Feature-based Optical Spectrum Monitoring for Failure Detection and Identification [Invited]

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Abstract
In this paper, we explore the benefits of analysing the optical spectrum of lightpaths for soft-failure detection and identification in Spectrum Switched Optical Network. We present a framework exploiting machine learning (ML) based algorithms that uses descriptive models of the optical spectrum of a lightpath in different points along its route to detect whether the optical signal experiences anomalies reflecting a failure in the intermediate nodes. Our proposal targets the two most common filter-related soft-failures; filter shift (FS) and filter tightening (FT), which noticeably deform the expected shape of the optical spectrum. In this regard, filter cascading is a key challenge as it affects the shape of the optical spectrum similar to FT. Our proposals avoid the misclassification of properly operating signals when normal filter cascading effects is present. Extensive numerical results are presented to compare the performance of the proposed approaches in terms of accuracy and robustness.
Keywords: optical spectrum monitoring, failure detection and identification

1. Introduction

Failure identification and localization utilizing network performance monitoring can reduce failure repair times and operational cost of optical networks. Currently, the performance of lightpaths is mainly monitored at the transponder side to verify their proper operation, as well as to detect BER degradations thus, anticipating connection disruptions [1]. However, monitoring the signal at the egress node does not allow localizing failures and therefore, monitoring techniques to analyse and evaluate QoT in-line are required. One of the recently proposal monitoring schemes is optical spectrum monitoring [2]; when a failure affects the optical spectra of the lightpaths in a noticeable way, optical spectrum analysers (OSA) can be used to monitor the spectrum along the transmission line aiming at detecting and localizing that type of failure. Practically speaking, the realization of such solutions become possible with the emergence of a new generation of compact cost-effective OSAs with sub-GHz resolution in the form of optical components [3] allowing real-time monitoring of the optical spectrum of the lightpaths.

Wavelength selective switches (WSSs) perform optical routing and switching operations at the intermediate nodes in a spectrum switched optical network. When a lightpath passes through a chain of WSSs (which is typical in mesh optical networks where a route comprises of several switching nodes), it experiences a phenomenon known as filter cascading. Due to filter cascading, the effective bandwidth (bandwidth at -3dB) of the lightpath reduces. This phenomenon deforms the optical spectra of the lightpaths and has a significant impact on optical spectrum monitoring solutions.

In this paper, we study two different approaches to detect filter related failures by monitoring the optical spectra of the lightpaths. The approaches are based on a set of classifiers that make predictions using meaningful features extracted from the optical spectra. These approaches are designed to circumvent the filter cascading effects: *i) the multi-classifier approach*, in which different classifiers are employed for signals experiencing different levels of filter cascading and *ii) the single-classifier approach*, in which the lightpaths' features are post-processed to compensate for the filter cascading effect allowing the use of a single classifier for lightpaths disregarding the level of filter cascading. We use decision tree (DT) and support vector machines (SVM) to model the classifers. Ultimately, the optical spectrum analysis can be used by centralized algorithms able to localize failures in the network.

2. OSA for Soft-Failure Detection and Identification

Real-time optical spectrum monitoring provides opportunities for soft-failure detection and identification; particularly, those failures significantly deforming the optical spectrum of a lightpath. For precise detection and identification, algorithms need to be capable of classifying a properly operating lightpath from a failed one, which entails that a set of descriptive features should be identified for classification purposes. Building upon such features, ML-based classifiers can be trained to perform the classification task. The failure detection, identification, and localization process involves modules running in the monitoring and data analytics (MDA) agents [4] and modules running in the MDA controller, as shown in *Fig. 1*. In the MDA controller, the FailurE causE

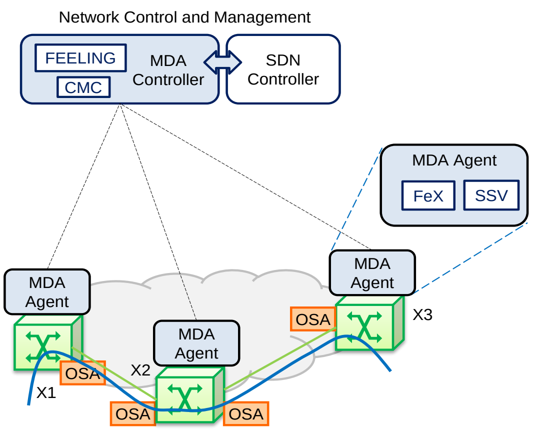

Fig. 1. Architecture for failure identification and localization

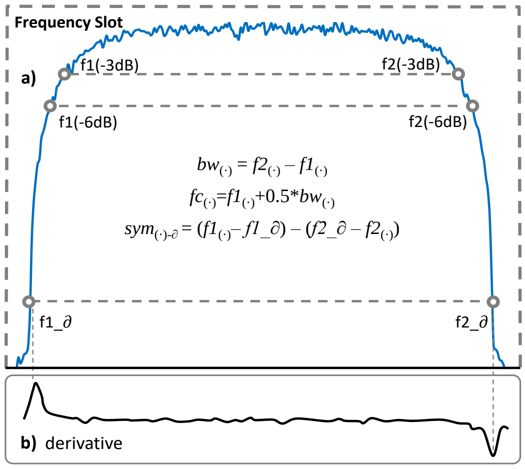

Fig. 2. Relevant points of a QPSK modulated signal

Localization for optIcal NetworkinG (FEELING) algorithm is primarily responsible for supervising the failure detection and identification modules running in the MDA agents [2]. Ultimately, it performs the failure localization task. Optical spectra acquired by OSAs are collected and becomes available in MDA agents, where it is used to feed the feature extraction (FeX) module [2]. An example of a 30-GBaud QPSK modulated optical spectrum acquired by an OSA of 312.5 MHz resolution is shown in Fig. 2.

The FeX module processes the acquired optical spectrum for a given lightpath, which consists of an ordered list of frequency-power (<*f*, *p*>) pairs in the allocated frequency slot. When the extracted features from the measured signal are available, a classification module, named Signal Spectrum Verification (SSV), running also in the MDA agents analyzes them to detect a soft-failure. The SSV module is implemented as a multiclass classifier that produces a diagnosis, which consists of: *i*) a predicted class among '*Normal*', and '*FilterFailure*'; and *ii*) a subset of relevant signal points for the predicted class. In the case that a filter failure is detected, another classifier is used to predict whether the failure is due to FS or to FT. To improve failure identification accuracy, the FEELING algorithm must be able to distinguish between actual failures and normal effects arising from filter cascading. Next, we will describe our proposed optical spectrum monitoring approaches.

3. Options for Classification using FeX

Let us first explain how the FeX relevant features can be used to classify different types of spectra [5]. As an example, *Fig. 4* shows where a pair of such features can discriminate different types of spectra. Assuming a set of measurements after 2 WSSs and belonging to normal operation, FS, and FT, *Fig. 4* (a-b) show $sym_{-3dB-\partial}$ w.r.t bw_{-3dB} and $sym_{-6dB-\partial}$., respectively. As represented, observations belonging to different classes can be easily discriminated with even just these two features in place. Now, let us take the same set of observations after 12 WSSs; the results are plotted in *Fig. 4* (c-d). As shown, it becomes very challenging to distinguish the observations belonging to different classes. It is worth mentioning that as a result of filter cascading signal features change in a similar way it happens when a FT failure takes place. Let's take a closer look at the figures to understand this issue. As shown in *Fig. 4* (a-b), just the observations belonging to FT are gathered in the bottom left corner of the figures; however, in *Fig. 4* (c-d), almost all the observations are gathered in the bottom left corner of the figures. In other words, filter cascading effect push the identified features in the direction that all observations look like FT observations. This increases the likelihood of misclassifying a properly operating lightpath as a failed one. Next, we describe the two different strategies preventing such misclassification. The strategies are based on processing the features extracted by the FeX module. Selected features for classification are: bw_{∂}, $bw_{5\sigma}$, bw_{-3dB}, bw_{-6dB}, $sym_{5\sigma-\partial}$, $sym_{-3dB-\partial}$, and $sym_{-6dB-\partial}$.

Multi-Classifier Approach

The most straightforward solution is to use different classifiers as a function of the number of WSSs that a given lightpath passes through through. A set of classifiers are required in every intermediate

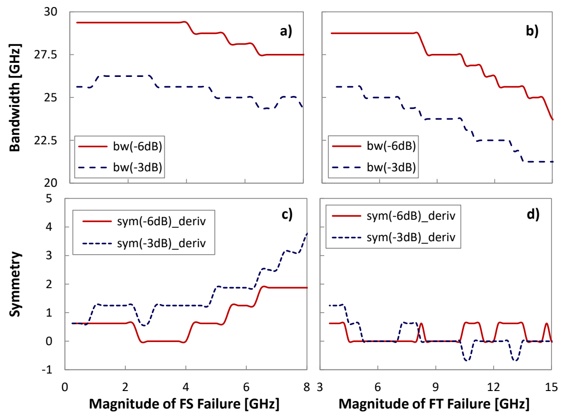

Fig. 3. The evolution of the features w.r.t magnitude of FS (a, c) and FT (b, d)

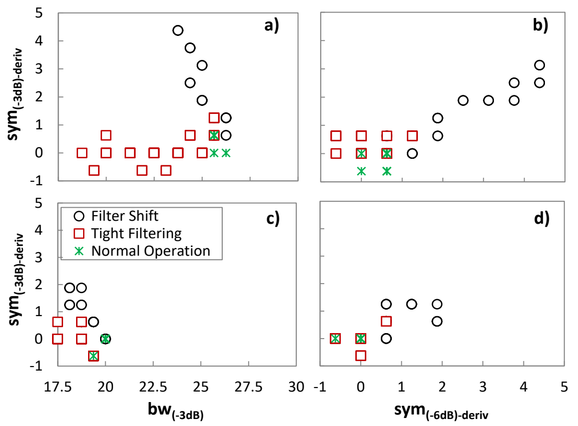

Fig. 4. The efficiency of the identified features after 2 WSSs (a, b) and after 4 WSSs (c, d)

node and the appropriate one is used when an optical spectrum is acquired. This approach can be considered as the baseline, as the selected classifier decides based on the features extracted directly from the acquired spectrum and do not need any kind of feature pre-processing. However, a very large dataset of optical spectra with different levels of filter cascading is required for training all the classifiers, which is the main drawback of this approach. To avoid using multiple classifiers, some pre-processing needs to be done so one single classifier can be used despite the level of filter cascading. The second approach is based on post-processing the extracted features [5].

Single-Classifier Approach

The features of a signal acquired after passing *N* filters can be compensated by adding/subtracting the differences between the values of a properly configured signal at that node w.r.t. those just after the transponder to compensate for the effects of filter cascading. These differences are stored in a vector called *correction mask*; note that, different levels of filter cascading require different correction masks to be used. Correction masks can be computed a priori, assuming the effects that the spectrum of a normal signal experiences while passing through different number of filters. It is worth mentioning that the calculation of the correction masks requires just the spectrum of a single properly configured lightpath passing through the desired number of filters, from zero to the maximum allowed cascaded filters in a network; this is in contrast to the previous approach, where the training phase requires that spectral data with different failures and with various magnitudes to be captured after every filter up to the maximum allowed number of filters. The Correction Mask Calculator (CMC) module placed in the MDA controller (see *Fig. 1*) is responsible for generating the correction masks to be sent to the MDA agents. Note that all the correction masks need to be available in the MDA agents, so the proper one can be selected. Following this approach, the classifier can be trained based on the observations of a passing through just a single filter, making the training phase less data-hungry by far compared to the previous approach.

4. Results and Discussions

In this section, we compare the performance of different approaches described in the previous sections. We have used VPI Photonics to generate datasets to perform our analysis. The VPI setup is described in [5]. Aiming at emulating failure scenarios, we modify the characteristics of the 2nd WSS of each node (from N1 to N8) in the set-up; its bandwidth and central frequency are modified to model FT and FS failures, respectively. A large dataset of failures was collected by inducing failures of magnitude in the range [1-8] GHz for FS and in the range [1-15] GHz for FT, both with 0.25 GHz step-size, where the magnitude of FT is defined as the difference between the ideal bandwidth of the filter (37.5 GHz) and its actual bandwidth during the failure.

First, we compare the performance of the proposed approaches in terms of its *accuracy*, defined as the number of correctly detected failures over the total failures. *Fig. 6* shows the accuracy of detecting FS and FT, respectively at node N1 in terms of the magnitude of the failure. Note that in N1 both multi-classifier and single-classifier are the same as no filter mask is required. Every point in *Fig. 6* (a-b)

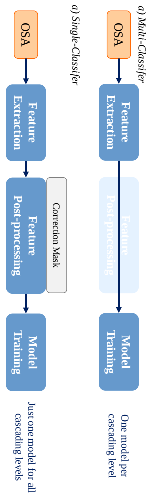

Fig. 5. Multi-Classifer and Single-Classifer

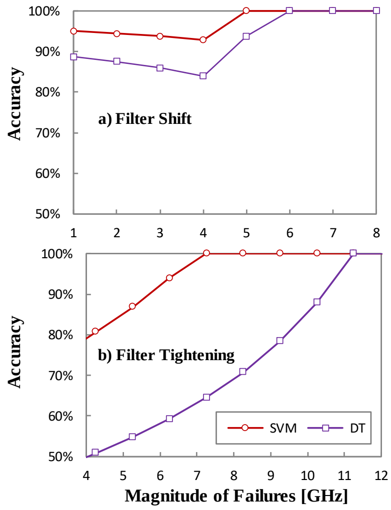

Fig. 6. Accuracy at N1 of DT and SVM for FS

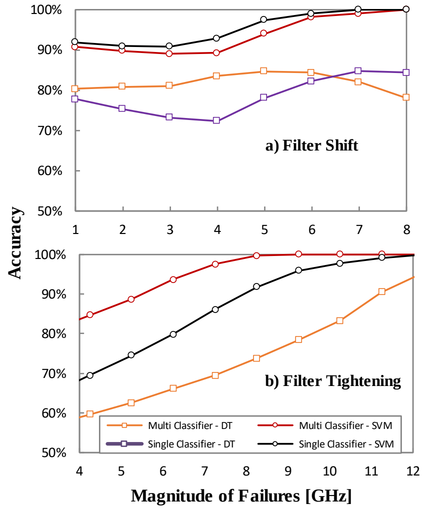

Fig. 7. Average accuracy over N1-N8 of DT and SVM for FS (a) and FT (b).

aggregates failure scenarios with different magnitude by considering all the observations belonging to a particular failure magnitude and above. As shown, the accuracy of detecting FS larger than 1 GHz is around ~96% when classifiers are based on SVMs, while it hardly approaches 89% when they are based on DTs. On the other hand, the accuracy of SVMs reaches 100% for failures larger than 5 GHz, while this level of accuracy for DTs is achieved for failures larger than 6 GHz. Regarding FT detection, the best accuracy of the proposed classifiers for low magnitudes (below 6 GHz) is around 80% (achieved for SVMs), which is due to the fact that the shape of the optical spectrum is quite similar to the normal scenario, making it very challenging for the classifier to distinguish. This is in contrast to the case of FS, whose effect is more evident even for low magnitudes due to its asymmetric impact on the optical spectrum. For the magnitudes above 7 GHz, the SVM-based classifier perfectly detects the failure. Note that DT-based classifiers achieve perfect accuracy for magnitudes above 10.5 GHz.

Let us now compare both approaches implemented with DT and SVM -based classifiers for detecting failures in all 8 nodes of the set-up. Recall that multiple classifiers are needed for the first approach and several filter masks are required for the second approach. The results are shown in *Fig. 7*(a-b) for FS and FT, respectively, where every point aggregates the results for all the nodes. As observed, SVM-based classifiers significantly outperform DT-based ones in both approaches and failures. As a result, SVM-based classifiers can be selected as the preferred option for feature-based approaches.

Comparing the different SVM-based approaches, the single-classifier performs slightly better in the case of FS detection while the performance of the multi-classifier approach is much better than the single-classifier one in the case of FT failure. Therefore, we can conclude that training multiple classifiers with the data collected at nodes experiencing different levels of filter cascading performs better than correcting the features with the purpose of using a single classifier, as the impact of filter cascading is similar to the effect of FT on the shape of optical spectrum.

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