QoT Estimation for Large-scale Mixed-rate Disaggregated Metro DCI Networks by Artificial Neural Networks

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Abstract: We proposed an artificial neural network (ANN)-based QoT estimator for large-scale mixed-rate disaggregated metro DCI networks with an estimation error standard deviation of 0.3 dB, outperforming analytical-based methods with vendor-specific transponder SNR characterization.

1. Introduction

Quality of transmission (QoT) estimation for optical transport network has been actively investigated in recent years. Researchers have proposed various algorithms including analytical models, data-driven parameter optimizations as well as machine learning (ML) to improve generalized signal-to-noise ratio (GSNR) estimation accuracy [1–4]. However, relatively few research on QoT estimation for large-scale metro data center interconnect (DCI) networks are reported. As multi-vendor mixed-rate coherent modules are becoming more common in DCI scenario, a more accurate QoT tool is needed for network performance monitoring and resource allocation [5]. Also, optical multiplex section protection (OMSP) with primary/secondary path switching is commonly adopted in metro DCI networks and accurate QoT estimation will significantly benefit the reliability in operations such as optical line protection (OLP) switching [6]. However, metro DCI networks have much shorter transmission distance with almost 90% of lightpaths less than 100 km and generally have higher SNR values than their long-haul counter parts. This nullify the advantages of accurate QoT estimation based on analytical models (such as the GN model) as amplifier noise and fiber non-linearity effects are no longer dominant impairments compared to transponder effects [7] that are difficult to model explicitly. Also, data rate for metro DCI networks covers a wide range from 200Gbps to 400Gbps, 600Gbps and 800Gbps with potentially different coherent transponder structure and DSP design and are more disaggregated with multiple coherent transponder vendors, which adds to the difficulty in accurate QoT. Even for the same model from a given vendor, our own experimental characterizations on a few transponders show that SNR performance exhibits a larger variation from one transponder to another for higher SNR values, making it difficult for accurate QoT in practical large-scale deployed networks. There are some related works for metro network field trial [8] and experimental test-bed [9], but a QoT study over large-scale metro production networks has yet to be investigated.

In this connection, we study large-scale disaggregated metro DCI networks and propose an artificial neural network (ANN) model to incorporate inherent transponder effects for accurate QoT estimations. Results show that the ANN model can outperform analytical models which incorporate amplifier noise, fiber nonlinearity distortions and transponder distortions with data-driven parameter estimation, thus suggesting the unique advantage of ML techniques in such scenarios. The effectiveness of such ANN-based QoT model is demonstrated in OLP switching scenarios that are common in metro DCI networks.

2. ANN-based QoT Estimation for Mixed-rate Disaggregated Metro DCI Networks

We started our QoT study by applying the same optimization methods i.e., refined physical parameters and bias leaning, proposed in [1] to disaggregated metro DCI case where have around 10,000 lightpaths across 300 OMSes at a given time. We mainly study 8 types of transponders from 4 vendors as shown in Table. 1. We randomly selected 200,000 data samples of each transponder type from June to August 2023 from metro DCI networks. Each data sample contains EDFA total input/output power, gain and noise figure, single-channel power from optical channel monitors (OCM) placed at the output of each EDFA, fiber length and loss along the links that an OCH has passed though, which will be used to estimate GSNR. At the receiver, pre-FEC BER will be mapped into ground-truth GSNR from pre-measured B2B curves. The training and testing datasets are randomly chosen from these 200,000 data samples with the ratio of 7:3 for bias optimizations and ANN-based method.

$$GSNR = \frac{1}{\sum_i \frac{1}{\left(\frac{1}{1/SNR_{i,\mathrm{ASE}}+1/SNR_{i,\mathrm{NLI}}}\right)\cdot\beta^{d}_{\mathrm{oms}_i}} + \frac{1}{SNR_{\mathrm{TRX}}}}\cdot\beta_{\lambda_k}\cdot\beta_{\mathrm{TRX}_{type}} = \frac{1}{\sum_i \frac{1/SNR_{i,\mathrm{ASE}}+1/SNR_{i,\mathrm{NLI}}}{\beta^{d}_{\mathrm{oms}_i}} + \frac{1}{SNR_{\mathrm{TRX}}}}\cdot\beta_{\lambda_k}\cdot\beta_{\mathrm{TRX}_{type}} \tag{1}$$

Table 1. Statistics of GSNR estimation error (test dataset) for different rate and vendor of transponders

Vendor	Rate [Gbps]	**Analytical Model with Refined Parameters**		**with Refined Parameters and Bias Learning**		**ANN**	
		Mean	Std	Mean	Std	Mean	Std
A	400	0.063	**1.828**	0.007	**0.521**	0.024	**0.164**
	600	−1.424	**0.888**	−0.008	**0.184**	0.008	**0.054**
B	400	−0.899	**2.119**	0.013	**1.173**	0.007	**0.29**
	800	−1.243	**1.774**	0.006	**0.584**	−0.019	**0.185**
C	200	2.363	**2.301**	0.005	**0.62**	0.002	**0.151**
	400	−0.407	**2.512**	0.011	**0.685**	0.008	**0.156**
D	200	0.118	**2.458**	0.000	**0.505**	0.005	**0.171**
	400	−0.133	**2.021**	−0.006	**0.504**	0.017	**0.173**

Analytical model with refined physical parameters by combining optical power measurements from EDFA input/output and optical channel monitors and EDFA gain profile estimation [1] was first used to estimate GSNR and compared to true GSNR (converted from the pre-FEC BER) to obtain the estimation error. The expression as shown in Eq. (1) where SNR_{ASE}, SNR_{NLI} and SNR_{TRx} denotes the GSNR if only ASE noise, nonlinearity or transponder effects are present. The mean and standard deviation (std) of GSNR estimation errors of this method are shown in the third and fourth columns of Table. 1. It can be seen that the mean and std (0.8∼2.5dB) obtained for each type of transponders in metro DCI networks are larger compared to around 0.4dB std in long-haul production network [1]. This is possibly because the refined physical parameters mainly improve the accuracy of SNR_{ASE} and SNR_{NLI} but these impairments are negligible in short DCI transmission distance as experimentally validated [7]. As SNR_{TRX} can play a more important role than SNR_{ASE} and SNR_{NLI}, we measured OSNR-BER characteristics of different transponders in our experimental test-bed and the results for 800Gbps transponders (vendor B) are shown in Fig. 1(a) for different received optical power (`opr`). We can see the minimum OSNR is largely affected by `opr` outside -8∼2 dBm. We can also deduce SNR_{TRX} from testing results and then put them in Eq.(1) with adding OMS/frequency/transponder type bias learning based on gradient descent algorithm. Additional OMS bias $\beta^{d}_{\mathrm{oms}_i}$ where $d \in (a \to z, z \to a)$ denotes the direction of the i^{th} OMS, frequency bias β_{λ_k} to capture frequency-dependent effects and $\beta_{\mathrm{TRX}_{type}}$ to compensate for different types of transponder's inherent effects are added in the GSNR model to be learnt from data. The results can be seen from the fifth and sixth columns of Table. 1 in which the mean and std are reduced to an acceptable level for most types of transponders except for the 400G transponder (vendor B) which still has estimation errors std of around 1 dB.

These results indicates that even with an accurate analytical model, input parameters with refined accuracy, SNR_{TRX} characterization from a pair of transponders in lab test-bed as well as data-driven linear bias parameter learning, such methodologies still falls short of accurately characterizing the GSNR of a great number of line cards/transponders in large-scale metro DCI networks. Hence, a completely data-driven neural network model may be needed to learn such characteristics unknown to network operators to realize more accurate QoT estimation in such disaggregated metro scenarios. A multi-layer perception (MLP) neural network with 5 hidden layers and number of nodes (4096, 2048, 1024, 128, 8) was built to train QoT estimation model. The activation function is ReLU and input features include EDFA total input/output power, gain, noise figure, single-channel output power from OCM, fiber length and loss, and center frequency of an OCH. Test results are shown in the seventh and eighth columns in Table. 1 with std of estimation errors below 0.3dB for all types of transponders.

3. Validation on Optical Line Protection (OLP) Switching

1+1 OMSP which prevents OCH services disrupting from fiber cut/bend and device/component failure, is preferred in metro DCI scenarios [6]. There are always two different physical paths in an OMS (i.e., primary path and secondary path) with the same source and destination and duplicated signals. The switching between primary and

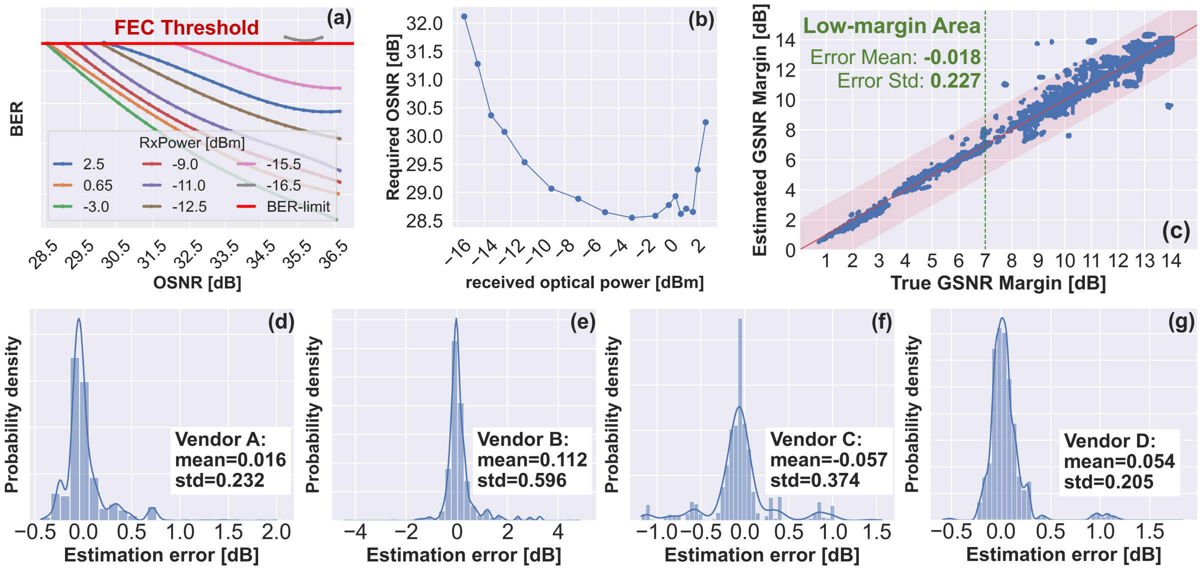

Fig. 1. (a) Measured BER vs. OSNR curves for B2B at different received optical power and (b) received optical power vs. required minimum OSNR of experimental results for 800G transponder(vendor B); (c) all data samples which have switched working paths in September and GSNR is estimated by the corresponding ANN model, and statistical results of estimation errors for (d)vendor A, (e)vendor B, (f)vendor C and (g)vendor D.

secondary path is performed through an automatic protection switch (APS) at the receiver side, which depends on the optical power difference at the OMS destination and the selected path is named as working path while another is backup path [6]. Statistically, the number of OLP switching that occur in a month can be around 200 in the metro DCI networks under study. As the received signal and its pre-FEC BER are only available for the working path but not the backup path, continuous QoT estimations of backup paths on top of monitored optical powers of the backup path are important to ensure enough operating margin in advance of next OLP switching event.

Since the BER/ground-truth GSNR can be reported from backup path only after the switching happened, we specially selected those lightpaths (around 700 lightpaths) that have switched its working paths to backup paths in September to validate the proposed ANN-model and the results are shown in Fig. 1(c-g). Due to mixed-rate multi-vendor transponders have different received SNR ranges and data disclosure confidentiality reasons, we present GSNR margin instead of true GSNR values, which is computed by measured/estimated GSNR minus the minimum SNR required for the specific modulation format and type of transponder and the results are shown in Fig. 1(c) where the red-shadow covers estimation errors within 2dB. As the QoT estimation accuracy in lower-margin areas should be more important and guaranteed than that in higher-margin area, Fig. 1(c) shows that the switched paths working in the lower-margin area ($<$ 7dB) has a small std is only 0.227dB which is a good guarantee of QoT estimation accuracy for most of the switching events. The distributions of GSNR estimation errors are shown in Fig. 1(d-g) for different vendors. It should be noted that since the OLP switching is mostly caused by the decreased optical powers of the original working path and most of these OCHs are highly likely at the high-margin region after the switching with higher QoT estimation errors as shown in Fig. 1(c). This in turn lead to a larger std in Fig. 1(d-g) than those in Table. 1 as the data from Table.1 do not differentiate between switched and unswitched paths. Overall, these results show that the trained ANN models can be used to accurately estimate QoT of backup paths in metro DCI networks.

4. Conclusion

In this paper, we proposed an artificial neural network(ANN)-based QoT estimator for large-scale mixed-rate disaggregated metro DCI networks with 4 transponder vendors and multiple transmission rates of 200, 400, 600 and 800Gb/s. A QoT estimation error standard deviation of 0.3 dB is achieved, outperforming analytical-based methods with transponder SNR characterizations and data-driven parameter optimizations. QoT estimations for protection switching scenarios are demonstrated its value for future disaggregated and mixed-rate metro DCI networks.

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