Estimating Network Components Polarization-Dependent Loss Using Performance Statistical Measurements

Joana Girard-Jollet^(1,2), Matteo Lonardi⁽³⁾, Petros Ramantanis⁽³⁾, Paolo Serena⁽⁴⁾, Chiara Lasagni⁽⁴⁾, Patricia Layec⁽³⁾, Jean-Christophe Antona⁽¹⁾

⁽¹⁾ Alcatel Submarine Networks, Paris-Saclay, France joana.girard jollet@asn.com

⁽²⁾ Télécom Paris, Institut Polytechnique de Paris, Paris-Saclay, France

⁽³⁾ Nokia Bell Labs, Paris-Saclay, France

⁽⁴⁾ University of Parma, Department of Engineering and Architecture, Parma, Italy

Abstract We propose a novel approach to estimate reconfigurable optical add-drop multiplexers (ROADM) polarization-dependent loss (PDL) using the signal-to-noise ratio distribution induced by PDL. We show an uncertainty cut between 40% and 80% compared to datasheet in several configurations.

Introduction

Todays' networks are evolving towards a more flexible technology to meet emerging applications increasing demand for high capacity, and to allow for dynamic service creation, restoration, and droppina. Recent research in optical performance estimation has pointed to the need for a complete characterization of light path (LP) components and parameters uncertainties to reduce margins when estimating the performance of unestablished LPs^{[1],[2]}. Indeed, in greenfield design, network engineers consider large margins to assure reliability for all the network life, resulting in a waste of resources. However, in existing networks, reducina components uncertainty when provisioning unestablished LPs allows cutting unnecessary system margins^{[3],[4]}.

With this goal in mind, in this paper, we aim to reduce the uncertainty due to the polarizationdependent loss (PDL). PDL is present in components such as erbium-doped fiber amplifiers (EDFA) and more dominantly in reconfigurable optical add-drop multiplexers (ROADMs). PDL causes a signal-to-noise ratio (SNR) difference between the two polarization tributaries depending their on relative orientations^[5]. PDL is thus a challenging impairment for coherent systems, particularly those employing numerous ROADMs^[6]. As the polarization of light is not maintained in the fiber, PDL produces a random oscillation on the LP performance. Therefore, we require extra margins to guarantee the LP availability^[3].



Fig. 1. Qualitative example of random oscillation of SNR. The coherent receiver collects SNR samples fluctuations and estimates SNR PDF, its variance σ^2 and mean m

This paper presents a method to estimate ROADMs' PDL values for an installed optical fiber network based on the performance monitoring capabilities of transponders. We use a network controller that collects from several transponders the statistical information on performance fluctuations induced by PDL and infers the PDL contribution of each different network component by simple regression.

Methodology

In this paper, we employ the per-polarization SNR as a performance metric without loss of generality^[7]. We consider a transparent network in which each node has add and drop capability, and in which a central controller can collect information from the transceivers (TRX)^[8]. We compute the propagation in the linear regime, i.e., the nonlinear Kerr effects are negligible compared to amplified spontaneous emission (ASE) noise and we suppose polarization mode dispersion (PMD) to be negligible.

As sketched in Fig. 1, performance oscillates in time randomly because of the PDL, eventually generating a probability density function (PDF)^{[9],[10]}. The statistical information related to the performance PDF, such as the mean and the variance can be determined and provided to the controller^[11]. The variance and the mean well characterize the SNR distribution since, in the linear regime, we observe an almost Gaussian PDF^[7]. Fig. 2 shows the principle of SNRstatistics measurement-based PDL monitoring. In an optical network, nodes, i.e., ROADMs, add and drop services, and, thanks to the coherent receivers (RXs), each service performance can be monitored in terms of the per-polarization SNR^[12]. The central controller, aware of the LP routes and performance statistics, can use both pieces of knowledge to infer information on the components' PDL since SNR statistics correlate to the PDL value of components^[13]. At the controller, we perform a regression using the



Fig. 2. Physical layer parameters monitoring with a centralized way to use TRX information. After observing PDL-induced perpolarization SNR oscillations we use their PDF parameters, variance σ^2 and mean m which are sent to the network controller. The simulation link is composed of three 2-degree ROADMs. At each ROADM, a cascade of 2 WSSs emulate PDL.

variances and the means of SNR PDFs. The output is a real number: the investigated ROADM PDL value prediction. We study two configurations: one to retrieve the PDL added by the ROADMs at emission and one to retrieve the PDL added by the ROADM in transit.

We first estimate the PDL added by the ROADM at emission, i.e., the PDL of the pair of wavelength selective switches (WSSs), responsible for adding LPs from the terminal to the network. Pragmatically, in Fig. 2. we target the regression on the PDL of the WSSs in the red boxes by using the LP depicted in solid red line. The LP is added at the ROADM investigated. ROADM 2, propagated along one section, and dropped at the next node, ROADM 3. For this configuration, we use as regression inputs the variance σ_3^2 and the mean m₃ of the SNR PDF obtained when the LP is dropped at ROADM 3.

We also estimate the PDL added by the ROADM in transit, i.e., by the pair of WSSs responsible for routing LPs. In Fig. 2. we target the regression on the PDL of the WSSs in the green boxes by using the LPs depicted in dashed and dotted green lines. Both LPs are added to the network through ROADM 3. From this ROADM, two LPs are investigated. One is dropped at ROADM 2 (dotted), where the variance σ_2^2 and the mean m_2 of the SNR PDF are collected. One is dropped at ROADM 1 (dashed), where variance σ_1^2 and mean m_1 of the SNR PDF are collected. (σ_1^2 , m_1) and (σ_2^2 , m_2) are used as inputs for the regression.

Before moving to numerical results, we remark that these investigations do not interrupt the information flow and require propagating LPs for a maximum of two sections. Therefore, the method is non-intrusive and can work with already established LPs. Moreover, a probing strategy that allocates LPs consciously when the network resources (wavelengths and TRX) are idle can be also be envisaged.

Data Generation Simulation Setup

In Fig. 2, we present the simulation setup. Throughout all the investigations, LPs are propagated over ROADM-to-ROADM sections made of a cascade of spans, each composed by a single-mode fiber (SMF) with length 100 km and attenuation 0.23 dB/km and an EDFA. While the fiber length is kept constant, the number of spans per section can vary depending on the target investigation. We consider ROADM-output and transmitters EDFAs with a gain of 20 dB. The channel power is 0 dBm.

ROADMs at emission and in transit are embodied by a two WSSs cascade that emulates PDL without adding filtering penalty. The ROADM PDL values are drawn from a uniform distribution between 0.1 and 0.9 dB. Hence, ROADM datasheet standard deviation (SD) is 0.23 dB. EDFAs also emulate PDL; values are drawn from a uniform distribution between 0.05 and 0.15 dB. EDFA noise figure (NF) values are drawn from a uniform distribution between 4.6 and 5.4 dB.

Since we assume the transmission to be linear, we simulated the SNR distribution by propagating the noise covariance matrix with the reversed channel method (RCM) presented in [13]. We used 10⁵ random polarization rotations to generate PDFs. At the RX, we recovered the zero-forcing equalization. signal by The regression was trained with 200 random PDL values and tested with 200 different values. Although we tested several regression models, we report linear regression results only. Linear regression provides an accurate estimate while being computationally simple.

To validate the minimum number of LPs required for an accurate regression, i.e., 1 LP (Fig.2-red) for emission and 2 LPs (Fig.2-green) when in transit, we investigated the PDL-value regression root-mean-square error (RMSE) for

different inputs set sizes. For this, the transmitted LPs are propagated over ROADM-to-ROADM sections of 3 spans. Pragmatically, we increased the linear regression input vector size by adding additional LPs statistical information, (σ_k^2 , m_k), by propagating over extra sections after the target ROADM to see if providing additional statistics delivers better accuracy (k from 1 to 4, instead of only 1 and 2).

To assess the accuracy of ROADM in transit when varying the configuration of the sections before and after it, we investigated the accuracy of the PDL regression versus the link noise ratio. The link noise ratio is the ratio of the noise accumulated in the section before the ROADM of interest (Fig.2-dotted) over the noise accumulated on the two sections before and after (Fig.2-dashed). We report the cases where LPs are propagated over a total of 10, 14 and 20 spans between ROADM 3 and ROADM 1, and we swipe the position of ROADM 2.

Model Training and Results

Fig. 3 shows, on the left axis, the RMSE in dB for the regressions on ROADMs PDL values for transit (circles) and emission (stars) vs. the number of LPs used, i.e., the number of nodes where variances and means are extracted to feed the regression's inputs. The right axis reports the percentage gain when comparing the regression RMSE against ROADM datasheet SD. For what concerns the ROADM at emission, the regression reaches an RMSE lower plateau already when using only one section. RMSE=0.05 dB, i.e., 80% gain against datasheet SD. The ROADM in transit, instead, by using one section, does not refine PDL knowledge since the RMSE equals







Fig. 4. PDL values estimation RMSE for a ROADM in transit vs. the ratio of noise accumulated before the ROADM investigated over the total noise of the transmission for links of 10, 14 and 20 spans.



Fig. 5. Predicted PDL values vs. PDL real values in the highest and lowest link noise ratio. We highlight regression RMSE in solid and datasheet SD (0.23 dB) in dashed.

the datasheet SD (0.23 dB). However, when using two sections, we see an RMSE=0.05 dB, i.e., 80% gain against datasheet SD. We note that, when considering extra nodes, the accuracy is not improved. This confirms that the information extracted at one node for the ROADM at emission and two nodes for the ROADM in transit provide sufficient statistics.

For the ROADM in transit, we observe that the regression accuracy depends on the link noise ratio. Fig. 4 depicts PDL regression RMSE for different link noise ratios for propagations over a total of 10 (o), 14 (*), and 20 (+) spans. The right axis, as always, reports the percentage gain compared to ROADM datasheet SD. We see that, independently of the total length, we have a favorable and stable PDL estimation RMSE (of about 0.05 dB, i.e., 80% uncertainty gain) until the link noise ratio reaches 0.7. In this region, we can substantially reduce PDL uncertainty. For noise ratios larger than 0.7, independently of the total link length, the accuracy lowers by increasing the link noise ratio. Yet, the RMSE is always below datasheet SD (lowest PDL uncertainty gain is about 40%). Fig. 5. shows scattered prediction plot for the lowest (a) and highest (b) link noise ratios for a total link length of 14 spans. In the figure, we report regression RMSE (red-solid) and datasheet SD (bluedashed). In the first case, Fig.5.a, the RMSE is 0.05 dB, and the accuracy percentage gain is 80%. In the second case, RMSE is 0.1 dB, and the percentage gain against datasheet SD is 50%. Even if it is not reported for the sake of space, we note that the regression RMSE for the ROADM at emission does not depend on the accumulated noise between the two ROADMs.

Conclusion

A method to monitor ROADM PDL values is proposed. We introduced a solution requiring no extra physical component. The method delivers a more accurate knowledge of the PDL value than the one provided by the datasheet. We gain on uncertainty margins 80% for ROADMs at emission and in the worst case 40% for ROADMs in transit.

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