Joint QoT Estimation and Soft-Failure Localization using Variational Autoencoder

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***Abstract*—We propose joint QoT estimation and soft-failure localization leveraging the latent space of a variational autoencoder trained on optical spectra. The framework shows F1-scores of 0.989 for soft-failure detection, 0.996 for identification and 0.908 for localization. The QoT estimator reaches an R2-score of 0.998 and a MAE of 0.17 dB.**

***Index Terms*—Quality of transmission estimation, failure localization, variational autoencoder.**

I. Introduction

In the present digital era, the demand for high-speed data is growing drastically. In such an all-connected world, a disruption of optical connections results in data losses as well as financial loss due to service-level-agreements (SLAs) not being met. Traditionally, optical networks ensure failure security with conservative design solutions based on guaranteed redundancies [1]. With increasing complexity and dynamicity of the networks, network assurance must be enhanced with automated and dynamic techniques. Instead of relying on threshold-based failure detection or probabilistic approaches, using machine-learning algorithms is a promising way of enabling possible self-management of future networks [2]. In recent years, great efforts have been made by the research community to realize reliable fault detection, fault identification, and fault localization in optical networks (e.g. [3]). However, most were focused on the management of hard failures (i.e., disruption of the service) and only a few focused on the handling of soft failures (i.e., events that progressively degrade the quality of transmission (QoT)). Since soft failures can potentially evolve into hard failures, handling the failures is of great interest regarding early detection, identification, and localization. To enable reliable failure management, optical performance monitoring (OPM) is indispensable. Network-wide OPM paves the way for tomorrow's optical networks, as the ingested data can be used for training and validation of machine learning algorithms. OPM may also include optical spectrum analysers (OSAs) at key nodes to extract information-rich spectra for further use. In our previous work on quality of transmission (QoT) estimation, we showed that the usage of spectral data for generalised optical signal-to-noise-ratio (GOSNR) prediction is beneficial (e.g. [4]). In this work, we focus on combining QoT estimation and failure detection, identification, and localization by leveraging automatic feature extraction from the spectrum using a variational autoencoder (VAE). The reconstruction probability of the VAE is used as a semi-supervised failure detection mechanism. Extensive simulations with heuristically varying input parameters based on realistic assumptions and margins to obtain a comprehensive data set for the training of the machine learning algorithms are the basis for a reliable machine learning based soft-failure management (SFM). The framework is then tested on an unseen dataset extracted from the COST266 European network [5]. Moreover, the failure detection is compared to an autoencoder-based failure detection mechanism. We show that the variational autoencoder based framework trained on optical spectra from sparsely deployed OSAs in combination with light-weight support vector machines (SVM) can detect, identify and localize laser dependent failures in an optical transmission. Also, the framework shows a high accuracy in the simultaneous QoT estimation based on the latent space from the VAE.

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II. Dataset Generation

A set of nine WDM channels with fixed grid spacing and equal launch power per channel is to be transmitted over a certain link consisting of several spans. The missing knowledge of the component parameters (due to unreliable information on fiber parameters, noise figures etc.) is represented following a heuristic approach with certain mean values and standard deviations based on realistic assumptions and margins [4]. The links are analyzed for various modulation formats, i.e., QPSK, 8-QAM and 16-QAM with coherent detection. The symbol rate is changed between 32, 64 and 69 Gbaud, while the channel spacing set to 37.5 GHz for 32 Gbaud and 100 GHz for 64 and 69 Gbaud. As for the launch power per channel P_{L}, values between -3 and +3 dBm are assumed. As for the uncertain parameters for example, the span length L_S is chosen as a random length with a mean $\overline{L_{\mathrm{S}}}$ of 80 km and a standard deviation σ of 5 km. The EDFA output power $\overline{P_{\mathrm{EDFA}}} = P_{\mathrm{L,Total}}$; σ: 0.5 dB and its noise figure $\overline{NF}$: 5 dB; σ: 0.5 dB are chosen for each EDFA in the link accordingly. The linear fiber

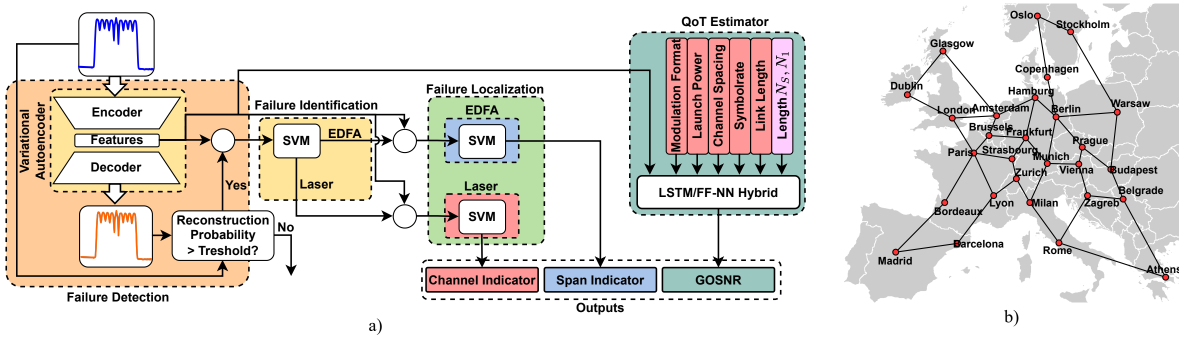

Fig. 1. a) QoT estimation and soft-failure detection, identification and localization framework based on a variational autoencoder; SVM: Support vector machine; GOSNR: Generalized optical signal-to-noise-ratio; b) COST266 European network topology.

parameters α and D are set to be $\overline{\alpha}$: 0.2 dB/km; σ: 0.02 dB/km and $\overline{D}$: 17 ps/(nm·km); σ: 0.2 ps/(nm·km), respectively. The nonlinear coefficient γ is assumed to be 1.295 $(\mathrm{W{\cdot}km})^{-1}$. Therefore, the parameters differ for each transmission, for each link and for each span. To generate the most balanced dataset possible for training the framework, simulations were performed over 1000 links with lengths drawn from a normal distribution with a maximum length of 3000 km. Each span in these links consists of a standard single-mode fiber (SSMF) followed by an EDFA with a flat gain characteristic in the C-band and an optical spectrum analyzer (OSA) with a resolution of 13 pm (according to the specifications of commercially available OSAs) at each intermediate node. Also, the number of intermediate nodes in each link is drawn from a normal distribution with up to 8 intermediate nodes. The propagation of the light through the links is calculated using the split-step Fourier method to achieve the most accurate values for OSNR and for the spectrum. The QoT is calculated over $GOSNR = P_{\mathrm{R}}/(P_{\mathrm{ASE}} + P_{\mathrm{NLI}})$ with the received power P_{R}, the linear noise power, i.e., the ASE noise power P_{ASE}, and the NLI noise power P_{NLI} of the channel under test (at 1550 nm) at the receiver. A total of 11 different channel scenarios are simulated, ranging from single channel transmission over the entire 9 channels to free adjacent channels. For the data generation, we have set up the mentioned scenario in our Matlab-based simulation tool. The extracted data from the simulations are the modulation format, launch power per channel, channel spacing, symbol rate, link length and the length between the intermediate nodes as well as the optical spectrum at each intermediate node. The created dataset for the QoT estimation and the non-failure case consists of approx. $6.5 \cdot 10^5$ feature sets. To extract as much information as possible from the spectra of intermediate nodes while maintaining a reasonable size for saving, they are reduced to 10,000 sampling points. However, this makes them only marginally usable as features, because the number of trainable parameters in the first layer of artificial neural networks depends directly on the number of features. Therefore, the dimensionality of the input data is reduced using an VAE leading to smaller sized classifiers and QoT estimation structures. In addition, the VAE is used for the semi-supervised anomaly detection. Since soft-failures per definition can result in hard failures over time, we are focusing on laser aging dependent failures in this work. For this purpose, we emulate failures of the transmit laser by reducing the launch power of one randomly selected channel by a random distribution with the mean value $P_{\mathrm{L}} - 1$ dBm and σ: 2 dBm. Moreover, a failure in an EDFA is emulated by increasing its noise figure artificially, since a degradation in the pump laser in output power controlled mode would only show in higher output noise. The flawed noise figure is drawn from a Gaussian random distribution with the mean value 6 dB and σ: 2 dB. The failure related dataset contains around 12,600 feature sets

A. Joint QoT estimation and soft-failure localization framework

Autoencoders (AE) have already been used for semi-supervised anomaly detection based on its reconstruction error in previous work (e.g. [6]). In this work, however, we are using a variational autoencoder which differs from a conventional autoencoder in mainly two ways: First, the latent variables are stochastic variables instead of deterministic mappings due to the probabilistic encoder that the VAE is using to generate the latent space. This extends the explanatory power of VAE compared to autoencoders, since normal and anomalous data may have the same mean values, but the variance may be different. Presumably, anomalous data have greater variance and have lower reconstruction probability [7], but autoencoders lack the ability to account for variance differences because the deterministic mappings of autoencoders are mappings to the mean of the input data. Second, the usage of the reconstruction probability of the VAE improves the anomaly detection compared to the autoencoder's reconstruction errors when the input data is heterogeneous, since no unique threshold is required to detect the anomaly. This is due to the fact that the probability distribution of each variable allows to be calculated separately according to its own variability. Thus, the decision on the threshold of the reconstruction error is much more objective, reasonable and understandable than that of the reconstruction error [7]. Furthermore, the threshold is not depending on the input data since probabilities are independent of the input data values. All of these points improve the handling of failures in optical networks when using spectral data obtained from OSAs. The developed framework for soft-failure detection, identification and localization as well as QoT

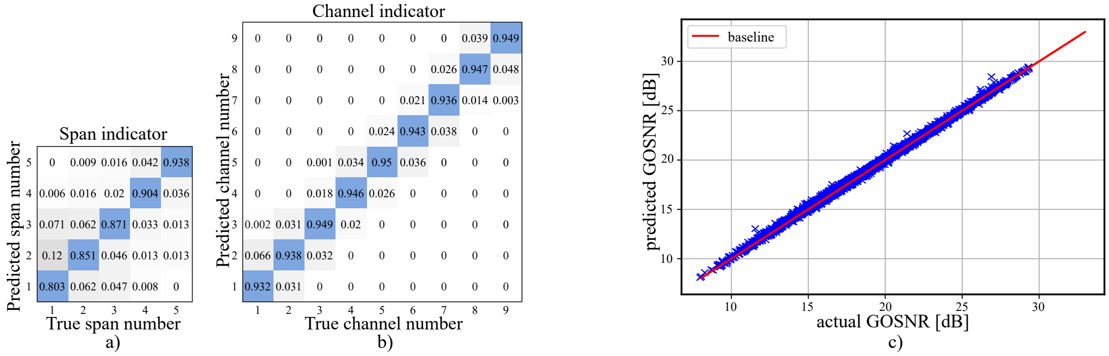

Fig. 2. a) Confusion matrix of failure localization of the EDFA failures in the spans, b) confusion matrix of failure localization of the transmitter laser failure, c) predicted GOSNR over actual GOSNR for feature extraction with the VAE; GOSNR: Generalized optical signal-to-noise-ratio; VAE: Variational autoencoder.

estimation is depicted in Fig. 1. The first stage is dedicated to failure detection based on the reconstruction probability of the spectrum by the VAE. The VAE is composed out of an encoder with an input layer with a size equal to the 10,000 points of the spectrum, followed by a fully-connected layer with 100 neurons, a batch normalization layer and another fully-connected layer with an output size of 10. These outputs are then processed in a sampling layer so that the output represents a normal distribution on the one hand and the input of the encoder on the other. A VAE in contrary to traditional AEs gives a variation value for each mean value of the latent space which can be used in further stages. The decoder is built to reverse the functions of the encoder. Afterwards the reconstruction probability is calculated. If the probability is above the set threshold, the next stage of the framework, i.e. the failure identification, is triggered. Failure identification is performed by a support vector machine (SVM), which is able to distinguish between an EDFA failure and a transmitter laser failure based on the latent space of the VAE. The third stage is divided into two parts: The first classifier is able to determine in which span the error of the EDFA occurred, while the second SVM determines which of the channels of the WDM transmission is affected by a lower launch power. Each of the three SVMs used in the framework has been optimized for the kernel coefficient γ_K and the regularization parameter C using a grid search algorithm with 250 steps per variable. The features of the latent space are also used for the QoT estimation. The estimator is a long-short term memory (LSTM) and feed-forward neural network (FF-NN) hybrid structure which is fed with sequential spectral data and transmission related data of the different links. For further information on the estimator, the reader is referred to our previous work on QoT estimation [4].

B. Results

The framework is tested on 1000 failures randomly distributed in an unseen dataset from the COST266 European network topology. The failure detection using the reconstruction probability of the VAE with an optimized threshold of 9 %, shows an F1-score of 0.989 whereas an AE failure detection mechanism based on a fixed threshold reaches only an F1-score of 0.913 [6]. The performances of the other stages are summarized in Fig. 2 a) and b). It shows the confusion matrices for failure identification and failure localization. The failure identification stage reaches an F1-score of 0.996 with a low false positive and false negative rate. However, since a supervised learning method is used, only previously seen classes can be labeled leading to other failures not being classified correctly. The framework shows to be capable of localizing the cause of the noise increase for an EDFA failure with an F1-score of 0.871. Also, the power drop in one channel is determined with an F1-score of 0.946. The performance of the QoT estimator is shown in Fig. 2 c). It can be seen that the predicted values are nearly on the actual GOSNR values. This is also represented in the R2-score of 0.998 and a MAE of only 0.17 dB, which is about the same as a QoT estimator with manually selected features [4].

C. Conclusion

We show that the latent space of a spectral data-driven VAE can be used for simultaneous QoT estimation and error prediction, with VAE exhibiting better anomaly detection performance than the standard AE. Furthermore, we show that lightweight SVMs are able to classify causes and locations of failures in the link with a high precision when they are trained on the latent space of the VAE. On top of that, the QoT estimation shows a similar performance with automated feature extraction as for the manual selected feature case when tested on an unseen topology dataset. The framework based on spectral data and VAE shows the capability of exact and reliable automated SFM.

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