Optical Performance Monitoring using Neural Network in WDM Network: A Review

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***Abstract*—The presence of reliable optical performance monitors plays the crucial role in achieving the robust, cost effective and self managed operation of optical network. There exist numerous OPMs based on the algorithmic approaches (LP's heuristic etc.) analyzing the eye diagram, constellation diagram and histogram. The performance of these conventional methods can be substantially increases by implementing the neural network for performance monitoring. The different approaches demonstrating application of neural network in optical network are summarized in this paper. The different network types, training techniques adopted till date are summarized.**

Keywords—WDM Networks, optical performance monitors, neural network.

I. Introduction

The network performance is dependent on the channel configuration and distance. While distance is a primary driver for increased optical monitoring to mitigate transmission impairments, the use of optical switching elements will affect the way in which different impairments need to be monitored. For example, in static point-to-point systems chromatic dispersion might only be monitored to verify correct network installation or for in-service compensation. In a reconfigurable network, chromatic dispersion may need to be monitored for faults because the accumulated dispersion and its impact will change as the network changes. Furthermore, in an optical switching environment the individual channels will have unique histories and thus performance and accumulated impairments should be measured on a per channel basis [1-5]. Single-channel impairments are also less likely to be correlated with component alarms, particularly for components that act on the entire WDM band. For these reasons, functions such as wavelength routing and network reconfiguration may require advanced per-channel OPM to assist in the diagnosis of failures.OPM consists of three major tasks

1. <u>The transport or WDM channel management layer monitoring:</u> It involves a determination of the optical domain characteristics essential for transport and channel management e.g. real time measurements of channel presence, wavelength registration, power levels and the spectral OSNR.
2. <u>The optical signal or channel quality layer monitoring</u>: It involves analyzing a single wavelength and performs signal transition sensitive measurements like eye statistics, Q-factor, the electronic SNR, and distortion that occur within the eye due to dispersion and nonlinear effects.
3. <u>Protocol performance monitoring (PPM)</u>: This includes digital measurements such as the BER, when used to infer properties of the analog optical signal.

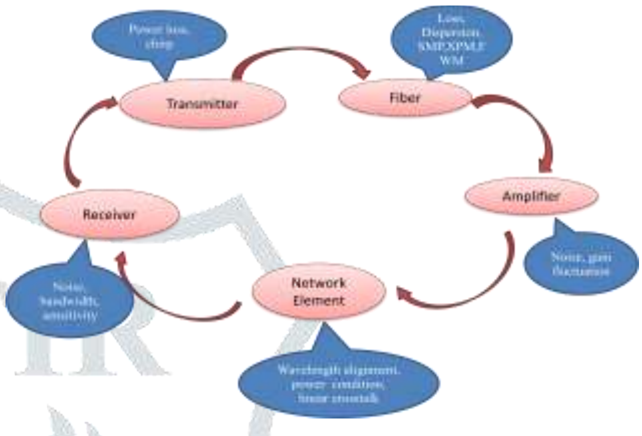

Fig. 1. : overview of various optical impairments in optical network [6]

There are several methods of implementing OPM in a line system.

1. *The non-disruptive dedicated monitor:* where the signal is tapped on a WDM fiber and the monitor is shared among many wavelengths on a single fiber
2. *Disruptive shared monitor:* this is the case in which one of multiple optical fibers can be switched to a monitor so the monitor is shared, but the monitoring is disruptive as it takes the fiber offline
3. *In-line monitor:* the full optical signal is transmitted through the monitor and a nondestructive measurement is performed. This approach is most effective when the signal is demuxed into single channels and is often integrated with optical regeneration devices.

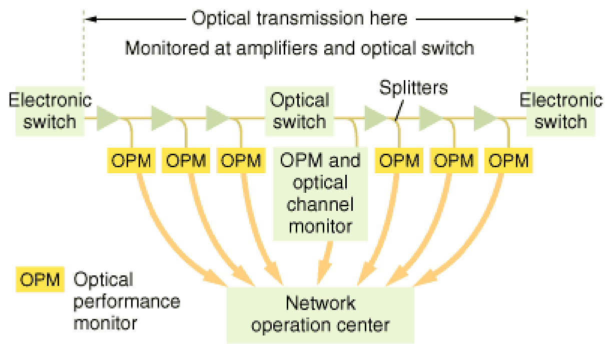

Fig. 2. : A system with optical performance monitors [6]

Several techniques have been proposed for OPM using off-line digital signal processing of received electrical data signals.

These methods utilize amplitude histograms, power distributions or asynchronous sampling to estimate bit error rate (BER); or to use either delay-tap plots or pattern recognition techniques to identify multiple impairments; or to use the parameters derived from eye diagrams and histograms for the same purpose. The latter approach is to probe the network upon initialization and train each receiver to record a specific data eye-diagram pattern that corresponds to a specified range of potential physical parameters. These eye diagrams can be generated either from a synchronized sampler, or by a technique that regenerates such diagrams from asynchronous samples. Once the network is fully operational, variations in the received eye diagram from the ideal formation can then be attributed to specific physical parameters derived from the prior network/receiver training.

In order to enable robust and cost-effective “self-managed” operation, it would be desirable for the network itself to agilely monitor the physical impairments and the quality of the data signals, and automatically diagnose and feedback information to control the network [7-8]. As we know, artificial neural networks are information-processing systems that learn from observations and generalize by abstraction, so are attractive alternative to conventional methods such as numerical modeling methods, analytical methods, or empirical modeling solutions. ANNs have the ability to model multi-dimensional nonlinear relationships and are simple to use. Furthermore, the neural network approach is generic (i.e., the same modeling technique can be re-used for passive/active devices/ systems) and the response is fast. The ANN approach has gained much attention as a powerful tool in a number of areas such as pattern recognition, speech processing, control, and bio-medical engineering etc. Now-a-days, researchers are showing keen interest in implementing these neural networks in optical performance monitoring. [9-10] has demonstrated use of a neural network approach to “train” receivers in an optical network to distinguish between resultant shapes of the data channel’s eye diagrams and the degrading effects of OSNR, CD, PMD and fiber nonlinearity. For the implementation of neural network on OPM, the coefficients of the algorithm are iteratively derived prior to live traffic being sent through the network. A similar technique has also been used for time misalignment monitoring in return-to-zero differential quadrature phase shift keying (RZ-DQPSK) transmitters [11-12], which extends the applications of our ANN approach to a broader sense of OPM. Neural Network based solutions are very accurate (98% of optimal throughput). It is found that while the human generated heuristics fail to find a solution in approximately 30% of cases, the best NN fails only in 4.9% of cases. Moreover, the mapping between high dimensional spaces is achieved with small number of weights and hidden nodes. The NN’s perform well on Grade of service data even if they are trained on non-Grade of service data indicating that they are flexible enough to deal with unexpected situations.

1.1. Performance monitoring using radial basis function (RBF) equalizer:

A radial basis function (RBF) equalizer is introduced in [13-14] for mitigation of Polarization mode dispersion optical communications systems. The presented equalizer can effectively adapt to the characteristics of the optical channel, which are nonlinear, time-varying and corrupted by non-Gaussian and signal dependent noises. A recursive learning algorithm is derived to track channel changes and design the RBF equalizer by incorporating the prior information about the channel distortion. An all order PMD channel is simulated with transmission of 10Gbit/s RZ Gaussian pulses with 50 ps FWHM is simulated for experimental verification. The mean DGD of the channel is 57 ps. Performance of the equalizer is evaluated by bit error rate (BER) that it can achieve.

1.2 Performance monitoring using multilayer perceptron:

As we know, ANN consists of multiple layers of processing elements called neurons. Each neuron is connected to other neurons in neighboring layers by varying coefficients that represent the strengths of these connections. ANNs learn the relationships among sets of input-output data that are characteristics of the device or system under consideration. After the input vectors are presented to the input neurons and output vectors are computed, the ANN outputs are compared to the desired outputs, and errors are calculated. Error derivatives are then calculated and summed for each weight until all of the training sets have been presented to the network. The error derivatives are used to update the weights for the neurons, and training continues until the errors reach prescribed low values [15-16]. The three layer perceptron neural network with feed-forward architecture is used in [17] with 4-input parameters, 4-output parameters and one hidden layer with twelve neurons. The number of hidden neurons is optimized via adaptive processes, which add/delete neurons during training The input parameters include Q-factor(the difference of the mean upper and lower levels divided by the sum of the upper and lower level standard deviations), eye closure(ratio of the outer eye height to the inner eye height) and root-mean-square (RMS) jitter(the standard deviation of the time data calculated in a narrow window surrounding the crossing amplitude) and crossing-amplitude which are derived from eye diagram. The impairments OSNR, CD, PMD, DGD (differential group delay) and fiber nonlinearity are calculated across output. The ANN is simulated using Neuro-modeller software package developed by [18]. The concept is verified via simulation in 40 Gb/s RZ-OOK and RZ-DPSK systems. The conjugate gradient method is used for training. The simulated fiber channel includes a laser with a full width at half maximum (FWHM) line-width of 10 MHz; a 40 Gb/s logic source; a single-arm, Mach-Zehnder modulator (MZM) biased at the quadrature point with driving voltage for generating OOK and at minimum point with driving voltage for generating DPSK, where is the half-wave voltage of the MZM, followed by another MZM for RZ pulse carving. Impairments are added through emulators in the link and then the signals are detected by using a single photodiode for RZ-OOK and a balanced receiver following a delay line interferometer (DLI) for RZ-DPSK, where the eye diagrams are recorded and the eye diagram parameters are extracted. The testing and ANN-modeled data are compared. The measured average errors for OSNR, CD and DGD are 0.58 dB, 4.68 ps/nm, and 1.53 ps, respectively for 40 Gb/s RZ-OOK, and are 0.77 dB, 4.74 ps/nm, and 0.92 ps, respectively for 40 Gb/s RZ-DPSK. Adding accumulated nonlinearity is also a challenge in terms of the neural network approach, due to its specific signatures on the eye diagrams. For calculating on-linearity component the four outputs are input optical power, OSNR, CD, and PMD, and the eight inputs include Q-factor, eye-closure, RMS jitter, ‘0’level crossing amplitude, mean of ‘1’s and ‘0’s, standard derivation (SD) of ‘1’s and ‘0’s. The testing and ANN-modeled data for optical power, OSNR, CD, and DGD shows the average errors for optical power, OSNR, CD and DGD as 0.46 dB, 1.45 dB, 3.98 ps/nm, and 0.65 ps, respectively. The application of neural networks for identification of impairment causing changes from a baseline and time misalignment identification in RZ-DQPSK transmitters is also discussed. Artificial neural network (ANN) model used to simultaneously identify three separate impairments that can degrade optical channels, namely optical signal-to-noise ratio (OSNR), chromatic dispersion (CD), and polarization-mode dispersion (PMD) is demonstrated by [19]. . The neural networks are trained with parameters derived from eye diagrams to create models that can predict levels of concurrent impairments..

A similar technique for optical performance monitoring by simultaneously identifying optical signal-to-noise ratio (OSNR), chromatic dispersion (CD), and polarization mode dispersion (PMD) using artificial neural networks trained with parameters derived from delay-tap asynchronous sampling is represented by [20]. An optical channel operating at 10 Gb/s and using non-return-to-zero, on-off keying (NRZ-OOK) is simulated for the same. The ANN architecture used in this work is a feed-forward, three-layer perceptron structure consisting of an input layer, a hidden layer, and an output layer. An asynchronous sampling based on a two-tap delay line, where each sample point is comprised of two measurements separated by a specific period corresponding to the length of the delay is done [21-22]. By creating a scatter plot of the measured pairs, it is observed that delay lengths of less than half of the bit period (B/2) represented the power evolution within each bit. Furthermore, plots making use of delays of B/2 highlight distortion effects. These impairments produce distinct features. To capture the behavior of these plots, the plot is divided into four quadrants, Q1-Q4. It is observed that quadrant 4 it contains data that is the mirror image of quadrant 2.So quadrant 4 is not used. For quadrants 1 and 3, the means and standard deviations of the magnitudes ($r1$,σ $r1$, $r3$,σ $r3$) are calculated and for quadrant 2, the means and standard deviations of the x's and y's are calculated separately. The parameter similar to the Q-factor, which is define as $Q31 = (r3 - r1) /(\sigma r1 + \sigma r3)$ is also used. The simulated fiber channel included a laser with a center wavelength of1550 nm and a FWHM line-width of 10 MHz; a 10 Gb/s logic source; a single-arm, Mach-Zehnder optical modulator biased at the quadrature point with a Vπ drive voltage; and a fourth-order Bessel-Thomson filter. The ANN has seven inputs (r1, σ$r1$, $r3$, σ$r3$, $x2$, $y2$, $Q31$), three outputs (OSNR, CD, and DGD), and 28 hidden neurons. [23] compared both the techniques of optical performance monitoring. When parameters from delay-tap plots were used, the root-mean-square (RMS) errors were 0.919 dB for OSNR, 6.368 ps/nm for CD, and 1.479 ps for DGD; when the parameters from eye diagrams were used, the RMS errors were 0.866 dB for OSNR, 14.642 ps/nm for CD, and 2.479 ps for DGD. In this particular case, results were slightly better when using parameters from the delay-tap plots.

A similar Low Cost Multi-Impairment Monitoring Technique for 43 Gb/s and 86 Gb/s DP-DPSK system is presented by [24]. The system is implemented using delay tap asynchronous sampling. The signal phase diagram patterns for the 43 Gb/s DPSK and 86 Gb/s DP-DPSK signals are obtained. The histograms of the sample vector norm, R and vector angle, Φ are calculated. Processing of the phase diagram pattern together with the vector norm and angle histograms provide 9 statistical parameters which are used to identify the impairments levels in the link. In order to estimate the CD, OSNR and DGD, the 9 statistical parameters derived from the signal phase diagram, feed an ANN which consists of a feed-forward 3 layer perceptron structure with an input layer of 9 neurons, a hidden layer of 100 neurons and an output layer of 3 neurons and optimum results are achieved. Performance monitoring of quadrature phase-shift keying (QPSK) data channels by simultaneously identifying optical signal-to-noise ratio (OSNR), chromatic dispersion (CD), and polarization-mode dispersion (PMD) using neural networks trained with parameters derived from asynchronous constellation diagrams is represented in [25]. The testing data is obtained from a 40 Gb/s RZ-QPSK system. The root-mean-square (RMS) errors of 0.77 dB for OSNR, 18.71 ps/nm for CD, and 1.17 ps for DGD is obtained. The conjugate gradient method is used as learning algorithm as it is nice compromise in terms of memory and implementation effort, since the descent direction runs along the conjugate direction, which can be determined without matrix computations [15]. There are no parameters like Q-factor, closure, jitter, and crossing amplitude available for constellation diagrams. Thus, as in case of delay-tap plots, new parameters are defined by dividing it in four quadrants that are used to calculate the behavior of asynchronous constellation diagrams. Quadrants 2 and 4 are not used in this particular application. For quadrants 1 and 3, the means and standard deviations of the magnitudes (r1, σ$r1$, $r3$, σ$r3$), are calculated because constellation diagrams contain data that are roughly symmetric about the 45° axis. Additionally, calculate the maximum and minimum values of the y's at the x = 0 axis ($y$max and $y$min), since these values vary with OSNR and DGD, and tend not to be symmetrical with CD. If additional impairments were to be included in the monitor, then the parameters from quadrants 2 and 4 would probably be required. The configuration used in the simulation includes RZ-DQPSK transmitter consisted of a continuous wave (CW) laser operating at 1550 nm with a line width of 100 KHz, a parallel-type DQPSK modulator, which was driven by two 20 Gbps non-return to zero (NRZ) 215-1 pseudo-random binary sequences (PRBS) and a Mach-Zehnder modulator (MZM) for pulse carving.. The generated RZ-DQPSK signal was then sent to a CD emulator, followed by a DGD (i.e. first order PMD) emulator. The output was sent to an Erbium-doped fiber amplifier (EDFA) with a variable optical attenuator in front to adjust the received OSNR. The signal was then filtered by a bandpass filter (BPF) with 0.8 nm bandwidth, and sent to the receiver, where the constellation diagrams and parameters were extracted. The receiver consisted of two out-of-phase delay-line-interferometers (DLI) followed by two balanced photo-receivers (BPDs) and the received I and Q signals were finally sampled with analog to digital converters (ADCs) asynchronously, the sampling rate of which can be much lower than the data rate. The outputs of ADCs formed the coordinates of the data in the complex plane for constructing the constellation diagrams, such that all the received samples could be plotted in one I/Q plane asynchronously during the offline processing. The ANN consisted of seven inputs ($\overline{r_1}, \overline{\sigma_{r1}}, \overline{r_2}, \overline{\sigma_{r2}}, y_{max}, y_{min}, Q_{31}$) , three outputs (OSNR, CD, and DGD), and 28 hidden neurons.

II. Conclusion

Conceptually, two approaches are possible for creating such NN-based control systems. First, when no algorithmic solution exists one can use empirical data for training a drawback here is the need for large training data sets. Second, if an algorithmic solution exists but is too complex to be implementable under practical restrictions like execution time or memory limitation constraints, a NN can replace the algorithm. In such a case, training data is not a problem since it can be easily created off-line by the algorithm. The problem of optimization of a meshed telecommunication network is a control problem of the latter type. It is a constrained integer optimization task with a nonlinear target function. It can have tens or even hundreds of input variables and an even larger number of output control parameters. Interestingly, it can be solved "optimally" with the use of classical linear programming (LP) techniques [19], but such an approach is several orders of magnitude too slow for real-time implementation for large networks, the task could even require hours to complete. Thus such algorithmic techniques are unsuitable for dynamic reconfiguration of such a telecommunications network, where the response time required can be as low as 60 ms. Although numerous techniques are proposed and implemented for optical performance monitoring, the application of neural network in the same still have a large potential to be explored.

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