Accurate PLI Modeling for Next Generation Ultra-Massive Network Management Using PCS Modulation

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***Abstract*—Future long-haul networks with a much flatter topology and numerous nodes will experience high physical-layer impairments (PLIs), making probabilistic constellation shaping modulation attractive. Therefore, the impact of modulation formats and demand spectrum shapes on PLIs is significant, whereas state-of-the-art methods are either too complex or lack sufficient accuracy for next-generation ultra-massive networks. In this work, a computationally-efficient impairment estimate capturing the effects of modulation and expected spectral distortion is proposed.**

***Index Terms*—optical networks, physical-layer impairments, modulation format correction, arbitrary spectral shape**

I. Introduction

In the era of rapid advances in large models and AI computing, network infrastructure is undergoing a new round of upgrades. Driven by heterogeneous computing and multiple artificial intelligence data centers (AIDCs), network demands from large language model applications are increasing, necessitating more powerful optical fiber infrastructures [1]. Meanwhile, with continuous traffic growth, AIDCs are being abstracted as new network nodes alongside traditional ones, requiring backbone-level interconnections. This calls for a flatter core network architecture, where a distributed control core manages diverse nodes and enables low-margin resource allocation, including service routing and spectrum, among traditional nodes, data centers, and AIDCs [2], thereby facilitating large-scale all-optical interconnected next-generation backbone networks.

In such long-distance optical fiber networks, physical-layer impairments (PLIs) accumulate during signal transmission, making accurate estimation of these impairments crucial for ensuring the quality of transmission (QoT) [3]. Due to the network's flat structure and large number of nodes, light paths traverse many nodes, and transmitted signals encounter a large number of neighboring channels along each light path. This leads to stronger filtering effects from wavelength-selective switches at each node [4] and severe nonlinear interference (NLI) due to interactions with neighboring channels. These effects distort the demand spectra, thereby degrading the accuracy of PLI estimation.

Moreover, in next-generation ultra-large networks, modulation formats play a crucial role in determining network throughput. Probabilistic constellation shaping (PCS) optimizes the probability distribution of constellation points, maximizing the mutual information of the transmission channel [5]. However, the modulation format not only determines the signal transmission rate but also significantly influences the nonlinear interactions with other channels along the transmission link, thereby affecting the accuracy of PLI estimation [6, 7].

Therefore, the desired PLI estimator for ultra-large networks requires accounting for the impact of 1) the choice of modulation format, 2) the spectral distortion and shaping, and 3) the numerous neighboring channels adding to fiber nonlinear degradation. The ground truth model in [8] can accurately estimate PLIs by considering the effects of modulation formats and spectral distortion. However, this model is too complex to apply in real-time to networks with a large number of demands and numerous network elements. Alternatively, the enhanced Gaussian noise (EGN) model is a widely used, low-complexity PLI estimation method. It introduces modulation-format correction terms [9], thereby addressing the traditional GN model's neglect of modulation format effects on PLIs. However, this model assumes rectangular signal spectra, whereas real signals are often shaped by root-raised cosine (RRC) filters to suppress inter-symbol interference (ISI) and are further distorted by the fiber channel. In addition, demands spectra shapes could be optimized utilizing machine learning methods for better transmission performance [10]. In this context, providing a computationally-efficient PLI estimate for arbitrary spectral shapes while accounting for modulation formats becomes a key challenge for cross-layer optimization.

To address the aforementioned challenges, we propose the enhanced component-wise GN (ECWGN) model as an extension to the computationally efficient CWGN model presented in [11]. The ECWGN model enables high-accuracy NLI correction for any modulation format, including PCS modulation, while accounting for the signal's non-rectangular

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spectrum. Simulation results show that, under typical RRC roll-off configurations and across various modulation formats, the ECWGN model keeps NLI estimation errors within 1% of the ground truth, with up to a 14.5% reduction in NLI overestimation compared to the EGN model for high-order and probabilistically shaped formats. When simulated on a typical link in an ultra-massive network with 88 transmitted demands, the ECWGN model takes only a few seconds, similar to the EGN model, and reduces computational time by up to 99.9% relative to the ground truth model, which requires about 7 days. Therefore, the ECWGN model is accurate, computationally efficient, and well-balanced between the EGN and ground truth models, making it suitable for next-generation ultra-massive networks.

II. Enhanced Component-Wise Gaussian Noise (ECWGN) Model of Correction

The EGN model accurately captures the impact of arbitrary modulation formats by adding a correction term for a specific modulation format to the standard GN model [12]. In this section, we derive the correction term for the C-band CWGN model in [11] for the signal of interest i based on [12, Eq. (8)]. Following the derivation methodology of the CWGN model proposed in [11], we adopt a similar theoretical approach by decomposing the interfering signal spectrum along the frequency axis into rectangular components and summing them via a Riemann sum to obtain the overall power spectral density (PSD) of the correction term contribution. Each interfering channel is assumed to consist of differential frequency elements df, such that $\sum df = B_k$, the total bandwidth of signal k. The contribution of each frequency differential component to the correction term depends on the frequency difference between the channel of interest signal and the corresponding interfering signal component. Therefore, the total correction term PSD contributed by all interfering signals k to the interest signal i is obtained by summing over all such frequency differentials, and is expressed as

$$G_{\rm corr}^{\rm ECWGN}(f_i) \approx \frac{80}{81}\,\Phi_k\, G_i^{\max} \sum_{\substack{k=1\\k\neq i}}^{N_{\rm ch}} \sum_{j=-B_k/(2\,df)}^{B_k/(2\,df)} G_k^2(f_k + j\,df)$$
$$\frac{\gamma^2 df}{\phi_{i,k}\,3\alpha^2}\Bigg[\frac{T_k-\alpha^2}{\alpha}\arctan\Big(\frac{\phi_{i,k}B_i}{\alpha}\Big) + \frac{4\alpha^2-T_k}{2\alpha}\arctan\Big(\frac{\phi_{i,k}B_i}{2\alpha}\Big)\Bigg], \tag{1}$$

where

$$\phi_{i,k} = -2\pi^2\,(f_k + df - f_i)\,[\beta_2 + \pi\beta_3\,(f_i + f_k + df)]\,, \tag{2}$$

and f_i and f_k represent the center frequencies of the signal of interest i and interfering signal k, respectively. $T_k = 4\alpha^2$, $N_{\rm ch}$ denotes the number of interfering channels, γ is the nonlinear coefficient, α is the fiber attenuation coefficient, $P_{\rm tot}$ is the total launched optical power, β_2 is the group velocity dispersion (GVD) parameter, and β_3 is its linear slope at the reference wavelength. The term $\Phi_k = \frac{{\rm E}[|X|^4]}{{\rm E}^2[|X|^2]} - 2$ represents the excess kurtosis of the transmitted modulation format, which characterizes the deviation of a non-Gaussian signal distribution from an ideal Gaussian distribution. $G_i^{\max} = \max_f G_i(f)$ denotes the maximum value of the actual PSD function of signal i, $G_i(f)$, and $G_k(f_k + jdf)$ is a sample of the non-rectangular PSD function G_k of interfering signal k at frequency $(f_k + jdf)$. The contribution to the overall correction term at this frequency has a differential bandwidth df. Therefore, it can itself be modeled as a band-limited signal with a rectangular spectrum over the differential df.

The summation in (1) uses a Riemann approximation assuming locally smooth $G_k(f)$ over df, with reduced accuracy for rapidly varying or complex spectra unless df is small; as $df \to 0$, it converges to an integral, simplifying the correction term as

$$G_{\rm corr}^{\rm ECWGN}(f_i) \approx \frac{80}{81}\,\Phi_k\, G_i^{\max} \sum_{\substack{k=1\\k\neq i}}^{N_{\rm ch}} \int_{-\infty}^{\infty} G_k^2(f)\,df$$
$$\cdot\frac{\gamma^2}{\phi_{i,k}\cdot 3\alpha^2}\Bigg[\frac{T_k-\alpha^2}{\alpha}\arctan\Big(\frac{\phi_{i,k}B_i}{\alpha}\Big) + \frac{4\alpha^2-T_k}{2\alpha}\arctan\Big(\frac{\phi_{i,k}B_i}{2\alpha}\Big)\Bigg]. \tag{3}$$

Equation (3) provides a method to calculate the modulation format correction term for any signal spectral shape, using the corresponding excess kurtosis values from [13] for different modulation formats.

III. Numerical Results

This section presents the numerical validation of the proposed ECWGN model and its potential to be applied in next generation ultra-massive network using the same system parameters as in [8]. Simulations consider a single-span 100 km fiber link. The EGN model is given by [12, Eq. (5)], and the ground truth model is from [8, Eq. (4)].

Although the ECWGN model is applicable to arbitrarily shaped spectra, our numerical analysis focuses specifically on signals with RRC spectra for demonstration purposes, as RRC shaping is widely used in practical optical network systems and filtering effects make the RRC pulse appear as having a higher roll-off factor (RoF) [11]. Therefore, we choose RoF $\leq$ 0.2 to represent the distorted spectra, and show the accuracy of PLI estimate. PCS-64QAM is compared to uniform-QPSK, uniform-16QAM, and uniform-64QAM. Each channel contains 2^{17} random symbols to compare the total NLI, thereby validating the adaptability and estimation accuracy of the ECWGN model.

Fig. 1 illustrates the estimation accuracy of the proposed ECWGN for non-rectangular spectrum signals compared with the ground truth, and its ability to reduce the overestimation error of the widely applied EGN model. Ten modulated and RRC-shaped demands with edge-to-edge bandwidths are uniformly allocated over the 4.4 THz C-band spectrum. The conventional EGN model in Fig. 1(a)–(c) overestimates the NLI

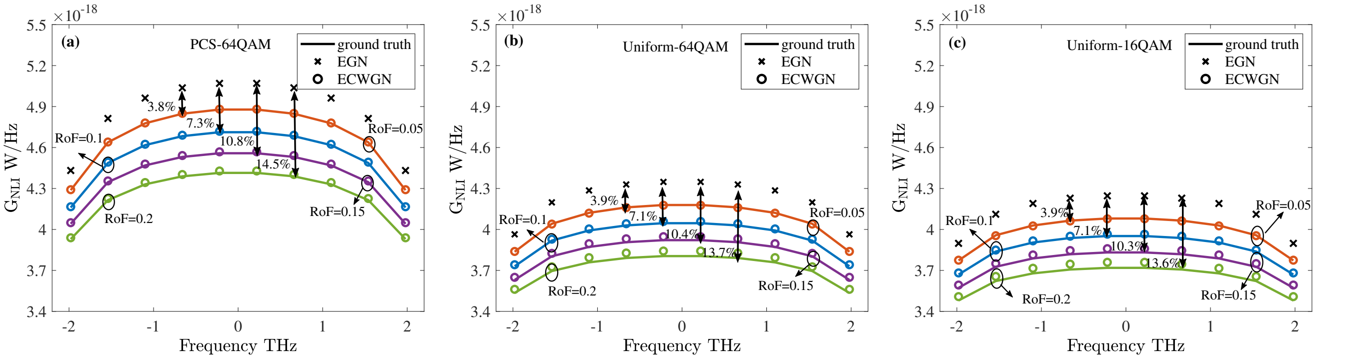

Fig. 1: NLI PSD estimated by the proposed ECWGN, the EGN, and the ground truth, as functions of roll-off factor under different modulation formats: (a) PCS-64QAM; (b) Uniform-64QAM; (c) Uniform-16QAM.

by 14.5%, 13.7%, and 13.6%, respectively for each different modulation compared, while the ECWGN model maintains its normalized error within 1% of the ground truth, significantly improving estimation accuracy. The figure also reveals that while PCS-64QAM reduces excess kurtosis Φ_k and exhibits "Gaussian-like" properties, its higher power concentration results in stronger cross-phase modulation. Therefore, modulation format selection requires a trade-off between spectral efficiency and nonlinear tolerance. By jointly modeling the modulation format and spectral shape, the ECWGN model offers high adaptability and accuracy to model the NLI of demands suffering spectral distortion.

Since the accuracy of the ECWGN model has been numerically validated, its scalability and suitability for ultra-massive-scale systems still need to be verified. To this end, a fully loaded fiber link with RRC-shaped demands (RoF $= 0.2$) is simulated to evaluate the applicability of the proposed ECWGN model in next-generation ultra-massive optical network systems. We then compare the computation time required by the proposed ECWGN model, the conventional EGN model, and the ground truth model assuming that the optical fiber link carries 88 RRC signals, as summarized in Table I. Each signal occupies an edge-to-edge bandwidth of 37.5 GHz, with a 12.5 GHz guard band between adjacent channels, covering a total C-band spectrum of 4.4 THz.

TABLE I: Running Time Comparison[1]

EGN	Ground truth	Proposed ECWGN
1.03 s	6.87×10^5 s	4.16 s

[1]MATLAB: R2023a; CPU: Intel Core i7-6600U, 2.60 GHz.

These results show that the proposed ECWGN model can compute NLI for all signals within seconds, achieving efficiency comparable to the EGN model. In contrast, the ground truth model requires several days to perform the computation. In dense long-haul backbone networks, the computation time increases significantly with the number of cascaded fiber spans. Given that modern optical networks rely on dynamic resource allocation and require real-time QoT prediction, models with excessive computational overhead are impractical for real-world deployment.

Hence, based on its demonstrated accuracy and scalability, the proposed ECWGN model is applicable to advanced PCS modulation techniques, allowing for reduced system margins. This effectively mitigates resource over-provisioning and improves the throughput of next-generation ultra-massive optical networks.

IV. Conclusion

The proposed ECWGN model is computationally efficient, reducing runtime by up to 99.9% relative to the ground truth and achieving EGN-comparable complexity, while maintaining high accuracy (1% error and avoiding the 14.5% overestimation of EGN). It is thus well suited for ultra-large next-generation optical backbone networks. The model can be easily extended to C+L-band PLI estimation by incorporating the inter-channel stimulated Raman scattering (ISRS) term, which will be explored in our future studies.

References

[1] S. Priyadarshi, "Advancing AI Scalability and Performance with Optical Interconnects," *IEEE Commun. Mag.*, 2025.

[2] P. Castoldi *et al.*, "Shaping the future of optical networks by integrating SDN, telemetry, and AI [Invited]," *J. Opt. Commun. Netw.*, 2025.

[3] O. Karandin *et al.*, "Probabilistic low-margin optical-network design with multiple physical-layer parameter uncertainties," *J. Opt. Commun. Netw.*, 2023.

[4] T. Inoue *et al.*, "Quality Analysis of Uniform and PS QAM Signals Distorted by Arbitrary Filtering Effects of WSS in ROADM-Based Optical Network," *J. Lightw. Technol.*, 2024.

[5] S. Hu *et al.*, "Supporting Probabilistic Constellation Shaping in 5G-NR Evolution," *IEEE Trans. Wireless Commun.*, 2024.

[6] J. Cho *et al.*, "Shaping lightwaves in time and frequency for optical fiber communication," *Nat. Commun.*, 2022.

[7] B. Chen *et al.*, "On Shaping Gain of Multidimensional Constellations in Linear and Nonlinear Optical Fiber Channel," *IEEE J. Sel. Areas Commun.*, 2025.

[8] D. Semrau *et al.*, "A Modulation Format Correction Formula for the Gaussian Noise Model in the Presence of Inter-Channel Stimulated Raman Scattering," *J. Lightw. Technol.*, 2019.

[9] H. Buglia *et al.*, "A Closed-Form Expression for the Gaussian Noise Model in the Presence of Inter-Channel Stimulated Raman Scattering Extended for Arbitrary Loss and Fibre Length," *J. Lightw. Technol.*, 2023.

[10] J. Song *et al.*, "Model-based end-to-end learning for WDM systems with transceiver hardware impairments," *IEEE J. Sel. Top. Quantum Electron.*, 2022.

[11] Y. Xu *et al.*, "Physical-layer impairment estimation for arbitrary spectral-shaped signals in optical networks," *Opt. Express*, 2022.

[12] N. Guo *et al.*, "Can Channel Power Optimization with GSNR Flatness Maximize Capacities of C+L-Band Optical Systems and Networks?" *J. Lightw. Technol.*, 2024.

[13] J. Cho *et al.*, "On the Kurtosis of Modulation Formats for Characterizing the Nonlinear Fiber Propagation," *J. Lightw. Technol.*, 2022.