorithms (LMS, NLMS & RLS) has been made based on their bit error rates and signal-to-noise ratio.

It is expected that we have contributed to a good comaparision of MC-CDMA with related modulation schemes. The experimental results indicate that BPSK-modulated MC-CDMA wireless communication system with RLS channel equalization technique provides satisfactory result in comparison with NLMS and LMS for such a MC-CDMA wireless communication system.

The present work can be extended in beyond 4G technologies to ensure high data rate transmission with implementation of powerful channel equalization scheme such as MG-LMS, GLMS, etc.

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