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REAL-time monitoring and mitigation of nonlinear effects in optical **NET**works [REAL-NET] GA 813144

Deliverable 3.3 – Experimental demonstration of advanced optical nonlinear real-time performance monitoring techniques for EON

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Contents

LIST OF ACRONYMS

ANN	Artificial Neural Networks
CR	Constellation Reconstruction
DNN	Deep Neural Networks
DSP	Digital Signal Processing
EON	Elastic Optical Networks
FeX	Features Extractor
GMM	Gaussian Mixtures Models
LI	Linear Interference
ML	Machine Learning
NLI	Nonlinear Interference
OCATA	Optical Constellation Analysis Tool
QoT	Quality-of-Transmission
REAL-NET	REAL-time monitoring and mitigation of nonlinear effects in optical NETworks
ROADM	Reconfigurable Optical Add/Drop Multiplexer
SSMF	Standard Single Mode Fiber
WDM	Wavelength Division Multiplexing
WSS	Wavelength Selective Switches

1 EXECUTIVE SUMMARY

This document is a deliverable in the scope of REAL-NET project, and it is about the demonstration of advanced optical nonlinear real-time performance monitoring techniques for Elastic Optical Networks (EON). Concretely, we present an extension of the optical line system abstraction based on concatenation of Artificial Neural Networks (ANN) to simulate optical constellations presented in the previous deliverable D3.2 [1] and published in [2]. That extension includes a comprehensive tool adapted to mixed open-proprietary scenarios. Particularly, we consider segmented and differentiated propagation and analysis of linear (LI) and nonlinear (NLI) interference noise. Finally, we present a methodology to integrate the proposed optical constellation analysis tool (OCATA) with other vendor proprietary tools, which allows e2e modeling of signals transiting both open and vendor proprietary optical segments.

2 REPORT

2.1 Introduction

The study and development of applications for Quality-of-Transmission (QoT) estimation of optical signals based on Machine Learning (ML) methods has received huge research interest in the last years [3]. Currently, main initiatives for both industry and academic research are tackling realistic scenarios with the aim of providing robust and practical ML-based solutions for a wide range of use cases. In this regard, the adoption of the open optical networking paradigm enables the ML-based control, monitoring and management of multi-vendor infrastructures [4]. One essential feature of this paradigm is that it facilitates a more segmented and deeper QoT analysis than that of the typical tools designed and trained for e2e QoT analysis purposes [5]. However, full information of the physical system to be modeled is required for these tools to work properly. Note that this is a hard requirement in common brown-field legacy infrastructures, where new open-based equipment might coexist with legacy vendor proprietary infrastructure. Such mixed scenarios are really challenging for ML-based e2e analysis.

2.2 E2e optical constellation modelling in mixed open-proprietary scenarios

Fig. 1 illustrates the considered scenario where an optical signal traverses three different segments (S1..3) (Fig. 1a). Segments S1 and S3 follow the open-based paradigm and hence, precise information about network topology and optical devices configuration is fully available for analysis purposes. In contrast, S2 is vendor proprietary, which results into a restricted information availability and limits interaction through its management tools.

In line with the approach presented and published in [1] and [2], respectively, the open segments S1 and S3 can be modeled as a concatenation of ANNs that propagate forward a set of relevant features *F* that overall characterize the probability distribution of the symbols in each of the constellation points (Fig. 1b). A transmitter (Tx) module generates the initial set *F*, which is afterwards propagated forward through each of the ANN models representing each reconfigurable optical add/drop multiplexer (ROADM) and link in the lightpath. Due to the heterogeneous nature of noise, every element requires differentiated models for LI and NLI noise propagation with different input and output features, as explained in Subsection 2.3. Once the receiver (Rx) is reached, a constellation reconstruction (CR) procedure is applied to get a constellation sample following the probability distribution characterized by the propagated features.

However, in the presence of an intermediate vendor proprietary segment (S2 in Fig. 1), an adaption module is required. Such module should be designed to integrate data from the vendor proprietary segment and allow e2e optical constellation analysis. The designed adaption module consists of three different blocks:

i) a CR module that transforms the propagated features from segment 1 (FS1) into constellation samples CS1;

ii) a dedicated interface I that interacts with the proprietary QoT tool (it pushes CS1 and gets the resulting constellation -CS2- after S2. Without loss of generality, we assume that the proprietary QoT tool is able to compute both LI and NLI noise introduced by S2 on the initial constellation CS1; and

iii) the feature extraction (FeX) module that processes CS2 and extracts the initial features FS2 for differentiated LI and NLI propagation in the last segment. Note that the inputs to the FeX module include both constellation CS2 and features FS1 in order to account for the effects of the accumulated distance from Tx, which is essential for accurate NLI modeling.

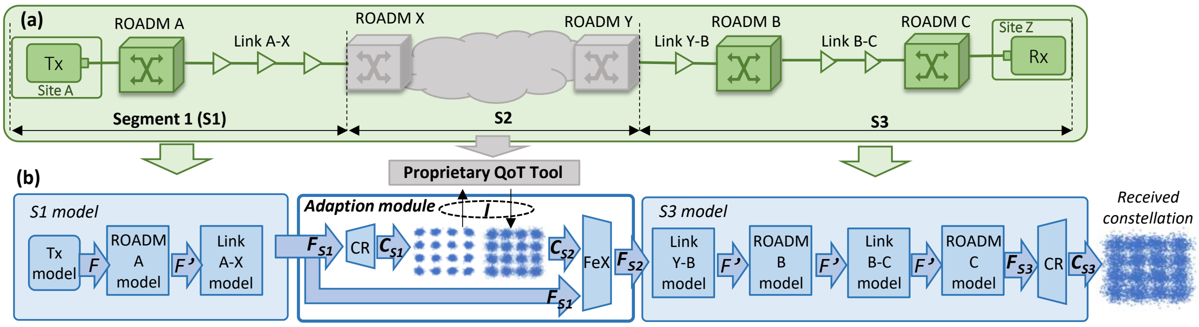

Fig. 1. Path example (a) and proposed e2e modeling (b).

2.3 OCATA LI and NLI modelling and adaption procedure

Error! Reference source not found. details OCATA for differentiated propagation of LI and NLI along the path. For the sake of simplicity, we represent a segment with the three elements that compose the path, i.e., Tx, ROADMs, and optical links. The Tx generates the initial features set F with the following components: i) XLI that contains, for every constellation point p, the features that characterize the dispersion of the symbols around the expected centroid due to LI. Accurate characterization is achieved by modeling constellation points as bi-variate Gaussian distributions with vectors μ and σ for the mean and deviation, respectively of both real and imaginary components [2]**Error! Reference source not found.**; ii) ΔXNLI that contains the variations (residuals) to be applied to each of the previous LI features due to NLI; and iii) d, which accounts for the total accumulated distance from the Tx. ROADMs introduce LI noise only and thus, they are modeled as DNNs that propagate XLI features, modifying them according to the specifications of the ROADM. Since they do not introduce NLI, input residuals ΔXNLI are just forwarded without modifications together with the accumulated distance. Finally, optical links are modeled as two specific DNNs for LI and NLI components. As previously introduced, the NLI DNN model receives as input the residuals from the previous elements, the distance of the link, and the accumulated distance of the path, which is updated with the distance of the link after NLI propagation.

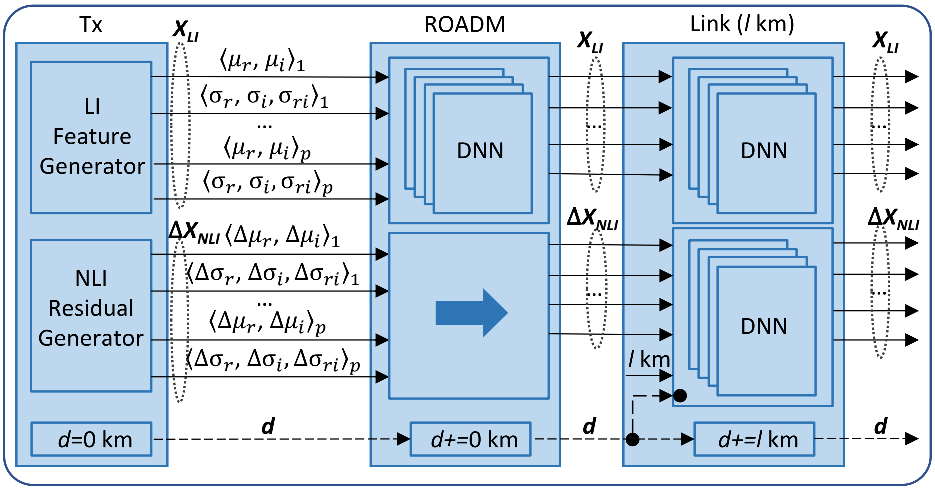

Fig. 2. Differentiated LI and NLI modeling in OCATA.

In addition to the above elements, Algorithm 1 presents the steps performed during the adaption procedure, which is needed when modeling a mixed scenario. For the sake of clarity, we have adapted the notation to the example in Fig. 1a. The algorithm receives the set of features FS1 obtained after propagating segment S1, interface I to communicate with the vendor's QoT tool, the total distance of segment S2, lS2, and the database DB of trained models. After some initialization, constellation reconstruction done by sampling bi-variate Gaussian distributions with features in FS1 is performed to obtain constellation sample CS1 (lines 1-2 in Algorithm 1). Then, the generated constellation is sent through interface I to the QoT tool, which will compute and return the resultant constellation CS2 (line 3). Note that this constellation combines both LI and NLI effects after passing segments S1 and S2. Therefore, before continuing with segment S3, we first separate LI and NLI components by by propagating the obtained residuals after S1 in a segment of length equal to S2; for this purpose, the NLI component of a trained link model of length lS2 is used (lines 4-5). Once the residuals characterizing those NLI after S2 are computed, the LI features can be easily extracted by firstly fitting μ and σ vectors on the received constellation CS2 (denoted as Xaux) and then, subtracting the obtained residuals (lines 6-7); the computation of μ and σ vectors in a given constellation is performed by means of Gaussian mixture model fitting techniques [6]. The accumulated distance d is updated with the length of S2 (line 8) and the set of features FS2 to be propagated through the next segment is eventually returned (line 9).

Algorithm 1. OCATA adaption procedure.

INPUT: F_{S1}; I, DB, l_{S2}
OUTPUT: F_{S2}

1: $F_{S2} \leftarrow \emptyset$
2: $C_{S1} \leftarrow$ constReconstr(F_{S1}.X$_{\mathrm{LI}}$, F_{S1}.ΔX$_{\mathrm{NLI}}$)
3: $C_{S2} \leftarrow I$.post(C_{S1})
4: $\lambda \leftarrow DB$.getModel('link', l_{S2})
5: F_{S2}.ΔX$_{\mathrm{NLI}}$ $\leftarrow \lambda$. NLI.forward(F_{S1}.ΔX$_{\mathrm{NLI}}$, F_{S1}.d)
6: $X_{aux} \leftarrow$ gmmFitting(C_{S2})
7: F_{S2}.X$_{\mathrm{NLI}}$ $\leftarrow X_{aux}$ - F_{S2}.ΔX$_{\mathrm{NLI}}$
8: F_{S2}.d $\leftarrow F_{S1}$.d + l_{S2}
9: **return** F_{S2}

2.4 Illustrative Numerical Results

A MATLAB-based digital coherent system simulator has been implemented to evaluate OCATA's performance. We assume an 11-channel Wavelength-Division Multiplexing (WDM) system, where all channels are configured with 16QAM@64GBd and 75 GHz channels spacing. At the transmitter side, 2^{15}-bit pseudo-random binary sequence are modulated and shaped by a root-raised cosine filter with a roll-off factor of 0.06. Next, an optical multiplexer aggregates the individual signals and creates the WDM signal to be propagated through the lightpath. The optical fiber spans are composed of standard single mode fiber (SSMF) characterized by an attenuation factor of 0.21 dB/km, a chromatic dispersion parameter of 16.8 ps/nm/km, and nonlinear parameter of 1.14 1/W/km. The pulse propagation is modeled by solving the nonlinear Schrödinger equation using the split-step Fourier method with a propagation step size of 100 m. Erbium doped fiber amplifiers with noise figure of 4.5 dB and ideal gain are considered. We assume ROADMs based on commercially available Wavelength Selective Switches (WSS), which are modeled as in [7]. Finally, digital signal process (DSP) blocks capable to perform ideal chromatic dispersion compensation and carrier phase recovery are considered in the receiver.

The simulator was used to generate the datasets needed for training, testing, and validating the models. Four different optical link configurations in terms of total length have been considered: 100-km (2x50-km spans), 240-km (4x60-km spans), 400-km (5x80-km spans), and 560-km (7x80-km spans). For each configuration, up to 4 hops were considered leading to total lightpath length ranging between 100 and 2240 km. To train the models, 30 signal samples with 8,200 symbols each were generated for each link and ROADM configuration.

In line with **Error! Reference source not found.** and [D3.2], we limit the number of constellation points to be propagated to the minimum providing just enough information to capture the overall constellation behavior. Particularly for 16QAM, two outer (-3+3i, 1-3i) and two inner (1+1i and -1-1i) constellation points are selected. In consequence, link and ROADM DNNs for LI modeling have 24 input and output neurons, with two hidden layers (12 + 12 neurons with hyperbolic tangent -tanh- activation function). In addition, DNNs for NLI modeling in links contain 26 inputs (24 residuals + link length + accumulated distance), three hidden layers (20 +10 + 5 with tanh activation function) and 24 outputs.

The first numerical study is intended to validate the proposed deep neural network (DNN)-based modeling approach for a fully open scenario, i.e., perfect information of all network elements in the path is available. **Error! Reference source not found.**a shows the maximum relative error for estimating received features μ and σ at Rx as a function of path distance. Negligible error for μ is observed, whereas σ error rapidly decreases with path length, being acceptably low (~15%) for a wide range of distances (>200 km). In **Error! Reference source not found.**b, simulated -3+3i constellation point samples obtained after 400 and 1200 km are depicted. The bi-variate Gaussian distribution that better fits such simulated sample is depicted in dashed red lines, whereas the Gaussian distribution obtained with the DNN-based concatenated model is plotted in solid black lines. We observe that both simulated and modeled distributions are virtually identical. Besides, the proposed Gaussian distribution-based characterization allows a likely modeling of the constellation points in the presence of NLI noise. Notice that, Gaussian Mixtures Models (GMM) are used to extract the bi-variate Gaussian distribution of the desired signal samples.

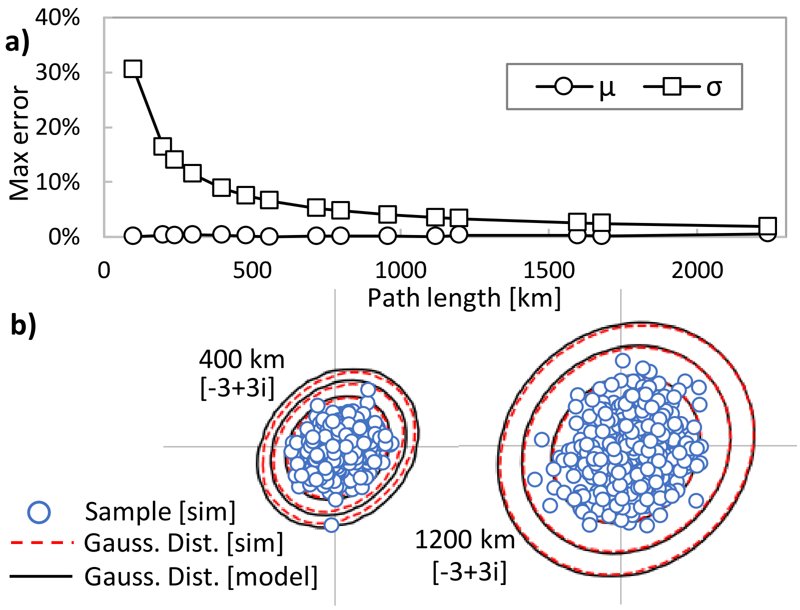

Fig. 3. DNN-based modeling performance

Let us now focus on a mixed scenario based on that in Fig. 1a, where the intermediate segment S2 uses a proprietary QoT tool and requires running the proposed adaption module to perform e2e modeling. For the sake of simplicity, we use as QoT tool an instance of our MATLAB simulator. Thus, after running S1 DNN concatenation model, constellation after S1 is reconstructed from features, sent to the simulator to compute the resultant constellation after S2 and returned back to features that are propagated through S3 model. For benchmarking purposes, open scenario assuming perfect knowledge of S2 devices was also evaluated. Fig. 4 shows the evolution of Gaussian distribution features for constellation points -3+3i and -1-1i as a function of path length. As expected, variance increases with path length. However, the use of the intermediate QoT tool underestimates its true value, although such under-estimation follows a simple behavior easy to correct (constant increment independent of path length). This suggests the use of additional models to estimate such corrections as part of the proposed DNN-based concatenation model.

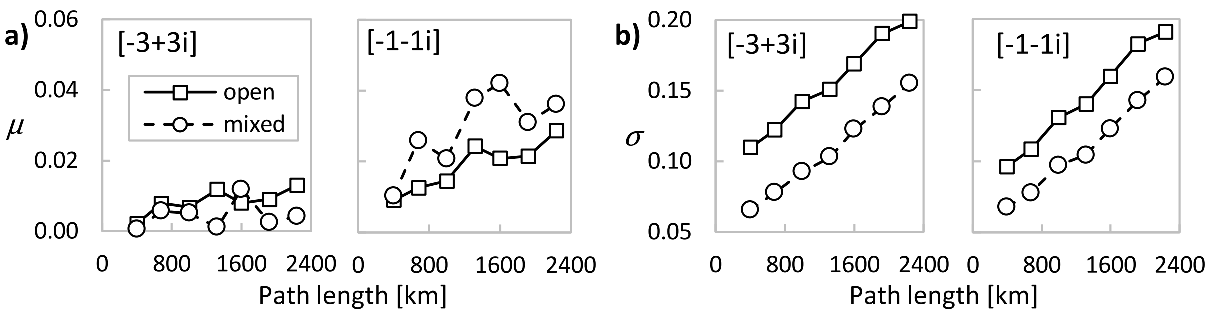

Fig. 4. Mixed vs open scenarios performance

Finally, Table 1 evaluates whether the proposed methodology is able to detect potential misconfiguration of the model due to inaccurate available information of S2. We account for the total difference between samples whose actual and expected S2 length differs, by using the logarithm of the chi-square statistic **Error! Reference source not found.**. This experiment was carried out for several combinations of S2 length and two different scenarios for total S1 + S3 length. In all the cases, differences between actual and expected S2 length are clearly detected since the statistic values are remarkably larger than a threshold value (around -3) for which all correct cases stay below.

Table 1. S2 length misconfiguration detection

***S1*+*S3*=200 km**

	S2 [km]	Expected 200	Expected 640	Expected 1120
Actual	*200*	**-3.8**	-1.7	-0.7
Actual	*640*	-1.5	**-4.2**	-1.5
Actual	*1120*	-0.9	-1.3	**-4.4**

***S1*+*S3*=1000 km**

	S2 [km]	Expected 200	Expected 640	Expected 1120
Actual	*200*	**-5.1**	-2.0	-0.9
Actual	*640*	-1.7	**-4.8**	-1.1
Actual	*1120*	-1.0	-1.2	**-4.7**

2.5 Conclusions

In conclusion, we have introduced an extension of our approach to model optical constellations by means of ANN concatenation, where we integrated a tool adapted to mixed open-proprietary scenarios. Nowadays, there is not full information about the physical systems, i.e., fiber parameters, then for those mixed open-proprietary network scenarios, adaptation modules are needed to e2e modelling proposes. In this way, we are able to optical constellations monitoring and analysis providing a comprehensive understanding of the several impacts in a modelled lightpath. For example, by real-time monitoring the optical constellations, we can predict the amount of the NLI noise added to the optical signal. Note that, NLI noise will turn the received constellation symbols more elliptical, and those impairments are presented in the features extracted by GMM fitting.

3 REFERENCES

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