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Autonomous Physical Layer Characterization in Cognitive Optical Line Systems

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Abstract: We develop a procedure to autonomously characterize the optical line system physical layer, span-by-span, using in-line OTDRs and OCMs. This procedure has been experimentally validated, showing a clear correlation between the experimental outcomes and emulations. © 2021 The Author(s)

1. Introduction

Given the outstanding increasing use of optical infrastructures and the growing demand of data traffic [1], network operators aim to maximize the optical fiber capacity, fully exploiting the installed resources. Cognitive optical networks have been theorized and implemented in order to address this purpose, focusing on the adaptation of the transmission system over the complete set of abstraction layers [2]. For this reason, the importance of the physical layer knowledge relies on the possibility to accurately determine the desired working point of each network optical line system (OLS). In particular, the knowledge of lumped loss entities present along the effective length of each span, together with the effective area and the loss coefficient function vs. frequency, allows to effectively intercept the nonlinear phenomena [3]. Often, operators are not aware of the infrastructure physical layer due to periodical damages, restorations and restructuring making the line performance difficult to predict. The following investigation aims to develop a methodology for a complete in-field OLS characterization, performed span-by-span, starting from the information provided by optical time domain reflectometers (OTDRs) and optical channel monitors (OCMs) integrated within the in-line amplifiers (ILAs) in a perspective of cognitive optical networks at the physical layer. For this purpose, an optimization tool has been set up in order to classify each fiber span according to the effective area and the attenuation profile, assuming uniform fiber span condition, and to estimate lumped losses due to connectors and splices.

2. Physical Layer Characterization Methodology

We focus on a C-band scenario with a single OLS composed of amplification sites and fiber spans (Fig. 1). Each amplification site includes an erbium-doped fiber amplifier (EDFA) with integrated monitoring devices as an OTDR and an OCM at both amplifier terminals, while each fiber span consists of a series of fiber spools connected through mechanical connectors. An optical line controller is able to exchange information with each amplifier, managing the operation and getting feedback from the monitoring devices. Starting from the latter, the proposed software tool is an optimization framework based on an evolutionary strategy able to identify the properties of the physical layer. Before the beginning of real transmission operations, the conceived probing step allows to enlarge the amount of knowledge related to the physical layer description, improving the precision of the working point definition. As first step, each in-line OTDR performs an analysis of the corresponding fiber span, collecting information regarding the fiber span lengths, the positions of the lumped losses and the estimations of the loss coefficients at the pulse frequency. Then, the booster is set in ASE mode and the other amplifiers in constant gain mode. OCMs measure the ASE spectra at both terminals of each fiber span. This measure is performed for two different booster power levels: the first one at low ASE power, having a negligible Raman cross-talk contribution, and the second one at higher ASE power to enhance the Raman cross-talk. The choice of the booster ASE power and amplifier gains strictly depends on the characteristics of the specific OLS fiber spans and OCM sensitivities. This approach does not need the use of a specific WDM comb and, once the OLS is configured, the measurements

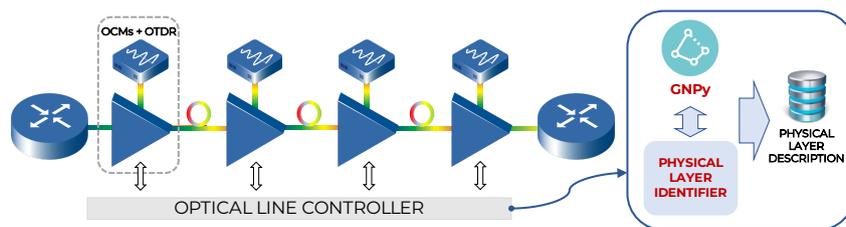


Fig. 1. Description of the autonomous physical layer characterization scenario.

can be performed rapidly in series. Given the availability of OTDR and OCM measurements, evaluated at the fiber span input and output for the two power levels, an optimization process is carried out for each fiber span in order to retrieve the fiber span characterization. The optimization procedure aims to determine the set of physical layer parameters that allows to faithfully reproduce the experiment behaviour through the emulation. The developed physical layer identifier is composed of two main elements. The first one is an optimization algorithm based on covariance matrix adaptation evolution strategy [6] that allows to find the optimal parameter set that matches the measurements behaviour. The second element is the GNPY Python open-source library [4, 5] that is used as core function of the optimization algorithm to compute the spectrum at the fiber span output for the generated sets of variables to optimize. After the creation of a population consisting of randomly-extracted parameter sets, the adaptive algorithm iterates the propagation function on each of these sets, in turn. For each span, a set of parameters is constituted by the Raman efficiency scale factor (its normalized profile is assumed), C_R , which is directly related to the effective area, A_{eff} , the complete fiber span attenuation profile vs. frequency, $\alpha(f)$, and the lumped losses, $l(z)$, at the position detected by the OTDR (input/output connectors and possible intermediate connectors or splices). Regarding the attenuation profile, we adopt a simplified phenomenological model that enables the definition of a complete profile over the entire C-band through the use of only 4 parameters [7], modelling Rayleigh scattering, infra-red absorption and OH^- peak at $1.39 \mu\text{m}$. The fundamental problem variables are: C_R , $\alpha(f)$ defined by 4 parameters, $l(z=0)$ and $l(z=L_S)$ where L_S is the fiber length. Moreover, the final dimension of the problem can increase including intermediate losses. The fitness of each case is computed relying on an objective function that evaluates the root mean square error (RMSE) between the emulated profile and the measured one. The enhancement brought by this probing procedure derives from the joint optimization of the entire parameter set involved in the optical propagation, allowing a complete characterization of each fiber span without the use any device datasheet. As no physical layer knowledge is available before the characterization step, the implemented methodology assumes uniform fiber condition; the spools that compose the fiber span are of the same type. Nevertheless, even if this condition is not verified, the optimization provides a set of average parameters that allows to identify the equivalent fiber type as if the fiber span were uniform.

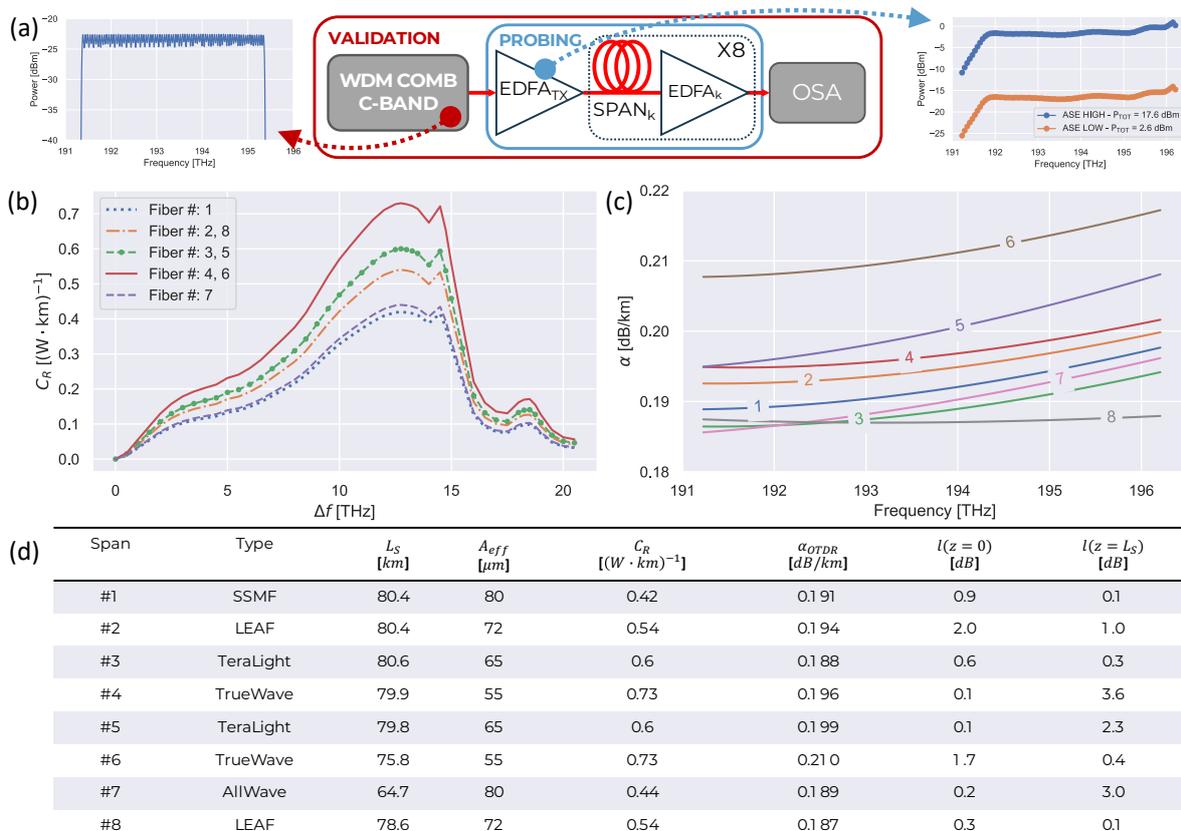


Fig. 2. (a) Experimental setup, (b) attenuation profiles, (c) Raman efficiency curves, (d) characterization results per fiber span: type, length, effective area, Raman efficiency coefficient, loss coefficient detected by OTDR, input connector loss, output connector loss.

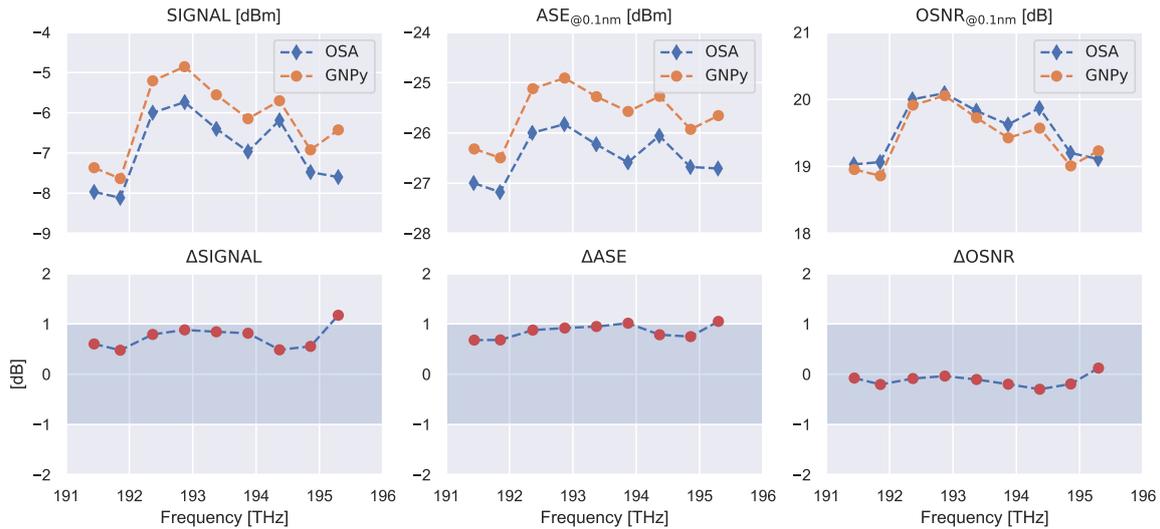


Fig. 3. OSA measure, GNPpy emulation and error at OLS output: signal, ASE and OSNR.

3. Experimental Setup & Results

The schematic block diagram of the experimental setup is depicted in Fig. 2(a). A commercial programmable WaveShaper© (1000S from Finisar) is used to generate a 80 channel WDM comb, centered at 193.35 THz with a WDM grid spacing of 50 GHz within the C-band, by shaping the output of a ASE noise source. The OLS is composed of a booster amplifier and 8 fiber spans, whose lengths and characteristics are summarized in Fig 2(d), each followed by a commercial EDFA operating with distinct gain and constant gain and tilt values. As anticipated in the previous section, during the probing phase we turn the WaveShaper output off and we set the booster in ASE mode, collecting the ASE spectra at both terminals of each fiber span using the integrated OCM placed at each EDFA input and output. The results provided by the optimization framework during the probing step are synthesized in Fig. 2(b)–(d). The fiber classification, defining its effective area and the dispersion, has been derived through the estimated Raman efficiency scale factor.

The efficiency of the performed characterization has been tested on a real scenario, connecting the ASE-shaped WDM comb at the OLS input and operating the amplifiers with gain and tilt levels that recover the total fiber span loss and the tilt induced by the Raman cross-talk and fiber attenuation profile. Then, we measure the power level of all 80 channels using an optical spectrum analyzer (OSA) at the OLS output. Moreover, we evaluate the ASE power of 9 selected channels, equally spaced over the investigated band, measuring the floor power level with these channels turned off. We then emulate the system with GNPpy exploiting all the extracted physical layer information. As reported in Fig. 3, the trends obtained for both OSA measurements and GNPpy emulations are extremely similar. This is clarified by the error curves of all the metrics, which show evident flat-biased profiles. The Δ OSNR curve is centered in 0 dB, whereas, it is noticeable that both Δ SIGNAL and Δ ASE curves have roughly the same bias values. These biases can be attributed to lumped losses outside the effective length of the fiber spans as the shapes and the tilts of both the profiles are accurately reproduced by the GNPpy emulation.

4. Conclusions

We propose and experimentally validate an autonomous procedure to characterize, span-by-span, the physical layer of an OLS in the perspective of cognitive optical networks. In addition, we demonstrate that, keeping under control the physical layer knowledge, it is possible to achieve excellent results in terms of prediction observing the absolute power of the transmission system.

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