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Training Strategy of Fuzzy-Firefly Based ANN in Non-Linear Channel Equalization

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ABSTRACT Channel equalization is remaining a challenge for the researcher. Especially for the non-linear channel as well as the extremely dispersive channel, an effective channel equalizer is required. It is common knowledge that non-linear channel equalizers based on the neural networks (NN) outperform adaptive filter-based linear equalizers. To train NN equalizers, gradient-descent-based approaches like the back-propagation algorithm are often utilized, although they have drawbacks such as trapping of local minima, slower convergence, and compassion to log in. In this work, we presented a novel training strategy using a fuzzy firefly algorithm (FFA) for channel equalization. By using proper network topology and parameters, the suggested training system offers stronger exploitation and exploration skills, as well as the ability to solve the local minima issue. The performance of the equalizer can be analyzed by estimating two parameters i.e. MSE and BER. To exhibit the suggested technique's resilience in performance, the burst error situation was used, and the outcomes showed that the strategy is more effective in managing such situations than previous methods. The outcomes of the proposed method are presented through simulation, Furthermore, it proved that the suggested method validates a wide range of SNR, and also it outperforms the existing NN-based equalizers.

INDEX TERMS ANN, fuzzy firefly algorithm, non-linear channel equalization.

I. INTRODUCTION

Because of the increasing usage of internet technologies, the techniques used to transfer high-speed data via communication channels have increased dramatically. The major reasons that contribute to ISI in wireless communication are multi-path effects and the band-limited nature of channels. To fight the distortion caused by ISI, noise, and nonlinearity, an equalizer is required at the front end of the receiver [1]–[4]. The technique which is to provide model-free methods for both modulation learning and channel impact learning in auto encoder-based communications systems is Generative adversarial networks (GANs) [5] which the channel is agnostic and does not require any prior knowledge of the channel. For the current channel, the conditional GAN can produce more particular samples [6]. Raj et.al, [7] proposed deep learning at the physical layer without channel models improves the performance of the blind channel equalizer approaches on CMA. The novel VAEBCE equalizer's performance was comparable to that of the MMSE equalizer, which is a supervised linear adaptive MMSE equalizer [8]. Caciularu et.al, [9] developed a variation-based auto encoding method for the unsupervised equalization and decoding of linear and nonlinear channels. Iterative BP-CNN [10] is a new linear decoding architecture that uses the well-known quadratic loss function that combines a trained CNN with a regular BP decoder and iterates between the two. It has been demonstrated that this design is capable of extracting noise correlation characteristics and increasing decoding performance.

LMS and RLS-based linear equalizers, on the other hand, fail to perform for highly non-linear and dispersive channels [11]–[13]. Thus, non-linear equalizers play an essential role in retrieving information that has been damaged owing to transmission over non-linear channels. The most important

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parameter which decides the robustness of an equalizer to deal with non-linearity in wireless channels is MSE and BER, which values are very much lower in the case of NN-based equalizers compared with linear equalizers [11]–[14]. The introduction of a multilayer perceptron (MLP) has been proven to be better than that of linear equalizers. [18], [19]. For equalization, single layer NNs such as polynomial perceptron networks [16], RBFs [14], [15], and FLANN with different polynomials [17]–[22] have also been used. Due to the inefficacy of BP-based NN-equalizers fails to perform because of lower convergence rate and problems in local minima. Therefore, these constraints prompted the researchers to develop NN-based channel equalizers using nature-inspired metaheuristic algorithms [23]–[28], they can avoid local optima and enable faster convergence [29]. Zhao et.al, [30]–[34] introduced several distinctive types of NN-based equalizers to solve these complex issues.

As far as the problem of equalization [11]–[19] is concerned, ANN has served as the best tool despite complex problems. Since conventional training algorithms like gradient-descent-based algorithms did not succeed in many cases, training ANN with different optimization algorithms involving bio-inspired computation [35]–[38] was used. In addition recently, Ingle et.al presented JAYA and Cuckoo search algorithms [39], [40] for efficient channel equalization. Carrera et. al, [41] proposed an ANN-based channel equalization method for operating the 28GHz band for mmWave communications. Liu et.al, [42] presented how an ANN equalizer can improve the performance of a UFMC-based radio over a fiber system. ANNs applied for 256 QAM symbol channel equalization over the OFDM Rayleigh channel [43]. Li et.al, [44] presented a constant modulus algorithm (CMA) to restrain impulse noise adaptively. The CMA algorithm operates in a simple unsupervised manner and was shown to be effective for non-linear channels. ANN uses an adaptive-slope squashing function (ASF) [45] for the estimation of channel state information (CSI) and detection of the symbol. The application of support vector machines to the equalization of communication networks that have been distorted by additive white Gaussian noise, intersymbol and co-channel interference has been well reported in [46]. Albu et. al, [47] presented the variable selection approach for optimizing radial basis function networks and MLP architectures for channel equalization using statistical sensitivity analysis. A 3D-CNN architecture is presented as a method of classifying modulated signals that have been corrupted by channel noise by Rahim et.al [48]. Rehman et.al., [49], demonstrate the effectiveness of wireless short-range communication technology.

Yang2008 [50] recently planned the firefly algorithm (FA), which idealizes some of the flashing features of fireflies. This approach stands on the idea to facilitate the result of an optimization issue may be represented while a firefly that flashes in proportion to its excellence in a given predicament situation. As a result, every brighter firefly draws its companions, expanding the search area. A novel adaptation of the FA (Levy FA), presented by Yang coupled Levy flight with a firefly-based search technique to improve FA randomization [51]. For enhancing FA's global search, we present a fuzzy firefly algorithm (FFA) [52]. More than one firefly represents the global optima and some brighter fireflies influence motions of other fireflies to search the landscape and discover the global best in the suggested algorithm to enhance the FA's convergence rate.

The attractiveness of each n-best firefly determines how efficient they are at moving another firefly in every iteration, which is a fuzzy variable in FFA. Mousavi et.al, [53] presented the firefly algorithm, which is based on fractional calculus and is used to estimate the parameters of disordered systems. It also describes the fractional order of FA which is the modified form of FA by using fractional calculus during the search process.

In this article, we look at how neural networks can be used to find optimal weights, transfer functions, and a suitable topology of a given network's neuron. The FFA to neural network training was utilized to find the optimal weights and transfer functions of a particular network's neurons. As a result, utilizing a Fuzzy firefly algorithm, this study presents a novel training strategy for ANN-based channel equalization. The FFA-based method was compared to the performance of popular algorithms such as FA [27] PSO [25] and GA [26].

A. MOTIVATION

The gradient algorithm-based equalizer has failed several times to accurately model the channel characteristics when dealing with burst errors. The radial basis function neural network (RBFNN) design, however, takes time and is, in many ways, suboptimal when using conventional hit and trial. The article describes a method for training FFA with ANN for channel equalization.

B. CONTRIBUTIONS

The following is a list of the work's major contributions:

- Channel equalization using NN has been trained to utilize a unique technique based on a Fuzzy firefly algorithm (FFA).
- The suggested training system provides stronger skills for exploitation and exploration, as well as solving the local minima issue, by taking advantage of correct network topology and parameters.
- A compassion investigation of the suggested training method concerning its crucial parameters was done, and the ideal values were utilized to conduct the simulation research.
- Examining the suggested training technique for three non-linear wireless channels establishes its superiority. In the simulations, the suggested method outperforms other current bio-inspired algorithms by evaluating MSE and BER.
- The burst error scenario was used to show the suggested scheme's resilience in performance, and the findings

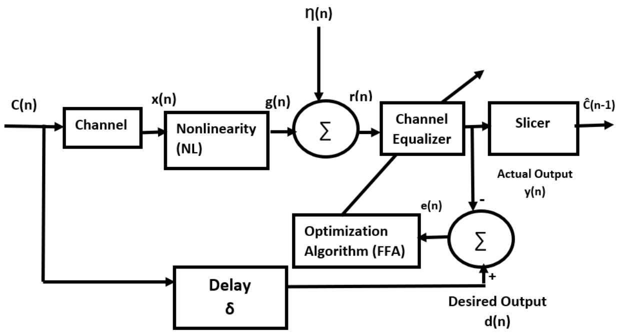


FIGURE 1. FFA based non-linear channel equalizer.

proved that the system is more successful in managing such circumstances than previous techniques.

- Comprehensive simulation tests have been performed on the suggested scheme's performance, over a wide range of SNR, approximately around (8-25) dB, and it has been discovered that the scheme beats the other methods even in low SNR situations.

The following are the main points of this article: The problem statement was addressed in Section 2, followed by the proposed system model in part 3. Features of the Fuzzy firefly algorithm and its training with ANN are shown in sections 4 and 5. Section 6 describes the simulation study for performance evaluation. At last, in Section 7, there was a conclusion.

II. PROBLEM DESCRIPTION

The communication system model is described in figure 1. The following expression [19], [22] was identified in terms of co-channel & impulse response of the channel.

$$x(n) = \sum_{m=0}^{L_h-1} h(m)c(n-m) \tag{1}$$

where L_h and $h(m)$ represent as length and tap weights of the h^{th} the impulse response of the channel. We suppose a parallel model, which creates the study is straightforward, even though the fact it can be expanded to any communication system in common. The following conditions satisfy transmitted symbols $c_i(n)$, $0 \leq i \leq n$ which are a set of independent, i.i.d dataset consists of $\{\pm 1\}$ which are mutually independent..

$$x(n) = \sum_{m=0}^{L_h-1} h(m)c(n-m) \tag{2}$$

Nonlinearity is introduced in the channel output which is identified as NL block, as shown in figure1. The output of the NL block is shown as follows:

$$g(n) = \Psi(c(n), c(n-1), c(n-2), \ldots\ldots c(n-L_h+1);\ h(0), h(1), \ldots h(L_h-1)) \tag{3}$$

Here, Ψ is denoted as nonlinearity produced by the NL block. At the receiver, the received signal $r(n)$ is shown in the following equation (4) which is nothing but the sum of noisy signal $b(n)$ due to non-linearity introduced in the channel and the element of noise supposed to be Gaussian with variance $E[(\eta^2)] = \sigma_n^2$

$$r(n) = \Psi(c(n), c(n-1), c(n-2), \ldots\ldots c(n-L_h+1);\ h(0), h(1), \ldots h(L_h-1)) + \eta(n) \tag{4}$$

The equalizer which is placed at the front end of the receiver to reconstruct the original signal $c(n)$ or its delayed form $c(n-\delta)$.

Now, $y(n) = [y(n), y(n-1), \ldots\ldots y(n-l+1)^T$, observation vector of the channel and the objective of the equalizer is to approximate the transmitted sequence $c(n-k)$, where the equalizer order is l and the delay factor is m. By comparing equalizer output, $y(n)$ with actual signal $d(n)$, the difference signal can be calculated as follows:

$$e(n) = d(n) - y(n) \tag{5}$$

The role of the slicer to provide the estimated transmitted symbol which shown in the following equation:

$$\hat{c}(n) = \begin{cases} -1 & \text{if } y(n < 0 \\ 1 & \text{if } y(n) > 0 \end{cases} \tag{6}$$

Because of $e^2(n)$, the error signal's instantaneous power can be identified as a cost function that is always positive and is replaced as $e(n)$. We will adopt an algorithm to update the weights iteratively so that $e^2(n)$ must be minimum and reduced to zero.

III. PROPOSED MODEL

In this paper, a fuzzy firefly algorithm [52] is used to optimize the weights and structure of an ANN. Each solution in the FFA algorithm population includes both a structure and a solution for weights. The change of light intensity and the formulation of attraction are the two key parameters of this algorithm. The paper's specialized points of interest are demonstrated by its originality and implementation. Proposed algorithms must be performed at least ten to fifteen times to get the best results. It is once again a typical technique to run FFA on a trial issue across many iterations, with the best results being evaluated as execution measures in the final product. In terms of the best ideal and factual outcomes, the author compares the execution of FA and PSO with the suggested algorithm. In contrast, FFA produces higher-quality results through rational iteration and avoids premature convergence.

A. ANN MODEL

In this case, the ANN is modeled after a human brain that is capable of adapting to changing conditions and learning quickly within the given context. It's a process that allows the human brain to regenerate. Neurons are the building blocks of ANN. Each ANN neuron is linked systematically. The neurons receive information from another neuron by firing across their synapse to create output. The sum of a neuron's weighted inputs may be created using a transfer function to generate the neuron's output. The hidden layers are where the ANN performs the network's real calculations. When given the correct collection of inputs, weights of neurons, and transfer function, the network will activate and generate the required output (it may be different for different neurons but usually the same). To make the proper configuration of a network easier. The ANN will need to be trained.

1) NEURAL NETWORKS TRAINING

A network is set to be trained once it has been planned for a specific application. Generally, there are two types of training methods considered for ANN: supervised training is one of the training methods in which inputs and outputs are well known and the network then analyses the inputs and compares the actual results to the desired results. Another training method is unsupervised training in which input is known but the output is unknown. The definition of the loss function and training schemes [54] are generally the two key pieces of information to provide in this type NN based scheme.

The objective function or criterion is the function we wish to minimize or maximize. It's also known as the cost function, loss function, or error function when we're minimizing it.

- To compute the model error, neural networks are trained using an optimization method that involves loss functions.
- In general, when training neural networks and machine learning models, a framework for selecting a loss function is provided by Maximum Likelihood.
- As far as training of neural network model is concerned, the two most common loss functions are cross-entropy and mean squared error.

Backpropagation is one of the few techniques available for ANN training. The data are necessary to train an ANN that accepts input and generates potential outputs. The following procedures are used for training:

1) [1] First, consider the inputs and potential outcomes.
2. In this step, calculate and add the weight of all inputs, then go via transfer functions.
3. Evaluate estimated output using actual output.
4. Based on the comparison the fitness value can be calculated and updated.
5. Do steps 2 and 3 again unless and until training reached the suitable stage.
6. To optimize fitness adjust weights in the right direction.
7. Repeat Steps 1-6 in anticipation of satisfactory fitness value is set up

To train a network, the back-propagation method [55] is supposed for modification of weights but it may get a long training time. The training algorithm proposed by the author of this work is FFA.

2) THE TRANSFER FUNCTIONS

The input of every neuron is connected with a transfer function that can activate it. The weighted sum of the inputs of neurons is calculated. A good choice of the transfer function is a sigmoid function which is applied in this work. Equation (6) shown below is expressed as a sigmoid function which is in the range [0, 1]:

$$Sigmoid\ (x) = \frac{1}{1 + e^{-ax}} \tag{7}$$

Since the sigmoid function exists between two points (0 and 1), we use it. As a result, it is particularly useful in models where the probability must be predicted as an output. Since only between 0 and 1 is the likelihood of anything occurring, sigmoid is the most reasonable option. The function can be differentiated.

It has the following applications in neural networks:

1. Activation function that converts linear inputs to non-linear outputs.
2. Limit the output to a range of 0 to 1, allowing it to be read as a probability.
3. Make computations more straightforward than arbitrary activation functions.

IV. FIREFLY ALGORITHM

There are three idealized rules in the FA algorithm [50] which Yang created in 2008: (1) There are no male or female fireflies. As a result, regardless of sex, one firefly will be paying attention to another firefly. (2) The brightness is related to their attractiveness. As a result, if there are two flashing fireflies, the less brilliant one will migrate toward the brighter one. The brightness is related to attractiveness, and both diminish in attraction as the distance between them grows. If there isn't another firefly that is brighter than it, it will travel at random. (3) The landscape of the goal function influences or determines the brilliance of a firefly. The change of light intensity and the formulation of attraction are two significant concerns in the firefly algorithm. Because the attractiveness of a firefly is related to the light intensity observed by nearby fireflies which can be defined in the following equation:

$$\beta\ (d) = \beta_0 e^{-\gamma d^2} \tag{8}$$

Here, β_0, γ defines attractiveness when $d = 0$ and light absorption coefficient respectively. Equation (9) shown below the Cartesian distance between any two fireflies i and j at a_i and a_j.

$$d_{i,j} = \left\| a_i - a_j \right\| = \sqrt{\sum_{k=1}^{r} a_{i,k} - a_{j,k}} \tag{9}$$

The equation (10) shows the trend of a firefly i is moved to a further attractive firefly j

$$X_i = a_i + \beta_0 e^{-\gamma d_{ij}^2} \left(a_j - a_i\right) + \alpha \left(rand - \frac{1}{2}\right) \tag{10}$$

In the vast majority of situations, implementations are effective, $\beta_0 = 1$ and $\alpha \varepsilon (0, 1)$. The value of γ determines the speed of convergence.

A. FUZZY FIREFLY ALGORITHM (FFA)

To address the flaws in the traditional FA and enhance firefly combined movement, we present an updated version of FA which is fuzzy-based [52] in which certain fireflies be able to affect the motions of others in every iteration. In the conventional FA, merely individual fireflies of every iteration can influence and attract their neighboring firefly. Each firefly's attraction is determined by its brightness. The rank of attraction of each n-best firefly is identified as a fuzzy variable. In this approach, the n-brighter firefly is chosen as a candidate in every iteration, where n is a parameter set by the user that relies on the intricacy and size of the population. The attractiveness membership function might have a variety of possibilities. Here, The Cauchy function is used as a membership function of the suggested method. The term $f\ (g_s)$ in the equation (10) identifies as the fitness of the local optima. The attractiveness Ψ(s) of firefly s can be evaluated as:

$$\Psi\ (s) = \frac{1}{\left(\frac{f(g_s)-f(g_h)}{\beta}\right)} \tag{11}$$

Here, the fitness function is $f\ (g_s)$ for $n-$brighter fireflies.

To eliminate reliance on the fitness function's scale, we consider

$$\beta = \frac{f\ (g_h)}{m} \tag{12}$$

To calculate the distance of fireflies we use Cartesian distance which same as FFA. As far as movement is concerned, we consider equation (13) in place of (10)

$$X_i = a_i + \beta_0 e^{-\gamma d_{ij}^2}\left(a_j - a_i\right) + \alpha\left(rand - \frac{1}{2}\right) + \sum\nolimits_{s=1}^{n} \Psi\ (s)\beta_0 e^{-\gamma d_{is}^2}\left(a_s - a_i\right)\alpha\left(rand - \frac{1}{2}\right) \tag{13}$$

In the above expression a_i represents the spatial position of the less bright firefly, the second component is attributable to the attraction of the brighter firefly, and the third term is a fuzzy variable indicating the amount of attractiveness of n-brighter fireflies in the advancement of the fireflies.

V. FFA, CONSTRUCTION, AND ANN TRAINING

Training ANN with FFA is the main concern of this paper. For this, we must build a population-based network. In this research, the 30-network populace performs well. Through this population, FFA communities are created and configured. This arrangement is termed the topology of the structure. The following training procedure is applied for FFA with ANN:

- First of all, set the parameters of fireflies.
- Observe the training samples for each network and report the number of network errors.
- Shift the firefly to a new location using FFA's firefly position and fitness update method.
- Obtain the best problem space network, and analyze all the errors.
- Identify the network which has achieved the desired minimum error, exit the program and record its weights.
- Else, for each network FFA can change its vectors of position and velocity.
- Do again step-2.

When a particle reaches the desired fitness, which means that a result has been obtained after it transitions from being an employee seeking a resolution to becoming a manager in ANN development. With several control variables, the equalization of the communication networks is a difficult issue. On this issue, ANN has yet to be an exceptional tool. The reason given is to build and train ANN for calculating channel state. Here, [± 1] take as training data. The input to the network which was built used these values. Equation (14) describes network fitness which was to calculate the MSE for the entire training collection.

$$\mathit{Value\ of\ Fitness} = \sum \mathit{Recorded\ Value} - \mathit{Predicted\ value\ of\ Network} \tag{14}$$

A network is deemed available after it has satisfied any marginal execution needs. The requirement used was the measurable computation identified as the coefficients of correlation which showed in equation (15)

$$\mu^2 = 1 - \frac{\mathit{Value\ of\ Fitness}}{\sum \mathit{Recorded\ value} - \mathit{Mean\ Recorded\ value}} \tag{15}$$

Here, in this work, FFA trains the entire network, which is built as a multilayer artificial neural network whose parameters such as weight; topology, transfer function, etc. are suitably optimized.

A. THE TRAINING PROCEDURE FOR FFA WITH ANN

The author proposed the training algorithm shown in figure 2, ANN defines rules for an organization that acts as a Boss of a company to supply assets(which are nothing but the parameters to be optimized) to FFA which behaves as a manager gives the directions for the employee. ANN learning the equalization problem. In this method, ANN acts both as a Boss and an employee. The flow chart shown below describes the pseudo-code for the problem. The number of particles and also the number of hidden nodes were identified by P and Q. This training algorithm's flow chart is shown in fig.2.

During evaluations of objective functions, especially for external black-box type objectives, the majority of computation costs will be incurred. In general, objective evaluations are the most computationally intensive part of all optimization problems. One inner loop can be used when n is rather large by sorting algorithms according to the attractiveness or brightness of all fireflies. The complexity of the firefly algorithm, in this case, will be *O(n t log(n))*. Where uniform distribution at time t.

VI. SIMULATION AND DISCUSSIONS

The equalization problem of the wireless channel was thoroughly simulated, using a variety of practical channels as well

```
Initialize ANN-as a BOSS
    For j = 1,2, ... ... P
        Make FFA-as manager (j)
        for ANN-as employee k = 1,2,3, ... ... P
        create ANN- as employee
        end
    end
whilst resolution is not established
    evaluate update
    put number of maximum iterations
    for (FFA-as manager j = 1,2,3 ... ... P)
        as (iterations<allocations)
        for (ANN-as employee k = 1,2,3, ... ... Q)
            test ANN-as employee(k)
        end
        for (ANN-as employee k = 1,2,3, ... ... Q)
    Modify the weights of ANN-as employee (k)
        end
    end
    Return global best
end
update global best
end
```

FIGURE 2. Training algorithm of the proposed equalizer.

TABLE 1. Types of channels.

SL. No	CHANNEL	EVR
CH1	$H(Z) = 0.260 + 0.930Z^{-1} + 0.260Z^{-2}$	11.12
CH2	$H(Z) = 0.304 + 0.903Z^{-1} + 0.304Z^{-2}$	21.71
CH3	$H(Z) = 0.341 + 0.876Z^{-1} + 0.341Z^{-2}$	46.82

as nonlinear models. The impulse response of the channel [1] can be described from an experimental point of view which shown in the following equation (16)

$$h(j) = \frac{1}{2}\left[\cos\left(\frac{2\pi}{\wedge}(j-2)\right)\right], \quad \text{for } j = 1, 2 \textit{ and } 3$$
$$= 0, \quad \textit{elsewhere} \tag{16}$$

Table: 1 gives the list of different non-linear channels based on their EVR. The Eigenvalue ratio of a channel is the ratio between the highest and least eigenvalues. The upper value of EVR means the channel is more dispersive in terms of channel spread and hence we will face more difficulty to equalize. The parameter $\wedge$ in equation (16) determines EVR. A higher value $\wedge$ (It was varied between 2.9 to 3.5 in the interval 0.2) means a larger EVR of the channel. When the value of $\wedge = 3.1, 3.3$ *and* 3.5 Then the EVR of the channel1,2 and 3 will be 11.12, 21.71, and 46.82 respectively. The different types of nonlinearities [28], [31], [38] are introduced in the channel which is shown in the table-2. NL1 is listed in table2 which is represented as the non-linear distortion that occurs because of the consequence of amplifier dissemination whereas NL2 and NL3 are two different nonlinearities in which NL3 is an extreme nonlinear distortion scenario [22], [23], [31], [34].

TABLE 2. Types of nonlinearity.

SL. No	TYPE OF NON LINEARITY
NL1	$g(n) = \tanh[x(n)]$
NL2	$g(n) = x(n) + 0.2x^2(n) - 0.1x^3(n)$
NL3	$g(n) = x(n) + 0.2x^2(n) - 0.1x^3(n) + 0.5\cos[\pi x(n)]$

TABLE 3. The deviation of α on MSE.

α	Best	Mean	Standard Deviation(S.D)
0	17.4562	18.6707	0.6654
0.25	16.4023	19.0897	0.7645
0.5	17.7563	19.4521	0.4543
1.0	16.4563	19.5543	0.8865
10	0.00763	0.0065	0.0345
20	**2.3452e-007**	**0.0072**	**0.0057**
50	5.45302-007	0.0070	0.0089
100	8.23045-007	0.0076	0.0063

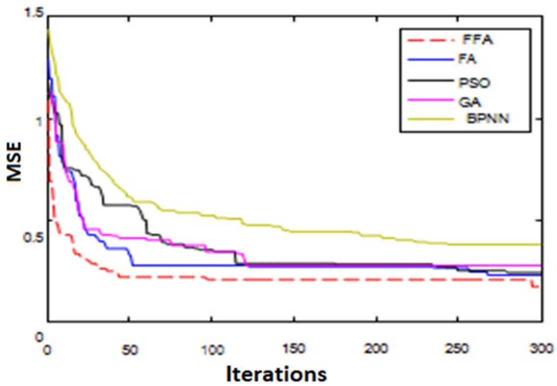
TABLE 4. Parameters used for simulation.

ALGORITHMS	PARAMETER	VALUE
BPNN	Scale factor W	3.5
	Learning rate (γ)	0.5
	Momentum factor	0.7
GA	Max.Iterations	300
	Population size	50
	Mutation ratio	0.03
	Crossover ratio	0.9
	Mutation type	Uniform
	Crossover type	Single point
PSO	Max.Iterations	300
	Population size	50
	Coefficient C1	2
	Coefficient C2	2
	Inertia weight	0.7
FA	Max.Iterations	300
	Population size	50
	α	0.2
	γ	1
	β_0	1
Proposed FFA	Max.Iterations	300
	Population size	50
	α	20
	γ	2
	β_0	1
	n	3
	m	2.6

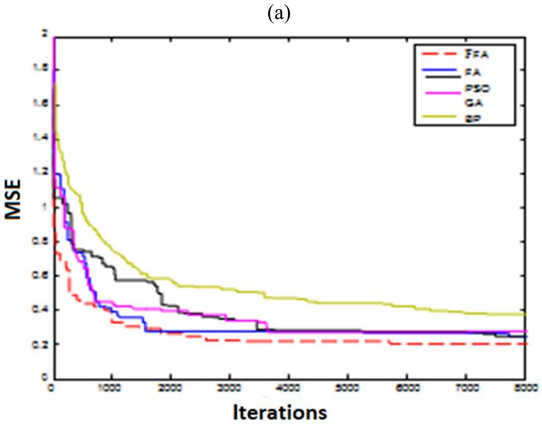
- **Distance between the fireflies** (Controlling parameter α)

The most vital parameter of the firefly algorithm is α which is also called as controlling parameter to control the distance between the fireflies. The exploring pace of the

As the firefly algorithm is modified using the fuzzy firefly membership function so the selection of the variable α helps for stable and faster convergence of the algorithm. Local minima are substantially avoided due to the Cauchy membership function which describes in equation (10) for optimization



(a)



(b)

FIGURE 3. **(a). MSE of Channel 1 with NL2 at SNR10 dB. (b). MSE of Channel 1 with NL3 at SNR20 dB.**

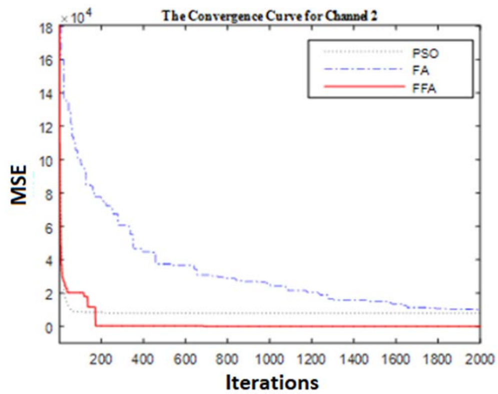
TABLE 5. **Evaluation of mean square error and standard deviation for channel equalization of channel-1 using proposed algorithm considering forty observations.**

Non Linearity	MSE	GA	PSO	FA	FFA
NL2	Best	1.7203e-0	1.4419e-05	4.4318e-05	8.6371e-06
	Worst	4.8023e-01	1.3302e-03	1.3022e-04	5.1234e-05
	Mean	2.6805e-04	2.9821e-05	1.5801e-06	**1.6821e-07**
	Standard deviation	2.6221e-04	4.7806e-06	8.6621e-06	**6.3721e-06**
NL3	Best	0.3786	0.3668	0.3649	0.04487
	Worst	0.4349	0.3649	0.3649	0.04786
	Mean	0.3649	0.3649	0.3649	**0.04488**
	Standard deviation	0.0489	0.0389	0.0089	**1.4186e-06**

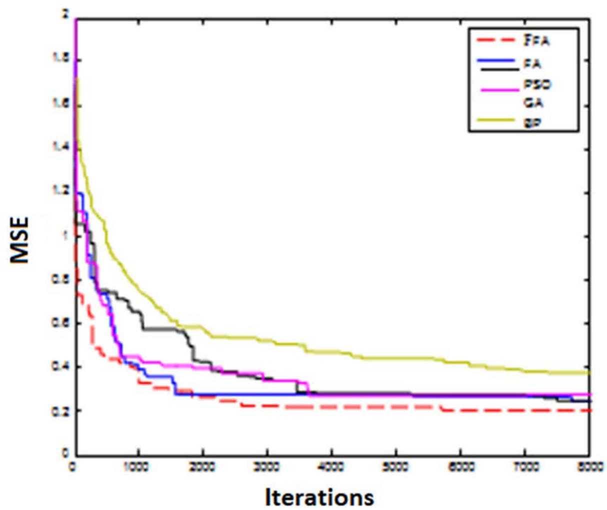
of the controlling parameter α. firefly along with the random motion of particles may both be improved by rising α. Several tests were carried out to determine the best value for α. To determine the global optima of the error function, we analyzed the influence of various values of this parameter. Experiments were conducted by taking the number of fireflies as 50,$\gamma = 1$ and β_0 also 1. Table 3 shows the deviation of α on MSE. From table-3, we observed that we cannot find the global optima between the range [0,1]. Therefore the result can be improved by enhancing this parameter to 20 and then again decreasing. We may argue to rising to 20 improves the movements of being firefly in general.

TABLE 6. **Evaluation of mean square error and standard deviation for channel equalization of channel-2 using proposed algorithm considering forty observations.**

Non Linearity	MSE	GA	PSO	FA	FFA
NL2	Best	8.7203e-04	8.4358e-04	8.4318e-04	6.8717e-04
	Worst	0.0247	0.0057	0.0052	6.4734e-04
	Mean	0.0069	0.0062	0.0042	6.6821e-04
	Standard deviation	0.0047	2.4841e-04	2.4621e-04	3.6717e-06
NL3	Best	0.0286	0.0154	0.0164	0.02187
	Worst	0.0539	0.0247	0.0247	0.02186
	Mean	0.0549	0.0239	0.0229	0.02188
	Standard deviation	0.0089	0.0029	0.0028	6.4186e-06



(a)



(b)

FIGURE 4. **(a). MSE of Channel 2 with NL2 at SNR10 dB. (b). MSE of Channel 2 with NL3 at SNR20 dB.**

A. PERFORMANCE ANALYSIS OF THE PROPOSED EQUALIZER

The transmitted symbol has the value in the form of [−1, +1] and AWGN of SNR10 dB and 20dB is the noise that is added to the output of a wireless communication channel after non-linear distortion is introduced. The training procedure of ANN uses the size of the block of symbols of 250 as put in. To create the required signal, two units are delayed as input

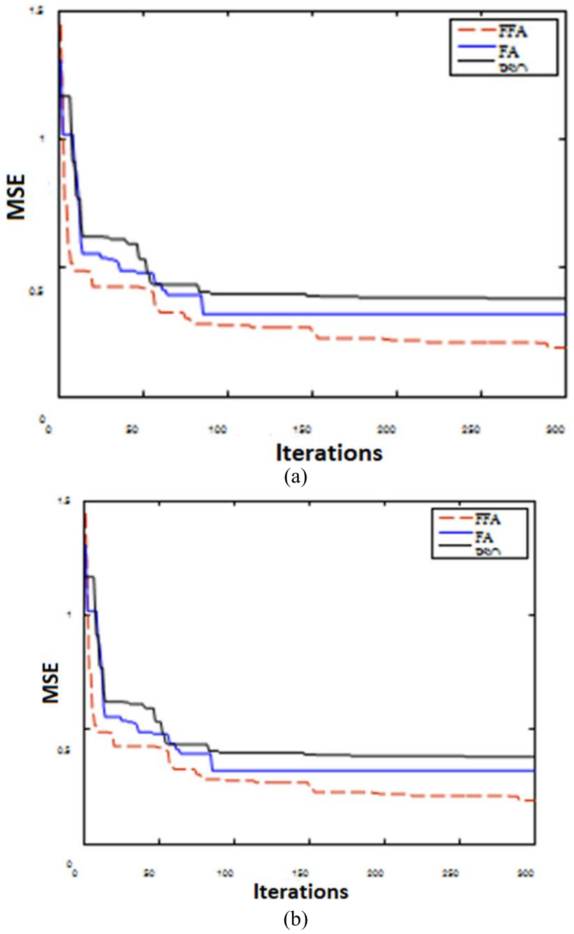


FIGURE 5. (a). MSE of Channel 3 with NL2 at SNR10 dB. (b). MSE of Channel 3 with NL3 at SNR20 dB.

symbols, which are used for error calculation. ANN equalizer was trained for some iterations across thirty independent runs using the suggested FFA-based training technique. The number of input symbols was considered is 10^5 to evaluate BER performance. From a statistical point of view the parameter mentioned in the table as Min, Max, Mean of MSE, and SD. The lower mean, which is MSE medial over forty runs, defines the ability to successfully avoid local minima and converge to an optimal resolution. The determine data's dispersion, the standard deviation is measured.

The performance of the FFA-based ANN in terms of channel equalization has been compared to BP-ANN [30] GA-NN [26], [56] PSO [25], [57] and FA [27], [52]. Table 4 presents the parameter value used in the simulation. As far as the proposed algorithm (FFA) is concerned, one of the major issues is the selection of a suitable value of n and it should be chosen by the population size and the complexity of the problem. If we will increase the value of n accordingly computation rate will increase further. Here, for FFA, the population size, n is chosen as 3 and the value 2.6 is set to form. Furthermore, α, γ and β_0 are 0.2,1 and 1 respectively for FA as well as FFA, but we have considered the value of $\alpha = 20$ for FFA.

TABLE 7. Evaluation of mean square error and standard deviation for channel equalization of channel-3 using proposed algorithm considering forty observations.

Non Linearity	MSE	GA	PSO	FA	FFA
NL2	Best	0.0039	0.0062	0.0043	0.0036
	Worst	0.0137	0.0064	0.0045	0.0039
	Mean	0.0049	0.0067	0.0044	0.0038
	Standard deviation	0.0027	2.7298e-04	4.2184 e-04	5.0792e-06
NL3	Best	0.0386	0.0354	0.0364	0.0358
	Worst	0.0839	0.0447	0.0557	0.0359
	Mean	0.0569	0.0519	0.0459	0.0358
	Standard deviation	0.0089	0.0134	0.0048	1.7186e-05

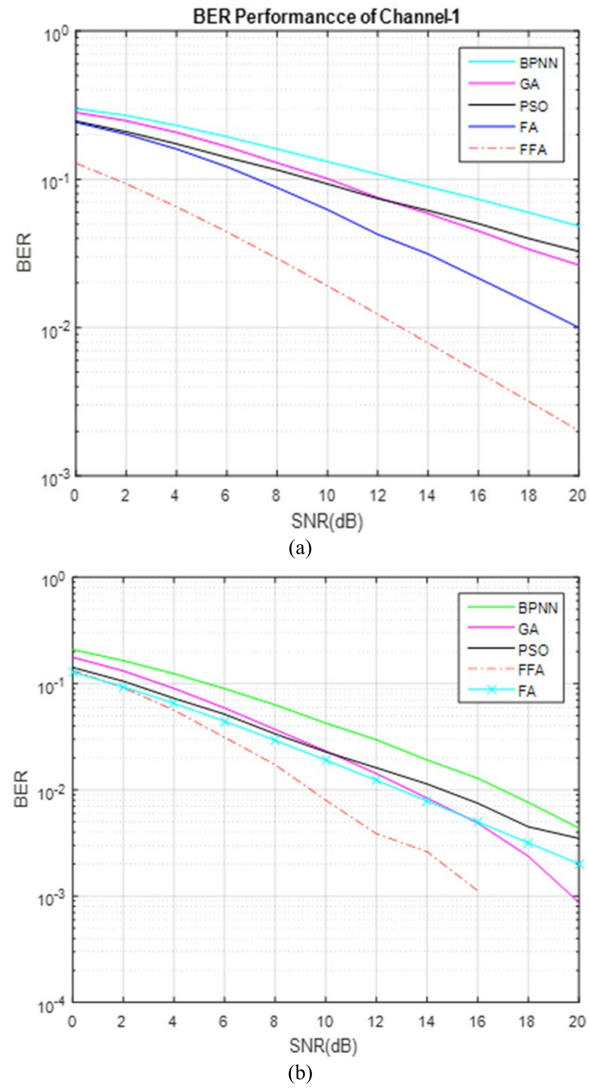
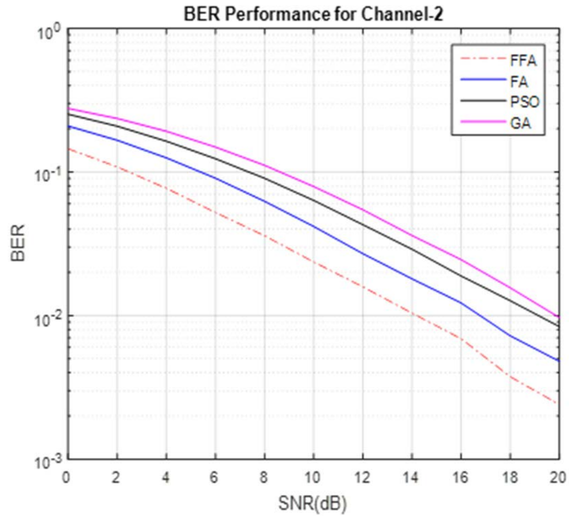


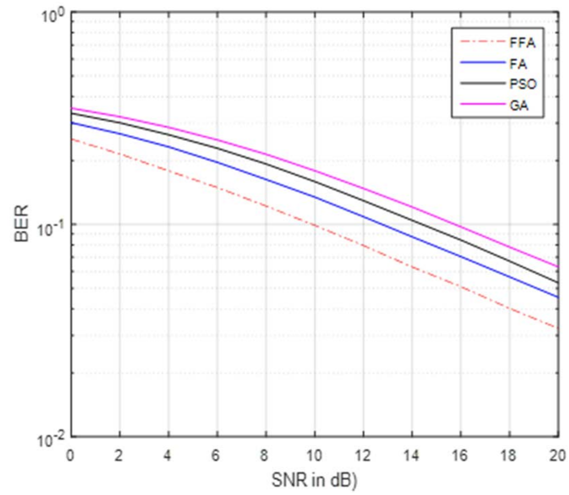
FIGURE 6. (a) BER of Channel 1 with NL2 at SNR20 dB. (b). BER of Channel 1 with NL3 at SNR20 dB.

1) MSE PERFORMANCE

The MSE was plotted for three different channels as described in table1, considering SNR of 10 dB and 20 dB with different non-linearities also shown in table 2. The convergence

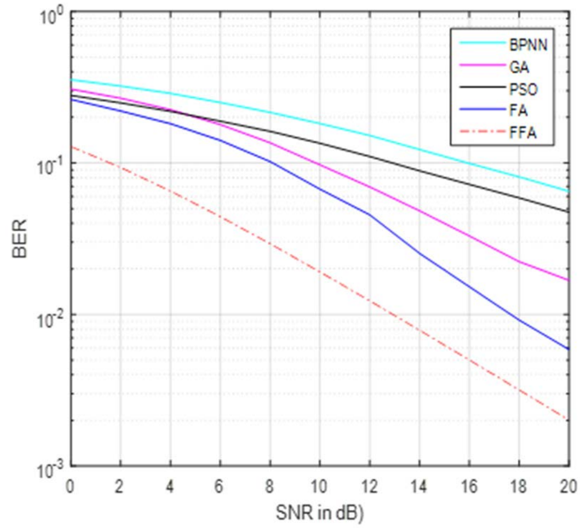


(a)

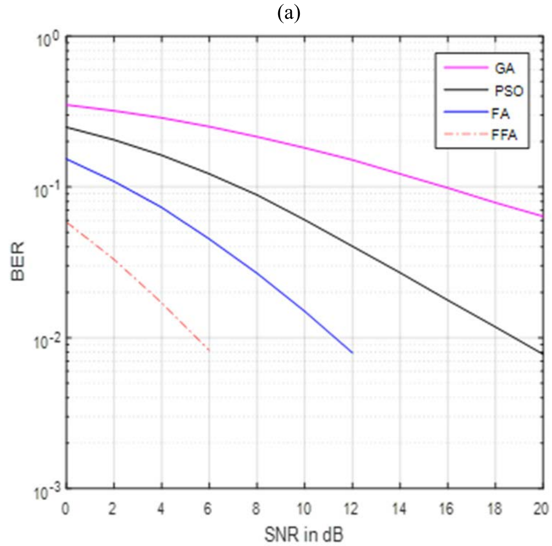


(b)

FIGURE 7. (a). BER of Channel 2 with NL2 at SNR20 dB. (b). BER of Channel 2 with NL3 at SNR20 dB.



(a)



(b)

FIGURE 8. (a). BER of Channel 3 with NL2 at SNR20 dB. (b). BER of Channel 3 with NL3 at SNR20 dB.

behavior of the suggested algorithm with other methods has been compared for some iterations which have already been shown in the figure. Mean square error is one of the most vital parameters to judge the performance of an equalizer, which was medial across forty runs.

Case A (Channel 1): Figures 3(a) & (b) show the MSE plot for channel 1 with two diverse nonlinearities added with the channel at SNR10 dB and 20dB. As described above channel 1 has EVR is 11.12 which is comparatively low dispersible than channel 2 and channel 3. From the figure shown below, it is clear that the performance of the proposed method is superior compared to other algorithms mentioned in the figure. The MSE performance for all techniques degraded as nonlinearity rose from NL=2 to NL=3, but the FFA was shown to behave consistently despite extreme nonlinearity and low SNR. Table 5 also shows the performance of the MSE at SNR 20 dB of the suggested algorithm's superior because S.D and Mean are the lowest among other methods.

Case B (Channel 2): Figures 4(a) & (b) shown below are the comparison of MSE performance of FFA with other schemes for channel 2 at SNR 10 dB &20dB added with non-linearities as NL2 and NL3 which are described in table2. From this figure, it is clear that the ability of equalization of the proposed scheme is better than the existing methods available in the literature. Convergence behavior of the suggested algorithm with other methods have been compared for 2000 and 8000 iterations at SNRs are 10 dB and 20 dB which are also shown in figure 4(a) & (b). From both the figures, it is observed that FFA has shown its best exploration ability as well as escape from local minima. Furthermore, the value of Mean and S.D of MSE of FFA have been shown in table 6 which are lower as compared to other methods.

Case C (Channel 3): In this case, as shown in table 1, Channel 3 is the extremely dispersive channel, with an EVR of 46.82 considered to validate the effectiveness of the proposed

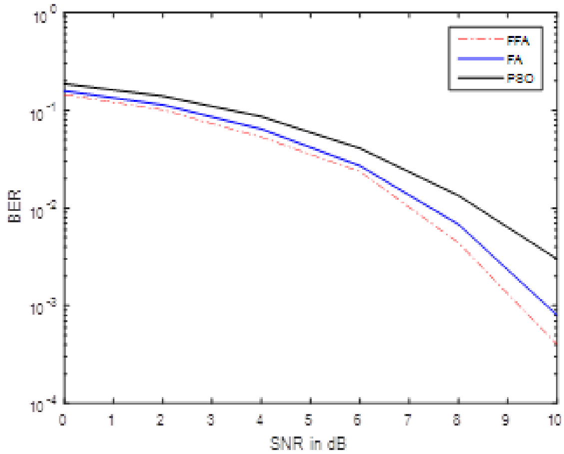


FIGURE 9. BER for Channel 2 in burst error situation with NL=2.

scheme. The MSE performance of the proposed method is shown in Figures 5(a) & (b) at SNR 10dB and 20 dB added with nonlinearities. (As illustrated in table 2; NL=2 and NL=3). From the figure, it is clear that FFA avoids stagnation problems and it has a better capability of exploration. Furthermore, even though MSE increases with increasing EVR from 11.12 to 46.82 for all methods, FFA outperforms other algorithms. More even, the mean and standard deviation value of MSE at SNR =20 dB in both NL=2 and NL=3 are lower as compared to other methods as shown in table7.

2) BER PERFORMANCE OF FFA

This section investigates the FFA trained with ANN's BER performances of three channels. To evaluate the consistency of the FFA's performance, AWGN with a broad range of SNR is added to the channel's output.

Case I (Channel 1): This instance uses Channel 1 with an EVR of 11.12 and two distinct nonlinearities (NL2 & NL3) added separately to the channel to assess the BER. Fig.6(a)and (b) show the BER plot of the proposed method with other schemes at SNR 20dB. In figure 6(a) as compared to other algorithms, FFA provides very less BER and it completely outperforms others. Similarly, figure6 (b) shows the BER plot of channel 1 with nonlinearity (NL3) at SNR 20 dB. In this plot, all algorithms are compared with each other up to 4 dB SNR after that FFA outperforms all previous four algorithms even under severe nonlinearity conditions.

Case II (Channel 2): Here, this example considers the channel more dispersible than channel 1with an EVR of 21.71 to show the BER performance of the suggested method. Figure 7(a) shows the BER plot of channel 2 with nonlinearity (NL2) at SNR 20 dB. In this plot, the performance of the proposed algorithm achieved around 2 dB gains SNR over other existing algorithms compared to simulation. In fig.(b) shows the BER performance of FFA in channel 2, considering nonlinearity (NL3). It shows that FFA gains above 1.75 dB SNR over the remaining algorithms.

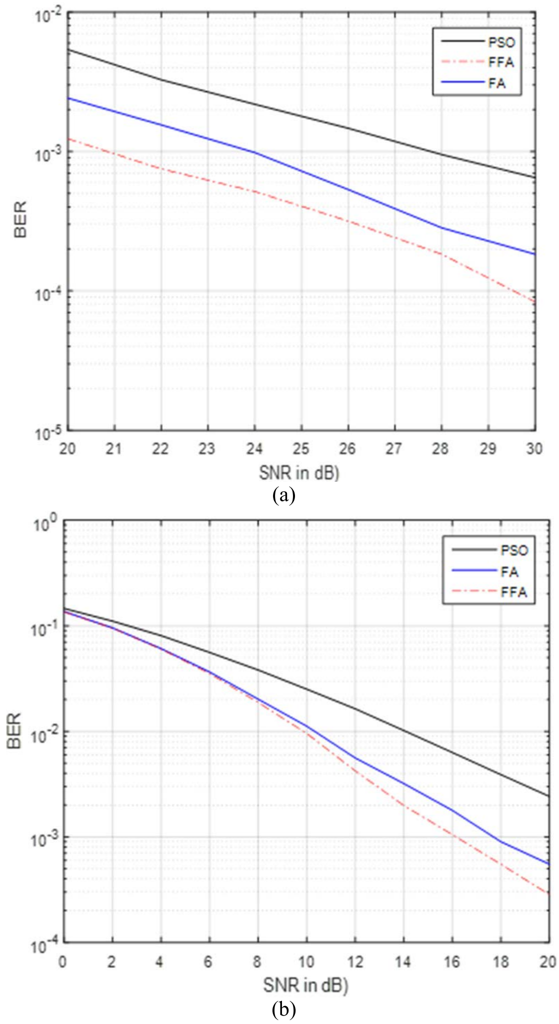


FIGURE 10. (a). BER for Channel 3 in burst error situation with nonlinearities NL=2. (b). BER for Channel 3 in burst error situation with nonlinearities NL=3.

Case III (Channel 3): Here, in this case, in the proposed training technique, the channel with the greatest EVR is used at an SNR of 20 dB. The channel considered here is highly dispersible having EVR 46.82. Fig.8 shows the BER performance of channel 3 with nonlinearity (NL 2&NL 3) is considered. From this figure, it is observed that, compared to BPNN, GA, PSO, and FA, FFA achieve considerable SNR improvement over them. Moreover, from Figures (a) and (b), it is clear that FFA outperforms all compared algorithms even more non-linearity (NL3). This demonstrates the influence of the proposed training method on improved exploration and exploitation capabilities, which results in increased channel equalization accuracy.

Normally the BER performance of an equalizer degrades under low SNR conditions. But in the proposed approach the equalizer provides better BER performance even in the range of low SNR (8dB-25dB). In all the three non-linear channels, the minimum BER value achieved by the proposed equalizer is around 10^{-3}. When SNR increases to a higher value, the low BER of the proposed equalizer at a high SNR condition is an essential requirement for the faithful reconstruction of the transmitted symbols. Thus the equalizer can perform equally well in both low and high SNR conditions for the wireless channel.

3) EQUALIZER PERFORMANCE IN BURST-ERROR SITUATION

The constant recurrence of 0's or 1's during a specific time frame is referred to as a burst error [29]. The performance of an equalizer is severely affected due to burst error situations [58]. The efficacy of the suggested training algorithm can be tested by trained with 300 iterations with distinct non-linearities (NL2 & NL3) which deal with burst situations for the channel equalization problem. As already explained in the above section, channel 3 is highly dispersible than channel 2 and channel1. From the simulation point of view, considering two dispersible channels. (channels 2 and 3). Once training is completed, testing can be carried out. The following figures have shown BER achieved in burst error situations for channels 2 and 3 throughout the testing procedure. From these figures (9 & 10), it is clear that burst error circumstances consequence in significant show deterioration for all algorithms, and curiously, FFA is capable of effectively overcoming the problems faced by employing other methods.

VII. CONCLUSION

In this article; we proposed a training strategy for the proposed FFA equalizer. The suggested approach's local minima avoidance skills and exploration competency aided in locating promising sections of the solution space. The said equalizer trained FFA with ANN in channel equalization. The scheme's combination of exploration and fine-tuning capabilities aided in achieving higher accuracy. Our empirical analysis shows that the proposed equalizer performs better in all noise situations than existing neural network-based equalizers. A wide range of signal-to-noise ratios has been studied to verify the effectiveness of the proposed scheme. Moreover, nonlinearities used in this work for the performance evaluation of different channels are different. The simulation results demonstrated that the FFA-based training technique outperforms previous methods in terms of mean square error and bit error rate.

Future directions

- The proposed approach can be used to train RBF for classification problems for channel equalization.
- Furthermore, the suggested method can be applied to leach energy calculation and node localization in wireless sensor networks, signal processing, and MIMO communications.

Fractional calculus-based models can be applied to the channel equalization problem and node localization in Wireless sensor networks etc.

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