Improving QoT Estimation Accuracy with DGE Monitoring using Machine Learning

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Abstract— **In optical transport networks, Dynamic Gain Equalizers (DGE) are typically used at each link. A DGE selectively attenuates the channels to compensate the cumulative Erbium Doped Fiber Amplifier (EDFA) gain ripple effect on the multi-span link, resulting in almost flat output power at the end of the link. We leverage monitored per link DGE attenuation profiles and coherent receivers Signal to Noise Ratio (SNR) information, and propose a machine learning (ML) based scheme to estimate the EDFA gain ripple penalties for new connections. Using that in realistic simulation scenarios we observed a design margin reduction from ~1dB to ~0.3dBs.**

Keywords—Optical Network, QoT Estimation, Monitoring, Machine Learning, Margins

I. INTRODUCTION

For effective network planning, it is necessary to estimate the Quality of Transmission (QoT) of the connections, prior to their establishment. This requires an accurate physical layer model (PLM) / a tool to estimate the QoT of existing and new connections [1]. In general, network designers add a significant margin, referred to as the *design margin* in such PLMs to cover several uncertainties (either in input parameters or within the PLM itself) [2], [3]. This ensures that all connections fulfill their target QoT performance but result in network inefficiency. Removing such uncertainties would allow the increase of estimation accuracy and an equivalent reduction in margins [3].

EDFAs are one of the key devices in wavelength division multiplexed (WDM) optical transport networks to ensure the required connection QoT level. However, EDFAs are the dominant noise source, referred to as amplified spontaneous emission (ASE) noise, in those networks [4]. Current generation commercial EDFAs are dual staged and have a low noise figure (NF), and a large dynamic range (up to 15 dB) [5]. However, even high quality EDFA have gain profile which is not flat (wavelength dependent) and also varies from one EDFA to another [4], [6]. The non-flat EDFA gain may be from imperfections in the gain flattening filters (GFF) at the amplifier output or wavelength dependent absorption/emission coefficients of erbium ions [7]. The wavelength dependent non-flat EDFA gain, referred to as the *gain ripple*, results in wavelength varying penalties, leading to inaccurate QoT estimation. Due to gain ripples, in deployed networks, a Dynamic Gain Equalizers (DGE) is used per link to compensate the cumulative EDFA gain ripple effect of the multiple spans of the link. The DGE employs a feedback loop driven from Optical Channel Monitors (OCMs) at the end of the link/ start of optical node. The DGE selectively attenuates the channels at a previous span to achieve almost flat output power at the end of the link/node input [8]. DGEs considerably reduce the gain ripple effect, but there is still some residual effect present, which affects the QoT estimation accuracy.

In this work, we assume per link installed DGEs that use feedback driven from OCMs. We also use the SNR performance monitored/identified at the coherent receivers. We use the information from those to fit a machine learning (ML) model that understands the gain ripple penalties of the established connections. Then we use that model to estimate the gain ripple penalty of new connections. Compared to our previous work in [9], where we used per node installed electrical SNR monitors, we only use optical information here, making this scheme much more cost effective. Keeping a realistic simulation environment, we observe a related margin reduction greater than 70% at a load of 400 connections on the 12 node Deutsche Telekom (DT) network.

II. RELATED WORK

QoT estimation for new connection requests ranges from older generation QoT tools based on PLM with analytical formulas to more advanced ML-estimation tools [10], [11]. Most approaches assume flat gain EDFAs. This assumption requires high design margins to address the QoT estimation inaccuracy (in total 2-3 dB in SNR) [2], [12]. The EDFA gain ripple effect was recently addressed in [13] for linear SNR (only ASE). However, [13] did not quantify the benefits in terms of accuracy improvement or margin reduction for QoT estimation. A hybrid approach based on joint fundamentals of analytical and machine learning modelling for EDFAs was also presented in [14]. In that work, the authors proposed a single EDFA modelling with 12000 sample points, which limits its practical usability. Moreover, the authors did not consider the cascading of EDFAs and its effect on gain ripple. In our previous work [9], we presented a ML based approach to estimate EDFA gain ripple penalty, addressed for the total SNR i.e. linear and non-

linear noise. We assumed electrical SNR monitors at each node, which is a quite strong assumption. Such assumption makes the overall scheme rather expensive in contrast to optical data monitoring-based schemes.

In this work, we assume that each link has a DGE (at mid-span) to flatten the channels' output power at the end of the link. To do so, the DGE uses an OCM at the end of the link as feedback. OCMs were used for monitoring purposes in [15], [16]. We also make use of SNR information measured at the coherent receivers. Using monitored DGE attenuation profiles and receivers SNR, we define a ML model and train it to understand the gain ripple penalties of the established connections. This ML model is then used to complement/ refine an estimation tool by predicting the EDFA gain ripple penalty for new connection. The use of OCMs employed by the DGEs makes this scheme more cost efficient than our previous work [9].

III. MATHEMATICAL MODELLING

We consider an optical network with links consisting of multiple fiber spans, an example of such link is shown in Fig. 1. Typically, span EDFAs are operated in Automatic Gain Controlled (AGC) mode with near to zero tilt (first order/ linear correction) to get a flat gain in the C-band as shown in Fig. 1. However, although the gain tilt profile is maintained at zero still there are gain fluctuations/ripples within the gain bandwidth of EDFAs [9]. For a typical scenario of a 6 span link without DGE, a penalty of ~1dB due to gain ripple is observed in [9]. For this 6-span link scenario, DGE is generally applied at the 3rd span to get flat output power at the link end as shown in Fig. 1. For longer links a new DGE is installed every ~6 spans [8]. In general, an EDFA gain profile with constant average gain g_{avg} and ripple profile $g_r(\lambda)$ (in linear scale) depending on wavelength λ (where λ is in the C-band) can be represented as:
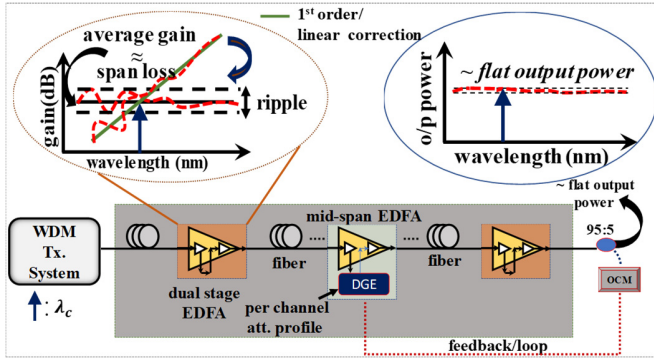
$$g(\lambda) = g_{avg} \cdot g_r(\lambda) \qquad (1)$$

Fig. 1. Multispan WDM transmission link with dual stage EDFAs indicating DGE location at mid span with flat output power at link end.

As a starting point, we assume the Gaussian Noise-GN model [17] and flat EDFA profiles as the PLM. Under flat gain assumption, the span EDFAs completely compensate for the span loss. We also assume that all channels are launched with the same power $P_{launch}(m)$ at link m. The SNR at the end of a link m for the connection c using wavelength λ_c, is given by

$$SNR_{RU}(m, \lambda_c) = \frac{G_o(m)}{G_{ase}(m) + G_{nli\_RU}(m,\lambda_c)} = \frac{G_o(m)}{G_{Noise\_RU}(m,\lambda_c)} \qquad (2)$$

where $G_o(m)$ is the output signal psd, which is independent of the wavelength λ_c under the flat power assumption, and $G_{Noise\_RU}(m, \lambda_c)$ is the accumulated noise (ASE + Non Linear interference, NLI) at end of link m under the flat EDFA gain assumption.

A typical assumption of PLMs is that the inverse SNR per link is additive. We denote a connection by $c=(p_c, \lambda_c)$ that traverses path p_c, consisting of links $m \in p_c$, with central wavelength, λ_c. With the ripple unaware PLM of Eq. (2), the total SNR at end of connection c is given by

$$[SNR_{RU}(p_c, \lambda_c)]_{dB} =$$
$$\left[1/\left(\sum_{m \in p_c} SNR_{RU}^{-1}(m, \lambda_c)\right)\right]_{dB} + design\ margin_1 \qquad (3)$$

The penalty due to gain ripple fluctuations is included in the *design margin₁*.We call this as ripple unaware (RU)-Qtool and denote it by Q_{RU}.

To capture the gain ripple effect and penalties due to it, we extended the standard GN model [9], [17]. For that, we assume that we know the EDFA gain profile $g(m, i, \lambda_c)$ along the spans i of link m. Based on that, for each channel we go span by span and we calculate the span output signal psd G_o, ASE noise G_{ase}, and NLI noise having contribution for ripple effect G_{nli_RA}. Once we reach the last span we feed these signal and noise containing factors in Eq. (4) to calculate SNR at end of link m. The SNR at the end of link m, using this extended GN model which accounts for ripple generated noise is given by

$$SNR_{RA}(m, \lambda_c) = \frac{G_o(m,\lambda_c)}{G_{ase}(m) + G_{nli\_RA}(m,\lambda_c)} =$$
$$\frac{G_o(m,\lambda_c)}{G_{ase}(m) + G_{nli\_RU}(m,\lambda_c) + G_{RA}(m,\lambda_c)} = \frac{G_o(m,\lambda_c)}{G_{Noise\_RA}(m,\lambda_c)} \qquad (4)$$

where $G_{Noise\_RA}(m, \lambda_c)$ is the total noise accumulated at the link m end, including the additional noise/penalty term $G_{RA}(m, \lambda_c)$ generated due to the EDFA gain ripples. Also, note that the psd of the signal $G_o(m, \lambda_c)$ is now wavelength dependent.

The total SNR at end of connection c is given by

$$[SNR_{RA}(p_c, \lambda_c)]_{dB} =$$
$$\left[1/\left(\sum_{m \in p_c} SNR_{RA}^{-1}(m, \lambda_c)\right)\right]_{dB} + design\ margin_2 \qquad (5)$$

The penalties due to other uncertainty effects (excluding gain ripple) are included in the *design margin₂*. We call this as ripple aware (RA)-Qtool and denote it by Q_{RA}.

IV. PROPOSED SOLUTION

A. DGE-based equivalent link model

The ripple aware Qtool (Q_{RA}) described above assumes that we know the gain profiles of all EDFAs with good accuracy, which is a strong and unrealistic requirement. So we propose to use monitoring information (DGE attenuation profile) in an operating network combined with machine learning (ML) to model the penalties due to the ripple effect. Then we use our

ML model to estimate the ripple penalties of the future connections.

To be more specific, the first step of our proposed solution uses monitoring information from mid span DGEs per link to create an equivalent link model m_{REA}. The DGE monitoring information pertains to the applied attenuation profile (for lighted channels) to get the flatten output at the link end. Consider that the DGE is applied on span d then the attenuation profile of that span for connection c is denoted by $a(m, d, \lambda_c)$.
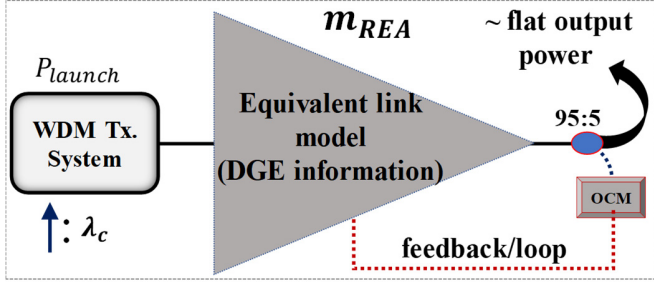

Fig. 2. Equivalent link model (for grey box of Fig. 1) based on collected DGE attenuation information.

For the WDM link m with uniform transmitted launch power (e.g. 0dBm for all lighted channels) $P_{launch}(m)$, we can map an equivalent power profile to span d as $P_{DGE}(m, d, \lambda_c) = P_{launch}(m) - a(m, d, \lambda_c)$ (in dB scale). Note that since the gain of the previous EDFAs (before span d) is also not flat. Hence the actual power profile upto span d also accumulates cascaded EDFA gain ripple effect of previous span EDFAs in the output power of span d EDFA as $\left[\prod_{n_s=1}^{d} g_{avg} \cdot g_r \right]_{(m,n_s,\lambda_c)} \cdot P_{launch}(m, n_s, \lambda_c)$. This is the ideal output power profile without any feedback from OCMs to DGE. Note that $P_{DGE}(m, d, \lambda_c)$ is the power profile at span d tailored by the DGE to get almost flat output power for connection c centered at λ_c. Hence the monitored $P_{DGE}(m, d, \lambda_c)$ is different from the one that is without the use of DGE (ideal one stated above). Since the number of spans within the link m is known, it is possible to replace the multispan link of Fig. 1 with an equivalent link model m_{REA} as shown in Fig. 2. For this, firstly we convert the $P_{DGE}(m, d, \lambda_c)$ to output signal psd of span d. For the connection c, we denote psd of output signal at span d as $G_o(m, d, \lambda_c)$. The $G_o(m, d, \lambda_c)$ depends upon the baudrate R_S of λ_c and is given by

$$G_o(m, d, \lambda_c) = \frac{P_{DGE}(m, d, \lambda_c)}{R_S(\lambda_c)} \qquad (6)$$

We then use our extended GN model (discussed in last part of the previous section and also in [9]) and feed it with $G_o(m, d, \lambda_c)$ to calculate the approximate mid-span noise psd of link m at channel λ_c, denoted by $\tilde{G}_{Noise\_mid}(m, d, \lambda_c)$. In general, the worst case of gain ripple occurs when all spans EDFAs are assumed to have the same ripple profile. So we assume that all spans have the same ripple profile. Under this worst case assumption, we calculate the approximated total accumulated noise psd at end of link m having N_S spans as

$$G_{Noise\_REA}(m, \lambda_c) = N_S \cdot \left(\tilde{G}_{Noise\_mid}(m, d, \lambda_c) \right) \qquad (7)$$

Note that $G_{Noise\_REA}(m, \lambda_c)$ contains an approximation error for link m as the equivalent model is made up from monitored information at a single point, extended with a worst-case assumptions, as described above. We use this per link equivalent model along with inverse linear additive assumption as Eq. (4) and Eq. (5) to calculate the overall accumulated noise along path p_c, $G_{Noise\_REA}(p_c, \lambda_c)$ for connection c, and $SNR_{REA}(p_c, \lambda_c)$. Since, we use the link equivalent model m_{REA} which approximates multiple cascaded EDFAs and fiber spans and contains an approximation errors, our SNR estimation is not perfectly accurate (but still better than standard Q_{RU}, as shown in results). We call this DGE-ripple aware equivalent link model Qtool as Q_{REA}.

B. Machine learning based ripple penalty estimation

We now describe how we further improve the ripple-DGE aware Qtool Q_{REA} using ML. In short, we make use of the SNR monitoring information at the connection coherent receivers, and by taking into account their used links, we move to the link level. At the link level, we correlate information of connections crossing the link to create a wavelength dependent gain ripple penalty model. So we use end-to-end information (SNR) to correct the approximation error of the DGE equivalent link model.
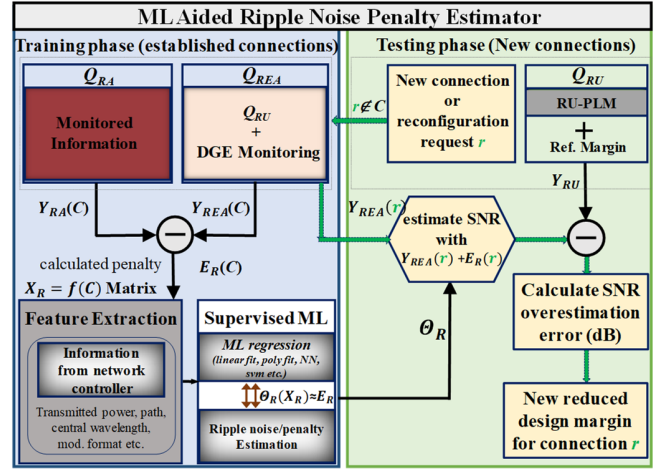

Fig. 3. Overall flowchart for EDFA gain ripple penalty estimation with DGE monitoring for training (blue box) and testing phase (green box)

In more detail, we assume an optical network with established connections and their attributes (also referred to as the *state* of network at a given time) denoted by C. Note that C contains attributes for each established connection such as, the traversed path p_c, central wavelength λ_c, modulation format etc. We also assume that the network has DGEs installed that use OCM feedback at the end of each link. We assume a ripple unaware (RU)-Qtool Q_{RU}, as discussed above, which calculates end-to-end noise of each established connection as $G_{Noise\_RU}(p_c, \lambda_c)$, for all connections $c \in C$. As a first step, using the monitored DGE attenuation (power) profiles P_{DGE} we can improve such estimations. We use the DGE-ripple aware

Qtool Q_{REA} as described above that takes into account the monitored P_{DGE} at the DGE spans. As discussed, the Q_{REA} calculates the (ASE and NLI) noise at the end of the path $G_{Noise\_REA}(p_c, \lambda_c)$. We denote this set of estimated values for all established connections C by $Y_{REA}(C)$.

We then monitor the electrical SNR of the established connections and thus their noise only at the receiver/ path level, $Y_{RA}(C)$ and store it in the Qtool database. Note that, this approach is generic and it can correct penalty due to any effect. But in this particular work, we used this approach to estimate the EDFA ripple penalties (and in particular we used Q_{RA} to generate the ground truth), and so we denote it here as Y_{RA}. This data serves as the ground truth, it defines the true $G_{Noise\_RA}(C)$, with zero margin (due to gain ripples). We denote the difference of the monitored G_{Noise_RA} and the estimated G_{Noise_REA} noise at path level as $E_R(C) = Y_{REA}(C) - Y_{RA}(C)$. E_R is a vector that includes the estimation errors of Q_{REA} of the established connections due to the real gain ripples. From established connections attributes C, we extract features which depend on connection's routes, central wavelengths and modulation format. To be more specific, for each connection c we assign its used wavelength λ_c on the links that it utilizes $m \in p_c$ (links used in the path are one hot encoded). Additional to these features, a *bias* is also considered to account for any monitoring calibration error and for the non-zero equalized tilt. The per connection features along with the bias term are merged into a *gain ripple features matrix* $X_R = f(C)$. The feature matrix enables the correlation among connections crossing the same link while accounting for their utilized wavelengths. Our goal is to identify the function $\Theta_R(X_R) \approx E_R$ that maps well the features matrix X_R to the penalty E_R generated due to gain ripple. Based on the monitored information of established connection, we can train supervised ML models on the above features and their corresponding labels, E_R, and thus find a good estimation model Θ_R. Assuming a new connection request $r \notin C$, we will use Q_{REA} to obtain the total approximated noise $G_{Noise\_REA} = Y_{REA}(r)$. Then we use our trained ML model Θ_R to estimate the ripple noise penalty on the new connection $\Theta_R(f(r))$ and estimate total noise including ripple as $G_{Noise\_REA} + \Theta_R(f(r))$. The testing error will be identified once we establish the connection, monitor its SNR at the receiver and compare it to our estimation. The interactions between the collected monitoring information, the Qtool Q_{REA} and the ML assisted ripple noise penalty estimation (both training and testing phase) are depicted in Fig. 3. The next step was to try several ML regression models and opt for the one that showed the lower prediction errors as discussed in next section.

V. RESULTS & DISCUSSION

The proposed ML model improves the QoT estimator accuracy, by estimating the EDFA gain ripple penalties for new connections. To quantify its benefits, we performed simulations to identify the amount of margin reduction on DT topology with 12 nodes and 20 bidirectional (40 unidirectional) links, shown in Fig. 4(a).

We assumed uncompensated bidirectional fiber links with spans of 80km of standard single-mode fiber (SSMF). We assumed 4 different traffic loads of {100, 200, 300, 400} total connections with uniformly chosen source-destination pairs. We served each demand with one wavelength, assumed to be modulated at 32Gbaud with a modulation-tunable pol-mux transponder. We assumed that the transponder could adapt to {QPSK, 8-QAM, 16-QAM} modulation formats, leading to {100, 150, 200} Gbps of datarate, respectively. We assumed a frequency slot size of 12.5GHz and allocated 3 spectrum slots for each 32Gbaud connection. We assumed a stable network state, where we have a specific set of connections established and we want to establish a new set of connections.
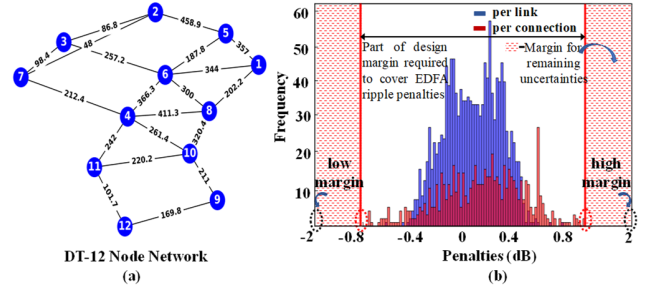

Fig. 4. (a) DT-12 node network topology (link lengths in km), (b) penalty distribution for 400 connections, indicating min. required design margin to accommodate ripple as well as high/low limits

To do so, we assume a number of connections e.g. 100 connections and divide them into two sets of 90%/10%, the training and testing datasets, respectively. Note that we did not use a validation set, because we did not tune any hyper-parameter. The training set was assumed to be the established connections C and the testing set to correspond to the new connections to be established, $r \notin C$. We assigned experimentally measured gain ripple profiles, $g(\lambda)$, to each span EDFA after applying random time shifting and amplitude scaling to them. We assumed that OCM are installed before each node and that we can also monitor the attenuation hence power profiles applied by DGEs through their feedbacks. All these were integrated in the Q_{RA}, that calculated the DGE power profiles and also the total noises at the receivers $Y_{RA}(C)$.
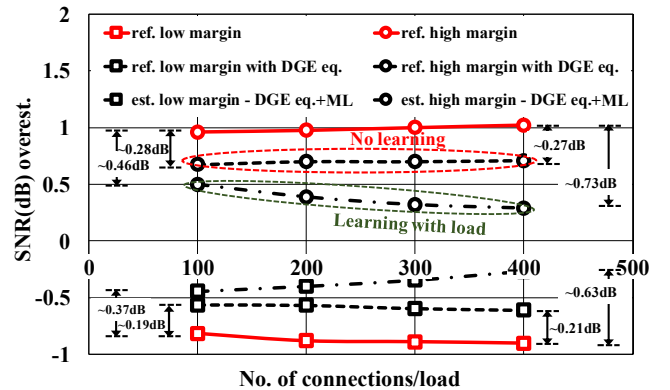

Fig. 5. Margin reduction and SNR (dB) overestimation error with DGE eq. model (without ML) and (DGE equivalent + ML) model

Taking as reference the Q_{RU}, we depict in Fig. 4(b) the estimation error for 400 connections, which pertains to the ripple penalty. Note that this estimation error, $E_R(C)=Y_{RA}(C)-Y_{RU}(C)$ is the noise difference between the ripple aware (monitoring) and unaware Qtool (the standard one). The penalties were distributed in positive and negative sides depending upon the ripple values and were ~1.8 dB in total. Positive/negative penalties result in upper/lower bounds for the design margin, which we call as "high/low margin". Typically, ~2dB of design margin is required to accommodate all uncertainties [1], [2]. Moreover, since these penalties/margins are directly related to the input parameters of the Qtool. Hence an error in input parameters (due to monitoring etc.) results in direct propagation from these input parameter uncertainties to QoT estimation uncertainty and should be considered for more accuracy [18]. Fig. 4(b) clearly shows that ~1dB of QoT tool design margin (out of the 2dB mentioned above) is required to accommodate ripple penalties only (shown by histogram plot in dotted red circle). The remaining part of the design margin takes care of the other uncertain effects as indicated in Fig. 4(b).

To improve the estimation accuracy, we used the monitored DGE power profiles with the Q_{REA} to obtain the noise at the receiver, $Y_{REA}(C)$. As shown in Fig. 5, the margin reduction from this *REA*-aware analytical model is constant with load i.e. no learning. But still, this *REA*-aware analytical model is better than Q_{RU} in terms of related margins. Now to make this Q_{REA} more intelligent, we subtract Y_{REA} and Y_{RA}, to obtain the penalty vector E_R. We then created the ripple features matrix X_R and evaluated several ML assisted regression techniques to fit $\Theta_R(X_R)$ on E_R, such as linear fitting, quadratic, polynomial fitting, neural network, Support Vector Machine Regression (SVMR) etc.
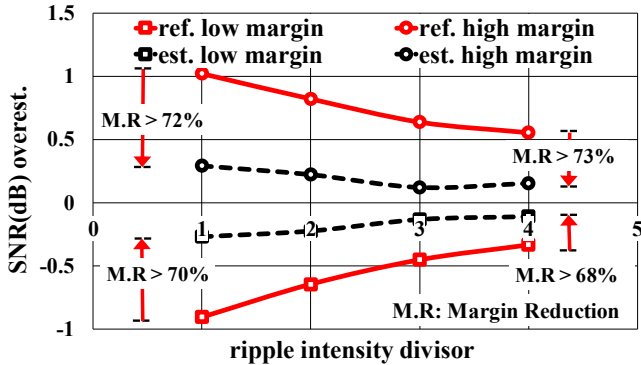

Fig. 6. ref. and est. high/low margins @ different intensities of peak-to-peak ripple at a load of 400 connections

In the presented results we used SVMR with linear kernel function that achieved maximum Mean Squared Error (MSE) of ~0.19 and ~0.096 on predicted SNR at a load of 100 and 400 connections respectively. For the above set of simulations, the maximum used peak-to-peak ripple intensity among all span EDFAs was about ± 0.5dB, which resulted in a reference margin ($design\ margin_1$) of ~1.02dB (red lines of histogram in Fig. 4(b)). Fig. 5 shows the maximum overestimation error

on SNR, relative to Fig. 4(b). This overestimation is the new reduced estimated high and low margin ($design\ margin_2$). For high margin, it is found to be ~0.28dB, yielding ~0.73dB margin reduction at a load of 400 connections. For low margin, we found ~0.63dB reduction as shown in Fig. 5.

To verify our model with different level of ripple intensities, we divided the gain ripple profiles by a factor of 1 to 4, resulting in peak-to-peak fluctuations of ± 0.5dB to ± 0.125dB. We then estimated the high and low margins at a fixed load of 400 connections. We observed in Fig. 6, over all those intensities, a reduction of >70% on high/low margin with our trained SVMR model at a load of 400 connections (reference max. peak to peak ripple of ± 0.5dB). For low values of peak to peak ripple of ± 0.125dB, high and low margin reduction varied from 68% to 73%, respectively.

VI. CONCLUSION

We presented a ML based approach to estimate EDFA gain ripple penalties with optical monitoring information at links and receivers information. In particular, by using monitored DGE attenuation profiles per link and SNR at the coherent receivers information, we trained an SVMR model. We used that model to estimate the gain ripple for new connection and we estimated the QoT more accurately with >70% reduction in the related margin.

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