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On the Pulsewidth Analysis in the Presence of PMD and PDL in Optical Fibers Using Neural Network Algorithm

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Abstract: In long haul networks, the random birefringence induced in the optical fiber leads to a considerable Polarization Mode Dispersion (PMD). Polarization Dependent Loss (PDL) mainly occurs in optical components and depends on the state of polarization of optical signals. The presence of PMD and PDL causes pulsewidth narrowing and the pulsewidth reduction depends on states of polarization at which the input light launched and also the input pulsewidth. A system comprising of a PDL element sandwiched between two PMD elements was considered. This system was characterized using neural network approach. Back propagation algorithm was applied to train the network with four input vectors namely PMD, PDL, input pulsewidth and the angle describing the input states of polarization and one output vector indicating effective squared pulsewidth difference. On analysis, it was found that the pulsewidth reduction was higher for a PMD of 30ps, a PDL of 3.5 and input pulsewidth of 100ps at various (Linear and Circular) input states of polarization with the angle describing the input state of polarization to be $|\pi/4|$. Similarly, for a given value of PMD, PDL, input pulsewidth and a specific pulsewidth reduction, the input state of polarization at which the light was to be launched can also be determined using neural network approach.

Key words: Polarization mode dispersion, polarization dependent loss, pulse narrowing, neural networks

INTRODUCTION

The birefringence properties of optical fiber systems are becoming important in optical fiber telecommunication and optical fiber networks as a limiting factor of the bit rate. They change the state of polarization of light wave on travel along the fiber. This change in state of polarization of light wave leads to various polarization effects such as PMD and PDL. PMD is due to random birefringence in optical fibers and components where signals with different states of polarization travel at different speeds. PMD causes random pulse distortion and pulse broadening[1]. Pulse broadening is due to the differential transmission time of two pulses polarized along orthogonal states of polarization. PDL induces random fluctuations of optical signal to noise ratio (OSNR)[2,3] in the system. PDL mainly occurs in optical components such as isolators and couplers, whose insertion loss is dependent on the states of polarization of input signals. Both PMD and PDL lead to significant performance degradation in long haul light wave transmission systems.

In the past decade, tremendous efforts has been made to understand the impairment in optical transmission systems caused by PMD, PDL and their combined effects[1-8]. Recent studies have shown that, the output pulsewidth becomes narrower than the input pulsewidth when PDL value is less than some critical value. It is also understood that, for a fixed value of PMD, whether the launched pulse shall spread or not depends on the input state of polarization.

A Radial Basis Function (RBF) equalizer based on neural network is used to mitigate the PMD induced intersymbol interference (ISI) in optical fiber communication systems[9]. In this paper, neural network is applied to analyse the combined effects of PMD and PDL on pulse propagation. A multilayer perceptron with four nodes at the input layer, three nodes at the hidden layer and one at the output layer is trained using τ (input pulsewidth), β (PMD), α (PDL) and θ_{in} (angle describing the direction of input states of polarization) as input vectors and σ^2_{eff} (effective squared pulsewidth difference) as output vector. Backpropogation algorithm is used for training the

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network with suitable input patterns. It is found that the root mean squared pulsewidth of the output pulse is reduced for a selective range of PMD and PDL at different input states of polarization (Linear and circular) leading to pulsewidth narrowing.

System Description

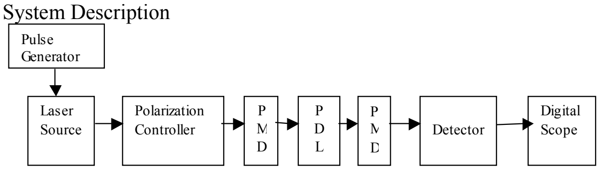

Fig. 1: System model

Neural algorithm is applied to a system model as shown in Fig. 1 where a PDL element is sandwiched between two PMD elements[10]. PDL element is aligned $3\pi/8$ with respect to PMD direction and it is parallel to the input polarization. The two identical PMD sections are arranged in parallel. Such a model is considered for analysing the effects of pulsewidth narrowing at different input states of polarization, different input pulsewidths and different values of PMD and PDL.

Neural network models are specified by their network topology, node characteristics and learning rules. These rules specify an initial set of weights and also indicate the method for changing the weights to achieve performance improvement. Appropriate activation functions are used in both hidden and output layers. Backpropagation learning requires the activation functions of the hidden units to be bounded and differentiable. For hidden units, sigmoid activation functions are usually preferable to threshold activation functions. Networks with threshold units are difficult to train because the error function is stepwise constant, hence the gradient either does not exist or is zero, making it impossible to use backpropagation or more efficient gradient-based training methods. With sigmoid units, a small change in the weights will produce a considerable change in the outputs, thereby deciding a correct value of the output whereas with the threshold units, a small change in the weights will not produce any appreciable change in the outputs.

Various activation functions are used in this simulator. Sigmoidal function (1/(1+exp(x))) is always used at the output since it produces a small percentage of error at a faster rate. Three different types of activation functions are used in the hidden layer namely sigmoidal, hyperbolic tangent ((exp(x)-1)/(exp(x)+1)) and linear activation function, out of which the linear function produces better results.

The backpropagation algorithm propagates an input through the network, the error is calculated and the error is propagated back through the network while the weights are adjusted in order to make the error smaller. Although it is desired to minimize the mean square error for all the training data, the most efficient way of doing this with the backpropagation algorithm, is to train on the data sequentially one input at a time, instead of training on the combined data. However, this means that the order in which the data is given in is of importance, but it also provides a very efficient way of avoiding getting stuck in local minima.

Multi layer perceptron architecture with one hidden layer made of three neurons using back propagation algorithm[11] is found to provide better results for the

Table 1: Training sequence for linear polarization

Input state of polarization	τ (ps)	β (ps)	θ_{in}(rad)	α	σ^2_{eff} (ps^2)
Linear	25	1	-0.785	-6	-0.6025
	25	1	-0.785	-3.5	-0.5979
	25	1	-0.785	-2.5	-0.5697
	25	1	-0.785	-1.5	-0.414
	25	1	-0.785	-1	-0.2491
	25	1	-0.785	-0.5	-0.084
	25	1	-0.785	0	0.0215
	25	1	-0.785	1.5	0.099
	25	1	-0.785	2.5	0.1029
	25	1	-0.785	5.5	0.1036
	100	30	-0.785	-6	-495.309
	100	30	-0.785	-2.5	-469.072
	100	30	-0.785	-1.5	-343.423
	100	30	-0.785	-1	-207.744
	100	30	-0.785	0	21.8049
	100	30	-0.785	0.5	65.0472
	100	30	-0.785	1.5	89.4533
	100	30	-0.785	2	91.9747
	100	30	-0.785	6	93.4509
	100	20	0.785	-6	41.4713
	100	20	0.785	-1	36.6275
	100	20	0.785	0	9.0762
	100	20	0.785	1	-96.412
	100	20	0.785	2	-200.158
	100	20	0.785	3	-226.973
	100	20	0.785	6	-231.685

Table 2: Training sequence for circular polarization

Input state of polarization	τ (ps)	β (ps)	α	σ^2_{eff} (ps^2)
Left Circular	50	20	-6	-111.035
	50	20	-3.5	-117.057
	50	20	-2	-136.639
	50	20	-2.5	-127.404
	50	20	-1.5	-148.48
	50	20	-1	-158.082
	50	20	-0.5	-148.043
	50	20	0	-86.5829
	50	20	1	138.8055
	50	20	2	242.599
	50	20	3	269.1603
	50	20	4	276.6374
	50	20	6	279.9082

system model shown in Fig. 1. The input layer has four neurons indicating τ, β, α and θ_{in}. However, the output layer has only one neuron to indicate σ^2_{eff} . A few of the sample data used for training the network with linear polarization is shown in Table 1 and that with circular polarization is shown in Table 2. The final weights obtained at the end of iteration are applied as the initial weights in the subsequent iteration and thereby faster convergence is achieved.

RESULTS AND DISCUSSION

Neural network is trained with an error tolerance of 10^{-5} and the network is tested for different input states of polarization, with different input pulsewidths and at different values of PMD and PDL. The test results are plotted in Fig. 2-5. For a case of linear polarization with θ_{in}= -π/4, σ^2_{eff} as a function of PDL value α has been plotted in Fig. 2 and 3, with PMD, β=1, 30 ps, input pulsewidth, τ=25, 100ps and ω_0=400π rad/ps (corresponding to a wavelength of 1.5 µm). It is observed from Fig. 2 and 3 that the output pulsewidth becomes narrower than input pulsewidth, when PDL value α is between -1 and -4. It is also found that, even with the existence of finite DGD, the pulsewidth reduces due to a high value of PDL. It is to be noted that the pulsewidth narrowing is significant for an input pulsewidth of 100 ps and a PMD of 30 ps. There is a 13.525% of pulsewidth reduction for a PDL of -3.5. The neural network simulator has produced results with an accuracy of 1.7191×10^{-4}.

For a case of linear polarization with θ_{in}= +π/4, σ^2_{eff} as a function of PDL value α is plotted in Fig. 4 with PMD, β =20 ps; input pulsewidth, τ =100ps; and ω_0=400π rad/ps. The results are similar as in the case of θ_{in}= -π/4, but the curves are the mirror image of each other at about α =0. This indicates that the magnitude of the pulsewidth reduction is the same for the case of θ_{in}= +π/4 and -π/4 with a PDL value of same magnitude but with opposite sign. The neural network simulator produces the test outputs with an accuracy of 1.0775×10^{-4}.

For a case of left circular polarization, σ^2_{eff} as a function of PDL value α has been plotted in Fig. 5, with PMD, β=20 ps, input pulsewidth, τ=50ps and ω_0=400π rad/ps (corresponding to a wavelength of 1.5 µm). It is found from Fig. 5 that the pulsewidth narrowing is prominent at α = -1.0, ω_0= 400π rad/ps for left circular polarization. The pulsewidth reduction calculated for circular polarization is 10.43%.

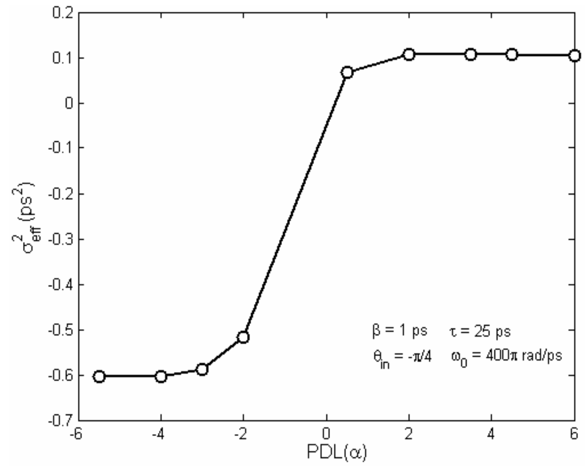

Fig. 2: Effective pulsewidth square difference between output and input pulses is plotted as a function of PDL value α for linear polarization β= 1 ps, ω_0=400π rad/ps, θ_{in}= -π/4 and τ=50 ps

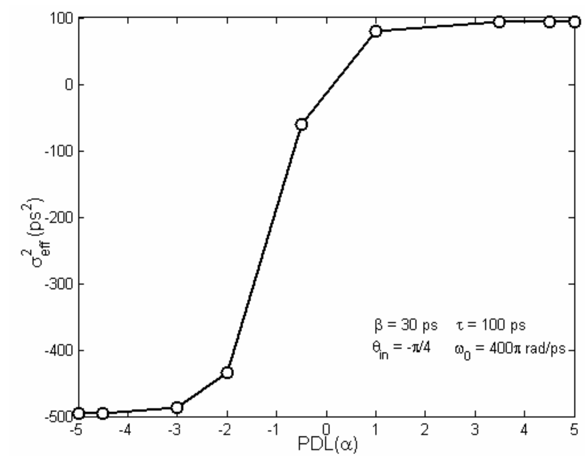

Fig. 3: Effective pulsewidth square difference between output and input pulses is plotted as a function of PDL value α for linear polarization β=30 ps, ω_0=400π rad/ps, θ_{in}= -π/4 and τ=100 ps

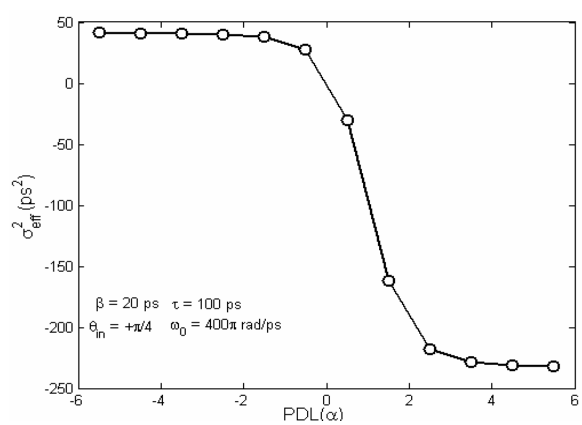

Fig. 4: Effective pulsewidth square difference between output and input pulses is plotted as a function of PDL value α for linear polarization. β=20 ps, ω_0=400π rad/ps, θ_{in}= +π/4 and τ=100 ps

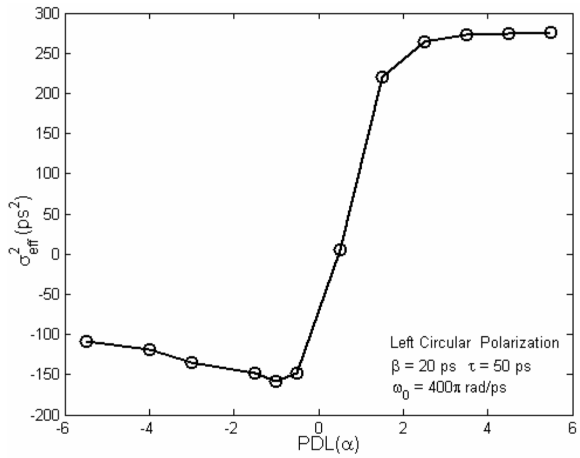

Fig. 5: Effective pulsewidth square difference between output and input pulses is plotted as a function of PDL value α for left circular polarization with β=20 ps, ω_0=400π rad/ps and τ=50ps

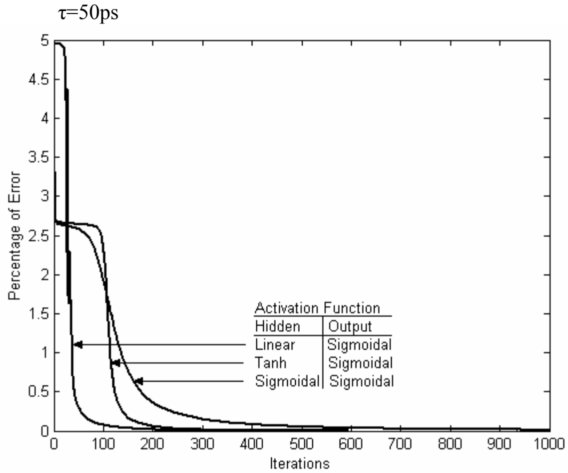

Fig. 6: A comparison of three different activation functions at the hidden layer with the sigmoidal function at the output layer

The neural network simulator produced the output with an accuracy of $6.4198\text{x}10^{-4}$.

Conversely, the neural network can also be trained to identify the input state of polarization for a given value of pulsewidth reduction, PMD, PDL and input pulsewidth. This can be done by chosing the input state of polarization as output vector and the remaining parameters as input vectors.

A comparison of the three types of activation functions considered in the hidden layer (Sigmoidal, hyperbolic tangent and linear) of this network are also presented in Fig. 6 by plotting the percentage of error versus number of iterations. It is found that the sigmoidal function at the output layer produces a smaller percentage of error with a faster convergence than compared to that of hyperbolic tangent and linear activation functions. However, at the hidden layer the linear activation function is found to produce a better result.

CONCLUSION

From the above results, it is found that the pulsewidth reduction is more for a PMD of 30ps, a PDL of 3.5 and input pulsewidth of 100ps at various (Linear and Circular) input states of polarization. The magnitude of pulsewidth reduction for θ_{in}= +π/4 and -π/4 is found to be the same with a PDL value of same magnitude but of opposite sign. To obtain a specified value of pulsewidth reduction for a given value of PMD, PDL and τ in a fiber transmission system, the required input state of polarization at which the light is to be launched can be determined using the neural network approach. A sigmoidal activation function at the output layer and a linear function at the hidden layer is found to converge with the smallest percentage of error at a less number of iterations.

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