CHANNEL ESTIMATION IN OFDM SYSTEM USING MULTI-LAYERED PERCEPTRON NEURAL NETWORK COMBINED WITH ARTIFICIAL BEE COLONY ALGORITHM

[1]NECMI TASPINAR, [2]SIDRA MEO RAJPUT, [3]NURCAN SARIKAYA BASTURK, [4]ALPER BASTURK

Department of Electrical and Electronics Engineering, Erciyes University, Kayseri, TURKEY
Institute of Natural and Applied Science, Erciyes University, Kayseri, TURKEY
Department of Aircraft Electrical and Electronics Engineering, Erciyes University, Kayseri, TURKEY
Department of Computer Engineering, Erciyes University, Kayseri, TURKEY
E-mail: taspinar@erciyes.edu.tr, sidra.rajput24@gmail.com, nurcanb@erciyes.edu.tr, ab@erciyes.edu.tr

Abstract- For many modern wireless and telecommunications systems, Orthogonal Frequency Division Multiplexing (OFDM) is being used as a modulation technique. OFDM has been adopted for the cellular telecommunications standard LTE / LTE-A, also it has been chosen by other standards including WiMAX, Wi-Fi and many more. In this study, a multi-layered perceptron based neural network has been trained with Artificial Bee Colony (ABC) optimization algorithm for channel estimation of an OFDM system. The results of proposed algorithm (ABCNN) are compared with conventional channel estimators such as Least Square (LS) and Minimum Mean Square Error (MMSE) and also with conventional back propagation neural network (BPNN). In this work, mean square error (MSE) and bit error rate (BER) have been used to evaluate the performance of ABC-NN. The simulation results show that channel estimation based on proposed algorithm gives better performance as compared to LS algorithm and BP-NN without the need of channel statistics and noise information. Although MMSE algorithm performs better than ABC-NN for channel estimation of OFDM, ABC-NN is less complex and does not require channel state information in advance.

Index Terms—OFDM, Channel Estimation, Neural Network, Artificial Bee Colony Optimization Algorithm

I. INTRODUCTION

Day by day demand for high data rate is increasing and due to this, wireless systems now and in future need technologies which are capable of providing high data rates. Orthogonal frequency division multiplexing (OFDM) and multiple input multiple output OFDM (MIMO-OFDM) techniques are considered as promising selection for providing high rates for future applications [1]. Single carrier system has a problem of inter-symbol interference (ISI) due to frequency selective nature of wireless channel. The problem of ISI can be resolved with the help of multicarrier system which divides the channel into several narrow-band channels. Therefore, most of the problems which exist in single carrier systems can be avoided by using multiple parallel carriers for transmission of data and increased the throughput of the system [2]. In multicarrier system, the bandwidth of channel is divided into many narrow individual sub-carriers and the frequency response of each sub-carrier is flat because every sub-carrier takes up a small portion of the original channel bandwidth [3]. The sum of the output of all the sub-carriers constitutes the overall throughput of a system. This feature provides us the opportunity to design a system which supports high data rates as well as maintain longer symbol durations [4]. OFDM is a multicarrier modulation technique which divides signal bandwidth into many narrow sub-carriers before transmitting the data. Parallel sub-channels in OFDM increase the symbol duration and thereby reduce or eliminate the ISI which is caused due to multi-path environments. OFDM is used in wireless communication systems to provide high-speed transmission of data in outdoor and indoor environment [5]. In wireless communication, transmitted signal passes through a radio channel before reaching to receivers, therefore estimation of the effect of the channel on the transmitted information is required to recover the signal [6]. Wireless channels cause ISI because of multi path fading. In order to remove effects of channel from the received signal, receiver need to have information of the channel impulse response (CIR), which is generally provided by channel estimator [7]. Commonly, channel estimation comprises of two types of techniques which include pilot based and blind channel estimation. In blind channel estimation, statistical properties of received signal are used to estimate channel coefficients and there is no need to insert a pilot signal or preamble. Apparently, blind channel estimation does not experience overhead issues connected to training signals; however, the performance of blind channel estimation method is normally not better than pilot based channel estimation methods as it needs substantial number of received symbols for obtaining statistical properties of channel. In pilot based channel esti mation method, a training sequence is inserted at the start of transmission, this sequence comprises of pilot (known data symbols) and provides initial channel estimation parameters [6]. There are various channel estimation methods which can be used with pilot based estimation such as Least square (LS) algorithm and

Minimum Mean Square Error (MMSE) algorithm. LS algorithm is comparatively simple and easy to implement but it does not perform well for time varying and fast fading channel. On the other hand, MMSE algorithm performs better than LS algorithm but at the same time it is far more complex to use for any system [8][9]. Until now LS and MMSE algorithms have been used for channel estimation hundreds of times. In [1] authors have compared LS and MMSE in terms of their performance and complexity in OFDM systems. In that study it is shown that, due to previous knowledge of channel covariance and noise variance, performance of MMSE algorithm is better than LS algorithm but at the same time need of prior knowledge makes MMSE algorithm more complex. In [6], LMS and LS algorithm are investigated for channel estimation of OFDM system. In recent years, not only the classical methods such as LS and MMSE algorithms have been used for channel estimation but other techniques have also been used such as neural networks (NN) and artificial optimization algorithms [9][10][11]. In [10] S¸ims¸ir and Tas¸pınar. have studied neural networks for channel estimation of OFDM-IDMA system. In [12], authors have used NN with Genetic algorithm (GA) for channel estimation in OFDM system and they have also compared the results with back propagation NN. In this paper, channel estimation has been performed by using NN whose weights are optimized with Artificial Bee Colony (ABC) optimization Algorithm. The outline of the paper is as follows: In Section II, OFDM system is described briefly. Training algorithms of NN are defined in Section III. In Section IV, the structure of our proposed algorithm for channel estimation of OFDM system is described. The simulation results are presented in Section V and finally, Section VI includes conclusion.

II. OFDM SYSTEM MODEL

Let say data sequence D is sent using OFDM. The first designing parameter in OFDM transmitter is to choose number of sub-carriers needed to send data. Let us consider that there are N sub-carriers and each sub-carrier is orthogonal to each other in terms of frequency. Based on the number of subcarriers, serial data stream D is convert into N parallel streams. Serial to parallel converter translates serial input sequence in N parallel outputs indexed from 0 to N-1. Now, each stream is individually modulated using BPSK, QPSK or QAM.

Once the parallel data is digitally modulated into required modulation format, the pilot tone is inserted to the signal. After that, inverse Fourier transform is taken to convert the signal into time domain and then these parallel streams are converted back to serial for transmission. Before transmission, guard interval is added to the signal to avoid ISI and to maintain

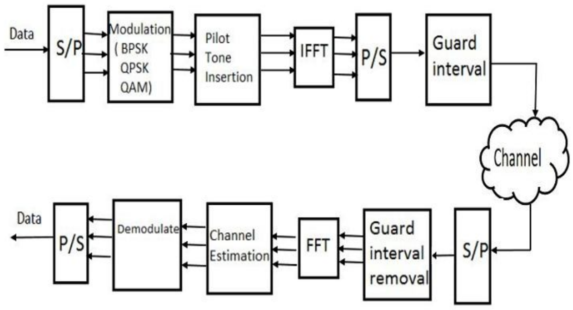

Fig. 1: OFDM System Model.

orthogonality of sub-carriers so that each sub-carrier can be completely and easily separated at the receiver. For guard interval, cyclic prefix is used which is aperiodic extension of the signal itself. After adding guard interval the total symbol duration Ttotal is the sum of useful symbol duration T and guard interval Tg i.e.

$$T_{total} = T + T_g \qquad (1)$$

Finally, the resultant OFDM signal is transmitted to channel for transmission as shown in Figure 1.

At the receiver side, first guard interval is removed and then serial to parallel conversion of data is performed. Now data is converted back to frequency domain by taking fast Fourier transform (FFT) of the parallel signal streams. After FFT, the process of channel estimation is implemented and channel frequency response is obtained with the help of pilot tone which was passed through channel and exposed to frequency selective multi-path fading. Later, data is converted to serial stream and demodulated to extract the transmitted data sequence.

III. NEURAL NETWORK COMBINED WITH ABC ALGORITHM

A. Neural Network Training Algorithm

An artificial NN is composed interconnected processing elements called neurons and the connections between them are called weights. NNs work similar to human brains and imitate learning process like human being [7]. ANN uses diverse types of training algorithms for adjusting weights in each iteration to get the desired output for a specified input. NNs have wide-ranging applications to real world problems and there are several types NNs employed for different applications in many fields [13][14]. There is a long list of algorithms which have been used so far for training of NN and every method has its own pros and cons. Most commonly used NN training method involve derivative based algorithms such as gradient descent to minimize the learning error. These derivative based algorithms sometimes have a problem of getting stuck in a possible local minima, also in order to find global minima the algorithm is needed to run exponential times [15]. On the other hand, heuristic algorithms such as GA , ABC are global search methods which can be used to find near optimal solutions mostly and also to avoid local minima problem. Nowadays, these heuristic methods are in highlights for training of NN due to their ability to search all search spaces. However, these algorithm have some disadvantages as well, best results cannot be achieved from these methods in first attempt and many trails have to be made to obtain the desired results [16]. In this paper, ABC algorithm has been used for training of NN and the structure of NN is shown in Fig. 2.

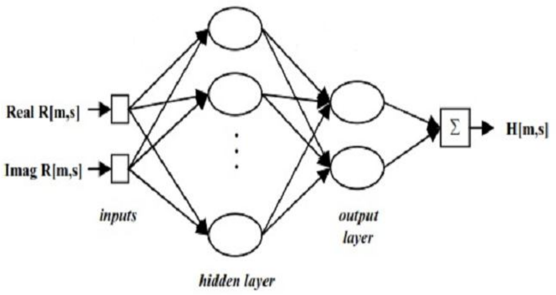

Fig. 2: Structure of neural network.

B. Artificial Bee Colony Algorithm

ABC algorithm is a swarm based intelligent algorithm inspired by foraging behavior of bees. This algorithm was introduced by Karaboga [ABC], and its working principle is similar to bees. Honey bees are assigned specified tasks to maximize the amount of nectar (food) in a hive [17]. In ABC algorithm, food sources (nectar) represents solutions and this algorithm has three types of bees i.e. employed bees, onlooker bees, and scout bees to search for the best solution. Each bee has a unique search characteristic: The employed bees are associated with specific food source while the onlooker (unemployed) bees observe the movement of employed bees in the hive to choose the rich sources depending on the information taken from employed bees. Scout bees search for undiscovered sources randomly [18]. From the view of a meta-heuristic, a population of solutions refers to the undiscovered food sources and the optimization task corresponds to finding the most beneficial source by exploiting the unique forage attributes of the employed bees and unemployed bees (onlooker and scout bees). Each type of bee is represented as a phase in the algorithm [19]. _ Initialization Phase: the population of food sources is initialized using Eq. (2):

$$x_{ij} = x_j^{min} + rand(0,1)(x_j^{max} - x_j^{min}) \qquad (2)$$

where i = 1; 2; :::; n, n = food source and j = index.

_ Employed bee phase: For each solution, bees search for new solution having more nectar amount in the neighborhood using equation (3) and make a greedy selection between Eq. (2) and Eq. (3). If the new solution is better than previous solution, it is kept in the memory and old one is discarded.

$$x'_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \qquad (3)$$

where k 2 [1; n] and i 6= k.

_ Onlooker bee phase: At this phase, bees observe the dance of the employed bee to learn locations of food source and the quality of nectar, also the size of the food source. The onlooker bee select a food source probabilistically depending on the amount of nectar as displayed by employed bee, probabilistic selection uses the probability values pi given by equation (4)

$$p_i = \frac{fitness_i}{\sum_{i-1}^{n} fitness_i} \qquad (4)$$

Where fitnessi is the fitness value of solution i, and again greedy selection is made same as in employed bee phase.

_ Scout bees phase: When some of the solutions/ food sources are abandoned new solutions are earched byscout bees randomly.

$$x_m = l_i + rand(0,1) * (u_i - l_i) \qquad (5)$$

Where ui and li are upper and lower bound of the solution space respectively. Here best solution is memorized and the process is continued.

C. Training of the Neural Network Using ABC Algorithm

So far, various optimization algorithms have been used to train NN. Training neural network using ABC algorithm can be useful to find near optimal values of connection weights of NN . The multi-dimensional search space is the space of network connection and bias weights, and the fitness is a standard measure of network output performance such as mean square error on the training data between desired and calculated output [20].

IV. CHANNEL ESTIMATION USING PROPOSED ALGORITHM

This study links ABC algorithm with a multi-layered perceptrons neural network (ABC-NN) for channel estimation. Firstly, at training stage input training sequence is fed to the neural network and output is calculated. Calculated output is compared with desired output data set and learning error is found which is used as the value of cost function for ABC algorithm. ABC algorithm optimizes the parameter value to minimize the cost function and updates the parameters of neural network until the stopping criteria is reached. The training setup is shown in Fig. 3. Secondly, at test stage, the channel estimation data is fed to the trained neural network and frequency response of the channel is obtained. The estimated frequency response is compared with real frequency response of the channel to calculate MSE for performance evaluation of the channel estimator.

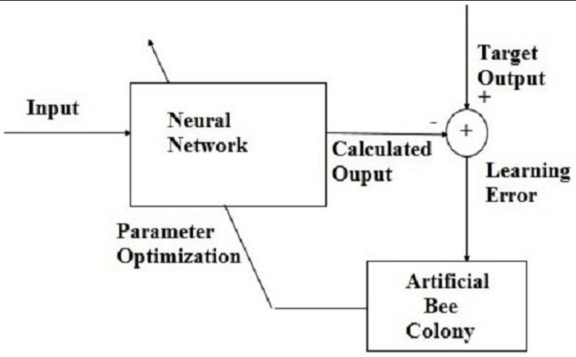

Fig. 3: Structure of proposed algorithm.

V. SIMULATION RESULTS

The parameters chosen for simulation are listed in Table I. In this paper, the proposed channel estimator is compared with LS, NN-BP and MMSE estimator with regards to bit error rate versus energy per bit to noise spectral density ratio (Eb/No) and also MSE versus Eb/No.

TABLE I: The parameters OFDM System.

Parameters	Values
FFT Size	256
Number of sub-carriers used	256
Guard interval type	Cyclic prefix
Modulation type	QPSK
Channel model	Rayleigh fading channel
Noise model	AWGN
Length of guard interval	64

After several experiments, optimum parameters are determined by ABC-NN for the excellent performance of neural network structure. Too many and too few hidden units would result in high generalization error due to over-fitting and under-fitting respectively. Thus, proposed network consists of one hidden layer and one output layer with 5 neurons and 2 neurons, respectively. Tangent sigmoid transfer function is used for hidden layer and linear transfer function is used for output layer. ABC algorithm is used for training the network and16000 training symbols are used in training process. Maximum number of cycles used for ABC-NN are 300. Firstly, the network is trained by using the correct channel state information, after that the received symbols are entered to ABC-NN and thus the estimated channel frequency responses
are found from the output of the proposed network. MSE and BER metrics are used for performance evaluation of different channel estimators. For MSE the estimation errors are calculated for separate Eb/No values at certain interval. MSE for each Eb/No value can be achieved by using following equation:

$$MSE = \frac{1}{N}\sum_{q=0}^{N-1} E[(h_{est} - h_{real})^H (h_{est} - h_{real})] \qquad (6)$$

where hest is estimated channel frequency response and hreal is real channel frequency response.
In Fig 4, MSE performance of LS, MMSE and back propagation algorithm is compared with proposed estimator for OFDM system. ABC-NN performance is better than LS and BP-NN. From Fig. 4, it can be clearly seen that LS estimator has deficient performance as it has more errors when compared to the other two channel estimation algorithms. Although LS estimator has low complexity, but it is not convenient to use LS algorithm in multipath fading channel because of its inferior performance. The Mean Square Error of neural network estimator is lower than LS and higher than MMSE algorithms. Initially, the learning method for the neural network requires a known pilot symbol as the target output. After multiple iterations, the input data gradually becomes the target output via learning.

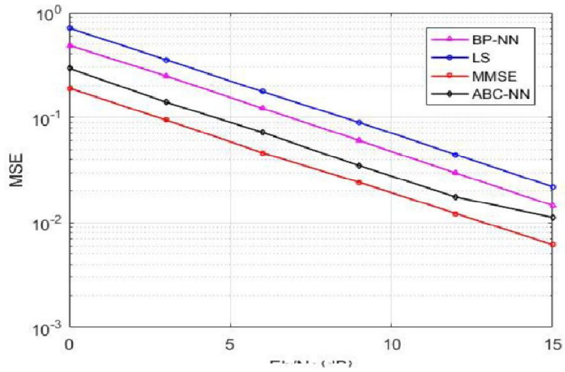

Fig. 4: Comparison of MSE graph for LS, BP-NN, MMSE and ABC-NN algorithms.

Although the MMSE algorithm performance is better than proposed algorithm, this method needs channel statistics and noise-related information to acquire channel impulse responses which is not feasible in real transmission situations. The proposed ABC-NN does not need channel information as in MMSE case, which simplifies implementation in real transmission environment. Second method used for performance evaluation of different channel estimators is BER . Figs. 5 and 6 show comparisons of BER using LS, conventional BP-NN, MMSE and the proposed ABC-NN algorithm for different FFT sizes. Clearly, the ABCNN offers superior estimation performance than conventional BP-NN and LS algorithms.

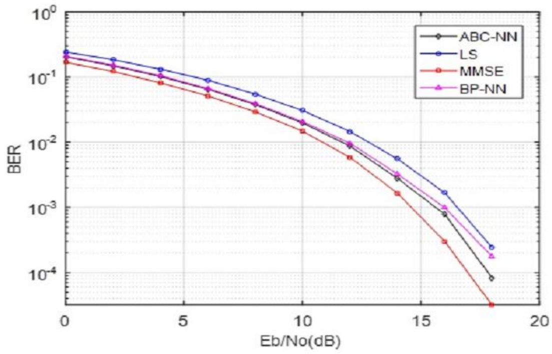

Fig. 5: BER comparison for various algorithms (FFT size =256).

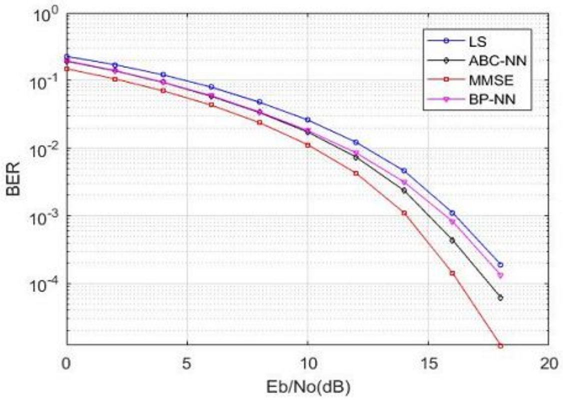

Fig. 6: BER comparison for various algorithms (FFT size =512).

CONCLUSION

In this study, ABC-NN method has been proposed for channel estimation in OFDM systems. A multi-layered perceptrons based neural network is combined with Artificial Bee Colony algorithm to increase the performance of channel estimation.The performance of the proposed algorithm is compared with LS, MMSE and BP-NN methods with regards to MSE and BER. According to detailed results, the proposed approach is more efficient than LS and conventional BP-NN algorithm and also it offers a better convergence rate. The proposed ABC-NN converges faster than conventional back propagation neural networks. The MMSE algorithm overreach the ABC-NN; but MMSE estimator is complex as compared to other estimators and it involves channel statistics and noise related data to get channel impulse responses. Obtaining this information is not easy in real transmission scenarios. Consequently, the proposed method is suitable as it does not require any information related to noise and channel.

ACKNOWLEDGMENTS

This research was supported by Erciyes University Scientific Research Center (BAP) under Grant No: FYL-2017-7242.

REFERENCES

[1] J-J. Van De Beek, O. Edfors, M. Sandell, S.K.Wilson, and P.O. Borjesson, ”On channel estimation in OFDM systems”, Proc. of 45th IEEE Vehicular Technology Conference, vol. 2, pp. 815-819, July 1995.

[2] M.K. Ozdemir and H. Arslan, ”Channel estimation for wireless OFDM systems”, IEEE Communications Surveys & Tutorials, vol. 9, no. 2, pp.18-48, 2007.

[3] Y. Li, N. Seshadri, and S. Ariyavisitakul, ”Channel estimation for OFDM systems with transmitter diversity in mobile wireless channels”, IEEE Journal on Selected Areas in Communications , vol. 14, no. 3, pp. 461- 471, 1999.

[4] L. Yinsheng, et al. ”Channel estimation for OFDM”, IEEE Communications Surveys & Tutorials 16.4, pp. 1891-1908, 2014.

[5] N. Tas¸pınar, and M.C¸ ic¸ek, ”Neural network based receiver for multiuser detection in MC-CDMA systems”, Wireless Personal Commun., vol. 68, no. 2, pp. 463-472, 2013.

[6] S. Coleri, M. Ergen, A. Puri, and A. Bahai, ”Channel estimation techniques based on pilot arrangement in OFDM systems”, IEEE Transactions on Broadcasting, vol. 48, no. 3, pp. 223-229, 2002.

[7] M.T. Hagan, and M.B. Menhaj, ”Training feedforward networks with the Marquardt algorithm”, IEEE transactions on Neural Networks, vol. 5, no. 6, pp. 989-993, 1994.

[8] N. Tas¸pınar and M.N. Seyman, ”Back propagation neural network approach for channel estimation in OFDM system”, IEEE International Conference on Wireless Communications, Networking and Information Security (WCNIS), 2010.

[9] C.H. Chia-Hsin, and Y.P. Cheng, ”Using back propagation neural network for channel estimation and compensation in OFDM systems”, Proc. Of IEEE 7th International Conference on Complex, Intelligent, and Software Intensive Systems (CISIS), pp. 340-345, 2013.

[10] S¸ . S¸ims¸ir and N. Tas¸pınar, ”Channel estimation using neural network in Orthogonal Frequency Division Multiplexing-Interleave Division Multiple Access (OFDM-IDMA”) system”, Proc. of International Telecommunications Symposium (ITS), pp. 1-5, 2014.

[11] M.N. Seyman and N. Tas¸pınar, ”Channel estimation based on adaptive neuro-fuzzy inference system in OFDM”, IEICE Transactions on Communications, vol. 91, no. 7, pp. 2426-2430, 2008.

[12] C.H. Chen, Y.H. Huang, and H.C. Chen, ”Channel estimation in OFDM systems using neural network technology combined with a genetic algorithm”, Soft Computing, vol. 20, no. 10, pp. 4139-4148, 2016.

[13] M.T. Hagan, and M.B. Menhaj, ”Training feedforward networks with the Marquardt algorithm”, IEEE Transactions on Neural Networks, vol. 5, no.6, pp. 989-993, 1994.

[14] K.Guney, and N.Sarikaya, ”A hybrid method based on combining artificial neural network and fuzzy inference system for simultaneous computation of resonant frequencies of rectangular, circular, and triangular microstrip antennas”, IEEE Transactions on Antennas and Propagation, vol. 55, no.3, pp. 659-668, 2007.

[15] R.V. S¸enyuva, G.Karabulut Kurt, and E.Anarım, ”Compressive sensing based joint frequency offset and channel estimation for OFDM”, EURASIP Journal on Wireless Communications and Networking, vol. 2016, no. 1, pp. 1-13, 2016.

[16] J.A. Bullinaria, and A.Y. Khulood, ”Artificial Bee Colony training of neural networks: comparison with back-propagation”, Memetic Computing, vol. 6, no. 3, pp. 171-182, 2014.

[17] B.A.Garro, S. Humberto, and A.B.Roberto, ”Artificial neural network synthesis by means of artificial bee colony (ABC) algorithm”, Proc. Of IEEE Congress on Evolutionary Computation (CEC), pp. 331-338, 2011.

[18] C. Ozturk,and D. Karaboga, , ”Hybrid artificial bee colony algorithm for neural network training”, Proc. of IEEE Congress on Evolutionary Computation (CEC), pp. 84-88, 2011.

[19] D. Karaboga, and B. Basturk, ”A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm”, Journal of Global Optimization, vol. 39, no. 3, pp. 459-471, 2007.

[20] A. Basturk and R. Akay, ”Performance analysis of the coarse-grained parallel model of the artificial bee colony algorithm”, Information Sciences, vol. 253, pp. 34-55, 2013.

★★★