Eng. & Tech. Journal , Vol.32,Part (A), No.2, 2014

OFDM Channel Estimation Based on Intelligent Systems

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Received on: 3/4/2013 & Accepted on: 15/8/2013

ABSTRACT

This work is dedicated to the study of reducing Bit Error Rate (BER) when transferring data in the system Orthogonal Frequency Division Multiplexing (OFDM) by estimating the carrier channel in different ways. The proposal design for Artificial Neural Network (ANN) is considered as a tool to improve performance BER and compared with the traditional method based on the use of the Least Square estimation algorithm (LS) to estimate the impulse response of frequency selective Rayleigh fading channel. A MATLAB 7.14 program is used in simulation.

The proposed method which integrates algorithm LS with ANN includes the following:

1. Training the neural network by Back-Propagation (BP) and using the trained neural network with algorithm (LS) to estimate the channel in different paths.
2. Using Resilient Back propagation algorithm (RProp)in the training of the neural network.
3. UsingLevenberg-Marquardt algorithm (LM) in the training of the neural network.
4.The comparison of results between the traditional method and the proposed method when taking BER = 0.001 at various tracks (one path, two path and three path) and showed that there profit of (1.5dB, 2dB, 2dB) between using the traditional method and the proposed method using RProp algorithm and a profit of (2dB,3dB, 2dB) using an algorithm LM. There is also comparison between the performance ofRProp algorithm and LMalgorithm and the results showed that the LM algorithm better thanRProp algorithm.

Keywords: OFDM, Channel Estimation, Artificial Neural Network (ANN), Back-Propagation (BP)

https://doi.org/10.30684/etj.32.2A.3
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تخمين القناة في نظام التقسيم الترددي المضاعف المتعامد (OFDM) المستند على الأنظمة الذكية

الخلاصة

هذا العمل مكرس لدراسة تقليل نسبة معدل الخطأ (BER) عند نقل البيانات في نظام التقسيم الترددي المضاعف المتعامد (OFDM) عن طريق تخمين القناة الناقلة بطرق مختلفة . قد تم اقتراح تصميم للشبكة العصبية الاصطناعية واعتبارها كأداة لتحسين أداء نسبة معدل الخطأ(BER)ومقارنتها مع الطريقة التقليدية المستندة على استخدام خوارزمية التقدير التربيعي الضئيل (LS)لتقدير الاستجابة النبضية الاختيارية التردد لقناة الخفوت نوع (Rayleigh). تم استخدام برنامج الماتلاب7.14للحصول على النتائج.

الطريقة المقترحة التي تدمج خوارزمية (LS) مع (ANN) تتضمن ما يلي:

1. تدريب الشبكة العصبية بواسطة الانتشار العكسي (BP) واستخدام الشبكة العصبية المدربة مع خوارزمية (LS) لتخمين القناةفي مختلف المسارات لقناة الخفوت الاختيارية التردد نوع (Rayleigh)
2. استخدام خوارزمية(Resilient Back-Propagation)في تدريب الشبكة العصبية.
3. استخدام خوارزمية (Levenberg-Marquardt) في تدريب الشبكة العصبية.
4. المقارنة بين أداء خوارزمية (Levenberg-Marquardt) وأداء خوارزمية (Resilient Back-Propagation)

تم مقارنة النتائج بين الطريقة التقليدية والطريقة المقترحة عند اخذ BER=0.001 في مختلف المسارات(الأول والثاني والثالث) وبينت إن هناك ربح مقداره(1.5dB, 2dB, 2dB) بين استخدام الطريقة التقليدية و الطريقة المقترحة باستخدام خوارزمية Resilient Back-Propagation) وربح مقداره(2dB, 3dB, 2dB) باستخدام خوارزمية (Levenberg-Marquardt) وتم أيضا المقارنة مابين أداء خوارزمية (Resilient Back-Propagation) و خوارزمية (Levenberg-Marquardt) وبينت النتائج إن خوارزمية (Levenberg-Marquardt) أفضل من خوارزمية (Resilient Back-Propagation).

INTRODUCTION

OFDM is becoming a very popular multi-carrier modulation technique for transmission of signals over wireless channels. Now OFDM is widely used for high-speed communications over frequency selective channels. OFDM divides the high data rate stream into parallel lower data rate and hence prolongs the symbol duration, thus helping to eliminate Inter Symbol Interference (ISI) [1].

In a mobile radio channel the transmitted signal is distorted during transmission through the frequency and time selective In order to lower BER in OFDM systems, the estimation of channel is necessary before the demodulation fading channel. The channel estimation is a process of characterizing the effect of the transmission medium on the input signal [2]. There are several techniques for channel estimation in OFDM system. Among these techniques, both pilot-based channel estimation and blind channel estimation techniques are most popular. The blind channel estimation is carried out by evaluating the statistical information of the channel and certain properties of the transmitted signals. Blind Channel Estimation has its advantage in that it has no overhead loss; it is only applicable to slowly time-varying channels due to its need for a long data record.In pilot based channel estimation algorithms, training symbols or pilot tones that are known a priorito the receiver, are multiplexed along with the data stream for channel estimation. The training-based method channel estimation can be performed by either block type pilots where pilot tones are inserted into all frequency bins within periodic intervals of OFDM blocks or by comb pilots where pilot tones are inserted into each OFDM symbol symbols with a specific period of frequency bins [3].

Semi-blind channel estimation is also another technique for channel estimation. Semi-blind channel technique is hybrid of blind and training technique, utilizing pilots and other natural constraints to perform channel estimation [3].

This paper proposes a technique, which based on artificial neural networks, carries out OFDM channel estimation over Rayleigh fading channels. Estimate 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. Simulation results obtained show that ANN is an effective aid to strengthen traditional methods of channel estimation and make reception quality better in wireless based communication.

The organization of this paper is as follows. In section 2**,** expression of related works is given. In section 3, description of OFDM system model is given. While in section 4 and 5, description of channel estimation and ANN is given. ANN based channel estimator is described in section 6. Simulation results are offered in section 7and finally, section 8Concludes the paper.

RELATED WORKS

Artificial Neural Networks (ANNs) perform complex mapping between its input and output space and are capable of forming complex decision regions with nonlinear decision boundaries [2]. Further, because of nonlinear characteristics of the ANN's, these networks of different architecture have found successful application in channel estimation problem [4-7]. One of the earliest applications of the ANN in digital communication channel estimation is reported by Syed Junaid Nawaz, et. al, proposed a technique, which based on artificial neural networks, carried out Multiple Input Multiple Output Orthogonal Frequency Division Multiplexing (MIMO-OFDM) channel estimation and compensation using comb-type pilot arrangement [4]. Semi-blind MIMO-OFDM channel estimation algorithm based on a two-layer neural network is described in [5]. The effect of used interpolation techniques on OFDM system performance with comb type based channel estimation is investigated and Adaptive Network Based Fuzzy Inference Systems (ANFIS) and GRNN (Generalized Regression Neural Networks) ANN structures can be used as an interpolation technique in [6]. a new channel estimation algorithm based on Adaptive Neuro-Fuzzy Inference System (ANFIS) for MIMO-OFDM systems is proposed in [7].

OFDM SYSTEM MODEL

The baseband OFDM system based on pilot channel estimation is given in Figure (1).On the transmitter side, binary information is grouped and mapped according to chosen modulation. After serial/parallel (S/P) conversion pilots are inserted either to all subcarriers with a specific period or uniformly between the information data. The modulated data X(k) is converted into a time domain signal by taking the N point IFFT. After IFFT, the time domain signal is given by following equation [8]:

$$x(n) = IFFT\big(X(k)\big), \qquad n = 0, 1, 2 \ldots, N-1$$

$$= \sum_{k=0}^{N-1} X(k)e^{j2\pi kn/N} \qquad \cdots (1)$$

Where *N* is the length of FFT, X(k)is baseband data sequence. After IFFT, cyclic prefix is inserted to prevent ISI. This interval should be chosen to be larger than the expected delay spread of the multipath channel. The guard time includes the cyclically extended part of the OFDM symbol in order to eliminate the inter-carrier interference (ICI). The symbol extended

$$x_f(n) = \begin{cases} x(N+n), & n = -N_g, -N_g+1, \ldots, -1 \\ x(n), & n = 0,1,\ldots,N-1 \end{cases} \qquad \cdots (2)$$

where $x(n)$ is data bit, *N* number of subcarriers, and N_g is the length of the guard interval. The transmitted signal $x_f(n)$ will pass through the frequency selective time varying fadingchannel with Additive White Gaussian Noise (AWGN). The received signal is given by following equation:

$$y_f(n) = x_f(n) \otimes h(n) + w(n) \qquad \cdots (3)$$

where $h(n)$ is the impulse response of the frequency selective channel and $w(n)$is AWGN.

The channel response *h(n)* can be represented by [8]:

$$h(n) = \sum_{k=1}^{K} a_k \, sinc\left[\frac{\tau_k}{T_{samp}} - n\right] \qquad \cdots (4)$$

Where,

- T_{samp} is the input sample period to the channel.
- τ_k, where 1 ≤ k ≤ K,is the set of path delays. K is the total number of paths in the multipath fading channel.
- $\{a_k\}$,where 1 ≤ k ≤ K , is the set of complex pathgains of the multipath fadingchannel. These path gains are uncorrelated with each other.
- N_1 and $N_2$are chosen so that $h(n)$is small when *n* is less thanN_1or greater thanN_2.

At the receiver, the guard time is removed:

$$y_f(n) \;\; for - N_g \le n \le N-1$$

$$y(n) = y_f\left(n + N_g\right) \quad n = 0, 1, \ldots, N-1 \qquad \cdots (5)$$

Then *y(n)* is sent to FFT block for the following operation

$$Y(k) = FFT\{y(n)\} \quad k = 0, 1, 2, \ldots, N-1$$

$$Y(k) = \frac{1}{N}\sum_{n=0}^{N-1} y(n)e^{-j\left(\frac{2\pi kn}{N}\right)} \qquad \cdots (6)$$

Following FFT block, the pilot signals are extracted and the estimated Channel $\widehat{H}$ for the data sub-channels is obtained in channel estimation block using LS estimator. Then, the transmitted data is estimated by [8]

$$\hat{X} = \frac{Y(k)}{\widehat{H}(k)} \quad ,k = 0,1,\ldots,N-1 \qquad \cdots (7)$$

Finally, the binary information data is obtained back in demodulator and signal demapper block.

CHANNEL ESTIMATION BASED ON BLOCK-TYPE PILOT ARRANGEMENT

In block-type pilot-based channel estimation, OFDM channel estimation symbols aretransmitted periodically, and all subcarriers are used as pilots. The task here is to estimate the channel conditions (specified by$H$ or h) given the pilot signals (specified by X) andreceived signals (specified by$Y$), with or without using certain knowledge of the channelstatistics. The receiver uses the estimated channel conditions to decode the received datainside the block until the next pilot symbol arrives. The estimation can be based on LS and minimum mean-square error (MMSE) estimators. The estimation that used in this paper is LS estimator.

LS channel estimation method finds the channel estimate in such a waythat weighted errors between the measurements and the model are minimized. The LSestimates H, given the received data Y and the transmitted symbols X is given by [9]:

$$\widehat{H}_{LS} = X^{-1}\mathrm{Y} \qquad \cdots (8)$$

ARTIFICIAL NEURAL NETWORKS (ANNS)

Artificial neural networks (ANNs) are one of the popular branches of artificial intelligence. They have very simple neuron-like processing elements (called nodes or artificial neurons) connected to each other by weighting. The weights on each connection can be dynamically adjusted until the desired output is generated for a given input [2].The artificial neuron is composed of a summer (net), which just likes the linear equation of the linear regression model, and a transfer function, which is linear or non-linear. The summing block is directly connected with the input vector (a_1, a_2, a_3, . . ., a_n) from outside of the neuron. There is a weight (w_1, w_2, w_3, . . ., w_n) connection (path) between each input and the neuron. In addition, a bias which input value is 1 is also associated with the neuron, a threshold value 'θ' that has to be reached or extended for the neuron to produce a signal, a nonlinear function 'F ' acts on the produced signal '*net*' and an output 'T ' after the nonlinearity function . The basic model of an artificial neuron is shown in figure (2). The following relation describes the transfer function of the basic neuron model [10].

$$T = F(net) \qquad \cdots (9)$$

Where

$$net = w_0 + \sum_{i=1}^{n} a_i \, w_i \qquad \cdots (10)$$

and the function firing condition is:
$F(net) \geq \theta$ [for nonlinear activation function]

Or

$$\sum_{i=1}^{n} a_i \, w_i \geq \theta$$

[for linear activation function]

All the neurons in a layer usually have the same activation function. Various multilayer Neural Network (NN) types have been developed. Feed forward neural networks such as the standard multilayer NN, functional link NN and product unit NN receive external signals and simply propagate these signals through all the layers to obtain the result (output) of the NN. The architecture of a multilayer neural network is shown in Figure (3) [11].

The most important characteristic of an artificial neural network is its ability to learn. Learning is a process in which the network adjusts its parameters the (synaptic weight) in response to input stimuli, so that the actual output response converges to the desired output response. There are three main types of learning, Supervised learning, Unsupervised learning, and Reinforcement learning. The Back Propagation (BP) learning algorithm is the most popular learning rule for performing supervised learning tasks [11].

Back-Propagation Algorithm (BP)

The back propagation (BP) algorithm was proposed in 1986 by Rumelhart, Hinton and Williams for setting weights and hence for the training of multi-layer perceptrons (MLP).The BP algorithm propagates backward the error between the desired signal and the network output through the network. After providing an input pattern, the output of the network is then compared with a given target pattern and the error of each output unit calculated. This error signal is propagated backward, and a closed-loop control system is thus established. The weights can be adjusted by a gradient-descent-based algorithm. In order to implement the BP algorithm, a continuous, nonlinear, monotonically increasing, differentiable activation function is required. The two most-used activation functions are the logistic function equation11 and the hyperbolic tangent function equation 12, and both are sigmoid functions. The linear transfer function calculates the neuron's output by simply returning the value passed to it as indicated in equation (13). Figure (4) shows the activation functions[12-13].

$$F(net) = \frac{1}{1+e^{-net}} \qquad \cdots (11)$$

$$F(\mathrm{net}) = \frac{\mathrm{e}^{\mathrm{net}} - \mathrm{e}^{-\mathrm{net}}}{\mathrm{e}^{\mathrm{net}} + \mathrm{e}^{-\mathrm{net}}} \qquad \cdots (12)$$

$$F(net) = net \qquad \cdots (13)$$

Where:

net is determined by using equation 10 and $F(net)$ represent the actual output. Figure (4) illustrates the flowchart of the error back-propagation training algorithm for a basic two-layer network as in Figure (3). The learning begins with the feed forward recall phase (Step 2). After a single pattern vector z is submitted at the input[14]
where

$$z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_I \end{bmatrix}, V = \begin{bmatrix} v_{11}\, v_{12} \ldots v_{1I} \\ v_{21} v_{22} \ldots v_{2I} \\ \vdots \quad \vdots \quad \ldots \quad \vdots \\ v_{J1}\, v_{J2} \cdots \; v_{JI} \end{bmatrix} \text{ and } W = \begin{bmatrix} w_{11}\; w_{12} \cdots w_{1J} \\ w_{21}\, w_{22} \cdots w_{2J} \\ \vdots \quad \vdots \quad \cdots \quad \vdots \\ w_{K1} w_{K2} \cdots w_{KJ} \end{bmatrix}$$

the layers' responses y and **o** are computed in this phase
where

$$o = \Gamma\big[W\Gamma[Vz]\big] \qquad \cdots (14)$$

$$y = \Gamma[Vz] \qquad \cdots (15)$$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_J \end{bmatrix} \quad \text{and } o = \begin{bmatrix} o_1 \\ o_2 \\ \vdots \\ o_k \end{bmatrix}$$

The desired (target) output vector is

$$d \triangleq \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_K \end{bmatrix}$$

Then, the error signal computation phase (Step 4) follows. Note that the error signal vectormust be determined in the output layer first

$$\delta_O \triangleq \begin{bmatrix} \delta_{O1} \\ \delta_{O2} \\ \vdots \\ \delta_{OK} \end{bmatrix}$$

and then it is propagated toward the network input nodes. The ***K*** X J weights are subsequently adjusted within the matrix W in step 5. Finally, J X ***I*** weights are adjusted within the matrix V in step 6 [14]

Resilient Backpropagation algorithm (RProp)

This is an improved adaptation of the batch back prop algorithm, and for numerous problems it converges very quickly [18]. It uses only the sign of the back propagated gradient to change the biases/weights of the network, instead of the magnitude of the gradient itself. This because, when a Sigmoid transfer function is used the gradient can have a very small magnitude, causing small changes in the weights and biases, even though the weights and biases are far from their optimal values. The aim of the RProp algorithm is to remove these harmful effects of the magnitudes of the partial derivatives[15].

Levenberg-Marquardt (LM) BP

The LM algorithm is an iterative technique that locates a local minimum of a multivariate function that is expressed as the sum of squares of several non-linear, real-valued functions. It has become a standard technique for nonlinear least-squares problems, widely adopted in various disciplines for dealing with data-fitting applications. LM can be thought of as a combination of steepest descent and the Gauss-Newton method. When the current solution is far from a local minimum, the algorithm behaves like a steepest descent method: slow, but guaranteed to converge. When the current solution is close to a local minimum, it becomes a Gauss-Newton method and exhibits fast convergence [16].

PROPOSED DESIGN OF OFDM WITH ANN

Figure (5) shows the block diagram of proposed NN with OFDM for channel estimation contains NN, which works on the received signals to recover signals transmitted from transmitter. The symbols after parallel to serial converter block are taken as target. The dataafter passing through the channel are taken as the training data. With these training data and target data the network will be trained for varying the SNR. Figure (5) shows the training data equals to $y_f(n)$ as indicated in equation 3, then the input to ANN can be expressed as

$$I = \begin{bmatrix} I_1 \\ I_2 \end{bmatrix} \qquad \cdots (16)$$

let$y_f(n)$ = y(received signal), then I_1 is the real part of y and I_2 is the imaginary part of y. The input layer plays the role of distributing the input to all neurons in the first processing layer, where, first hidden layer (layer (1)) contains ten neurons and every input in the input layer is connected to every neuron inlayer (1). The output of layer (1) is computed as

$$O = tansig\left\{(W\{1\}.I) + B\{1\}\right\} \qquad \cdots (17)$$

O Represents the output of layer (1), W{1} represents the weights that connect the input layer with layer (1). B {1} represents the bias values of layer (1) and $tansig$ represents the activation function as mentioned in equation (12) for layer (1). $W\{1\}$, $B\{1\}$and O can be expressed as

$$W\{1\} = \begin{bmatrix} w\{1\}_{1,1} w\{1\}_{1,2} \\ w\{1\}_{2,1} w\{1\}_{2,2} \\ \vdots \quad \vdots \\ w\{1\}_{10,1} w\{1\}_{10,2} \end{bmatrix}, B\{1\} = \begin{bmatrix} b\{1\}_1 \\ b\{1\}_2 \\ \vdots \\ b\{1\}_{10} \end{bmatrix} \text{and } O = \begin{bmatrix} o_1 \\ o_2 \\ \vdots \\ o_{10} \end{bmatrix}$$

Then the output of layer (1) is considered as input to the second hidden layer (layer (2)). The output of layer (2) is computed as

$$Z = tansig\left\{(W\{2\}.O) + B\{2\}\right\} \qquad \cdots (18)$$

Z Represents the output of layer (2), W {2} represents the weights that connect the layer (1) with layer (2). B {2} represents the bias values of layer (2) and $tansig$

represents the activation function for layer (2). $W\{2\}$, $B\{2\}$and Z can be expressed as

$$W\{2\} = \begin{bmatrix} w\{2\}_{1,1} & w\{2\}_{1,2} & \cdots & w\{2\}_{1,10} \\ w\{2\}_{2,1} & w\{2\}_{2,2} & \cdots & w\{2\}_{2,10} \\ \vdots & \vdots & \cdots & \vdots \\ w\{2\}_{10,1} & w\{2\}_{10,2} & \cdots & w\{2\}_{10,10} \end{bmatrix},\ B\{2\} = \begin{bmatrix} b\{2\}_1 \\ b\{2\}_2 \\ \vdots \\ b\{2\}_{10} \end{bmatrix} \qquad Z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_{10} \end{bmatrix}$$

After layer (2), there is an output layer. The output of this layer is computed as

$$R = purelin\left\{(W\{3\}.Z) + B\{3\}\right\} \qquad \cdots (19)$$

R represents the output of output layer, W{3} represents the weights that connect the layer (2) with output layer. B{3} represents the bias values of output layer and $purelin$ represents the activation function as mentioned in equation (13) for output layer. $W\{3\}$, $B\{3\}$and R can be expressed as

$$W\{3\} = \begin{bmatrix} w\{3\}_{1,1} w\{3\}_{1,2} & \cdots & w\{3\}_{1,10} \\ w\{3\}_{1,1} w\{3\}_{1,2} & \cdots & w\{3\}_{1,10} \end{bmatrix},\ B\{3\} = \begin{bmatrix} b\{3\}_1 \\ b\{3\}_2 \end{bmatrix} \text{and} R = \begin{bmatrix} r_1 \\ r_2 \end{bmatrix}$$

$r_1$is the output received from first neuron of output layer. $r_1$represents the estimation of real part of transmitted signal (target data) and r_2 is the output received from second neuron of output layer. $r_2$represents the estimation of imaginary part of transmitted signal (target data). The architecture of NN can be seen in figure (6). After training r_1 and r_2 are merged again then, the steps from removing of guard time as indicated in equation (5) to (7) will be repeated. In Table (1), the parameters of ANNs are given and in Table (2), the parameters of OFDM are given.

SIMULATION RESULTS

The BER for different values of SNR is calculated in different paths of Rayleigh fading by using LS channel estimation. Figure (8) shows when the number of paths increases, the ISI increases and BER performance gets worse. Table (3) lists the SNR values obtained at BER=0.001 for different number of paths delay. To illustrate performance of the NN based design results of the proposed Neural Network based system are compared with the Least squares without ANN estimator. Figures (9-14) show the comparisons between LS and LS with ANN and the case of no estimation. Table (4) lists the SNR values obtained at BER=0.001 for different number of paths delay and for two different algorithms that used for training neural networks between LS estimator and LS with ANN estimator. Both LM and R Prop back propagation training algorithms based systems are compared with each other in figures (15-16). Table (5) lists the SNR values obtained at BER=0.001 between R Prop back propagation training algorithm and LM algorithm in flat and two paths.

CONCLUSIONS

This paper presents a NN-based technique to estimate and compensate channel effect for OFDM communication systems. Through experimentation, whereby, two different algorithms (i.e. R Prop& LM) have been tested to train neural networks, it has been established that LM can effectively train neural networks and track channel effect better than R Prop. Table (4) shows that the gain in (dB), obtained at BER=0.001 for different paths and for different algorithms is (1.5 in flat,2 in 2-paths,2 in 3-paths) (dB)between using the traditional method and the proposed method using R Prop algorithm and (2 in flat, 3 in 2-paths, 2 in 3-paths)(dB) between using the traditional method and the proposed method using LM algorithm. The paper also, encompasses a comparison of the proposed system with conventional LS and the case of no estimation, which measures performance in terms of BER for a range of SNR values.

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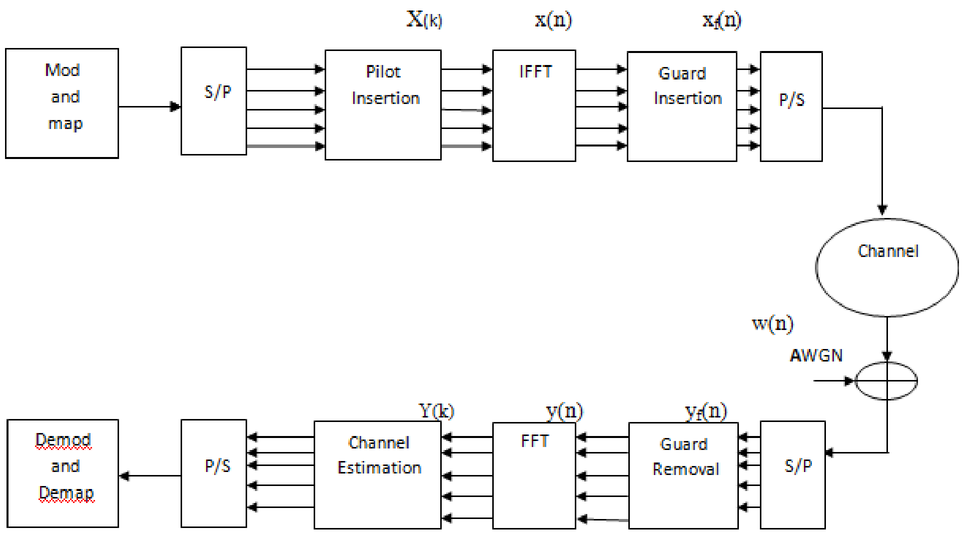

Figure (1) OFDM system based pilot channel estimation.

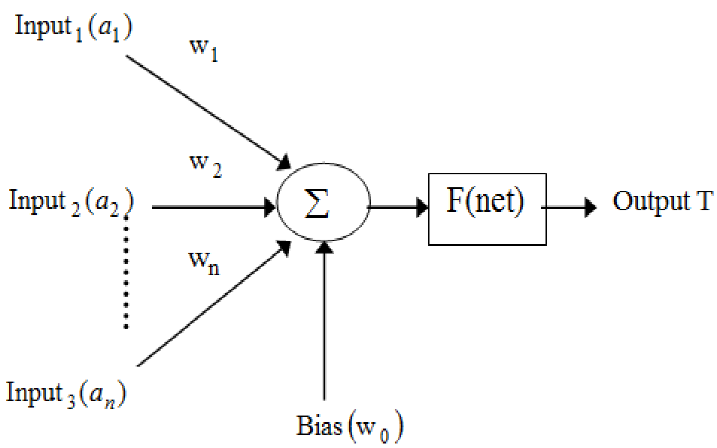

Figure (2) Basic neural mode.

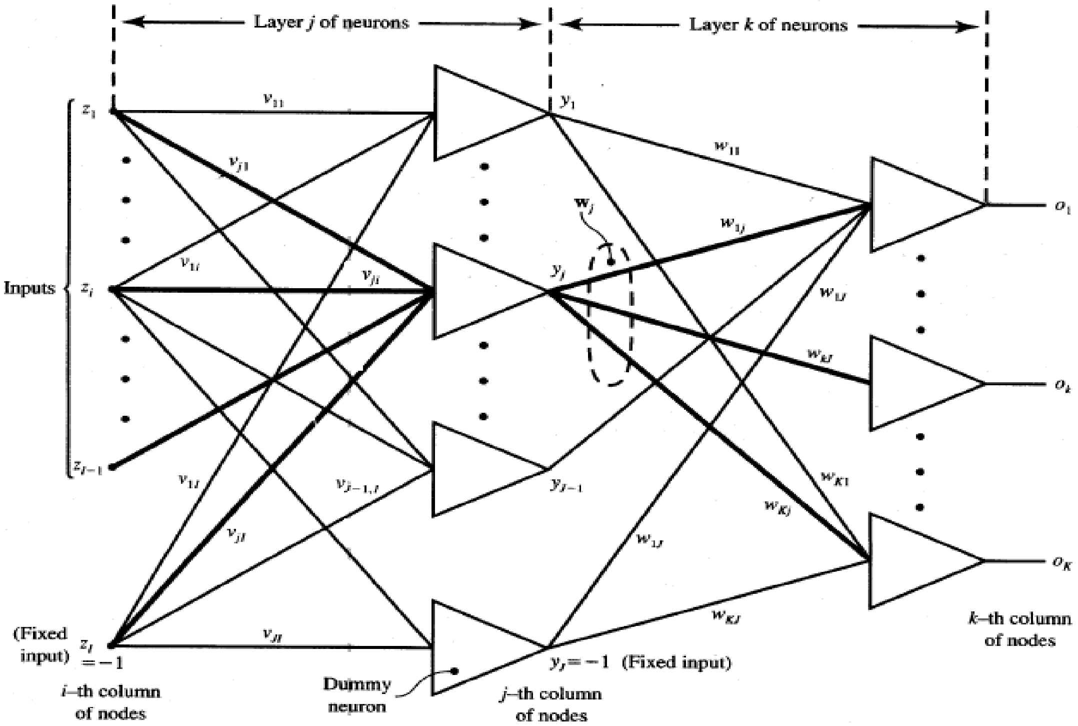

Figure (3) Layered feed forward neural network with two continuous perceptron layers.

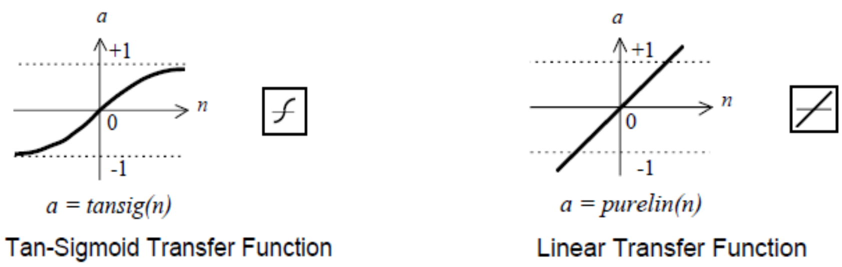

Figure 4. Activation functions

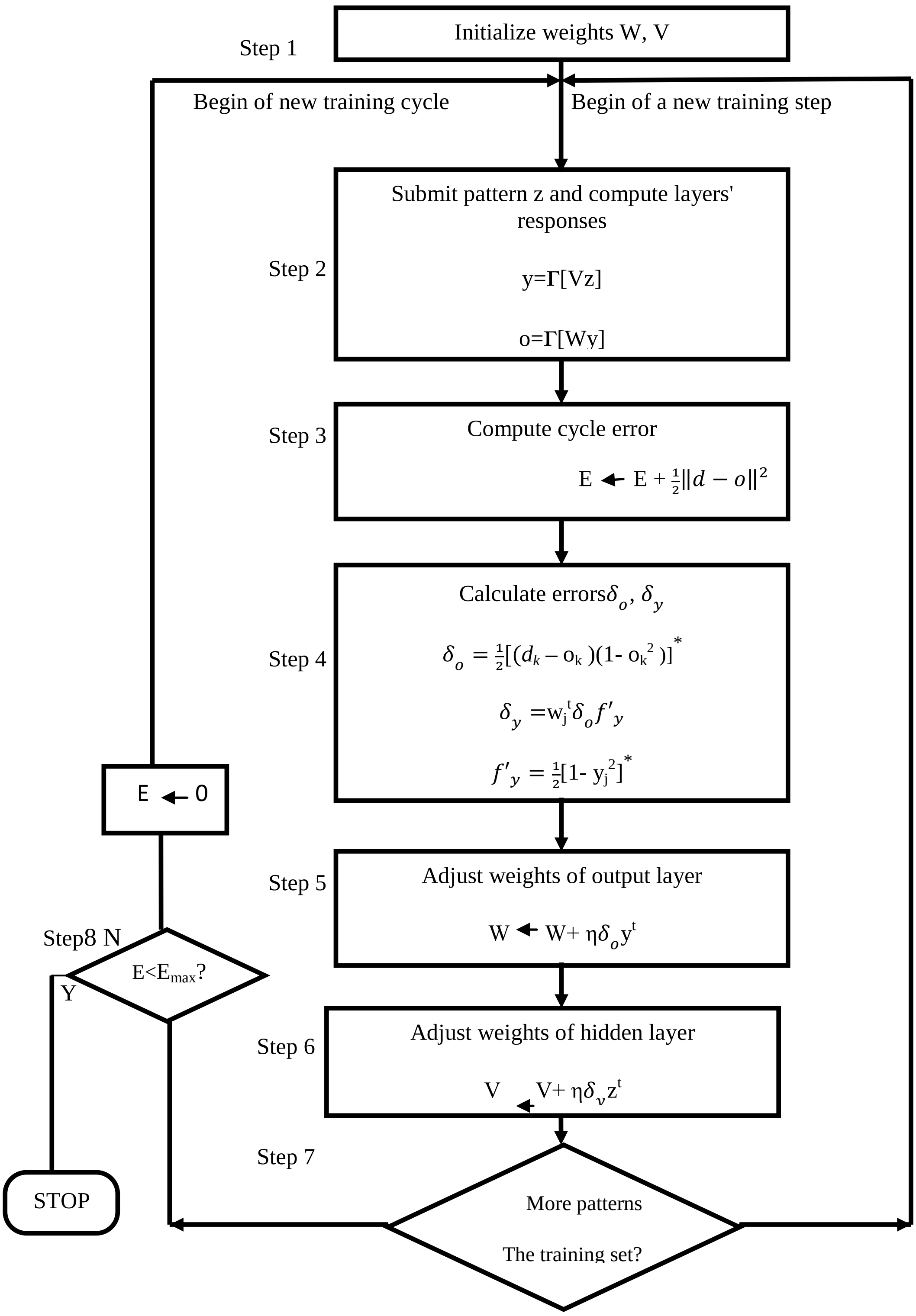

Figure 5. Error back-propagation training algorithm flowchart

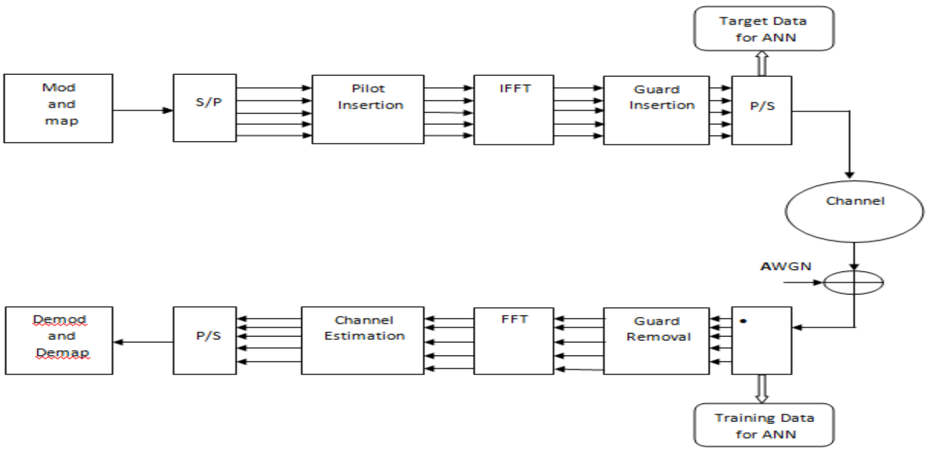

Figure .6 block diagram of proposed NN with OFDM.

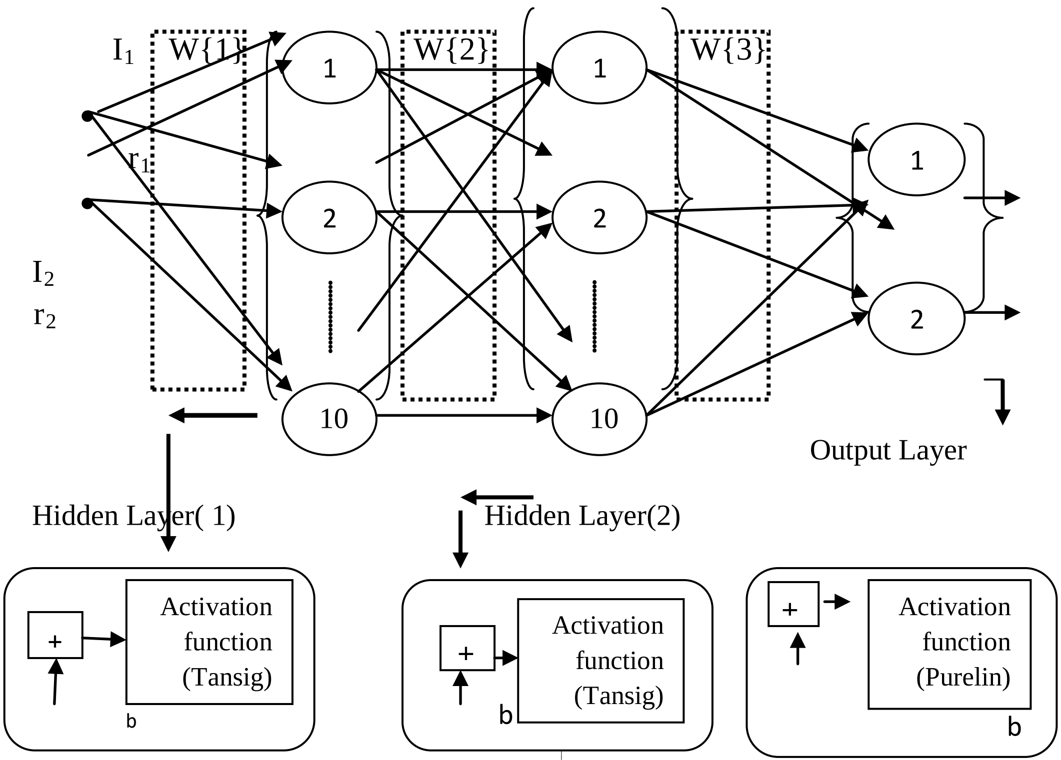

Figure 7.Architecture of ANN

Table (1) Parameters of ANN.

Parameter	Value
Number of inputs	2
Number of hidden layers	2
Number of neurons	10, 10
Epoch number	1000
Training functions	LM, RPROP

Table (2) OFDM system parameters.

Parameter	Value
Modulation type	QPSK
FFT size	128
Number of carrier	128
Guard length	32 symbols
Type of guard interval	Cyclic prefix

Table (3) SNR values obtained for different paths using LS estimator at BER = 0.001

SNR (dB) for one-path	SNR (dB) for two-path	SNR (dB) for three-path
28	29	29.5

Table (4)SNR values obtained for different paths using LS estimator and LS with ANN at BER = 0.001

SNR (dB) for one-path			SNR (dB) for two-path			SNR (dB) for three-path		
LS	LS with ANN (RProp)	LS with ANN (LM)	LS	LS with ANN (RProp)	LS with ANN (LM)	LS	LS with ANN (RProp)	LS with ANN (LM)
28	26.5	24	29	27	26	29.5	27.5	26.5

Table (5)SNR values obtained for different algorithm in flat and two paths at BER = 0.001

SNR (dB) for one-path		SNR (dB) for two-path	
RProp	LM	RProp	LM
26.5	24	27	26

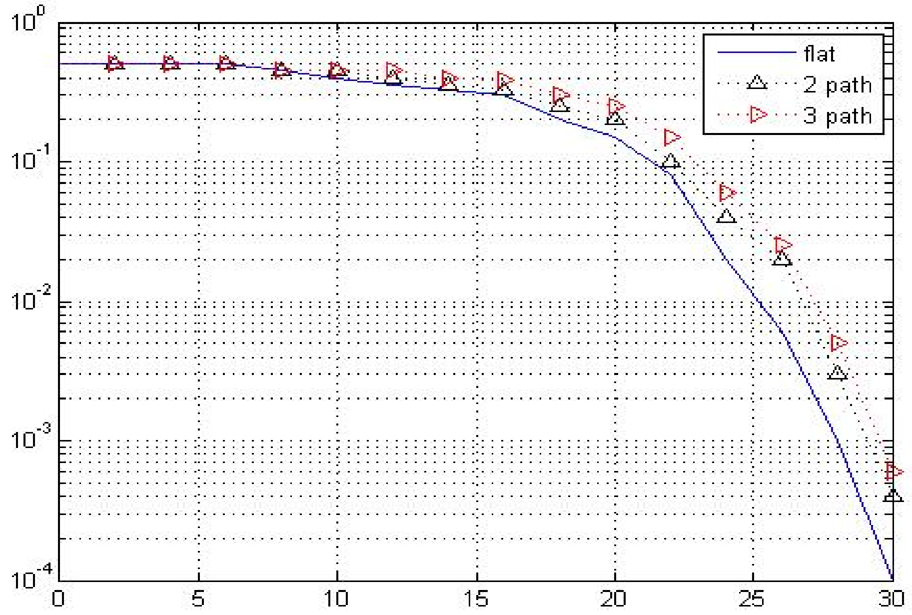

Figure (8) BER performance of OFDM system for different paths.

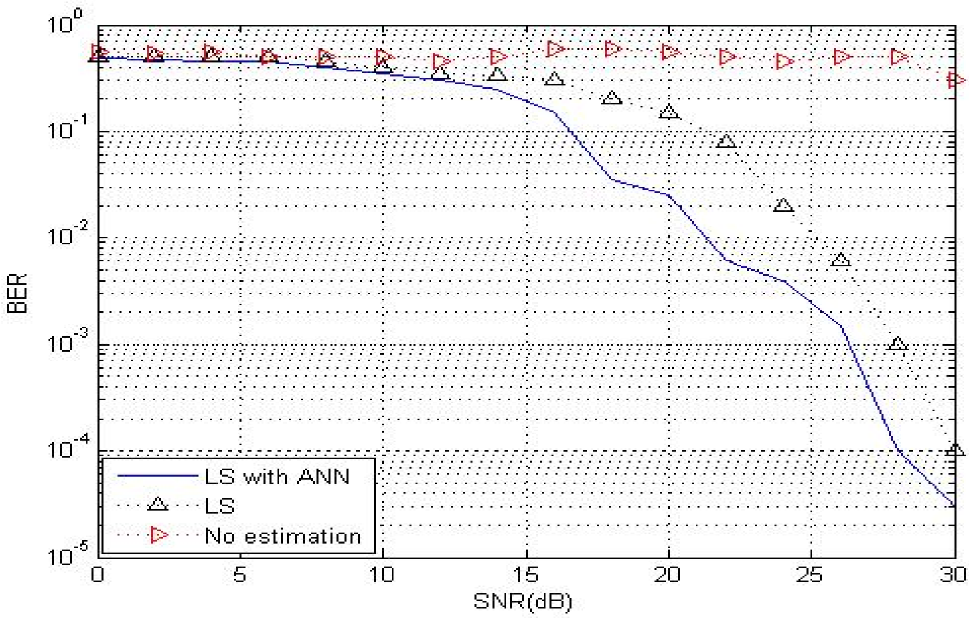

Figure (9) BER comparison of OFDM with ANN (RProp), without ANN and with no estimation for flat fading channel.

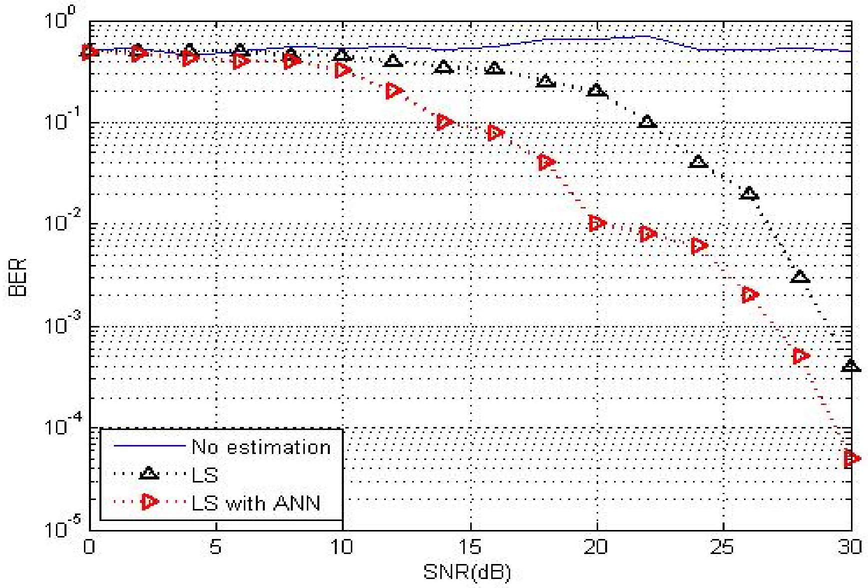

Figure (10) BER comparison of OFDM with ANN (RProp), without ANN and with no estimation for two path fading channel.

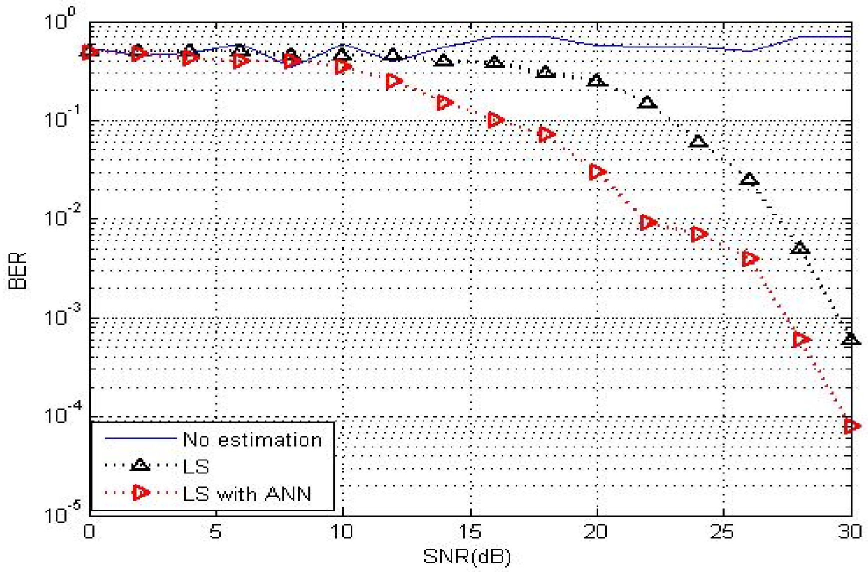

Figure (11) BER comparison of OFDM with ANN (RProP), without ANN and with no estimation for three path fading channel.

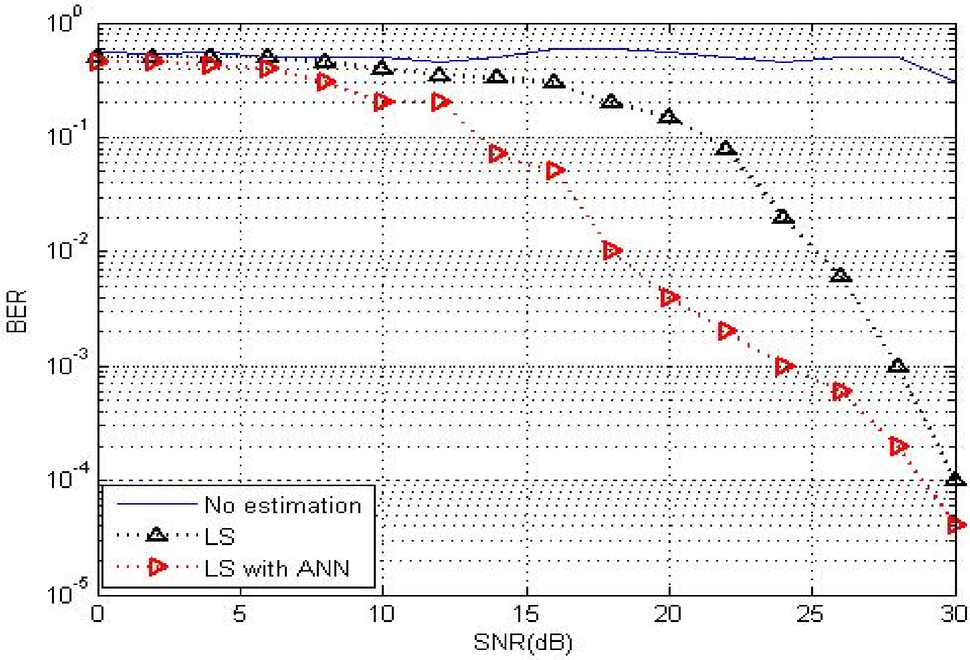

Figure (12) BER comparison of OFDM with ANN (LM), without ANN and with no estimation for flat fading channel.

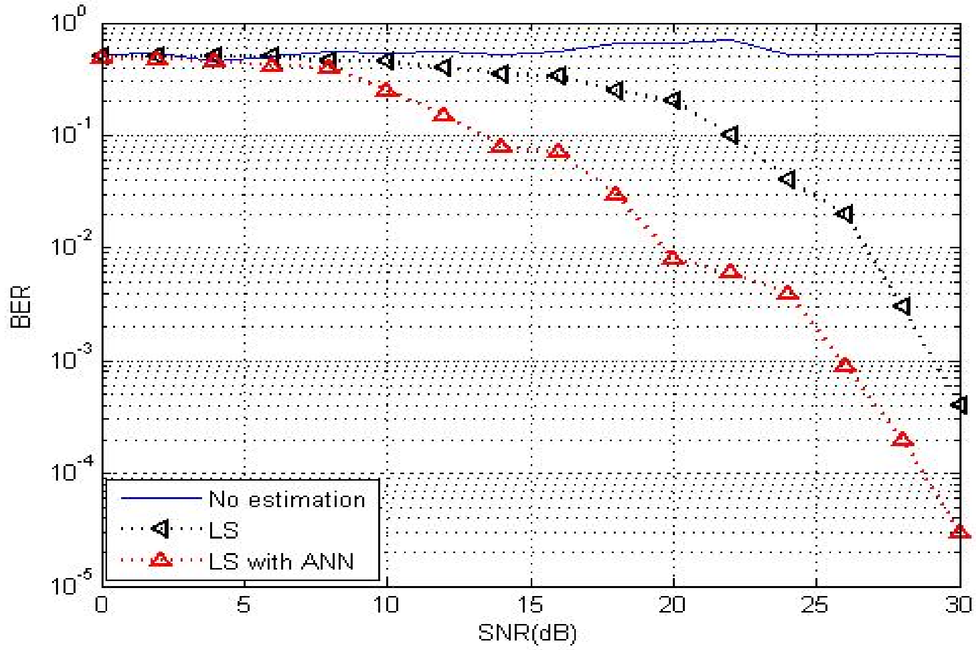

Figure (13) BER comparison of OFDM with ANN (LM), without ANN and with no estimation for two path fading channel.

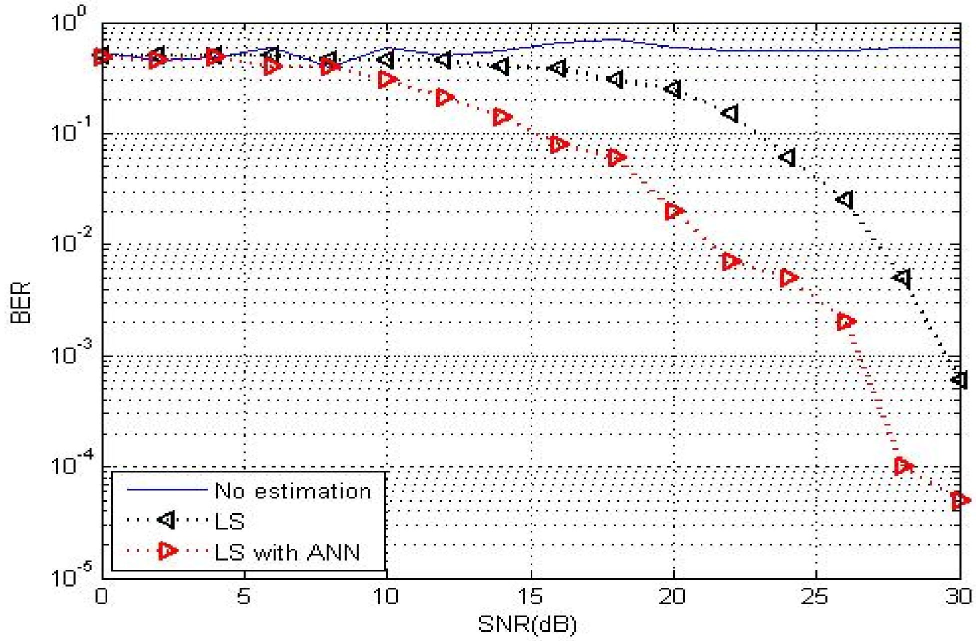

Figure (14) BER comparison of OFDM with ANN (LM), without ANN and with no estimation for two path fading channel.

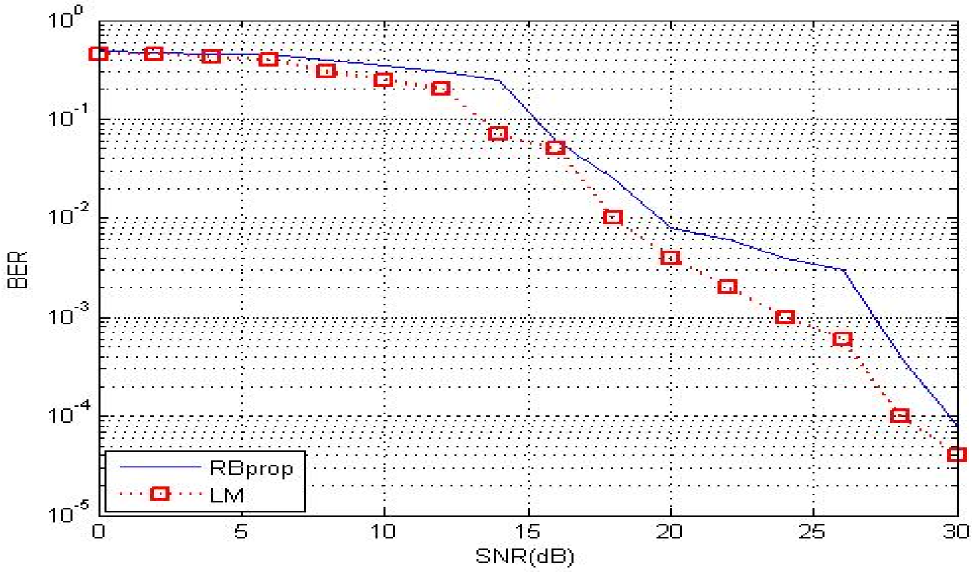

Figure (15) BER comparison of OFDM with ANN (LM) and OFDM with ANN(RPROP) estimation for flat fading channel.

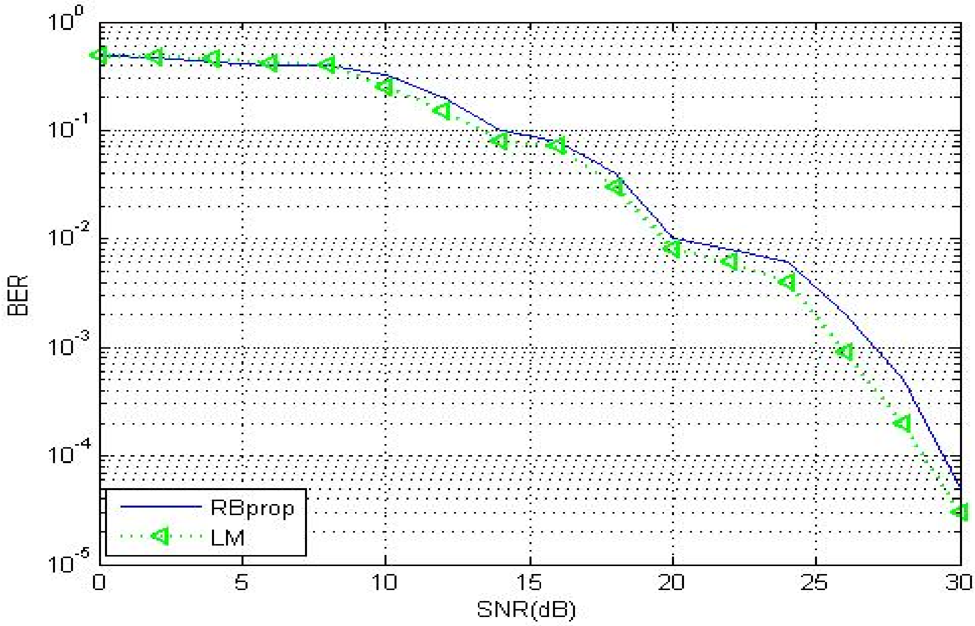

Figure (16) BER comparison of OFDM with ANN (LM) and OFDM with ANN(RPROP) estimation for two path fading channel.