On Reducing Optical Monitoring Uncertainties and Localizing Soft Failures

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***Abstract*— We propose a scheme to reduce monitoring uncertainties in optical networks. The proposed scheme uses monitoring data of optical connections (lightpaths) which can be obtained from coherent optical receivers that can also function as optical performance monitors (OPM). We exploit both space and time correlation of the monitoring data in order to reduce the monitoring uncertainties. The improved accuracy can result in various benefits, the most common one is that the Quality of Transmission (QoT) can be estimated with higher accuracy which can in turn lead to more optimized decisions and lower provisioning costs. In this paper we present another application, we show how to use the obtained accurate monitoring data to localize soft failures (also referred to as QoT problems) on a per link level.**

Keywords—optical networks; reduce monitoring uncertainty; network optimization; soft failures; failure localization;

I. Introduction

Optical transport networks are quite static in the sense that they are not dynamically re-configured unless there is a hard failure (such as a fiber cut). Hard failures are handled with protection/restoration mechanisms, which involve the dynamic re-routing of the affected traffic. Optical connections (lightpaths) can travel over multiple consecutive links, bypassing transparently the intermediate optical switches. In this process they accumulate noise from inline amplifiers but also suffer from other physical degradations, typically referred to as Physical Layer Impairments (PLIs) which deteriorate their Quality of Transmission (QoT).

As a matter of fact, a lightpath needs to have acceptable QoT. When planning or upgrading the optical network, the QoT of the lightpaths is estimated using a certain physical layer model [1][2]. When estimating the QoT, s*ystem margins* are used to anticipate future degradations due to equipment ageing, interference from increases in load, and failures until the end of life (EOL) of the system [1][3]. Moreover, the *design margin* is used on top of the system margins to account for the QoT estimation model inaccuracies [1][3]. The high margins result in the deployment of equipment that is not strictly necessary at the initial set-up time. Clearly reducing the margins can yield significant cost savings [4].

The reduction of the margins, makes the equipment to operate closer to their limits. The increased efficiency yields cost savings but requires a more dynamic network. Lightpaths operated close to their QoT limits are subject to *soft failures*: subject to equipment (e.g. transceivers, amplifiers, filters, bends of fiber, etc.) malfunctioning or ageing, increase of interference due to new connections or other operations that deteriorate the QoT such as performing a maintenance task. The key distinction of a soft failure as opposed to a hard failure is that the soft failure does not cause complete loss of the signal, and therefore correcting the soft failure is not urgent; the lightpath can live for a short time with deteriorated QoT.

To give an example of a soft-failure, it has often been observed that after fixing a failure the performance of the system is significantly different. A fiber repair could result in unpredictable situations, such as higher insertion loss, worse back-reflections, longer path, or a mix of different fiber types, when e.g. the one used in the network is not commercially available anymore (e.g. dispersion shifted fiber G.653). Increased span loss or back-reflections are particularly harmful in Raman amplified spans, because they affect the Raman gain and degrade the achieved OSNR. Soft failures are generally difficult to locate and the task usually relies on the analysis of alarms reported by certain devices. However not all soft failures generate alarms and certain failures may exist before the alarm goes off. While hard failure localization has received significant attention [5][6][7], not much research exists for soft failures.

In modern optical networks there are devices (such as power monitors) in certain locations that are used to report hard failures [5][8]. ORCHESTRA project [9] proposes to exploit coherent receivers and to operate them as optical performance monitors (OPM). This can be done with negligible additional cost, as coherent receivers are already packed with digital signal processing (DSP) capabilities and can be programmed to measure (with certain accuracy) various impairments. In this paper we assume that OPM information is available at the termination node of each lightpath, i.e. at the receiver. A monitoring plane, as the one proposed in [10], can be used to collect the monitoring information in an efficient way, and perform some processing distributedly, although in the following we assume that OPM information is collected in a central entity (the network controller) which stores and processes all data.

We propose a scheme that relies on OPM information of lightpaths and uses space and time correlation techniques to improve the monitoring accuracy, reducing thus the uncertainty of the reported measurements. Increased monitoring accuracy helps in more accurate QoT estimation [11], which in turn enables the network operator to reduce the margins, make more optimized decisions and reduce the total provisioning costs [4]. Certain routing algorithms can take into account the QoT inaccuracies [12], but even such algorithms can benefit from more accurate QoT metrics. What is more, the proposed

correlation scheme which harvests the space dimension can be used to infer certain QoT parameters per link. This, in turn, can be used to localize soft failures to a link level. The localization of a QoT problem helps the network operator resolve the problem (if it can be resolved) or take relevant measures before the failure affects significantly the QoT of any lightpath or the operation of the network as a whole. It stands to reason that the better the QoT measurements accuracy, the smaller the soft failures we are able to localize. Our simulation results show the improvements in the monitoring accuracy that the proposed scheme achieves and also showcase how this can be used to localize at a link level two noise related soft failures.

II. Network Model

We assume a fixed- or flex-grid [13] optical transport network employing reconfigurable optical add/drop multiplexers (ROADM) and coherent transceivers. The ROADM nodes are connected through uncompensated fiber links. Each fiber link consists of a number of fiber spans that terminate at an EDFA amplifier that compensates the span loss. We assume that there is no wavelength (or slot) conversion and thus the wavelength (or slots) continuity constraint holds for each lightpath. For long connections regenerators are placed, and each segment between regenerators is considered a separate lightpath that can use different wavelength (or slots).

We also assume that the DSP capabilities of the coherent receivers are extended to function as OPMs [9]. Thus OPMs are located at the termination point of each lightpath (receiver) and can provide information about various physical parameters (e.g. residual dispersion, OSNR, Non-linearities, Q factor) of the lightpath. We focus on parameters that are (or their inverse) *additive per link*, or that considering them additive per link introduces a small error [2]. Typically, Amplified Spontaneous Emission noise (ASE) and dispersion effects (chromatic and polarization mode dispersion / residual or not), depend lightly on the used wavelength and thus considering them link-additive introduces a small error. Even self-phase modulation (SPM), which is a nonlinear PLI can be considered additive per link. However, inter-channel interference, linear (crosstalk) or nonlinear (cross-phase modulation, four wave mixing), depends on the load of the network and is different for different channels crossing the same link. If they are considered additive then an error is introduced which depends on the specificities, e.g. the error is small at heavy loads where all channels have similar neighbors and therefore suffer similar interference. We also assume that the value reported by an OPM has some level of uncertainty (we will discuss this in more detail in the next subsection) that depends on the DSP algorithm used to measure the specific (additive) parameter at the receiver. Our goal is to improve the accuracy of the monitored parameter and to also localize any soft failure that affects this parameter.

The space correlation framework that we will use towards this end is described next. Consider a network $G=(V,E)$ with V denoting the *set* of nodes, and E the *set* of unidirectional fiber links and assume a *set* of M already established lightpaths in it. The routing matrix of established lightpaths is defined as $R_M \in \{0,1\}^{|M|x|E|}$, where $R_M[m,l]=1$ when a lightpath m contains link l. Consider the end-to-end *vector* of parameters $\mathbf{y_M} \in \mathbb{R}^{|M|}$, with y_m member of $\mathbf{y_M}$ and a value for lightpath m. Vector $\mathbf{y_M}$ can be written as linear combination of link-level vector parameters $\mathbf{x} \in \mathbb{R}^{|E|}$ so that $\mathbf{y_M} = R_M\mathbf{x}$. We assume that we want to estimate the end-to-end parameters of a set N of new lightpaths, denoted by vector $\mathbf{y}_N \in \mathbb{R}^{|N|}$, assuming that we know their routing $R_N \in \{0,1\}^{|N|\times|E|}$. Thus, we have

$$\mathbf{y} = \begin{bmatrix} \mathbf{y}_M \\ \mathbf{y}_N \end{bmatrix} = \begin{bmatrix} R_M \\ R_N \end{bmatrix} \mathbf{x} \tag{1}$$

Note that the above formulation models lightpaths sharing the same link (of course at different channels) as having the same value. This is the assumption of link additivity we discussed above, which introduces a certain error to the accuracy that we can obtain (as will also be discussed in the results section).

The objective is to determine the unknown end-to-end parameters $\mathbf{y}_N$, where $\mathbf{y}_N = R_N\mathbf{x}$. The Network Kriging (NK) technique [2][11] can be used to obtain the best (mean-square error) linear estimate of $\mathbf{y}_N$ which is

$$\hat{\mathbf{y}}_N = R_N R_M^T \left(R_M R_M^T\right)^+ \mathbf{y}_M \tag{2}$$

where $(.)^+$ denotes a pseudo-inverse. The complexity of the algorithm is $O(|M|^3)$ [2] [11] where $|M|$ denotes the number of monitored lightpaths. Since, the estimation accuracy also depends on the number of monitored lightpaths, we can select the monitors used in the formulation to tradeoff between execution time and accuracy. When the routing matrix is full rank we obtain perfect estimation accuracy, assuming that the estimation model is perfect, which is, however, not the case in physical layer monitoring, since the link additivity assumption introduces some error.

III. Reducing The Uncertainty Of The Monitored Impairments

Our first objective is to reduce the uncertainty of the monitoring impairments. An OPM reports monitoring information with a certain error [15][15][16]. The error in the end-to-end measurements of a path can be substantial (e.g. for OSNR this is about 0.5-1 dB [15][17]). A significant percentage of this error is introduced by the imperfection of the measuring algorithm. This is further broken down to a systematic error and a random error. We assume that any systematic error is removed by the monitor with proper calibration, so we focus on the random zero-mean part of the measuring error. Moreover, the actual parameter that we want to measure can fluctuate with time. For example the actual OSNR depends on certain polarization effects that might change over time. Still in this case, there is a well-defined average that represents the short-time scale state of the network, which is what we actually want to monitor. In other words, we assume that the factors of the error (the zero-mean random measuring error and the fluctuation of the actual value) have short time-scales and we want to suppress that error. On the other hand, medium/long scale effects represent changes in the network state, and not an error. The errors of different lightpaths may or may not be correlated (or one of the factors can be correlated and another not). In the following we assume that they are not correlated, which is the

hardest case. To improve monitoring accuracy we will exploit both space and time correlation of the available monitoring data.

The typical way to improve monitoring accuracy is to leverage the available information in the context of time. As mentioned above, the accuracy of the monitoring information depends among others on time varying phenomena. In order to reduce the uncertainty, we can collect monitoring information at various time periods, where the monitored values are expected to be different. The exact timing for the collection of information depends on the studied parameter and is outside the scope of this paper, but measurements every minute or few tens of minutes would be appropriate for the short-time scale effects that we target. Time averaging can help us reduce the error variance linearly to the number of periods that we average.

However, we can also use space correlation. We can use the NK technique outlined in the previous Section II in order to estimate the link level metrics by setting R_N equal to the identity matrix and obtaining $\mathbf{y_N} = [x_1, x_2, \dots, x_{|L|}]$. The estimated link metrics are calculated by taking into account all the values of the observed lightpaths (some of which may contain the same links) thereby exploiting space correlation to reduce the errors. Afterwards, the path level metrics are re-calculated using the additive estimated link values. We can actually combine the space with time correlation. The information monitored in different periods is used to enrich the $\mathbf{y_M}$ vector (and the respected R_M matrix) so that NK is run with additional information in order to further reduce the error.

For example, consider the network of Fig. 1, which has three links and three established lightpaths. The equation (1) is:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix} \tag{3}$$

Where $\mathbf{y_M}=[y_1\ \ y_2\ \ y_3]^T$ corresponds to the established lightpaths in the network for which the QoT parameters are monitored, and $\mathbf{y_N}=[y_4\ \ y_5\ \ y_6]^T$ corresponds to the link level metrics that we want to estimate. In order to exploit time correlation and measurements taken over multiple periods, we populate the vector $\mathbf{y_M}$ with these measurements while we also insert the additional required rows in the R_M matrix. However, as discussed in Section III, the execution time of the algorithm depends on the size of R_M. In order to decrease the execution time of the algorithm for a large number of observation periods, we can create groups of observations, run independently NK for them, and then execute NK with the combined results. For example, if we want to exploit 100 periods, we can create 10 groups with 10 periods each. Then we execute NK to estimate the link level parameters and subsequently the path level metrics of each group. Finally, we combine the grouped path level metrics and execute NK again, obtaining the final link and path metrics where the noise is substantially reduced. Note that the optimum noise reduction would be achieved if we execute NK with all the observations at the same time, because the correlation of the data would be more efficient, but this would require substantially more execution time.

The combination of the above two methods can significantly increase the monitoring accuracy, as shown in the performance evaluation section. Applications that rely on monitoring information can benefit from using these more accurate values. For example, as discussed in the introduction, a crucial part of planning and upgrading a network is to have accurate QoT estimations [11] so that margins are reduced [1][4]. In the next Section we will describe another use of the higher monitoring accuracy, that of soft-failure localization.

IV. Soft Failures and Localization

A. Network Components and Failure Types

We now describe some failures of basic optical components that are not self-reported through the network management systems, according to [5][8]. Some of these failures can be a targeted to be localized through a monitoring system with high accuracy as described in Section III.

1) Amplifiers

The role of an amplifier is to boost the attenuated signal. Power loss and high output power are reported, however variations in the gain or in the pump laser may increase the noise (therefore decreasing OSNR) and not raise an alarm.

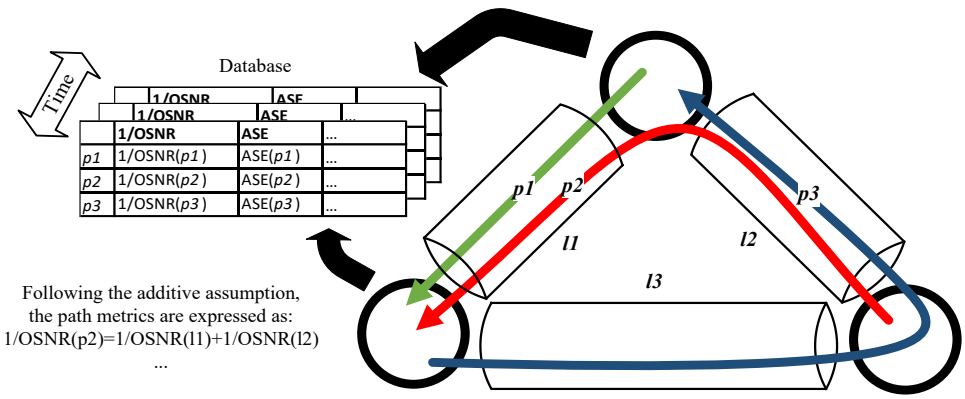

Fig. 1 An optical network with the database information that can be used for correlation in both space and time.

2) Fibers

Fiber bending, aging, lossy (e.g. due to dust) connectors can cause partial power loss that will eventually be compensated at the closest amplifier, which will, however, cause subsequent noise increase.

3) Tunable Filters, Optical Switches, Transmitters

A common problem of these devices is the slight drifting in the frequency or misalignment of the filters (WSSs) that can increase the noise due to crosstalk which in turn will lead to decreased OSNR. Depending on the severity of the problem, it may or may not be self-reported.

B. Soft Failures Localization

We now turn our attention to the second objective of this paper, which is to identify and localize a soft failure at a link level. We assume that for specific time periods the estimated link level parameters (found with the method described in Section III) are stored in a database. These parameters can then be compared with monitored values reported periodically, or used as the threshold to trigger soft failure alarms.

The process that we consider in this study is as follows: at the end of each period or upon an alarm trigger, we run the NK algorithm with the new monitored parameters in order to estimate the link-level parameters. Any significant (above the estimation error threshold of the stored values) difference of the monitored parameter indicates a possible soft failure. Figure 2 describes this process.

In this scheme, the failure is localized per link; the source/cause of the failure can be indicated if we take into account the specific impairment that is affected (dispersion, OSNR, EDFA noise) and the fluctuation of the related values over time. Even though it is hard to always infer the exact source/cause of the failure, still the localization of specific link and the affected parameters can give valuable information to the network operator before the failure affects significantly the operation of the network. The proposed soft failure localization

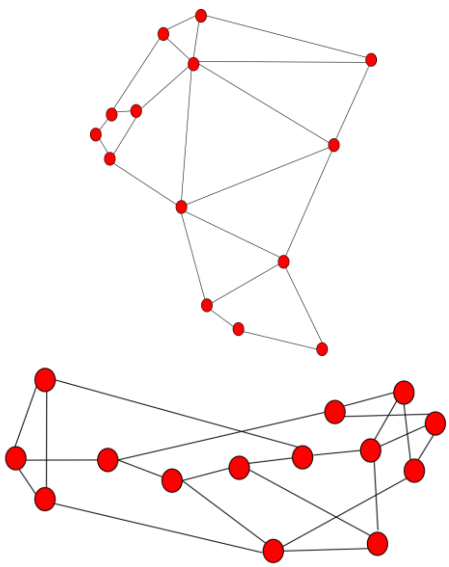

Fig. 3. The DT and NSFNET topologies.

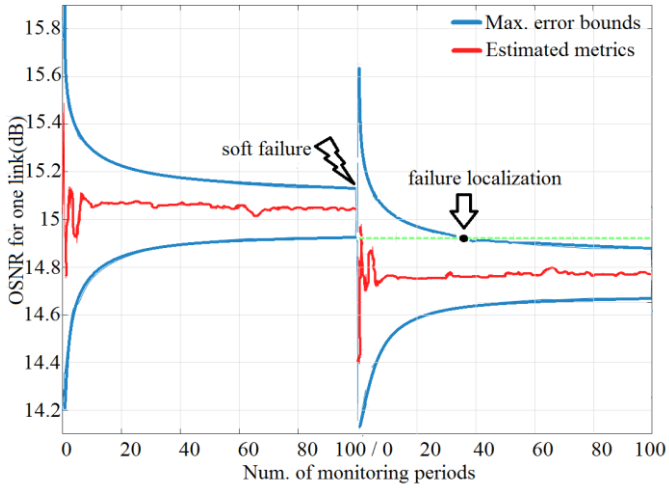

Fig. 2. A depiction of a soft failure localization.

scheme can utilize the schemes of Section III for reducing the uncertainty thereby providing more accurate link estimates.

V. Performance Evaluation

We evaluated the performance of our proposed uncertainty reduction (Section III) and soft failure localization (Section IV) techniques using simulation experiments. We used the DT (consisting of 14 nodes and 23 bi-directional links) and the NSFNET (consisting of 14 nodes and 22 bi-directional links) topologies depicted in Fig. 3. The fiber types were assumed to be SSMF with attenuation coefficient 0.22 dB/km, dispersion parameter 16.7 ps/nm/km, and nonlinear coefficient 1.3 1/W/km. The span length was set at 100 km and EDFA noise figure to 5 dB. Lightpaths in the network are either 100G (32Gbaud-QPSK) or 200G (56Gbaud-QPSK) and are established using the RWA/RSA algorithm of [4], but the results should hold for any RWA/RSA algorithm

A. Reducing The Uncertainty

We first examine the improvement of the accuracy of the monitored lightpaths that the techniques of Section III provide. In order to simulate the uncertainty of the monitored values, we insert Gaussian error with zero mean and standard deviation of 0.16 dB to the OSNR of each lightpath (other additive parameters can be similarly considered), corresponding to a maximum error of 0.6 dB with high probability (>0.9995), a typical error value for many OPMs [15][17]. The respective mean square error (MSE) per path was 0.0387 dB. Table 1 presents the results of applying the space and time correlation techniques of Section III with monitoring information taken at various time periods. In the second column of Table 1 we also report the expected error when only time correlation (time averaging of monitored paths) is used.

The MSE per path after our scheme is applied with 100 monitoring periods is in the order of 10^{-4} dB. The maximum estimation error for a single link is approximately 0.14 dB for the DT topology and 0.09 dB for the NSFNET. These values correspond to the shortest links of the networks (100km for the DT and 360km for the NSFNET). These links have very high OSNR values and therefore small deviations in the estimation

TABLE 1 OSNR accuracy metrics for DT (and NSFNET in parentheses)

Num of periods	Time correlation $\frac{\sigma^2}{N}$ per path in dB	Proposed method Mean Square Error (MSE) per path in dB	Proposed method Max path error in dB	Proposed method Mean Square Error(MSE) per link in dB	Proposed method Max error for a single link in dB
1	0.0256	0.0093 (0.0074)	0.9236 (0.7186)	0.0670 (0.0273)	1.995 (1.0182)
2	0.0128	0.0050 (0.0039)	0.5182 (0.4194)	0.0380 (0.0141)	1.3733 (0.734)
10	0.00256	0.0012 (0.0010)	0.3295 (0.2542)	0.0035 (0.003)	0.612 (0.39)
50	5.12e-4	5.12e-4 (3.8721e-4)	0.1332 (0.098)	6.8493e-4 (5.8321e-4)	0.22 (0.1410)
100	2.56e-4	2.56e-4 (2.56e-4)	0.1309 (0.0967)	3.5627e-4 (2.7854e-4)	0.1391 (0.0857)

result in high error. The error (both mean and maximum) is large when the data of only one time period are used and it drops with the use of monitoring data from additional time periods. When the number of periods is low, our proposed method which combines space correlation (NK) is much more accurate than the simple average of the monitored metrics. As the monitoring periods increase, the accuracy of the NK reaches a floor and converges to that of the simple average. The reason is that the network model that we employ assumes that the link-level metrics of lightpaths that cross the same links are equal, while in reality they are not due to their different parameters (e.g central frequency, spectrum). Also, we have assumed that the error of the different lightpaths is uncorrelated. This further disrupts the link level equality assumption of the impairment metrics. The result is that a perfect estimation of the link metrics is not possible regardless of the number of monitoring periods. For 100 monitoring periods the error at the longest link in NSFNET (3400Km) is in the order of 10^{-4} dB and in DT (460Km) is in the order of 10^{-3} dB. As expected, the accuracy of the proposed method improves as a function of the lightpaths that are available in the network.

Overall we notice that our uncertainty reduction method significantly improves the accuracy of the reported parameters. Regarding time correlation, there is an almost 40% improvement from going from one to two observation periods, while the use of further periods provide additional but reducing benefits. Note, however, that for every period of observations that is considered, we essentially add more lightpaths in the R_M matrix, which affects the execution time of the algorithm. In particular, the execution time of NK for one period of observations (213 lightpaths) is 0.02 seconds, while for 6 periods (1278 lightpaths) it is 1.3 seconds (Matlab and Core i5u). The reason is that the complexity of the NK algorithm depends on the cube of the number of lightpaths (Section II). When the observations are too many (>10) we use the grouping technique described in Section III in order to reduce the execution time. For 10 groups of 10 observations each (100 total observations), the total execution time is 80 seconds. The execution time is irrelevant for applications such as QoT estimation. For soft-failure localization, the execution time plays a small role, but is still not a crucial factor. The problematic lightpaths have not failed, they operate very close to their limit and the localization of the failure provides the means to take the appropriate actions to avoid further problems. In any case, the execution time close to a minute that was observed seems reasonable for such application. Another important metric is the margin that the network operator can conserve by applying our proposed framework. Assuming that the maximum error of the monitors (before applying any error suppression) is 0.6 dB, this is the margin that the operator should add in the acceptable threshold in order for the related parameter to always be within the appropriate limits. In our case, the maximum error for a *lightpath* can be dropped to approximately 0.13 dB. Reduced margins can result in various benefits [1][3].

B. Soft Failure Localization

To evaluate the proposed soft failure localization scheme we assumed two soft-failure cases: (i) increase of the noise figure of one EDFA in the network and ii) increase of the fiber attenuation coefficient of one span. In particular, for each link of the studied topology, we either increase the noise figure of a *single* amplifier from 5 to 7 dB in steps of 0.5dB, or increase the fiber attenuation coefficient of a *single* span from 0.22 to 0.26 dB/km in steps of 0.01 dB/km. The increased EDFA noise figure results in additional ASE noise and therefore decreases the OSNR. The increased fiber attenuation forces the EDFA of the corresponding span to increase its gain in order to compensate for the additional span loss which in turn results again in increased ASE noise. These degradations may correspond e.g. to a soft failure in the pump laser of the amplifier and to fiber bending or some bad splices after repairing a fiber cut. After inducing the failure, we compare the resulting OSNR degradations per link in dB and record the minimum and the maximum differences for each case when compared to the initial OSNR metrics. The results are presented in Tables 2 and 3. The minimum difference corresponds to the longest link, since this link consist of many spans and thus the soft failure of a single span does not play an important role in the total QoT metric of that link. On the other hand the maximum difference is observed in the single span links. Note that since the maximum estimation error of our techniques for a *link* is approximately 0.14 dB, the minimum degradation that can be observed with strong certainty when comparing two values of the same link in time is twice this value (0.28dB) regardless of the link length (see Fig. 2). Therefore our estimation framework can be used to locate a soft failure (of whatever reason) that causes a link OSNR degradation of more than 0.28 dB.

In Table 2 we investigate the deterioration of the link OSNR as a function of a given EDFA noise figure increase. We notice that in the case of the DT network, when the noise figure of an EDFA is degraded more than 2 dB it causes a link OSNR deterioration of at least 0.34 dB, which is more than the

threshold of our estimation framework (0.28 dB). Thus, such a soft failure in any single link is detectable. If we take into account the best link, then a 1 dB noise figure increase can be detected. As we have mentioned in Section V.A, the reason is that the maximum estimation error for the longest link in DT is in the order of 10^{-2}dB. At the same time, the minimum degradation, as mentioned in the previous paragraph, corresponds to the longest link and equals to approximately 0.15 dB (third row-second column of Table 2). Similar metrics are observed for the NSFNET network. In this case, however, the longest link (3400Km) suffers much less degradation from a single span OSNR deterioration, and in order to be detectable, the corresponding threshold for this link (which is in the order of 10^{-4} dB) should be taken into account.

In Table 3 we report on the deterioration as a function of the fiber attenuation coefficient increase. We notice that in the case of DT a single span fiber attenuation coefficient increase of 0.02 dB/km can be detectable by our framework for all the links. IN some specific links even an increase of 0.01 dB/km can be detected. Similar metrics are observed for the NSFNET and similar degradations can be detected if we use the corresponding accuracy thresholds.

TABLE 2: OSNR degradations for variable values of noise figure increase of a single EDFA for DT (and NSFNET in parentheses)

Additional noise figure of a single EDFA	Min. OSNR degradation of a link in dB	Max. OSNR degradation of a link in dB
0.5	0.0744 (0.0160)	0.1749 (0.1733)
1	0.1564 (0.0339)	0.3631 (0.3599)
1.5	0.2465 (0.0539)	0.5650 (0.5602)
2	0.3455 (0.0763)	0.7808 (0.7744)

TABLE 3: OSNR degradations for variable values of fiber attenuation coefficient increases of a single span (and NSFNET in parentheses)

Additional fiber attenuation coefficient of a single span	Min. OSNR degradation of a link in dB	Max. OSNR degradation of a link in dB
0.01	0.1569 (0.034)	0.3642 (0.440)
0.02	0.3466 (0.078)	0.7831 (0.959)
0.03	0.5742 (0.1326)	1.2588 (1.5624)
0.04	0.8448 (0.2004)	1.7920 (2.2476)

VI. CONCLUSION

We presented a framework that a) improves the accuracy of the reported monitoring data and b) can locate soft failures to a link level. Monitoring accuracy improvement can be used to reduce the margins of the network, which can translate to a series of benefits, such as accurate QoT estimation and soft failure localization. Soft failure localization can help the network operator identify and locate failures before they become disruptive for the operation of the network. Using reference network topologies and realistic physical layer parameters we observed an approximate MSE in the order of 10^{-4} dB and a maximum error of 0.14 dB for the estimated OSNR of the established lightpaths. Our scheme can be used to locate 1dB or more of an EDFA noise figure increase and 0.01dB/km increase of fiber attenuation coefficient of a single fiber span.

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