ML-Assisted Restoration Planning and Upgrade with Low Design Margins

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Abstract   *Analytical QoT models require safety margins to account for uncertain knowledge of input parameters. We propose a new design procedure for restoration planning and upgrade and show up to 19% savings in transponders from lower margins estimated via ML. ©2023 The Author(s)*

Introduction

Machine Learning (ML) and signal quality monitoring enable low margin optical network design aimed at reducing network cost[1]. However, low margin design for resilient optical networks is still under-investigated. As optical networks are used by applications with high availability requirements in most of today's deployments, resilience to failures is achieved by either protection or restoration[2]. Protection pro-actively reserves spectrum along a backup path that guarantees service recovery, while restoration is best-effort as it re-actively seeks a path with available spectrum after the failure happens. As restoration paths are unknown during network planning, transponders installed to operate along primary paths may not have enough capacity to fully restore traffic along potentially longer restoration paths. Pre-planned restoration[3], the resiliency technique investigated in this study, solves this problem by precomputing restoration paths and installing additional transponders as needed during commissioning.

Network operators are always looking to reduce the cost of protection/restoration schemes. To install fewer transponders one needs to precisely predict Quality of Transmission (QoT) (e.g., Signal to Noise Ratio, SNR) for unestablished lightpaths along protection/restoration paths. Existing analytical QoT models[4] achieve high accuracy, assuming exact knowledge of input parameters (e.g., connector loss, amplifier gain profile). However, in real-life these inputs are often not known precisely[5], and safety design margins are imposed to guarantee that modulation format assigned to the lightpath based on predicted QoT is feasible in the field deployment. The extent of these margins depends on the available information about the network and its size, but can easily reach 2-3 dB in core networks[6], leading to significant under-utilization of resources. Notable research effort has been recently dedicated to lowering these margins by either estimating the precise values of uncertain input parameters[7, 8, 9] or directly predicting QoT metrics using measurements from previously established lightpaths[10].

The only existing work that combines ML-based low-margin design and resilience in optical networks is[6], where authors demonstrate savings from ML-based QoT-estimation for dedicated and shared protection. In this work, for the first time to the best of our knowledge, we investigate possible savings from ML-estimated design margins in 2 restoration scenarios: 1) Restoration Planning and 2) Restoration Upgrade. Our numerical results on realistic network instances show up to 19% savings in transponders by simply leveraging SNR data monitored at the receivers.

Restoration Planning and Upgrade

<u>Example</u>. In Fig. 1 we demonstrate how lower design margins allow to save transponders when planning restoration. Consider a 500 Gbit/s traffic request provisioned along the primary path (green solid line) using 1 transponder operating at 500 Gbit/s. With a conservative worst-case margin only 400 Gbit/s can be sent along the longer restoration path (red dotted line), and hence an
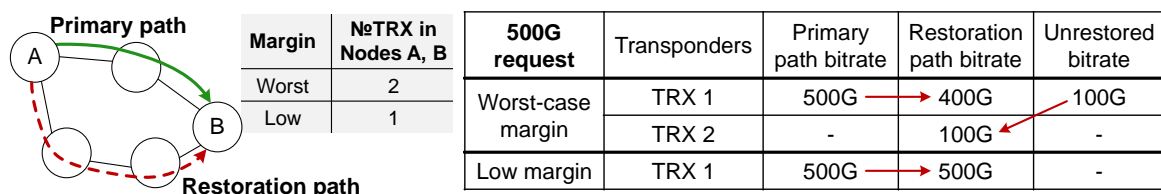

500G request	Transponders	Primary path bitrate	Restoration path bitrate	Unrestored bitrate
Worst-case margin	TRX 1	500G → 400G		100G
	TRX 2	-	100G	-
Low margin	TRX 1	500G → 500G		-

Margin	№TRX in Nodes A, B
Worst	2
Low	1

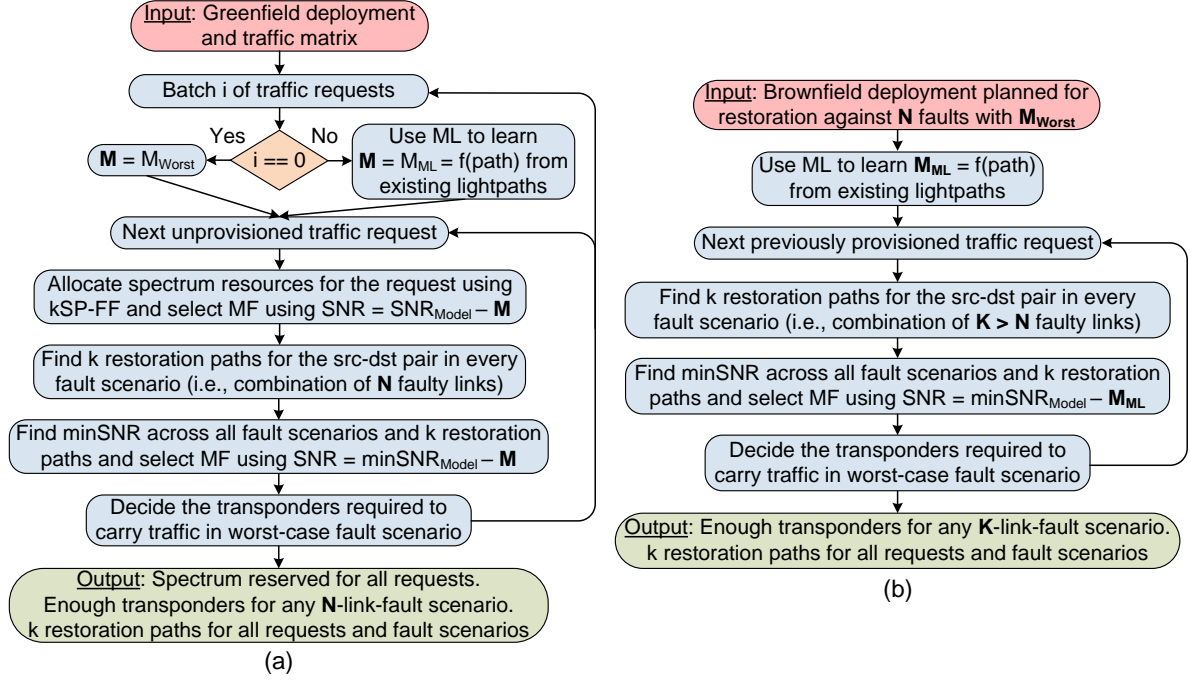**Fig. 1:** An example of benefits of low-margin restoration planning

Fig. 2: (a) Restoration Planning and (b) Restoration Upgrade algorithms

extra transponder is needed to restore the remaining 100 Gbit/s. With a lower margin all 500 Gbit/s can be provisioned along the restoration path with 1 transponder, and an extra transponder is not installed. Note that, in the example with the worst-case margin restoration is supported by inverse multiplexing, as the aggregated 500 Gbit/s traffic request is split between two transponders. Physical-layer uncertainties modeling. In this work, we consider that uncertainties in physical-layer parameters that cause inaccurate analytical QoT estimations and motivate the use of design margins are 1) non-flatness of EDFA gain profile (i.e., gain ripple), 2) unaccounted losses in optical connectors and 3) wrong fiber type specifications. We emulate SNR_{Model} (i.e., SNR predicted with the analytical model) using values of parameters known during planning and SNR_{Field} (i.e., SNR actually measured in the field) using actual parameter values. See[11] for more details.

Restoration scenarios. We simulate two restoration scenarios: 1) Planning and 2) Upgrade.

In *Restoration Planning* (Fig. 2a) we start from greenfield deployment and want to incrementally provision requests in the traffic matrix and install enough transponders to guarantee restoration in all *N*-link fault scenarios. We assume that traffic requests arrive in batches. For the first batch of requests we use a worst-case margin M_{Worst} estimated by a-priori testing of a large number of gain ripple profiles, connector loss values and fiber types. For every next traffic batch we use

per-path predictions of $M_{ML} = SNR_{Model} - SNR_{Field}$ by a Gradient Boosted Tree regressor that is trained using SNR_{Field} of the existing lightpaths. For each new traffic request we allocate spectrum resources using k-Shortest-Path routing and First-Fit spectrum allocation and compute *k* restoration paths for all *N*-link fault scenarios (except the ones that make restoration impossible due to topology constraints). Then we ensure that enough transponders are installed to carry the requested traffic along any of the *k* restoration path. With our ML-assisted approach, we save transponders with an estimated $M_{ML} \leq M_{Worst}$ when determining the modulation formats (MFs) for the primary lightpaths and for the potential lightpaths along the candidate restoration paths.

In *Restoration Upgrade* (Fig. 2b) we start from a brownfield deployment, already planned for restoration against *N*-link faults, as described in *Restoration Planning* but using only M_{Worst}, and want to install enough transponders to guarantee restoration in all *K*-link fault scenarios, where $K > N$ (i.e, we upgrade restoration capabilities from *N*- to *K*-link failures). We train the ML margin-estimator using SNR_{Field} from all the established lightpaths, compute restoration paths for all *K*-link fault scenarios and ensure that there are enough transponders to carry the requested traffic along any restoration path. Also in this case, we save transponders by using ML-estimated design margin $M_{ML} < M_{Worst}$ when determining MFs for the potential lightpaths along

Tab. 1: Savings in the number of primary, extra restoration and total TRX in Restoration Planning scenario (S) in GE17 (EU19)

Number of faulty links (N)	Savings in primary TRX, %		Savings in extra restoration TRX, %		Total savings in TRX, %	
	k = 5	k = 10	k = 5	k = 10	k = 5	k = 10
1	5.6 (8.2)	5.7 (8.3)	8.8 (25.7)	13.3 (21.8)	6.4 (12.2)	7.6 (11.8)
2	4.9 (8.1)	4.6 (8.2)	19.5 (19.4)	19.8 (14.6)	8.5 (11.3)	9.2 (10.1)
3	3.4 (7.7)	4.1 (7.9)	16.7 (15.6)	13.6 (12.5)	7.2 (10.2)	7.3 (9.2)

Tab. 2: Cost of restoration upgrade in Restoration Upgrade scenario (C_U) with worst-case and ML-margin in GE17 (EU19)

Upgrade in number of faulty links (N-to-K)	C_U with worst-case margin		C_U with ML-margin		Savings from ML-margin	
	k = 5	k = 10	k = 5	k = 10	k = 5	k = 10
0 to 1	22.7 (29.4)	31.1 (34.8)	13.4 (12.8)	19.0 (15.9)	9.3 (16.6)	12.1 (18.9)
1 to 2	7.3 (7.1)	8.9 (5.2)	-4.5 (-6.4)	-4.3 (-7)	11.8 (13.5)	13.2 (12.2)
1 to 3	11.6 (10.7)	17.2 (12.3)	0.7 (-2.5)	2.2 (-3.6)	10.9 (13.3)	15.0 (15.9)

the candidate restoration paths, while MFs assigned to primary lightpaths are not modified to avoid disruption of existing services.

Numerical Results

We perform our numerical evaluations on two realistic topologies, a 19-node European network (EU19) with links scaled to 70% of their actual length to perform restoration without the use of regenerators and a 17-node German network (GE17)[12]. Results are averaged considering 20 mesh traffic matrices with data rate requests randomly distributed between 200 Gb/s and 1000 Gb/s with 100 Gb/s step. We keep provisioning traffic requests till there is enough spectrum to guarantee restorability in any fault scenario. More requests can be provisioned with a larger number k of pre-computed restoration paths.

We assume EDFAs with 5 dB noise figure placed every 80 km. We operate in a 6-THz C-band with ASE-loading. Traffic is provisioned by 90 Gbaud transponders capable of 300-800 Gbit/s with 20 dB back-to-back SNR and SNR thresholds from[13] with a 1 dB system margin.

Connector losses are 0.5 dB in the model and are uniformly distributed in [0.5; 1.5] dB in the field. 75% of fiber spans are SMF, while 25% are LEAF fibers. We assume that 20% of spans have incorrect fiber type specified. For each field EDFA we randomly select one of 18 ripple profiles measured on amplifiers in our testbed. We use M_{Worst} for the first $N = 25$ requests (2 dB in GE17 and 2.5 dB in EU19), then start estimating M_{ML} and retrain the model every 25 requests.

In Tab. 1 we show savings (in %) in the number of transponders (TRX) from the use of M_{ML} w.r.t. M_{Worst} in *Restoration Planning* scenario:

$$S = \frac{TRX_{\text{ML margin}} - TRX_{\text{Worst margin}}}{TRX_{\text{Worst margin}}} \times 100\% \quad (1)$$

In GE17 (EU19) with k=5 pre-computed restoration paths, we save 5.6 (8.2)% of primary TRX, 8.8 (25.7)% of extra restoration TRX and 6.4 (12.2)% in total. Savings in primary TRX decrease as the number of potentially faulty links increases and only slightly change for k=10. Savings in extra restoration TRX in GE17 grow to 19.5% for N=2 and decrease to 16.7% for N=3, while in EU19 they monotonically decrease with an increase in N. Total savings in TRX increase and then decrease in GE17, and decrease in EU19.

In Tab. 2 we show relative cost of restoration upgrade (in %) in *Restoration Upgrade* scenario with M_{Worst} and M_{ML} margins:

$$C_U = \frac{TRX_{\text{Restor. K>N}} - TRX_{\text{Restor. N}}}{TRX_{\text{Restor. N}}} \times 100\% \quad (2)$$

Use of ML-estimated margins lowers the cost of a restoration upgrade in GE17 (EU19) by as much as 15 (19)%. Cost of upgrade is highest in the 0-to-1 scenario (no restoration to restoration against a single-link failure) and decreases for the 1-to-2 and 1-to-3 scenarios. In 1-to 2 scenario cost of upgrade becomes negative as more restoration transponders get installed for a single failure than are necessary for a double failure with the reduced margin. Cost of a restoration upgrade increases between k=5 and k=10 as more transponders are needed to restore traffic along longer restoration paths with lower SNR. In all upgrade scenarios high savings come from the fact that network before the upgrade was planned using M_{Worst}, and the number of extra restoration transponders was significantly overdimensioned.

Conclusion

We proposed a new design procedure for low-margin restoration planning and upgrade and demonstrate up to 19% savings in transponders. Achieved savings are significant especially considering that they are enabled by simply collecting monitored data in standard coherent receivers.

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