What if AI Fails: Protection against Failure of AI-Based QoT Prediction

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Abstract: We propose and simulate a new mechanism to protect against the failure of AI-based QoT prediction by assigning OSNR margins for working lightpath using the AI-based prediction method and for protection lightpath using the traditional, conservative method. This guarantees reliability of lightpath services, while not significantly increasing network spectrum resources used.
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1. Introduction

Artificial Intelligence (AI) can help in more accurate prediction of quality of transmission (QoT) of a lightpath [1]. This helps reduce the optical signal to noise ratio (OSNR) margin set for a lightpath in an optical network and improves network capacity utilization. However, many AI-based prediction methods are based on data only from laboratory tests in a stable known environment. Applied in a real optical network, these AI-based QoT predictions may fail to provide reliable lightpath services. To protect against this failure of AI-based QoT prediction, we propose a protection mechanism based on the conventional 1+1 dedicated path protection. We assign OSNR margins for working lightpath using the AI-based prediction method and for protection lightpath using the traditional, conservative method. This work is novel to incorporate the AI-based QoT prediction to take advantage of its reduced OSNR margins but makes it more robust when applied in a real network. For this, we evaluate how the AI-based QoT prediction can help reduce the spectrum resources used in an elastic optical network (EON), while ensuring that lightpath services can still continue even when the AI-based QoT prediction fails. We also evaluate how network reliability changes when different OSNR margins are set under 1+1 path protection. Simulation studies show that the proposed mechanism effectively protects against the failure of AI-based QoT prediction, while taking advantage of the OSNR margin reduction because of more accurate QoT prediction.

2. Two OSNR Margin Setting Methods

In calculating the OSNR of a lightpath, two aspects are generally considered, i.e., optical amplifier amplified spontaneous emission (ASE) noise and non-linear interference (NLI). For the ASE noise, as in [2], we find a noise figure (NF) by looking up a gain-NF table, specifically pre-built based on amplifier types. For the NLI, as in [3], we adopt a closed-form approximate solution of the so-called incoherent Gaussian-noise (IGN) model. Based on the calculated OSNR, three types of OSNR margins are often set for a lightpath, including system margins (S-margins), unallocated margins (U-margins), and design margins (D-margins) [4]. S-margins account for varying network operating conditions, which include fast varying penalties, operator margins, slow aging, and nonlinearities. U-margins refer to the difference of capacity between the demand and that of the equipment. D-margins account for the inaccuracy of the design tool used for evaluating QoT. We next describe two methods for OSNR margin setting.

(1) Traditional method: In this method, both S and D-margins are considered. As in [4], we assume a 2-dB OSNR margin for the nonlinearities, 2.3 dB for slow aging, and 0.4 dB for the fast varying effects at beginning of life (BoL), which corresponds to a total of 4.7-dB S-margin, and also assume a D-margin of 2 dB. With these margins, we calculate the OSNR required for each lightpath to choose a modulation format based on the following equations [4].

$$FEC_{limit} + U_{margin} \le OSNR_{lightpath} - D_{margin} - S_{margin} = OSNR_{lightpath} - 6.7\text{ dB} \quad (1)$$

$$U_{margin} \le OSNR_{lightpath} - 6.7\text{ dB} - FEC_{limit} \quad (2)$$

FEC_{limit} is the threshold required for the modulation format used, above which the signal is deemed recoverable and "error-free." For each modulation format, Fig. 1 shows its FEC limit required and its frequency slot (FS) capacity [5].

(2) AI-based prediction method: As in (1), in this method the S-margin is still set as 4.7 dB at the BoL. Since the AI-based OSNR prediction evaluates the lightpath QoT more accurately, the D-margin need not be set or can be significantly reduced. In this study, we set the D-margin to zero. For accurate OSNR prediction, we need enough data for AI training. Since it is difficult to collect enough actual network data, we simulate the data by calculating OSNRs for all the routes in an EON using the approach described earlier in Section 2. To simulate a network's statistical feature, we add an error to NLI. This has a maximum value of ±0.3 dB [3] and follows a Gaussian distribution. We use this to find ONSR for each route in the network and use these as the training data to train an artificial neural network (ANN) [1]. This simulation of training data will not affect the effectiveness of the approach proposed because if we can collect enough actual system data to replace these simulated data, nothing else needs to be changed. Here, the ANN used for training has seven input neurons, which correspond to seven features, i.e., (1) number of hops, (2) total length, (3) length of the longest link of lightpath, (4) total ASE, (5) total NLI of lightpath, (6) number of 15-dB EDFAs and (7) number of 22-dB EDFAs traversed by lightpath. The output neuron of the ANN estimates the OSNR value. After training, we obtain an AI-based OSNR prediction model. Based on this predicted OSNR, we select a modulation format using equations similar to (1) and (2), however ignoring the D-margin (2 dB).

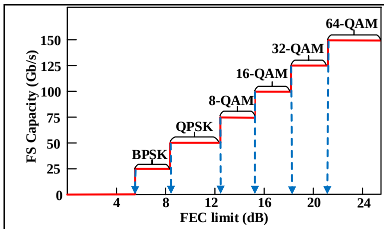

Fig. 1. FS capacities and FEC limits [5].

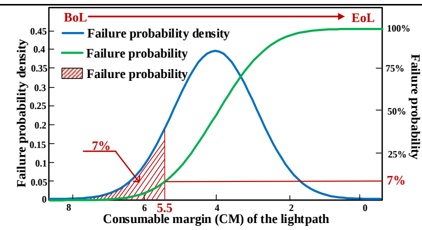

Fig. 2. CM vs. failure probability.

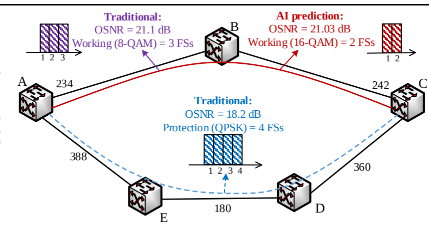

Fig. 3. Protecting AI prediction failure.

At the BoL of a lightpath, its actual OSNR metric is the sum of the FEC limit and the total margins set, including the S, D and U-margins. At this time, its transmission quality is the best and its failure rate is the lowest. Going forward to its end of life (EoL), the lightpath may fail because its OSNR is lower than the sum of the FEC limit and the system margin for the fast time-varying effects [4]. We define the difference between the margins at BoL and EoL as the *consumable margin* (CM) of a lightpath, which is the lightpath total margin T_{margin} minus the fast time-varying system margin F_{margin}, i.e., $CM = T_{margin} - F_{margin}$. Based on this CM, we can estimate the transmission failure probability of a lightpath based on a Gaussian distribution as shown in Fig. 2, where the shadow area is the integral of the failure probability density function.

3. Mechanism for Protecting against Failure of AI-Based QoT Prediction

As the AI-based prediction method removes the D-margin, a lower margin is reserved for each lightpath compared to the traditional method. Therefore, the AI-based method can use more advanced modulation formats for the same FEC limits. However, its disadvantage is that the reduction in the preserved margin can affect the reliability of data transmission on a lightpath (modeled to follow a Gaussian distribution as shown in Fig. 2). To still enable reliable lightpath services, this paper proposes a mechanism to protect against the failure of AI-based OSNR prediction.

Fig. 3 shows an example of protecting against the failure of AI-based OSNR prediction. Assuming that traffic demand between node pairs (A-C) is 180 Gb/s, we find the shortest route (A-B-C) for the working lightpath. Using the calculation method of Section 2, we find the OSNR of the working lightpath to be 21.1 dB. Then under the traditional margin setting method, both the S and D-margins should be considered, which totals to 6.7 dB. According to (1), we can find $FEC_{limit} + U_{margin} \leq 14.4$ dB and according to Fig. 1, we choose the modulation format 8-QAM since its FEC limit is in the range of [12.43, 15.13] dB. With this modulation, 3 FSs are required on links (A-B) and (B-C) to carry the traffic demand. Under this configuration, the U-margin is further calculated to be 1.97 dB, which corresponds to a 8.27-dB CM if $F_{margin} = 0.4$ dB. Therefore, according to the failure curve in Fig. 2, the failure probability of this working lightpath is close to 0 at the BoL.

In contrast, if we use the AI-based method to predict the OSNR of the working lightpath, it is 21.03 dB. Thus, we can find $FEC_{limit} + U_{margin} \leq 16.33$ dB without considering the D-margin. Then according to Fig. 1, we can choose the modulation format 16-QAM since its FEC limit is in the range of [15.13, 18.11] dB. With this modulation, 2 FSs should be reserved on links (A-B) and (B-C). Under this configuration, the U-margin is further calculated to be 1.2 dB, corresponding to a 5.5-dB CM, and according to Fig. 2, the failure probability of the working lightpath is ~7%.

We see that the failure probability of the AI-based prediction is higher than that of the traditional method although the former can use a more advanced modulation format. Therefore, to improve the reliability of lightpath services, we propose to set up a protection lightpath in addition to the working lightpath based on 1+1 path protection. To ensure that the lightpath service is fully recovered in case of failure of the AI-based prediction, we further employ the traditional method to set the OSNR margins for the protection lightpath. This takes advantage of the spectrum efficiency on the working lightpath due to its more accurate OSNR prediction, while not suffering from a service interruption even when the prediction fails (as we have a reliable protection lightpath to take over). In Fig. 3, a protection lightpath is set up along the route (A-E-D-C), which has an OSNR of 18.2 dB and for which the traditional margin setting method is applied. Therefore, we have $FEC_{limit} + U_{margin} \leq 11.5$ dB, which corresponds to the modulation format QPSK since its FEC_{limit} range is [8.38, 12.43] dB. Accordingly, 4 FSs should be reserved on the links (A-E), (E-D), and (D-C). Under this configuration, the U-margin of the protection lightpath is found to be 3.12 dB, which corresponds to a 9.42-dB CM, and thus the lightpath failure probability is close to 0 according to Fig. 2.

4. Simulation and Performance Analyses

To evaluate the performance of the proposed mechanism, we consider the 14-node, 21-link NSFNET and 24-node, 43-link USNET networks as our test networks. Traffic demand between each node pair is assumed to be uniformly distributed in the range of [100, X] Gb/s, where X is maximum required capacity, with X as 600 and 200 for NSFNET and USNET, respectively. The bandwidth granularity of each FS is assumed to be 12.5 GHz, and six modulation formats (i.e., BPSK, QPSK, 8-QAM, and 16-QAM, 32-QAM, and 64-QAM) are employed as shown in Fig. 1.

We use the first shortest path for setting up the working lightpath. For the protection lightpath, we employed the most efficient spectrum window plane (SWP)-based algorithm [6] to adaptively choose a route to set it up. We consider three different scenarios for protected lightpath service establishment. The first scenario assumes both working and protection lightpaths are set with OSNR margins based on the traditional method. The second scenario sets margins for working lightpath based on the AI-based method, and for protection lightpath based on the traditional method. The third scenario sets margins for both working and protection lightpaths based on the AI-based method.

We consider the number of FSs used after serving all the traffic demands. The results are shown in Fig. 4, in which "W" represents working lightpath, "P" represents protection lightpath, and thus "W: AI_P: traditional" means AI-based OSNR margin set for working lightpath and traditional margin setting for protection lightpath. As "W: traditional_P: traditional" sets margins for both working and protection lightpaths in the traditional, conservative way, higher margins are required and therefore more spectrum resources are needed to accommodate traffic demands. This scenario has the largest number of FSs used compared to the other two scenarios. In contrast, because "W: AI_P: AI" employs the AI-based method for both working and protection lightpaths, more efficient spectrum resource allocation can be done. Therefore, this scenario has the smallest number of FSs used. As an intermediate case, "W: AI_P: traditional" uses an intermediate number of FSs between the two. However, compared to the most efficient "W: AI_P: AI," their difference in the number of FSs used is small, i.e., only 10.2% vs. 14.6% and 14.5% vs. 17.1% reductions respectively from the most conservative scenario for NSFNET and USNET, respectively.

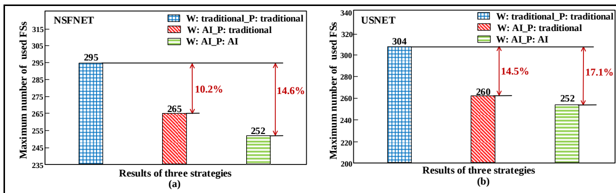

Fig. 4. Maximum numbers of FSs used. (a): NSFNET; (b): USNET.

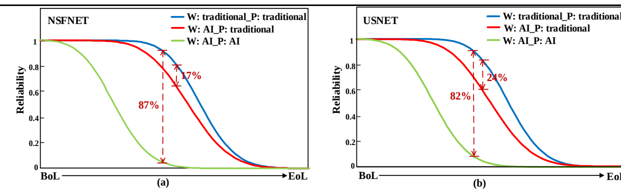

Fig. 5. Reliability analyses. (a): NSFNET; (b): USNET.

We also evaluate the reliabilities of lightpaths for the above three scenarios. The lightpath service reliability R_{lp} is calculated as $R_{lp} = 1 - F_w \cdot F_p$, where F_w and F_p are the failure probabilities of the working and protection lightpaths, respectively. In this study, we average the reliability of all the lightpath services and show the related results in Fig. 5. Because "W: traditional_P: traditional" employs the most conservative method, it shows the highest reliability. In contrast, because "W: AI_P: AI" employs the most advanced prediction method, it sets the lowest margins for both working and protection lightpaths. Therefore, it demonstrates the lowest reliability. "W: AI_P: traditional" falls in the middle because while the working lightpath uses the AI-based method, the protection lightpath uses the conservative method. Moreover, it is interesting to see that although for "W: AI_P: traditional" and "W: AI_P: AI," the numbers of FSs used are close to each other, the former shows much higher reliability than the latter. The reliability reduction by "W: AI_P: AI" relative to "W: traditional_P: traditional" is up to 87%, while such reduction is only 17% for "W: AI_P: traditional" in NSFNET. These values are 82% vs. 24% in USNET. We therefore conclude that the proposed approach for protecting against failure of AI-based QoT prediction significantly enhances the reliability of lightpath services, without greatly increasing spectrum resources used.

5. Conclusion

We proposed a new mechanism to protect against the failure of the AI-based QoT prediction, in which a protection lightpath was set up based on the traditional margin setting method for protection of working lightpath that was set up based on the AI-based method. We evaluated the benefit of this strategy and found that the proposed mechanism is efficient in the number of FSs used, close to the scenario that applies the AI-based margin setting method for both working and protection lightpaths, but provides much higher lightpath service reliability than the latter.

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