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

Oleg Karandin[1,*], **Alessio Ferrari**[2], **Francesco Musumeci**[1], **Yvan Pointurier**[2], **and Massimo Tornatore**[1]

[1] *Politecnico di Milano, Milan*
[2] *Huawei Technologies France, Paris Research Center*
[*] *Corresponding author: oleg.karandin@polimi.it*

Compiled March 2, 2023

Analytical models for Quality of Transmission (QoT) estimation require safety design 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 (namely, connector loss, EDFA gain ripple and fiber type) by leveraging monitoring data to build a probabilistic Machine-Learning-based QoT regressor. We evaluate the savings from margin reduction in terms of occupied spectrum and number of installed transponders in C and C+L band and demonstrate that (4-12)% transponder/spectrum savings can be achieved in realistic network instances by simply leveraging SNR monitored at receivers and paying off a low increment in lightpath disruption probability (at most 1-4%).

http://dx.doi.org/10.1364/ao.XX.XXXXXX

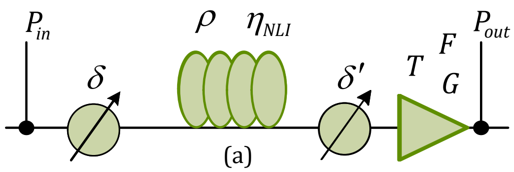
1. INTRODUCTION

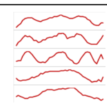
Signals in optical networks are affected by various impairments that impose a maximum transmission distance or, more precisely, a minimum Quality of Transmission (QoT) (e.g., Signal to Noise Ratio, SNR or Bit Error Rate, BER) for each Modulation Format (MF). Reliable QoT estimators are essential to predict the QoT of unestablished lightpaths during network planning and configure the appropriate MF. Existing analytical QoT models account for major impairments, such as nonlinear interference (NLI) [1], amplified spontaneous emission (ASE) noise and optical filtering [2]. They achieve high accuracy, assuming exact knowledge of physical-layer (PL) parameters. However, in real-life, PL parameters such as the EDFA gain ripple, connector loss and, sometimes, even the fiber type are not known precisely, so safety (design) margins [3] are imposed to guarantee that the MF configured based on predicted QoT is operable in the field deployment, and the correct number of transponders is installed to satisfy traffic requests. The extent of design margins depends on the available information about the network, its size and available monitoring capabilities, but, to account for the worst-case deviation of the predicted vs. the actual SNR, in presence of multiple PL uncertainties, they can easily reach up to (2-3) dB in core networks [4], leading to significant resource under-utilization.

Notable research effort has been recently dedicated to lowering design margins and effectively utilizing resources. One approach, called "input refinement", uses monitoring information from optical-network devices to estimate the precise values of PL parameters and fine-tune the accuracy of the analytical QoT models by removing uncertainties regarding its inputs. For example, Ref. [5] shows how to estimate EDFA noise figure (NF) and output power profile by minimizing difference between predicted and measured SNR using gradient descent. Similarly, Ref. [6] estimates input/output lumped losses and EDFA gain profile at each span by minimizing the difference between predicted and measured power spectrum at the optical nodes and total input/output power at each in-line amplifier. Ref. [7] uses an evolutionary metaheuristic to find the values of connector losses, fiber attenuation coefficient and coefficient characterizing Raman power transfer that minimize the difference between predicted and measured power spectrum in each span.

Another approach to lowering design margins, that we define as "Machine Learning (ML)-based end-to-end QoT modelling" uses QoT measurements of already established lightpaths to learn the effects of PL impairments without learning the values of distinct parameters. This can be done directly, by predicting the QoT value, as in [8, 9], or by predicting QoT penalties, as in [10]. However, extrapolation of learnt effects to the new paths and frequency channels is not precise, and, to account for the uncertainty, ML models can be trained to predict not the mean QoT value, but its distribution (we refer to this approach as "Probabilistic QoT estimation". Knowing the QoT distribution, one can decide to set conservative (high) or aggressive (low) design margins, based on the desired tolerance to lightpath having an unfeasible MF configuration.

Probabilistic QoT estimation has so far been predominantly



Uncertain parameter	Design value	Field value
Connector loss	0.5 dB	> 0.5 dB
Optical Amplifier gain ripple	Flat gain	
Fiber type	Fiber type A	Fiber type B ≠ A

(b)

Fig. 1. (a) Optical span including an amplifier, a fiber and input/output lumped loss (b) Examples of design and field values of the uncertain physical-layer parameters

applied to learn dynamic QoT variation (e.g., due to Polarization Dependent Loss, PDL) and decrease system margin [3]. Authors in [11] consider both random QoT penalty (system margin) and uncertainty in amplifier noise figure (design margin) and compare multiple approaches for parametric and non-parametric estimation of SNR distribution in terms of probability of configuring inappropriate MF. In [12] authors consider uncertainty due to random QoT fluctuations, estimate Q-factor distribution using quantile regression and Bayesian Neural Networks and demonstrate how probabilistic QoT estimations reduce blocking probability. In [13] authors also consider uncertainty due to random QoT fluctuations and use ML to predict parameters of a Gaussian distribution, but then perform "calibration" to better fit the true probability distribution. In [14] ML is used to predict the distribution of PDL for distinct devices along the optical signal path.

Differently, in this work we consider multiple "static" PL uncertainties (amplifier gain ripple, connector losses and fiber types) and follow a hybrid approach: we estimate SNR values analytically and use ML to predict a distribution of deviation of the analytical SNR from the SNR value in the field (i.e., the design margin) for the unestablished lightpath. This deviation is theoretically deterministic (in presence of sufficient monitoring information), but, because of the limited monitoring information, it is characterized by a statistical distribution, i.e., it can only be predicted with an unavoidable uncertainty due to the lack of knowledge about its actual value. This lack of monitoring information represents an issue especially at the early phase of network deployment. During the lifespan of the network, as we provision more services and learn more about the PL uncertainties from QoT monitoring, the distribution of the difference between model and field SNR shrinks and tends to a single value.

So, in this study, we incorporate the probabilistic ML QoT regressor into a resource allocation procedure, so that safety design margins are lowered to save spectrum and optical transponders. In [15] we predicted different quantiles of the design margin distribution and showed that, with this approach, (5-8)% less spectrum and transponders can be used in realistic network instances by simply leveraging SNR monitored at receivers, and paying off a very low increment in lightpath disruption probability (1-2%). In this study, we extend the work in [15] by performing our evaluations also in the C+L-band scenario and by introducing the adaptive quantile selection procedure to set the design margin.

The remainder of this paper is organized as follows. In Section 2 we describe QoT modelling with multiple uncertain PL parameters. In Section 3 we introduce the investigated low-margin design scenarios: baseline scenario with worst-case design margin, two scenarios that apply ML to monitoring information to predict either the mean value of the design margin or the distribution of the design margin (proposed approach) and two upper-bound scenarios with partial or full knowledge of PL parameters and no design margin. In Section 4 we describe the proposed ML-based probabilistic QoT-estimator and its integration into the resource allocation heuristic. In Section 5 we specify network and traffic assumptions and present numerical results. In Section 6 we summarize the results and discuss future work.

2. MODELLING ASSUMPTIONS

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. 1a), 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 (see Fig. 1b) are due to 1) unaccounted losses in optical connectors, e.g., coming from dust and dirt [16], 2) non-flatness of EDFA gain profile (i.e., gain ripple), and 3) wrong fiber type specifications, due to, e.g., inventory problems [17]. Uncertain knowledge of PL parameters results in two main shortcomings, i.e., powers launched into the span are set suboptimally, and analytical QoT estimation is inaccurate.

For the power setting, we assume that power profile at the output of a WSS (before the booster amplifier) is flat and use Locally-Optimized Globally-Optimized (LOGO) strategy [1] to find an optimal trade-off between ASE and NLI noise in every fiber span and set P_{in} at each span (or, equivalently, P_{out} at the previous span) along the path to achieve the highest SNR at the receiver. Incorrect values of PL parameters lead to incorrect estimations of ASE and NLI noise, and, in turn, suboptimal powers and lower SNR at the receiver. For instance, difference in the optimal power when equivocating two fiber types is in the order of multiple dB (e.g., 3.3 dBm for SMF and -0.3 dBm for LEAF fiber for a 80 km long span and 100 GHz channels). We also consider power equalizers placed every 5 spans along the link to reduce the effect of gain ripple.

For QoT estimation, by using incorrect PL parameter values in GN-model [1], we obtain analytical SNR estimations different from SNR that is measured at the receiver.

Focusing on the PL parameters defined above, let us now overview the difference between *design values* used in analytical models and *field values* in network devices (see Fig. 1b):

- *connector losses*: field values of δ and δ' are typically higher than design ones due to contamination,
- *EDFA ripple*: design gain profile is assumed to be flat, while field gain profile is affected by gain ripple,
- *fiber parameters*: if an incorrect fiber type is specified in the inventory, design and field values for η and ρ are different.

SNR data	Model (Design)		Field (Deployment)		Ideal (Oracle)	
Physical Layer parameters	Known by operator	Used to emulate SNR	Known by operator	Used to emulate SNR	Known by operator	Used to emulate SNR
	Design values		Design values	Field values	Field values	
Amplifier gain and tilt configuration (based on operator knowledge)						
Fiber loss is compensated	Only for spans with known fiber type		Yes (EDFAs guarantee configured P_{out})		Yes	
Con. loss is compensated	No					
Freq.-dep. loss compensated			No			
Optimal P_{out} is guranteed						

(a)

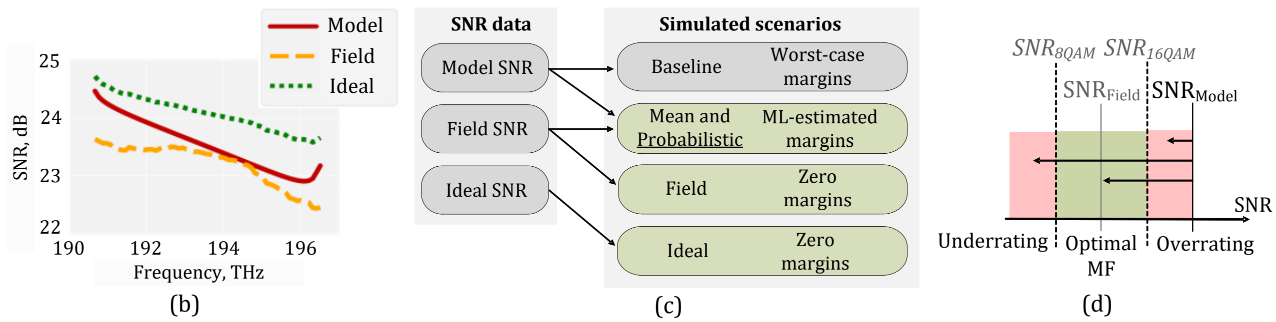


Fig. 2. (a) Physical-layer parameters and EDFA configuration used to emulate Model, Field and Ideal SNR (b) Model, Field and Ideal SNR profiles for a 80 km fiber span (c) Simulated scenarios with corresponding SNR data (d) Incorrect margin estimation can lead to MF overrating (insufficient margin) or MF underrating (excessive margin)

Note that incorrect knowledge of fiber type and connector losses leads to the suboptimal configuration of EDFAs parameters, namely, average gain (G) and gain tilt (T). We will discuss this in details in the next section. Note also that we assume design and field values of noise figure (F) to be equal, constant, and independent from the gain.

3. EMULATED SNR CALCULATION AND LOW-MARGIN DESIGN SCENARIOS

A. Emulated SNR Calculation

Fig. 2a describes the three types of emulated SNR (Model, Field and Ideal) used in this work. We distinguish between field values of PL parameters being known by operator (i.e., operator can set optimal power) and being used to calculate SNR (to emulate SNR measured in the field).

- SNR_{Model} is the SNR predicted with the analytical model and available at network design stage. It is calculated using design values of PL parameters. As described in Fig. 2a, EDFA gain G is set to compensate for propagation loss in the specified fiber type, for design connector losses, and to reach P_{out} computed by LOGO model using design values. EDFA tilt T is set to compensate for design value of ρ.

- SNR_{Field} is the SNR actually measured in the field. In this work we emulate SNR_{Field} using the field values of PL parameters. EDFA gain G is set to compensate for actual field loss, as EDFA can auto-tune its gain, so that EDFA still reaches P_{out} that was computed with design values (as field values of the PL parameters are not known to the operator), and that is suboptimal in the field. Differently from G, tilt T cannot be monitored at every span, so it is always set to compensate for design value of ρ. Suboptimal power setting and tilt configuration together with our assumption that loss in the field is always higher than in the model leads to $SNR_{Field} < SNR_{Model}$.

- 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 of PL parameters *and* optimal tilt and power setting (hence $SNR_{Ideal} > SNR_{Field}$).

Fig. 2b shows an example of Model, Field and Ideal SNR profiles over a single 80 km long span (numerical values of used PL parameters are specified in Section 5).

B. Low-margin Design Scenarios

We use the three types of emulated SNR described above to simulate one baseline and four low-margin design scenarios, as shown in Fig. 2c. In current practice SNR_{Model} is used to set modulation format, and since it is overestimated, a safety margin M is imposed, such that $SNR_{Model} - M \leq SNR_{Field}$.

- **Baseline** scenario uses a worst-case margin M_{Worst}. This is the state-of-the-art design approach that does not make use of monitoring data.

- **Mean** scenario applies Machine Learning to monitoring data to predict a mean value of the design margin: $M_{ML} < M_{Worst}$. This is the design approach that has been recently adopted in research.

- **Probabilistic** scenario also applies Machine Learning to monitoring data, but to predict a distribution of design margin and choose $M_{ML} < M_{Worst}$. This is the novel design approach that we investigate in this work.

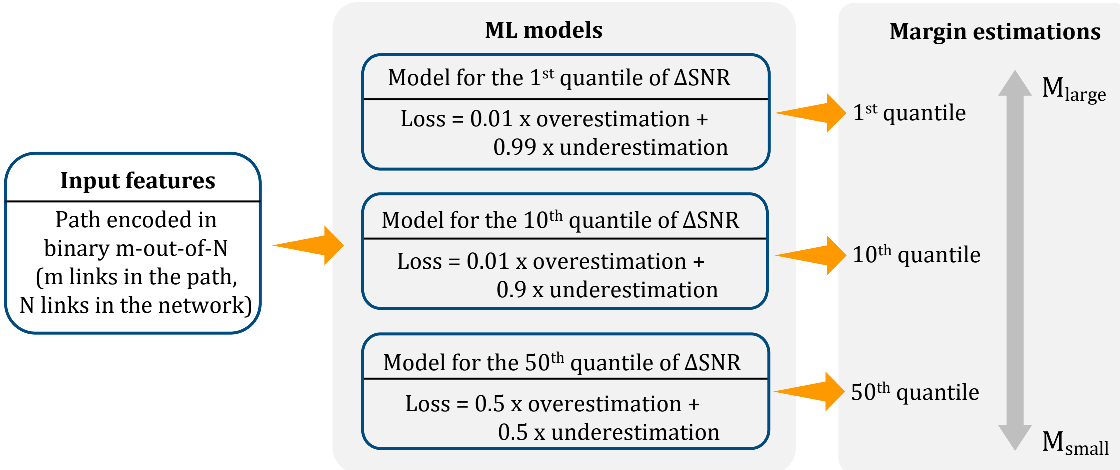


Fig. 3. Probabilistic QoT estimator. Conservative and aggressive design margins can be predicted by penalizing under- and over-estimations of $\Delta SNR = SNR_{Model} - SNR_{Field}$

- **Field** scenario assumes that QoT estimations are perfect, and uses SNR_{Field} to set the MF without safety margins. This scenario provides an upper bound on resource savings in any design approach that leverages monitoring data to improve SNR prediction.
- **Ideal** scenario assumes that field values of PL parameters are known, and MF is set using SNR_{Ideal} without safety margins. This scenario provides an upper bound on resource savings in case "input refinement" is used.[1]

4. METHODOLOGY

To evaluate network resource savings in different low-margin design scenarios, we integrate them with the Routing, Modulation format selection and Spectrum Allocation (RMSA) procedure.

A. Integration of Probabilistic ML-based QoT Estimator with RMSA Procedure

We provision traffic requests using k-Shortest-Path routing and First-Fit spectrum allocation. To obtain the training dataset for ML-based QoT estimation we configure modulation formats of the first N lightpaths in the network based on $SNR_{Model} - M_{Worst}$. To estimate a single network-wide value of M_{Worst}, we use a Monte-Carlo approach and test a large number of random gain ripple profiles, connector loss values and fiber type assignments (numerical values of used PL parameters are specified in Section 5) to find the worst-case value of $\Delta SNR = SNR_{Model} - SNR_{Field}$ across different paths.

Fig. 4 demonstrates how we integrate ML-based QoT estimator in **Probabilistic** design scenario with the RMSA procedure. After the first N lightpaths are deployed, we use N values of measured SNR_{Field} to train a ML regressor predict the distribution of ΔSNR. Knowing the distribution, we choose a single value $M_{ML} = \Delta SNR$ as a margin for the next lightpaths instead of M_{Worst}. By choosing different values from the same distribution, we can set conservative (high) or aggressive (low) design margin. We retrain the regressor on all available data after N new lightpaths are established.

[1]Note that "input refinement" can address both suboptimal power and inaccurate QoT prediction, and can potentially achieve performance of *Ideal* scenario, while "ML-based QoT estimation" only decreases margins by making better QoT predictions and is limited by the performance of *Field* scenario.

Note that if the estimated M_{ML} is too small, and MF configured based on $SNR_{Model} - M_{ML}$ is below FEC threshold, we call it a disruption and reconfigure the transponder with a lower MF, if possible, or reroute the lightpath. Another lightpath is then established to fully satisfy the traffic request. Incorrect estimation of M_{ML} leads to a disruption or inefficient resource utilization only when requested bitrate is high enough, and transponder must operate close to capacity. However, in our evaluations we also account for all potential cases of MF "overrating" (when highest MF that can be configured with $SNR_{Model} - M_{ML}$ is not feasible with SNR_{Field}) and "underrating" (when higher MF can be configured with SNR_{Field} than with $SNR_{Model} - M_{ML}$) (see an example in Fig. 2d).

B. Probabilistic ML-based QoT Estimator based on Quantile Regression

The logic of the probabilistic QoT estimator is illustrated in Fig. 3. We predict ΔSNR per path, and feature vector encodes it 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 ΔSNR at the receiver to predict it for new paths. To estimate the distribution of ΔSNR, we use a weighted loss function (known as quantile or pinball loss [18]) and penalize under- or over-estimations for a conservative (high) or aggressive (low) margin prediction, respectively. Note that as more monitoring data becomes available, per-path distribution of ΔSNR shrinks and accounts only for randomness caused by gain ripple.

Differently, in the **Mean** design scenario ML-based estimator

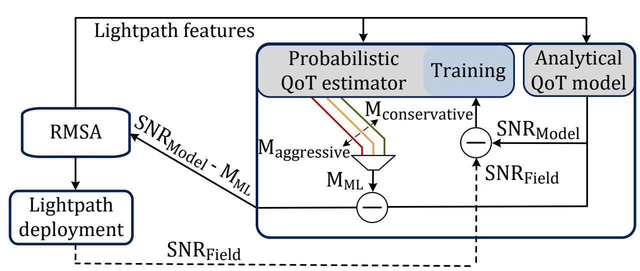
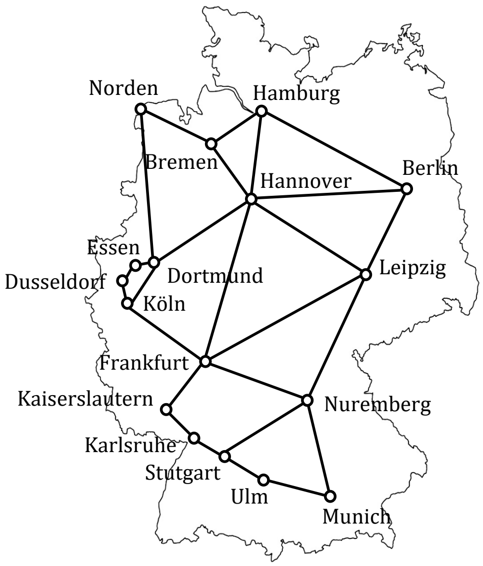
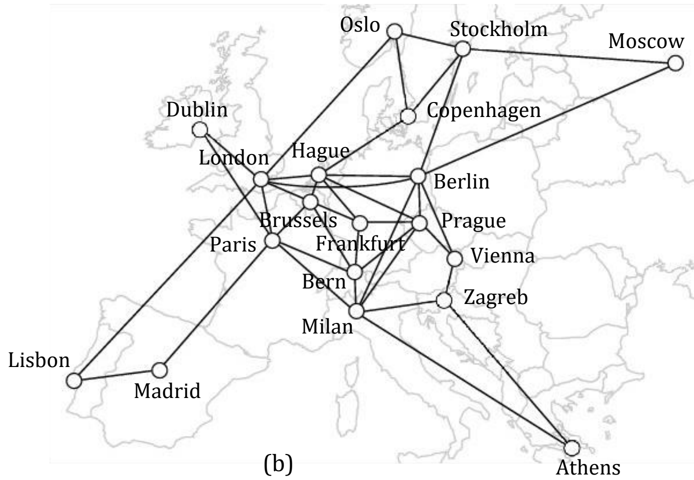


Fig. 4. Proposed probabilistic QoT estimator integrated into Routing, Modulation format selection and Spectrum Allocation (RMSA) procedure



(a)



Metric	GE17	EU19
Av. link length, km	147	576
Av. SP length, km	415	1441
Av. node degree	3.06	4

(c)

Fig. 5. (a) 17-node German and (b) 19-node European topologies (c) Topology parameters

is trained to predict only the mean of $SNR_{Model} - SNR_{Field}$ by minimizing mean squared error.

We also propose an adaptive quantile selection procedure to choose the quantile that leads to the optimal MF. We keep a score for each quantile and choose the quantile with the highest score as the margin for the new lightpath. Scores are initialized on the first N lightpaths by adding 1 if MF is set optimally, and subtracting 1 in case of over- or underrating, and are updated after every provisioned lightpath. We have tested different reward/penalty values and found these to perform best.

5. ILLUSTRATIVE NUMERICAL RESULTS

We perform our numerical evaluations on two realistic topologies, a 17-node German network (GE17) and 19-node European network (EU19) (Fig. 5) [19]. Results are averaged considering 20 traffic matrices with bidirectional 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 exchange traffic. Traffic is provisioned by 90 Gbaud transponders capable of 300-800 Gbit/s with 20 dB back-to-back SNR and SNR thresholds from [20] with a 1 dB system margin.

Established lightpaths are not affected by QoT degradation (e.g., due to aging), as in this work we focus on reducing the design margins arising from uncertainties in the knowledge of physical-layer parameters and not margins corresponding to other effects.

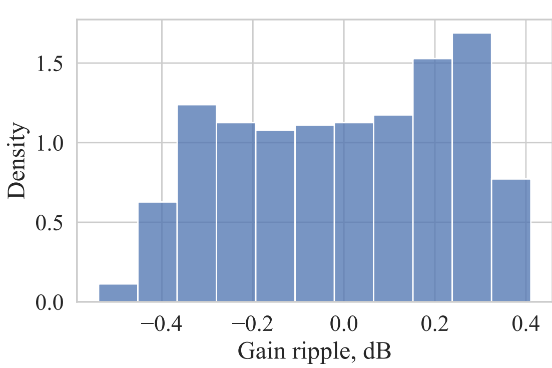


Fig. 6. Distribution of EDFA gain ripple

In C-band scenario we operate in a 6 THz band, while in C+L scenario we consider 10 THz available and allocate spectrum starting from the L-band. We increase traffic by 65% (by increasing the probability of high bitrates) to match 66% increase in available spectrum. We assume that EDFAs are placed every 80 km and consider F equal to 5 dB in C-band EDFAs and to 6 dB in L-band EDFAs. We use Generalized Gaussian Noise model [21] to estimate NLI and assume ASE-loading (i.e., spectrum is always fully loaded, and EDFA ripple profiles do not change) in both C- and C+L-scenarios.

Connector losses are 0.5 dB in the design 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 at design stage. For each field EDFA we randomly select one of 18 ripple profiles measured on testbed amplifiers. Ripple distribution is shown in Fig. 6. We consider $M_{Worst} = 2\,dB$ in GE17 and $M_{Worst} = 2.5\,dB$ in EU19.

We use M_{Worst} for the first $N = 50$ lightpaths, then start estimating M_{ML} and retrain the ML model every 50 established lightpaths after that. Training dataset reaches up to 250 (400) samples in the GE17 (EU19) networks. Input vector of the ML regressor contains 104 (152) binary elements (each link in 2 directions) in the GE17 (EU19) networks.

We compare four low-margin design scenarios defined in Section 3B: *i*) *Probabilistic* scenario that estimates 5 quantiles of ΔSNR (1st, 25th, 50th, 75th or 99th quantile, where small and large quantiles correspond to conservative and aggressive M_{ML} estimations, respectively) and either always considers the same quantile as M_{ML} (e.g., always the 1st) or chooses one out of five using adaptive quantile selection procedure, *ii*) a *Mean* scenario that estimates the mean of ΔSNR, *iii*) a *Field* scenario, and *iv*) an *Ideal* scenarios w.r.t. *Baseline* scenario that uses M_{Worst}.

We present the results in terms of savings in occupied spectrum slots (SO) and number of deployed transponders (TRX), in

Table 1. Savings in Spectrum Occupation (SO) and number of Transponders (TRX), and probability of disruption w.r.t. *Baseline* scenario with M_{Worst} = 2.0 dB in GE17 in C-band

		Savings (%) in SO				Savings (%) in TRX				Prob. (%) of disruption			
Algorithm		LR	DNN	RF	GBT	LR	DNN	RF	GBT	LR	DNN	RF	GBT
Mean		6.2	6.3	6.6	6.5	5.6	5.7	5.9	5.8	0.2	0.2	0.1	0.1
Proposed	25 q.	6.1	6.1	6.4	6.4	5.4	5.5	5.7	5.7	0.1	0.2	0.1	0.04
	50 q.	6.6	6.5	6.6	6.5	5.9	5.9	5.9	5.9	0.1	0.2	0.1	0.1
	75 q.	6.8	6.8	6.7	6.7	6.0	6.0	5.9	5.9	0.3	0.3	0.2	0.1

Table 2. Savings in Spectrum Occupation (SO) and number of Transponders (TRX), decrease in Residual Capacity (RC) and probability of disruption, potential overrating and underrating w.r.t. *Baseline* scenario with M_{Worst} in GE17 (EU19)

(a) C-band. Uncertainty in connector losses, EDFA gain ripple and fiber types. M_{Worst} = 2.0 (2.5) dB

		Savings (%) in		Decrease (%) in	Probability (%) of		
Scenario		SO	TRX	RC	Disruption	Overrating	Underrating
Worst-case baseline		-	-	-	0	0	89.9 (98.6)
Proposed	1 q.	5.8 (7.6)	5.4 (7.3)	2.6 (14.4)	0.1 (0.1)	0.4 (0.8)	33.8 (46.4)
	25 q.	6.3 (7.9)	5.7 (7.6)	3.3 (17.7)	0.1 (0.8)	1.1 (2.9)	25.2 (33.0)
	50 q.	6.4 (8.1)	5.8 (7.8)	3.4 (17.7)	0.3 (0.6)	2.0 (3.1)	24.4 (31.2)
	75 q.	6.5 (8.1)	5.9 (7.8)	3.5 (18.7)	0.2 (1.0)	2.6 (4.2)	22.8 (28.7)
	99 q.	6.6 (8.4)	6.0 (8.2)	4.6 (20.7)	1.0 (2.6)	8.5 (9.5)	20.9 (21.4)
	Adaptive q.	6.8 (7.8)	6.0 (7.6)	3.0 (19.3)	0.1 (0.8)	2.6 (3.8)	24.1 (29.0)
Mean		6.4 (8.0)	5.8 (7.7)	3.4 (18.3)	0.3 (0.7)	2.2 (3.3)	23.9 (30.7)
Upper bound	Field	7.8 (9.8)	7.4 (9.4)	4.2 (23.7)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	Ideal	8.8 (12.0)	8.4 (11.6)	4.6 (28.8)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)

(b) C-band. Uncertainty in connector losses and EDFA gain ripple. Known fiber types. M_{Worst} = 1.5 (2.0) dB

		Savings (%) in		Decrease (%) in	Probability (%) of		
Scenario		SO	TRX	RC	Disruption	Overrating	Underrating
Worst-case baseline		-	-	-	0	0	80.4 (98.6)
Probabilistic	1 q.	2.7 (4.1)	2.5 (3.8)	4.0 (15.3)	0.0 (0.3)	0.5 (1.3)	30.6 (40.4)
	25 q.	3.6 (4.3)	3.2 (4.1)	3.9 (17.6)	0.1 (0.7)	2.0 (3.4)	22.7 (30.8)
	50 q.	3.6 (4.5)	3.2 (4.3)	4.1 (17.8)	0.2 (0.9)	2.3 (3.7)	21.6 (27.2)
	75 q.	3.6 (4.7)	3.2 (4.4)	4.4 (18.2)	0.2 (1.2)	2.6 (5.2)	20.2 (25.8)
	99 q.	3.6 (4.8)	3.2 (4.6)	6.0 (20.9)	0.4 (3.5)	10.3 (13.3)	18.9 (19.4)
	Adaptive q.	3.6 (4.5)	3.2 (4.3)	4.2 (18.2)	0.1 (0.9)	2.5 (3.7)	21.5 (26.9)
Mean		3.6 (4.6)	3.2 (4.3)	4.2 (18.0)	0.1 (0.8)	2.3 (4.3)	21.1 (27.4)
Upper bound	Field	5.1 (5.8)	5.0 (5.5)	2.6 (21.7)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	Ideal	5.7 (7.1)	5.7 (6.9)	2.5 (23.8)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)

terms of decrease in residual capacity (in Gbit/s) of the deployed transponders (RC) and in terms of % of disrupted, potentially overrated and underrated lightpaths.

A. ML-model Selection

In Table 1 we show average savings in GE17 topology (C-band and $M_{Worst} = 2\ dB$) for the state-of-the-art mean estimator and the proposed estimator of 25/50/75th quantiles, while using

Table 3. Savings in Spectrum Occupation (SO) and number of Transponders (TRX), decrease in Residual Capacity (RC) and probability of disruption, potential overrating and underrating w.r.t. *Baseline* scenario with M_{Worst} in GE17 (EU19) in C+L-band

		Savings (%) in		Decrease (%) in	Probability (%) of		
Scenario		SO	TRX	RC	Disruption	Overrating	Underrating
Worst-case baseline		-	-	-	0	0	94.8 (99.6)
Probabilistic	1 q.	4.3 (10.9)	5.1 (9.7)	6.9 (23.0)	0.5 (1.2)	1.0 (2.1)	29.8 (40.1)
	25 q.	4.7 (11.4)	5.7 (10.2)	6.9 (25.6)	0.9 (2.6)	2.2 (4.8)	21.4 (29.8)
	50 q.	4.6 (11.8)	5.6 (10.6)	7.6 (26.3)	1.3 (3.0)	3.2 (5.9)	21.1 (25.6)
	75 q.	4.8 (12.0)	5.8 (10.7)	7.5 (27.0)	1.6 (4.0)	4.2 (8.0)	18.8 (23.6)
	99 q.	4.9 (12.2)	5.9 (10.9)	9.3 (31.6)	4.6 (6.5)	11.9 (14.1)	14.7 (16.2)
	Adaptive q.	4.8 (11.7)	5.7 (10.5)	7.3 (26.4)	0.7 (2.7)	3.2 (5.9)	20.2 (26.1)
Mean		4.7 (11.5)	5.7 (10.4)	7.3 (26.4)	1.2 (3.4)	3.3 (6.7)	20.8 (27.6)
Upper bound	Field	5.2 (13.5)	6.1 (12.1)	11.9 (31.9)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	Ideal	5.6 (17.0)	6.6 (15.1)	14.3 (36.5)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)

Linear Regression (LR), Deep Neural Network (DNN), Random Forest (RF) and Gradient Boosted Trees (GBT).

Results show negligible variations in savings for different ML algorithms in the order of tenths of %. RF and GBT allow more savings than LR and NN for the mean and 25th quantile, while guaranteeing lower probability of disruption. For 50th and 75th quantiles LR and NN save 0.1-0.2% more, but at the cost of higher disruption probability. For the following results we will consider GBT regressor as a ML model, as it guarantees highest savings and lowest disruption probability.

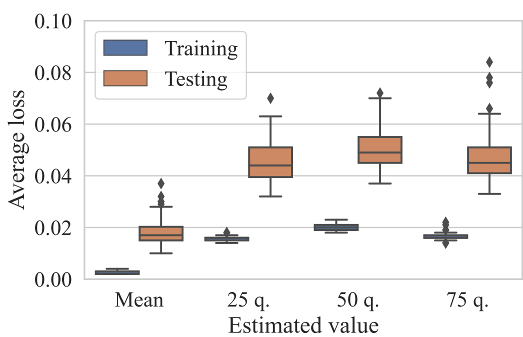


Fig. 7. Average loss on the training and testing datasets

To verify that the regression algorithm does not over- or underfit, in Fig. 7 we plot the loss of the GBT regressor (mean square error for the mean estimator and pinball loss for the quantile estimator) on the training and testing datasets. We can see that the error is lower for the training dataset (suggesting that there is no underfitting), while it still remains low for the testing dataset (suggesting that there is no overfitting).

B. C-band. Uncertain connector losses, EDFA gain ripple and fiber type

Results in Table 2a show that by using conservative, but not worst-case margins (1st quantile) we can save 5.8 (7.6)% in SO, 5.4 (7.3)% in TRX while losing 2.6 (14.4)% in RC with only 0.1 (0.1)% of disrupted and 0.4 (0.8)% of potentially overrated lightpaths in GE17 (EU19) networks. % of potentially underrated lightpaths decreases from 89.9 (98.6)% to 33.8 (46.4)% in GE17 (EU19). As we use more aggressive estimations (higher quantiles), savings increase and eventually reach 6.6 (8.4)% in SO and 6.0 (8.2)% in TRX with 99th quantile estimations, while RC decreases by 4.6 (20.7)% and 1.0 (2.6)% of lightpaths are disrupted in GE17 (EU19). % of potentially underrated lightpaths is lower-bounded by 18.5 (14.3)%, as the first 50 lightpaths are provisioned with worst-case margins, and by using the 99th quantile estimations we arrive close to this lower bound with 20.9 (21.4)% of potentially underrated lightpaths in GE17 (EU19).

Adaptive quantile selection procedure enables further savings in GE17, 6.8% in SO and 6.0% in TRX with 0.1% of disrupted lightpaths. In EU19 it closely follows the performance of the median and provides no advantage. *Mean* scenario performs similarly to the scenario that uses median estimation. These results demonstrate the advantage of the *Probabilistic* QoT estimation approach that is capable of trading savings in network resources with probability of disruption, while *Mean* scenario does not have this degree of freedom.

Perfectly accurate QoT estimation in *Field* scenario can potentially save 7.8 (9.8)% in SO and 7.4 (9.4)% in TRX with a 4.2 (23.7)% decrease in RC, meaning that with aggressive margin estimations we are just a few % from the field optimum. If we could also set powers and tilts optimally in *Ideal* scenario we can save 8.8 (12.0)% in SO and 8.4 (11.6)% in TRX with a 4.6 (28.8)% decrease in RC.

C. C-band. Uncertain connector losses and EDFA gain ripple

We repeat the same analysis considering that inventory human-errors do not happen, and fiber types are always known, and worst-case margins reduce by 0.5 dB to $M_{Worst} = 1.5\ dB$ for the GE17 and $M_{Worst} = 2.0\ dB$ for EU19. Results in Table 2b show that we can save only 2.7 (4.1)% in SO and 2.5 (3.8)% in TRX with 0.0 (0.3)% of disrupted and 0.5 (1.3)% of potentially overrated lightpaths when using the 1st quantile estimation. Savings increase by approximately 1% with the 99th quantile estimation and reach 3.6 (4.8)% in SO and 3.2 (4.6)% in TRX, while probability of disruption increases to 0.4 (3.5)%. We see that in GE17 savings in both SO and TRX remain constant for a wide range of quantiles. This can be explained by the fact that when small margins are used, difference in dB between two quantile estimations is too small to change MF assignment. Both adaptive quantile selection and *Mean* margin estimations closely follow the performance of the scenario that uses median estimation. Perfectly accurate QoT estimation in *Field* scenario can save 5.1 (5.8)% in SO and 5.0 (5.5)% in TRX, and with optimal settings of gains and tilts in *Ideal* scenario we can save 5.7 (7.1)% in SO and 5.7 (6.9)% in TRX.

D. C+L-band. Uncertain connector losses, EDFA gain ripple and fiber type

We then repeat the analysis for the 10 THz C+L-band scenario. We keep $M_{Worst} = 2\ dB$ for the GE17 and $M_{Worst} = 2.5\ dB$ for EU19. Results in Table 3 show that by using the 1st quantile estimation we can save 4.3 (10.9)% in SO, 5.1 (9.7)% in TRX with 0.5 (1.2)% of disrupted and 1.0 (2.1)% of potentially overrated lightpaths. Underrating decreases from 94.8 (99.6)% to 29.8 (40.1)%. Savings increase with smaller margins (higher quantiles) and reach 4.9 (12.2)% in SO and 5.9 (10.9)% in TRX with 4.6 (6.5)% of disruptions. In EU19 savings increase significantly w.r.t. C-band scenario, as paths are long enough to make high-order MFs (required to carry increased bitrates) unfeasible with worst-case margins, so that more lightpaths can benefit from lower margins compared to GE17. Adaptive quantile selection achieves similar performance to the case when 50th quantile estimation is used, but decreases probability of disruption by 0.5 (0.3)%. In *Mean* scenario performance is similar to the median estimation. % of disrupted and overrated lightpaths increases by a couple of % w.r.t. C-band scenario, emphasizing the benefits of the resource savings vs. disruption probability trade-off. Perfectly accurate QoT estimation in *Field* scenario allow to save 5.2 (13.5)% in SO and 6.1 (12.1)% in TRX, and optimal settings of gains and tilts in *Field* scenario provide 5.6 (17.0)% savings in SO and 6.6 (15.1)% in TRX.

6. CONCLUSION

Considering 3 practical sources of uncertainty at the physical layer (connector losses, EDFA gain ripple and fiber types), we identified 4 low-margin design scenarios that allow to numerically evaluate the gain from improved knowledge of physical-layer behaviour. We demonstrate how a probabilistic ML regressor can be integrated into resource allocation heuristic to set lower design margins and save (4-12)% of spectrum and transponders in C- and C+L-band scenarios at a cost of a small probability of lightpath disruption (at most 1-4%).

Considering high cost and energy consumption of transponders [22], proposed approach noticeably reduces optical network deployment cost, while only using monitoring data already available at the receivers (in other words, our proposed solution does not require any additional capital expenditure for monitoring). Note that different optimization strategies that lead to a flat SNR profile can make the proposed approach less effective, but they will require a precise knowledge of physical layer parameters.

As future work, we aim at improving adaptive quantile selection procedure to choose the best quantile based on lightpath features and also at improving the accuracy of the proposed probabilistic QoT estimation approach in multi-band scenarios.

REFERENCES

1. P. Poggiolini *et al.*, "The GN-Model of Fiber Non-Linear Propagation and its Applications," in IEEE/OSA 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), pp. 1-4, 2019.
3. Y. Pointurier "Design of low-margin optical networks", in IEEE/OSA Journal of Optical Communications and Networking vol. 9, no. 1, pp. A9-A17, Jan. 2017.
4. N. Guo *et al.*, "Protection against failure of machine-learning-based QoT prediction," in IEEE/OSA Journal of Optical Communications and Networking, vol. 14, no. 7, pp. 572-585, July 2022.
5. E. Seve *et al.*, "Associating machine-learning and analytical models for quality of transmission estimation: combining the best of both worlds," in IEEE/OSA Journal of Optical Communications and Networking, vol. 13, no. 6, pp. C21-C30, June 2021.
6. 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), pp. 1-3, March 2022.
7. G. Borraccini *et al.*, "Cognitive and autonomous QoT-driven optical line controller," in IEEE/OSA Journal of Optical Communications and Networking, vol. 13, no. 10, pp. E23-E31, Oct. 2021.
8. C. Rottondi *et al.*, "Machine-learning method for quality of transmission prediction of unestablished lightpaths," in IEEE/OSA Journal of Optical Communications and Networking, vol. 10, no. 2, pp. A286-A297, Feb. 2018.
9. 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.
10. A. Mahajan *et al.*, "Modeling EDFA Gain Ripple and Filter Penalties With Machine Learning for Accurate QoT Estimation," in IEEE/OSA Journal of Lightwave Technology, vol. 38, no. 9, pp. 2616-2629, May 2020.
11. M. Ibrahimi *et al.*, "Machine learning regression for QoT estimation of unestablished lightpaths," in IEEE/OSA Journal of Optical Communications and Networking, vol. 13, no. 4, pp. B92-B101, April 2021.
12. H. Maryam *et al.*, "Learning quantile QoT models to address uncertainty over unseen lightpaths," in Computer Networks, 108992, April 2022.
13. N. Di Cicco *et al.*, "Calibrated Probabilistic QoT Regression for Unestablished Lightpaths in Optical Networks," 2022 International Balkan Conference on Communications and Networking (BalkanCom), pp. 21-25, 2022.
14. J. Girard-Jollet *et al.*, "Estimating Network Components PDL Using Performance Statistical Measurements," in IEEE/OSA Journal of Lightwave Technology, vol. 40, no. 16, pp. 5407-5415, Aug. 2022.
15. O. Karandin *et al.*, "Low-Margin Optical-Network Design with Multiple Physical-Layer Parameter Uncertainties," in 48th European Conference on Optical Communication (ECOC 2022), Sep. 2022.
16. A. Ferrari *et al.*, "Assessment on the in-field lightpath QoT computation including connector loss uncertainties," in IEEE/OSA Journal of Optical Communications and Networking, vol. 13, no. 2, pp. A156-A164, Feb. 2021.
17. E. Seve *et al.*, "Automated Fiber Type Identification in SDN-Enabled Optical Networks," in IEEE/OSA Journal of Lightwave Technology, vol. 37, no. 7, pp. 1724-1731, April 2019.
18. R. Koenker *et al.*, "Quantile Regression," in Journal of Economic Perspectives, vol. 15, no. 4 pp. 143-156, 2001.
19. A. Betker *et al.*, "Reference transport network scenarios," in Tech. Rep. BMBF MultiTeraNetProject, July 2003.
20. 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.
21. D. Semrau *et al.*, "A Closed-Form Approximation of the Gaussian Noise Model in the Presence of Inter-Channel Stimulated Raman Scattering," in IEEE/OSA Journal of Lightwave Technology, vol. 37, no. 9, pp. 1924-1936, May 2019.
22. Metro-HAUL project Deliverable D2.4: Techno-economic Analysis and Network Architecture Refinement, April 2020.