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Piranha fish optimization for multi user detection in OFDMA system

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ABSTRACT

The Fish swarm based algorithms are proposed by studying the habitat of Piranha Fish that is found in North American Sea. Therefore, algorithm is named as Piranha Fish optimization (PFO). The PFO is also proposed with opposite learning concept which is named as Opposite Piranha Fish Optimization (OPFO). The both algorithms are tested on Orthogonal Frequency Division Multiple Access (OFDMA) systems for Multi User Detection (MUD). It is found that both PFO and OPFO give attractive results in terms of Bit Error Rate (BER) and Convergence Rate (CR) as compared to conventional GA based method.

1. Introduction

The Multiple Input and Multiple Output (MIMO) systems replaced Single Input and Single Output (SISO) antennas due to their effective utilization of available bandwidth as it have multiple antennas at both transmitter and receiver. Therefore, it gives high data rate as compare to SISO. Multiple user systems like Orthogonal Frequency Division Multiple Access (OFDMA) and Multi-Carrier Code Division Multiple Access (MC-CDMA) are recommended along MIMO in (Verdú, 1998).

OFDMA (Li et al., 2002; Qing and Kim, 2012) is multi-user version of Orthogonal Frequency Division Multiplexing (OFDM) for accommodation of multiple users in same bandwidth concurrently. The multiple access mechanism is provided by transferring subsets of sub carriers' individually. This helps in low data rate transmission from multiple antennas simultaneously (Hara and Parsad, 1997; Haas and Belfiore, 1994).

Alamouti's codes are the most commonly used Space Time Block Codes (STBC) in OFDMA systems as they offer diversity gain (Alamouti, 1998). In this scheme, two consecutive symbols are to be transmitted in first symbol interval and their complex conjugate with or without sign change is transmit in next symbol interval. OFDMA offers orthogonal multiplexing among users which eliminates the Multi User Interference (MUI) (Yin and Alamouti, 2007). The interference in OFDMA is produced due to realistic orthogonally loss such as Doppler shift, long path delay, etc. Therefore, Multi User Detection (MUD) is needed at OFDMA receiver for the detection of multiuser data (Li et al., 2002).

The multiuser receivers are of two types. The first type is optimal and second is suboptimal. The suboptimal receivers are realistic as compare to optimal receivers as they are easily understandable due to low complexity. One of the famous suboptimal receivers is Minimum Mean Square Error (MMSE) which is designed to minimize the Mean Square Error (MSE) of filter coefficients. Batch-processed MMSE multiuser receivers have been proposed in (Seo et al., 2010) MCCDMA systems. The batch processing receivers require the estimation of the inverse autocorrelation matrix of received signal. This inverse auto correlation matrix is very frequently altered due to channel conditions. Due to immediate change with channel conditions such receivers should be implemented by using adaptive algorithms. Therefore, it is recommended to implement the receiver adaptively.

Many researchers focused different adaptive algorithms like Least Mean Square (LMS) and Recursive Least Square (RLS) algorithm in order to perform MUD and channel estimation in multi-user systems. The limitation of such algorithms is that they have slow convergence rate due to sequential search mechanism (Qing and Kim, 2012). This can be seen by the study of Bangwon in which slow convergence of LMS based MC-CDMA receiver can be observed even after improved cost function (Umair et al., 2013).

Zahedi proposed GA for MUD in DS-CDMA system in order to improve convergence rate and BER which is based on GA (Zahedi and Bakshi, 2013). However, the further improvement is possible in BER and convergence rate. The swarm optimization algorithms like Particle Swarm Optimization (PSO) have attractive convergence rate as compare to evolutionary methods and classical algorithms

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(Kennedy and Eberhart, 2001; Bonabeau and Dorigo, 1999). Such algorithms give good performance at cost of high complexity. Zarif studied GA for resource allocation in OFDMA systems (El-Zarif and Awad, 2012). Similarly, GA is studied with multi objective functions for OFDMA systems in (Sharma and Anapalagan, 2014). The GA is adopted for MUD in MC-CDMA system by using single objective function (Seo et al., 2010).

The drawback of GA is that it needs generations of chromosomes in order to move towards the solution by using only local intelligence. Similarly, the PSO adopts swarm behavior in order to give optimum solution by using global intelligence. The idea is that local intelligence can be improved up to an extent with average velocity factor such that the algorithm gives better results as compare to conventional intelligence mechanism.

Initially, prey hunting a natural phenomenon of Piranha Fish is kept in view. The habitat of Piranha fish showed that it is only found in North American Sea. The Piranha Fish moves towards its prey in swarm by focusing its local sea. Thus, it is similar to local intelligence behavior of GA where there is the population of chromosomes as fish in swarms. The whole Piranha swarm swims towards prey for hunt with high velocity. The fish in swarm which can be a gene of any chromosome in GA that moves closer to the solution is a signal for the whole swarm about prey. The whole swarm starts movement in that direction and vice versa. This property of Piranha Fish can improve the local intelligence of conventional Genetic Algorithm. When the Piranha swarm reaches its prey, the velocity of swarm is slowed down. The swarm starts rotating around the prey for eating it. Finally, the prey is hunted by Piranha swarm. The algorithm is developed using above concept is named as Piranha Fish Optimization (PFO). Secondly, the opposite learning concept is also used for PFO. This algorithm is named as Opposite Piranha Fish Algorithm (OPFO). Both PFO and OPFO are used for MUD in OFDMA receiver.

In this paper, PFO and OPFO are used on OFDMA receiver for Multi User Detection (MUD). It is seen that PFO and OPFO gives better results as compare to conventional GA based OFDMA system.

The rest of the paper is organized as follow: section 2 explains the proposed PFO and OPFO, section 3 presents the OFDMA system model, section 4 derives the cost function which is followed by the simulation results in section 5 and section 6 gives the final conclusion. The references are furnished in the end.

2. System model

The Fig. 1 represents an Orthogonal Frequency Division Multiple Access (OFDMA) system. The K active transmitters (TX) use Space Frequency Block Codes (SFBC) to transmit simultaneous signals to the receiver (RX) over the frequency selective fading channels [14, 15] with L_m taps. Using the Alamouti's coding each block of data symbols of user $k \in \{1,2,\cdots,K\}$ is space frequency encoded using the following encoding matrix (Eq. 1).

$$X^k[q] = \begin{bmatrix} X_1^{(k)}[q] & X_2^{(k)}[q] \\ -X_2^{(k)*}[q] & X_1^{(k)}[q] \end{bmatrix} \tag{1}$$

Where, q is the frequency such that $q\epsilon\{0,1,\cdots,Q-1\}$; $X_n^{(k)}[q]\epsilon C$ are the transmit symbols from antenna $n \in [1,2]$ of user k at time slot $t\epsilon[1,2]$; $(.)^*$ denotes the complex conjugation operation; C is the signal constellation. The coding rule in (1) is explained for user k as follows:

The Fig. 2 represents the OFDMA transmitter structure. At time slot $t = 1$, the first antenna transmits $X_1^{(k)}[q]$ while the second antenna transmits $X_2^{(k)}[q]$. At the next time slot $t = 2$, the first antenna transmits $-X_2^{(k)*}[q]$ while the second antenna transmits $X_1^{(k)}[q]$. Next, the inverse fast Fourier transform (IFFT) is applied to convert each Q length block of symbols into the time domain and the last C symbol are copied and appended in front of each block as the cyclic prefix. The length of the OFDM symbol is thus $(Q + C)T_s$, where, T_s is sampling interval which also means the symbol duration for the symbol-spaced signals considered in this paper. The transmitted signals from the nth antenna of user k at time t on lth tap is given by (Eq. 2):

$$x_{n,t}^{(k)}[l] = \sum_{q=0}^{Q-1} X_{n,t}^{(k)}[q] e^{\frac{j2\pi q(1-C)}{Q}} \tag{2}$$

The Fig. 3 represents the OFDMA receiver structure. The receiver is assumed to have M antennas, which forms a $2 \times M$ multiple input multiple output (MIMO) channel between each transmitter and receiver. It is also assumed that antenna elements are spaced larger enough such that fading are spatially uncorrelated at the base station antenna array. The multipath channels $h_{mn,t}^{(k)}[q]$ between the transmitter antenna n of user k and receiver antenna m can be described by B resolvable multipath components $b = 0,1,\cdots,B-1$, which can be expressed for the case of symbol-spaced signal under quasi-static condition as (Eq. 3):

$$h_{mn,t}^{(k)}[l] = \sum_{b=0}^{B-1} \gamma_{mn}^{(k)}[b]\delta[1-b] \tag{3}$$

where, $h_{mn,t}^{(k)}[l]$ is lth tap of the channel impulse response from nth transmit antenna to mth receiver antenna at time t for user k, $\gamma_{mn}^{(k)}[b]$ is channel coefficient from nth transmit antenna to mth receiver antenna. $\delta[1-b]$ represents the delay function. Then, the received signals on receiver antenna m at time t can be written as Eq. 4:

$$y_{m,t}[l] = \sum_{k=1}^{K} \sum_{n=1}^{2} \sum_{b=0}^{B-1} \gamma_{mn}^{(k)}[b] x_{n,t}^{(k)}[l-b] + g_{m,t}[l] \tag{4}$$

where, the path index b can also be interpreted as the channel delay in units of symbol intervals; $g_{m,t}[l]$ are the local complex Gaussian noise samples on antenna m at time t on lth tap, which are assumed to be independent and identically distributed (i.d.d) with zero mean and variance δ_g^2 .

At base station, after discarding the cyclic prefix (assumed larger than the maximum channel delay spread) and performing FFT the modulated signals in the frequency domain are given by (Eq. 5):

$$y_{m,t}[l] = \sum_{k=1}^{K}\sum_{n=1}^{2} X_{n,t}^{(k)}[q]\mathbf{H}_{mn}^{(k)}[q] + g_{m,t}[q] \quad (5)$$

Where, $\mathbf{H}_{mn}^{(k)}[q]$ are the channel frequency response from the nth transmit antenna of user k to the mth receive antenna during time slot $t\epsilon\{1,2\}$. Further (Eq. 6 and 7),

$$\mathbf{h}_{mn}^{(k)} = [\gamma_{mn}^{(k)}[0] \quad \gamma_{mn}^{(k)}[1] \quad \dots \quad \gamma_{mn}^{(k)}[b-1]]^{H} \quad (6)$$

$$\mathbf{e}_{Q}^{qb} = \left[1 \quad e^{\frac{-j2\pi q}{Q}} \quad \dots \quad e^{\frac{-j2\pi q(B-1)}{Q}}\right]^{H} \quad (7)$$

Where, $(.)^{T}$ and $(.)^{H}$ represents the vector/ matrix transpose and the Hermitian operation, respectively. $\mathbf{h}_{mn}^{k}$ is the channel response from mth transmit antenna to nth transmit antenna for user k. For the tolerable leakage, the channel frequency response $\mathbf{H}_{mn}^{(k)}[q]$ can be given by

$$\mathbf{H}_{mn}^{(k)}[q] = \sum_{b=0}^{B-1}\gamma_{mn}^{(k)}[b]e^{\frac{-j2\pi qb}{Q}} \quad (8)$$

$$\mathbf{H}_{mn}^{(k)}[q] = \mathbf{h}_{mn}^{(k)H}e_{q.b}^{Q} \quad (9)$$

The received signals $y_{m,t}[q]$ are then parallel-to-serial (P/S) converted into two streams $y_{m,1}[l]$ and $y_{m,2}[l]$. Then, the complex conjugation is applied to $y_{m,1}[q]$ and $y_{m,2}[q]$ as shown in Fig. 3.

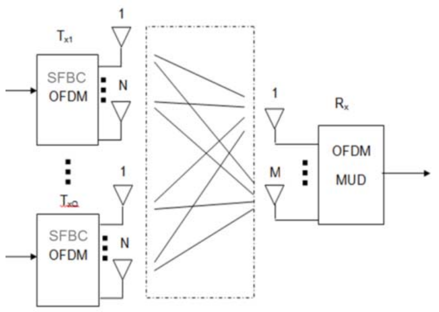

Fig. 1: OFDMA System Model

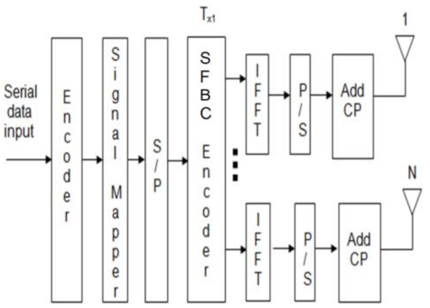

Fig. 2: OFDMA Transmitter

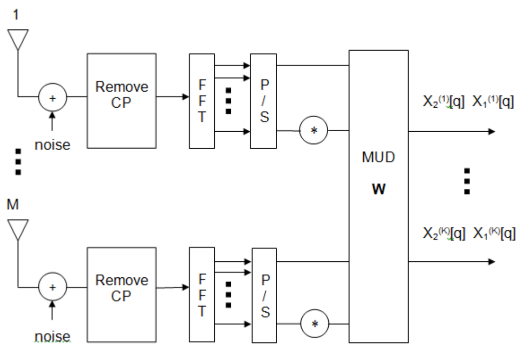

Fig. 3: OFDMA Receiver

3. Cost function

The configuration by attempting to rewrite (1) into the vector form Eq. 10 and similarly, the transmitted, received signal and noise vectors are (Eqs. 10, 11, 12 and 13):

$$\mathrm{h}_{1n}^{(k)} = [H_{1n}^{(k)} \quad H_{2n}^{(k)} \quad \dots \quad H_{mn}^{(k)}] \quad (10)$$

$$\mathrm{x}^{k}[q] = \left[X_{1}^{(k)}[q] \quad X_{2}^{(k)}[q]\right]^{T} \quad (11)$$

$$\mathrm{y}_{t}[q] = [Y_{1,t}[q] \quad Y_{2,t}[q] \quad \dots \quad Y_{m,t}[q]]^{T} \quad (12)$$

and

$$\mathrm{g}_{t}[q] = [G_{1,t}[q] \quad G_{2,t}[q] \quad \dots \quad G_{m,t}[q]]^{T} \quad (13)$$

Then, the stack $\mathrm{y}_{t}[q]$, $\mathrm{g}_{t}[q]$ and $\mathrm{H}^{K}[q]$ is given by such that $t \in [1,2]$ (Eqs. 14, 15 and 16).

$$y[q] = [y_{1}^{T}[q] \quad y_{2}^{H}[q]]^{T} \quad (14)$$

$$\mathrm{g}[q] = [g_{1}^{T}[q] \quad g_{2}^{H}[q]]^{T} \quad (15)$$

and

$$\mathrm{H}^{K}[q] = \begin{bmatrix} h_{1}^{(k)} & h_{2}^{(k)} \\ h_{2}^{(k)*} & h_{1}^{(k)} \end{bmatrix} \quad (16)$$

The input signal vector $\mathbf{x}$[k] and the known channel matrix H[k] can be re-written as (Eqs. 17 and 18):

$$\mathrm{x}[q] = [x^{(1)T}[q] \quad x^{(2)T}[q] \quad \dots \quad x^{(K)T}[q]]^{T} \quad (17)$$

$$\mathrm{H}[q] = [H^{(1)T}[q] \quad H^{(2)T}[q] \quad \dots \quad H^{(K)}[q]] \quad (18)$$

Now, the Eq. 5 can be conveniently expressed in the vector form using Eqs.13, 14, I5 and 16 as (Eq. 19):

$$\mathrm{y}[q] = \mathrm{H}[q]\mathrm{x}[q] + \mathrm{g}[q] \quad (19)$$

Since, the carrier index q is common, so (Eq. 20):

$$\mathrm{y} = \mathrm{Hx} + \mathrm{g} \quad (20)$$

Now, defining the linear combining weight matrix used to decouple user's transmitted signals $\mathrm{x}^{K}[q]$ as (Eq. 21):

$$\mathrm{W} = [W^{(1)} \quad W^{(2)} \quad \dots \quad W^{(F)}] \quad (21)$$

Where, F is total number of particles which forms a population, and $W^{(f)} = \left[w_{1}^{(f)} \quad w_{2}^{(f)}\right]$.

Now, w_{1}^{f} and w_{2}^{f} are the two vectors used to decouple the desirably transmitted symbols $X_{1}^{(k)}$ and $X_{2}^{(k)}$. The Minimum Mean Square Error (MMSE) solutions for the detector are defined as (Eqs. 22 and 23):

$$J_{1}(w_{1}) = \arg \min_{w_{1}^{(f)}} E\left\{\left|X_{1}^{(k)} - w_{1}^{(f)H}y\right|^{2}\right\} \quad (22)$$

$$J_{2}(w_{2}) = \arg \min_{w_{2}^{(f)}} E\left\{\left|X_{2}^{(k)} - w_{2}^{(f)H}y\right|^{2}\right\} \quad (23)$$

The MMSE receiver can also be written as (Eq. 24),

$$J(w_{1}, w_{2}) = \arg \min_{w_{1}, w_{2}} J_{1}(w_{1}, w_{2}) = \min_{w_{1}} J_{1}(w_{1}) + \min_{w_{2}} J_{2}(w_{2}) \quad (24)$$

Specifically, for the user of interest k, the estimate $\widetilde{X_{1}^{(k)}}$ and $\widetilde{X_{2}^{(k)}}$ is decided as (Eqs. 25 and 26):

$$\widetilde{X_{1}^{(k)}} = sgn\left[w_{1}^{(f)H}y\right] \quad (25)$$

$$\widetilde{X_{2}^{(k)}} = sgn\left[w_{2}^{(f)H}y\right] \quad (26)$$

It is needed to compute $W^{(f)}$ using some algorithm with good computation properties due to its varying behavior. The $W^{(f)}$ is computed using proposed PFO and OPFO algorithms. The detail of these algorithms is given below in section 4.

4. Piranha fish optimization

In Piranha Fish Optimization (PFO), the concept of swarm velocity is taken in to consideration. As discussed in introduction, its two variants are proposed. Firstly, PFO is proposed without opposite learning concept. Later, the opposite learning concept based PFO is proposed named as Opposite Piranha Fish Optimization (OPFO) (Table 1).

Table 1: Algorithm of piranha fish optimization without opposition learning and with opposition learning

1	Start
2	Initiate all K particle population in the swarm randomly with binary strings in search space.
3	Initiate each position velocity in a particle for whole population.
4	Initiate the current positions of particles from particle personal best positions.
5	Compute the fitness of each particle by fitness function given in (9).
6	Repeat until convergence or maximum number of iterations a) Select the best parents and calculate the children using cross over. b) Update the fitness of each particle i using the current position of the particle and the fitness function. c) Update individual's best position of every particle. d) Update the local superlative particle location. e) Update the velocity vector for each particle as follows: $v_{im}(n) = v_{im}(n) \mp \Phi_1 \underbrace{\left(p_{im} - x_{im}(n-1)\right)}_{Local\ Intelligence}$ where, $v_{im}(n)$ is the velocity of mth position of ith particle in nth iteration. x_{im} is the mth position of ith particle. p_{im} is the local best of ith particle. Φ_1 weights for local intelligence. f) Apply the bounds on velocity vectors as follows if $(v_{im} > v_{max}) then\ v_{im} = v_{max}$ if $(v_{im} < -v_{max}) then\ v_{im} = -v_{max}$ where, v_{max} is constant representing the maximum velocity. g) Calculate mutation operator of each particle $M(i) = \frac{\sum_{j=1}^{K} v_{ij}}{K}$ h) Mutation Process: Update value of all the particles as follows $x_{im}(n+1) = x_{im}(n) - M(i) * rand()$ i) Calculate the fitness of the mutated population j) Update the population
7	Stop

In PFO, the particle swarm is supposed to be a fish swarm that moves towards solution with fast velocity from start. The detail of PFO is shown below in Table 1.

The 5e is helpful in moving the whole swarm with the same velocity towards prey as it averages the velocity. The particles values are changed in PFO at index 5h. The PFO flow chart is explained in Fig. 4 encircled as 1.

Secondly, OPFO works by initiating a population of opposite particles as well. After initialization and fitness calculation of K particles, the lower bound and upper bound of population is calculated as shown in Fig. 4 encircled as 2. Afterwards, the Opposite Population (OP) is computed for these K particles. So, the best parents are selected from both of these populations.

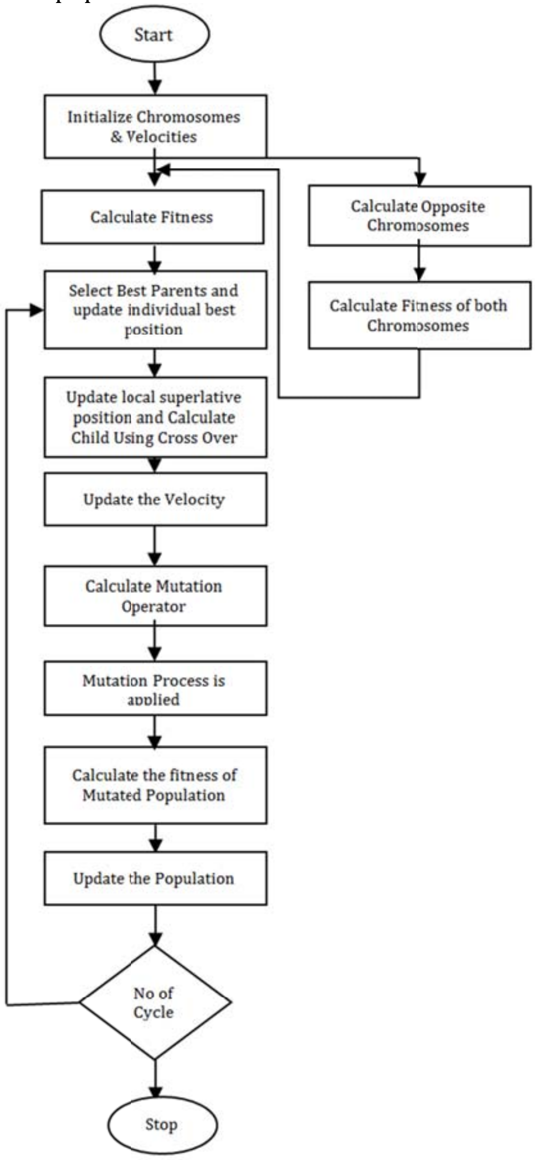

Fig. 4: Flow Chart of Piranha Fish Optimization (PFO) and Opposite Piranha Fish Optimization (OPFO)

5. Results

We implemented uplink OFDMA system with M=32 subcarriers. The number of subcarriers is equal to spreading code length. The spreading code real and imaginary parts are selected using the Walsh-Hadamard codes from 1 and - 1 independently at random. We implemented Rayleigh flat fading with four paths. The power of each tap from path 1 to path 4 is [0.217 0.173 0.304 0.086]. The channel coefficients are fixed along spreading codes in all cycles. The Fig. 5 to 10 represents performance of proposed PFO and OPFO with comparison to conventional GA based OFDMA system.

The Fig. 5 presents Mean Square Error Vs Number of Cycles of proposed Piranha Fish Optimization (PFO) and Genetic Algorithm (GA) based OFDMA systems. It can be seen due to included velocity factor of swarm the convergence rate of PFO is very fast as compare to conventional GA based OFDMA system. The PFO approaches the BER of 10-3 at almost 500th cycle which is far better than conventional GA.

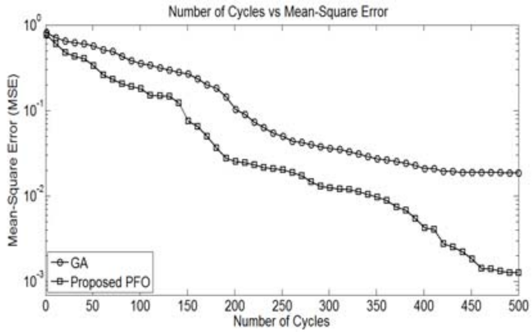

Fig. 5: Mean Square Error (MSE) Vs Number of Cycles (NOC) of proposed PFO and GA based OFDMA systems

The Fig. 6 presents Mean Square Error Vs Number of Cycles of proposed Opposite Piranha Fish Optimization (OPFO) and Genetic Algorithm (GA) based OFDMA systems. It can be seen due to included opposite learning factor; the convergence rate of OPFO is very fast as compare to conventional GA based OFDMA system. The PFO approaches the BER of 10-3 at almost 400th cycle which is far better than conventional GA.

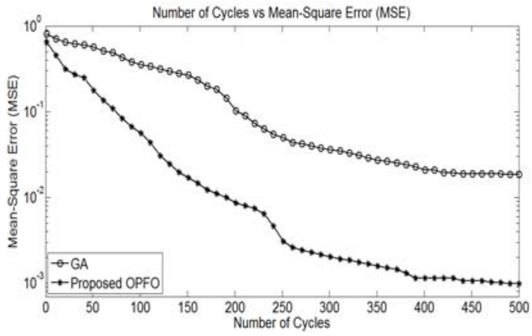

Fig. 6 Mean Square Error (MSE) Vs Number of Cycles (NOC) of proposed OPFO and GA based OFDMA systems

The Fig. 7 presents Mean Square Error Vs Number of Cycles of proposed Piranha Fish Optimization (PFO), Opposite Piranha Fish Optimization (OPFO) and Genetic Algorithm (GA) based OFDMA systems. It can be seen due to included opposite learning and velocity factor; the convergence rate of OPFO is very fast as compare to proposed PFO and conventional GA based OFDMA system. The OPFO approaches the BER of 10-3 at almost 400th cycle which is far better than other schemes. Moreover, the PFO also performed well as compare to conventional GA based OFDMA system.

The Fig. 8 presents Bit Error Rate (BER) Vs Signal to Noise Ratio (SNR) of proposed Piranha Fish Optimization (PFO) and Genetic Algorithm (GA) based OFDMA systems. It can be seen due to included velocity factor of swarm the PFO gives attractive BER as compare to conventional GA based OFDMA system. The PFO approaches the BER of 10-3 at almost SNR 25 dB which is far better than conventional GA. The PFO keep minimizing BER even after 25dB. However GA not approached BER 10-2 even at SNR = 25 dB.

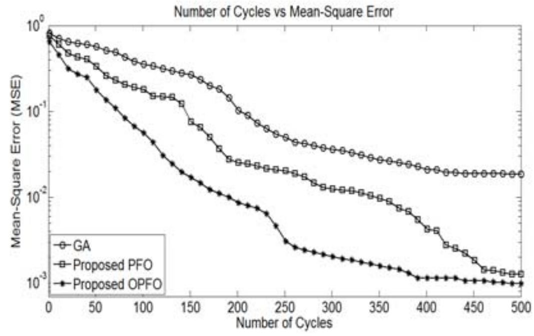

Fig. 7 Mean Square Error (MSE) Vs Number of Cycles (NOC) of proposed PFO, OPFO and GA based OFDMA systems

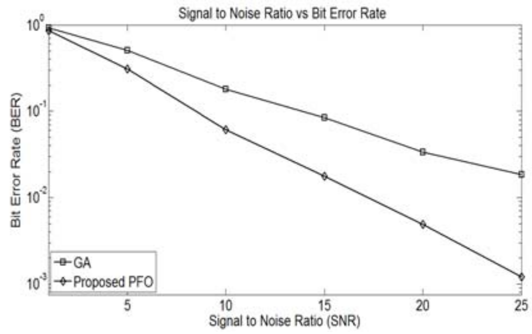

Fig. 8 Bit Error Rate (BER) Vs Signal to Noise Ratio (SNR) of proposed PFO and GA based OFDMA systems

The Fig. 9 presents Bit Error Rate (BER) Vs Signal to Noise Ratio (SNR) of proposed Opposite Piranha Fish Optimization (OPFO) and Genetic Algorithm (GA) based OFDMA systems. It can be seen due to included opposite learning and velocity factor of swarm the OPFO gives attractive BER as compare to conventional GA based OFDMA system. The OPFO approaches the BER of 10-3 at almost SNR 25 dB which is far better than conventional GA. The OPFO keep minimizing BER even after 25dB. However, GA not approached BER 10-2 even at SNR = 25 dB.

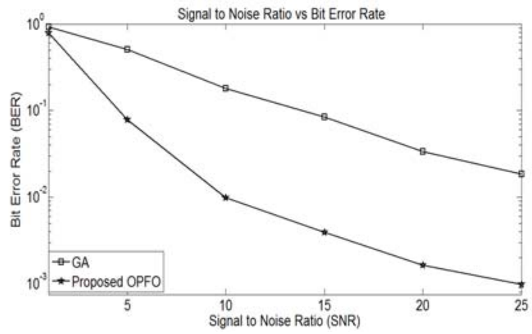

Fig.9 Bit Error Rate (BER) Vs Signal to Noise Ratio (SNR) of proposed OPFO and GA based OFDMA systems

The Fig. 10 presents Bit Error Rate (BER) Vs Signal to Noise Ratio (SNR) of proposed Piranha Fish

Optimization (PFO), Opposite Piranha Fish Optimization (OPFO) and Genetic Algorithm (GA) based OFDMA systems. It can be seen due to included opposite learning and velocity factor of swarm the OPFO gives attractive BER as compare to conventional GA based OFDMA system. Moreover, the graph of OPFO converges faster as compare to other schemes. The PFO and OPFO approach the BER of 10-3 at almost SNR 25 dB which is far better than conventional GA. The PFO and OPFO keep minimizing BER even after 25dB. However, GA not approached BER 10-2 even at SNR = 25 dB.

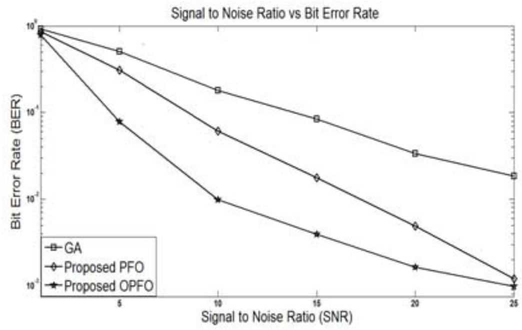

Fig. 10: Bit Error Rate (BER) Vs Signal to Noise Ratio (SNR) of proposed PFO, OPFO and GA based OFDMA based OFDMA systems

6. Conclusion

In this paper, we tried to improve the MUD operation of OFDMA system with proposed Piranha Fish Optimization (PFO) and Opposite Piranha Fish Optimization (OPFO) on the basis of local intelligence with averaging velocity factor. The results are compared with conventional local intelligence based Genetic Algorithm (GA) based OFDMA system. It is seen that both PFO and OPFO gives attractive results in terms of convergence rate and Bit Error Rate (BER) as compare to GA. However, OPFO is exceptionally well.

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