Modeling Filtering Penalties in ROADM-based Networks with Machine Learning for QoT Estimation

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Abstract: Monitoring 3dB bandwidth and other spectrum related parameters at ROADMs provides information about quality of their filters. We propose a machine-learning model to estimate end-to-end filtering penalty for more accurate QoT estimation of future connections. © 2020 The Author(s)
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1. Introduction

Reconfigurable Optical Add/Drop Multiplexers (ROADMs) are the key switching elements of deployed core and metro optical networks [1]. Several implementations of ROADMs are possible using optical devices including MUX/DEMUX, optical splitters/combiners, wavelength blockers and wavelength selective switches (WSSs) [2]. The use of WSS provides the advantages of colorless, and/or directionless and/or contentionless node operation and higher degree design, making them industry's choice for current generation ROADMs [1, 2].

Generally, a signal that traverses a ROADM node suffers from filtering penalty due to the involved WSS(s) resulting in signal quality of transmission (QoT) degradation. Over longer paths the cascade of ROADM filters introduces stronger filtering, which narrows the signal's transmission bandwidth (BW) [3]. During the lightpath provisioning , such optical filtering penalty is covered inside margins of the QoT estimation tool (or Qtool). Research works [3, 4] confirmed that ROADM node penalty (in OSNR) increases exponentially with the number of nodes and depends on the modulation format and the grid spacing. An analytical model based on a higher order SNR-OSNR relation to capture cascaded filtering effects is presented in [5]. These prior works focus on characterization of the cascade (*either* by looping single filter, *or* by replacing cascaded filters with a tunable BW filter) and do not focus on the identification of the quality of the individual filters. Although these works consent that filtering penalty is non-linear to the number of filters, still there are uncertainties in these penalties. The misalignment of the filters to the grid, deviations in filters shape and 3dB BW are quite common in deployed networks and are covered in the aforementioned Qtool margins. Such issues are expected to exacerbate in disaggregated optical networks where ROADM/filters and Tx. lasers could come from multiple vendors with diverse characteristics [5, 6]. In disaggregated (at node level) networks margins of 3.5-5dB (core) and 3-3.5dB (metro) would be required [6] mainly due to uncertainties/variability of the multi-vendor components; the filtering penalty of ROADM nodes play a significant part in those increased margins. In a network (either single or multi-vendor), connections traverse different ROADMs and experience different degrees of filtering penalty. Using cheap optical channel monitors (OCM) [7] we can understand the filters alignment to the grid and their shape. Such understanding could be used to correct the Tx/cascade alignment and improve the QoT of existing connections [8] or improve QoT estimation and reduce margin for future connection establishments.

In light of the above herein, we firstly examine filters behavior under uncertainties and corresponding penalties. We then propose a Machine Learning (ML) regression model based on link formulation that leverages monitoring data of established connections to accurately estimate end-to-end filtering penalty for new connection requests.

2. Methodology and Proposed Solution

ROADMs consists of amplifiers and filters to boost and route the signal. Now, consider a channel having central wavelength λ that is routed through multiple ROADMs over a path p before finally detected at the receiver. This can be viewed as a line transmission system with filters along the path (1 or 2 per ROADM for Broadcast and Select-B&S, or Switch/Route and Select-S&S architecture). We denote the spectrum of an individual filter in the path as $F_i(\lambda)$, $i \in \boldsymbol{p}$ and by p_i the part of the path before i^{th} filter. We also denote by $C_{p_i}(\lambda)$ the overall filter spectrum before i^{th} filter due to the cascade of previous filters over p_i and by $C_p(\lambda)$ the overall filter spectrum at end of the path (Rx.), is given by:

$$C_{p_i} = \prod_{k \in p_i} F_k(\lambda), \qquad C_p(\lambda) = \prod_{k \in p} F_k(\lambda) \qquad (1)$$

Assuming that i' is the next filter after i on the path, by monitoring $C_{p_i}(\lambda)$ and $C_{p_{i'}}(\lambda)$ we can calculate $F_i(\lambda)$ which gives us valuable information about key properties (filter shape and alignment to the grid) of the ith filter at wavelength λ. Typically, such properties hold for all λs of the same filter. From monitored $C_{p_i}(\lambda)$, we extract a set of features j that reflects the properties of cascade before i, denoted by $C_i^j(\lambda)$, such as 3dB BW, cascaded filter central frequency, signal distribution parameters (1st/2nd order statistical moments), or $C_i^j(\lambda) = \{C_i^{3dB}(\lambda), C_i^{fc}(\lambda), \dots, C_i^{sym.}(\lambda)\}$. Figure 1(a) shows
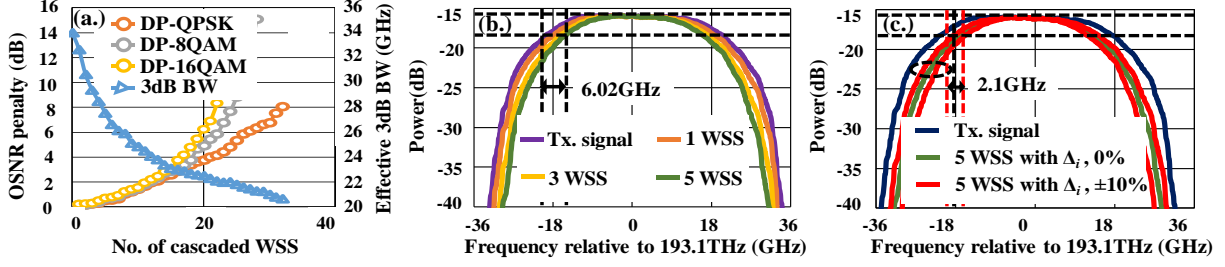
Fig. 1: (a) OSNR penalty & 3dB BW, (b) spectrum for increasing number of cascaded WSSs (identical $F_i(\lambda)$ for all WSSs), (c) spectrum for 3dB BW uncertainty $\Delta_i^{3dB} = \pm 10\%$ (non-identical $F_i(\lambda)$), resulting in ~2.1GHz of uncertainty at 5th cascaded WSS, compare to Fig. 1(b) (red region)

the non-linear/exponential degradation of one such feature, i.e. 3dB BW, $C_i^{3dB}(\lambda)$, in a cascade of *identical* filters (3dB BW=37.5 GHz, 2nd order Gaussian shape) obtained with simulations in VPI. It also shows the OSNR (in dB) penalty for three modulation formats (@ 32Gbaud, α=0.1). Focusing on spectral response, Fig. 1(b) shows the spectral shape of the signal $C_{p_i}(\lambda)$, which degrades as the number of cascade increases, even for identical filters. We observed a 3dB BW degradation of $C_i^{3dB}(\lambda)$=6.02GHz after 5 identical filters. However, in real networks slight variations are typical within the spectral responses even of identical filters, while such variations would exacerbate in disaggregated scenarios if filters/ROADMs come from different vendors. Such variations result in uncertainties in the features $C_i^j(\lambda)$, which we denote as $\Delta_i^j(\lambda) = \{\Delta_i^{3dB}(\lambda), \Delta_i^{fc}(\lambda), .., \Delta_i^{sym.}(\lambda)\}$. Fig. 1(c), shows the resulted $C_p(\lambda)$ for a 3dB BW uncertainty of $\Delta_i^{3dB} = \pm 10\%$ per filter after a cascade of 5 filters, simulated in VPI. We observed ~2.1GHz uncertainty in the 3dB BW, $C_p^{3dB}(\lambda)$, at the end of the cascade/path, which contributes to inaccurate filter penalty estimation.
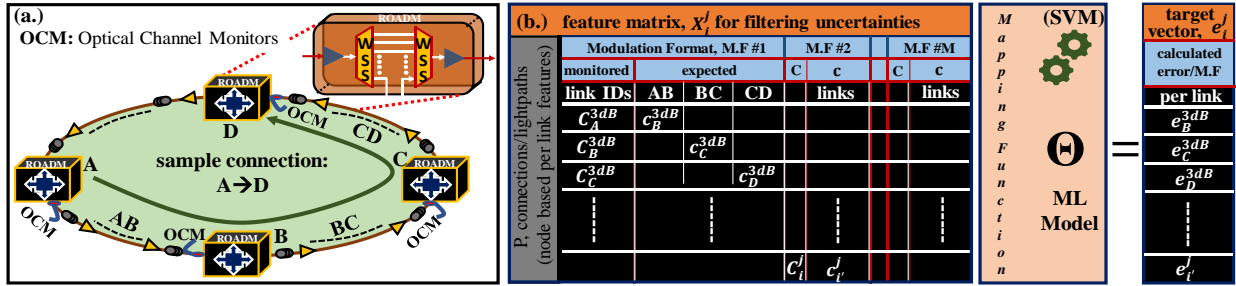

Fig. 2: (a) distributed OCM locations for a sample network (4 nodes, with established connection from A to D) with switch & select, S&S ROADM architecture (in inset), (b) end to end (link formulation approach based) ML model along with feature matrix, *X* and target vector, *e*

Focusing on filter penalty modeling, a standard Qtool (denoted by Q_s) calculates the features (e.g. 3dB BW) and filter penalty along a path assuming identical filters (Fig. 1(a)) and uses a high margin on top to account for penalties from inaccuracies (filter alignment and shape). By exploiting monitoring information, we can extend Q_s to understand the actual network state and behavior of deployed filters, reduce inaccuracies and lower the margin for new connections [9, 10]. Today cheap OCMs [7] can be installed at ROADM nodes to monitor $C_{p_i}(\lambda)$ on any channel. Each ROADM includes WSS/filters depending on its degree and architecture. Depending on add/drop or crossing direction, different filters are encountered in the network, hence in the following we account the filters *i* on a per link bases. We assume an optical network with established connections and their attributes denoted by *P*. We use OCMs to *monitor* $C_i(\lambda^P)$, and extract $C_i^j(\lambda^P)$ before each ROADM node along the paths of established connections (*P*). So, the features $C_i^j(\lambda^P$ suppress to simplify the notation) serve as the ground truth and are stored in Qtool database. Typically, a standard Qtool would start from the Tx. parameters and iteratively calculate the cascaded features for a specific filter F_i with no uncertainty, Δ_i^j=0, down the path until the receiver and add a margin for not accounting for uncertainties. So the standard Qtool, Q_s, includes a function that takes the features before ROADM *i*, c_i^j, and calculates the *expected* features after ROADM *i*, $Q_s(c_i^j, F_i)$ assuming no uncertainty Δ_i^j=0 (Fig. 1(a) shows such a Q_s function). Since we have OCM information C_i^j, we can correct Q_s and reduce the margin as follows. We denote the expected feature as $c_{i'}^j = Q_s(C_i^j, F_i)$ and the monitored-expected error as $e_{i'}^j = C_i^j - c_{i'}^j$, which is due to unknown uncertainties Δ_i^j. Then we extract a per link features matrix, $X_i^j = f(C_i^j, c_i^j)$. Our goal is to identify a per link dependent error function, $\Theta(X_i^j) \approx e_i^j$, which maps the features matrix X_i^j to the error e_i^j. We rely on ML for training and fitting of *X* on *e* and finding Θ. Fig. 2(b) shows the features matrix *X* utilizing OCM data C_i^j, Q_s expected features $c_{i'}^j$ and error *e* for the toy network of Fig.2(a). Assuming a new connection request $p \notin P$ using wavelength *l*, we start with its transmission spectrum parameters $c_{p_0}^j(l)$, use Q_s to obtain the *expected* feature set $c_{p_1}^j(l)$ after the ingress node, extract $X_{p_0}^j(l)$ correct that by calculating

$e_{p_0}^j = \Theta(X_{p_0}^j(l))$, and repeat that link by link down the path until destination. The estimation error will be identified once we establish the connection, monitor $C_{p_i}^j(l)$ at available OCMs and compare it to estimations by the above algorithm.

3. Results & Discussion

To quantify the benefits of developed QoT estimator with more accuracy and reduced margins, we considered DT topology with 12 nodes and 40 bidirectional links with lengths from 48 to 458 km as (inset Fig. 3(a)). The span was assumed to be standard single-mode fiber and span length equal to 80km. Each demand is carried by one wavelength and modulated at 32Gbaud with {QPSK, 8-QAM, 16-QAM} modulation formats leading to {100, 150, 200} Gbps of datarate. The frequency slot size was assumed to be 12.5GHz (fixed) and we allocated 3 spectrum slots of 12.5GHz.
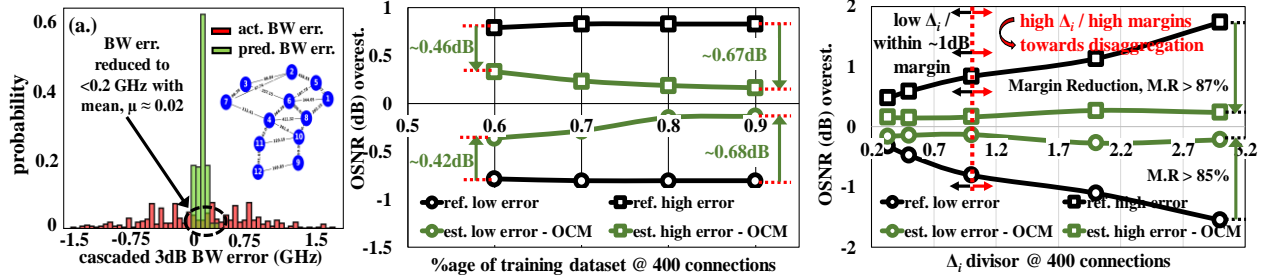

Fig. 3: (a) end to end effective 3dB BW error and reduced ML estimated error, (b) errors (±ve) in OSNR (dB): reference (black), ML max overestimation with OCM data (green), (c) new margin & their reduction with different Δ_i intensities

We assumed a network with OCMs installed at each node (Fig. 2(a)) and generated monitoring data (ground truth), by randomly applying small Δ_i (resulted in end to end ±1.5GHz 3dB variation) reflecting Tx. & filters-grid mismatch, and small variations in filters shape. The corresponding OSNR penalties are also distributed in ±ve sides depending upon Δ_i. +/-ve penalties result in upper/lower bound for design margins and we call them as, "high/low margin or errors". We assumed a stable network state, where a set of connections is established and the aim is to provision a new set of new connections. To do so, we divided the connections into two sets for training and testing, assumed to be the established and the new connections, respectively. Then from the training dataset, we calculated errors, e based on the expected and monitored 3dB BW, central wavelength, symmetry, link IDs, route etc. information. We also generated, the per link feature matrix, X. We used support vector machine, SVM, fitting technique with gaussian kernel function, to train our ML model, and we achieved least max. MSE of ~0.02 dB on predicted OSNR at a maximum load of 400 connections (200 times average @ 400 connections). Fig. 3(a) shows the calculated error in 3dB BW at a load of 400 connections and also the error reduction in BW (from ±1.5GHz → ~0.18GHz) with trained SVM. Fig. 3(b) reflects these accurate (per link) estimation of 3dB BW in end-to-end accurate estimation of filtering/OSNR penalty (green lines). Fig. 3(b) shows that at 90%/10% train/test split, maximum error reduction/accuracy improvement was ~0.67dB for high error and ~0.68dB for low errors, respectively. These are the new reduced high and low margins for the actual and unknown filtering uncertainties. For high/low margin, we found an overall reduction of 80.4/83.4% at a load of 400 connections. We also varied Δ_i (multiplied by a factor of 1/3 to 3) and estimated high and low margins/errors at a fixed load of 400 connections. In Fig. 3(c), the high Δ_i scenario (> 1dB, right of red dashed line) reflects ROADMs nodes with higher uncertainty, which are expected in disaggregated/multi-vendor networks. As expected, higher reference margins are required there, and our accurate modeling results in more pronounced savings that reach >85% and >1.5 dB on both high and low margins.

4. Conclusion

We proposed ML model to estimate end-to-end penalty generated at ROADM nodes due to filter spectral uncertainties & their cascaded effects. Harnessing monitored data and leveraging ML techniques, we estimated QoT accurately for new connections with max. of ~0.68dB of OSNR accuracy and >80% reduction in related margin.

5. References

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