ISSN: 2278-0181
Vol. 2 Issue 10, October - 2013

Optimization of Performance of MIMO-OFDM system using Neural Network as Channel Estimator and Compensator

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ABSTRACT

MIMO-OFDM systems are one of the systems which have become the basis of many communication researches nowadays. Combination of both stands a good possibility of being the next-generation (4th generation) of mobile wireless systems. The increased complexity of channel equalization is a major challenge. Wireless channels are responsible for adding Inter Channel Interference (ICI) and Inter Signal Interference (ISI) . For removing the effect (imposed by channel) from received signal, the receiver needs to have knowledge of CIR (Channel impulse response) it is usually provided by a separate channel estimator. Here we proposed the technique of Neural Network(NN) as channel estimator and compensator. We train the NN with different algorithms. Then length of known training sequence varied and observations are made. Further the whole system is compared with the traditional algorithms and observations are made to show the effectiveness of NN based channel estimator and compensator for MIMO-OFDM system.

Keywords-MIMO-OFDM; channel estimation; neural network

I. INTRODUCTION

The targets of communication systems are to provide services that include video, voice and data with high speed and reliability. MIMO (Multiple Input Multiple Output) and OFDM (Orthogonal Frequency Division multiplexing) together give rise to 4th generation technology. MIMO communication system is a technology to achieve the targets of high data rates by taking advantage of multipath signals [1]. OFDM provides resistance to ISI (Inter symbol Interference) and ICI (Inter carrier interference) [2]. With both technologies (MIMO & OFDM) bringing a good possibility of being the next-generation (4^{th} generation) of fixed and mobile wireless systems [3]. The wireless channels are multipath fading channels, causing ISI (inter symbol interference), whereby, for each path there is an independent path delay, independent path gain (or loss) and independent path phase shift. So to remove channel effect from the received signal, the receiver needs to have knowledge of CIR (Channel impulse response), it is usually provided by a separate channel estimator. Channel estimation is based on the known sequence of bits, which is unique for each transmitter and is transmitted in each transmission burst. Multiple transmit and receive antennas are used in MIMO in same frequency band [4] which increases the capacity linearly with the number minimum of transmit and receive antennas. However it imposes a challenge that is the increased complexity [5] of channel equalization (to separate all the signal paths and to remove the changes caused by the channel) on receiving side. Because of high degree of non-linearity of NN, they can be effectively used to decode symbols transmitted through difficult channels. Equalization and compensation of channel can be also regarded as a classification task [6]. In particular, due to their universal approximation capability, NN can form arbitrarily shaped decision boundaries [7]. In recent years NN have been often proposed for digital equalization of communication channels. The research proposes a technique, which based on artificial neural networks, carries out (MIMO-OFDM) channel estimation and compensation.

Estimation of channel is calculated in terms of synaptic weights and bias values of neural network, whereby, different training algorithms have been analyzed to calculate those weight and bias values. This research also attempts the usefulness of neural network based channel estimator by comparing results obtained by use of different NN-training algorithms. To ascertain the flexibility and performance of the proposed technique; length of the training sequence has been varied over a reasonable range and the result has been observed. Then, the results obtained by using different algorithms for training NN have been compared with each other and against the traditional least square algorithm for channel estimation.

II. PROPOSED DESIGN

Following are the Phases of Implementation of Proposed Design

Phase I

As shown in below fig.1 the 2*2 MIMO channel is chosen from Matlab Simulink. Random signals are passed through MIMO channel. BPSK modulation is used for modulating the data. BPSK modulation technique is used because it is very efficient modulation technique.

The mathematical model for 2*2 MIMO system is given by

In MIMO systems, a transmitter sends multiple streams by multiple transmit antennas. The transmit streams go through a matrix channel which consists of all $N_t N_r$ paths between the N_t transmit antennas at the transmitter and N_t receive antennas at the receiver. Then, the receiver gets the received signal vectors by the multiple receive antennas and decodes the received signal vectors into the original information. A narrowband flat fading MIMO system is modeled as

$$y=Hx+n \quad ....(1)$$

where y and x are the receive and transmit vectors, respectively, and H and n are the channel matrix and the noise vector, respectively.

Referring to information theory, the ergodic channel capacity of MIMO systems where both the transmitter and the receiver have perfect instantaneous channel state information is[13]

$$C_{\text{perfect-CSI}} = E\left[\max_{\mathbf{Q};\,\mathrm{tr}(\mathbf{Q})\le 1} \log_2 \det\left(\mathbf{I}+\rho\mathbf{H}\mathbf{Q}\mathbf{H}^H\right)\right] = E\left[\log_2 \det\left(\mathbf{I}+\rho\mathbf{D}\mathbf{S}\mathbf{D}\right)\right] \quad ....(2)$$

where $()^H$ denotes Hermitian transpose and ρ is the ratio between transmit power and noise power (i.e., transmit SNR). The optimal signal covariance $\mathbf{Q}=\mathbf{V}\mathbf{S}\mathbf{V}^H$ is achieved through singular value decomposition of the channel matrix $\mathbf{U}\mathbf{D}\mathbf{V}^H = \mathbf{H}$ and an optimal diagonal power allocation matrix $\mathbf{S}=\mathrm{diag}(s_1,\ldots,s_{\min(N_t,N_r)},0,\ldots,0)$. The optimal power allocation is achieved through waterfilling,[14] that is

$$s_i = \left(\mu - \frac{1}{\rho d_i^2}\right)^+, \quad \text{for } i=1,\ldots,\min(N_t,N_r), \quad ...(3)$$

where $d_1,\ldots,d_{\min(N_t,N_r)}$ are the diagonal elements of D, $(\cdot)^+$ is zero if its argument is negative, and μ is selected such that $s_1+\ldots+s_{\min(N_t,N_r)} = N_t$.

If the transmitter has only statistical channel state information, then the ergodic channel capacity will decrease as the signal covariance can only be optimized in terms of the average mutual information as

$$C_{\text{statistical-CSI}} = \max_{\mathbf{Q}} E\left[\log_2 \det\left(\mathbf{I}+\rho\mathbf{H}\mathbf{Q}\mathbf{H}^H\right)\right] \quad ...(4)$$

The spatial correlation of the channel have a strong impact on the ergodic channel capacity with statistical information.

If the transmitter has no channel state information it can select the signal covariance Q to maximize channel capacity under worst-case statistics, which means $\mathbf{Q}=1/N_t\mathbf{I}$ and accordingly

$$C_{\text{no-CSI}} = E\left[\log_2 \det\left(\mathbf{I}+\frac{\rho}{N_t}\mathbf{H}\mathbf{H}^H\right)\right]. \quad .....(5)$$

Depending on the statistical properties of the channel, the ergodic capacity is no greater than $\min(N_t,N_r)$ times larger than that of a SISO system. System Model under a Time-Varying Channel.

These modulated signals are now given to the OFDM transmitter. The known Pilot symbols are also added to the OFDM transmitter.

The mathematical model for OFDM is given as follows.

The problem of inter channel interference(ICI) existing in an OFDM system under a time -varying channel is given and properties are discussed. fig 1 shows a discrete-time baseband equivalent model for OFDM system. Input bits are encoded into a symbol Xm. and N symbols are sent to serial to parallel converter(S/P). The inverse fast Fourier transform(IFFT) is then applied. The nth output of the IFFT Xn can be expressed as follows.

$$x_n = \frac{1}{\sqrt{N}}\sum_{m=0}^{N-1} X_m e^{j2\pi nm/N}, \quad n=0,\ldots,N-1. \quad ....(6)$$

Before the parallel to serial converter(P/S), the cyclic prefix is added to avoided inter-block interference and preserve orthogonality between subchannels. Generally the length of the cyclic prefix is chosen such that the guard interval is longer than or equal to the delay spread of the channel. the cyclic prefix is ignored for simplicity in this analysis, however. By assuming that the channel consist of L multipath components, and changes at every sample, the output of the channel can be given by

$$y_n = \sum_{l=0}^{L-1} h_{n,l} x_{n-l} + w_n, \quad n=0,\ldots,N-1 \quad ....(7)$$

where hn;l and wn represent the channel impulse response (CIR) of lth path and additive white Gaussian noise (AWGN) at time n, respectively. From (2.1), yn can be written as

$$\begin{aligned} y_n &= \frac{1}{\sqrt{N}}\sum_{l=0}^{L-1} h_{n,l}\sum_{m=0}^{N-1} X_m e^{j2\pi(n-l)m/N} + w_n, \quad n=0,\ldots,N-1 \\ &= \frac{1}{\sqrt{N}}\sum_{m=0}^{N-1} X_m e^{j2\pi nm/N}\sum_{l=0}^{L-1} h_{n,l} e^{-j2\pi lm/N} + w_n. \end{aligned} \quad ....(8)$$

$$H_n^{(m)} \equiv \sum_{l=0}^{L-1} h_{n,l} e^{-j2\pi lm/N}, \quad n,m=0,\ldots,N-1 \quad ....(9)$$

where hn;l and wn represent the channel impulse response (CIR) of lth path and additive white Gaussian noise (AWGN) at time n, respectively. From (6.7), yn can be written as

ISSN: 2278-0181
Vol. 2 Issue 10, October - 2013

$$y_n = \frac{1}{\sqrt{N}} \sum_{l=0}^{L-1} h_{n,l} \sum_{m=0}^{N-1} X_m e^{j2\pi(n-l)m/N} + w_n, \quad n = 0, \ldots, N-1$$
$$= \frac{1}{\sqrt{N}} \sum_{m=0}^{N-1} X_m e^{j2\pi nm/N} \sum_{l=0}^{L-1} h_{n,l} e^{-j2\pi lm/N} + w_n.$$

$$H_n^{(m)} \equiv \sum_{l=0}^{L-1} h_{n,l} e^{-j2\pi lm/N}, \quad n, m = 0, \ldots, N-1 \qquad \text{..................................(10)}$$

where H n (m) is the Fourier transform of the channel impulse response at time n.

Then, yn can be rewritten as

$$y_n = \frac{1}{\sqrt{N}} \sum_{m=0}^{N-1} X_m H_n^{(m)} e^{j2\pi nm/N} + w_n, \quad n = 0, \ldots, N-1. \qquad \text{............. (11)}$$

After removing the cyclic prefix, the demodulated symbol Ym at the receiver is

obtained by applying the fast Fourier transform (FFT) so that

$$Y_m - \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} y_n e^{-j2\pi nm/N}, \quad m - 0, \ldots, N-1. \qquad \text{........................ (12)}$$

From (6.5), Ym can be written as

$$Y_m = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} \left(\frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k H_n^{(k)} e^{j2\pi nk/N} + w_n \right) e^{-j2\pi nm/N}, \quad m = 0, \ldots, N-1$$
$$= \frac{1}{N} \sum_{k=0}^{N-1} X_k \sum_{n=0}^{N-1} H_n^{(k)} e^{-j2\pi(m-k)n/N} + \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} w_n e^{-j2\pi nm/N}$$
$$= \left[\frac{1}{N} \sum_{n=0}^{N-1} H_n^{(m)} \right] X_m + \frac{1}{N} \sum_{k=0, k \neq m}^{N-1} X_k \sum_{n=0}^{N-1} H_n^{(k)} e^{-j2\pi(m-k)n/N} + W_m$$
$$= \alpha_m X_m + \beta_m + W_m \qquad \text{.. (13)}$$

Where

$$\alpha_m = \frac{1}{N} \sum_{n=0}^{N-1} H_n^{(m)},$$

$$\beta_m = \frac{1}{N} \sum_{k=0, k \neq m}^{N-1} X_k \sum_{n=0}^{N-1} H_n^{(k)} e^{-j2\pi(m-k)n/N}, \qquad \text{......(14)}$$

$$W_m = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} w_n e^{-j2\pi nm/N}. \qquad \text{....................(15)}$$

Here, Wm, ®m, and ¯m represent the Fourier transform of wn, the multiplicative distortion of a desired subchannel m, and the interchannel interference caused by a time-varying channel, respectively. Note that ®m is the average frequency response of the CIR over one OFDM symbol period. If the channel is timeinvariant, in other words, H(k) n is not a function of n, then ®m simply becomes the frequency response of the CIR, as expected.

We can express (6.7) in a compact vector-matrix form as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{w} \qquad \text{.. (16)}$$

$$\text{where } \mathbf{y} = [Y_0, \ldots, Y_{N-1}]^T, \mathbf{x} = [X_0, \ldots, X_{N-1}]^T, \mathbf{w} = [W_0, \ldots, W_{N-1}]^T$$

and

$$\mathbf{H} = \begin{bmatrix} H_{0,0} & H_{0,1} & \cdots & H_{0,N-1} \\ H_{1,0} & H_{1,1} & \cdots & H_{1,N-1} \\ \vdots & \vdots & \ddots & \vdots \\ H_{N-1,0} & H_{N-1,1} & \cdots & H_{N-1,N-1} \end{bmatrix} \qquad \text{........(17)}$$

Here, Hm;k is defined as

$$H_{m,k} = \frac{1}{N} \sum_{n=0}^{N-1} H_n^{(k)} e^{-j2\pi(m-k)n/N}, \quad m, k = 0, \ldots, N-1 \qquad \text{.................. (18)}$$

In an OFDM system over a time-varying channel, the inter channel interference can be characterized by the normalized Doppler frequency fdT where fd is the maximum Doppler frequency and T is the time duration of one OFDM symbol. Hence we can think of the normalized Doppler frequency as a maximum cycle change of the time-varying channel per OFDM symbol duration in a statistical sense.

¯m's or off-diagonal elements of H in represent the inter channel interference (ICI) caused by the time-varying nature of the channel. In a time invariant channel, one can easily see that ¯m is zero, or H becomes a diagonal matrix, due to the orthogonality of the multicarrier basis waveforms. In a slowly time-varying channel, i.e., the normalized Doppler frequency fdT is small, we can assume Efj¯mj2g ¼ 0. On the other hand, when the normalized Doppler frequency is high, the power of the ICI cannot be ignored, and the power of the desired signal is reduced.

Phase II

The OFDM receiver receives the signals and this data is now used as the Training dataset for the Neural Network.The training dataset is shown in fig 2. Neural network is provided with the input value and the target value for output, training algorithm calculate the weights & bias values of the network using input and target values provided. Received data sequences are passed through the network and straight computations are made to calculate the estimate of transmitted signal. The output of layer#1 is computed as

$$Z = purelin\ \{(W\{1\} \cdot I) + B\{1\}\}$$

Where I is the input to the neural network and is providedwith the received signals.

$$I = \begin{bmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \end{bmatrix} \quad \text{.................(19)}$$

$$I_1 <= \Re(y_1)\ ,\ I_2 <= \Im(y_1)\ ,\ I_3 <= \Re(y_2)\ ,\ I_4 <= \Im(y_2)$$

Z represents the output of layer #1.

$$Z = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \end{bmatrix} \quad \text{......(20)} \qquad R = \begin{bmatrix} r_1 \\ r_2 \end{bmatrix} \quad \text{........(21)}$$

$$R = purelin\ \{(W\{2\} \cdot Z) + B\{2\}\} \quad \text{.....(22)}$$

$$R = purelin\ \{(W\{2\} \cdot (purelin\{(W\{1\} \cdot I) + B\{1\}\})) + B\{2\}\} \quad \text{........(23)}$$

R represents the output of Layer#2 (the output layer).

$$r_1 => \Re(\hat{x}_1 \mid \hat{x}_2)\ ,\ r_2 => \Im(\hat{x}_1 \mid \hat{x}_2) \quad \text{....(24)}$$

$r1$ is the output received from first neuron of layer#2 (estimate of the real part of transmitted signal) and $r2$ is the output received from second neuron of layer#2 (estimate of the Imaginary part of transmitted signal).

The Neural Network is trained using this dataset. We use Levenberg-Marquradt algorithm for training of NN .

After training the MATLAB creates a trained NN block separately .The trained NN box is shown in fig 3. This trained block of NN can be used anywhere in the system.

Phase III

Now we apply this trained NN block to our MIMO-OFDM system.After applying trained NN block to previous system as shown in fig 1. our system looks as shown in fig below

Phase IV

The whole system is now complete as shown in fig.4.Now vary the Signal-To-Noise (SNR)ratio using AWGN channel and observe the changes of Bit-Error-Rate (BER).

III. Simulation of MODEL

Simulate the model from 0-25 dB SNR and make observations. And Graphs are plotted for SNR vs BER.

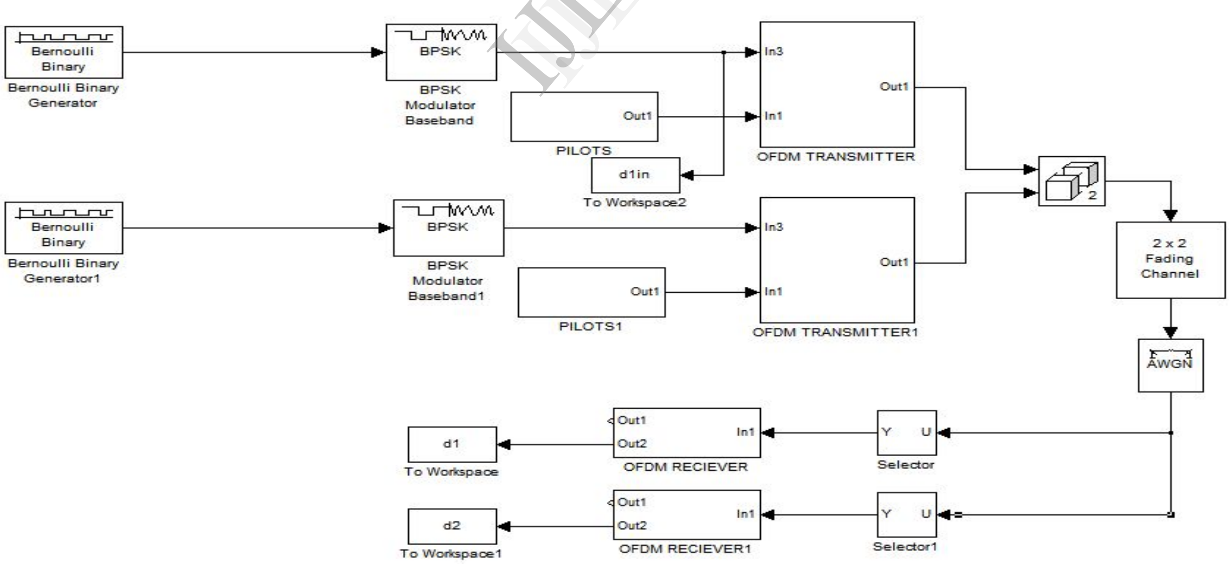
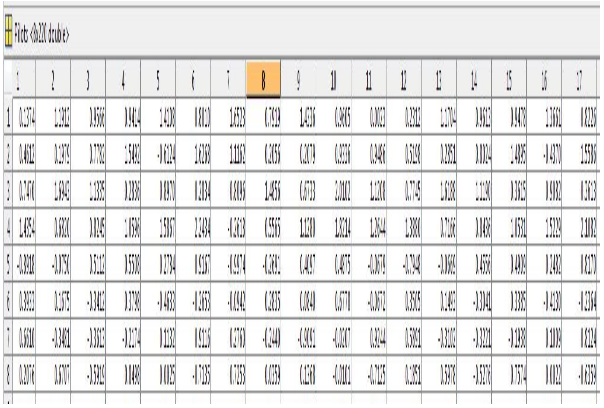


Fig 1: MIMO-OFDM model with BPSK modulation.



Pilots <8x220 double>

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	0.1374	1.1912	0.9566	0.9414	1.4108	0.8010	1.6523	0.7919	1.4336	0.9605	0.0023	0.2312	1.1704	0.9613	0.9478	1.3661	0.8226
2	0.4612	0.1979	0.7782	1.5492	-0.6124	1.6268	1.1162	0.2056	0.2079	0.9336	0.9486	0.5198	0.2851	0.8024	1.4895	-0.4370	1.5586
3	0.7470	1.6943	1.1335	0.2836	0.8970	0.2834	0.8096	1.4856	0.6733	2.0102	1.1208	0.7745	1.6188	1.1190	0.3615	0.9082	0.3613
4	1.4354	0.6820	0.8245	1.0596	1.5867	2.2434	-0.2618	0.5565	1.1280	1.8214	1.2644	1.3880	0.7166	0.8436	1.0531	1.5229	2.1082
5	-0.8918	-0.0750	0.5112	0.5508	0.2784	0.9167	-0.9974	-0.2691	0.4097	0.4875	-0.0679	-0.7948	-0.0669	0.4556	0.4909	0.2482	0.8170
6	0.3933	0.1675	-0.3412	0.3798	-0.4633	-0.2653	-0.0942	0.2835	0.0840	0.6778	-0.0672	0.3505	0.1493	-0.3041	0.3385	-0.4130	-0.2364
7	0.6610	-0.3481	-0.3613	-0.2174	0.1132	0.9116	0.2760	-0.2440	-0.9091	-0.0207	0.9244	0.5891	-0.3102	-0.3221	-0.1938	0.1009	0.8124
8	0.2076	0.6707	-0.5919	0.8498	0.0025	-0.7135	0.7253	0.0359	0.1368	-0.0101	-0.7125	0.1851	0.5978	-0.5276	0.7574	0.0022	-0.6359

Fig 2: Dataset from MIMO-OFDM system.

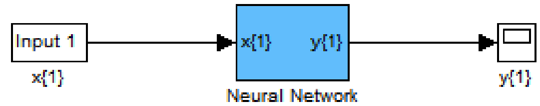


Fig 3: Trained Neural Network Block.

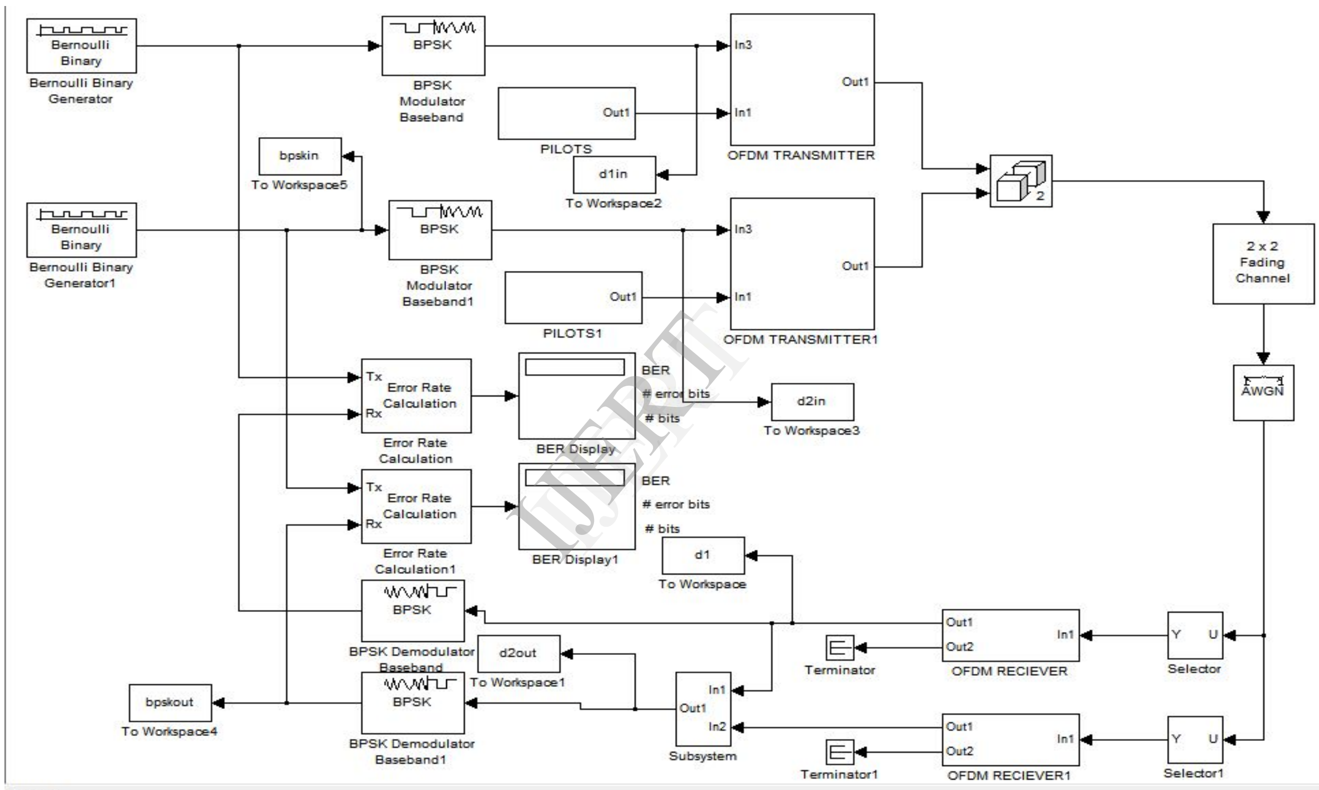


Fig 4: MIMO-OFDM system using Neural Network as Channel Estimator and Compensator

IV. RESULT AND CONCLUSION.

The model is simulated .The simulation takes place for SNR 0-25 and the observation is made for varying BER.The Graphs are plotted for SNR vs BER for different values of SNR. Following are the graphs for whole system. Graph shows the relation between SNR vs BER. It shows the performance of MIMO-OFDM system for varying value of SNR in AWGN channel and its corresponding BER for the system. The graph shows two channels. The channel 1 is without estimation and channel 2 is with NN estimation. The significant difference is observed in both channel. It is observed that the performance of MIMO-OFDM is improved when the NN as channel estimator is used.

This paper presents a NN-based technique to estimate and compensate channel effect for MIMO-OFDM communication systems. Through experimentation, algorithm Levenberg-

Marqurdt (LM) has been tested to train neural networks, it has been established that LM can effectively train neural networks and track channel effect, which measures performance in terms of BER for a range of SNR values. The curves drawn as result of the simulation; corroborate the aforementioned fact that LM provides better results.

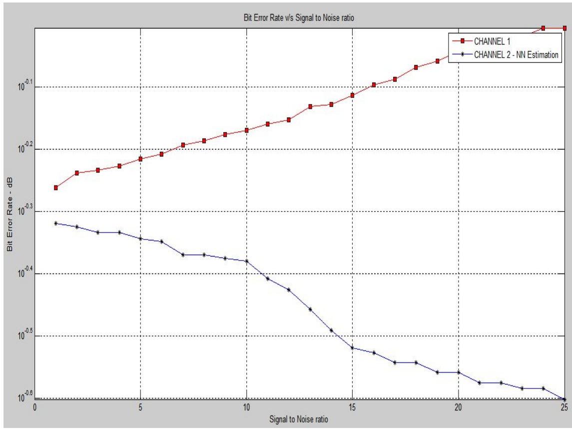


Fig 5: SNR vs BER in dB.

Channel 1

Channel 2

Performance of MIMO-OFDM with NN channel estimator

Performance of MIMO-OFDM without channel estimator

V. FUTURE SCOPE

Length of known training sequences in the proposed system is a constraint over the speed of communication, so less the length of training sequence more will be the speed. In future work is to reduce length of training sequence by maintaining the performance of system. Reducing the computational power demand can be possibly achieved by having pre-calculated synaptic weights for different environments. Unsupervised learning of neural network may get the work done with less computational power.

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