Smart Filterless Optical Networks Based On Optical Spectrum Analysis

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ABSTRACT
Dynamic network operations can produce power fluctuations of the established connections in filterless optical networks. In addition, the gridless nature of filterless networks make that some (un)intentional effects such as transponders laser drift might disrupt the proper operation of lightpaths. To overcome these issues, we present a monitoring system exploiting data analytics and cost-effective optical spectrum analyzers to achieve smart filterless network operation. Experimental measurements are used to validate the proposed data analytics-based approaches, as well as to find the optimal resolution to achieve maximum performance with minimum cost.
Keywords: Filterless optical networks, optical spectrum analysis, smart operation.

1. INTRODUCTION

Filterless optical networks (FON) have recently attracted significant attention as a cost-effective metro solution to interconnect 100G coherent-based nodes in a drop and waste network architecture [1]. Note that, since the operating lightpaths do not pass filtering nodes, FONs can be considered as a kind of *gridless* network where frequency slots are not rigidly defined, which could drive to a better use of spectrum resources. However, filterless networks suffer from some limitations [2] in contrast with spectrum switched optical networks (SSON) that can seriously affect proper lightpaths' operation. On the one hand, optical power fluctuations produced by provisioning, i.e., set-up and teardown, as well as re-configuration operations can be critical since a cascade of amplifiers may be traversed with no wavelength selective switches that could provide equalization and control of power levels. On the other hand, (un)intentional laser drift of a tunable transponder (Tp) can disrupt proper operation of a neighboring lightpath, in contrast to SSON, where laser drift effects are much more moderate.
In view of the above, cost-effective approaches to monitor FONs are needed to allow network operators to take prompt actions in case of improper operation of a device in their domain. Most of the current monitoring systems rely on the capabilities of coherent receivers to collect measurements [3]. With the development of cost-effective optical spectrum analyzers (OSAs) with sub-GHz resolution [4] deployable in the optical nodes, a new horizon has been seen for the development of monitoring and data analytics (MDA) platforms that can benefit from the optical spectrum captured by OSAs [5]. Due to the broadcast nature of FONs, just one OSA per fiber is enough to capture the aggregated spectrum. Since OSA resolution is related to its cost, a target OSA resolution should be studied to achieve remarkable cost savings.
In this paper, we propose to use OSAs to enable smooth operation of filterless optical networks. Specifically, two use cases are detailed. First, smooth operation (i.e. setup and teardown of lighpaths during provisioning or reconfiguration) consists in tuning signal power levels to prepare the network before the operation is carried out, based on monitored data, and performing a fine tunning of signal power levels after the operation. Second, a surveillance system that continuously scan the whole C-band aiming at monitoring the healthiness of the active lightpaths and detecting failure ahead of having a service disrupted is presented. Experimental results are provided to show how power fluctuates as a result of network operations in filterless optical networks, as well as to find the most appropriate OSA resolution to achieve target accuracy at minimum cost is performed.

2. SMOOTH FILTERLESS NETWORK OPERATION

Power level of a lightpath is a key parameter determining its Quality of Transmission (QoT), which also has a significant impact on the overall performance of the network. In particular, two conditions must be satisfied: *i*) the signal of every individual lightpath should arrive to the receiver with a power level enough to satisfy the receive sensitivity and, *ii*) both individual channels', as well as the total power level injected into a fibre strand should not exceed a certain level in order not to signify the impact of nonlinearities or, in an extreme case, make the photodiode of the receiver unusable. These issues become more critical in the context of filterless optical networks, where optical signals propagate far beyond their receiver point.
In addition, dynamic changes as a result of network operation affect the power levels of the active lightpaths. Therefore, monitoring the power levels of different lightpaths becomes essential to keep the abovementioned phenomenon under control. The power level of individual channels can be measured in the receiver side. However, such measurements are available just at the local node and do not provide any insight on the power fluctuations in the other portion of the operating amplification band (e.g., C-band). As already mentioned, just one OSA per filterless segment is enough to capture the aggregated spectrum and measure the power level of all the active

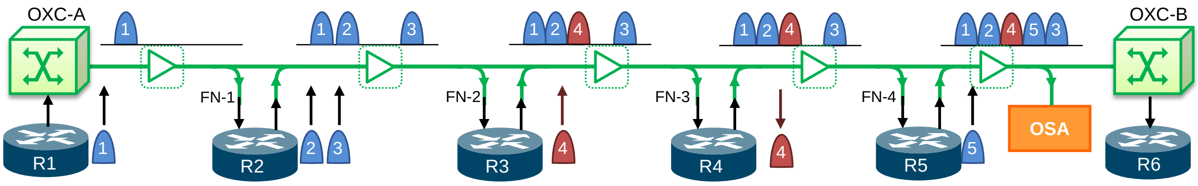

Fig. 1. A filterless optical network segment.

channels at the end of the segment (as shown in Fig. 1). However, such measurement does not reveal meaningful information on the power level of the channels arriving at intermediate nodes.

Aiming at solving that issue, we propose to collect the power levels measured by the receivers, as well as the ones measured by the single OSA of the segment in the MDA system allowing the overall monitoring of power fluctuations in the network. In addition, a Machine Learning (ML) algorithm can perform a network-wide analysis providing guidelines on the power fluctuations and their possible impact on the performance of the network avoiding undesired events to happen. The outputs of the ML algorithm can be then used to perform component re-tuning in a network operations phase or to execute periodical component power level adjustment.

Among network devices, the transmitters and the optical amplifiers, including Erbium Doped Fiber Amplifiers (EDFA), are the ones that mainly contribute to power level fluctuations. The level of their contributions and the impact they may have on the overall performance depend on their characteristics, as well as the network configuration. For instance, while the launch power is the only parameter to be tuned at the transmitter side, the gain and the tilt are among the reconfigurable parameters of the amplifiers. In the context of filterless metro networks, transmission power can be configured in the typical range between -10dBm to 0dBm, and amplifiers are typically configured in gain-mode to compensate for span and splitter/coupler loss, with large flexibility in gain configuration and limited flexibility in tilt (few dBs). Actual reconfiguration time is in the order of few milliseconds, which could increase to few seconds considering the whole control system.

In view of that, an enhanced network operation procedure that includes power-related parameter adjustment is proposed. The procedure consists of prior and posterior to the network operation power-aware stages to prepare and adjust the network to assure a smooth operation if a detrimental effect is anticipated in the network.

1. *Preparation Phase*: this phase estimates whether the requested network operation, i.e., the actual set-up/teardown of a lightpath or a network re-configuration, may have a harmful impact of the network healthiness. It analyzes the impact of the specific operation by considering the network configuration, as well as the currently established lightpaths and the target of the operation itself.
2. *Network operation*: the actual set-up, teardown, or re-configuration.
3. *Fine Tuning Phase*: This phase observes the post-operation status of the network by monitoring the power level, analyzes the fluctuations in different locations, and implements fine tuning of network devices.

To implement the proposed smooth network operation, we assume the control architecture depicted in Fig. 2; a SDN controller is in charge of configuring the network devices, including power levels. The network is continuously monitored, and measured power levels are stored in the MDA controller. Finally, the optional planning tool reflects the fact that a system to compute network-wide power levels based on monitored data is needed. Fig. 4 shows also the proposed workflow that implements smooth network operations. The workflow starts after a new request arrives at the SDN controller (labeled 1). In this case, the SDN controller issues a request to the planning tool to find the optimal use of resources for the incoming operation request, as well as to compute optimal power levels to be implemented in the network in advance (2). Such computation needs from monitoring data that the planning tool retrieves from the MDA controller (3). The results are replied to the SDN controller (4), which first implements the recommended power levels, and then the network operation itself (5). The continuous network monitoring might trigger the posterior tuning phase. A ML algorithm running in the MDA controller analyzes measured power levels and might decide to fine tune some of the network devices to maximize network performance. This decision is notified to the SDN controller as a recommended action (6), which eventually reconfigures the network devices (7).

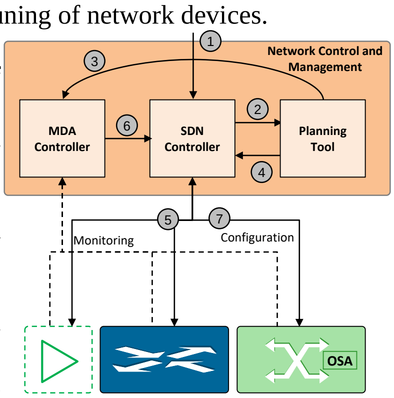

Fig. 2: Proposed workflow

3. REAL-TIME SPECTRUM SURVEILLANCE

The example in Fig. 1 illustrate a network were five lightpaths has been established following the smooth operation procedure explained in the previous section. Let us imagine now that Tp of lightpath R3->R4 (signal 4) experiences a problem where its central frequency (CF) drifts to the right; in this case, lightpath R5->R6 (signal 5) will be affected since the spectrum of signal 4 overlaps it, even though the spatial route of the two lightpaths do not intersect. As a result, a surveillance method should be considered to detect laser drifts, while determining whether a drift will impact a neighboring lightpath. Our proposal has an advantage while exploited for FONs, which is the small number of OSAs required for real-time network spectrum monitoring; note that in a similar SSON, one OSA per link (five in total) would be required. In this work, we propose to use one single OSA installed in the last span, where all signals in the FON can be acquired. Captured spectrum needs to be analyzed real-time so active lightpaths in the FON are monitored and prompt actions are taken before a properly operating lightpath becomes affected by a failed Tp. Therefore, we assume the distributed hierarchical MDA architecture in [5], which includes computation capabilities close to the network nodes.

Note that the frequency range of a signal might not be exactly determined and slightly change along lightpaths' lifetime. Therefore, an algorithm examining the captured optical spectrum cannot select a frequency range in the whole C-Band acquired by an OSA and focus on analyzing it in the hope that the whole spectrum of a target lightpath and only of such lightpath is confined within that frequency range. In consequence, in the next section, we propose algorithms that periodically scan the whole C-band and rely on an ordered list of lightpaths, including relaxed frequency ranges for each one, obtained from the SDN controller; the scan process is intended to ensure that signals in the network and lightpaths in the list match in terms of frequency ranges. Any found difference (i.e., signals not in the list and lightpaths not in the FON), as well as detected anomalous signal CF shifts that might end in impacting neighboring lightpaths are reported to the SDN controller. Analyzing the current signals' spectrum allocation and lightpaths information from the controller, we thus aim at checking whether each signal is confined within the frequency range allocated to a lightpath (*normal* signals); conversely, three anomalies can be identified (Fig. 3a), namely: *i*) a signal is partially out of the spectrum allocated to a lightpath (*outOfRange*); *ii*) a signal is in a spectrum range no allocated to any lightpath (*unknown*); and *iii*) no signal has been detected in the spectrum allocated to a lightpath (*missing*). The detection of any of these anomalies triggers a notification with *critical* severity level to the controller, whereas *normal* signals need to be tracked afterwards to predict a potential anomaly.

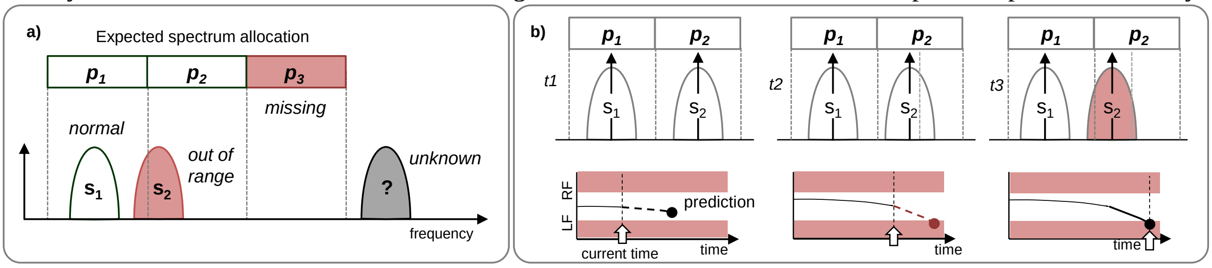

Fig. 3. Signal classification example (a) and anomaly prediction (b)

The proposed data analytics procedure starts when a new C-band scan is acquired by the OSA, which generates an ordered list of *frequency-power* pairs. The first step is to detect the allocated spectrum to each signal; by using the derivative of the power w.r.t. the frequency [6], the sharp power rising at the left frequency edge followed by the power falling at the right frequency edge of each signal in the spectrum can be detected. Next, the algorithm in Table 1 is used to classify the set of identified signals *S* w.r.t to the list of lightpaths *P*.

After some initializations (lines 1-2), the algorithm iterates on the signals to find the lightpaths where the allocated spectrum includes part of their range (lines 3-4); if no lightpath is found, the signal is classified as *unknown* (line 5), whereas it is classified as *normal* if the allocated spectrum of just one lightpath totally overlaps the signal (lines 6-8). Otherwise, signals are classified as *outOfRange* and assigned to the first overlapping lightpath (lines 9-15).

Finally, the set of *missing* lightpaths (if any) are obtained and the classification results eventually returned (lines 16-17).

Non- *normal* signals trigger notifications to the controller and they can be discarded for further analysis. The next step focuses on tracking *normal* signals to predict any possible violation of their spectrum allocation that could impact on neighboring signals. In this step, the optical spectrum of each signal is analyzed to find relevant points, such as the *CF* and the left and right frequencies (*LF/RF*) computed at -3dBs [6]; the relevant points are used to track the evolution of the signal with time and to predict whether it is likely to exceed the spectrum allocation within a given future time window. An example of this procedure is illustrated in Fig. 3b, where signal *s2* is gradually approaching neighboring signal *s1*. In this case, the prediction of *s2 LF* at time *t2* states that it will exceed its spectrum allocation and thus, a notification with *warning* severity level is triggered towards the controller before an *outOfRange* anomaly is detected (actually at time *t3*)

Table 1 Signal Classification Procedure

```
INPUT S, P
OUTPUT N, O, M, U
1:  N=O=M=U=S'←Ø
2:  ID←getAllIds(P)
3:  for each s∈S do
4:    P'←findOverlaps(P, s)
5:    if P'≠Ø then U←U ∪ {s}
6:    else if |P'|==1 and totalOverlap(s,P') then
7:       N←N ∪ {<P'.getId(), s>}
8:       ID←ID \ {P'.getId()}
9:    else s.I← P'.getId()
10:      S'← S' ∪ {s}
11: if S'≠Ø then
12:   for each s∈S do
13:      I←{s.I} ∩ ID
14:      O ← O ∪ {<I.first,s>}
15:      ID←ID \ I.first
16: if ID≠Ø then M←M ∪ ID
17: return N, O, M, U
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4. EXPERIMENTAL RESULTS AND CONCLUSIONS

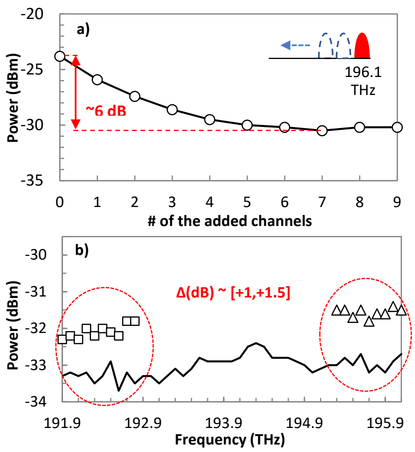

Fig. 4. Power variations in operation

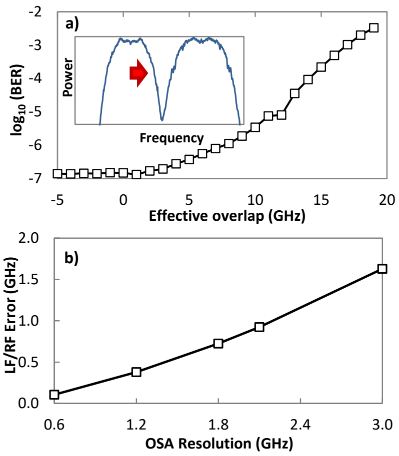

Fig. 5.Overlap impact and detection

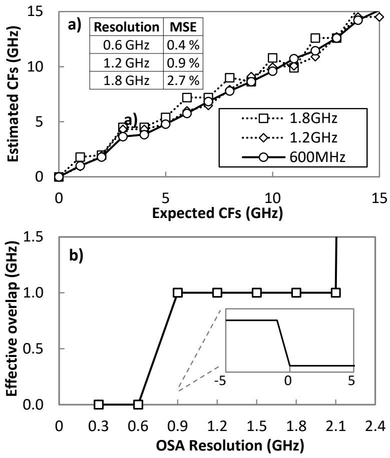

Fig. 6. OSA resolution

An optical network composed of two 80 km long G.652 optical links and three EDFAs configured in gain-mode has been considered for the experimental measurements of power variations due to the setup and teardown of optical connections (Fig. 4). In a first experiment, we observe how the power level of a lightpath fluctuates when other lightpaths are sequentially established (Fig. 4a). Specifically, the power level of the lightpath in the extreme right side of C-band (196.1 THz) suffers from increasing power loss when more lightpaths are established on its left side (up to 6dB for 5 new established lightpaths). This motivates the proposed adaptive power adjustment before new lighpaths are set-up in order to avoid that the power level goes below the receiver sensitivity. In a second experiment, we observe how network reconfiguration operations affect the power level of the lightpaths (Fig. 4b). To evaluate those effects, we start from a scenario with 43 lightpaths allocated in a contiguous C-band portion (line). To emulate network reconfiguration, 33 lightpaths are torn down, remaining 10 (markers), either in the left or right side of the spectrum. As illustrated, the power level of the remaining lightpaths experiences up to 1.5 dB increase right after massive torn down, which shows the need of real-time adjustments to avoid detrimental effects thus, smoothening network operations.

To validate real-time spectrum surveillance, we setup another experimental test-bed where two neighboring 100 Gb/s signals (*s1* and *s2*) were launched. While *s2* was considered to operate properly, *s1* is forced to move toward the neighboring one at 1 GHz steps from an initial 6 GHz spacing between signals, simulating a laser drift failure. Fig. 5a shows how pre-FEC BER degradation increases when overlap increases. The signal classification algorithm perfectly identifies both signals and matches them to two existing lightpaths (*s2* as *normal* and *s1* as *outOfRange*) Nonetheless, it is worth studying the accuracy of signals' detection vs. OSA resolution. To that end, we emulated 5000 different lightpath frequency ranges for every spectrum capture with no overlap. The accuracy on *LF* and *RF* computation vs. OSA resolution are reported in Fig. 5b and the results of the *CF* computation for three OSA resolutions are reported in Fig. 6a, where the inner table inside Fig. 6a details the mean squared error (MSE) for each OSA resolution. It is clear that the finer the OSA resolution the lower the error in points computation, which impacts on signal identification. Fig. 6b shows the results of the detection for different OSA resolutions; with 300 MHz and 600 MHZ OSA resolution, the overlap is perfectly detected; the inner graph inside Fig. 6b shows how the sudden change in LF of signal *s2* allows detecting the overlap. When OSA resolution is up to 2.1 GHz, 1 GHz of effective overlap is needed to detect it, whereas the overlap is not detected for coarser resolutions. Therefore, 1.2 GHz OSA resolution can be identified as the coarsest one for accurate signal tracking and overlap detection.

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