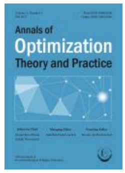
Annals of Optimization Theory and Practice

Volume 3, Number 3, 1-13
December 2020

DOI: 10.22121/aotp.2020.242757.1037



A smart channel estimation approach for LTE systems using PSO algorithm

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(Received: August 6, 2020 / Accepted: December 4, 2020)

Abstract This study focuses on developing an effective channel estimation approach using swarm Intelligence. The Orthogonal Frequency Division Multiplexing (OFDM) is a modulation technique used to counter transmission channel frequency selection to reach high data rate without disruption. The theory of OFDM is to gain prominence in the field of wireless communication. OFDM is combined with the transmitter and receiver antenna to amplify the variety gain and improve system capacity on selective time and frequency channels, resulting in a Multiple Input Multiple Output (MIMO) pattern. The most commonly used channel estimation techniques are the Least Square (LS) approaches and Minimum Mean Square Error (MMSE) approaches. In LS, the estimation process is simple but the problem is that the square error has a high mean. The MMSE is better in Low SNR than in LS, but its main problem is its high computational complexity. A unique method is proposed in this research study that combines LS and MMSE to overcome the aforementioned problems. Upgraded PSO is introduced in this study to select the best channel. This proposed approach is also more efficient and requires less time compared to other techniques to estimate the best channel.

Keywords Channel estimation; Improved PSO; LS, MMSE; OFDM

1. Introduction

High data wireless networks that typically face inacceptable inter symbol interference (ISI) with very short symbol cycles emerged from multipath propagation and spread of their inherent latency. The OFDM is a multi carrier method used to mitigate ISI to increase spectral efficiency capacity in the wireless system is measured in terms of (bps / Hz).

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An OFDM is a multicarrier modulation strategy that is commonly used owing to its fast implementation and power in addition to frequency selective fading channels, achieved by transforming the channel into flat fading subchannels. OFDM is homogeneous for a multitude of uses, including Digital Audio Transmission (DAB), Digital TV transmission, Wireless Local Area Networks (WLANs), and Asymmetric Cable Subscriber Lines (ADSLs)

OFDM is an effortless, well accepted strategy for enhancing the impact of inter symbol interference on narrow frequency channels (Bahai *et al.*, 2004). OFDM exchanges a selective broadband frequency channel to narrowband channel sequences by simultaneously transmitting data across several subcarriers (Karaa et al.,2007). Multiple Input Multiple Output systems have increased their interest in the wireless academic society and industry as they are promised. Increase efficiency and output in relation to the amount of antennas, with sufficient BER.

OFDM based MIMO transmission is well thought out as an important wireless broadband technology to come. MIMO OFDM systems consist of several front ends and thus, maintaining the expense, size and power usage of such front ends within an acceptable limit is very critical. The system design based on direct conversion presents a fine alternative implementation as it has a small form factor compared to conventional architecture (Abidi, 1995). It has been seen that the combination of OFDM with multiple antennas provides a substantial improvement in efficiency during transmitter and receiver diversity use (Bölcskei *et al*, 2002). By joining OFDM with MIMO, producing the so called MIMO OFDM, the complexity of the receiver in wireless broadband multiuser systems is greatly reduced (Bölcskei *et al.*, 2002b), thus building it as a competitive choice for upcoming wireless broadband communication systems MIMO communication systems develop multiple transmission and receiving antennas, increase data rates without increasing bandwidth, diversity and improve performance as opposed to fading space time channels (Ozbek and Yilmaz, 2005). It has been verified that the efficiency of MIMO OFDM systems increases linearly with the number of antennas, when optimum wireless channel information is accessible

At receiver. In functional use the state of the channel is unclear. Channel estimation (channel identification) thus plays a vital role in the system of MIMO OFDM (Feng *et al.*, 2007).

Path estimation was developed by Lopes and Barry (2005) as one of the main sections of contact networks.

For OFDM systems, an accurate channel estimation algorithm should include both the time and frequency domain features (Naganjaneyulu and Prasad, 2009). OFDM device efficiency can be improved by allowing for coherent demodulation by using a specific channel estimation algorithm (Vidhya and Shankar kumar, 2011; Li *et al.* 1998). In the OFDM transmission network, under the assumption of a slow fading signal, many channel estimation techniques were proposed in which the channel transfer feature stays stable within one OFDM data block (Pradhan *et al.*2011).

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For MIMO OFDM systems a considerable amount of channel estimation techniques were added beforehand. These approaches are widely divided 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).

Estimation of channels is determined using the Least Square (LS) and Minimum Mean Square Error (MMSE) form. The assessment method in LS is clear but the issue is that it has high mean square error. The MMSE is greater than the least square in Low SNR but its biggest concern is its strong computational difficulty. Because of these drawbacks, a new channel estimation method is proposed here by combining LS and MMSE method with improved PSO method. The existing method is Evolutionary approaches to programming do not provide the best optimal results.

The main disadvantages of Evolutionary programming used in the existing system that often require large amounts of computational efforts to solve complex issues. Evolutionary programming has its disadvantages 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

2. LITERATURE REVIEW

The CSI is very critical for data identification and for the equalization of channels. By using statistical knowledge and/or transmitted symbol properties such as finite alphabet, constant modulus (Vidhya and Shankarkumar, 2011; Zhou and Giannakis, 2001; Bölcskei *et al*., 2002a), it can be obtained in different ways which are training symbols that are a priori identified to the recipient, while the other is blind, relies only on recognised symbols and obtains CSI. Therefore, it is confined to networks that slowly differ in time and involves high difficulty. For this cause, the emphasis on training based channel estimation is reduced.

Classic channel finding procedures focused on training use of multiple OFDM symbols and consists entirely of pilot symbols. This technique can be found in Deneire *et al.* (2001), Edfords *et al.* (1998) and Van De Beek *et al.* (1995) for single input single output (SISO) systems, whereas it can be seen in Jeon *et al.* (2000) for multiple input multiple output (MIMO) systems. The CSI is expected to be in these systems prior to any data transmission. A retraining series shall be transmitted when the CSI varies drastically. Thanks to their obsolete channel approximation, these systems exercise an expanded BER is obtained with retraining. Wiener filtering (in time and/or frequency) can be used to establish the channel estimation, based on a well known channel correlation function (Li *et al*., 1999). Negi and Cioffi (1998), provided pilot tones to get CSI, where an ideal orientation of the pilot tones with respect to the Least Squares (LS) channel approximation of Mean Square Error (MSE) is suggested for SISO OFDM systems. By engthening this design to MIMO OFDM systems it is not easy, because it is necessary to optimize not only the placement of the pilot tones but also the pilot sequences themselves to obtain the minimal MSE of the estimate of the LS channel. Note that optimum preparation for SISO OFDM systems is examined in Ohno and Giannakis (2001a, b) in which the LS channel estimate and MSE at the performance of a zero forcing receiver is centered on the LS channel estimate.

Chung and Phoong (2008) present a channel calculation for multiplexing schemes in the Orthogonal Frequency Division where the in phase and quadrature (I / Q) mismatch observations of the transmitter and receiver are mixed. By exploiting the assumption that the block size of an OFDM network is typically greater than the channel value, a novel approach that can jointly approximate mismatch and channel reaction between the transmitter and receiverI / Q. The estimates of the imbalance parameters for transmitter and receiver I / Q are specified in a closed form. Experimental tests indicate that the efficiency of the proposed system by Bit Error Rate (BER) is far closer to the ideal case where the I / Q mismatch and channel response are perfectly known at the receiver.

3. 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 $x_t; t = 0 \dots n1$ transmitted signals and y_t received signals. The x_t is a transmitted signals which are taken from multi amplitude signal collection.

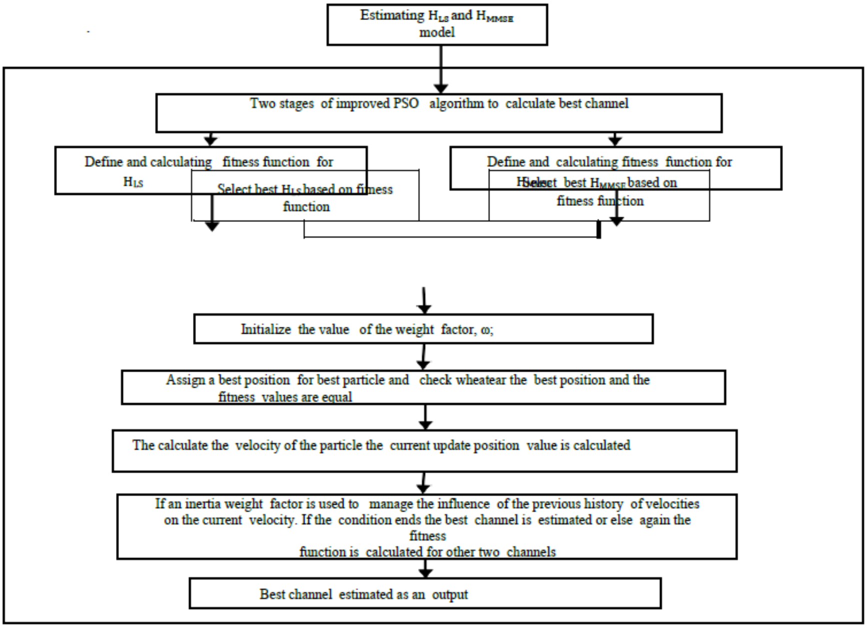

Fig 1. Proposed method for channel estimation using improved PSO algorithm

The impulse channel response is given by

$$g(t) = \sum_{m} \alpha_m \delta(t - \tau m T s)$$

T= Sampling Interval

α_m= The amplitude

τm = The delay

Received signal will be

y = XFg + n

where, X is a matrix with the elements of x on its diagonal and $x = [x_0, x_1, \dots, x_{N-1}]^c$ n is the noise

MMSE channel model: This model is given by:

$$\mathrm{HMMSE} = \mathrm{T.QMMSE}.T^H.X^H.Y$$

LS model:

$$\mathrm{HLS} = \mathrm{T.QLS}.T^H.X^H$$

Y QLS $= (T^H.X^H.X.T)^{-1}$

where, H_{LS} and H_{MMSE} are calculated 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:

Kennedy and Eberhart (1995) suggested a PSO. The PSO algorithm is disturbed by a community of migrant birds' social activity attempting to find an unknown goal. Any solution in the flock is called 'cat' and is classified as a 'particle.' In Genetic Algorithms (GAs) a particle corresponds to a chromosome (Al Tabtabai and Alex,11999). Not like Water, the PSO's evolutionary technique struggles to produce new birds from ancestors. Instead, the birds in the population are only building up their social behavior and thus moving to a destination (Shi and Eberhart, 1998).

Improved PSO: Particle swarm optimization algorithm, modified to automate complicated computational functions focused on an individual social experience model, is capable of impersonating human societies' capacity to process information (Naganjaneyulu and Prasad, 2009). Artificial existence and biological estimation are the main component of the methodologies. Key idea is that the Potential solutions pass through hyperspace and on more suitable solutions are accelerated to the superior. Its design can be used in simple type of computer codes and in terms of both memory requirements and speed is computationally inexpensive. It lies wherever in between the genetic algorithms and the evolutionary programming. The concept of health functions in evolutionary computation paradigms and nominee approaches to the problems are called as Particles or individuals, each of which regulates its flying due to both and its companion's flying experiences. Vectors are taken as particle arrangement as Additional problems with optimization are appropriate for these presentations to aspect. The fundamental concepts of swarm intelligence are of course adaptability, varied reaction, competence and constancy. If it is adaptive, the distribution of responses between the person and community values ensures a answer to change the better group interest.

The PSO's higher dimensional space calculation is performed over a series of phases in time. The population reacts to the factors of quality of the earlier best individual values and group values. Stability principle is a population surface that varies its status if and only if the best value of the group changes. Li *et al.* (1998) will use this strategy of optimization to solve different forms of problems like GA. It is resilient in overcoming the complexity of the nonlinear characteristic, non differentiability and high dimensionality.

PSO is the search based method used to improve convergence speed and the global optimum fitness function value identified Within a D dimension space.

Within a D dimension space PSO initiates "particles" with a community of random solutions.$x_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ denotes the ith atom. In hyperspace, each particle

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remains the track of its co ordinates, which are liked by the most fit solution. Partikel I (pbest) fitness value is also accrued as $P_{i1} = (p_{i1}, p_{i2}, \dots, p_{iD})$. The PSO's global definition keeps track of the overall best value (gbest) and its location, thus any particle in the population has reached distant At each step, PSO comprises the velocity of each particle varying in the direction of its p_{best} and g_{best}. Particle I velocity compares to that of $V_{i1} = (v_{i1}, v_{i2}, \dots, v_{iD})$. Acceleration is weighted by a random term, produced for acceleration towards pbest and gbest by means of individual random numbers. The ith particle 's location is then modified dealt with (Naganjaneyulu and Prasad, 2009; Li *et al*)

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

$$x_{id}(t+1) = x_{id}(t) + c v_{id}(t+1)$$

Where, pid and pgd are best. Several improvements were proposed to increase the speed and convergence of the PSO algorithm toward the global minimum. One of the improvements that should be created is a local oriented model (best) for various neighborhoods. Tap here. The gbest implementation eventually processes to converge best in terms of mean amount of iterations. On the other hand, Pbest version with two neighborhoods is most against local minima. The findings of previous studies on PSO indicate that at an earlier point of the PSO algorithm, uncertainty was not calculated. However, if you want to find an optimal solution, it affects the iteration number. If the valueof ubiquity is low, convergencewill be fast, but the solution will drop to the minimum local. If the value rises, the amount of iteration will also rise, rendering the convergence sluggish. In general, for starting the PSO algorithm, value of inertia weight is varied in training process. It is accepted that the best element place is proportional to pbesti. When the actual location of a particle corresponds with the optimal global position (gbesti), the particle can actually abandon this stage because the weight of the momentum and its current velocity vary from zero. If the current particle velocities in swarm are nearer to zero, then these particles will not move once they hold on to the best global particle, meaning all the particles will converge to the best position (gbest) revealed by swarm so far (Bölcskei *et al.* 2002a). At this point, if this positioning capacity is not the emitter of the predicted optimum world, then the concept of premature convergence falls into focus. In this study, an Advanced Particle Swarm Optimization (IPSO) is suggested to address this drawback and improve the optimization combination by introducing the mutation operator commonly used in genetic algorithm (Deneire *et al.* ,2001). The IPSO algorithm is expressed in the Fig. 2.

```
Algorithm of the improved PSO algorithm
Pseudo code for IPSO
Begin;
Generate random population of N solutions
(particles);
For each individual i ∈ N: calculate fitness (i);
Initialize the value of the weight factor, ω;
ω = w_end + (w_start − w_end) * β
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. IPSO Algorithm

This process can cause some particles to jump out local optima and search for space in another area of the solution. The mutation likelihood (PM) in this proposed approach is dynamically varied depending on the complexity that is provided in the swarm.

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:

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

The best channel estimation is selected with the help of fitness function.

Calculation of fitness function in MMSE channel:

$$\boldsymbol{H_{MMSE}} = Best[H^1, H^2, \ldots, H^r]$$

The new channel estimation is obtained using MMSE is

Selecting best channel estimation: Evaluate the channel estimate obtained from stage 1 , 2 and 3 for best channel estimation and pick the best estimate from that channel using mutation properties. The optimal channel is selected based on the lowest risk for mistakes. The lowest estimation of error frequency channel is chosen as the strongest estimation of channel

$$H_{Best} = \text{error min}\{\widetilde{H}_{LS}, \boldsymbol{H_{MMSE}}, \boldsymbol{H_C}\}$$

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H_{Best} gives the best estimation of channels obtained from our method. For this the error factor is determined separately for HMMSE. Then compare the error values obtained from all estimation of the channel, and then select the estimation of the channel with minimum error as the best estimation of the channel.

RESULTS AND DISCUSSION

In MATLAB 2010, the initial channel estimation method was applied, and its efficiency is evaluated using various metrics. Signal to Noise Ratio (SNR), Mean Square Error (MSE), Bit Error Rate (BER), Selective Error Rate (SER), and Throughput are the parameters used for study. The results will be analyzed by changing the number of iterations, mutations and the rate of crossover. For this experimental study three channels are listed, namely Rayleigh, Racian, and AWGN.

Performance evaluation

SNR vs BER Rayleigh channel:

Figures 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.

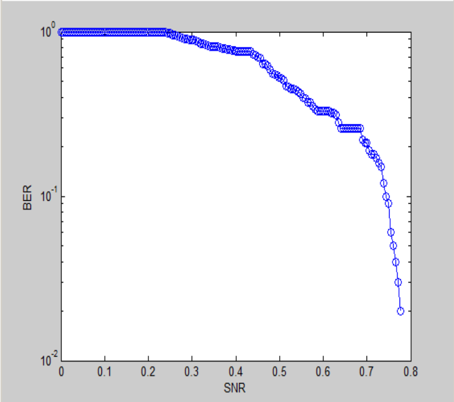

Fig.3 BER vs SNR in Rayleigh Channel

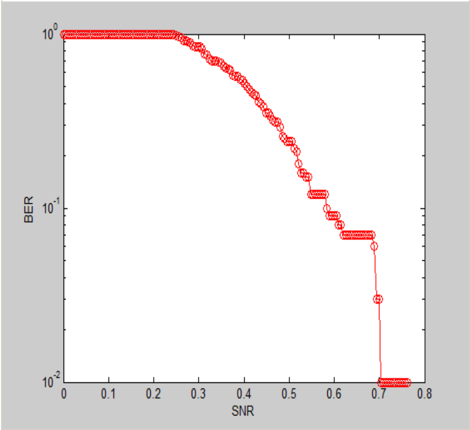

Fig.4 : BER vs SNR in Racian Channel

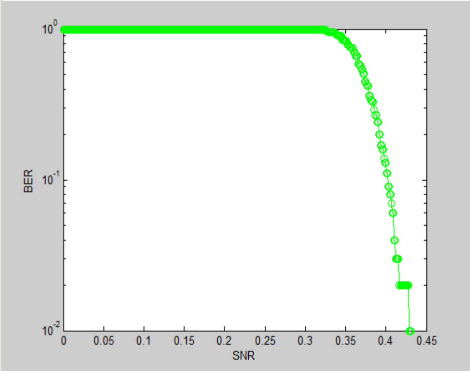

Fig.5 : BER vs SNR in AWGN Channel

Figure 6 shows the1Throughput1vs. SNR graph

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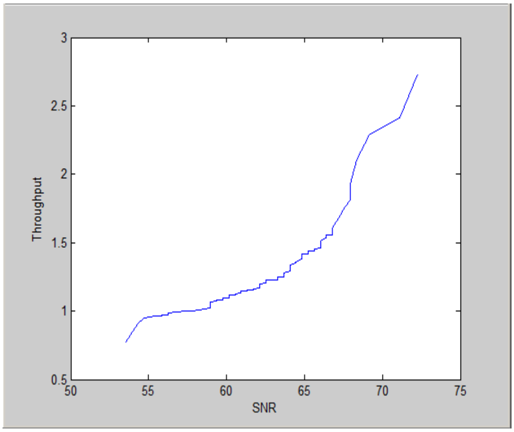

Fig.6:Throughput vs SNR in AWGN Channel

Performance comparison: This section shows the comparison of the channelmodels such as LS, MMSE, LS MMSE EP and LS MMSE PSO. The comparison is done for various metrics such as SNR,BER,MSE, SER and Throughput. Fig 7 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

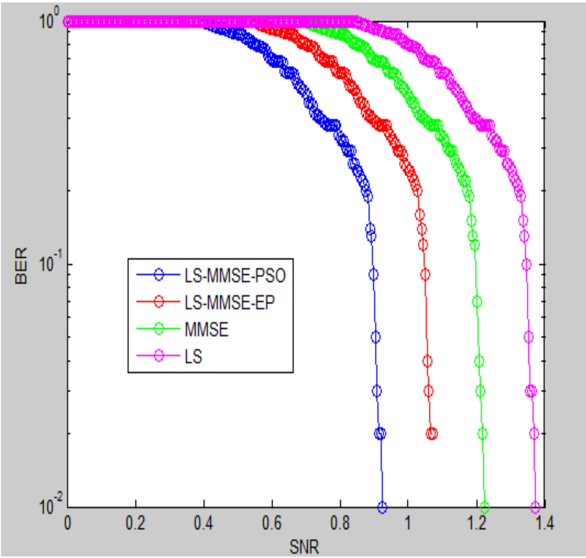

Fig.7. SNR vs BER Comparison of Proposed Technique

CONCLUSION

Indeed, even as of late, MIMO OFDM frameworks have picked up ubiquity because of its heartiness in multipath conditions along with the noteworthy data limit. This examination study centers around new channel estimation strategy for OFDM by joining LS and MMSE utilizing a Meta heuristic improvement approach. At first, LS and MMSE channel model is determined an effective Meta heuristic methodology called Improved PSO is applied in LS and MMSE channels. The best divert acquired in each phase of Improved PSO is chosen. Best channel with least mistake is chosen from the two best channels that are acquired from two phases of improved PSO. The presentation of the proposed approach is assessed dependent on the measurements like BER, SER, MSE, Throughput and SNR. From the exhibition results, unmistakably this strategy is superior to the next existing LS and MMSE strategies. The proposed strategy is broke down by changing the quantity of position and speed.

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