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# Improving Channel Capacity of Code Division Multiplexing Access Cellular Network Using Modified Least Means Square Adaptive

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**Abstract**
*There are various challenges in adaptive antenna beamforming such as increase in bit error rate (BER) and channel degradation. These can be minimized or improved by using various techniques. This paper enumerates the achievements and challenges of the traditional least mean square (LMS) algorithm for adaptive antenna system and developed a novel LMS algorithm which achieved BER reduction through the manipulation and introduction of phi in the desired signal model. This results in algorithm that is less sensitive to noise with weak autocorrelation and fast convergence, high time-varying tracking accuracy and small steady-state error. The simulation results show that the developed modified least mean square (MLMS) algorithm outperformed the traditional LMS algorithm with fixed step size in convergence speed, tracking accuracy and noise suppression. The MLMS algorithm produced lowest Bit Error Rate of 0.004142 which is very low compared to the measured Bit Error Rate result of 0.125 in LMS and other enumerated algorithms. The Modified Least Mean Square algorithm also offers performance improvement of 98.95% over existing Least Means Square algorithm.*

***Keywords:*** *Adaptive, Beamforming, Cellular, Algorithm, Modified least mean square*

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## 1. Introduction

Some major drawbacks of the cellular network environment are the issues of limited bandwidth and associated network impairments due to insufficient channels. Since the available broadcast spectrum is limited, attempts to increase traffic within a fixed bandwidth create more interference in the system and degrade the signal quality. These challenges necessitate the need for cellular operators to find new ways of increasing the capacity of their networks. Adaptive antenna technology offers significantly improved solution to reduced interference level and network channel capacity. The adaptive antenna is equipped with smart signal processing algorithms for identification of signal signature such as the direction of arrival (DOA) of the signal and calculation of beamforming vectors. This is then used to track and locate the antenna beam on the mobile target. To minimize interference from different directions, Adaptive Antenna can be used at the receiver to form the beam (beamforming) in the direction of the multipath and reject signals from interferers. In beamforming, each user signal is multiplied with complex weights that adjust the magnitude and phase of each signal to and from each antenna (Imo et al., 2020).

The adaptive antenna system, however, cannot effectively address some of the problems affecting the general performance and channel capacity of the cellular network due to its slow convergence problem on the Least Mean Square (LMS) algorithm which determines the function of the adaptive antenna technology. This limitation of the adaptive antenna is primarily due to the fact that the LMS algorithm applied for the signal processing to achieve performance improvement of the network uses single variable, the adaptive weight variable (Nwabueze and Ibegbunam, 2016). To address this issue, the adaptive antenna was studied and the LMS algorithm modified to obtain an improved algorithm based on two dependent variables $w_0$ and phi instead of the adaptive weight variable ($w_0$) alone for Bit Error Rate (BER) level reduction, which improved the performance of the network and also increases the channel capacity.

## 2. Beamforming algorithms

### 2.1 Least mean square (LMS) algorithm

In the adaptive smart antenna system as demonstrated in Fig. 1, the adaptive antenna system receives the incoming signal x(t), and the input signal is multiplied with weight factor W, which basically modifies the phase and amplitude of incoming signal x(t). The modified weighted signals are added together to give the output signal y(t).

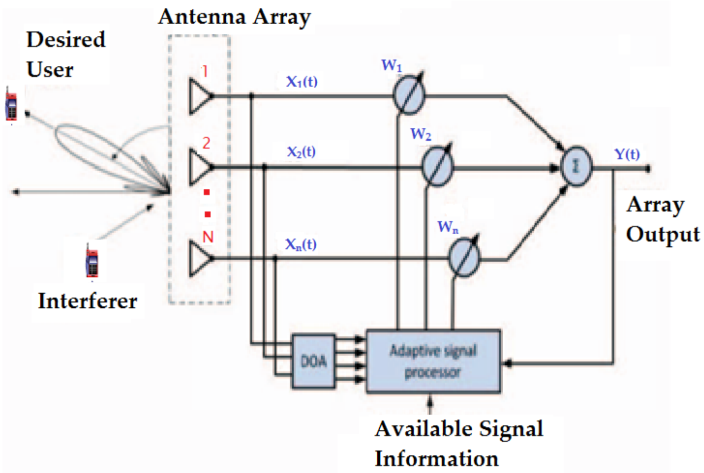


**Fig. 1:** Block diagram of smart antenna (Ashwim and Khyati, 2018)

The least mean squares algorithm is a gradient based approach. Gradient based algorithms assume an established quadratic performance surface. When the performance surface is a quadratic function of the array weights, the performance surface *J*(*w*) is in the shape of an elliptic paraboloid having one minimum. One of the best ways to establish the minimum is through the use of a gradient method. The performance surface (cost function) can be established by finding the mean square error (MSE). The error is indicated in Equation (1) as (Griffiths, 1996):

$$e(k) = d(k) - y(k) \quad (1)$$

where $y(k) = w^H x(k)$, *and* ∴ $e(k) = d(k) - w^H x(k)$ (2)

Squaring the error gives

$$|e(k)|^2 = |d(k) - w^H x(k)|^2 \quad (3)$$

Expanding the squared error gives

$$|e(k)|^2 = |d(k)|^2 - 2d(k)\, w^H\, x(k) + w^H\, x(k)\, x^H(k)\, w \quad (4)$$

Simplifying Equation (4) gives:

$$E[|e(k)|^2] = E[|d(k)|^2] + w^H(k) R_{xx} w(k) - 2w^H(k) r \quad (5)$$

In terms of the cost function, Equation (5) becomes

$$J(w) = D - 2w^H r + w^H R_{xx} w \quad (6)$$

where $D = E[|d(k)|^2]$

and employing the gradient method to locate the minimum gives

$$\nabla w(J(w)) = 2R_{xx} w - 2r \quad (7)$$

The minimum occurs when the gradient is zero. Thus, the solution for the weights which is the optimum Wiener solution (w or $w_{opt}$) is given by:

$0 = 2R_{xx} w - 2r$ hence,

$$w = w_{opt} = R_{xx}^{-1} r \quad (8)$$

The solution in Equation (8) is predicated on knowledge of all signal statistics and thus in the calculation of the correlation matrix. In general, the signal statistics is not known and thus the resort to estimating the array correlation matrix ($\bar{R}_{xx}$) and the signal correlation vector ($\bar{r}$) over a range of snapshots or for each instant in time (Ram and Rajesh, 2010). The instantaneous estimates of these values are given as:

$$\bar{R}_{xx}(k) \approx x(k) x^H(k) \quad (9)$$

and

$$\bar{r} \approx d^*(k) x(k) \quad (10)$$

The LMS algorithm can also employ an iterative technique called the method of steepest descent to approximate the gradient of the cost function. The direction of steepest descent is in the opposite direction as the gradient vector. This method recursively computes and updates the sensor array weights vector ($w$). It is intuitively reasonable that successive corrections to the weights vector in the direction of the negative of the gradient vector should eventually lead to minimum mean square error (MMSE), at which point the weights vector assumes its optimum value. The method of steepest descent can be approximated in terms of the weights using the LMS method. The steepest descent iterative approximation is given as:

$$w(k+1) = w(k) - \frac{1}{2}\mu \nabla w\, (J(w(k))) \qquad (11)$$

where, $\mu$ is the step size parameter and $\nabla w$ is the gradient of the performance surface. The gradient of the performance surface is given in Equation (11). Substituting the instantaneous correlation approximations, the LMS solution will be:

$$w(k+1) = w(k) - \mu\, [\bar{R}_{xx}\, w - \bar{r}\,] \qquad (12)$$

$$= w(k) + \mu\, [\bar{r} - \bar{R}_{xx}\, w]$$

$$= w(k) + \mu\, e^*(k)\, x(k) \qquad (13)$$

where $e(k) = d(k) - w^H(k)x(k)$ = error signal, $d(k)$ is the desired signal at the receiver which is equal to the transmitted signal and $w(k+1)$ denotes the weights vector to be computed at iteration $(k+1)$. LMS gradient step size controls the convergence characteristics of the algorithm, that is how fast and close the estimated weights approach the optimal weights. The smaller the step size the longer it takes the LMS algorithm to converge. This means that a longer reference or training sequence is needed, which would reduce the payload and subsequently the bandwidth available for transmitting data. Also, if the step size is too small, the convergence is slow leading to an overdamped case. If the convergence is slower than the changing angles of arrival, it is possible that the adaptive array cannot acquire the signal of interest fast enough to track the changing signal. If the step size is too large, the LMS algorithm will overshoot the optimum weights of interest. This is called the underdamped case. If attempted convergence is too fast, the weights will oscillate about the optimum weights but will not accurately track the solution desired. It is therefore imperative to choose a step size in a range that insures convergence. In order to ensure the stability and convergence of the algorithm, the adaptive step size should be chosen within the range specified as:

$$0 < \mu < \frac{1}{2\lambda_{\max}} \qquad (14)$$

where $\lambda_{\max}$ is the maximum eigenvalue of the input covariance matrix $R_{xx}$.

The LMS algorithm requires knowledge of the desired signal $d(k)$. This can be done in a digital system by periodically transmitting a training sequence that is known to the receiver, or by using the spreading code in the case of a direct-sequence CDMA system. The least mean square (LMS) algorithm is important because of its simplicity and ease of computation and because it does not require off-line gradient estimations or repetition of data. If the adaptive system is an adaptive linear combiner and if the input vector and desired response are available at different iterations, the LMS algorithm is generally the best choice for many different applications of adaptive signal processing (Twinkle, 2011). Errors between reference signal and array output have been calculated using standard methods. In RLS (recursive least square) algorithm, µ from LMS is replaced by gain matrix, weight vector and error signal are calculated using standard methods. The flow chart for implementing LMS algorithm is shown in Fig. 2.

The computational procedure for the LMS is summarized in four steps as follows:

1) Initially set each weight, $W_m(k)$ for m=1, 2, … M to an arbitrary fixed value, such as 0; $W_m(k)=0$
2) Compute the beam former output: Y (k) =$\sum W_m$ (k) X (k)
3) Compute the error estimate: e(k)=d*(k)-Y(k)
4) Update the next weights.

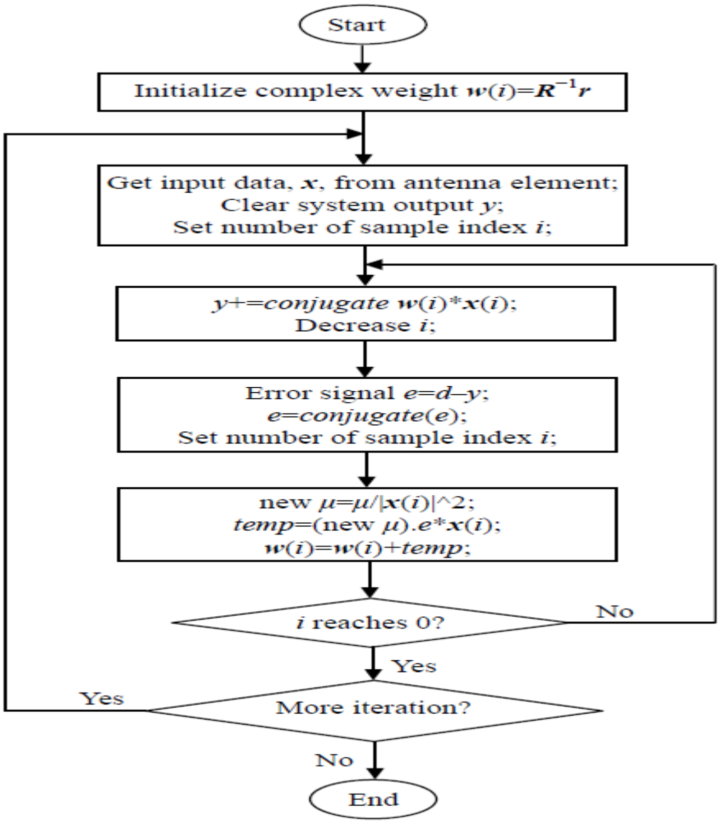


**Fig. 2:** Flow chart diagram for implementing LMS algorithm (Griffith, 1996)

### 2.2 Direct matrix inverse (DMI) algorithm

One of the drawbacks of the LMS adaptive scheme is that the algorithm must go through many iterations before satisfactory convergence is achieved. If the signal characteristics are rapidly changing, the LMS adaptive algorithm may not allow tracking of the desired signal in a satisfactory manner. The rate of convergence of the weights is dictated by the eigenvalue spread of the array correlation matrix (Prachi et al., 2014). One possible approach to circumventing the relatively slow convergence of the LMS scheme is the sample matrix inverse (SMI) algorithm method. The sample matrix is a time average estimate of the array correlation matrix using *K*-time samples. This algorithm is used to obtain the weights, but with $R_{xx}$ and $r$ estimated from data sampled over a finite interval (over k samples). If a prior information about the desired and the interfering signals is known, then the optimum weights can be calculated directly by using the Weiner solution (Bin-Saeed and Zerguine, 2013):

$$w_{opt} = R_{xx}^{-1} r \tag{15}$$

In practice, signals are not known, and the signal environment keeps changing. Therefore, optimal weights can be computed by obtaining the estimates of the covariance matrix $R_{xx}$ and the correlation matrix $r$, by time averaging from the block of input data.

The correlation matrix and vector can be estimated by calculating the time average such that:

$$\bar{R}_{xx} = \frac{1}{K}\sum_{i=1}^{K} x(k)x^{H}(k) \tag{16}$$

and $$\bar{r} = \frac{1}{K}\sum_{i=1}^{K} d^{*}(k)x(k) \tag{17}$$

### 2.3 Recursive least square (RLS) algorithm

Even though the SMI method is faster than the LMS algorithm, the computational burden and potential singularities can cause problems. However, it is possible to recursively calculate the required correlation matrix and the required correlation vector. Since the signal sources can change or slowly move with time, RLS algorithms tend to deemphasize the earliest data samples and emphasize the most recent ones i.e. forgetting the earliest time samples. The RLS algorithm estimates $\bar{R}_{xx}$ and $\bar{r}$ using weighted sums so that:

$$\overline{R}_{xx} = \sum_{i=1}^{N} \gamma^{n-1} x(k) x^H(k) \quad (18)$$

and

$$\overline{r} = \sum_{i=1}^{N} \gamma^{n-1} d^*(k) x(k) \quad (19)$$

where the scalar $0 < \gamma < 1$ and $\gamma$ is the forgetting factor. The forgetting factor is also sometimes referred to as the exponential weighting factor. In recursive least-square (RLS) algorithm, the weights are updated by Equation (20) (Gurpreet and Gurmet, 2014):

$$w(k) = R^{-1}{}_{xx}(k) r(k) = \gamma\ R^{-1}{}_{xx}(k) r(k-1) + R^{-1}{}_{xx}(k) x(k) d^*(k) \quad (20)$$

Simplifying the equation further results in:

$$w(k) = w(k-1) + q(k)[d^*(k) - w^H(k-1)x(k)],\ n = 1,2,\ldots.. \quad (21)$$

where

$$q(k) = \text{gain} = \frac{\gamma^{-1} R_{xx}{}^{-1}(k-1)x(k)}{[1 + \{\gamma^{-1} x^H(k) R_{xx}{}^{-1}(k-1)x(k)\}]} \quad (22)$$

and

$$R_{xx}{}^{-1}(k) = \gamma^{-1}[R_{xx}{}^{-1}(k-1) - q(k)x(k)R_{xx}{}^{-1}(k-1)] \quad (23)$$

This algorithm was chosen for its fast convergence rate and ability to process the input signal before demodulation. While the first reason is important especially when the environment is changing rapidly, the later reason decreases the algorithm dependency on a specific air interface (Yasin et al., 2010). The recursive least square (RLS) algorithm does not require any matrix inversion computations. It requires reference signal and correlation matrix information i.e. it requires an initial estimate of $R_{xx}{}^{-1}$ and a reference signal. An important feature of the recursive least square algorithm is that its rate of convergence is typically an order of magnitude faster than that of the simple least mean square algorithm, due to the fact that recursive least square algorithm whiten the input data by using the inverse correlation matrix of the data, assumed to be zero mean. This improvement however is achieved at the expense of an increase in computational complexity of the recursive least square algorithm (Alok et al., 2012).

## 3. The modified least mean square (MLMS) algorithm

In the adaptive smart antenna system as demonstrated in Fig. 3, the actual output signal y(n) of the antenna is compared with a desired output or reference input to generate a cost function also known as error. In practice, the input delayed signal contains noise signals with other interfering signals. These interfering signals cause degradation or reduction of the quality of received signal naturally. As a result, this causes the cost function to be very high and reduce the performance of the smart antenna final output. In order to improve the antenna output performance, it is required that the error be minimized as much as possible.

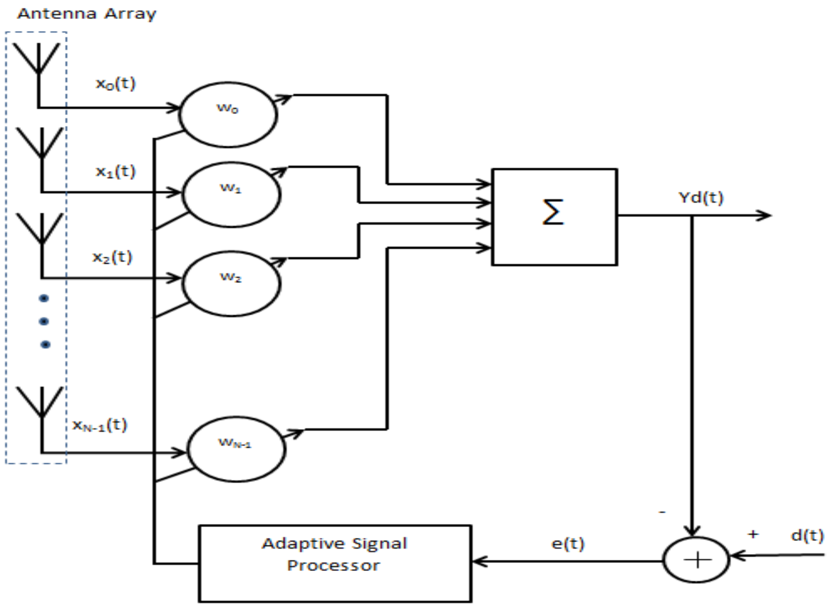


**Fig. 3:** Block diagram of adaptive antenna for MLMS algorithm

The modification of the LMS algorithm for the network performance which is centered on BER reduction was achieved in this work with the introduction and manipulation of phi in the desired signal model. This scenario is demonstrated in the flow chart of Fig, 4 for the modified LMS algorithm adaptive antenna system. The initial weight function of adaptive antenna and phi at the desired signal were manipulated to start iteration at the beginning of the computation of the LMS program for an experiment. This was repeated until a desired system performance was achieved.

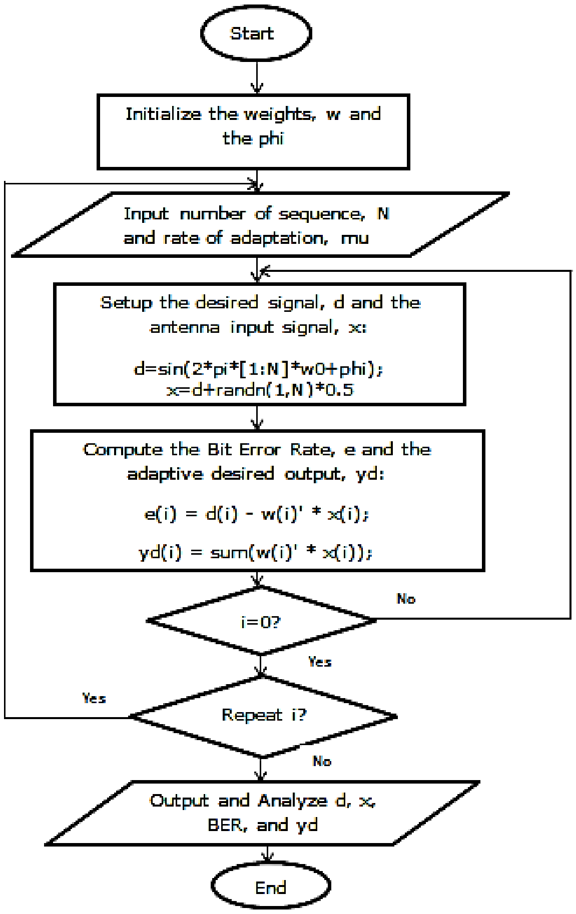


**Fig. 4:** Flowchart of the BER improvement

## 4. Results and discussion

### 4.1 Bit error rate performance analysis of simple adaptive antenna array

Fig 5 shows a graphical representation of the Bit Error Rate performance of simple adaptive antenna array based on LMS algorithm. Analysis of the graphical representation shows that the bit error rate varies rapidly with increase in the number of connections. Since the performance of the network is determined by the bit error rate, the continuous change in bit error rate will have negative effect on the general performance of the network. The variation in bit error rate with respect to the number of connections results in degradation in the network throughput with significant drop in network channel utilization.

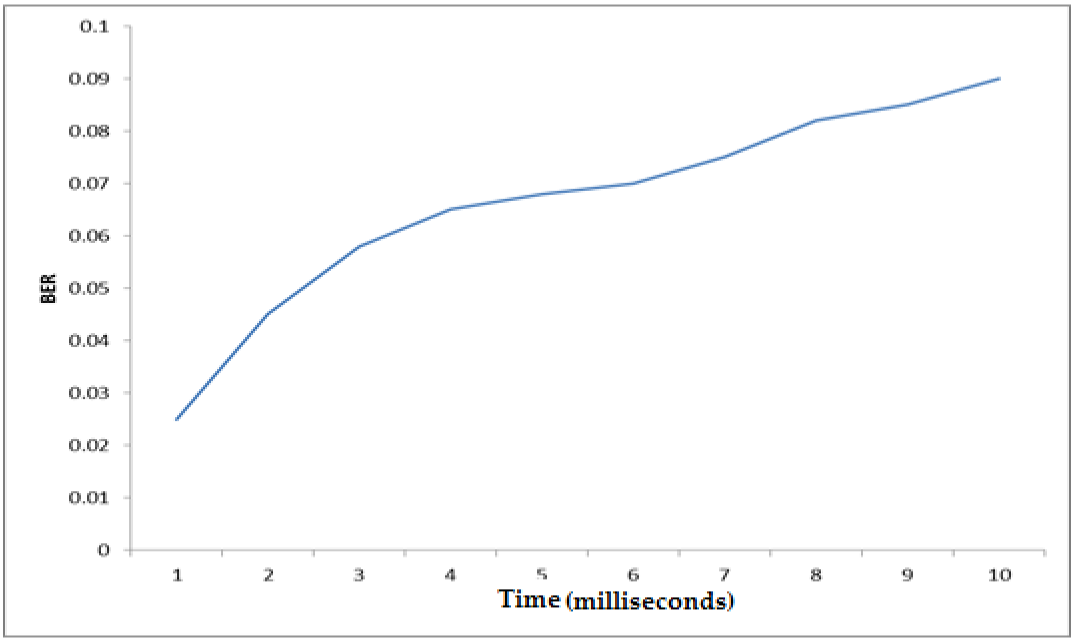


**Fig. 5:** Bit error rate performance analysis of simple adaptive antenna array using LMS algorithm

### 4.2 Bit error rate performance analysis based on MLMS adaptive algorithm

Fig. 6 illustrates a graphical representation of the Bit Error Rate performance analysis of adaptive antenna based on the MLMS algorithm using two adaptive variables of w0 and phi. To achieve the desired BER improvement, the number of sequence N and the rate of adaptation mu, were kept constant and the values of w0 and phi were varied. The number of sequence N, for the iteration was chosen arbitrarily and the rate of adaptation mu, was chosen from the range (0<mu<1). N=11, mu=0.01. The result shown in Figure 6 demonstrates the behaviour of the output of the adaptive antenna system based on the BER level reduction when initial weight and phi are 0.0001 and 0.0001 respectively. The least Bit Error Rate level achieved is 0.0004142 which means that the system performance improved significantly. This shows that the performance of the network system has improved more significantly with more reduced bit error rate. This indicates that the network speed will also improve, and the network channel utilization will also improve due to the reduced bit error rate. This will solve the problem of network congestion because the speed of data processing and transfer will be significantly increased to enhance the network throughput. Significant improvement was achieved with more change in the phi while keeping the initial weight of the adaptive antenna constant at 0.0001. This means that the introduction of more variables in the adaptive antenna algorithm achieved more bit error rate reduction and therefore, achieves better network performance and will also improve general network throughput. The change in the phi variable achieved more bit error rate reduction than the change in the weighting factors of the adaptive antenna array system.

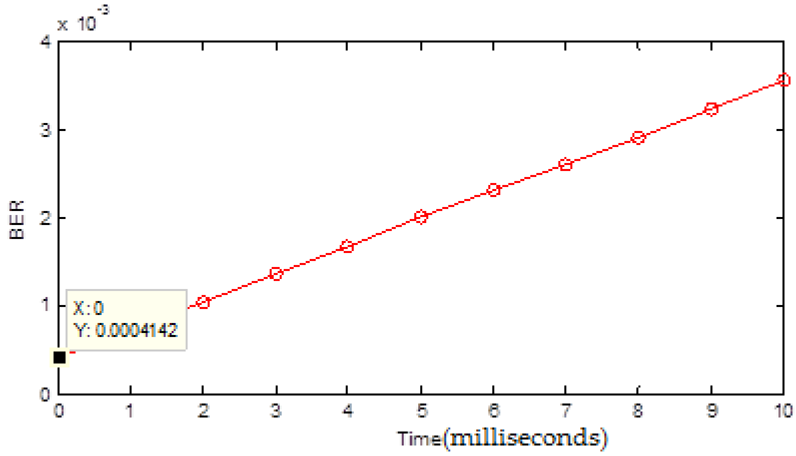


**Fig. 6:** Bit error rate graph when w0=0.0001 and phi=0.0001

## 5. Conclusions

The modified Least Mean Square Adaptive Antenna model is a proven method for Bit Error Rate and interference reduction and channel capacity improvement of cellular network system. The performance of the Modified Least Mean Square based Adaptive Antenna Array was compared with that of the Least Mean Square Adaptive Algorithm. The simulation results demonstrate that the Modified Least Mean Square has better performance and reduced bit error rate. The BER results obtained confirmed the effectiveness of the proposed modified LMS Adaptive antenna model. It can therefore be inferred that there is significant cellular network performance improvement using Modified Least Mean Square algorithm.

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