

Learning process for reducing uncertainties on network parameters and design margins

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Abstract: Using monitored physical parameters in a learning process, we decrease design margins by reducing uncertainties on the input parameters of a Quality of Transmission (QoT) tool, improving the accuracy of the signal-to-noise ratio prediction.

OCIS codes: (060.1155) All-optical networks; (220.4830) System design; (060.4256) Networks, network optimization

1. Introduction

The design of optical networks always relies on a software tool to predict the QoT for all traffic demands, in order to ensure that the quality of a signal carrying a light path is above a predefined threshold. Such a QoT tool typically includes a QoT physical model, and input parameters describing network elements. 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]. A significant amount of margins - design margins - are added to compensate for prediction errors of the QoT tool, resulting in 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. The latter comes from imperfect knowledge of the actual properties of deployed network elements. In a deployed network, optical performance monitoring of some of the most sensitive optical layer parameters can reduce parameters uncertainties.

Correlating information collected from a set of already established demands to predict the QoT of new demands has been initiated for the worst case with a full spectrum [3] or for a realistic wavelength allocation with nonlinear interactions between demands [4]. However, the reduction of the uncertainties on the QoT input parameters was not treated yet. Uncertainties reduction has been studied in [5] for a 6-nodes network experimental test-bed. However, it assumes that the error on the Signal-to-Noise ratio (SNR) estimation for a complete light path is distributed to the links according to their relative weigh comparing to the total SNR of the light path. We propose a different method to reduce design margins stemming from QoT parameters uncertainties by leveraging SNR measurements from coherent receivers deployed to receive previously established light paths. After describing our solution, we benchmark it on the European backbone network [6], for which we reduce design margins for new demands.

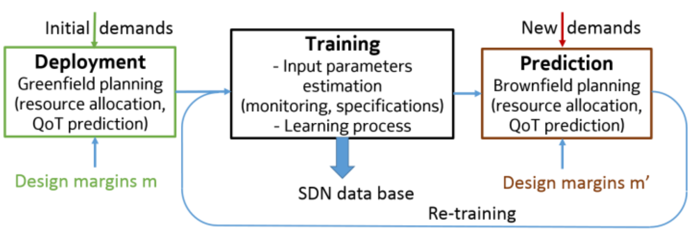

Fig. 1 Illustration of the complete network design cycle. Cycle consists of three phases: deployment, training and prediction.

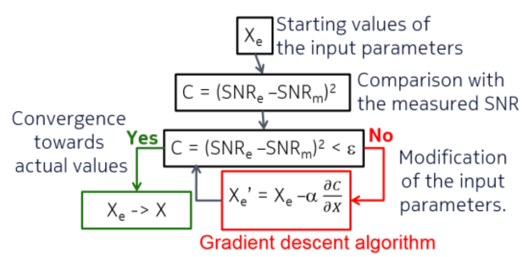

Fig. 2 Block diagram of the learning algorithm. X_e is the estimated data (by monitoring) and C is the cost function.

2. Learning process

We represent in Fig. 1 the complete cycle of the network design, including greenfield (initial deployment, left) and brownfield (upgrades, right). Cycle consists of three phases: deployment, training and prediction. In greenfield design margins m (typically 2 dB) are allocated due to imperfect knowledge of the input parameters of the QoT tool. After light paths for initial demands are established (Fig. 1 – Deployment phase), we collect all the monitored data issued from direct field measurements. This data is sent to a centralized Software Defined Network (SDN) controller data base, which also contains a QoT tool. All other network information, not measured but given by the equipment specifications, can also be added to this database. Like the measured data, these specification values suffer from uncertainties and a fortiori differ from the actual values.

This database will be used to train a learning process and after convergence, it will lead to a better knowledge of all uncertain input parameters (Fig. 1 – Training phase) and an improvement in the QoT prediction for all new demands (Fig. 1 – Prediction phase). Fig. 2 represents the block diagram of this learning algorithm based on a gradient descent algorithm. We start by using all the estimated input parameters of the QoT tool contained in the SDN database (X_e). An estimated SNR (SNR_e) can be then evaluated using the QoT tool. Since SNR_e is obviously different from the measured one (SNR_m), we can build a cost function $C = (SNR_e\text{-}SNR_m)^2$. This cost function is minimized by iteratively modifying all the input parameters of the QoT tool simultaneously. Once C converges towards a value smaller than a predefined threshold ε, the QoT tool can be used with the new values of the input parameters yielding reduced design margins (m' < m) for new traffic demands (Fig. 1 – Prediction phase). If we update the SDN database with information coming from the new demand(s) the QoT predictor may be iteratively refined through re-training as shown in Fig. 1.

3. Simulation setup and assumptions

We consider the European backbone network consisting of 28 nodes, 41 uncompensated links and 258 standard SMF fibers [6]. Already established demands are carried by 9 wavelengths with 28Gbaud PDM-QPSK modulation. Channel spacing is uniformly set at 50 GHz. All nonlinear interactions between wavelengths of a same demand are considered (self/cross -phase modulation and four wave mixing) but the interaction between two groups of 9 channels issued from two different demands in shared links are not considered. We also assume that all demands are carried transparently; optimization of regenerator position is out of the scope of this article. Each demand follows the shortest path. We use the model from [7], according to which the combined effect of chromatic dispersion and Kerr nonlinearity generates a nonlinear distortion after the fiber span k leading to a nonlinear distortion-to-signal ratio defined by $SNR_{NL} = 1\big/\sum_{k=1}^{N} P_k^2 \sigma_k$, where P_k is the total input optical power and σ_k is the normalized nonlinear noise variance for span k numerically computed for 9 wavelengths as in [7]. Assuming independent probability distributions, we add the nonlinear noise to the amplifier linear noise. We finally write the SNR accounting for system performance as follows:

$$\frac{1}{SNR} = \frac{1}{OSNR} + \frac{1}{SNR_{NL}}\ , \quad \text{with} \ \frac{1}{OSNR} = h\nu \cdot B_{ref} \cdot e^{\alpha L} \sum_{k=2}^{N} \frac{NF_k}{P_k} \tag{1}$$

α is the unitary fiber loss and L is the common fiber span length, both known without any uncertainties. B_{ref} is the reference spectral bandwidth, h is the Planck constant and ν the optical frequency. To include the nonlinear interactions between demands, a model giving the nonlinear SNR for any wavelength allocation would be needed and, it is under construction. We focus on the reduction of the uncertainties on powers (P) and noise figures (NF). The noise figure is estimated from the amplifiers specifications (NF_e). We assume that span input powers are identical for all wavelengths and for all demands for each of the 258 fiber spans of the network. This assumption is based on two points: first, the power is not adapted to the reach of the demand and, secondly, amplifier gains are perfectly flat. Non-zero excursion of power levels across the spectrum multiplex is out the scope of this proof of concept and will be the subject of a future work. At the output of each line amplifier, we monitor the total power and form a set of 258 estimated values $\{P_e\}$. From this data, an estimated SNR (SNR_e) is evaluated with Eq. (1). The last monitored term is the SNR at the receiver side. In a real network, this SNR would be either deduced from the Rx signal constellation or from a bit-error-rate measurement (SNR_m). In this numerical study, due to lack of network-wide experimental data, we use also Eq. (1) with an arbitrary set of powers {P} and noise figures {NF} to emulate the actual values. In other words, we assume that our QoT model itself is perfect and we focus on decreasing the input parameters uncertainties. The uncertainty of the model, which is out of the scope of this article, will be included in a future study. The cost function C, defined in Fig. 2, is then computed and minimized by the gradient descent algorithm.

4. Results

The learning process previously presented is tested for various configurations of input parameters. The actual power set {P} has a normal distribution around 1 dBm with a standard deviation of 0.5 dBm. The actual noise figure set {NF} has a uniform distribution with boundaries 5 dB and 7 dB. To construct the set of estimated powers $\{P_e\}$, we add to actual powers {P} a random contribution to emulate the power measurement uncertainties. This random contribution comes from two sources of uncertainty: a systemic error caused by a not perfect equipment calibration (ΔP = [-2, -1, 0, 1, 2] dB) and a statistical error due to the measurement itself (σ_p = 1 dB). The estimated power can be different from one span to another, due to amplifier gain fluctuation and/or due to a difference of span loss. The estimated noise figures NF_e were constant (5, 6 or 7 dB) and we tested 5 different number of demands (N_d) in the training set (N_d = 50, 100, 200, 400 or 600).

In Fig. 3, we plot the error probability on the SNR prediction (SNR_e-SNR_m) with learning (solid line) and without learning (dashed line) for all demands that are not in the training set. We choose one configuration of input parameters: ΔP = 0 dB, NF_e = 6 dB, N_d = 600. The benefit of the learning process is rather visible since the width of the SNR error distribution almost vanishes after convergence of the learning process: the distribution is almost reduced to a Dirac function around 0 dB, leading to a reduced design margins (m' < m). To quantify more precisely this SNR error reduction, we plot in a subset the error histogram obtained with learning with a x100 zoom. The SNR error reaches ±1 dB without learning and is reduced to ±0.01 dB thanks to the learning process It shows well that the QoT model is much more accurate for new demands thanks to the learning process, suppressing almost all the input parameters uncertainties.

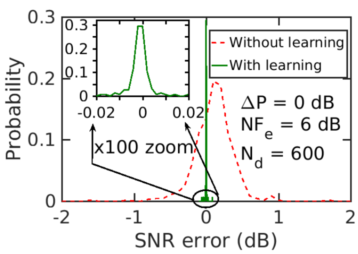

Fig. 3 Probability the SNR prediction error (SNR_e-SNR_m) with learning (solid line) and without learning (dashed line). ΔP=0 dB, NF_e = 6 dB and N_d = 600. The inset is a x100 zoom on the SNR error scale for the histogram obtained with learning.

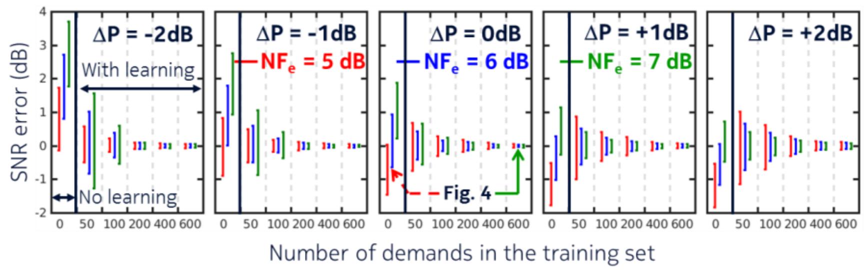

Fig. 4 Range of the SNR prediction error (mean ± 3σ) for one demand among all the remaining demands as a function of the number of demands N_d in the training set and for 5 values of systematic power shift: (a) to (e). The three error bars for each size of the training set correspond to various estimated noise figure NF_e: 5, 6 and 7 dB, respectively. Zero demand means that there is no training.

In Fig. 4, we further show all tested configurations. Each sub-figure corresponds to one value of systematic power shift ΔP. The vertical bar represents the 3σ-spread of the SNR error prediction for one demand among all the remaining demands. The x-axis represents the varying number of demands in the training set. Zero demand means that there is no training. For each number of demands, we have a group of three vertical bars, one for each NF_e value. Without the learning process, the SNR error varies between +3.7 dB and -1.8 dB. Thanks to learning, the SNR error spread decreases progressively with the number of demands and finally reduces to ± 0.1 dB with 600 demands in the training set. This evolution of the SNR error is almost identical whatever the initial error on the measured powers and the estimated noise figure NF_e. For all tested configurations, the average SNR error converges to almost 0dB. Moreover, a learning process trained with 200 demands is enough to provide a SNR prediction with ± 0.3 dB accuracy, which corresponds to one third of the total number of possible connections.

5. Conclusion

By feeding a learning process based on a gradient-descent algorithm with a set measured/monitored data (SNR, powers), we have reduced the uncertainties of two input parameters of the QoT tool: total output powers and noise figure of all the network amplifiers assuming the same power levels for all channels. Design margins have been then reduced for new demands in the brownfield scenario of a European backbone network whatever the amount of uncertainties of the initial parameters. The over-provisioning can be strongly reduced which cut down the cost of the network. This work was partly supported by H2020 EU project ORCHESTRA under grant agreement n°645360.

6. References

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