Combining a Machine Learning and Optimization for Early Pre-FEC BER Degradation to Meet Committed QoS

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ABSTRACT

Monitoring the physical layer is key to detect bit error rate (BER) degradation caused by failures and to identify the cause of the failure and localize the failed elements. Once the failure has been detected, actions can be taken to reduce as much as possible its impact on the network. Commercially available optical equipment are able to correct degraded optical signals by means of Forward Error Correction (FEC) algorithms. A value of pre-FEC BER over a pre-defined threshold would imply a non-error-free post-FEC transmission and, as a result, communication would be disrupted. Therefore, a prompt detection of lightpaths with excessive pre-FEC BER can help to greatly reduce such SLA violations, in particular when supporting vlinks. As a result of the above, it would be desirable to anticipate such degradations and apply re-optimization to re-route those affected demands according to their SLAs in order to reduce the affected traffic after the degradation is detected. Designing algorithms capable of promptly detect distinct BER anomaly patterns would be desirable. The objective would be to anticipate intolerable BER values as much as possible aiming at leaving enough time to plan a re-routing procedure during off-peak hours. In this paper, we propose an effective machine learning-based algorithm to localize and identify the most probable cause of failure impacting a given service, as well as a re-optimization algorithm to re-route affected demands, targeting at reducing SLA violation. Results show that the proposed detection and re-routing algorithms noticeably reduce bandwidth and number of demands affected.

Keywords: data analytics, cognitive networking.

1. INTRODUCTION

A gradual degradation in the optical layer could impact a large number of client demands. However, the degradation might affect differently each client demand; specifically, those demands related to a Service Level Agreements (SLA) need especial attention since a SLA violation represents money losses for the network operator [1]. Although commercially available optical equipment is able to correct degraded optical signals by means of Forward Error Correction (FEC) algorithms, a value of pre-FEC Bit Error Rate (BER) over pre-defined threshold would imply a non-error-free post-FEC transmission and, as a result, communication would be disrupted. Therefore, a prompt detection of optical connections with excessive pre-FEC BER can help to greatly reduce such SLA violations, in particular when supporting virtual links (vlink) in multilayer MPLS-over-optical virtual networks.

In our previous work [2] we focused on localizing failures in the optical layer and identifying the most probable cause of failure after its detection. This paper aims first at detecting in advance excessive BER in optical connections supporting vlinks and propose the BER Anomaly Detection (BANDO) algorithm. BANDO can be placed inside the network nodes, closer to the monitoring points, to reduce the amount of monitoring data to be conveyed to the control/management plane [3]. Second, we propose the SCULPTOR algorithm to be triggered for pro-actively re-routing those demands affected by QoS degradation.

2. BER ANOMALY DETECTION AND QOS DEMAND RE-ROUTING

As introduced before, a gradual degradation of the optical signal might cause service losses to client demands. For illustrative purposes, Figure 1 plots the pre-FEC BER evolution with time when a gradual BER degradation starts impacting an optical connection; we assume that BER is monitored by the receivers of the connection. Many commercial equipment, such as the ones used in our experiments in section 4, tolerate some amount of errors until automatically tear-down the connection when some BER threshold is exceeded. Notwithstanding, a restoration procedure could be started to recover the affected traffic after the disruption is detected, it would be desirable to anticipate such event and re-route those demands according to SLAs. The proposed BANDO algorithm focuses on anticipating such detection as much as possible and leaving enough time to plan a re-routing procedure during off-peak hours.

The proposed re-routing is illustrated in Figure 2, where three client demands are being served. Each demand is denoted by: *i*) a demand identifier d_j, *ii)* the required bandwidth, and *iii)* whether the demand requires some QoS level. In the example, demands have different bandwidth requirements (30Gb/s, 70Gb/s and 40Gb/s

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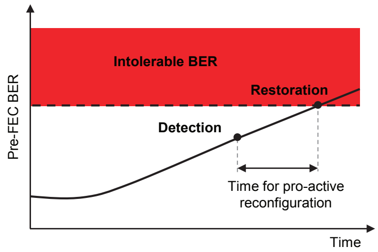

Figure 1. Monitoring data stream.

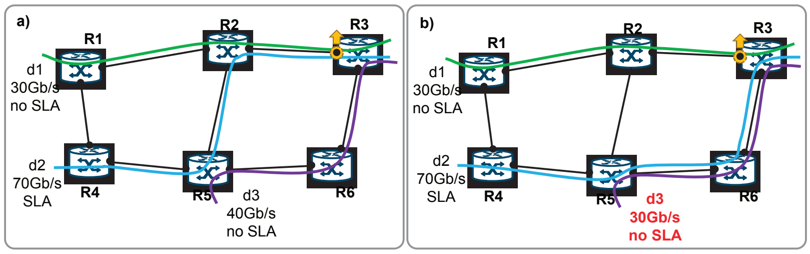

Figure 2. Demand routing before link degradation (a) and after re-routing (b).

respectively), they are all ending in the same router (*R3*) but with diverse origins; let us assume 100Gb/s vlinks.

Figure 2a shows the initial routing just when the BANDO algorithm has detected a service degradation in vlink *R2-R3*, detected in *R3* endpoint. It is worth noting that since demand d_2 requires (high) QoS, when a BER degradation affects one of the links in its path, re-routing for this demand is mandatory to fulfill its SLA contract. On the contrary, both demands d_1 and d_3 do not require any particular QoS (best effort traffic), so when a BER degradation affects their paths no re-routing is strictly required. When the degradation is detected, the SCULPTOR re-routing algorithm is triggered to find re-routing paths for those affected demands degradation and requiring QoS. SCULPTOR can also re-route no-QoS demands (affected or not by the BER degradation) with the objective of releasing resources that can be used to re-route affected demands with QoS requirements.

Figure 2b shows the re-routing suggested by SCULPTOR. The initial path for SLA-related demand d_2 was affected by the BER degradation and it has been re-routed using an alternative path to avoid the BER degraded vlink. However, the available capacity in vlinks *R5-R6* and *R6-R3* would be exceeded unless the bandwidth of some of the demands being served through those vlinks are squeezed. The solution is to squeeze the bandwidth of not SLA-related demand d_2. Finally, demand d_1 does not require QoS and thus, it was not re-routed although its path is using the degraded *R2-R3* vlink.

3. BANDO AND SCULPTOR ALGORITHMS

In this section, we propose an algorithm to promptly detect distinct BER anomaly patterns with the objective of anticipating intolerable BER values. BANDO detection is based on analyzing the monitored pre-FEC BER data that are received at a given rate (e.g., every 15 minutes). The aim of this method is to provide real-time detection of the three different anomalies illustrated in Figure 3: *i*) gradual BER increment (*BER drift,* Figure 3a) as a result of some hardware component degradation. Its detection entails triggering the SCULPTOR algorithm; *ii*) unusual and fleeting BER peak due to some incorrect measurement (*BER blip,* Figure 3b); and *iii*) the effect of physical layer impairments that could suddenly appear when neighboring connections are dynamically established (*BER shift,* Figure 3c).

BER monitoring data streams are evaluated by using a fixed-size slicing window algorithm that moves forward as soon as new monitoring data is received, as proposed in [4]. Initially, a number m of BER values are stored in an empty window and next, its average μ is computed to summarize the collected data before emptying the window and repeating the process. Decisions about BER trend evolution can be taken by comparing summarized μ values; we define the function $\Delta(i, j)=|(\mu_i - \mu_j)/\mu_j|$ that returns the relative difference of window i with respect to window j. We highlight the special case $\delta_i=\Delta(i, i\text{-}1)$ as the distance between window i and its previous one. While BER data stream fluctuates around a constant mean, δ_i values are typically below a threshold ε. The value of ε can be easily computed during a training phase from several δ_i values; ε is defined as the maximum of them times a multiplier k. In the event of an atypical BER, Δ exceeds ε and consequently, analyzing a possible anomaly is triggered.

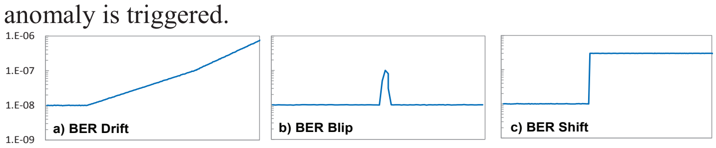

Figure 3. Different BER time variations.

Table 1. BANDO algorithm.

INPUT: δ_i, δ_{i-1}	**OUTPUT:** *Decision*
1:	**if** *training* **then**
2:	$\varepsilon \leftarrow \max(\varepsilon, k\cdot\delta_i)$
3:	**return** Ø
4:	**if** $\delta_i \le \varepsilon$ **then**
5:	**if** $\delta_{i-1} \le \varepsilon$ **then** $n \leftarrow 0$
6:	**return** '*No anomaly*'
7:	**else** $\delta_{aux} \leftarrow \Delta(i,j)$
8:	**if** $\delta_{aux} \le \varepsilon$ **then return** '*BER blip*'
9:	**else if** $\delta_{i-1} > \varepsilon$ **then** n++
10:	**else** $j \leftarrow i$-1
11:	**return** '*No anomaly*'
12:	$\varepsilon \leftarrow$ Ø
13:	**if** $n < \alpha$ **then return** '*BER shift*'
14:	**else return** '*BER drift*'

The BANDO algorithm is presented in Table 1. The new computed δ_i can be used to train ε (lines 1-3) or to detect some BER anomaly (lines 4-14) in case that δ_i and δ_{i-1} are above ε, where n (accounting for consecutive threshold violation) is incremented. In case that only $\delta_{i-1} \le \varepsilon$, a BER blip can be detected by comparing the variation between the values in the windows before and after the anomaly, with a threshold. If no decision has been made before line 12, BER is experiencing a remarkable variation that requires re-training ε to fit with the new situation. Such variation is tagged as a BER shift if n is below the limit α; otherwise, it is labeled as BER drift. Note that an accurate detection fully depends on parameters $\{m, k, \alpha\}$.

Only in the case that BANDO returns BER drifting, the SCULPTOR algorithm needs to be triggered. The SCULPTOR reconfiguration problem can be stated as follows:

The problem can be formally stated as:

Given:

- A VNT represented by a graph $G(N, E)$, where set N contains the MPLS nodes and the set E of vlinks.
- Set D of demands currently being served. Each demand d is characterized by the tuple: $<s_d, t_d, b_d, d_p, q_d>$, where s_d is the source node for the demand, t_d is the target node, b_d is the required bandwidth, d_p is the current path serving the demand, and q_d is related to a SLA contract.
- The monitored BER (in particular, that for which BANDO detected BER degradation) for every vlink $e \in E$.

Output: The demands to be re-routed and the new paths.

Objective: Minimize the amount of bandwidth entailing SLA violation, as well as the amount of unserved bandwidth (affected by bitrate squeezing).

The following parameters have been defined.

Demands and paths:

$P(d)$	Subset of pre-computed paths for demand d.
δ_{ep}	Equal to 1 if path p uses link e.
q_p	Equal to 1 if path p meets QoS requirements.
d_p	Current path for demand d.

The decision variables are:

x_p	Binary, equal to 1 if demand d uses path p; 0 otherwise.
y_{dp}	Real, served bitrate for demand d through path p.
z_d	Binary, equal to 1 if demand d is re-routed, 0 otherwise.

The SCULPTOR formulation is as follows:

$$\min \sum_{d\in D}\sum_{p\in P(d)}\begin{pmatrix} q_d \cdot (1-q_p)\cdot y_{dp} + (b_d - y_{dp}) \\ +\alpha \cdot (1-q_d)\cdot z_d \end{pmatrix} \tag{1}$$

subject to:

$$\sum_{p\in P(d)} x_p = 1 \quad \forall d \in D \tag{2}$$

$$x_p \geq d_p - (1 - q_p \cdot q_d) \quad \forall d \in D, p \in P(d) \tag{3}$$

$$x_p \leq d_p + q_p + (1 - q_d) \quad \forall d \in D, p \in P(d) \tag{4}$$

$$y_{dp} \leq x_p \cdot b_d \qquad \forall d \in D, p \in P(d) \tag{5}$$

$$y_{dp} \geq q_d \cdot x_p \cdot b_d \qquad \forall d \in D, p \in P(d) \tag{6}$$

$$\sum_{d\in D}\sum_{p\in P(d)} \delta_{pe} \cdot y_{dp} \leq b_e \qquad \forall e \in E \tag{7}$$

$$\sum_{p\in P(d)} (1-d_p)\cdot y_{dp} \leq b_d \cdot z_d \quad \forall d \in D \tag{8}$$

The objective function (1) minimizes the amount of bitrate that cannot be served (rejected, lost) with no QoS and minimizes bitrate affected by errors. Constraint (2) ensures a demand is routed by only one single lightpath (not multi-path routing is allowed). Constraint (3) ensures that if both the demand and the path have QoS requirements, the current path is not modified. For other cases, the path can be changed. Constraint (4) ensures that a demand with QoS requirements (q_d=*1*) should not be rerouted to a path with no QoS (q_p=*0*). Constraints (5) and (6) prevents squeezing the bitrate for demands with QoS requirements. Constraint (7) guarantees that the available bitrate b_e in each link is not exceeded. Finally, constraint (8) accounts for demands that are re-routed.

To implement SCULPTOR, we first generate a set of possible paths for each demand and label them according to the fulfillment of the specific QoS requirements for that demand. As an illustrative example, let us assume that demand d_2 in Figure 2 requires QoS $\leq 10^{-7}$ and BER in R3 is 10^{-8} then the SLA agreement is currently met. However, in the case that BER in R3 would be 10^{-6}, the SLA would be violated and therefore the demand would be candidate to be re-routed through other path fulfilling the required QoS. Finally, note that the SCULPTOR problem always returns a feasible solution, i.e., the current one.

4. ILLUSTRATIVE RESULTS

Measurements were performed on a commercial 100Gb/s card based on polarization multiplexing quadrature phase shift keying (PM-QPSK) and coherent detection. Back-to-back transmission was tested with a waveshaper filter between transmitter and receiver; the filter was centered with the central frequency of the signal. Physical layer degradations, i.e., pre-FEC BER drift, were emulated by changing the bandwidth of the filter from 46 GHz to 26 GHz. Pre-FEC BER measurements are shown in Figure 4, where BER increases when the filter bandwidth decreases. Finally, 48-hours monitoring was performed with the bandwidth set to 30GHz and, because laser drift of the commercial card, pre-FEC BER was observed as if the bandwidth was 28GHz.

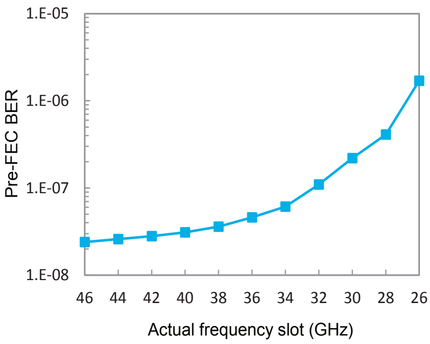

Figure 4. Measurements on the 100Gb/s card.

According to the experiments, we generated synthetic monitoring BER data streams (at a rate of one measure each 15 minutes) reproducing BER anomalies in Figure 3, as well as normal streams without BER anomalies. Normal BER was set to 10^{-8} and increases up to 10 times in case of blip or shift. For the drifting case, we considered an incremental BER lasting from 2 to 10 days to reach intolerable BER = 10^{-6}. We found that the best configuration for BANDO parameters was $\{m=10, k=3, \alpha=2\}$. With those parameters, the minimum time between detection and intolerable BER value was 40 hours, more than enough to plan the application of the SCULPTOR algorithm.

We implemented SCULPTOR in Python and solved using CPLEX [5] and we simulated a 30-node and 56-link MPLS network, where initially, 870 demands are being served. To evaluate SCULPTOR, we compared the affected bandwidth and number of demands when the algorithm is applied or not. Figure 5a and Figure 5b present the gain obtained by using SCULPTOR in terms of affected bandwidth when 30% or 50% of the demands require QoS. Interestingly, the amount of affected bandwidth is reduced by at least 30% when SCULPTOR is applied. It is also worth noting that the affected bandwidth increases circa 60% when the amount of SLA-related demands increases from 30% to 50%, while the affected bandwidth remains mostly constant when SCULPTOR is applied. The same study can be applied to the number of affected demands (Figure 5c and Figure 5d) obtaining similar conclusions as for affected bandwidth.

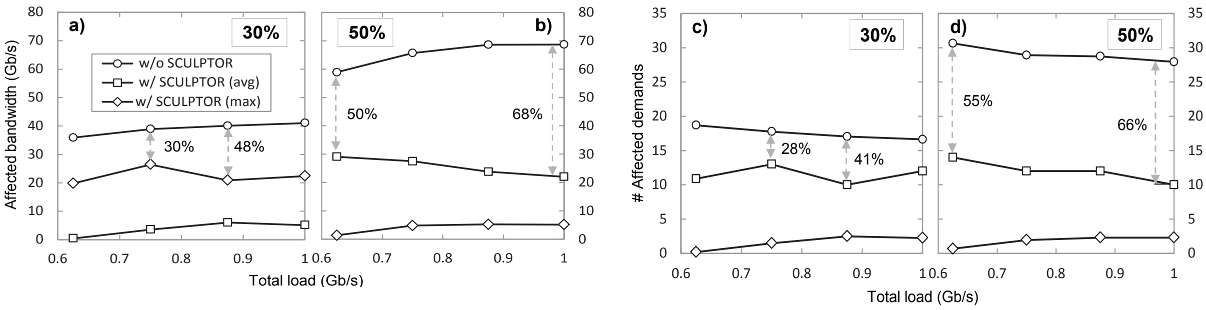

Figure 5. Affected bandwidth and number of affected demands when 30% and 50% of the demands requiring QoS.

5. CONCLUDING DISCUSSION

BER degradation in the optical layer could impact a large number of client demands, which can translate into money losses for network operators when violating SLAs. Targeting at anticipating intolerable BER, the BANDO algorithm was proposed for detecting, among other anomalies, BER drift; that detection helps meeting the committed demand QoS by re-routing the affected SLA-related demands. To that end, the SCULPTOR algorithm was proposed.

Experimental measures carried out with commercial equipment revealed the effects of physical layer degradations, which were reproduced to train BANDO that showed good anticipation. Finally, results showed that SCULPTOR noticeably reduces the number of affected bandwidth and demands.

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