Soft Failure Localization in Elastic Optical Networks

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ABSTRACT

Soft failure localization to early detect service level agreement violations is of paramount importance in elastic optical networks (EONs), while it allows anticipating possible hard failure events. Nowadays, effective and automated solutions for soft failure localization during lightpaths' commissioning testing and operation are still missing. In this paper, we focus on presenting soft failure localization algorithms based on two different active monitoring techniques. First, the Testing optIcal Switching at connection SetUp timE (TISSUE) algorithm is proposed to localize soft failures during commissioning testing phase by elaborating the estimated bit-error rate (BER) values provided by low-cost optical testing channel (OTC) modules. Second, the FailurE causE Localization for optIcal NetworkinG (FEELING) algorithm is proposed to localize failures during lightpath operation using cost-effective optical spectrum analyzers (OSAs) widely deployed in network nodes. Results are presented to validate both algorithms in the event of several soft failures affecting lasers and filters.

Keywords: soft failure localization, monitoring and data analytics, machine learning algorithms.

1. INTRODUCTION

Failure localization is a very useful technique since it helps to reduce failure repair times greatly. When a hard failure occurs at the optical layer, the affected traffic needs to be immediately restored using currently available resources. Nonetheless, some hard failures start as soft failures, and they can be detected as incipient degradations. Therefore, it would be desirable to anticipate and resolve hard failures in order to plan proper actions like traffic rerouting. Even though some soft failures evolution might take a long time, they can affect the quality of optical connections (*lightpaths*) while in operation.

In addition, to guarantee that the resources supporting a lightpath (optical switching and amplification) perform properly before it can enter into operation thus avoiding service level agreement (SLA) violations, telecom operators test its performance by injecting a test signal in the ingress node and measuring the bit error rate (BER) in the egress node (commissioning testing). However, optical connection commissioning tests usually need human intervention, where typically two technicians with test equipment travel and stay in front of the end nodes to carry out the end-to-end tests. In addition, if high BER is measured at the egress node, more testing in intermediate nodes need to be performed to localize its cause.

To reduce human intervention, active monitoring techniques based on those developed in the context of IP networks can be adapted for the optical layer. In this regard, the authors in [1] introduced the optical supervisory channel (OSC) technique to monitor the BER of a lightpath in different points along its route by using low-speed (few hundreds of MHz) electro-optical components. The OSC technique consists in over-modulating the lightpath to be monitored with a low modulation index and low-speed On-Off Keying (OOK) signal, thus allowing accurate BER estimation provided that reference BER correlation curves are calculated a priori.

Once the lightpaths are in-operation, the identification of soft failures can be done by means of in-line monitoring techniques specially designed for analyzing and evaluating optical signal quality. In this regard, although Optical Spectrum Analyzers (OSA) could be used to analyze the spectrum of optical signals, until recently, the use of OSA in the network was very limited due to the high cost of accurate OSAs. However, improvements in OSA technology are taking place, and a new generation of cost-effective OSAs with sub-GHz resolution is now available to be integrated into a new generation of optical nodes [2]. Note that sophisticated algorithms able to identify and localize failures are needed. These algorithms can be deployed in the network controller, as well as in nodes' agents, close to the monitoring points, to reduce the amount of monitoring data to be conveyed to the control/management plane [3].

In this paper, we review soft failure localization algorithms in Elastic Optical Networks (EON) during commissioning testing and once lightpaths are in operation [4]. Based on the OSC concept, an optical testing channel (OTC) is designed to be used during commissioning testing. An algorithm to detect unexpected BER degradation and localize its cause along the route is firstly presented. Then, in-operation lightpaths are monitored using OSAs. The collected signals 'spectrum is transformed into a number of features that are exploited by machine learning-based algorithms to detect degradations and identify failure classes. Running in the network controller, a failure localization algorithm uses the output of such modules to localize, classify and estimate the magnitude of the failure.

2. MONITORING SYSTEMS FOR FAILURE LOCALIZATION

Two monitoring systems to be installed in the optical network nodes are proposed: a redesigned OSC and OSAs. Here, the concept of OSC is redefined and renamed as OTC, where the OTC_{Tx} module is equipped with a tunable laser and a pseudo-random bit sequence (PRBS) generator to create a test signal. Then, the OTC_{Rx} receives the test signal and estimates the BER. Figure 1 presents a very simplified diagram of the architecture of an optical node, where only one incoming and one outgoing links, as well as the local signals being dropped and added are represented. The node consists of wavelength-selective-switches (WSS), optical amplifiers (OA), dispersion compensation fiber (DCF) and channel equalizers; on the architecture, OTC and OSA monitoring systems are highlighted. OTC modules are connected to local WSS in the architecture in Fig. 1. Since OTC modules use low-speed electronics, its expected cost is very small. In addition, only one single OTCTx and one single OTCRx modules per node need to be equipped, which although limits the number of concurrent test that can be carried out, also limits the number of consumed local WSS ports, which has a significant impact on the cost of the ROADMs. On the other hand, OSAs are placed in every outgoing link, so the number of OSAs per node equals to the nodal degree. In this case, we have limited the number of OSAs due to its cost, and although failure localization can still be carried out, the granularity of the localization would be at the node level. To achieve a finer failure location granularity, more OSAs should be placed, consequently increasing the node cost.

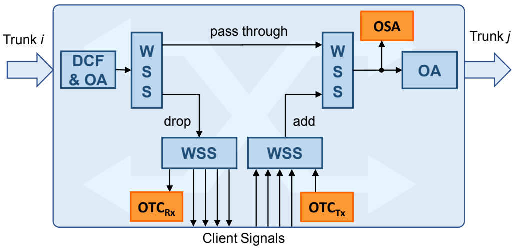

Figure 1. Simplified node architecture.

Figure 2 shows an example of the use of the proposed OTC monitoring system for before-operation tests and failure localization. One OTC_{Tx} is used in the ingress node to generate the test signal, and one OTC_{Rx} per intermediate and egress node is used to estimate the BER. Note that, since the lightpath has not been delivered to the customer yet, the client signal is not connected to the lightpath neither in the ingress nor the egress node at this stage. A module named as Signal Quality Estimation (SQE) running in the node's agent is in charge of receiving the measured BER in the local OTC and correlate to what the client signal would observe.

The *Testing optIcal Switching at connection SetUp timE* (TISSUE) algorithm running in the network controller, is in charge of allocating the OTC modules in the network nodes, setting-up the local connections from them to the lightpath in the end nodes, receiving BER estimations and deciding whether the tests pass or not, and estimating the elements that participate in the excessive BER.

Figure 3 depicts the use of OSAs to localize soft failures once the lightpath is in operation. OSAs acquire the whole C-band spectrum, and then, data for the portion of the spectrum allocated to the lightpath under study is extracted. OSAs passive monitoring is carried out in the ingress and every intermediate node (but not in the egress one). Two modules running in node's agent are in charge of analyzing the spectrum: i) the *Feature Extraction* (FeX) module first finds the set of relevant points in the signal spectrum that are used to compute meaningful signal features; and ii) the *Signal Spectrum Verification* (SSV) module that targets at analyzing the extracted features to detect misconfigurations, i.e., central frequency drift and filtering problems.

The *FailurE causE Localization for optIcal NetworkinG* (FEELING) algorithm, running in the network controller, is in charge of commanding the modules in the nodes and to receive a diagnosis, as well as the relevant signal points from them to localize the failure and estimate its magnitude. It is worth mentioning that FEELING must be able to distinguish between actual failures and normal effects that could lead to similar evidence, specifically tight filtering effects due to filter cascading of a normal signal. FEELING takes advantage of the *Signal Spectrum Comparison* (SSC) module that generates a diagnosis of one signal focusing specifically on filtering problems. In addition, failure magnitude estimation modules (Laser Drift Estimator, Filter Shift Estimator (FSE), and Filter Tightening Estimator (FTE)) quantify specific failure effects.

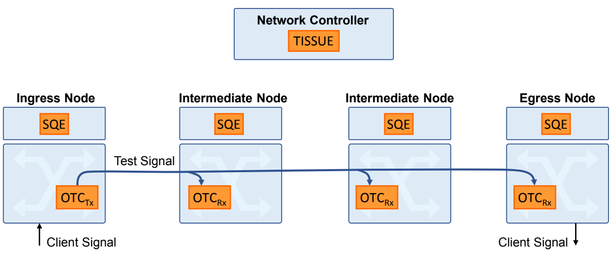

Figure 2. Before operation failure localization.

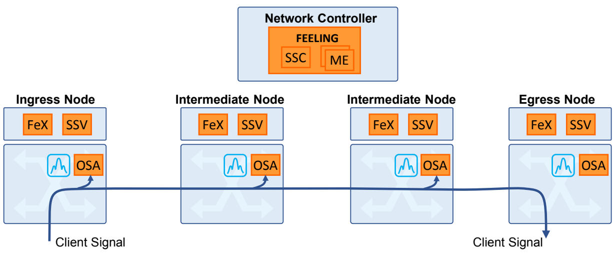

Figure 3. In-operation failure localization.

3. COMMISSIONING TESTS AND FAILURE LOCALIZATION

As introduced above, the TISSUE algorithm running in the network controller is in charge of collecting the QPSK signal estimated BER from each of the intermediate nodes; the SQE module is in charge of acquiring the OTC BER and use a BER conversion model (e.g., table or function) to translate the OTC measured BER value into a client QPSK signal estimated BER.

Initially, TISSUE algorithm (Table 1) allocates the OTC modules in the network nodes along the route of the lightpath and sets up the needed connections between the OTC modules and the lightpath so the OTC_{TX} module injects the test signal in the ingress node and all the OTC_{RX} modules get the test signal to measure BER (lines 1-2 in Table 1).Next, the QPSK BER estimated values are collected from the SQE modules, and theoretical BER values are computed based on OSNR values (lines 3-5). Finally, we compute the difference between the slopes of both estimated and theoretical BER in each span to determine the existence of a failure; if the slopes difference is above a maximum value, a failure has been detected in such span (lines 6-11). The OTC modules are released (line 12) and the list of spans in failure is eventually returned (line 13).

Table 1. TISSUE algorithm.

```
INPUT lightpath
OUTPUT FailureList
 1: <otc_Tx, OTC_Rx> ← allocateResources (lightpath)
 2: setupConnections (lightpath, {otc_Tx} ∪ OTC_Rx)
 3: for each r ∈ OTC_Rx do:
 4:     BER.estim[r] ← getEstimatedBER(r)
 5:     BER.theo[r] ← computeTheoBER(r.node, lightpath)
 6: failures ←Ø
 7: for i = 1..|OTC_Rx|-1 do:
 8:     estimSlope ← compSlope(BER.estim[i],BER.estim[i+1])
 9:     theoSlope ← compSlope(BER.theo[i], BER.theo[i+1])
10:     if estimSlope / theoSlope > α then
11:         failures ←failures ∪ {<i, i+1>}
12: deAllocateResources (lightpath, otc_Tx, OTC_Rx)
13: return failures
```

4. IN-OPERATION FAILURE LOCALIZATION

This process involves both, modules running in node agents and modules running in the controller. Running in node agents, the FeX module receives the C-band optical spectrum acquired by the local OSA and extracts the data for the portion of the spectrum allocated to the lightpath under study. Then, the ordered list of frequency-power pairs is converted into several relevant features such as central frequency, symmetry, bandwidth at selected power levels, just to mention few. Features feed the SSV module that implements a decision tree [5] that identifies if the signal is normal or on the contrary, if either laser problem or filter problem exists. In case of filter problem, a finer classification between filter shifting and tight filtering is performed by the SSC module running in the controller, which implements a support vector machine [5]. Detailed description as well as numerical performance analysis of all these modules can be found in [6].

The FEELING algorithm that uses the above-defined modules is detailed in *Table 2*; recall that FEELING is called upon the detection of excessive BER at the reception side of an optical signal. The algorithm first calls FeX and SSV modules in the ingress and last intermediate extended nodes to perform signal verification and obtain a diagnosis (lines 1-5 in Table III). In the case that the diagnosis of both nodes is normal, FEELING ends with no failure detected (lines 6-7). Otherwise, in the event of laser drift diagnosis at the ingress, the Laser Drift Estimator (LDE) module is run to measure failure magnitude (lines 8-10);

In the case of a different diagnosis, FEELING starts a procedure to detect filter related problems at intermediate nodes using the SSC module to compare diagnosis and magnitudes between nodes in the route of the lightpath. This process starts with the diagnosis at the ingress node that it is used as the initial reference node (lines 11-14). Then, the diagnosis of every intermediate node is compared against the one of the reference changing node and failure set is updated if either a new filter failure is detected or the magnitude increased above a certain threshold (lines 15-22). After processing all intermediate nodes, the list of failures detected is eventually returned (line 23).

Table 2. FEELING algorithm.

```
INPUT lightpath
OUTPUT {<node, class, magnitude>}
 1: ingress ← lightpath.getNodeFromRoute (1)
 2: lastInterm ← lightpath.getNodeFromRoute (-2)
 3: FM ← getFilterMasks(lightpath)
 4: diagIngress ← getFailureDiagnosis (ingress, FM (1))
 5: diagLast ← getFailureDiagnosis (lastInterm, FM (-2))
 6: if diagIngress.class = diagLast.class AND
                        diagIngress.class = Normal then
 7:         return {<1, Normal, ->}
 8: if diagIngress.class =LaserDrift then
 9:     magn← LDE(diagIngress.X)
10:     return <1, LaserDrift, magn>
11: XNodeChange ← diagIngress.X
12: diagChange = <class, magn> ←SSC (diagIngress.X)
13: if diagChange.class<> normal then
14:     FailureSet←<1, diagChange>
15: else FailureSet ← ∅
16: for i=2..lightpath.RouteLength()-1 do
17:     node_i ← lightpath.getNodeFromRoute (i)
18:     Xi← getSignalPoints (node_i)
19:     diagNode_i ← SSC (Xi)
20:     if diagNode_i.class <> diagNodeChange.class OR
            diagNode_i.magn - diagNodeChange.magn > α then
21:         XNodeChange ← Xi
22:         FailureSet ← FailureSet ∪ {<i, diagNode>}
23: return FailureSet
```

5. NUMERICAL RESULTS AND CONCLUSIONS

Regarding commissioning testing, we performed simulations with a 250 Mb/s channel transmitted through 1000 km of single mode fiber (ten 100 km spans), configuring all tunable physical parameters so that a BER lower than 3.7×10^{-3} is measured at 1000 km. After several tests, we set TISSUES's parameter α to 2.

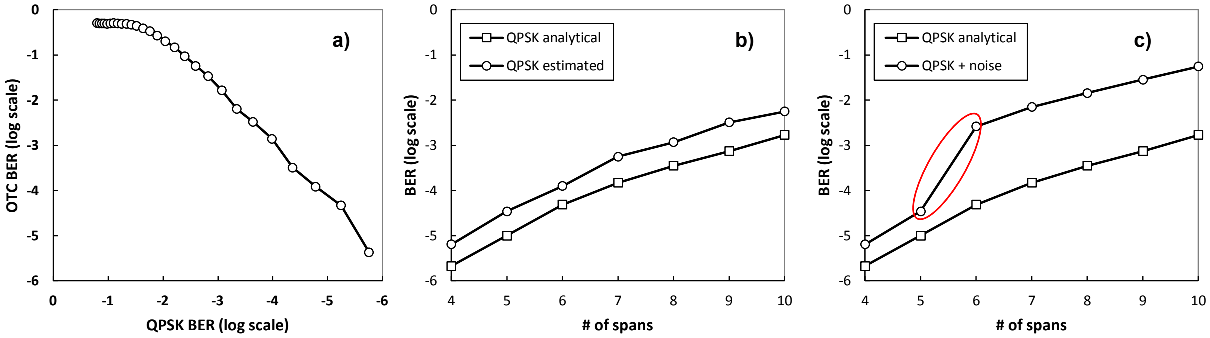

Figure 4. TISSUE performance.

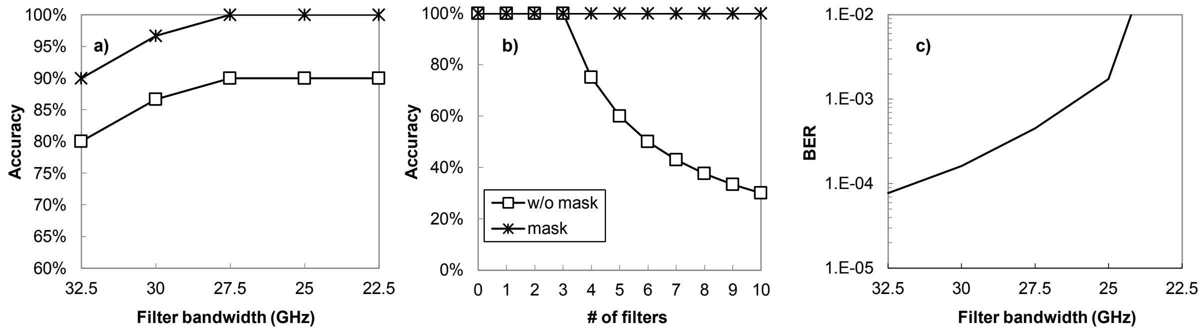

Figure 5. FEELING performance.

First of all, the correlation between simulated OTC measured BER and QPSK signal estimated BER is shown in Fig. 4a. It can be shown that there is an almost near linear relationship between both BER curves. Note that the above BER relation is specific for the particular case where the signal does not traverse any filter; then, a family of models can be used to convert from the measured OTC BER to the estimated QPSK signal BER as a function of the number of filters the lightpath traverses. Figure 4b plots an example of theoretical and estimated BER for the last seven 100km spans of the simulated 10-span. As observed, values are very close (about half decade difference in BER values), proving that the OTC scheme is an effective testing technique for operators to check the quality of a new lightpath, as well as to localize spans with excessive BER. In that regard, we added 2 dB of noise after span #5 (Fig. 4c). In light of the evident slope change right after span #5, we can validate TISSUE to accurately localize the failure after noticing large estimated BER slope compared to theoretical one.

Regarding in-operation failure localization, we set up simulations where a 120 Gb/s DP-QPSK lightpath traverses 10 optical filters with 37.5 GHz of bandwidth and a 2nd order Gaussian transfer function. We focus on the detection of *TightFiltering* failures of different magnitudes. Accuracy in terms of the proportion of correct localizations is provided as a function of the magnitude of the failure and the number of filters before the failed one (Fig. 5a-b) for two distinct cases: with and without applying filter mask to correct filter cascading effects. Without mask, the localization accuracy decreases sharply when the lightpath passes through more than 3 filters. On the other hand, filter mask correction compensates filter cascading effects and 100% of localization accuracy for filter tightening small that 30 GHz is achieved. Note that, in case of gradual filter degradation, that detection will be actually done before observing significant BER increase in the affected lightpath (Fig. 5c). This result eventually validates FEELING for detecting soft failures before detecting critical BER degradation.

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