Various Types of Functional Link Artificial Neural Network Based Nonlinear Equalizers used in CO-OFDM System for Nonlinearities Mitigation

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Abstract

Artificial neural network based nonlinear equalizers (ANN-NLEs) have received much attention in the last three years due to its ability of complex mapping between the complex input and output spaces.In the history of ANN-NLE, the focus has always been improving the performance of coherent optical orthogonal frequency division multiplexing (CO-OFDM) system. Recent developments in ANN-NLE have led to a decision that a single neuron based ANN i.e., functional link artificial neural network (FLANN) has been considered as an efficient technique of performance improvement with less computational complexity.There are many types of FLANN available in literature depending on the expansion technique used in network such as PPN (Polynomial Perceptron Network), T-FLANN (Trigonometric Functional link Artificial Neural Network), Le-FLANN (Legendre Functional link Artificial Neural Network) and Ch-FLANN (Chebyshev Functional link Artificial Neural Network).Until now this methodology has only been applied to Ch-FLANN based NLE. It has not yet been established whether other types of FLANN can do the task of nonlinearity mitigation in CO-OFDM system. In this context authors tried to use other types of FLANN-NLE for the mitigation of nonlinearities in CO-OFDM system.

Keywords

Chebyshev Functional Link ANN (Ch-FLANN); Coherent Optical Orthogonal Frequency Division Multiplexing (CO-OFDM); Legendre Functional Link ANN (Le-FLANN); Multilayer Perceptron (MLP); Polynomial Perceptron Network (PPN); Trigonometric Functional Link ANN (T-FLANN).

I. INTRODUCTION

In coherent optical orthogonal frequency division multiplexing (CO-OFDM) techniquepartial overlapping subcarriers is the main cause of a high spectral efficiency [1]. Addition of cyclic prefix code is responsible for elimination of chromatic dispersion (CD) and polarization mode dispersion (PMD) [1, 3]. Nonlinear effects such as self-phase modulation (SPM) and cross-phase modulation (XPM) has become a critical issue in CO-OFDM system. It is well known that SPM and XPM are the nonlinear phase shifts depending on the intensity of an optical pulse due to the pulse itself and a nearby pulse, respectively [4]. Linear equalizer based solutions to optical fiber nonlinearity compensation are inadequate due to linear decision limits present in them [5]. Recent findings regarding nonlinearity compensation in CO-OFDM system have led to Artificial Neural Network based equalizer as an alternative technique. Multilayer Perceptron (MLP) based Artificial Neural Networks are attracting considerable interest due to its capability to accomplish complex mapping between input and output spaces with noteworthy achievement [6]. In [7] the authors studied MLP based ANN-NLE with the Riedmiller's resilient BP algorithm for linear and nonlinear impairment's compensation in coherent optical OFDM system. The pitfalls of their method have been clearly recognized. The main limitation of MLP model is its complexity which made neural network training difficult.

A recent review of the literature on this topic [2016] found that the convenient way to remove these difficulties is to use a single neuron based functional link ANN (FLANN) [8, 9]. FLANN is a network in which the original input pattern is expanded to a higher dimensional space using nonlinear functions and it has a capability to provide arbitrarily complex decision regions. Until now Chebyshev type FLANN has been considered as nonlinear equalizer in CO-OFDM system. As per author's knowledge there is a lack of comparative study between various types of FLANN for nonlinearity mitigation in CO-OFDM system. Including this fact into consideration, authors tried to present the comparison of various types of existing FLANNs for nonlinear effects mitigation in CO-OFDM system. The remainder of this paper has been organized as follows. In second section the simulation setup has been outlined; third section presents the theory of various types of artificial neural networks. Simulation results have been discussed and compared with MLP based NLE in section four. The conclusion has been outlined in fifth section.

II. CO-OFDM SIMULATION SETUP

In this study the simulation set up bears a close resemblance to the one proposed by M.A. Jarajreh in 2010 [10] and has been presented in Fig. 1. This model was chosen because it is one of the most practical ways to mitigate the nonlinearity in CO-OFDM system. The design of the CO-OFDM system was based on the idea of dividing the input complex data of an equalizer into two parts i.e., real and imaginary, applying separately these parts to ANN networks and recombining the output of the ANN equalizer [11]. In this study, various artificial neural network techniques for fiber nonlinearity compensation have been validated by carrying out numerical simulations in MATLAB. More details can be found in author's previous paper [12].

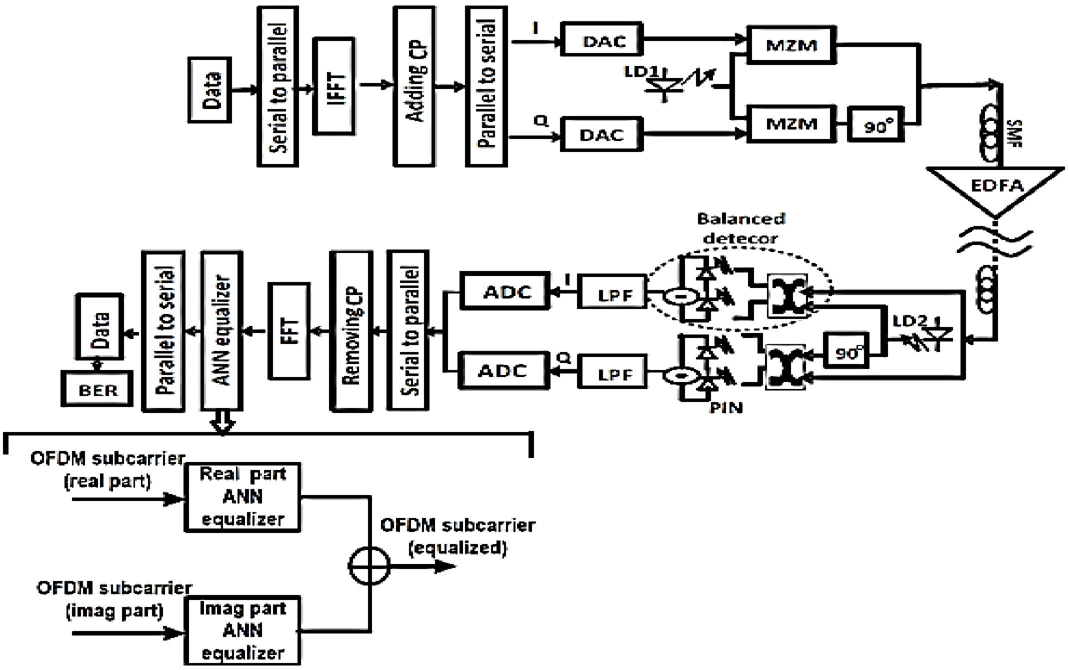


Fig.1 CO-OFDM modem block diagram used for numerical simulations [10]

Various transceiver parameters have been summarized in Table 1.

Table 1. Transceiver parameters for the CO-OFDM transmission model

Parameter	Value
Bit Rate	80Gb/s
Operating Wavelength	1550nm
Fiber Length	200-1000km
Modulation Technique	16-QAM
Cyclic Prefix Overhead	25%
Number of OFDM subcarriers	64
Clipping Ratio	13dB
Chromatic Dispersion	17ps/nm/km
Polarization Mode Dispersion	0.1ps/km$^{(1/2)}$
Fiber Loss	0.2dB/km
Nonlinear kerr coefficient	2.6x10^{-20} m^2/w
Photo Detector	PIN

III. TYPES OF ARTIFICIAL NEURAL NETWORKS

In this section the network structure for each artificial neural network used for the nonlinearity compensation under study has been presented.

A. Multilayer Perceptron (MLP)

First, Multilayer perceptron is the most widely used and basic structure of artificial neural network. The final output of the MLP shown in Fig. 2 is expressed in equation (i).

$$y_k = \psi_k \left[\sum_{k=1}^{P_2} w_{kj} \psi_j \left(\sum_{j=1}^{P_1} w_{ji} \psi_i \left\{ \sum_{i=1}^{n} w_i s_i + b_i \right\} + b_j \right) + b_k \right] \dots .(i)$$

where $s_1, s_2 \dots \dots \dots s_n$ denotes the inputs and y_k represents the output of the final layer of the neural network. The connecting weights between the input layer to the first hidden layer, first to second hidden layer and the second hidden layer to the output layer are represented by w_i, w_{ji} and w_{kj} respectively.

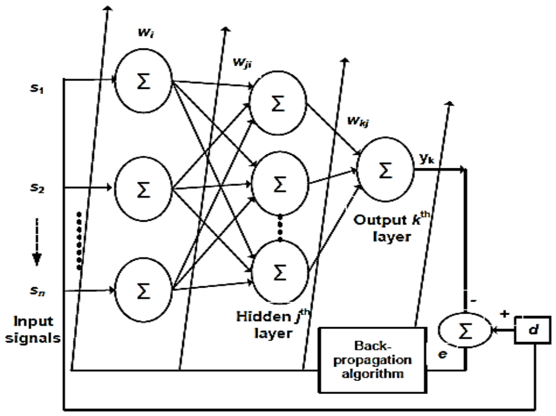


Fig. 2 MLP Neural Network using Back-Propagation Algorithm

In Fig. 2 the most popular form of activation functions used for signal processing application are Sigmoid and the hyperbolic tangent function since these are differentiable. For nonlinearity compensation in CO-OFDM, mostly MLP is trained using popular Riedmiller's resilient back-propagation (RR-BP) algorithm [13].

B. Polynomial Perceptron Network

Weierstrass approximation theorem asserts that any continuous function in a closed interval can be uniformly approximated within any given tolerance over same interval by some polynomial [14].

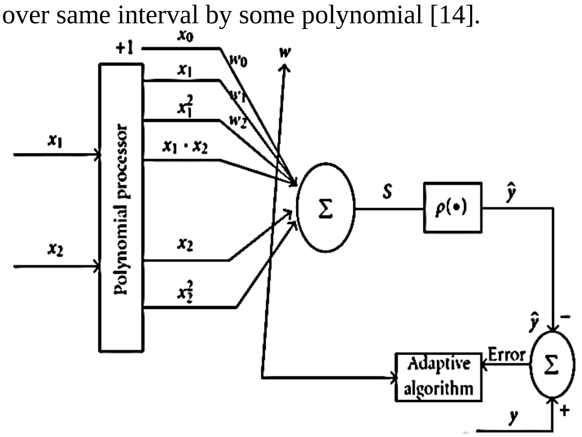


Fig. 3 Polynomial Perceptron Network [15]

PPN structure is shown in Fig. 3. Let us consider a two-dimensional input pattern $X = [x_1 x_2]^T$. This pattern has been enhanced by polynomial processor expressed as X^* given in equation (ii)[15].

$$X^* = [1 \;\; x_1 \;\; x_1^2 x_1 x_2 \;\; x_2 \;\; x_2^2]^T \ldots\ldots\ldots (ii)$$

The PPN is a single layered network and thus the training time is much less than that of the MLP structure. However, in the case of the PPN, the number of weights grows rapidly as the polynomial order and the dimension of the input pattern increases.

C. Functional Link Artificial Neural Network

Functional Link Artificial Neural Network (FLANN) is a type of higher Order Artificial Neural Networks that uses higher combination of its inputs [15-17]. It has been successfully used in many applications [18]. Here, the FLANN for the channel equalization to compensate the nonlinearities in optical OFDM has been used. In this paper, three types of functional expansions i.e., trigonometric expansion, Chebyshev expansion and Legendre expansion have been used to mitigate the nonlinear effects and their respected structures are shown in Fig. 4.

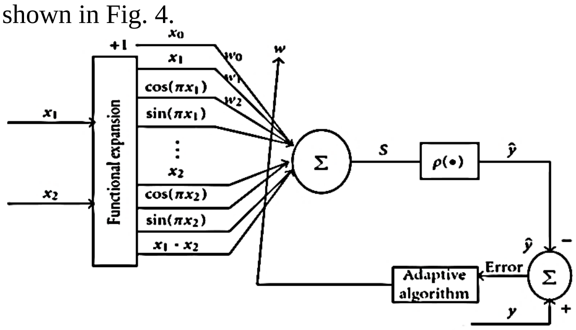


Fig. 4 (a) Trigonometric expansion

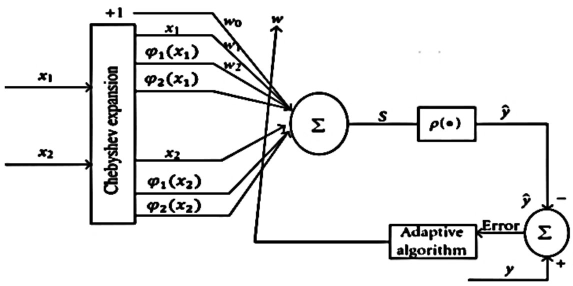


Fig. 4 (b) Chebyshev expansion

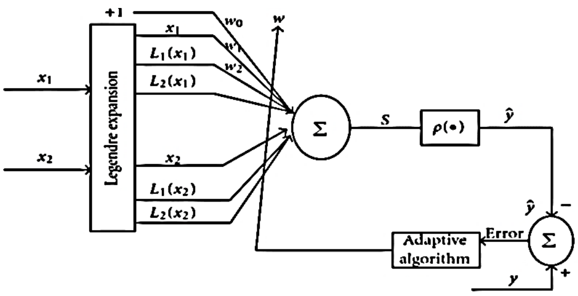


Fig. 4(c) Legendre Structure

1) Trigonometric expansion

Let us consider a two-dimensional input pattern $X = [x_1 x_2]^T$. This input pattern of an equalizer has been enhanced by functional expansion using Trigonometric functions as shown in equation (iii).

$$[x_1 \cos(\pi x_1) \; \sin(\pi x_1) \ldots \cos(2\pi x_1) \sin(2\pi x_1) \ldots x_2 \cos(\pi x_2) \sin(\pi x_2) \ldots \cos(2\pi x_2) \sin(2\pi x_2) \ldots x_1 x_2]^T \ldots\ldots (iii)$$

2) Chebyshev expansion

The input of CO-OFDM system is expanded using Chebyshev polynomial and shown in equation (iv).

$$\varphi = [\varphi_1(x_i(k)), \varphi_2(x_i(k)), \ldots\ldots \varphi_p(x_i(k))] \ldots\ldots (iv)$$

3) Legendre expansion

Legendre functional link artificial Neural Network (Le-FLANN) has a wonderful striking feature of faster training rate as compared to T-FLANN and Ch-FLANN. The Legendre expansion polynomials are represented by $L_n(X)$, where n is the order of polynomial. The 0^{th} and 1^{st} order Legendre polynomials are given by $L_0(x)$=1 and$L_1(x) = x$. Legendre network higher order polynomials are formed by following mathematical equation (v).

$$L_{n+1}(x) = \frac{1}{n+1}[(2n+1)xL_n(x) - nL_{n-1}(x)] \dots\dots (v)$$

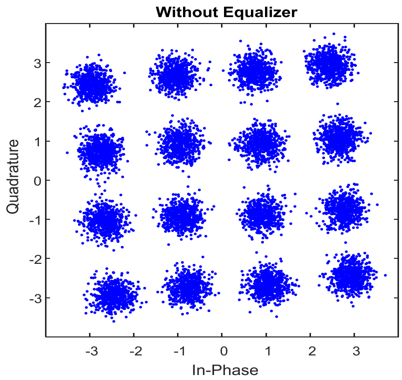
For a two-dimensional input pattern $X = [x_1 x_2]^T$. This input pattern has been enhanced by Legendre functional expansion using the equation (vi).

$$X^e = [1, L_1(x_1), L_2(x_1), L_3(x_1), L_1(x_2), L_2(x_2), L_3(x_2)] \dots (vi)$$

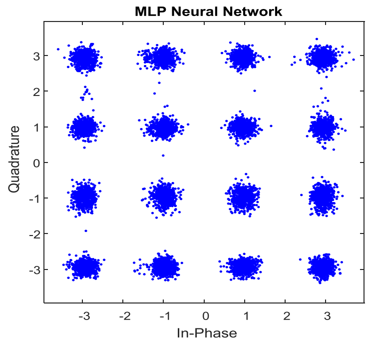
For Legendre neural network, training procedure of network is same as that in FLANN and PPN. Hence FLANN and Le-FLANN is appropriately used as nonlinear equalizer in CO-OFDM system due to less computational cost.

IV. SIMULATION RESULTS AND DISCUSSIONS

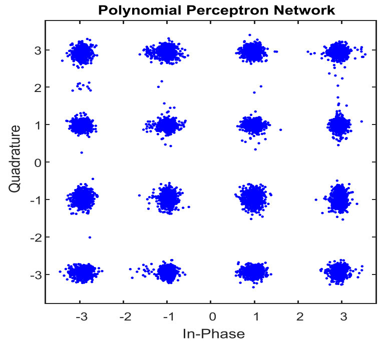
The results obtained without ANN equalizer, with MLP based ANN equalizer, with PPN based ANN equalizer and with various types of FLANN equalizers by performing various simulations, have been summarized in Fig. 5 to Fig. 8. In the Fig.5 (a) - 5(f) various scatter plots has been presented. From these scatter plots, it has been clear that Chebyshev FLANN provides more converged points as compared to all other techniques under study.



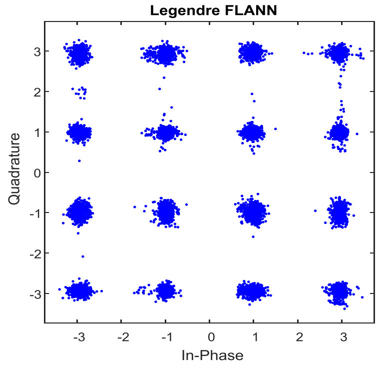
(a)



(b)



(c)



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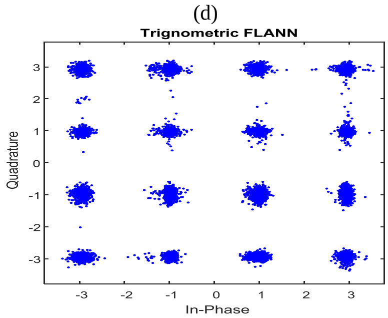
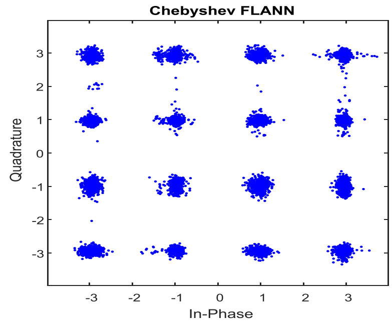


(e)



(f)

Fig. 5 Received 16-QAM Scatter plots with various NLEs

Fig. 6 shows the Input launch power (dBm) versus Q-Factor (dB) for the CO-OFDM system without NLE, with ANN based NLE's over fiber length 1000km, at payload bit rate 80Gbps. As shown in Fig. 6, the value of Q-Factor gets improved with all the techniques under study. But with Chebyshev based FLANN technique achieved Q-Factor is maximum as compared to all other techniques. This plot shows that maximum improvement is achieved at -3dBm.

Fig. 7 shows the Bit error rate (BER) versus OSNR (dB) without ANN equalizer and with different equalizers on fiber length of 1000km at typical dispersion value of 17ps/nm-km. With the 60% change in OSNR (i.e., 8dB to 20 dB), the BER change without equalizer is 92% and with various ANN based equalizer it is almost 99.9% which means that the change in BER is almost same in all types of ANN equalizers. At specified value of OSNR at 15dB the percentage improvement in BER is 96.16%, 98.05%, 98.88%, 99.25% and 99.4% for ANN-MLP, PPN, Le-FLANN, T-FLANN and Ch-FLANN respectively. This result shows that with the increase in value of OSNR, the BER improvement is more in Chebyshev-FLANN as compared to that of all other techniques.

Fig. 8 shows the fiber length (km) versus Q-factor (dB) without ANN equalizer and with different equalizers on fiber length of 1000km at typical dispersion value of 17ps/nm-km. At specified value of fiber length-1000km the percentage improvement in Q-factor is 5.35%, 6.44%, 7.21%, 7.86% and 8.3% for ANN-MLP, PPN, Le-FLANN, T-FLANN and Ch-FLANN respectively. This implies that with the increase in value of optical fiber length, the Q factor improvement is more in Chebyshev-FLANN as compared to that of all other techniques of FLANN and basic MLP based ANN.

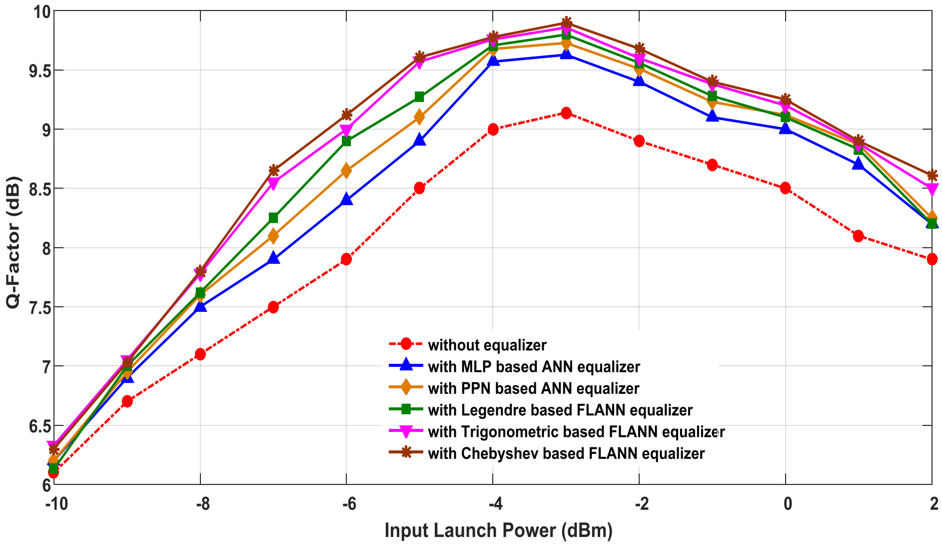


Fig. 6 Input Launch Power (dBm) versus Q- Factor (dB)

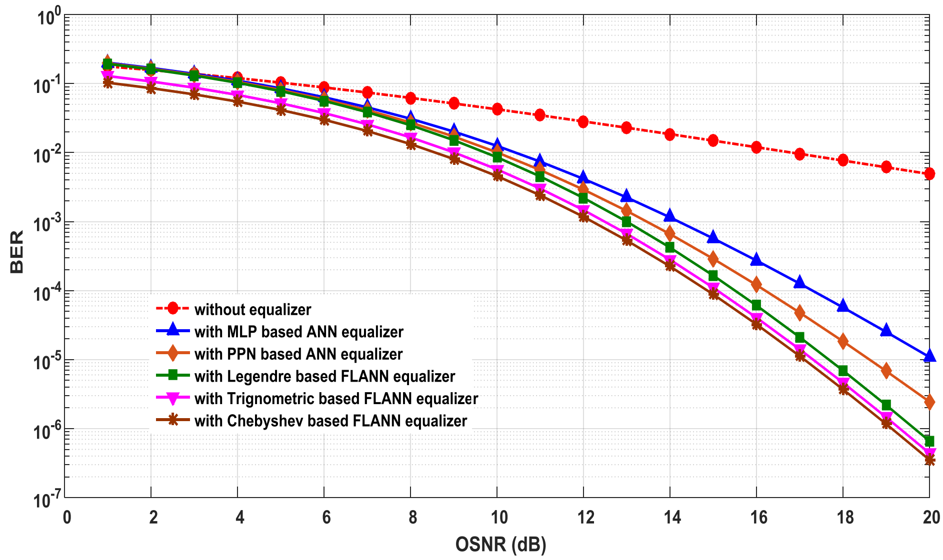


Fig. 7 OSNR (dB) versus BER

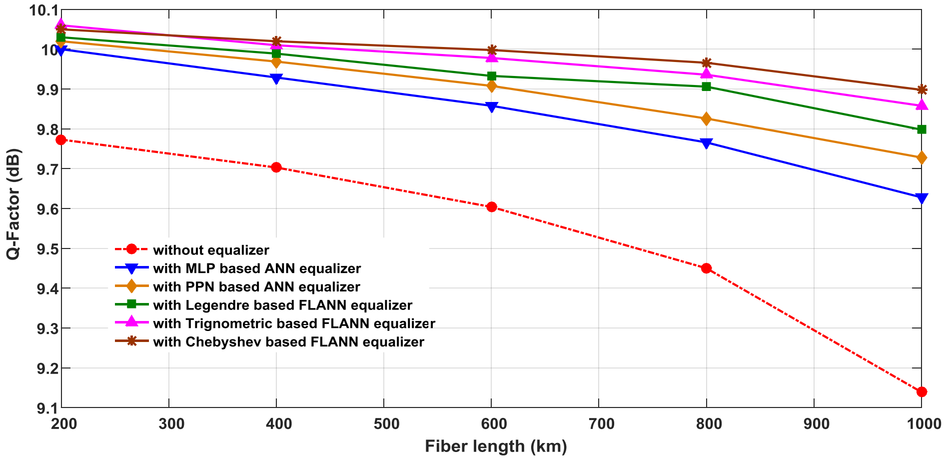


Fig. 8 Fiber length (Km) versus Q-Factor (dB)

V. CONCLUSION

It is clear from the comparison between the results of BER and Q- factor performance for the different types of ANN based equalizer, that the FLANN based non-linear equalizers provides better results over other equalizers. It has been found from this study that different FLANN based nonlinear equalizers such as Le-FLANN, T-FLANN and Ch-FLANN provides almost same performance improvement for the variation in fiber length (i.e., 98.88%, 99.25% and 99.4% improvement in BER performance and 7.21%, 7.86% and 8.3% improvement in Q-factor for Le-FLANN, T-FLANN and Ch-FLANN nonlinear equalizers respectively). If the system computational cost is the main factor to be considered than the Le-FLANN based nonlinear is the preferred technique because it requires less computational effort. It has been seen in above simulation result values, the Ch-FLANN provides 8.3% improvement in Q-factor which is more than the other techniques of FLANN equalizer such as Le-FLANN and T-FLANN. Therefore it has been concluded that Ch-FLANN technique is preferred over other techniques of FLANN if the performance improvement is the most important factor of the system under consideration.

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