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The Glass of Machine Learning for Quality of Transmission Estimation Is Half Full

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Abstract *We discuss an elastic optical network-based approach for evaluating QoT model substitution. Assessing QoT substitution is based on the fundamental idea that different QoT estimators should be examined by analysing their impact integrated with the routing and spectrum allocation algorithm. Machine learning is no exception. ©2022 Nokia Bell Labs*

Introduction

Machine learning (ML) in optical networking is on the rise [1], [2]. Specifically, when designing and planning optical networks, it is often deemed as a promising tool for making quality of transmission (QoT) predictions in modern optical links, especially when physics states are hard to deduce and considerable design uncertainty margins of errors are expected [3].

Nevertheless, when examining the implementation of a QoT estimation model based on ML, we – as a community – have largely not considered how capacity is affected by a model substitution. Indeed, as reported in the survey paper [3, B. Evaluation Metrics], the main metrics to compare the performance of different QoT estimation tools, depending on cases, are the actual versus estimated errors, percentiles, and distances. We believe that we have been overly preoccupied with our own models' performance and have overlooked the most critical task when testing the actual impact of model substitution when designing low-margin optical networks, namely, assessing network throughput capacity.

The glass is half full: on the one hand, ML is revealed to be of great potential for QoT estimation; on the other hand, the studies lack an exhaustive assessment of the implications of a QoT estimation substitution when designing low-margin optical networks. Lately, literature ([4]–[6]) has started exploring these impacts yet has not completed a network capacity analysis to the best of the authors' knowledge.

This paper advocates for an exhaustive assessment of the gain/loss of the network throughput capacity when targeting the substitution of a QoT estimator by incorporating design margins and error distribution characterization. Rehashing our previous works [7]–[9], this paper highlights a procedure to evaluate the substitution of the QoT estimation tool from a holistic point of view comprising the physical QoT model and the heuristic routing and spectrum allocation (RSA) algorithm.

Methodology: comparing performance estimators for low margin design

We compare the substitution of QoT models (e.g., analytical and ML-based) by evaluating the impacts when solving the RSA problem in case of uncertain network parameters and related design margins. Precisely, we use design margins to ensure the same lightpath (LP)-feasibility reliability when comparing different QoT models. Eventually, we analyze the capacity throughput delivered by the RSA algorithm based on the different QoT margined models.

The following two subsections underline the details of the discussed comparison procedure.

Overestimation probability and design margins

One of the primary goals when investigating ML for QoT is the improved resilience that ML guarantees against design parameter uncertainty, i.e., the unknown discrepancy between design parameter values and actual ones [10]. QoT estimators, conventional or ML-based, account for design parameter uncertainty by adding extra margins to the performance estimate [11]. This way, we prevent performance overestimation (OE), which may result in deploying unfeasible LPs. ML delivers high uncertainty resilience, requiring smaller margins.

The proposed comparison method roots in the design margins to cap LP OE probability in the presence of parameters uncertainty. We employ design margins intended to guarantee LP-feasibility reliability as a common ground to compare different QoT estimation models [12], i.e., we analyse the different solutions at the same OE probability.

In math jargon, we write the QoT estimator (conventional or ML-based) as follows:

$$\hat{\rho} = f_{\mathrm{QoT}}(\boldsymbol{\phi}_{\mathrm{design}}), \quad (1)$$

where $\hat{\rho}$ is the QoT estimate (e.g., the generalized optical signal-to-noise ratio

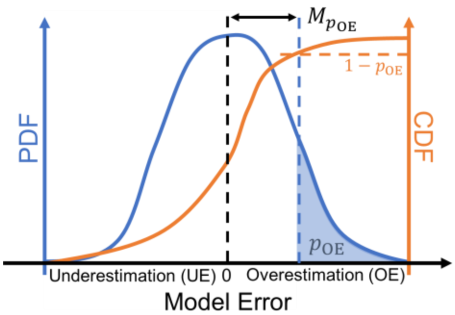

Fig. 1 Qualitative definition of OE margin $\boldsymbol{M_{p_{\mathrm{OE}}}}$, i.e., the additional margin to cap OE probability to $\boldsymbol{p_{\mathrm{OE}}}$.

(GOSNR), the Q²-factor, etc.), $f_{\mathrm{QoT}}(\cdot)$ is the QoT model function, and $\boldsymbol{\phi}_{\mathrm{design}}$ is the LP design parameters vector (including fibre lengths, amplifier noise figures, position of optical filters and wavelength-routing optical nodes, etc.). Independently on implementation, the estimators suffer from inaccuracy errors, namely:

$$\epsilon = \hat{\rho} - \rho, \qquad (2)$$

where $\hat{\rho}$ is the estimated performance and ρ the actual one. If $\epsilon > 0$, we have performance OE, i.e., actual performance is smaller than predicted one ($\hat{\rho} > \rho$). If $\epsilon < 0$, we have underestimation (UE), i.e., actual performance is greater than estimated one ($\hat{\rho} < \rho$). OE is troublesome since it can result in unfeasible LPs, i.e., resulting in rejections of LPs. Being the estimation a probabilistic game, we can characterize the error as in Figure 1, where we show the probability density function (PDF) and the analogous cumulative distribution function (CDF) of ϵ. We determine the OE margin, i.e., the additional margin to cap OE probability to a given value, p_{OE}. For instance, if we require p_{OE} = 5%, we consider an additional margin for which 95% of evaluations produce UE, namely $M_{p_{\mathrm{OE}}}$. This procedure is sketched in Figure 1.

The model inaccuracy may originate from two factors. First, the estimate suffers from intrinsic inaccuracy due to the limitations of the model's theoretical description. Second, the estimate can suffer from input design parameter uncertainty inaccuracy, i.e., the actual parameters are different from the design ones, $\boldsymbol{\phi}_{\mathrm{actual}} \neq \boldsymbol{\phi}_{\mathrm{design}}$. Without loss of generality, we focus on this latter inaccuracy source. A thorough investigation of input parameter uncertainty causes and effects can be found in [10]. To quantify the input design parameter uncertainty, we combine Equations (1) and (2), and we write the error of a general QoT model as follows:

$$\epsilon^{\mathrm{u,QoT}} = f_{\mathrm{QoT}}(\boldsymbol{\phi}_{\mathrm{design}}) - f_{\mathrm{GT}}(\boldsymbol{\phi}_{\mathrm{actual}}), \qquad (3)$$

where $f_{\mathrm{GT}}(\cdot)$ is the function providing the actual quality of transmission, i.e., the ground truth (GT), and u labels the input parameter uncertainty level. We define the error as the difference between the QoT estimated with design parameters and the ground truth QoT with actual parameters. As customary when studying ML applied to QoT estimation, we assume the GN-model as the GT, i.e., $f_{\mathrm{GT}} = f_{\mathrm{GN}}$. Therefore, for what concerns GN-model we can sharpen Equation (3) in the following terms:

$$\epsilon^{\mathrm{u,GN}} = f_{\mathrm{GN}}\big(\boldsymbol{\phi}_{\mathrm{design}}\big) - f_{\mathrm{GN}}(\boldsymbol{\phi}_{\mathrm{actual}}). \qquad (4)$$

By assessing the distribution of $\epsilon^{\mathrm{u,GN}}$ we determine the OE margin for the GN-model, $M^{\mathrm{u,GN}}_{p_{\mathrm{OE}}}$. Similarly, for the ML-based estimator:

$$\epsilon^{\mathrm{u,ML}} = f_{\mathrm{ML}}\big(\boldsymbol{\phi}_{\mathrm{design}}\big) - f_{\mathrm{GN}}(\boldsymbol{\phi}_{\mathrm{actual}}). \qquad (5)$$

By assessing the distribution of $\epsilon^{\mathrm{u,ML}}$ we determine the OE margin for the ML-based model, $M^{\mathrm{u,ML}}_{p_{\mathrm{OE}}}$. Finally, we formalize our framework by comparing the two margined versions of the inquired physical layer models at the equality of the OE rate, p_{OE}, as follows

$$\widehat{GOSNR}^{\mathrm{GN}}_{p_{\mathrm{OE}}} = f_{\mathrm{GN}}\big(\boldsymbol{\phi}_{\mathrm{design}}\big) - M^{\mathrm{u,GN}}_{p_{\mathrm{OE}}}, \qquad (6.a)$$

$$\widehat{GOSNR}^{\mathrm{ML}}_{p_{\mathrm{OE}}} = f_{\mathrm{ML}}\big(\boldsymbol{\phi}_{\mathrm{design}}\big) - M^{\mathrm{u,ML}}_{p_{\mathrm{OE}}}. \qquad (6.b)$$

Routing and spectrum allocation algorithm

To deliver a holistic comparison accounting for the impacts of a QoT model substitution at the network level, we run the RSA algorithm based on the margined QoT estimators - Equations (6.a) and (6.b). We target the network throughput as a comparison metric to study the impact at the network level. The overall comparison procedure is sketched in Figure 2. After determining the design margins, we compare the network throughput at OE rate parity.

The throughput is the sum of the data rates delivered to every optical network transceiver. By solely reporting estimation accuracy or margins, we cannot quantify the benefits of a performance model substitution from a network perspective.

Explanatory results and observations

With this contribution we aim to advocate a for comparison methodology. Hence, results are characteristic of the scenarios and models

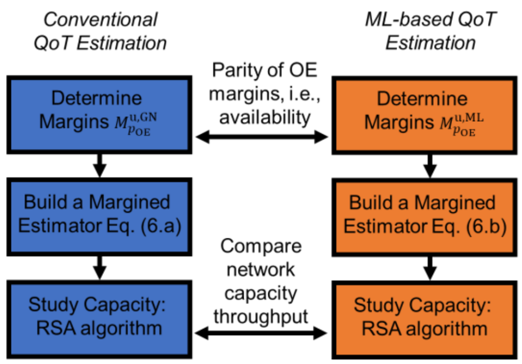

Fig. 2 Sketch of the comparison procedure of QoT model substitutions in a nutshell.

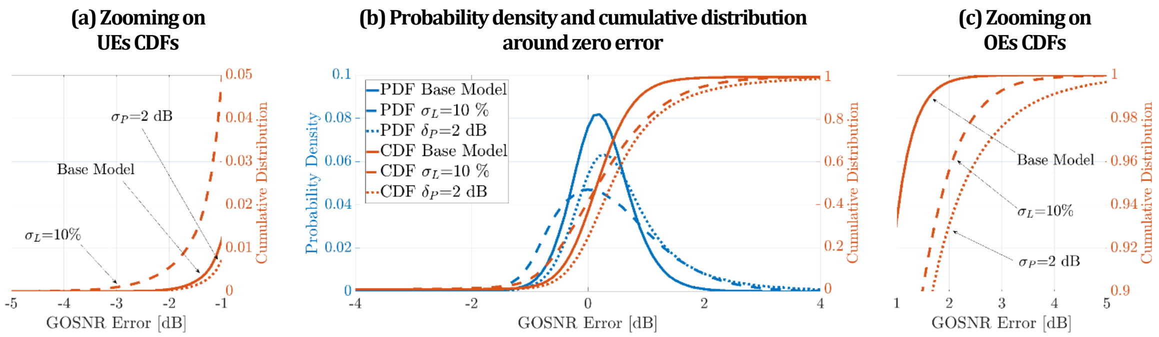

Fig. 3 GOSNR error distribution function for GN-model for different uncertainty conditions (base model, higher length uncertainty, higher power uncertainty) (b). PDF in blue and CDF in orange. We depict a zoom on the error CDF at high UE (a) or OE (c) levels.

investigated and not conclusive as general remarks for *any* model substitution. Results are from our paper [9], where details can be found thoroughly. We report only the main results highlighting remarkable pitfalls when not studying a model substitution from a network view.

We investigate the impact of a QoT model swap when varying the prevailing source of uncertainty on top of an uncertainty reference model, i.e., *base model*, [9, Table 6]. We report results for a German-like network topology (G50) [9, Figure 4] with elastic optical transponders [9, Table 1]. We investigate the swap of the *de-facto* standard GN model against an ML-based one built on artificial neural networks (ANN) - like [8].

Figure 3 shows three instances of error distributions in the presence of different design parameter uncertainty. Solid lines denote the error distribution of the base model [9, Table 6]. Dashed lines are for span length uncertainty standard deviation doubled, from 5% to 10%. Dotted lines are for optical launch power standard deviation doubled, from 1 dB to 2 dB. We recognize that the error distributions are not Gaussian. Moreover, we observe that the three scenarios have distinctive distributions, presenting diverse skewness and kurtosis. Hence, we understand that we need a percentile approach to determine the margins.

Figure 4 shows the margins for ensuring a 5% OE probability (see Figure 1). Circles are GN-model and crosses are ML. We note smaller margins for ML-based estimation when doubling uncertainty on power, length, and attenuation.

Finally, Figure 5 shows capacity gain/loss for G50 topology after running the RSA algorithm in [9, Figure 3] with the two different margined QoT models as per Equations (6.a) and (6.b). Bars represent different capacity gain/loss when substituting the traditional GN model with the ML-based one and employing different margins, i.e., OE probability (5%, 1%, and 0.1%). Results are reported for different uncertainty scenarios.

We note that swapping the traditional GN-model with an ML-based does not guarantee a higher network throughput even when providing a smaller margin. These counterintuitive outcomes happen because the GOSNR error distribution shape (Figure 3) plays a paramount role in determining the network capacity's impact when performing resource allocation to establish new LPs with elastic transponders. Aggregated metrics, such as margins, cannot fully describe the modulation format allocation policy. Thus, they do not effectively represent the impacts on the overall network throughput.

Conclusions

We showed the importance of having a complete assessment of the network capacity throughput when assessing QoT model substitutions in low-margin elastic optical network design. We should consider QoT tool and RSA algorithm combined for a fair comparison of different models. Indeed, observing only statistical properties of the estimation error of a ML-based estimator is not sufficient to conclude that it will lead to better global networking.

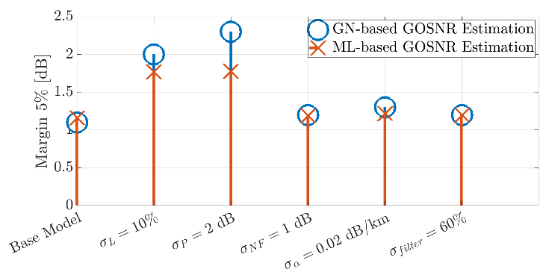

Fig. 4 5% OE margins with different uncertainty scenarios for GN-model (circles) and ML-based GOSNR estimation (crosses).

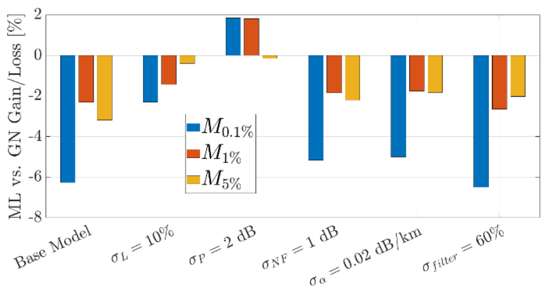

Fig. 5 Capacity gain or loss (% [9, Equation 14]) for substituting the GN-model with an ML-based model for G50 topology. Different uncertainty scenarios and OE probability margins.

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