# Formulating QoT Estimation with Machine Learning

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**Abstract:** *We investigate two machine learning approaches to formulate QoT estimation where we use monitoring information to train i) the inputs of an analytical physical layer model or ii) a machine learning model. We study their suitability for various uncertainty scenarios.*

## Introduction

Elastic Optical Networks (EON) promise significant benefits such as higher spectral efficiency, increased capacity and reduced network costs[1]. These benefits stem mainly from the large optimization dimensions that elastic optical transceivers offer, but the latter also perplex network optimization. Estimating the Quality of Transmission (QoT) is an important feature when planning, upgrading or dynamically operating optical networks. Accurate QoT estimation is necessary to harvest the full potential of EONs, to reduce the provisioning margins[2] and to enable optimized and dynamic reconfiguration in an evolving (traffic and ageing) network. For such purposes the feedback from the physical layer through monitoring is necessary [3,4].

Machine learning has been applied in various aspects of Optical Networks. Recently a lot of effort was directed on QoT estimation. Most works use end-to-end lightpath parameters, e.g. monitor information from coherent receivers[4], but there are some cases where link or node monitors are used[5]. Moreover, most prior works, and the focus of this paper, is on the estimation of an end-to-end QoT parameter, i.e. the SNR or BER of a new or a reconfigured lightpath[6,7,8]. In this context, some papers use machine learning classification[8] to estimate the acceptability or not of a new lightpath. However, this poses several disadvantages since in real networks there are no failed lightpaths to train the classifier. Moreover, the classification does not give information about the margin, the distance from the acceptable threshold, which is very useful for operators.

A key distinction of the proposed solutions and the one that we investigate in this paper, pertains to the model that is trained. The first approach is to use an analytical physical layer model (APLM) (e.g. the GN model[9] or [10]) with specific input parameters to estimate the QoT. Then we use machine learning to improve the accuracy of the input parameters and thus improve the accuracy of the APLM. The second approach is to use a machine learning model (MLM) as the QoT estimator with features representing physical layer parameters, such as the length of the lightpath, the number of crossed EDFAs, the baudrate, etc[8]. Depending on the chosen features this approach might be prone to errors mainly due to the non-homogeneous nature of the network. Span lengths, EDFA noise figures, fiber coefficients, etc. vary, making the lightpath length a low information feature. As we will see in the following, proper feature definition can avoid such problems. In this paper we present formulations for the two above approaches, and evaluate their performance under various uncertainty scenarios.

## QoT estimation with Machine Learning

We assume an EON[1] with elastic transceivers that can adapt a number of parameters (modulation format, and/or baud rate). The nodes consist of Reconfigurable Optical Add/Drop Multiplexers (ROADMs) with flex-grid capabilities connected through uncompensated fiber links. Each fiber link consists of a number of fiber spans that terminate at an EDFA that compensates the span loss. A lightpath is established between two nodes and is allocated the same spectrum throughout the path. For long connections regenerators are placed. We represent the network by graph $G=(N,L)$ were $N$ are the nodes and $L$ the links. The set of established lightpaths is denoted by $P$ and lightpath $p$ uses links $l_p \in L$.

We also assume that we can obtain monitoring information from the coherent receivers deployed in the network that can be used for optimization purposes. We use this information to improve the QoT estimation accuracy, which in turn can lead to provisioning new lightpaths with reduced margins or dynamically optimize the network. For the set of established lightpaths $P$ we denote by $y$ their monitored QoT parameters. We assume that the monitored QoT metric is the SNR, but other metrics can be used. We investigate two approaches for estimating the QoT (SNR) using machine learning.

The first approach assumes the use of an APLM (e.g. GN[9] or[10]), $Q(P,B)$, that takes as input the parameters of the lightpaths $P$ and also the physical layer parameters $B$, and estimates $y^e$ the QoT (SNR) of the lightpaths. The lightpath parameters $P$ can include: the routes, central frequency, baudrate, modulation format, launch power, etc. $B$ includes physical layer parameters for each span such as: the length, fiber attenuation, dispersion and nonlinear coefficients, the noise figure of the EDFAs, the gain, etc. We denote by $b$ a parameter in $B$.

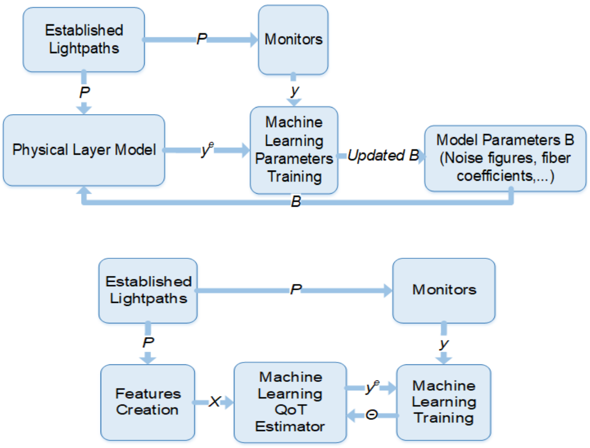


**Fig. 1:** Block diagrams of Analytical Physical Layer Model (APLM) and Machine Learning Model (MLM)

Using the monitored SNR $y$ values, and depending on the APLM we can use appropriate machine learning techniques to improve the accuracy of the input parameters $B$. For example, if we have a closed form for the partial derivatives of the physical layer parameters $\partial Q/\partial b$, for all $b \in B$, we can use gradient decent to obtain better estimates of $B$. In the general case where function $Q$ is complicated, we can use a nonlinear fitting method. We obtain the updated parameters $B'$ that minimize some function of the error $y^e$-$y$ (e.g. the mean square error) where $y^e=Q(P,B')$ is the output/estimation of the APLM model for the established lightpaths. When we want to serve new lightpaths (and/or reconfigure existing ones), we have a new set $P'$, and we estimate $y^{e\prime}=Q(P',B')$ using the updated physical layer parameters $B'$. We establish the new lightpaths, monitor them to get the actual SNR $y'$ and obtain the (test) error. Then we repeat the training with the new network state to further improve the accuracy of $B$ and of the APLM.

The second investigated approach uses a function $f(P)$ to create features $X$ for the established lightpaths, using parameters $P$ and making certain assumptions for the physical layer (e.g. additivity of noise). Features can include the lightpath length, the link load, the number of crossed EDFAs, etc., that indirectly capture the physical layer. Then we train a MLM $M(X)$ with an appropriate regression technique, such as linear regression, neural networks, SVM, etc.

After implementing and testing several of such methods and several functions $f$ to create the features, we observed that the choice of features is the most important for the accuracy, at least considering medium size optical networks (10-20 nodes) and various loads. So in the following we present a formulation based on linear regression that achieved good performance.

The basic feature vector $X_p$ of lightpath $p$ in $P$ has $|L|$ elements, equal to the number of network links. The elements $l_p$ of $X_p$ that correspond to the links that the lightpaths crosses are set to $b_p$, the baudrate of the lightpath. We extend the basic vector using features mapping to include the square root and/or other powers of the basic feature. We then use multiple linear regression to obtain the coefficients described in vector $\Theta$. This model estimates the inverse of SNR: $1/y^e= X \cdot \Theta$.

The intuition behind the above formulation is that lightpaths crossing a link for a given load suffer from similar levels of linear and non-linear impairments. A new lightpath for which we want to estimate its QoT, will not change substantially the load (and thus increase cross-lightpath interference). So the features are designed to represent the noise/impairments (both linear and non-linear) of a link which depends on the power spectral density (PSD). The noise is assumed to be additive for the links that comprise a path. Actually, the same assumptions are made by the analytical coherent version of the GN model which has been shown to exhibit good accuracy[9]. The above formulation uses the baudrate instead of the PSD, since we assumed constant power transmissions in our simulations, but it can extended for different powers. In a sense, the above formulation relies on monitoring and machine learning to approximate the GN model, without complicated analytical functions, leveraging the key assumptions of the GN model.

## Simulations

We evaluated the proposed formulations through simulations. We assumed the DT topology, SSMF fiber with attenuation coefficient 0.22 dB/km, dispersion coefficient 16.7 ps/nm/km, and nonlinear coefficient 1.3 1/W/km, span length of 80 km and EDFA noise figure 5 dB. We used the GN model to obtain the ground truth metrics for these settings. We assumed 4 traffic loads of 100, 200, 300 and 400 total connections with uniformly chosen source-destinations and random baud rates from the set {32, 43, 56}. We examined the following uncertainty scenarios: i) the attenuation coefficient of all spans is constant ($u_a$=0) or varies uniformly between $\pm$25% ($u_a$=0.25), ii) the nonlinear and the dispersion coefficients ($n\&d$) of all spans are constant ($u_{n\&d}$=0) or vary randomly by $\pm$25% ($u_{n\&d}$=0.25). We considered all four

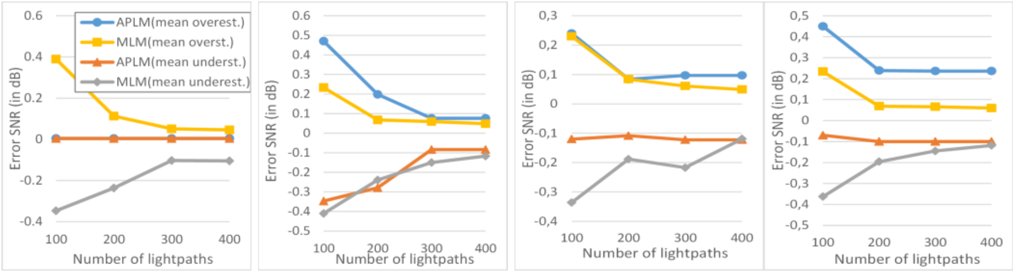


**Fig. 2:** Mean overestimation and underestimation for various loads and coefficient variations: a) $u_a$=0, $u_{n\&d}$=0, b) $u_a$=0.25, $u_{n\&d}$=0, c) $u_a$=0, $u_{n\&d}$=0.25, d) $u_a$=0.25, $u_{n\&d}$=0.25

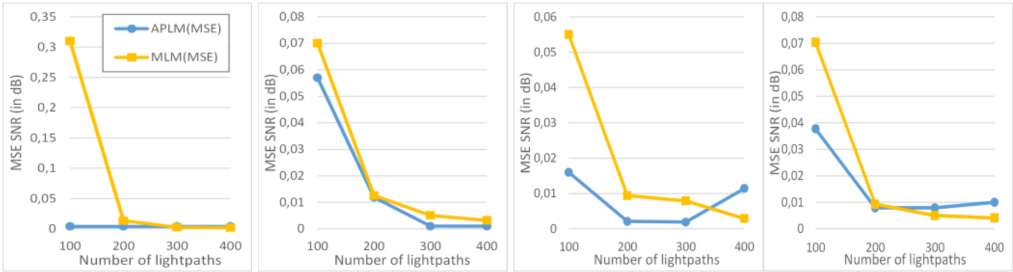


**Fig. 3:** Mean square error for various loads and coefficient variations: a) $u_a$=0, $u_{n\&d}$=0, b) $u_a$=0.25, $u_{n\&d}$=0, c) $u_a$=0, $u_{n\&d}$=0.25, d) $u_a$=0.25, $u_{n\&d}$=0.25

combinations of the above. In the case of the APLM we deliberately initialized the parameters to the average coefficient values and we used as ground truth the model with the varied values. Training of APLM was done with nonlinear regression, while linear regression is used for the MLM. We used 80% of the lightpaths for training, 10% for validation and 10% for testing. We executed 100 iterations for each (load and uncertainty) case and used the following three metrics to evaluate the estimation performance: the mean squared error (MSE), the mean overestimation and underestimation. Note that we obtained results for other types of features that use only end-to-end parameters of the lightpaths (length, number of hops, etc.), as opposed to the link-level that our model uses, and we observed inferior estimation performance.

In the case where all the coefficients remain constant (Fig. 2a), we can see that the APLM fitting outperforms the MLM. This is expected since in this case the APLM has accurate knowledge of the input/physical layer parameters. Still the MLM is able to reduce the error for a high number of lightpaths (≥300). When the values of the coefficients vary, we notice that the APLM has in certain cases worse performance, especially for the case of uncertainty in the nonlinear and the dispersion coefficients ($u_{n\&d}$=0.25) and high load. A possible reason for this is that these coefficients contribute to the nonlinear impairments that are harder to fit. When compared to our previous approach[6] we noticed that the techniques proposed in this paper achieve better performance with less information (lightpaths). This is due to the simpler modeling of the load metrics (there is no auxiliary graph in this case), and the additional information that the chosen features provide.

## Conclusions

We studied two machine learning approaches for QoT estimation: analytical physical layer model (APLM) and machine learning model (MLM). Both achieve high accuracy using monitoring from few established lightpaths. The MLM has better accuracy under high nonlinear and dispersion coefficients uncertainties, since APLM is hard to be trained to fit those.

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