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An Optimal Filter to Reduce BER Utilizing RLS and Firefly

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Abstract*: Data communication network suffers due to symbol interference and un-optimized channel response. In recent years faster communication architectures like OFDM were designed to transmit the data as fast as and compatible with modern day communication devices. In order to utilize the channel efficiently, data should be filtered and precise. Swarm Intelligence based recursive least square algorithm has been developed utilizing Extended Firefly Algorithm for the geometric transformation of the data. The optimized filtered data has been cross-verified using Support Vector Machine approach. The permutation matrix of proposed work has been compared with results obtained using Kalman filtering. Results demonstrate that if a filter is designed significantly relative to the single objective function of the optimization algorithm, it generates quite good estimates. The performance of the proposed structure is evaluated using Bit Error Rate and Average Logarithmic Error measures

***Index Terms*: Data Communication, OFDM, RLS, SVM, SI**

I. INTRODUCTION

The Recursive Least Squares (RLS) algorithm is a well-known algorithm for adaptive filtering. It is an adaptive filtering algorithm that recursively determines the coefficient which reduces a "weighted linear least square cost function" according to the input data. Generally, the RLS algorithm can be utilized to resolve the problem that can be solved by the adaptive filter. For example, a signal $e(n)$ is transmitted over a noisy channel and the received noisy signal is written by the equation below:

$$y(n) = \sum_{l=0}^{r} b_n(l)e(n-l) + w(n) \quad (1)$$

As shown in equation (1), w (n) signifies the adaptive noise. The main goal of the RLS filter is to find the wanted signal e(n) with the help of q+1 tap filter.

$$e(n) \approx \sum_{l=0}^{q} T(l)\, y(n-l) = x^T y_n \quad (2)$$

where $y_n = [y(n)y(n-1) \dots y(n-q)]^T$ represents the column vector that consists of most common sample $q+1$ of $y(n)$ and x=[T(0) T(1) ... T(q)]T. The approximate value of the recovered wanted signal is represented by:

$$\hat{e}(n) = \sum_{l=0}^{q} x_n(l)y(n-l) = x_n^T y_n \quad (3)$$

The aim is to compute the filter parameter x, and at every n time the present estimate is represented by x_n, whereas the "adaptive least square value is given by x_{n+1}. Here, x_n^T is the row vector, $x_n^T y_n$ represents the matrix product and $\hat{e}(n)$ represents the estimated value at every instant n. The main advantage of using RLS algorithm is that it is optimal in second-order statistics and does not require any matrix inversion and hence save computation cost. The main aim of the RLS filter is to decrease a cost function by choosing the appropriate value of the filter coefficient x_n and then modify the filter as per the new signal. The generated error signal error (n) and the wanted signal e (n) are shown in Fig.1.

The error value error (n) = $e(n) - \hat{e}(n)$ depends upon the filter coefficient via the estimate $\hat{e}(n)$. The cost function depends upon the coefficient of the filter is given by:

$$f_c(x_n) = \sum_{i=0}^{n} \lambda^{n-i}\, \mathrm{error}^2(i) \quad (4)$$

Here, the value of λ lies between 0 and 1 and it is known as the forgetting factor. The minimization of the cost function can be obtained by taking the partial derivative for the entire l entries with x_n as a coefficient vector and hence reducing the results to zero value.

$$\frac{\partial C(x_n)}{\partial w_n(l)} = \sum_{i=0}^{n} 2\lambda^{n-i}\, \mathrm{error}(i)\frac{\partial \mathrm{error}(i)}{\partial x_n(l)} = -\sum_{i=0}^{n} 2\lambda^{n-i}\, \mathrm{error}(i)y(i-l) = 0 \qquad l = 0,1,\cdots,q \quad (5)$$

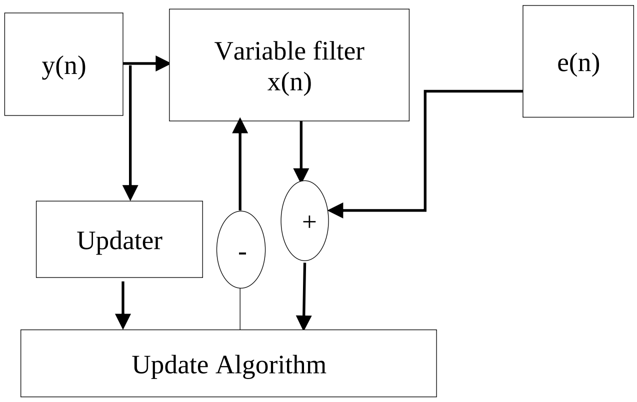

Fig.1 RLS filter with Negative feedback

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Now, replace the error (n) with the definition of the error signal as written below

$$\sum_{i=0}^{n} \lambda^{n-i} \left[e(i) - \sum_{l=0}^{p} x_n(l)\, y(i-m)\right] y(i-l) = 0 \quad l = 0,1,\cdots,q \tag{6}$$

The above equation can be represented in the matrices form as written below:

$$S_y(n)x_n = s_{ey}(n) \tag{7}$$

Here, $S_y(n)$ defines the weighted sample covariance matrix for y(n), $s_{ey}(n)$ represents the identical approximate value for the cross co-variance between $e(n)$and $y(n)$. On the basis of the above equations the cost function that can be reduced is determined by the following equation written below:

$$x_n = S_y^{-1}(n)s_{ey}(n) \tag{8}$$

A. Channel Modeling

The main aim of the equalizer is to reconstruct the originally transmitted data at the receiver from received data that is corrupted. The output of the channel is modified as compared to the transmitted input. To remove the effect of the channel we generally use an equalizer at the output end to estimate the input from this received output of the channel. Kalman filter is an optimal recursive data processing algorithm which produces estimates of the true values by predicting a value, estimating the uncertainty of the predicted value and computing a weighted average of the predicted values and the measured value. The estimates produced by the method tend to be close to the true values than the original measurements [4-6].

B. Filters for channel equalization

The categorization of filters in channel equalization is into four types, as defined below:

a. Chebyshev Filter

Chebyshev active filter is also called equal ripple filter. It provides a sharper cutoff than the Butterworth filter in the passband as shown Fig.2. Both Chebyshev and Butterworth filters exhibit large phase shifts close to the cutoff frequency. A disadvantage of the Chebyshev filter is that it is outside the minimum and maximum values of the gain below the cutoff frequency.

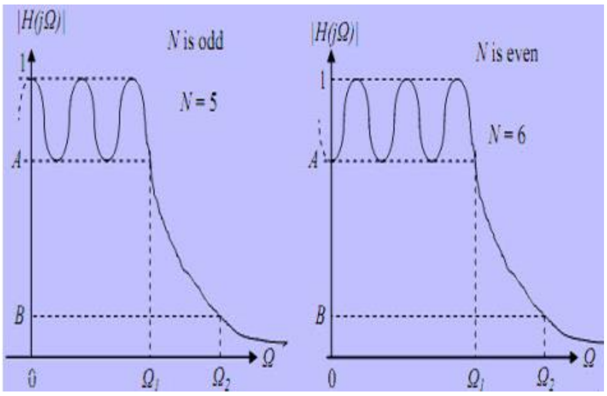

Fig.2 Chebyshev Filter

Adjustable parameters in filter design; gain ripple is expressed in dB. Implementing these filters will significantly reduce roll-off, but because of the ripple in the passband, it is not used in audio systems. However, it is much better for applications that have only one available frequency within the passband, but many other frequencies are required to remove them.

b. Butterworth Active Filter

Butterworth active filters are also called flat filters. The implementation of Butterworth active filter ensures a flat response and sufficient roll-off within the passband.

This filter contains a nearly flat amplitude and frequency response up to the cutoff frequency. The roughness of the cutoff is shown in Fig.3. It is well known that all three filters achieve roll-off angles of - 40 dB / decade at much higher frequencies than the cutoff. This filter has characteristics of Chebyshev filter and Bessel filter somewhere. It has sensible rolloff of the skirt and a slightly nonlinear phase response. This type of filter is very easy to understand and is ideal for audio processing applications.

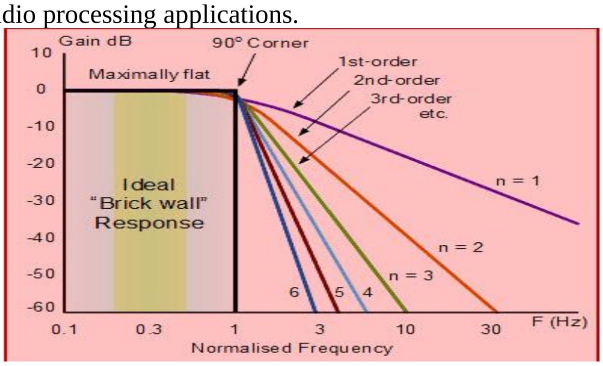

Fig.3 Butterworth Filter

c. Bessel Filter

The Bessel filter gives an ideal phase characteristic with a nearly linear phase response up to the cutoff frequency. Nonetheless, it contains a very linear phase response, but it includes a very gentle skirt slope. The purpose of this filter is where phase characteristics are important. The cutoff characteristic is not that intelligent, but it is a small phase shift. The Bessel filter shows stable propagation delay over the I/P frequency spectrum. Therefore, applying a square wave to the input of the filter yields a square wave that does not exceed O/P. It is clear that this is beyond the O/P waveform.

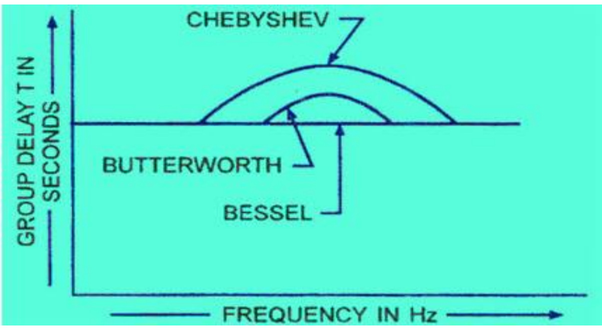

Fig.4 Bessel Filter

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d. Elliptical Filter

Elliptic filters are much more complex filters like Chebyshev. This includes significant roll off at the expense of passband ripple and stopband ripple. This filter has roll off of all filters in the transform domain, but it has regions of both stopband and passband. This filter can be designed to pay particular attention to specific frequencies within the stopband, thereby reducing further frequency attenuation within the stopband.

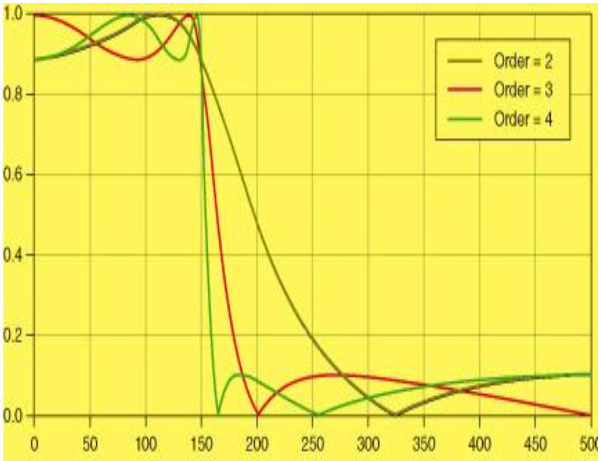

Fig.5 Elliptical Filter

C. Equalization for Stationary Channel

A discrete time filter with Additive White Gaussian Noise (AWGN) and the output of the channel z(n) with noise v(n) can be written as,

$$z(n) = C^T e(n) + v(n) \tag{9}$$

As shown in equation (9), $C = [c_0, c_1, \dots c_{M-1}]^T$ is the channel coefficients, subscript T denotes transpose and input signal vector is given by

$$e(n) = [e(n), e(n-1), \dots\dots, e(n-M+1) \tag{10}$$

If we want to represent this transversal filter into state space equations then we can consider the time delayed input as states. By considering the time delayed input as state variables, the state space model of the channel can be obtained by [16-20].

$$X(n+1) = AX(n) + Be(n) + w(n) \tag{11}$$

$$z(n) = C^T X(n) + v(n) \tag{12}$$

As shown, $X(n) = [x(n), x(n-1), \dots, (x(n-M+1)]^T$ are the state variables of the state model, w(n) is the process noise and v(n) is the measurement noise. The state transfer, input and output matrices are:

$$A = \begin{bmatrix} 0 & \cdots & \cdots & \cdots & 0 \\ 1 & 0 & \cdots & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & \cdots & 1 & 0 \end{bmatrix}, B = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ \vdots \\ 0 \end{bmatrix} \tag{13}$$

$$C = [c_0, c_1, \dots c_{M-1}]^T \tag{14}$$

Since at the receiving end the actual state is unknown and actual input so we will model a filter where input, as well as original states, are estimated. The estimated input and estimated states equations are represented as:

$$\hat{X}(n+1) = A\hat{X}(n) + B\hat{e}(n) \tag{15}$$

$$Z^n = C^T X^n \tag{16}$$

D. Equalizer for Non-Stationary Channel

The system for a time-invariant channel whose coefficients C are known is considered first. But in practical cases, most of the channel is time-varying. So to implement such channels in the above scheme it is required to estimate the channel coefficients $C = \hat{C}(n)$

$$Z^n = \hat{C}^T X^n \tag{17}$$

This estimated output Z^n is compared with actual output z(n) and the estimated states are updated by equation

$$X^{n+1} = X^n + K[z(n) - Z^n] \tag{18}$$

As shown in equation (18), K is the Kalman gains which guarantee the minimization of error. To estimate the channel a known input sequence at the receiving end is required. So the two modes are used i.e. training and decision directed mode. To implement the training mode a finite training sequence is transmitted from the input, which is also known at receiving end. The system parameters are compensated in training mode. The frequent training may lead to the interruption in the communication; therefore, the system mainly operates in decision directed mode in when during actual transmission and receiving information the updating of the filter coefficients takes place. In the decision directed mode, the output of slicer is used as input for the adaptive filter. We are already using e(n) and $\hat{e}(n)$as input for training and decision directed mode to adaptive filter at the receiving end. The similar input can be provided to Kalman i.e. in decision directed mode $\hat{e}(n) =$ Sliceroutput whereas in training mode $\hat{e}(n) = e(n)$. This input choice will work better in this case rather than using the mean value of the actual signal as input.

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II. RELATED WORK

Morteza Esfandyari et al. (2016) has utilized an Adaptive Neuro-Fuzzy Inference System or Adaptive-Network-Based Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN) for the microbial fuel cell. The performance has been contrasted with the proposed mechanism of ANFIS and ANN with Average Relative Error (ARE), Standard Deviation (SD), Correlation Coefficients (R2) and Average Absolute Relative Error (AARE) values. Better regression observations have been shown by developed ANFIS and ANN in R2 with the 0.98 to 1 range. The resulted outcome has demonstrated that ANFIS and ANN could be utilized for the prediction of CE of MFC and power density on the basis of initial pH, ionic strength, temperature, and medium nitrogen concentration.

M. Mirahmadi et al. (2013) has proposed an effective method to mitigate the server Bit Error rate (BER) performance degradation by Impulsive Noise (IN) with multiple fading in the system of broadcast transmission. The proposed mechanism is dependent on the process of low complexity interleaving and Inverse Fast Fourier Transform (IFFT) in Orthogonal Frequency Division Multiplexing (OFDM), though it is considered as Time Domain Interleaving (TDI). The proposed TDI mechanism has introduced frequency and time diversity with an amalgamation of frequency and IN selective fading. TDI never degrades the spectral effectiveness and has less computational complexity. With frequency selective fading channels, the BER for proposed mechanism is equivalent to Wash Hadamard pre-coded OFDM system. With IN, the simulation outcome has depicted that TDI has lessened the error floor level. TDI has achieved BER for 10-5 for less than 1dB distinction from IN-free case

Shaoen Wu et al. (2014) has provided a decisive investigation for current development in VLC research that could be utilized as a 5G wireless communication system. The research has enlightened the weakness and strengths of VLC in contrast with RF-based communication in spatial reuse, spectrum, energy efficiency, and security. The research has also examined varied lighting sources for VLC systems. Literature has been provided on the basis of mobile VLC communication and fixed VLC communication.

Shao-Wei Wang et al. (2015) has demonstrated high-performance blue filter and has employed for the increment in modulation bandwidth and has to lessen the BER for white LED on the basis of the VLC system. It consists of high transmittance passband, wide stopband with a range of 500 to 1050 nm with a precise and sharp cut off edge. The proposed work not only removes the slow phosphorescent component from modulated signals and even efficiently refuses the ambient solar radiation. In the interim, the blue light signals of LED could be retained almost. It results in high SNR and has enhanced the VLC system performance with enhancement in modulation bandwidth and lessens BER. The reduction in BER is from 3.6 × 10 -2 to 1.7 × 10 -4 on 50 MHz bandwidth, plus as of 2.6 × 10 -2 towards 1.9 × 10 -5 on a distance of 30 cm as contrasted to VLC system without a blue filter. Essentially, the stop band covers the entire response range for a receiver than a blue signal band that enhances the VLC ability utilized in outdoors and in sun.

Tao Jiang et al. (2015) have proposed an authentic multi-block tone reservation (MB-TR) mechanism for PAPR lessening in OQAM-OFDM system. The main objective of MB-TR mechanism is the exploitation of overlapping architecture of OQAM-OFDM signals and has considered adjoining data blocks for obtaining the clipping noise. For the elimination of OQAM-OFDM peak signals, the Mb-TR schemes obtain the peak-canceling signals with the employment of weighted least square algorithm to fit into the peak canceling signal waveform to clipping noise waveform. The simulation results have shown that MB-TR method has provided better PAPR reduction with less computational complexity as contrasted to the scheme of clipping control tine reservation in the OQAM-OFDM system.

Jing Xu et al. (2016) have proposed an underwater wireless optical communication system based on IM / DD-OFDM and experimentally proved it. Researchers investigated the dependence of BER performance on the number of training symbols as well as the bias voltage and driving voltage of the LED. Using a single small blue LED and a low-cost PIN photodiode, with 16-QAM at a BER of 1.54 × 10 -3 with a net bit rate of 225.90 Mb / s, a BER of 3.28 × 10 -3. It realizes 231.95 Mb / s. 2 m air channels, each using 32 QAM. For 2 m submersible channels, 161.36 Mb / s using 16-QAM, 156.31 Mb / s using 32-QAM, 127.07 Mb / s when using 64-QAM. The corresponding BERs are 2.5 × 10 - 3, 7.42 × 10 - 4, and 3.17 × 10 -3, respectively. These all are under the FEC threshold.

Abdul rahman Ikram Siddiq et al. (2015) has proposed a technique for reducing peak-to-average power ratio (PAPR) of orthogonal frequency division multiplexing (OFDM) signals by peak insertion (PI). PI depends on the duality of DFT and the PAPR duality of the impulse. A relatively high peak is inserted into the frequency domain OFDM symbol such that the PAPR of the transmitted time domain signal decreases. A PAPR CCDF of 10-4 can achieve a PAPR reduction of up to about 11 dB, but at the expense of increased signal power, it can be reduced by scaling to the desired level without affecting PAPR. Computer simulation tests show that tradeoffs can be made easily between BER and PAPR of the transmitted signal to achieve the desired system performance. PI technology does not require any type of side information transmission, search, optimization, and iterative or parallel application of IDFT. PI is suitable for use in PAPR reduction of OFDM signals because PI can achieve faster, simpler and larger PAPR reduction compared to other similar techniques that increase transmission power it seems to be.

III. PROPOSED WORK MODEL

The proposed work structure crucially aims to reduce the BER of the data and it also focuses on utilizing most of the channel to equalize the channel.

A. Application of Symbol Interference

Symbol Interference (SI) is to be applied over the data which is ready to be transferred.

Firefly Swarm Intelligence Algorithm (FFSI) is used from SI series. In order to transfer the data through a channel, the data is passed through a system model which is as follows:

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Algorithm 1 implements EFA and introduces a new fitness function in EFA. Each bit value of each time frame is processed. The fireflies fly with a small speed with light blinking speed. The firefly is judged on the base of the intensity of the light of the firefly. The Firefly will also feel some weakness after flying to an extent. The fitness function ensures the flying speed and the intensity of the light both are considered. If the light intensity of the individual fly is less than that of the group light intensity then the fly is considered to be out of the group. In such scenario, the existing fly will be boosted with an average light source of all the flies that is bit value will be replaced by the average bit value of all the bit values scanned till now. The designed fitness function is a new proposed fitness function and hence its cross-validation is required.

Algorithm 1: Application of FFSI

Input: Bit Stream for each Time frame t (BSSt),
Output: Optimal Bit Stream (OBS)
OBS=Zeros (BSSt) // Generating zeros equal to the BSSt count. The total domain value is divided into 4 time domains and they will be termed as fly_group
Total_fly_group=4;
Range= [0,Total_fly_group];
Total_Flies_Per_Slot = Total BSS Length/ Total_fly_group ;
Foreachisi in Range
Light_threshold=
∑_(k=0)^(BSS[Range[isi]](BSS[k] /@TotalElementsinBSSofpaticulartimerange)
Fly_in_range=0; // To check whether the fly lies within the group or not, If it is 0 then the fly is not in a range which is the default assumption.
Foreachfv in BSSt
Current_Fly_Light_Value = fv;
Fly_Speed_Current_Fly= Fly_Speed_Random ( );
Total_Flies_Iteration=1000;
Group_Movement=.1;
For Tf=1: Total_Flies_Iteration
Light_Value=Fly_Speed_Current_Fly*Tf;
Weakness=Math. Random(); // The flies will suffer through some weakness due to fly fatigue
Flygroup_light_value=
((Flygroup_change+tf+Group_Movement+Fly_speed_current_Fly) * Weakness)/ Total_Flies ;
If
Flygroup_light_value>Light_Value // If the group light value is greater than the individual light
Fly_in_range=1; // The fly is in range
OBS[isi , fy]= BSSt[isi,fy];
Else
Fly_in_range=0; // The fly is not in range , the bit value to be changed here, it should be equal to the optimal bit value of streamed bit till now
OBS[isi,fy]=
∑_(k=0)^(BSSt[isi,1:fy])(BSS[k] /@TotalElementsinBSSofpaticulartimerange) // If the fly is out of range, then replace the bit value
End IF
Cross-Validation

The only judgment about the bit value is whether the fitness function has optimized it correct or not that is either 0 for not valid and 1 for valid. Support Vector Machine (SVM) is cross validator which is based on Machine Learning architecture. Each bit in each time frame is trained individually against all the rest available bits in the stream. Fig.2 represents the architecture of SVM.

Algorithm 2: The Cross Validator()

Input: OBS,BSSt
Output: Cross Validated Data (CVD)
CVD= [ ] // Initializing empty array
Range=[0: BSSt.length];
For KI=0: Range // Taking each time frame
Data_to_Validate=OBS[KI , :] // All the values of the time frame
Target_Set=Ones[Data_to_Validate.Length;
For each bit in Data_to_Validate
Bit position=bit.positionvalue;
Target_Set[Bit position]=2; // All the bit values are initialized with label set 1 and the current bit value //is labelled as 2
SVMStruct=Train_Svm(Data_to_Validate,Target_Set, 'Kernel Type=polynomial') // Training SVM
//with Training set and its corresponding label with polynomial type of kernel
Test Data=Data_to_Validate ; // Keeping the test data same as that of training data for supervised //learning
Output Label= SVMClassify(SVMStruct, Test Data) ;
If(Output Label[Bit position]== Target_Set[Bit position]) // If the output label of the test data is same as //that of the training label then keep the data as it is
CVD [KI, Bit position]= bit;
Else
Apply Algorithm 1 for bit of this time stream
End If
End For
End For
Return CVD
End Algorithm

The SVM is provided with each bit value which is optimized by the EFA. Polynomial Kernel structure is supplied for the training. The bit getting cross validated is labelled with 2 whereas every other bit is labelled with 1. If the training label is equal to the classification label then the bit is termed to be verified else EFA will be again applied to the bit.

The training structure is a search space which contains two different classes namely 1 and 2. Label 2 is for the processing bit value whereas Label 1 is every other bit value in the presented scenario. The category is bifurcated by a polynomial kernel and supported by Support Vectors.
The values nearby the kernel are selected for the trained SVM network as shown in Fig.6.

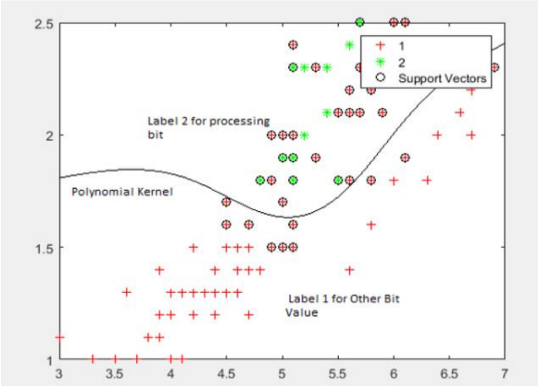

Fig.6

IV. RESULTS ANALYSIS

The following parameters are evaluated

A. A-BER

It is the Average Bit Error Rate (A-BER) of the network which is generated after 10000 simulation rounds. After every simulation round, the BER is stored in the BER-Tray as shown in Fig.7 .

$$A-BER=\frac{\sum_{k=0}^{n=10000} BER}{n} \qquad (19)$$

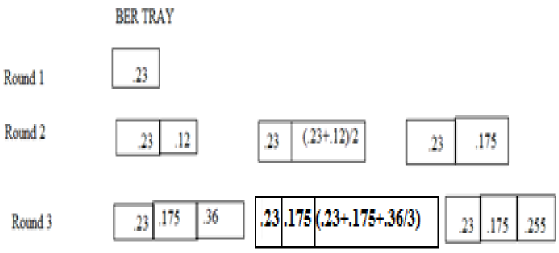

FIG.7 BER TRAY

B. L-BER

It is the logarithmic scale of the A-BER but it is taken again the SNR value of the communication channel. The evaluated parameter shows improvement in both the parameters for the proposed work.

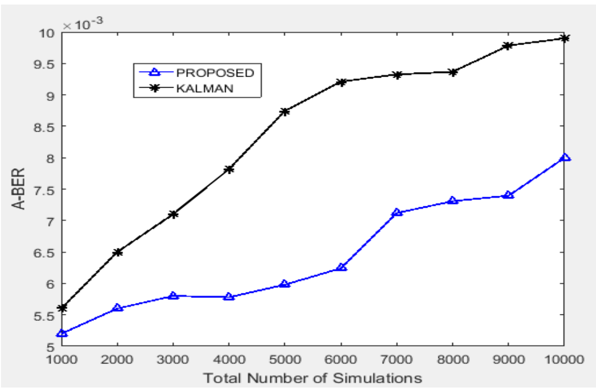

Fig.8 A-BER

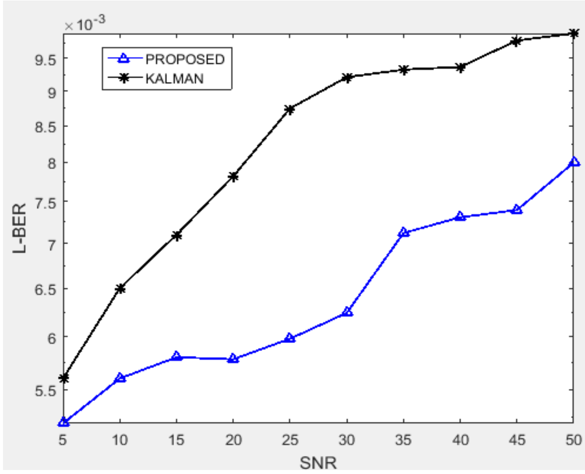

Fig.9 L-BER

The dual optimization and verification technique ensured that both the error rates stand low. The Signal to Noise Ratio (SNR) ranges from 5 to 50 whereas a total number of simulation rounds is 10,000. The logarithmic BER is decreased by .0089 units on an average whereas the average BER is decreased by.0045 units on an average.

V. CONCLUSION

An extended filter mechanism utilizing SI and SVM has been implemented for random data initialized before passing it to the channel and optimized using FFSI. A new fitness function is proposed which considers the light intensity, flying speed and range of the firefly in the proposed work. The output of FFSI is cross verified utilizing SVM. The results are evaluated utilizing A-BER and L-BER. For both the parameters, the proposed work stands a healthy growth .0089 units in L-BER and .0045 units in A-BER when compared to Kalman Filter.

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