Demonstrating Lightpath Operation with the OCATA Digital Twin in Multiband Optical Networks

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***Abstract* – In this work, the outline for a live demonstration of the multiband OCATA digital twin is presented. This digital twin enables intelligent functions such as quality of transmission (QoT) estimation and adaptive model tuning, among other functionalities. This demonstration highlights the integration of deep neural networks (DNNs) to simulate end-to-end multiband lightpaths across C+L+S spectral bands. A live deployment on a virtualized testbed at UPC, Barcelona, showcases the OCATA DT's abilities in two main scenarios. Attendees will engage with an interactive dashboard to explore how the DT estimates QoT and refines its internal models using telemetry data. This demonstration aims to illustrate the practical benefits of digital twins for autonomous network operation, performance assurance, and cost-efficient scaling of next-generation optical infrastructure.**

Keywords: Optical digital twin, network automation, quality of transmission estimation

I. OVERVIEW

Digital Twins (DTs) are popular tools for the operation and automation of optical networks. A DT is essentially a high-fidelity virtual model of a physical system [1]. They can be used for many different purposes within the optical network including the prediction of performance, detection of anomalies, and help inform decision-making for operation. They are especially valuable due to the nature of the complex behaviours they are able to model. As networks often use multiple spectral bands (C+L+S) to maximize bandwidth, the more channels added and transmission distances increased, signal impairments become more pronounced which can lead to degraded performance.

Among the various approaches to DT modelling optical transmission systems, machine learning (ML) has shown particular promise for DT development due to its ability to approximate complex behaviours. The OCATA DT [1] is one that has been proposed for using ML techniques for various network operation applications such as light path provisioning and failure management [3]. One of OCATA DT's applications is to precisely predict the pre-forward error correction (FEC) bit error rate (BER) in multiband (MB) optical transmission systems, where non-linear impairments (NLI) such as inter-channel stimulated Raman scattering plays a significant role.

OCATA DT simulates the propagation of optical signals in the time domain, specifically the in-phase (I) and quadrature (Q) components across multiple optical spans. The approach employs DNNs grounded in first-principal models, which are pre-trained and stored in a dedicated model database. These DNNs are then combined to build an end-to-end (e2e) lightpath model, formed by linking span-specific DNNs according to the lightpath's route characteristics, such as span length and channel. To reduce the number of pre-trained models needed a limited set of reference channels (RCh) are selected [4]. A feature composition method is used to generalize this model, enabling the estimation of transmission characteristics for any channel across the C+L+S bands by leveraging the outputs from the reference models.

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Further works showed the tuning of end-to-end lightpath DNN models as an additional building block of the MB OCATA DT [5]. Here, telemetry data was used for the tuning process proposing this new block in the MB OCATA DT architecture for the maintenance and accuracy of the pre-trained span models.

The live demonstration of the MB OCATA DT integrates many of the features and functionalities aforementioned to present a real-time demonstration of the OCATA DT and how it functions. The demonstration aims to showcase the practical benefits of DT-driven network intelligence, including how ML-enhanced models can be used for the management of optical networks, but also how the fine-tuning and maintenance of the DT itself is carried out. As next-generation services place increasingly stringent demands on optical transport systems, DTs like OCATA emerge as essential tools for ensuring reliability and efficiency. The demonstration will underline how intelligent DTs can assist in provisioning and performance assurance, contributing to a scalable and cost-efficient network.

II. INNOVATION

In this demonstration, we aim to showcase the capabilities of the MB OCATA DT. This DT leverages machine learning to provide a virtual representation of optical transmission systems, enabling intelligent data-driven decision-making incorporating feedback from the network for the fine-tuning of models.

This demonstration has been designed to resonate with the ICTON audience, especially those interested in autonomous network operation, intelligent monitoring, and the integration of AI/ML into optical infrastructure. The live testbed at UPC in Barcelona will highlight the dynamic behavior of the OCATA DT in a real-time setting, illustrating its role not only in predicting network performance but also in maintaining its own accuracy via continuous model tuning using telemetry feedback.

III. DEMO CONTENT AND IMPLEMENTATION

A. Goals

The goals for this demonstration can be divided into general goals and technical goals.

Firstly, the general goal of this demonstration is to provide people with an understanding of DTs and how they can be an important too for optical networks. The demonstration will allow for people to interact and promote conversations surrounding DTs and how they can be used in future networks.

The technical goals of this demonstration are to provide people with the understanding of the OCATA DT, including the principles and technologies that make it function, and how it can be used in optical networks. This will be achieved by the live demonstration of two OCATA DT functions:

i) QoT estimation
ii) OCATA model tuning

B. Testbed Setup

The OCATA DT will run in a Virtual Machine (VM) deployed in UPC infrastructure using OpenStack as virtualization platform and Ubuntu Server 24.04.2 LTS as operating system. A visual representation of the testbed to be used in the demonstration is shown in Fig. 1.

All the components of the OCATA DT have been implemented in Python 3.12.3. The OCATA DT exposes a REST API implemented using the Flask library that offers the capabilities of OCATA to external entities. A Redis instance is used as a message broker for the communication among the internal components of OCATA. The Telemetry DB has been implemented by means of an Influx DB 2.7.1 instance and the Model DB runs a MongoDB 6.0.23 instance. Each component runs in an independent Docker container and is deployed using the Docker Compose tool. Both Telemetry and Inventory DB have been previously populated with data to enhance the reproducibility of the experiments. A Python client script simulating a Software-Defined Networking (SDN) Controller has been developed to facilitate the interaction between the attendees and the system. This client features the following operations:

i) estimation of the QoT of a lightpath,
ii) establishment of a lightpath triggering the automatic model tuning
iii) the decommission of an established lightpath.

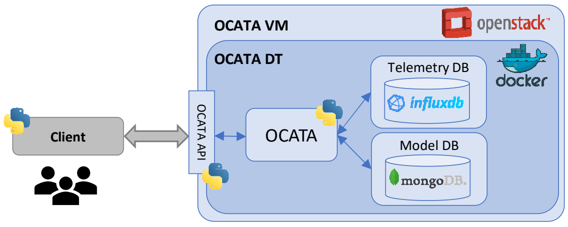

Fig. 1: OCATA demonstration test bed set up

C. OCATA

This section provides technical details on the OCATA DT and its architecture which are necessary for understanding the outputs the demonstration will produce.

OCATA represents IQ constellation samples X as sequences of symbols $x \in X$, where each symbol corresponds to one of m constellation points (CPs) in an m-QAM signal. These samples are summarized into a set of constellation features Y, with each Y^i describing the properties of CP i. The feature extraction (FeX) process uses Gaussian Mixture Models (GMMs) to model each CP as a bivariate Gaussian distribution. Each feature vector $Y^i = [\mu^I,\mu^Q,\sigma^I,\sigma^Q,\sigma^{IQ}]$ includes the mean positions (μ^I,μ^Q), variances ($\sigma I,\sigma^Q$), and covariance (σ^{IQ}) of the symbols around the mean.

Two samples (X_1, X_2) can be compared by calculating the Euclidean distance between their features Y_1 and Y_2, as shown by:

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

Additionally, the pre-FEC BER can be estimated from the features Y. The parameter Φ^i_{out} represents the probability of a symbol from CP i falling outside its detection area A^i. This is computed as:

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

Finally, the estimated pre-FEC BER is obtained by averaging Φ^i_{out} over all CPs, assuming Gray coding:

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

The scenario in Fig. 2 shows an MB optical network with optical transponders and amplifiers, where EDFAs are used for C and L bands and TDFAs for the S band. A SDN controller handles lightpath provisioning and telemetry collection, while the OCATA digital twin operates alongside to support QoT estimation and failure management. An example lightpath between sites A and Z is illustrated.

OCATA includes a database of pre-trained span DNN models to quickly build lightpath models which is performed in the OCATA MB block. A detailed view of this block and its components is shown in Fig. 3. The OCATA MB estimates features for some of the selected CPs using DNN models for related RChs target channels. Then, estimated features are passed through another DNN model, called feature composition to obtain the features of the selected CPs for the target channel.

Once completed the constellation Reconstruction block estimates the features for the non-selected CPs which is followed by a NLI mitigation procedure.

Improving the QoT in multiband optical networks requires adapting detection areas to mitigate NLI, but this is computationally intensive. OCATA MB efficiently computes near-optimal detection maps during provisioning, enhancing QoT and reducing blocking. The detailed procedure and algorithms can be found in [4].

However, using the initial constructed models introduces some errors due to device variations, aging effects, the use of reference channels that may not match the actual channel, and differences in span lengths between training and real network spans. While device and channel mismatches have limited impact on QoT estimation after provisioning, span length differences can notably affect model accuracy.

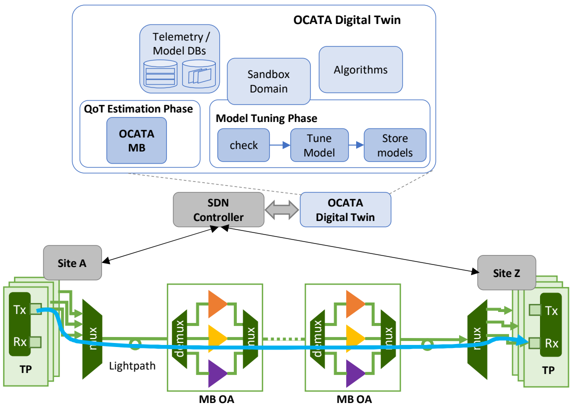

Fig. 2: OCATA digital twin architecture

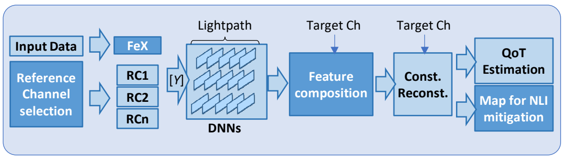

Fig. 3: Detailed view of OCATA MB block

In MB optical transmission, algorithms are applied to the two reference RChs adjacent to the allocated channel, when the allocated channel is not itself an RCh. The QoT estimation is then obtained using eq (3) on features generated through a feature composition process. Additionally, the lightpath model built from the span models of the nearest RCh is saved in the model database. After deploying a lightpath, its end-to-end model is established and requires tuning with telemetry data. For this purpose, a Model Tuning block periodically checks for significant deviations and if found, the lightpath model is updated by minimizing the error defined by eq (1). The cause of the deviation can then be analysed to identify potential degradations.

D. Implementation

This demonstration highlights the core capabilities of the OCATA DT in assisting an SDN controller with optical network management, focusing specifically on QoT estimation and model tuning. These two phases reflect the intelligent decision-making and adaptive learning processes central to the OCATA framework.

The first phase of the demo involves the estimation of QoT for a prospective lightpath. Upon receiving a request from the SDN controller, the OCATA DT collects relevant information about the network components that form the end-to-end path. This includes static parameters such as link lengths, amplifier configurations, and other physical properties. The DT then triggers the procedure on this information in order to predict whether the proposed lightpath can meet the required QoT thresholds. This prediction is returned to the controller to assist in path selection and service provisioning decisions. The estimated QoT serves as a proactive measure to avoid setting up low-quality or unfeasible lightpaths.

In the second phase of the demonstration, the focus shifts to the adaptive behaviour of the OCATA DT through model tuning. Once the lightpath has been established and is operational, telemetry data is collected from the network. This real-world data is then used to refine the internal DNN model, allowing it to better reflect current network conditions and improve its future predictions. The demo will show a comparison between the initial QoT estimation (based on static descriptors) and the updated estimation (after the model has been tuned with live telemetry), illustrating the model's learning and correction process.

The expected output of the demo includes:

i) A visual comparison of QoT estimations before and after model tuning, demonstrating improved accuracy.
ii) Details of input data used in each estimation phase
iii) Indications of how telemetry influences the internal model
iv) Clear evidence of the DT's feedback loop and adaptation mechanism.

The demo will be delivered via an interactive dashboard. This dashboard provides all the relevant input and output information from the OCATA DT. Attendees will see the incoming QoT requests, the corresponding estimations, the injection of telemetry data, and how the internal model adjusts. The interface will be presented using graphs, tables, and status indicators to help clarify the internal workings of the DT without requiring deep technical knowledge.

Attendees can interact with the demonstration directly by triggering new QoT estimations and initiating the model tuning phase with telemetry from various network conditions. By adjusting inputs and observing the resulting changes, participants will gain insights into how the OCATA DT processes information, adapts over time, and supports smarter optical network management.

We believe that this demonstration will provide a clear, concise, and impactful view of how the OCATA DT enhances decision-making in optical networks through intelligent, data-driven processes.

IV. CONCLUSIONS

This demonstration will show the live operation of the OCATA DT through a VM deployed at the UPC premises in Barcelona, Spain. The demonstration focuses on two main cases of operation, the first being QoT estimation, and the second, model fine tuning of the OCATA DT DNN models. The demo is designed to promote conversation about the role of digital twins in optical networks, and provide attendees with an understanding of the OCATA DT and how it works through the interactive demonstration.

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REFERENCES

[1] D. Wang, Z. Zhang, M. Zhang, et al., "The role of digital twin in optical communication: fault management, hardware configuration, and transmission simulation," IEEE Commun. Mag. 59(1), 133–139 (2021).

[2] D. Sequeira et al., "OCATA: A Deep Learning-based Digital Twin for the Optical Time Domain," JOCN, vol. 15, pp. 87-97, 2023.

[3] M. Devigili et al., "Applications of the OCATA Time Domain Digital Twin: from QoT Estimation to Failure Management," JOCN, vol. 16, 2024.

[4] S. Ghasrizadeh et al., "DT-Assisted Lightpath Provisioning and Nonlinear Mitigation in C+L+S MB Optical Networks," Sensors, vol. 24, 2024.

[5] S. Ghasrizadeh, N. Costa, M. Ruiz, A. Napoli, J. Pedro, and L. Velasco, "Creating and Tuning Multiband Optical Transmission Digital Twin Lightpath Models," accepted in International Conference on Optical Network Design and Modeling (ONDM), 2025.