Modified Form of PSO and Its Variation in Channel Equalization

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Abstract: Novelty of PSO is the techniques of parameter improvement. Using many "strategy principles" for the PSO is important for its convergence performance and the optimisation job. In the proposed work, we applied PSO and its advanced form trained with our proposed algorithm for channel equalization. Since particle swarm optimization is matured in the literature ,we apply PSO in its optimized structure trained with radial basis function Artificial Neural Network (ANN). Therefore, this work introduces most favourable design of RBFNN equalizers using OPSO. We treat equalization problem as a classification problem. We assessed a set of fitness functions of modified form of PSO and analysed with it to the presentation of existing PSO .

Keywords: ANN,OPSO, Channel equalization.

I. INTRODUCTION

In a modern digital communication, there might be possibilities of the signal which can be corrupted by the effect of noise. Therefore for efficient transmission and reception we need an equalizer that is positioned at the front end of the receiver to recover useful information from corrupted channel samples. In the literature Artificial Neural Networks (ANN) [1-4] have seen in last few decades on equalization process. On the other hand RBFNN equalizers performs improved show [5] because of its reward like

- a simplified arrangement and need simple training process therefore it requires smaller time [6] and
- improved capability to simplify non-linear functions which is more specific [7].
- It provides a steady equalization with convergence speed [8] is superior. This is additional showed in the works of [3, 9-14].

In conventional trained RBFNN equalizer based on hit and trial method but also require more more training time..Modeling of RBFNN based equalizers using PSO in [15] . In our work, we proposed optimized form of PSO trained RBFNN equalizer.

In this work we treat equalization process as classification problem which spotted as optimization problem in the literature.. One of the advantage of PSO is that its ability and execution of multiple local optima in optimization problems. As far as global optimization is concerned PSO propositionhas been modified further considering variation of some parameter of original PSO which called as Constriction type PSO (CPSO) [16] along with a variety of others (see, e.g. [17-19] . The convergence behavior [20-22] of PSO itself contains some parameter which can be dealt with classic optimization techniques.

II. PARTICLE SWARM OPTIMIZATION (PSO):

PSO is kind of optimization technique which was first introduced by Dr. Eberhart and Dr. Kennedy in 1995.In this method which is motivated by social behaviour of bird flocking. PSO imparts many similitude's to developmental computation methods.. For example, in GA, the optimum solution can be found by initial started the structure with population with random solution by updating generations. The evolution operators in GA , of this crossover and mutation is not found in PSO. The possible results known as particles which can be fly during the problem space by subsequent the present optimum particles. The benefits of PSO over GA is that PSO easy to execute and there are hardly any limiting factors to regulate the following areas in which PSO can be successfully implemented.

- Function optimization
- Training of ANN
- Fuzzy system control

In a PSO every particle was started at a random location in search area. The location of particle i is specified with the vector $S_i = S_{i1}, S_{i2}, \ldots, S_{iD}$ and $v_i = v_{i1}, v_{i2}, \ldots, v_{iD}$ represents velocity vector .Generally the movement of the particles can be influenced because of implementation of two kind of memory i.e, $P_i = P_{i1}, P_{i2}, \ldots, P_{iD}$ shows cognitive memory which is the greatest preceding location call on with every entity particle i is in save. Now , the location of the most favourable position in search space call on by each and every one swarm particles called as "social memory" i.e, $P_{Best} = P_{Best1}, P_{Best2}, \ldots, P_{BestD}$.

So the particle velocity in each epoch were updated is

$$(t + 1) = (t) + n_1 r_1 (P_i S_i(t)) + n_2 r_2 (P_{Best} - S_i(t)) \qquad (1)$$

Here ,W is the weighting factor for the velocity ,called as the inertia weight and n_1 and n_2 constants called "cognitive" and r_1 and r_2 varies between 0 and 1.

For each epoch , a new value of W can be calculated

$$W = W_{Start} - W_{end} MaxEpochs . Epochs \qquad (2)$$

Where W_{Start} is the primary worth for W and W_{end} is the final assessment the $MaxEpochs$ which identifies as the maximum number of epochs.

Equation (3) shown below describes the positions of the particles which were updated.

$$(t + 1) = (t) + (t + 1) \qquad (3)$$

PSO with Variants:

One more frequent operation of particle swarm optimization as PSO variant which we may consided as"CPSO". The velocity vector can be evaluated as :

$$(t + 1) = ((t) + n_1 r_2 (P_i - S_i(t)) + n_2 r_2 (P_{Best} - S_i(t)) \qquad (4)$$

Here, ξ shown in equation (5) is regulates the of the particle velocity which called as the constriction ratio or dampening ratio. It has two special quality[23] i.e convergence rate is faster and another is swarm has the potential to execute extensive actions in search area So CPSO has the capable to keep away from being trapped into local optima and have the greater achievement than the standard PSO [23].

$$\xi = \frac{2}{\left|2 - \sqrt{\rho^2 - 4\rho}\right|} \qquad (5)$$

and ϕ can be determined by i.e

$$\emptyset = n_1 + n_2, \text{Generally}, \phi > 3 \qquad (6)$$

Modified form of PSO

Modified form of PSO is nothing but optimized particle swarm optimization which have classified as"superswarm" and "subswarms".

If we will go for a optimization ,Subswarms with parameters that are compatible for their presentation will get a superior fitness than the other.

We utilized the superswarm as a covering for the subswarms . We played out numerous improvement runs per subswarm and after that determined the normal of the accomplished wellness esteems to maintain a strategic distance from such conduct.

Algorithm of the OPSO

Step (i) Initialize superswarm
Step (ii) Evaluate fitness for each particle
Step (iii) Evaluate Particle dimensions or swarm parameters
Step (iv) Initialize sub swarms
Step (v) for evaluate objective function go to step (vi)
Step (vi) if condition 2 is satisfied then move to step (iv) else move to step (vii)
Step (vii) measured fitness value &go to termination condition 1

Step (viii) If termination condition 1 true then stop the process and Measured optimised swarm parameters else go to step (xi)
Step (xi) update particles & go to step (ii)

PSO parameters

We analyze the performance of the modified PSO and taking five diverse test equations i.e (7-11), and considered it to the SPSO and the CPSO algorithms. Parameters i.e, w_{start}, w_{end}, n_1, and n_2 with split up the extent of the superswarm's particles in diverse cycles need to be optimized.

Test Functions [24] :

Rastrigin:
$(S) = 10\, D + \sum_{i=1}^{D}(S_i^2 - 10.\cos(2.\pi.S_i)$
Global minimum: $(S) = 0$, $S_i = 0$.
De jongs Sphere $f(s) = \sum_{i=1}^{D} S_i^2$
Global minimum: $(S) = 0$, $S_i = 0$.
Schaffer F6:

$$(S) = 0.5 + \frac{Sin^2 \sqrt{(S_i^2 + y^2) - 0.5}}{((1 + 0.001(S_i^2 + y^2))^2)}$$

Global minimum: $(S) = 0$, $S_i = 0$

Table 1 : Swarm configurations

Parameters	Superswarm	Subswarms
Max. No. of iteration	200	1000
Number of particles	50	50
W	0.7	–
N1	4	–
N2	4	–
V_{max}	50	–

III.   RADIAL BASIS FUNCTION NEURAL NETWORKS (RBFNN):

RBFNN comprises of three different layers. The hidden units give a collection of functions that establish an discretionary basis for the input patterns. Each node of the hidden layer unit are called as radial basis centre .RBFNN transforms non linear feature vector to the linear one.Every hidden unit has its possess receptive field in input space. Target output can be obtained when an input vector posses receptive field c_j ,would activate c_j by appropriate selection of weights

Hence the output can be expressed as: $y = \sum^{h}_{j=1} \emptyset j w_j$

Where $\emptyset j = \emptyset (\|x - c_j\|)$ Gaussian function (φ_j).
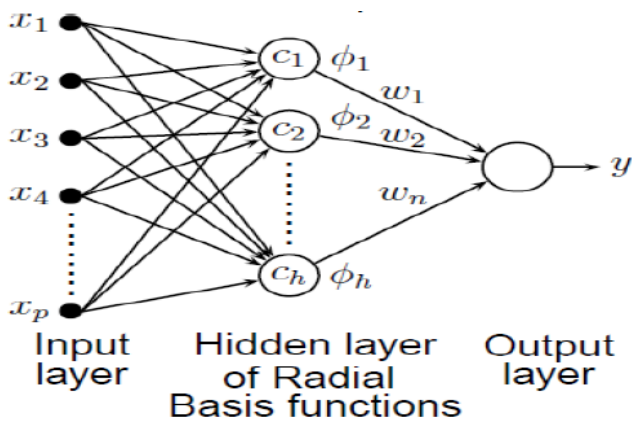
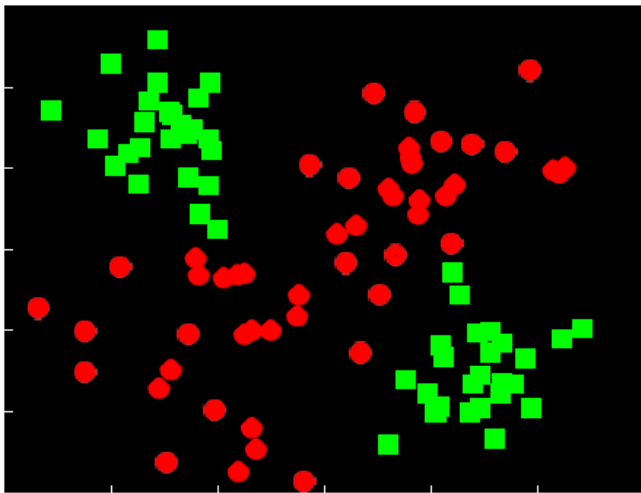**Fig 1. Network Architecture**

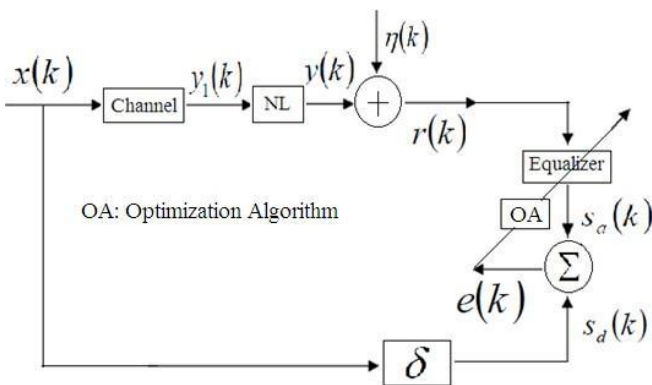**Fig 2: RBF Non-linear data classification**

IV. PROBLEM STATEMENT

Fig-3

In FIR model, sequence which is to be transmitted is binary, shown as x (k) at k^{th} time instance and corresponding output at the same instant *is* $Y_1(K)$, as

$$Y_1(K) = \sum_{i=0}^{N-1} h_i \, x(k-i) \qquad (7)$$

Here $h_i (i = 0,1,2, \ldots \ldots N-1)$ are the channel taps. 'NL' represents the nonlinearity present in the channel. In this paper, introduced non-linear function is:

$$Y(k) = F(y_1(k)) = (y_1(k) + b(y_1(k))^3 \qquad (8)$$

The channel output y(k) is added with noise η(k) inserted in channel. The signal at the receiver is r(k) and as follows
r(k) = Y(k) + η(k). (9)

Proposed Training:

In the proposed training process, OPSO plays the character as a teacher to optimize the structure. Again neural networks act as a student which teaches by OPSO. Hence ANN perform dual role.
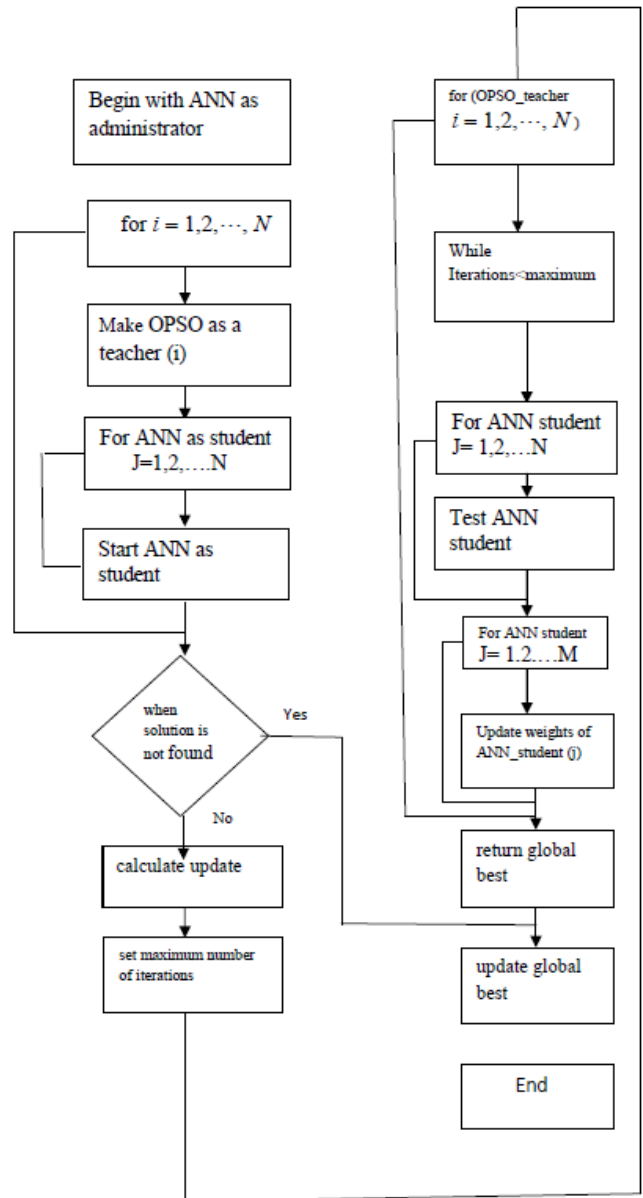

Fig-4 Proposed training algorithm flow chart:

V. RESULT AND SIMULATIONS:

Due to interference of noise and unwanted signals, the useful signals is distorted and it can be measured interms of a parameter which called as bit error rate (BER). Another parameter which can be analysed during transmission of signals is known as bit error probability (p_e) which is the expectation value of the BER. Simulations can be done by considering the parameters as shown in the above table.

Following examples showsn in this part for simulation which is intended to assessment of the presentation of the proposed equalizer.Liang & Zhi, 2004 introduced a widely used channel for simulations. The 3rd order channel model having system transfer function is:

$$Z = 1 - 0.9Z^{-1} + 0.385Z^{-2} + 0.771Z^{-3} \qquad (10)$$

In the above equations zeros at 0.6 and $0.75 \pm j0.85$.

We have chosen another following non linear channel i.e.

$$H(z) = 0.303 + 0.9029z^{-1} + 0.304z^{-2} \qquad (11)$$

To illustrate the consequence of nonlinearity on the equalizer presentation, nonlinear channel models with the following nonlinearity are added.In this work,channel noise is additive white Gussian noise with zero mean modelled in this paper. As far as assessment of recital of the equalizer is concerned, BER and MSE are the most suitable parameters.

Simulation Parameters for Proposed Equalizers

Number of Iteration	1000
Number of Particles	50
Coefficient C1	0.7
Coefficient C2	0.7

VI. COMPARISON WITH ANN BASED EQUALIZERS

In simulation point of view ANN combined equalizers in the existing system is compared with, Equalizers planned in Zhao et al. [25-27], i.e., PFLADFRNN Zhao et al.[25] ,C-PSO,S-PSO with planned equalizer to assess BER under like situations and ensuing plot is shown in Fig. 6. From the Fig. 6 it is clear that the planned equalizer dominates equalizers proposed in the literature, PFLADFRNN C-PSO, and S-PSO at all noise situation. From figure 7 established that the planned equalizer converges superior than traditional PSO trained ANN based equalizer. Bit error rate frequently expressed as a probability.

As far as error probability is concerned, It is seen from figure 5 that

- Between 1dB to 5 dB SNR C-PSO is better than our proposed equalizer but after 5 dB SNR proposed equalizer out perform the ANN based equalizers.
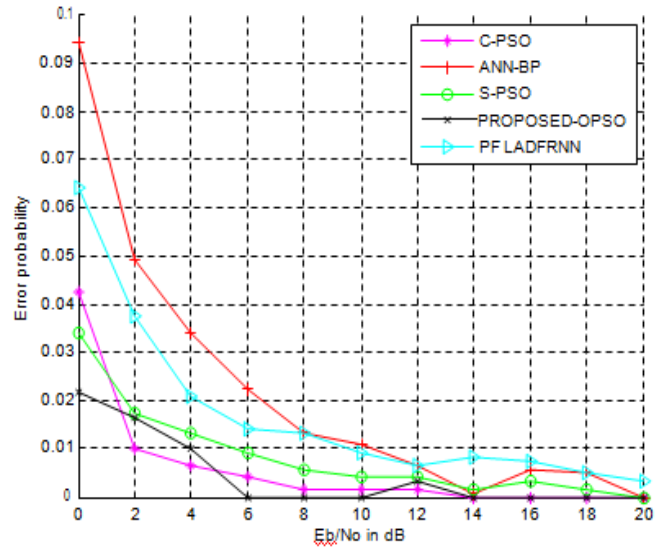

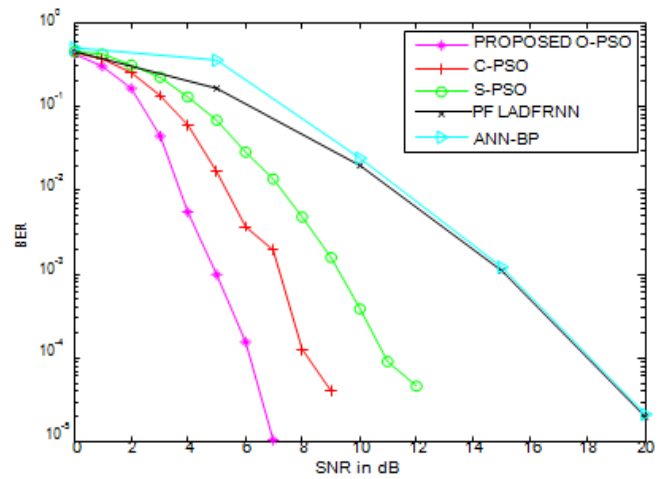**Fig. 5. Error Probability for channel of equation (10)**

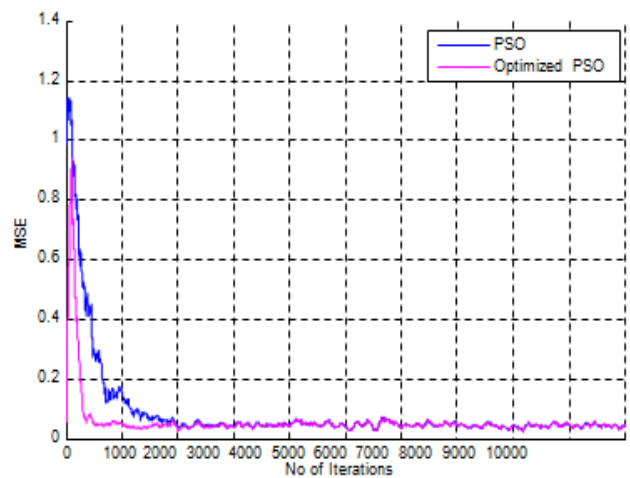**Fig. 6. BER for channel of equation (10)**

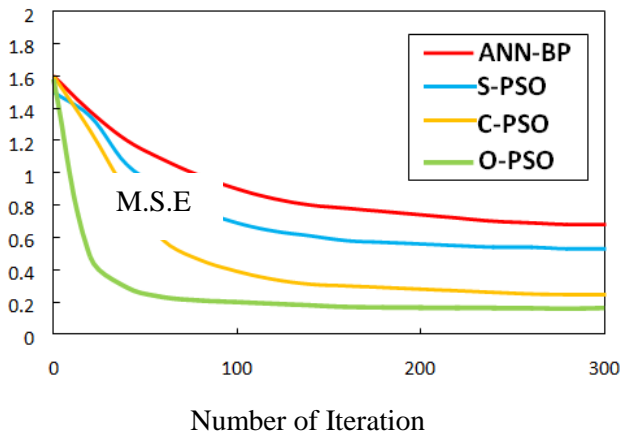Fig. 7. MSE for channel of equation (10)

Fig 8 MSE for channel of equation (11)

VII. CONCLUSION

In this paper, we have applied PSO and its modified form trained with our proposed algorithm for channel equalization. It has been observed that from the Fig(5),Fig (6),Fig (7) and Fig (8) both error probability and Bit error rate is less in Optimized PSO as compared to traditional PSO techniques.

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