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# Spatially Disaggregated Modelling of Coherent Cross-Channel Interference in Dispersion-Managed Optical Links

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**Abstract**—Accumulation of non-linear noise in transmission of coherent signals over dispersion-managed network segments can be severe due to the small chromatic dispersion accumulated in each span due to optical inline dispersion compensation resulting in noise contributions originated in different spans to sum up coherently. Moreover, small chromatic dispersion slows down the signal to take on gaussian distribution. These effects are properly accounted within traditional modeling schemes such as the gaussian noise model family, especially when mixed fiber types are considered. In this work, we propose a machine learning-assisted, spatially disaggregated approach extending the classic GN model, able to provide instantaneous and accurate non-linear noise estimation of coherent channels propagating in sections of mixed fiber types, dispersion managed links.

**Index Terms**—optical networks, digital twin, NLI

## I. INTRODUCTION

Modern high-capacity optical networks rely on dual-polarization (DP) coherent transmission, which performs best over uncompensated transmission (UT) links [10]. Never-

theless, numerous legacy links based on dispersion-managed (DM) infrastructures—originally designed for IMDD systems—are still present in metro, access and even submarine segments. While new cable deployments adopt UT to support coherent transmission, enabling coherent channel routing over pre-existing DM infrastructures would notably enhance network throughput and maximize operators' return of investments. The dominant impairment in coherent optical systems is non-linear interference (NLI), mainly composed of self-channel interference (SCI) and cross-channel interference (XCI) [3], [5], [8]. In UT links, disaggregated models allow precise spectrally (per-channel) and spatially (per-span) disaggregated NLI estimation due to the high accumulated dispersion, which ensures minimal correlation between fiber spans and supports the assumptions of the Gaussian Noise (GN) model [1], [2]. In DM systems, the use of in-line dispersion compensation schemes leads to reduced accumulated dispersion in each system span, leading to two effects that violate GN model assumptions [3]. As shown in Fig.1, on one side, the signal distribution reaches the gaussian distribution (the signal *gaussianization*) more slowly, so that the amount of intrinsic SCI/XCI noise estimated by the classic GN model is largely conservative [3], [9], [11]. On the other side, SCI/XCI noise contributions sum up coherently at the receiver as they are not properly decorrelated by dispersion [4], [5]. This spatial correlation among nonlinear contributions introduces a memory effect, which complicates the spatial disaggregation property. As optical networks are leaning towards open and disaggregated networking is crucial to develop disaggregated NLI estimation models to build the physical layer digital twin [1], supporting realistic optical segments made up of mixed fiber types and non-periodic dispersion compensation schemes. In this context, accurate models have been proposed and validated, such as the enhanced GN (EGN) model [11], although computationally intensive and based on an *aggre-*

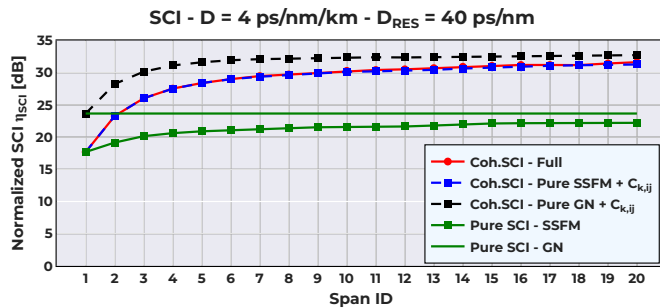


Fig. 1. Example of the per-span normalized SCI power modeling in periodical DM link with inline residual dispersion of 40 ps/nm and fiber dispersion coefficient of 4 ps/nm/km. Red curve is the overall ground truth SCI intensity. Green continuous is the pure SCI terms using GN model, green/squares curves account for the *Gaussianization*. Adding coherency effects deliver the blue and black curves based on the respective baseline pure terms.

gated approach. A spatially disaggregated approach was first proposed in [4]. In [5] we extended the GN model to address SCI spatial coherency to account for SCI coherency and in [6] we extended the approach to XCI. Nevertheless, signal non-gaussian distribution and correlation effects - key contributors to model inaccuracy — were previously addressed only heuristically. In this work, we build on previous contributions by combining machine learning (ML) techniques with the GN model to enable accurate and conservative estimation of both coherency and Gaussianization in mixed fibers DM links for a per-span, spectrally disaggregated NLI prediction. By training machine-learning (ML) regressors on large split-step Fourier method (SSFM) simulation datasets, we demonstrate that the resulting model achieves high accuracy while enabling NLI evaluation in the millisecond timescale, thus enabling real-time quality-of-transmission (QoT) estimation in heterogeneous optical networks digital twins featuring legacy DM spans.

## II. NLI SIMULATION AND MODELING

The most general system abstraction considered for the presented modeling approach is depicted in Fig.2. The  $i$ -th fiber span introduces a *pure*, intrinsic XCI random noise field process  $n_{XCI,k,i}$  which undergoes its own and the subsequent's span chromatic dispersion, being  $k$  the pump index relative to channel under test (CuT) (we refer to SCI as the XCI term with  $k = 0$  for brevity). After dispersion compensation and matched filtering at the coherent digital-signal-processing (DSP) receiver, the total XCI noise power of the  $k$ -th pump up to the span  $i$ ,  $P_{XCI,k,i}$ , is calculated as the power of the sum of the pure XCI noise processes propagated up to the receiver. Assuming that their cross-correlation is not negligible due to the small amount of accumulated dispersion, the overall amount of XCI noise power introduced in the  $i$ -th span  $\Delta P_{XCI,k,i} = P_{XCI,k,i} - P_{XCI,k,i-1}$  can be modeled similarly to [5]. We will consider however the *normalized* SCI/XCI power  $\Delta\eta_{XCI,k,i} = \Delta P_{XCI,k,i} / P_{ch}^3$ , analogous to the classic GN model NLI efficiency [3]:

$$\Delta\eta_{XCI,k,i} = \rho_{k,i}^2 \sigma_{k,i}^2 + 2 \sum_{j=1}^{i-1} C_{k,ij} \cdot \rho_{k,i} \sigma_{k,i} \cdot \rho_{k,j} \sigma_{k,j} \quad (1)$$

Here,  $\sigma_{k,i}^2$  is the pure  $k$ -th pump,  $i$ -th span XCI power assuming worst case, gaussian distributed signal, thus well modeled by the classic GN model,  $\rho_{k,i} \in [0, 1]$  is the *gaussianization* coefficient, which accounts for non-Gaussian signal distribution. We refer then to the product  $\rho_{k,i} \cdot \sigma_{k,i}$  as the *pure* SCI/XCI term: the noise generated intrinsically by the  $i$ -th span alone, excluding any additional coherency power arising from correlation with other span contributions.  $C_{k,ij} \in [-1, 1]$  is a correlation coefficient quantifying the coherency between  $i$ -th span pure XCI term and each of the  $j$ -th ( $j < i$ ) preceding pure XCIs caused by the  $k$ -th pump. We define  $D_{ACC,(i,j)} = \sum_{k=j}^i D_k L_k$  as the cumulative dispersion from span  $j$  to  $i$ . Then  $\rho_{k,i} \rightarrow 1$  as  $D_{ACC,(i,1)}$  increases and with larger modulation formats [11], while the  $C_{k,ij}$  intensity decreases with larger  $D_{ACC,(i-1,j)}$  [5], [6].

Since a full analytical theory of  $C_{k,ij}$  and  $\rho_{k,i}$  is not yet fully understood, we decided to train two independent random forest regressors with 100 estimators assuming that their value is sufficiently described using the following features:

$$C_{k,ij} = f(D_i, D_j, D_{acc,(i-1,1)}, D_{acc,(j-1,1)}, D_{acc,(i-1,j)}, \alpha_i, \alpha_j, L_{s,i}, L_{s,j}, R_s, k \cdot \Delta f) \quad (2)$$

$$\rho_{k,i} = f(D_i, D_{acc,(i-1,1)}, \alpha_i, \gamma_i, L_{s,i}, R_s, k \cdot \Delta f) \quad (3)$$

The random forest regressors have been trained with an extensive dataset of  $C_{k,ij}$  and  $\rho_{k,i}$  values obtained with SSFM simulations utilizing the pump and probe approach, i.e. propagating each time only the CuT and a single  $k$ -th pumps spaced  $k \cdot \Delta f$  Hz. We run SSFM simulations accordingly to the scheme depicted in Fig.3, turning on the Kerr effect only in a single  $i$ -th span to extrapolate the pure XCI term and in a couple of spans ( $i, j$ ) to extrapolate the correlation coefficients.  $\rho_{k,i}$  is calculated as the ratio between the SSFM pure XCI and the GN model result ( $\Delta P_{XCI,k,i} / \sigma_{k,i}^2$ ).  $C_{k,ij}$  is obtained combining the  $\Delta\eta_{XCI,k,i}$  of the simulation with ( $i, j$ ) spans Kerr effect on and the respective pure terms. A first example test of Eq.1 is obtained using entirely simulated  $C_{k,ij}$  and  $\rho_{k,i}$  and reported in Fig.1 for the SCI term of the periodic link in [6], with residual dispersion at each span  $D_{RES} = 40$  ps/nm and  $D = 4$  ps/nm/km. Green curves show the progressive *gaussianization* by comparing the pure XCI terms to the GN model estimation. Reconstructing the coherency intensity using  $C_{k,ij}$  on top of the SSFM pure terms delivers the blue curve, which is perfectly overlapped to the ground truth red curve encompassing the overall phenomenon, thus confirming the validity of the coherency model approach.

To gather the ML dataset, we have considered a wide range of line configurations w.r.t. the fiber physical parameters and the dispersion compensation scheme. These, in particular, include periodic maps with a fixed residual dispersion left at the end of each span and more realistic maps with sparse, non-lumped, dispersion compensation fibers, similar to the test cable shown in Fig.4. The models' R2 score and MSE are 0.9969 and 0.0003 for the  $C_{k,ij}$  and 0.9772 and 0.001 for the  $\rho_{k,i}$ , respectively. We have validated the model against a multichannel SSFM simulation scenario with  $N_{ch} = 9$  channels at  $P_{ch} = -1.5$  dBm using DP-QPSK at  $R_s = 63$  GBaud with 6.25% rolloff, spaced  $\Delta f = 63$  GHz and taking the center channel as the CuT. SSFM provides the ground truth  $SNR_{NLI}$  value by estimation on the received constellation after adaptive equalizer using a DSP receiver placed at the end of each span.  $SNR_{NLI}$  is isolated by turning off ASE noise generation in simulation. The test cable dispersion map is reported in Fig.4. The cable is composed by 3x repetitions of a 7-spans module. Physical parameters and lengths of each fiber segments are slightly variable as they are measured from real hardware. The first 6 spans are composed by two NZ-DSF fiber segments (with dispersion coefficient  $D$  between -3.2 and -4 ps/nm/km and loss  $\alpha_{dB}$  around 0.2 dB/km) of 25 km in average, accumulating negative dispersion. Dispersion is then compensated by the 7th span,

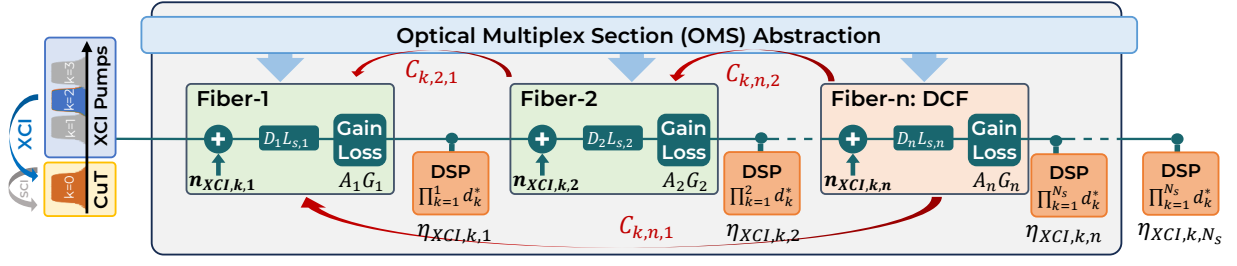


Fig. 2. Block diagram abstraction of a generic DM/UT OMS considered in this paper. SCI/XCI noise is modeled as a lumped noise field at the fiber input.

made up of about 50 km of SSMF fiber ( $D = 16$  ps/nm/km,  $\alpha_{dB} = 0.2$  dB/km) followed by about 10 km ( $D = -2.1$  ps/nm/km,  $\alpha_{dB} = 0.25$  dB/km) of LS fiber, leaving around 360 ps/nm residual dispersion at the end of each loop, thus representing a real deployed cable configuration. An optical amplifier operating in transparency with an assumed noise figure of 5.5 dB is placed after each 2x segments fiber span. For each pump, including SCI, we estimate the  $C_{k,i,j}$  for each couple of spans and the gaussianization correction  $\rho_{k,i}$  using the ML models. Simulated  $C'_{k,i,j}$  for SCI and XCI pumps  $k = [2, 4]$  are reported as heatmaps in Fig.5 (top). Stronger correlation on sub-diagonals corresponds to span couples  $(i, j)$  whose  $D_{ACC,(i-1,j)}$  is nearly zero. These values have not been used to train the ML model. The absolute error between the simulated  $C_{k,i,j}$  and the ML estimation is reported inside each cell when it's greater than 0.05. We observe weaker correlation and thus smaller estimation errors as the pump-to-probe frequency distance  $k \cdot \Delta f$  increases due to the walk-off effect. SCI correlation is instead stronger because this noise term is generated by the CuT signal itself. Fig.5 (bottom) compares also the pure XCI terms obtained using SSFM (blue) to the GN model corrected using  $\rho_{k,i}$  ML prediction, showing an almost perfect fit to the SSFM the ground truth.

We finally estimate the GSNR evolution along the link as  $GSNR_i^{-1} = SNR_{ASE,i}^{-1} + SNR_{NLI,i}^{-1}$ .  $SNR_{ASE}$  is trivially calculated using the common analytical formula. The accumulated non-linear SNR up to the  $i$ -th span  $SNR_{NLI,i} = P_{ch}/P_{NLI,i}$  model estimation is calculated using the spectral

disaggregation property by summing the noise contributions originated by each XCI pump and SCI using Eq.1 cumulatively over the  $N_s$  link spans:

$$P_{NLI,i} = \sum_k \sum_{n=1}^i \Delta P_{XCI_{k,n}} \quad (4)$$

where  $n$  is the span summation index up to the  $i$ -th span and  $k$  is the pump index.  $k = 0$  stands for the SCI contributions.  $k = [\pm 1, \dots, \pm 4]$  indexes the XCI pumps. To properly evaluate the model accuracy we report the GSNR estimation error, calculated as the dB difference  $GSNR_{SSFM} - GSNR_{Model}$  in Fig.6.  $GSNR_{SSFM}$  is the ground truth obtained using the  $SNR_{NLI}$  of the multichannel SSFM simulation. We consider instead three  $GSNR_{Model}$  versions to show the weight of the correlation and gaussianization effect in NLI estimation. The green curve considers the NLI estimated using the classic GN model. At the link end the estimation is non-conservative by 0.5 dB because it does not consider the coherency buildup and the gaussianization. We should note that the error is relatively small because the missing coherency power is compensated by pure terms overestimation due to the gaussian signal distribution worst-case hypothesis. However, this trend may easily worsen with longer links or different compensation schemes. The blue curve takes into account coherency but neglects the gaussianization, thus largely overestimation of 1.8 dB at the link end due to the worst-case GN model hypothesis. Finally, including the non-gaussian distribution correction (black) we get a conservative error of 0.9 dB, thus operating on the safe side and ensuring proper scaling of the physical effects.

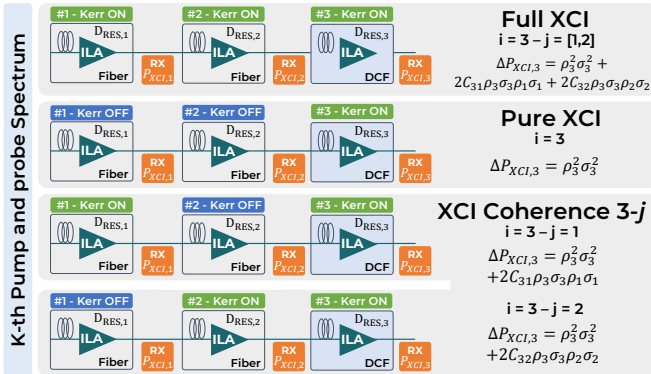


Fig. 3. Schematic of the three types of simulations carried out to isolate XCI components for a sample 3x span system. Pump index  $k$  omitted for clarity.

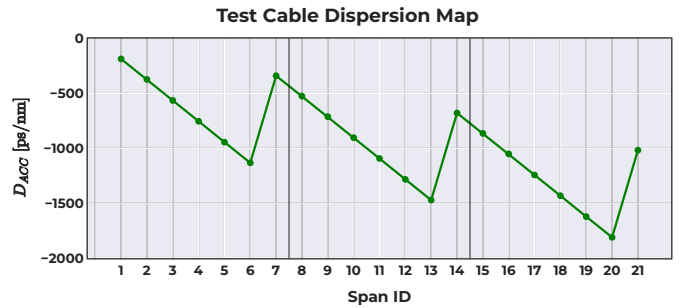


Fig. 4. Dispersion map of the tested cable.

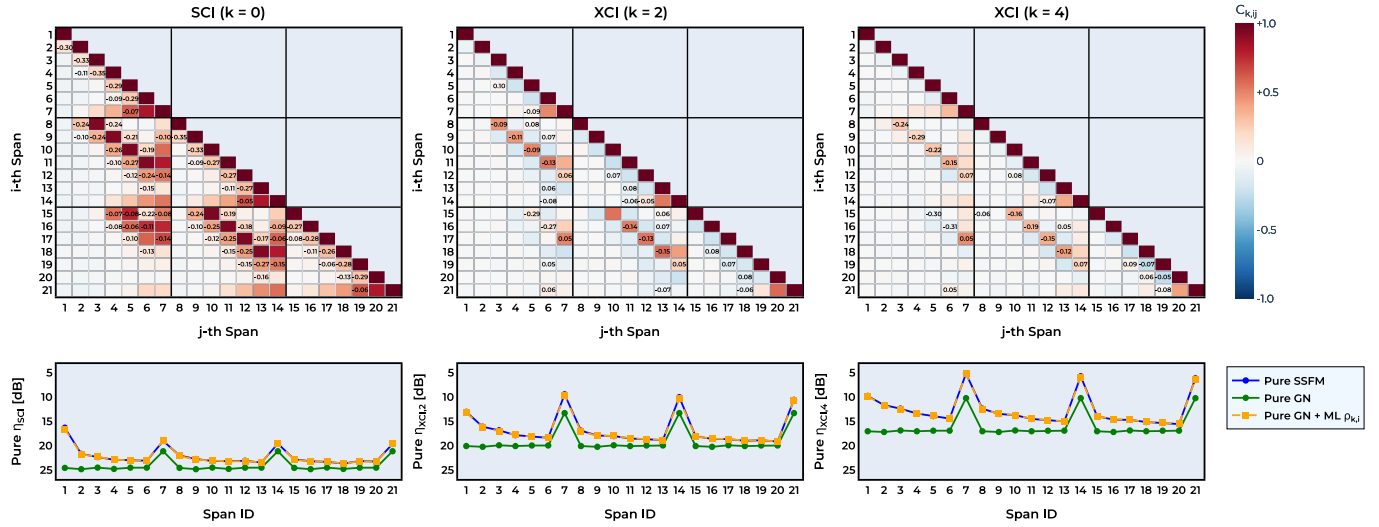


Fig. 5. ML model validation on the SCI (1st column), 2nd XCI pump (2nd column), 4th XCI pump (3rd column) on tested cable. Top: heatmaps of the ground truth correlation coefficients  $C_{k,ij}$  obtained with SSFM. Cell colors represent the correlation intensity between the  $i$ -th span (rows) and  $j$ -th span (columns). ML model absolute estimation error is reported with text when greater than 0.05. Bottom: Pure SCI/XCI term estimation vs span: worst case classic GN model (green), ground truth  $\eta_{XCI,k,i}$  obtained by SSFM (blue), corrected GN model estimation using ML  $\rho_{k,i}$  (orange).

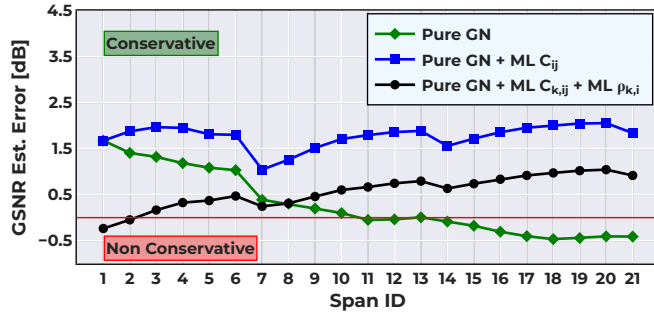


Fig. 6. GSNR estimation error  $\text{GSNR}_{\text{SSFM,dB}} - \text{GSNR}_{\text{Model,dB}}$ : GN model only (green), plus coherency effect  $C_{k,ij}$  (blue), plus non-gaussian distribution correction  $\rho_{k,i}$  (black).

## CONCLUSIONS

We introduced a semi-analytical framework for modeling NLI of coherent signals in DM network sections. This approach leverages the disaggregated structure of the GN model while explicitly incorporating the effects of spatial coherency and non-gaussian signal distribution enhanced by small accumulated dispersion. These two phenomena are here independently estimated through machine learning regressors trained on SSFM-generated datasets. Their integration enables a per-span, spectrally disaggregated NLI estimation, and allows for millisecond timescale, conservative GSNR prediction suitable for near real-time physical layer abstraction and digital twins.

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