Machine Learning Assisted Quality of Transmission Estimation and Planning with Reduced Margins

Konstantinos Christodoulopoulos[1(✉)], Ippokratis Sartzetakis[2], Polizois Soumplis[2], and Emmanouel (Manos) Varvarigos[2]

[1] Nokia Bell Labs, Stuttgart, Germany
konstantinos.1.christodoulopoulos@nokia-bell-labs.com
[2] School of Electrical and Computer Engineering, National Technical University of Athens, Athens, Greece

Abstract. In optical transport networks, the Quality of Transmission (QoT) using a physical layer model (PLM) is estimated before establishing new or reconfiguring established optical connections. Traditionally, high margins are added to account for the model's inaccuracy and the uncertainty in the current and evolving physical layer conditions, targeting uninterrupted operation for several years, until the end-of-life (EOL). Reducing the margins increases network efficiency but requires accurate QoT estimation. We present two machine learning (ML) assisted QoT estimators that leverage monitoring data of existing connections to understand the actual physical layer conditions and achieve high estimation accuracy. We then quantify the benefits of planning/upgrading a network over multiple periods with accurate QoT estimation as opposed to planning with EOL margins.

Keywords: Overprovisioning · Static network planning · End-of-life margins · Physical layer impairments · Monitoring · Cross-layer optimization · Incremental multi-period planning · Marginless

1 Introduction

Coherent transmission and Elastic Optical Networks (EONs) deployed today promise higher spectral efficiency, increased capacity, and reduced network costs [1]. However, optical networks are traditionally planned to be operated statically; planning relies on abundant margins [2, 3] to ensure that all connections/lightpaths have acceptable Quality of Transmission (QoT) until the end of life (EoL). Lowering the margins and increasing efficiency reduces network costs, motivating various research directions [4]. Refs. [5, 6] studied the planning of an EON over multiple periods to harvest the evolution of margins over time. Certain connection parameters are adjusted at a given time granularity (e.g., 1–2 years) and new equipment is added, when actually needed, according to current traffic and physical layer conditions. Therefore, instead of overprovisioning to reach EoL, the network is operated with just in time provisioning, increasing the efficiency, postponing or avoiding equipment purchase, and reducing the network costs. An EON can

Published by Springer Nature Switzerland AG 2020
A. Tzanakaki et al. (Eds.): ONDM 2019, LNCS 11616, pp. 211–222, 2020.
https://doi.org/10.1007/978-3-030-38085-4_19

be operated even more dynamically, by adapting the transmission parameters at shorter timeframes. Refs. [7, 8] and other works consider the dynamic spectrum/capacity adaptation according to traffic demands. The efficient management of failures also pertains to dynamic network operation. [9] studies the dynamic adaptation of the connections' parameters to current physical layer conditions (e.g., in case of QoT degradation). The dynamic operation of a marginless network is experimentally demonstrated in [10].

Considering the above, an accurate QoT estimator is the key component for (i) reducing the margins during planning/upgrades, and (ii) realizing a more dynamic operation of the network. Figure 1a shows how a QoT estimation tool (or Qtool) is used by an optimization (planning or dynamic) algorithm. The Qtool consists of a physical layer model (PLM), which is analytical or semi-analytical and makes certain assumptions to estimate with certain accuracy the QoT (e.g. SNR, BER) of new or reconfigured connections. The Qtool takes as input the parameters of the established connections (in case of an operating network), and also certain physical layer parameters, such as spans, fibers, amplifiers and node parameters, etc. The values of the physical layer input parameters are not accurately known, due to lack or limited accuracy of measuring equipment, outdated measurements, etc. To cover the model and input parameter inaccuracies, the design margin is used (2 dB in SNR as a references [2, 3]). Moreover, traditional network planning targets for new connections to have acceptable QoT at EOL, e.g. after 10–15 years. Modeling equipment ageing, increase of interference, reparations of fiber cuts, etc. contributes to the system margin (3 dB in SNR as a references [2, 3]). A great deal of recent research effort was directed towards the application of Machine Learning (ML) in various areas of optical networking both at the physical and network layers [11]. ML has also been applied to improve the accuracy of QoT estimation and reduce the design and system margins [12–17] (Fig. 1b).

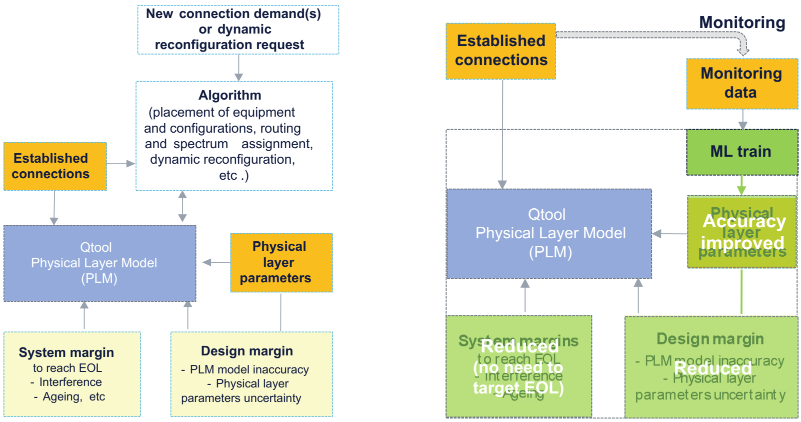

Fig. 1. (a) QoT estimation tool (Qtool) used by an algorithm to reconfigure or establish lightpaths, its inputs, and design and system margins, (b) Machine learning assisted QoT estimation to reduce the margins.

In this paper, which outlines [19] and [6, 20] we start by presenting two ML assisted QoT estimators. We then evaluate the accuracy of the estimators under various scenarios and observe quite low estimation error with relatively low information (few established lightpaths). We then quantify the cost savings that can be obtained by accurate QoT estimation in a multiperiod planning network scenario. To do so we interface the ML assisted QoT estimator with the incremental algorithm of [6, 20] and use that to (accurately) estimate the QoT of new and existing lightpaths and provision/reconfigure them with reduced margins.

2 Quality of Transmission (QoT) Estimation

We assume an EON with Reconfigurable Optical Add/Drop Multiplexers (ROADMs) connected through uncompensated fiber links. Each link consists of a number of fiber spans that terminate at an EDFA that compensates the span loss. We assume that there are no spectrum converters and thus a lightpath is allocated the same spectrum throughout its path. For long connections, regenerators are placed. The set of established lightpaths and their attributes (e.g., modulation format, baudrate) is denoted by P which will also be referred to as the *state* of the network at a given time. We also assume that we can obtain monitoring information from the coherent receivers. Coherent receivers deployed today are packed with DSP capabilities, so they can function as Optical Performance Monitors (OPMs) [4]. So we assume that an OPM (receiver) monitors the lightpath's SNR with certain accuracy. We use this information to improve the QoT estimation accuracy and reduce the margins of new or reconfigured lightpaths.

In particular, we denote by $Q^*(P)$ the *vector* that contains the SNR values of all established lightpaths $p \in P$. The mapping $Q^*(P)$ is nonlinear and unknown to us. For the set of established lightpaths P we denote by $Y(P)$ the vector of their monitored SNR values. The monitoring error consists of a systematic and a random error. The systematic error can be reduced through proper calibration, while the random error can be reduced by averaging measurements over time (at a shorter timescale than a natural change of the monitored value would occur). As monitoring errors are small and can be reduced, we ignore them here for simplicity. So, we will assume we monitor the true SNR for the paths ($Y(P) = Q^*(P)$ for $p \in P$).

We consider the case where a new lightpath $w \notin P$ is about to be established, and we want to estimate (i) the QoT of that new lightpath w, and (ii) how QoT of existing lightpaths $p \in P$ will be affected by the establishment of w. Stated formally, we are given the measurements $Y(P) = Q^*(P)$ of QoT metrics at the current network state P. Our objective is to *estimate* the new QoT metrics $Q^*(P \cup \{w\})$ after the new lightpath $w \notin P$ is established. Note that $Q^*(P \cup \{w\})$ contains the (new) QoT metrics of existing lightpaths $p \in P$, which in general will be affected by the establishment of w. Also note that the above problem definition can be extended to include the establishment of a set or the reconfiguration of a single or a set of lightpaths.

3 Machine Learning Assisted QoT Estimation

In QoT estimation, our goal is to identify a parametric function $\widetilde{Q}(r, P)$ that approximates well the actual QoT of the connections $Q^*(P)$. Here r is a set of parameters of the model. The parametric function $\widetilde{Q}(r, P)$ does not have to be a closed form expression; it can also be the output of a simulation. What is important is that (i) $\widetilde{Q}(r, P)$ approximates $Q^*(P)$ relatively well and that (ii) given the set *r*, it is relatively easy computationally to obtain $\widetilde{Q}(r, P)$ for the given state *P*. The following two subsections describe two approximating architectures, corresponding to different parametric function choices, the first based on a physical layer model (PLM) and the second based on a machine learning (ML) model and features extraction (Fig. 2).

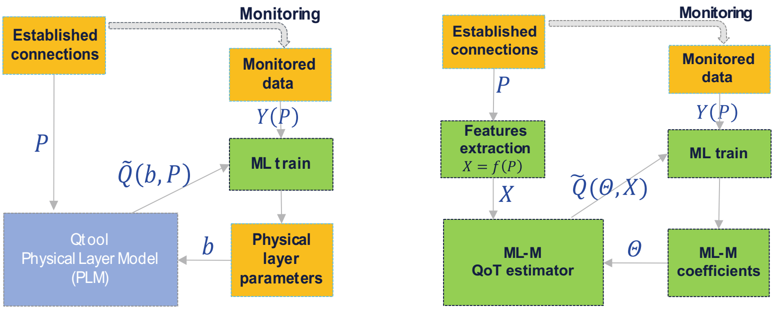

Fig. 2. Flowcharts of (a) machine learning physical layer model (ML-PLM) and (b) machine learning model (ML-M) QoT estimators.

3.1 Machine Learning Physical Layer Model (ML-PLM)

The first approach considers a physical layer model (PLM) as the approximating architecture. In this case, $\widetilde{Q}(r, P)$ takes as input *r* the PLM input parameters, denoted by *b*, which can include: per span length, fiber attenuation, dispersion and nonlinear coefficients, the noise figure of each EDFA, its gain, etc. So, following the above we denote the PLM model with $\widetilde{Q}(b, P)$. In this paper, we will use the GN model [18] as the PLM, but the method is generic and applicable to other PLMs. The assumption is that the initial parameter values are close to the actual ones but not close enough to provide accurate QoT estimation. They could be based on datasheets or even field measurements that however cannot be taken continuously and with high accuracy, so they would be partially outdated/inaccurate. The objective of the machine-learning (ML)-PLM is to use monitoring information from the established lightpaths $Y(P)$ to train and learn the physical layer parameters and thus improve the accuracy of future QoT estimations. The model also uses the set of lightpaths' parameters included in the network state *P*, which can be: the route, central frequency, baudrate, modulation format, launch power, etc. The parameters in *P* are assumed to be perfectly known, as opposed to the parameters in *b*. Regarding the learning algorithm, if we have closed forms for the partial derivatives $\partial\widetilde{Q}/\partial b_j$ with respect to all physical layer parameters b_j of *b*, we could use gradient decent to obtain better estimates of *b* as in [16]. Here we assume a generic case where $\widetilde{Q}(b, P)$ is unknown. Assuming that QoT depends non-linearly on some input parameter, we use a nonlinear method to fit the model.

3.2 Machine Learning Model (ML-M)

The second investigated approach uses a Machine Learning Model (ML-M) and features extraction. Features extraction maps the state P into a matrix $X = f(P)$, called the *features matrix*. The mapping function f is chosen to summarize in a heuristic way the important characteristics of P with respect to QoT estimation. The main idea is that through the change of variables from P to $X = f(P)$, the unknown mapping $Q^*(P)$ of the true QoT is approximated well by the function $\widetilde{Q}(\Theta, X) = \widetilde{Q}(\Theta, f(P))$, where Θ are the ML-M parameters (coefficients). The type of coefficients Θ depends on the particular model (linear regression, neural network-NN, Support Vector Machine-SVM, etc.). The ML-M $\widetilde{Q}(\Theta, X)$ is trained with an appropriate regression algorithm, using, as in previous section, training data $(P, Y(P))$. After implementing and testing several such models, we observed that the choice of features is of utmost importance for the estimation accuracy, at least considering medium size networks (10–20 nodes). So, in the following we present the formulation that achieved the best performance.

We follow a link-level feature formulation to account for network heterogeneity. So, in our ML estimation model we consider each lightpath's link attributes separately. Thus, the model distinguishes, for example, two lightpaths that have similar lengths but cross different links and possibly exhibit different QoT due to heterogeneities of link attributes. We do not consider span level features since a lightpath will always cross all spans of a link. We organize the feature matrix X so that each row corresponds to one lightpath $p \in P$, while the columns represent (link, impairment) features. We defined three sets of link-impairment features corresponding to the major impairment classes affecting the QoT. More specifically, we define A as a $|P| \times |L|$ link-level feature matrix designed to account for the ASE noise. Element A_{pl}, corresponding to lightpath p and link l, is set equal to 1 if it contains link l, and is set to zero, otherwise. We also define the link-level feature matrix S to account for Self-Channel Interference (SCI) noise [18]. Element S_{pl} is set equal to the inverse of the square of the lightpath's baudrate if lightpath p contains link l, and is set to zero, otherwise. Finally, we define a link-level feature matrix W to account for the interference of neighboring lightpaths (cross channel interference-XCI [18]). The elements of this matrix are derived from an equation that involves the baudrate of the lightpath under consideration, and for each of its neighboring lightpaths the spectrum distance and its baudrate, following Eq. (40) of [18]. We also consider an additional feature, the bias term (denoted by BT). Bias can account for the monitoring error in $Y(P)$, impairments not modeled, etc. We concatenate all the link-level feature matrices and the bias into one feature matrix $X = f(P)$:

$$X = [\,BT \;\; A \;\; S \;\; W\,]_{|P|x(3|L|+1)}$$

Focusing on a lightpath p, its features are designed to represent its noise contributing parameters (considering the major types of impairments, both linear and non-linear) per link. Assuming $x_{p,j}$ is the j^{th} feature of lightpath p, the noise contribution of the related impairment/link is approximated well with a linear function, i.e. $n_j(x_{p,j},\Theta) = x_{p,j}.\theta_j$, where θ_j is the related impairment-link coefficient. We assume that the noise of the different types of impairments is additive on a link level and over the path, following the assumptions of the GN model [18]. In other words, the total noise accumulated over lightpath p is given by $\sum_j n_j\left(x_{p,j}, \Theta\right)$. This assumption makes possible the correlation of the noise contributions at impairment and link levels. Based on these assumptions we estimate the total noise of the lightpaths by

$$\widetilde{N}(\Theta, \mathrm{X}) = X \cdot \Theta.$$

From that we obtain the SNR of the lightpaths by

$$\widetilde{Q}(\Theta, X) = \frac{B_N \cdot l_p}{B_r \cdot \widetilde{N}(\Theta, X)}$$

where B_N is the noise bandwidth, l_p is the launch power, and B_r is the baudrate of the lightpaths. Then we use the SNR measurements $Y(P)$ and a linear regression/gradient descent algorithm to learn Θ.

Note that we derived a linear model to approximate $\widetilde{Q}$. However, we performed a non-linear transformation f of the input P, carefully designed so that the subsequent fitting would be well approximated using a linear model. The above described ML-M concept is quite generic. We can define different features X, and model more complicated features – noise functions n_j with other ML models, such as NN or SVM, and train them with appropriate algorithms. Another possibility, under the linear feature – noise functions assumption, is to use a constrained least squares solver, where we can add constraints that exploit certain expected QoT relationships. For example, a link that is 200 km longer is highly unlikely to contribute lower noise. The additional constraints help the model to provide better estimations especially in cases with low amount of information (lightpaths).

4 Machine Learning Assisted QoT Estimation

We evaluated the proposed machine learning QoT estimators through simulations. We considered the DT topology with 12 nodes and 40 bidirectional links. We assumed 4 traffic loads of 100, 200, 300 and 400 total connections with uniformly chosen source-destinations and random baudrates from the set $\{32, 43, 56\}$ Gbaud. Regarding the physical layer, we assumed a span length of 80 km, EDFA noise figure 5 dB and SSMF with mean attenuation coefficient 0.23 dB/km, mean dispersion coefficient 16.7 ps/nm/km, and mean nonlinear coefficient 1.3 1/W/km. We set the launch power at 0 dbm. The actual (unknown) values of the fiber coefficients for each span were drawn from uniform distributions ranging by 0%, 10% or 20% around the above means, thus defining 3 uncertainty scenarios. The GN model was used as the ground truth with these values. For the ML-PLM case, the b vector consisted of the attenuation, dispersion, and nonlinear coefficients, initiated with their mean values. So, the case with 0% variation implies that the ML-PLM estimator has accurate knowledge of the physical layer parameters. The training of ML-PLM was done with nonlinear regression and in particular the Levenberg-Marquardt algorithm. For ML-M, we tried various models and we finally used the features described in Sect. 3.2 and the constrained least square solver that provided the best results.

For each traffic load and physical layer parameters uncertainty setting we executed 500 iterations with random traffic and span parameters. For each instance we used 85%

of the lightpaths for training and 15% for testing. We excluded from the testing set the lightpaths that include links for which we have no QoT information (links that no lightpath from the training set cross). The training goal was to minimize the MSE but the max overestimation is also a very useful metric because it defines the design margin. This has to be used to be on the safe side, so that we never overestimate the QoT and establish a lightpath with unacceptable QoT.

Figure 3a shows the MSE and Fig. 3b the max overestimation error. For both estimators the MSE decreases as the number of lightpaths increases. The ML-M has consistent performance for all the uncertainty scenarios (0% to 20% variations) since it does not assume any previous knowledge. On the other hand, ML-PLM's performance is affected by the magnitude of the uncertainty, since the ground truth values deviate from the model's initial values. The ML-PLM is more accurate than ML-M in all cases except for the case with high uncertainty ($>10\%$) and few connections (100) where the ML-M achieved lower max overestimation. This is expected since the ML-PLM is a good approximation of the actual physical layer, in the sense that the ground truth function $Q^*(P)$ was taken to be the GN model, which is also the ML-PLM function $\widetilde{Q}(b, P)$. So, ML-PLM only needs to fit the parameters b that are uncertain and starts from good (mean) values. The ML-PLM's max overestimation was around 0.05 dB for more than 200 lightpaths while ML-M's max overestimation was 0.2 dB. The training time was in the order of seconds for the ML-M/linear regression and minutes for the ML-PLM/nonlinear regression. Once trained, estimations are quite fast (<0.1 s). So, the estimators can be used even in dynamic (re)configuration cases. We also obtained results for other ML estimators with end-to-end features as opposed to the link-level features. As expected, end-to-end features resulted in larger MSE and max overestimation for the high uncertainty cases, since in those cases the network is non-homogeneous and end-to-end features do not cover that. Detailed results are presented in [19].

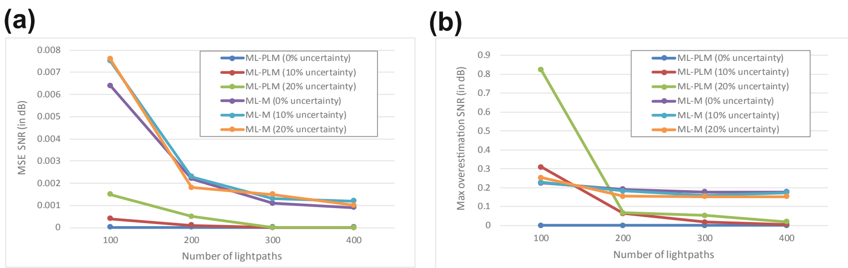

Fig. 3. (a) MSE and (b) maximum overestimation for 0%, 10% and 20% uncertainty.

5 Planning with Reduced Margins - Algorithm

In Sect. 3 we presented two ML QoT estimators that were shown in Sect. 4 to achieve good accuracy and a low design margin. To quantify the benefits of an accurate QoT estimator we use/interface that to an incremental planning algorithm [21, 22] and in particular to the incremental planning algorithm of [6, 20]. This incremental planning algorithm is involved before a planned network upgrade or even at the initial period (greenfield). So, the algorithm starts from a given network state P, with a set of deployed equipment, e.g. transponders/regenerators, established lightpaths with known transmission parameters, routes and spectrum, or even from an empty network. The algorithm takes as input a new set of demands and the available equipment at that time, e.g. available transponders, their capabilities and costs. To serve the demands, it interfaces with a QoT Estimator (see Fig. 1a) to account for the physical layer behavior.

If the network is planned with high margins, which is the traditional approach, then the QoT Estimator uses a high design margin and EOL system margin (to target acceptable QoT after e.g. 10–15 years). So, the efficiency is low, more transponders/regenerators are placed, but lightpaths are ensured to be uninterrupted, to have acceptable QoT, until EOL. Instead, if we leverage an accurate QoT estimator we can use an appropriate algorithm to plan the network with reduced margins. In the first period, we will serve the new demands with a high design margin (no feedback/no establish connections to monitor, train and refine the QoT estimator), and with a reduced system margin to reach the next upgrade period (several months - few years, but lower than EOL). Then at an intermediate period, we train the QoT estimator, and we reduce the design margin. So, at each period the incremental planning algorithm performs two tasks: (i) checks the remaining margins of previously established connections and reconfigures/adds transponders or regenerators to restore those that run out of margins (will have unacceptable QoT performance before the next or a targeted period), (ii) serves the new demands by placing transponders/regenerators. In both cases it chooses the configuration of the transponders/regenerators, and decides the routes, and spectrum allocation, by interacting with the QoT estimator to check the physical layer performance.

In more detail, the algorithm starts in phase 1 by freeing resources for removed connections (not demanded anymore). This equipment can be repurposed, reused at its current position (for free) or moved (with a penalty) to serve some other demand. Then the algorithm in phase 2 fixes the established connections that are running out of margins. The algorithm decides how to reconfigure and/or add new transponders/regenerators so that they have enough margins to reach the next or certain periods ahead. The algorithm's objective is to minimize the added cost, and as a secondary objective (controlled through a weight) to avoid extensive reconfigurations. For example, when adding a regenerator, the used path is broken into two segments and the same spectrum is allocated at both segments, avoiding any reconfiguration to other lightpaths. Then the algorithm in phase 3 serves the new demands by adding adequate transponders/regenerators and choosing the routes and spectrum. Since, adding new lightpaths (phases 2 and 3) increases interference, the algorithm rechecks with the QoT estimator the QoT all lightpaths. The algorithm repeats phase 2 considering all previous and new lightpaths. Since the algorithm in phase 2 might add new lightpaths to restore some problematic, interference can increase again, and the algorithm repeats phase 2 until QoT is acceptable for all lightpaths.

The incremental algorithm is a heuristic. It processes the previously established lightpaths and serves new demands one by one, in some particular order. Since the performance depends on that order, we can use simulated annealing or some other meta-heuristic to search among orderings and find better solutions. Note that the execution time is not a major concern, since calculations are supposed to be offline, to decide the changes for the next upgrade. In any case planning is NP-hard. Jointly planning and accounting for the physical layer (also called impairment-aware or cross-layer) requires the integration of the planning algorithm and the Qtool. Some optimal formulations for DWDM [23] and EON [24] have appeared, where the resource allocation formulation is extended to include (simplified) impairment/Qtool constraints. Such simplifications would require a higher design margin. In this paper we consider the Qtool as an external optimization module; such separation could result in some loss of optimality. Nevertheless, the Qtool can be more complicated and accurate, and we can use techniques such as ML to reduce and regulate the related margins, which in the end could yield better performance than a joint algorithm.

6 Planning with Reduced Margins – Case Study

To quantify the benefits of the developed accurate QoT estimators and the incremental planning algorithm with low margins we dimensioned a network over multiple periods and calculated the capital expenditure (CAPEX) at each period. We compare that with planning with EOL margins. The network topology we studied was the 12 node DT network topology as in Sect. 4. We planned the network over 11 periods (initial/brownfield and 10 incremental/greenfield periods); one period would roughly correspond to one year. The initial traffic (period τ_0) consisted of 200 connections with uniformly chosen source-destination pairs and uniformly demanded traffic between 100 to 200 Gbps. So, the initial traffic was 30 Tbps and it was increased by 20% each period by creating new demands in the same way. We assumed two types of elastic transponders (ET): (i) 32 Gbaud, modulating with DP-QPSK, or DP-8QAM, or DP-16QAM, supporting capacities of 100, 150, and 200 Gbps, respectively, and (ii) 64 Gbaud, modulating from DP-QPSK to DP-32QAM, supporting capacities of 200 up to 500 Gbps, respectively. The first ET of 32 Gbaud was assumed to be available at the initial period τ_0 with price equal to 1 cost unit (CU) and the second ET of 64 Gbaud was assumed available at period τ_5 with price again 1 CU (at that period). The ET prices were assumed to fall by 10% per period (so when the second ET is introduced the price of the first was 0.59 CU).

We again used the GN model to model the physical layer. In the first period τ_0 we initialized the model with heterogeneous span parameters with 10% uncertainty, similar to Sect. 4. We executed 10 problem instances with different traffic and span parameters and averaged the results. To model the ageing of the network we considered the increase of fiber attenuation (e.g. due to cuts), ageing of ETs, EDFAs, and nodes (OXC). The interference was modeled according to the network load. Table 1 shows the increase of the model parameters per period. Note that the increase was uniform for all spans, but since we started with heterogeneous and uncertain conditions, they remained heterogeneous and unknown for all subsequent periods.

When planning the network with EOL margins, the Qtool uses a system margin based on the parameters of Table 1 assuming 10 periods (~3 dB), and full network load (each link with 60 × 32 Gbaud connections). The design margin was set to 2 dB (1 dB

Table 1. Parameters to model the network evolution over time.

Physical layer parameters evolution		Increase per period
Ageing	Transponder margin (dB)	0.05
	Attenuation (dB/km)	0.0015
	EDFA noise figure (dB)	0.1
	OXC loss (dB)	0.3
	Interference	According to load

for the model inaccuracy and 1 dB for the input parameters inaccuracy). When planning the network with reduced margins, we used the ML-M estimator (Sect. 3.2). The system margin was based on the parameters of Table 1 assuming 2 periods (~0.6 dB). Then we assumed that at each period we monitor and obtained the SNR values, $Y(P)$, for the established connections (the monitored parameters were calculated by the GN model, with the random created initial parameters and ageing according to the period and Table 1 – unknown to the used QoT estimator). We used the monitored SNR values to train the ML-M and obtain the coefficients for that period, and also the max overestimation error. The design margin was set equal to 1 dB for the model inaccuracy, plus the maximum between 0.2 dB (the design margin of the extensive simulations in Sect. 4) and the max overestimation in the training for that period. Note that we chose the system margin for the next 2 periods and a design margin greater than 1.2 dB to be conservative. In total when we plan the network with reduced margins we harvest ~3 dB when compared to EOL planning.

Figure 4a presents the total cost of the deployed elastic transponders (ET) per period for the two provisioning approaches. As expected, reducing the margins yields lower

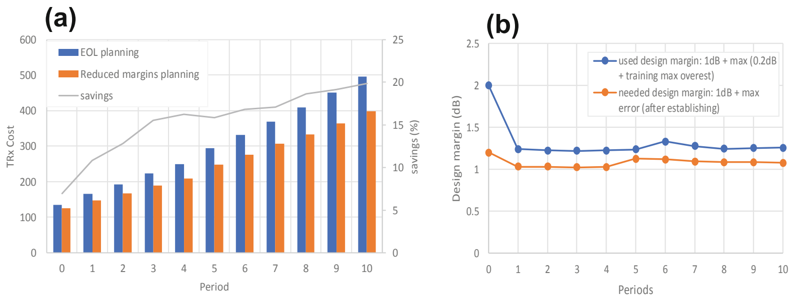

Fig. 4. (a) Total cost (in cost units) and savings of elastic transponders (ET) per period when planning with accurate QoT estimation/reduced margins and with high margins, (b) Used and needed design margin.

costs. Reducing the system margins postpones the purchase of ET and we obtain savings from the 10% depreciation. Reducing the design margin avoids the purchase of equipment. Figure 4a also presents the relative savings, found to be about 20% at the end of the examined periods. Note that the savings would reduce at later periods if we only assumed a single type of ET for all periods. The introduction of the higher rate transponder boosts the savings after period τ_5. Figure 4b shows the design margin used and the actual maximum estimation error. In all simulations (10 instances $\times$ 11 periods) we never observed a QoT problem, all lightpaths had adequate QoT when reaching the next period. The closest we got to margins limit was at period τ_5, where the new ET (thus a new baudrate) was introduced, and some parameters were not learned accurately enough with only the first ET (32 Gbaud).

A factor not included in the above evaluation is the time value of money; money saved at intermediate periods can be invested (or loans can be avoided) resulting in extra savings. Additional savings can be also obtained by power optimization [6].

7 Conclusions

Estimating the Quality of Transmission (QoT) is typically performed before establishing new or re-configuring existing connections using a physical layer model (PLM). Traditional planning uses high margins to account for inaccuracies and to target connections with acceptable QoT after several years (EOL). Reducing the margins increases network efficiency but requires accurate QoT estimation. We presented two machine learning (ML) assisted QoT Estimators that leverage monitoring information of existing connections to understand the actual physical conditions and achieve good estimation accuracy. We then quantified the benefits of planning/upgrading a network with accurate QoT estimation. We interfaced the developed accurate ML QoT estimator with an incremental planning algorithm that handles the reduction of margins. We compared the multi-period planning of the network with accurate QoT estimation/reduced margins to planning with EOL margins, and observed savings that reach 20% at the end of the examined periods.

Acknowledgment. I. Sartzetakis was supported by IKY Greek State PhD scholarship co-funded by the European Social Fund and the Greek State.

References

1. López, V., Velasco, L. (eds.): Elastic Optical Networks. ON. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-30174-7
2. Pointurier, Y.: Design of low-margin optical networks. JOCN **9**(1), A9–A17 (2017)
3. Auge, J.L.: Can we use flexible transponders to reduce margins? In: OFC (2013)
4. Christodoulopoulos, K., et. al.: ORCHESTRA-optical performance monitoring enabling flexible networking. In: ICTON (2015)
5. Pesic, J., Zami, T., Ramantanis, P., Bigo, S.: Faster return of investment in WDM networks when elastic transponders dynamically fit ageing of link margins. In: OFC (2016)

6. Soumplis, P., Christodoulopoulos, K., Quagliotti, M., Pagano, A., Varvarigos, E.: Network planning with actual margins. JLT **35**(23), 5105–5120 (2017)
7. Christodoulopoulos, K., Tomkos, I., Varvarigos, E.: Time-varying spectrum allocation policies and blocking analysis in flexible optical networks. IEEE J. Sel. Areas Commun. **31**(1), 13–25 (2013)
8. Rafique, D., Velasco, L.: Machine learning for network automation: overview, architecture, and applications. JOCN **10**(10), D126–D143 (2018)
9. Sartzetakis, I., Christodoulopoulos, K., Varvarigos, E.: Cross-layer adaptive elastic optical networks. JOCN **10**(2), A154–A164 (2018)
10. Delezoide, C., et al.: Marginless operation of optical networks. JLT **37**(7), 1698–1705 (2019)
11. Musumeci, F., et al.: An overview on application of machine learning techniques in optical networks. arXiv:1803.07976, December 2018
12. Samadi, P., Amar, D., Lepers, C., Lourdiane, M., Bergman, K.: Quality of transmission prediction with machine learning for dynamic operation of optical WDM networks. In: ECOC (2017)
13. Barletta, L., Giusti, A., Rottondi, C., Tornatore, M.: QoT estimation for unestablished lighpaths using machine learning. In: OFC (2017)
14. Aladin, S., Tremblay, C.: Cognitive tool for estimating the QoT of new lightpaths. In: OFC (2018)
15. Morais, R.M., Pedro, J.: Machine learning models for estimating quality of transmission in DWDM networks. JOCN **10**(10), D84–D99 (2018)
16. Seve, E., Pesic, J., Delezoide, C., Bigo, S., Pointurier, Y.: Learning process for reducing uncertainties on network parameters and design margins. JOCN **10**(2), A298–A306 (2018)
17. Bouda, M., et al.: Accurate prediction of quality of transmission based on a dynamically configurable optical impairment model. JOCN **10**(1), A102–A109 (2018)
18. Poggiolini, P.: The GN model of non-linear propagation in uncompensated coherent optical systems. JLT **30**(24), 3857–3879 (2012)
19. Sartzetakis, I., Christodoulopoulos, K., Varvarigos, E.: Accurate quality of transmission estimation with machine learning. JOCN **11**(3), 14–150 (2019)
20. Soumplis, P., Christodoulopoulos, K., Quagliotti, M., Pagano, A., Varvarigos, E.: Multi-period planning with actual physical and traffic conditions. JOCN **10**(1), A144–A153 (2018)
21. Meusburger, C., Schupke, D.A., Lord, A.: Optimizing the migration of channels with higher bitrates. JLT **28**(4), 608–615 (2010)
22. Eira, A., Pedro, J., Pires, J.: Optimal multi-period provisioning of fixed and flex-rate modular line interfaces in DWDM networks. JOCN **7**(4), 223–234 (2015)
23. Christodoulopoulos, K., Manousakis, K., Varvarigos, E.: Offline routing and wavelength assignment in transparent WDM networks. IEEE/ACM Trans. Networking **18**(5), 1557–1570 (2010)
24. Yan, L., Agrell, E., Dharmaweera, M.N., Wymeersch, H.: Joint assignment of power, routing, and spectrum in static flexible-grid networks. JLT **35**(10), 1674–1766 (2017)