On the Robustness of a ML-based Method for QoT Tool Parameter Refinement in Partially Loaded Networks

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Abstract: The robustness of a ML-based QoT input parameters refinement technique in partially loaded networks (both static and dynamic) is assessed using experimental data. SNR prediction error is reduced by up to 1dB over >40000 services. © 2021 The Author(s)

1. Introduction

Accurate Quality of Transmission (QoT) tools are needed to predict the performance of coherent optical fiber networks. Current tools include advanced theoretical models accounting for all main system impairments including fiber nonlinearities [1], optical in-line filtering [2], transponder back-to-back impairments, and amplifier spontaneous emission noise (ASE) [3]. These models can be effectively used to increase network capacity through *accurate* QoT estimation and low design margin. However, after network deployment, uncertainties of the corresponding QoT input parameters inherent to real-life conditions degrade; therefore challenging accurate performance estimation for online (re-)optimization, resource (re-)allocation, and service upgrade, thereby increasing QoT margins [4-6]. In this sense, different Machine Learning (ML)-based methods for parameters refinement have been presented [7-9]. Specially, in [9] we presented a novel ML method called Inputs Refinement (IR) exploiting only realistic network monitoring data and leveraging the physics behind light propagation to refine two main parameters highly affecting QoT estimation: span input/output lumped losses, and amplifier gain spectrum. However, method in [9] was restricted to *fully loaded* networks (e.g., with ASE dummy channels) such that EDFA gain spectra were load-independent. In a dynamic, partially loaded network, EDFA gain spectra are load-dependent, making SNR estimation complex. This paper deals with the *partial load* case.

The contribution of this paper is two-fold. In Section 2, we experimentally demonstrate the robustness of IR in the context of static partially loaded networks. Experimental validation shows 2dB maximum SNR estimation improvement over datasheet assumptions. Then, in Section 3, we address the problem of dynamic networks for a wide range of service loading configurations as well as variations in each span lumped losses, both effects accounting for different possible network states. We combine IR with a ML technique able to predict EDFA gain profile for arbitrary loadings. We experimentally improved SNR prediction accuracy by up to 1dB compared to datasheet assumptions.

2. Experimental Validation for performance *estimation* in static partially loaded scenario

Fig. 1(a) depicts a generic optical multiplexing section (OMS) composed of wavelength selective switches (WSS), a concatenation of EDFAs described by their gains (G), noise-figures (F), and output powers (P) profiles, and fiber spans described by their wavelength dependent losses (ρ), and other typical fiber coefficients. At each span, input (δ) and output (δ') lumped losses accounting for dirty connectors, optical distributors, etc., are included. Optical Power Monitoring (OPM) modules are placed only at the first and last amplifiers to measure EDFA output power per channel.

A complete description of the IR method can be found in [9]. It consists of a 3-step learning process where each OMS in the network is refined in parallel. **Step 1** first estimates each span input/output lumped losses by exploiting the nonlinear Raman effect modeling, while **Step 2** estimates amplifier gain profiles. Both steps employ a fast gradient descent process using available OPM monitored power spectral information, and monitored total input/output power

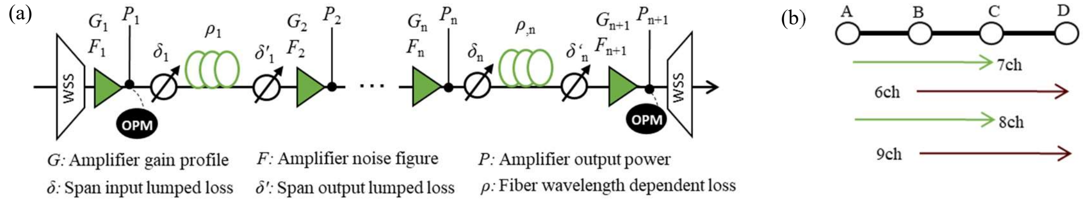

Fig. 1. (a) OMS configuration composed of wavelength selective switches (WSS), optical amplifiers, and fiber spans. Optical Power Monitoring (OPM) points are placed at the output of the first and last OMS amplifiers. (b) Network topology used in experiments and services allocation.

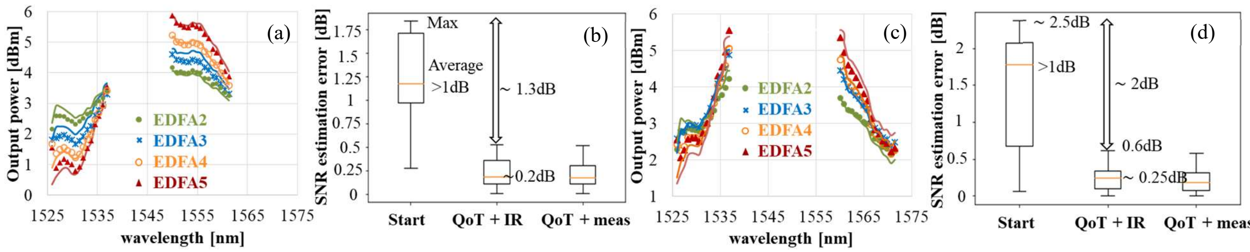

Fig. 2. (a) Refined (lines) versus measured (markers) power profiles for each in-line amplifier of OMS BC for a first channel loading. (b) SNR estimation error before IR vs. after IR vs. using ground truth (measured) QoT inputs. (c) Refined vs. measured power profiles for each in-line amplifier of OMS BC for a second channel loading. (d) SNR estimation error before IR vs. after IR vs. using ground truth (measured) QoT inputs.

of each in-line amplifier. **Step 3** further refines the lumped losses leveraging Kerr effect modeling using transponder monitored end-to-end SNR (or BER). The technique was validated for a fully-loaded meshed scenario [9]. In this section, we show that, despite the reliance of Steps 1 and 3 on nonlinear (Raman, Kerr) effects which are stronger for higher launch power, IR is still valid in partially loaded scenarios where nonlinear effects are small.

The experimental setup consists of 3 OMS sections (AB, BC, CD) of 5 spans each (5x80km SMF, 5x100km PSCF, 5x100km PSCF). A 4-node network is used with service allocation shown in Fig. 1(b). Channel loading consists of 15 to 30 (depending on OMS) ASE-shaped 37.5 GHz channels allocated over a 50 GHz grid. 2 different channel loadings are studied. A real-time 200 Gb/s PCS16QAM channel is swept over the 30 spectral positions for SNR ground truth (GT) *measurement*. Only power profiles at OPM level, total input/output EDFA powers, and measured SNR are used for refinement: $G(\lambda)$, $P(\lambda)$ and lumped losses are assumed to be unknown. Lumped losses up to 3dB are considered by adjusting span input/output variable optical attenuators (VOA). Experimentally measured $G(\lambda)$, $P(\lambda)$, and $F(\lambda)$ at each amplifier and known span lumped losses are fed into our QoT for "benchmark-only" performance estimation. Figs. 2(a), (c) show the estimated (lines) vs. measured (markers) output power profiles of all intermediate EDFAs for the two different partial loading configurations, while Figs. 2(b), (d) show the SNR estimation error of all 30 channels using starting point assumptions ("start", assuming flat and tilted $G(\lambda)$ and 50/50% lumped input/output span loss distribution), after IR ("QoT+IR"), and using all measured inputs ("QoT+meas"). After step 2, per-EDFA output power profiles are estimated within 0.2dB compared to measured power profiles for both loading configurations. At the end of the refinement procedure, up to 2dB SNR estimation improvement is achieved compared to initial values hypothesis. 0.2/0.6dB avg/max SNR error is obtained down from more than 1dB, similar to the QoT benchmark that uses all measured inputs.

3. Experimental Validation for performance *prediction* in dynamic partially loaded scenarios

Section 2 showed the validity of the IR technique for SNR *estimation* in a static, partially loaded scenario. In a dynamic network (e.g., with new services, or during power re-equalization), EDFA gain profiles vary with the load thereby impacting SNR *prediction* [8]. To overcome this limitation, we predict SNR of unseen services by combining IR to estimate lumped losses (which are load-independent) with a ML model for EDFA gain prediction (to account for load dependence). For this last, we train a multilayer-perceptron based EDFA-ML model using 7745 loading configurations (80%/20% train/test ratio). The model predicts single module EDFA gain profiles given its nominal gain/tilt and input power profile within 0.18 dB of the true values for 99% of the test set. Exact details of the model do not change the conclusions of our IR method.

We perform an experimental measurement campaign on OMS AB depicted in Fig. 1(b) for 90 random channel loadings (each between 5 and 40 ASE-shaped 62.5GHz WDM channels among the 80 possible 75GHz channel slots in the 6THz C-band) and 25 different lumped loss configurations. Measured power/gain profiles, and lumped losses values are mapped into our QoT tool to *emulate* ground truth (GT) SNRs.

We first assess the IR technique for lumped loss estimation only (i.e., considering GT measured gains). Fig. 3(a) shows the prediction error distribution for all ~40000 predicted services SNRs. We launch IR for lumped loss estimation on the lowest channel loading configuration (5 channels "ON"), emulating beginning of life (BOL) conditions and use those lumped losses for all other 89 available loadings. This process is repeated for the 25 different link configurations. IR lumped loss estimation achieves 0.3/0.6 dB avg/max SNR prediction gain compared with starting point assumptions (i.e., 50%/50% lumped losses at span input/output).

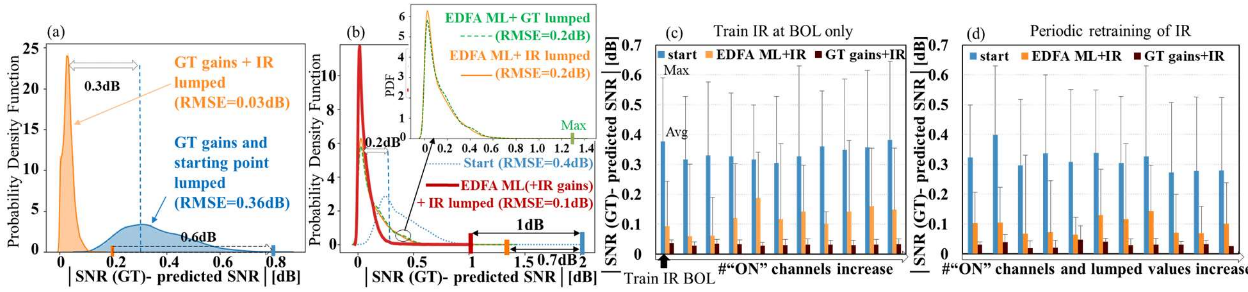

Fig. 3. Absolute SNR prediction errors distribution over all aggregated services (~40000) using (a) Ground Truth (GT) EDFA gains and starting point assumption for lumped losses vs. IR lumped losses, (b) starting point, EDFA-ML gains + GT/IR lumped losses, EDFA-ML(+IR) gains + IR lumped losses; (c) absolute SNR prediction errors with training of IR at BOL only and (d) with periodic retraining of IR along network lifetime.

Secondly, we assess the problem of lumped loss estimation plus EDFA gain prediction in Fig. 3(b). For this case, the EDFA-ML model is used to predict gain profiles while IR is used for lumped loss estimation ("EDFA ML+IR lumped"). We also consider a hybrid case where EDFA-ML is used to predict gain profiles while the number of "ON" channels is lower than 30, while for more than 30 "ON" channels our IR technique is directly used to estimate gain profiles of existing channels with linearly extrapolated values to predict gains for non-existing channels ("EDFA-ML(+IR) gains"). For the "EDFA ML+IR lumped" case, both the RMSE and maximum absolute error are reduced by 0.2 and 0.7dB respectively compared to starting point assumptions ("start" using flat-tilted gain and 50%/50% lumped loss distribution). We verified that large values for maximum error are in general due to outliers after EDFA-ML is applied. If EDFA-ML is replaced by the gains estimated by IR when the number of "ON" channels is higher than 30, ("EDFA-ML(+IR) gains") the RMSE is reduced to 0.1dB while the maximum error is reduced by 1dB. Fig. 3(b) also shows the case where GT lumped losses are used such that the SNR error is only due to EDFA gain prediction inaccuracy ("EDFA ML+GT lumped"). The results are the same as for the "EDFA ML+IR lumped" case showing that final SNR prediction error is limited by gains prediction accuracy rather than lumped losses estimation.

Fig. 3(c) shows the absolute SNR prediction error for 11 random loading configurations where the number of established services increases from 5 to 40 (with loading configurations being independent from each other) while assuming constant lumped losses. IR is trained at BOL only (when only 5 services are established) for lumped losses estimation along with EDFA-ML gains to estimate/predict SNR for existing/new services. We then investigate a "network life" scenario (Fig. 3(d)) in which an increasing number of services are established while lumped losses values at both input and output of the fibers are changing during the network lifetime. This time, periodic retraining of IR is performed to capture lumped losses variations using available number of established services. In both scenarios (without and with retraining of IR along lifetime, Figs. 3(c) and (d)), both average and maximum SNR prediction error are reduced ("EDFA ML+IR") compared to starting point assumptions ("start"). For each scenario, even in lightly-loaded network where nonlinear effects are not dominant, the maximum absolute error only due to uncertain lumped losses (considering GT gains) is reduced to less than 0.1dB after IR ("GT gains +IR").

4. Conclusions

The Robustness of a ML-based QoT inputs refinement technique to partially loaded cases has been assessed over an experimental meshed-network scenario using experimentally measured SNR for cross-validation. Our IR technique for lumped losses and gains estimation allows to reduce the SNR estimation error by up to 2dB in the static case. For the dynamic case, when IR is used together with an EDFA-ML model to predict SNR of existing and new established services, the maximum SNR prediction error is reduced by 1dB.

5. References

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