Optimal Design of Band Pass FIR Digital Filter Using Predator Prey Optimization Technique

Navnoor Brar[1], Balraj Singh[2]
[1, 2]Department of Electronics and Communication Engineering (ECE),
Giani Zail Singh Campus College of Engineering and Technology, Bathinda-151001, Punjab (India)

ABSTRACT
This paper demonstrates the nature inspired optimization technique known as predator prey optimization (PPO) in order to design an optimal band-pass FIR digital filter. PPO technique being a stochastic optimization procedure, avoids confined stagnation (that occurs in case of PSO) as preys play the role of diversification to look for optimum solution due to predator's fear. In this paper, performance of PPO has been compared with PSO. Parameters of both the algorithms such as acceleration constants, weighting function, and population size have been varied in order to optimize the value of objective function. A comparison of these two techniques has been done on the basis of obtained values of objective function of the designed filter.

Keywords *– Band-Pass FIR digital filter, Magnitude and ripple errors, Magnitude and Phase response, Predator Prey Optimization.*

1. INTRODUCTION

The field of science and technology is filled with signals such as voltages generated by the brain and heart, images from the remote space probes and numerous other applications. Signal processing is a technology with the aim of encompasses the fundamental theory, algorithms, applications and implementations of processing information contained in various different figurative, physical or conceptual formats generally nominated as signals [7].

Digital Signal Processing (DSP) is the mathematical handling of data and signals in discrete time signals. Because of its good performance, more flexibility, lesser equipment production cost, better time response and environment stability, it turn out to be a popular application in electronics engineering. DSP has ample variety of applications in the field of wireless communication, pattern recognition, image processing, speech processing etc. The main component in DSP that helps in performing all the basic functions like filtering, adding or separating signals is the digital filter [10]. A digital filter is a structure with the purpose to perform numerical operations on a sampled, discrete-time signal in order to enhance or to reduce certain aspects of that signal. Digital filters are classified as FIR and IIR.

FIR filters are digital filters that have finite impulse response. If a single impulse is available at the input and all succeeding input's are zero then the output of FIR filter also turn out to be zero after finite time. It happens because its present response depends only on input and shows no dependence on past values of input and output. Thus, it is termed as non-recursive filter. IIR filters are recursive type of filters as feedback connection is present from output side to input side. As IIR filter operates on current and past input values as well as current and past output values so its impulse response never reaches zero and is an infinite response [12]. FIR filters have several advantages over IIR filters such as: (1) FIR filters are always stable (2) Round off noise errors are minimum (3) Linear Phase Response (4) Finite impulse response. Along with advantages, it has some shortcoming too such as: (1) in order to implement FIR filters, it is required to use complex computational techniques (2)

Optimization is the method to modify the inputs or characteristics of a device. It is desirable to lessen the cost of production or to raise the efficiency of production. It is a process which is executed by comparing various values or solutions until an optimum solution is obtained. Therefore, to design band pass FIR digital filter, various optimization techniques have been developed. Optimization techniques are classified into two categories: (1) Classical optimization techniques (2) Nature inspired optimization techniques. Direct search method and gradient method comes under the category of classical optimization whereas Differential Evolution (DE), Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Predator Prey Optimization fall under nature inspired optimization techniques [4].

The Gradient optimization method is not appropriate for the discontinuous functions and for the functions in which derivatives do not exist. This is the main disadvantage of gradient method. Though, in Direct search method, only the values of objective function are used to realize the search strategy for locating the least point and these methods doesn't use any derivative of the objective function. So, the direct search method is appropriate only for finding the local solution. This method is not applicable to find the global optimum point. The nature inspired methods have grown to be more popular due to number of advantages. These are globally robust and preserve many solutions in single run [11].

Dr. Russell Eberhart and Dr. James Kennedy presented Particle Swarm Optimization in 1995. It is a population based technique which is inspired from social behavior of bird flocking or fish schooling. PSO is a robust optimization technique which is based on the movement and intelligence of swarms. It makes use of number of particles that makes up a swarm that moves around in the search space looking for the best solution. Each particle is treated as a point in N-dimensional search space that adjusts its speed according to its own flying experience in addition to the flying experience of other particles [1]. PSO has incomparable advantages in precision and searching speed. Even though, it has some shortcoming as well i.e. convergence behaviour of PSO depends upon its parameters. If the parameters of PSO are chosen wrongly then it may result in divergent particle trajectories that cause trapping into local minimum value. The premature convergence problem may suffer when PSO is applied to high-dimensional optimization problem that results in low optimization precision or sometimes even failure.

Thus, in order to improve the performance of PSO, Silva *et al*. has developed the predator prey model [2]. It introduces divergence in the swarm position at any moment throughout the run of the algorithm, that doesn't depend on the level of convergence that has been already achieved. Silva *et al.* and Higashitani *et al.* [5] have developed the predator-prey optimization (PPO) method and compared with PSO method. They concluded that PPO performed appreciably better than the standard PSO while applying on benchmark multimodal functions. In PPO technique, due to the fear of predator(s), preys play the role of diversification in the search of optimum solution and hence avoid local stagnation. PPO method is highly advantageous to clustering as keeping the particles moving is very essential because a good point obtained at present, may not be good afterwards [9].

The objective of this paper is (1) to design the FIR band-pass digital filter using PPO technique, so that it randomly explores the search space globally as well as locally (2) to reduce the value of magnitude error in pass band as well as stop band (3) to minimize the value of ripple error in pass band (4) to check the robustness of the designed filter. Constraints are taken care of by applying exterior penalty method.

This paper has been arranged in five sections. Section II describes the problem formulation of band-pass FIR digital filter. Section III presents a brief summary of proposed PPO algorithm. Section IV describes the simulation results that have been achieved by evaluating proposed PPO algorithm and these results have been compared with the design results of PSO. Finally, in section V, the conclusions have been discussed.

2. PROBLEM FORMULATION OF FIR DIGITAL FILTER

The FIR filter is a digital filter with finite impulse response. They are also known as non-recursive digital filters as they do not have feedback from output back to input. FIR filters are implemented using a transversal filter. The transversal filter is also known as a tapped delay line filter. It consists of three basic elements: unit delay element, multiplier and adder. The difference equation of FIR filter is given below:

$$y(n) = \sum_{k=0}^{M-1} a_k x(n-k) \qquad (2.1)$$

where a_k is the set of filter coefficients. The output y(n) is the function of only input signal x(n). M is the order of filter. FIR filter specifications include the maximum tolerable pass band ripple, maximum tolerable stop band ripple, pass band edge frequency and stop band edge frequency. The difference equation can be expanded as:

$$y(n) = a_0 x(n) + .. + a_{M-1}(x - M + 1) \qquad (2.2)$$

The transfer function of FIR filter is given as:

$$H(z) = \sum_{k=0}^{M-1} a_k z^{-k} \qquad (2.3)$$

The unit sample response of FIR system is identical to the coefficients (a_k), that is

$$h(n) = \begin{cases} a_n & 0 \le n \le M-1 \\ 0 & otherwise \end{cases} \qquad (2.4)$$

FIR filters have symmetric and anti-symmetric properties, which are related to their h(n) under symmetric and asymmetric conditions as described below by equations:

$h(n) = h(N-1-n)$ for symmetric (2.5)

$h(n) = -h(N-1-n)$ for asymmetric (2.6)

For such a system the number of multiplications is reduced from N to N/2 for N even and to (N-1)/2 for odd.

Errors: The FIR filter is designed by optimizing the coefficients in such a way that the approximation error function in Lp-norm for magnitude is to be kept minimal. The magnitude response is specified at K equally spaced discrete frequency points in pass band and stop band.

$$e_1(x) = \sum_{i=0}^{K} \left| H_d(\omega_{i)} - \left| H(\omega_i, x) \right| \right| \qquad (2.7.1)$$

$$e_2(x) = \left\{ \sum_{i=0}^{K} \left(\left| H_d(\omega_i) - \left| H(\omega_i, x) \right| \right| \right)^2 \right\}^{1/2} \qquad (2.7.2)$$

where e_1 (x) is absolute error L_1-norm for magnitude response and e_2 (x) is squared error L_2-norm of magnitude response.

Desired magnitude response of FIR digital filter is:

$$H_d(\omega_i) = \begin{cases} 1, for\ \omega_i \in passband \\ 0, for\ \omega_i \in stopband \end{cases} \qquad (2.8)$$

For the design of digital FIR filters, the inclusion of stability constraints is compulsory. The ripple magnitudes of pass-band and stop-band have to be minimized which are given by $\delta_p(x)$ and $\delta_s(x)$ respectively:

$$\delta_p(x) = max_{\omega i}|H(\omega_i, x)| - min_{\omega i}|H(\omega_i, x)| \quad \ldots \ldots for\ \omega_i \varepsilon\ passband \qquad (2.9)$$

$$\delta_s(x) = max_{\omega i}|H(\omega_i, x)| \quad \ldots \ldots for\ \omega_i\ \varepsilon\ stopband \qquad (2.10)$$

Three objective functions for optimization are:

Minimize f_1 (x) = e_1 (x) (2.11.1)
Minimize f_2 (x) = e_2 (x) (2.11.2)
Minimize f_3 (x) = δ_p (x) (2.11.3)

The multi- objective function is converted to single objective function:

$$\text{Minimize } f(x) = \sum_{k=1}^{3} \omega_k f_k(x) \qquad (2.12)$$

where ω_k are the weights.

3. PREDATOR PREY OPTIMIZATION

Predator Prey Optimization (PPO) is a technique which is used for global search where as exploratory search is exploited as a local search technique. PPO technique being a stochastic optimization procedure, avoids confined stagnation as preys play the role of diversification to look for optimum solution due to the fright of predator(s). The PPO technique is usually based on PSO with added predator effect i.e. another population of particles are included that are called as predators. PSO is a population based search technique that makes use of swarm intelligence such as bird flocking, fish schooling. It uses the concept of social interaction to problem solving. Then based on its own knowledge and knowledge of neighboring particles, particles changes its location with time. Then by adding the velocity vector to the position vector of the particle, the position mechanism of the particle is updated in a search space [9].

In PPO model, predator population is included among swarm particles. Predators have different dynamic behaviour from that of swarm particles; they are attracted towards the best individuals among swarm, while the other particles are repelled by their presence. Prey particles avoid predator's attack by attaining best suited position. The influence of predator on any individual particle of the swarm is controlled by the probability fear (P_f). In this model, predator plays the role of searching around global best in a concerted manner, whereas preys travel around roughly on a solution space in order to escape from predators. It helps to avoid premature convergence to local optima. Exponential term will also be included in velocity vector in case if predator attacks the prey [9].

Evolutionary optimization techniques begin with a few initial solutions and then attempt to improve them towards some optimal solutions. The procedure of searching stops as soon as some predefined criteria are fulfilled. It is generally started with a random guesses, in case, if the former information about the solution is absent. The possibility to begin with a better solution can be improved by checking the opposite solution simultaneously. Thus, the better one (either random guess or opposite guess) can be selected as an initial solution by using opposition based learning. According to probability hypothesis, about 50% of time, a guess is farther away from the solution than its opposed guess. Thus, to begin with the closer of the two guesses (as judged by its objective function) has the potential to accelerate convergence. The same approach can be applied not only to initial solutions but also continuously to each solution in the current population.

$$x_{i+Sp,j}^{t} = x_j^{min} + x_j^{max} - x_{ij}^{t} \qquad (3.1)$$

where (j =1, 2, ……, S; i =1, 2, ……, Sp). x_j^{min} and x_j^{max} are the lower and upper limits of filter coefficients [6].

3.1 INITIALIZATION OF POSITION AND VELOCITY OF POPULATION

Prey and predator's starting positions are randomly initialized within their upper and lower limits.

$$x_{ik}^{0} = x_i^{min} + R_{ik}^{1}(x_i^{max} - x_i^{min}) \qquad (3.2)$$

$$x_{pi}^{0} = x_i^{min} + R_i^{2}(x_i^{max} - x_i^{min}) \qquad (3.3)$$

where i = 1,2…,S and k = 1,2,…….S_p.

Prey and predator's position is denoted by x_{ik}^0 and x_{pi}^0 respectively. S_p is the total prey population. x_i^{min} and x_i^{max} is the range of i^{th} decision variable. R_{ik}^1 and R_i^2 are random numbers having values within the range of 0 and 1.

After positions, velocities of prey i.e. V_{ik}^0 and predator i.e. V_{pi}^0 are randomly initialized within their predefined range.

$$V_{ik}^{0} = V_i^{min} + R_{ik}^{1} + (V_i^{max} - V_i^{min}) \quad (3.4)$$

$$V_{pi}^{0} = V_{pi}^{min} + R_i^{2} + (V_{pi}^{max} - V_{pi}^{min}) \quad (3.5)$$

where i = 1,2…,S and k = 1,2…,S_p. Minimum and maximum prey velocities are set by using the following relation:

$$V_i^{min} = -\alpha\left(x_i^{max} - x_i^{min}\right) \quad (3.6)$$

$$V_i^{max} = +\alpha\left(x_i^{max} - x_i^{min}\right) \quad (3.7)$$

where i = 1,2….,S. Minimum and maximum velocities for preys are obtained by varying the value of α. α is taken as 0.25.

3.2 PREDATOR VELOCITY AND POSITION EVALUATION

The velocity and position of predator at the end of each iteration is updated by using Equ. 3.8 and Equ. 3.9:

$$V_{P_i}^{t+1} = C_4(\mathrm{GP}best_i^t - x_{Pi}^t) \quad (i=1, 2,.,S) \quad (3.8)$$

$$x_{Pi}^{t+1} = x_{Pi}^t + V_{Pi}^{t+1} \quad (i=1, 2,.......,S) \quad (3.9)$$

where $\mathrm{GP}best_i^t$ is global best position of prey of i^{th} variable, C_4 is the random number whose value lies between 0 and its upper limit.

3.3 PREY VELOCITY AND POSITION EVALUATION

Preys velocity and position are updated at the end of each iteration by using the Equ.3.10 and Equ.3.11:

$$V_{ik}^{t+1} = \begin{cases} wV_{ik}^t + AC_1R_1(xbest_{ik}^t - x_{ik}^t) + AC_2R_2(GPbest_{ik}^t - x_{ik}^t) & ;P_f \le P_f^{max} \\ wV_{ik}^t + AC_1R_1(xbest_{ik}^t - x_{ik}^t) + AC_2R_2(GPbest_{ik}^t - x_{ik}^t) + C_3 a(e^{-b_{ek}}) & ;P_f > P_f^{max} \end{cases}$$

$$\ldots. \ (i=1,2,....,S;\ k=1,2,...,S_p) \quad (3.10)$$

$$x_{ik}^{t+1} = x_{ik}^t + c_{cf}V_{ik}^{t+1} \quad (i=1,2..,S;k=1,2,.,S_p) \quad (3.11)$$

where AC_1 and AC_2 are the acceleration constants, w is inertia weight, $xbest_{ik}^t$ is local best position and $GPbest_{ik}^t$ is the global best position of prey, R_1 and R_2 are the random numbers having values between 0 and 1, C_3 is a random number lies in the range 0 and 1 and it influences the effect of predator on prey, the term $a\left(e^{-b_{ek}}\right)$ introduces the predator effect that increases exponentially. Every time predator goes closer to prey, this exponential term introduces disturbance in the prey population, constant 'a' represents the maximum amplitude of the predator effect over a prey and 'b' allows controlling the effect. The distance between predator and prey position is defined by Euclidean distance i.e. e_k for k^{th} population which is given as:

$$e_k = \sqrt{\sum_{i=1}^{S}\left(x_{ik} - x_{pi}\right)^2} \quad (3.12)$$

The inertia weight is calculated by using Equ.3.13:

$$w = [w^{max} - (w^{max} - w^{min})(t/t_{max})] \quad (3.13)$$

C_{cf} is the constrict factor and is defined by the following equation:

$$C_{cf} = \begin{cases} \left|2 - \emptyset - \sqrt{\emptyset^2 - 4\emptyset}\right| & if\ \emptyset \ge 4 \\ 1 & if\ \emptyset < 4 \end{cases} \quad (3.14)$$

The elements of prey positions x_{ik}^t and velocities V_{ik}^t may violate their limits. This violation is set by updating their values on violation either at lower or upper limits.

$$V_{ik}^t = \begin{cases} V_{ik}^t + R_3V_i^{max} & ;if\ V_{ik}^t < V_i^{min} \\ V_{ik}^t + R_3V_i^{max} & ;if\ V_{ik}^t > V_i^{max} \\ V_{ik}^t & ;no\ violation\ of\ limits \end{cases} \quad (3.15)$$

where R_3 is any uniform random number having value between 0 and 1. The process is repeated until the limits are satisfied.

Algorithm: Predator Prey Optimization

1. Initialize the parameters of PPO such as population size (Sp), acceleration constants (AC_1/AC_2), maximum and minimum limit of velocity of prey and predator, maximum probability fear (P_f^{max}) etc.
2. Initialize the prey and predator positions and velocities randomly.
3. Apply opposition based strategy.
4. Calculate objective function.
5. Select Sp best preys from total 2Sp preys.
6. Calculate the personal best position (pbest) of each prey and then select best value among all pbest values of prey and assign that pbest position to all preys.
7. Calculate global best position (gbest) among local best position of prey.
8. Update predator velocity and position by using Equ.3.8 and Equ.3.9.
9. Generate the probability fear factor between 0 and 1 randomly.
10. IF (probability fear > maximum probability fear) THEN

Update prey velocity and position with predator affect by using Equ. 3.10 and Equ. 3.11.

ELSE

Update prey velocity and position without predator affect by using Equ. 3.10 and Equ. 3.11.

ENDIF

11. Calculate objective function again for all prey population.
12. Then update local best positions of prey particles.

13. Calculate global best position of prey particles based on fitness.
14. Check stopping criteria, if not met, repeat step 8.
15. Stop.

4. SIMULATION RESULTS

In this section, FIR band-pass digital filter has been designed by using Predator Prey Optimization (PPO) technique. The main advantage of PPO technique is that due to the fear of predator(s), preys play the role of diversification in the search of optimum solution and hence avoids premature convergence.
The prescribed design conditions for band pass filter are shown below in the Table 4.1.

Table 4.1: Design conditions for band-pass FIR filter

Filter Type	Pass Band	Stop Band	Max. value of |H(w,x)|
Band Pass	$0.4\pi \leq \omega \leq 0.6\pi$	$0 \leq \omega \leq 0.25\pi$ $0.75\,\pi \leq \omega \leq \pi$	1

The PPO algorithm has been implemented by varying the filter order along with PPO parameters. At every filter order, algorithm has been run for 100 times in order to obtain the best result. MATLAB software has been used to perform simulation results for band-pass FIR digital filter. The magnitude response and phase response graphs have been plotted. The initial values of parameters that have taken for PPO algorithm are given below in Table 4.2.

Table 4.2: PPO parameters

Parameter	Value
Run	100
Iterations	100
AC_1,AC_2	2.0
W_{max}	0.4
W_{min}	0.1
Population Size	100
W_1, W_2	1.0
W_3	12
W_4	5.0
P_f	0.7
P_f^{max}	1.0
a	0.0007
b	0.007

Firstly, the filter order has to be decided. So, the filter order has been varied from 20 to 32. The achieved objective function with respect to filter order has been shown in Table 4.3.

Table 4.3: Filter Order v/s Objective Function

Sr. No.	Filter Order	Objective Function
1	20	2.019536
2	21	2.153868
3	22	2.032915
4	23	1.989793
5	24	1.972155
6	25	1.869314
7	26	2.011379
8	27	1.203096
9	28	0.85007
10	29	1.099424
11	30	9.504536
12	31	17.14684
13	32	40.2233

Figure 4.1: Filter Order versus Objective Function of band pass FIR digital filter at filter order 28

Fig. 4.1 shows the graph of objective function versus filter order of PPO. The objective function of PSO [13] is minimum at order 28 where as objective function of PPO is also minimum at filter order 28 as seen from graph. So, PPO has been compared with PSO at filter order 28 in terms objective function, pass band and stop band performance.

Table 4.4: Design results of band-pass FIR digital filter at filter order 28

Algorithm	PPO	PSO [13]
Objective function	0.850066	0.981329
Pass-band performance (ripple magnitude)	0.008975	0.009994
Stop-band performance (ripple magnitude)	0.034941	0.021230

From Table 4.4, it is observed that PPO has minimum objective function and pass-band ripple magnitude as compared to PSO at order 28 but stop-band ripple magnitude of PPO is little bit more than PSO. It proves the conflicting nature of pass band and stop band ripples i.e. if pass band ripple magnitude is low then stop band ripple magnitude comes out to be high or vice-versa. The resulting optimized coefficients are given in Table 4.5.

Table 4.5: Optimized coefficients of band pass FIR filter at order 28

Sr. No.	Coefficients	Value of coefficients
1	A(0) = A(28)	–.009731
2	A(1) = A(27)	.002818
3	A(2) = A(26)	.011427
4	A(3) = A(25)	–.001339
5	A(4) = A(24)	.016189
6	A(5) = A(23)	–.004007
7	A(6) = A(22)	–.052165
8	A(7) = A(21)	.005378
9	A(8) = A(20)	.024998
10	A(9) = A(19)	.001527
11	A(10) = A(18)	.108129
12	A(11)= A(17)	–.007336
13	A(12) = A(16)	–.282714
14	A(13) = A(15)	.004163
15	A(14)	.364435

PPO parameters like population size and acceleration constants (AC_1/AC_2) have been tuned in order to get more optimum results. So firstly, the population size of PPO algorithm has been varied in the range of 20 – 140.

Table 4.6: Population size v/s Objective function

Sr. No.	Population Size	Objective Function
1	20	0.854905
2	40	0.850066
3	60	0.850539
4	80	0.850087
5	100	0.850238
6	120	0.871079
7	140	0.927756

From the above table, it is observed that population 40 has the minimum value of objective function which is even better than population 100 that was used initially.

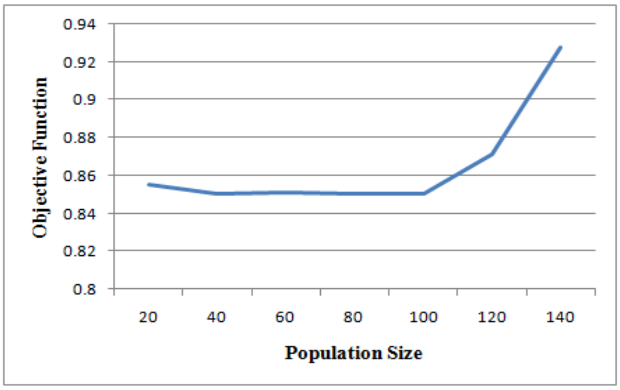

Figure 4.2: Population versus Objective Function at filter order 28

From Fig 4.2, it is seen that the value of objective function starts decreasing from population 20 and at population 40, objective function is minimum. From population 40 to 100, objective function remains almost constant. After 100, it starts increasing. Furthermore, at this population i.e. at 40, the acceleration constants i.e. AC_1 and AC_2 have been varied from 1 to 3.5.

Table 4.7: Acceleration constants v/s Objective function at order 28

Sr. No.	Acceleration Constants (AC_1/AC_2)	Objective Function
1	1.0	0.924233
2	1.5	0.876162
3	2.0	0.850066
4	2.5	0.85021
5	3.0	0.854645
6	3.5	0.867404

From Fig 4.3, it is observed that the value of acceleration constants that yields the best results is 2.0.

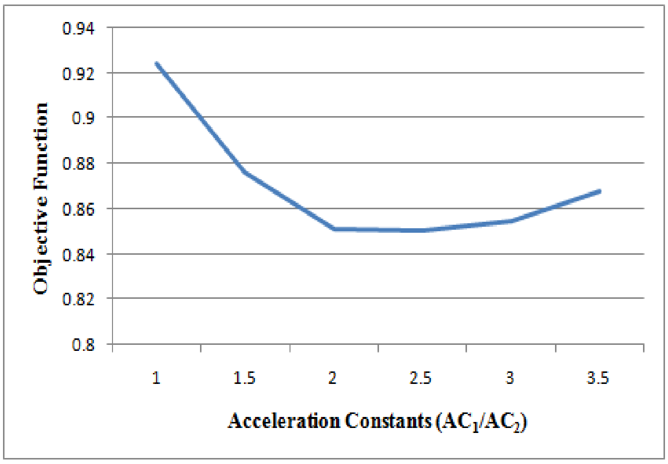

Figure 4.3: Acceleration constants versus Objective Function at filter order 28

Fig 4.4 shows the graph that how the value of objective function varies at different iterations at population size 40.

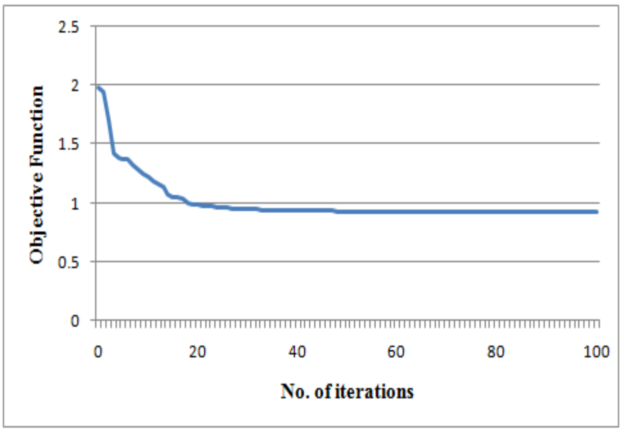

Figure 4.4: Plot of Iterations versus Objective function at order 28

After observing the results, it has been cleared that the population size has to be taken as 40 with acceleration constants (AC_1/AC_2) to be 2.0 at filter order 28. So, band pass FIR filter has been designed by using these parameters.

Table 4.8: Design results for band pass FIR digital filter at filter order 28

Objective Function	0.850066
Magnitude Error $e_1(x)$	0.506384
Magnitude Error $e_2(x)$	0.064815
Pass band ripples(δ_p)	0.008475
Stop band ripples (δ_s)	0.034941

After obtaining the best results, graph of magnitude response versus normalized frequency has been obtained at filter order 28. Fig 4.5 shows the plot for variation in magnitude response with variation in normalized frequency.

The ideal range of pass-band in band pass FIR filter varies from $0.4\pi \leq \omega \leq 0.6\pi$ and that of stop band varies from $0 \leq \omega \leq 0.25\pi$ to $0.75\pi \leq \omega \leq \pi$ which is shown respectively in Fig 4.5, 4.6 and 4.7.

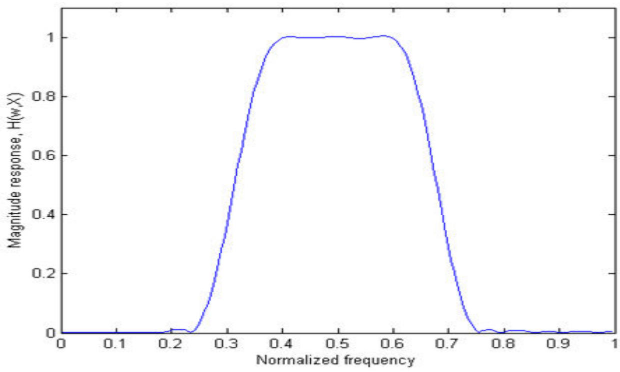

Figure 4.5: Magnitude response v/s Normalized frequency at filter order 28

Fig 4.6 shows the graph of Magnitude Response with variation in Normalized Frequency in db for Order 28 to design band pass FIR digital filter.

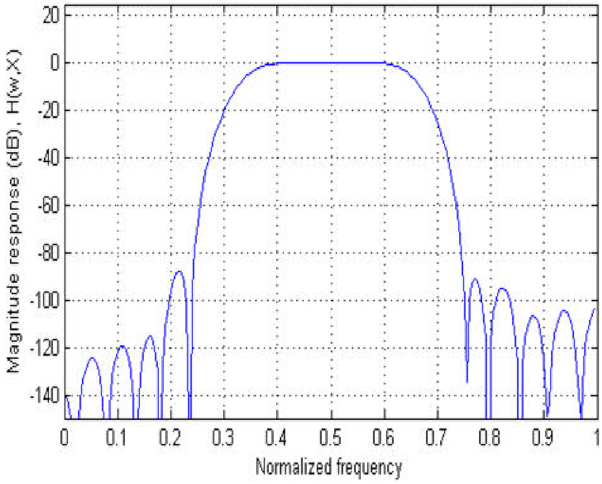

Figure 4.6: Magnitude response v/s Normalized frequency in db at filter order 28

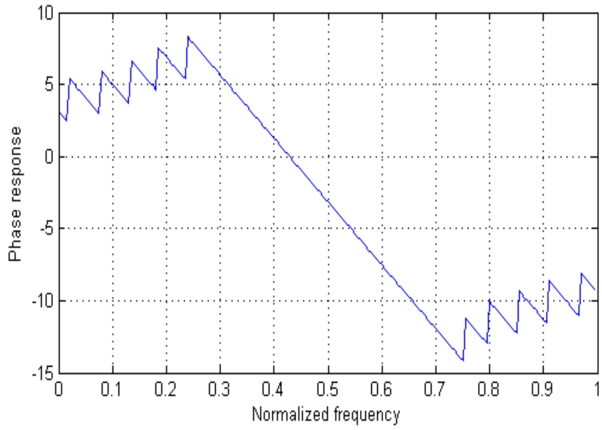

Figure 4.7: Phase response v/s Normalized frequency at filter order 28

The average and standard deviation values of filter order 28 have been calculated to be:

Table 4.9: Statistical calculation for band-pass FIR digital filter at order 28

Algorithm	PPO	PSO [13]
Maximum value of objective function	0.936724	1.244792
Minimum value of objective function	0.850066	0.981329
Average value Of objective function	0.868812	1.011679
Standard Deviation	0.019292	0.095284

From the above table, it is clear that PPO has less standard deviation as compared to PSO. Lower the value of standard deviation, more robust will be the filter.

5. CONCLUSION

This paper presents a robust and optimal method to design band pass FIR digital filter by using predator prey optimization (PPO). Firstly, the filter order has been varied from 20 - 32 and it is observed that the minimum objective function i.e.0.85007 has been achieved at filter order 28. From the simulation results, it is clear that the PPO gives better results in terms of objective function, pass band ripple magnitude and standard deviation as compared to PSO [13]. In order to get more optimum results at filter order 28, PPO parameters such as population size and acceleration constants have been varied. So, firstly population size has been varied between 20- 140 and the minimum objective function has been achieved at population 40. Then at this population i.e. at 40, acceleration constants (AC_1/AC_2) has been varied between 1.0 - 3.5 and minimum objective function has been achieved at 2.0 respectively. Thus, after parameter tuning, the value of objective function achieved to be 0.850066. The value of standard deviation obtained by choosing these parameters is 0.019292, which is less than 1 that authenticates that the band pass FIR digital filter is robust and stable. PPO technique can also be used to design band stop, low pass, high pass FIR digital filters.

REFERENCES

[1] James Kennedy and Russell Eberhart, (1995), "Particle Swarm Optimization", IEEE, vol. 4, pp. 1942-1948.
[2] A. Silva, A. Neves and E. Costa, (2002) ,"An Empirical Comparison of Particle Swarm and Predator Prey Optimization", Irish International Conference on Artificial Intelligence and Cognitive Science, vol. 24, no. 64, pp. 103-110.
[3] A. Silva, Ana Neves and Ernesto Costa, (2002), "Chasing the Swarm: a Predator Prey Approach to Function Optimization" 8th International Conference on Soft Computing, Brno, Czech Republic.
[4] K. Deb, (2005), "Optimization for Engineering Design: Algorithms and Examples", PH1 Learning, Eighth Edition.
[5] M. Higashitani, A. Ishigame and K. Yasude, (2006), "Particle Swarm Optimization Considering the Concept of Predator Prey Behavior", IEEE Congress on Evolutionary Computation, pp. 434 - 437.
[6] Shahryar Rahnamayan, Hamid R. Tizhoosh, and Magdy M. A. Salama,(2008), "Opposition-Based Differential Evolution", *IEEE Transaction on Evolutionary Computation*, vol. 12, no. 1, pp. 64-79.
[7] R.K. Johnson and F. Sahin, (2009), "Particle Swarm Opimization methods for Data Clustering", Fifth International Conference on Soft Computing, Computing with Words and Perceptions in System Analysis, Decision and Control, Famagusta.
[8] R. A. Barapate and J. S. Katre, (2012), "Digital Signal Processing", Tech-Max, 2012 Edition.
[9] Balraj Singh, J.S. Dhillon and Y.S. Brar, (2013), "Predator Prey Optimization for the Design of IIR Filter", *WSEAS Transactions on Signal Processing*, vol. 9, no. 2, pp. 51-62.
[10] John G. Proakis and Dimitris G. Manolakis, (2013), "Digital Signal Processing", Pearson, Fourth edition.
[11] Raminder Kaur and Balraj Singh, (2015s "Optimization of Control Parameters of Differential Evolution Technique for Design of Digital FIR Band Pass Filter", *International Journal of Advanced Research in Computer Science and Software Engineering,* vol. 5, no. 6, pp. 328-336.
[12] Shalika Sharma and Balraj Singh, June (2015), "Design of Digital Band Pass FIR Filter Using Heuristic Optimization Technique", *International Journal of Scientific Research Engineering and Technology,* vol. 4, no. 6, pp. 677-683.
[13] Haroon Sidhu, Darshan S. Sidhu and Balraj Singh, (2015), "Nature Inspired Optimization Technique for the Designing of Band Pass Digital FIR Filter", *International Journal of Advance Technology in Engineering and Science,* vol. 3, no. 6, pp. 159-167.