QoT Estimation Improvement with Inputs Refinement Tool for C+L Networks

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Abstract: We propose a technique to estimate lumped losses thus OSNR, nonlinear SNR, GSNR, and SNR in C+L optical networks. We show with simulations that SNR estimation accuracy is within 0.5dB and that the technique is robust to uncertainty due to aging. © 2022 The Author(s)

1. Introduction

Estimating accurately quality of transmission (QoT), such as signal to noise ratio (SNR) of services can help increase network capacity by reducing overestimated design margins for WDM optical fiber networks [1]. SNR inaccuracies come from both the QoT models [2-3] and the inputs to the model. This paper focuses on the latter. "Inputs refinement" tools were proposed e.g. in [4-6] to refine the knowledge of key sources of uncertainty, namely, the lumped losses e.g. connector losses at the beginning and end of each span of a *single-band* transmission system. As *multi-band* systems such as C+L are deployed in commercial networks, any uncertainty of the real power entering into the fiber after the connector will impact estimation of the Kerr effect and of the loss of each band induced by the stimulated Raman scattering (SRS); this will ultimately exacerbate the uncertainty on SNR estimation.

In this paper, we propose an inputs refinement tool for C+L networks to tackle the per band uncertainties. We show, using simulations over a 3-span optical multiplex section (OMS), that optical SNR (OSNR), which takes into account amplified spontaneous emission (ASE) noise, is estimated with root-mean-square error (RMSE) lower than 0.2dB, nonlinear SNR, which takes into account the Kerr effect, with RMSE lower than 1.2dB and hence the generalized SNR (GSNR), wich considers both the ASE noise and the Kerr nonlinearity, with RMSE lower than 0.5dB. In addition, we extend simulations to a cascade of 10 OMS of 3 spans each with highly heterogeneous lengths, and the RMSE of the estimated SNR, wich considers transponder and wavelength selective switches (WSS) filtering penalties in addition to GSNR, is lower than 0.4dB. We also show that inputs refinement is accurate (RMSE<0.5dB) even in aging scenarios where the loss of the splices in fibers are not accurately known.

2. Setup and assumptions

Fig. 1 depicts a generic N-span C+L OMS. Parameters in green are monitored hence known in real networks: total input ('*in*')/output ('*out*') power at each amplifier $P^B_{tot,\{in,out\}}$ for each band $B\in\{C,L\}$, output power spectrum after the first (booster, "*1*") and last ("*N+1*") amplifier of the line $P^B_{out,\{1,N+1\}}(\lambda)$. Parameters in red are unknown in real networks and need to be refined: lumped (connector and band multiplexer (MUX) and de-multiplexer (DEMUX)) loss $\delta^B_{k,\{a,b\}}$ at input ('*a*') and output ('*b*') of the k^{th} span, rippled gain spectrum $G^B_k(\lambda)$ for the k^{th} amplifier, and output power spectrum $P^B_{out,k}$ of the k^{th} in-line amplifier. In addition, nominal (mean) gain of amplifier GN^B_k and tilt TN^B_k are set for each span *k* and band *B*, hence known. For simplicity, we assume all amplifiers have the same noise figure NF. Finally, we assume using a standard single mode fiber (SMF) which includes the wavelength-dependent loss as characterized in our lab.

3. Method description

In this paper, we compare the GSNR and SNR estimation in a transmission with 3 different methods: inputs refinement (IR), IR with ground truth gain spectrum (IR_{GT}), and a naïve baseline.

Inputs Refinement (IR) (outline)

Initialization: each amplifier is assumed to be exactly linearly tilted with nominal gain GN^B_k and tilt TN^B_k.

Step 1: Using a gradient descent technique, we propagate $P^B_{out,1}(\lambda)$ through the OMS using our QoT tool and find the optimal lumped loss combination $[\delta^B_{k,\{a,b\}}]$ for each span *k* and band *B* to minimize the estimation error on $P^B_{out,N+1}(\lambda)$.

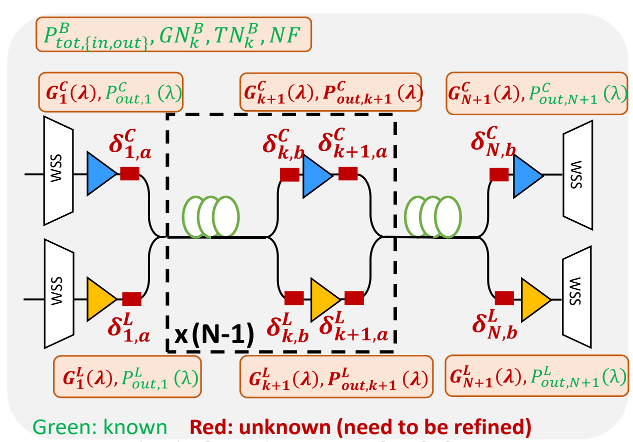

Fig. 1. Generic N-span OMS C+L system.

Step 2: We estimate $G_k^B(\lambda)$ applying *[*$\delta_{k,\{a,b\}}^B$*]* from Step 1, to minimize the same error cost function.

We iterate step 1 and step 2 until the error cost function is below a predefined threshold.

Inputs Refinement with ground truth gain spectrum ($\mathrm{IR_{GT}}$**):**

To assess whether inaccuracies of IR come from lumped losses or amplifier gains spectra estimation, we use ground truth gain spectrum (with ripples) instead of the linear tilted gain spectrum in the algorithm above.

Baseline:

We obtain the total lumped loss per span per band, as span loss (measured by photodiodes on each amplifier) minus fiber loss (estimated through linear attenuation and fiber length), then for each band, this value is uniformly distributed 50%/50% before and after the span. Afterwards, we distribute output power spectrum difference $P_{out,1}^B(\lambda) - P_{out,N+1}^B(\lambda)$ uniformly among all in-line amplifiers to set the per-span per-band launch power $P_{out,k}^B(\lambda)$, then we obtain $P_{in,k}^B(\lambda)$, k>1 for in-line amplifiers and pre-amplifier by per-span propagation with $P_{out,k}^B(\lambda)$, k>1, then we configure G_k^B=$P_{out,k}^B(\lambda) - P_{in,k}^B(\lambda)$, k>1, thus the output power spectrum at the last amplifier of each band $P_{out,N+1}^B(\lambda)$ is consistent with the ground truth power spectrum at the end of the OMS, finally we use our QoT model to estimate the (G)SNR.

4. Simulation results

We run all the simulations in a 6+6 THz C+L system with 75GHz channel spacing, 80 channels for each band. The baud rate of emulated channels is 68Gbaud with 200Gb/s PDM-QPSK. Lumped losses (connector losses + band MUX/DEMUX losses) are uniformly randomly varied within [1.5, 4]dB; gain ripples are heterogeneous and randomly drawn from a set of 5 real lab measured spectra. Amplifiers are configured with the strategy proposed in [7] and the booster output power has been optimized to set the ASE to nonlinear power to 3dB. In the simulations, we set NF=4.5dB, without loss of generality.

<u>Scenario 1:</u> We first consider a single OMS system of 3 SMF spans of 80 km each. Results are reported for 54 independent simulations each corresponding to a random allocation of the lumped loss for each span and each band. Figs. 2(a,b,c) and Fig. 3(a) depict probability density function (pdf) of OSNR, nonlinear SNR, GSNR, and lumped loss estimation error, respectively. The inset tables report statistics in dB over the 54 simulations. Considering the OSNR (Fig. 2(a)), the baseline is inaccurate up to 2.9/1.7dB for C/L band while IR improves the maximum error to 0.40/0.32dB for C/L. Moreover, IR improves the RMSE from 1.8 to 0.18dB, which is close to the accuracy achieved with $\mathrm{IR_{GT}}$ (maximum error: 0.29, RMSE: 0.11dB). This residual inaccuracy is mainly due to lumped losses estimation, since $\mathrm{IR_{GT}}$ makes use of the ground truth gain spectrum of each span and each band.

Fig. 2(b) shows the pdf for nonlinear SNR estimation. The baseline is inaccurate up to 3.4/3.2dB for C/L, while IR improves the accuracy (max error: 2.1/0.84dB for C/L), RMSE can be improved from 1.9 to 1.2dB. If we know the ground truth gain spectrum ($\mathrm{IR_{GT}}$), the accuracy is significantly improved (max error: 0.38, RMSE: 0.11dB).

Fig. 2(c) shows the pdf of GSNR estimation. The baseline is inaccurate by up to 1.6/0.92dB for C/L while IR improves the GSNR estimation accuracy (max error: 0.87/0.45dB for C/L) and the total RMSE can be improved from 0.77 to 0.48dB.

Fig. 3(a) shows the pdf for the lumped loss estimation. The baseline is inaccurate by up to 2.5dB (RMSE: 1.3dB), which is in fact the complete range [1.5, 4]dB over which lumped losses are randomly drawn; meanwhile, IR strongly improves the accuracy (max error: 1.5, RMSE: 0.67dB). If we additionally know the ground truth spectrum ($\mathrm{IR_{GT}}$), the maximum error can be improved to better than 1dB and RMSE around 0.3dB.

<u>Scenario 2:</u> Then, we consider the following system: a cascade of 10 OMSes including 3 spans each with random fiber length per span (max: 116 km, min: 40 km, mean: 75 km, standard deviation: 20km) and we estimate the SNR,

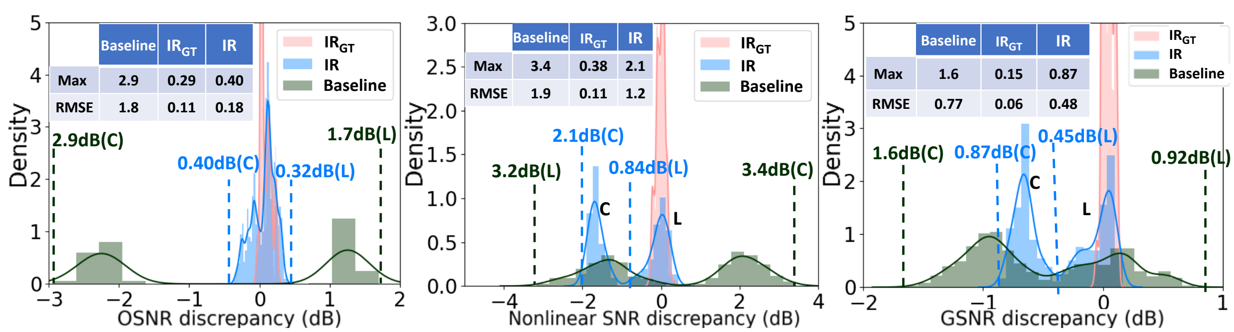

Fig. 2. (a) OSNR, (b) Nonlinear SNR, (c) GSNR estimation in scenario 1 (3-span single OMS).

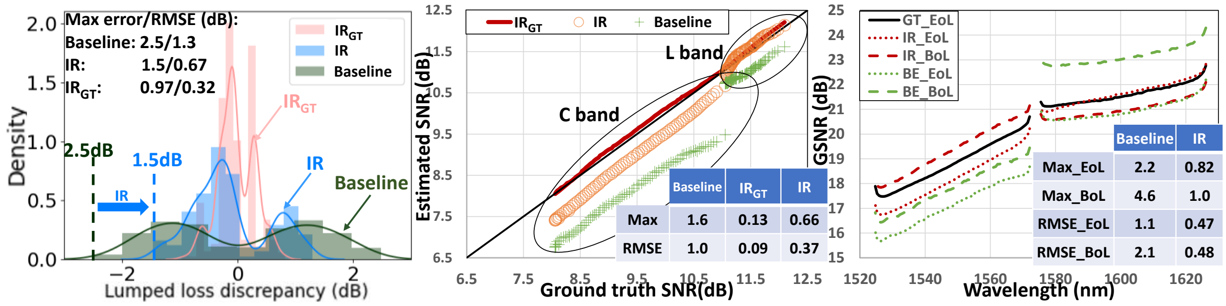

Fig. 3. (a) Lumped loss estimation in scenario 1 (3-span single OMS); (b) SNR estimation after 10 OMSes in scenario 2 (10 OMSes with 3 spans); (c) GSNR estimation with aging in scenario 3 (aging).

which now includes the transponder back-to-back and the WSS filtering penalties computed using the transfer function of commercial 75 GHz filters characterized in our lab.

Fig. 3(b) shows the SNR estimation for a sample draw of the lumped losses (each of the 120 lumped losses, for the 30 spans x 2 bands x 2 (span in/out), are independently drawn in [1.5, 4]dB as before). We report SNR estimation vs. ground truth SNR for all 160 channels in the line. The inset table reports results at the end of the cascade in dB. We observe that, compared to the baseline, IR improves the maximum error from 1.6dB to 0.66dB and RMSE is improved from 1.0dB to 0.37dB. If we apply the ground truth gain spectrum, IR_{GT} estimates very well the SNR with a maximum error below 0.2dB and RMSE below 0.1dB, meaning that all remaining uncertainty with IR comes from lumped loss misestimation.

<u>Scenario 3:</u> Finally, we test the aging robustness of IR tool on the same 3-span OMS as scenario 1. Inputs refinement assumes average fiber attenuation is known to compute the total lumped losses per span per band as explained above. However, as the network ages and fiber cuts are being repaired, splices increase the fiber loss and the average fiber attenuation becomes uncertain. We assess the robustness of inputs refinement by running the tool for an uncertain value of the linear attenuation. In particular, let the beginning of life fiber attenuation be α_{BoL} and end of life attenuation be α_{EoL}= α_{BoL}+0.05 [dB/km]. We set the network to EoL to obtain the ground truth using α_{EoL} (GT_EoL), and run inputs refinement assuming either an incorrect attenuation α_{BoL} (IR_BoL), or the correct attenuation α_{EoL} (IR_EoL). Consider Fig. 3(c) (The inset table reports statistics in dB over 54 simulations):

a) The maximum error and RMSE are very similar for IR_EoL (max error: 0.82, RMSE: 0.47dB) and IR_BoL (max error: 1.0, RMSE: 0.48dB): when attenuation is set incorrectly (IR_BoL), IR maps the extra fiber attenuation to lumped losses such that the physics of the propagation is respected and the GSNR estimation error is the same whether correct (IR_EoL) or incorrect (IR_BoL) linear attenuation is assumed. With the baseline, any uncertainty on the fiber linear attenuation translates into large maximum GSNR estimation error of 4.6dB (up from 2.2dB if the correct linear attenuation is assumed).

b) In addition, IR with $\alpha = \alpha_{BoL}$+0.05 (IR_EoL, Fig. 3(c)) estimates GSNR as accurately as IR_BoL with $\alpha = \alpha_{BoL}$ (table within Fig. 2(c)); in both cases, inputs refinement is used with the correct value of α. However, the maximum error/RMSE of the baseline is degraded from 1.6/0.77dB with $\alpha = \alpha_{BoL}$ to 2.2/1.1dB with $\alpha = \alpha_{BoL}$+0.05. This shows that IR also improves QoT estimation with different values of linear attenuation.

5. Conclusions

We proposed and validated with simulations an inputs refinement tool which can be used to improve QoT estimation for C+L systems. On a 3-span OMS, the RMSE of estimated OSNR is as low as 0.2dB, the maximum error of estimated nonlinear SNR can be improved by 1.3dB, RMSE of estimated GSNR can be improved to below 0.5dB, and RMSE for estimated connector loss is around 0.7dB. For a network of 10 OMSes of 3 spans each with high span length heterogeneity, the SNR estimation accuracy is also better than 0.5dB (RMSE). Finally, we show that the inputs refinement tool estimates GSNR accurately when the fiber loss is not accurately known, e.g., in the context of aging.

6. References

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