Digital Twin-based Insertion Loss Estimator for Anomalous Loss Localization and Network Equalization Enhancement

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Abstract: We propose and experimentally validate a novel accurate digital-twin-based span-level insertion losses estimator. This enables detection and localization of anomalous insertion losses; when combined with equalization, 1.3dB SNR margin improvement is demonstrated despite inaccurate physical layer knowledge.

1. Introduction

Accurate estimation of insertion losses is essential for identifying and localizing anomalies caused e.g. by dirty or aged connectors in real networks. Moreover, knowledge of insertion losses, which influence Kerr and Stimulated Raman Scattering (SRS) effects, is crucial for: accurate Signal to Noise Ratio (SNR) estimation of existing services [1,2]; accurate SNR prediction when loading new services; and network physical-layer optimization, i.e., launch power re-optimization [3] and optimized setting of amplifiers' gains/tilts [4], that increase network capacity and robustness to unforeseen events [5].

In this paper, we propose a novel parameter-refinement tool termed "Active Inputs Refinement" (AIR) that actively probes the network through amplifier-gain adjustment, resulting in accurate insertion-losses estimation at each span. This improves previous work on "inputs refinement" [6], where the overall amount of insertion losses was correctly estimated at link (Optical Multiplex Section, OMS) level, but was incorrect at the span level (i.e., the value of insertion loss per span was not precisely estimated, hence, localizing anomalous losses to specific spans and localizing the anomaly before vs. after the fiber are challenging). AIR is applicable to both single- and multi-band networks, i.e., C or C+L networks and beyond. The method relies on detecting channel power variation induced by the SRS variation resulting from (actively) changing each amplifier's nominal gain, hence altering power entering each fiber span. We experimentally validate the proposed AIR technique on a transmission line based on commercial equipment with 4 heterogeneous OMSs, utilizing solely real-network monitoring information. We demonstrate accurate insertion-loss estimation for each of the 15 spans, enabling anomalous loss detection and localization; then, we demonstrate how accurate insertion-loss estimation enables the optimization of services' launch power and amplifiers' gains/tilts setting. Note that, even though the SNR of existing services may be adversely impacted during the execution of our AIR technique, the AIR is meant to be run at commissioning or after a network repair, when connectors are more likely to get dirty due to human-interference repair. Nonetheless, we can show that the impact of AIR is both small and predictable, such that AIR is also suitable for live networks.

2. Setup, notations, and assumptions

Without loss of generality, we focus on a single-band OMS of N spans, as in Fig. 1. Nominal gain G_n and tilt T_n are set and known for each amplifier n. Noise figure F_n is obtained from a look-up table, while the *total* input ('*in*')/output ('*out*') power $P^{tot}_{\{in,out\},n}$ are monitored by photodiodes for each amplifier n. Output power spectrum $\boldsymbol{P^m_n}$ is monitored only at the first and last amplifiers by an optical spectrum analyzer (OSA). Fiber characteristics, such as attenuation coefficient $\boldsymbol{\alpha}$ and fiber length L, are known from design. However, insertion losses before (resp., after) the n[th] fiber span, δ^{in}_n , resp. δ^{out}_n, need to be estimated. The system is assumed to be fully ASE-noise loaded to stabilize the amplifiers and emulate end-of-life conditions. Inline amplifier gain spectra are not known, however, the calibrated spectrum $\boldsymbol{G^{cal}_n}(G_n)$ for several nominal gains G_n is known from factory calibration. Parameters in bold are vectors i.e. $\boldsymbol{G^{cal}_n}$, $\boldsymbol{P^m_n}$. Parameters with "m/e" notation, i.e. $\boldsymbol{P^m_n}$, $\boldsymbol{P^e_n}$ correspond to parameters that are "monitored/estimated". Parameters with a prime notation, i.e. G'_n , $\boldsymbol{P^{e\prime}_n}$, $\boldsymbol{P^{m\prime}_n}$ correspond to parameters following adjustments of amplifier gain during AIR. ΔG is an algorithm parameter (see below).

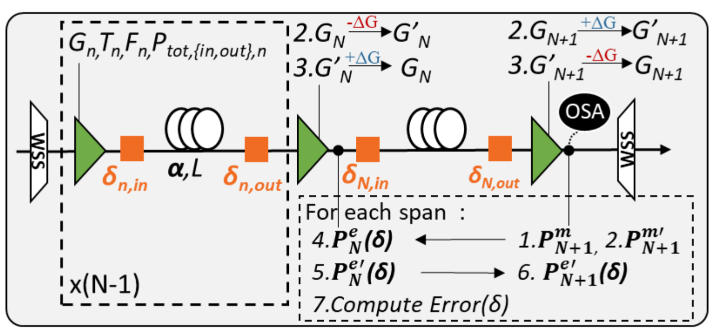

Fig. 1. Generic N-span single band system, with 7-step AIR method for per-span insertion loss estimation.

3. Methods description

In this paper, we compare 3 different methods for insertion losses estimation (to be used for SNR prediction): Active Inputs Refinement (AIR), All monitoring Information (All_Info), and a Baseline (Baseline).

Baseline: We consider previous work on inputs refinement, without the active part, as the baseline [6].

All_Info: $\delta_n^{in}, \delta_n^{out}$ (implemented in our lab using VOAs to emulate and control insertion losses), input and output power spectra at each amplifier are known. This is an ideal scenario as, in the field, there is no OSA on each amplifier for power spectra monitoring and connector losses are unknown.

AIR (outline): The proposed AIR algorithm consists of 7 iterated steps, see Fig. 1; for each amplifier *n*=N to 1:

Step 1: Monitor the OMS output power spectrum $\boldsymbol{P_{N+1}^{m}}$;

Step 2: Set $G_n' = G_n - \Delta G$ and $G_{n+1} = G_{n+1} + \Delta G$, then monitor the OMS output power spectrum $\boldsymbol{P_{N+1}^{m'}}$;

Step 3: Set amplifiers *n* and *n+1* back to their nominal gains;

For each δ in a predefined list of values between 0 and δ_n^{tot}(=$\delta_n^{in} + \delta_n^{out}$ = span loss - fiber loss), iterate steps 4-7:

Step 4: Estimate spectrum $\boldsymbol{P_n^{e}}$ at amplifier *n* assuming insertion loss $\delta_n^{in} = \delta$ by back-propagation of $\boldsymbol{P_{N+1}^{m'}}$;

Step 5: Estimate spectrum $\boldsymbol{P_n^{e'}}$ using $\boldsymbol{P_n^{e'}} = \boldsymbol{P_n^{e}} + \boldsymbol{G_n^{cal}}(G_n) - \boldsymbol{G_n^{cal}}(G'_n)$;

Step 6: Estimate spectrum $\boldsymbol{P_{N+1}^{e'}}$ at end of OMS assuming $\delta_n^{in} = \delta$ by forward propagation of $\boldsymbol{P_n^{e'}}$;

Step 7: Compute the error function $Error(\delta)$=$\sqrt{|\boldsymbol{P_{N+1}^{m'}} - \boldsymbol{P_{N+1}^{e'}}|^2}$.

We then retain the refined insertion loss δ_n^{in} at nth span that minimizes $Error(\delta)$, then δ_n^{out} is calculated by $\delta_n^{tot} - \delta_n^{in}$. The refined insertion losses δ_n^{in} and δ_n^{out} are then utilized for the insertion loss estimation of the remaining spans on the OMS. After refining insertion losses of all the spans on each OMS, gain spectra of amplifiers of the OMS are then refined by the gain refinement technique in [6].

4. Experimental testbed

We experimentally validate our proposed AIR technique on a tandem network of 4 heterogeneous OMSs (OMS1-2-3-4), encompassing a total of 15 spans, each with varying fiber lengths (60, 80, 100km) and types (SMF, PSCF, TW, LEAF), as depicted in Fig. 2. At each span, VOAs are set before and/or after fiber to emulate insertion losses, as indicated in Fig. 2 above each VOA. The values of attenuation of the VOA located before the fiber range from 0 to 5 dB, while the VOA values after the fiber range from 3 to 11.6 dB including a 3dB coupler for power monitoring access (only used in All_Info). 80 point-to-point services are loaded in the network, traversing all 4 OMSs. These services are emulated using an ASE source with 75GHz channel spacing. The bit error rate (BER) and SNR of 7 services uniformly spread across 6 THz C-band are monitored using a real-time 200 Gb/s QPSK commercial transponder. In the initial network state, the launch power spectrum is set to be flat at fiber input, with the total power calculated by LOGO [1], assuming a 50/50% distribution of total insertion loss as insertion loss before and after each span; the nominal gain of amplifiers is set to compensate for span loss, and amplifier tilt is set to compensate for SRS tilt at each span. In this study, the nominal gain change ΔG ranges from 2 to 3 dB for each amplifier, depending on the available tuning margin at each span in the network.

5. Insertion loss estimation and insertion loss anomaly localization

Fig. 3(a) presents the estimated insertion losses before each of the 15 spans δ_n^{in} (δ_n^{out} is calculated based on the estimated δ_n^{in}) using both the AIR (orange circles) and the baseline (blue diamonds). To test the localization ability of large anomaly losses with AIR, we set 2.9 dB and 5 dB at the VOAs before the third/first span on OMS2/OMS4 (Fig. 2, red rectangles). The corresponding estimated losses are marked with solid orange circles. The inset table shows the maximum absolute error (MAE) and root-mean-square error (RMSE) of loss estimation obtained with AIR and baseline. AIR demonstrates a substantial improvement compared to the baseline, reducing the MAE from 4.3 to 1.6 dB and the RMSE from 1.1 to 0.3 dB. Moreover, AIR can effectively identify and localize large 2.9 dB and 5 dB anomaly insertion losses at the corresponding spans and before the fiber, indicated in the red dashed circle.

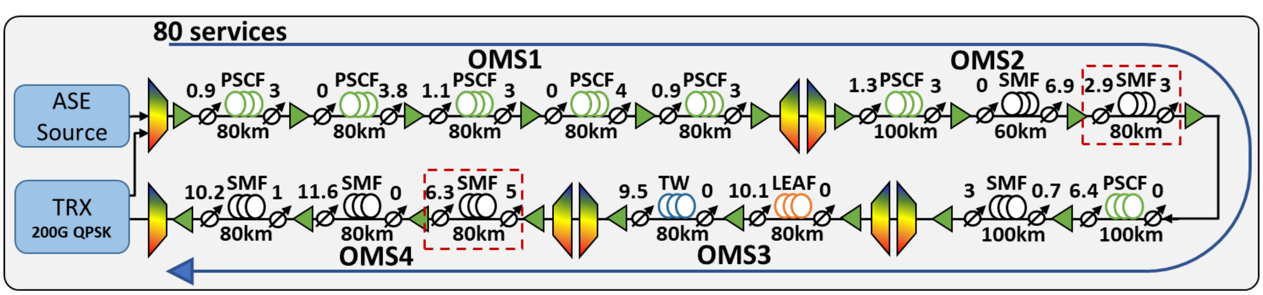

Fig. 2. Tandem network testbed with 80 point-to-point services crossing 4 heterogeneous OMSs.

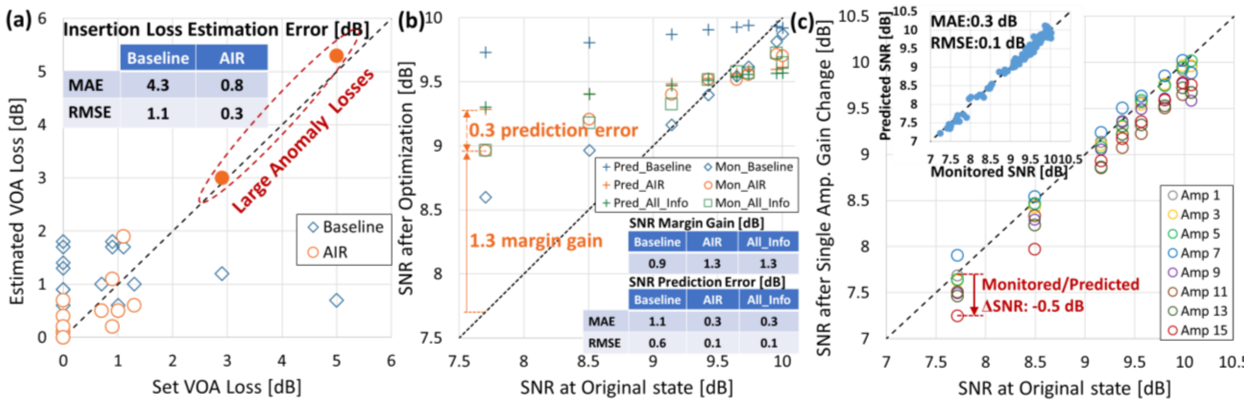

Fig. 3. (a) Insertion loss estimation and insertion loss anomalies localization; (b) SNR optimization with predicted SNR and monitored SNR; (c) Monitored and predicted varied SNR after each single amplifier gain change during AIR process.

6. Impact of insertion loss estimation on QoT optimization

Fig. 3(b) shows the SNR optimization results based on a digital twin (DT) that estimates insertion losses using three different methods: baseline (blue), AIR (orange), All_Info (green). The optimization process consists of both amplifier gain/tilt optimization, and launch power spectrum optimization. We apply the amplifier gain/tilt optimization method proposed in [7] based on LOGO algorithm, then the output power spectrum at first amplifier of each OMS is optimized to flatten generalized SNR (GSNR), which considers both the ASE noise and the Kerr nonlinearity at the end of each OMS. Both optimization methods require accurate knowledge of insertion losses. Axis x shows the monitored SNR at the initial network state, while axis y shows the design (predicted by DT) SNR and monitored SNR after optimization implementation. Markers "+" show the design SNRs with different methods ("Pred_X" for each method X). After pushing the design parameters to the network, monitored optimized SNRs are also shown in Fig. 3(b) ("Mon_X"). The top inset table shows the SNR margin improvement, which corresponds to the SNR improvement of the worst service. AIR improves network margin by a further 0.4 dB compared to baseline, achieving the same performance as All_Info thanks to better design with accurate insertion loss estimation per span. Notably, incorrect inputs from the baseline method can result in prediction errors of up to 1.1 dB, whereas AIR significantly enhances prediction accuracy, achieving a MAE of 0.3 dB and an RMSE of 0.1 dB to the same accurate level as All_Info. Thus, AIR enhances the accuracy of the digital twin and bolsters the reliability of network optimization implementations.

7. Discussion on SNR penalty during AIR

During the AIR process, each amplifier nominal gain is changed by up to 3 dB to induce SRS variation. This can cause undesirable SNR variation of existing services. Fig. 3(c) shows the SNR variation that occurs during the change of amplifier nominal gain required by AIR for each amplifier; no more than 0.5 dB SNR degradation is observed during the gain change across all 15 amplifiers (main plot). The inset plot provides a prediction of SNR variation before implementing AIR using the baseline [6]; the degradation can be precisely predicted with a 0.1 dB RMSE (inset plot). Thus, it is safe to implement AIR while ensuring the SNR margin remains acceptable in a network with live traffic.

8. Conclusion

In this paper, we proposed a novel method for accurate insertion loss estimation at the span level. The insertion loss estimation accuracy is validated experimentally in a 4-OMS tandem network, where 2.9 dB and 5 dB large anomaly losses are detected and localized. We also demonstrate that such accurate insertion losses knowledge enables power re-equalization: the SNR of the worst service is improved by 1.3 dB, a 0.4 dB further improvement compared to our previous work. The QoT prediction accuracy (maximum error) is also improved to 0.3 dB with the refined insertion losses, which is the same accuracy level as knowing all information that is difficult to be acquired in the field. Finally, the technique has a small and predictable impact on existing traffic.

9. References

[1] P. Poggiolini et al., "The GN-Model of Fiber Non-Linear Propagation and its Applications," JLT, vol. 32, no. 4 (2014).
[2] D. Semrau et al., "A modulation format correction formula for the Gaussian noise model in the presence of inter-channel stimulated Raman scattering," JLT, vol. 37, no. 19 (2019).
[3] I. Roberts, et al., "Convex channel power optimization in nonlinear WDM systems using Gaussian noise model," JLT, vol. 34, no. 13 (2016).
[4] X. Yang, et al., "Experimental impact of power re-optimization in a mesh network," JOCN, vol. 15, no. 7 (2023).
[5] Y. Pointurier, "Design of low-margin optical networks," JOCN, vol. 9, no. 1 (2017).
[6] N. Morette et al., "Machine learning enhancement of a digital twin for WDM network performance prediction leveraging Quality of Transmission parameter refinement," JOCN, vol. 15, no. 6 (2023).
[7] A. Ferrari et al., "Power Control Strategies in C+L Optical Line Systems," OFC, W2A.48 (2019).