Swarm Intelligence Based MMSE Frequency Domain Equalization for MIMO Systems

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ABSTRACT

The automatic upgradation of equalizer weights in channel equalization demands a low-complexity, highly accurate estimation of recovery at the minimum possible time. The low-complexity frequency domain equalization improves the minimum mean square error (MMSE) of the equalization process. Adding the superiority of particle swarm optimization (PSO) to the equalizer coefficient selection process enhances the MMSE. This work proposes frequency-domain channel equalization along with a modified PSO (MPSO) as an adaptive algorithm for equalizer weight selection in MIMO systems. The simulation results validate the performance with the time domain linear and decision feedback equalizer structures for BPSK and QAM systems. The parameters are carefully selected by analyzing MMSE thoroughly under time-varying channel conditions.

Keywords: Frequency domain equalization, Particle swarm optimization, Decision feedback equalization, Minimum mean square error

1. INTRODUCTION

In recent years, the use of artificial intelligence and machine learning (ML) for wireless communication has increased due to its speed and efficiency. In future 6G networks, AI-aided techniques are unavoidable for intelligent optimization [1]. The THz band in future 6G wireless communication systems needs an efficient adaptive algorithm for finding the best coefficients in channel equalizers. The conventional derivative techniques lost their popularity due to a lack of estimation in non-linear time-varying channel conditions. Integrating AI and ML methods along with model-based classical techniques can match the vision of 6G and beyond. Since a decision-feedback model-based conventional equalizer (DFE) [2] mitigates interference much better than a linear equalizer, it can be integrated with derivative-free algorithms (bio-inspired) for improving the MMSE of equalization at the receiver. Also, the known efficiency of decision feedback nonlinear structure in severe nonlinear channels triggers the selection of a structure as DFE among the available structures such as the linear transversal equalizer (LTE) [3], the artificial neural network (ANN) [3], the Chebyshev ANN (CANN) [13], the functional link ANN (FLANN) [14], the fuzzy neural system [15], and the Volterra filter [11].

Adding the superiority of swarm optimization (SO) to the equalizer coefficient selection processes of MMSE and BER can enhance their performance. The limitations of basic gradient algorithms, for example, LMS (Least-Mean Square) [1], Recursive Least Square (RLS), Least Mean Fourth (LMF), and Affine Projection (AP), require an alternative solution for searching the global optimum. The local minima problem in gradient-based optimization restricts its performance [2], mainly in non-linear channel conditions. The proved efficiency of derivative-free optimization algorithms like Genetic Algorithm (GA) [5], Artificial Bee Colony Optimization (ABC) [7], Simulated Annealing (SA) [6], and PSO [2] [8] [9] triggered the search for intelligence-based swarm optimization in channel equalization over the last decades. The common process steps such as selection, mutation, crossover, reproduction, group best experience, and personal best experience lead to the popularity and performance of these algorithms at the higher level of wireless communication applications.

The evolutionary algorithms such as GA and SA lack in optimization process due to many process steps and delayed convergence. The ABC algorithm optimizes the filter coefficients with increased complexity. The balance between the best personal and group experience makes PSO popular and effective. The PSO algorithm finds MMSE in minimum iterations [4].

Initially, the genetic algorithm was ineffective in terms of convergence speed [16] for channel equalization. The ABC method is applied to update a Volterra equalizer [18], which has similar performance to PSO but is more sophisticated. For channel equalization, PSO finds a MMSE in a lower number of iterations than GA [16]. The low complexity of FDE makes it a viable alternative that offers a reasonable solution to the high PAPR problem. Before equalizing the signal, the received sequence is translated into the frequency domain (FD). Before detecting data symbols, the inverse FFT transfers the equalized FD signal into the time domain (TD). In channels with acute delay spread, the FD equalization is simpler than the TD equalization in terms of computational complexity. For high-speed transmissions, traditional time-domain equalizers are ineffective. In the frequency

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domain, adaptive algorithms have the advantage of faster convergence and more stable outcomes.

A hybrid PSO–LMS–DFE algorithm for MIMO channels was presented [23] to improve performance in terms of complexity. In single-carrier (SC) modulation methods, FDE is proposed, which is less sensitive to radio frequency impairments than OFDM [24]. In [25], an adaptive FD PSO equalization is used for a SC-FD (single carrier FD) multiple access system. To optimize the MSE and convergence of the channel equalization, a position update method and a new inertia weight update method for PSO are proposed [26].

This paper makes use of modified PSO (MPSO) in adaptive decision feedback channel equalization and modifies the process to achieve optimal equalizer coefficients. The modification proposed speeds up the equalization process, and the modified equation proposed leads the optimization to the global optimum. Also, the same is applicable for frequency domain equalization, whereas the weights are optimized in the frequency domain after taking the FFT of the samples. Once the weights are updated, the samples will be converted again to the time domain for further processing. The proposed MPSO outperforms the basic gradient algorithms and other swarm-based intelligence algorithms such as ABC and GA in terms of MMSE and BER. The FD ADF shows superiority in MMSE, BER, and complexity.

2. METHODOLOGY

2.1 Equalizer Model

Figure 1 shows the transceiver baseband model [2] developed from the pass band model. Transmit and receive filters are identified as the pulse-shaping filter and the matched filter. A single channel filter is used to simulate the effects of the channel, transmit, and receive filters. The channel filter takes into account noise, nonlinearity produced on the transmitter side, and multipath with various delay spreads. With impulse responses hn and cn, the main channel and the equalizer were modelled as LTE filters. The binary value 1 of the supplied training data is 180 degrees out of phase (-1). The channel's impulse response and transmitted data are combined to create the channel's output. White additive band-limited noise samples are added to the channel output (AWGN).

Eq. (1) uses the three-path linear channel model [4] as the ISI channel model

$$h_n = \begin{cases} \frac{1}{2}\left[1+\cos\left(\frac{2\pi}{W}(n-2)\right)\right] & n = 1,2,3 \\ 0 \quad \text{otherwise} & \end{cases} \tag{1}$$

In this case, the amplitude distortion parameter W has been set to 2.9. The SUI-1 and SUI-5 models are additional channel models chosen with variable delay widths for broadband wireless channels. SUI-1 has an RMS delay spread of 0.12 s (low), whereas SUI-5 has a 3.05 s (high) RMS delay spread. The power delay profiles of SUI-1 and SUI-5 channel variants are shown in Table 1. After the tapped delay line model with power delay profile was transformed into a discrete model, it was taken into account for the simulation using a discrete baseband model. A common filter is denoted as hn for transmit, channel, and receive. Due to the nonlinearity effect and the channel response, the input signal to the equalization is distorted. The noise element, vn, is represented by band-limited white Gaussian noise with a variance of 0.001. The equalizer receives the signal that has been degraded and has noise added. For MIMO frequency-selective block time-invariant channel, the mxn channel matrix is used for simulation on a system having n broadcast and m receive antennas. The ith receiving antenna's discrete output is

$$y_i(l) = \sum\nolimits_{j=1}^{m} x_j(l) * h_{i,j}(l) + v_i(l) \tag{2}$$

where $y_i(l)$ is the discrete output of the j^{th} receiving antenna at time l, $x_j(l)$ is the discrete input to the jth transmitting antenna, $h_{i,j}(l)$ is the impulse response of a discrete channel to the receiving antenna i at time l from the transmitting antenna j and $v_i(l)$ is additive white Gaussian noise at the output of the i^{th} receiving antenna at time l. The 3 path MIMO channel with the power delay profile given in Eq. (1) and Table 1 is used for three paths randomly.

Figures 2 and 3 depict a linear transversal and a nonlinear decision-feedback adaptive equalization. DFE works on the concept that once the current transmitted symbol is identified, the symbol's ISI contribution on future received symbols is precisely removed. The decision device, which attempts to decide which symbol among a series of discrete levels was actually communicated, is responsible for the nonlinearity. Once the current symbol is determined, the filter structure calculates the effect of ISI, which is likely to occur with consecutively received symbols, and compensates the input to the decision device for subsequent samples. A feedback filter structure is used to remove the ISI once the cursor has been removed.

The SC-FD equalization scheme is a good alternative for solving the high PAPR problem [21]. SC-FDE inherits the low complexity advantage, and the received sequence is converted into the frequency domain before equalizing the signal. Then the inverse FFT restores the equalized signal to TD before the observation of data symbols. For channels with a high delay width, FDE is computationally simpler (shown in Figure 4) than the corresponding TDE. Conventional time-domain equalizers are not appropriate for the transmission of high-speed data. The time-varying fading channels necessitate adaptive signal processing in order to track the variations of the channel at the receiver. In the frequency domain, the adaptive algorithms normally converge faster and are more stable.

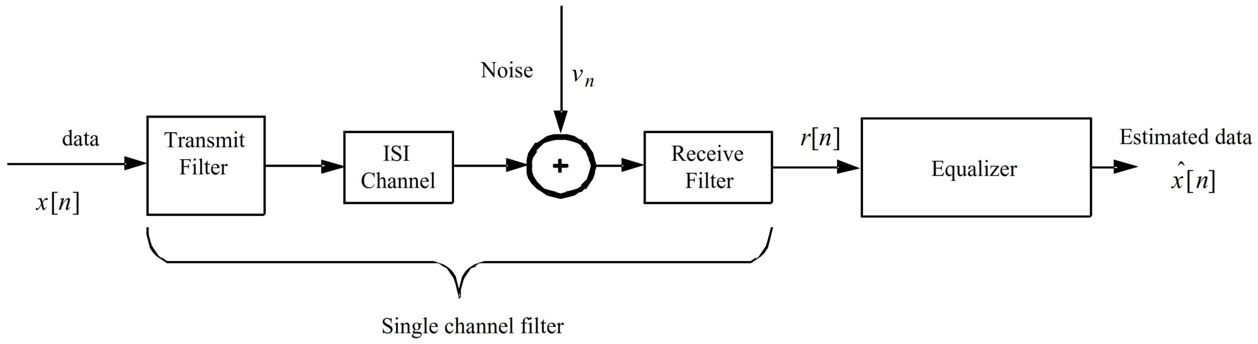

Fig. 1*: Transceiver - Baseband model.*

Table 1*: Channels Power delay profile.*

SUI-1 Channel		SUI-5 Channel	
Delay for Taps (μs)	Relative Power in dB	Delay for Taps (μs)	Relative Power in dB
0	0	0	0
0.5	-15	5	-5
1	-20	10	-10

Table 2*: MPSO Algorithm Flow.*

Algorithm MPSO

For LTE

Input:*Initialize particles (P), no of equalizer coefficients (T)*

Input data samples or training data (N)

Output *Estimated samples of Equalizer*

Fittness Criteria: *MMSE*

$$MSE(P) = \frac{\sum_{i=1}^{ws} e_i^2}{ws} \qquad (7)$$

Where P represents the current particle number. The fitness value is minimized using MPSO-based optimization.

- At iterations, equalizer weight sets are updated by Eqs. (3), (4), and (5).

Evaluation and Selection:

- *Best fitness among all as* G_{best}
- *Best fitness in each population* P_{best}
- *Repeat for all populations or until convergence occurs for all populations.*

For DFE:

Input :*Equalizer weight set for each subgroup (T) for forward filter and feedback filter*

Input data samples or training data (N)

Output :*Estimated samples of Equalizer*

Fitness Criterion: *MMSE*

$$MSE(P) = \frac{\sum_{i=1}^{ws} e_i^2}{ws}$$

Where P represents the current particle number. The fitness value is minimized using MPSO-based optimization.

- *At iterations, equalizer weight sets are updated by Eqs. (3), (4), and (5).*

For FDE Equalization:

- *The received sequence is converted into the frequency domain before equalizing the signal.*
- *The inverse FFT restores the equalized signal into the time domain before observation of the data symbols.*

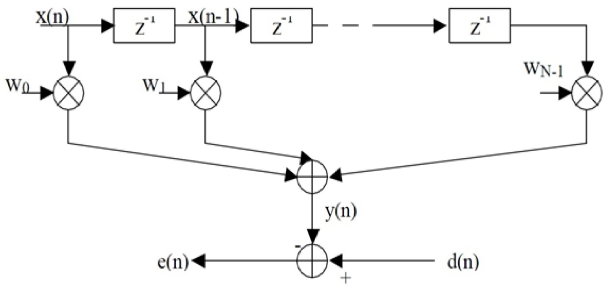

***Fig. 2**: LTE.*

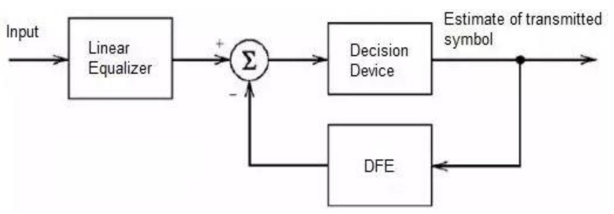

***Fig. 3**: DFE.*

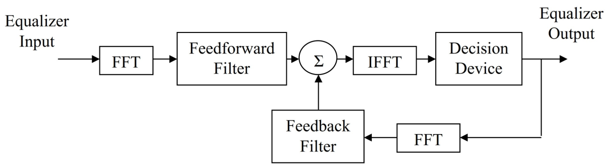

***Fig. 4**: Frequency Domain Equalization.*

2.2 MPSO Algorithm

PSO works on the cognitive and social behavior of the particles in the population by starting with a random swarm of particles in a random search space [23]. The candidate solutions, known as 'particles,' wander through the n-dimensional search space along with a velocity V_p that is constantly changed based on the experiences of the corresponding particle and its companion. P_{best} denotes each particle's best position, while G_{best} denotes the collective experience of all the particles. Each particle in the PSO takes two parameters: velocity and position, which may be assessed using the optimization problem's objective function and updated using G_{best} and P_{best}. During each update process, the latest G_{best} is encountered, causing all the other particles to take off toward it. A particle's velocity and position are updated as

$$V_p(n+1) = w * V_p(n) + C_1 * rand_1 * (P_{best} - X_p) + C_2 * rand_2 * (G_{best} - X_p) \quad (3)$$

$$X_p(n+1) = X_p(n) + V_p(n+1) \quad (4)$$

Here the cognitive and social acceleration coefficients are denoted as C_1 and C_2 and the $rand_1$ and $rand_2$ are two random functions in the range [0, 1]. In the nth iteration, the $V_p(n)$ and the $X_p(n)$ represent the velocity and position of the particle P, respectively. The P_{best} denotes the position of particle P's best solution vector, while the G_{best} is among the best solutions obtained by all particles in the population. The w is the inertia weight in Eq. (3), which gives the swarm diversity by altering particle momentum and normally decreases in the range [0, 1]. The w is one of the elements that affects the particle's velocity and, as a result, their position updates. The larger the w, the greater the global impact, and the smaller the w, the more local impact on the solution.

A fuzzy complement sugeno function [24] was used as an inertia weight decline curve and is defined by the Eq. (5).

$$w = a = \frac{1-\beta}{1-s\beta} \quad (5)$$

where β is represented as n/m and the s is constant which is larger than -1.

***Table 3**: PSO Parameters.*

Simulation Parameters	Values
No. of particle	20
Acceleration coefficient	2,2
Feed forward taps	11
Feedback taps	7
Modulation Scheme	BPSK, 32QAM
Maximum Iteration	200
Training sequence	32
Equalizer Structure	LE, DFE
Noise variance	0.001
Noise Mean	0

3. RESULTS AND DISCUSSION

The MSE and the BER of equalizers LTE and DFE are simulated for an average of 10 runs using MATLAB version 2013. The process of non-blind, time-domain equalization in linear transversal and decision feedback equalizer (LTE and DFE) structures is implemented for equalization. Also, the weights are updated based on the MMSE criteria. The basic BPSK modulation technique utilized in wireless standards such as WiMAX and WLAN is used. For channel modeling, a 3x3 MIMO Rayleigh multipath model with different delay spreads is used as given in Section 2. Table 3 lists the parameters that were chosen for the MPSO simulation.

3.1 Convergence Analysis

For this convergence analysis, all the other parameters except the number of training sequences are constant, as given in Table 3. The number of training sequences is the same as the window size and FFT used to convert this training sequence into the frequency domain. Here, the QAM modulation scheme is used to modulate the

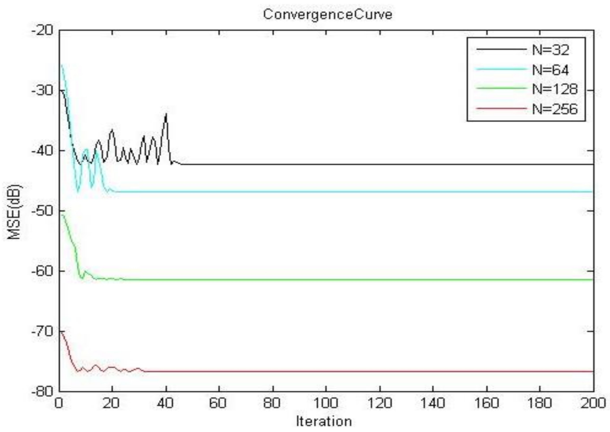

***Fig. 5**: Convergence for different sets of training data.*

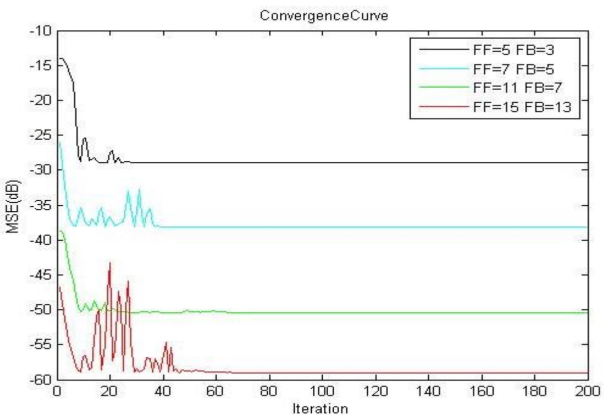

***Fig. 6**: Convergence for different tap weights.*

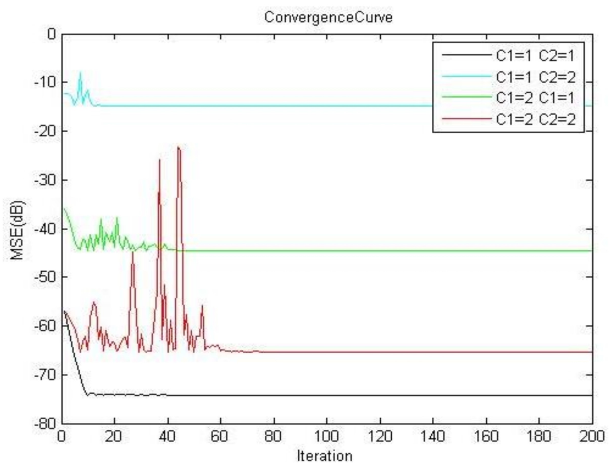

***Fig. 7**: Convergence for different sets of acceleration coefficients.*

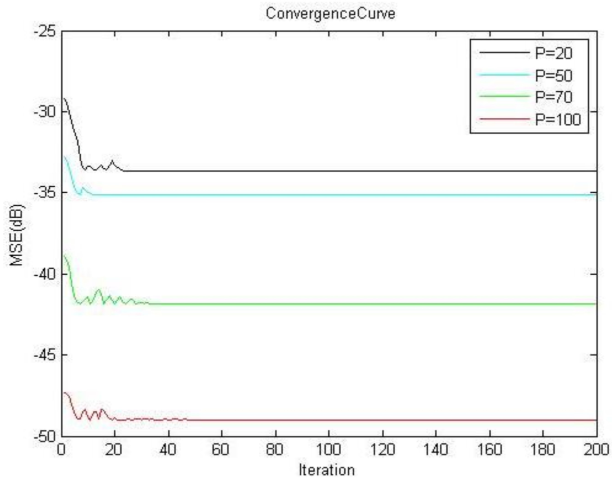

***Fig. 8**: Convergence for different population size.*

***Table 4**: Comparison Table for BPSK and QAM system.*

Parameters	MMSE for BPSK(dB)		MMSE for 16QAM (dB)	
	TDE	FDE	TDE	FDE
DFE-MPSO	-34.7	-45.01	-54.6	-82.3
LE-MPSO	-27.82	-38.23	-46.4	-67.2
DFE-PSO	-24.3	-30.05	-32.76	-46.07
LE-PSO	-24.03	-25.04	-30.27	-45.21

sequence. The curve is plotted for the 32, 64, 128, and 256 numbers of the training sequence. As the training sequence is increased, the curve is brought closer to the minimum MSE. This indicates that the higher the number of training sequences, the better the channel's performance. For N = 32, the MSE is -40.5 dB, which is the maximum when compared to the other N values in the plot, and N = 256 gives the minimum MSE of -77.3 dB, as shown in Figure 5. In general, powers of two are the ideal length for training data. Analysis is done on windows sizes of 16, 32, 64, 128 and 256. The performance is stabilized by increasing the window size. Here, a 128-bit window size is chosen for the remainder of the experiment. The equalizer weights must be adjusted every 1000 samples if coherence time and sampling rate are taken to be 1 ms and 1 Mbps, respectively.

The convergence curve is plotted for feed-forward taps of 5, 7, 11, and 15 and feedback taps of 3, 5, and 13, respectively. The sequence is modulated using the QAM technique. The number of taps is the same as the number of equalizer coefficients. The complexity of the equalizer structure grows as the number of taps in the equalizer grows. It is observed that with an increase in the number of taps in the equalizer, MSE decreases, but after a certain point, as complexity increases, it leads to degradation of performance, as observed from the plot. The number of taps in the equalizer is always kept in the lower range in order to keep complexity under check. From Figure 6, it is observed that at $FF = 5$ and $FB = 3$, the MSE is -28.38 dB, which is quite high. For $FF = 7$, $FB = 5$, MSE is -37.38 dB, and for $FF = 11$, $FB = 7$, MSE is -50.1 dB. MSE is low for $FF = 15$ and $FB = 13$ taps, which have -59.65 dB.

This convergence curve is plotted for various com-

***Table 5**: Comparison Table for Various Channel Models.*

Parameters	MMSE for BPSK (dB)		MMSE for QAM (dB)	
	TDE	FDE	TDE	FDE
UDL	-25.67	-27.23	-50.02	-67.39
SUI-1	-22.78	-25.7	-31.78	-43.45
SUI-5	-19.42	-24.04	-25.15	-32.27

binations of the acceleration coefficient of the PSO algorithm. If $C_1 = 1$, $C_2 = 1$ the high MSE is -14.31 dB. In this convergence plot, $C_1 = 2$, $C_2 = 2$, and $C_1 = 2$, $C_2 = 1$ converged to the minimum MSE, and the first one has -43.25 dB and the second combination has -74.31 dB, as shown in Figure 7. Almost these two converge to the same MSE. Anyone of these two can be used to achieve a better convergence rate.

Figure 8 represents the convergence plot for various population sizes P. Position and velocity of the particle are computed from Eqs. (3) and (4). The variation in the number of particles may give a better convergence rate. All other parameters are kept constant. If the number of particles is high, it consumes more time. From the figure, it is inferred that for P = 20, the MSE is -33.2 dB, which is high when compared to the other number of particles, and for P = 100, the MSE is -48.76 dB, which gives the lowest MSE value among the four numbers of particles.

In this section, the performance of the PSO algorithm for BPSK and the QAM system in the time and frequency domain was investigated using four scenarios, such as MPSO using LE and DFE structure and PSO using LE and DFE structure. FD converges to the minimum MSE in these two modulation schemes better than time domain. Since TDE has a more complex structure compared to FDE, it affects the convergence curve. In TDE as well as FDE, DFE using MPSO reaches the minimum MSE. From the figure, it is inferred that DFE gives better accuracy when compared to the LE and because of inertia weight modification in MPSO.

Also, DFE-MPSO is analyzed for various channel models with different modulation schemes and different domains of equalization. In this section, the performance of the channel model is analyzed for the PSO algorithm in time and frequency domain equalization, which belongs to BPSK and QAM systems. The MSME values for different channel models are extracted from Table 5. Figures 13, 14, 15, and 16 clearly show that the Uniform Delay line model outperforms the SUI model. because the SUI model has a high rms delay spread. The frequency domain equalization for the Uniform Delay line outperforms the corresponding time domain equalization. It was already proven in the previous section. Frequency domain decision feedback equalization using the MPSO algorithm gives better performance in the uniform delay line model.

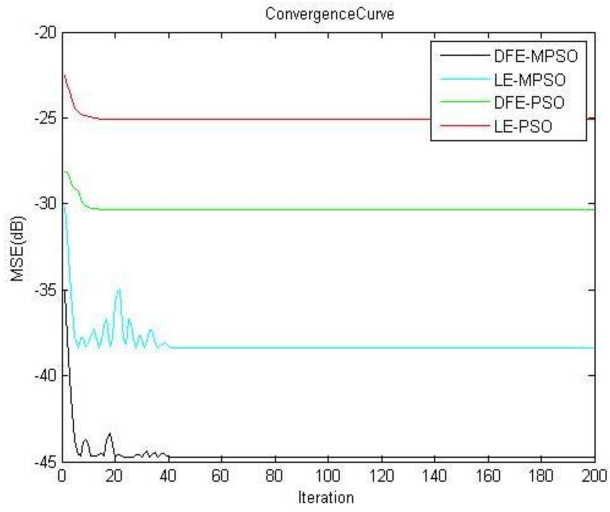

***Fig. 9**: FDE with BPSK.*

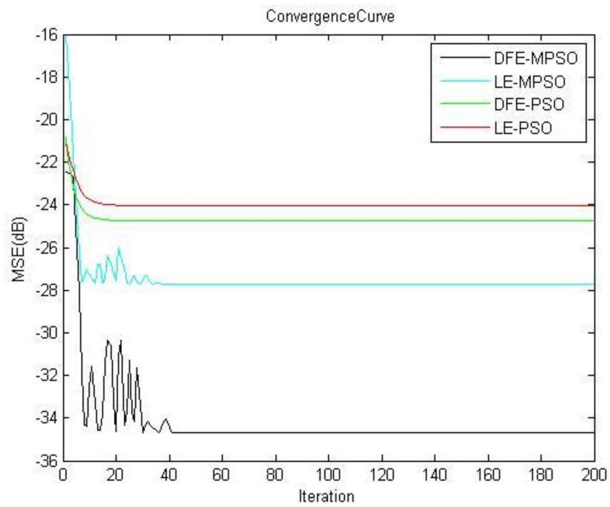

***Fig. 10**: TDE with BPSK.*

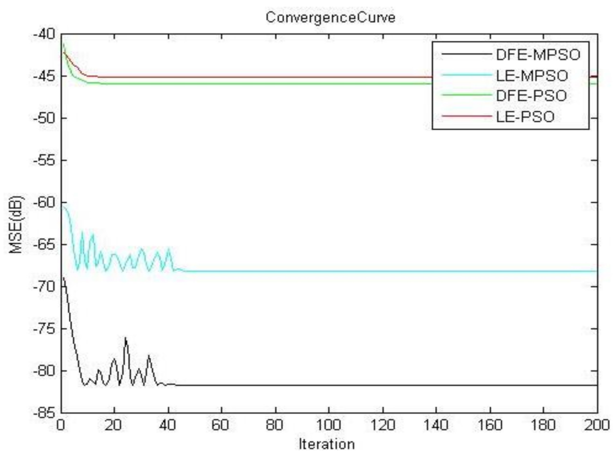

***Fig. 11**: FDE with QAM.*

3.2 Complexity and BER Analysis

This section examines the complex multiplications and additions required per iteration, considering that PSO

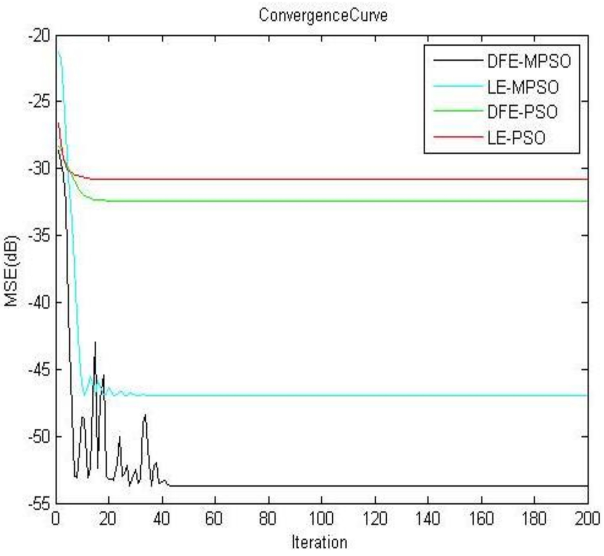

***Fig. 12**: TDE with 64 QAM.*

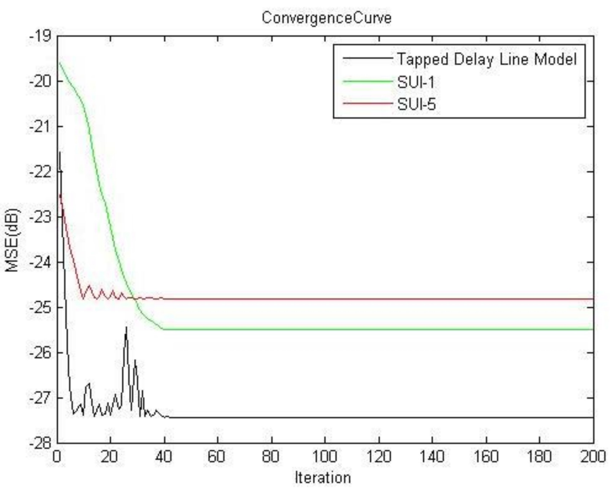

***Fig. 13**: FDE for BPSK in different channel model.*

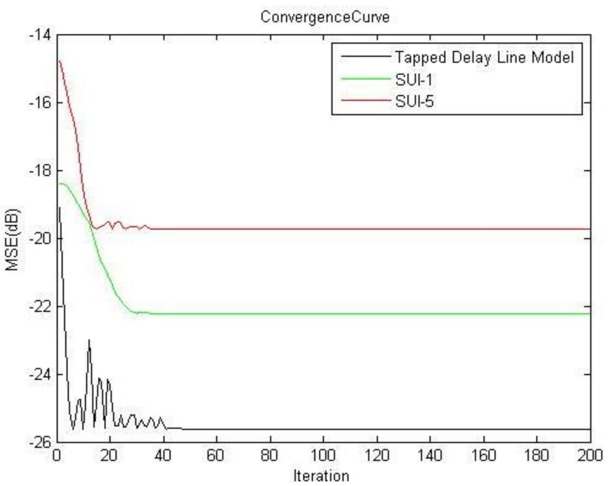

***Fig. 14**: TDE for BPSK in different channel model.*

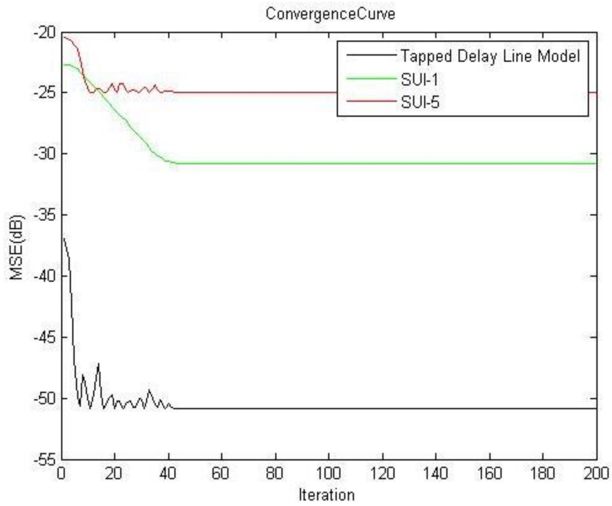

***Fig. 15**: TDE for QAM in different channel model.*

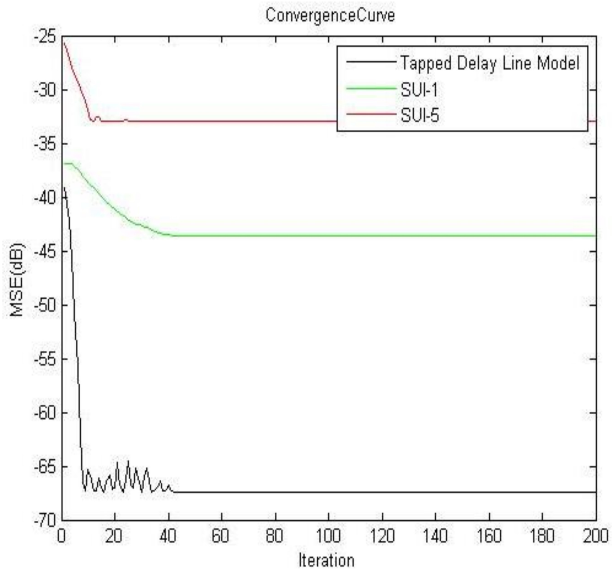

***Fig. 16**: FDE for QAM in different channel model.*

works with complex data. If decimation-in-frequency FFT is used to compute N-point DFT , it necessitates $N\log_2 N$ complex additions and $(N/2)\log_2 N$ complex multiplications. For time-domain convolution calculation , an $N-1$ number of additions and multiplications are required. The velocity update in the SISO case requires three complex multiplications and four complex additions for each particle in each dimension. If C_1 and C_2 are both set to 4, shift registers can be used to implement it. $3*i*n$ complex multiplications and $5*i*n$ complex multiplications are necessary for i dimensions. There are six times as many complex multiplications and additions in the 3x3 MIMO scenarios as in the SISO case.

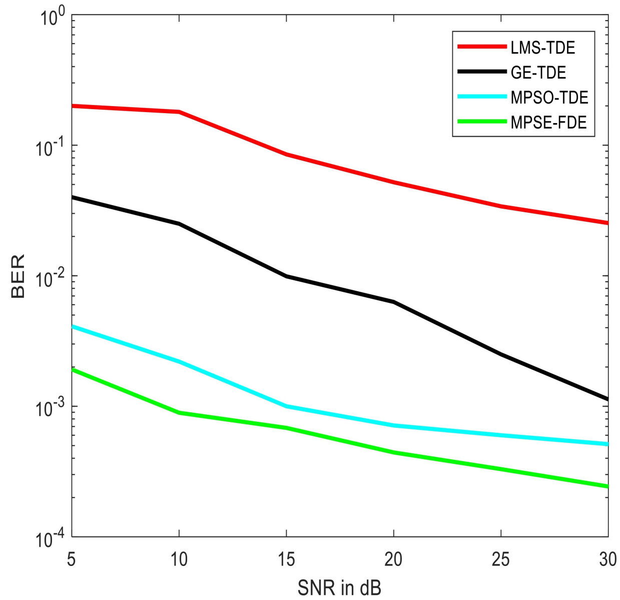

Fig. 17: *BER plot for different algorithms.*

Table 6: *Computational complexity of adaptive algorithms in Time and Frequency domain.*

Algorithm	Multiplications	Additions
MPSO-Time Domain	[iNn+3in+3] [N-1]	[(i-1)Nn+5in+3+(N-1)n] [N-1]
MPSO-Frequency domain	[iNn+3in+3]* (N/2) $\log_2$N	[(i-1)Nn+5in+3+(N-1)n] N$\log_2$N
PSO-Time Domain	(iNn + 3in + 3) [N-1]	iNn + 5in + 3+Nn) [N-1]
PSO-Frequency Domain	(iNn + 3in + 3) [N-1] * (N/2) $\log_2$N	iNn + 5in + 3+(N − 1)n) [N-1]* (N) $\log_2$N
GA-Time Domain	[iNn+3in] [N-1]	[iNn+4in] [N-1]
GA-Frequency Domain	[iNn+3in]* (N/2) $\log_2$N	[iNn+4in] N$\log_2$N
LMS-Time Domain	(2in) [N-1]	((i− 1)n + 2i) [N-1]
LMS-Frequency Domain	(2in) * (N/2) $\log_2$N	((i − 1)n + 2i) * (N) $\log_2$N
LMS-PSO-Time Domain	0.75(2Nn+ 3(N/2)$\log_2$N) +.25(Nn+ 3(N/2)$\log_2$N + 3Nn+ 3) [N-1]	0.75(((N −1)+N)n+ 3N$\log_2$N)+0.25((N −1)n + 3N$\log_2$N + 5Nn+ 3+(N −1)n+Nn) [N-1]
LMS-PSO-Frequency Domain	0.75(2Nn+ 3(N/2)$\log_2$N) +.25(Nn+ 3(N/2)$\log_2$N + 3Nn+ 3)* (N/2) $\log_2$N	0.75(((N −1)+N)n+ 3N$\log_2$N)+0.25((N −1)n + 3N$\log_2$N + 5Nn+ 3+(N −1)n+Nn) (N) $\log_2$N

1. Two complex additions and three complex multiplications are essential to calculate the inertia weight equation in Eq. (5).
2. One complex addition is required for the particle update.
3. For a block of size N, computing the equalization output vector for each particle involves $i * N * n$ complex multiplications and $(i-1) * N * n$ complex additions.
4. To calculate the error signal, $N * n$ complex additions are needed.
5. Calculating MSE using the formula in Eq. (7) necessitates $(N-1) * n$ complicated additions. We may skip computations for calculating the error square, since PSO compares the MSE brought on by all the particles and, hence, chooses the one with the smallest MSE. Therefore, the identical results could be reached with the error mean rather than the MSE.

Table 6 summarizes the complexity of PSO in TD and FD. In FD only (N/2) log2N multiplications are needed instead of N-1 multiplications required in time domain. Similarly Nlog2N additions are required instead of N-1 addition in time-domain. The MPSO inertia weight equation saves one complex 2 complex additions in each iteration.

Figure 17 gives the analysis of BER for different algorithms along with frequency domain PSO equalization. The BER is plotted for SNR from 5 to 30dB.

The Frequency domain equalization trained by PSO enhances the BER compared to Time Domain Equalization.

4. CONCLUSION

In this proposed work, a frequency domain decision feedback equalization based on the MPSO algorithm is analyzed for different values of the number of particles, taps of the equalizer, acceleration coefficients, and training sequence. Based on the analysis, frequency domain decision feedback equalization for the QAM system is achieved with a minimum MSE while analyzing the time and frequency domain equalization for BPSK and QAM systems in terms of MSE. The PSO performance is improved by proper selection of the algorithm coefficient and other parameters in high Doppler spread. The performance of the frequency domain PSO in the uniform delay line channel model is better when compared to the SUI-1 and SUI-5 channel models. Because the rms delay spread of the SUI model is high when compared to the uniform delay line model. The frequency domain equalization technique helps to achieve adequate anti-multipath performance compared to time domain equalization. The simple inertia weight equation used in this work reduces the complexity better than other inertia weight calculations.

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