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***Abstract*—We propose a transfer learning-based technique that assists in estimating the Quality-of-transmission (QoT) of the lightpaths in an extended C-band network on 400ZR. The proposed scheme develops the cognition using the traditional C-band operating network knowledge.**

***Index Terms*—Transfer learning, Wide-band Optical Networks, QoT-Estimation**

I. Introduction

The modern optical network exploits various technologies such as Elastic optical networks (EONs) and Software-defined networking (SDN) to allow the dynamic and adaptive provisioning of network resources. The introduction of these technologies paved a path towards partially or fully disaggregated optical networks. The main step towards flexible and disaggregated optical networks is to provide the abstraction of the WDM transport as a topology graph weighted by the Generalized signal-to-noise ratio (GSNR) degradation on transparent Lightpaths (LPs) introduced by each traversed Network element (NE), mainly by Optical line systems (OLSs) [1]. Typically, the OLS controller [2] sets the amplifier operating point and subsequently defines the GSNR degradation. The more correct the nominal operating point is set, the more is the potential to depend on the overall LP GSNR. Thus, a smaller system margin is demanded, and, subsequently, larger traffic can be deployed. The NEs are mainly influenced by variations on the working point vs. the nominal values due to the aging effect, change in spectral load, and different effects of infield operations. These induced fluctuations create a difference between the actual vs. the nominal GSNR computed by the QoT-Estimation engine [3]. The main sources of GSNR uncertainties are ripples on amplifiers' gain and Noise figure (NF), to cater to these uncertainties, a system margin must be deployed to avoid network Out-of-service (OOS) [4]. In this work, we propose a Transfer learning (TL) scheme utilizing the dataset of the traditional C-band fully operational network to train a Machine learning (ML) agent operating together with a reliable QoT-Estimation engine in the network controller of the extended C-band sister network. The ML agent's scope is to correct the GSNR uncertainties due to Erbium-doped fiber amplifiers (EDFAs) ripples and spectral load dependence, for LP on the extended C-band sister network whose nominal NE parameters have been perturbed to include a realistic degree of uncertainty reduced by the TL scheme. The two considered networks have different topologies based on the same hardware: fiber type and EDFAs. The perturbed uncertainty in this work is only EDFA ripples and varying spectral load.

II. Simulation Model and Dataset Analysis

A software-defined optical network is considered where the edges are modeled by OLSs, while nodes are characterized as Reconfigurable optical add-drop multiplexing (ROADM) sites. The OLSs are supposed to work at the optimal working point, and the random behavior of the physical layer is only considered through amplifier gain ripple. The $GSNR$ of any LP traversed through all the OLSs is given by $1/GSNR = \sum_n 1/GSNR_n$, where n is the traversed number of OLSs for the routing of given LP. The $GSNR$ metric provides the effect of both Amplified spontaneous emission (ASE) and Non-linear interference (NLI). The OLSs of traditional C-band carry 80 channels over the standard 50 GHz grid with a total bandwidth $\approx 4\,\mathrm{THz}$. The transceivers of the traditional C-band operate at 32 GBaud. In contrast, the extended C-band carries 64 channels over the 75 GHz grid with a total bandwidth of $\approx 4.8\,\mathrm{THz}$. The transceivers of the extended C-band operate at 64 GBaud. The considered EDFAs of both the networks are set to work at a constant output power model having 0 dBm power/channel by OLSs controller. The links of both networks are supposed to operate on standard Single-mode fiber with a span length of 80 km. The In-line amplifiers (ILA) of both networks are supposed with NF randomly selected for each amplifier between a range of 3.5 to 4.5 dB along with random gain ripple having a variation of 1 dB. The above scenario is mimicked to generate synthetic datasets using an open-source GNPy library, which provides the physical layer's abstraction [5]. The dataset retrieved against traditional C-band is the subset of 2^{80}, total possible realizations of spectral load given by 80 channels. The traffic variation from 34% to 100% of total bandwidth utilization is considered. The traditional C-band dataset is mimicked against the European (EU) network topology, used as an operating network, and for

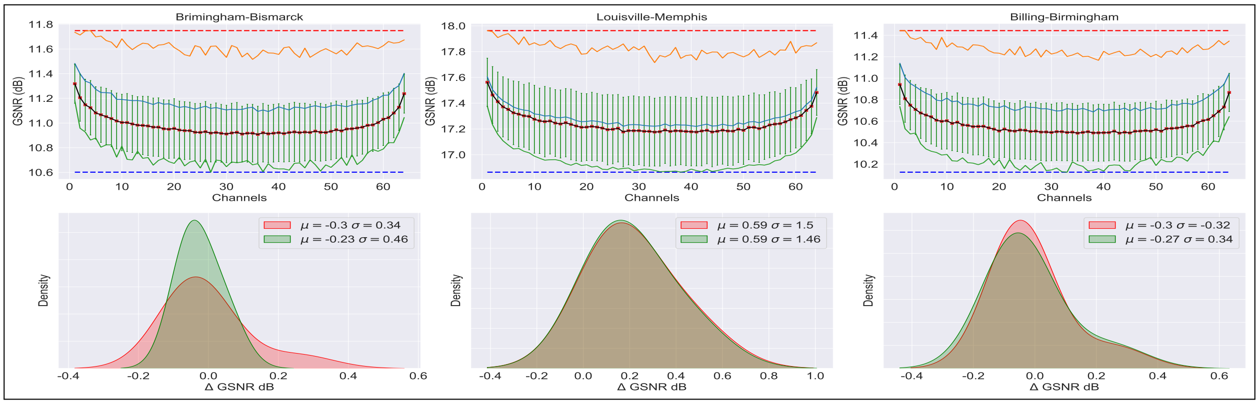

Fig. 1: GSNR statistics and ΔGSNR distribution: USA Network Paths

newly deploying network case, the dataset is produced against the USA network. The knowledge of different paths of the EU network is used to train the TL agent fabricated in the USA network's controller, assisting in correcting the estimation of GSNR by its QoT-Estimator engine.

III. Transfer learning agent and Results

During the initial deployment of the USA network, to estimate the GSNR, the network controller can rely only on the nominal description of system parameters (Flat EDFA ripple gain, NF = 4dB). This estimated nominal GSNR has some degree of uncertainty due to the variation in NEs' working points. In Fig. 1 upper three plots illustrate the dataset GSNR statistics of the three paths of the newly deployed sister network. In this figure, the GSNR statistics against all the 64 channels and all the samples of the three USA test paths is demonstrated in the frequency domain. The precise ranges of variations are depicted in the figure. The red points represent the mean (μ) value of the entire realization for each channel; the error bars exhibit the standard deviations (σ). The blue curve represents the nominal GSNR values for each particular path. The upper (orange) and bottom (green) curves outline each channel's maximum and minimum GSNR. The dashed red and dashed blue lines exhibit the overall maximum and minimum GSNR, respectively. Observing the GSNR variations in Fig. 1, it can be seen that the actual GSNR fluctuates across the nominal GSNR values. In general, the system encounters uncertainties or error in GSNR estimation given by $\Delta\text{GSNR} = \text{GSNR}^{\text{nominal}} - \text{GSNR}^{\text{actual}}$. In particular, case when $\Delta\text{GSNR} > 0$, the actual GSNR is smaller than the estimated one and so relying on the QoT-E computation leads to unwanted OOS while when $\Delta\text{GSNR} < 0$ leads to underutilization of available capacity. To cater to these effects, a TL agent is used to predict the uncertainties or errors in actual GSNR estimation, i.e., ΔGSNR.

The proposed TL agent in the SDN controller is based on a homogeneous Artificial neural network regression model. It comprises an input layer, two hidden layers (64 neurons/layer), a dropout layer, and an output layer. The input layer is fed with the features data of 80 channels along with the delta GSNR of the target channel. We considered power, ASE noise, NLI, number of spans, and total distance in feature space as input features. The hyper-parameters are optimized with minimized Mean square error (MSE) $= \frac{1}{n}\sum_i^n \left(\Delta\text{GSNR}_i^{\text{predicted}} - \Delta\text{GSNR}_i^{\text{actual}}\right)^2$. The agent is trained on 12000 training samples, validated on 6000 samples acquired from the traditional C-band (EU network dataset) to estimate the error in QoT (ΔGSNR) of the channel, and testing is performed on 6000 data samples (EU network). The well-trained and tested model acquired from the C-band dataset is then used to start the TL scheme with the small supplementary dataset retrieved from the extended C-band network to tune the weights of the hidden layers. A new input layer is added as the number of input features is less in the extended C-band network.

After defining the TL agent, we evaluated the agent performance on three test paths of (3000 samples) extended C-band network. The performance of the TL agent on the USA network's three paths is demonstrated as a distribution plot in Fig. 1. The distribution of $\Delta GSNR^{actual}$ (green) and $\Delta GSNR^{predicted}$ (red) with a μ and σ is illustrated in the second row of Fig. 1. Looking over the statistics μ and σ in Fig. 1, it is observed that the TL agent exhibits excellent performance by reducing uncertainty or total error. The total error in GSNR estimation is dramatically reduced using a TL agent. The MSE is 0.032 dB for the path Birmingham $\rightarrow$ Bismarck, 0.019 dB for Louisville $\rightarrow$ Memphis, and 0.021 dB for Billings $\rightarrow$ Birmingham of the USA network.

In conclusion, observing these preliminary results, it is pretty clear that the proposed TL agent can reduce the uncertainties in QoT-E in the extended C-band network by using the "learned knowledge" of the traditional C-band operating network. The proposed TL work synergically with the QoT-estimator engine of extended C-band to assist it in correcting the GSNR estimation.

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