Cross-Train: Machine Learning Assisted QoT-Estimation in Un-used Optical Networks

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Abstract. The quality of transmission (QoT) estimation of lightpaths (LPs) has both technological and economic significance from the operator's perspective. Typically, the network administrator configures the network element (NE) working point according to the specified nominal values given by vendors. These operational NEs experienced some variation from the given nominal working point and thus put up uncertainty during their operation, resulting in the introduction of uncertainty in estimating LP QoT. Consequently, a substantial margin is required to avoid any network outage. In this context, to reduce the required margin provisioning, a machine learning (ML) based framework is proposed which is cross-trained using the information retrieved from the fully operational network and utilized to support the QoT estimation unit of an *un-used* sister network.

Keywords: Machine Learning · QoT-estimation · Generalized SNR.

1 Introduction

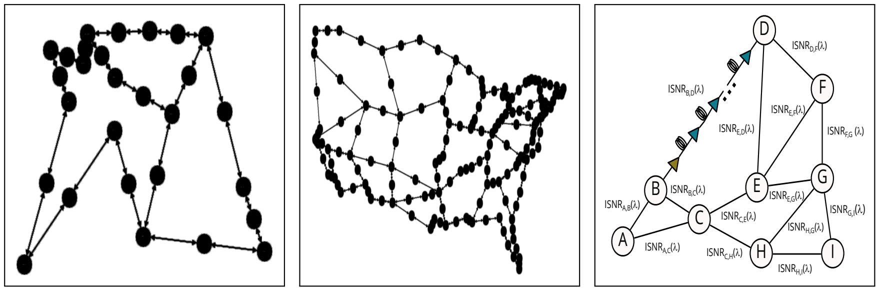
The latest evolving technologies such as 5G, virtual and augmented reality, internet of things (IOTs), and different cloud platforms increase the trend of the global internet traffic [1]. This upsurge of the latest technologies and bandwidth-hungry applications has put on high demand and new requirements for capacity improvement and optical networks' reliability. To accommodate this remarkable growth of internet traffic and maximize profits on *CAPEX* assets, the network operator always requests the full exploitation of the remaining capacity of the already deployed infrastructure. To this aim, the data transport layer must be pushed to reach the maximum capacity limit. The primary technologies for exploiting data transport are the dense-wavelength-division multiplexed (DWDM) together with coherent transmission. These technologies pave a path for evolving technologies like elastic optical networks (EONs) and optical software-defined networking (Optical-SDN). The EONs enable efficient utilization of the available spectrum by enabling the network controller to offer flexible assignment of spectrum slices to the particular traffic request [2]. At the same time, the SDN controller empowers the separate configuration of the working points of each NE and provides the mean for a customized network management system.

The foundation step towards elastic and customized network management is the abstraction of the optical transport network as a topological grid subjective with the GSNR degradation during the propagation through optical line systems (OLSs) which comprise fiber spans followed by amplifies [3]. Typically, OLSs are managed with the centralized operating system in the control plane [4]. This centralized controller adjusts the amplifier operations and subsequently defines the QoT deprivation. The exploitation of the exact nominal working point enables well estimation of the total LP QoT. Hence, during the provisioning of LP, a smaller system margin is demanded, and subsequently, more traffic can be accommodated, assisting improved utilization of the mounted infrastructure.

In the current frame of reference, QoT is characterized in terms of the generalized SNR (GSNR), which incorporates the impact of ASE noise and NLI accumulation [5]. The flexible transceiver considered in this work is characterized by providing an OSNR threshold for a given modulation format; the existing GSNR of a given LP describes the path viability. Thus, the main application of SDN towards the transport layer is a QoT estimator (QoT-E); providing the network information, the QoT-E engine calculates the GSNR over a particular LP. Referring to the Telecom Infra Project [5, 6], it has been widely validated by providing the precise information of the physical layer; a QoT-E engine can deliver a precise estimation of GSNR. Generally, NEs suffered from a variation in the working point due to the hardware (HW) aging, the variation of spectral load at OLS, and different environmental effects during field operations. These induced variations affect the actual GSNR estimation using the nominal values by the QoT-E engine [7]. Additionally, amplifiers' ripples gain, noise figure, and the fiber connector/insertion losses also yield GSNR uncertainties. Consequently, the calculated nominal GSNR on a given LP demands a reasonable margin deployment to prevent any network outage [8].

This work's primary motivation is to reduce the GSNR uncertainty of a particular LP and, consequently, facilitate reliable path calculation for the LP provision at the lowest possible margin. The proposed work is simulated considering an open optical network setup, where the network controller deploys the QoT-E engine as an application program interface (API). Suppose the controller is provided with the exact knowledge network condition, i.e., an *accurate characterization* of operating parameters of every NE. In this case, the QoT-E can calculate the GSNR with reasonable precision, as demonstrated in [5, 6]. In contrast to this, during the unavailability of the *actual characterization* of the operating point of every NE, the QoT-E depends on the *nominal characterization* of the working point of every NE. The QoT-E engine exploits this *nominal characterization* and calculates a nominal GSNR. The obtained nominal GSNR has an uncertainty in its measurement as formerly described.

In the current investigation, the information retrieved from an *in-service* operating network is used to cross-training the ML framework operating in the controller of another *un-used* sister network. This cross-trained module supports the QoT-E unit of an *un-used* network in estimating accurate GSNR of LP. The proposed work considers two different networks based on topology, but both are



(a) (b) (c)

Fig. 1: (a) EU Network Topology (b) USA Network Topology (c) Abstraction of Optical Network

the same on the install HW, like fiber class and erbium-doped fiber amplifiers (EDFAs). The networking topologies considered in this analysis; the European Union (EU) network topology as a well-operative network and USA network topology as *un-used* sister network (see Fig. 1a and Fig. 1b). The dataset is obtained synthetically by perturbing the estimated QoT of LP with proper random spectral-load-dependent NE parameters; specifically, we focused on EDFA ripples and uncertainties in connector losses.

The ML framework proposed in the current simulation scenario reduces the GSNR uncertainty of the LP of an *un-used* sister network. The presented ML module corrects the GSNR calculation of the QoT-E unit of an *un-used* sister network, which exploits nominal NE parameters to estimate it. The data-driven techniques based on ML are already used in the optical networks for different applications; in [9, 10] the authors proposed an ML-based technique for network performance monitoring. In [11, 12] ML framework is proposed for QoT estimation. More than a few data-driven procedures for QoT estimation of LP prior to its real deployment in the network are demonstrated in [13–15]. In [16], the domain adaptation method is used to estimate the QoT of LP. The authors in [17] achieved the precision in QoT estimation using active learning and domain adaptation procedures. Finally, a comprehensive review of ML-employed applications in optical networks is reported in [18].

The core distinction of this work from the already performed investigations is that this scheme proposed the cross-training technique to train an ML module efficiently. Besides this, the cross-trained ML module operates synergically with the QoT-E engine in the network controller. This synergic use's primary purpose is to reduce the GSNR uncertainties induced by EDFA gain ripples, noise figure, and the uncertainties induced by fiber connector losses.

2 Networks Model & Data Generation

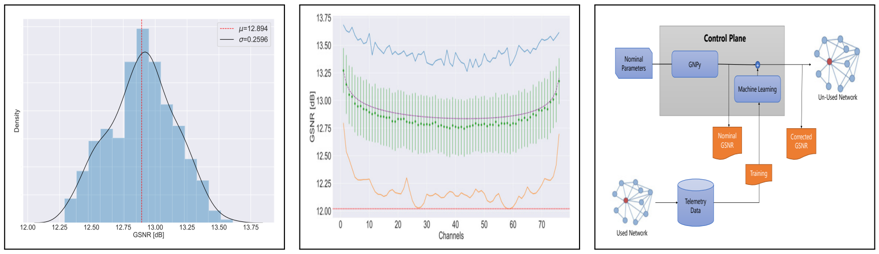
In the present work, a core optical network is mapped as a topological graph having edges represented as OLSs. In contrast, nodes are portrayed as a site of reconfigurable optical add-drop multiplexing (ROADM). The considered OLSs include a span of fibers separated by equidistant amplifiers. The OLSs are managed by a centralized controller and are supposed to be operated at optimal operating point [19]. The controller responsible for configuring the OLS exploits the parameters related to the physical layer. Regarding these parameters, the more vulnerable parameters are the fiber connector/insertion losses, amplifier ripples gain (Uniform Variation of 1 dB), and noise figure ([6 - 11] dB), typically varying with the spectral-load. Besides this, fiber losses such as fiber attenuation ($\alpha = 0.2\ dB/km$) and dispersion ($D = 16.0\ ps/nm/km$) also take into account to get a realistic simulating environment. The statistics of considered connector losses are defined by an exponential distribution ($\lambda = 4$) termed in the analysis [20]. The metric of QoT, i.e., the $GSNR$ of any given LP propagated from source node towards destination node traversing through a definite OLSs connected them is presented as $1/GSNR = \sum_n 1/GSNR_n$, where n is the total number of OLSs connecting the given source node to the destination node revealed in Fig. 1c. The $GSNR$ metric of the given LP is presented by:

$$\mathrm{GSNR} = \frac{P_{\mathrm{Rx}}}{P_{\mathrm{ASE}} + P_{\mathrm{NLI}}} = \left(\mathrm{OSNR}^{-1} + \mathrm{SNR}_{\mathrm{NL}}^{-1}\right)^{-1} , \tag{1}$$

where $\mathrm{OSNR} = P_{\mathrm{Rx}}/P_{\mathrm{ASE}}$ is the optical signal to noise ratio detectable by optical channel monitors, $\mathrm{SNR}_{\mathrm{NL}} = P_{\mathrm{Rx}}/P_{\mathrm{NLI}}$ is the nonlinear SNR induced by NLI only and is recovered using the digital signal processing constellation. P_{Rx} is the channel power at the receiver end, P_{ASE} is the ASE noise power, and P_{NLI} is the accumulated NLI power. The GSNR is associated with the bit error rate (BER) by the BER vs. OSNR description for the particular modulation format [5].

To limit the computational effort, the considered OLSs operate no more than 76 channels around the basic 50 GHz grid on the C-band, having entire bandwidth of almost 4 THz. Indicating standard 96 channels on the entire C-band does not anticipate significant differences in the results. The considered transceivers work at 32 GBaud, and the configured EDFAs work at a fixed output power mode supplying 0 dBm power against each channel. The simulated network connections are supposed to be operated using standard single-mode fiber (SSMF) with a maximum span-length of 80 km. An open-source network simulation tool called GNPy is used to mimic the real field data to obtain a realistic dataset. Moreover, the considered tool is selected as it is more reliable and well-tested (see [21, 22]). Usually, this library creates the network templates for the physical layer by simulating an end-to-end environment [23]. The open-source GNPy library is resolved spectrally and is instituted on the generalized-Gaussian-noise (GGN) model [24]. Exploiting the spectral resolution capability, the GNPy is constituted to clone the network data in the real field environment. The cloned dataset includes channel power at receiver, ASE noise, NLI accumulation, the GSNR for every LP, and finally, the total spans traversed from source-to-destination (s $\rightarrow$ d). Considering the optimal signal power, the ASE noise is the main factor as at optimal level ASE is always duple the NLI [3][25]. Unusually, ASE is also very tricky to estimate, as it varies with the operating condition of EDFAs [26], which ultimately hinges on the spectral-load [27]. In this perspective, the engendered dataset is perturbed by changing the highly fragile characteristics of EDFA, typically amplifier ripple gain and noise figure.

The mimicked dataset comprises two separate datasets; one section describes an *in-service* network, whereas the other denotes an *un-used* network. The considered networks are characterized by distinct topologies having similar fiber



(a) (b) (c)

Fig. 2: (a) GSNR Distribution (b) Train path GSNR Statistical Analysis (c) Model Orchestration

class and transmission apparatus. Nevertheless, they are exclusive in amplifier parameters like amplifier ripple gain, noise figure, and fiber connector losses. Following the network composition of both datasets *(in-service & un-used)*, the next section is the spectral-load. In the present simulation, the spectral-load of a given simulated link is the subset of 2^{76} possible realization of spectral-load against considered 76 channels. In the reflected subset of spectral-load, each (s $\rightarrow$ d) pair has 1024 combinations of random traffic having maximum occupation ranges between 34% to 100% of overall considered bandwidth. The initial subset of the dataset is created against the EU network topology (*in-service* network). In contrast, the other subset of the dataset is created against the USA network topology (*un-used* network).

3 GSNR Statistical Analysis

In the current frame of reference, to compute the GSNR of *un-used* network, the network controller of this nascent network can only depend on the nominal explanation of the system (noise figure = $8.75\,dB$, gain ripple = flat ripple and insertion losses = $0.3\,dB$). Exploitation exclusively this nominal behavior of a network, the network controller calculates GSNR, a nominal one. This estimated GSNR has a certain level of ambiguity anticipated by the discrepancy in NEs operating points. Fig. 2a indicates the GSNR distribution for the entire WDM comb for the given path *Vienna* $\rightarrow$ *Warsaw*. Observing Fig. 2a, it is well demonstrated that the given GSNR for path *Vienna* $\rightarrow$ *Warsaw* is distributed across the mean value, observing the probability density function it is well approximated as Gaussian. Similar behavior is observed for the other simulated links of *un-used* network. Going into more details, Fig. 2b reveals similar outcomes for all wavelengths on the same *Vienna* $\rightarrow$ *Warsaw* path. In Fig. 2b, the statistical breakdown of a particular variation is depicted. Besides this assessment, a small number of significant concerns evolve by calculating the average of the GSNRs for full train realizations of the given path, introduced in Fig. 2b. The average of GSNRs presented by green dots characterizes the OLSs module, ranging between 12.75 dB, and 13.27 dB, with standard deviations (error bars) 0.20 dB to 0.28 dB. A purple line depicts the nominal GSNRs for the given path. The bluish and orange lines bordered the maximum and the minimum GSNRs values for every channel. The dotted reddish line specifies the global minimum GSNR of

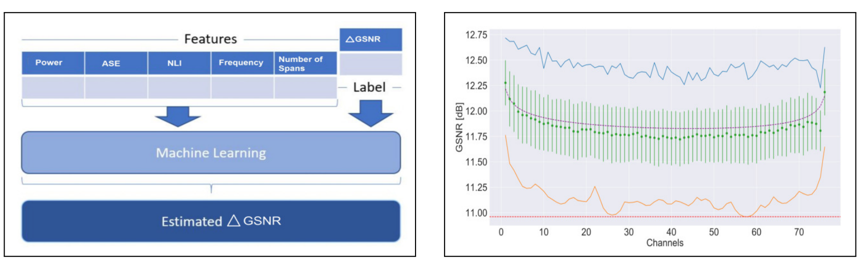
12.02 dB for the given path. The current GSNR indicators show up two methods to deliver QoT.

In the first approach, reflecting a worst-case (WC) setup without any knowledge, the constant GSNR threshold should be applied for all the channels with a value smaller than an anticipated global minimum (12.02 dB) to avoid any network outage. In this approach, the fluctuation in GSNR values ranges between 13.68 dB to 12.02 dB; this creates almost a 1.6 dB of margin requested by the GSNR uncertainty.

In the second approach, we considered the nominal GSNR estimation of the core QoT-E engine. In this method, we have two states of GSNR description around the nominal one. The first one comprises those channels having GSNR values higher than the nominal GSNR estimation. The second one is those channels having GSNR values lower than the nominal estimation. To measure the uncertainty in GSNR estimation in this approach, we calculate the difference between the nominal and actual one using Eq. 2. Considering the first case, the

$$\Delta\text{GSNR} = \text{GSNR}_{\text{nominal}} - \text{GSNR}_{\text{actual}} \,, \tag{2}$$

one with higher GSNR values than the nominal estimation reporting a maximum GSNR uncertainty of *0.85dB* (the maximum difference between purple line & blue line) having negative $\Delta GSNR^{-}$ description. This $\Delta GSNR^{-}$ case is not critical as the available GSNR threshold of these channels at a transceiver is higher than the estimated nominal GSNR. The transceiver, in this case, can quickly deploy a reliable LP. In contrast to this, the second case, the one having lower GSNR values than the nominal estimation unfolding a maximum GSNR uncertainty of almost 1.25 dB (the maximum difference between purple line & orange line) having positive $\Delta GSNR^{+}$ description. Unlike the first case, the $\Delta GSNR^{+}$ case is much more critical as the available GSNR threshold of these channels at a transceiver is lower than the estimated nominal GSNR. The transceiver, in this case, will be configured with a high margin to deploy an LP reliably and keep the network in-service state.



(a) (b)

Fig. 3: (a)Machine Learning Module (b) Test path GSNR Statistical Analysis

Consequently, the main challenge in the current simulating environment is dealing with a more critical $\Delta GSNR^{+}$ case. In the current study, the main objective is to decrease the error ($\Delta GSNR^{+}$) in the estimation of the QoT-E engine of the GNPy unit, in the absence of *exact* system parameters. To this aim, we consider the exploitation of the data retrieved from the EU network to cross-train ML unit operating on the controller of the USA network. The proposed cross-trained ML element is utilized to assist the main QoT-E engine of *un-used* USA network shown in Fig. 2c. The proposed scheme delivers a QoT rectifying apparatus that can provide precise QoT estimation of LP prior to its actual provisioning in the network.

4 Visual Inspection of Machine Learning Module

The present simulation scenario employs the data-driven ML model, which is initially cross-trained. It is then deployed in the controller of an *un-used* network, where it helps to correct the $GSNR$ estimation of the core QoT-E engine. Similar to other data-driven methods, the proposed ML prototype training and testing procedures need to define the features and response variable, indicating the structural inputs and outputs. The operated well-defined features incorporate channel power at receiver, NLI accumulation, ASE noise, frequency of the channel, and the fiber spans between the given s $\rightarrow$ d node. Along with this, the manipulated response variable is the GSNR correction parameter; $\Delta GSNR$ of the given LP depicted in Fig. 3a. The overall sum of the participation features comprises 305 definitions; (1+(4x76) = 305) the number spans plus the channel power at receiver, the NLI accumulation, the ASE noise, and channel frequency.

The proposed ML unit obtained the perceptive ability to provide the $GSNR$ correcting metric by mapping the features and response variable of an *in-service* network. The defined functionality is achieved by using Deep Neural Network (DNN) [28], which is an excellent data-driven model to discover the correlation among the given features and required response variable. The presented DNN in this work is structured by utilizing open-source APIs of TensorFlow© library [29], and is configured by numerous set of hyper-parameters like *training steps* = 1000, supplied by default Keras optimizer as *adaptive gradient algorithm* along with *learning rate* = 0.01 coupled with regularization $L_1 = 0.001$ [30]. Additionally, *Relu* is nominated as an activation function to allows the efficient interpretation of the provided input features into the desired response variable with minimum complexity [31]. Lastly, the important hyper-parameter like *hidden-layers* size, DNN is configured with several combinations of *hidden-layers* size along with different neuron units to attain the good compromise between accuracy and complexity. To this aim, the DNN developed for QoT correction utilizes three *hidden-layers*, holding twenty *neurons* respectively. Moreover, *mean square error (MSE)* is used as a loss function (see Eq. 3) to assessed the proposed DNN,

$$\mathrm{MSE} = \frac{\sum_{j=0}^{N} \left(\Delta\mathrm{GSNR}_j^{\mathrm{p}} - \Delta\mathrm{GSNR}_j^{\mathrm{a}}\right)^2}{N}\,, \tag{3}$$

where $\Delta\mathrm{GSNR}_j^{\mathrm{r}}$ and $\Delta\mathrm{GSNR}_j^{\mathrm{p}}$ are the actual and DNN generated predicted measurements of error in GSNR estimation of a channel under test for the jth spectral-load, correspondingly, and N is the over-all sum of ΔGSNR combination of the test set. The proposed DNN is further shaped for training, authentication,

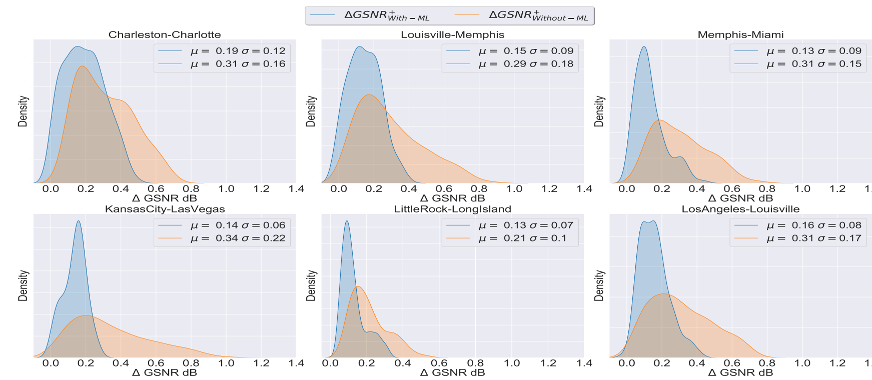


Fig. 4: Distribution of $\Delta\text{GSNR}^+_{With-ML}$ and $\Delta\text{GSNR}^+_{Without-ML}$

and examination by the traditional regulation 70/15/15 and is crossed-trained by ΔGSNR responses of a random spectral-load of an already deployed EU network. After proper cross-training, the cross-trained ML module is used synergically with the QoT-E agent of GNPy to assist the QoT-E agent in precisely estimating LP GSNR value before its deployment. In the current setup, the training set data entails 4096 combinations for four s $\rightarrow$ d paths (1024 realizations for each s $\rightarrow$ d pair) *Frankfurt* $\rightarrow$ *Istanbul, London* $\rightarrow$ *Madrid, Brussels* $\rightarrow$ *Bucharest, Vienna* $\rightarrow$ *Warsaw* of an EU network having span length of 34, 19, 30 and 7 respectively. The test set in the proposed frame work contains 6144 combinations for six s $\rightarrow$ d paths *Charlotte* $\rightarrow$ *Chicago, Louisville* $\rightarrow$ *Memphis, Memphis* $\rightarrow$ *Miami, Kansas City* $\rightarrow$ *Las-Vegas, Little Rock* $\rightarrow$ *Long Island, Los Angeles* $\rightarrow$ *Louisville* of the USA network having span length 20, 7, 24, 30, 26, 46 respectively.

5 Results and Discussion

The performance of the proposed DNN to reduce the error in the $GSNR$ estimation of the QoT-E engine of an *un-used* network is summarized in this section. The proposed work considers the $\Delta GSNR^+$ case only, as this is a more critical margin as compared to $\Delta GSNR^-$ described in Sec. 3.

To simplify the description of the acquired outcomes, we initially describe the results related to one Louisville $\rightarrow$ Memphis path of the USA network. Specifying the statistical analysis of GSNR of this path, we put the base reference, $\Delta GSNR^+$ retrieved by mirroring minimum GSNR measurement (10.81) dB demonstrated in Fig. 3b. This particular case represents a rough estimation, and it offered a reference level. This approach creates a margin of $\Delta GSNR^+_{without-ML}$ = $GSNR_{nominal}$ - $GSNR_{Globalminimum}$ = 1.1 dB on the WC scenario. Next the QoT-E unit is assisted by the cross-trained DNN, the given framework delivers a definitive QoT-E allowing reduction in the margin of $\Delta GSNR^+_{with-ML}$ = $GSNR_{nominal}$ - $GSNR_{predicted}$ = 0.6 dB on the similar path. The results are illustrated in Fig. 4. The reliability and scalability of the proposed scheme are further verified on five additional paths of the USA network defined in Sec. 4.

The results related to all the studied paths are shown in Fig. 4 which reported the error distribution with and without ML assistance. In Fig. 4, it is seen that the proposed DNN unit dramatically decrease the error in QoT estimation.

6 Conclusion

The proposed work exploits a data-driven method to assist in predicting the QoT of a given LP. The proposed scheme is cross-trained by using the dataset of *in-service* network and utilize it to decrease the GSNR margin of an *un-used* network. The core DNN unit of the cross-trained framework is developed by utilizing the *TensorFlow*© platform. The generated dataset is obtained synthetically for the two considered networking topologies utilizing the open-source GNPy library. The generated dataset explicitly considered the uncertainties induced in GSNR measurement owed by fiber connector losses, amplifiers gain ripple, and noise figure. Promising results are achieved, showing that the synergetic utilization of an ML along with the core QoT-E significantly reduces the uncertainty in GSNR estimation and, consequently, enables a reduction in the required system margin.

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