

# Comparative Performance Analysis of ANN Based MIMO Channel Estimation for downlink LTE-Advanced System employing Genetic Algorithm

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**Abstract**—Paper propose a robust channel estimator for downlink Long Term Evolution-Advanced (LTE-A) system using Artificial Neural Network (ANN) trained by backpropagation algorithm (BPA) and ANN trained by genetic algorithm (GA). The new methods use the information provided by the received reference symbols to estimate the total frequency response of the channel in two phases. In the first phase, the proposed method learns to adapt to the channel variations, and in the second phase it predicts the channel parameters. The performance of the estimation methods is confirmed by simulations in Vienna LTE-A Link Level Simulator. Performances of the proposed channel estimator, ANN trained by GA and ANN trained by BPA is compared with traditional Least Square (LS) algorithm for Closed Loop Spatial Multiplexing-Single User Multi-input Multi-output (2X2) (CLSM-SUMIMO) case.

**Keywords**-LTE-A, MIMO, Artificial Neural Network, Back- Propagation, Genetic Algorithm

## I. INTRODUCTION

The Long Term Evolution (LTE) is a step towards the fourth generation (4G) of mobile radio technologies to increase the spectral efficiency and to obtain higher throughput. LTE-Advanced (LTE-A) refers to the evolved version of LTE that is being developed by 3rd Generation Partnership Project (3GPP). LTE Release10 [1] is set to provide higher bit rates in a cost efficient way and, at the same time, completely fulfill the requirements set by

International Telecommunication Union (ITU) for International Mobile Telecommunications-Advanced (IMT Advanced) also referred to as 4G [2]. The features supported by LTE-A are Carrier and spectrum aggregation, Enhanced Multiple-Input Multiple-Output (MIMO) Techniques, Coordinated multipoint (CoMP) transmission and reception, Relaying and support for Self-Organizing Networks (SON) [3]. Release 10 support enhanced MIMO Techniques with 8X8 in downlink and upto 4X4 in uplink.

LTE-Advanced downlink uses an Orthogonal Frequency Division Multiplex Access (OFDMA) radio interface and MIMO techniques, that is more resilient against severe channel conditions and support high data rate transmission capabilities. It increases spectral efficiency, and improves link reliability without additional bandwidth or transmit power [3]. OFDMA technique basically distributes the symbols on a large number of carriers. By implementing this new access technique in the context to mobile broadband transmission, new approaches for time and frequency synchronization, equalization and channel estimation are needed.

The receiver in MIMO system, requires the knowledge of Channel State Information (CSI) in order to recover the transmitted signal properly. Channel estimation in MIMO-OFDM systems is an active research area and challenging task. Several channel estimation methods have already been studied by

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different researchers for MIMO systems. In certain channel estimation methods, reference symbols are inserted and transmitted over the channel, and are estimated at the receiver. [3-4]. The most efficient training based methods are the Least Square (LS) method [5] [6], Minimum Mean Square Error (MMSE) method [7-8] and Adaptive Filtering channel estimation method [9-10]. Channel estimation by artificial neural network has been deployed in OFDM system, with different neural network architectures [11-15]. In this contribution, we propose a new channel estimation technique for LTE-A downlink using neural network architecture trained by Genetic Algorithm. The principle of this method is to exploit the information provided by the reference symbols to estimate the channel response. In section II, the LTE-A Downlink Physical Layer is described. The Vienna LTE-A Link Level Simulator is explained in Section III. Section IV describes different channel estimation techniques like Least Square (LS) and ANN based techniques. Followed by simulation results and performance analysis of proposed ANN based channel estimation techniques in Section V. Finally Conclusion and further development is discussed in Section VI.

## II. LTE-A DOWNLINK PHYSICAL LAYER

Downlink LTE-A system is based on OFDMA air in-

terface transmission scheme [2]. OFDMA system is de- scribed in [4]. The orthogonal frequency subcarriers are used to share spectrum among users using access technique. The LTE-A Physical layer employs advanced technolo- gies of wireless cellular systems. These includes multi-plexing schemes: OFDMA and Single-Carrier Frequency Division Multiple Access (SC-FDMA), MIMO antenna schemes: 2x2, 4x4 upto 8x8, Adaptive modulation and coding schemes (AMC), duplexing schemes: Time Divi- sion Duplexing (TDD) and Frequency Division Duplexing (FDD), and bandwidth flexibility from 1.4MHz to 20 MHz. As shown in Figure 1, 2x2 MIMO system with two antennas at eNodeB and UE. The uplink feedback values Channel Quality Indicator (CQI), Rank Indicator (RI) and Precoding Matrix Indicator (PMI) are calculated at the receiver, and are feedback to the eNodeB. Physical channel processing at eNodeB consists of Scrambling which breaks long strings of 1s and 0s into scrambled bits, Modulation converts scrambled bits into complex-valued symbols uses either QPSK, 16-QAM OR 64-QAM modulation, Layer mapper and

precoder performs symbol transformations to enable MIMO transmission techniques, Resource element (RE) mapper maps the symbols to the appropriate locations in the time-frequency Resource grid, OFDM signal mapper generates time domain baseband signals for each antenna port (Antenna Port 0,1,2 or 4) for transmission [4]. Similarly at UE descrambling, demodulation and demapper operations and MIMO Receiver processing to receive the transmitted data streams. LTE-A Downlink modulation is based on OFDMA which provides multi user access, robustness to time dispersion of radio channel, and low complexity for receiver design. Also, the multicarrier concept enables the operation of LTE-A in various system bandwidths up to 20

MHz by adapting the number of subcarriers used.

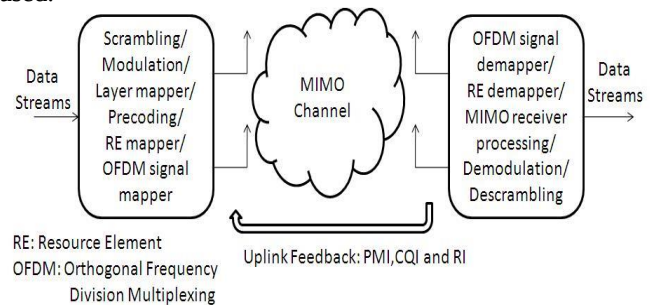


Figure 1: LTE-A Downlink Physical Layer

## III. VIENNA LTE-A LINK LEVEL SIMULATOR

Link Level Simulator is used to emulate the transmission of information from an eNodeB transmitter to a UE receiver

modeling the physical layer with high precision [14-15]. They include models for coding/decoding, MIMO process- ing, scrambling, modulation, channel, channel estimation and equalization, and so forth. The Link level parameters for the presented simulations are as in Table I. Simulated MIMO scheme followed CLSM (Close-loop spatial multiplexing) transmission mode specified by the 3GPP. The multiple transmission antennas at the eNB in combination with multiple receiver antennas at the UE can be used to achieve higher peak data rates by enabling multiple data stream transmissions between the eNB and the UE by using MIMO Spatial Multiplexing. Hence, in addition to larger bandwidths and high-

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order modulations, MIMO spatial multiplexing is used in the LTE-A system to achieve the peak data rate targets. The MIMO spatial multiplexing also provides improvement in cell capacity and throughput as UEs with good channel conditions can benefit from multiple streams transmissions [16].

#### IV. CHANNEL ESTIMATION TECHNIQUES

##### A. LS channel estimation technique.

The receiver, in MIMO system, requires the knowledge of CSI in order to recover the transmitted signal properly. Least square channel estimator is obtained by minimizing the square distance between the received signal and the transmitted signal [17-18].

In general, LS channel estimation technique for OFDM systems has low complexity but it suffers from a high mean square error [7].

##### B. Channel Estimation Technique based on ANN trained by

##### Back propagation Algorithm

Neural networks are algorithms for optimization and learning based on concepts inspired by research into the nature of the brain [19]. A Feedforward neural Network (FFNN) [20] 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 [21]. The connections between nodes are initialized with random weights. A set of reference symbols from the training set is presented in 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 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 total channel frequency response. The input of the neural network is the received reference symbols  $Y$  and output i.e. channel  $H$  is estimated as shown in Figure 2.

#### V. PROPOSED CHANNEL ESTIMATION TECHNIQUE BASED ON ANN TRAINED BY GENETIC ALGORITHM

Feedforward neural networks (FFNN) possess a number of properties which make them particularly suited to complex classification problems. However, their application to some real-world problems has been hampered by the lack

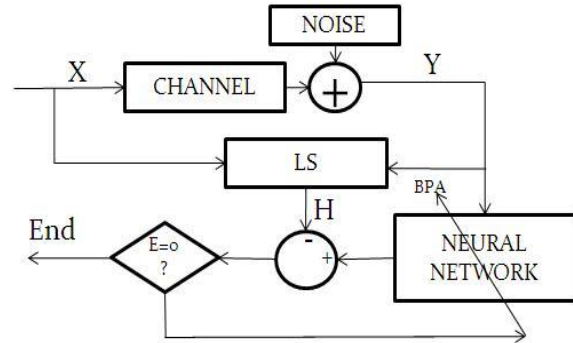


Figure 2: Channel Estimation using ANN trained by Back-Propagation Algorithm

of a training algorithm which reliably finds a nearly globally optimal set of weights in a short time. Genetic Algorithms [22] are a class of optimization procedures which are good at exploring a large and complex space in an intelligent way to find values close to the global optimum. Hence, they are well suited to the problem of training feedforward networks. In this contribution, first neural network is initialized with training pair (Inputs and Targets), and then configuration of neural network is done for the dataset. A handle to the "MSE\_TEST" function [23] is created, that calculates MSE (mean square error between output and targets of FFNN) 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 3.

#### VI. SIMULATION RESULTS

##### A. Simulation Parameters for LS Channel Estimator

The simulation parameters for Vienna LTE-A Link level simulator for LS channel estimator are listed in Table I.

Table I: Simulation Parameters for LS Channel Estimator

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| Parameters               | Value                |
|--------------------------|----------------------|
| Number of Sub frames     | 25                   |
| SNR Range                | [0,5,10,15,20,25,30] |
| Transmission Bandwidth   | 1.4 MHz              |
| Sub-frame duration       | 1ms                  |
| Sub-carrier spacing      | 15 kHz               |
| FFT size (N)             | 128                  |
| Number of occupied sub-  | 72                   |
| TTI length               | 1 ms                 |
| Channel Coding Turbo     | 1/3                  |
| OFDM Cyclic Prefix       | Extended             |
| Simulation Configuration | SU-MIMO              |
| Antenna schemes          | CLSM-MIMO 2x2        |
| MIMO receiver equalizer  | ZF (Zero Forcing)    |
| Channel type             | AWGN                 |

### B. ANN based simulation parameters

The simulation parameters for Channel Estimation based on ANN trained by BPA and GA are as in Table II.

Table II: Simulation Parameters for ANN Trained by BPA and GA

| 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                   | Mean Square Error  | Mean Square Error |

In Back-Propagation method, the ANN is trained with reference symbols, which is complex type matrix. 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. The ANN is trained for 100 epochs. Proposed ANN based channel estimator (ANN-GA),

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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. Figure 4 shows the Throughput versus

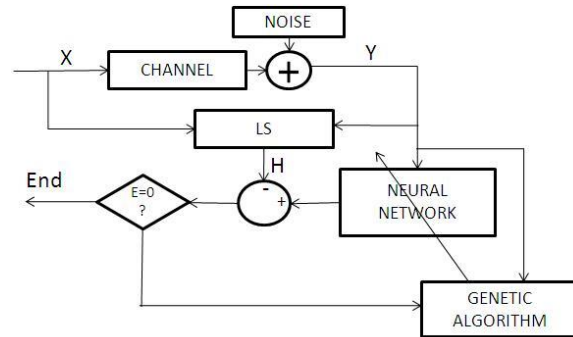
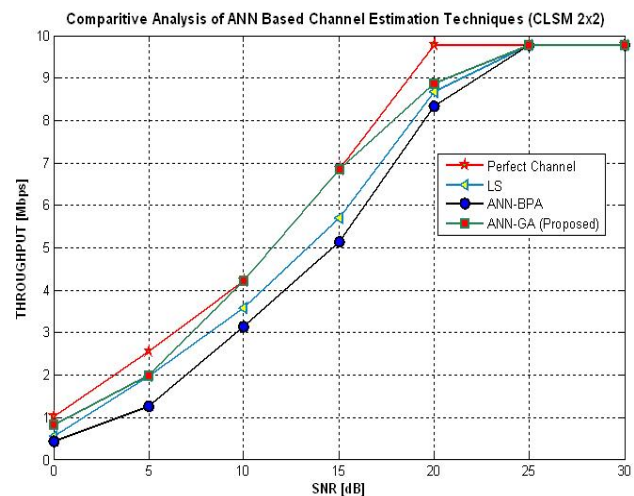


Figure 3: Proposed Channel Estimation using ANN trained by Genetic Algorithm

SNR results for comparison of proposed methods with LS channel estimator. It is seen that 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. Figure 5 shows the Throughput values of channel estimation techniques for all SNR values. 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.



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Figure 4: Throughput vs SNR for ANN-GA and ANN-BPA in comparison with LS and Perfect Channel

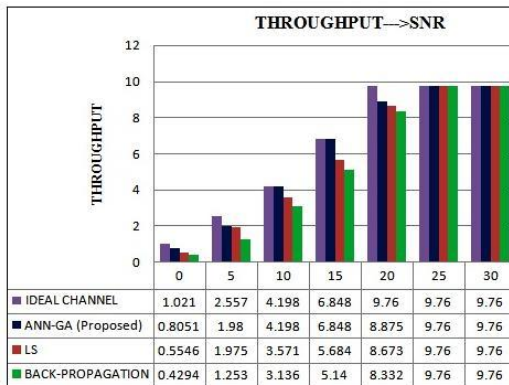


Figure 5: Comparison of ANN-GA Channel Estimator with LS estimator, ANN-BPA method and Perfect channel

## VII. CONCLUSION

In this paper, ANN Based Channel Estimation for down-link LTE-Advanced System employing Genetic Algorithm is introduced. The proposed channel estimation method uses received reference symbols to estimate the channel variations both in time and in frequency. This method is based on a learning process that uses a training sequence for adaptation to achieve a desired performance. Comparative analysis with traditional LS channel estimation technique is carried out. Simulation results show better performance in terms of throughput for the proposed ANN Based Channel Estimation employing Genetic Algorithm. It also shows better results when compared to ANN based Channel estimation trained using back-propagation algorithm. The performance of channel estimator can be further enhanced by using different Neural Network Architectures and Hybrid techniques can be used for training of Artificial Neural Networks.

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