Accurate QoT Estimation by Means of a Reduction of EDFA Characteristics Uncertainties with Machine Learning

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***Abstract*—Using machine learning and Signal-to-Noise Ratio (SNR) monitoring, we reduce uncertainties on output power profile and noise figure (NF) of each EDFA in an optical network. The Quality of Transmission (QoT) tool margin is reduced to 0.1dB for new traffic demands. The learning process is based on a gradient-descent algorithm where the parameters of an analytical model are iteratively modified to match the emulated light paths QoT of a European optical network. © 2020 Nokia Bell Labs.**

Keywords—Optical networks, QoT, Machine Learning, Monitoring.

I. Introduction

The design of optical networks always relies on a software tool to predict the Quality of Transmission (QoT) for all traffic demands, which must be above a predefined threshold. To ensure that all traffic demands in an optical network fulfill their target capacities, network designers add significant (up to several dBs) pre-defined "design margins" to the values predicted by the QoT tool [1-2]. It results with a network over-dimensioning. Design margins compensate for errors both from the QoT physical model itself and from the uncertainties on the QoT tool input parameters. For example, the influence of fiber length uncertainty and its type of distribution on the accuracy of the QoT estimation is recently analyzed in a machine-learning based model [3]. Correlating information from a set of already established demands to predict the QoT of new demands has been initiated in [4-5]. More recently, similar results were obtained by integrating a machine learning method in a route and spectrum assignment [6]. Uncertainties reduction has been studied experimentally in [7] for a 6-nodes network testbed. In [8], we proposed a different method to reduce design margins stemming from QoT parameters uncertainties by leveraging Signal-to-Noise Ratio (SNR) measurements. The goal is to reduce uncertainties on two QoT parameters: the noise figures (NF) and the output power of all Erbium Doped Fiber Amplifiers (EDFA) in the optical network. We were assuming that the EDFA output power is flat over the C-band. However, we may have some fluctuations/ripples within the gain bandwidth of the EDFA. This non-flatness of the EDFA gain profile has been recently addressed for the (linear) SNR in [9] and the total SNR (linear + nonlinear) in [10]. In [10] the gain ripple noise penalty for each network connection is estimated at the link level with a supervised machine learning fed by the monitoring of the SNR at the receiver side and the estimated gain profiles (at nodes and at each gain equalizer). In this work, we monitor the EDFA gain power profile coming from the Automatic Gain Equalizer (AGE). Since this measurement can be inaccurate, we use the monitoring of the electric SNR of all light paths (LPs) established in the network to find the actual NF and EDFA output power profiles at the span level. Our method is based on a gradient-descent algorithm using correlated information coming from all the established LPs in the optical network. With 400 LPs, we decrease the error on the QoT for new traffic demands (from few dBs to ~0.1 dB) for the European backbone network thanks to a more accurate QoT tool.

II. Learning process

The learning process is based on a gradient-descent method like the one used in [8]. The only difference comes from the presence of additional parameters in the QoT tool due to the non-flatness of the output power profile. The main idea behind is to modify iteratively the two uncertain QoT parameters (power profile and NF), starting from their estimated values to match the measured QoT values. We choose the electric SNR to characterize the QoT. In absence of experimental data, the five steps of the learning process are:

1. Numerical emulation for the actual and estimated values of the QoT parameters (all the measured EDFA output power profiles and the noise figure of all the EDFAs).
2. Evaluation of the electric SNR (actual and estimated) using analytical QoT model, namely the Extended Gaussian Noise model (EGN) [11]: SNR_{actual} and $SNR_{estimated}$.

We assume that the uncertainty on the measured electric SNR is much lower than the uncertainties on the output power profile and the noise figure of all the EDFAs. Therefore, the actual SNR corresponds to the ground-truth values.

3. Construction of the cost function defined by $C = \Sigma(SNR_{estimated} - SNR_{actual})^2$.

The summation in the cost function is realized over all the established LPs.

4. Initial values of the QoT parameters are then modified iteratively until the cost function C converges towards a value smaller than a predefined threshold ε.

The EGN analytical model is also used for all the iterative steps of the gradient-descent algorithm.

5. Using the new converged EDFA output power profiles and NF values, we evaluate more accurately the QoT of new traffic demands.

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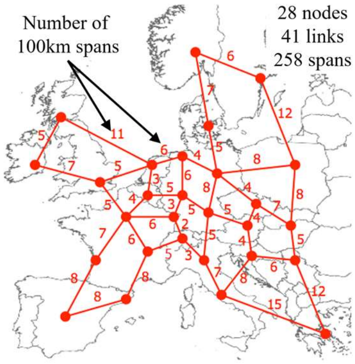

Fig. 1 European network topology [12]

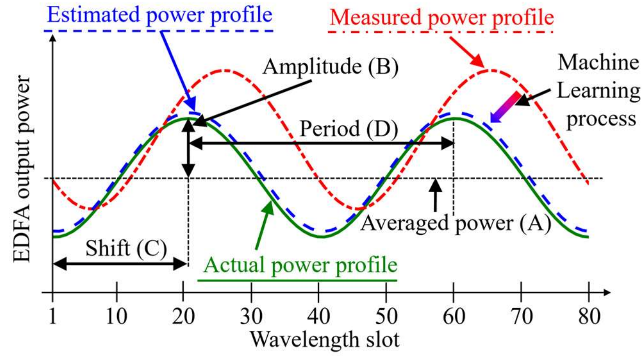

Fig. 2 Illustration of the power profile convergence: from the measured profile (dot-dashed curve) to the estimated one (dashed curve).

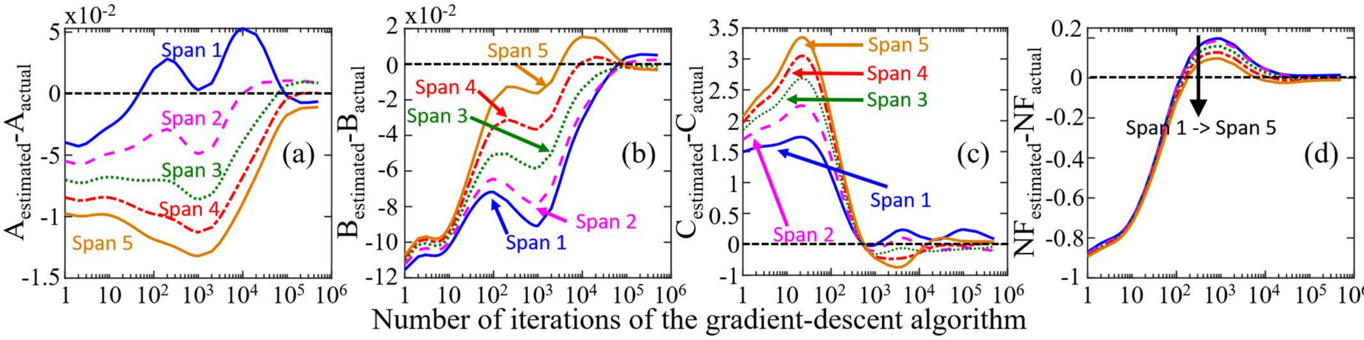

Fig. 3 (a), (b) and (c): Evolution of the error (estimated-actual, linear scale) during the gradient-descent algorithm on the EDFA output power profile of one typical link (made of 5 spans): on the averaged power A, the amplitude B and the wavelength shift C. (d): on the NF.

If we update the training database with information coming from the new demands, the QoT prediction tool may be refined through a re-training.

III. Simulation setup and assumptions

In all our simulations, we consider the European network consisting of M = 28 nodes, 41 dispersion uncompensated links and 516 standard SMF spans [12] as illustrated in Fig. 1. All already established demands are carried with 28Gbaud PDM-QPSK modulated wavelengths based on a 50GHz channel spacing, yielding 100Gb/s net bitrate. To build the training set, we consider a uniform traffic matrix where all connections are chosen equally among the Mx(M-1) = 756 pair of nodes. We use Dijkstra's algorithm to find the shortest path and the random-fit rule for wavelength allocation. We also assume that all demands are carried transparently. To illustrate the assumption of the non-flat EDFA output profile, we draw in Fig. 2 a sample sinusoidal shape as function of the 80 wavelength slots of 50GHz in the C-band. The solid, dash and dot-dashed curves correspond to the actual, estimated and measured EDFA output power profile, respectively. Each curve is characterized by 3 independent parameters with uncertainty: the average power (A), the amplitude (B) and the wavelength peak shift measured from the first wavelength of the C-band (C). No uncertainty is considered on the period D. Without loss of generality, the same learning process could be performed with a an arbitrary function for the power profile. The gradient-descent method would be applied on the coefficients of the polynomial expansion instead of the parameters of the sinusoid function. The goal of our learning process is to converge the measured EDFA output power profile (dot-dashed curve) towards the estimated power profile (dashed curve) as close as possible to the actual power profile (solid curve). For actual values, we consider a uniform distribution for the averaged power A and NF: [0.75, 1.25] dB and [5.5, 6.5] dB; and constant values for B and C: 1dB and 21 wavelength slots. In case of one AGE per node, the amplitude B increases by 1dB for each fiber span until the next AGE. To initiate the gradient-descent algorithm, we emulate the uncertain estimated values by adding a uniform noise around each of the actual values: Δ = [-0.5, 0.5] dB or [-1, 1] dB, emulating monitoring inaccuracy. The initial values for the NF are not coming from datasheets specifications: 5dB for all EDFAs in the network. For the training set, we consider several numbers of LP (N^{LP}) (from 100 to 1000) and each of them is chosen randomly and uniformly among the 756x80 possible wavelength slots. Please note that several wavelengths can be allocated for each set of source/destination. For each value of N^{LP}, 10 random selections of LPs are considered giving a uniform distribution of the traffic matrix inside the network. No correlation between fiber spans has been considered on the EDFA output power profile. The gradient of each QoT parameter is then independently evaluated for each fiber span by averaging over all light paths passing through each fiber span. We also performed studies with a first fit wavelength allocation or a normal noise distribution to

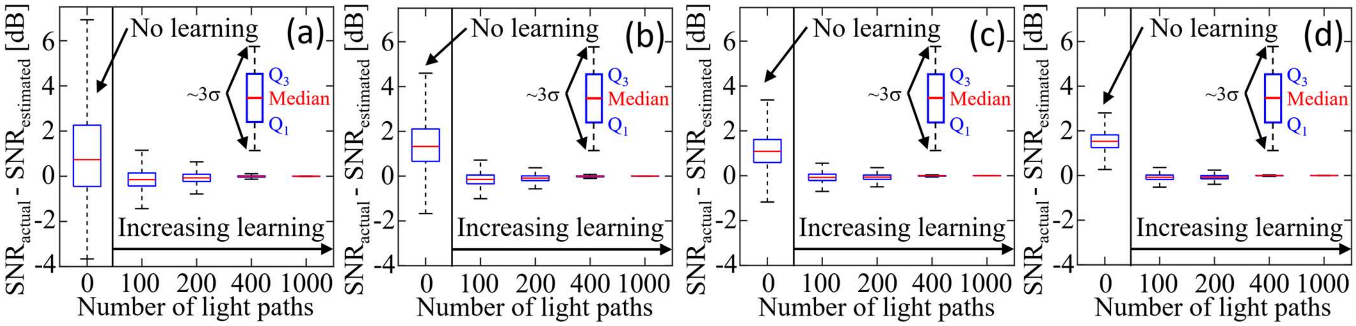

Fig. 4 Box plots of the SNR error without and with machine learning as function of the number of light paths in the training set. One AGE per link: Δ=1dB (a), Δ=0.5dB (b). One AGE per fiber span: Δ=1dB (c), Δ=0.5dB (d).

emulate the estimated values of the QoT parameters. Similar results are obtained. The accuracy obtained during the learning process is even slightly lower with the first-fit allocation, due to a denser repartition of data in the first half of the power profile. With a more complex and non-symmetric power profile, we would obtain a similar accuracy level with a larger number of light paths or with a random-fit wavelengths allocation.

IV. Results

In Fig. 3, we show the evolution of the error on all estimated QoT parameters {A, B, C, NF} during the gradient-descent process for a random set of 1000 training LPs. We took a typical link from the network made of 5 fiber spans. There were 10^6 iterations in the learning process, taking about one hour on a standard desktop PC without any optimization, scaling linearly with the number of LPs. Before all QoT parameters converge towards the actual values at the end of the learning process, the error reduction follows a path which is completely different for the QoT parameters of each fiber span. It is a sign that all parameters of the gradient-descent algorithm are free to evolve, as mentioned earlier in the method description. In Fig. 3(a) we even see that the error on the parameter A starts to decrease for some fiber spans in the link (i.e. 1 and 2) and increase for the other fiber spans (3, 4 and 5). With these accurate EDFA output power profiles and NF values at the end of the learning process, we evaluate the electric SNR for all the new traffic demands. This testing set of the machine-learning algorithm is built in the following way: for each traffic matrix at the end of the greenfield deployment, we are listing all possible LPs for which we have a possible wavelength to be allocated. For all the number of LPs we have considered (100, 200, 400 and 1000), the percentage of the number of LPs in the training set with respect to the maximal allowed traffic volume is equal to [0.2 0.5 1.6 10.6] %. The number of LPs in the testing set is well above the usual 15% used in machine-learning method. For each LP from this testing set, we evaluate the SNR using the EGN model fed by the QoT parameters obtained either with the learning process or with the actual values. Fig. 4 represents the box plot of the SNR error (SNR_{actual} - $SNR_{estimated}$) as function of the number of training LPs (from 100 to 1000). Each box plot is defined by the 3σ, median, first (Q1) and third (Q3) quartile values. The cases of one AGE per link/span are shown in Fig. 4(a)(b) and Fig. 4(c)(d), respectively. We consider two amounts of uncertainties on the QoT parameters: $\Delta = \pm 1$dB for Fig. 4(a), (c) and $\Delta = \pm 0.5$dB for Fig. 4(b), (d). In the worst-case scenario (1dB of uncertainty and one AGE per link, Fig. 4(a)), the SNR error evolves from +10dB (no learning) to 0.1dB with 400 training LPs for 99.7% of cases (3σ). We obtain a lower margin reduction (from +2dB to 0.15dB) in the best-case scenario (Fig. 4(d)) with only 200 training LPs, representing 0.5% of the maximal allowed traffic volume.

V. Conclusions

We consider uncertainties on two QoT input parameters: the output power profile and the noise figure for all the EDFA amplifiers of the network. By feeding a learning process based on a gradient-descent algorithm with a set measured/monitored data (SNR, EDFA output power profile) and NF values issued from datasheets, we reduce those uncertainties. Consequently, we reduce design margins from few dBs to 0.1dB for new demands in the brownfield scenario of a European network topology. The over-provisioning can be strongly reduced which cuts down the cost of the network.

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