




## **Chapter 6**

# **Artificial Neural Network Based MIMO Channel Estimation**



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### 6.1 Introduction

MIMO Wireless systems have been shown to provide dramatic increase in channel capacity and throughput performance of LTE-A Downlink Physical Layer. MIMO provides promising solutions for the increasing demands for high channel capacity systems. The capacity gain, however, requires perfect knowledge of the instantaneous channel fading at both the transmitter and receiver [1]. The efficiency of channel estimation affects the system performance by introducing a channel estimation error that reduces the channel capacity and by dedication of a fraction of its bandwidth to the transmission of pilots or training symbols [2, 3]. Channel estimation techniques for MIMO Communication systems has been reviewed in [4, 5].

The receiver in MIMO system, requires the knowledge of CSI in order to recover the transmitted signal properly. MIMO channel capacity has been widely investigated under different assumptions on CSI at the receiver or both at the transmitter and receiver [6, 7]. The bounds on Mutual Information with imperfect CSI for time-varying SISO and MIMO channels and their effect on achievable rates is already analyzed in [8–10].

Channel estimation in MIMO systems is an active research area and challenging task. Several channel estimation methods have already been studied by different researchers for MIMO systems. In LTE-A Downlink channel estimation methods, reference symbols are inserted and transmitted over the channel, and are estimated at the receiver [11]. The most efficient training based methods are the Least Squares (LS) method [12], Minimum Mean Square Error (MMSE) method [13, 14] and Adaptive Filtering channel estimation method [15]. Channel estimation by artificial neural network has been deployed in OFDM system, with different neural network architectures [16–20].

ANN based MIMO channel estimation techniques for LTE-A Downlink Physical layer is proposed and discussed in this chapter. The performance analysis of channel estimation techniques in terms of Throughput of Downlink Physical layer is analyzed using LTE-A Link Layer Simulator. The ANN weights are further trained by Genetic Algorithm (GA) to increase the performance of system. Further details of ANN based MIMO Channel estimation design and simulation results are discussed in following sections.

### 6.2 LTE-A MIMO channel estimation

The distortion imposed by the wireless channel on the transmitted data stream in a MIMO communication system is normally observed in the form of errors at the receiver. The main objectives

of communication system is to minimize the number of these errors and to maximize the throughput of the system. In order to optimize the system performance in response to channel conditions, an estimate of the channel at the receiver is a vital part. A Reference Signal (RS) is a pre-defined signal, pre-known to both transmitter and receiver. RS when transmitted through wireless channel is affected by multipath fading and distortions.

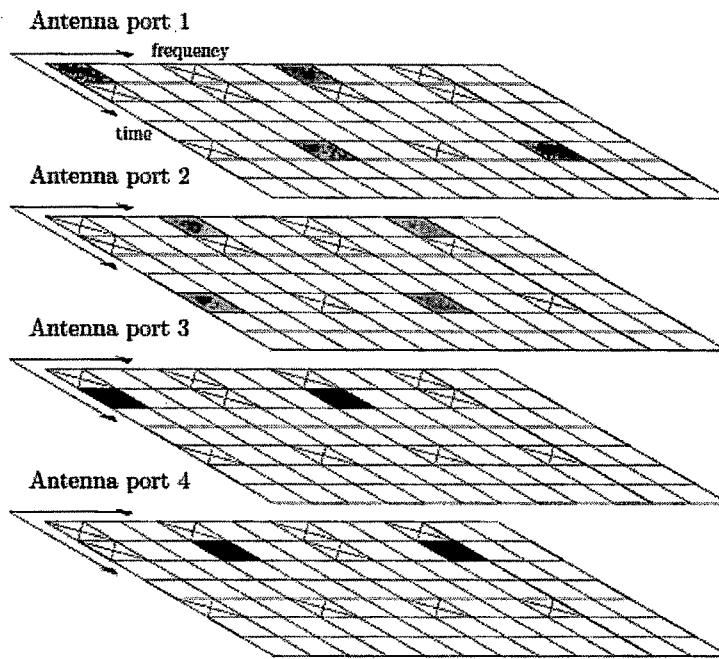


Figure 6.1: Reference Signals for LTE-A antenna ports

In LTE-A, the Downlink transmission uses the OFDMA feature with 15 kHz subcarrier spacing of the resource grid as discussed in Section 4.3. During subcarrier mapping the RS are inserted in both time and frequency directions so that it can be estimated at the receiver [21]. This pilot symbols are used to estimate the channel at given specific locations within a subframe. The RS signals are transmitted with 1, 2 or 4 antennas. It is transmitted every first and Fifth OFDM symbol of a slot as shown in Figure 6.1. For the case of two antennas, reference signal is sent on the first OFDM symbol of first antenna and the first OFDM symbol on the second antenna is not used to avoid interference. Using this estimates, the channel across an arbitrary number of subframes can be estimated using interpolation [22]. The pilot symbols in resource grid have unique position which depends on the eNB cell identification number and transmit antenna being used. The pilot symbols are positioned so that they do not interfere with one another and can be effectively used to

estimate the channel gains.

In Release 8, the reference signal is added after precoding i.e Cell-specific Reference Signal (CRS) per antenna. Using the received CRS the UE estimates the wireless radio channel, which is used by the receiver for demodulation of the received signal. In Release 10, the UE-specific reference signal Demodulation Reference Signals (DM-RS) is added to different data streams before precoding. Hence the channel is estimated using DM-RS which provides information about the combined effect of the wireless channel and precoding.

### 6.3 ANN based MIMO Channel Estimation

ANN are algorithms for optimization and learning based on concepts inspired by research into the nature of the brain [23]. ANN based channel estimation for throughput optimization of LTE-A Downlink Physical Layer is carried out in this work. Different ANN Network Architectures are tested for its effect on channel estimation and hence throughput.

Considering a 2x2 MIMO system, the received symbol  $y$  can be written as:

$$y = XH + n \quad (6.1)$$

where  $H$  is the channel matrix,  $n$  is the AWGN noise at the receiver and  $X$  contains the data symbols  $x_d$  and pilot symbols  $x_p$ . The Least-Squares (LS) channel estimator for subcarriers on which pilot symbols are located, is given by:

$$h_p^{LS} = X_p^H y_p \quad (6.2)$$

where  $H$  is for Hermitian matrix. LS channel estimator is obtained by minimizing the square distance between the received reference symbols  $Y$  and the transmitted reference symbols  $X$  as follows [14, 24]. The channel estimated by the LS channel estimator is used as target for training ANN. The algorithm developed for MIMO Channel estimation in LTE-A Link Level Simulator is given in Algorithm 6.1. As shown in Figure 6.2  $X$  is the transmitted reference symbol through wireless channel and is affected by noise. The received reference symbols is assigned a  $Y$ . LS Channel estimator estimates the unknown channel given by  $H$ .

The training pairs for ANN is generated using set of reference symbols as input and LS Channel estimate as output pairs. Reference symbols from the training set is presented to the input layer of the network and the error at the output layer is calculated. The error is propagated backwards towards the input layer and the weights are updated. This procedure is repeated for all the training

**Algorithm 6.1** ANN based MIMO Channel Estimation Algorithm

- Initialization:

- Assign Received Reference Symbol to variable X
- Assign Reference Symbols to variable Y
- Initialize ANN Simulation Parameters

- Estimate MIMO Channel using Least Square Algorithm and assign to variable  $H_{ls\_one\_channel}$ .

- Determine the Real and Imaginary parts of the Estimated channel and Received reference Symbols.

- Design ANN Network Architecture specifying the simulation parameters.

- Generate Training Pairs for ANN by taking Received Reference Symbols as Input and LS Estimated Channel as output (X,  $H_{ls\_one\_channel}$ ).

- Train the ANN using Training Algorithm Specified.

- Once the ANN is trained, take Received Reference Symbol as input and simulate ANN for Estimated Channel.

signals. At the end of each iteration, test data are presented to ANN and the performance of ANN is evaluated. Further training of ANN is continued till the desired performance is reached. The estimator uses the information provided by received reference symbols of sub channels to estimate the channel.

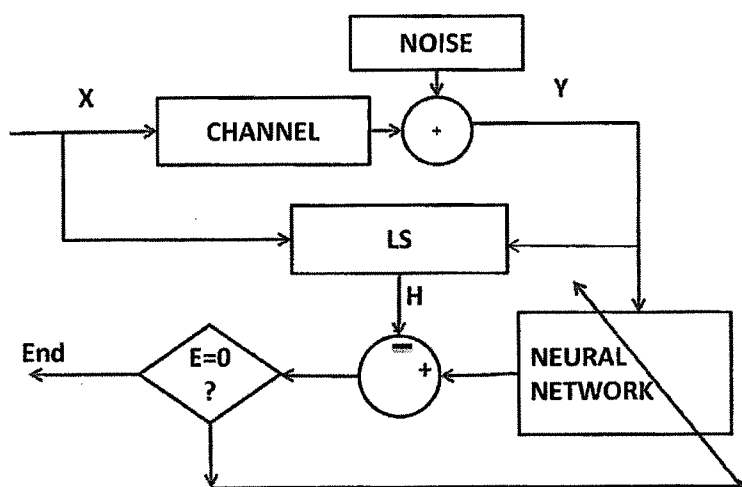


Figure 6.2: ANN based Channel estimation

Four types of ANN Architecture are design for MIMO Channel Estimation for LTE-A Downlink Physical Layer as follows:

- 1). Feedforward Neural Network (FNN): A FNN [25] is one whose topology has no closed

paths. Its input nodes are connected to the output nodes without any feedback paths. The Back-Propagation Algorithm (BPA) uses the steepest-descent method to reach a global minimum. The flowchart of the BPA is given in [26]. FNN consists of one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons as shown in Figure 6.3. This network can be used as a general function approximator. It can approximate any function with a finite number of discontinuities arbitrarily well, given sufficient neurons in the hidden layer.

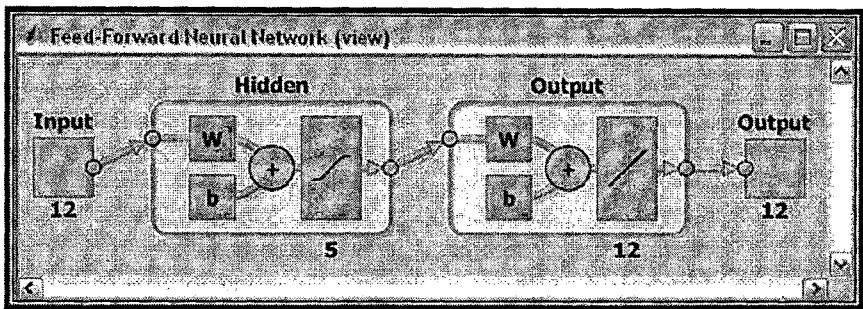


Figure 6.3: Feedforward Neural Network

2). Radial Basis Neural Network (RBNN): It is an alternative to the more widely used Multi-layer network and is less computer time consuming for network training [27, 28]. Radial basis networks consist of two layers: a hidden radial basis layer of radial basis function neurons, and an output layer of linear neurons. as shown in Figure 6.4. The nodes within each layer are fully connected to the previous layer. This network is mainly used for fitting a function application.

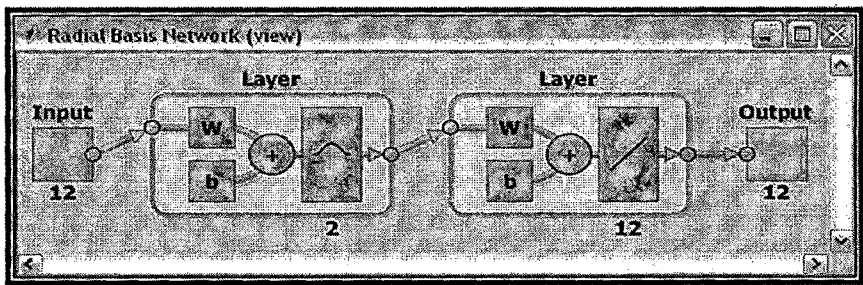


Figure 6.4: Radial Basis Network

3). Layered Recurrent Network (LRN): In the LRN, there is a feedback loop, with a single delay, around each layer of the network except for the last layer. The method of training is similar to that of the FNN. In addition to this, a neuron taking input from the output layer and connected to

the hidden layer as shown in Figure 6.5. The inputs are presented to the input units and the output from the network is calculated. The process is repeated for all the patterns. After finding the system error, the training of the network is based on the steepest gradient method.

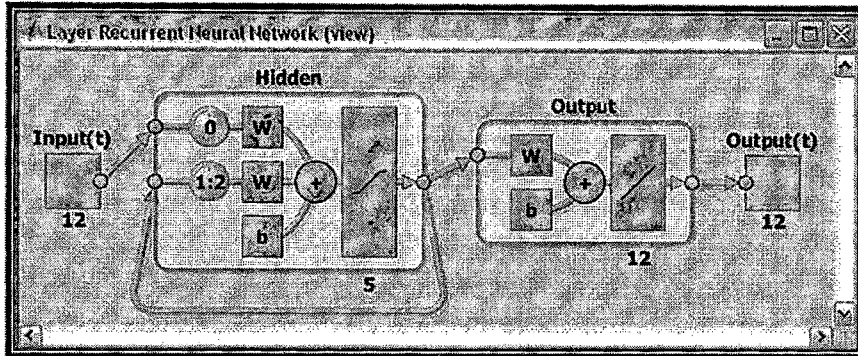


Figure 6.5: Layer Recurrent Neural Network

4) General Regression Neural Network (GRNN): A GRNN [27, 29] is a variation of the radial basis neural networks. A GRNN is often used for function approximation. It has a radial basis layer and a special linear layer. A GRNN does not require an iterative training procedure as back propagation networks. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero.

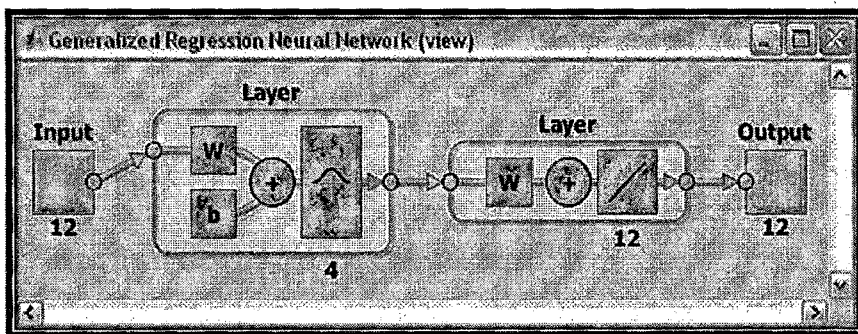


Figure 6.6: Generalized Regression Neural Network

### 6.3.1 ANN Simulation Parameters and results

ANN based MIMO Channel Estimation methods for LTE-A Downlink Physical Layer are design and simulation is carried out using Neural network Toolbox. The results are validated with

Perfect and LS Channel Estimation methods in LTE-A Link Level Simulator. The functions used for simulation of the ANN Networks are as listed in Table 6.1.

ANN Network	MATLAB Function
Feedforward network	feedforwardnet(hiddenSizes,trainFcn)
Radial Basis Network	newrb(P,T,goal,spread)
General regression Neural network	newgrnn(P,T,spread)
Layered recurrent Neural network	layrecnet(layerDelays,hiddenSizes,trainFcn)

Table 6.1: MATLAB Function to design ANN Networks

The Simulation parameters for the simulation of Channel estimation Techniques for LTE-A Downlink Physical Layer is as given in Table 6.2. GRNN network does not require training using train function, because the *newgrnn* function itself trains the network.

Parameters	FNN	RBNN	GRNN	LRN
Number of Layers	1	1	1	1
Hidden Sizes	5	5	5	5
Training Function	'trainlm'	'trainlm'	-	'trainlm'
Number of Epochs/Iteration	1000	1000	1000	1000
Spread	-	1.0	1.0	-
Goal	-	0.0	0.0	-
layerDelays	-	-	-	1:2

Table 6.2: Simulation parameters for ANN

The simulations are carried out modifying the LTE-A Channel estimator files. The MIMO Channel being complex, the real and imaginary part of the reference symbols and the received reference symbols are generated and two different neural networks are designed to estimate the channel at the receiver. Figure 6.7 shows the throughput analysis for 2x2 MIMO System for Tx-D transmission mode for flat Rayleigh channel. It can be observed that RBFN and GRNN gives better result compared to LS Channel Estimation. FNN and LRN gives worse result when compared to LS Channel Estimation technique. At SNR equal to 20 dB, throughput for perfect channel is 4.8 Mbps and for RBFN and GRNN is approximately same and equal to 4.5 Mbps. LS Channel Estimation gives Throughput of 3.55 Mbps, but FNN and LRN gives approximately same throughput of 2.75 Mbps.

Figure 6.8 shows the throughput analysis for 2x2 MIMO System for CLSM transmission mode for flat rayleigh channel. It can be observed that GRNN gives better result compared to LS Channel Estimation. FNN gives worse result when compared to LS Channel Estimation technique. RBFN



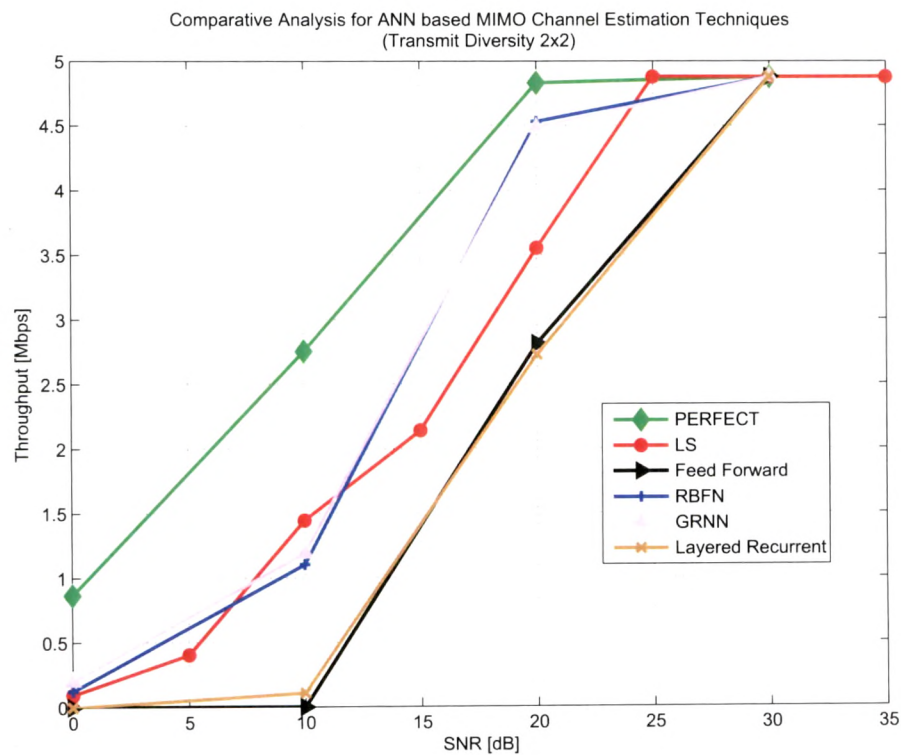


Figure 6.7: Throughput v/s SNR for TxD 2x2 for various ANN Channel estimation

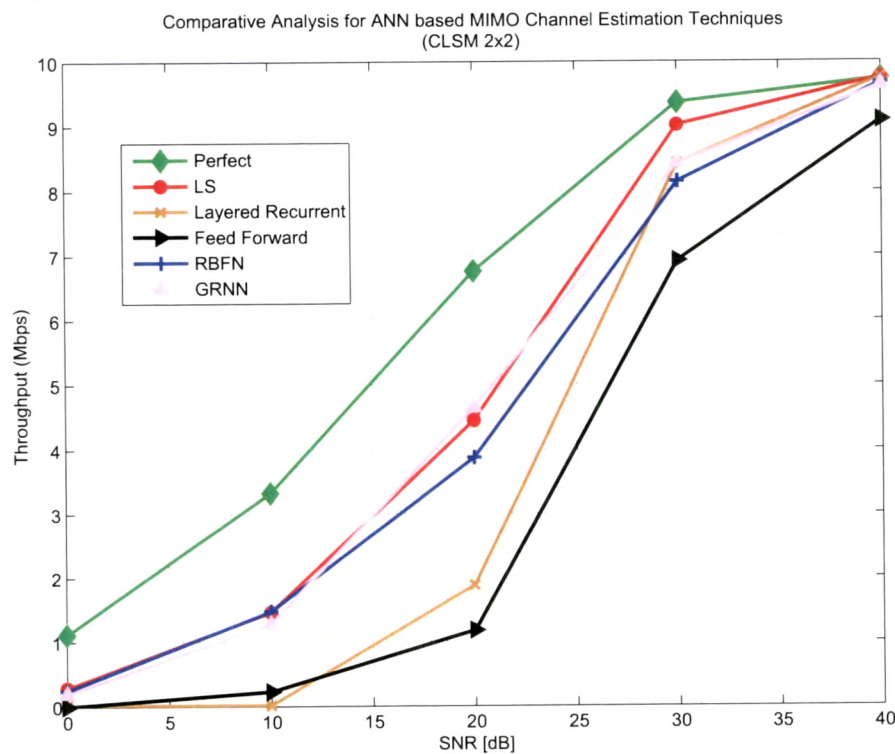


Figure 6.8: Throughput v/s SNR for CLSM 2x2 for various ANN Channel estimation

Network also gives equivalent performance to LS Channel Estimation technique.

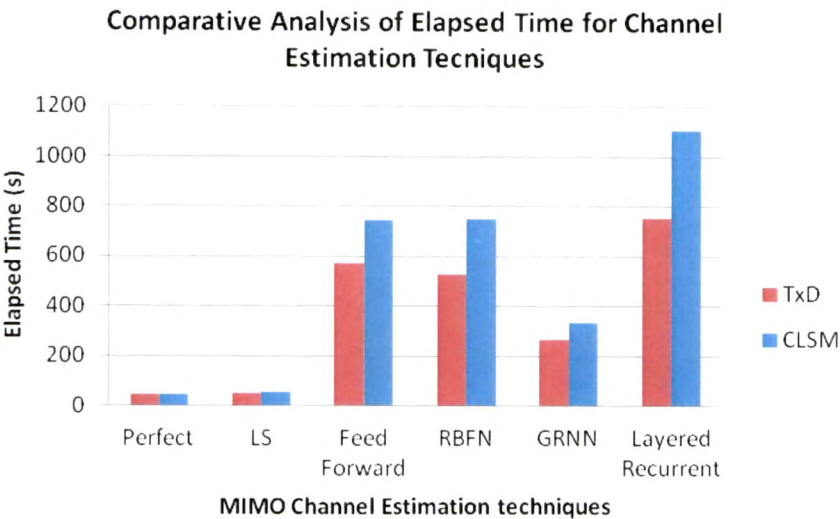


Figure 6.9: Comparison of Elapsed Time for different MIMO Channel Estimation Techniques

Figure 6.9 shows the performance analysis of different ANN based MIMO Channel estimation in term=ms of Elapsed time for simulation. The results are compared with the perfect channel and LS Channel Estimation Technique. As seen the GRNN Network takes minimum time of all ANN based Channel estimation technique of 266.54s for TxD and for 337.8s CLSM transmission mode. Whereas LRN takes maximum simulation time of for 757.7s TxD and for 1106.77s CLSM mode as it consists of feedback loop and layer delays for simulation.

6.4 ANN trained by Genetic Algorithm for MIMO Channel Estimation

Genetic algorithms are optimization algorithms based on several features of biological evolution. It proceeds in an iterative manner by generating new populations of individuals from the old ones. This algorithm applies stochastic operators such as selection, crossover, and mutation on an initially random population in order to compute a new population [30]. GA are used in conjunction with ANN to set the weights of ANN architectures, to learn ANN topologies and to select training data [31,32]. GA have been successfully applied to train FNNs using GA for various decision and optimization problems [33–35].

Multi-layer feedforward (MLF) neural networks, trained with a back-propagation (BPA) learning algorithm, are the most popular neural networks. During training, the network topology and/or

the weights and/or the biases and/or the transfer functions are selected based on some training data. In many approaches, the topology and transfer functions are held fixed, and the space of possible networks is spanned by all possible values of the weights and biases [36,37]. The BPA is a widely used method for FNN learning in many applications [38]. GA is widely used for optimization of parameters of FNN Network like weights and biases, network structures [39,40]. GAs are found to be superior algorithm for training FNN as compare to BPA [40,41]. This work has motivated the author to apply the GA for training FNN for MIMO Channel Estimation in LTE-A Downlink Physical Layer.

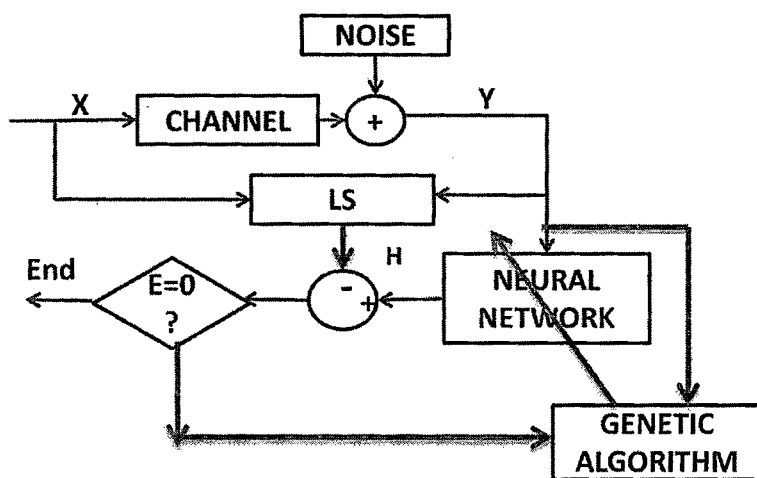


Figure 6.10: ANN-GA based Channel Estimation

BPA [42] is a famous learning algorithms among ANNs. In the learning process, to reduce the inaccuracy of ANNs, BPLAs use the gradient-decent search method to adjust the connection weights. The algorithm for FNN trained by BPA and FNN trained by GA is discussed in detail in [41]. In ANN-BPA, the ANN is trained with transmitted reference symbols. Optimization of the weights is made by backward propagation of the error during training or learning phase. The ANN reads the input and output values in the training data set and changes the value of the weighted links to reduce the difference between the received reference symbol and reference symbol values. The error in prediction is minimized across many training cycles (iteration or epoch) until network reaches specified level of accuracy. A complete round of forwardbackward passes and weight adjustments using all inputoutput pairs in the data set is called an epoch or iteration. The target sample set is presented to the ANN in the form of result or estimated channel obtained by Least Square (LS) complex type matrix. The learning of the ANN is done in the training phase

during which the ANN adjusts its weights according to training algorithm.

Similarly, ANN-GA is designed, the target sample set is presented same as in backpropagation neural network. The training of the ANN is done using GA. In the training phase, the GA adjusts its weights according to the Genetic algorithm applied between the receiver and result of LS estimator. First neural network is initialized with training pair (Inputs and Targets), and then configuration of neural network is done for the data set. A handle to the “MSE \_ TEST” function [43] is created, that calculates MSE (mean square error between output and targets of FNN) by changing weights using GA. In GA, lower the error, the higher is the fitness. The weights for which function is to be the lowest will be stored in the neural network and applying Inputs to FFNN, output will give estimated channel output as shown in Figure 6.10.

6.4.1 ANN-GA Simulation Parameters and Result

The ANN-BPA and ANN-GA based MIMO Channel Estimation are simulated in LTE-A Link Level Simulator. Comparative Analysis of these techniques are carried out in terms of throughput v/s SNR for 2x2 CLSM MIMO mode as shown in Figure 6.11. FNN developed for channel estimation, is further optimized in terms of weights and biases of network architecture by GA. MATLAB Toolboxes usage and description for Neural Network and Genetic Algorithm design is discussed in detail Chapter 5. The simulation parameters for MIMO Channel Estimation based on ANN trained by BPA and GA are as in Table 6.3.

Parameters	ANN Trained by BPA	ANN Trained by GA
Number of inputs	1	1
Number of hidden layers	1	1
Number of neurons	5	5
Epoch number / Iteration	1000	100
Training Function / Algorithm	Levenberg- Marquart	Genetic Algorithm
Performance Metric	Mean Square Error	Mean Square Error

Table 6.3: Simulation Parameters for ANN-BPA and ANN-GA for MIMO Channel Estimation

Throughput analysis of proposed methods MIMO Channel estimation techniques are compared with LS channel estimator. It is seen that MIMO Channel estimator based on ANN trained by GA exhibits better performance in terms of throughput and is giving performance similar to Perfect channel from 10 to 15 SNR range. At SNR of 20 dB, ANN-GA has higher throughput of 8.875 Mbps compare to ANN-BPA (8.332 Mbps) and LS (8.673 Mbps) channel estimator.

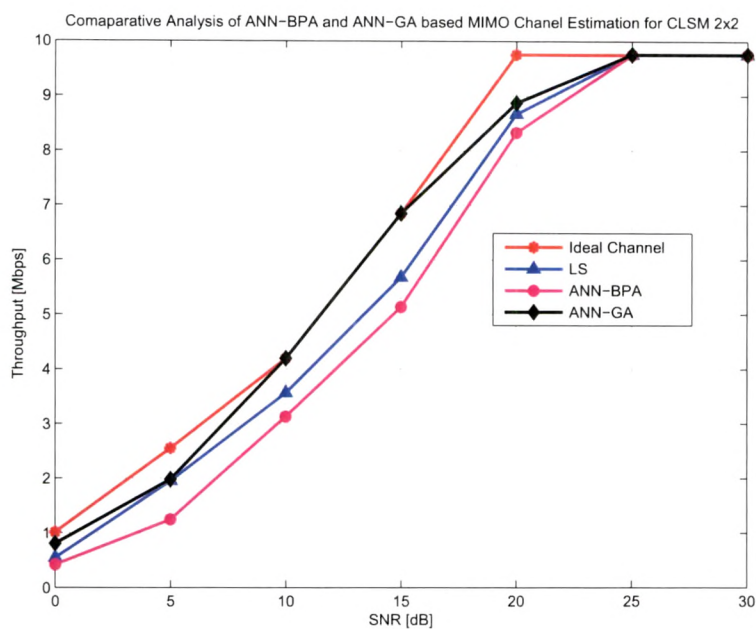


Figure 6.11: Throughput v/s SNR for ANN-BPA and ANN-GA MIMO Channel Estimation

6.5 Concluding Remarks

MIMO Channel Estimation being the vital part for detecting the received data at receiver, is studied in detail in this chapter. The imperfect CSI at receiver affects the Throughput of LTE-A Downlink Physical Layer. Various ANN based MIMO Channel estimation techniques are designed and simulation are carried out in this work. ANN based channel estimation methods developed for channel estimation are based of ANN Architectures: FNN, GRNN, RBFN and LRN. The throughput analysis shows that the proposed techniques gives better performance of the system as compared to traditional LS Channel estimator. The ANN is further trained by GA to optimize the ANN weights to enhance the channel estimation. By using ANN-GA based Channel Estimation technique the throughput can be maximized as compared to traditional LS Channel estimation method.