Experimental Demonstration of Soft-Failure Management Using Variational Autoencoder and GAN on Optical Spectrum

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Abstract *We show combined soft-failure detection, identification und localization enabled by machine learning using experimentally obtained optical spectra as inputs. Our VAE and GAN-based framework shows high F1-scores requiring only 6% of total training data while being able to identify unknown failure spectra with 99.81% accuracy. ©2023 The Author(s)*

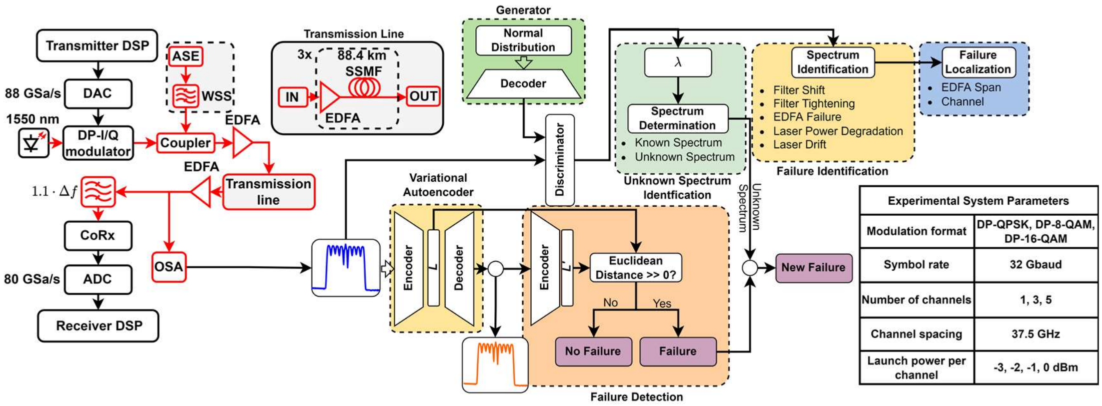
Introduction

The demand for high-speed data is growing exponentially in today's digital age. In such an interconnected world, any disruption to optical links will result not only in loss of data, but also in financial loss due to service level agreements not being met. In this context, the complexity and dynamism of optical networks is increasing, leading to the need to enhance network assurance with automated and dynamic techniques. Instead of relying on conservative design approaches, guaranteed redundancies, and threshold-based fault detection alarms, machine learning algorithms have emerged as a promising way to enable proactive maintenance of future networks [1, 2]. However, most machine-learning algorithms require a large amount of training data for reliable and accurate operation. To obtain such data, optical performance monitoring (OPM) is essential. Network-wide OPM is key to training, validating, and developing machine learning algorithms for fault management. This may include optical spectrum analyzers (OSAs) at key nodes in the network to extract the optical spectrum for further use in machine learning based frameworks. Soft failures, i.e. failures that progressively degrade the quality of transmission, can potentially evolve into hard failures. Dealing with soft failures is becoming increasingly important. In recent years, the community has made great efforts to find applicable machine learning algorithms for soft-failure management, which includes soft-failure detection (SFD), identification (SFI), and localization (SFL). In [3], received power and BER are used to detect and identify a soft failure caused by signal overlapping, filter tightening (FT) or filter shifting (FS). In [4], SFD and SFI of EDFA aging, FS, FT and laser drift were achieved by adding spectral features to the inputs. In [5], power spectral density is used as an input feature for a convolutional neural network to identify possible failures of EDFAs, filters, and fibers. In [6], SFL was achieved using an artificial neural network fed with telemetry from software-defined networks. However, all these algorithms need a high amount of training data to achieve high accuracies.

In this paper, we show for the first time soft-failure detection, identification and localization together in a single framework based on analyzing optical spectra while working with a very low amount of training data. This is achieved by including a variational autoencoder (VAE) in a generative adversarial network (GAN). While a conventional discriminator of a GAN contains a single supervised branch, we extend it to a two-branch approach with one unsupervised branch for unknown spectrum identification (USI) and one supervised branch for soft-failure identification based on the advanced training methods for GAN [7]. This enables not only the detection of unknown failure types but also provides the ability of SFI on low amounts of training data due to the generative nature of GANs. Together with the superior generation capabilities of VAEs over conventional autoencoders, the optical spectra driven VAE-based GAN framework shows excellent performance in all detection and identification tasks given a very small amount of training data.

Soft-Failure Management Framework

The soft-failure management framework proposed here consists of 4 stages in total including SFD, SFI, SFL and USI and is depicted in Fig. 1. Autoencoders have been shown to be a capable mechanism for semi-supervised anomaly detection (e.g. [8,9]). In this work, we use a variational autoencoder (VAE) which differs from conventional autoencoders. The latent variables are stochastic variables instead of deterministic mappings due to the probabilistic encoder. This extends the power of the VAE regarding anomaly detection, since normal and anomalous data may have the same mean values but not the same variance. The stochastic nature of the latent space gives the opportunity to generate outputs from the decoder by drawing latent space variables from its normal distribution



Experimental System Parameters	
Modulation format	DP-QPSK, DP-8-QAM, DP-16-QAM
Symbol rate	32 Gbaud
Number of channels	1, 3, 5
Channel spacing	37.5 GHz
Launch power per channel	-3, -2, -1, 0 dBm

Fig. 1: Experimental setup and soft-failure management framework with failure detection, identification, and localization stages in combination with a generative adversarial network (GAN) for unknown spectrum identification; λ: layer with a custom activation function, *L*: latent space; DAC: digital-to-analog converter, ASE: amplified-spontaneous emission, WSS: waveshaper, EDFA: Erbium-doped fiber amplifier, SSMF: standard single-mode fiber, OSA: optical spectrum analyzer, ADC: analog-to-digital converter, DSP: digital signal processing.

because the distribution of the latent space is known in contrast to conventional autoencoders. SFD is achieved using the described VAE by calculating the Euclidean distance between the latent space encoded input spectrum *L* and the latent space *L'* of the encoded reconstructed spectrum. An anomaly is thus detected, if the Euclidean distance is much larger than 0 which favors this approach over other threshold-based reconstruction error comparison since no threshold optimization must be done. The described advantage of a VAE enables its usage in a generative adversarial network (GAN) for the generation of more realistic output spectra. GANs are a class of methods for learning generative models based on game theory [7]. The goal of a GAN is to train a generator network that produces samples from the data distribution by transforming vectors of noise. The discriminator network is trained to distinguish between a real input and a generated input, meaning that the generator learns by fooling the discriminator, while the discriminator is trained to identify generated samples. Due to this adversarial approach both models enhance each other. In this work, we use the approach from [7] to include an unsupervised branch and a supervised branch in the discriminator for USI and SFI. In Fig. 1, the discriminator has two output branches which are the lambda layer, i.e., a custom activation function, and the spectrum identification. First, the supervised model is created for 5 classes using a softmax activation function. Afterwards, an unsupervised model is created using a lambda layer which enables the implementation of a custom activation function. The layer takes the softmax output from the supervised model and calculates a normalized sum of the exponential inputs [7]. This means that the output from the lambda layer lies between 0 and 1 and thus can be used to distinguish between known and unknown samples. Both branches share their weights in the hidden layers, which means that their classification performance depends on each other. For the training of the framework, the gradient is passed through the VAE, the generator, which uses the decoder from the VAE, and the discriminator. This results in the VAE not only being trained for optimal reconstruction performance but also on separating the latent space in such a way that the discriminator can separate real from unknown samples. For SFL a support vector machine is used on the input spectrum. The framework was optimized using an extensive grid search spanning 80,000 configurations.

Experimental Dataset Generation

For training and testing of the framework a dataset is generated with the experimental setup depicted in Fig. 1. For an in-depth description of the setup the reader is referred to [10]. The spectrum of the transmitted signal is obtained using an OSA with a resolution of 10 pm after the receiver side EDFA. The dataset is obtained using the transmission setup for a channel count of 1, 3, and 5 as well as launch powers per channel of -3, -2, -1, and 0 dBm. The experimental setup can be used to emulate different types of errors. To emulate an increase in EDFA noise, we placed a variable optical attenuator (VOA) at the midstage access of the inline EDFAs within the transmission line and varied the attenuation from 0.2 to 2 dB in 0.2 dB steps. The transmit laser for the center channel was varied from its center frequency by -2.5 to 2.5 GHz in 0.5 GHz steps to emulate a laser drift. A power drop of the laser was created by deriving the laser power by -2.5 to 2.5 dBm in steps of 0.5 dBm. The same is achieved for the loaders by randomly selecting a channel with the same magnitude in the waveshaper which performs the noise shaping of the loaders. Two types of filter failures were generated: filter tightening and filter shift. For filter tightening, the waveshaper was used to narrow the channels by 1 to 5 GHz in 1 GHz steps. Filter shifting is achieved by shifting the center frequency of the waveshaper from -2 to 2 GHz in 1 GHz steps. The different failure types were all examined for the specified configurations of the transmission link. With repeating the measurements twice, approximately 800 spectra per failure type were recorded.

Results and Discussion

The results for the soft failure management capabilities are summarized in Table 1 and Fig. 2. Assuming all training data being available to the framework, the VAE achieves an F1-score of 0.9941 for the SFD, the SFI stage achieves an F1-score of 0.9820, the SVM localizes the EDFA failures, and the laser power drop with an F1-score of 0.9916. The USI achieves an F1-score of 0.9912 while a comparable approach using DBSCAN for determination of unknown failures achieves 0.8352. To show the extended capabilities of the framework, we reduce the number of training samples per failure. In Fig. 2, the maximum achieved F1-scores of the 4 stages are summarized over the percentage of total training data being available to the algorithms. It has to be noted, that the remaining part of the dataset is used as the (unseen) test data. It can be seen that the SFD F1-score is always high, even with a low amount of training data. This is because the VAE is trained on non-faulty data only and the discrepancy between a faulty spectrum and a non-faulty spectrum are distinctive. The USI is also not strongly dependent on the available training data size since the GAN is highly fitted to known spectra and generates its own training data for the unknown spectra. For SFI, an F1-score above 0.9 can be reached with only 3% of the total training data reaching up to 0.97 for 6% and above. Only the SFL suffers from a lower number of available training data, since the SVM as a supervised learning algorithm needs a high amount of

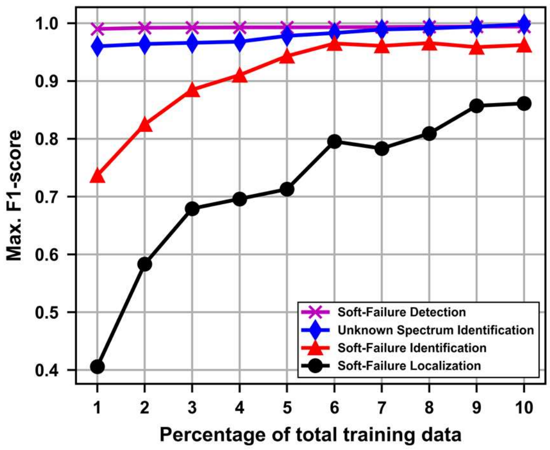


Fig. 2: Maximum F1-score for the different soft failure management stages over the percentage of used training data from the total number of training data.

training data being available. The SVM approaches an F1-score of 0.8 with 8% of the total training data.

Conclusion

We have shown a high-performance soft failure management framework including a VAE-based GAN for soft-failure detection and identification as well as unknown failure spectrum identification running on optical spectra as inputs. Also, a highly accurate localization algorithm is included in the framework. Comparing our approach to the literature, we can state, that our soft-failure identification performance is comparable to the state of the art with an F1-score of 0.97, however requiring only 6% of the total training data being available. Summarizing, our optical spectrum driven framework combines all parts of the soft failure management in a single framework with high prediction accuracies.

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Tab. 1: Results and comparison.

Literature	Task			OPM Data	ML-Algorithm	SFD Acc.	SFI Acc.	SFL Acc.
	SFD	SFI	SFL					
[4]	✓	✓		Rx power, BER	SVM	99.06%	99.55%	
[5]		✓		PSD	CNN		Up to 100%	
[6]			✓	Tx Power, OSNR	ANN			Up to 100%
Here:	✓	✓	✓	Optical spectrum	VAE-GAN + SVM	99.72%	98.21%	99.23%

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