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An Artificial Bee Colony Optimization based Channel Estimation Design for MIMO-OFDM Systems

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ABSTRACT

Background: Orthogonal Frequency Division Multiplexing (OFDM) is a modulation approach used to fight with the selection of frequency of the transmission channels to attain high data rate without any disturbances. OFDM principle is to gain popularity in the wireless transmission area. OFDM is united with antenna at the transmitter and receiver to amplify the variety gain and to improve the system capacity on time-variant and frequency selective channels, ensuing in a multiple-input multiple-output (MIMO) pattern. **Objective:** Least Square (LS) and Minimum Mean Square Error (MMSE) approaches are the most commonly used channel estimation techniques. In LS, the estimation process is simple but the problem is that it has high mean square error. In Low SNR, the MMSE is better than that of LS, but its main problem is its high computational complexity. In order to overcome the above said problems, a novel method called Artificial Bee Colony (ABC) technique is proposed in this research work which combines LS and MMSE and also it is introduced to select the best channel. **Results:** The proposed approach is more efficient and also requires less time to estimate the best channel when compared with other techniques. **Conclusion:** The experimental results show the performance of the proposed channel estimation method over the existing methods.

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INTRODUCTION

In wireless communication system the channel estimation is one of the serious issues. Training-signal-based channel estimation is used in a single carrier system for the channel estimation in (Milewski, 1983; Crozier *et al*, 1991). The optimal training sequences and pilot tones for OFDM channel estimation in (Manton, 2001). Energy allocation for OFDM is well thought-out for frequency-selective block-fading channel estimation by reducing the Cramer-Rao bound in (Dong and Tong, 2002). In (Ma *et al*, 2002) by exploiting lower hurdle on the average capacity the similar problem may occurred.

The optimal training signal is constructed in MIMO OFDM for frequency block fading channel assessment to reduce MSE value is explained in (Barhumi *et al*, 2003). An optimal pilot tone is based on symbol of OFDM for channel estimation and the pilot tones are of phase-shift orthogonal. In Q OFDM symbols, for one symbol of OFDM is spread on Q symbols for channel estimation. Like MIMO OFDM systems, a BPSK pilot symbols is proposed to broadcast two antennas and the more (Tung *et al*, 2001).

MIMO communication systems exploit multiple transmit and receive antennas, increase the data rate without increasing the bandwidth, increase the diversity and enhance the performance against fading channels by means of space-time codes (Berna Ozbek and Reyat Yilmaz, 2005). It has been proved that the capacity of MIMO-OFDM systems grow linearly with the number of antennas, when optimal knowledge of the wireless channel is available at the receiver. The channel condition is not known in practical application. Hence, the channel estimation (channel identification) plays a key role in MIMO-OFDM system (Feng Wan *et al*, 2007).

Channel estimation is one of the important portions in communication systems (Renato R. Lopes and John R. Barry, 2005). An exact channel estimation algorithm should encompass both the time and frequency domain characteristics for the OFDM systems (Naganjaneyulu and Satya Prasad, 2009). The performance of OFDM system can be enhanced by allowing for coherent demodulation when a precise channel estimation algorithm is employed (Ye (Geoffrey) Li *et al*, 1998). In OFDM transmission system, several channel estimation techniques have been proposed under the assumption of a slow fading channel, in which the channel transfer function remain stable within one OFDM data block (Prasanta Kumar Pradhan *et al*, 2011).

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A considerable number of channel estimation techniques have been already proposed for MIMO–OFDM systems. These techniques are broadly classified into three classes: the training based technique, the blind technique, and the semi blind technique, which is a combination of the first two techniques (Yonghong Zeng *et al*, 2006).

Channel estimation is calculated using the least square (LS) and minimum mean square error method (MMSE). In LS, the evaluation procedure is simple but the problem is it has high mean square error. In Low SNR, the MMSE is better than that of least square, but its main problem is its high computational complexity. Due to these drawbacks, here a new method for channel estimation is proposed by combining LS and MMSE method using ABC algorithm.

The existing system for PSO algorithm has certain drawbacks like

- Require high computation time
- The method easily suffers from the partial optimism, which causes the less exact at the regulation of its speed and the direction
- The method cannot work out the problems of scattering and optimization.

Literature Survey:

In (Khachan *et al*, 2006) a linear precoding algorithm is proposed to solve the power allocation problem in MIMO-OFDM system. The author says that the algorithm is to minimize the computational load of OFDM by increasing the connection among precoding and decoding matrices of the subcarriers. This work be able to outlook as a step towards a true multiuser orthogonal frequency division multiple access (OFDMA) system that allows unlike quality of service (QoS) constraints for each data stream of a given user.

Duplicy *et al*. lengthen the presented algorithms and evaluate the complication and performance of three iterative schemes to minimize the system bit error rate (BER) subject to a power constraint (Duplicy *et al*, 2005). Though, they do not think about any methods to save on computational load. Computational and response saving methods were investigated (Choi and Heath, 2004) in the context of a single-user system. The author propose a method to limit the feedback necessities for a MIMO-OFDM system: a part of the precoding matrices is chosen for subcarriers are getting at the receiver, quantized and fed back to the transmitter. The entire set of matrices is then improved by means of interruption at the same time consider the precoding matrices are unitary. The interpolator's parameters are optimized based on a mean square error (MSE).

The author described in (Yuan-Hwui Chung, and See-May Phoong, 2008) consider channel estimation for orthogonal frequency division multiplexing (OFDM) systems when both the transmitter and receiver suffer from in-phase and quadrature-phase (I/Q) imbalance. By exploiting the fact that the block size of an OFDM system is usually larger than the channel order, a new method which can jointly estimate the transmitter and receiver I/Q mismatch and channel response. The estimates of the transmitter and receiver I/Q imbalance parameters are given in a closed form. Using only one arbitrary OFDM block for training, the proposed method can accurately estimate these parameters and a very good performance can be achieved. Simulation results show that the bit error rate (BER) performance of the proposed method is very close to the ideal case where I/Q mismatch and channel response are perfectly known at the receiver.

The author explained that a channel estimation method which has less complexity than the simplified method of (Li *et al*, 1999). By decoupling the effect of different transmit antennas, the sizes of the matrix inverse and FFTs required in the channel estimation for every OFDM data symbol are reduced by half. The significant tap catching approach requires the knowledge of the number of considerable taps. In this paper, describe an alternative approach which adaptively finds this number. Moreover, a simple modification which reduces the channel energy leakage lost in the channel estimation of both and the reduced complexity method is also proposed. This modified approach achieves a substantial performance improvement.

Methodology:

3.1. Channel Estimation in OFDM using ABC Algorithm:

In the proposed method LS and MMSE methods are combined using proposed algorithm.

Here two stages are used to calculate the channel estimation in OFDM. In the first and second stage a fitness function parameters is defined is applied to LS and MMSE channel respectively and in the third stage mutation operation is applied between the LS and MMSE channel. Then from the two channel models that are obtained from three stages using proposed algorithm, the best channel model with minimum error is selected. The process takes place in each stage is explained briefly in below sections. Figure.1 shows the overall process takes place in proposed method.

3.2. OFDM System Model and Channel Estimation:

Let us consider a MIMO-OFDM system model as given in (Karaboga and Basturk, 2007), which consist ofx_t ; $t = 0, \ldots N - 1$, transmitted signals and y_t received signals. The transmitted signals x_t are taken from

multi amplitude signal constellation. The channel impulse response of the system is calculated using the equation given below.

$$g(t) = \sum_{m} \propto_m . \delta(t - \tau_m T_s$$

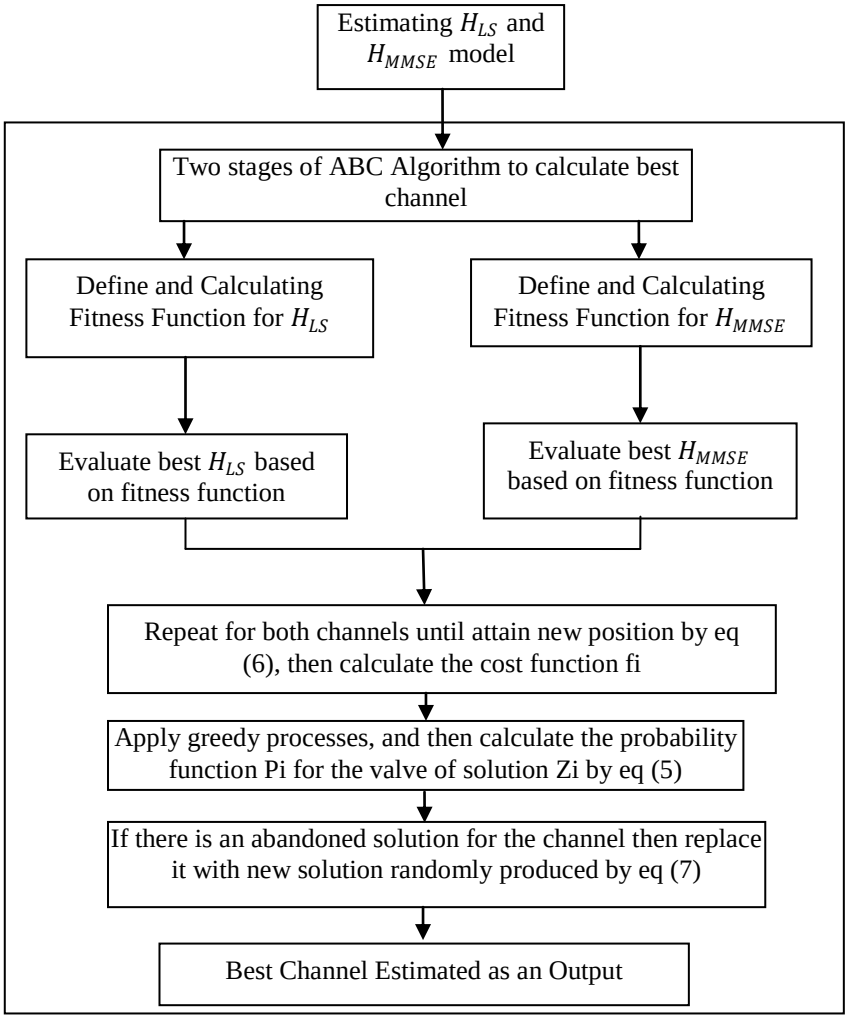

Fig. 1: Proposed method for channel estimation using ABC Algorithm.

Where, T_s is the sampling interval, α_m is the amplitude and τ_m is the delay.
The received signal is given as y = XFg + n
Where, X is a matrix with the elements of x on its diagonal and $x = [x_0, x_1 \ldots . x_{N-1}]^{\tau}$ n is the noise; $n = [n_0, n_1 \ldots . n_{N-1}]^{\tau}$.

$$F = \begin{bmatrix} W_N^{00} & W_N^{0(N-1)} \\ \cdot & \cdot \\ \cdot & \cdot \\ W_N^{(N-1)0} & W_N^{(N-1)(N-1)} \end{bmatrix}$$

$$W_N^{nk} = \frac{1}{\sqrt{N}} . e^{-j2\pi\frac{nk}{N}}$$

$$g = [g_0, g_1 \ldots . g_{N-1}]^{\tau}$$

3.3. MMSE Channel Model:

MMSE channel model is estimated using the equation given below

$$H_{MMSE} = T. Q_{MMSE} . T^H . X^H . Y$$

$$Q_{MMSE} = R_{gg}\left[(T^H . X^H . X. T)^{-1} . \sigma_n^2 + R_{gg}\right]^{-1} . (T^H . X^H . X. T)^{-1}$$

Where, σ_n^2 is the noise variance and R_{gg} R is the upper left A× A corner of auto covariance matrix g

$$A = \frac{T_G}{T_S}$$

Where, T_G is the time length to eliminate inter block interference, and to preserve the orthogonality of the tones, T is the first A columns of the DFT matrix.

3.4. LS Channel Model:

LS channel model is estimated using the equation given below.

$$H_{LS} = T.Q_{LS}.T^H.X^H.Y$$

$$Q_{LS} = (T^H.X^H.X.T)^{-1}$$

Where,

H_{LS} and H_{MMSE} are estimated using the above equations. From this H_{LS} and H_{MMSE} values, the error reduced channel is calculated by combining LS and MMSE channel using Evolutionary Programming.

3.5. Estimating Channel Model by Combining LS and MMSE using ABC Algorithm:

Karaboga *et al*., proposed an Artificial Bee Colony (ABC) algorithm in (Karaboga, 2005). The algorithm is used to find an optimal solution to the problem. The algorithm works based on the honey bee foraging behavior. The performance of the ABC algorithm is studied in (Karaboga and Basturk, 2007). The performance of ABC algorithm on training neural networks is examined by (Karaboga, 2007) and by (Karaboga and Ozturk, 2009), a pattern classification beside extensively used in gradient-based and population based optimization algorithms.

<u>Pseudo-code of the ABC algorithm:</u>

Load training samples
Generate the initial population $z_i, i = 1, \ldots\ldots sN$
Evaluate the fitness (f_i) of the population
Set cycle to 1
Repeat
FOR each employed bee {
    Produce new solution v_i by using (6)
    Calculate the value of f_i
    Apply greedy selection process}
Calculate the probability value p_i for the solution (z_i) by (5)
FOR each Onlooker bee {
    Produce new solution v_i by using (6)
    Calculate the value of f_i
    Apply greedy selection process}
If there is an abandoned solution for scout
Then replace it with a new solution which will be randomly produced by (7)
Memorize the best solution so far
Cycle=cycle+1
Until cycle=MCN

In ABC algorithm, three bees are present employed bees, onlookers and scouts. To choose a food source a bee is waiting to take decision is called as onlooker bee and the bee which is already visited that food source is called as employee bee. A scout bee is used to find out a new source in a random manner. The position of the food source signify the finite solution to the optimization problem and the nectar amount of the food source is match with the fitness value is measured by

$$fit_i = \frac{1}{1+f_i} \quad (4)$$

The cost function is calculated f_i according t is studied in (De Falco *et al*, 2007).

An artificial onlooker bee selects a food source based on the likelihood value linked with that food source, p_i computed by the following expression (5):

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (5)$$

where SN is the number of food sources equal to the number of employed bees, and fit_i is the fitness of the solution given in Eq. (4) which is inversely proportional to the f_i given in Eq. (3) where f_i is the cost function of the clustering problem.

In order to generate a candidate food position from the old one in memory, the ABC exploits the following expression (6):

$$v_{ij} = z_{ij} + \emptyset_{ij}\left(z_{ij} - z_{kj}\right) \quad (6)$$

Where $k \in \{1,2, \ldots\ldots SN\}$ and $j \in \{1,2, \ldots\ldots D\}$ are randomly chosen indexes. Although k is identified randomly, it has to be different from i. ϕ_{ij} denotes a random number between [-1,1]. It controls the production of neighbor food sources around z_{ij} and represents the comparison of two food positions visually by a bee. As

can be seen from (6), as the difference between the parameters of the z_{ij} and z_{kj} decreases, the perturbation on the position z_{ij} gets decreased, too. Therefore, as the search reaches the optimum solution in the search space, the step length is minimized.

The food source of the nectar is vacant by the bees is replaced with a new food source by the scouts. In ABC, this is simulated by generating a position at random and replacing it with the abandoned one. In ABC, if a position cannot be further enhanced via a preset number of cycles, then that food source is consider as abandoned. The value of preset number of cycles is an essential control parameter of the ABC algorithm, which is called ''limit" for abandonment. It is to be assumed that the abandoned source is z_i and$j \in \{1,2,\dots,D\}$, then the scout discovers a new food source to be replaced with z_i . This operation can be defined as in (7).

$$z_i^j = z_{min}^j + rand(0,1)\left(z_{max}^j - z_{min}^j\right) \quad (7)$$

After each candidate source position v_{ij} is generated and then estimated by the artificial bee, its performance is assessed with that of its old source position. If a new food source has equal or better nectar than the old source, it is replaced with the old source in the memory. If not, the old one is retained in the memory. Alternatively, a greedy selection approach is employed as the selection process between the old and the candidate one. The global optimal solution is obtained.

3.6. Calculation of Fitness Function in LS Channel:

The new channel model is generated to calculated the fitness function,

The new channel estimation obtained using LS is

$$\widetilde{\mathrm{H}}_{\mathrm{LS}} = \mathrm{Best}[\mathrm{H}_{\mathrm{LS}}^1, \mathrm{H}_{\mathrm{LS}}^2, \dots\dots \mathrm{H}_{\mathrm{LS}}^{\mathrm{r}}] \quad (8)$$

The best channel estimation is selected with the help of fitness function. The fitness formula used for selecting the best channel estimation is

$$\mathrm{fitness} = \mathrm{fit_i} = \left(\frac{\mathrm{H}-\mathrm{H_{LS}}}{\mathrm{H}}\right)^2 \quad (9)$$

Where, H is the reference channel model.

The probability p_i is to be calculated:

$$p_i = \frac{fit_i}{\sum_{n=1}^{sN} fit_n} \quad (10)$$

3.7. Calculation of Fitness Function in MMSE Channel:

The new channel estimation is obtained using MMSE is

$$\breve{\mathrm{H}}_{\mathrm{MMSE}} = \mathrm{Best}[\{\mathrm{H}_{\mathrm{MMSE}}^1, \mathrm{H}_{\mathrm{MMSE}}^2 \dots\dots \mathrm{H}_{\mathrm{MMSE}}^{\mathrm{r}}\}. \quad (11)$$

The best channel estimation is selected with the help of fitness function. The fitness formula used for selecting the best channel estimation is

$$\mathrm{fitness} = fit_i = \left(\frac{\mathrm{H}-\mathrm{H_{MMSE}}}{\mathrm{H}}\right)^2 \quad (12)$$

Then for a new channel estimation the value of $p_i$is to be calculated:

$$p_i = \frac{fit_i}{\sum_{n=1}^{sN} fit_n} \quad (13)$$

3.8. Selecting Best Channel Estimation:

For best channel estimation, compare the channel estimation obtained from stage 1, 2 & 3 and selects the best among that channel estimation using mutation property. The best channel is selected based on the minimum error value. The minimum error value channel estimation is selected as the best channel estimation.

$$\mathrm{H_{best}} = \mathrm{error}\min\{\widetilde{\mathrm{H}}_{\mathrm{LS}}, \widetilde{\mathrm{H}}_{\mathrm{MMSE}}, \mathrm{H_c}\} \quad (14)$$

$\mathrm{H_{best}}$ gives the best channel estimation obtained from the proposed method. For that, the error value is calculated for $\mathrm{H_{MMSE}}$ separately. Then compare the error values obtained from all the channel estimation and then select the channel estimation with minimum error as the best channel estimation.

RESULT AND DISCUSSIONS

The proposed channel estimation technique was implemented in MATLAB 2010 and its performance is analyzed through various metrics. The metrics taken for analysis is Signal to Noise Ratio (SNR), Mean Square Error (MSE), Bit Error Rate (BER), Selective Error Rate (SER) and Throughput. Results are analyzed by changing the number of iterations, mutation and crossover rate. Three channels are considered for this experimental analysis namely Rayleigh, Racian and AWGN.

4.1. Performance Evaluation:

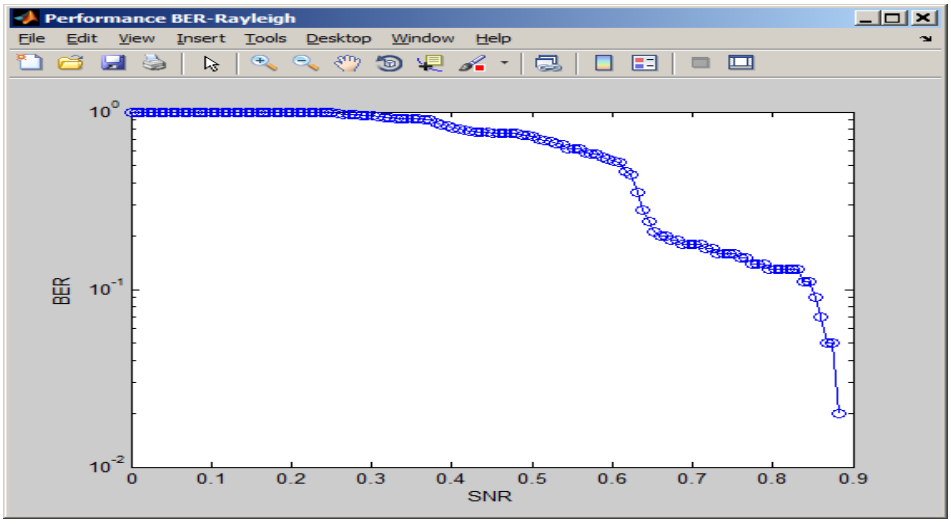

Fig. 2: SNR vs BER graph in Rayleigh Channel.

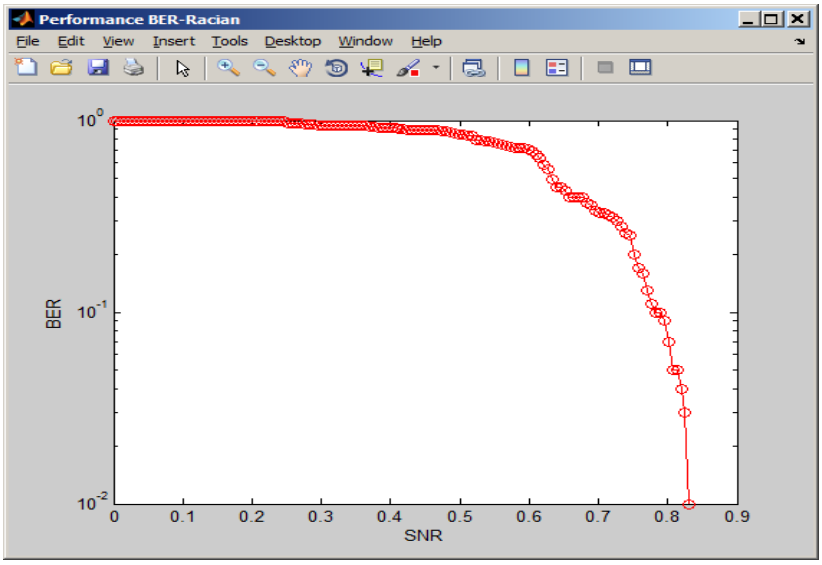

Fig. 3: SNR vs BER graph in Racian Channel.

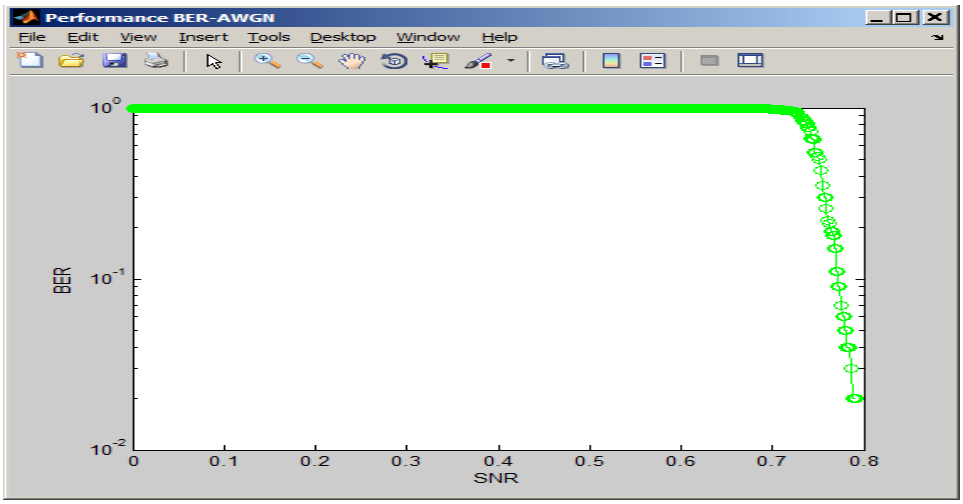

Fig. 4: SNR vs BER graph in AWGN Channel.

Figure 2, 3 and 4 shows the SNR vs BER graph in three different channels taken for consideration. It is observed from the graphs that the proposed approach provides significant result for all the three channels taken for consideration.

4.2. Performance Comparison:

This section shows the comparison of the channel models such as LS, MMSE, LS-MMSE-EP, LS-MMSE-PSO and LS-MMSE-ABC. The comparison is done for various metrics such as SNR, BER, MSE, SER and Throughput.

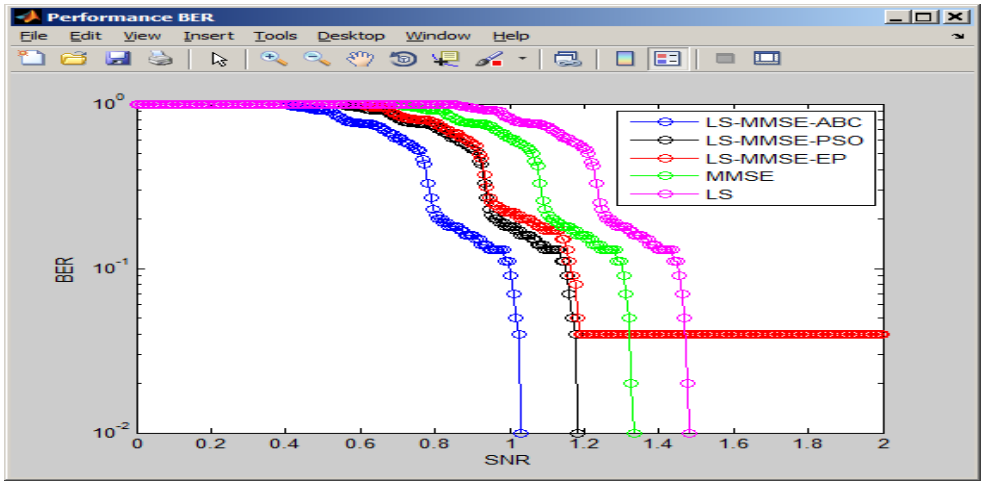

Fig. 5: SNR vs BER Comparison.

Figure 5 shows that the proposed LS-MMSE-ABC approach provides better results when compared with the other approaches taken for consideration such as LS, MMSE, LS-MMSE-EP, LS-MMSE-PSO. The proposed approach produces least BER when compared with other techniques.

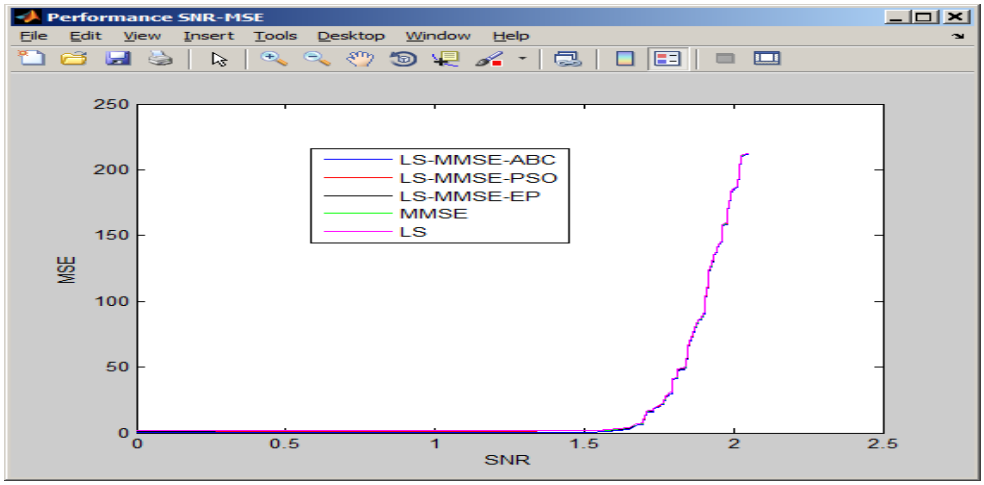

Fig. 6: SNR vs MSE Comparison.

Figure 6 shows the MSE vs SNR comparison of the models such as LS, MMSE, LS-MMSE-EP, LS-MMSE-PSO and LS-MSSE-ABC. It is observed from the figure that the proposed LS-MMSE-ABC approach provides least MSE when compared with the other approaches.

Figure 7 shows the SNR vs SER comparison of the models such as LS, MMSE, LS-MMSE-EP, LS-MMSE-PSO and LS-MSSE-ABC. It is observed from the figure that the proposed LS-MMSE-ABC approach provides least SNR when compared with the other approaches.

Figure 8 shows the Throughput vs SNR comparison of the proposed and existing approaches. The graph clearly shows that the Throughput provided by the proposed LS-MMSE-ABC approach is very high when compared with the other approach.

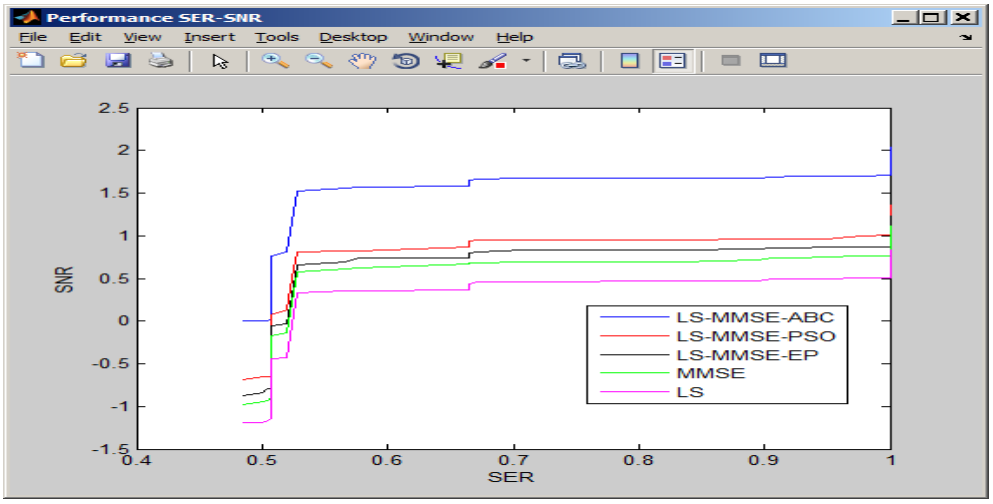

Fig. 7: SNR vs SER Comparison.

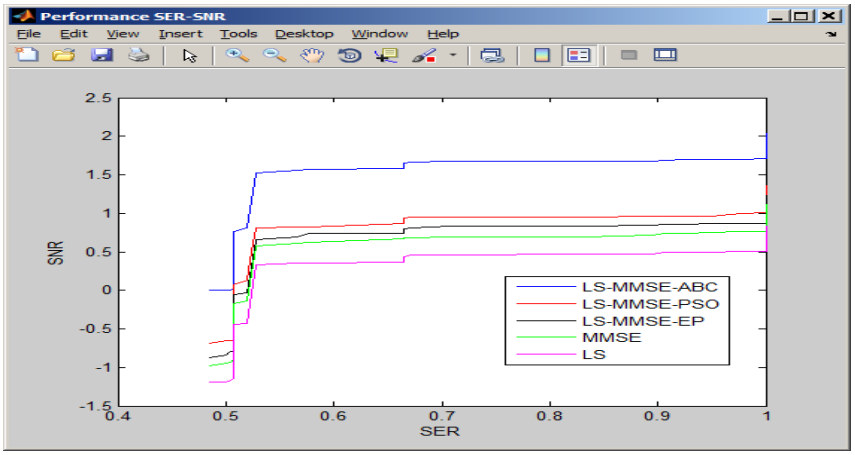

Fig. 8: SNR vs Throughput

Conclusion:

In recent years, MIMO-OFDM systems have gained esteem due to its robustness in multipath environments together with the significant information capacity. This research work focuses on new channel estimation technique for OFDM by combining LS and MMSE using a Meta heuristic optimization approach. Initially, LS and MMSE channel model is calculated an efficient approach called ABC is applied in LS and MMSE channels. The best channel obtained in each stage of ABC is selected. Best channel with minimum error is selected from the two best channels that are obtained from two stages of ABC. The performance of the proposed approach is evaluated based on the metrics like BER, SER, MSE, Throughput and SNR. From the experimental results, it is clear that the proposed method is better than the other existing LS and MMSE methods.

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