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Research Article

An Intelligent Channel Estimation Approach for MIMO-OFDM Systems using Meta-heuristic Optimization Algorithm

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Abstract: This research study mainly focuses to develop an efficient channel estimation approach through swarm intelligence approach with lesser computational complexity. 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. 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 is proposed in this research study which combines LS and MMSE. In this study improved PSO is introduced to select the best channel. Also that this proposed approach is more efficient and also requires less time to estimate the best channel when compared with other techniques. The experimental results show the performance of the proposed channel estimation method over the existing methods.

Keywords: Channel estimation, improved PSO, LS, MMSE, Orthogonal Frequency Division Multiplexing (OFDM)

INTRODUCTION

High date rate wireless systems which having very small symbol periods generally face unacceptable Inter-Symbol Interference (ISI) originated from multipath propagation and their intrinsic delay spread. The OFDM is a multicarrier method used for mitigating ISI to enhance the capacity in the wireless system with spectral efficiency is measured in terms of (bps/Hz) (Suthaharan *et al*., 2002).

An OFDM is a multicarrier modulation technique used widely due to its easy execution and strength besides frequency-selective fading channels, which is obtained by converting the channel into flat fading sub channels. OFDM is homogeneous for various ranges of applications, such as Digital Audio Broadcasting (DAB), digital television broadcasting, Wireless Local Area Networks (WLANs) and Asymmetric Digital Subscriber Lines (ADSLs) (Barhumi *et al*., 2003).

OFDM is a effortless and well-accepted technique to improve the effects of inter symbol interference in frequency selective channels (Bahai *et al*., 2004). OFDM exchange a broadband frequency selective channel to sequences of narrowband channels by transmitting data in parallel over several subcarriers (Karaa *et al*., 2007). Multiple-Input Multiple-Output systems have growing their interest of the wireless academic society and industry since their promise is to increase capacity and performance with suitable BER proportionally with the number of antennas.

OFDM based MIMO transmission is well thought-out to be an forthcoming significant broadband wireless technology. MIMO OFDM systems consist of multiple front-ends and therefore it is very significant to keep the cost, size and power consumption of these front-ends within a suitable limit. The direct-conversion based system design presents a fine implementation alternative as it has a small form factor compared to the conventional architecture (Abidi, 1995).

Combining OFDM with multiple antennas has been shown to provide a significant raise in capacity throughout the use of transmitter and receiver diversity (Bölcskei *et al*., 2002a). By joining OFDM with MIMO, producing so called MIMO-OFDM, greatly shrinks the receiver complexity in wireless multiuser broadband systems (Bölcskei *et al*., 2002b), so building it as a competitive choice for upcoming broadband wireless communication systems.

MIMO communication systems develop multiple transmit and receive antennas, increase the data rate without increasing the bandwidth, diversity and enhance the performance in opposition to fading channels with space-time codes (Ozbek and Yilmaz, 2005). It has been confirmed that the capacity of MIMO-OFDM systems grow linearly with the number of antennas, when optimal knowledge of the wireless channel is available

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at the receiver. The channel condition is not known in practical application. Thus, the channel estimation (channel identification) plays a vital role in MIMO-OFDM system (Feng *et al*., 2007).

Channel estimation is one of the chief part in communication systems was introduced by Lopes and Barry (2005). An accurate channel estimation algorithm be supposed to include both the time and frequency domain features for the OFDM systems (Naganjaneyulu and Prasad, 2009). The performance of OFDM system can be enhanced by permitting for coherent demodulation when a precise channel estimation algorithm is in use (Vidhya and Shankarkumar, 2011; Li *et al*., 1998). In OFDM transmission system, several channel estimation techniques have been proposed under the supposition of a sluggish fading channel, in which the channel transfer function remain stable within one OFDM data block (Pradhan *et al*., 2011).

A substantial amount of channel estimation approaches have been introduced before for MIMO-OFDM systems. These approaches are widely separated into three classes, namely the training based technique, the blind technique and the semi blind technique, which is a combination of the first two techniques (Zeng *et al*., 2006).

Proposed work is an extension of the work carried out in Vidhya and Shankarkumar (2011). 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 improved PSO. The existing method is Evolutionary programming approaches do not provide best optimal results.

The main drawbacks of Evolutionary programming that has been used in the existing system that are often required large amount of computational efforts to solve complex problems. The disadvantages of Evolutionary programming are as shown below.

Drawbacks:

- To encode phase-space position is difficult
- In presence of lots of noise, convergence is difficult
- Models with many parameters are computationally expensive
- Sometimes not particularly good models are better than the rest of the population and cause premature convergence to local minima
- The fitness of all the models may be similar, so convergence is slow

So to overcome the drawbacks of the evolutionary programming discussed above, improved PSO technique is proposed in this study to select the best channel in MIMO-OFDM as an extension carried out in Vidhya and Shankarkumar (2011).

LITERATURE REVIEW

The CSI is very important for data detection and also for channel equalization. It can be obtained in different ways that is training symbols that are a priori known at the receiver, while the other is blind, relies only on the recognized symbols and it obtain CSI by exploiting statistical information and/or transmitted symbol properties like finite alphabet, constant modulus (Vidhya and Shankarkumar, 2011; Zhou and Giannakis, 2001; Bölcskei *et al*., 2002a). Hence, it is restricted to gradually time-varying channels and entails high complexity. Owing to this reason it limit attention to training-based channel estimation is done.

Classic procedures for finding the channel based on training use of multiple OFDM symbols that consist fully of pilot symbols. For Single-Input Single-Output (SISO) systems, this technique can be found in Deneire *et al*. (2001), Edfords *et al*. (1998) and Van De Beek *et al*. (1995), while for Multiple-Input Multiple-Output (MIMO) systems, it can be seen in Jeon *et al*. (2000). In these systems, the CSI is expected prior to any transmission of data. When the CSI varies drastically, a retraining series is transmitted. With retraining, these systems practice an enlarged BER is obtained due to their outdated channel approximation. Wiener filtering (in time and/or frequency) depends on a well-known channel correlation function can be used to develop the channel estimate (Li *et al*., 1999).

Negi and Cioffi (1998), presented pilot tones to get CSI, where an optimal placement of the pilot tones with regard to the Mean Square Error (MSE) of the Least Squares (LS) channel estimate is proposed for SISO OFDM systems. With lengthening this design to MIMO OFDM systems is not simple, because not only the placement of the pilot tones also the pilot sequences themselves should be optimized to obtain the minimal MSE of the LS channel estimate. Make a note that optimal training for SISO OFDM systems, in which the MSE of the LS channel estimate and MSE at the output of a zero-forcing receiver is based on the LS channel estimation is studied in Ohno and Giannakis (2001a, b).

Chung and Phoong (2008) introduces a channel estimation for Orthogonal Frequency Division Multiplexing systems when together the transmitter and receiver experiences from In-phase and Quadrature-phase (I/Q) imbalance. By developing the fact that the block size of an OFDM system is generally larger than the order of the channel, a novel method which can mutually estimate the transmitter and receiver I/Q mismatch and channel response. The estimates of the transmitter and receiver I/Q imbalance parameters are specified in a closed form. Experimental results show that the Bit Error Rate (BER) performance of the proposed method is very nearer to the ideal case where the I/Q mismatch and channel response are perfectly known at the receiver.

METHODOLOGY

Channel estimation in OFDM using improved PSO algorithm: In the proposed method LS and MMSE methods are combined using proposed algorithm is shown in Fig. 1.

OFDM system model and channel estimation: Let us consider a MIMO-OFDM system design as given in Ohno and Giannakis (2001b), which consist of x_t; t = 0, ...N-1 transmitted signals and y_t received signals. The x_t is a transmitted signals which are taken from multi amplitude signal collection. The channel impulse response of the system is calculated by means of the equation given below:

$$g(t) = \sum_m \propto_m . \delta(t - \tau_m T_s)$$

where,
T_s = The sampling interval
α_m = The amplitude
τ_m = 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:

$$n = [n_0, n_1 \ldots . n_{N-1}]^{\tau}$$

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

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

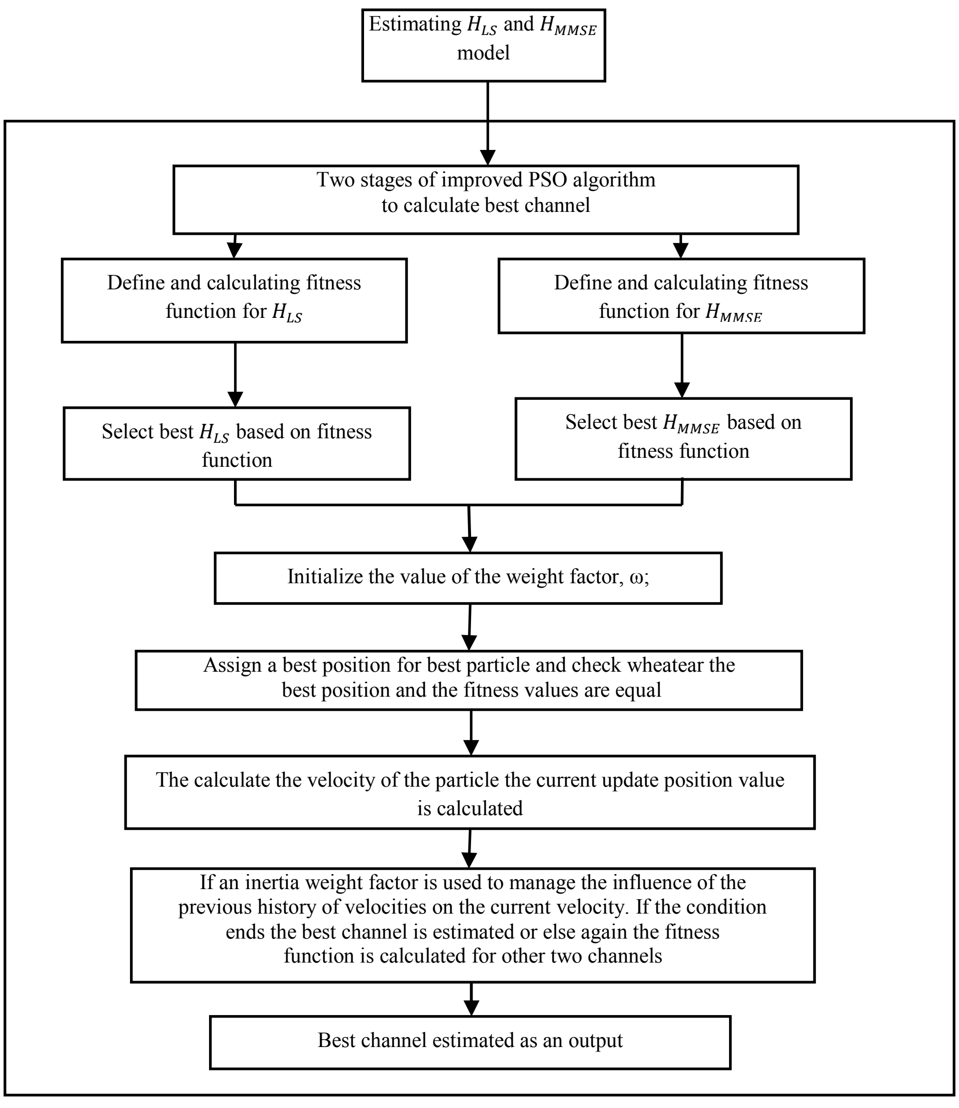

Fig. 1: Proposed method for channel estimation using improved PSO algorithm

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

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 = The noise variance
R_{gg} = R is the upper left A×A corner of auto covariance matrix g:

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

where,
T_G = The time length to eliminate inter block interference and to preserve the orthogonality of the tones
T = The first A columns of the DFT matrix

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.

Estimating channel model by combining LS and MMSE using improved PSO algorithm: PSO proposed by Kennedy and Eberhart (1995). PSO algorithm is annoyed by the social behavior of a group of migrating birds trying to reach on indefinite destination. Each solution is termed as 'bird' in the flock and is known to as a 'particle'. A particle is corresponding to a chromosome in Genetic Algorithms (GAs) (Al-Tabtabai and Alex, 1999). Not like GAs, the evolutionary procedure in the PSO does not create new birds from parent ones. Instead the birds in the population only build up their social behavior and as a result their movement towards a destination (Shi and Eberhart, 1998).

Improved PSO: Particle swarm optimization algorithm, is adapted for optimizing tricky numerical functions based on metaphor of individual social interaction, is capable of impersonating the ability of human societies to process knowledge (Naganjaneyulu and Prasad, 2009). The major part of the methodologies is artificial life and evolutionary calculation. Key idea is that the potential solutions are run all the way through hyperspace and are accelerated towards superior on more optimum solutions. Its pattern can be employed in easy form of computer codes and is computationally cheap in terms of both memory requirements and speed. It lies wherever in between evolutionary programming and the genetic algorithms. In evolutionary computation paradigms, the idea of fitness is functioning and candidate solutions to the problems are named as particles or individuals, each of which regulate its flying owing to flying experiences of both and its companion. Vectors are taken as arrangement of particles as additional optimization problems are appropriate for such variable presentations. Certainly, the basic principles of swarm intelligence are adaptableness, diverse response, excellence and constancy. If it is adaptive, to alter the best group value the allocation of responses among the individual and group values guarantee a response. The higher dimensional space computation of the PSO are processed over a sequences of time steps. The population react to the quality factors of the earlier best individual values and group values. The principle of stability is a surface to the population varies its state if and only if the best group value changes. Li *et al*. (1998), this optimization technique can be used to resolve several types of problems as GA. It is robust in solving difficulty of characteristic non-linearing, non-differentiability and high dimensionality. PSO is the search based method used to improve the speed of convergence and identify the global optimum value of fitness function.

PSO initiates with a population of random solutions ''particles'' in a D-dimension space. The ith particle is denoted by Xi = (xi1, xi2,..., xiD). Each particle remains the track of its coordinates in hyperspace, which are liked with the fittest solution. The value of the fitness for particle i (pbest) is also accumulated as Pi = (pi1, pi2,..., piD). The global description of the PSO keeps track of the overall best value (gbest) and its position, attained hence distant by some particle in the population. PSO comprises at each step, varying the velocity of each particle in the direction of its pbest and gbest according to Eq. (6). The velocity of particle i is correspond to as Vi = (vi1, vi2... viD). Acceleration is weighted by a random term, by means of individual random numbers being produced for acceleration toward pbest and gbest. The position of the ith particle is then updated based on Eq. (6) is discussed by (Naganjaneyulu and Prasad, 2009; Li *et al*., 1998):

$$V_{id}(t+1) = w \times V_{id}(t) + c_1 r_1 \left(P_{id} - x_{id}(t)\right) + c_2 r_2 (P_{gd} - x_{id}(t))$$

$$x_{id}(t+1) = x_{id}(t) + cv_{id}(t+1)$$

where, P_{id} and P_{gd} are pbest and gbest. Several changes have been presented to enhance the PSO algorithm speed and convergence toward the global minimum. A local-oriented paradigm (lbest) with different neighborhoods is one of the changes that may done over

Table 1: Rate of parameters for IPSO algorithm

Parameter	Rate
Problem dimension	11
Number of particles	100
Number of iteration	100
Mutation probability P_m	0.1
Inertia weight factor	$\omega_{min} = 0.4, \omega_{max} = 0.9$
r_1, r_2	Selected randomly in (0, 1)
C_1	1
C_2	1.5
C	0.9

Algorithm of the improved PSO algorithm
Pseudo code for IPSO
Begin;
Generate random population of N solutions (particles);
For each individual $i \in N$: calculate fitness (i);
Initialize the value of the weight factor, ω;
$\omega = w_{end} + (w_{start} - w_{end}) * \beta$
For each particle;
Set $pBest$ as the best position of particle i;
If fitness (i) is better than $pBest$;
$pBest(i) = fitness\ (i)$;
End;
Set $gBest$ as the best fitness of all particles;
For each particle;
Calculate particle velocity according to Eq. (3);
Update particle position according to Eq. (4);
End;
Update the value of the weight factor, ω;
Check if termination = true;
End:

Fig. 2: Algorithm of the IPSO algorithm

here. Finally the gbest version processes best in terms of median number of iterations to converge. On the other hand, Pbest version with neighborhoods of two is most opposed to local minima. The results of previous experiments about PSO presents that ω was not measured at an earlier stage of PSO algorithm. However, ω affects the iteration number to find an optimal solution. If the value of ω is low, the convergence will be quick, but the solution will drop into the local minimum. If the value will raises, the iteration number will also increase and so the convergence will be slow. In general, for starting the PSO algorithm, value of inertia weight is varied in training process. It was revealed that PSO algorithm is further enhanced by means of time decreasing inertia weight, which leads to a decrease in the number of iterations (Pradhan *et al*., 2011).

In (9), term of $C_1 r_1 (P_{id} - X_{id}(t))$ represents the individual movement and term of $C_2 r_2 \left(P_{gd} - X_{id}(t)\right)$ represents the social behavior in finding the global best solution. In this study, in order to obtain exact solution and fast convergence of algorithm, parameters are used in IPSO algorithms have been initialized according to Table 1.

According to (6), the velocity update of the particle consists of three parts: The first term is its own current velocity of particles; the second term is cognitive part which represents the particle's own experiences; the third term is social part which represents the social interaction between the particles (Zeng *et al*., 2006; Vidhya and Shankarkumar, 2011; Zhou and Giannakis, 2001). Based on (6), it is recognized that best position of particles take place proportional to pbesti. When a particle's current position coincides with the global best position (gbesti), the particle will merely leave this point if the inertia weight and its current velocity are different from zero. If the particles current velocities in swarm are nearer to zero, then these particles will not move once they hold up with the global best particle, which means that all the particles will converge to the best position (gbest) revealed so far by the swarm (Bölcskei *et al*., 2002a).

At this moment if this positions fitness is not the issuse of expected global optimal, then the premature convergence phenomenon come into view. To overcome this disadvantage and improve optimization combination, an Improved Particle Swarm Optimization (IPSO), by presenting the mutation operator frequently used in genetic algorithm (Deneire *et al*., 2001) is proposed in this learning. The algorithm of IPSO is shown in the Fig. 2.

This process can make some particles jump out local optima and search in other area of the solution space. In this proposed method, the Mutation Probability (PM) is varied dynamically based on the diversity presented in the swarm. The objective with mutation probability is to prevent the preamture convergence of PSO to local minima value. It must be well-known that the PM is considered as 0.1 in this study.

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:

$$\widetilde{H}_{LS} = Best[H_{LS}^1, H_{LS}^2, \ldots \ldots H_{LS}^r]$$

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

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

where, H is the reference channel model.

Calculation of fitness function in MMSE channel: The new channel estimation is obtained using MMSE is:

$$\breve{H}_{MMSE} = Best[\{H_{MMSE}^1, H_{MMSE}^2 \ldots \ldots . H_{MMSE}^r\}$$

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

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

Selecting best channel estimation: For best channel estimation, compare the channel estimation obtained from stage 1, 2 and 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:

$$H_{best} = \text{error min}\ \{\tilde{H}_{LS}, \tilde{H}_{MMSE}, H_c\}$$

H_{best} gives the best channel estimation obtained from our method. For that, the error value is calculated for 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.

RESULTS AND DISCUSSION

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.

Performance evaluation:
SNR vs. BER-Rayleigh channel: Figure 3 to 5 shows the BER vs. SNR 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.

Figure 6 to 8 shows the Throughput vs. SNR graph and MSE vs. SNR graph in AWGN channel.

Performance comparison: This section shows the comparison of the channel models such as LS, MMSE,

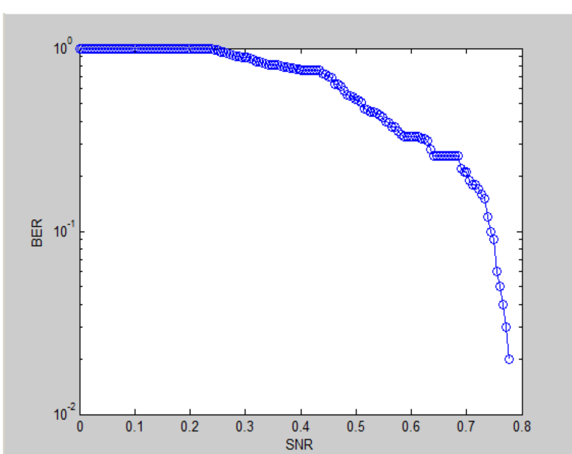

Fig. 3: BER vs. SNR graph in Rayleigh channel

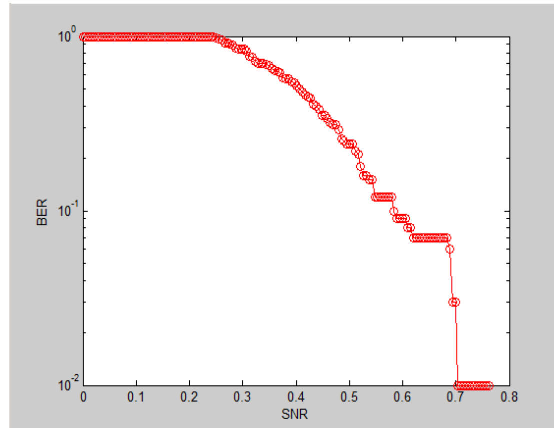

Fig. 4: BER vs. SNR graph in Racian channel

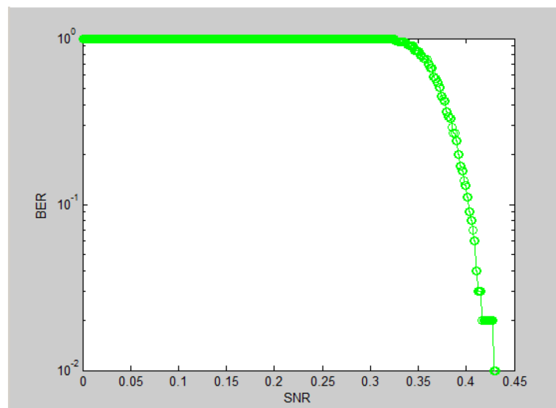

Fig. 5: BER vs. SNR graph in AWGN channel

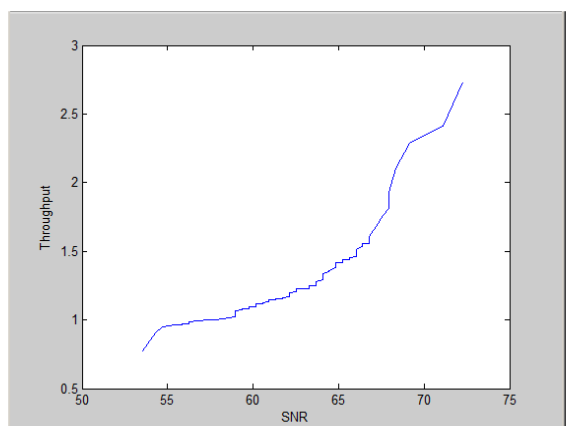

Fig. 6: Throughput vs. SNR graph in AWGN channel

LS-MMSE-EP and LS-MMSE-PSO. The comparison is done for various metrics such as SNR, BER, MSE, SER and Throughput.

Figure 9 shows that the proposed LS-MMSE-PSO approach provides better results when compared with the other approaches taken for consideration. The proposed approach produces least BER when compared with other techniques.

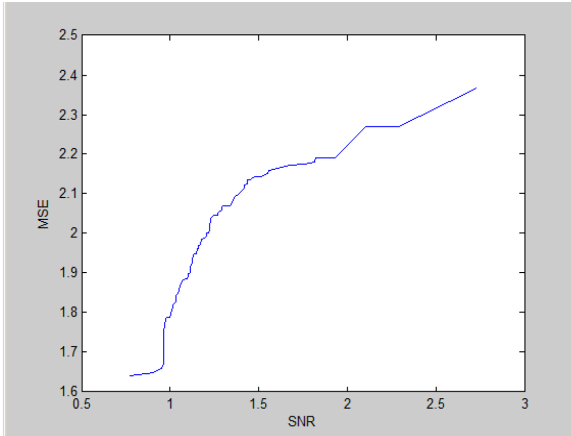

Fig. 7: MSE vs. SNR graph in AWGN channel

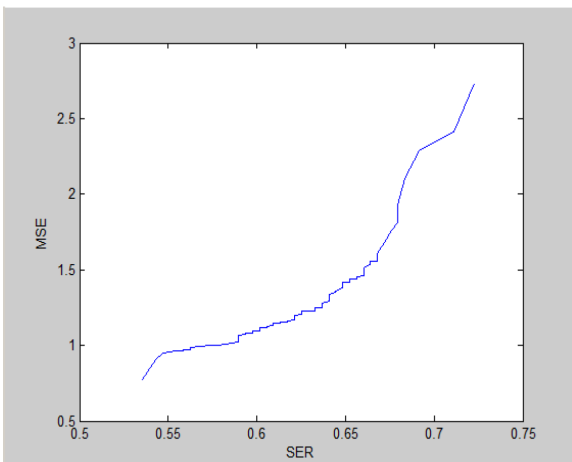

Fig. 8: MSE vs. SER graph in AWGN channel

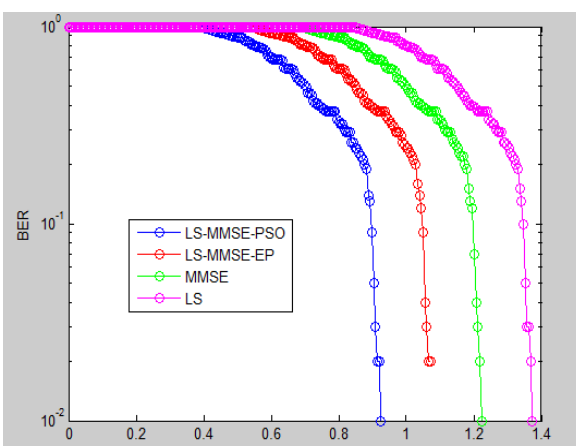

Fig. 9: SNR vs. BER comparison

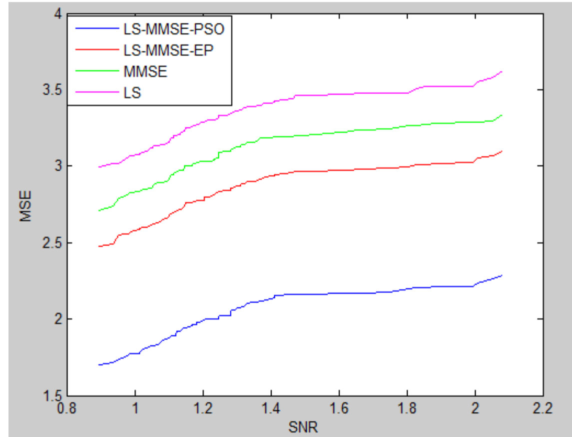

Fig. 10: MSE vs. SNR comparison

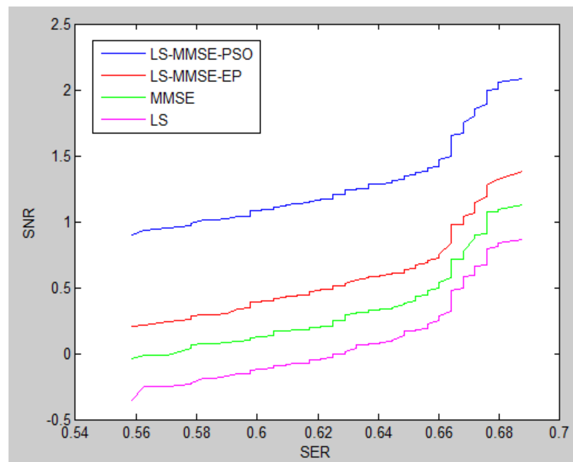

Fig. 11: SNR vs. SER comparison

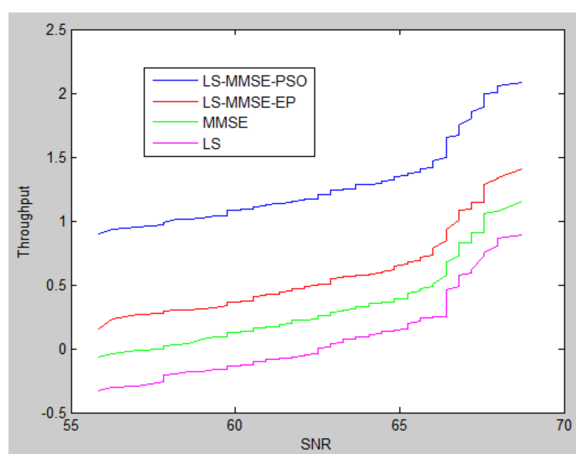

Fig. 12: Throughput vs. SNR

Figure 10 shows the MSE vs. SNR comparison of the models such as LS, MMSE, LS-MMSE-EP and LS-MMSE-PSO. It is observed from the figure that the proposed LS-MMSE-PSO approach provides least MSE when compared with the other approaches.

Figure 11 shows the SNR vs. SER comparison of the models such as LS, MMSE, LS-MMSE-EP and LS-MMSE-PSO. It is observed from the figure that the proposed LS-MMSE-PSO approach provides least SNR when compared with the other approaches.

Figure 12 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-PSO approach is very high when compared with the other approach.

CONCLUSION

Even In recent years, MIMO-OFDM systems have gained popularity due to its robustness in multipath environments together with the significant information capacity. This research study 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 Meta heuristic approach called Improved PSO is applied in LS and MMSE channels. The best channel obtained in each stage of Improved PSO is selected. Best channel with minimum error is selected from the two best channels that are obtained from two stages of improved PSO. The performance of the proposed approach is evaluated based on the metrics like BER, SER, MSE, Throughput and SNR. From the performance results, it is clear that this method is better than the other existing LS and MMSE methods. The proposed method is analyzed by changing the number of position and velocity.

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