Review of Information Engineering and Applications
2016 Vol. 3, No. 2, 11-21.
ISSN(e): 2409-6539
ISSN(p): 2412-3676
DOI: 10.18488/journal.79.2016.32.11.21

OFDM CHANNEL ESTIMATION BASED ON NOVEL LOCAL SEARCH PARTICLE SWARM OPTIMIZATION ALGORITHM

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Article History
Received: 27 January 2017
Revised: 23 February 2017
Accepted: 21 March 2017
Published: 18 April 2017

Keywords
MC-CDMA
OFDM
CE
LS-PSO.

ABSTRACT

A novel Channel Estimation (CE) approach in multi-carrier wireless communication systems, such as Orthogonal Frequency Division Multiplexing (OFDM) system and Code Division Multiple access (CDMA) via a combination of Local Search (LS) and Particle Swarm Optimization (PSO) algorithm is proposed in this study. The CE is vital towards overcoming the effect of channel fading, which causes the degradation of the Bit Error Rate (BER) and the jamming of pilot symbols. The CE expressions were derived as an objective function to study the effect of improving BER in MC-CDMA/OFDM for a frequency selective Rayleigh fading environment. The number of particles for each single swarm was used to determine the best fitness solution, and is being computed from an average BER value. The proposed channel estimator was tested under the fast fading channel in a multi carrier communication system with and without interpolation methods. The simulation showed that the proposed CE of the MIMO-OFDM system can significantly result in better BER performance compared with other techniques at different modulation types, mean square error (MSE), Signal-to-Noise Ratio (SNR) values, and channel lengths.

Contribution/ Originality: This study originates new formula for modify local search and particle swarm optimization algorithm LS-PSO.

1. INTRODUCTION

Recently, multi-carrier communications, such as MC-CDMA and OFDM, are commonly employed to provide high transmission capacity that is efficient for high bandwidths in wireless communication systems [1]. The channel suffers from time-varying factors and frequency selective fading that diminishes the quality of service of the mobile communication system. Therefore, CE is the most important factor that needs to be done, mostly via inserting pilot symbols to reduce BER and to realize a distortion-less output data. This approach has been used in a wireless communications standard, especially the multi-media wireless broadband services.

There are several CE methods, such as frequency/time domain analysis, blind or pilot-based methods, adaptive or non-adaptive techniques, and decision-directed and blind technique applications [1-6]. In Fazel and Fettwis [2] the block kind pilot arrangement discussed the estimation of the channel based on Minimum Mean-Square Error (MMSE) and Least Square Estimator (LSE). Another method is a comb-type-based CE, where pilot symbols are transmitted on a number of sub-carriers of every OFDM symbol. This approach typically used various interpolation schemes such as linear, time cubic spline interpolation area, and a low pass. The performance of the MMSE estimation minimizes complexities such as Singular Value Decomposition (SVD) while improving the modified MMSE via the development of various methods [3, 4]. In Oyerinde and Mneney [5] the CE for MC-CDMA is based on the pilot sub-carrier that further improves CE, which are analyzed with pilot superimposed data time-domain filtering. However, channel estimation has not been studied based on the frequency or time domain filtering shapes. In Li, et al. [6] a comb kind pilot arrangement is proposed, and the second order interpolation technique was used for CE. In Amiri, et al. [7] a new algorithm is proposed, which details the performance of the second-order interpolation to be superior to linear interpolation. The best threshold value is obtained based on wavelet decomposition, which could then be enhanced with CE Lee, et al. [8]. In Kaiser and Hoeher [9] have been the introduction of 2D simulation results of the pilot CE with Wiener filtering. In addition, the evolutionary PSO algorithm was developed in Eberhart and Shi [10] where the search for the optimal is shown by updating the generations of random particles. Finally, a new method of local search makes PSO algorithms precisely and fast convergence to the Pareto optimal front of multi-objective local search proposed by [11, 12].

In this study, the Local Search Particle Swarm Optimization (LSPSO) algorithm is proposed for the purpose of improving CE's performance. This approach is divided into two steps. The first step involves using the LSE to calculate the initial channel estimation condition, while the second calculates the objective function based on BER using the LSPSO algorithm to obtain pilot coefficients. Finally, the best estimated channel is selected based on de-noised estimated coefficients.

2. SYSTEM DESCRIPTION

2.1. OFDM System

In the OFDM technique, a selective channel frequency divides the spectrum into many narrow bands and some overlapping sub-channels [13]. Figure 1 illustrates the OFDM system block diagram. The scheme converts a serial bit stream into parallel and maps according to the modulation in the block of constellation mapper. Quadrature amplitude modulation (QAM) symbols are then superimposed on orthogonal sub-carriers using the Inverse fast Fourier transform (IFFT), given by:

$$x(k) = \sum_{n=0}^{N-1} s(n)\sin(\frac{2\pi kn}{N}) - j\sum_{n=0}^{N-1} s(n)\cos(\frac{2\pi kn}{N}) \qquad 1$$

Where is *(n)* is QAM symbols, and *N* is the IFFT length. The next stage after IFFT is adding the cyclic prefix (CP) of length *D*, which should be greater than the channel impulse response, CP used to mitigate both inter-carrier interference and inter-symbol interference in the manner shown below:

$$C(t) = [xcp(k)x(k)]^{x(k)} \qquad 2$$

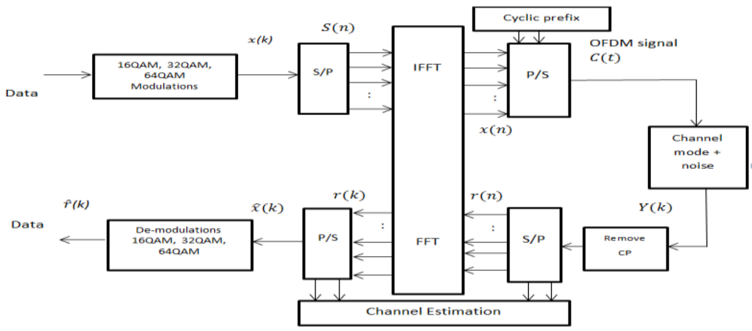

Figure-1. Basic OFDM system

Source: Nahar and Bin Gazali [14]

The OFDM transmitted signal which it is crossing the channel, $Y(k)$ can be written:

$$Y(k) = x(k) \times h(l) + n(k) \quad 3$$

Where, $n\ (k)$ is the noise channel and $h\ (l)$ is the channel impulse response. As mentioned previously, the channel length should be less than the length of the CP. In OFDM, noise is also generated in terms of symbols as:

$$n(k) = 10^{-Es/20No} \times AWGN \quad 4$$

Where, Additive white Gaussian noise (AWGN), and Es/No is the symbol error ratio (SER), and can be expressed as:

$$(Es/No)dB = (N/N_{cp} + N)dB + (N_{st}/N)dB + (Eb/No)dB \quad 5$$

Here, N is the length of the FFT or the number of sub-carriers; N_{st} is the number of sub-carriers is used while N_{cp} symbolizes the length of CP. Then, the received signal is taken into consideration via the addition of CP in the transmitted signal. Thus, it should compensate for that as a scale received signal as:

$$r(k) = \sqrt{\frac{N_{cp} + N}{N}} \times y(k) \quad 6$$

On the receiver side, the steps are completely inverse. In addition, a frequency domain equalizer is used to match the received data as De Beek, et al. [15].

$$\hat{x}(k) = \frac{y(k)}{H(k)} \quad 7$$

Where, $H\ (k)$ is the response of the channel in the frequency domain. The frequency domain equalization is beneficial to the symbol equation that has been faded as a result of suffering multiple.

2.2. Least Square Estimator (LSE) Technique

A pilot arrangement of CE, which have been used in several application systems, particularly power line communication channels, and wireless communication, can be divided into two main categories; comb and block types [16]. These arrangements are shown in Figures 2 (a) and (b). In these figures, the parameters 'Tc' and 'Bc' refers to the time and the bandwidth of the channel's cohesion.

The LSE method can be applied to both comb and block types. In the subsequent arrangement, the frequency domain at the beginning extracts the channel output in the pilot locations. In the next step, CE can be calculated using the extracted subcarriers, which is familiar with the receiver.

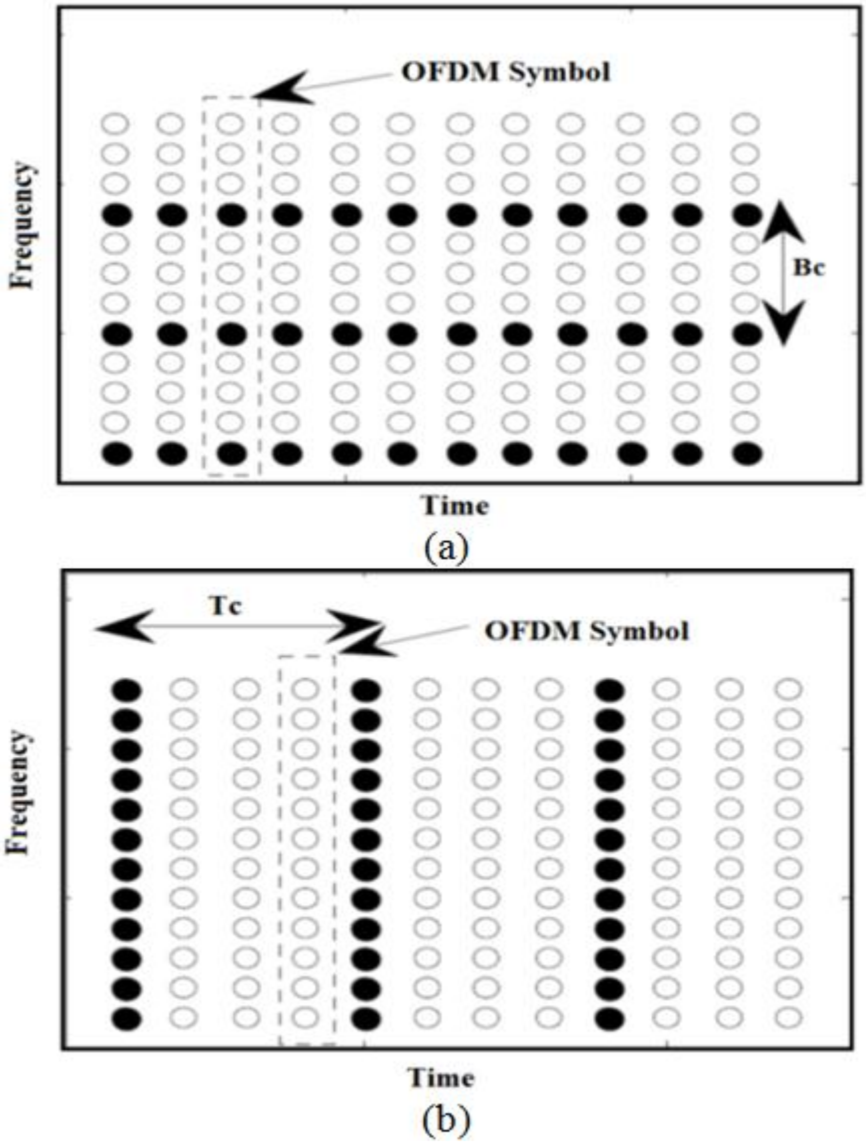

Figure-2. OFDM symbols a) block type b) comb type
Source: De Beek, et al. [15]

The corresponding equation can be written as the following:

$$\hat{H}_{Ls}(k_p) = \frac{Y(k_p)}{x(k_p)} = H(k_p) + W'(k_p), k_p = 1,2,\ldots N_p \quad 8$$

where $W'(k_p) = W(k_p) / X(k_p)$ is the noisiest component at the estimated channel coefficients in the frequency domain, and k_p represents a sub-carrier index at the p^{th} pilot. At one time, in order to obtain the CE at the data sub-carriers, an interpolation technique is required. Interpolation methods are created up of pilots in all sub-carriers and are transmitted periodically, which is equal to the time coherency of the channel and related to the Doppler effects and other types in this manner. The linear interpolation methods are rather simple, which can be written as described in the equation [1]:

$$\hat{H}(k) = [1 - \frac{k - k_p}{L} \hat{H}(k_p) + \frac{k - k_p}{L} \hat{H}(k_p + L)] \quad 9$$

Where, L indicates the distance between two adjacent pilot sub-carriers.

2.3. The PSO Algorithm

A PSO is a population-based stochastic optimization model, taken from the simulation of the social behavior of flocks of birds. In the PSO algorithm, a swarm of particles 'fly' through the search space of n-dimensional space searching, in a cooperative method, for the global optimum. Kennedy and Eberhart established, for the first time, a solution to the problem of the complex nonlinear optimization by imitating the behavior of flocks of birds. They generated the concept of function optimization by means of a particle swarm [17]. Therefore, some parameters might affect the PSO's performance in this algorithm; also, the choice of the parameter values is significantly influential upon the efficiency of the PSO approach, while it remains ineffective for other parameters. The types of PSO parameters are the swarm size or particle numbers, the iteration number, acceleration coefficients, and velocity components, all of which will be illustrated in subsequent sections. In addition, PSO is also affected in terms of weight inertial, clamping velocity, and the velocity of contraction of these parameters.

Generally, the particles of two features are associated with a position and a velocity. Every particle is also regarded as the finest location memory in the search space, which converge at (*p*-best), where the best site was found so far by all the particles in the population (*g*-best). In every step of the algorithm, particles are transferred from the present position via the application of the velocity vector [18]. The velocity and direction against the magnitude are affected by the velocity in the prior iteration and the location of a particle comparative to its *g*-best and *p*-best. So, at each iteration, the direction and the size of every particle's movement represents a purpose of its own history and the social influence of its respective group. Generally, the PSO algorithm can be created by these stages:

1. Firstly, particle velocity and position are suggested randomly in the search space. The particle should have a position and velocity vectors in terms of the length of the solution space.
2. The fitness value of the particle is determined. Thus, the present value of fitness is greater than the best fitness found in the particle.
3. The particle location is calculated according to the best fitness.
4. Evaluation of the velocity, for every particle, is based on these equations:

$$v_i^d(1+t) = wv_i^d(t) + c_1 r_i^1(t)(p - best_i^d(t) - x_i^d(t)) + c_2 r_i^2(t)(g - best_i^d(t) - x_i^d(t)) \quad 10$$

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iteration_{\max}} \times iteration \quad 11$$

Where c_1 and c_2 are constants.

Also, there is the impact weight of individual learning and social influence, respectively, and r_i is varied between 0 and 1 randomly. These are representative of a free movement of every particle, with W being the inertia of the system.

5. Particle position (x) is updated according to the following equation,

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad 12$$

6. Repeat steps 2 -5 up till termination, where the precision is reliant upon the number of iterations. Furthermore, the velocity is restricted to the update of any dimension (d) to the maximum value for W_{max} for each iteration of the algorithm. A particle is randomly accelerated to its previous best position and global best position. Also, the force being applied to the particles remains constant. The PSO pseudo code has been applied in the manner shown in Figure 3.

```
The pseudo code of the procedure is as follows:
For each particle
Initialize:  parameters of PSO
             END
             Do
             For each particle
Identify: Calculate fitness value
        If the fitness value is better than the best fitness value (p-best) in history
           Set: current value as the new p-best
        End if

        While: Choose the particle with the best fitness value of all the particles as the g-best
        For each particle
Identify: Calculate particle velocity according equation
           Set: Update particle position according equation
        End while
While maximum iterations or minimum error criteria is not attained
```

Figure-1. PSO pseudo code

Source: Nahar, et al. [16]

2.4. The Proposed Method

The optimal level for the pilot tones can be realized using the MSE function from the LSE for an objective function algorithm LS-PSO. Therefore, the proposed scheme is implemented to introduce a high-quality solution of local searching. For non-dominated solutions, it plans to explore the area less congested in the current archive. Thus, it is a modified local search scheme (LSS) using the Hooke-Jeeves technique [19]. Many steps are required to create the LSS for the implementation of the LS-PSO algorithm that is easy to describe in a flow chart, as shown in Figure 4 while Figure 5 shows the proposed LS-PSO algorithm in multiple steps.

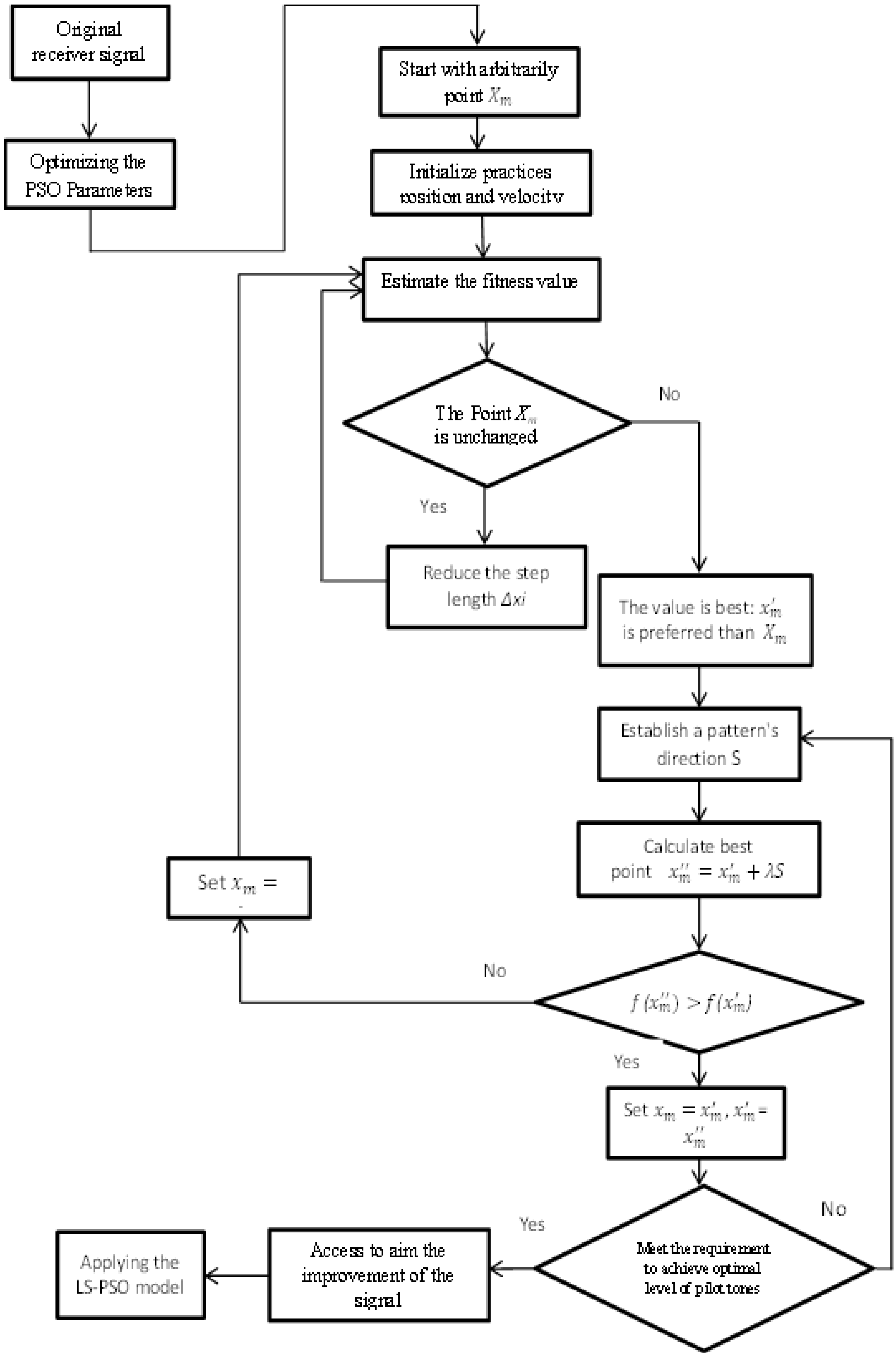

Figure-4. Block Diagram of LS-PSO Proposed

Source: Nahar, et al. [16]

Initialize: Parameters for LS
Identify: local set= {},
Identify: global set; {The nearest member in $G^{t=0}$ to the *i-th* particle is $GP^{t=0}$}
Set: the external set;
While: travel not completed MLS algorithm
  While: sub-travel not completed
  Generate
    Evolve the infeasible particle unit they can be feasible
  Update
  Identify: GP_i^{t+1}
  Update: E^t
  END
END
LS Scheme
Start: with x_m
Generate
While: stopped criterion satisfied **do**
  If Δx_i Reduce **then**
    $\Delta x_i = \Delta x_i(1-(r)^{k/k_{max}})$
  END
  Establish a pattern's direction S
    $S = x'_m - x_m$;
    $x''_m = x'_m + \lambda S$;   λ is the step length
  If $f(x''_m) > f(x'_m)$
  Set: $x_m = x'_m, x'_m = x''_m,$
  Else if Set: $x_m = x'_m,$
  END
END

Figure-5. LS-PSO proposed algorithm.

3. RESULT AND DISCUSSION

In this section, the empirical results are taken into account when comparing the performance of CE using the LSPSO algorithm, which is coded in Matlab. The specification for the LSPSO parameters that has been used for the optimization is: swarm size = 10, 20, number of particles = 20 and the number of iterations equal 40. Furthermore, the specification for the OFDM model parameters that has been used is shown in Table 1.

Table-1. OFDM Simulation Parameters

Parameters	Value
Number of transmitting bits	300000
FFT size	128
Number of sub-carrier	64,128
Pilot numbers	10, 20
Additive noises	20dB
PSO iteration	40
Number of particles	20
QAM modulation indexes	16,32,64
Cognitive parameter c1	2.6
Social parameter c2	1.2
Inertia weight	0.5

Source: Nahar, et al. [16]

3.1. BER Performance

Figures 6 show the various QAM modulation indices with it was applied the SNR upon BER performance using Matlab is plotted. The observed improvement in the SNR is almost 1.3dB at a BER of 10^{-3} in Figure 6 (a), modulation index 16. Figure 6 (b) enhancement around 1.45 dB respect with PSO at modulation index 32. Finally, development 1.67dB at a BER of 10^{-3} as shown in Figure 6 (c) with modulation index 64.

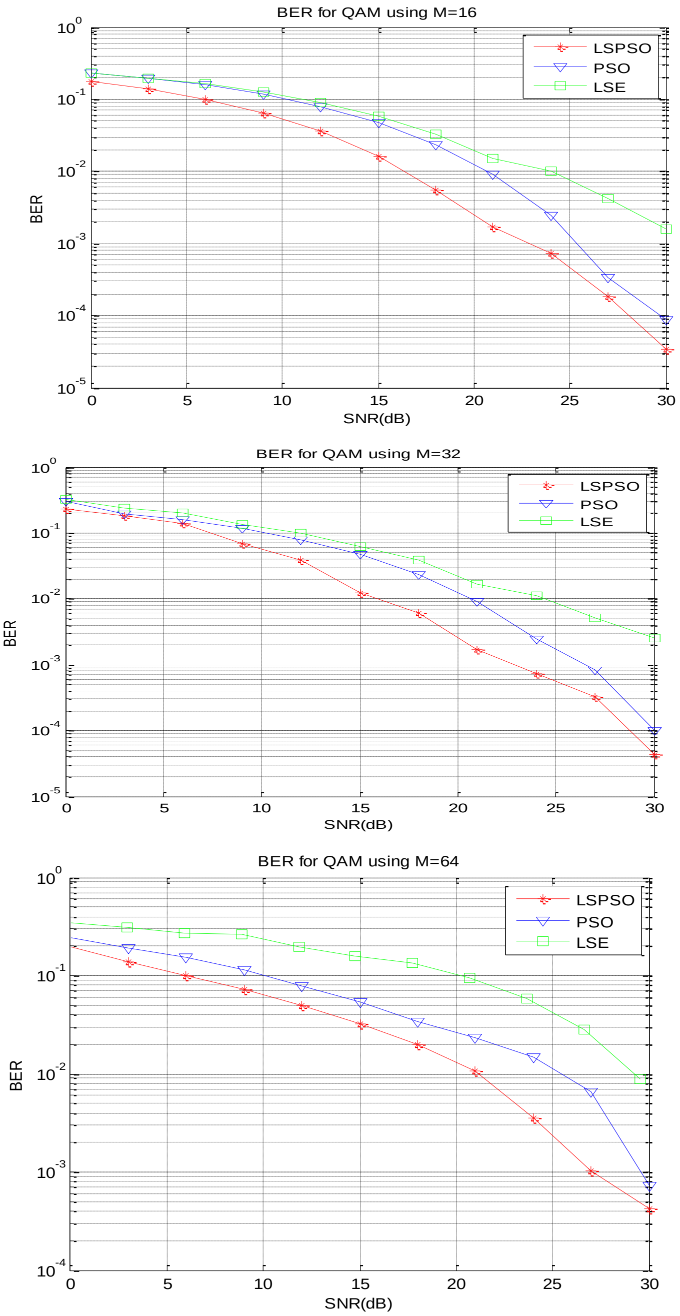

Figure-6. Convergence performance

3.2. LSPSO Performance

Figure 7 (a) shows the MSE versus the SNR in dB for pilot tones of64 sub-carriers, while the pilot tones for 128 sub-carriers over the channels are shown in Figure 7 (b). These figures show the case of pilot tones being placed randomly, leading to a high performance system. At a 30 dB SNR, $0.9*10^{-1}$ is the MSE difference between the random and orthogonal pilots. By analyzing the complexity, the location of pilot tones based on LSPSO exhibited a computational complexity, which may lead to optimization processing, which will subsequently improve the results. Additionally, the increased number of subcarrier benefits the orthogonal placement of the pilot tones.

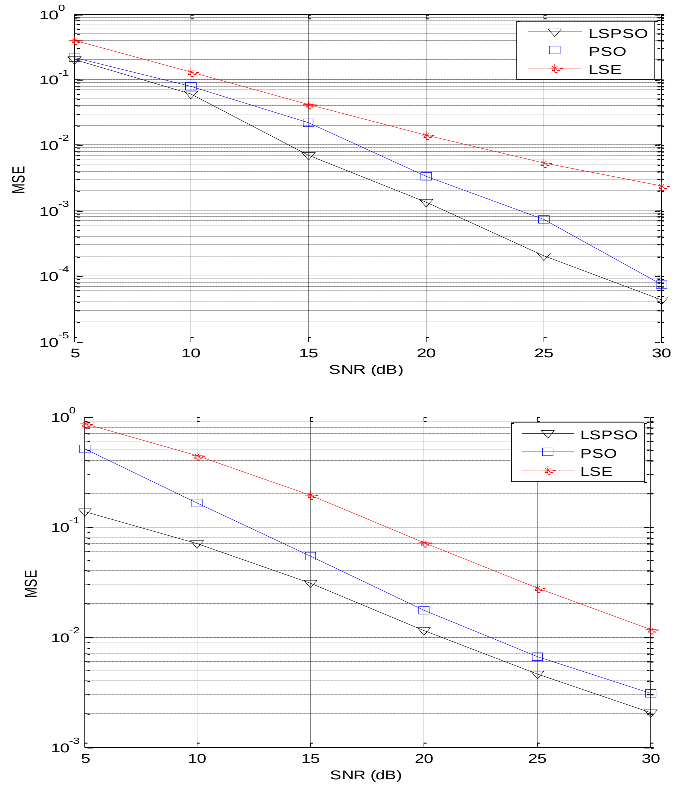

Figure-7. SNR vs. MSE for OFDM system based on different type of estimation a) sub-carrier =64 b) sub carrier =128

4. CONCLUSION

This work proposed the usage of the LSPSO approach in optimizing the power of the pilot tones being used in the LSE algorithm, based on the comb-type pilot tones in MIMO-OFDM systems. Traditional PSO has its benefits and drawbacks. To try to overcome the existing weaknesses in a traditional PSO, we suggest a novel method that will help reduce defects. Furthermore, estimators that can be used to estimate the efficiency of the channel in an OFDM system were provided with knowledge about the channel statistics. The simulation results and the PSO and LSPSO estimator for high SNRs are both adequate and simple. The PSO estimator has low complexity; however, its performance is not as good as the LSPSO estimator at low SNRs. The LSPSO algorithm is very important in solving problems, because every particles facing a convergence of premature or recession in the search process outperforms the random ones significantly while improving the orthogonal pilot tones in relation to BER and MSE.

Funding: This study received no specific financial support.
Competing Interests: The authors declare that they have no competing interests.
Contributors/Acknowledgement: All authors contributed equally to the conception and design of the study.

REFERENCES

[1] 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, pp. 223-229, 2002. *View at Google Scholar* | *View at Publisher*

[2] K. Fazel and G. Fettwis, "Performance of an efficient parallel data transmission system," *IEEE Transactions on Communication Technology*, vol. 15, pp. 805-813, 1967. *View at Google Scholar* | *View at Publisher*

[3] O. Edfors, M. Sandell, J. Beek, and S. K. Wilson, "OFDM channel estimation by singular value decomposition," *IEEE Transactions on Communication*, vol. 46, pp. 931 – 939, 1998. *View at Google Scholar* | *View at Publisher*

[4] M. R. Raghavendra and K. Giridhar, "Improving channel estimation in OFDM systems for sparse multipath channels," *IEEE Transactions on Signal Processing Letters*, vol. 12, pp. 52-55, 2005. *View at Google Scholar* | *View at Publisher*

[5] O. O. Oyerinde and S. H. Mneney, "Recursive MMSE-based iterative channel estimation for OFDM-IDMA systems," in *Proc. IEEE AFRICON, Conf*, 2013, pp. 1-5.

[6] 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. 17, pp. 461-471, 1999. *View at Google Scholar* | *View at Publisher*

[7] I. S. Amiri, M. Ebrahimi, A. H. Yazdavar, S. Ghorbani, S. E. Alavi, S. M. Idrus, and J. Ali, "Transmission of data with an orthogonal frequency division multiplexing technique for communication networks using GHz frequency band solutions carrier," *IET, Communications*, vol. 8, pp. 1364-1373, 2014. *View at Google Scholar* | *View at Publisher*

[8] Y. S. Lee, H. Shin, and H. N. Kim, "Channel estimation based on a time-domain threshold for OFDM systems," *IEEE Transactions on Broadcasting*, vol. 55, pp. 656 -662, 2009. *View at Google Scholar* | *View at Publisher*

[9] S. Kaiser and P. Hoeher, "Performance of multi-carrier CDMA system with channel estimation in two dimensions," in *Personal, Indoor and Mobile Radio Communications, 1997. Waves of the Year 2000. PIMRC'97., The 8th IEEE International Symposium on. IEEE*, 1997, pp. 115-119.

[10] R. C. Eberhart and Y. Shi, "Comparing inertia weight and constriction factors in particle swarm optimization [A]," in *Proceedings of the IEEE Congress on Evolutionary Computation [C]. San Diego, CA: IEEE Press*, 2000, pp. 84-88.

[11] Y. Xu, R. Qu, and R. Li, "A simulated annealing based genetic local search algorithm for multi-objective multicast routing problems," *Annals of Operations Research*, vol. 206, pp. 527-555, 2013. *View at Google Scholar* | *View at Publisher*

[12] A. Jaszkiewicz, "Genetic local search for multiple objective combinatorial optimizations," *European Journal of Operational Research*, vol. 137, pp. 50-71, 2002. *View at Google Scholar* | *View at Publisher*

[13] S. A. Ghauri, S. Alam, M. F. Sohail, A. Ali, and F. Saleem, "Implementation of OFDM and channel estimation using LS and MMSE estimators," *International Journal of Computer and Electronics Research*, vol. 2, pp. 41-46, 2013. *View at Google Scholar*

[14] A. K. Nahar and K. H. Bin Gazali, "Local search particle swarm optimization algorithm channel estimation based on MC-CDMA system," *ARPN Journal of Engineering and Applied Sciences*, vol. 10 pp. 9659-9766, 2015.

[15] J. V. De Beek, O. Edfors, M. Sandell, S. K. Wilson, and P. O. Borjesson, "On channel estimation in OFDM," presented at the Vehicular Technology Conference (Chicago), 1995.

[16] A. K. Nahar, Y. Rahayu, and A. Y. Jaber, "Design the MC-CDMA system with LS-PSO channel estimation based FPGA," *Research Journal of Applied Sciences, Engineering, and Technology*, vol. 10, pp. 1051-1061, 2015. *View at Google Scholar* | *View at Publisher*

[17] A. K. Nahar and Y. Rahayu, "Design of selectable modems for MC-CDMA based on software defined radio," *International Journal of Engineering Technology and Sciences*, vol. 3, pp. 1-7, 2015. *View at Google Scholar*

[18] J. He and H. Guo, "A modified particle swarm optimization algorithm," *TELKOMNIKA*, vol. 11, pp. 6209-6215, 2013. *View at Google Scholar*

[19] L. Costa, S. I. Espırito, and F. M. G. P. Edite, "A hybrid genetic pattern search augmented lagrangian method for constrained global optimization," presented at the International Congress on Computational and Applied Mathematics (ICCAM 2009), Antalya, Turkey, 2009.