

## MIMO-OFDM Channel Estimation Using ANFIS

**M. N. Seyman**

*Department of Electronic Communication, Kirikkale Vocational Technical High School, Kirikkale University, Ankara yolu 7. km. Yahşihan, Kirikkale, Turkey, phone: 0090 318 357 4242, e-mail: mnseyman@kku.edu.tr*

**N. Taspinar**

*Department of Electrical and Electronic Engineering, Erciyes University, Kayseri, Turkey, phone: 0090 352 437 4901, e-mail: taspinar@erciyes.edu.tr*

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### Introduction

The multiple-input multiple-output (MIMO) combined with space time coded orthogonal frequency division multiplexing (OFDM), is one of the promising scheme that provides large system capacity without additional power or bandwidth consumption for high speed wireless communication systems [1].

However, in these systems modulated bits are distorted in channel as the channel introduces amplitude and phase shifts due to frequency selective and time varying nature of wireless channel. So these changes must be considered for coherent demodulation. For this reason, the estimation of channel state information (CSI) is crucial task for MIMO-OFDM systems [2, 3]. In order to estimate CSI, classical methods such as the least square error (LS), and least mean square error (LMS), which are based on pilot tones, are implemented. Because the implementation of LS algorithm is quite easy and it has low computational complexity, this algorithm is considered more robust for OFDM systems, but the performance of this algorithm is poor [8]. In conventional LMS algorithm, the choose of step size is critical because choosing larger size results faster rate converge but higher steady MSE. To perform good tracking ability, larger step size is needed to achieve rate of converge in transient state and smaller step size is needed to achieve lower MSE in steady state. [4–6]. There are some works for channel estimation using classical algorithms and heuristic approaches in the literature [2–12]. In [6] LMS and in [7] LS channel estimation schemes for OFDM systems based on pilot tones were described. Also tree layered artificial neural network with feedback was offered for channel estimation MIMO wireless communication systems in [8] and radial basis function network that is a kind of neural network and neural network based on least mean error algorithm were applied to get CSIs of SISO-OFDM [9,10]. Besides, in [11]

adaptive neuro-fuzzy inference system was proposed for channel estimation in SISO OFDM systems. In [12], Takagi-Sugeno-Kang fuzzy model was proposed for channel estimation in MIMO-OFDM systems.

In this paper, we propose a new channel estimation algorithm based on adaptive neuro-fuzzy inference system (ANFIS) for MIMO-OFDM systems. In our proposal, by utilizing the learning capability of ANFIS, the ANFIS is trained with correct channel state information then the trained network is used as a channel estimator. For the performance evaluation, our proposal was compared to classical algorithms by computer simulations.

### MIMO-OFDM system model

The simplified block diagram of MIMO-OFDM system with  $N_T$  transmitter and  $N_R$  receiver antennas is presented in Fig. 1.

Space-time encoder encodes modulated signals after binary information data are mapped. Then the pilot symbols are inserted to the signal to estimate the channel state information and each of the data streams are turned into OFDM symbols by applying IFFT as

$$s_i(n) = \sum_{k=0}^{N-1} S_i(k) e^{j(2\pi nk / N)}, \quad (1)$$

where  $S_i(k)$  is the coded symbol at the  $k_{th}$  sub carrier, which is transmitted from  $i_{th}$  antenna.  $s_i(n)$  is the time domain sample at the  $n_{th}$  moment and  $N$  is the subcarrier number. In order to prevent inter symbol interference (ISI), cyclic prefix (CP) that is a repeat of the end of the symbol at the beginning is inserted. After removing the CP from signals at the  $j_{th}$  receiver antenna FFT is taken and FFT output for  $m = 0, 1, \dots, N/2 - 1$  can be written as

$$Y_j(k) = \sum_{i=1}^N H_{i,j}(k)S_i(k) + W_j(k) \quad (2)$$

where  $W_j(k)$  is channel noise and  $H_{i,j}$  is the channel state information from  $i_{th}$  antenna to  $j_{th}$  antenna. In channel estimation block,  $H_{i,j}$  is estimated then signals are decoded and demodulated [2, 3].

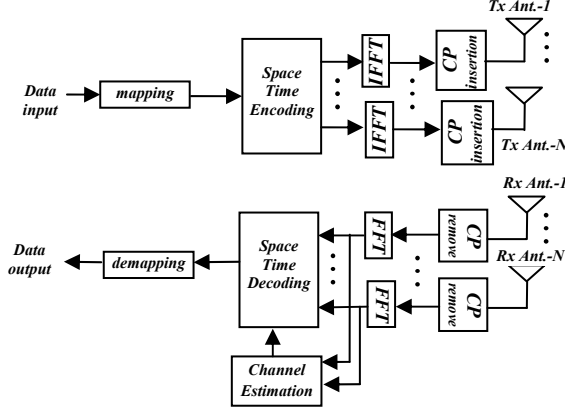


Fig. 1. MIMO-OFDM system model

### Adaptive neuro-fuzzy inference system (ANFIS) for channel estimation

Adaptive neuro-fuzzy inference system (ANFIS) is a Sugeno fuzzy model which is in the framework of adaptive systems to facilitate learning and adaptation. The neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data [13,14]. The structure of the ANFIS that we use to get channel state information is shown in Fig. 2. In our proposed channel estimator, we train the ANFIS with the correct channel state information. In working process, received data signals are inputted to the trained ANFIS and the output of the network will be the estimated channel state information.

As it is seen from the Fig. 2, in order to adopt ANFIS to OFDM system, each signal is separated into real and imaginary parts. Because OFDM signals consist of complex signals whereas ANFIS uses real signals.

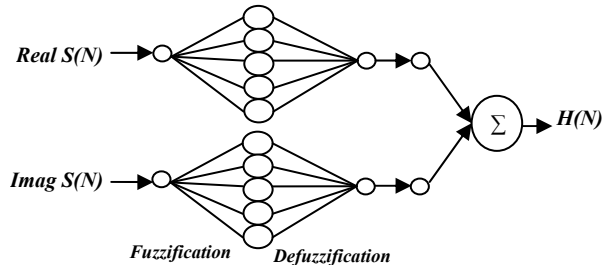


Fig. 2. ANFIS structure for channel estimation

In our ANFIS model, we construct 5 Sugeno type fuzzy rules given below:

$$\text{Rule1: if } S \text{ is } A_1 \text{ then } y_1 = k_{11}S + k_{12}, \quad (3)$$

$$\text{Rule2: if } S \text{ is } A_2 \text{ then } y_2 = k_{21}S + k_{22}, \quad (4)$$

$$\text{Rule3: if } S \text{ is } A_3 \text{ then } y_3 = k_{31}S + k_{32}, \quad (5)$$

$$\text{Rule4: if } S \text{ is } A_4 \text{ then } y_4 = k_{41}S + k_{42}, \quad (6)$$

$$\text{Rule5: if } S \text{ is } A_5 \text{ then } y_5 = k_{51}S + k_{52}, \quad (7)$$

where  $k$  is consequent (design) parameters that are determined during the training process and  $A_i$  fuzzy sets. We use generalized bell (gbellmf) membership function which is given as

$$\mu_{A_i}(S) = \frac{1}{1 + \left( \frac{S - c_i}{a_i} \right)^{2b_i}}, \quad (8)$$

where  $a_i$ ,  $b_i$ ,  $c_i$  are the premise parameters of the membership function governing the bell shaped functions accordingly which are related to the input membership function.

The output of the ANFIS is given as

$$H = \frac{\sum_{i=1}^5 \mu_{A_i}(S) \cdot y_i}{\sum_{i=1}^5 \mu_{A_i}(S)}. \quad (9)$$

Finally, the output of ANFIS is the estimated channel state information.

### Simulation results

The bit error rate (BER) and mean square error (MSE) performances of our proposed channel estimator are compared to LMS and LS algorithms. The simulation parameters, which are given in Table 1, have been used for MIMO-OFDM system with 2 transmitter and 2 receiver antennas.

Table 1. MIMO-OFDM simulation parameters.

Parameter	Value
Carrier frequency ( $f_c$ )	5 GHz
Sampling frequency ( $f_s$ )	3 MHz
FFT size	64
Symbol part duration	$64 T_s = 21.33 \mu s$
Cyclic prefix duration	$T_{FFT}/4 = 5.33 \mu s$
Modulation type	QPSK
Channel type	COST 207 TU

6 tap COST 207 TU channel model [15] which has [0, 200, 600, 1600, 2400, 5000]ns relative delays and [-3, 0, -2, -6, -8, -10] dB power paths is used as transmission environment.

To train ANFIS, 1200 training symbols and 100 epochs are used. The bit error rate performance of channel estimators versus signal to noise ratio is shown in Fig. 3.

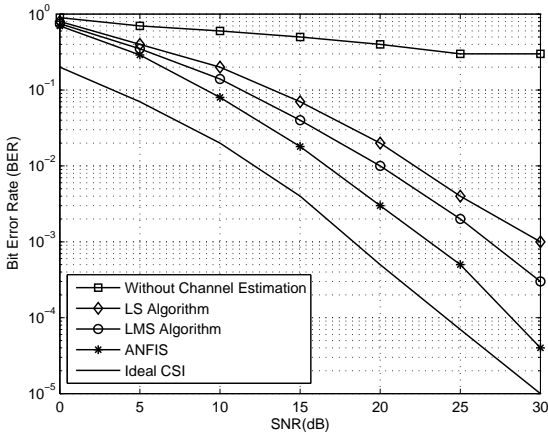


Fig. 3. BER performances of channel estimators

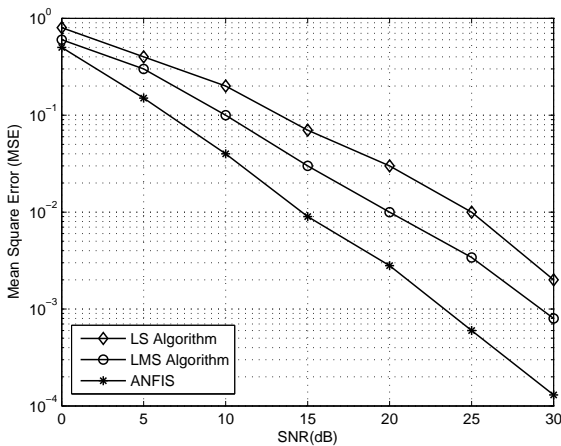


Fig. 4. MSE performances of channel estimators

Fig. 3 indicates that the performance of our proposed channel estimator based on ANFIS is better than other algorithms. Not only at low SNR values but also at high SNR values BER performance of ANFIS is better than LS and LMS algorithms considerably. For instance, at 15 dB SNR value bit error differences between ANFIS and LS is about  $10^{-1}$  and also at 30 dB SNR value it is about  $10^{-2}$ . The BER differences between LMS and ANFIS is  $10^{-1}$  at 30 dB SNR value. Besides the performance of ANFIS is close to ideal CSI at increasing SNR values. Especially at 30 dB BER of ANFIS dropped down below the  $10^{-4}$ .

The performance of estimators is also measured by mean square error (MSE) in Fig.4. The MSE is expressed as

$$MSE = \frac{1}{N} \sum_{k=1}^N |H_{est} - H_{real}|^2, \quad (10)$$

where  $H_{est}$  is the estimated channel state information and  $H_{real}$  is the real channel impulse response. As it is seen from Fig. 4, estimation error of ANFIS is less than LS and LMS algorithms.

If we investigate the estimators in terms of computational complexity; in LS algorithm  $N_T N_R N^2$

complex valued multiplications and  $N_T N_R (N^2 - N)$  complex valued additions; in LMS algorithm  $N_T N_R (3N^2)$  complex valued additions,  $N_T N_R (4N^2)$  complex valued multiplications; in MMSE algorithm  $2N_T N_R N^2$  complex valued multiplications,  $N_T N_R (2N^2 - N)$  complex valued additions and  $N_T N_R N^3$  both complex valued multiplication and addition; and in ANFIS  $N_T N_R (3M_R N_D N)$  non complex valued multiplications,  $N_T N_R (2M_R N_D N)$  non-complex valued division,  $N_T N_R (4M_R N_D N)$  non-complex valued addition and  $N_T N_R (M_R N_D N)$  non complex valued subtractions are carried out where  $M_R$  is the number of membership functions,  $N_D$  is the number of data symbols which are carried by each sub carriers and  $N$  is the number of sub carriers. All of the addition and the multiplication computations in LS and MMSE algorithms are complex valued; for this reason real computational complexity will be much more. According to the analysis, computational complexity of ANFIS is not as much as MMSE's.

## Conclusions

In this paper, the adaptive neuro-fuzzy inference system (ANFIS) is proposed for channel estimation in space-time block coded MIMO-OFDM systems. In our proposal, by using learning capability of ANFIS the network is trained by correct channel state information; then we use this trained network as a channel estimator. Our proposed estimator performs better than the LS and LMS algorithms. Although the implementation of the LS algorithm is quite easy the performance of this algorithm is poor. The LMS performs worse than ANFIS. Besides in LMS algorithm choosing step size is critical because larger step size results in faster convergence but higher steady MSE. However, if step size is too small it will take long time the convergence. According to the simulation results our proposed channel estimator based on ANFIS performs better than classical algorithms based on pilot tones. Also ANFIS is not complex channel estimation algorithm.

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**M. N. Seyman, N. Taspinar. MIMO-OFDM Channel Estimation Using ANFIS // Electronics and Electrical Engineering. – Kaunas: Technologija, 2012. – No. 4(120). – P. 75–78.**

In this paper, adaptive neuro fuzzy inference system (ANFIS) model is proposed for channel estimation in MIMO-OFDM system and the performance of this estimator is compared to the least square error (LS), least mean square error (LMS) algorithms by computer simulations. According to the simulations, ANFIS performs better than LS and LMS algorithms. Moreover, there is no need of sending pilot tones which are necessary for classical algorithms, in ANFIS. Therefore the ANFIS is bandwidth efficient algorithm. III. 4, bibl. 15, tabl. 1 (in English; abstracts in English and Lithuanian).

**M. N. Seyman, N. Taspinar. MIMO-OFDM kanalo vertinimas naudojant ANFIS // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2012. – Nr. 4(120). – P. 75–78.**

Pasiūlytas adaptivus neuroneraiškosios logikos interferencijos sistemos modelis skirtas MIMO-OFDM sistemos kanalams vertinti. Šio vertinimo mechanizmo našumui palyginti naudoti kvadratų klaidos, mažiausių kvadratų vidutinės klaidos algoritmai ir kompiuterinis imitavimas. Pasiūlytas algoritmas yra pranašesnis už tirtus algoritmus, be to, šiam algoritmui nereikia bandomųjų tonų. II. 4, bibl. 15, lent. 1 (anglų kalba; santraukos anglų ir lietuvių k.).