QoT Violation in Low-Margin Optical Networks

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Abstract: We approach the QoT estimation problem from a novel perspective revealing the hidden aspects of QoT violation avoidance procedure during lightpath provisioning and quantify the potential complexity when applied to low-margin networks.

1. Introduction

Impairment validation is one of the key steps in the realization of low-margin optical networks. Quality of Transmission (QoT) metrics such as Optical Signal to Noise Ratio (OSNR), Signal to Noise Ratio (SNR), and pre-FEC Bit Error Rate (BER) are the commonly used benchmarks for impairment validation. Considering a trade-off between accuracy and complexity, Gaussian Noise (GN) based analytical models have proven to be reasonably successful to accomplish impairment validation step as shown by Telecom Infra Project (TIP) partners working on GNpy framework [1]. However, like other solutions, it can only validate one lightpath at a time. While performing the impairment validation step in the provisioning phase of a Lightpath Under Test (LUT), it is essential to make sure that the QoT metrics of the active lightpaths are not violated. The QoT violation avoidance imposes extra complexity, as there might be many active connections, affected by the LUTs, which require QoT value verification.

Regardless of the numerous works focused on QoT estimation and classification, either using analytical formulas [2] or Machine Learning (ML) based approaches [3][4], the impact of QoT violation avoidance has been largely overlooked. Such developments and analysis are necessary for the evolution towards low-margin optical networks, to reveal not only the accuracy but also the scalability of those solutions when applied in a network with few 1000s of lightpaths affecting each other.

In this work, we focus on the QoT violation issue and provide contributions to allow future developments in the community. The key contributions of this work are three-fold. We publish two datasets that allow studying the impact of QoT violation from different perspectives, as an extension of our previous efforts on public dataset release [5][6]. The dataset offers Beginning-of-Life (BoL) to the End-of-Life (EoL) QoT metrics of all lightpaths, reflecting mainly the impact of network utilization on the QoT evolution. We quantify the impact of QoT violation on the complexity of impairment validation procedure. Finally, we propose two novel formulations of ML assisted solutions (i.e., one lightpath-based and one network-wide formulations [7]) for QoT violation identification.

2. Reference Datasets, Structure, and Potential Applications

Considering the computational complexity and required resources for the development of datasets, we believe it is crucial to have publicly available and well-structured datasets to allow our community to focus on innovation and novel research questions. Moreover, such public datasets provide a reference benchmark to compare different proposals on a particular research question in comparison to the case when each research group develops and uses its in-house datasets. In this regard, we already published a collection of four datasets for QoT estimation studies [5][6]. In addition, we are working on the development of experimental datasets for many other use-cases [8].

Following the same procedure described in [5], in this work, we publish two new datasets to allow studying in particular the impact of QoT violation for lightpath provisioning in optical networks. In order to generate the datasets, we consider *QoT Violation Awareness* capability in PLATON. You may refer to [5] for a detailed description on PLATON. Once *QoT Violation Awareness* is enabled, PLATON recalculates the QoT of all active lightpaths that share a link with the new lightpath when a new lightpath is established. This has two consequences. First, the minimum OSNR assurance during provisioning phase guarantees not only the OSNR of the new lightpath to be equal to or above the pre-defined minimum, but also guarantees that the OSNR of all affected active lightpaths remains above or equal to the required minimum after they suffered from the QoT degradation. Second, the QoT metrics of affected lightpaths are updated after the establishment of a new lightpath.

Under these conditions, each LUT faces three situations in the provisioning phase with respect to its QoT status: 1) *validated* if minimum OSNR threshold is guaranteed (QoT_{val}), 2) *rejected* if its establishment violates the QoT of already active lightpaths (QoT_{vio}), and 3) *rejected* if LUT does not satisfy the minimum OSNR threshold (QoT_{rej}). In this categorization, we distinguish the LUTs not only based on its QoT being validated or rejected, but also based on its dominating rejection reason. The rejection reason is important as for LUTs with QoT_{rej} status, it is possible that they also violate the QoT of already active lightpaths. However, the dominating reason is their insufficient QoT level. This particular categorization, which is only possible due to the incorporation of *QoT Violation Awareness* in

Table1. The number of samples in each class of each datasets

dataset \ # of samples	total	lightpaths with QoT_{val}	lightpaths with QoT_{vio}	lightpaths with QoT_{rej}
dataset05	217,701	143,769	11,518	14,587
dataset06	169,874	22,266	168,010	27,425

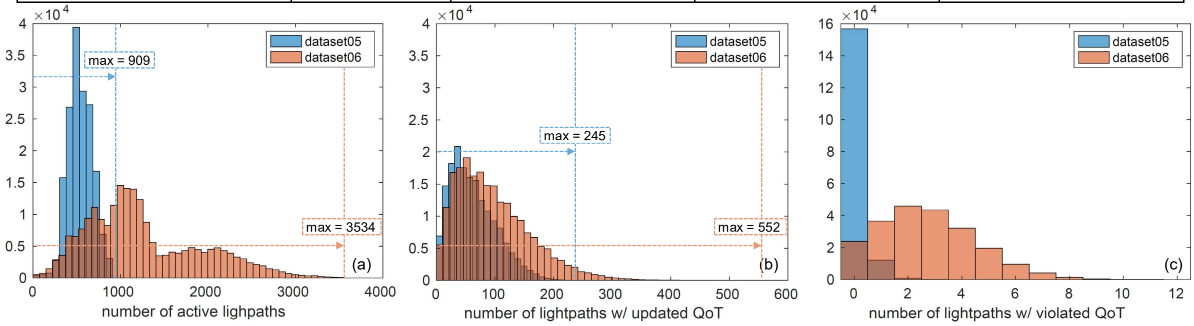

Fig1. Histograms of number of (a) active lightpaths, (b) lightpaths with updated QoT, and (c) lightpaths with violated QoT. The figures show samples of dataset05 and dataset06.

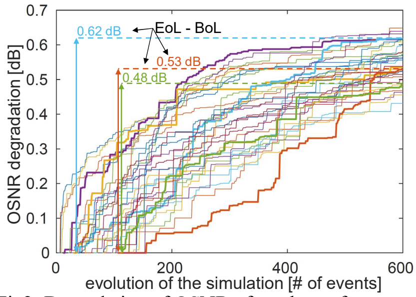

Fig2. Degradation of OSNR of a subset of lightpaths from BoL to the EoL.

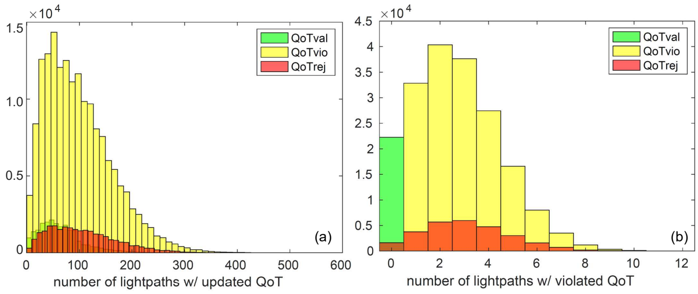

Fig3. Histograms of number of (a) lightpaths with updated QoT, and (b) lightpaths with violated QoT, representing three classes (i.e., QoTval ,QoTvio ,QoTrej) of dataset06.

the dataset generation, is one of the novel contributions here. This unique contribution and the introduction of several new features, compared to all other works in the literature, enable formulation of different problems of relevance to low-margin optical network design and planning.

Considering the same assumptions made for dataset04 in [5], we present how the new datasets are developed. We should first note that dataset04 was obtained using two rounds of four simulation sets assuming holding times of 300s-450s (with steps size of 50s), each with 100,000 events per simulation [5]. We describe the additional changes in the simulations next. The key difference comes from having the QoT violation awareness active for the new dataset. Moreover, in contrast to dataset04, we only run four set of simulations each with 50,000 events to generate dataset05. As for dataset06, we considered holding times 9800s-10200s (with step size of 100s) for five different simulations each with 50,000 events. Everything else in generation of these two datasets remained identical to dataset04. The new datasets have lightpath-based and network-wide representation of each sample as in [5]. Considering the categorization presented before, we introduce three classes in these datasets as presented together with the number of samples per each class in Table1. As observed, the different ranges of holding time considered for the datasets significantly affect the sample distribution among the three classes. Consequently, dataset05 has a significantly larger number of QoT_{val} samples and smaller number of QoT_{vio} samples compared to dataset06.

In order to reflect such behavior into the datasets, we defined several novel features and incorporated them in the datasets. These features reflect network-wide impact of QoT violation awareness during provisioning of LUT. Three of them relevant to this work are: 1) number of active lightpaths in the network, 2) number of lightpaths affected if LUT is provisioned, 3) number of lightpaths with their QoT violated if LUT is provisioned. We provide the histograms of these three features in Fig1 to compare dataset05 and dataset06. Fig1a shows clearly the impact of holding times on the number of active lightpaths in the network. Due to the presence of more active lightpaths in dataset06, as shown in Fig1b, the number of lightpaths affected by provisioning LUT is higher. Provisioning one LUT could affect up to 245 and 552 active lightpath in the case of dataset05 and dataset06, respectively. That means impairment validation should be carried out 245 (or 552) times every time one LUT is going to be provisioned, which adds a tremendous complexity to the network management system. The impairment validation step should be carried out one way or another to assure that the existing lightpaths satisfy the QoT requirements regardless of the impact of the LUT and prevent QoT violation. The histograms of the number of violated lightpaths are shown in

Fig1c. In the case of dataset06, which represents a more crowded network, the QoT of up to 12 lightpaths could be violated as the result of provisioning just one lightpath.

The developed datasets also provide the evolution of the QoT values of all the lightpaths from the BoL to the EoL. Such an information-rich dataset allow scientists to look into unexplored areas such as the impact of network on the QoT evolution of lightpaths and study the importance of network behavior on them. For a subset of lightpaths, Fig2 shows the evolution of QoT in terms of OSNR degradation as simulation progresses. Finally, in Fig3, we show histograms of the three classes of dataset06. There are two interesting observations in Fig3b. First, the fact that the samples of QoT_{val} have violated no other lightpaths. Second, even though the samples of QoT_{rej} are rejected because the QoT of the LUT does not satisfy the requirement, they would also violate other lightpaths if provisioned. One could even distinguish them into two different classes and study them in detail. In the next section, we propose two different multi-class classifiers for the classification of the three classes presented in Table1.

4. ML Model for QoT Violation Identification

ML-assisted QoT classification have been studied thoroughly in the literature [3-5]. However, none of the works so far made an effort to distinguish samples with QoT_{vio} characteristics. In this work, we propose two alternatives, one lightpath-based multi-class classifier and one network-wide QoT classifier based on the definition proposed in [7] to identify lightpath candidates that would violate QoT if provisioned. For the lightpath-based we use a feed forward neural network with input size of 34 (the same features introduced in [5]) and a single hidden layer of size 512. For the network-wide scenario we employ the Convolutional Neural Network (CNN) which was originally used in [7]. In both lightpath-based and network-wide scenarios the neural networks maps the input into one of the three distinct classes namely, QoT_{val}, QoT_{vio}, and QoT_{rej}. Adam optimizer with learning rate of 0.0001 is used for all experiments. We train models based on full and balanced versioned of dataset05 and dataset06. The datasets are randomly split into 70% training, 15% validation, and 15% test sets. The training process runs for 150 epochs and the best model is chosen according to the model accuracy over the validation set. The results over the test set are presented in Table2. Along with the accuracy, we also report the average F1-score of the three predicted classes. The models for both lightpath-based and network-wide classifiers work better for dataset06 (even better for full dataset) considering all three metrics mainly due to the presence of more QoT_{vio} samples, which is the result of higher holding times in the simulation, i.e., more crowded network. Comparing the two approaches, lightpath-based shows the superior performance. We believe that the reason lies in the low number of samples that affect the training of CNN-based classifier. For dataset05, the low F1-score is due to the very low number of QoT_{vio} samples in the dataset. It gets worse for the balanced scenario of the network-wide classifier, as there are only 8062 samples (70% of 11518) in the training set. Note that, similar to [7], when network-wide classifier is trained to perform binary classification between QoT_{val} and QoT_{rej}, the accuracy in the balanced case of dataset05 and dataset06 approaches 96% (~20% improvement) and 98% (9% improvement), respectively. Similar improvement are observed for lightpath-based binary classification of the samples.

Table2. Performance of *lightpath-based* and network-wide QoT multi-class classifier

Scenario	lightpath-based		network-wide	
	Accuracy	F1-Score	Accuracy	F1-Score
dataset06_bal	95.15%	95.14%	89.57%	89.46%
dataset06_full	97.04%	94.35%	92.93%	86.58%
dataset05_bal	92.30%	92.25%	76.99%	76.61%
dataset05_full	94.76%	84.72%	92.45%	71.01%

4. Concluding Remarks

We developed and published two datasets that allow studying the impact of QoT violation in the lightpath provisioning phase. We showed that provisioning one lightpath could affect up to 552 (and, if network runs with zero margin, possibly violate the QoT of up to 12) lightpaths. In order to identify lightpath candidates that violate QoT of other lightpaths, we proposed two ML-assisted approaches and reported initial evaluation of their performance. Our future endeavors focus on expanding the published datasets, thorough error analysis of the proposed solutions, and improving the performance of the proposed ML-assisted solutions.

5. Acknowledgement

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6. References

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