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QoT Estimation for Light-path Provisioning in Un-Seen Optical Networks using Machine Learning

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ABSTRACT

We propose the use of machine-learning based regression model to predict the quality of transmission (QoT) of an un-established lightpath (LP) in an un-seen network prior to its actual deployment, based on telemetry data of already established LPs of different network. This advance prediction of the QoT of un-established LP in an un-seen network has a promising factor not only for the optimal designing of this network but also enables the possibility to automatically deploy the LPs with a minimum margin in a reliable manner. The QoT metric of the LPs are defined by the Generalized Signal-to-Noise Ratio (GSNR) which includes the effect of both Amplified Spontaneous Emission (ASE) noise and Non-Linear Interference (NLI) accumulation. In the response of present simulation scenario, the real field telemetry data is mimicked by using a well reliable and tested network simulation tool GNPy. Using the generated data set, a machine-learning technique is applied, demonstrating the GSNR prediction of an un-established LP in an unrevealed network with maximum error of 0.53 dB.

Keywords: Machine learning; Quality of Transmission estimation; Generalized OSNR.

1. Introduction

With each passing day the statistics of global IP traffic shows a remarkable increase, due to the evolution of bandwidth intensive applications and newly emerging 5G technology [1]. To sustain this exceptional rise in IP traffic the key operator not only requests of full exploitation of the residual capacity of already deployed network infrastructure but also starts to deploy a new network foundation to enhance the network capacity. In order to fully utilize the capacity of any network infrastructure, the data transport layer needs to be pushed to reach the maximum available capacity. The main key enabler for optimal exploitation of data transport is the Dense Wavelength Division Multiplexed (DWDM) transmission technique along with network disaggregation. This features paves a path for the Elastic Optical Networks (EONs) and Software-Defined Networking (SDN) paradigm in optical network. The striking feature of EON and SDN in optical networks is dynamic and adaptive provisioning of network resources. Considering the control plane, SDN controller is able to manage separately the working points of the various network elements, enabling the management to be user-defined. In the present scenario, the QoT degradation relies on the Optical Line Systems (OLSs) controllers which configure OLSs to operate at the optimal working point [2], [3]. The more precisely this margin (lower margin) is achieved, the larger the deployed traffic. In addition to this, it also helps in the automatic recovery of network failures, which reduces the downtime. Thus to reduce the margin, it is mandatory to rely on a QoT estimator (QoT-E) that enables the reliable prediction of the performance of LP before its actual deployment, i.e., the generalized SNR (GSNR), that includes the effect of ASE noise and and Non-Linear Interference (NLI) accumulation [4] in an *un-seen* network scenarios, i.e., the networks where the key operator doesn't have any specific knowledge of the physical layer parameters such as fiber type, amplification method, control planning, available bandwidth, fix- or flex-grid spectral use, grid size, and transceiver characteristics etc.

The main motivation of this work is to explore the relaxation of uncertainty in the GSNR prediction and consequently, to enable the *un-seen* network controller to reliably deploy the LP at the minimum margin. In this work we suppose a completely blind scenario, by relying only on available data of *seen* network, i.e., the network where the key operator have complete knowledge of the physical layer parameters. Typically, analytical models are used for the provisioning of QoT in the case of *seen* network, as analytical approach requires the *exact* description of system parameters which are not possible to achieve in the current context of unrevealed network, where the key operator doesn't have any info about the network characteristics. This means that an analytic approach is almost unfeasible to achieve prior provisioning of QoT of LP in such agnostic scenario. Moreover, the uncertainty on the working point of the amplifiers is generally induced by a mixed effect of physical phenomena [5] and implementation issues, pointing that an analytic method is almost impossible to accomplish in an open environment. To countervail this, we make a selection to use machine-learning (ML) technique, a stratagem which has already been expertly used in the optical networks; consider [6], [7], [8], [9] for network performance monitoring, [10], [11] for QoT prediction using ML approach. An overall survey of

ML applied applications in optical networks are discussed in [12]. The major difference between the previous literature and the present work is that we focus on the GSNR response to specific traffic configurations of a particular LP of completely *un-seen* network in an open environment. Exploring this, we obtain a reliable QoT-E that can be used both in network planning and for the wavelength assignment in the on-line scenario.

2. SIMULATION MODEL & DATA GENERATION

A typical SDN empowered backbone optical network is considered, in which edges are modeled by OLSs, while nodes are defined as Re-configurable Optical Add Drop Multiplexing (ROADM) sites. The given OLSs comprise of fibers and amplifiers and are managed by a controller supposed to operate at the nonlinear-propagation optimal working point. The random behavior of physical layer is considered through amplifier gain ripple. The merit of QoT i.e., the $GSNR$ of any candidate LP routed through a particular OLSs is given by $1/GSNR = \sum_n 1/GSNR_n$, where *n* is the number of OLSs contributing in the routing of particular LP. The $GSNR$ metric of candidate LP is given by equation (1) where P_{Rx} is the power of the channel at the receiver, P_{ASE} is the power of the ASE noise and P_{NLI} is the power of the NLI [13], [14]. Because of the limitation of computational resources, the considered OLSs carry only 76 channels over the standard 50 GHz grid on the C-band, having total bandwidth close to 4THz. We do not expect substantial difference in results when considering standard 96 channels on the entire C-band. We supposed to rely on transceivers at 32 GBaud, shaped with a Root-Raised-Cosine (RRC) filter. The In-Line Amplifiers (ILA), particularly Erbium-Doped Fiber Amplifiers (EDFAs) in the optical line are configured to work at a constant output power of 0 dBm per channel. All network links are supposed to operate on Standard Single Mode Fiber fiber (SSMF) with span length of 80 km.

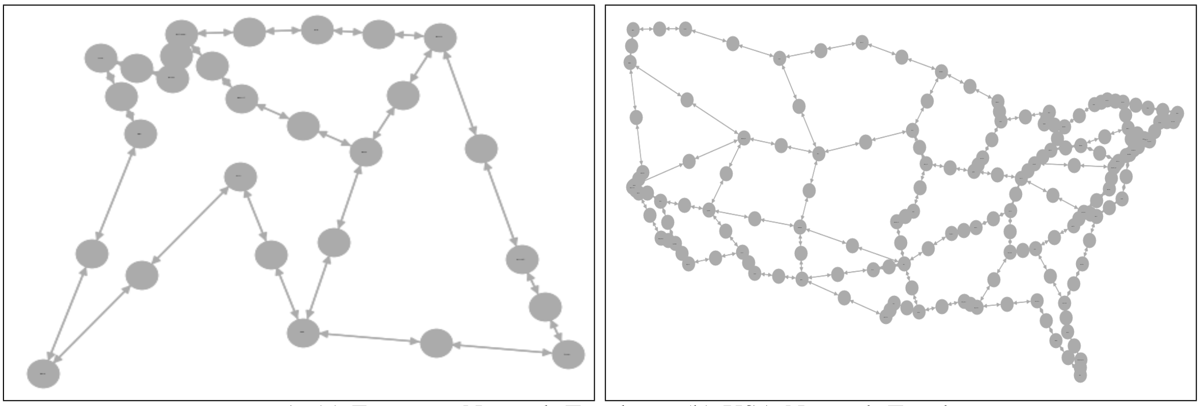


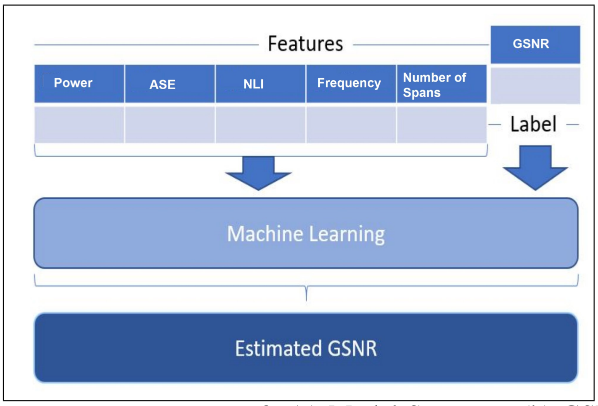
Figure 1: (a) European Network Topology; (b) USA Network Topology;

To obtain a data set, in the absence of real field data, a reliable and well tested open source network simulation tool GNPy [15][16] is used to generate the synthetic data against the proposed scenario. Basically, this library outlines an end to end simulation environment which develops the network models for physical layer [17]. Characterizing this particular capability, the GNPy is configured to mimic the telemetry data of a network. The mimic parameters of telemetry data are: signal power at receiver, ASE noise accumulation and NLI generation during the propagation of LP, GSNR against each propagating LP from a particular source to a destination and finally number of spans traversed by candidate LP from source to destination. Taking into account the ASE noise and NLI augmentation, the ASE is the more dominant, because it is twice the NLI when the system operates at optimal power [2][18]. Remarkably, it is also the most challenging to measure. In fact, the ASE noise power depends on the working point of EDFAs [19], which ultimately depends on the spectral load [5].

In the above context, the generated data set is basically perturbed by varying most delicate parameters of EDFA: noise figure and amplifier ripple gain. The selection of noise figure is made by uniform distribution varying between 6 to 11 dB while the amplifier ripple gain is varied uniformly with almost 1 dB of variation. The mimicked data set consists of two different sub-set of data, one set refers to a *seen* network while the other refers to an *un-seen* network. The configuration used for an unrevealed network scenario is the same as for the former revealed network case with the exception of perturbed EDFA noise figure and ripple gain which is normally the most random part in the optical line system already described. After finalizing the network configuring of both data sets *(seen & un-seen)* the next most delicate part is the spectral load of simulated links, which in the proposed model is the subset of 2^{76}, overall possible combinations of spectral load are given by 76 channels. Among this sub-set each source-to-destination (s –> d) pair has 3000 realizations of random traffic ranging from 34% to 100% of total bandwidth utilization. The first data set is generated against the European Union (EU) network topology, used as a *seen* network and for an *un-seen* network case the required data set is generated against the USA network topology shown in Fig.1a, Fig.1b.

3. MODEL ORCHESTRATION, DATA SET STATISTICS

The proposed work presents ML model for the prediction of the $GSNR$ belonging to a specific LP prior to its actual deployment in an *unseen* network, based upon a particular spectral load realization of *seen* network. In this particular agnostic scenario, ML based learning method is able to compensate for the lack of knowledge of the OLS parameters related to *un-seen* network. Like all other ML based learning methods, the proposed model training and prediction processes require the definition of the features and labels, which indicate the system inputs and outputs, respectively. The manipulated features include received signal power, NLI, ASE, channel frequency and the number of spans between source to destination node, while the exploit label is $GSNR$ of the candidate LP shown in Fig. 2a. The total number of input features for proposed ML models consists of *380* entries, as we have 76 entries against each manipulated parameter *(76 X 5 = 380)*.



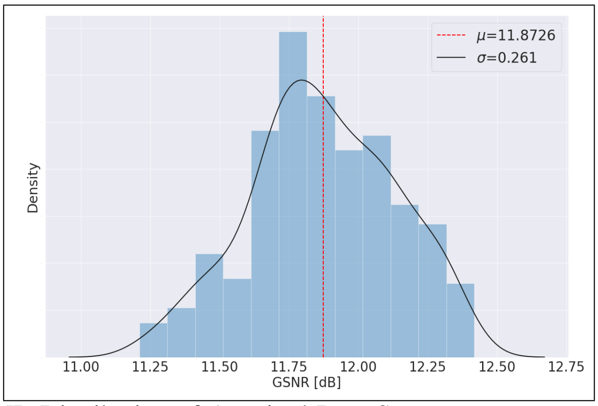


Figure 2: (a) Model Structure; (b) GSNR Distribution of Acquired Data Set;

The proposed model cognate the features and labels of the spectral load realization of *seen* network utilizes the functionality of ML, specifically Artificial Neural Network (ANN) [20], which is a powerful tool to find the relationship between the provided features and desired label. The proposed ANN is developed by MATLAB® platform, consists of 3 hidden layers along with 10 neurons for each hidden layer, having *tan-sigmoid* as activation function that allows translation of the given input features into the prediction of label of our point of interest. The proposed ML model is evaluated by *Mean Square Error (MSE)* as a loss function given by equation (2) where $\mathrm{GSNR}_i^{\mathrm{a}}$ and $\mathrm{GSNR}_i^{\mathrm{p}}$ are the actual and predicted values of any candidate channel for the ith spectral load, respectively, and n is the total number of realizations to be tested. The model is configured for training,

$$\mathrm{GSNR} = \frac{P_{\mathrm{Rx}}}{P_{\mathrm{ASE}} + P_{\mathrm{NLI}}}\,, \qquad (1) \qquad\qquad \mathrm{MSE} = \frac{\sum_{i=0}^{n} (\mathrm{GSNR}_i^{\mathrm{p}} - \mathrm{GSNR}_i^{\mathrm{a}})^2}{n}\,, \qquad (2)$$

validation and testing by the conventional rule 70/15/15 having training-steps of 1000, in order to give the model sufficient intelligence. In addition to this, the model is empowered by Levenberg-Marquardt(LM) back-propagation[21], as it is the fastest back-propagation algorithm along with an early stopping over to avoid over-fitting of the model. The weight and bias values are updated according to LM optimization. Moreover, we used the default value of learning rate which is 0.01, since it is performing well in our defined problem. The two different sub-set of data already discussed in the previous Section2, one set refers to a *seen* network is used for the training of model while the other refers to an *un-seen* network is used for testing of the model. As described in Section 2, the two data sets are completely different in terms of EDFA noise figure and ripple gain which is normally the most random part in the optical line system. The train set in the present scenario consists of 18000 data realizations for 6 source to destination (s –> d) pairs (3000 combinations for each (s –> d) pair) of *seen* EU network *Amsterdam-Berlin, Brussels-Bucharest, Frankfurt-Istanbul, Vienna-Warsaw, London-Madrid, Paris-Rome* with the span length of 8, 30, 34, 7,19 and 34 respectively while the test set consists of 24000 data realizations against 8 (s –> d) pairs (3000 combinations for each (s –> d) pair) *Houston-Jacksonville, LosAngeles-Louisville, Milwaukee-Minneapolis, Orlando-Philadelphia, Phoenix-Pittsburgh, Nashville-NewOrleans, Memphis Miami, Oklahoma-Omaha* of an *un-seen* USA network having span length of 23, 46, 6, 22, 44, 11, 24 and 11 respectively. The $GSNR$ distribution of data set against one mimicked simulated link {Vienna-Warsaw} is depicted in the Fig. 2b due to space constraints.

4. RESULTS

As described earlier the ANN is deployed in our model, as it is one of the most widely used model in the state of the art ML literature [20]. The model is fed with the training data set of 6 (s–> d) pairs of a visible EU network having 18000 spectral load realization and tested on a test data set of 8 (s –> d) pairs of completely invisible USA network having 24000 spectral load realization, as already mentioned in the Section 3. The accuracy of the model is verified by calculating the $\Delta GSNR$, where $\Delta GSNR$ = $GSNR_{Predicted}$ - $GSNR_{Actual}$. As the target goal of the proposed work is to predict the GSNR of the candidate LP of an *un-seen* USA network before its actual deployment. For generalization, we validate the model by predicting the GSNRs of all the 76 channels of 8 (s –> d) pairs of completely *un-seen* network. Fig.3 shows the box plot of $\Delta GSNR$ distribution against all the 8 (s –> d) pairs of an *un-seen* network.

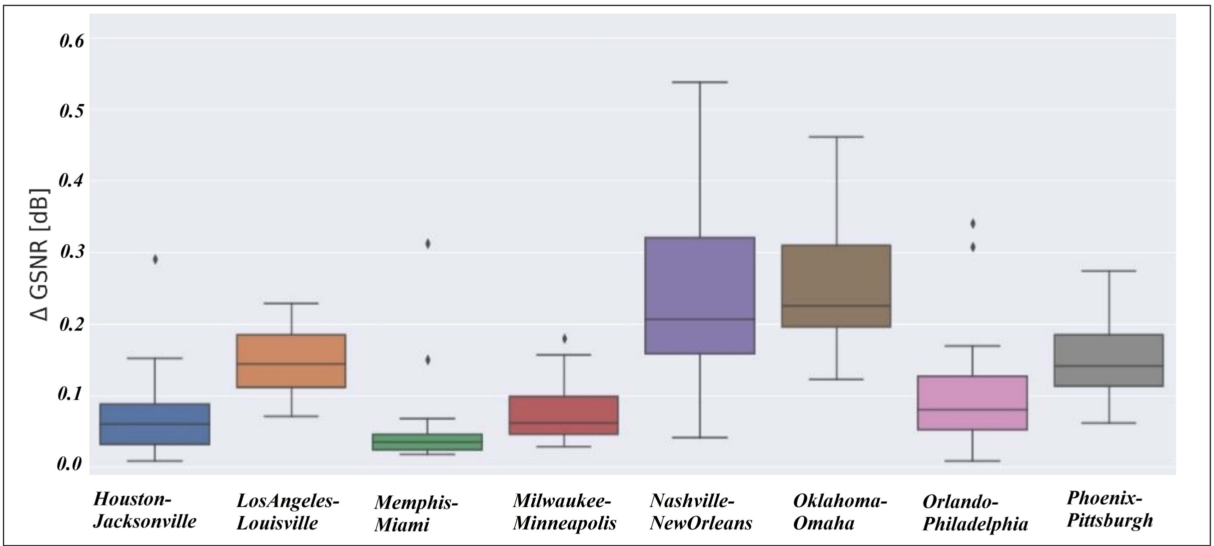


Figure 3: Box representation of the prediction error for the given simulated links

In Fig.3, the central rectangle span specifies the first quartile (Q_1) to the third quartile (Q_3) (the inter-quartile range or *IQR*). A segment inside the rectangular box shows the *median* of $\Delta GSNR$ and *whiskers* above and below the rectangular box show the locations of the minimum (*min*) and maximum (*max*) values of $\Delta GSNR$.

5. Conclusion

In this work we demonstrated a low margin reliable prediction of the QoT given by the GSNR against particular LP prior to its actual deployment in an *un-seen* network. We presented that ANN technique enables an accurate GSNR estimation with a maximum error of 0.53 dB over the {Nashville-NewOrleans} path, representing the worst-case scenario in terms of prediction performance. Furthermore, ANN estimations produces a result where almost 95% of the predictions are fully conservative and gives a reasonable error below 0.30 dB.

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