Low Complexity Soft Failure Detection and Identification in Optical Links using Adaptive Filter Coefficients

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Abstract: We demonstrate an autoencoder scheme that utilizes readily available adaptive filter coefficients to accurately detect and identify soft-failures in optical links with >99% accuracy. Detected impairments include low OSNR, nonlinearity, ROADM filtering and adjacent-channel crosstalk.

1. Introduction

Optical networks are prone to multiple link impairments. If left unidentified and unmanaged, they can lead to severe service disruption. Current optical network failure management (ONFM) systems rely on complex and time-consuming human methodologies to combat these issues. However, as networks scale and become more flexible, it becomes important to automate ONFM systems. In recent years, machine-learning (ML) methods have attracted a lot of attention to improve these ONFM systems [1-4]. Nonetheless, these techniques have their own limitations. Methods that utilize pre-FEC BER captured over long durations (>5 minutes) to accurately detect and identify impairments have been previously investigated in [1,2]. However, in many instances, such durations may not be desirable. Support vector machines (SVM) employing filter coefficients as features to detect impairments were explored in [3], but the methodology provided no solution to identify the cause of the impairments. A dual stage scheme that detects impairments using the pre-FEC BER and received optical power [4], and along with the optical spectra employs a semi-supervised SVM scheme to identify the impairment was also investigated. However, this technique can only identify impairments that directly affect the optical spectra.

Here, we propose a dual stage scheme that utilizes readily available adaptive filter coefficient (AFC) at the receiver DSP to detect and identify impairments in optical links. We experimentally demonstrate that the technique easily detects impairments arising from ROADM filter impairments, OSNR degradation, interchannel interference (ICI) and fiber nonlinearity (NL) well before the pre-FEC BER reaches the SD-FEC limit. Additionally, whenever an impairment is detected, the technique identifies the cause of the impairment with >99% accuracy. While the identification scheme is limited by what impairments it is trained for, the detection scheme can in principle detect any impairments and is not limited to the four described above.

2. Methodology

The technique consists of two steps – Impairment prediction/detection based on autoencoders and impairment identification based on a feed forward neural network, Fig. 1. Autoencoders are a type of neural network that are

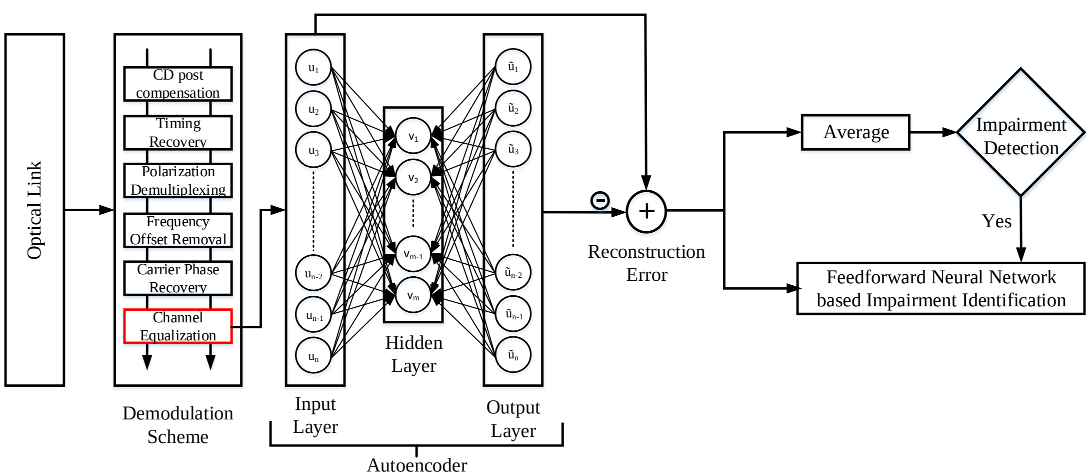


Figure 1: Two step impairment detection and identification scheme based on autoencoders. The input to the autoencoder is the adaptive filter coefficients used at the receiver DSP. The mean reconstruction error (MRE) from the autoencoder is used to detect impairments. If detected, the reconstruction error is sent to a feed-forward neural network to identify the cause of the impairment.

used to efficiently learn how to compress data in an unsupervised manner [4]. They typically consist of three layers, the input layer, the hidden layer and the output layer. During training, the network constructs a code for the input in the hidden layer and then reconstructs the input from the code in the output layer. The performance of the network is assessed based on how close the input and the output are. The size of the code is determined by the user and is equal to the number of neurons in the hidden layer. The error between the input and the output is called the reconstruction error. In the event that the input is not representative of the training data, the reconstruction error will be large. We utilize this feature of an autoencoder to detect impairments in the link.

Here, the input to the autoencoder is the absolute value of the AFCs from the receiver DSP. The autoencoder is trained on multiple AFCs obtained from our experimental setup under normal operations. The input size is 182 and the code size is fixed to 10. Other code sizes were explored, but 10 provided the optimum tradeoff between code size and performance. Note that perfect reconstruction can never be achieved since the AFCs vary slightly based on the noise statistics in the link and because there is loss of information based on how large your code is. Therefore, even under normal operation, the reconstruction error will conform to a probability distribution with appropriate attributes. Once fully trained, we compute the mean reconstruction error (MRE) for the AFCs under normal operation and fit it to a probability distribution function (PDF), Fig. 2(a). A log-normal distribution was chosen to fit the reconstruction error distribution.

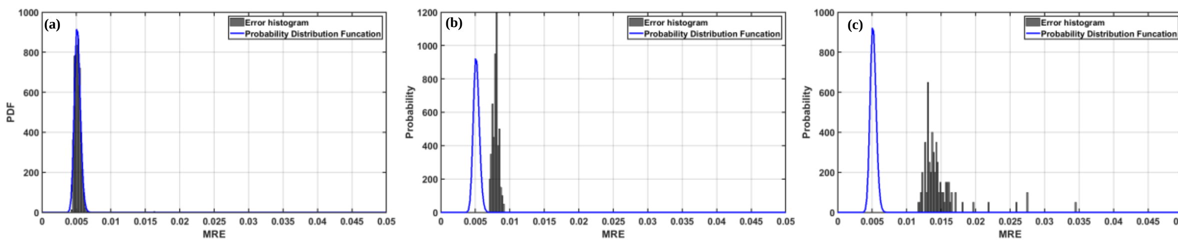


Figure 2: Distribution of MRE for (a) normal operation (b) link launch power = 9 dBm (c) link launch power = 9 dBm and WSS bandwidth = 24 GHz. The log-normal distribution used to fit the MRE under normal operation is described in blue.

In the event of an impairment, the AFCs will react to the impairment to reduce its effect on the signal. Since these AFCs are not representative of the AFCs under normal operation, the reconstruction error will be large and the MRE would lie in the tail of the PDF, Fig. 2(b-c). By appropriately defining this region, we can detect any impairment affecting an optical link. Here, we set this region to occupy 10% of the total tail probability.

When an impairment is detected, the reconstruction error is sent to a feed forward neural network to identify the cause of the impairment, Fig. 1. In this work, we employ a simple neural network with 1 hidden layer and 10 hidden neurons. The output is one of the four impairments included in the training data – ICI, OSNR degradation, ROADM filter induced penalties or NL. Additionally, using the soft outputs from the neural network, we test the capability of the neural network to detect multiple impairments affecting an optical link.

3. Experimental Setup

We use a 3-channel 32GBaud DP-QPSK link to validate our impairment detection and identification scheme, Fig. 3. Under normal operation the link OSNR is set to 14 dB (corresponding to BER ~ 10^{-3}), the WSS is set to 37.5 GHz, the side channels are spaced at 37.5 GHz and the fiber launch power is set to 2 dBm. Conventional receiver side DSP is used to process the data [5]. In order to test our algorithm, we artificially introduced impairments in the link by applying the following changes

- Varying the interchannel spacing between 15 and 35 GHz to introduce ICI
- Adding ASE noise to the link to degrade the OSNR and vary it between 7 and 14 dB
- Changing WSS bandwidth between 20 and 36 GHz to introduce ROADM filter induced penalties

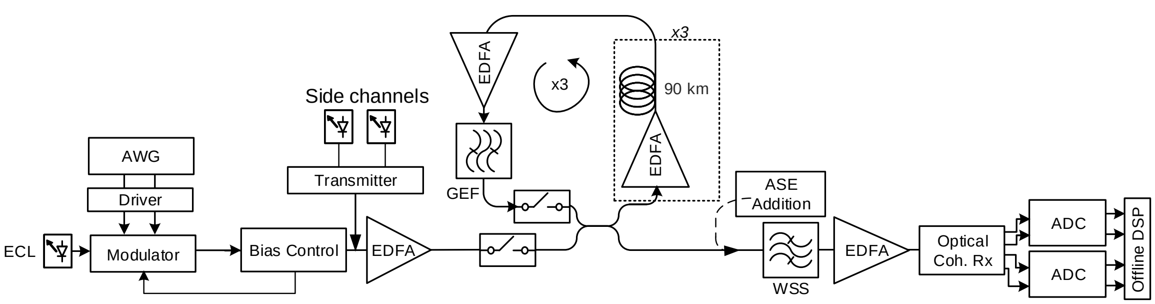


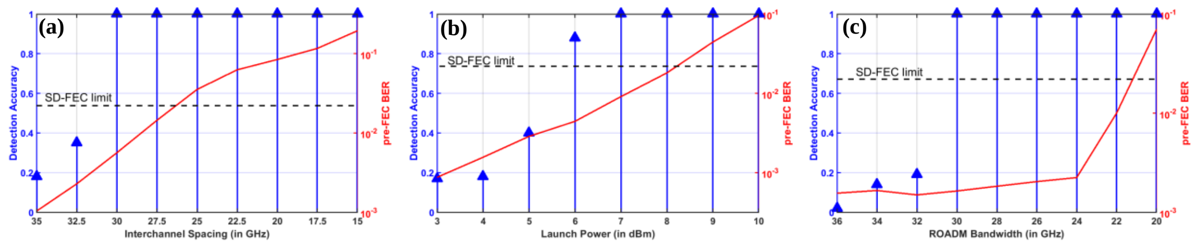
Figure 3:Experimental Setup employing 3 channels at 32GBaud DP-QPSK

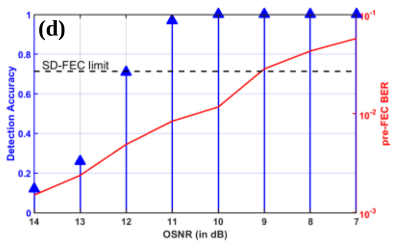
- Changing fiber launch power between 3 dBm and 10 dBm to introduce NL penalties

We considered the following thresholds as impairments: Interchannel spacing ≤ 30 GHz, launch power ≥ 6 dBm, ROADM filter bandwidth ≤ 30 GHz and OSNR ≤ 11 dBm. The thresholds were chosen based on the experimental setup and the associated signaling rate. Thresholds need to be appropriately modified for other links.

4. Results

Figure 4 shows the performance of the impairment detection scheme. The red curves show the evolution of pre-FEC BERs as a function of various impairment parameters and the blue stems show the scheme's detection accuracy. For the thresholds described above, the scheme is able to detect impairments with near 100% accuracy well before the BER hits the SD-FEC limit at $2.2\text{x}10^{-2}$. Note, the method also detects certain impairments before the threshold is reached, but the detection accuracy is low since the MRE is close to the threshold (tail probability < 10%).





(e)

Confusion Matrix

Output Class					
1	20.30%	0%	0%	0%	100%
2	0%	22.70%	0%	0%	100%
3	0.20%	0	22.70%	0%	99.30%
4	0%	0%	0	34.10%	100%
	99.30%	100%	100%	100%	99.80%
	1	2	3	4	

Target Class

(f)

# actual	# detected	Accuracy
1	1	99.80%
2	at least 1	98.30%
2	2	73.60%

Figure 4: Performance of the impairment detection scheme along with the pre-FEC BER in the presence of impairments caused by (a) Interchannel interference (ICI), (b) Fiber Nonlinearity (NL) (c) ROADM filters (d) OSNR degradation. (e) Confusion matrix of the feedforward neural network used to identify impairments. Class 1 – NL, 2 – ROADM filter anomalies, 3 – OSNR degradation and 4 - ICI (f) Performance of the neural network in the presence of multiple impairments.

We then test the accuracy of the impairment identification scheme. Figure 4(e) shows the confusion matrix of the feed forward neural network describing the sources of classification errors for the four impairments investigated here. The network is able to identify impairments arising from ROADM filters, OSNR degradation and ICI with 100% accuracy; however there is a small error (<1%) when detecting impairments arising from NL. These impairments tend to be misclassified as OSNR degradation possibly because these two impairments manifest similarly for QPSK signals [7]. Finally, we test the schemes performance in the presence of multiple impairments, Fig. 4(f). In the presence of two impairments, the scheme is able to identify at least one of the impairments with >98% accuracy and both impairments simultaneously with > 70% accuracy. While the performance of identifying multiple impairments simultaneously is poor, the method is able to identify at least one impairment with high accuracy and if the impairments are solved sequentially, both impairments will be identified accurately.

5. Conclusions

We presented a novel technique to detect and identify multiple impairments in optical links using a two-step machine learning technique utilizing autoencoders. By choosing AFCs as the input features, we demonstrated that both impairment detection and identification can be achieved with accuracies >99%. The impairment identification scheme can be extended to include other impairments based on the availability of appropriate data affected by those impairments. This technique can be employed in ONFM systems to automate the fault management process and reduce service disruptions.

6. References

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