Fast BER Distribution and Neural Networks for Joint Monitoring of Linear and Nonlinear Noise-to-Signal Ratios

Ali Salehiomran, Zhiping Jiang
Huawei Technologies Canada, 303 Terry Fox Dr., Ottawa, Canada
zhiping.jiang@huawei.com

Abstract: Experimentally observed long-tail fast BER (10ns–1μs) histogram (FBH) in presence of NLIN is explained through simulation. Features from FBHs are applied to train an ANN to estimate linear and nonlinear NSRs with <5% error. © 2020 The Author(s)

1. Introduction

As demand for higher capacity is increasing, the ability to characterize channel conditions accurately and reporting it to higher network layers for performance optimization is becoming crucial. Signal-to-noise ratio (SNR) is the most important channel parameter to be monitored, as it directly affects overall system performance and quality of transmission. Various noise sources degrade the SNR in optical communication systems. The two major noise sources are amplified spontaneous emission noise (ASE) and nonlinear interference noise (NLIN). ASE results from Erbium doped fiber amplifiers that compensate propagation losses, and NLIN is result of interactions among all electromagnetic waves within the optical fiber [1]. The total SNR at the receiver is

$$SNR_{Total}^{-1} = \frac{\sigma_{ASE}^2 + \sigma_{TR}^2}{P_{ch}} + \frac{\sigma_{NL}^2}{P_{ch}} = SNR_{Linear}^{-1} + SNR_{\mathrm{NLIN}}^{-1} \tag{1}$$

where σ_{ASE}^2, σ_{TR}^2, and σ_{NL}^2 represent ASE, transceiver implementation noise, and NLIN powers, respectively. P_{ch} denotes channel launch power. Accumulated noise from ASE and transceiver is referred to as linear noise. For better management/optimization of the optical network, fault detection, and margin estimation, it is highly desired to monitor and resolve the linear noise and NLIN contributions separately. Analytical models such as the extended Gaussian noise (EGN) model [1] provide accurate predictions of nonlinear noise power, when all information about the light propagation path such as fiber parameters, neighboring channels, modulation format, symbol rate, and transmitted power is available. In practice, such detailed information is not readily available in optical networks. NLIN exhibits temporal correlation properties that differentiates it from linear (ASE) noise [2] and could be used to separate linear and nonlinear noises. In recent years, several approaches have been proposed to monitor the nonlinear noise. The works presented in [3,4] examine the difference in the temporal correlation and constellation geometric shapes between the ASE noise and NLIN, and uses artificial neural networks (ANNs) to separate those two noise contributions at the Rx DSP. In [5], the proposed algorithm employs an amplitude modulated pilot tone and zero-power gaps in the amplitude of the transmitted signal to directly measure the ASE and the NLIN. In a recent work [6], we reported on existence of long tails in measured fast (10 ns – 1 us) BER histograms (FBHs) in presence of nonlinear noise. This proof of concept work has considered a fixed link comprising of 12 spans of 80 km s with 40 WDM channels operating close to the threshold BER. In practice, link propagation parameters and average BER operation point could vary broadly. In particular, average BER operation point could be far from the threshold BER.

In this paper, we apply a simulation approach based on estimation of the temporal properties of nonlinearities through time-varying ISI matrices [2] to reproduce experimentally observed long-tail FBHs with excellent agreement. We expand our previous contribution [6] over an extensive set of realistic simulation conditions that covers various total SNR values (average BER), launch powers, number of spans, and number of neighboring channels. Finally, we investigate how features extracted from FBHs could be applied to train an ANN to estimate the linear and nonlinear noise-to-signal ratios (NSRs) over this expansive dataset.

2. The proposed method

In this section, the existence of long tails in FBH is experimentally verified and is linked to NLIN. Then, simulation methodology based on time-varying ISI matrices is considered that matches the experimentally measured FBHs with excellent agreement. This verified simulation methodology is used to generate FBHs at various conditions shown in Table 1. Based on simulated FBHs, application of an ANN to relate the FBH to linear and nonlinear noises is demonstrated.

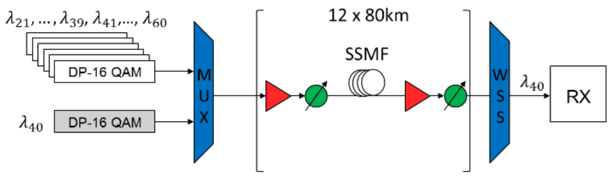

Fig. 1. Experimental setup used to collect fast BER histogram. MUX is multiplexer and WSS is wavelength selective switch. SSMF denotes standard single mode fiber.

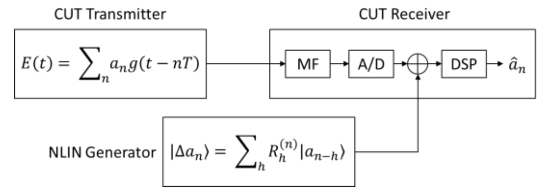

Fig. 2. The proposed method of assessing system BER performance. MF: Matched filter, A/D: Analog to digital converter, CUT: Channel under test

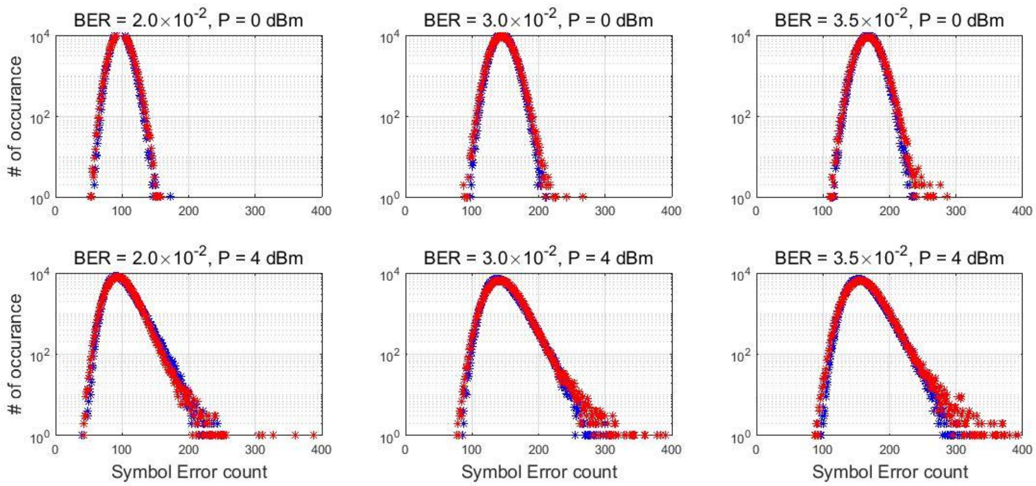

Fig. 3. Measured (red) vs simulated (blue) fast BER histogram for various conditions with 20×16384 BER samples calculated over 1280 symbols.

Fig. 1 shows the experimental setup used to verify existence of long tails in FBH. In this setup, 40 channels each modulated by dual-polarization 16-QAM and separated by 50 GHz are combined using a multiplexer and propagated through 12 spans each with 80 km of standard single mode fiber (SSMF). At the end of the link, a wavelength selective switch separates the channel of interest (λ_{40}) and directs it to a coherent receiver. To achieve a given BER target, ASE noise is loaded at the receiver side. In each measurement, the coherent receiver reports 16384 consecutive symbol error counts, each evaluated on 1280 symbols. Each symbol error count is converted to a BER reading through a constant normalization factor. Thus, for the rest of this paper, symbol error count and BER are used interchangeably. To exemplify long-tail BER (symbol error count) histogram, the experimental setup of Fig. 1 is utilized to gather the FBH at various conditions. Data is gathered at long-period average BERs of 3.5×10^{-2}, 3×10^{-2}, and 2×10^{-2}. For each average BER, channel launch powers are set to 0 and 4 dBm. Fig. 2 shows block diagram of the simulation methodology opted to generate NLIN and to assess the system performance. The generated NLIN terms related to SPM and XPM are added to the received signal from the channel under test (CUT) transmitter prior to the digital signal processing (DSP) stage. The ASE and the FWM-induced NLIN are added as AWGN processes with the appropriate variance [1], whereas the SPM and XPM-induced NLIN contribution ($|\Delta a_n\rangle$) is generated via the time-varying ISI model [2].

$$|\Delta a_n\rangle = \sum_h R_h^{(n)} |a_{n-h}\rangle \tag{2}$$

where $|\Delta \boldsymbol{a}_n\rangle$ represents a 2×1 column vector whose two components are the complex data symbols transmitted over the x and y polarization channels of the CUT in the $\boldsymbol{n^{th}}$ time-slot. The term $\boldsymbol{R_h^{(n)}}$ is the $\boldsymbol{h^{th}}$ 2×2 ISI matrix produced as Gaussian random matrices with the correct second order statistics [2]. For each condition considered in simulation (Table. 1), the second order statistics of the NLIN are extracted from the SSFM simulation. The 35 Gbaud, probability shaped DP-16QAM with spectral efficiency of 3.5 and roll-off factor of 0.05 is transmitted over various number of WDM channels, number of spans, and launch powers. Length of each span is 80 km. The 50 GHz spaced WDM system was simulated as noise-free, while ASE is loaded into the receiver according to target long-term (1s – 1min)

Table 1. Simulation scenarios considered for the proposed technique

Fiber Type	SSFM
Propagation Distance [km]	320, 640, 960, 1280
WDM Channels	1,3,7,11,21,41
Average BER	3.5×10^{-2} , 2×10^{-2}, 1×10^{-2} , 5×10^{-3}
Launch Power [dBm]	0,1,2,3,4

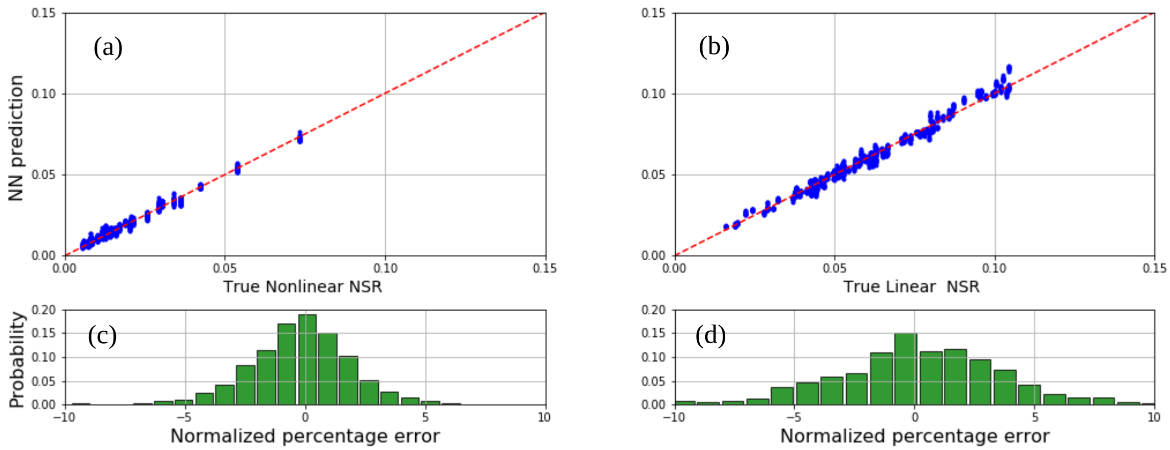

Fig. 4. True vs estimated (a) nonlinear NSR, (b) linear NSR. Probability density function of difference between true and estimated NSRs normalized to total noise for (c) nonlinear noise and (d) linear noise.

average BER value. Table 1 summarizes the 480 conditions considered for this paper. Fig. 3 compares the FBHs from experimental setup of Fig. 1 and simulation block diagram shown in Fig. 2 at 3 different BER values and two launch powers. Excellent agreement between the measured and simulated FBHs is observed.

3. Results

The statistical features extracted from FBHs, in combination with number of spans and number of WDM channels are used as input of an ANN, consisting of 2 hidden layers each having 5 neurons. The ANN uses scaled exponential linear units as non-linear function, and is trained by the 70/20/15 rule for the train/dev/test sets. Fig. 4a and 4b, show the true vs estimated nonlinear and linear NSRs, respectively. Good agreement between expected and estimated values is observed corresponding to NSR estimation error standard deviation of approximately 1.5×10^{-3} and 10^{-3} for linear and nonlinear noises, respectively. Fig. 4c and 4d, show the probability density function of the difference between true and estimated nonlinear and linear NSRs normalized to total noise. This measure of accuracy is more meaningful than absolute error, when one of the noise components is much smaller than the other. Normalized percentage error is approximately 5% for both linear and nonlinear noises.

4. Conclusion

We have shown that experimentally measured long-tail fast BER (10ns–1µs) histogram from a 1000-km 12 spans link could be excellently matched through simulation methodology based on time-varying ISI model for generation of NLIN. This simulation methodology is applied to generate FBHs for 480 conditions shown in Table 1 and used to train an ANN that predicts both linear and nonlinear NSRs with less than 5 percent of normalized estimation error. This extensively verifies the application of FBHs to monitor and separate linear and nonlinear noises over a broad range of average BER, from 5×10^{-3} to the threshold BER, and link configuration. This approach is transparent to modulation format, significantly simplifies feature extraction, and could be readily implemented in DSP.

5. References

[1] A. Carena,"EGN model of non-linear fiber propagation," Opt. Express 22, 16335-16362, 2014.
[2] O. Golani, "Modeling the Bit-Error-Rate Performance of Nonlinear Fiber-Optic Systems," in JLT, vol. 34, no. 15, pp. 3482-3489, 2016.
[3] A. Kashi, "Fiber Nonlinear Noise-to-Signal Ratio Monitoring Using Artificial Neural Networks," ECOC, paper M2F.2, 2017.
[4] C. Vaquero, "Joint Estimation of Linear and Nonlinear Signal-to-Noise Ratio based on Neural Networks," OFC, paper M2F.4, 2018.
[5] Z. Jiang, "Nonlinear Noise Monitoring in Coherent Systems Using Amplitude Modulation Pilot Tone and Zero-Power Gap," OFC, paper Th2A.34, 2019.
[6] A.Salehiomran, "Linear and Nonlinear Noise Monitoring in Coherent Systems Using Fast BER Measurement and Neural Networks," ECOC, paper W3D.3, 2019.