Field Trial of Marginless Operations of An Optical Network Facing Ageing and Performance Fluctuations

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Abstract *Leveraging machine learning for monitoring-based performance estimation and closed-loop SDN-based network control, we demonstrate the first fully automated reconfiguration of marginless connections undergoing critical performance variations over 228km of field-deployed fiber.*

Introduction

Today's optical networks are designed with significant underestimations of link performance - margins - to guarantee service despite many deployment unknowns[1]. In marginless mode, the network operates as close as possible to forward error correction (FEC) limit to optimize costs. Doing so, natural performance variations e.g. from polarization effects, network loading and ageing threaten error-free transmission.

The solution is automated network control. Leveraging physical-layer monitoring, optical networks can sense threats or soft-failures (SF) and optimize reconfiguration actions. To achieve this, accurately predicting bit error ratio (BER) in a flexible and dynamic environment is critical.

Machine learning can rise to this challenge. For instance, neural networks were recently used to predict BER-related metrics for spectral efficiency adaptation[2] and impairment aware service provisioning[3]. At current state-of-the-art however, it remains unclear how such neural networks could be trained to consistently predict BER accurately in full-size deployed networks.

In this paper, we leverage simpler machine learning techniques but combine them with analytical models and monitoring to perform accurate, up-to-date BER predictions with minimal training complexity. We leverage these novel BER prediction tools to demonstrate the first fully automated operation of marginless connections undergoing major performance variations over 228km of field-deployed fiber. In a first use case, we present the capacity adaptation of a best-effort connection with BER variations from emulated amplifier and fiber ageing. Secondly, we present the net capacity maintenance of a gold class connection facing BER variations from emulated laser and wavelength selective switch (WSS) ageing.

Field trial setup

The fiber cable is deployed between Torino (Stampalia) and Chivasso network exchanges and is composed of eight 76km-long G.652 fiber spans. We use 5 spans to create two lightpaths of 3 and 2 spans, denoted as LP1 (228km) and LP2 (152km) respectively (cf. Fig.1). Two lab-hosted reconfigurable optical add-drop multiplexers (ROADMs) switch traffic from LP1 to LP2. The transmitter (TX) supports QPSK, 8QAM, 16QAM modulation formats, and 28 and 32GBd baudrates to achieve net capacities of 100, 150 and 200 Gb/s with 12% (low-FEC) and 28% (high-FEC) coding rates. The receiver (RX) integrates a 40Gsamples/s oscilloscope, offline signal processing to handle both signal demodulation and monitoring of multiple transmission parameters, and a software agent to report monitored values and raise alarms. The various ageing scenarios are emulated through a combination of tunable optical filter (TOF) and variable optical attenuator (VOA).

For control plane, we use ORCHESTRA's hierarchical and programmable management infrastructure whose key building blocks are the OAM Handler and the ABNO controller[4] (cf. Fig.1). The ABNO controller implements use case workflows and uses DEPLOY[5] as an enhanced PCE. DEPLOY performs monitoring-based BER predictions and determines recovery

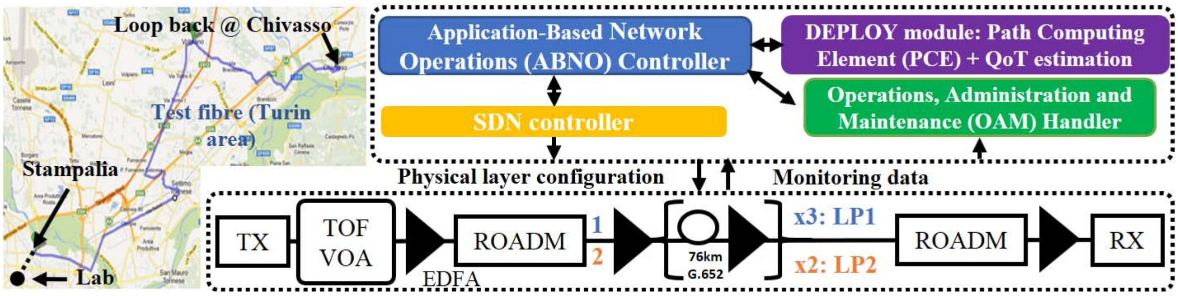

Fig. 1: Field trial setup at TIM premises in Turin (Italy)

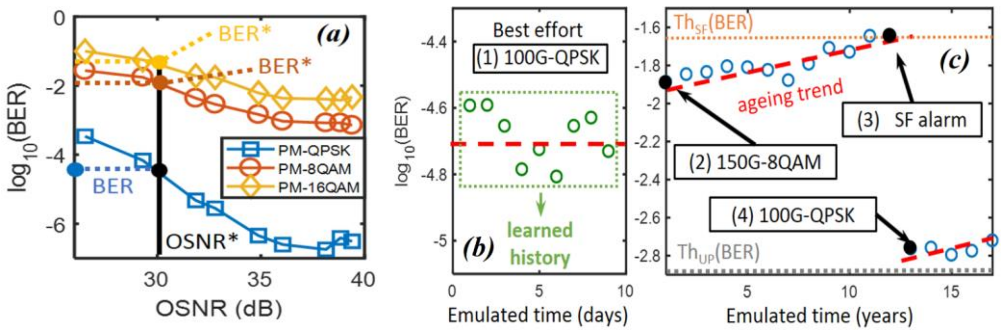

Fig. 3: Best-effort automatic rate adaptation in presence of emulated fiber/amplifier ageing

actions. Finally, the ABNO controller (re)configures the lightpath (LP) - TX/RX and/or ROADMs - through a provisioning manager and SDN controllers. The control logic is applied via NETCONF following YANG model and REST.

Automatic adaptation to fiber/EDFA ageing

Here, we consider a best-effort connection that leverages end-of-life (EOL) margins[1] to first increase its capacity and operate as close as possible to FEC limit. In the following, OSNR refers to the generalized optical signal-to-noise ratio, including both linear and nonlinear optical noises[6]. Emulating fiber and amplifiers ageing with increased optical attenuation from the VOA (Fig.1), the OSNR evolves as illustrated in Fig.2a, where fluctuations on top of the aging trend naturally occur in the field. From startup at 100G-QPSK, the system progressively adapts as depicted in Fig.2b by relying on soft-failure detection and a novel BER prediction based on monitored BER and machine learning.

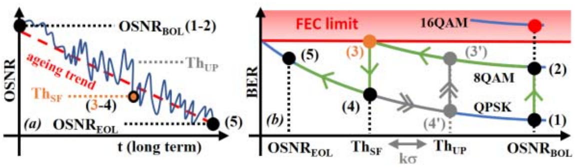

Fig. 2: OSNR variations and format adaptations

The soft-failure (SF) detection is based on a threshold Th_{SF} (Fig.2a-b) defined according to FEC scheme. When detected, the failure triggers a reconfiguration (Fig.2b). Reversely, the capacity is upgraded when DEPLOY judges it possible. Because of OSNR fluctuations, this reversibility could lead to a ping-pong effect between modulation formats. To mitigate this, we implemented a history-based hysteresis so that DEPLOY only allows capacity upgrade when OSNR exceeds $Th_{UP}=Th_{SF}+k\cdot\sigma$, where σ is the learned standard deviation of the OSNR and k=4. The parameter k balances modulation format stability with minimal margin operation.

The live evaluation of OSNR - and thus σ - from BER measurements stems from DEPLOY's ability to learn the bijective function *f* as in BER = *f*(OSNR) for all supported modulation formats. It has been clearly established that *f* only depends on transponder and its configuration, and is fully determined by back-to-back measurements[6]. Thus, prior to deployment, we measure in back-to-back nine sets of BER and OSNR for each modulation format (Fig.3a). Inputting the collected data into a stochastic-gradient-descent-based polynomial[7] regression, we train DEPLOY to convert BER into OSNR and reciprocally: during operation, using that OSNR does not depend on modulation format, DEPLOY provides, as depicted in Fig.3a, BER* values as BER estimations for other formats from both monitored BER average and knowledge of BER = *f*(OSNR).

In Fig3.b-c, we plot the BER data obtained during a typical field trial experiment. During a short period, i.e. few minutes during the trial emulating days or weeks of operation, DEPLOY learns BER average and standard deviation σ (Fig.3b) in state (1). Based on monitored BER value at $2.5.10^{-5}$, DEPLOY estimates the BER to be at 1.10^{-2} in 150G-8QAM and $3.5.10^{-2}$ in 200G-16QAM. With a FEC threshold at 2.10^{-2}, the lightpath is reconfigured to 150G-8QAM (2) and reaches a BER of $1.3.10^{-2}$ (cf. Fig.3c), within the 0.5dB of prediction uncertainty margin. After a few emulated years of fiber/amplifier ageing, the control plane detects a failure in state (3). The connection is downgraded to 100G-QPSK corresponding to state (4). At this point, despite natural BER fluctuations, the history-based hysteresis prevents the system from reverting back to state (3). The connection remains in QPSK until network's end of life.

Automatic adaptation to filter ageing

In this section, we consider a gold-class 100G-QPSK connection automatically maintaining its net capacity through FEC (hence baudrate) and/or allocated bandwidth adaptation. For marginless operation, we aim to convert EOL margins into a 33% gain in spectral efficiency by allocating the connection 37.5GHz of bandwidth instead of the typical 50GHz. Here, we use EOL margins through the increase of filter penalty. But the bandwidth reduction also makes the connection more vulnerable to filter ageing. This effect typically stems from the progressive detuning of crossed WSSs and transmitter laser over the years, further increasing filter penalty. Here, DEPLOY's BER predictions clearly need

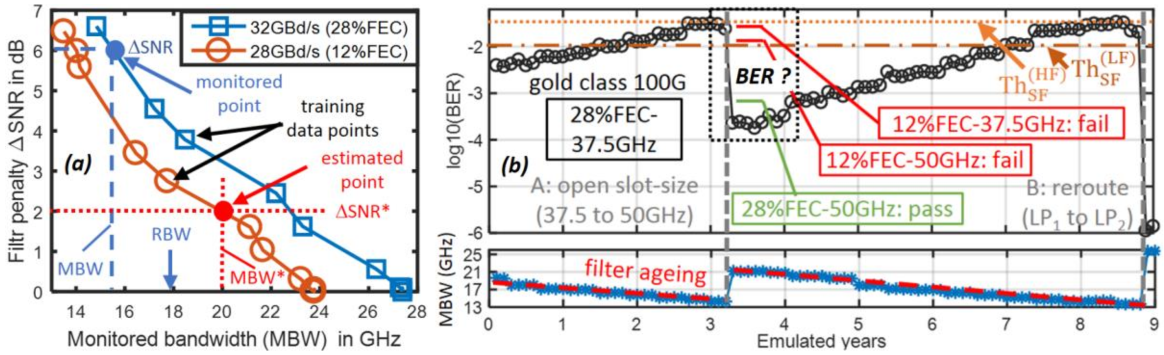

Fig. 4: Gold class automatic FEC and slot-size adaptation for net capacity maintenance under filter ageing

to account for filter penalty and its variations. To achieve this, we implemented a new method based on monitored signal bandwidth (MBW), measured within the receiver as the 10dB width of the signal's spectrum after analog-to-digital conversion. We assume that, for a given baudrate and filter type, there is a bijective function g verifying ΔSNR = g(MBW), where ΔSNR is the filter penalty. Before deployment, we measure for 28 and 32GBd/s baudrates, using a specific setup[7], sets of ΔSNR and MBW for ten bandwidth settings of a tunable optical filter (Fig.4a). Similarly to the previous section, this data is used to train DEPLOY. We also evaluate reference bandwidths (RBW) defined as theoretical estimations of MBW based on general knowledge, e.g. baudrate, number of crossed WSSs, filter technology and slot-size. We expect MBW to differ from RBW due to device variability, including ageing. In operation, from MBW feed in current configuration (τ), DEPLOY calculates MBW* as estimations of the monitored BW for candidate configurations (τ*): MBW* = MBW.RBW*/RBW. Using its learning, DEPLOY converts MBW and MBW* into ΔSNR and ΔSNR*: the estimated filter penalties for (τ) and (τ*). The process is illustrated in Fig.4a. DEPLOY then determines SNR* from:

$$SNR^* = SNR + \Delta SNR - \Delta SNR^* + \Delta_R - \varepsilon$$

where SNR is monitored at RX, Δ_R is the calibrated SNR penalty due to baudrate change, and $\varepsilon=0.5$dB an added margin to account for model error. Finally, DEPLOY converts[7] SNR* into BER*, the estimated BER for (τ*).

Experimentally, we emulate ten cascaded filters and filter ageing through initial setting and progressive reduction of bandwidth of a tunable optical filter (TOF in Fig.1). We plot data from a typical run in Fig.4b. The gold class 100G-QPSK connection is first established with high-FEC (HF=28%) and 37.5GHz slot-size. When, because of filter ageing, the HF BER threshold is reached, DEPLOY computes BER estimates for available combinations of FEC and slot-size. DEPLOY then informs ABNO to maintain high-FEC and increase slot-size to 50GHz. This drastically reduces filter penalty and successfully recovers the LP with a 2.10^{-4} BER, within 0.5dB estimation margin. After this first adaptation, the emulated filter cascade keeps ageing and BER reaches the FEC threshold once again. This time, the only option left to DEPLOY is to order a reroute to a new, shorter lightpath (LP2) with reduced filter penalty.

Conclusion

We demonstrated in a field trial a full cross-layer network solution able to steadily operate with minimal margins despite ageing and short-term performance fluctuations. In two use cases, we applied a new machine-learning-based BER prediction methods to adapt capacity to actual margins and to handle BER fluctuations. Under fiber/amplifier ageing, the SDN-based optical testbed dynamically adapted modulation format to upgrade and downgrade capacity according to measured margins. Under filter ageing, we leveraged a new filter-aware BER prediction based on bandwidth and BER monitoring for FEC and slot-size adaptation.

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