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Estimation of highly selective channels for downlink LTE MIMO-OFDM system by a robust neural network

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Abstract

In this contribution, we propose a robust highly selective channel estimator for downlink Long Term Evolution (LTE) multiple-input multiple-output (MIMO) orthogonal frequency division multiplexing (OFDM) system using neural network. The new method uses the information provided by the reference signals 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 method in terms of complexity and quality is confirmed by theoretical analysis and simulations in an LTE/OFDMA transmission system. The performances of the proposed channel estimator are compared with those of least square (LS), decision feedback and modified Wiener methods. The simulation results show that the proposed estimator performs better than the above estimators and it is more robust at high speed mobility.

Keywords: *Channel estimation, LTE, MIMO, Neural network, OFDMA.*

1. Introduction

The Long Term Evolution (LTE), also known as Evolved Universal Terrestrial Radio Access (E-UTRA), is a step toward the 4th generation (4G) of mobile radio technologies to increase the spectral efficiency and to obtain higher throughput. The transmission scheme for E-UTRA is based on multiple-input multiple-output (MIMO) orthogonal frequency division multiplexing (OFDM) technique that is more resilient against severe channel conditions and support high data rates transmission capabilities [1].

The combination of powerful technologies like OFDM and MIMO techniques in the same system increases spectral efficiency, and improves link reliability without additional bandwidth or transmit power [1]. MIMO concept can be implemented either for increasing the system capacity by sending different sets of data at the same time through the different MIMO antennae. Otherwise, the advantage of MIMO diversity can be used to overcome the channel fading by sending the same signals through the different MIMO antennas. Efficient implementation of MIMO-OFDM system is based on the Fast Fourier Transform (FFT) algorithm and MIMO encoding, LTE system use Alamouti Space Frequency Block coding (SFBC) as MIMO coding.

The LTE standard proposes the use of the OFDMA access technique in downlink, which basically distributes the symbols on a large number of carriers. By implementing this new access technique in the context of mobile broadband transmission, new approaches for time and frequency synchronization, equalization and channel estimation are needed [1]. The use of neural network has been deployed in OFDM system and has not been explored in MIMO-OFDM system with different neural network architectures [2],[3].

In this contribution, we propose a new estimation technique for an LTE downlink highly selective channel using new neural networks architecture and pilot channels. The principle of this method is to exploit the information provided by the reference signal to estimate the channel frequency response. The paper is organized as follows:

In section II, the OFDMA-based transmission system is described. The multipath mobile radio propagation channel model and LTE MIMO-OFDM system are described in section III and IV, respectively. Then, three commonly used channel estimation methods; Least Square (LS) [4], estimation with decision feedback [5], modified Wiener filter [6] and the proposed neural network-based mobile radio channel estimation technique are presented in section V. Subsequently, the performances of the proposed channel estimation technique

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are demonstrated via simulations and a comparative study with the well-known mentioned estimation methods is also conducted in section VI. Finally, conclusion are drawn In section VII.

2. Downlink LTE System Model

Downlink LTE system is based on OFDMA air interface transmission scheme. OFDMA is a combination of OFDM and TDMA [1]. The basic idea of OFDMA systems is the division of the frequency spectrum into several orthogonal subcarriers using the OFDM multiplexing technique. Those orthogonal frequency subcarriers are shared among users using TDMA access technique.

A scheme of a baseband OFDM system is shown in Figure 1.

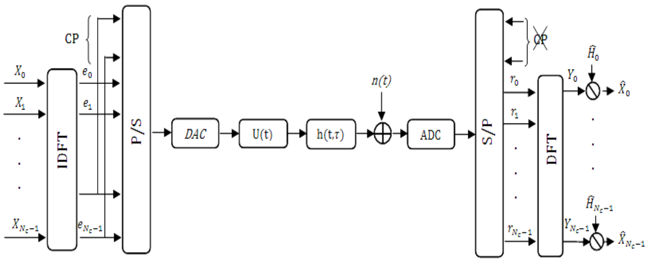

Figure. 1: *Baseband OFDM system model.*

Let us consider an OFDM system which comprises N_c carriers, occupying a bandwidth *B*. The OFDM symbols are transmitted in time T_s, including a cyclic prefix of a duration denoted by T_{cp}. The total duration of one OFDM symbol is $T_u = T_s - T_{cp}$. The spacing between two adjacent carriers is indicated by $\delta f = 1/T_u$. The addition of a cyclic prefix longer than the temporal dispersion of the transmission channel is used to prevent interference between symbols and to preserve orthogonality between carriers [7]. Figure 1 shows the baseband OFDM system model. X_k denote the complex symbols of a downlink LTE system where 16-QAM, 64-QAM and QPSK modulations can be used [6], $U(t)$ is the filter impulse response, $h(\tau,t)$ represents the impulse response of the mobile radio transmission channel, and $n(t)$ is an additive white Gaussian noise (AWGN) with power spectral density $N_0/2$.

Let $\overline{X} = \left[X_0\, X_1 \, .\,.\,.\, X_{N_c-1}\right]^T$ and $\overline{Y} = \left[\, Y_{0,I}\;\; Y_{1,I}\;\; .\,.\,.\;\; Y_{N_c-1}\right]^T$

denote the input data of IDFT block at the transmitter and the output data of DFT block at the receiver, respectively.

Let $\overline{h} = \left[h_0\, h_1 \, .\,.\,.\, h_{N_c-1}\right]^T$ and $\overline{n} = \left[n_0\, n_1 \, .\,.\,.\, n_{N_c-1}\right]^T$

denote the sampled channel impulse response and AWGN, respectively. Define the input matrix $\underline{X} = diag(\,\overline{X}\,)$ and $\underline{F}$ is the DFT-matrix [9]

$$\underline{F} = \begin{bmatrix} W_N^{0,0} & W_N^{0,1} & .\,.\,. & W_N^{0,N_C-1} \\ W_N^{1,0} & W_N^{1,1} & .\,.\,. & . \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ W_N^{N-1,0} & & .\,.\,. & W_N^{N-1,N_C-1} \end{bmatrix} \qquad (1)$$

where, *N* is the FFT size and

$$W_N^{i,k} = \left(1/\sqrt{N}\right) exp^{-j2\pi(ik/N)} \qquad (2)$$

Also, the channel frequency response is given by

$$\overline{H} = DFT_N\left(\overline{h}\right) = \underline{F}\,\overline{h}, \qquad (3)$$

and the noise in frequency domain is represented by

$$\overline{N} = \underline{F}\,\overline{n}. \qquad (4)$$

By assuming that the cyclic prefix length is larger than the channel delay spread, the interference between the OFDM symbols can be eliminated. Therefore the OFDM received signal is expressed by [9]

$$\overline{Y} = DFT_N\left(IDFT_N\left(\underline{X}\right) \otimes \overline{h} + \overline{n}\right) = \underline{X}\,\underline{F}\,\overline{h} + \overline{N}$$
$$= \underline{X}\,\overline{H} + \overline{N}. \qquad (5)$$

The relationship between the input and the output for each OFDM subcarrier can be written as

$$Y_{k,i} = H_{k,i}\, X_{k,i} + N_{k,i}. \qquad (6)$$

For a given symbol i, $H_{k,i}$ is the channel frequency response of the subcarrier f_k given by

$$f_k = f_c + k/\,T_u. \qquad (7)$$

Where, f_c is the carrier frequency and $N_{k,i}$ are obtained by applying a DFT to the vector $\overline{n}$ where $n_{k,i}$ is the result of sampling $n(t)$ at time $T_{k,i}$ given by the following equation

$$T_{k,i} = iT_s + T_{pc} + \frac{k\,T_u}{N}. \qquad (8)$$

As shown in Fig. 2, each LTE radio frame duration is 10 ms [8], which is divided into 10 subframes. Then, each subframe is further divided into two slots, each of 0.5ms duration.

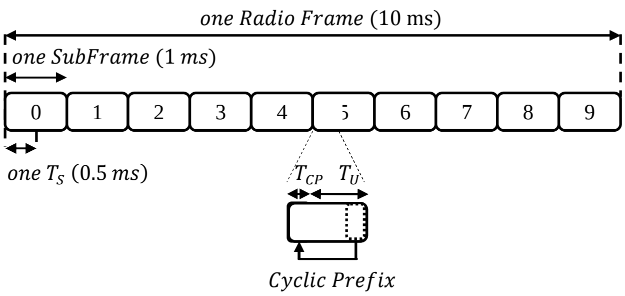

Figure. 2: *LTE Frame structure* [10].

The physical resource block (PRB) consists of 12 subcarriers with frequency spacing of 15 kHz. In time domain, each PRB has one slot with either 6 or 7 OFDM symbols, depending on the chosen cyclic prefix, extended or normal. The transmission parameters of the LTE/OFDMA standard are shown in the following Table 1 [11].

Table 1: LTE OFDMA Parameters [11].

Transmission BW (MHz)	1.25	2.5	5	10	15	20
Sub-frame duration (ms)	0.5					
Sub-carrier spacing (kHz)	15					
Sampling frequency	1.92	3.84	7.68	15.36	23.04	30.72
FFT size (*N*)	128	256	512	1024	1536	2048
Number of occupied sub-carriers	76	151	301	601	901	1201

Table 2: Extended Vehicular A model (EVA) [12].

Excess tap delay [ns]	Relative power [dB]
0	0.0
30	-1.5
150	-1.4
310	-3.6
370	-0.6
710	-9.1
1090	-7.0
1730	-12.0
2510	-16.9

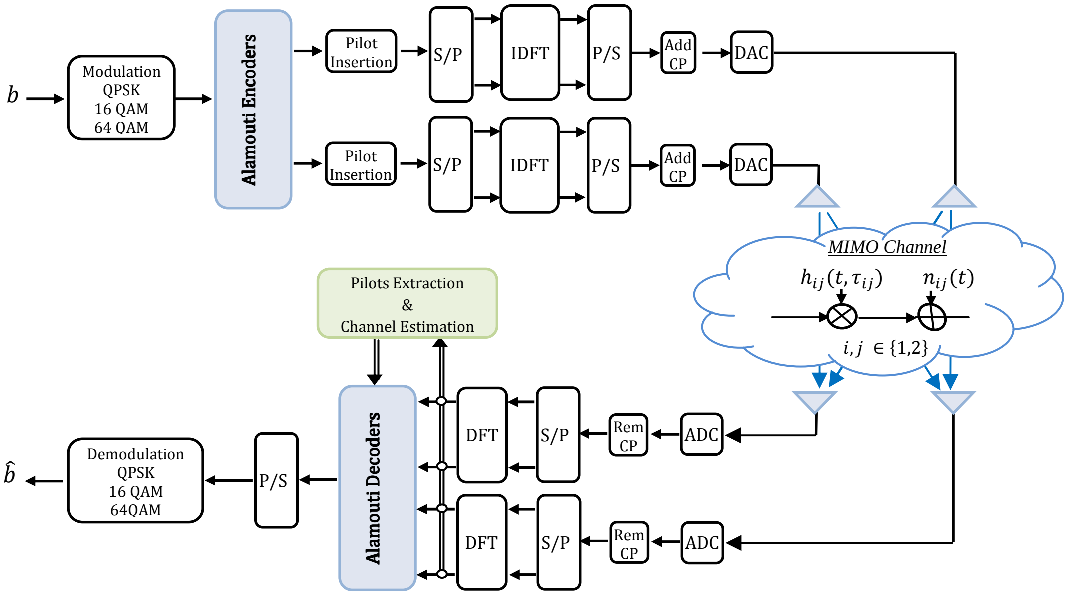

Figure 3: *MIMO-OFDM System model*.

3. Multipath Channel Model

The channel impulse response is given by [6]

$$h(\tau, t) = \sum_{m=0}^{M-1} h_m(t)\, \delta(t - \tau_m) \qquad (1)$$

here, M denotes the number of multipaths, $h_m(t)$ and τ_m are the impulse response and the multipath delays of the channel, respectively. The channel frequency response $H_{k,i}$ for the k^{th} subcarrier f_k is given by the Fourier transform of the channel impulse response. Table 2 shows the specification parameters of an extended vehicular A model (EVA) with the excess tap delay and the relative power for each path of the channel. These parameters are defined by 3GPP standard [12].

4. LTE MIMO-OFDM System

Figure 3 shows a MIMO-OFDM system model. The modulation block is used to modulate the original binary symbol b using the complex constellation QPSK, 16-QAM or 64-QAM according to the LTE standard [12]. Multiple antennas can be used at the transmitter and receiver, therefore multiple-input multiple-output (MIMO) encoders are needed to increase the spatial diversity or the channel capacity. MIMO systems can be implemented in a different ways to obtain either a diversity gain to combat signal fading or to obtain a capacity gain.

Generally, there are three types of MIMO receivers as presented in [13]. The first improves the power efficiency by maximizing spatial diversity like space–time block codes (STBC). The second type is used to increase the capacity, for example V-BLAST. Finally, the third type exploits the knowledge of the channel at the transmitter. Then, It decomposes the channel coefficient matrix using singular value decomposition (SVD) and uses these decomposed unitary matrices as pre- and post-filters at the transmitter and the receiver to achieve maximum capacity.

In our case we are using Alamouti STBC coding. The OFDM modulation scheme consists of transmitting a block of information symbols in parallel on channel subcarriers. An OFDM modulator can be easily and efficiently implemented using the inverse discrete Fourier transform (IDFT) on a block of information symbols. Each block of IDFT coefficients is typically preceded by a cyclic prefix (CP) with length at least equal to the channel delay spread to prevent inter symbol interference (ISI) that can be caused by multipath channel propagation. Commonly, a pilot sequence insertion is used in the channel estimator to predict a refined channel frequency response at the receiver to equalize for the channel impairments and consequently to estimate the transmitted signal.

5. Channel Estimation

5.1. Least Square Channel Estimation (LS)

Least square channel estimator is obtained by minimizing the square distance between the received signal $\overline{Y}$ and the transmitted signal $\underline{X}$ as follows [4]

$$\min_{H^T} J(H) = min_{H^T}\left\{\left|\overline{Y} - \underline{X}\,.\,\overline{H}\,\right|^2\right\}$$
$$= min_{H^T}\left\{\left(\overline{Y} - \underline{X}\,.\,\overline{H}\,\right)^T\left(\overline{Y} - \underline{X}\,.\,\overline{H}\,\right)\right\} \qquad (10)$$

where, $(.)^T$ is the conjugate transpose operator.

By differentiating expression (10) with respect to $\overline{H}^T$ and finding the minima, we obtain

$$\frac{\partial}{\partial \overline{H}^T} J(H) = -\underline{X}^T\,\overline{Y} + \underline{X}^T\,\underline{X}\,\overline{H} = 0. \qquad (11)$$

Finally, the LS channel estimation is given by [4]

$$\widehat{\overline{H}}_{LS} = \underline{X}^{-1}\,\overline{Y} = \left[\begin{array}{ccccc} \frac{Y_0}{X_0} & \frac{Y_1}{X_1} & . & . & . & \frac{Y_{N_c-1}}{X_{N_c-1}} \end{array}\right]^T. \qquad (12)$$

In general, LS channel estimation technique for OFDM system has low complexity but it suffers from a high mean square error [2].

5.2. Estimation with Decision Feedback

OFDM channel estimation with decision feedback uses the pilots to estimate the channel response $\widehat{\overline{H}}_i = \{\widehat{H}_{k,i}\}$ using LS or MMSE algorithms [3]. Here, $k = \{0, \ldots, N-1\}$ denotes the k^{th} subcarrier and i the i^{th} symbol. For each coming symbol and for each subcarrier, the estimated transmitted symbol is found from the previous $\widehat{H}_{k,i}$ according to the formula

$$\widehat{X}_{k,i+1} = \frac{Y_{k,i+1}}{\widehat{H}_{k,i}}. \qquad (13)$$

The estimated received symbols $\{\widehat{X}_{k,i+1}\}$ are used to make the decision about the real transmitted symbol values $\{\tilde{X}_{k,i+1}\}$. The estimated channel response is updated by [5]

$$\widehat{H}_{k,i+1} = Y_{k,i+1}\,/\,\tilde{X}_{k,i+1}. \qquad (14)$$

Consequently, $\widehat{H}_{k,i+1}$ is used as a reference in the next symbol, i+2, for the channel equalization.

5.3. Modified Wiener Filter

The advantage of this technique is that there is no need for continuous transmission of training data, just a single OFDM pilot symbol at the beginning of each frame is sufficient. The principle of this technique is shown in Figure 4.

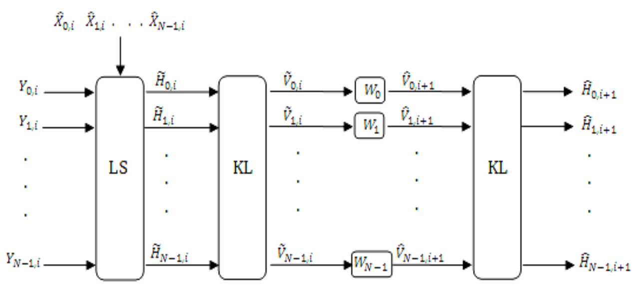

Figure. 4: *Modified Wiener Estimator.*

For a given symbol i, the prediction of the channel frequency response at i+1 is given by the ratio between the received symbol, $Y_{k,i}$, and the transmitted symbol, $X_{k,i}$, as follows

$$\tilde{H}_{k,i} = \frac{Y_{k,i}}{\hat{x}_{k,i}} = H_{k,i} + n_{k,i}, \qquad (15)$$

where, $n_{k,i}$ is the estimation error.

A Karhonen Loeve transform (KLT) is applied to $\tilde{H}_{k,i}$ to separate the multipath channel space from the noise space, to obtain the output vector $\widehat{\overline{V}}_i$ with uncorrelated components $\tilde{V}_{k,i}$ expressed as [6].

$$\tilde{V}_{k,i} = \langle\, \tilde{H}_i | v^{(k)} \rangle \qquad (16)$$

where, $\langle\,.\,|\,.\,\rangle$ is the Hermitian product operator and $\{v^{(k)}\}_{k=0}^{N-1}$ are the N eigenvectors of the covariance matrix $\underline{R}_{HH}$ of the channel vector $\tilde{\overline{H}}_i$.

At the output of the KL block, the corresponding N_c elementary linear Wiener predictors $(W_0, W_1, \ldots, W_{N-1})$ are used for the estimation of $\tilde{V}_{k,i+1}$ from previous observations $\hat{V}_{k,j}(i - p < j \le i)$ according to the following formula [6]

$$\hat{V}_{k,i+1} = \sum_{p=0}^{P-1} \alpha_p^{(k)}\,\tilde{V}_{k,i-p} = \alpha^{(k)^t}\,Z_i^{(k)} \qquad (17)$$

where, P is the filter length assumed to be identical for all predictor P_k , $\alpha^{(k)} = (\alpha_0^{(k)}, \ldots, \alpha_{P-1}^{(k)})^t$ is the k^{th} filter coefficient and $Z_i^{(k)} = (\hat{V}_{k,j}\hat{V}_{k,i-1}, \ldots, \hat{V}_{k,i-P+1})^t$ denotes the vector containing the last p samples at the output of the KL block. Finally, an inverse KL transform (IKL) is applied to estimate the channel coefficients $\widehat{\overline{H}}_{i+1}$.

5.4. Proposed Neural Network Channel Estimation

5.4.1. Principle

The principle of the proposed estimation technique is inspired from the use of shape recognition in neural network. The estimator uses the information provided by the pilots of sub channels to estimate the total channel frequency response. The estimation technique uses as input the information given by the pilots of each sub-channel. The input of the neural network, $\overline{P}$, is defined by the following equation

$$\overline{P} = \underline{XP}^{-1}\,\overline{YP} = \left[\begin{array}{cccccc} \frac{YP_0}{XP_0} & \frac{YP_1}{XP_1} & . & . & . & \frac{YP_{2N_p-1}}{XP_{2N_p-1}} \end{array}\right]^T$$
$$= \left[\begin{array}{cccccc} P_0 & P_1 & . & . & . & P_{2N_p-1} \end{array}\right]^T. \qquad (18)$$

By making use of neural network, the following term will be estimated

$$\overline{A} = \underline{X}^{-1}\,\overline{Y} = \left[\begin{array}{cccccc} \frac{Y_0}{X_0} & \frac{Y_1}{X_1} & . & . & . & \frac{Y_{N_c-1}}{X_{N_c-1}} \end{array}\right]^T$$
$$= \left[\begin{array}{cccccc} A_0 & A_1 & . & . & . & A_{N_c-1} \end{array}\right]^T \qquad (19)$$

$\underline{X}$ denote the transmitted OFDM symbols matrix, $\overline{Y}$ are the received OFDM symbols vector, $\underline{X}_p$ are the transmitted OFDM pilot, and $\overline{Y}_p$ are the corresponding received OFDM pilots.

The estimated output of the neural Network is given by

$$\widehat{\overline{A}} = \overline{A} + \overline{e} = \left[A_0 + e_0\; A_1 + e_1 \,.\,.\,.\; A_{N_c-1} + e_{N_c-1}\right]^T \quad (20)$$

At the output of the channel equalization, we obtain the following expression

$$\left(diag\left(\widehat{\overline{A}}\right)\right)^{-1}\overline{Y} = \begin{bmatrix} \frac{Y_0}{\hat{A}_0} & \frac{Y_1}{\hat{A}_1} & . \; . \; . & \frac{Y_{N_c-1}}{\hat{A}_{N_c-1}} \end{bmatrix}^T$$

$$= \begin{bmatrix} \frac{Y_0}{A_0+e_0} & \frac{Y_1}{A_1+e_1} & . \; . \; . & \frac{Y_{N_c-1}}{A_{N_c-1}+e_{N_c-1}} \end{bmatrix}^T$$

$$\backsimeq \begin{bmatrix} \frac{Y_0}{A_0} & \frac{Y_1}{A_1} & . \; . \; . & \frac{Y_{N_c-1}}{A_{N_c-1}} \end{bmatrix}^T, \left(if\ \overline{e} \approx \overline{0}\right)$$

$$= \left(diag\left(\overline{A}\right)\right)^{-1}\overline{Y}$$

$$= \left(diag\left(\overline{A}\right)\right)^{-1}\underline{X}\ \overline{A}\ , because\ \left(\overline{A} = \underline{X}^{-1}\,\overline{Y}\right)$$

$$= \underline{X} \tag{21}$$

The proposed method is based on Perceptron type of neural network having two separate phases i.e., learning phase and estimation phase.

The adopted architecture of neural network is carefully chosen after multiple tests of convergence by minimizing the learning time and keeping low implementation complexity, in order to increase the overall system performance.
The output of a single neuron is given by the following equation

$$\hat{A}_j = f\left(\sum_{i=0}^{2N_{p-1}} w_{j,i}\, P_i + b_j\right). \tag{22}$$

Equation (21) can be presented in matrix form as follows

$$\hat{A}_j = f\left(\overline{W_j}^T\overline{P} + b_j\right). \tag{23}$$

Here, $\overline{W_j}^T = \begin{bmatrix} w_{j,0} & w_{j,1} & . \; . \; . & w_{j,2N_p-1} \end{bmatrix}$, $w_{j,i}$ is a value of the synaptic weight connecting the stimulus i to the neuron j, P_i is the input stimulus, $\hat{A}_j$ is the neuron output in the range of $(0 \le j \le 2\,N_c - 1)$, because there are N_c real part of $\hat{A}_j$ and N_c imaginary part of $\hat{A}_j$, f is the neuron output linear function and b_j is the bias of the neuron j.

5.4.2. Learning

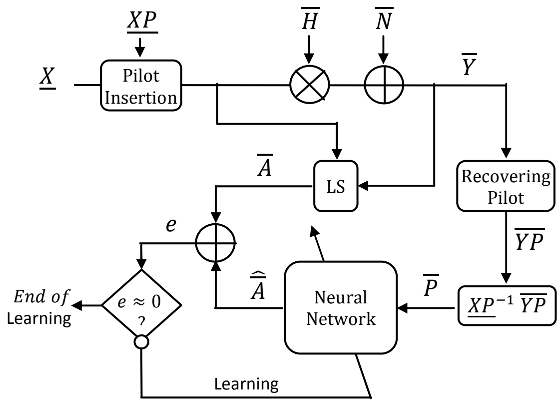

Figure. 5: *Schematic diagram of the learning phase.*

The estimator learning operation consists of changing the values of interconnection weights using learning algorithms for obtaining the desired performance. The learning algorithm in our proposed neural network is the efficient gradient back propagation which minimizes the average square error between the outputs $\widehat{\overline{A}}$ and $\overline{A}$, by modifying the weights values. Figure 5 shows the principal of the learning phase.
The total squared error (for all output neurons $2N_c$) defining the network performance is given by:

$$E = \frac{1}{N_l}\sum_{l=0}^{N_l-1}\sum_{j=0}^{2N_c-1}\left(e_j^l\right)^2, \tag{24}$$

where, e_j^l is the error on the jth neuron output and l is the example of the training set, calculated by

$$e_j^l = f\left(\overline{W_j}^T \cdot \overline{P}^{\,l}\right) - A_j^l = \hat{A}_j^l - A_j^l \tag{25}$$

The weights $\overline{W_j}^T$ are updated with the following algorithm [2]:

Learning algorithm for the neural network

1 – Initialize weights to low magnitude random values.

2 - Calculate the weight changes during an iteration:

$$\overline{\Delta W_j} = -2\mu\sum_{l=0}^{N_l-1} e_j^l\ f'\left(\overline{W_j}^T\,\overline{P}^{\,l}\right)\overline{P}^{\,l}. \tag{26}$$

3 - Update synaptic weights of each network:

$$\overline{W_j}(k+1) = \overline{W_j}(k) + \overline{\Delta W_j}(k). \tag{27}$$

4 - If the error is large then it returns to Step 2, else we continue to Step 5.

5 - Desired performance of the neural network.

5.4.3. Estimation

After completing the learning phase, the network uses the input data from the pilot channels $\overline{P}$ to estimate $\overline{A}$. Subsequently, the equalization followed by a decision estimate of the OFDMA symbols. For a single learning operation, the neural network estimates a large number of OFDM symbols in the range of 7000 symbols, corresponding to 50 radio LTE frames.

6. Simulations Results

6.1. SISO Case

OFDM SISO System is simulated using the following parameters shown in Table 3. These parameters are based on downlink LTE system.

Table 3. Simulations Parameters [11],[12] and [14].

Parameters	Specifications
Constellation	16-QAM
Mobile Speed (Km/h)	120/350
T_s (µs)	72
f_c (GHz)	2.15
δf (KHz)	15
B (MHz)	5
Size of DFT/IDFT	512
Number of paths	9

The performance of the proposed estimator is compared with other well-known estimation techniques. In this part of analysis, we are interested in comparing the proposed algorithm with the well-defined LS [4] (it is the simplest method in terms of complexity and is used for comparison to evaluate the execution time of the proposed methods), decision feedback [5] (typically performs better than LS) and modified Wiener technique [6] (commonly optimal filter and is used to evaluate the performance of the proposed method).

Figure 6 presents the variations in time and in frequency of the channel frequency response under a mobile speed equal to 120 Km/h. While, figures 7 presents the variations in time and in frequency of the channel frequency response under a mobile speed equal to 350 Km/h. From these two scenarios, we remark that the channel variations are large in the presence of high channel selectivity and frequency shifting. Thus, robust algorithms for channel estimation are needed.

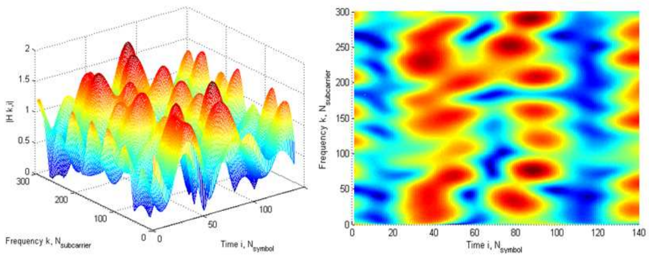

Figure.6: *Variations in time and in frequency of the channel frequency response (mobile speed = 120 Km/h).*

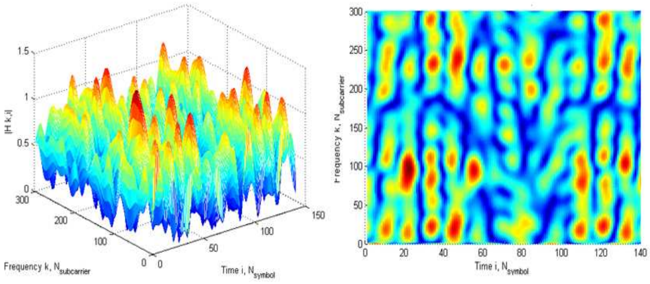

Figure. 7: *Variations in time and in frequency of the channel frequency response (mobile speed = 350 Km/h).*

Figure 8 shows the variation of BER as a function of E_s/N_0. Noticeably, the proposed method outperforms all other estimators, for example at a BER = 10^{-2} a gain of 5 dB over the modified Wiener filter is obtained. At high mobility, the same results are confirmed by figure 9.

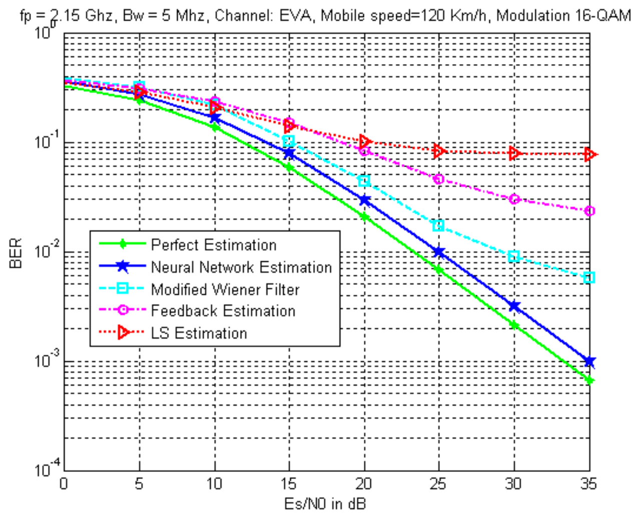

Figure.8: *BER as a function of E_s/N_0 for a mobile speed at 120 Km/h in SISO case.*

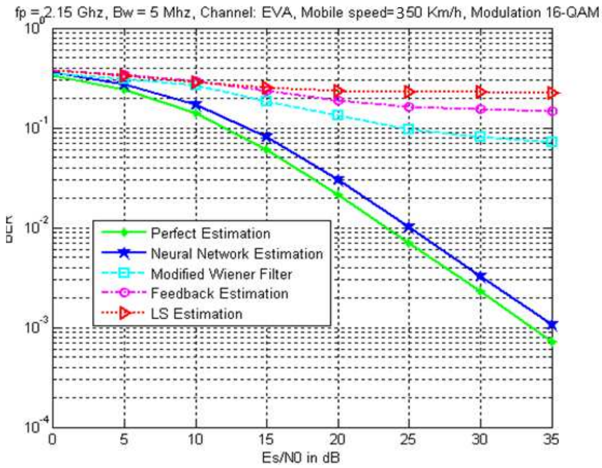

Figure. 9: *BER as a function of Es/N0 at a mobile speed of 350 Km/h in SISO case.*

Table 4 shows the performance of our estimator in terms of simulation complexity in time and in terms of number of matrix operations. In fact, in the estimation phase, the proposed method needs just one multiplication matrix and requires just 64.3 μs to estimate one OFDM symbol.

Table 4. Complexity of Estimation Algorithms per OFDM Symbol

Methods / Matrix Operations	LS	Modified Wiener Filter	Decision Feed-back	Neural Network Estimator	
				Learning	Estimation
Inversion	1	2	2	2	0
Multiplication	1	6	2	1	1
Addition	0	3	0	1	0
Soustratction	0	0	0	1	0
Simulation duration/ Symbol	2.5 μs	502.8 ms	1.1 ms	721.4 μs	4.3 μs
				785.7 μs	

6.1. MIMO Case

LTE MIMO-OFDM downlink system with parameters shown in Table 3 is simulated. Also, these parameters are based on downlink LTE system and the Alamouti space time block coding (STBC).

The performance of the proposed estimator is also compared to the MIMO case and to other estimation techniques; like LS [4], decision feedback [5] and modified Wiener method [6].

Figure 10 shows the variations of BER as a function of E_s/N_0. Noticeably, the proposed method in MIMO case performs better than other estimators, for example at BER = 10^{-4} a gain of 3 dB over the modified Wiener filter is obtained. At high mobility and in MIMO case, the same results are confirmed in figure 11.

The simulation complexity in time and in terms of number of matrix operations for the MIMO case is comparable or even less when compared to the other techniques as shown in table 4, because the learning phase of our proposed estimator is done in parallel for each channel between the transmit and the receive antennae.

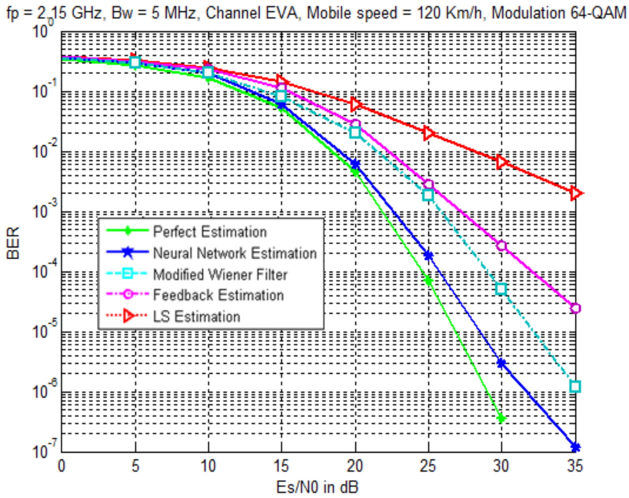

Figure. 10: *BER as a function of E_s/N_0 at a mobile speed of* 350 *Km/h in MIMO case.*

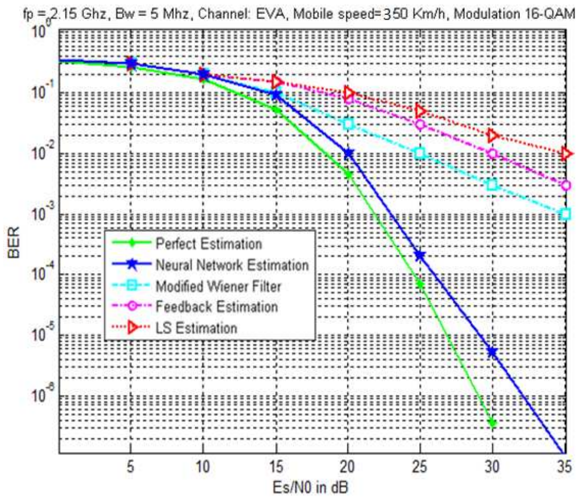

Figure. 11: *BER as a function of E_s/N_0 at a mobile speed of* 350 *Km/h in MIMO case.*

7. Conclusion

In this paper, a new neural-network-based channel estimation technique for a highly selective downlink MIMO-OFDM LTE system is introduced. The proposed channel estimation method uses reference signals of OFDMA system 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 study with robust and well established techniques such as the LS, decision feedback and Wiener estimation methods have been conducted. Simulation results show clearly the high performance of the proposed neural-network-based LTE downlink channel estimation technique when compared to these standard methods. Also, the performance of the proposed estimator, in terms of computation complexity and number of required operations, are evaluated. Overall, once the neural network learning phase is performed ($\sim 721.4\ \mu s$), the proposed technique outperforms in terms of complexity compared to the considered estimators. In fact, in the estimation phase, the proposed method needs just $64.3\ \mu s$ to estimate one OFDM symbol. However, the modified Wiener filter methods needs $502.8\ \mu s$ to estimate one OFDM symbol. Particularly, for a highly selective LTE downlink system, the obtained results are very promising and further comparative studies will be performed.

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