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Generalizable QoT Estimation Based on Spectral Data Driven LSTM in Exact Component Parameter Agnostic Networks

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Abstract *We investigate the robustness of our spectral data driven machine learning based QoT estimator by artificially noising the input features. The estimator shows superior robustness against feature changes compared to a non-spectral estimator. We validate its generalization ability and robustness on an unseen experimental dataset. ©2022 The Author(s)*

Introduction

The emergence of flexible add-drop multiplexers and elastic optical networks resulted in more versatile but also more complex optical networks. Reasoned by the increased complexity, the monitoring of the performance is of increasing importance. Furthermore, the reduction of margins and the optimizing of network parameters enables more efficient optical networks. An accurate estimation of the quality of transmission (QoT) allows to maximize capacity and may enable full self-management of future networks. QoT estimation has been around for many years in the community, however, the emergence of performant artificial intelligence techniques renewed the interest to overcome the limitations of currently used QoT estimation tools, which are especially runtime, accuracy and vulnerability to uncertainties.

Different approaches to evaluate the performance of lightpaths have been proposed, including analytical [1], machine learning-based techniques [2,3], and hybrid ones [4-6]. However, all these techniques require detailed information of the component and OLS parameters for the QoT estimation. In practice, these parameters are not always exactly known (e.g. real noise figures of EDFAs, exact fiber parameters, etc.). Such a scenario will be referred to as component parameter agnostic or 'agnostic' for short in the following.

As the primary metric for optical link performance, the optical signal-to-noise ratio (OSNR) is used. The OSNR is closely connected to the bit-error-rate (BER), the Q-factor or the error-vector-magnitude (EVM). The knowledge of these parameters enables network operators to respond proactively to performance degradations. However, transceiver impairments limit their informative value since the transceiver characteristics are system specific. Therefore, the generalized OSNR (GOSNR) was defined as the required OSNR to achieve the same BER as in a back-to-back (B2B) scenario.

We have recently shown the advantage of the inclusion of spectral features extracted from sparsely deployed optical spectrum analyzers over traditional (ML-based) QoT-estimators in exact component parameter agnostic scenarios [7]. However, the proposed long short-term memory (LSTM) and neural network (NN) hybrid structure for the regression task was not analyzed regarding its ability to generalize to unseen scenarios or its robustness to parameter fluctuations.

In this paper, we investigate the generalization capability of the proposed QoT estimator by varying the values of the most important features by deliberately adding noise-like parameter variations from a normal distribution with a feature specific standard deviation. By this we can show the impact of each feature on the GOSNR prediction and evaluate, which feature has to be most accurate for the estimation. Furthermore, the generalizability of the purely simulatively trained estimator is verified by testing it on an (unseen) experimental dataset obtained from a recirculating loop setup.

Spectral Data based QoT Estimator

The QoT estimator based on LSTM and NN is trained with a simulation dataset obtained through solving the nonlinear equations using the split-step Fourier method for the propagation of the light through the fiber. The dataset consists of four different feature vectors. The transmission-related features are composed of a vector $\vec{T} = [MF, P_L, \Delta f, b,\ L]$ with modulation format (MF), launch power per channel (P_L), channel spacing (Δf), baudrate (b), the total link length (L) and the length vector $\vec{L} = [L_{N_S-k,N_S-(k-1)}, \dots, L_{N_S-1,N_S}]$ with N_S being the total number of spans and k representing the number of intermediate nodes. Therefore, $\vec{L}$ is built of the lengths between the intermediate nodes and the end of the link. The features obtained from the spectrum are the vector $\vec{A} = [A_{N_S-k,N_S-(k-1)}, \dots, A_{N_S-1,N_S}]$ that contains the area under the envelope of the power spectral density (PSD) obtained by the sparsely deployed OSAs, i.e. the total signal power and the vector $\vec{H} = [H_{c_1}, \dots, H_{c_{11}}]$ which is composed of the heights of the PSD of the considered channels. The target of the estimator is the GOSNR, which is calculated from the constellation points. The training dataset contains $15 \cdot 10^6$ feature sets, generated from the results of simulations of a dual-polarization transmission system with a huge variety of feature combinations regarding e.g. modulation format, channel assignments and launch powers. For more detailed information refer to our previous work [7].

Generalization Investigation

An ML-based estimator is generalizable and robust, if the estimator can reliably react to variations in the input features without major reduction in accuracy for an unseen dataset [8]. To investigate the impact of the QoT estimator, it is important to define, which parameters could be changing in another dataset, especially if an agnostic network scenario is considered in which for example the exact fiber lengths are not known. We consider the total link length L, the length vector $\vec{L}$, the power vector $\vec{A}$ and the vector $\vec{H}$ as possible features that may change in another dataset. Therefore, we deliberately vary the values of every feature contained in the vectors according to Gaussian distributed random processes with standard deviations of 10% of the assumed exact values. For changes in the length vector $\vec{L}$, the total link length L is adjusted accordingly. For each parameter, the prediction is repeated 1000 times to investigate the specific impact on the GOSNR prediction. Furthermore, another estimator is trained without incorporating the spectral features ($\vec{A}$ and $\vec{H}$) for comparison.

To validate the generalization performance, the estimator is tested on an unseen dataset obtained from experiments. The experimental setup is depicted in Fig. 1. The digital signal processing (DSP) is based on Matlab routines and is executed offline. At the transmitter side, for the generation of the channel under test (CUT), a PRBS of length 2^{17}-1 is generated and mapped to QPSK or 16-QAM. The 32 Gbd signal is upsampled to the sample rate of the DAC (88 GSa/s) followed by a pulse shaping using a root-raised cosine filter with a roll-off factor of 0.2. The digital-to-analog conversion is done by an arbitrary waveform generator (AWG) running at 88 GSa/s. An external laser with a wavelength of λ_{CUT} = 1550.004 nm in combination with a DP-IQ modulator that is driven by the DAC via 4 driver amplifiers generates the CUT. The other WDM channels (loaders) are generated using a programmable wavelength-shaping filter (II-VI WS4000A) with an ASE noise source as input source. The waveshaper has a periodically repeating filter bandwidth of 37.5 GHz corresponding to the channel spacing and is configured to level all channels at the output. The loaders and the CUT are combined using a 3 dB-coupler before being amplified using an EDFA. The output of the EDFA is then fed into the recirculating loop. The loop contains a polarization scrambler at the beginning followed by 3 spans. A span is composed of an EDFA to compensate the fiber losses, a variable optical attenuator (VOA) to set the desired launch powers and a standard single mode fiber (SSMF) with a length of 88.4 km. After one circulation the signal is flattened using another wavelength-shaping filter to compensate the EDFA gain characteristics. At the receiver side, the signal is first amplified by another EDFA and afterwards the CUT is filtered out before coherent reception. The analog-to-digital conversion is performed by an oscilloscope with 80 GSa/s. In the offline

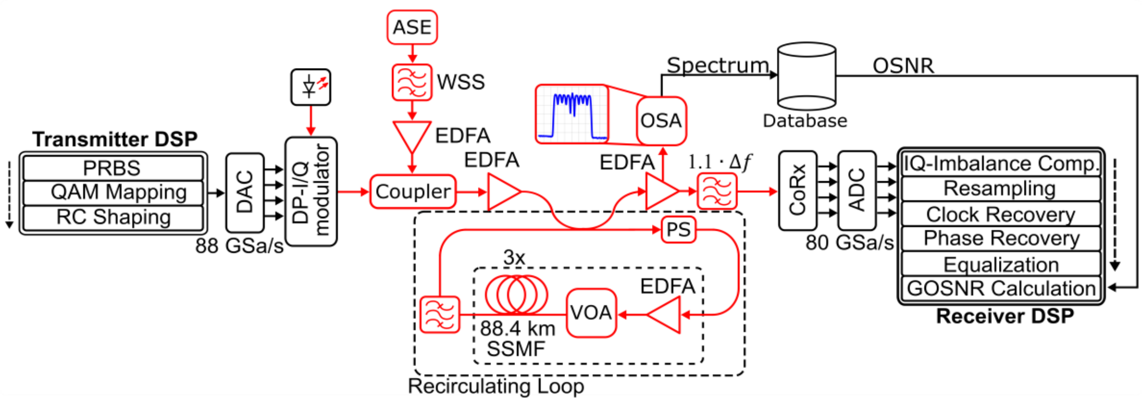

Fig. 1: Experimental transmission system setup and DSP with an exemplary spectrum with all active loaders. PRBS: pseudo-random bit sequence, QAM: quadrature amplitude modulation, RC: root cosine, DAC: digital-to-analog converter, DP: dual-polarization, WSS: WaveShaper, EDFA: Erbium-doped fiber amplifier, VOA: variable optical attenuator, SSMF: standard single mode fiber, PS: polarization scrambler, CoRx: coherent receiver, ADC: analog-to-digital converter.

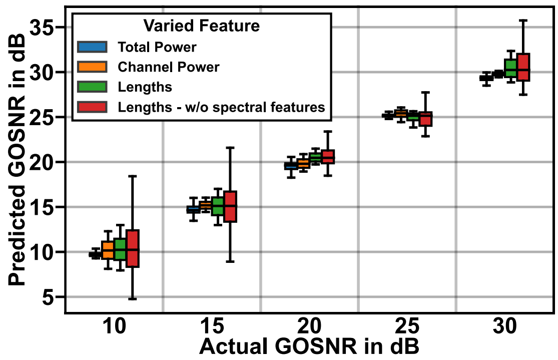

Fig. 2: Impact of varying the feature vectors length $\vec{L}$, total power $\vec{A}$ and channel power $\vec{H}$ with their corresponding standard deviations on the estimator trained on spectral data (blue, orange, green) and on the estimator trained without spectral data (red) for DP-QPSK.

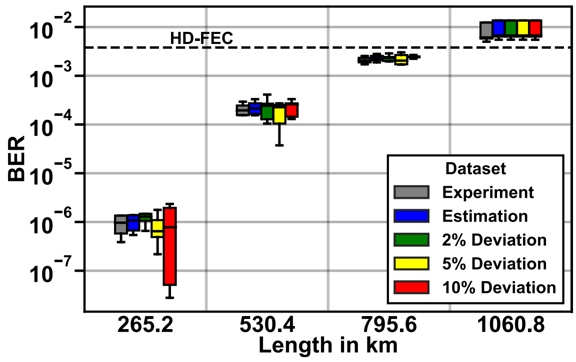

Fig. 3: BER over length for 5 different scenarios; grey: distribution of BER in the experimental dataset; blue: estimation of the QoT-E on the dataset; green: 2% change in the standard deviation (std) of the dataset; yellow: 5% change in the std of the dataset; red: 10% change in the std of the dataset.

receiver DSP, the signal is compensated for possible IQ-imbalances before upsampling to twice the baudrate. After the constant amplitude zero autocorrelation (CAZAC) sequence-based synchronization, the signal is matched filtered and equalized using a 2x2 MIMO-equalizer followed by the phase recovery. Afterwards, a 4x4 MIMO-equalizer compensates for the polarization-induced interferences. At the end of the DSP chain, the GOSNR is calculated using pre-measured look up tables of relations of OSNR and Q-factor for the considered configurations. The measurements include DP-QPSK and DP-16-QAM modulated WDM signals over 3 to 12 spans of SSMF with different channel assignments of 9 channels (adding in neighboring pairs of two around the COI) in a 37.5 GHz ITU-grid operating at 32 Gbaud.

Results and Discussion

The results of the generalization investigation are shown in Fig. 2. It can be seen that the length vector $\vec{L}$ and the total link length L have the strongest impact on the GOSNR estimation indicated by the larger error bars, followed by the channel powers extracted from the spectrum. Varying the total power by its standard deviation results in only small deviations of the estimator. This is due to the fact that most information about the total power is already included in the channel powers. The robustness of the estimator is lower in the lower GOSNR regime at 10 dB due to the lower number of high distance transmissions in the dataset. However, there are no significant outliers visible in the graphs. Furthermore, the estimator trained without spectral features shows much higher deviations when varying $\vec{L}$. Thus, our spectral data driven estimator shows a significantly higher robustness than an estimator trained without spectral features.

Using the estimator, which has been trained by idealized simulation only, on the (unseen) experimental dataset results in an overall good estimation with an R^2-score of 0.86 and a mean absolute error (MAE) of 0.76 dB. In Fig. 3, the reference and 4 different scenarios for the estimation can be seen. The smaller the error bars are, the more accurate is the estimation. For lower distances, the impact of a change of the standard deviation is larger than for higher distances, since the BER increases strongly with lower GOSNR. Above 1000 km, the deviations in the experimental are larger than before and so are the deviations in the estimations due to low GOSNR values in the experimental dataset.

Conclusion

We investigated the generalization ability and robustness to parameter fluctuations of our QoT estimator based on an LSTM/NN-hybrid implementation trained on simulative data by artificially noising the input features. The influence of the transmission lengths and the channel powers on the accuracy turned out to be larger than that of the total power. For the investigated scenarios, the estimator trained with only simulative data achieved a good performance on an (unseen) experimentally recorded dataset with an R^2-score of 0.86 and an MAE of 0.76 dB. Overall, the estimator convinces with its ability to generalize by using spectral data obtained from sparsely deployed OSAs, especially in comparison to the non-spectral case.

Acknowledgements

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