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1 Executive Summary

In this document, we report the progress and goals achieved so far with respect to the produced deliverable D2.1 submitted by ESR2 in Dec 2018. As a follow-up of D2.1, we provide a basic introduction which specially outlines the limitations of applying Machine Learning (ML) techniques to compute Quality of Transmission (QoT) estimation (further details were reported in D2.1). To accomplish reliable and efficient optical network planning and operation, accurate estimation of QoT before establishing connections is necessary. To deal with such a critical requirement, we develop a tool and a system aiming at estimating / predicting the QoT of unestablished optical connections. This macroscopic objective is attained through leveraging the well-known ML benefits on providing estimations and predictions.

In this document, the first two sections provide a brief introduction to the devised and deployed QoT tool used to perform the QoT computation of any connection to be established. This encompasses the details and aspects related to the adopted mathematical formulation and the required migration / improvement from single link scope towards a network model. The developed QoT tool poses the pillar to explore ML solutions aiming at improving its estimation accuracy.

The “design margin” is traditionally applied/added to regular QoT tools, to absorb possible uncertainties on the physical layer parameters of devices or effects, and also to cover modelling simplification assumptions. In other words, the design margin is an additional contribution to the QoT estimation to embrace network and systems effects for which the QoT model is unable to cover. One of this effect is the span EDFA gain ripples. The EDFA gain ripple affects the overall noise but it is not typically modelled, and thus it affects the QoT estimation accuracy and is covered by a part of the design margin. As mentioned, a ML solution is devised to estimate the EDFA gain ripple penalty by monitoring established connections. We then verify the resulting accuracy of proposed ML tool by testing it on unestablished connections within a specific network topology. The attained results do lower margins of ~1dB.

The second problem we investigate is the uncertainties in ROADM penalties in the commonly used “Switch & Select” optical node architecture. The primary assumption is that removing such uncertainties leads to further reduce margins from the QoT tool. To do that we again exploit the advantages of ML for estimating the uncertainties caused by ROADM penalties. By doing so, we achieve a significant margin reduction of ~0.69dB.

Last but not least, this report concludes with the achievements done so far along with the activities planned for the upcoming short and medium term by ESR2.

We also provide at the end of this report a separate section to discuss the collected suggestions and comments from the advisory committee and the actions taken to address them.

2 QoT Estimator & Margin in Optical Networks

The emergence of Elastic Optical Networks (EONs) has introduced flexibility in the optical transport supporting heterogeneous data rates, optical spectrum channels, modulation formats, etc. This leads to attain higher spectral efficiency and capacity, while keeping the network costs as low as possible [1]. Prior to the deployment of a new connection, it is very important to estimate the Quality of Transmission, QoT, for the new connection, as well as for the already existing ones. The definition of QoT generally refers to several physical layer parameters, such as received Optical Signal-to-Noise Ratio (OSNR), Bit Error Ratio (BER), Quality or Q-factor, etc., which provides the information about the quality level of the optical signal at the receiver [2][3]. These parameters give a quantitative measure to check if a predetermined level of QoT would be guaranteed or not. Also, these parameters itself affected by several design parameters, such as, modulation format, symbol rate, launch power, physical path in the network, etc. For reliable and efficient optical network planning and operation, accurate estimation of Quality of Transmission, QoT before establishing the connections is necessary. QoT prediction of unestablished connections relies on an ***estimation tool***, also referred to as ***Qtool***, capable of predicting whether connection request will meet the required quality or not. The Qtool is a physical layer model (PLM), generally an analytical or semi-analytical model of the physical layer based on certain assumptions that estimates with certain accuracy the QoT (e.g. OSNR, SNR, BER etc.) of new or reconfigured connections.

Traditionally, QoT estimation is performed with some analytical Physical Layer Model (PLM), while, recently Machine Learning (ML)-based estimation has gained a lot of attention [4][11][12]. The main sources of noise accounted in these QoT estimators are the Amplified Spontaneous Emission (ASE) noise generated at both span and node amplifiers and the Non-Linear Interference (NLI) noise, which considers fiber non linearities, self and cross channel interferences (SCI, XCI). Apart from these major sources of noises in a network, physical layer conditions continuously evolve with time (with load, traffic, aging etc.). These evolution or changes in physical layer condition and their parameters, leads to deviation of quality parameter values estimated by the QoT tool. To accommodate these changes generally physical layer margins are used to cover the evolution of the physical and traffic conditions and uncertainties related to those [4]. Removing such uncertainties would allow to reduce the margin from the QoT tool without compromising the QoT estimation accuracy. By doing this, appealing advantages such as higher efficiency and/or lower cost can be achieved during the network planning and upgrading phases.

2.1 Problem Statement

Erbium Doped Fiber Amplifiers (EDFAs) are key devices in Wavelength Division Multiplexed, WDM and EON transport networks to ensure the required connection QoT level at the receivers. Nevertheless, EDFAs are the dominant noise source, specifically Amplified Spontaneous Noise, ASE in those networks. Typically, span EDFAs are operated in Automatic Gain Controlled (AGC) mode having average gain equal to the insertion loss of the fiber span. All these span EDFAs in the network are generally operated with near to zero tilt (Fig. 2.1(a)) by applying first order/ linear correction. This linear correction results in almost zero tilt of the span EDFAs result in negligible gain slope in the C-band as shown in Fig. 2.1(b)[5]. However, although the gain tilt profile is maintained at zero still there are gain fluctuations/ripples within the gain bandwidth of EDFAs (Fig. 2.1(b)) [6]. These gain ripple effects may be due to: i) imperfections in the gain flattening filters at the amplifier output; or ii) wavelength dependent absorption/ emission co-efficients of Er^{3+} ions [7]. These gain ripples add uncertainty in estimation accuracy of QoT tool and to cover this, design margin (~2dB) is added on top of the Qtool [4].

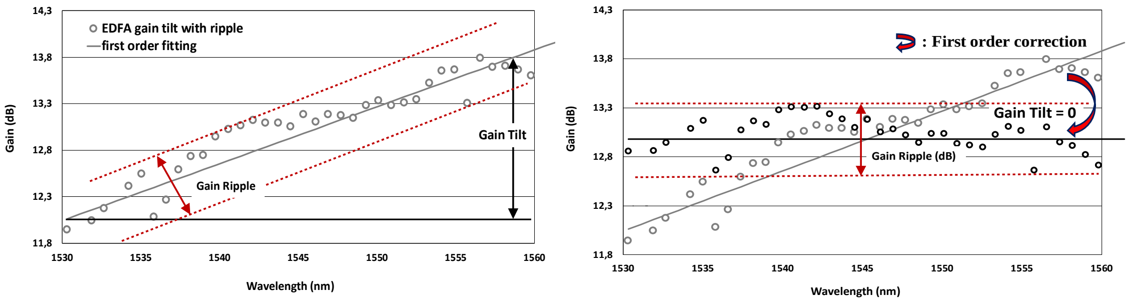

Fig. 2.1: **(a)** Experimentally collected EDFA gain ripple and gain tilt at EDFA output, **(b)** Gain tilt control with zero order / linear correction

Optical networking has evolved through many generations, from unamplified, repeated single-wavelength-per-fiber links to wavelength agile reconfigurable optical add/drop multiplex (ROADM)-enabled mesh networks. Each generation has provided a range of new features and capabilities [8]. The current generation of ROADM-based optical networks leverages the wave-length selectable switch (WSS) and provides software-controlled wavelength channel cross-con-necting capabilities through each optically meshed node. The WSSs that are integrated in ROADMs induce penalties on the optical signal due to tight optical filtering, which increases as several ROADMs are cascaded in a meshed network. In the literature techniques are presented to mitigate these penalties with the help of optical wave shapers [9]. But in real world, these filtering penalties coming mainly from the filtering narrowing effect due to multiple ROADM nodes within connection’s path (or simply filter cascading) are always present and are covered in the design margins as discussed above. Although these node penalties tend to have exponen-tial nature with respect to the number of ROADMs, still there are uncertainties especially in the presence of heterogeneous nodes with different characteristics (e.g., in multi-vendor scenarios, 3-dB bandwidth or central frequency mismatch etc. [9][10]).
Concluding, the EDFA gain ripple and filter cascading uncertainties affect the QoT estimation accuracy which is covered by the design margin. In light of the above the following two topics are investigated:

i) the contribution of the wavelength dependent EDFA gain ripple on the QoT

ii) the contribution of filter cascading uncertainties within ROADM nodes on the QoT

A ML regression model based on a link formulation approach is proposed separately to tackle both the above-mentioned problems to estimate the end to end penalties and hence QoT for a connection.

3 Design and Implementation of Developed QoT Tool

In this section, we highlight the basic used mathematical expressions and their extensions to deploy and implement the proposed QoT tool. Firstly, a basic introduction is provided addressing the well-known Gaussian Noise (GN) model [14]. Afterwards, it is discussed how extend the GN model to capture the span EDFA gain ripple effect. The background to migrate these mathematical expressions from static link to network model (with 4-nodes) is also thoroughly discussed. All the equations used and discussed in this section are implemented for DT-12 node network topology in MATLAB.

3.1 Detailed Gaussian Noise (GN) Model per Link

Most of the QoT tools relies on some model that gives information about the physical layer condition of a network and, in general is known as Physical layer Model (PLM). As presented in section 2, the main sources of noise accounted in QoT estimators are the ASE noise generated at both span and node amplifiers and the NLI noise, which considers fiber non linearities, self and cross-channel interference, SCI and XCI. The knowledge of these noises along with additional design margin in a PLM is a basic requirement for most of the existing QoT tools.

The calculation related to the ASE noise is quite straightforward and majorly depends upon the gain of the EDFA [1] [7]. The expression used for the Power Spectral Density (PSD) calculation of ASE noise, G_{ASE} is given below by Eq. 1.

$$G_{ASE} = NF * h * v * \left(g_{n_s} - 1\right) \quad (1)$$

Where, *NF* is the Noise Figure of the amplifier and is equal to 2*n_{sP}, n_{sP} is the spontaneous emission factor, h is the Planks constant, v is the emission frequency and g_{n_s} is the average gain of the amplifier placed in the n_s-th span.

The NLI noise calculation is comparatively a bit more complex and needs proper knowledge of the number of neighbouring channels, their frequency spacing, baud rates and many other physical layer parameters. For the NLI noise calculation, many models in the literature are available ranging from time consuming direct split step calculation, less accurate semi-analytical models to less time consuming with good accuracy value models based on the inverse noise addition assumption. Out of all these, the model based on inverse noise addition is the widely accepted model due to its trade-off between computation time and accuracy. One such perturbative model to capture the non-linear effects generated during fiber propagation in uncompensated optical transmission systems is known as Gaussian Noise, GN-model [14][15]. The GN-model has proved itself a relatively simple and, at the same time, sufficiently reliable tool for performance prediction over a wide range of system scenarios, effective for both system analysis and design.

In our case, to deal with the NLI calculation along a link with multiple spans in closed form, the incoherent accumulation of noise is the basic assumption used in the GN model. With this assumption, the NLI noise spectrum at the end of the link can be simply calculated as the sum of the NLI noise spectra produced in each single span considering the loss and gain in each span. For the simulation results presented in this report, we adopted (and extended as described in the following) the GN model for non-identical channel (each channel has different power, baud rate and uneven spacing) and non-identical spans (each span has different length, possible) system. Fig. 3.1 shows an example of the PSD of non-identical channels in a span. This flavour of the GN model is the most practical and well-suited for our application. The different colours in the Fig. 3.1 are only meant to highlight the channel diversity.

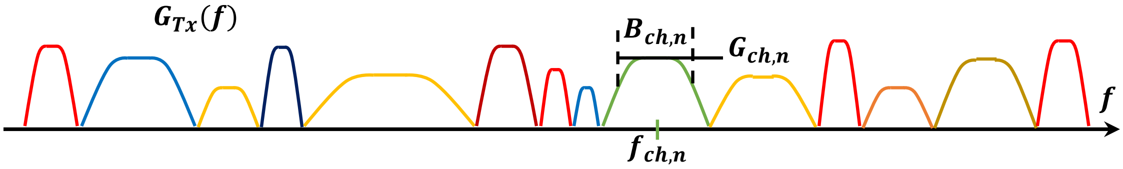

Fig. 3.1: Example of possible WDM overall transmission spectrum $\boldsymbol{Tx(f)}$ having different channels power spectral density, $\boldsymbol{G_{ch,n}}$ with transmitting lasers at frequencies, $\boldsymbol{f_{ch,n}}$ and 3dB bandwidth, $\boldsymbol{B_{ch,n}}$

The index n runs from 1 to the number of channels in the system, N_{ch}. The center frequency and the PSD values for individual channel are represented by the quantities $f_{ch,n}$ and $G_{ch,n}$. So, the overall transmitted PSD, $G_{Tx}(f)$ can be written as;

$$G_{Tx}(f) = \sum_{n=1}^{N_{ch}} G_{ch,n}(f) \quad (2)$$

In GN model, the total NLI noise contribution is defined and calculated as contribution from three categories: self-channel interference (**SCI**), cross-channel interference (**XCI**) and multi-channel interference (**MCI**). Specifically:

i. **SCI** is the NLI perturbing a given channel, produced by that channel onto itself
ii. **XCI** is the NLI perturbing a given channel, produced by the non-linear interaction of that channel with one other channel
iii. **MCI** is the NLI perturbing a given channel, produced by the non-linear interaction of that channel with two other channels or by three channels other than the affected one.

Let us consider a static link with no. of channels, N_{ch} at fixed frequency spacing of Δf GHz and flat average gain of $g_{i,avg}$, which is equal to the span loss, Γ (dB) as shown in Fig. 3.2. In this static link schematic, the gain of EDFA is assumed to be ripple free or perfectly flat.

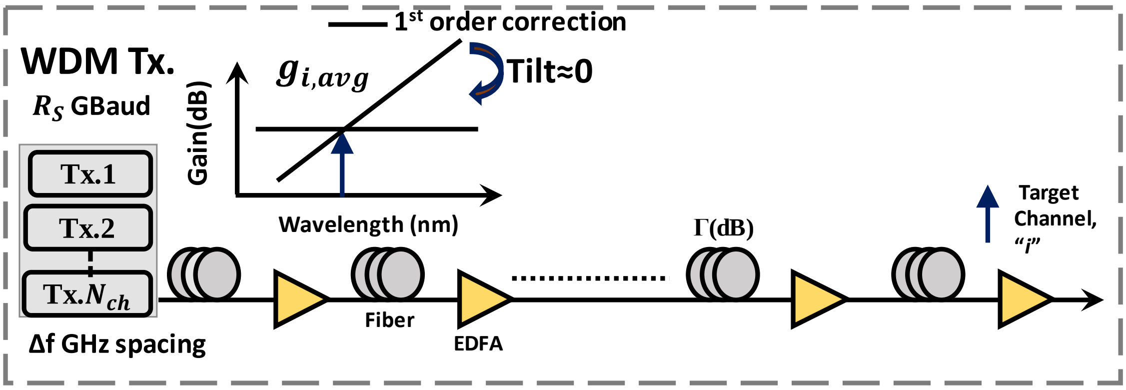

Fig. 3.2: Static link model for Flat span EDFA profile

Based on the WDM system depicted in Fig. 3.2, the detailed closed form analytical expression for the PSD calculation of NLI noise, G_{NLI} on any "i-th" channel due to "n-th" neighbouring channels (including self-channel interference) is given by:

$$G_{NLI}(f_{ch,i}) = \frac{16}{27} \sum_{n_s=1}^{N_s} \gamma^2{}_{n_s} L^2{}_{eff,n_s} *$$

$$\sum_{n=1}^{N_{ch}} G_{ch,n} G_{ch,n} G_{ch,i} \, (2-\delta_{ni}) \, \Psi_{n,i,n_s} * \qquad (3)$$
$$\prod_{n'_s=1}^{n_s-1} g^3{}_{n'_s} \, e^{-6\alpha_{n'_s} L_{s,n'_s}} \quad \prod_{n'_s=n_s}^{N_s} g_{n'_s} \, e^{-2\alpha_{n'_s} L_{s,n'_s}}$$

where "Ψ" is the phased array factor and under the assumption of incoherent accumulation, it is given by:

$$\Psi_{n,i,n_s} \approx \frac{\operatorname{asinh}\left(\Pi^2 [2\alpha_{n_s}]^{-1} \, |\beta_{2,n_s}| \, [f_{ch,n} - f_{ch,i} + B_{ch,n}/2] \, B_{ch,i} \right)}{4\Pi (2\alpha_{n_s})^{-1} \, |\beta_{2,n_s}|} - $$
$$- \frac{\operatorname{asinh}\left(\Pi^2 [2\alpha_{n_s}]^{-1} |\beta_{2,n_s}| [f_{ch,n} - f_{ch,i} - B_{ch,n}/2] \, B_{ch,i} \right)}{4\Pi (2\alpha_{n_s})^{-1} \, |\beta_{2,n_s}|}, \qquad n \neq i$$

$$\Psi_{i,i,n_s} \approx \frac{\operatorname{asinh}\left(\frac{\Pi^2}{2} [2\alpha_{n_s}]^{-1} |\beta_{2,n_s}| B_{ch,i}{}^2 \right)}{2\Pi (2\alpha_{n_s})^{-1} \, |\beta_{2,n_s}|} \qquad (4)$$

where a number of quantities appear, which refer to the n_s-th span: , L_{s,n_s} its length; α_{n_s} its loss parameter; β_{2,n_s} its dispersion parameter; γ_{n_s} its non-linearity coefficient; g_{n_s} the power gain of the EDFA placed at the end of the n_s-th span. "δ" is the factor that represents the SCI and XCI terms and is given by;

$\delta_{ni} = 1$ if n= i, i.e. SCI and $\delta_{ni} = 0$ otherwise (XCI, MCI are neglected to get closed form expression)

Note that, if one assumes that span loss is exactly compensated for at the end of each span, then $g_{n_s} \, e^{-2\,\alpha_{n_s} L_{s,n_s}} = 1, \forall \, n_s$ and therefore the gain-loss related products appearing in above Eq. simplify:

$$\prod_{n'_s=1}^{n_s-1} g^3{}_{n'_s} \, e^{-6\alpha_{n'_s} L_{s,n'_s}} = 1 \qquad (5)$$

$$\prod_{n'_s=n_s}^{N_s} g_{n'_s} \, e^{-2\alpha_{n'_s} L_{s,n'_s}} = 1 \qquad (6)$$

If we use the Gaussian Noise-GN model, as the PLM for NLI noise calculations in the QoT tool, then the typical assumption is a flat EDFA gain (no information of ripple generated noise) requiring a high design margins to compensate the uncertainties in noise calculation as given by following equations

$$OSNR_{Flat}(\lambda) = \frac{G_O\,(\lambda)}{G_{ASE} + G_{NLI}(\lambda)} + design\ margin_1 = \frac{G_O\,(\lambda)}{G_{Noise\_flat\_p}} + design\ margin_1 \qquad (7)$$

where $G_O\,(\lambda)$ is the signal PSD at the end of link and $G_{Noise\_flat\_p}$ is the total noise PSD accounting for both ASE and NLI. The reason for using "flat" in the notation is because the span amplifiers are assumed to be perfectly flat. "$design\ margin_1$" are the additional margins added in the QoT tool to compensate for gain fluctuation of amplifier, polarization dependent losses etc.

3.2 Extended GN Model with EDFA Ripple Profiles per Link

In practical scenarios and real network deployments, the EDFA gain is not constant throughout its bandwidth range but there are fluctuations. Such a fluctuation in EDFA gain is generally referred to as "gain ripple". This gain ripple results in a deviation from the overall accumulated noise in Eq. 7 and hence in the OSNR. Generally, a part of margins, "**design margin$_1$**" are included in the QoT tool to compensate these uncertainties in the PLM. Typically, an additional design margin is adopted and applied to the QoT tool to accommodate estimation errors and other uncertainty parameters [16][18]. Reduced margins leads to attain appealing advantages such as higher efficiency and/or lower cost during the network planning and upgrading phases. To this end, we extend the existing GN model by providing EDFA ripple profile to each span EDFA and capturing its effect in overall noise, more specifically through the NLI noise calculated in this extended GN model.

In Eq. 3, $\boldsymbol{g_{n_s}}$ is the power gain of the EDFA placed at the end of the $\boldsymbol{n_s}$-th span. We experimentally generated EDFA gain ripple profiles. We denote these gain profiles as $\boldsymbol{g_i(\lambda)}$ having an average gain value of $\boldsymbol{g_{i,avg}} = \boldsymbol{g_{n_s}}$ (= span loss, Γ (dB)) and wavelength dependent ripple, $\boldsymbol{g_{i,R}(\lambda)}$ given by Eq. 8.

$$g_i(\lambda) = g_{i,avg} + g_{i,R}(\lambda) \tag{8}$$

where *i* represent profile index

Let us consider the same static link with number of channels, N_{ch} at fixed frequency spacing of Δf GHz and flat average gain of $g_{i,avg}$, which is equal to the span loss, Γ (dB) as shown in Fig. 3.3. In this static link schematic, this time, the gain of each span EDFA is assumed to have different gain ripple profiles to capture penalties due to it and reduce design margins.

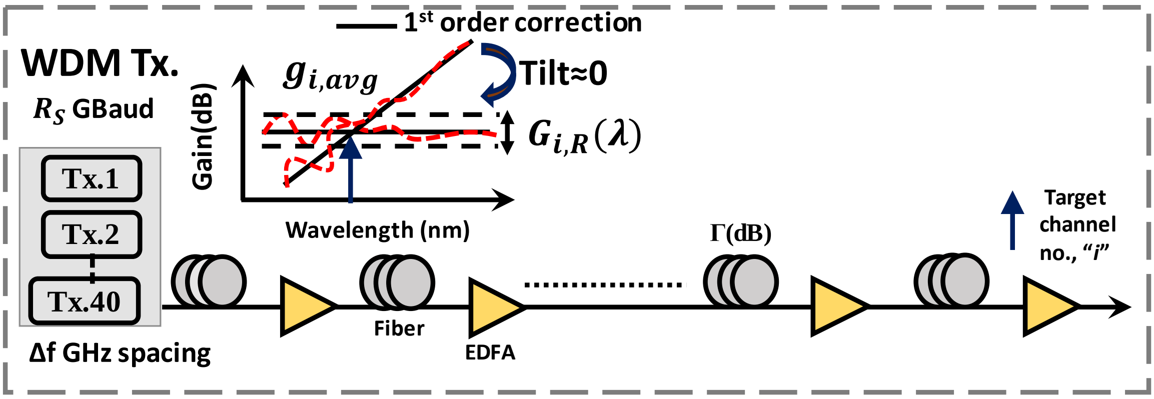

Fig. 3.3: Static link model for span EDFA having Ripple profile

Based on the WDM system depicted in Fig. 3.3, the detailed closed form analytical expression for the power spectral density (PSD) calculation of NLI noise, G_{NLI_ripple}, having different gain ripple profiles at each span EDFAs, is given by:

$$G_{NLI\_ripple}(f_{ch,i}) = \frac{16}{27}\sum_{n_s=1}^{N_s} \gamma^2{}_{n_s} L^2{}_{eff,n_s}$$

$$\sum_{n=1}^{N_{ch}} G_{ch,n} G_{ch,n} G_{ch,i}\,(2-\delta_{ni})\,\Psi_{n,i,n_s} \tag{9}$$

$$\prod_{i,n'_s=1}^{n_s-1} (\boldsymbol{g_{n_s}} + g_{i,R}(\lambda))^3{}_{i,n'_s}\, e^{-6\alpha_{i,n'_s}L_{s,n'_s}} \quad \prod_{i,n'_s=i,n_s}^{N_s} (\boldsymbol{g_{n_s}} + g_{i,R}(\lambda))_{i,n'_s}\, e^{-2\alpha_{i,n'_s}L_{s,n'_s}}$$

where i, n'_s, represent *i-th* gain ripple profile assigned to span n'_s EDFA, and α_{i,n'_s} is the loss parameter for span n'_s having gain ripple profile *i.*

Now, since each EDFA has gain ripples, which are wavelength dependent, so Eq. (5) and Eq. (6) now have non-unity residual gain due to the ripple which is given as

$$\prod_{n'_s=1}^{n_s-1}((\boldsymbol{g}_{\boldsymbol{n}_s})^3 + \left(3 * \left(\boldsymbol{g}_{\boldsymbol{n}_s}\right)^2 * g_{i,R}(\lambda)\right) + \left(3 * \left(g_{i,R}(\lambda)\right)^2 * \boldsymbol{g}_{\boldsymbol{n}_s}\right) + \left(g_{i,R}(\lambda)\right)^3{}_{i,n'_s}) \, e^{-6\alpha_{n'_s}L_{s,n'_s}} = \neq \ 1 \quad (10)$$

$$\prod_{n'_s=1}^{n_s-1}((\boldsymbol{g}_{\boldsymbol{n}_s})^3 + \left(3 * \left(\boldsymbol{g}_{\boldsymbol{n}_s}\right)^2 * g_{i,R}(\lambda)\right) + \left(3 * \left(g_{i,R}(\lambda)\right)^2 * \boldsymbol{g}_{\boldsymbol{n}_s}\right) + \left(g_{i,R}(\lambda)\right)^3{}_{i,n'_s}) \, e^{-6\alpha_{n'_s}L_{s,n'_s}} = \neq \ 1 \quad (11)$$

If we use the above extended version of GN model with Eq. (10) and Eq.(11) accounting for wavelength dependent residual gain due to ripple, as the PLM for the QoT tool, which can capture ripple effect in overall noise, then Eq. 7 will change to Eq. 12 having $design\, margin_2$; $with\, design\, margin_2 < design\, margin_1$ as gain ripple information is there in the noise for this case. The OSNR then in this case is given by;

$$OSNR_{Ripple}(\lambda) = \frac{G_O\,(\lambda)}{G_{ASE} + G_{NLI\_ripple}(\lambda)} + design\, margin_2 = \frac{G_O\,(\lambda)}{G_{Noise_{ripple_p}}(\lambda)} + design\, margin_2 \quad (12)$$

where $G_O\,(\lambda)$ is the signal PSD at the end of link and $G_{Noise_{ripple_p}}(\lambda)$is the total noise PSD accounting for both ASE and NLI. The reason for using "ripple" in the notation is because each span amplifiers are assigned gain ripple profiles. "design margin_2" are the additional margins added in the QoT tool to compensate for other uncertainties such as polarization dependent losses etc., but not (almost zero) EFDA gain ripple penalty.

3.3 Migration form Link to Network Model

On a network, the fiber links can have several intermediate spans and multiple in-line amplifiers as shown in Fig. 3.4(b). It represents an example network model with 4 nodes and a connection established between 1 to 4 through nodes 2 and 3. As a connection may have many intermediate ROADM nodes, it is therefore important to migrate our understanding of gain ripple based overall noise or extended GN model from static link towards a network. From Eq. 9 to Eq. 12, it is seen that the NLI contribution on the total noise is significantly dependent upon the ripple profiles of the EDFAs. It is therefore important to either tune the launch power based on the span EDFA ripple profile to reach some predefined OSNR level or estimating the overall noise based on span ripple to calculate accurate QoT parameter and hence to reduce the design margins from $design\, margin_2$ to $design\, margin_1$. The latter is one of the problems tackled in this work in next section with the help of advance technology, i.e. Machine Leaning.

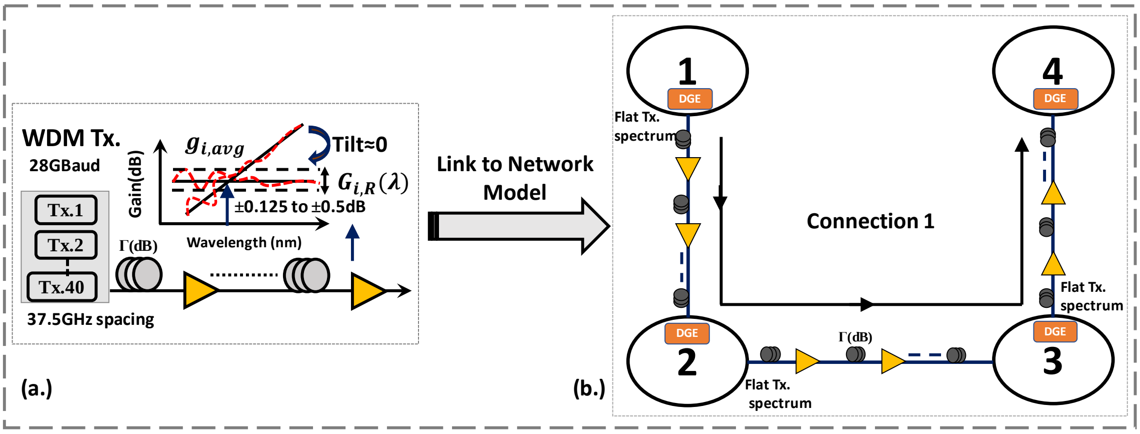

Fig. 3.4: Overall migration from **(a)** STATIC Link Model to, **(b)** Example of a Network Model

In the network model, Dynamic Gain Equalizers (DGE) are considered to flatten the gain ripples at every ROADM node, i.e. at the end of each link. Hence, as shown in Fig. 3.4(b), the transmitted spectrum at each node including source node is assumed to be perfectly flat with nearly zero gain ripple with the help of DGE. Also, all EDFAs used in the network model are operated in AGC mode with zero tilt by pre-adjusting their operating points as discussed in introductory section. Each span EDFA has assigned a ripple profile denoted by $g_i(\lambda)$ and given by Eq. 8. For an individual connection request, the end to end OSNR is calculated by inverse addition of linear SNR of each link given utilized by Eq. 12 as:

$$\frac{1}{OSNR_{connection}} = \sum_{l=1}^{N_l} \frac{1}{OSNR_l} \tag{13}$$

Keeping Eq. 12 in mind, if $OSNR_{12}$, $OSNR_{23}$ and $OSNR_{34}$ is the individual OSNR of links 12, 23 and 34, then end to end OSNR for connection 1 is given by:

$$\frac{1}{OSNR_{connection}} = \sum_{l=1}^{3} \frac{1}{OSNR_l} = \frac{1}{OSNR_{12}} + \frac{1}{OSNR_{23}} + \frac{1}{OSNR_{34}} \tag{14}$$

In the following sections, we will find the penalty distribution on per link and per connection basis over network topology (DT-12) with the help of Eq.1 to Eq. 14 for optimum launch power of 0dBm [14][17].

4 Proposed ML Assisted QoT Margin Reduction Solution

In this section we study the contribution of the wavelength dependent EDFA gain ripple on the QoT by taking OSNR as the quality parameter. First, we provide the basic idea about the penalty distribution due to EDFA gain ripple on a static link. Then it is addressed the penalty distribution on the targeted DT-12 node topology by assigning different gain ripple profile to span EDFAs. At the end, the overall flowchart and architecture of the proposed ML assisted model to estimate this ripple generated penalty for unestablished connection request is provided. By doing so, reduction in the design margin when setting up a new connection request is accomplished with the proposed ML tool.

4.1 Ripple based Penalty Distribution

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. 3.3 [5][6]. However, although the gain tilt profile is maintained at zero still there are gain fluctuations/ripples within the gain bandwidth of EDFAs. To understand the trends of gain ripple profiles, we performed experiments on EDFAs to capture the gain fluctuations in the optical spectrum band of ~1530 – 1563nm (40 channels, 100GHz apart). All EDFAs used in experiments were operated in AGC mode with zero tilt by pre-adjusting their operating points (inset of Fig. 4.1 shows EFDA gain ripple characterization with 40 channels). Based on collected experimental data, we created realistic sets of individual spans EDFA gain profiles. We assign these ripples profiles to span EDFAs and we emulated a static link set up in VPI Transmission Maker version 9.9 as shown in Fig. 4.1 [19].

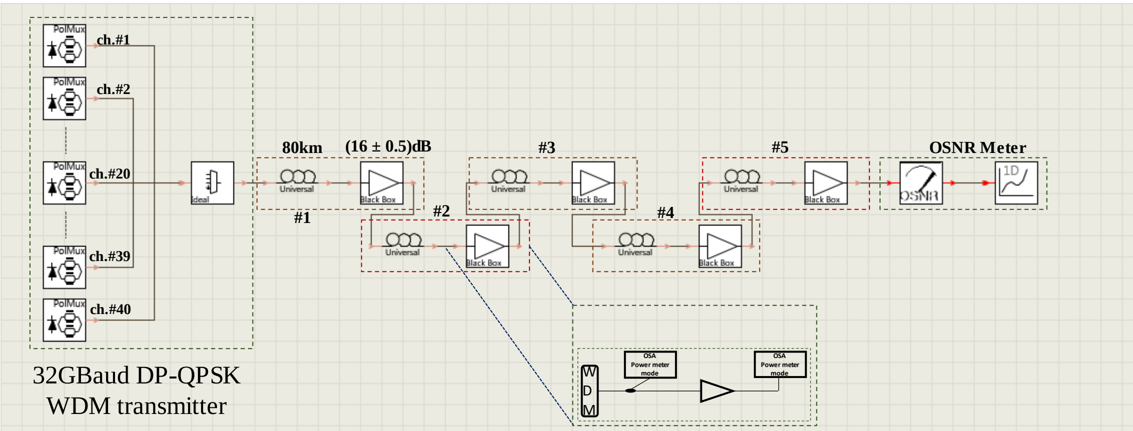

Fig. 4.1: VPI Tx. Maker set up for static link having ripple profiles at each span EDFA with peak to peak gain fluctuation, $g_{i,R}(\lambda)$ = ±0.5dB

We found ~1dB (see Fig. 4.2(a)) of fluctuation with increasing number of spans. These fluctuations are plotted for the channel no. 20, λ_{20} having ripple value, $g_{i,R}(\lambda_{20})$ of ±0.5dB. We then extended these static link simulation experiments in entire C-band to capture the effect of gain ripples on OSNR. Fig. 4.2(b) represents the relative OSNR variation distribution over 40 channels in C-band with respect to flat EDFA profiles. We observe that with the cascade of spans (80km length used in simulations), the OSNR variation increases (~1dB in C-band as also shown in Fig. 4.3(a)). The trend in Fig. 4.2(b) indicates less fluctuation on spectrum band edge channels. This is because the ripple profile used contains more rapid fluctuations in the center, keeping $g_{i,avg}$

constant. The shape of the ripple can vary over longer time (aging), leading to higher peak to peak variations, but this is slowly time varying. So, in short and medium term there is clear trend which makes modelling of these variations possible. These variations impact the accuracy of the QoT estimator within a margin range as described in Fig. 2 and Fig. 7 of [20].

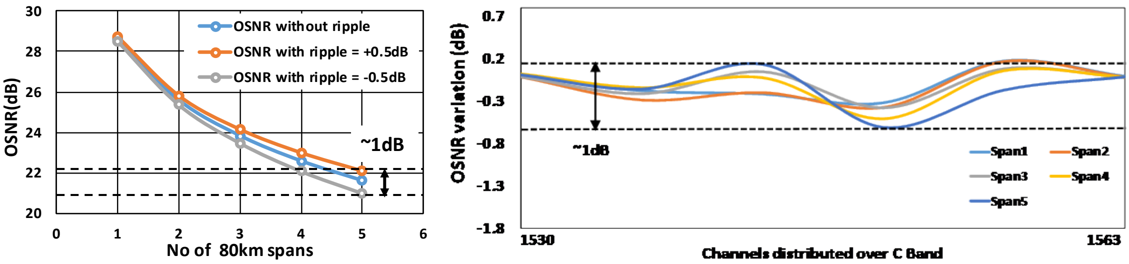

Fig. 4.2: (a) OSNR fluctuation of ~1dB observed due to the EDFA gain ripple after 5 spans, **(b)** EDFA gain ripple effect on OSNR (dB) over the C-band

4.2 Methodology & Proposed Solution

We consider a Flexi-grid EON with ROADMs connected through uncompensated fiber links. Each link consists of multiple fiber spans that terminate at an EDFA to compensate the span loss. We assumed that span EDFAs are operated in AGC mode with zero tilt having gain ripple profiles. DGE are also considered to flatten the gain ripples at every ROADM node.

If we use a PLM, such as the GN model described in section 3, the typical assumption is a flat EDFA gain [14] requiring a high design margins as given by Eq. 7. $G_{Noise\_flat\_p}$ in Eq. 7 corresponds to the “total noise” of the path estimated by the PLM having no EDFA gain ripple information. We call it as, “ripple unaware PLM”. The penalty due to gain ripple fluctuations is within the *design margin*$_1$ (which is flat and equal to the worst case). In this case, we had to model all EDFAs in the network in a calibration face, which would be time consuming and would need to be repeated, when the ripple function changes (aging). In this work, we use the well accepted GN model as PLM. We extend the *ripple unaware* PLM model to capture the ripple penalties to ultimately reduce the required margin for new connections. We call it as “ripple aware PLM”. We considered accumulated ripple penalties at link ends which are then added over the path. Our extended *ripple aware* PLM estimates OSNR by Eq. 10. $G_{Noise\_ripple\_p}\ (\lambda)$ in Eq. 12 is the sum of $G_{Noise\_flat\_p}$ and $G_{ripple\_p}\ (\lambda)$ and is not flat but models the wavelength (λ) dependent ripple noise leading to lower margin (*design meagin*$_2$ < *design meagin*$_1$). To improve in this way, the accuracy of QoT estimation, we use monitoring information from Optical Performance Monitors (OPMs) assumed to be installed at the end of each link [21] and at the end of connections. Such information is used to fit per link noise ripple penalty functions, which in turn are used to calculate the end-to-end ripple penalties, $G_{ripple\_p}\ (\lambda)$.

We assume an optical network with established connections and their attributes (also referred as *state* of network at a given time) denoted by *P*. We assume a ripple unaware PLM model as represented in Eq. 2, which calculates the noise of the established connections end-to-end as $G_{noise\_flat\_p}(P)$, and the related per link noise as $G_{noise\_flat\_l}(P)$. Note that *P* contains attributes for a connection such as, the traversed links, central wavelength etc. We also assume that we monitor the OSNR of the established connections and thus their noise at the path level $Y_p(P)$ and at the link level $Y_l(P)$ and store it in QoT tool database. This data serves as the ground truth, it defines the true $G_{Noise\_ripple\_p}(\lambda)$, so with zero margin. The flowchart representing the integration between collected monitoring information and the ML assisted penalty estimation function is depicted in Fig. 4.3(a).

We denote the difference of Y and G_{noise_flat} as i) $E_l(P)=Y_l(P)$- $G_{noise\_flat\_l}(P)$ which is a vector with the ripple penalties at the end of each link, accumulated over the links, spans and ii) $E_p(P)=Y_p(P)$-$G_{noise\_flat\_p}(P)$ which is a vector with the ripple penalties at connections' end, accumulated over all used links. We let E be the concatenation of both penalties vector E_l and E_p. From corresponding connections attributes, P, we extract per link and per path features matrices. Additionally, a *bias term* (per link) is also considered to account the monitoring error and for non-zero equalized ripple. The per link and per path features are merged into a single *features matrix*, $X=f(P)$. Our goal is to identify the function $G_{ripple\_p}=\Theta(X)\approx E$ that maps well the features matrix X to the penalty E generated due to the gain ripple. We rely on ML for training and fitting of X on E and finding the function Θ. Assuming a new connection request $l \notin P$, we will use the ripple unaware PLM to obtain the total flat noise $G_{Noise\_flat\_p}$. Then we train our model and obtain Θ and use that to find the ripple noise penalty on the new connection $G_{ripple\_p}(l)=\Theta(f(l))$, and estimate the total noise with ripple $G_{Noise\_flat\_p}+\Theta(f(l))$. The estimation error will be identified once we establish the connection, monitor its values $Y_p(l)$ and compare it to that.

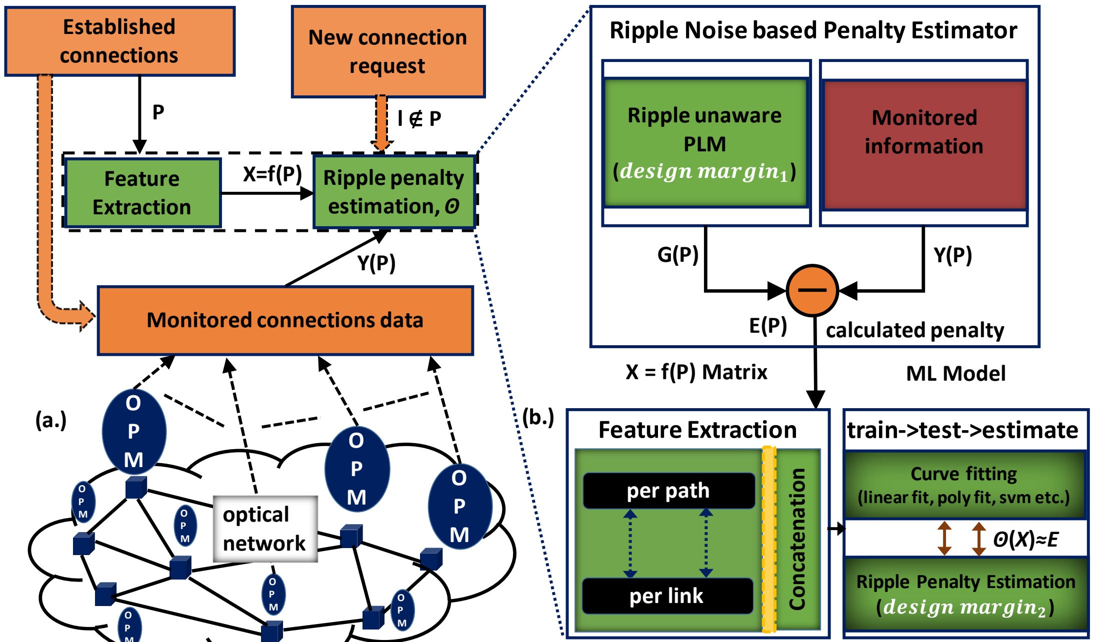

Fig. 4.3: (a) Overall Flowchart and architecture, **(b)** ML-based penalty estimator (i.e., train/test/estimate)

4.3 Result & Discussion

The DT topology formed by 12 nodes and 40 bidirectional links whose lengths range from 48 to 458 km (see Fig 4.4(a)) is considered for conducting the tests. 4 traffic loads of [100, 200, 300, 400] connections are used where selected source-destination node pairs have fixed symbol rate of 32GBauds requiring 3 spectrum slots (i.e., 3*12.5GHz = 37.5 GHz). We experimentally captured some EDFA gain ripple profiles in laboratory. To emulate all span EFFAs with individual ripple profiles, we randomly applied time shifting and amplitude scaling on them to obtain a vast set of gain ripple for each span amplifier as, $G_i(\lambda)$. A set of connections are assumed to be established (according to the load) and *monitored*. Monitoring in the simulations is performed with a ripple aware PLM (extended GN) model, which gives $Y(P)$. A stable network *state* is considered with a specific set of established connections. Such a set of connections is divided into two sets, 90% / 10%, the training and testing datasets, respectively. The training set is assumed to be the established connections P and the testing set the connections to be established. We use the ripple unaware PLM (GN) model to obtain $Q(P)$ depending on the attributes P of the established connections.

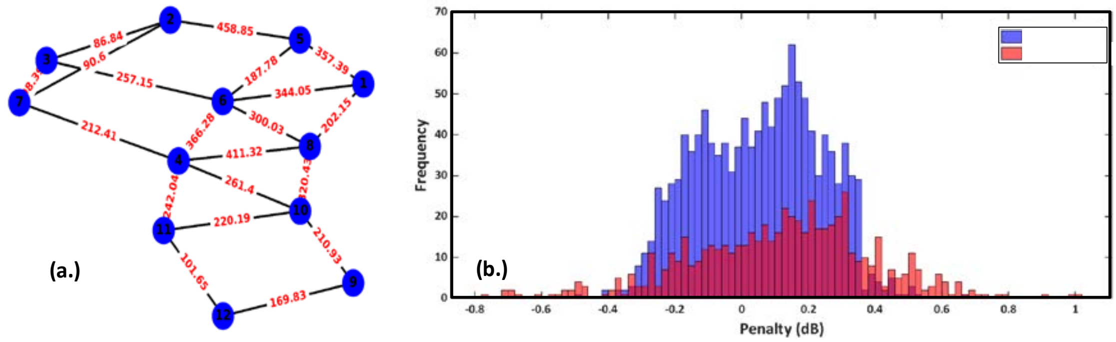

Fig. 4.4: (a) DT 12 network topology, **(b)** per link & per path penalty distribution

By subtracting Q and Y, we obtain the penalty vector E (*ripple noise-based penalty estimator* block in Fig. 3b). The E vector distributions are depicted in Fig. 4.4(b) for 100 connections, which clearly shows the error values of ~1dB. The penalties are distributed in positive and negative sides depending upon the ripple values. Positive/negative penalties result in upper/lower bound for design margins and we call them as, “high/low margin”. We evaluated several ML assisted regression techniques to fit Θ on E, such as linear fitting, quadratic, polynomial fitting, support vector machine (SVM) etc. In the presented results we used polynomial regressions of degree 4 that achieved maximum Mean Squared Error (MSE) of 4.5E-2 on predicted OSNR with load of 100 connections as shown in Fig. 4.5(a). With increase in load from 100 to 400, max MSE converge to a value of ~4E-3. Results presented here are averaged over 200 iterations at each load.

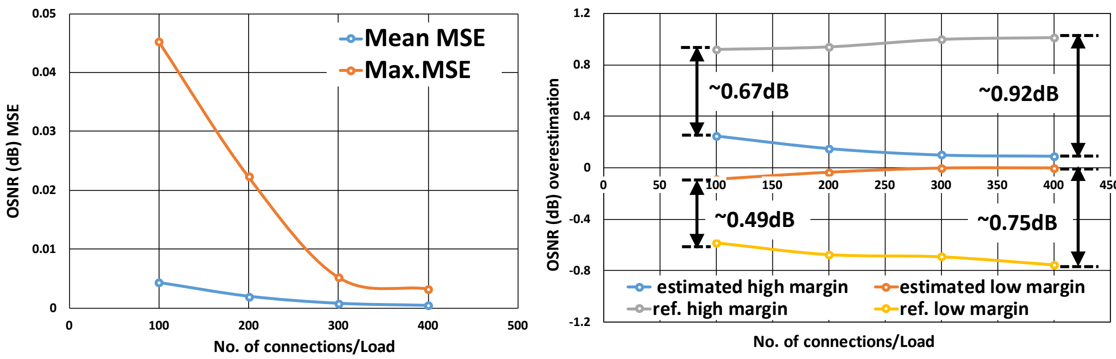

Fig. 4. 5: Effect of load variation on, **(a)** OSNR (dB) MSE, **(b)** Max. overestimation error

From the above set of simulations, the maximum used peak to peak ripple intensity among all span EDFAs is about ±0.5dB, which results in a reference margin ($design\ margin_1$) of 1.02dB at a load of 400 connections. Fig. 4.5(b) shows the maximum overestimation error on OSNR estimation, relative to Fig. 5a. This overestimation is the reduced estimated high and low margin

($design\ margin_2$). For high margin, it is found to be 0.08dB, yielding a ~0.92dB margin reduction with 400 connections. For low margin, this reduction value is ~0.75dB as the distribution of penalties is less for low margin side.

We also varied the gain ripple intensity (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) and estimated the high and low margins at a fixed load of 400 connections. We observe in Fig. 6, a reduction of >90% on both

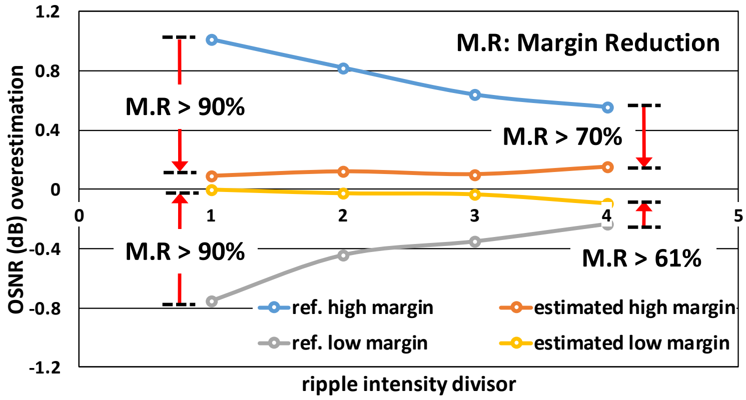

Fig. 4.6: New margin for different intensities of peak to peak gain ripple among all EDFAs with reference as ±0.5dB

high and low margin for peak to peak intensity fluctuations of ±0.5dB. For low values of peak to peak ripple of ±0.125dB, high and low margin reduction varies from 60% to 70% respectively.

4.4 Further extensions and applications for the QoT tool

In the following, it is presented extensions to the proposed QoT tool, highlighting some preliminary results.

4.4.1 Filter Cascading Uncertainties Estimation

In the above model, the EDFA ripple is the sole reason for the deviation of the QoT estimation from its true value. We thus leveraged a ML based solution that used monitoring information to estimate the contributed noise penalty. We can view this as an uncertainty in the input parameters of QoT estimation tool, the QoT tool assumes a flat EDFA profile. As discussed, such uncertainties are covered with a portion of the design margin. Another source of uncertainty, which we tackle in this subsection is related to the ROADM nodes penalties.

ROADMs are the key switching elements of core and metro deployed optical networks [22]. The properties of dynamic reconfigurability and channel add/drop in the optical domain make them suitable candidates for the realization of meshed optical networks [8]. Several implementations of ROADM are possible using optical devices including MUX/DMUX, optical splitters/combiners, wavelength blockers and Wavelength Selective Switches (WSSs). The use of WSS provides the advantages of colourless add/drop ports and simpler higher degree design which make them the industry choice for the current generation ROADMs [23] [24]. Fig. 4.7(a) shows a “switch and select” ROADM node architecture using WSS for channel add/drop and EDFAs (pre and booster) to recover fiber and filtering losses [9].

Generally, a signal that traverses a ROADM node encounters some OSNR penalty due to the filters or WSS inside the ROADM nodes. Over long paths, where the signal traverses multiple links the filters are cascade, resulting in a nonlinear penalty with respect to the number of nodes. An example of this effect is shown in Fig. 4.7(b) for 16-QAM as modulation format operating at 28Gbaud with 37.5GHz frequency spacing [9], where it is clearly shown that the penalty increases exponentially with the number of nodes. This is a simplified model. Since the WSSs inside the ROADM nodes have different characteristics, the penalty due to these WSS and their cascading leads to some uncertainties. Removing these uncertainties allows reducing the margin from the QoT tool. Thus, a dedicated analysis on this uncertainty and its estimation via ML are worth to be explored.

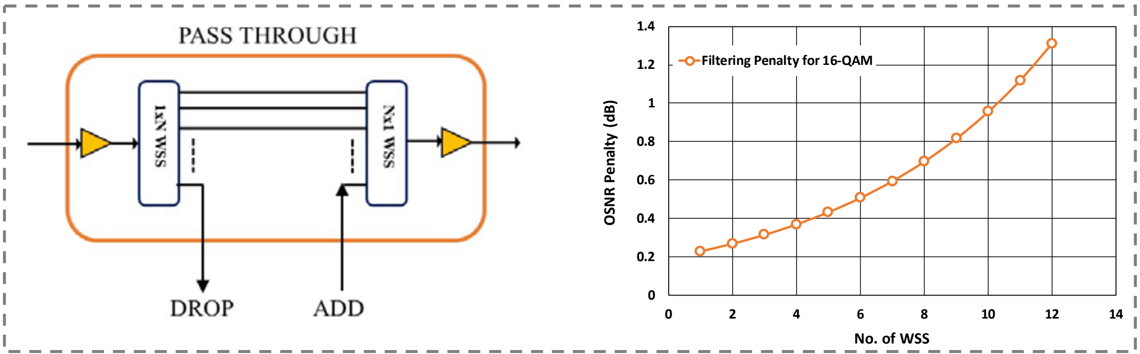

Fig. 4.7: (a) A simple switch and select ROADM node architecture, **(b)** OSNR penalty in dB due to tight optical filtering for 16-QAM

Let us consider a connection, p that traverses 3 links and ROADM node with switch & select architecture as shown in Fig. 4.7(a) For the link1, we assume that the filter inside the nodes are perfectly ideal and possess some penalty according to Fig 4.7(b) depending upon the no. of nodes traversed. Filtering penalty due to cascaded nodes in this case has no uncertainty and have integer values as shown in Fig. 4.7(b). Based on this, the OSNR for this case, $OSNR_{int\_p}$ by standard QoT tool is given by

$$OSNR_{int\_p} = \frac{G_O(\lambda)}{G_{noise\_filt\_p}} \tag{15}$$

In this work, monitoring port are assumed to be available at the output of each link just after the last fiber span repeater or preamplifier as shown in Fig. 4.8(a). As discussed in previous chapter in case of heterogeneous nodes, multivendor network, different 3-dB Bandwidth of filter inside nodes etc. leads to some sort of uncertainties and hence the OSNR penalty due the traversed nodes for a light path can take non-integer values from the plot shown in Fig. 4.7(b). Even though, the nodes are equipped with DGEs and monitoring is available at link ends, still per link monitoring port captures cumulative/cascading filtering effect at monitoring port. For ease of understanding, we call them as per subpath monitoring and is well indicated for understanding in Fig 4.8(b). This filter cascading uncertainties will surely affect the estimation accuracy of the QoT tool. Keeping this scenario in mind, we monitor the actual per subpath OSNR for the established connections, having random uncertainty factor, Δ in dB (within a range as shown in Fig. 4.8(a)) in the noise penalty (output power is constant with the help of pre and booster EDFA inside nodes) is given by

$$OSNR_{uncert\_p} = \frac{G_O(\lambda)}{Y_{noise\_uncert\_p}} \qquad (16)$$

After going through some simple mathematical operations on Eq. 15 and Eq. 16, the noise generated at the node due to filter cascading effect is given by Eq. 17as

$$Y_{noise\_uncert\_p} = \frac{G_O(\lambda)F_{noise\_int\_p}}{G_O(\lambda) - G_O(\lambda)(OSNR_{int_p} - OSNR_{uncert\_p})} \qquad (17)$$

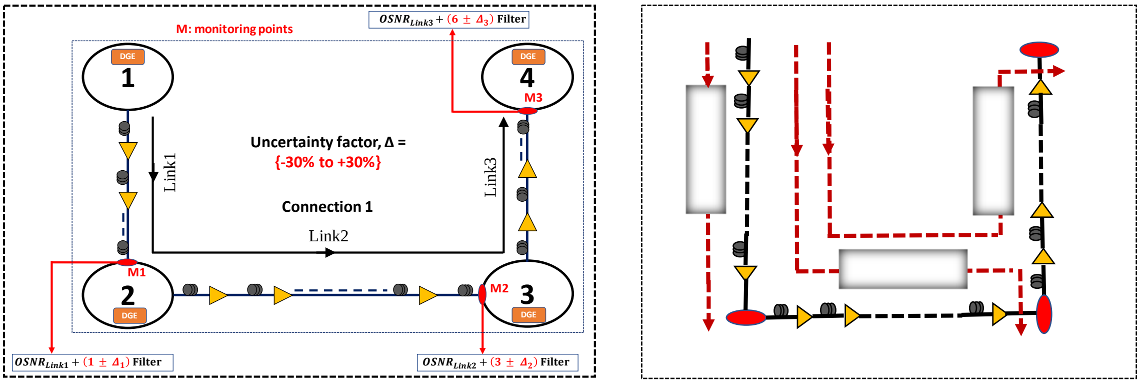

Fig. 4.8: **sample connection having filtering uncertainties indicating per** (a) **link** (b) subpath **monitoring ports**

The difference between this $Y_{noise\_uncert\_p}$ and $F_{noise\_int\_p}$ per subpath for a connection gives the penalty in overall accumulated noise due to filtering uncertainty. Properly trained ML model on this monitored data (noise difference) has the potential to estimate these penalties accurately for new connection requests leading to more accurate QoT estimation as discussed in next section.

4.4.2 Methodology & Proposed Solution

Keeping the same notation as above, we assume an optical network with established connections and their attributes (also referred to as network *state*) which is denoted by *P*. From Fig 4.7(b), for connection, P, we define OSNR filtering penalty, $Filt_p$ as a function of no. of cascaded WSS or ROADM nodes traversed within end to end established connection and is given as

$$Filt_p = a \exp(-b * no.of\ ROADM\ nodes) \qquad (18)$$

where *a* and *b* are the constants and depends specifically upon modulation format and wavelength grid spacing

We assume a filtering uncertainty unaware PLM model that has perfect integer penalty values as discussed in last section. Such a model calculates the noise of the established connections as $G_{noise\_filt\_p}(P)$, and the related per subpath accumulated noise with filter cascading effect as $FG_{noise\_filt\_s}(P)$ as given in Eq. 15. Note that *P* here contains only two attributes for a connection i.e., the link IDs traversed and modulation format to establish the connection. We also assume that monitored OSNR of the established connections with their noise at the path level $Y_{noise\_uncert\_p}(P)$ and at the subpath level as $Y_{noise\_uncert\_s}(P)$ are stored in QoT tool database. This data serves as the ground truth, it defines the true $FG_{Noise\_filt\_p}$, so with zero margin.

We denote the difference of *Y* and G_{noise_filt} as i) $E_{filt\_s}(P) = Y_{noise\_uncert\_s}(P) - FG_{noise\_int\_s}(P)$ which is a vector with the difference in filtering penalties at the end of each subpath, accumulated over the previous nodes and ii) $E_{filt\_p}(P)= Y_{noise\_uncert\_p}(P)- G_{noise\_int\_p}(P)$ which is a vector with the difference infiltering penalties at connection's end, accumulated over all used subpaths. We let E_{filt} be the concatenation of both penalty vectors E_{filt_s} and E_{filt_p}. From corresponding connections attributes, P, we extract per subpath and end to endpathpath features matrices. Additionally, a *bias term* (per subpath) is also considered to account the monitoring error. The per subpath and per path features are merged into a single *features matrix*, $X_{filt} = f(P)$. Our goal is to identify the function $Y_{noise\_uncert} = \mho(X_{filt}) \approx E_{filt}$ that maps well the features matrix X_{filt} to the penalty E_{filt} generated due to the uncertainties in the filter cascading. We rely on ML for training and fitting of X_{filt} on E_{filt} and finding the function $\mho$. Assuming a new connection request $l \notin P$, we will use the filtering uncertainty unaware PLM to obtain the total noise difference, $Y_{noise\_uncert\_p}$. Then we train our model and obtain $\mho$ and use that to find the filtering uncertainty penalty difference on the new connection $G_{Noise\_uncert\_p}(l) = \mho(f(s))$, and estimate the total noise with filtering having uncertainty effect as $G_{noise\_filt\_p} + \mho(f(s))$. The estimation error will be identified once we establish the connection, monitor its values $Y_{noise\_p}(s)$ and compare it to that.

4.4.3 Preliminary Results

Again, the DT topology with 12 nodes and 40 bidirectional links is considered. A set of established connections (according to the load) with their monitored parameters are provided. As discussed acove, monitoring on subpath basis is performed with a filtering uncertainty aware PLM model, which give us $Y(P)$. A stable network *state* having a specific set of established connections is given, where the objective is to set up a pool of new connections. To do so we divide connections in two sets, 90% / 10%, the training and testing datasets, respectively. The training set is assumed to be the established connections P and the testing set the connections to be established. We use the filtering uncertainty unaware PLM model to obtain $G(P)$ depending on the attributes P of the established connections. By subtracting F and Y, we obtain the penalty vector E_{filt} (*ROADM noise-based penalty estimator* block in Fig. 4.8(b)). We evaluated several ML assisted regression techniques to fit $\mho$ on E_{filt}, such as linear fitting, quadratic, polynomial fitting, SVM etc. In the presented results we used linear fitting that achieved maximum MSE of 5.1E-3 on predicted OSNR with load of 100 connections as shown in Fig. 4.9(a).

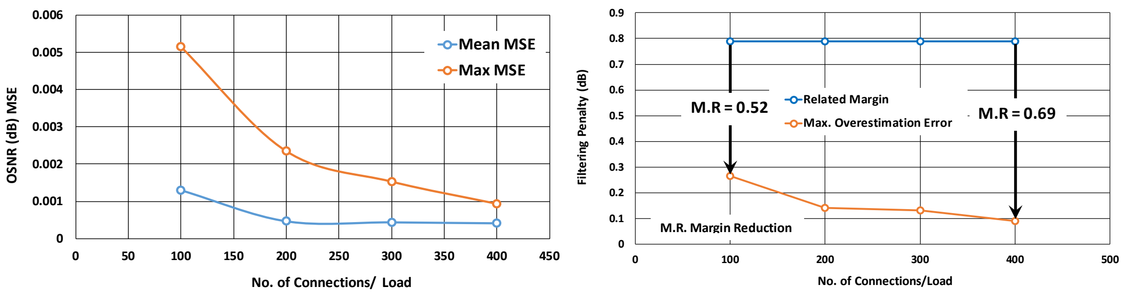

Fig. 4.9: Effect of load variation on, **(a)** OSNR (dB) MSE, **(b)** Max. overestimation error

With increase in load from 100 to 400, max MSE converge to a value of ~1E-3. Results presented here are averaged over 200 iterations at each load.

For the above set of simulations, the maximum no. of ROADM nodes traversed for the connection are 4, leading to 10 WSS or filters, which results in a reference margin ($design\ margin_1$) of ~0.8dB at a load of 400 connections. Fig. 4.9(b) shows the maximum overestimation error on

OSNR estimation, relative to Fig. 4.9(a). This overestimation is the reduced estimated high margin ($design\ margin_2$) and it is found to be 0.09dB, yielding a ~0.69dB margin reduction with 400 connections.

5 Conclusions & Future Plans

In this document, we summarized the activities and achievements conducted so far by ONFIRE ESR2 within WP2. The research focus has been concentrated on exploring the adoption and application of ML methods aiming at enhancing the QoT tool estimation accuracy and lowering the related margins. In this context, we firstly addressed the problem of modelling the noise penalty caused by the EDFAs gain ripple effect. We leveraged a ML regression technique that makes use of monitored data from established connections to enhance the accuracy of the QoT estimation when serving a new connection. Our results showed that we can lower by >90% (0.92dB) the related margin due to EDFA gain ripple. We provided a detailed description of the proposed approach and the obtained results. As an outcome of this study, a paper was submitted and accepted as a top-scored paper in ECOC 2019 [25].

In the same direction, we presented a second application which addresses uncertainties in modelling the WSS cascading effect, using ML. Similarly, this yields a more accurate QoT estimation, which in turn lowers the related margin. Our simulations showed margin savings of ~0.69dB.

With the previous use cases/applications (i.e. EDFA gain ripple and filter cascading effects) in mind, we devised the next research steps. We plan to merge both aspects and models in a single model (PLM), which would act as the ground truth. In other words, the purpose is to have a reference model that considers simultaneously both effects. Next, we are planning to generate synthetic data from the created PLM and implement a single ML model accounting for both uncertainties collectively.

6 Review & Feedback from Advisory Committee

During the 1st ONFIRE symposium held at CTTC, Castelldefels on 29th January 2019, some comments were pointed out by the advisory committee, AC. Along with each mentioned comment, a brief clarification is provided below:

I. ***It should be better explained why the extension is needed to the packet layer. Does this not involve too much effort for the project?***

As already discussed and agreed with AC, the research work with respect to the packet layer will be carried out by ESR2 in future.

II. ***The link between the quality of transmission machine learning tool and the reconfiguration of networks supported by SDN is missing.***

The research work done so far in this report is more focused on the improvement of the estimation accuracy which leads to the design margin reduction of the existing QoT tool. In real systems, QoT estimation tool interact with routing and spectrum assignment (RSA), which can be optimised further, if the QoT estimation is more accurate with some margin savings.

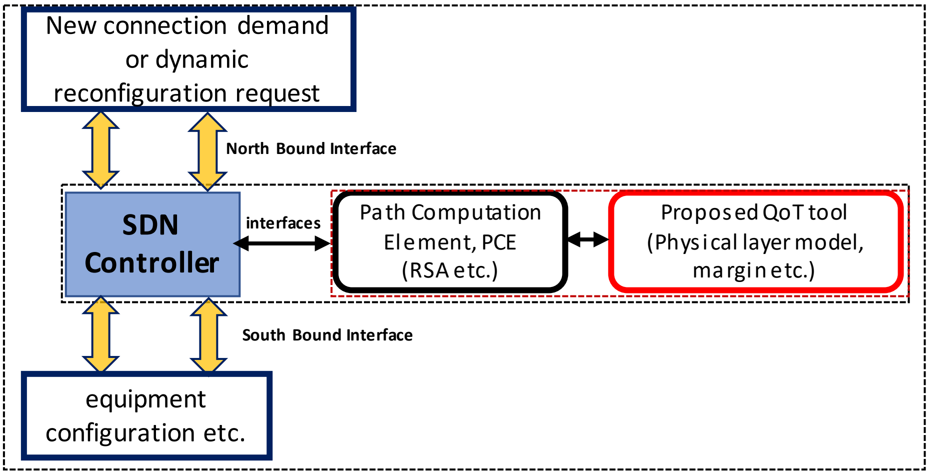

Fig. 6. 1: QoT estimation tool interaction with different algorithms

For new connection request or dynamic reconfiguration request of an existing connection within a network, the SDN controller is the main interacting unit to accept/block these requests. From Fig. 6.1, the Qtool provides the signal quality estimation for these requests and this overall system is interacting with SDN controller through proper interfaces. Since, with the proposed Qtool in this work, the noise (hence OSNR) is estimated more accurately than the existing Qtools. Hence with real time interaction with the SDN controller, better path, more robust modulation format, low blocking probability with the RSA algorithms is possible, since our Qtool can predict the quality with least uncertainties due to EDFA gain ripple and filter cascading effect. This is just a brief introduction of interaction/link between proposed ML assisted QoT tool and reconfiguration of networks supported by SDN. In any case, we will accommodate/clarify all the comments/doubts during the upcoming meetings and discussion with the AC.

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