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Robust Nonlinear Channel Equalization using WNN trained by Symbiotic Organism Search Algorithm

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ABSTRACT

In the present world of 'Big Data,' the communication channels are always remaining busy and overloaded to transfer quintillion bytes of information. To design an effective equalizer to prevent the inter-symbol interference in such scenario is a challenging task. In this paper, we develop equalizers based on a nonlinear neural structure (wavelet neural network (WNN)) and train it's weightedbyarecentlydevelopedmeta-heuristic(symbioticorganismssearchalgorithm).Theperformanceoftheproposedequal- izer is compared with WNN trained by cat swarm optimization (CSO) and clonal selection algorithm (CLONAL), particle swarm optimization(PSO)andleastmeansquarealgorithm(LMS).Theperformanceisalsocomparedwithotherequalizerswith structure basedonfunctionallinkartificialneuralnetwork(TrigonometricFLANN),radialbasisfunctionnetwork(RBF)andfinite impulse response filter (FIR). The superior performance is demonstrated on equalization of two non-linear three taps channels and a linear twenty-three taps telephonic channel. It is observed that the performance of the gradient algorithm based equalizers fails in the presence of burst error. The robustness in the performance of the proposed equalizers to handle the burst error conditions are also demonstrated.

Keywords: Wavelet Neural Network, Symbiotic Organism Search Algorithm, Channel Equalization, Burst Error.

INTRODUCTION

Withtheadvancementincomputingandsignalprocessingtechniques in this era of big data, everyone wishtosharehugevolumeofinformation(movies,audio-videofiles,graphicgames etc.) to many users simultaneously. Thisincreasestheload on the band-limited communication channelscausingin-tersymbolinterference(ISI)[1].Inordertoneutralizetheef-fectofISI,asignalprocessingmoduleisintroducedatthere-ceiver known as channel equalizer [2, 3]. Since inrecentpastthe volume of information sharing hasincreased, theinterfer-ence level in the channel has simultaneously increasedto manyfolds.Thus the problems that equalizers havetotakeupwiththesecrowdedchannelsaregetting morecomplicatedthanever.Adaptivechannelequalizerwasfirstproposedby Luckyin1965[4].Intheoriginalformoftheequalizer,thereceivedsignal passed through a tapped delay line followed byanadap-tive linear combiner. The adjustable weights ofthemodelare trained by least mean square (LMS) [5],NormalizedLMS[6], recursive least square (RLS) [7], fast RLS[8],square-rootRLS[9]etc.Howevertheselinearmodelswithgradientde-scent algorithms most of the time fails to equalizethechannelswith deep spectral nulls [10]. Therefore neuralnetworkbasedequalizers are introduced which formulatesnonlineardecisionboundariestohandlecomplexclassificationtasks[11].Thefirstof this kind was Multilayer Perceptron (MLP) trainedbyBackPropagation (BP) algorithm [12, 13]. In order tohandleequal-ization of QAM signal complex domain MLP andextendedBPis proposed [14]. To improve the convergence speed ofMLP, natural gradient (NG) descent algorithms based equalizers are proposed [15], which provide faster convergence than BP.

In order to reduce the complexity of multilayer structure, lateron,single-layerstructureslikeRadialBasisFunctionNeu-ralNetwork(RBF)[16],FunctionalLinkArtificialNeuralNet- work (FLANN) [17, 18] are employed for equalization. For QAM equalization the complex valued RBF aredeveloped [19, 20]. Based on the type of nonlinearities associated with the channel the Chebyshev artificial neural networks [21, 22], Legendre neural networks [23, 24] are introduced which be- come popular in the last decade. Recently the hybrid FLANN (combinationofFIRstructurewithFLANN)[25]andpipelined FLANN are proposed by [26] Zhao et al. which provide accu- rate results and efficient hardware architecture than the tradi- tionalFLANN.

In order to handle the time-varying phenomenon of fading channels (a dynamic system with it's coefficients varying with time) Kechriotis et al. proposed the use of Recurrent Neural Network (RNN) [27]. The RNN structure comprises an IIR fil- ter with feedback system, along with nonlinearities associated with the neurons [28] . The RNN outperforms the MLP and RBFstructures[29],andcanbeusedforbothtrainedaswellas blind equalization [30]. Choi et al. in 2005 used Kalman Filter to train the weights of RNN equalizer [31]. Recently Wangand Huang analyzed the convergence of RNN trained by extended Kalman Filter [32] considering the covariance of measurement noise (R) and process noise (Q) intoaccount.

PatraandMulgrewusedfuzzylogicforadaptivenonlinear equalization[33].TheextendedKalmanfilterisusedby Liand Er to train the fuzzy neural equalizer [34]. Recently a neuro- fuzzy system based on clustering and gradient techniques is used for equalization [35]. The review article by Burse et al. highlights the detail of the evolution of various neural network models for channel equalization[10].

Wavelet Neural Network (WNN) [36] consists of a feed- forward single hidden layer neural network with a linear com- biner at the output. The activation function used at the hidden layer neurons are mother wavelets.Thewaveletfunctionwithdilationandtranslationparameterscaneffectivelyapproximatenonlinearfunctionsorformulatenonlineardecisionboundariesfor classificationtask[37].InthelastdecadetheWNNhasbeen widely been applied for nonlinear system identification [38], prediction of Chaotic time series [39], rainfall prediction [40], wind power forecasting [41]cancer classification ofmicroarray geneexpressiondata[42],humanlowerextremityjoint moment prediction [43]. Pradhan et al. [44] applied the WNN for com- munication channel equalization. They reported the superior performanceof WNNtrained byextended Kalmanfilter(EKF) over multi-layered perceptron (MLP) and radial basis function neural network(RBFNN).

The recursive derivative based algorithms like LMS, RLS, BP, NG, EKF discussed above follows the hill-climbing ap- proach with fixed step size to achieve optimality. During the process of moving towards optimality if they come across the local optimums they get stuck to it and thus the process leads to inaccurate modeling. Nature-inspired algorithms [45] use a group of elements (known as population) who combined use their intelligence to explore the search space and determine the optimality. Therefore these algorithms ensure greaterprobabil- ity to achieve accurate modeling andequalization.

In the last decade number of nature inspired algorithmshave been used for channel equalization including : genetic al- gorithm [46, 47], simulated annealing [48], bacterialforag-

ing optimization [49, 50], differential evolution [51], artificial immune systems[52,53], artificialbee colony[54],particleswarmoptimization[55,56,57],shuffledfrogleapingalgo-

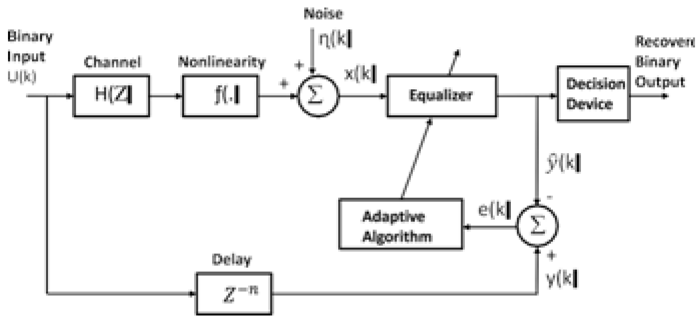

Figure 1: Block diagram of an adaptive communication channel equalizer.

algorithms for channel equalization. The performance of the proposed equalizer is compared with other WNN based equal- izers where training is carried out by CSO, CLONAL, PSO andLMS.TheperformanceisalsocomparedwithTrigo nomet- ric FLANN, RBF and FIR based equalizers trained with above mentioned nature inspired and gradient based algorithms. Ex- tensive simulation studies of the above equalizers are demon- strated on two non-linear and a linear twenty-three taps tele- phonic channel. Many times the gradient algorithm based equalizers fail to accurately model the channel characteristics in the presence of burst error. The robustness of the proposed equalizers to handle burst error conditions are alsoanalyzed.

1. Adaptive Communication ChannelEqualization

The block diagram of an adaptive communication channel equalizerisshowninFigure.1.TheinputsignalU(k)israndom binary in nature, taking values in the form either -1 or +1. The input pass through a nonlinear communication channel having transfer function H(z) and associated non-linearity f (.). While passing through the channel the signal gets contaminated with additive white Gaussian noise (AWGN) η(k). The output ob- tained at the receiveris

rithm [58], krill herd algorithm [59]. Recently published sur- vey article by Gotmare et al. [60] highlight the use of swarm and evolutionary techniques for system identification, filterde-

$$x(k) = f\left(\sum_{i=1}^{N} h(i)u(k-i)\right)+\eta(k) \qquad (1)$$

sign and channel equalization. Cheng and Prayogo developed a new meta-heuristic optimization algorithm Symbiotic Organ- isms Search (SOS) [61] by observing the interaction strategies adopted by various organisms to survive and propagate in the ecosystem. The benefit of SOS is, it's parameter-free. Only commoncontrolparametersthatarepopulationsizeand amax- imumnumberoffunctionevaluationsaretobeadjusted. There- fore the performance of SOS is consistent for different opti- mizationproblems. Theauthorshavedemonstratedthesuperior performance of SOS on unconstrained optimization of twenty- six mathematical functions and four optimal design problems of structuralengineering. Basedontherecenttrendofresearchinthispaperwedevelop equalizers based on wavelet neural network trained by symbi- otic organisms search algorithm. We have not come across any literatureonthetrainingofWNNstructurewithnatureinspired

where h(i), i = 1, .., N represent the impulse response of the channel, u(k) and η(k) are the input data sample and noise at kth instant, with k = 1, .., K. The K is the total number ofinput sampleapplied.

At the receiver, the equalizer has a transfer function W(z), where W(z) 1/H(z) (zero force equalization to compensate inter-symbol interference (ISI) of the channel). In nonlinear channel, the equalizer has to neutralize the ISI as well as the nonlinearity associated with the channel. The output of the equalizer at kth instant is given

$$\hat{y}(k)= \sum_{j=1}^{Q} x(k-j)w(j) \qquad (2)$$

where Q is the order of the equalizer and w(j) is the associated adaptiveweightvectortoit.The desiredoutputy(k)isobtained

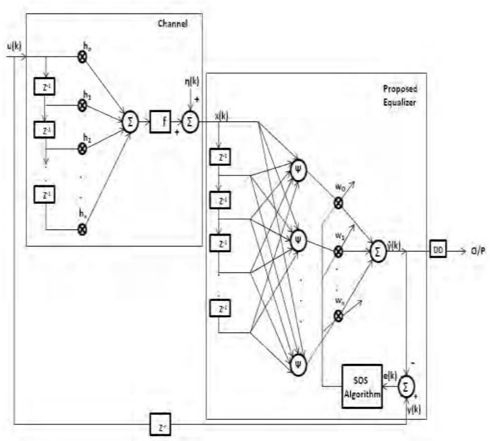

Figure 2: Block diagram of proposed WNN trained by SOS equalizer.

at the receiver by delaying the input sample u(k) by n samples. In practice the delay n Q/2. The error signal e(k) generated at the receiver is givenby

$$e(k)=y(k)-\hat{y}(k) \qquad (3)$$

Theobjectiveistorecursivelyreducetheerrorsothatŷ(k) approaches y(k). The decision device recovers the desired sig- nal which is also used for evaluating the bit error rate (BER) performance. The decision device is represented by a symmet- ric hard limit transfer function and it's output d(k) given by

$$d(k) = \begin{cases} 1 & \text{for } \hat{y}(k) \geq 0 \\ -1 & \text{otherwise} \end{cases} \quad (4)$$

2. Proposed WNN trained by SOSEqualizer

Wavelet Neural Network(WNN)

The WNN [36] is a single hidden layer neural network with a weighted linear combiner at the output. The nonlinear acti- vation function used at hidden layer neuron nodes are mother wavelets. Pradhan et al. [44] initially applied the WNN struc- ture for communication channel equalization. They reported thesuperiorperformanceofWNNtrainedbyextended Kalman filter(EKF)equalizerovermulti-layeredperceptron(MLP)and radial basis function neural network (RBFNN) based equaliz- ers. The estimated output of the WNN equalizer is givenby

$$\hat{y} = \sum_{j=1}^{k} W_j \Psi_j(x)$$

where $W_j$is the weight between j^{th} hidden layer and output layer. k is the number of hidden units. The $\Psi_j(x)$ is multi- dimensional wavelet associated with j^{th} unit of hidden layer. It is constructed with the product of m scalar wavelets with x.

The block diagram of proposed Wavelet neural network (WNN) trained by Symbiotic organism search (SOS) equalizer

$$\Psi_j(x) = \prod_{i=1}^{m} \psi\left(\frac{x - b_i}{c_i}\right)$$

is shown in Figure.1. The various component of the equalizer is outlined below.where ψ is the mother wavelet and $b_i$and $c_i$are translationanddilationparametersofthemotherwaveletfunction. Thexisinput vector i.e. the output of the channel and m is number of inputs to the WNN structure.

In this case we have selected the same ‘Mexican Hat’ as mother wavelet function which has already been reported by Pradhan et al. [44] to provide better results for equalization purpose.The‘MexicanHat’basedwaveletfunctionisgiven by

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$$\psi\left(\frac{x-b_i}{c_i}\right) = \left[1 - \left(\frac{x-b_i}{c_i}\right)^2\right] \times \exp\left[-0.5\left(\frac{x-b_i}{c_i}\right)^2\right] \quad (7)$$

TheestimatedWNNequalizeroutput$\hat{y}(k)$iscomparedwith the desired target during training to produce error

$$e(k) = y(k) - \hat{y}(k) \quad (8)$$

a significant amount of benefit while interacting with j (grass). But when j (grass) interacts with i (horse) it may get onlynom- inal or adequate benefit. Therefore the scaling term ’benefit factor’ is used which randomly takes the value as either 1 or 2 (corresponds to partial or full benefit by theorganism).

The MV is termed as ’Mutual Vector’ which describes the similarity of characteristic or average characteristics of organ- ism i and j. The part of equation ($O_{best} - MV * BF_2$) reflects

TheestimatedWNNequalizeroutput$\hat{y}(k)$iscomparedwith the desired target during training to produce error

The aim is to train the weights of the WNN equalizer recur- sivelysothatthe$\hat{y}(k)$approachesy(k) whichisessentialfortheequalization. In this paper, the Mean Square Error (MSE) is minimized on every iteration with symbiotic organism search (SOS)algorithm.

Symbiotic organism search (SOS)algorithm

The Symbiotic organism search (SOS) is a nature inspired metaheuristic algorithm recently developed by Cheng and Prayogo [61]. It is based on the interaction strategies adopted byvariousorganismstosurviveandpropagateintheecosystem. The algorithm avoids the fall to the local minima and therebyavoidstheprematureconvergence.Theflowchartforthealgorithmisshownin Figure.3.Thenaturalorganismsinanecosys-temnormallytrytolivetogether.Theprocessoflivingtogether is termed as ’Symbiosis’. It’s essential for the organisms to stay together as the organisms of different spices dependent on each other either for their survival or for common growth. The fundamentalsymbioticrelationshipsobservedinthenaturalor- ganisms are mutualism, commensalism, and parasitism. These three natural phenomenon are encoded in the form of SOS al- gorithm. The in-detail steps are outlined below :

Mutualismphase

In this phase, the interaction between two organisms of dif- ferent spices results in benefiting both the organisms. There- fore it is also termed as ’Phase of benefits’. As shown in Fig- ure.4, the relationship between horse and grass is mutualism. By grazing the grass horse fill it's stomach, also it en-reaches the growth of grass.

InSOSalgorithmconsideranecosystem**O** =[O1,O2,..OM]. The mutualism between two organisms [Oi, Oj] **O** and i Çj

(i.e. consider Oias horse and Ojas grass) is given by

$O_{i-new}=O_i+rand(0,1)*(O_{best}-MV*BF_1)$ (9)

$O_{j-new}=O_j+rand(0,1)*(O_{best}-MV*BF_2)$ (10)

$MV = \frac{O_i+O_j}{2}$ (11)

whererand(0,1)representsarandomnumberintherange[0,1]. BF_1, BF_2, are termed as benefit factors which reflect the inter- action between the organisms. Organism i (horse) mayachievetowards the best organism. The organism O_{best}represents the organism which has the highest degree of adaptation to the ecosystem. Therefore, the principle obeys Darwins theory of 'survival of the fittest'.

Finally,theorganismsareupdatedwiththeaboveproceduredureonlywhentheirpresentevaluatedfitnessarebetterthanthepre- viousone.

Commensalismphase

In commensalism phase the interaction between two organ- isms benefit one, the other one neither gets benefit nor suf- fers from the relationship. In Figure.4, the interaction between Remora fish and Shark is commensalism. The tiny Remora at- tachitselfbehindthebodyofSharkandtakesit'sleftover food, thus get benefited from the relation. The Shark do not get af- fectedbytheactivityofthesmallfish.Also,thebenefitreceived by Shark from the relationship isinsignificant.

Consider two organisms [O_i, O_j] **O** and i Ç j. Consider O_i asRemorafishand$O_j$asShark.Thecommensalisminteraction between them is givenby

$O_{i-new}=O_i+rand(-1,1)*(O_{best}-O_j)$ (12)

where rand(1, 1) represents a random number in the range [- 1, 1]. The term (O_{best} O_j) represents the beneficial advantage provided by O_j(Shark) to organism O_i(Remora fish) by in- creasing it's survival advantage in the ecosystem.

Parasitismphase

In parasitism phase, the interaction between two organisms eliminates a weaker organism from the ecosystem. InFigure.4, the interaction between a mosquito and another bird is a phe- nomenon of parasitism. Once the mosquito bites the bird it creates parasite thrives in the birds body. The germs inside the bird body reproduce themselves and the bird may get affected by a disease and possibly die. But if the bird is a healthier one and have good immunity power then it can cure itself and the parasite will get eliminated from thatecosystem.

Consider two organisms [O_i, O_j] **O** and i Ç j. The para- sitism interaction between them is implemented as follows :

1. $O_i$is given the role of mosquito. It create a 'Parasite Vector' by cloning (duplicating) the organism $O_i$and ran- domly replacing selected dimension values with random numbers.
2. $O_j$is given the role of hostbird.
3. Evaluate the fitness f (.) of 'Parasite Vector' andO_j.
4. Iff(ParasiteVector)betterthanf(O_j),then$O_j$isreplaced by the 'ParasiteVector'.

Figure 4: Diagram representing the process of symbiosis in an ecosystem.

put combiner are optimized using SOS algorithm. There- fore an ecosystem is initialized consist of the M number of organisms. Each organism has N dimension same as the number of a number of weights present in the WNN structure. Let the ecosystem be representedas

4. Performance Evaluation of WNN-SOSEqualizer

Channel Characteristics forSimulation

In order to evaluate the performance of the proposed WNN- SOS equalizer simulation studies are carried out on twobench- mark channels. The channel 1 is taken from Pradhan et al.[44] and channel 2 is taken from Nanda et.a al. [52]. The transfer function of these channels are givenby

$$\text{Ch1} : H_1(z) = 0.2602 + 0.9298z^{-1} + 0.2602z^{-2} \quad (15)$$

$$\text{Ch2} : H_2(z) = 0.3040 + 0.9030z^{-1} + 0.3040z^{-2}$$

Eachoftheabovementionedchannelareassociatedwithtwo different kind of nonlinearities representedby

$$\text{NL1} : f_1(k) = \tanh(g(k)) \quad (16)$$

$$\text{NL2} : f_2(k) = g(k) + 0.2g^2(k) - 0.1g^3(k)$$

Calculate desired output of the equalizer : Thedesired output y(k) of the equalizer is obtained by delaying theinput signal U(K) by 'n' samples.

5. **Evaluate fitness and determine** O_{best}**:** The output of the equalizer$\hat{y}(k)$is calculatedusing (5)foreverykthinputsample and mth weight vector O_m**O**. The obtained out- put is compared with the desired output y(k) to produce error signal e(k) using(8).

For mth organism (i.e. weight vector) the mean square error (MSE) is evaluated and used as it's fitness function given by

K

tained by applying the input samples 4 unit delay. ThetrainingoftheWNNstructureweightswithSOSalgorithmiscarriedoutfor200iterationsaspertheproceduredefinedinSection 3.3. The obtained MSE during training is reported. Once the training is completed the testing of the equalizer is carried out using 1,00,000 input samples. The obtained BER is reported.

Comparative Models and ParameterSettings

The performance of the proposed equalizer is compared with other WNN equalizers trained by cat swarm optimization(CSO),CLONALselectionalgorithmsofartificialimmunesystemsandparticleswarmoptimization(PSO).Theparameter

MS E_{Om} settings of the heuristic algorithms for comparative analysis in

k=1

The objective is to minimize the MS E. Determine the

O_{best}which has minimum MS E.

6. **Perform Mutualism phase :** Using the obtained O_{best}andequations(9)-(11)performthemutualismphaseasde- scribed in the Section3.2.1.
7. **Perform Commensalism phase :** Similarly with the ob- tained $O_{best}$and equation (12) perform the commensalism phase as narrated in the Section3.2.2.
8. **PerformParasitismphase:** Performtheparasitismphase as per the procedure described in the Section3.2.3.
9. **Stopping criteria :** The organism (weight vector) which provide the minimum MS E corresponds to the best sur- vival in the ecosystem. The steps 6-9 are repeated until a desirable minimum MS E isobtained.

Table 1: Parameter Settings for proposed WNN-SOS, WNN-CSO and WNN- CLONALequalizer.

Table 1: Parameter Settings for proposed WNN-SOS, WNN-CSO and WNN-CLONALequalizer.

Parameters	WNN SOS	WNN CSO	WNN CLONAL	WNN PSO
Pop	20	20	20	20
Iter	200	200	200	200
Off-springs	Mutualism Commen--salism Parasitism	Tracing Seeking Elimination	Cloning Hyper--mutation Selection	
Other Para-meters	MR=0.9	Prob. SRD=20% $c=2$ $r \in [0,1]$ $w \in [0.9, 0.4]$	Cl=100% Prob.Hy=10%	C1=2 C2=2 r1∈[0,1] r2∈[0,1]

the identical environment are described in Table.1. The weight update procedure using CSO is narrated in [39] and that with CLONAL is outlined in [52]. The other comparative used are radial basis function (RBF) with 12 neurons in a single layer, the trigonometric FLANN where each term is expanded into twousingsin(πx)andcos(πx)therebyproducing16terms. The finite impulse response (FIR) filter structure is designed with eighttaps.

Simulation Environment

The simulation studies of proposed WNN-SOS,comparative WNN-CSOandWNN-CLONALequalizersarecarried outina MATLABversionR2011platformonanInteli7-3540M3GHz CPU,witha8GBRAMin Windows8.1(64-bit)environment.

RESULT ANDDISCUSSIONS

The MSE curves obtained during training of the equalizers for channel 1 with nonlinearity 1 and nonlinearity 2 are shown in Figure.5(a) and Figure.5(c) respectively. Similarly, theMSE for channel 2 with nonlinearity 1 and nonlinearity 2 are shown in Figure.6(a) and Figure.6(c). In all the four case studies it is observed that the proposed WNN-SOS based equalizer pro- vides faster convergence and lower MSE than that achievedby the WNN-CSO and WNN-CLONAL. Among the WNN-CSO and WNN-CLONAL the WNN-CLONAL equalizer has faster convergence but

WNN-CSO provides lowerMSE.

The BER plots obtained during testing of the equalizers for channel 1 with nonlinearity 1 and nonlinearity 2 are shown in Figure.5(b) and Figure.5(d) respectively. For nonlinearity 1the performance of proposed WNN-SOS is better than WNN- CSOwhichisbetterthanthatachievedbyWNN-CLONAL.For nonlinearity 2 the performance of WNN-CLONAL and WNN- CSO are better up to 8dB after which the WNN-SOS provides better performance. In this case, the performance of WNN- CLONAL is marginally better than WNN-CSO. The BER plot of channel 2 with nonlinearity 1 and nonlinearity 2 are shown in Figure.6(b) and Figure.6(d) respectively. In both nonlineari- ties, the performance of the proposed WNN-SOS is betterafter 6dB. Prior to 6dB, the performance of WNN-CSO and WNN- CLONAL are better. However, the performance of the WNN-CLONALforthischannelbecomesinferiortothatachievedby SOS and CSOequalizers.

The performance of the proposed WNN-SOS equalizer with other comparative models for nonlinear channel 1 and 2 are demonstrated in Table 2. During training the settled value of MSE and Normalized MSE in dB are reported. During test- ing the BER value obtained at 20dB SNR are reported. It is observed that in SOS based training provides lower MSE is case of most of the structures (which are highlighted in bold letters). The WNN-SOS combination has the superior perfor- mance other other equalizers in both the nonlinear channels. It is also observed that for Channel 1 the performance of most of the equalizers is better for nonlinearity 2 compared to non- linearity 1. But in case of Channel 2 the performance of the equalizers with Non-linearity 1 is better. For channel 1 theper-formanceofWNNisfollowedbyRBF,FLANNandFIR.For Channel 2 the WNN is followed by FLANN, RBF and FIR. Among the training algorithms the SOS has greater accuracy followed by CSO then CLONAL/PSO and LMS.

5. WNN-SOS equalizer for Telephone Channel with 16- QAM

The example taken here is a telephone channel with 21 taps listed in Table.3. Earlier Chen et al. [62] designed multi-satge blind clustering equalizer for this channel. Here a pseudo- random binary sequence is generated of period 256 bits. The generated signal is contaminated by Gaussian noise of SNR 30 dB. Every four bit are converted into 16-QAM symbol. The equalizer with FIR filter comprised of 23 taps. Similarly, for proposed WNN-SOS equalizer number of neurons taken are 25. In RBF is designed with 25 neurons and FLANN has 42 expansions (21 tap with each one expanded one sin and one cos term).

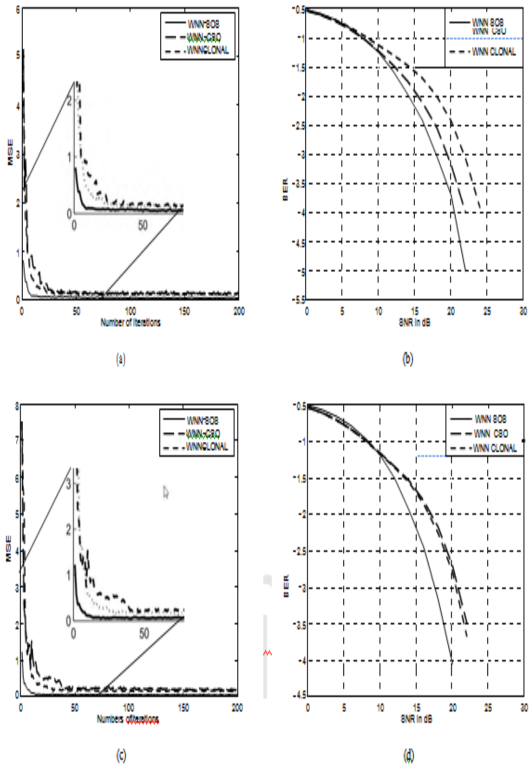
The constellation diagram of the noisy telephone channel output without equalization is shown in Figure.7 (a). Followed by the constellation output for the proposed WNN-SOS equal- izer along with WNN-CSO and WNN-CLONAL are shown in Figure.7(b-d). The comparative performance of the proposed equalizer along with the other models for this telephonic chan- nel is shown in Table.4. It is observed that the performance of the WNN based equalizers are superior followed by RBF, FLANN and FIR. Among the training algorithms the SOS pro- vides lower MSE followed by CLONAL/PSO andLMS.

6. Ability of WNN-SOS Equalizer to Handle BurstError

The recent US Patent [63] by Taher and Al-Banna focus on the usage of an equalizer to handle burst error. The burst er- ror refers to the appearance of ’consistent ones’ or ’consistent zeros’ for certain duration of time. It happensinthephysicalchannelsastheyareimperfectandcauseanerrorat thereceiver.Thebursterrorinanequalizermayoccurafterthe convergence of the algorithm and it always degrades the performance of the equalizer.

The simulation of a traditional FIR filter based equalizer trained by least mean square (LMS) algorithm response during the burst error is shown in Figure.9. The simulation is carried out on channel 1 with nonlinearity 1 in presence of AWGN 30 dB. After 100 samples of the input signal, the LMS is about to settledownwhenthebursterroroccurredfor20samples (inthe simulation from 10 th bit to 120th bit all samples are taken as ones). During this period the error in the channel immediately increasedtomanyfoldsandthealgorithmagaintookanappre-ciableamountoftimeforconvergenceasshowninFigure.9(a). The NMSE representation of the same shown in Figure.9(b) which reveals the algorithm initially trying to achieve a con- vergence near about 30 dB around the 100th sample where the burst error occurred and the algorithm took the time to achieve the convergenceagain.

The block diagram shown in Figure.8 represents the imple- mentation of the proposed WNN-SOS equalizer to handle the



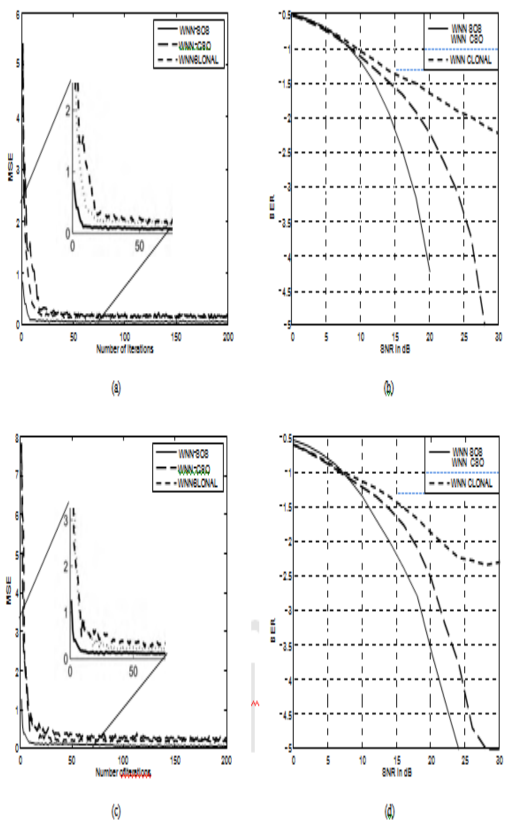
(c) (d)

Figure 5: Simulation study of Channel 1 using proposed WNN-SOS with other comparative models : (a) MSE convergence during training with non-linearity 1 (b) BER obtained during testing with non-linearity 1 (c) MSE convergence during training with non-linearity 2 (d) BER obtained during testing with non-linearity 2.

burst error. The training is carried out with the evolutionary algorithms for 200 iterations. The same environment as men- tioned above (i.e. burst error occurrence after 100th samples for duration 20 samples) is used for simulation. The Wilcoxon norm [64] is used to handle the burst error. The detailed math- ematical formulation of the fitness function is given in [65].

The MSE curves obtained during training for channel 1 with nonlinearity1andnonlinearity2areshowninFiguer.10 (a)and Figure.10(c) respectively. Similarly, the MSE for channel 2 withnonlinearity1andnonlinearity2areshowninFigure.11(a) and Figure.11(c). In all the four case studies it is observed that with the use of evolutionary learning the ability of the equal- izertohandletheburstterrorhasbecomemucheffective. Itcan effectively overcome the hurdles faced by LMS (as the popu- lation use collaborative epoch based learning of the weights). However compared to the MSE curves of normal condition(i.e Figure.5(a)-5(c) for Ch1) in burst error condition (Figure.10(a) and Figure.10(c)) the initial errors occurred in the trainingpro- cess are high (i.e. in Figure.5(a) the start level is 5 whereas in Figure.10(a) it's 8, similarly in Figure.5(c) the start level is 8 whereas in Figure.10(c) it's 18). The algorithm achieves the convergence to reduce the error. Almost similar observation is also found for Channel2.

After the training is completed the testing is carried out for burst error conditions. Among the 1,00,000 testing samples, 60 samples were used as burst error conditions (20 samples af- ter 10,000, then 20 samples after 40,000, then 20 samples af- ter 60,000 were made ones). The BER plots obtained during this testing for channel 1 with nonlinearity 1 and nonlinearity2 are shown in Figure.10(b) and Figure.10(d) respectively. Sim- ilarly, the BER for channel 2 with nonlinearity 1 and nonlin- earity 2 are reported in Figure.11(b) and Figure.11(d) respec- tively.ComparedtothenormalconditionsofBER(Figure.5(b), Figure.5(d), Figure.6(b), Figure.6(d)) in burst error conditionstheperformanceofWNNCSOandWNNCLONALequalizershavebeenaffected(Figure.6(b),Figure.6(d),Figure.11(b),Fig-



(c) (d)

Figure 6: Simulation study of Channel 2 using proposed WNN-SOS with other comparative models : (a) MSE convergence during training with

non-linearity 1 (b) BER obtained during testing with non-linearity 1 (c) MSE convergence during training with non-linearity 2 (d) BER obtained during testing with non-linearity 2.

ure.11(d)) whereas the WNN-SOS equalizer performance still remains better. Therefore the WNN-SOS equalizer is a poten- tial candidate under burst error scenario.

CONCLUSION

Inthispaper,anewchannelequalizerisproposedbytraining the weights of a wavelet neural network structurewithrecentlydevelopedsymbioticorganismsearchalgorithm.Theperformanceoftheproposedequalizeriscomparedwith Trigonomet- ric FLANN, RBF and FIR based structures trained by CSO, CLONAL, PSO and LMS algorithm. The performance of the equalizers is accessed over two nonlinear channels for regular noisy conditions and burst error scenarios. The performance is also demonstrated on a twenty-one taps telephonic channel. TheMSEandBERresultsinallsimulatedscenariosrevealthat the WNN-SOS equalizer provides superior performance than thatachievedbytheotherequalizers.Thereforeinupcoming daysit'sworthwhiletotrythishybridcombinationofWNNSOStosolvecomplexidentificationandnonlinearclassification problems.

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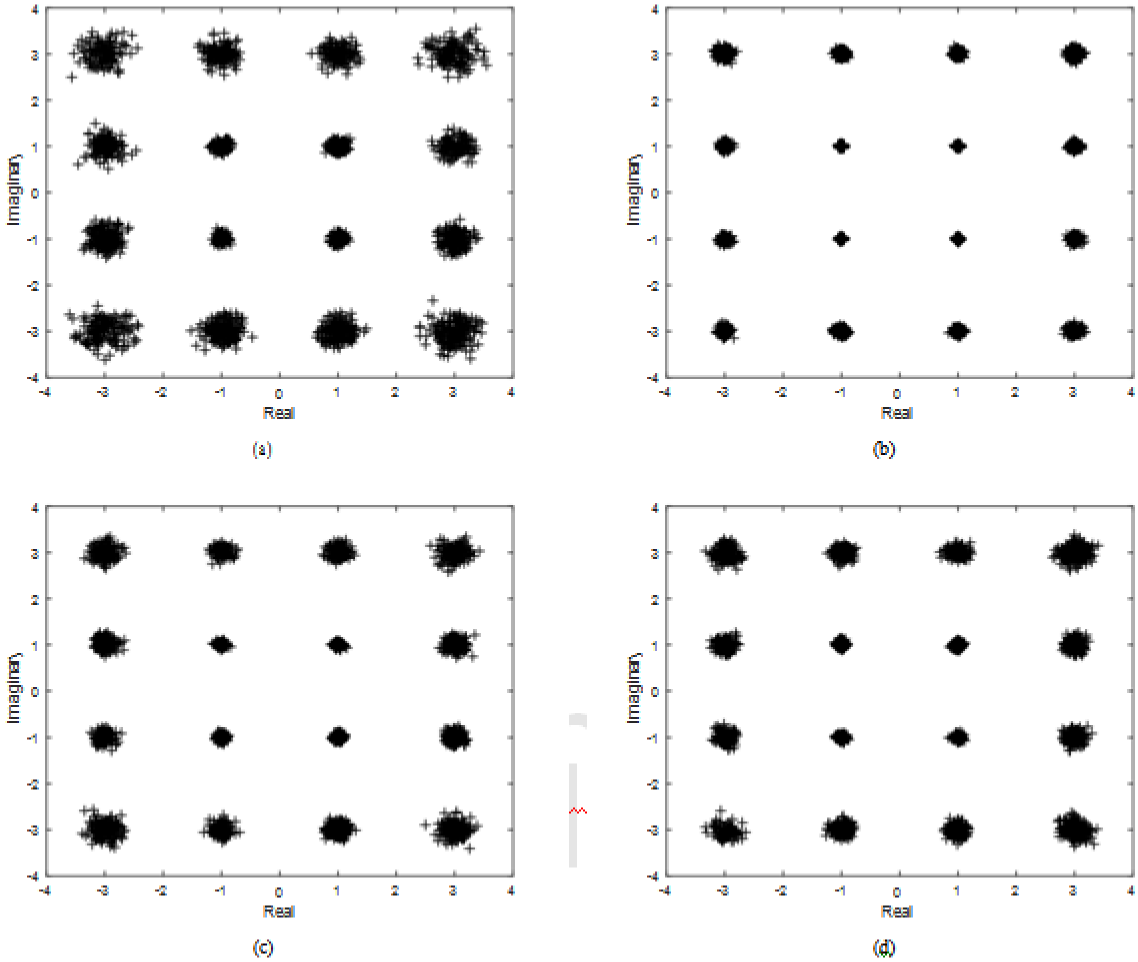
Table 2: Comparative performance analysis of the proposed WNN-SOS equalizer with other neural network and FIR based equalizers for both the non-linear channels.

Structure	Algorithm	Training		Testing	Training		Testing
		MSE	NMSE (dB)	BERvalue 20 dBSNR	MSE	NMSE (dB)	BERvalue 20 dBSNR
Channel 1		Non-linearity 1			Non-linearity 2		
WNN	SOS	**0.1021**	**-28.6240**	**-3.7100**	**0.1560**	**-28.8321**	**-4.1232**
	CSO	0.2114	-25.4210	-3.2332	0.2525	-24.3210	-2.8530
	CLONAL	0.2515	-23.3762	-2.5604	0.2620	-23.8020	-2.6126
	PSO	0.2604	-23.124	-2.5412	0.2633	-23.2126	-2.6324
	LMS	0.3510	-21.8022	-2.3020	0.3622	-21.8085	-2.4212
FLANN	SOS	**0.1430**	**-28.3102**	**-3.5212**	**0.2120**	**-28.3218**	**-3.8236**
	CSO	0.2245	-24.6810	-3.1024	0.2411	-24.7064	-2.9166
	CLONAL	0.2412	-23.3546	-2.4105	0.2513	-23.3712	-2.4212
	PSO	0.2652	-22.9020	-2.3320	0.2688	-23.2012	-2.3410
	LMS	0.3632	-21.2255	-2.0243	0.3650	-21.0115	-2.1210
RBF	SOS	**0.1356**	**-28.3530**	**-3.6140**	**0.2094**	**-28.4125**	**-4.0135**
	CSO	0.2215	-25.2104	-3.1614	0.2366	-25.6124	-2.8842
	CLONAL	0.2414	-23.3633	-2.5245	0.2518	-23.4012	-2.5446
	PSO	0.2632	-22.9255	-2.4432	0.2673	-23.1014	-2.5020
	LMS	0.3576	-21.2570	-2.1340	0.3642	-21.754	-2.3110
FIR	SOS	**0.3240**	**-23.5014**	**-2.8246**	**0.3267**	**-23.7125**	**-2.9137**
	CSO	0.3634	-21.0350	-2.5411	0.3735	-22.0024	-2.6325
	CLONAL	0.3685	-20.2013	-2.4628	0.3822	-21.4320	-2.6405
	PSO	0.3710	-20.1105	-2.2014	0.3884	-20.1836	-2.1225
	LMS	0.4012	-19.8620	-1.9940	0.4168	-19.9448	-2.0010
Channel 2		Non-linearity 1			Non-linearity 2		
WNN	SOS	**0.0912**	**-30.0114**	**-4.2032**	**0.1114**	**-28.1056**	**-3.6010**
	CSO	0.1322	-28.3206	-2.5216	0.1426	-27.1136	-2.5024
	CLONAL	0.1284	-27.3122	-1.8224	0.1385	-26.7762	-1.8520
	PSO	0.1466	-26.2160	-2.2012	0.1532	-24.9824	-2.2688
	LMS	0.2104	-21.3028	-1.7050	0.2307	-20.0240	-1.8846
FLANN	SOS	**0.1134**	**-29.5440**	**-4.0114**	**0.1245**	**-26.9832**	**-3.5204**
	CSO	0.1452	-27.8002	-2.4616	0.1604	-25.2014	-2.4022
	CLONAL	0.1296	-26.4226	-1.8054	0.1424	-24.6780	-1.8337
	PSO	0.1530	-26.1012	-2.0524	0.1614	-23.6120	-2.2304
	LMS	0.2354	-20.0822	-1.6218	0.2466	-19.6812	-1.6830
RBF	SOS	**0.1202**	**-28.4245**	**-3.9126**	**0.1326**	**-26.5031**	**-3.4540**
	CSO	0.1530	-27.3248	-2.4124	0.1649	-26.2310	-2.3986
	CLONAL	0.1322	-26.2120	-1.8210	0.1486	-25.2114	-1.8210
	PSO	0.1645	-25.8040	-2.0114	0.1682	-23.8220	-2.2210
	LMS	0.2540	-19.8825	-1.6100	0.2578	-19.1014	-1.5810
FIR	SOS	**0.2566**	**-21.0422**	**-2.7145**	**0.2632**	**-22.0120**	**-2.6023**
	CSO	0.2583	-20.1321	-2.2010	0.2614	-19.2014	-2.1986
	CLONAL	0.2710	-20.0124	-1.7132	0.2927	-18.8933	-1.7004

	PSO	0.2654	-19.6482	-1.8240	0.2982	-19.3020	-1.7925
	LMS	0.3022	-17.2125	-1.5232	0.3215	-17.1015	-1.5126



(c) (d)

Figure 7: Constellation diagrams for telephone channel with 16-QAM : (a) Channel output without equalization (b) Performance after WNN-SOS equalizer (c) Performance after WNN-CSO equalizer (d) Performance after WNN-CLONAL equalizer.

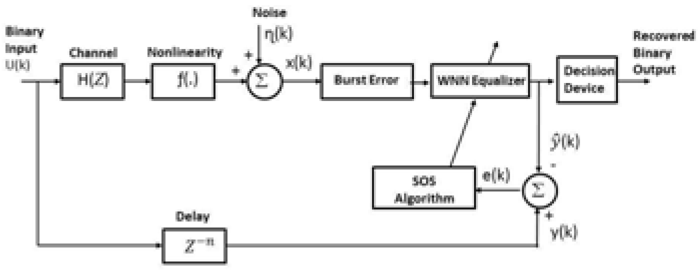


Figure 8: Block diagram of proposed WNN-SOS equalizer to handle burst error.

Table 3: Impulse response of telephone channel

Tao No.	Real	Imaginary
0	0.0145	-0.0006
1	0.075	0.0176
2	0.3951	0.0033
3	0.7491	-0.1718
4	0.1959	0.0972
5	-0.2856	0.1896
6	0.0575	-0.2096
7	0.0655	0.1139
8	-0.0825	-0.0424
9	0.0623	0.0085
10	-0.0438	0.0034
11	0.0294	-0.0049
12	-0.0181	0.0032
13	0.0091	0.0003
14	-0.0038	-0.0023
15	0.0019	0.0027
16	-0.0018	-0.0014
17	0.0006	0.0003
18	0.0005	0.0000
19	-0.0008	-0.0001
20	0.0000	-0.0002
21	0.0001	0.0006

Table4: ComparativeperformanceanalysisoftheproposedWNNSOSequalizerwithotherneuralnetworkandFIRbased equalizersforTelecommunication channel3

Channel 3		Training		Testing
Structure	Algorithm	MSE	NMSE (dB)	BERvalue 20 dBSNR
WNN	SOS	**0.0812**	**-29.5432**	**-6.2320**
	CSO	0.0945	-29.2120	-5.9824
	CLONAL	0.1084	-27.8912	-5.7432
	PSO	0.1220	-26.3430	-4.9120
	LMS	0.1448	-24.1058	-4.6214
FLANN	SOS	**0.1124**	**-29.1014**	**-5.9040**
	CSO	0.1231	-28.6218	-5.8025
	CLONAL	0.1288	-27.5238	-5.7202
	PSO	0.1482	-26.1226	-4.8024
	LMS	0.1513	-23.5014	-4.3212
RBF	SOS	**0.1012**	**-29.4230**	**-6.0452**
	CSO	0.1134	-28.3421	-5.9126
	CLONAL	0.1236	-26.6324	-5.8428
	PSO	0.1322	-26.0324	-4.9037
	LMS	0.1475	-23.8010	-4.5166
FIR	SOS	**0.1535**	**-26.3050**	**-4.8020**
	CSO	0.1642	-25.4510	-4.7125
	CLONAL	0.1688	-24.5046	-4.6830
	PSO	0.1715	-23.6628	-4.6021
	LMS	0.1820	-21.0213	-4.3033

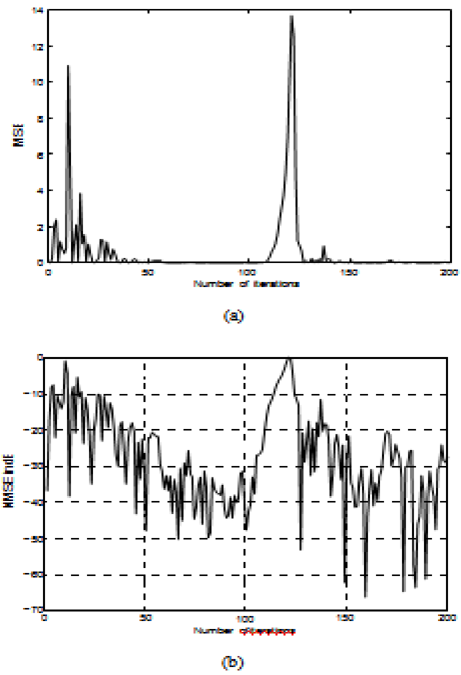


Figure 9: Simulation study of of a traditional FIR equalizer trained by LMS algorithm to handle burst error : (a) MSE convergence plot of Channel 1 with non-linearity 1 and AWGN 30dB (b) NMSE plot.

Dr. Ravi Narayan Panda " Robust Nonlinear Channel Equalization using WNN trained by Symbiotic Organism Search Algorithm" *International Journal of Engineering Research and Applications (IJERA*), vol.8(10), 2018, pp 92-106.