Digital Twin-Enabled Optical Network Automation: Power Re-Optimization

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Abstract: A digital twin-enabled network automated power optimization method is proposed and experimentally validated in a ring network. Proposed algorithms prevent SNR degradation during re-optimization, while closed-loop operation further improves SNR estimation accuracy. © 2024 The Author(s)

1. Introduction

Methods to optimize optical networks through per-channel launch power setting (also known as power equalization) have been proposed for a long time [1]. Signal-to-noise ratio (SNR), as a significant criterion to assess the quality of transmission (QoT) of a communication system, can be improved with power equalization. However, when networks are operating for a long time, e.g. in “set and forget” mode or after some unforeseen event that changes the underlying physical layer (e.g., increasing span loss after repairing a fiber cut), power settings hence SNR may become suboptimal [2]. For this reason, it is important to periodically re-optimize the network.

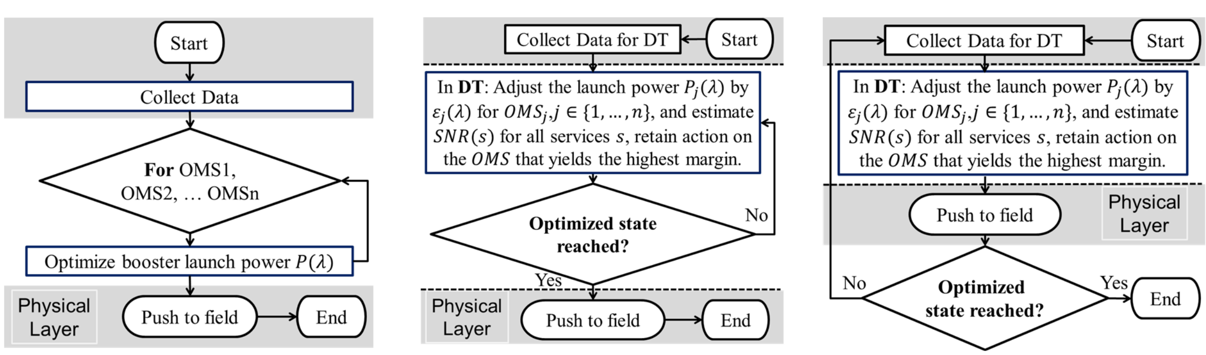
However, as the desired network equalization state cannot be reached at the same time for all Optical Multiplex Sections (OMSes), it is possible that the SNR of the service to be re-optimize actually decreases during the equalization process, before increasing again and reaching the desired value. This may be caused by nonlinear inter-channel noise or power transfers phenomena across the channels when power changes on one OMS propagates to further OMSes [3].

Hence, network-wide re-optimization and autonomous optical networking require the ability to search an appropriate sequence of OMS actions and automatically adjust channel powers, enabled by SNR estimation or real-time performance monitoring, i.e. a network digital twin (DT). In addition, an accurate SNR estimator requires accurate knowledge of the physical parameters, in which their values may be unknown, incorrect, or outdated when powers are changed during the re-optimization process. Online monitoring and updating of the physical parameters to close the monitoring–decide–act control loop is needed for accurate SNR estimation [4].

In this work, we propose open-loop and closed-loop digital twin-enabled algorithms to find the sequence of actions for power re-optimization, and experimentally validate the methods in a ring optical network consisting entirely of commercial equipment. Network SNR margin is improved by 1.5dB with re-optimization. With a naïve sequential single-step method (baseline), the margin drops by 0.7dB (reaching only 0.3dB) during re-optimization, while the proposed method keeps the SNR ascending. Moreover, a parameters refinement technique based on online monitoring maintains the DT performance without all monitoring information of physical layer.

2. Network Automation Algorithms for Booster Launch Power Re-Optimization

Re-equalization consists of adjusting the per-channel booster launch power (using the wavelength selective switch (WSS) located before the booster) OMS by OMS in a certain sequence. Some arbitrary, pre-defined ordering may be



(a) Baseline: sequential, open-loop. (b) Proposed; open-loop. (c) Proposed; closed-loop.

Figure 1. Work flow for the power re-optimization algorithms.

used, e.g., OMS1-OMS2-...-OMSn, as shown in Fig. 1(a), which is the baseline. Although this sequential, open-loop (there is no feedback from the network during re-optimization) method is fast, the network SNR margin may degrade during the process.

Instead, we propose 2 DT-enabled algorithms as shown in Fig. 1(b, c); after data collection and DT initialization, the algorithm finds a sequence of actions (power adjustment of all channels on an OMS) with a fixed power step δ; to do so we greedily select the OMS for which the power adjustment of all channels λ maximizes network SNR margin (defined as $\min_s\{SNR(s)\}$, where s is a service).

Open-loop DT-enabled algorithm: re-optimize the network to obtain the optimized state power $P_{j,opt}(\lambda)$ of each wavelength λ on each OMS_j ($j \in \{1,2,\dots,n\}$), then perform the simulation to predict SNR ($SNR(s)$) for each service s assuming adjustment of the booster power $P_j(\lambda)$ by $\varepsilon_j(\lambda) = \delta \cdot \mathrm{sign}(P_{j,opt}(\lambda) - P_j(\lambda))$ of OMS_j; then find the action (and associated OMS) that maximizes network SNR margin, until all the OMSes reach the optimized state. Then push the offline sequence of actions step-by-step to the field.

Closed-loop DT-enabled algorithm: apply the same method to find the optimized state and action for which OMS should be touched, then push the new configuration to OMS. Afterwards, re-collect the online monitoring data to update the DT for the next optimization and SNR estimation, until all the OMSes reach the optimized state.

3. Experimental Setup

Experiments are performed on a network testbed (Fig. 2 and Table 1) automated with our software-defined networking (SDN) framework named AI-Light [5], as shown in Fig. 2. We load 60 services (60% average spectrum usage) from the traffic demands table in Fig. 2 (right) in random order, with "first-fit" allocation (in wavelength) and with the "set and forget" strategy (each service is loaded with a target power, without re-adjusting the powers of the previous services) [2]. Then up to 6dB power discrepancy with ideal target state can be observed as shown in the Fig. 2 (top left) and steps of δ=1dB are used in our DT-enabled algorithm. The re-optimization is required and the instances of target are shown in Fig. 2 (bottom left). We use a Gaussian Noise model-based SNR estimator to implement the DT. The AI-Light controller can automatically collect physical layer parameters as input of the DT to feed the SNR estimator. The span lumped losses uncertainty is assumed to be known (there are emulated with variable optical attenuator (VOA) with known values in our testbed). An optical channel monitor (OCM) is deployed at each optical amplifier (OA) for reference. To mimic realistic networks, the DT may use spectra at amplifiers co-located with WSS only; in this case, we use our parameters refinement technique to improve the accuracy of the DT [6].

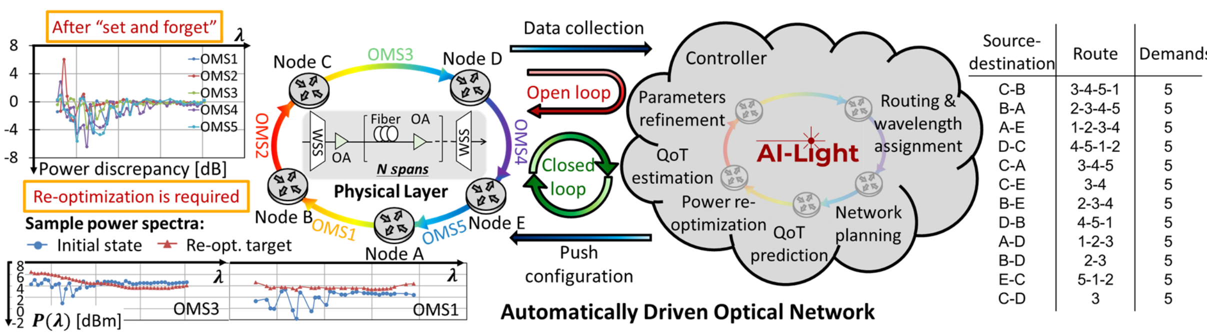
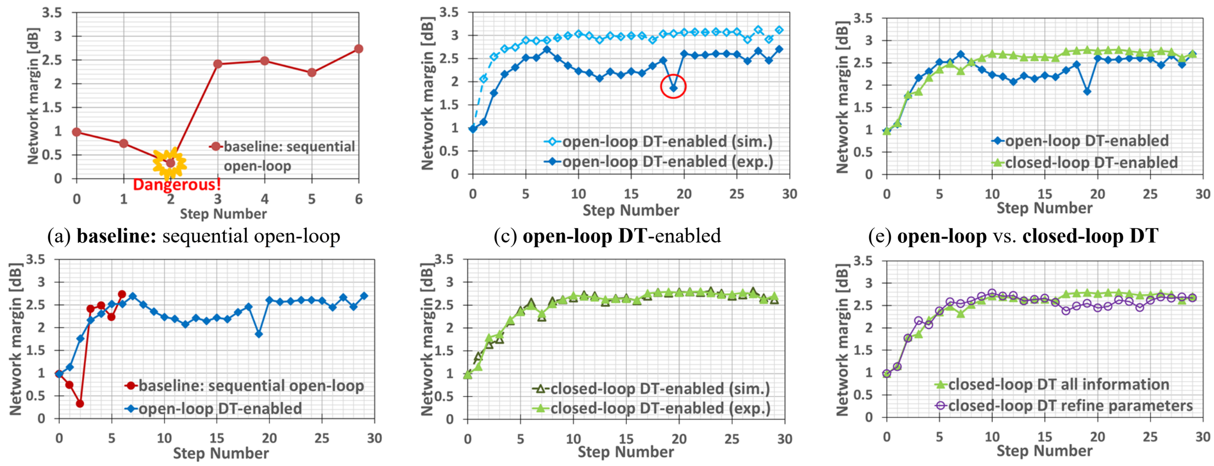


Figure 2. Network automation testbed, digital twin, software-defined networking architecture and traffic demands.

Table 1. Physical layer description. (**All commercial equipment**)

Item	OMS1	OMS2	OMS3	OMS4	OMS5
Number of spans	2	2	5	2	1
Span details	40+80 km LEAF	80+20 km SMF	5x80 km SMF	80 km LEAF + 80 km TW	20 km SMF
Total length	120 km	100 km	400 km	160 km	20 km
Min/Avg/Max span loss [dB]	16.3/18.3/20.9	16.3/18.7/21.0	19.6/19.6/19.6	23.5/23.5/23.5	16.0/16.0/16.0
Span lumped loss uncertainty [dB]	3.5/1.9	1.4/5.0	2.0/2.3/2.0/2.2/1.9	3.2/2.9	6.0
# channels	30	35	45	40	30
Channel information	400 Gb/s (90 Gbaud, CS16QAM) transponder,100 GHz grid in the 6 THz C-band.				



(a) **baseline:** sequential open-loop (c) **open-loop DT**-enabled (e) **open-loop** vs. **closed-loop DT**

(b) **baseline** vs. **open-loop DT**-enabled (d) **closed-loop DT**-enabled (f) **closed-loop DT** with all information vs. parameters refinement

Figure 3. Experiment validation results. Network margin SNR evolution with steps.

4. Experimental Validation Results

We first use all available power spectra (per span) to assess the validity of our method. Fig. 3 shows the network-wide margin for the different scenarios. Fig. 3(a) shows that with the baseline method, SNR first decreases during re-optimization: the margin drops by 0.7dB to 0.3dB, which is very close to the FEC limit. Fig. 3(b) shows that the DT-enabled algorithm addresses the issue: the SNR margin never drops below the initial value during re-optimization. Note that, as the optimization is performed network-wide, re-optimization improves not only the network SNR margin (SNR of the worst channel network-wide), but also other channels' SNR.

The gain profile of each optical amplifier is varying during the power re-configuration; this effect is not considered during optimization by the open-loop algorithm. Consequently, SNR prediction becomes slightly inaccurate with time, as shown in Fig. 3(c) where (sim.) denotes the DT prediction and (exp.) the monitored (ground truth) value. This prediction inaccuracy causes the observed SNR drop (Fig. 3(c), red circle) where the power of the service with worst SNR is different from prediction, leading to a wrong optimization choice in the DT and the SNR drop; Still, the SNR margin is much higher than the FEC limit. By closing the loop, DT can update the input parameters in real-time to improve SNR estimation accuracy, as shown in Fig. 3(d). Though both open and closed loop DT-enabled power re-optimization improve the network SNR margin by 1.5dB without interrupting the other services, the additional information gained through real-time monitoring stabilizes the SNR margin (no oscillation), see Fig. 3(e).

Per-span power spectra are usually not available in commercial networks; we now use only the monitored power spectra at first and last amplifier of each OMS and perform the parameters refinement technique described in [6] to estimate the missing information. As shown in Fig. 3(f), we obtain the same results either with realistic inputs supplemented with the refinement technique, or with full knowledge of all physical layer information.

5. Conclusion

Digital twins will play a significant role in network automation. We propose and experimentally validate DT-enabled power re-optimization algorithms in an open or closed loop environment. We demonstrate autonomous network optimization with a gain of 1.5dB in network-wide SNR margin and prevent the potential risk of out of service. The framework is also validated in the context of unknown parameters, as is customary in realistic networks. As future work, per-span connector losses, which are unknown in real networks, could be estimated with [7] and used in the DT.

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