Inputs Refinement with Incremental Learning for Accurate Digital Twin of Optical Networks

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Abstract: We propose a parameter refinement method based on incremental learning, leveraging multiple network snapshots to provide accurate estimated inputs (i.e., lumped losses, gain spectra, and offset noise) to digital twins, improving QoT prediction and optimization.

1. Introduction

Given the continuously evolving ("living") nature of the optical-network physical layer, leveraging network snapshots (each representing a distinct network state) is essential for building an accurate Digital Twin (DT) of optical networks [1], which facilitates efficient automation and management throughout the network life cycle, enabling Quality of Transmission (QoT) prediction [2,3], launch power and amplifier gain optimization [4,5,6], anomaly detection [2].

However, improper data usage can degrade parameter estimation accuracy, e.g., due to overfitting. For example, in previous work [3], using data (e.g., channel power, BER) from only a single network state to estimate lumped losses and amplifier gain spectra while overfitting fiber nonlinear noise (NLI) by absorbing transponder back-to-back (b2b) noise and Wavelength Selective Switch (WSS) filtering penalty, led to the underestimation of lumped losses.

In this study, we propose a novel parameter-refinement method leveraging *multiple network snapshots*, called Incremental Inputs Refinement (IIR). Multiple network snapshots can be generated using incremental data collected at each WSS adjustment, e.g. during launch power optimization [5]. IIR tracks changes in collected data across snapshots and estimates uncertain parameters as (*i*) lumped losses, (*ii*) amplifier gain spectra, and (*iii*) offset noise, that consists of transponder b2b noise (due to imperfect digital signal processors and analog-to-digital converters) and WSS filtering. IIR can discriminate among various noise sources, i.e., Amplified Spontaneous Emission (ASE), fiber Kerr nonlinearity (NLI), and offset noise, hence avoid overfitting. IIR accurately models various physical effects to build an accurate digital twin of optical networks, improving QoT prediction and optimization.

2. Setup, notations, and assumptions

Fig. 1 (a) shows the topology of a generic N-span Optical Multiplex Section (OMS) with transponders. The variables *s/j/i/n* represent the snapshot/service/OMS/span index, respectively. For example, in snapshot *s*, service *j* is transmitted by Tx(*j*) and received by Rx(*j*), passing through OMS *i*, with BER(*s*,*j*) monitored by Rx(*j*). The output power spectra at amplifier *n=1* and *n=N+1* are monitored and known by Optical Performance Monitors (OPM) as $P_{i,1}^{s}(\lambda), P_{i,N+1}^{s}(\lambda)$.

The red parameters indicate unknown network parameters to be estimated by IIR, such as the (*i*) output power spectra of in-line amplifiers $P_{i,n}^{s}(\lambda)$, (*ii*) gain spectra of all amplifiers $G_{i,n}^{s}(\lambda)$, and (*iii*) the connector/splice losses, which are converted into equivalent lumped losses at the input/output $\delta_{i,n}/\delta'_{i,n}$ of each span. Note that *(i)* and *(ii)* vary across network snapshots (states). The total uncertain lumped loss of each span ($\delta_{i,n}+\delta'_{i,n}$) is known and calculated as span loss minus fiber loss, where span loss is monitored by amplifier photodiodes, and fiber loss is calculated from fiber length and attenuation coefficient. Noise figure is assumed known from a lookup table. Additionally, the transponder b2b noise can be represented by SNR^{TRX}, which is the maximum achievable SNR in a b2b configuration, as shown in Fig. 1(b). We only know nominal SNR^{TRX}, and the real SNR^{TRX} is difficult to pre-calibrate since it depends on both Tx and Rx, and their pairing is unknown before deployment. Therefore, SNR^{TRX} is also treated as an unknown for each transponder pair (service). All the known and unknown parameters will be fed into the DT.

3. IIR method description

The monitored BER can be converted into equivalent Signal-to-Noise Ratio (SNR) and Noise-to-Signal Ratio (NSR). The NSR of service *j* at snapshot *s*, as represented in Eq. (1) in Fig 2, consists of several components: NSR from Amplified Spontaneous Emission (ASE) noise generated by each amplifier crossed by service *j* at snapshot *s* ($NSR^{ASE}(s,j)$), fiber Kerr nonlinearity (NLI) strongly influenced by the launch power of each span ($NSR^{NLI}(s,j)$), transponder b2b noise ($NSR^{TRX}(j)$), and WSS filtering penalty ($Filtering\ Penalty(j)$).

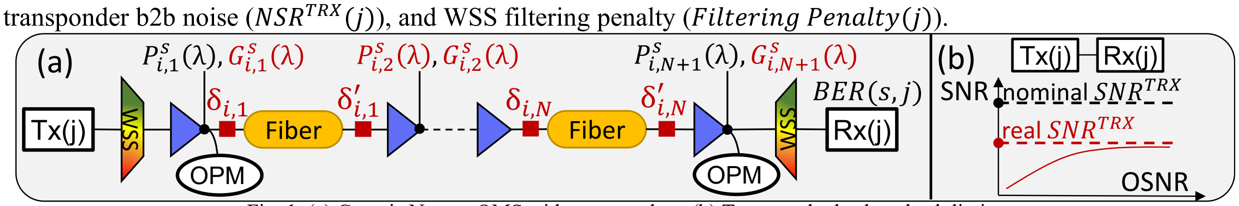

Fig. 1. (a) Generic N-span OMS with transponders; (b) Transponder back-to-back limit.

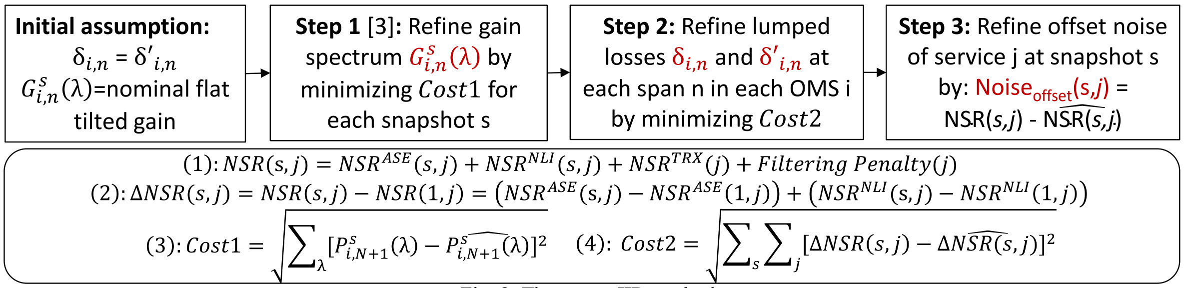

Fig. 2. Three-step IIR method.

The IIR method refines lumped losses, amplifier gain spectra, and offset noise in three steps:

Initialization: The total uncertain lumped loss is split 50/50% to the lumped loss "in"/"out" of each span ($\delta_{i,n} = \delta'_{i,n}$). The rippled gain spectrum of each amplifier is initially assumed to be linearly tilted.

Step 1: For each snapshot s, a gradient-descent method [3] is used to refine amplifier gain spectra $G^s_{i,n}(\lambda)$, minimizing *Cost1* in Eq. (3) for each OMS. Here, $P^s_{i,N+1}$ is the monitored power spectrum at the end of the OMS, and $\widehat{P^s_{i,N+1}(\lambda)}$ is the estimated spectrum calculated based on power propagation starting at the first amplifier, considering stimulated Raman scattering (affected by assumed lumped losses), fiber attenuation, and refined gain spectra.

Step 2: For each snapshot s, calculate the variation in services NSR vs. the initial snapshot #1, as shown in Eq. (2). The variation in NSR^{ASE} is computed by the refined $G^s_{i,n}(\lambda)$ from *Step 1*, while the variation in NSR^{NLI} is computed by refining lumped losses ($\delta_{i,n}/\delta'_{i,n}$) to minimize *Cost2* in Eq. (4) using gradient descent. Note that in Eq. (2), $NSR^{ASE}(s,j)$ and $NSR^{NLI}(s,j)$ are snapshot-dependent variables, as adjustments to booster power spectrum at each snapshot cause changes in gain spectra and power entering the fiber, leading to variations in ASE and NLI. In contrast, we neglect the variation of $NSR^{TRX}(j)$ and *Filtering Penalty (j)* and considered as constant noise across snapshots.

Step 3: For each service j at snapshot s, compute the offset noise by $\mathrm{Noise_{offset}}(s,j) = \mathrm{NSR}(s,j) - \widehat{\mathrm{NSR}(s,j)}$, where NSR($s,j$) is monitored and $\widehat{\mathrm{NSR}(s,j)}$ is estimated based on the refined lumped losses and gain spectra.

4. Simulation testbed

We validated the proposed IIR method via simulations using experimental data from [5], which involved 16-step WSS adjustments in a ring-topology network for power optimization with a constant channel load. The testbed, shown in Fig. 3(a), consists of 5 OMSs with heterogeneous fiber lengths and types, with 12 routes. Each route carries 5 services crossing 1 to 4 OMSs, totaling 60 services in this partial-load network. Per-step WSS adjustment alters the attenuation of several channels (up to 1 dB/channel) on one OMS, changing its booster power spectrum. Fig. 3(b) shows the average booster power variation across 5 OMSs $\overline{\Delta P}$ at each step of 16. More details are provided in [5].

As shown in Fig. 3(d), we generate 16 network snapshots using both experimental and randomly generated data. The experimental data includes, from per-step WSS adjustment, the booster power spectra $P^s_{i,1}$, amplifier gain spectrum $G^s_{i,n}(\lambda)$, the total lumped losses $\delta^{total}_{i,n}$ varying from 3.5 to 12 dB (as shown in Fig. 3(d)), nominal SNR^{TRX}, and fiber details. Randomly generated data includes lumped loss 'in' $\delta_{i,n}$ from U[0,3] dB, lumped loss 'out' $\delta'_{i,n} = \delta^{total}_{i,n} - \delta_{i,n}$, and real SNR^{TRX} with added uncertainty U[-1,1] dB to nominal SNR^{TRX}. For each snapshot, booster power spectrum $P^s_{i,1}(\lambda)$ is propagated to generate in-line/pre amplifiers spectra $P^s_{i,n=\{2,\dots,N\}}(\lambda)$/ $P^s_{i,N+1}(\lambda)$, and SNR(j) is calculated using Gaussian noise model [7]. All the exp./random/sim. data are considered as Ground Truth (GT) parameters to generate 16 snapshots. Then, IIR is applied to estimate the unknown parameters (in red) given known parameters (in black) using generated snapshots. We generate 10 cases to validate IIR performance statistically.

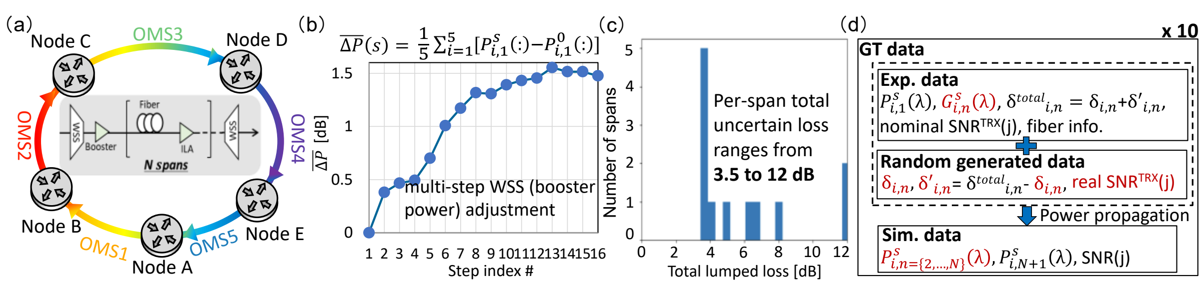

Fig. 3. (a) 5-OMS ring network; (b) Average booster power variation; (c) Histogram of total lumped losses; (d) Data usage assumption.

5. Simulation results

Lumped loss refinement: Fig. 4(a) shows the accuracy of lumped loss refinement by IIR using different numbers of snapshots, indicating Root-Mean-Square Error (RMSE) and Maximum Absolute Error (MAE). The dots represent the

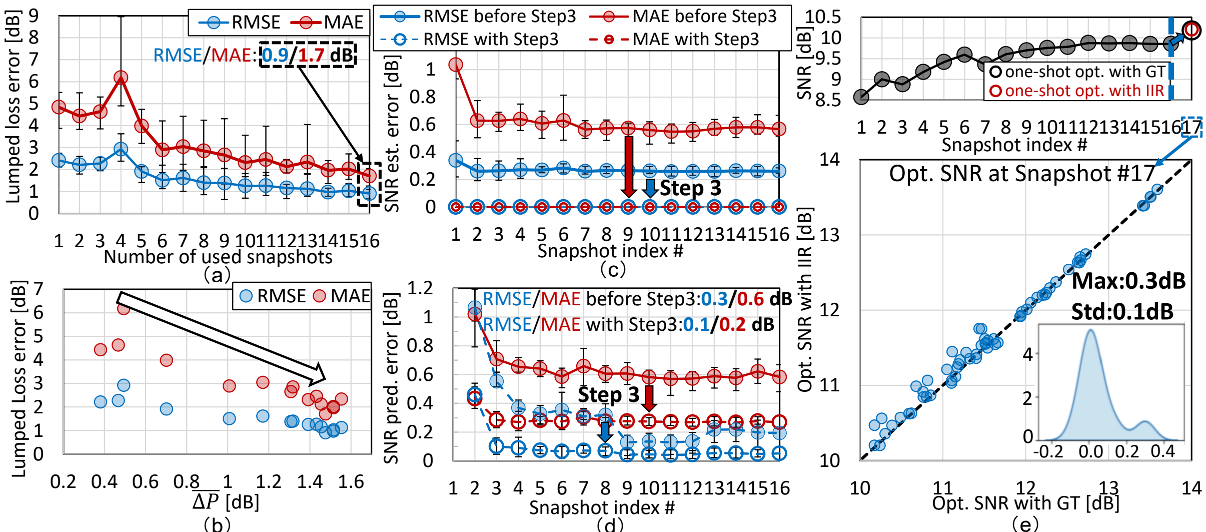

Fig. 4. (a) Lumped loss estimation accuracy; (b) Correlation between lumped loss estimation accuracy and power variation; (c) SNR estimation without/with step 3; (d) SNR prediction without/with step 3; (e) Optimized network margin (top) and optimized SNR of all services (bottom).

average across 10 cases, with caps indicating the range. In the first snapshot, the initial assumption of $\delta_{i,n} = \delta'_{i,n}$ results in an RMSE/MAE of ~2.4/4.8 dB. With only a few snapshots (e.g., 4 snapshots), the MAE increases to ~6.2 dB due to insufficient data, leading to inaccurate estimation, but, as more snapshots are leveraged, IIR significantly improves accuracy, reaching ~0.9/1.7 dB (RMSE/MAE) when using all 16 snapshots. Fig. 4(b) shows the correlation between lumped-loss error and average booster power variation $\overline{\Delta P}$. As power variation and corresponding BER variation increase, lumped loss estimation accuracy improves, reaching ~0.9 dB RMSE with ~1.5 dB power variation.

QoT estimation, prediction, and optimization: Fig. 4(c) shows estimated SNR at snapshot *s* with IIR-refined parameters (based on data collected from snapshot #1 to *s*) as inputs to DT. Despite refined lumped losses and gain spectra at snapshot #16, the error remains ~0.3/0.6 dB (RMSE/MAE) mainly due to uncertainty of $\text{Noise}_{\text{offset}}$. Step 3 of IIR is then applied to fit $\text{Noise}_{\text{offset}}$ by reducing the *SNR estimation* error to zero by construction; we will see later that the refined $\text{Noise}_{\text{offset}}$ enables accurate *SNR prediction*.

Fig. 4(d) shows DT-predicted SNR at snapshot *s+1* with IIR-refined parameters using data from previous snapshots #1 to *s*. Without Step 3, IIR improves prediction accuracy to ~0.3/0.6 dB (RMSE/MAE) at snapshot #16; using the refined $\text{Noise}_{\text{offset}}$ from Step 3 further reduces the error to ~0.1/0.2 dB. The remaining error is due to inaccuracies in the refined parameters and variations in amplifier gain spectra, which are not accounted for in the method.

Fig. 4(e) (top) shows one sample (from 10 cases) of network margin improvement (worst SNR at snapshot *s*) through power optimization with 16-step WSS adjustments using GT parameters from snapshot #2 to #16 (black filled dots, left of blue dashed line). A one-shot power optimization is performed by adjusting the booster launch power at snapshot #16 to the DT-computed optimal power at snapshot #17 to achieve ASE/NLI=3 dB at each OMS end [7] using respectively GT/IIR-refined parameters (black/red circles for GT/IIR, right of blue dashed line). The network margin increases from 9.8 to 10.2 dB using both IIR-refined and GT parameters (overlapping black and red circles), thanks to accurate parameters refined by IIR. Fig. 4(e) (bottom) compares DT-optimized SNR using IIR-refined vs. GT parameters for all 60 services at snapshot #17. The inset plot shows the probability density function of the SNR difference optimized by IIR and GT. With IIR-refined parameters as inputs, the DT-optimized SNRs closely match ones with GT parameters, achieving 0.1/0.3 dB standard deviation/maximum difference.

6. Conclusion

The proposed IIR method leverages multiple network snapshots to refine lumped losses, gain spectra, and offset noise, improving lumped loss estimation error from 2.4 to 0.9 dB RMSE, enabling accurate DT-based QoT prediction with 0.1dB RMSE and QoT optimization, achieving the similar optimum QoT with a 0.1 dB standard deviation from GT parameters.

7. References

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