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Low-Margin Optical-Network Design with Multiple Physical-Layer Parameter Uncertainties

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Abstract *Analytical QoT models require safety margins to account for uncertain knowledge of input parameters. We propose and evaluate a design procedure that gradually decreases these margins in presence of multiple physical-layer uncertainties, by leveraging monitoring data to build a ML-based QoT regressor. ©2022 The Author(s)*

Introduction

Quality of Transmission (QoT) estimators are essential to predict the performance of unestablished lightpaths during network planning. Existing analytical models account for major impairments, such as nonlinear interference (NLI)[1], amplified spontaneous emission (ASE) noise, optical filtering[2]. They achieve high accuracy, assuming exact knowledge of input parameters[3]. However, in real-life these inputs are often not known precisely, so safety margins are imposed to guarantee that modulation format (MF) configured with predicted QoT is above the FEC threshold in the field deployment, and lightpath is not disrupted.

Notable research effort has been recently dedicated to lowering these margins and effectively utilizing resources. One approach, "input refinement", aims at estimating the precise values of uncertain physical-layer (PL) parameters[4, 5, 6]. Another approach, "probabilistic QoT modelling", accepts the lack of precision from multiple uncertain PL parameters and estimates the distribution (or its statistics) of a QoT metric[7, 8]. Knowing this distribution, we can decide to set conservative (high) or aggressive (low) margins, based on the desired tolerance to lightpath being disrupted and reestablished with lower MF.

In this work we follow this second approach and incorporate a probabilistic ML QoT regressor into a design procedure that gradually decreases safety margins, which are then consumed to save spectrum and optical transponders. Differently from most of previous literature (e.g.,[8]), we jointly consider multiple PL uncertainties (uncertain amplifier gain ripple, connector losses and fiber types) and predict a range of SNR margins for the analytical model. Our numerical results on realistic network instances show (5-10)% resource savings by simply leveraging SNR data monitored at receivers, and paying off a very low increment in lightpath disruption probability (within 0.3-4%).

Sources of Uncertainty

SNR at the receiver depends on the noise accumulated in optical spans along the path. Each span is composed of a fiber and an Erbium-Doped Fiber Amplifier (EDFA) (see Fig. 1c), that introduce NLI and ASE noise, respectively. The EDFA is characterized by average gain (G), gain tilt (T), noise figure (F) and output power (P_{out}), while the fiber is characterized by nonlinear coefficient (η) and wavelength-dependent loss (WDL) (ρ), both including Raman effects. Optical connectors between EDFA and fiber are modelled as input (δ) and output (δ') lumped losses.

Uncertainties in parameter values in this work are due to 1) non-flatness of EDFA gain profile (i.e., gain ripple), 2) unaccounted losses in optical connectors, e.g., coming from dust and dirt, and 3) wrong fiber type specifications, due to, e.g., inventory problems[9]. This uncertain knowledge of PL parameters results in two main shortcomings, i.e., launch powers are set suboptimally and analytical QoT estimation becomes inaccurate.

For the power setting, we use Locally-Optimized Globally-Optimized (LOGO) strategy[1] to achieve the highest SNR at the receiver. But incorrect values of PL parameters lead to suboptimal powers and lower QoT at the receiver. More generically, by using incorrect PL parameter values in Generalized GN-model[10], we obtain analytical QoT estimations different from actual QoT.

Focusing on the PL parameters defined above, let us now discuss the difference between *model values* used in analytical modelling and *field values* in the network devices. *Fiber parameters*: if

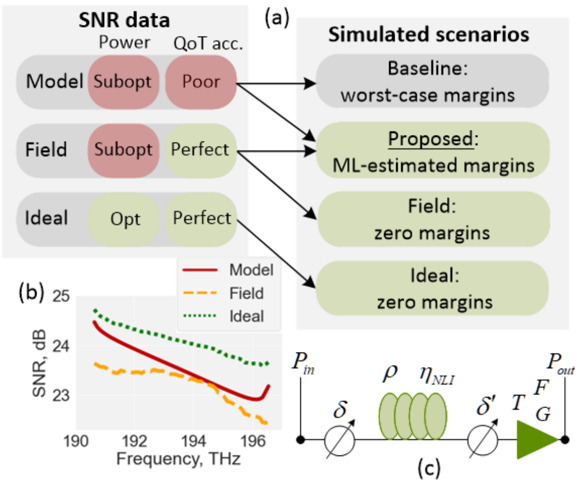


Fig. 1: (a) Simulated scenarios (b) Single span SNR profiles with three modelling assumptions (c) Fiber span parametrization

an incorrect fiber type is specified in the inventory, then model and field values for η and ρ are different. *Connector losses*: field values of δ and δ' are typically higher than model ones due to contamination. *EDFA parameters*: the model value of G is set to compensate for propagation loss in the specified fiber type, for model connector losses, and to reach P_{out} set by LOGO model. Instead, field value of G is set to compensate for actual field loss, yet to reach the same P_{out} computed with model values, that is now suboptimal. Differently from G, both model and field values of T are set to compensate for model value of ρ. Note also that model gain profile is assumed flat, while field gain profile is affected by gain ripple. We assume model and field F to be equal, constant, and independent from the gain.

Fig. 1b illustrates the SNR (over a single span) obtained for three modelling assumptions with model and/or field parameter values (used values are specified in the Numerical Results section). SNR_{Model} is calculated using model values of PL parameters, i.e., it is the SNR predicted with the analytical model. SNR_{Field} represents SNR actually measured in the field; in this work we emulate SNR_{Field} using the field values of PL parameters, but with suboptimal model power setting (for this reason, $SNR_{Field} < SNR_{Model}$). SNR_{Ideal} is the SNR that could ideally be achieved in the field if all field parameter values were perfectly known beforehand, and it is calculated using the field values *and* optimal power setting (hence $SNR_{Ideal} > SNR_{Field}$).

Simulated Scenarios

We simulate four scenarios, that are related to the three SNR modelling assumptions, as shown in Fig. 1a. In current practice, SNR_{Model} is used to set MF, and since it is typically overestimated (due to model power setting being suboptimal in the field and inaccurate QoT prediction), a safety margin M is imposed, such that $SNR_{Model} - M \leq SNR_{Field}$. In **Baseline** scenario we consider a worst-case margin M_{Worst}, while in **Proposed** scenario we estimate a lower margin M_{ML} using ML over monitoring data. **Field** scenario assumes that our estimations of M are perfect, and we use SNR_{Field} to set the MF. Finally, in **Ideal** scenario we assume that field values of PL parameters are known, and MF is set using SNR_{Ideal} [1].

Methodology

We provision traffic requests using k-Shortest-Path routing and First-Fit spectrum allocation. Starting from greenfield we configure MFs of the first N lightpaths based on $SNR_{Model} - M_{Worst}$.

To estimate M_{Worst}, we test a large number of gain ripple profiles, connector loss values and fiber types to find the worst-case value of $SNR_{Model} - SNR_{Field}$ in every link, and then aggregate these per-link values into per-path values.

After N lightpaths are established, we use N values of measured SNR_{Field} to train a ML regressor that predicts $M_{ML} = SNR_{Model} - SNR_{Field}$, and use it as a margin instead of M_{Worst} (Fig. 3). We retrain it on all available data after N new lightpaths are established.

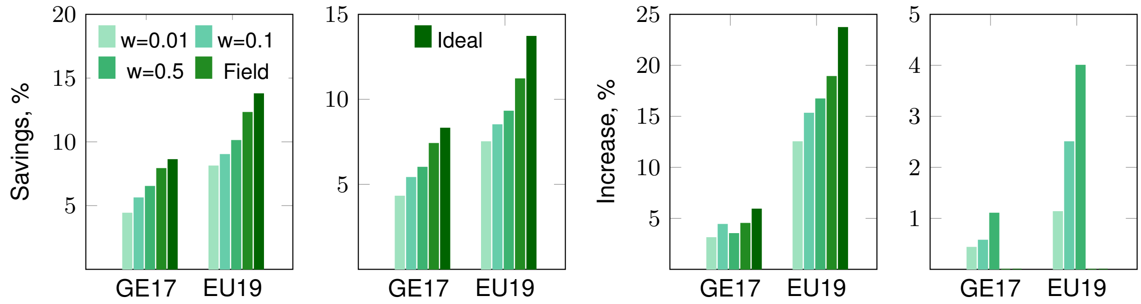
To estimate M_{ML}, we use Neural Network with a weighted loss function $L(w)$ (known as quantile or pinball loss[11]). Weight w can be set to penalize under- or over-estimations for a conservative or aggressive prediction, respectively[2]. We predict M_{ML} per path, and the feature vector encodes the path as following: links of the path are represented by 1s, remaining network links - by 0s. In other words, we learn the contribution of each link uncertainties to $SNR_{Model} - SNR_{Field}$ at the receiver, to predict it for new paths.

Numerical Results

We perform our numerical evaluations on two realistic topologies, a 19-node European network (EU19) and a 17-node German network (GE17)[12]. Results are averaged considering 40

[1]Note that "input refinement" addresses both suboptimal power and inaccurate QoT prediction, and can potentially achieve performance of *Ideal* scenario, while "probabilistic QoT modelling" only decreases margins with better QoT predictions, and is limited by the performance of *Field* scenario.

[2]Note that if estimated M_{ML} is too small, and configured MF is below FEC threshold, we reconfigure the transponder with a lower MF, if possible, or reroute the lightpath. Another lightpath is then established to fully satisfy the traffic request.



(a) SO savings (b) TRX savings (c) RC increase (d) DP increase

Fig. 2: Savings in Spectrum Occupation (SO) and Transponders (TRX), increase in Residual Capacity (RC) and Disruption Probability (DP) w.r.t. *Baseline* scenario with M_{Worst}

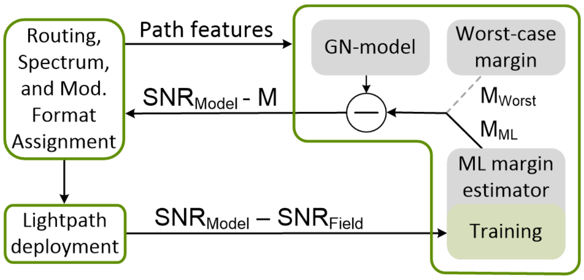


Fig. 3: Proposed low-margin RMSA procedure

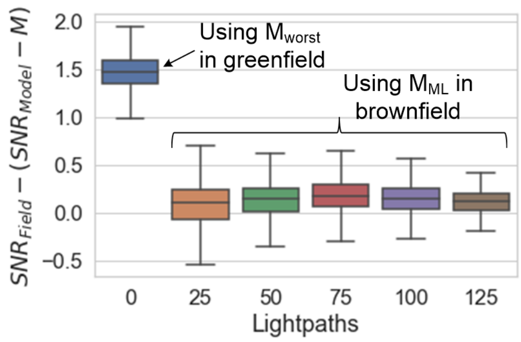


Fig. 4: Difference between SNR_{Field} (actual) and $SNR_{Model} - M$ (used to set MF) in GE17 with $w = 0.1$

traffic matrices with data rate requests randomly distributed between 200 Gb/s and 1000 Gb/s with 100 Gb/s step. We consider mesh traffic matrices, where 70% of random node pairs transmit traffic.

We assume that EDFAs are placed every 80 km, with F equal to 5 dB. We operate in a 6-THz C-band with ASE-loading. Traffic is provisioned by 90 Gbaud transponders capable of 300-800 Gbit/s with 20 dB back-to-back SNR and SNR thresholds from[13] with a 1 dB system margin.

Connector losses are 0.5 dB in the model and are uniformly distributed in [0.5; 1.5] dB in the field. 75% of fiber spans are SMF, while 25% are LEAF fibers. We assume that 20% of spans have incorrect fiber type specified. For each field EDFA we randomly select one of 18 ripple profiles measured on amplifiers in our testbed.

We use M_{Worst} for the first $N = 25$ lightpaths, then start estimating M_{ML} and retrain the model every 25 lightpaths after that. In Fig. 4 for GE17 and loss function with $w = 0.1$ we demonstrate the difference between SNR_{Field} and $SNR_{Model} - M$. As more lightpath measurements become available, $SNR_{Model} - M_{ML}$ tends to SNR_{Field}, and MF is set based on SNR closer to the field value.

In Fig. 2 we present savings in the *Proposed* scenario with conservative and aggressive M_{ML} estimations (w close to 0 and 1, respectively) and in *Field* and *Ideal* scenarios, w.r.t. *Baseline* scenario with M_{Worst}, in terms of occupied spectrum slots (SO), number of transponders (TRX), residual capacity in Gbit/s in the deployed transponders (RC) and disruption probability (DP).

In GE17 (EU19) we start with conservative margins and save 4.4 (8.1)% in SO and 4.3 (7.5)% in TRX, having 2.7 (12.5) % more RC at a cost of 0.32 (1.13)% lightpaths disrupted (and re-established to satisfy traffic request). Savings increase for more aggressive margins, and with $w = 0.5$ reach 6.5 (10.1)% in SO and 6 (9.3)% in TRX with 3.5 (16.7)% higher RC and 1.1 (4)% of reconfigured lightpaths, so that less spectrum and transponders can be used at a cost of more lightpaths disrupted after provisioning.

Perfectly accurate QoT estimation in *Field* scenario can potentially save 7.9 (12.3)% in SO and 7.4 (11.2)% in TRX with a 4.5 (18.9)% increase in RC, meaning that with aggressive margin estimations we are just a few % from the field optimum. If we could also set powers optimally, in *Ideal* scenario we can save 8.6 (14.9)% in SO, 8.3 (13.7)% in TRX with a 5.9 (23.7)% increase in RC.

Conclusion

Considering 3 practical sources of uncertainty at the physical layer, we demonstrate how a ML regressor can be used to set lower margins, and save spectrum and transponders at a cost of a very small probability of lightpath disruption.

References

[1] P. Poggiolini *et al.*, “The GN-Model of Fiber Non-Linear Propagation and its Applications,” *in Journal of Lightwave Technology* vol. 32, no. 4, pp. 694-721, Feb. 2014.

[2] I. F. de Jauregui Ruiz *et al.*, “An accurate model for system performance analysis of optical fibre networks with in-line filtering,” 45th European Conference on Optical Communication (ECOC 2019), 2019, pp. 1-4.

[3] M. Lonardi *et al.*, “The Perks of Using Machine Learning for QoT Estimation with Uncertain Network Parameters,” in OSA Advanced Photonics Congress (AP) 2020, OSA Technical Digest (Optica Publishing Group, 2020), paper NeM3B.2.

[4] N. Morette, *et al.*, “On the Robustness of a ML-based Method for QoT Tool Parameter Refinement in Partially Loaded Networks,” 2022 Optical Fiber Communications Conference and Exhibition (OFC), March 2022, pp. 1-3.

[5] G. Borraccini *et al.*, “Cognitive and autonomous QoT-driven optical line controller,” in Journal of Optical Communications and Networking, vol. 13, no. 10, pp. E23-E31, Oct. 2021.

[6] E. Seve *et al.*, “Associating machine-learning and analytical models for quality of transmission estimation: combining the best of both worlds,” in Journal of Optical Communications and Networking, vol. 13, no. 6, pp. C21-C30, June 2021.

[7] M. Ibrahimi *et al.*, “Machine learning regression for QoT estimation of unestablished lightpaths,” in Journal of Optical Communications and Networking, vol. 13, no. 4, pp. B92-B101, April 2021.

[8] H. Maryam *et al.*, “Learning quantile QoT models to address uncertainty over unseen lightpaths,” in Computer Networks, 108992, April 2022.

[9] E. Seve *et al.*, ”Automated Fiber Type Identification in SDN-Enabled Optical Networks,” in Journal of Lightwave Technology, vol. 37, no. 7, pp. 1724-1731, April, 2019.

[10] D. Semrau *et al.*, “A Closed-Form Approximation of the Gaussian Noise Model in the Presence of Inter-Channel Stimulated Raman Scattering,” in Journal of Lightwave Technology, vol. 37, no. 9, pp. 1924-1936, May 2019.

[11] R. Koenker *et al.*, “Quantile Regression,” in Journal of Economic Perspectives, vol. 15, no. 4 pp. 143-156, 2001.

[12] A. Betker *et al.*, “Reference transport network scenarios,” *in Tech. Rep. BMBF MultiTeraNetProject*, July 2003.

[13] O. Karandin *et al.*, “Quantifying Resource Savings from Low-Margin Design in Optical Networks with Probabilistic Constellation Shaping,” 2021 European Conference on Optical Communication (ECOC), Sep. 2021.