Deep Learning for QoT Estimation in SMF and FMF Links

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M. A. Amirabadi
*Iran University of Science and Technology*
Tehran, Iran
m_amirabadi@elec.iust.ac.ir

M. H. Kahaei
*Iran University of Science and Technology*
Tehran, Iran
kahaei@iust.ac.ir

S. A. Nezamalhosseini
*Iran University of Science and Technology*
Tehran, Iran
nezam@iust.ac.ir

A. Carena
*Politecnico di Torino*
Torino, Italy
andrea.carena@polito.it

***Abstract*—We explore deep learning-based classification and regression algorithms to estimate quality of transmission in single-mode and few-mode fiber links. Both approaches are shown to be effective and low complexity.**

***Index Terms*—Quality of transmission estimation, single mode fiber, few-mode fiber, deep learning.**

## I. Introduction

The single-mode fiber (SMF) optical communication systems are achieving their capacity limit because of the SMF nonlinearity, and cannot afford an exponentially growing demand. Recent advances in space division multiplexing show the capability of simultaneously independent data transmission through several spatially orthogonal modes through few-mode fiber (FMF). This, as a result, can increase the transmission capacity [1]. Properly estimating the quality of transmission (QoT) is important before deploying SMF and FMF links to assure the optimized design and planning. The QoT estimation requires the prediction of linear and nonlinear interference (NLI) noise. The linear noise calculation is simple, while the NLI noise computation is challenging. To predict the NLI, one can use either exact analytical models such as the enhanced Gaussian noise (EGN) model [2], [3], which have high accuracy and high computational complexity, or approximate analytical models including the closed-form (CF)-EGN model [4], [5] that are asymptotic and have low complexity. The third, alternative method, to estimate the QoT is machine learning (ML) which removes these drawbacks by considering the records form already employed experiments. ML algorithms can be developed as classifier or regressor to estimate the QoT. The output of classifier is a binary value, and does not show any difference whether this value is close to or far from the threshold. The regressor estimation is continuous and indicates the difference between predicted value and threshold. In [6], authors employed ML-based classifier and compared the results by a bit error rate (BER) threshold. Different ML algorithms are deployed in [7] as regressor for generalized signal to noise ratio (GSNR) estimation considering a full-load SMF link. Authors of [8] showed the outperforming of artificial neural network over other ML algorithms for estimating QoT. In [9], a deep neural network (DNN)-based regression algorithm is developed for estimating GSNR considering a full-load SMF link. Deep learning (DL) is capable of learning highly nonlinear relationships which makes it proper for estimating QoT [10]. In this work, we deploy DL for estimating QoT in SMF and FMF links. We train DL-based classifier and regressor models to estimate whether the BER meets the predefined threshold. Considering partial-load SMF and FMF links with two different granularity, we generate four datasets using the EGN model [2], [3]. The performance and complexity of the CF-EGN model, classifier, and regressor [4], [5] are compared. The obtained results indicate efficient performance and low complexity for both classifier and regressor, however, classifier is faster and regressor performs better. Therefore, the proposed DL-based approaches are proper for real-time QoT estimation applications, e.g. autonomous network planning.

## II. Generated Datasets and DL-based QoT estimation methods

DL-based algorithms need huge dataset to be applied in QoT estimation for a variety of link and system configurations. We consider transmission over SMF and FMF links with up to 66 channels centered at the $1550$ $nm$ wavelength, 75 $GHz$ channel spacing, and 64 $GBaud$ symbol rate with 1 and 3 spatial modes in SMF and FMF cases, respectively. Links analyzed have a number of spans ranging from 1 to 8 with a span length uniformly distributed between 80 and 120 $km$. The dispersion coefficient, nonlinear (coupling) coefficient, differential group delay, and attenuation are reported in [1]. An ideal optical amplifier by 5 $dB$ noise figure compensates the fiber losses after each span. For each channel and mode, we randomly dedicate a modulation format between PM-B/QPSK and PM-MQAM with M selected between 8,16,32, and 64.

We consider a link-state partially-loaded with $50\%$ *randomly ON* channels which, as a result, should be considered as feature and in turn increases a lot the feature dimension as we add a vector of 66 elements. Therefore, we reduce this dimension by generating the dataset on a sub-band basis [11] and group each 6 channels into a sub-band. Thus, considering number of ON channels, we have a shorter vector (11 elements) but 7 possible sub-band levels. To further simplify we also consider a simpler case by reducing the number of levels to 3. We want to investigate whether DL-model can learn the knowledge about the whole feature space (7-level sub-band) by training based on the smallest feature sub-space (3-level sub-band). The 3-level case is a smaller subset where the channels inside a sub-band are with uniform probability all-ON, all-OFF, or 50%-randomly-ON. We generate 3 and 7 level sub-band datasets for SMF named D1 and D2, and for FMF named D3 and D4, respectively, each with 60000 training and 6000 testing points.

We characterize each link configuration by some features. We add modulation format and the indices of channel and mode under test to the features. We also include span length and number of spans as features due to the dependency of NLI on these parameters. Following, we assign some features to the right and left traffic-volumes and the number of right and left empty frequency slots considering the channel under test. Likewise, we add the modulation format of the right and left neighbors of channel under test to the features. Finally, we dedicate some features to the sub-band level. Selecting similar features for FMF case, 22 and 48 features are chosen for the SMF and FMF links, respectively. Note that the left and right modulation format in SMF goes from 10 to 11, and the link-state goes from 12 to 22. We are working with 3 modes, thus in FMF, the number of left and right modulation formats is tripled, from 10 to 15, and also the link state, from 16 to 48.

The GSNR of $m$th channel and $q$th mode under test can be obtained by $GSNR_{m,q} = P_{m,q}/(P^3_{m,q}\eta_{NLI,m,q} + \sigma^2_{ASE,m,q})$ with $P_{m,q}$, $\eta_{NLI,m,q}$, and $\sigma^2_{ASE,m,q}$ respectively as the launched power, the NLI noise power, and amplified spontaneous emission noise (ASE) power [2], [3]. We generate the label for each feature set by first calculating the GSNR considering the optimum uniform launch power per channel and mode. Then, depending on the modulation format, we calculate BER based on the GSNR via relationships defined in [12]. We define the class labels by comparing the obtained BER with a threshold BER set at $1e-3$ considering employed forward-error code with 28% overhead.

The outputs of regressor and CF-EGN model are continuous values ($\eta^{pred}_{NLI,m,q}$) and should be converted to the class labels. We consider the same structure for DNN in classification and regression with the only exception about the last layer type which is *sigmoid* in classification and *linear* in regression. Therefore, we apply a DNN with $N_1$ input neurons (equal to number of features), one output neuron, two hidden layers each by respectively $N_1$ and 1000 hidden neurons. The DNN training is done based on instruction provided by [11].

## III. Simulation results

Here, we present the simulation results for CF-EGN model, classifier, and regressor considering train:test combinations D1:D2, D2:D2, D3:D4, and D4:D4. Fig. 1 depicts the normalized runtime-accuracy values for a) D1:D2, b) D2:D2, c) D3:D4, d) D4:D4. D1 is based on 3-level sub-band which can be counted as a very small portion of a 7-level sub-band dataset. However, the accuracy in D1:D2 and D2:D2 scenarios is almost the same which it also shows that the reduced complexity (3-level) dataset is enough. An important issue in deploying DL for estimating QoT in SMF and FMF links is generating large training dataset, this procedure is consumes a lot of time even synthetically.However, results indicate that the classifier and regressor do not need different training datasets for different system and link configurations. Note that D1 and D3 dataset are faster to be generated to guarantee same accuracy as D2 and D4, since the 3-level space is smaller. The accuracy in D3:D4 and D4:D4 is the same for the regressor and CF-EGN model. However, in a DL-based classifier, the accuracy in D3:D4 degrades a little comparing with D4:D4. There are two claims adaptable for this observation, first, the last layer of regressor is linear activation function while it is the sigmoid activation function for the classifier, therefore regressor has higher degrees of freedom while training. Secondly, FMF nonlinearity is more complicated and thus harder for learning by DNN rather than the SMF case. Classifier is twice faster than regressor considering different train:test combinations, as binary classification is simpler than regression which results in less activating neurons in DNN-based classifier [11]. The CF-EGN model is four orders of magnitudes slower than the classifier and regressor, this has an important impact in real-time applications including network control and planning [6]–[8].

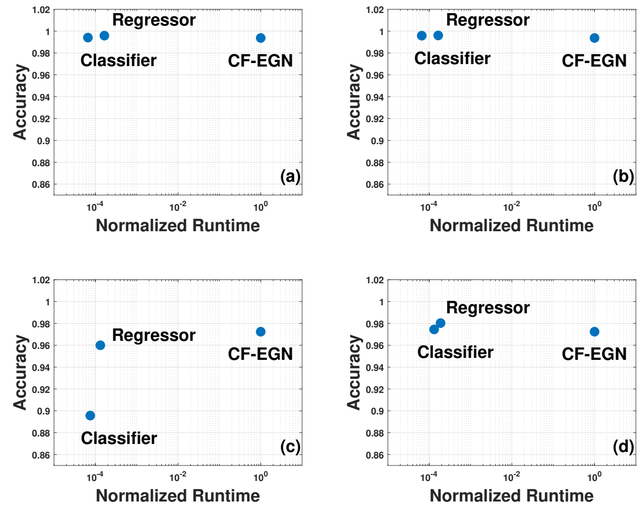

Fig. 1. Normalized runtime-Accuracy for CF-EGN model, classifier, and regressor, for a) D1:D2, b) D2:D2, c) D3:D4, d) D4:D4.

Fig. 2 plots the precision, recall, and accuracy for CF-EGN model, classifier, and regressor, for a) D1:D2, b) D2:D2, c) D3:D4, d) D4:D4. In D1:D2, D2:D2, D4:D4 the precision and recall values are quite high, also D3:D4 has a high precision value. Although classifier has high precision value in D3:D4, its recall value is small which shows its false negative (FN) decisions are more than false positive (FP) ones. Here, the positive and negative decisions mean predicting BER above and below BER, respectively. Thus, FN classifying as a bad link while it is not true.

The confusion matrix is demonstrated in Fig. 3 for CF-EGN model (top), classifier (center), and regressor (bottom), for D1:D2 (a,e,i), D2:D2 (b,f,j), D3:D4 (c,g,k), D4:D4 (d,h,l).

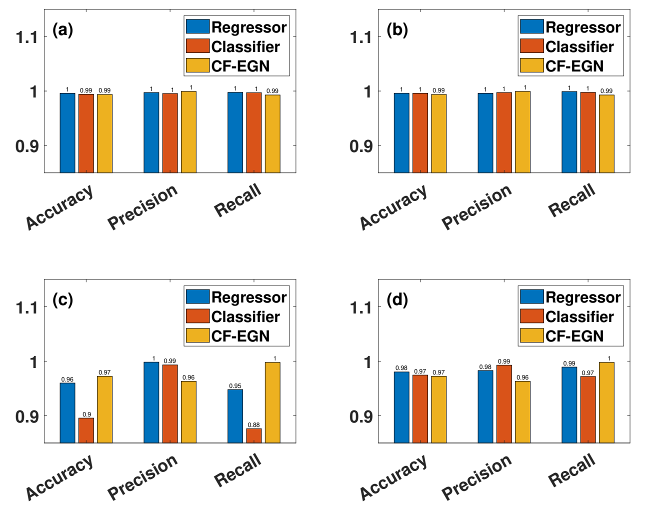


Fig. 2. Precision, recall, and accuracy for CF-EGN model, classifier, and regressor, for a) D1:D2, b) D2:D2, c) D3:D4, d) D4:D4.

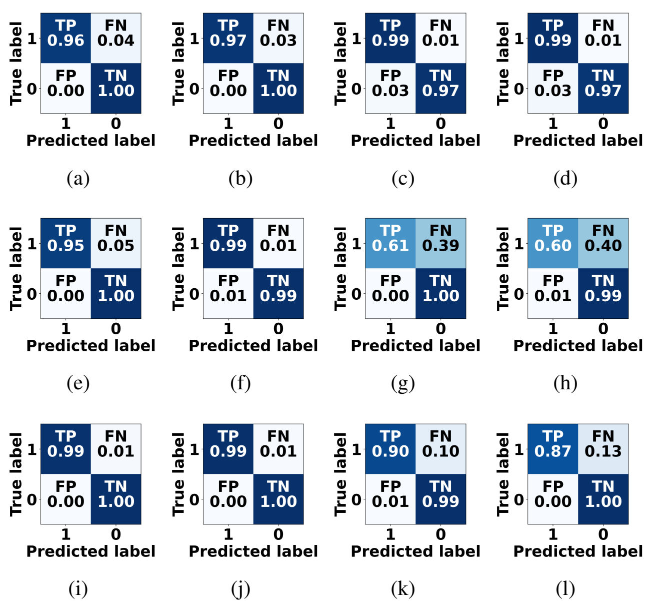


Fig. 3. Confusion matrix for CF-EGN model (top), classifier (center), and regressor (bottom), for D1:D2 (a,e,i), D2:D2 (b,f,j), D3:D4 (c,g,k), D4:D4 (d,h,l).

Considering D1:D2, and D2:D2, in all cases, FN is more than FP which indicates that the CF-EGN model, classifier, and regressor are all on the safe side in SMF.

## IV. Conclusion

In this work, we presented DL-based algorithms for QoT estimation in SMF and FMF links. The presented DL-based regressor, classifier and CF-EGN model performed almost the same considering different train:test combinations with an exception in D3:D4 where the classifier provided a biased classification. The reported results indicate safe classification for the classifier and regressor in both SMF and FMF links, while CF-EGN model was only on the safe side in SMF.

## Acknowledgement

Computational resources for dataset generation were provided by HPC@POLITO. This research was supported by the Italian Government through project PRIN 2017 FIRST.

## References

[1] G. Rademacher, K. Petermann, "Nonlinear Gaussian noise model for multimode fibers with space-division multiplexing", *Journal of Lightwave Technology*, Vol. 34, No. 9, pp. 2280-2287, 2016.

[2] A. Carena, G. Bosco, V. Curri, Y. Jiang, P. Poggiolini, and F. Forghieri, "The EGN model of non-linear fiber propagation", *Optics Express*, vol. 22, no. 13, pp. 16 335–16 362, 2014.

[3] M. A. Amirabadi, M. H. Kahaei, S. A. Nezamalhosseini, and L. R. Chen, "Joint power and gain allocation in MDM-WDM optical communication networks based on extended Gaussian noise model", *IEEE Access*, vol. 10, pp. 23 122–23 139, 2022.

[4] P. Poggiolini, G. Bosco, A. Carena, V. Curri, Y. Jiang, and F. Forghieri, "A simple and effective closed-form GN model correction formula accounting for signal nongaussian distribution", *Journal of Lightwave Technology*, vol. 33, no. 2, pp. 459–473, 2015.

[5] M. A. Amirabadi, M. H. Kahaei, S. A. Nezamalhosseini, F. Arpanaei, and A. Carena, "Closed-form EGN model for FMF systems", *In Asia Communications and Photonics Conference, T4A–33*, 2021.

[6] C. Rottondi, L.Barletta, A. Giusti, and M. Tornatore, "Machine-learning method for quality of transmission prediction of unestablished lightpaths", *Journal of Optical Communications and Networking*, vol. 10, no. 2, A286–A297, 2018.

[7] R. M. Morais and J. Pedro, "Machine learning models for estimating quality of transmission in DWDM networks", *Journal of Optical Communications and Networking*, vol. 10, no. 10, pp. D84–D99, 2018.

[8] S. Aladin, A. V. S. Tran, S. Allogba, and C. Tremblay, "Comparison of domain adaptation and active learning techniques for quality of transmission estimation with small-sized training datasets", *Journal of Optical Communications and Networking*, vol. 13, no. 1, A56–A66, 2021.

[9] J. Muller, T. Fehenberger, S. K. Patri, et al., "Estimating quality of transmission in a live production network using machine learning", *In 2021 Optical Fiber Communications Conference and Exhibition (OFC)*, pp. 1– 3, 2021.

[10] M. A. Amirabadi, M. H. Kahaei, S. A. Nezamalhosseini, and A. Carena, (2022, June). Deep Learning Regression vs. Classification for QoT Estimation in SMF and FMF Links", *In 2022 Italian Conference on Optics and Photonics (ICOP)*, 2022.

[11] M. A. Amirabadi, M. H. Kahaei, S. A. Nezamalhosseini, F. Arpanaei, and A. Carena, "Deep Neural Network-Based QoT Estimation for SMF and FMF Links", *Journal of Lightwave Technology*, 2022.

[12] J. G. Proakis and M. Salehi, "Digital communications", *McGraw-hill*, 2008.