Creating and Tuning Multiband Optical Transmission Digital Twin Lightpath Models

Sadegh Ghasrizadeh [1], Nelson Costa [2], Marc Ruiz [1], Antonio Napoli [3], Joao Pedro [2,4], and Luis Velasco [1,*]
[1] *Universitat Politècnica de Catalunya*, Spain, [2] *Infinera*, Portugal, [3] *Infinera*, Germany, [4] *Instituto de Telecomunicações*, Portugal
*email: *luis.velasco@upc.edu*

***Abstract*—Optical Digital Twins (DT) require pre-trained models for estimating the Quality of Transmission (QoT) of candidate lightpaths in multiband (MB) optical networks before they are provisioned. Once lightpaths are established, those models need to be tuned to be used for failure management, e.g., degradation detection. In this paper, we concentrate on the MB OCATA DT, which models optical signal propagation in the time domain. We first evaluate strategies for creating end-to-end lightpath models from span DNNs and then, we implement model tuning, as a building block of the MB OCATA DT. Simulation results show the accuracy of pre-trained models for QoT estimation and how they are tuned with telemetry measurements and improved compared to the initial pre-trained models.**

Keywords—Optical Digital Twin, Multi-band Optical Transmission, Digital Twin Lightpath Models

I. Introduction

Optical layer digital twins (DT), like OCATA [1], have many applications for network operation, from lightpath provisioning to failure management [2]. Specifically, the OCATA DT is able to accurately estimate the pre-forward error correction (FEC) bit error rate (BER) of C+L+S multiband (MB) transmission systems, where the inter-channel stimulated Raman scattering becomes a major effect [3]. OCATA models the propagation of in-phase (I) and quadrature (Q) optical constellations along optical spans. *First principle* Deep Neural Networks (DNN) are pre-trained beforehand and stored in a model database (DB), where they are available to become part of an end-to-end (e2e) lightpath model, which are created by concatenating span DNNs of the characteristics defined by the route of the lightpath, i.e., the span length, and channel. In [3], we reduced the number of pre-trained models to just a selection reference channels (RCh) and proposed a feature composition method to estimate the features for any channel in the C+L+S bands, based on the output of the models propagating the features of the RChs.

In this work, we face the problem of creating accurate e2e lightpath models from pre-trained span models. Several sources of error can be found in the process of creating e2e lightpath models. We focus on the fact that span models are trained for specific span lengths, which might not match with the ones in the network. Even though e2e models can be used for pre-FEC BER estimation for candidate lightpaths during provisioning, discrepancies between them and the real optical system once the lightpath is established can reduce their effectiveness for failure management. To that end, lightpath models are tuned using telemetry after provisioning.

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II. OCATA DT Modeling and QoT Estimation

OCATA defines IQ optical constellation samples X as sequences of symbols $x \in X$, with each symbol corresponding to one of m constellation points (CP) in an m-QAM optical signal [1]. Samples are then condensed into a set of constellation features Y, where each Y^i represents the characteristics of a CP i. The feature extraction (FeX) process employs Gaussian Mixture Models (GMM) [4] to model a given sample X as a set of bivariate Gaussian distributions, one per each CP. Consequently, the vector $Y^i=[\mu^I,\mu^Q,\sigma^I,\sigma^Q,\sigma^{IQ}]$ is defined by five features, i.e., the mean I and Q positions (μ) within the constellation, and the real and imaginary variance and symmetric covariance terms (σ) experienced by the symbols of CP i around the mean.

Two constellation samples (X_1, X_2) can be compared by computing the difference between them in terms of the Euclidean distance of their features (Y_1 and Y_2) [1], as follows:

$$diff_Y(X_1, X_2) = \|Y_1 - Y_2\|_2 \quad (1)$$

Furthermore, pre-FEC BER can be estimated from features Y. Specifically, the parameter Φ^i_{out} was defined in [2] to represent the probability of receiving a symbol originally sent as part of CP i, out of the detection area A^i assigned to that CP.

$$\Phi^i_{out} = 1 - P\left(x \subset A^i \middle| x \sim \mathcal{N}(Y^i)\right) \quad (2)$$

Then, the estimated pre-FEC BER can be computed based on Φ^i_{out} for all the CPs as eq. (3), where the average probability Φ_{out} is interpreted as an estimation of the symbol error rate, and the pre-FEC BER is derived assuming that 1 symbol error causes only 1 bit with error, i.e., assuming Gray coding.

$$\text{pre-FEC BER} \sim \frac{1}{m \cdot \log_2(m)} \sum_{i=1}^{m} \Phi^i_{out} \quad (3)$$

III. Lightpath Model Composition and Tuning

We assume the scenario represented in Figure 1, where a MB optical network is composed of MB optical transponders (TP) and optical amplifiers, and each amplifier includes erbium-doped fiber amplifier (EDFA) for C and L bands and thulium-doped fiber amplifier (TDFA) for the S band. A Software-Defined Networking (SDN) controller is in charge of lightpath provisioning and telemetry data collection, while the OCATA DT runs besides the SDN controller to provide QoT estimation and failure management. For illustrative purposes, a lightpath between the TPs in sites A and Z is represented.

The model DB in OCATA includes pre-trained span DNNs, so lightpath models can be easily created. Using pre-trained span models introduces some error coming from: *i*) data used

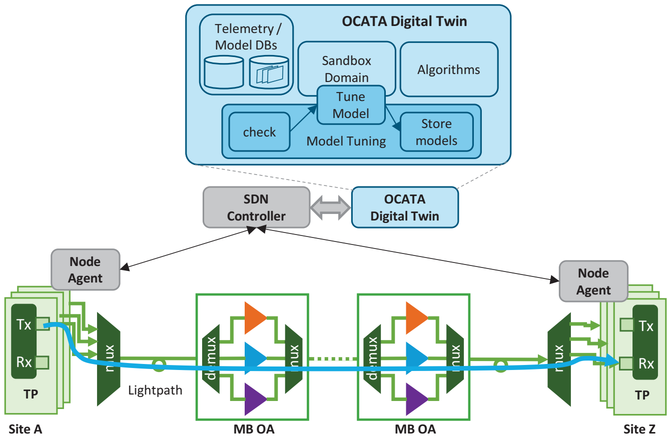

Figure 1: OCATA digital twin architecture

for pre-training can come from slightly different devices than the ones in the network and aging impacts also their behavior; *ii*) span models are trained only for RChs, which might not match the channel allocated for the lightpath; and *iii*) span models are trained for specific span lengths, which might not match with the ones in the network. The first two sources of error impact the accuracy of the models mainly for their use after the lightpath is established, as the final error for QoT estimation should be insignificant [3]. However, that of the span lengths might have a significant impact on the accuracy of the models.

In this paper, we explore and evaluate the error of lightpath models under two alternative approaches for lightpath model composition: *i*) the *per-span composition* (Algorithm 1) finds the span DNNs modelling the closest as possible span length for each of the spans in the links (*E*) of the route of the lightpath. However, this approach can lead to significant inaccuracy on the total distance modelled by the resulting concatenated DNN; and *ii*) the *distance-based composition* (Algorithm 2) selects the span models finding both the correct per-link span models, as well as reducing the total distance error. The algorithm keeps track of the accumulated error in the distance and finds the best sequence of span lengths that results in minimum length error. The span models are concatenated into a single DNN that can be used for QoT estimation.

In MB optical transmission, the algorithms are executed for the two RChs adjacent to the actual channel allocated to the lightpath, in the general case where the allocated channel is not one of the RChs, and QoT estimation is performed by applying eq. (3) on the features resulting from the feature composition procedure in [3]. In addition, the lightpath model created from span models of the RCh closest to the allocated one is stored in the model DB.

Once the lightpath is deployed, the e2e lightpath model will be in place. Therefore, it needs to be tuned using telemetry data. Specifically, the new *Model Tuning* building block is proposed and integrated in the OCATA DT architecture. The block runs Algorithm 3 periodically to check whether major deviations are detected, in which case, the lightpath model is updated using eq. (1) as loss function. The reason of the model update can be analyzed afterwards to detect degradations.

Algorithm 1. Per-span LP model composition

```
INPUT: E, RCh                OUTPUT: e2e_dnn
DNNList ← []
for each e in E do
    for each s in e.spans do
        DNNList.add(ModelDB.get(RCh, s.length))
return concatenate(DNNList)
```

Algorithm 2. Distance-based LP model composition

```
INPUT: E, RCh                OUTPUT: e2e_dnn
DNNList ← []; dtraversed ← 0; dmodels ← 0
for each e in E do
    d ← e.length + dtraversed – dmodels
    spanLengths ← findOptimalSpans(d, e.spans)
    for each l in spanLengths do
        dnn ← ModelDB.get(RCh, l))
        dmodels ← dmodels + dnn.getLength()
        DNNList.add(dnn)
    dtraversed ← dtraversed + e.length
return concatenate(DNNList)
```

Algorithm 3. Model Tuning

```
INPUT: lp                    OUTPUT: Updated
1: M ← ModelDB.get(lp))
2: [X] ← TelemetryDB.getSamples(lp, period, K)
3: [Y] ← FeX([X])
4: lpBER← estimateAvgBER([Y])
5: if RE(M.getBER(), lpBER) ≤ MAX_ERROR do return False
6: dnn ← SANDBOX.tune(M.getDNN(), [Y])
7: ModelDB.store(M.setDNN(dnn), lp)
8: return True
```

Algorithm 3 receives the Id of the lightpath and returns whether the lightpath e2e model has been or not updated. The algorithm first gets the last version of the model *M* from the model DB (line 1). *M* includes the concatenated model together with some additional metadata. Next, telemetry samples are retrieved from the telemetry DB (line 2). *K* samples are randomly selected from the ones collected during the last period and features are extracted (line 3). The vector of features is used to estimate the average pre-FEC BER that the lightpath has experienced during the period (line 4). That value is compared to model estimation and the relative error (RE) is checked against a maximum allowable relative error and, in case the maximum error is not exceeded, the model is not updated (line 5). Otherwise, the concatenated DNN is retrieved from *M* and sent to the Sandbox to be trained with the features from telemetry. The tuned DNN is replaced in *M* and updated in the model DB, and the algorithm returns model updated (lines 6-8).

IV. Results and Discussion

To evaluate the algorithms proposed in the previous section, we use the data from the MB optical transmission simulator in [5]. 16QAM signals at 32 GBaud using pseudorandom 2^{16}-bit sequences for each channel were generated with 0.06 root-raised cosine roll-off. Signals were launched with 0 dBm in a 50 GHz grid and transmitted through standard single-mode fiber. At the receiver, IQ constellations are collected after ideal chromatic dispersion compensation and phase recovery. To clearly observe the error in models' accuracy, two very different span scenarios were simulated, with spans of 50 and

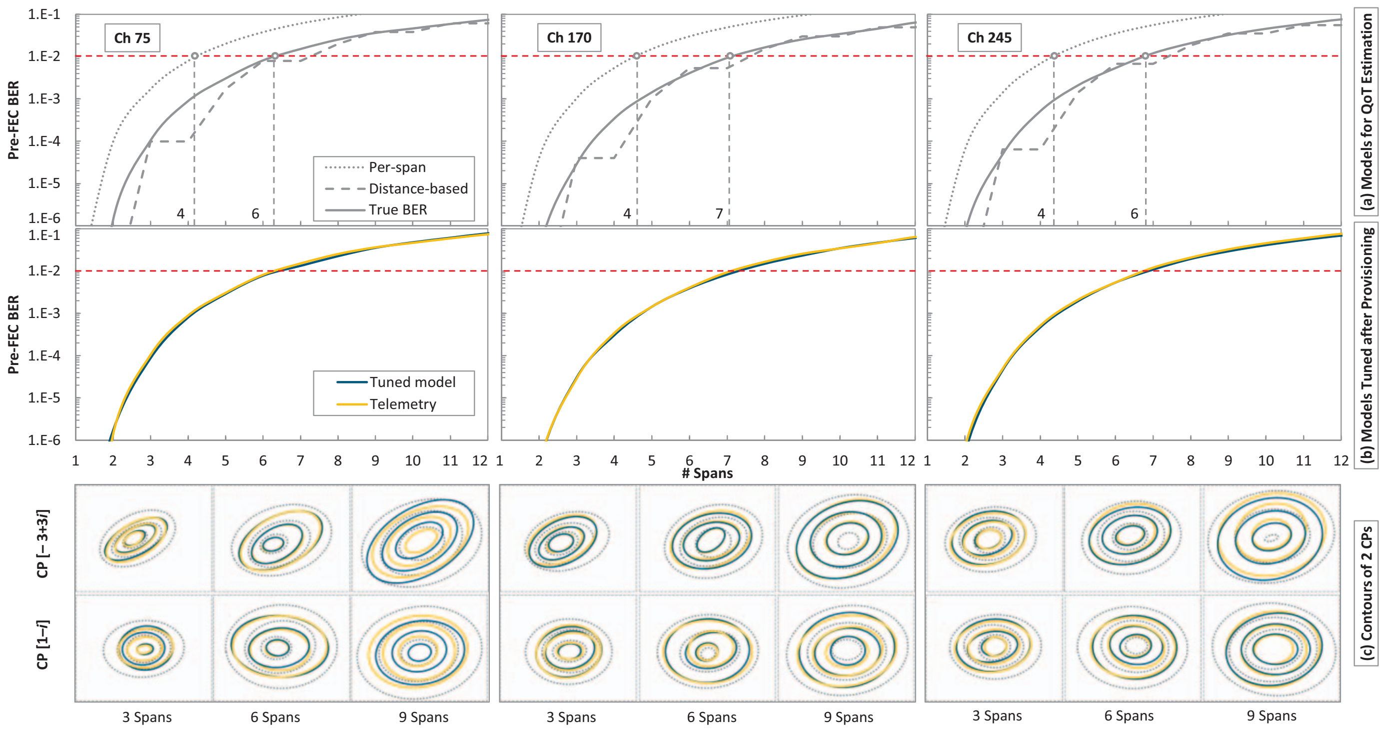

Figure 2: Pre-FEC BER vs # of spans (50 km) before (a) and after tuning (b). (c) Contours of bivariate Gaussian distribution for two CPs.

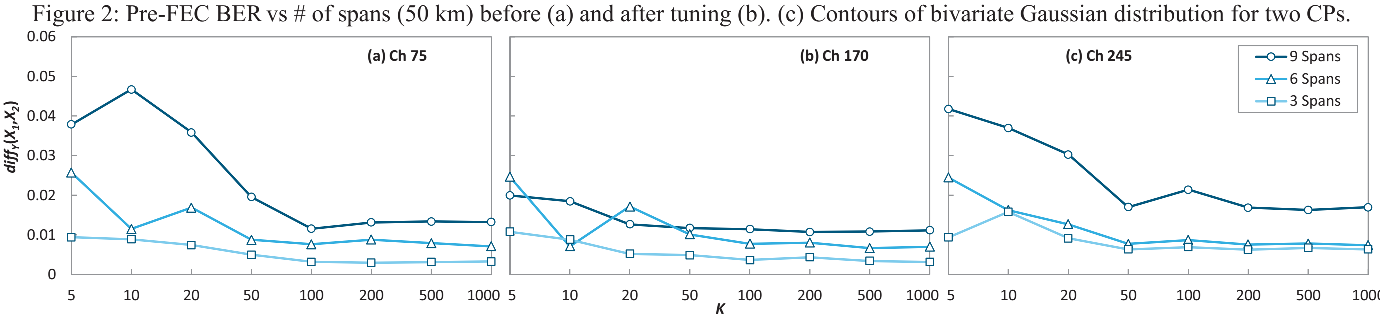

Figure 3: Average error between model and telemetry features vs number of samples *K* for three non-reference channels.

80 km. Samples from 80 km span scenarios were used for modelling spans for 7 RChs, as in [3], whereas lightpaths were evaluated and established on 50 km span scenarios using non-reference channels 75, 170, and 245, in the S, C and L bands, respectively.

Figure 2a shows the estimated QoT when e2e model composition is carried out using the per-span and the distance-based approaches for the three Chs vs the number of spans of the lightpath (each of 50 km). We observe that the per-span tends to overestimate the QoT, which results in provisioning requests rejected for lightpath exceeding 4 spans in all the bands, i.e., 2-3 spans shorter, when compared with the true BER. On the opposite, the distance-based approach is much more accurate, with the level of accuracy depending on the number of traversed spans, which is a result of the difference of span lengths between the real ones (50 km) and the ones used for modelling (80 km). Even though the results show poor performance for both approaches in several cases, the proposed algorithms are still powerful tools to optimize the characteristics of the models to be pre-trained, so to minimize the error in the QoT estimation of candidate lightpath.

Figure 2b shows the QoT estimation of the e2e models after model tuning. In this case, we observe remarkable accuracy in the QoT estimation for all three Chs. Figure 3 plots the evolution of eq. (1) with the number of samples during model tuning in the sandbox domain. In all the cases, 200 samples are enough to produce very low difference between the samples from telemetry and the model. Finally, Figure 2c shows the contours for one external and one internal CP of the models after composition and after tuning. It is clear, in the view the noticeable similarity, the observed improvement in the accuracy of the models.

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