Accurate Prediction of Quality of Transmission with Dynamically Configurable Optical Impairment Model

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Abstract: We propose a dynamically configurable optical impairment model for a physical layer abstraction enabling physical parameters learning in multi-vendor networks. We experimentally demonstrate quality of transmission prediction in mesh networks with 0.6 dB Q-factor accuracy.
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1. Introduction

The growing flexibility, configurability, and granularity of control of deployed optical hardware, deployment of SDN optical network controllers, and the concept of open, multi-vendor optical networks are expected to reduce cost of optical transport. The importance of network resource utilization is also leading to increasing granularity of resource management, evolving from wavelength channels to narrow spectral slices, and more recently from optical reachability to dBs of optical transmission margin. In other words, optical margin is becoming a first-class "resource," subject to careful network-level optimization through control [1-4], and monitoring [5-8]. In open, multi-vendor systems such as OpenROADM [9], where greater variety of implementations may lead to increased uncertainty about the optical characteristics of the deployed network, monitoring is expected to be particularly valuable. Monitoring can both compensate for any new uncertainties as well as further reduce margins beyond conventional levels. By monitoring quality of transmission of existing optical connections in terms of BER or equivalent Q-factor, and using this to estimate the amount of noise introduced in each span, it was shown that higher accuracy of Q prediction could reduce required margins significantly [8].

However, the accuracy of Q prediction was limited by a strong dependency on the number of spans. This was believed to be due to the overly simplistic model used. In this paper we go further and address the issue by applying a comprehensive optical impairment model including both linear and non-linear effects and that is dynamically configured on-the-fly to account for each change in the network as it occurs, such as the adding of a new optical connection, resulting in different impairments due to nonlinear interactions in optical fiber and other components where optical signals interact.

We first propose a control architecture and physical layer abstraction using our model, to control and manage practical open systems utilizing BER monitoring, and next demonstrate the feasibility and benefits of the comprehensive model for improving Q prediction accuracy.

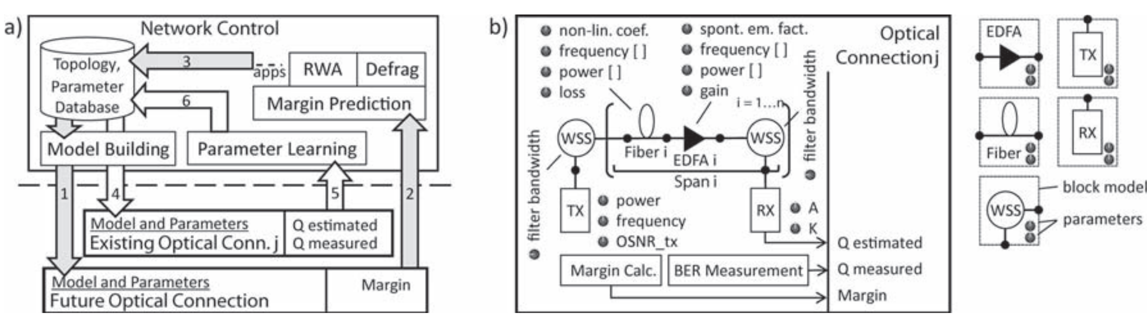

Fig. 1a) Physical layer control and management architecture, and b) abstraction of optical connection with block models and parameters.

2. Architecture

To control and manage physical layer operating parameters and margins in an environment where the different parts may be from different vendors, demarcation of responsibilities for realizing diverging goals such as guaranteeing a reliable connection under set conditions, and maximizing network resource utilization. We propose a clear separation between network control functions or "concern" of the optical network controller or network management apps, and optical connection functions associated with each of the existing and prospective optical connections, as shown in Fig. 1a. There are two closed loops with different purposes. The outer loop is for allocation of network resources. For example, to allocate route and wavelength (RWA) for a new connection, the controller provides in step 1) for a desirable route a sequence of model blocks with parameters to an optical connection entity, 2) receives a fixed, guaranteed margin, based on which it makes a decision whether or not to provision the connection, and 3) store new parameters in its database. Optical connection entity guarantees the margin by keeping an internal margin for itself, based on the information available to it. The second, inner loop is for parameter learning, to improve the accuracy of the model of the network. In step 4) the controller provides latest parameter values to existing optical connection entities, which in step 5) return an estimated Q based on those parameters along with a measured Q. Controller adjusts parameter estimates to reconcile estimated and measured Q, and in step 6) stores the updated values in the database. In the remainder of this paper we focus on the inner loop.

Communication between the two groups of functions occurs using the physical layer abstraction shown in Fig. 1b, consisting of sequences of block models with parameters, representing network configuration and state as seen by the controller. Parameters are generally shared with multiple optical connections. For example to model interaction between signals within a same fiber span, the signals will share access to signal launch powers, frequencies, and loss and nonlinear coefficients of the fiber. Similarly, physical coupling exist in EDFAs and WSS.

We have implemented an on-the-fly programmatically configurable meshed optical network impairment simulator in Java, achieving millisecond-order computation speeds on a laptop with an Intel i7 CPU, even with hundreds of parameters per connection and hundreds of coupled connections in a network with hundred multi-degree nodes. Each block model is based on simple theoretical models. EDFAs compute noise density based on gain, frequency and spontaneous emission factor or corresponding noise figure (NF). Fiber uses the GN model [10] and avoids time-consuming numerical integrations by computing an intermediate non-linear noise relation for each fiber type, following [3]. The receiver calculates the symbol electrical SNR based on accumulated linear noise density and non-linear optical noise. Two fitting parameters were used to adjust the SNR for implementation penalties before computing Q-factor using for DP-QPSK signals for example the relation $Q = \frac{1}{2}.\mathrm{erfc}(\sqrt{(SNR/2)})$. We assumed complete compensation of chromatic and polarization mode dispersion in the DSP.

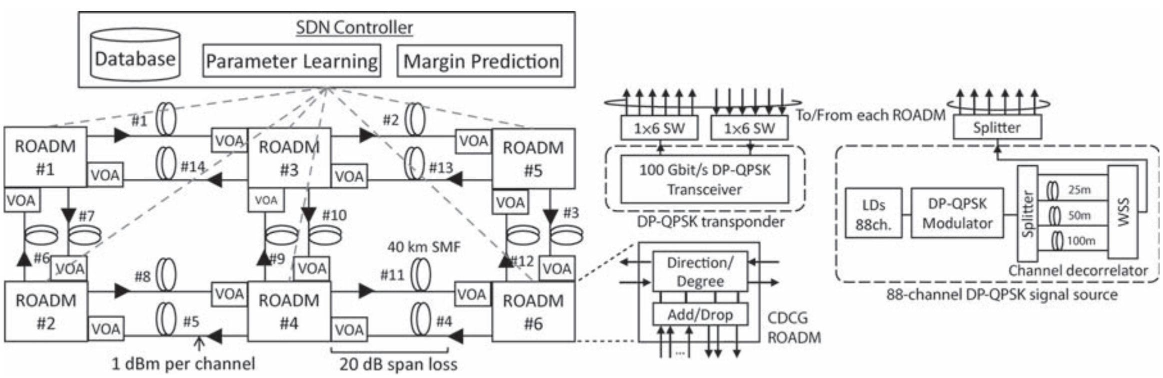

Fig 2. Optical mesh CDCG-ROADM network testbed with six nodes and fourteen spans.

3. Experiment

We applied the comprehensive impairment simulator for the estimation of operating parameters including EDFA effective noise-figures and fiber non-linear coefficients of the 14 spans of the optical mesh ROADM testbed shown in Fig. 2). The fiber was 40 km SMF with total span losses adjusted to 20 dB using a VOA at the end of each span. EDFA gain compensated span losses, and launch powers of all 100 Gbps, 32 GBd DP-QPSK signals were tuned to +1 dBm per channel. The system accommodated 88 channels on a 50 GHz grid. Q measurements were performed using a same DP-QPSK transceiver, and the presence of any interfering signals was emulated using an 88-channel DP-QPSK signals source. The data acquisition procedure was the same as reported in [8], but the use and processing of measurement data was different. Fiber spans between adjacent ROADMs and express path through a ROADM were modeled each as a fiber with 20 dB loss, and EDFA with fixed 20 dB gain, and this time with fiber nonlinear coefficient, and EDFA noise figure as model parameters to learn.

The basic learning procedure operated as follows: For each new route, we calculated $Q_{estimate}$, based on the model and set of latest estimated parameter values $\{p_i\}$. We next retrieved $Q_{measured}$ and used the difference with the estimate to adjust estimated operating parameters $\{p_i\}$ using an approach based on maximum likelihood principles; adjustments were proportional to the expected standard deviation of each parameter type, and to the relative impact on the value of Q as expressed by the derivatives dQ/dp_i which were easily calculated using the model. This resulted in robust learning and accurate prediction, even when the model had a higher degree of freedom than necessary to perform accurate prediction based on a measurements obtained under a limited variety of operating conditions.

The experimental procedure started with probing each of the 14 single spans in the testbed at 1528.77, 1545.72, and 1563.45 nm wavelength and collecting in total 14x3=42 measured values $Q_{measured}$. No correlation was found with wavelength. Next this set of data was applied repeatedly in sequential parameter learning of the per-span noise figures only, keeping all other parameters fixed, until noise figures converged. The initial values were an effective 10 dB per-span NF, and 1.4 $W^{-1}km^{-1}$ fiber nonlinear coefficient. This procedure resulted in an initial distribution of per-span NF values forming the basis for further parameter learning during regular network operation. The initial values of the parameters that were kept fixed did impact the converged NF values, but did not degrade maximum Q_{error}. Fig. 3a) shows the Q (over)estimation error defined as $Q_{error} = Q_{estimate} - Q_{measured}$ in dB, for each of the spans. The standard deviation in Q_{error} was 0.3 dB with a zero mean.

Next, in regular network operation phase we generated random routes with up to 13 spans to simulate connection demands, and allocated subsequent wavelength channels up to the 88th, after which we applied first-fit wavelength allocation starting over from first channel, until the first the occurrence of blocking after 101 connections. The final spectrum allocation map is shown in the inset in Fig. 3b. During the learning in regular operation, both per-span NF and non-linear coefficients were adjusted based on each new measurement. Fig. 3b shows Q_{error} for each new connection added. The initial upward trend corresponds to increasing NF and decreasing non-linear coefficient based on the new information on longer, multi-span connections. Fig. 3c shows Q_{error} as function of span count. Maximum Q_{error} was reduced to 0.6 dB from the 1.4 dB reported previously in [8], and more importantly the dependency on number of spans was strongly suppressed.

After study by selectively disabling certain aspects of the model, we could attribute the improvement to better modeling of the noise generated in ROADM and nonlinear effects. We believe the achieved Q accuracy is limited by repeatability in the experiment of setting of operating parameters, and fast time-dependent effects, and not by the model. However, the accuracy of parameters of the model, such as NF or nonlinear coefficient, can be improved by data under a wider variety of operating conditions such as various launch powers, or additional information such as measured OSNR.

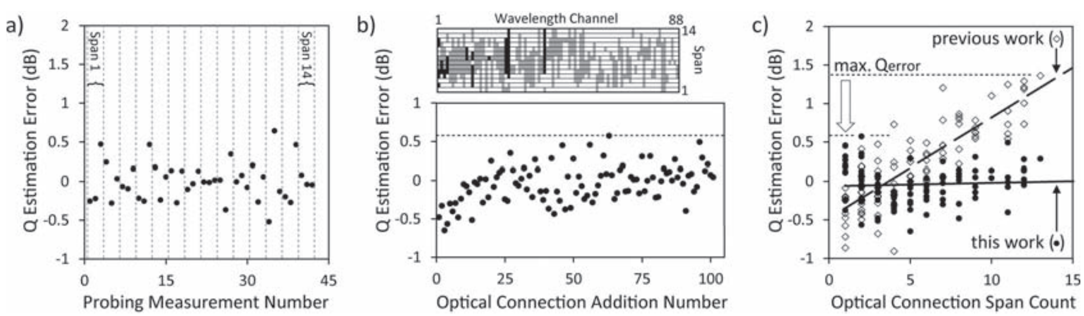

Fig. 3a) Q_{error} after initial network probing, b) Q_{error} in operating phase as function of added optical connection number, with final wavelength allocation shown in the inset, and c) Q_{error} as function of number of spans, comparing previous work (diamonds) to this work (filled circles).

4. Summary

We presented a control and management architecture with a dynamically configurable optical impairment simulator based physical layer abstraction enabling optical parameters learning and accurate quality of transmission prediction in optical mesh networks, taking into account physical coupling between signals. We experimentally evaluated its performance in a mesh network with 101 incrementally provisioned connections with up to 13 spans. The comprehensive model reduced the maximum Q estimation error to 0.6 dB and strongly reduced dependency on span count. This will allow further margin reduction in multi-vendor optical networks with Q measurement capability.

5. References

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