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Channel estimation using an adaptive neuro fuzzy inference system in the OFDM-IDMA system

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Abstract: In this paper, a channel estimator based on an adaptive neuro fuzzy inference system (ANFIS) is proposed for the purpose of estimating channel frequency responses in orthogonal frequency division multiplexing-interleave division multiple access (OFDM-IDMA) systems. To see the performance of our proposed channel estimation method, five different techniques including well-known pilot-based estimation algorithms such as least squares (LS) and minimum mean square error (MMSE) with other heuristic methods like multilayered perceptron (MLP) trained by a backpropagation (BP) algorithm (MLP-BP), MLP trained by the Levenberg–Marquardt (LM) algorithm (MLP-LM), and radial basis function neural network (RBFNN) are compared with our proposed method by computer simulations. The comparisons are made with the aid of bit error rate and mean square error graphs. According to the simulation results, our proposed channel estimator based on ANFIS shows better performance than both the LS algorithm and the other considered heuristic methods like MLP-BP, MLP-LM, and RBFNN, whereas the MMSE algorithm still shows the best performance as expected because of exploiting channel statistics and noise information, which makes it very complex to be used in any system. As well as being less complex compared to the MMSE algorithm, the estimator based on ANFIS does not need pilot tones for channel estimation. These properties bring our proposed method to an advantageous position among the other estimation techniques.

Key words: Channel estimation, adaptive neuro fuzzy inference system, multilayered perceptron, radial basis function neural network, orthogonal frequency division multiplexing-interleave division multiple access

1. Introduction

Interleave division multiple access combined with orthogonal frequency division multiplexing, which is briefly known as the OFDM-IDMA system, has recently been one of the most promising schemes from which the accomplishment of high data transfer rates is expected [1]. The combination of two schemes gathers the advantages of both systems that are the capability of solving intersymbol interference (ISI) and multiple access interference (MAI) problems [2,3]. ISI and MAI, two main obstacle in wireless communication systems, are prevented by the OFDM and IDMA parts, respectively [4,5]. In the OFDM-IDMA system, the signals belonging to different users are separated by the interleavers generated particularly for each user [6–9]. MAI is prevented with the aid of a chip-by-chip multiuser detection algorithm in a low-cost way [10,11].

However, in wireless communication systems, the fading effect of the channel must be considered to obtain the transmitted bits with minimal error at the receiver side. Therefore, even though the OFDM-IDMA

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system has many advantages, channel estimation is the prior task to do in which the channel state information is acquired [12].

To be able to attain channel frequency responses, classical pilot-based estimation algorithms such as least squares (LS) and minimum mean square error (MMSE) can be utilized. These two algorithms differ in their complexity and performance. The LS algorithm is simple and easy to apply in any system but its performance in fast-fading and time-varying channels is poor and it is not logical to use this algorithm in systems where more importance is given to performance compared to complexity. On the other hand, the MMSE algorithm gives better results in estimating channel frequency responses because of utilizing the information of noise variance and channel covariance in the process of channel estimation. However, the need for this channel information makes the MMSE algorithm too complex to be used in any transmission technology [12–14].

Although no work has been performed related to channel estimation using the adaptive neuro fuzzy inference system (ANFIS) for OFDM-IDMA system, there are some studies in which the ANFIS and the other heuristic methods are applied to estimate channel frequency responses for single-input single-output (SISO) and multiple-input multiple-output (MIMO) OFDM systems [15–19]. One study was conducted to estimate channel frequency responses in the OFDM-IDMA system by using a radial basis function neural network (RBFNN), which is one of the heuristic methods used for channel estimation [20].

In [15], an estimator based on a backpropagation neural network with three layers was proposed for SISO-OFDM transmission technology and the system performance was evaluated by using bit error rate (BER) and mean square error (MSE) graphs. In [16] and [17], an ANFIS-based channel estimator was offered for MIMO and SISO OFDM, respectively, and a comparison was made with conventional estimation algorithms such as LS and MMSE with regards to performance and complexity. In [18], a multilayered perceptron (MLP)-based estimator trained by the Levenberg–Marquardt algorithm was proposed for the MIMO-OFDM system, and in [19], a RBFNN was utilized to build a channel estimator for the same system. In [20], a RBFNN was employed for channel estimation in the OFDM-IDMA system and the performance of the proposed method was compared not only with well-known classical pilot-based channel estimation algorithms such as LS and MMSE, but also with MLP, which is another common type of neural network.

The outline of this paper is as follows: in Section 2, the model of the OFDM-IDMA system is described. In Section 3, the structure of our proposed ANFIS-based channel estimator and its usage in the OFDM-IDMA system is explained. In Section 4, the computational complexity analysis is made. In Section 5, the simulation results are given, and finally, the paper ends with the conclusions in Section 6.

2. OFDM-IDMA system model

The OFDM-IDMA system consisting of two parts, the transmitter and receiver, is depicted in Figure 1. As seen from the Figure 1, there are K data blocks allocated to different users, each of which comprises S OFDM symbols, and each symbol consists of m subcarriers. For every single data block numbered from 1 to K, the first S_p OFDM symbol of each user is reserved for the purpose of using pilot tones, whereas the remaining S-S_p symbols form real data.

In the working process of the OFDM-IDMA system, first of all, the information bits are allocated to different users and these bits are encoded by forward error correction (FEC) coding techniques. The spreading operation is then performed for each encoded bit belonging to different users by using the same spreading sequence. After that, the code words obtained from the spreader outputs are interleaved by user-specific interleavers, which are generated randomly for each user. Following the quadrate phase shift keying (QPSK) modulation process, pilot tones are inserted, and finally an inverse fast Fourier transform (IFFT) operation is performed before transmitting the signals over a frequency-selective multipath fading channel. The expression of the received signal after the fast Fourier transform (FFT) operation is as follows:

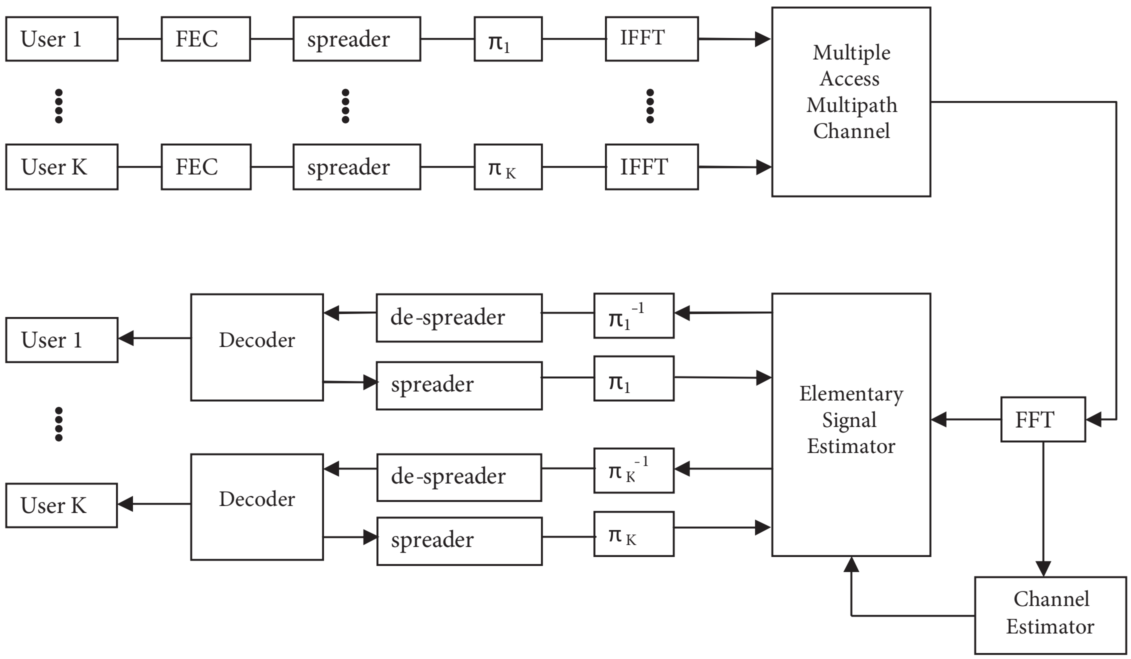

Figure 1. Transmitter and receiver structure of an OFDM-IDMA scheme with K simultaneous users.

$$R\left[m,s\right]=\sum_{k=1}^{K}H_k\left[m,s\right]X_k\left[m,s\right]+W\left[m,s\right], \tag{1}$$

where $H_k\left[m,s\right]$, $X_k\left[m,s\right]$, and $W\left[m,s\right]$ correspond to channel frequency response consisting of complex numbers, transmitted symbol, and additive white Gaussian noise, respectively. m symbolizes the subcarrier number in OFDM symbol s.

After the FFT operation, one of the channel estimation methods is performed to estimate channel frequency responses that are essential for eliminating channel fading effect and these channel coefficients are employed in an elementary signal estimation (ESE) process [1,21,22].

2.1. ESE process

In the ESE operation in which the interference plus noise is accepted as a complex Gaussian process, in the first place, extrinsic log-likelihood ratio (LLR) outputs of the received signals are produced by an elementary signal estimator. Following the ESE process, LLR streams generated for each user are deinterleaved and despread, respectively, before being fed to soft-input soft-output (SISO) decoders (DECs). Outputs of the decoders are then respread and reinterleaved before being fed back to the elementary signal estimator. This loop is repeated for a certain iteration number, and for each iteration, LLR streams and decoder outputs are updated. The ESE procedure for a frequency-selective fading channel is briefly summarized below. More detailed description about OFDM-IDMA receivers can be found in [1,10].

If the signal transmitted from user k is taken into account, after rearranging Eq. (1), the received signal can be expressed as:

$$r[m,s] = h_k[m,s]\,x_k[m,s] + \xi_k[m,s], \tag{2}$$

where $\xi_k[m,s]$ is known as the collected interference plus noise term, which influences user k. By considering the model expressed above, the LLR output of the elementary signal estimator is written as:

$$e_{ESE}\left[Re\left(x_k[m,s]\right)\right] = 2\left|h_k[m,s]\right|^2 \cdot \frac{Re\left(h_k^*[m,s]\,r[m,s]\right) - E\left\{Re\left(h_k^*[m,s]\,\xi_k[m,s]\right)\right\}}{Var\left\{Re\left(h_k^*[m,s]\,\xi_k[m,s]\right)\right\}}, \tag{3}$$

where the similar form expressions of $ERe\left(h_k^*[m,s]\,\xi_k[m,s]\right)$ and $VarRe\left(h_k^*[m,s]\,\xi_k[m,s]\right)$ are given in [1]. A similar expression can be obtained for $e_{ESE}\left[Im\left(x_k[m,s]\right)\right]$.

3. The use of ANFIS in channel estimation

ANFIS is an adaptive network using a hybrid learning rule and has the capability of being adaptive, which makes it suitable to be employed in both linear and nonlinear functional problems. ANFIS incorporates the benefits of both a fuzzy inference system (FIS) and neural network by utilizing neural learning methods in adjusting the membership function parameters and the structure of the FIS [23–25]. The structure of our proposed channel estimator based on ANFIS is depicted in Figure 2. As can be seen from Figure 2, a two-input one-output ANFIS model is built to be able to employ the system as a channel estimator in an OFDM-IDMA scheme in which the received data used for estimating channel state information consist of complex signals. As in the other artificial intelligence techniques, since ANFIS can only deal with real numbers, each complex signal is separated into real and imaginary parts before being fed to the input of our proposed estimator.

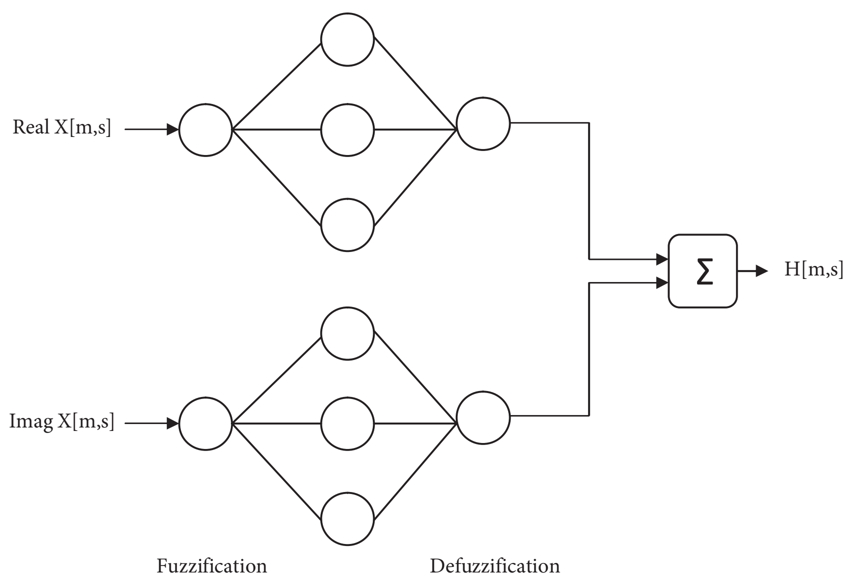

Figure 2. The structure of the ANFIS channel estimator.

First of all, the proposed ANFIS structure is trained by employing correct channel frequency responses as a training sequence. This training phase transforms ANFIS to a channel estimator that is available to be used in the receiver of the OFDM-IDMA system. After the training phase, received signals are separated into real and imaginary parts and fed to the input of our proposed ANFIS based estimator so that estimated channel frequency responses are obtained from the output by collecting real and imaginary parts together.

Three Sugeno-type fuzzy rules that we construct for our proposed ANFIS model are given below:

$$\text{Rule 1: if } X_k[m,s] \text{ is } A_1 \text{ then } y_1 = k_{11}X_k[m,s] + k_{12}, X_k[m,s] \tag{4}$$

$$\text{Rule 2: if } X_k[m,s] \text{ is } A_2 \text{ then } y_2 = k_{21}X_k[m,s] + k_{22}, X_k[m,s] \tag{5}$$

$$\text{Rule 3: if } X_k[m,s] \text{ is } A_3 \text{ then } y_3 = k_{31}X_k[m,s] + k_{32}, X_k[m,s] \tag{6}$$

where k corresponds to consequent (design) parameters adjusted throughout the training process and A_i represents fuzzy sets. The generalized bell membership function that we use for our ANFIS model is as follows:

$$\mu_{A_i}(X_k[m,s]) = \frac{1}{1+\left(\frac{X_k[m,s]-c_i}{a_i}\right)^{2b_i}}, \tag{7}$$

where a_i, b_i, and c_i are called premise parameters controlling the bell-shaped function. The change in the value of these parameters gives rise to change in the bell-shaped function. The ANFIS output, which is actually the estimated channel state information, is as follows:

$$H_k[m,s] = \frac{\sum_{i=1}^{3}\mu_{A_i}(X_k[m,s]).y_i}{\sum_{i=1}^{3}\mu_{A_i}(X_k[m,s])}. \tag{8}$$

4. The computational complexity analysis

Channel estimation with the MMSE algorithm can be performed as follows:

$$\bar{g}_{MMSE} = R_{gy}R_{yy}^{-1}y, \tag{9}$$

$$R_{gy} = E\left\{gy^H\right\} = R_{gg}F^HX^H, \tag{10}$$

$$R_{yy} = E\left\{yy^H\right\} = XFR_{gg}F^HX^H + \sigma^2 I_N, \tag{11}$$

$$\hat{h}_{MMSE} = F\bar{g}_{MMSE}, \tag{12}$$

In the equations above, R_{gy} is the cross-covariance matrix between g and y , where $g$is the channel energy and y is the received signal. R_{yy} is the autocovariance matrix of y. R_{gg} is the autocovariance matrix of g and σ^2 denotes the noise variance $E\left\{|n_k|^2\right\}$. $\bar{g}_{MMSE}$ is the channel impulse response and $\hat{h}_{MMSE}$ is channel frequency response. X is the transmitted signal, I_N is the identity matrix, and F is the DFT matrix [13].

The computational complexity of the MMSE algorithm depends on Eqs. (9)–(12), including the expressions of $\hat{h}_{MMSE}$, $\bar{g}_{MMSE}$, R_{gy}, R_{yy}, and F.

4.1. The complexity of DFT matrix F

$$O\left(F\right) = O\left(DFT\right) = N(\log N), \tag{13}$$

where N is the subcarrier number and F is a matrix of $N \times N$ size.

4.2. The complexity of R_{gy}

$$O\left(R_{gy}\right) = O\left(R_{gg}F^H X^H\right) = N^3 + N^2 = N^2\left(N+1\right), \tag{14}$$

where R_{gg} is an $N \times N$ matrix, F is an $N \times N$ matrix, and X is a $1 \times N$ matrix. The operation number required for square matrix $(N \times N) \times (N \times N)$ is $O(N^3)$ and the operation number for matrix multiplication of $(N \times N) \times (N \times 1)$ is $(N \times N \times 1) = O(N^2)$.

Consequently, the computational complexity of R_{gy} becomes $N^2(N+1)$.

4.3. The complexity of R_{yy}

$$O\left(R_{yy}\right) = O\left(XFR_{gg}F^H X^H + \sigma^2 I_N\right) = N^2 + N^3 + N^3 + N^2 + N^2 = N^2\left(2N+3\right) \tag{15}$$

The operation number needed for square matrix $(N \times N) \times (N \times N)$ is $O(N^3)$ and the operation number for matrix multiplication of $(N \times N) \times (N \times 1)$ is $O\left(N \times N \times 1\right) \mathit{or}\, O(N^2)$.

4.4. The complexity of $\bar{g}_{MMSE}$

$$O\left(\bar{g}_{MMSE}\right) = O\left(R_{gy}R_{yy}^{-1}y\right) = N^3 + N^2 + N^3 = N^2\left(2N+1\right) \tag{16}$$

The operation numbers needed for square matrix $(N \times N)\times(N\times N)$, matrix multiplication of $(N \times N)\times(N\times 1)$, and the inverse operation are $O(N^3)$, $O(N^2)$, and $O(N^3)$, respectively.

4.5. The complexity of $\hat{h}_{MMSE}$

From Eq. (12):

$$O\left(\hat{h}_{MMSE}\right) = O\left(DFT(\bar{g}_{MMSE})\right) = N(\log N)\,. \tag{17}$$

As a result, the computational complexity of the MMSE algorithm becomes:

$$O\left(MMSE\right) = N(\log N) + N^2\left(N+1\right) + N^2\left(2N+3\right) + N^2\left(2N+1\right) + N(\log N)$$

$$= 2N\left(logN\right) + N^2\left(5N+5\right) \tag{18}$$

4.6. The complexity of ANFIS

In the ANFIS method, $3M_RN_DN$ noncomplex valued multiplications, $2M_RN_DN$ noncomplex valued divisions, $4M_RN_DN$ noncomplex valued additions, and M_RN_DN noncomplex valued subtractions are performed where N is the subcarrier number, M_R is the number of membership functions, and N_D is the number of OFDM symbols including N subcarriers. Thus, the computational complexity of the ANFIS method becomes as follows:

$$O\left(ANFIS\right) = 3M_RN_DN + 2M_RN_DN + 4M_RN_DN + M_RN_DN = 10M_RN_DN\,. \tag{19}$$

In our simulations, subcarrier number $N = 256$, number of membership functions $M_R = 3$, and number of OFDM symbols $N_D = 16$. In this way, the computational complexity of the MMSE algorithm and ANFIS can also be obtained numerically in terms of operation number as demonstrated in Table 1. As can be seen from Table 1, this complexity analysis shows that the computational complexity of our proposed method is less than that of the MMSE algorithm [26].

Table 1. Total computational complexity of MMSE algorithm and ANFIS.

Variables	Number of operations
F	616
R_{gy}	16,842,752
R_{yy}	33,751,040
$\bar{g}_{MMSE}$	33,619,968
$\hat{h}_{MMSE}$	616
Total (MMSE)	84,214,992
ANFIS	122,880

5. Simulation results

In this study, we propose a channel estimator based on ANFIS for the OFDM-IDMA system and make a comparison to conventional pilot-based channel estimation algorithms such as LS and MMSE along with other heuristic-based channel estimators like multilayered perceptron-backpropagation (MLP-BP), multilayered perceptron-Levenberg–Marquardt (LM), and RBFNN with the help of MSE and BER graphs. In the MLP-BP estimator the BP algorithm is used for training the MLP neural network, while in the MLP-LM estimator, the LM algorithm is used.

In the first stage of the simulations, we compare our proposed estimator to LS, MMSE, MLP-BP, and RBFNN with regard to BER and MSE criteria by using a four-tap frequency-selective fading channel that has [0, 4, 8, 12] μs relative delays and [0, –3, –6, –9] dB power paths. After that, the OFDM-IDMA system performance is observed for two different user numbers with the considered channel estimation techniques with regard to BER criteria.

In the second stage, to be able to support the reliability and stability of our proposed method, the OFDM-IDMA system is also simulated using the ITU Vehicular-A channel environment, which has [0, 310, 710, 1090, 1730, 2510] ns relative delays and [0, –1, –9, –10, –15, –20] dB power paths with more users. One more state-of-the-art channel estimator like MLP-LM is utilized for comparison.

In our simulations, we used a rate 1/2 convolutional code with $(171{,}133)_8$ generator polynomial followed by a rate 1/16 spreading sequence. The other parameters are given in Table 2. Our proposed ANFIS model, which includes three generalized bell membership functions, is trained for 100 epochs with 10,000 training symbols consisting of correct channel frequency responses. On the other hand, both MLP-BP and MLP-LM have one hidden layer with five neurons and one output layer with two neurons. The same number of training symbol is used for these MLPs and RBFNN, too.

In Figure 3, the performance of the OFDM-IDMA system is observed under LS, MLP-BP, RBFNN, ANFIS, and MMSE with regard to BER criteria to be able to see the efficiency of our proposed channel estimator among the other estimators. For this simulation, the user number is 20 and the other parameters are determined as in Table 2. As can be seen from Figure 3, ANFIS shows better performance than LS, MLP-BP, and RBFNN at each dB value. If the attention is paid especially to the curve of LS and ANFIS, it can be clearly seen from the graph that, from 0 dB to 6 dB, the distance between the two curves is increasing because of the growing performance of our proposed estimator in this interval. Starting from 6 dB, the distance becomes stable. If the graph is looked at from a different perspective, it can be seen that the closest curve to the MMSE, which still shows the best performance with the disadvantage of being too complex, can be acquired by employing our proposed estimator based on ANFIS in the OFDM-IDMA system. The complexity of the MMSE algorithm makes it useless in practical systems. On the other hand, unlike the MMSE algorithm, the ANFIS estimator does not need any statistical information to estimate channel frequency responses and it is easy to apply in the OFDM-IDMA system.

Table 2. OFDM-IDMA simulation parameters.

Number of used subcarriers	256
FFT size	256
Sampling frequency	500 kHz
Sampling period	2 μs
Symbol part duration (TFFT)	256.Ts = 512 μs
Cyclic prefix size	FFT/4 = 64
Cyclic prefix duration	TFFT/4 = 512/4 = 128 μs
Modulation type	QPSK

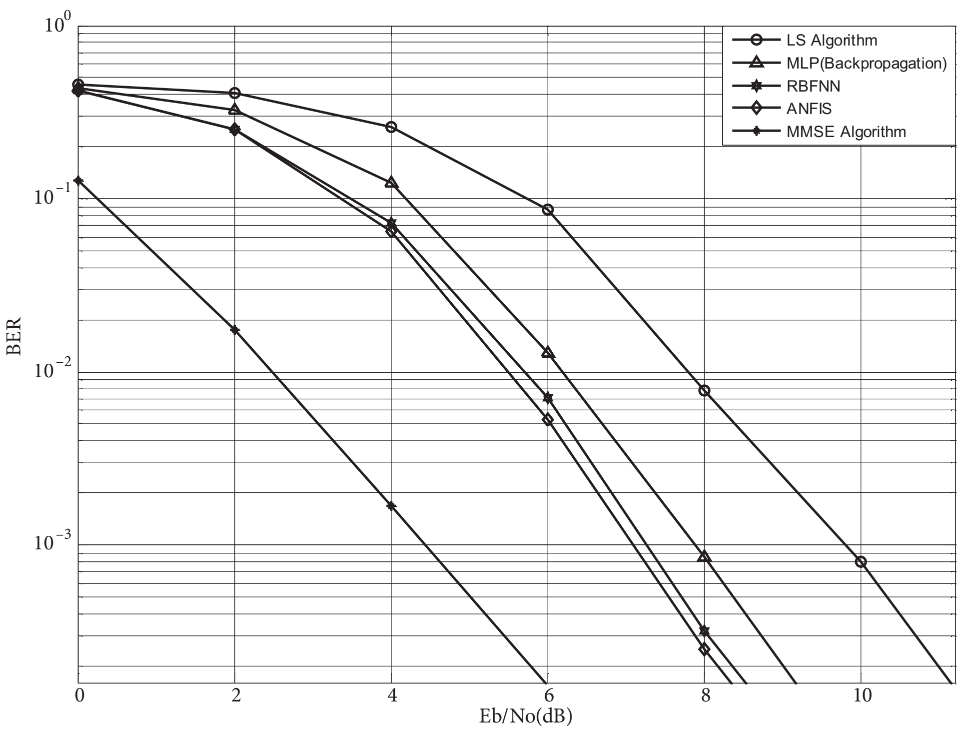

Figure 3. Bit error rate performance of the channel estimators.

The second performance evaluation method utilized in this study is MSE. In the MSE technique, the estimation errors made by each channel estimator are calculated for discrete E_b/N_0 values in a certain interval. The MSE can be obtained by the expression given below:

$$MSE = \frac{1}{N} \sum_{q=0}^{N-1} E[(h_{est} - h_{real})^H (h_{est} - h_{real})], \tag{20}$$

where h_{real} is the real channel frequency response and h_{est} is the estimated channel frequency response. As in Figure 3, the same results can be observed from Figure 4 with regard to the performance of the considered channel estimators. As can be seen from Figure 4, estimation error of our proposed estimator based on ANFIS is between RBFNN and MMSE for each dB value. On the other hand, the LS algorithm shows the worst performance among the estimators because of its weakness in fast-fading and time-varying channels.

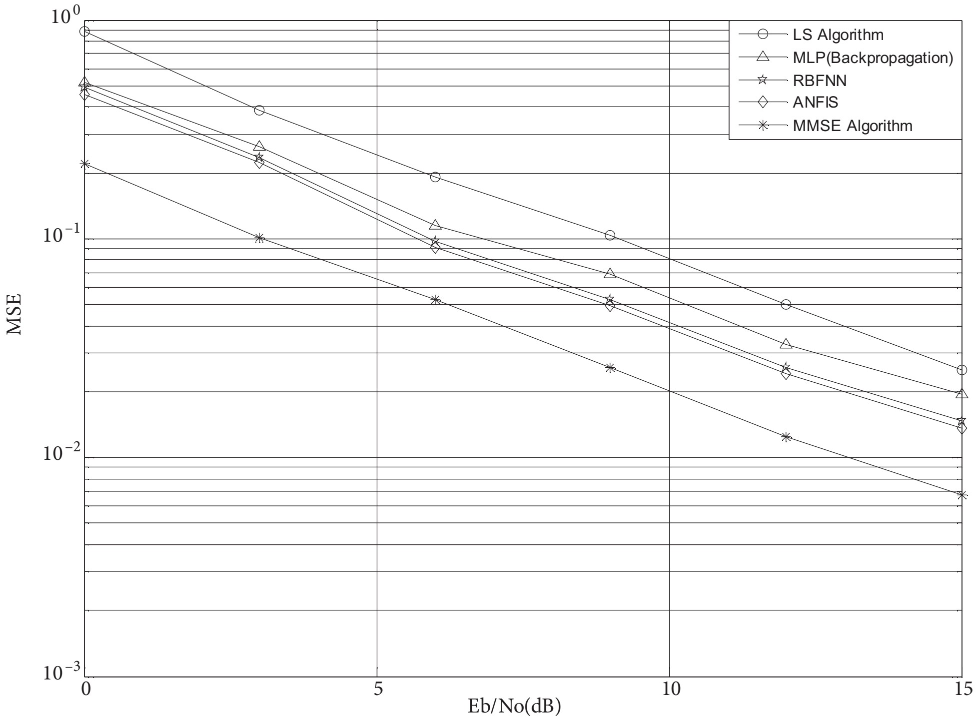

Figure 4. Mean square error performance of the estimators.

In Figure 5, the performance of the OFDM-IDMA system is observed for different user numbers with the considered channel estimation techniques. The BER graph of the OFDM-IDMA system is obtained for 20 and 21 users under each channel estimator. The other parameters are determined as in Table 2. As can be seen from Figure 5, the BER of the system with 20 users is less than the BER of the system with 21 users at every dB value for each estimator due to the fact that more users give rise to further parameters to be estimated and processed, which will naturally induce poor performance at the same time.

In Figures 6–8, the OFDM-IDMA system is simulated under the ITU Vehicular-A channel environment to demonstrate that our proposed ANFIS method is stable and adaptive to any condition. At this stage of the simulations, in addition to the RBFNN and MLP-BP estimator, one more state-of-the-art channel estimator like MLP-LM is used to show the advantage of our proposed method more clearly. Additionally, in Figure 8, the OFDM-IDMA system is simulated for more user numbers, which are 18, 20, and 22, compared to Figure 5 to support the reliability of our method. In Figures 6 and 7, our proposed ANFIS estimator shows better performance than LS and the other heuristic methods, which are MLP-BP, MLP-LM, and RBFNN, with regard to both BER and MSE criteria. In Figure 8, the BER of the system increases for each estimator with the increase in the number of users, just like in Figure 5.

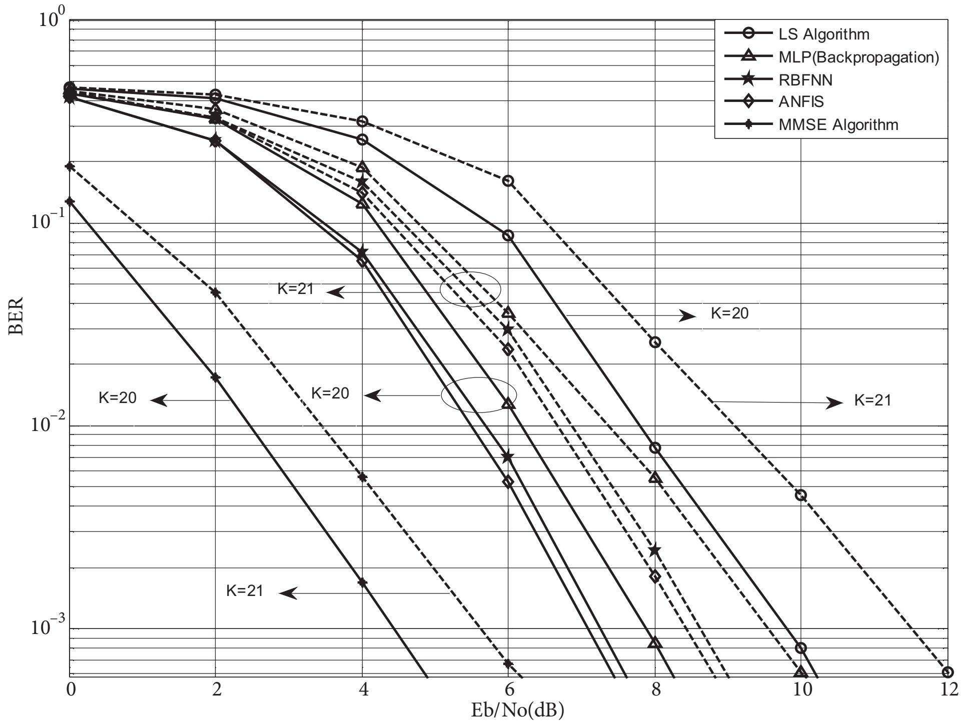

Figure 5. Bit error rate performance of the estimators for different user numbers.

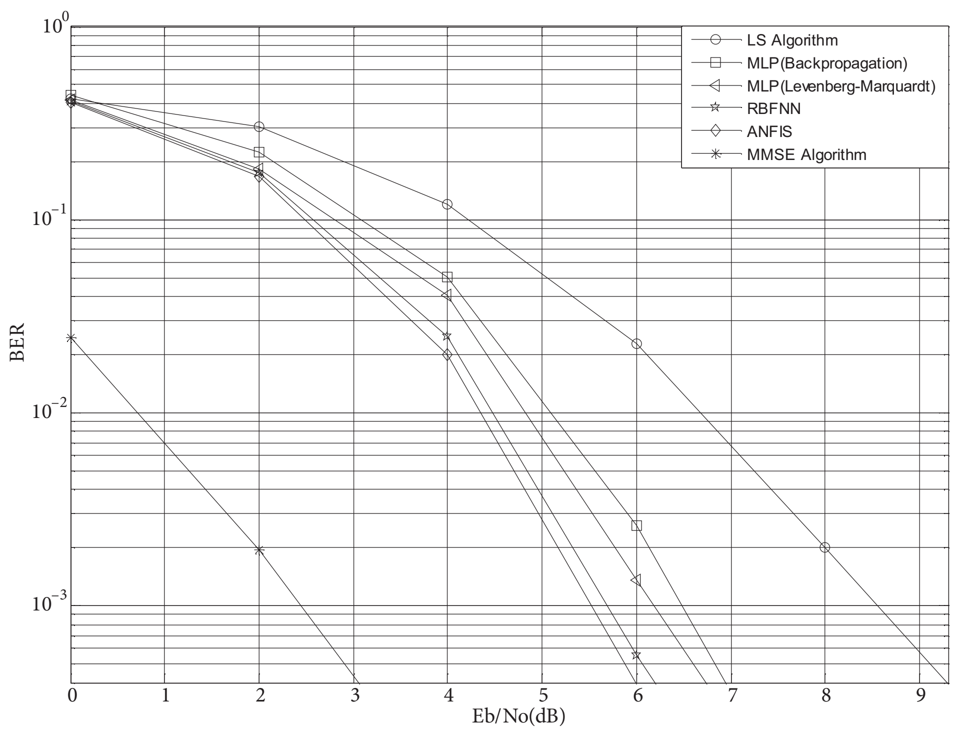

Figure 6. Bit error rate performance of the channel estimators over ITU Vehicular-A.

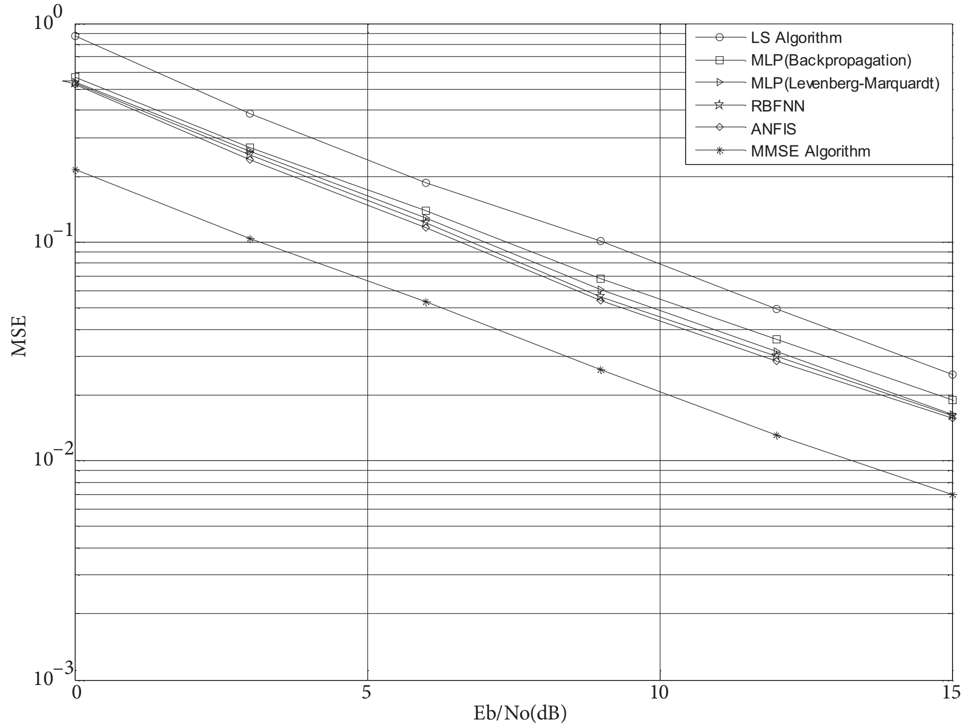

Figure 7. Mean square error performance of the estimators over ITU Vehicular-A.

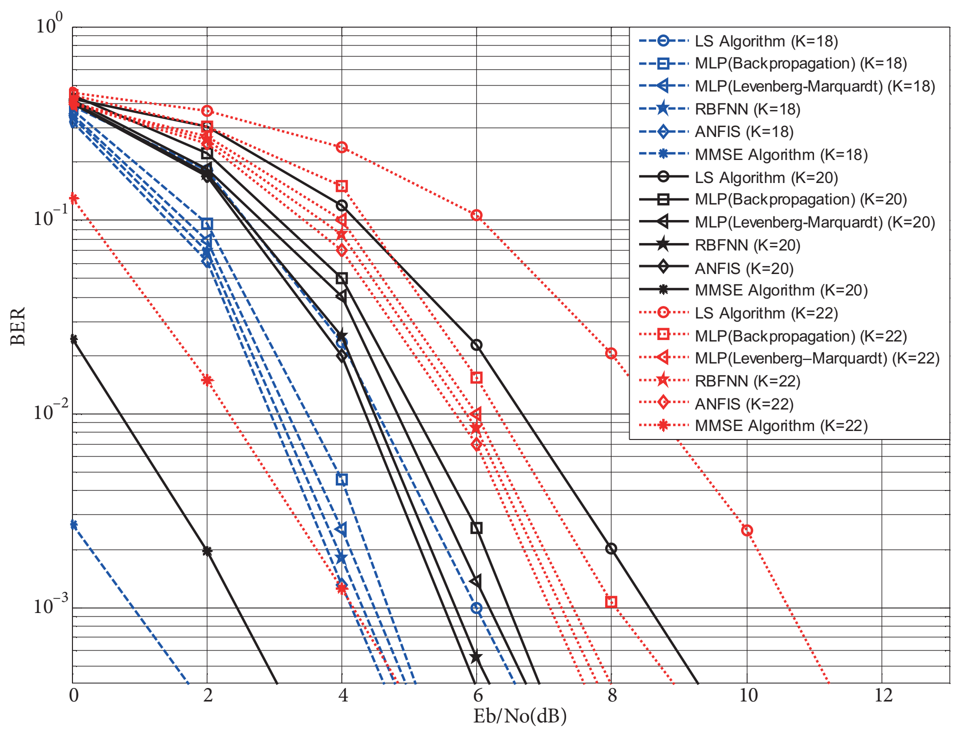

Figure 8. Bit error rate performance of the estimators for different user numbers over ITU Vehicular-A.

6. Conclusion

In this study, a new channel estimation technique based on ANFIS for the OFDM-IDMA system is proposed. In our study, we trained ANFIS by correct channel coefficients to be able to use it as a channel estimator. After that, we adopted this trained network to OFDM-IDMA system. To evaluate the performance of our proposed ANFIS-based channel estimator, we considered LS, MLP-BP, MLP-LM, RBFNN, and MMSE and made comparisons with regard to MSE and BER criteria. According to the result of computer simulations, our proposed estimator shows better performance than LS, MLP-BP, MLP-LM, and RBFNN estimators with regard to both BER and MSE criteria, excluding the MMSE algorithm, which still shows the best performance with the disadvantage of being too complex and unpractical to be used in any system due to the need for channel covariance and noise variance in the estimating process. Unlike the MMSE algorithm, our ANFIS model does not need any channel statistics or noise information to estimate channel frequency responses. Moreover, there is no need to send pilot tones in estimating channel coefficients and this feature of our proposed estimator makes it advantageous among the conventional estimation algorithms because of efficient bandwidth usage.

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