Implementation Penalties for Nonlinear Interference Estimation with Linear Least Squares Longitudinal Power Monitoring

Estimating the Nonlinear Interference at the Receiver: Methods and Pitfalls

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Abstract: We review methods for separating ASE and nonlinear interference noise in coherent receivers, emphasizing techniques and potential pitfalls. Accuracy and practical challenges are evaluated, with a focus on the Longitudinal Power Monitoring-based approach.

1. Introduction

In an optically-amplified coherent link, there are three primary sources of noise: transceiver noise, amplified spontaneous emission (ASE) noise introduced by optical amplifiers, and nonlinear interference (NLI) noise resulting from fiber Kerr nonlinearity [1]. An accurate separation of these noise components is crucial for optimizing the network's performance, as the optimal optical transmit power for each span is directly influenced by the ratio of NLI power to ASE power [1]. In general, transceiver noise can be easily quantified through a factory calibration procedure, typically performed using a Variable Optical Attenuator (VOA) [2]. However, isolating the ASE and NLI components is a much more complex task, and remains an active research topic.

In this invited presentation, we will review the main techniques, with a particular focus on our proposed method based on Longitudinal Power Monitoring (LPM) [3].

2. System model and methods

Assuming that all three noise components can be modeled as Additive White Gaussian Noise (AWGN), statistically independent from each other, the overall Signal-to-Noise-Ratio (SNR) affecting the communication can be expressed as [1]

$$\mathrm{SNR} = (\mathrm{SNR}_{\mathrm{TRX}}^{-1} + \mathrm{OSNR}^{-1} + \mathrm{SNR}_{\mathrm{NL}}^{-1})^{-1}. \qquad (1)$$

In this equation, $\mathrm{SNR}_{\mathrm{TRX}}$ represents the transceiver SNR, OSNR corresponds to the SNR due to ASE noise and $\mathrm{SNR}_{\mathrm{NL}}$ refers to the SNR due to NLI. We assume that the $\mathrm{SNR}_{\mathrm{TRX}}$ is known (e.g. from an optical back-to-back measurement), and that the overall SNR is provided by the transceiver's telemetry (e.g. by means of pilot symbols). Then, to segregate the different noise components, either the OSNR or the $\mathrm{SNR}_{\mathrm{NL}}$ need to be estimated.
This information is crucial for network optimization techniques that exploit the so-called "3-dB rule" [1]; this rule states that the optimal launch power condition is achieved when

$$\mathrm{OSNR} = \mathrm{SNR}_{\mathrm{NL}} - 3\ \mathrm{dB}. \qquad (2)$$

Formally, it is valid only only over strict conditions [1], such as identical and equispaced WDM channels over a link made of identical spans. However, it was empirically found that it is valid (with a good approximation) over a much wider range of scenarios [4]. Therefore, an accurate estimation of $\mathrm{SNR}_{\mathrm{NL}}$ (or, equivalently, the OSNR) would enable a very simple and direct optimization of the WDM channel under consideration.

3. Estimating the NLI

3.1. Statistics of NLI

The techniques that can estimate the NLI in the receiver's DSP can be divided into two large categories. The methods in the first category are based on the fact that NLI is not a pure AWGN source, but rather a deterministic beating of the WDM channel with itself (Self-Channel Interference – SCI) and with the other WDM channels (Cross-Channel Interference – XCI) [9].

Examples of such methods can be found in [5–8], where the authors measured the statistical correlations of the noise [6–8] or analyzed the output of the carrier phase recovery (CPE) [5] to estimate the power of NLI. However, those techniques do not provide a direct estimate of the NLI; rather, they produce a quantity that is proportional to it. Therefore, some regression techniques (e.g. Machine-Learning-based) are needed to obtain the absolute NLI power. In other works, such as [12–15] the authors directly applied ML methods to the received data, such as the received constellation or the Polarization Dependent Loss-induced SNR fluctuations [15]. These methods were evaluated under various conditions and scenarios, yielding mixed overall performance. Under certain conditions, such as strong NLI (e.g., low-dispersion fiber or high transmit power) or ideal scenarios (e.g., single-channel transmission or simulations without phase noise), these methods demonstrated excellent performance. In more realistic scenarios, instead, the performance of most of them was poor. This is because, under most practical conditions, the NLI power is relatively small compared to ASE. Furthermore, the power of the non-AWGN components of NLI is even lower, making accurate estimation particularly challenging. In general, deep learning-based methods demonstrated superior performance, but at the cost of being non-interpretable. On the other hand, this category of techniques can be easily applied to commercial transceivers [7], as they can be implemented through passive monitoring of the receiver's DSP.

3.2. *Transmit sequence modification*

The second category of methods assumes full control over the transmitter. In this approach, the transmitter periodically introduces notches, either in the time domain [10] or the frequency domain [11], enabling the receiver to accurately estimate the ASE power. These methods demonstrated improved performance compared to the previous category, particularly in realistic scenarios, but require modifications to the transmitted sequence.

3.3. *Longitundinal Power Monitoring*

Longitudinal Power Monitoring refers to a set of algorithms that leverage the nonlinear interaction between chromatic dispersion and NLI to estimate the power evolution of a WDM channel within a network [17]. Since LPM relies on NLI generation, it can also be used for direct estimation of the NLI power. This was first demonstrated in [16], where the entire WDM spectrum was measured, and later validated under more realistic conditions in [3]. The main advantage of LPM-based NLI estimation is its ability to determine the power profile, providing network operators with valuable insights for optimizing channel launch power. However, LPM has a significant limitation compared to other methods: it can only estimate the SCI component of NLI. Estimating XCI, which is the dominant NLI component in fully loaded WDM systems, requires alternative approaches, such as NLI modeling techniques.

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