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Evolving fuzzy neural network equalization of channel impulse response in optical mode division multiplexing

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ABSTRACT

Optical mode division multiplexing (MDM) systems suffer from the inter-symbol interference (ISI) issues due to nonlinear channel impairments in multimode fiber from mode coupling and modal dispersion. Existing equalization algorithms in MDM systems such as least mean square (LMS) and recursive least squares (RLS) operate linearly and thus far, are unable to effectively mitigate the nonlinear channel impairments. To address this issue, a nonlinear evolving fuzzy neural network (EFuNN) equalization scheme was developed in MATLAB to reshape the channel impulse response of a MDM system comprising five Laguerre-Gaussian (LG) modes at the transmitter to five reference Gaussian pulses at separate time intervals at the receiver in order to mitigate the effects of ISI from nonlinear channel impairments.

1. INTRODUCTION

The remarkable growth of traffic volume caused by the exponential increase of the number of Internet users and continual development of increased bandwidth has led to a huge capacity of communication system [1] and the creation of various applications [2]. One of the most well-established communication technologies is fiber optic, which has easily become indispensable, standing prominently as the mainstay of the modern-day information infrastructure [3]. The existing infrastructure in high-speed local area networks is extensively based on the multi-mode fiber (MMF) due to its easy usage, good performance and its provision of the required bandwidth for a short distance at a more reasonable cost than the fundamental single-mode fiber (SMF) [4]. In order to meet the expansion in growth of data traffic, the ability of SMF has been improved consistently last a few decades, and is converging to nonlinear capacity limit [5]. For managing the future bandwidth predicament, in the last years, mode-division multiplexed (MDM) transmission over MMF has garnered in much attention as an intelligent way to deal with the capacity limits of SMF [6]. This is possible because the capacity of an MDM system

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increases relative to the number of modes. In a practical MMF, nonlinear mode coupling is induced as a result of the fiber manufacturing defects caused by non-circularity of the core, micro-bending, macro-bending, or twists. Consequently, the signal on each fiber mode propagates down the fiber with its own distinguished speed signal strength. Modes that take shorter paths arrive at the receiver earlier than the ones taking longer paths. Mode coupling leads to linear and nonlinear modal dispersion of the signal or spreading of the optical pulse in time. A short pulse becomes longer and ultimately joins with the pulse behind, making it less probable for a reliable bit stream for recovery due to inter-symbol interference (ISI) [7]. To date, compensation for MDM nonlinear channel impairments, in particular, for de-multiplexing of the output signals and reshaping of the received channel impulse response, has been realized by utilizing linear equalization strategies such as least mean square (LMS) and recursive least squares (RLS) algorithms. The linear equalization strategies are inaccurate considering the nonlinearity of the channel impairments. Accordingly, MDM equalizers should be developed to be adaptive to time variation and nonlinear characteristics. Based on nonlinear characteristics of the MDM channel impairments, it is of great interest to adapt the EFuNN algorithm for nonlinear equalization of the channel impulse response at the receiver. EFuNN is capable of modelling nonlinear system relationships and has been proven by Kasabov (1999) to be a very powerful tool when used to data which is comparatively interference, uncertain, and changeable. EFuNN which has been successfully applied in applications such as, adaptive learning, knowledge-based systems and for prediction. Many studies have used either neural networks or fuzzy logic in equalization communication systems. Most of these studies focus on the combination of NN and fuzzy logic, in designing a system that uses the neural network for a self-learning characteristic. This increases the data transmission accuracy, whereas, fuzzy logic allows the complexity of the data to be reduced and it is able to represent knowledge in an interpretable manner for any uncertainty to be dealt with. The fuzzy neural network evolves over time because of the nature of the constructional development and the adaptation of the entire evolving connectionist system (ECOS) of which it has become part. In this research, an equalization scheme for MDM base on EFuNN is developed to reduce ISI which is caused by mode coupling by reshaping the channel impulse response and measured the performance of the proposed equalization scheme in MDM based on root mean square error (RMSE) and CPU-time. Furthermore, to obtain the distorted channel impulse response, an MDM system over MMF is simulated in OptiSystem in conjunction with its Multimode Component Library.

2. RELATED WORK

The existing equalization schemes for MDM system are based on several algorithms such as LMS, RLS, and (RLSCMA).

NO	Title	Author	Algorithm	Summery
1.	"MIMO Signal Processing For MDM With RLSCMA Algorithm [8]."	Zhao et al. (2014)	RLSCMA	"It applies RLSCMA algorithm as the equalization scheme in MDM in FMF. The received signal suffers from mode coupling and mode delay, unless the limitations are compensated by multi-input multi-output (MIMO)-(digital signal processing) DSP equalizers."

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2.	"MIMO Signal Processing for MDM. [9]."	Kahn et al. (2014)	LMS/RLS.	"The adaptation cost for RLS is high. Adapting LMS suffers from higher asymptotic SERs and low cyclic prefix efficiency. It was found that cyclic prefix transmission reduces system throughput and average-power efficiency and decreases complexity. "

Table 1. Currently available equalization schemes in MDM

NO	Title	Author	Algorithm	Summery
1.	EFuNN Based Load Prediction Model In Dynamic Cell Sizing [10].	Amphawan (2003)	The EFuNN	EFuNN computational model was utilized making prediction. It works through one pass learning and automatically adapts the parameter values as operating. The study found that EFuNN is able to learn traffic sequences in an adaptive way.
2.	"Neuro-Fuzzy Equalizers for Mobile Cellular Channels [11]. "	Raveendranathan, (2013).	Neuro-fuzzy	The study made use of a nonlinear, fuzzy adaptive equalizer. It was attached in mobile broadband and Ultra-Wide Band (UWB) communication channels.

Table 2. Previous nonlinear equalization schemes in radio

substantial research effort has been made for several studies to investigate about the efficient using of equalization techniques in wireless communication like artificial neural network (ANN), fuzzy systems and their combinations. They have received attention in the various divisions of wireless communication. This is because of their ability to mitigate the ISI as well as adaptation to the nonlinear nature. It motivates the efforts to a potential of applying these techniques to the optical fiber according to the similarity between them in terms of ISI. The optical system over MMF behaves similarly with the radio system and shares the multipath nature of transmitted channel. It leads to an overlap in the transmitted signal, causing random variations of the power of signals propagating in different modes, which means that the transmitted signal arrives at the receiver in different times. This phenomenon in a radio system is known as fading and it is called mode coupling in the optical system over MMF. Both radio and optical systems have the same strategies to manage fading and mode coupling. One of the techniques is equalization, widely used in radio networks. It can be used in MDM system, in which RLS and LMS are the conventional algorithms. The aim of conventional adaptive algorithms based channel equalizers is to reduce or mitigate the effects of ISI, which has happened in the communication channel. These are gradient-based learning algorithms and hence, its weights never reach their optimum values because of the mean square error (MSE) being trapped in local minimum due to the possibility of training mode of the channel equalizer. This means that they suffer from long training time, power consumption, and slow convergence. Channel non-linearity, additive noise, and distortion, are issues that affect the performance of linear equalizer.

One of the robust alternative nonlinear constructions is the evolving fuzzy neural networks, which offers superior performance than that of linear models due to its capability to represent nonlinear functions, allowing the use of small number of parameters, is fast and easy trained

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equalizer, learn fast from a large amount of data (using fast training), adaptive incrementally in an online mode, has an open structure, and memorizes information that can be used at a later stage.

3. DESIGN THE PROPOSED ALGORITHM

In order to implement the EFuNN equalization scheme for MDM, the distorted data comprising the channel impulse response from the receiver of the MDM system. It is required as an input into the EFuNN equalization scheme. The distorted data embodies the nonlinear channel impairments from mode coupling and modal dispersion in the MDM system as shown in FIGURE 1. The transmitter consists of five lasers at a wavelength of 1550nm, each launching a specific Laguerre-Gaussian (LG) mode into the MMF: Channel 1 launches LG 0 1 mode, Channel 2 launches LG 1 0 mode, Channel 3 launches LG 1 1 mode, Channel 4 launches LG 2 1 mode and Channel 5 launches LG 1 2 mode. Each mode carries an independent data channel at 7 GB/s, thus achieving an aggregate data rate of 35 GB/s for the 5 channels. The five independent data channels are propagated through a 5km parabolic refractive index MMF. The presumed value for peak-index refractive index is 1.4, attenuation is 0.25 dB/km, with consideration of modal coupling. The signal is then de-multiplexed into five received data streams.

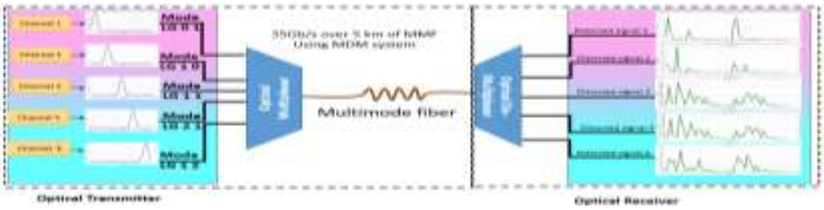

FIGURE 1. Simulation MDM system

FIGURE 2. Channel impulse responses of five channels

FIGURE 3. Channel Impulse Response of Five Time-Separated Gaussian Reference Signals

Results from the MDM system demonstrate that ISI is prevalent due to nonlinear channel effects from mode coupling and modal dispersion, resulting in each mode at the transmitter to excite fifty-five modes at end of the MMF and detected by the photodetector. The distorted channel impulse response of fifty-five modes at the receiver for each channel is shown in FIGURE.2. This will be used as the input to the EFuNN equalizer. After data collection, two data processing procedures will be conducted in MATLAB to prepare for the training stage in the EFuNN equalization. These procedures are:

3.1 Design of Gaussian Reference Signal

In any communication system, the transmitter sends the signals while the receiver detects and receives the signals. The primary objective at the receiving end is to sample the received signal in a manner that enhances the probability of reducing ISI. It is vital because real receivers sampling point cannot be optimal always for every signal since any communication system will contain some distortions and ISI [12]. The ISI lead to errors in the identified signals and causing information loss in MDM systems, which is usually caused by the mode coupling. The signals should be-reshaped in such a way that they avoid interfering each other at the optimal sampling point and should equalize the input source signals well. FIGURE. 1. shows that the received channel impulse response of all channels after the MDM system have broadened and overlap with one another due to mode coupling and modal dispersion. The Gaussian reference signal is used to make some changes in the pulse shape

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of the transmitted signals, so that it better suits its purpose for the communication channel, and avoids ISI in the data transmission typically by limiting the effective bandwidth of the transmission. In this research, MATLAB is used to simulate the Gaussian reference signal, which is based on Equation 1. The Gaussian reference signal is described as:

$$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-mu)^2/2\sigma^2} \text{ .... (1) [13]}$$

Where sigma is the channel impulse width, mu is the mode at which the channel impulse response is maximum, *x* is the mode number.

The performance of an EFuNN equalization scheme is the result of a training process to produce an approximation as close as possible to the optimal signal with less RMSE and CPU-time. To come up with a better performance of the equalization scheme, there is a need to design at least 5 Gaussian reference signals for 5 distorted signals, σ = 5.5. Each one has a length of 11, adopting the proper characterization of the Gaussian reference signals, as illustrated in Figure. 3.

3.2 Normalization process of the distorted signal, and the Gaussians reference signal

Normalization process of distorted signal is required because of the equalization scheme link and learning with sequential and time-varying signals. It consists of a normalization of pre-processed data to the network's working range from their natural range, therefore the normalized signal is highly shaped to meet the reference signal of the equalization scheme and are adjusted to the nonlinearities of the neurons, therefore their outputs should not beyond the capacity bounds. It can be fixed between 0 and 1. Regarding that, this study needs five channels and five Gaussian reference signals. Based on Equation 2:

$$(x_{ni}) = (x_i)/(\max(x_i)) \text{ .... (2) } [\mathbf{14}]$$

Where x_i = original level of the channel impulse response

3.3 Implementing the EFuNN equalization scheme

The distorted signals will be inserted along with the Gaussian reference signals after normalization to implement the EFuNN equalization for MDM. The implementation was executed using MATLAB R2014a (8.3.0.532) 64-bit (win64). A computer with 8GB memory (RAM) and due CPU core i5 (2.40) GHz has been utilized. Principally, the EFuNN is a five-layer neural network that is able to incorporate expert knowledge (Kasabov & Woodford, 1999). The structure and parameters are driven by the input variables. Koprinska and Kasabov (1999) showcase this five-layer structure as seen in FIGURE. 4.

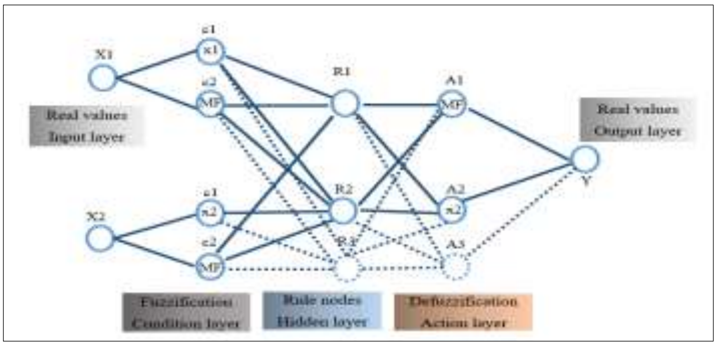

FIGURE. 4 Evolving fuzzy neural network (EFuNN)

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Principally, the first layer of the network is characterized by the distorted signals and Gaussian reference signals as input variables. Meanwhile, executives of the fuzzification for the inputs will be in the second layer. Practically, this layer characterizes fuzzy quantization of the distorted signals and Gaussian reference signals. During the process of learning, the system creates the (rules / knowledge), it has learned in the form of if-then rules. In addition, the Membership Function node (MF) is used in EFuNN to represent the fuzzy values. There are two 'neurons' values represent fuzzy values of different sizes, in which MF related with these neurons. In this layer, new neurons evolved together with the input values. If the variable value does not belong to any of the existing MF, it means the value is more than that of the membership threshold. Therefore, new fuzzy input neuron will be created through the system by implementing the EFuNN steps. The main task of the fuzzy input nodes is to transfer the distorted signal and Gaussian reference signal values into membership degrees to which belong to the MF. The third layer consists of rule nodes that evolve through learning. Evolving means all nodes in the third layer are created during training. Each one of the rule nodes is defined by two connection vectors (weights); W1(r) from the fuzzy input layer to rule nodes and W2(r) from rule nodes to the fuzzy output layer. These nodes represent the prototypes of input and output data association. In this layer, a linear activation function or a Gaussian function will be used and the weights will be adjusted. This layer represents the most important layer which determines the number of rule nodes that will be created in order to make the output equalized signals as close as possible to the Gaussian reference signals by minimizing the RMSE and lead to reduce ISI from the distorted signals. The fourth layer is fuzzy output layer where each node is represented the fuzzy quantization of the output variables. Finally, the output variable layer creates the defuzzification for fuzzy output equalized signal. The output error ($Err = \| D – D' \| / Ni$) should be less than an error threshold E, where D is Gaussian reference signal, D' is shaped by EFuNN output equalized signal, Ni is the number of outputs and E is the error threshold (tolerance) of the system for fuzzy output.EFuNN equalizer parameters either be kept constant during training in equalization scheme, or adjusted according to the subsequent incoming data. The determination of the network parameters like number and types of MF for each input variable, sensitivity threshold, error threshold and the learning rates were determined by the previous experiments. The parameter values for optimal performance have been used as follows: Initial value for sensitivity threshold (radius of role nodes) S= 0.5, Error threshold (The level of error tolerance for the output) E= 0.01, Number of membership functions= 5, Rule extraction thresholds (weight of first layer) W1= 0.5, (weight of second layer) W2= 0.5, and the consecutive data examples used= 55. The training process involves an iterative modification of the biases of the network by reducing the (RMSE) of the distorted signals and Gaussian reference signals in the EFuNN. FIGURE. 5 showcases the training for the five channels. Furthermore, in testing mode in EFuNN equalization scheme in this research has tested the data EFuNN without Gaussian reference signal and determined the bias according to the appropriate parameters that are set in the training mode and was achieved the best desired signal with less ISI. The rules were extracted from the training stage.

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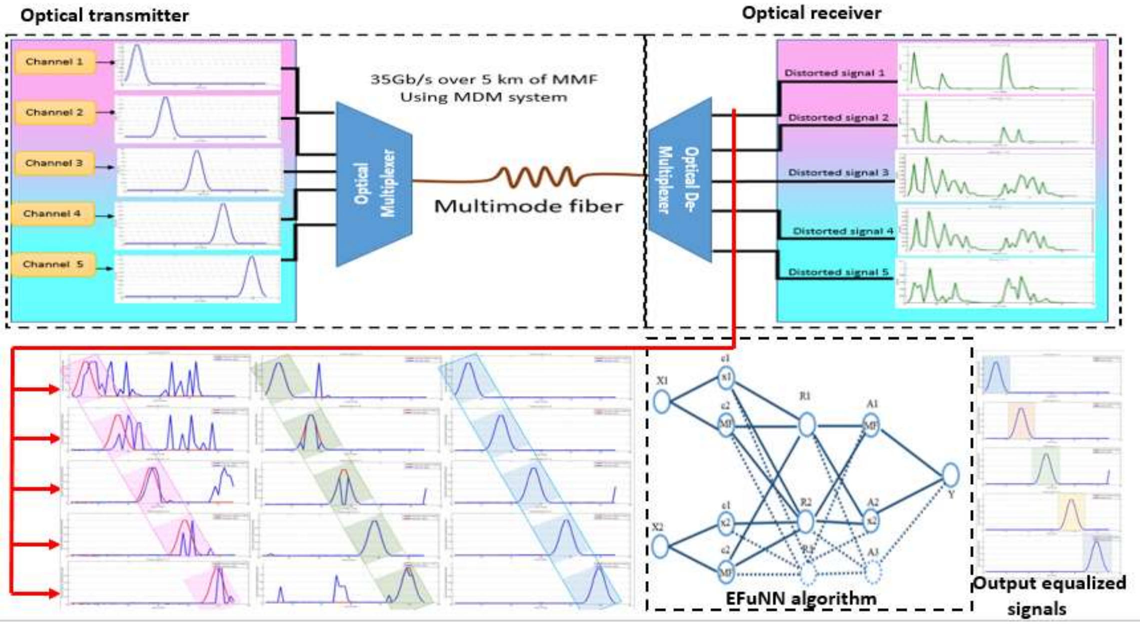

FIGURE 5. Training of five channels in EFuNN equalization in MDM

Results and Discussion

Referring to the collected data from the training process, the Performance of the EFuNN equalization scheme (detailed in Table 1), is evaluated by the lower RMSE and CPU-time. The RMSE is calculated using Equation (3).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(X_i - Y_i)^2} \quad \text{……… (3) [15]}$$

In Equation (3), N is the number of data input samples, X_i is the distorted signal, and Y_i is the Gaussian reference signal. When the CPU-time is, the time taken for both the training and testing stages of the equalization given pre-inserted distorted and measured channel impulse response signals, measured in seconds. After analyzing the results, EFuNN equalization scheme illustrates for fast adaptive learning and the lower RMSE values via the learning process. To evaluate the performance of EFuNN equalization scheme, there is a need to compare the EFuNN equalization in terms of RMSE and CPU-time with previous equalization schemes such as LMS and RLS which have been used before in MDM system, (detailed in Tables 2 and 3), The goal of the comparison is to show that the nonlinear equalization scheme can compensate the nonlinear problem of ISI in the distorted signals in MDM system better than linear equalization schemes.

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Table 2 RMSE and CPU-time for the EFuNN Equalization

Channel	RMSE Before Training	RMSE After Training	CPU-Time/ s
Channel 1 - (LG 0 1)	0.3658	0.0002	0.000674
Channel 2 - (LG 1 0)	0.3612	0.0002	0.000671
Channel 3 - (LG 1 1)	0.2548	0.0605	0.000714
Channel 4 - (LG 2 1)	0.228	0.0002	0.000678
Channel 5 - (LG 1 2)	0.1949	0.0004	0.000734

Table 3 RMSE and CPU-time for LMS Equalization

Channel	MSE Before equalization	MSE After equalization	RMSE of MSE After equalization	CPU-time/s
Channel 1 - (LG 0 1)	0.1042	0.0350	0.1871	0.005545
Channel 2 - (LG 1 0)	0.0925	0.0481	0.2194	0.005428
Channel 3 - (LG 1 1)	0.1038	0.0572	0.2392	0.005012
Channel 4 - (LG 2 1)	0.0840	0.0262	0.1620	0.004627
Channel 5 - (LG 1 2)	0.1434	0.0073	0.0852	0.004585

Table 4 RMSE and CPU-time for RLS Equalization

Channel	MSE before equalization	MSE after equalization	RMSE of MSE After equalization	CPU-time
Channel 1 - (LG 0 1)	0.1042	0.0616	0.2482	0.011242
Channel 2 - (LG 1 0)	0.0925	0.0666	0.2629	0.010120
Channel 3 - (LG 1 1)	0.1038	0.0669	0.2588	0.008881
Channel 4 - (LG 2 1)	0.0840	0.0367	0.1918	0.011353
Channel 5 - (LG 1 2)	0.1434	0.0501	0.2240	0.010503

4. Future work and Expected result

As coming to the end of this research, our expectation is to adopt a nonlinear fuzzy neural network training algorithm utilized in MDM to overcome the problem of ISI for the first time. This will overcome RLS, LMS equalization limitations.

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