Digital Twin Enabled Automatic Power Adjustment with Multi-Step Lookahead Prediction

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Abstract *We speed up network automatic power re-optimization by 2x with an algorithm leveraging prediction of SNR variations of all services when power adjustments are made, in a meshed optical network testbed based on commercial products. ©2024 The Author(s)*

Introduction

Quality of transmission (QoT), e.g., signal-to-noise ratio (SNR) optimization methods for optical networks based on Gaussian noise (GN) or machine learning models have been proposed and widely applied [1]-[2]. Since optical networks need to be optimized periodically while ensuring that services are not interrupted during commissioning (service power variation), closed-loop control for optimization based on digital twins (DTs) has been proposed and experimentally validated [3]-[5].

However, the previous works were not demonstrated in meshed networks nor optimized for speed.

In this paper, we present a *fast* approach to optimize SNR margin (related to the system robustness to unforeseen events) as well as system capacity by predicting SNR performance with "multi-step lookahead" operations via digital twins. The method is experimentally shown in a *meshed* network testbed based on commercial products to ensure parallel commissioning safely, i.e., without disturbing existing services.

Principle

Optical transport networks consist of optical multiplexing sections (OMSs): a pair of wavelength selective switches (WSSs) for adding/dropping optical channels (services), N fiber spans and N+1 optical amplifiers (OAs), typically erbium-doped fiber amplifiers. The power spectra at the first OA (booster) and the last OA (preamplifier) are monitored by optical channel monitors (OCMs). The launch power profile of the booster in the OMS can be tuned by adjusting the WSS attenuation profile, so that power equalization can be implemented to optimize the performance of services – e.g., by balancing the amplified spontaneous emission (ASE) and the non-linear (NL) noises to 3dB to optimize services' SNR [1]. In the following, a "power adjustment step" (or "step") denotes the modification of the power spectrum $P_n(.)$ at the booster amplifier of a given OMS_n.

The booster launch power adjustment of an OMS yields power profile modification on the other OMSs by power propagation, possibly leading to disruption of existing services. Hence, a DT should be used to predict the network-wide QoT impact before configuring an OMS. Moreover, the DT needs periodical updates and closed-loop control to ensure the performance, and achieving optimized state may take many small steps, e.g., more than 20 steps to achieve a target state in a 5-node ring network [5]. Then, we can write the total commissioning time T_{tot} as:

$$T_{tot} = T_{update} + T_{sim} + T_{op} \tag{1}$$

where T_{update} is total time consumption for updating the DT, T_{sim} is total simulation time in QoT tool including optimization and SNR estimation/prediction, T_{op} is total operation time for WSS setting. Specifically:

$$T_{update} = \left(\lceil N_{op}/K_{update} \rceil + 1\right) \cdot t_{update} \tag{2}$$

$$T_{sim} = \left(N_{op} + 1\right) \cdot t_{sim} \tag{3}$$

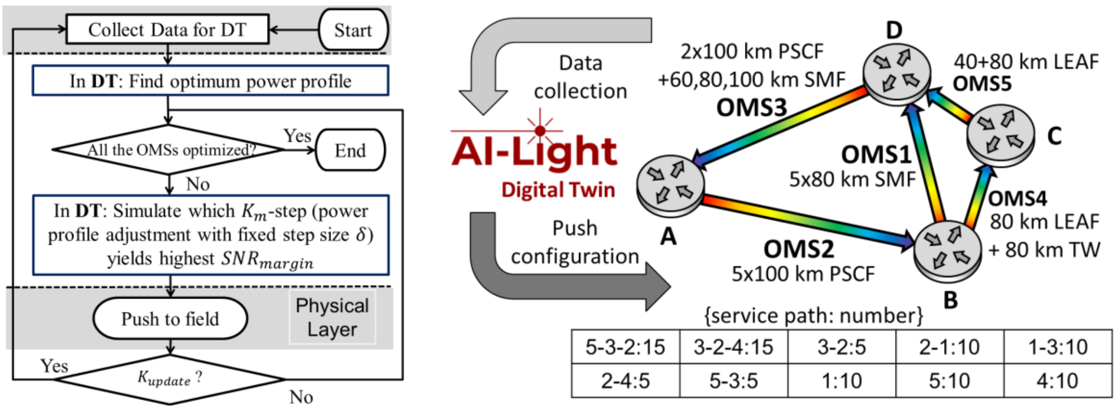
$$T_{op} = N_{op} \cdot t_{WSS} \tag{4}$$

where N_{op} is total number of power adjustment steps, $\lceil\,\rceil$ is the ceiling function, the DT is updated (through monitoring) every K_{update} power adjustment steps, t_{update}, t_{sim}, t_{WSS} are single-step time consumption for updating DT, QoT prediction, and setting WSS, respectively.

In this paper, we reduce N_{op} hence T_{tot}. As chess players consider multiple moves ahead, we propose to predict the consequences of each step on the system margin with multi-step lookahead instead of predicting the one next step only. The network-wide system margin is: $SNR_{margin} = \min(SNR_i - SNR_{FEC})$ for $i = 1, \dots, N_{svc}$, where N_{svc} is the number of services.

The algorithm (see pseudo-code below) leverages DT to find the optimum launch power $P_{n,optim}(\lambda)$ to equalize the noises ASE/NL=3dB for each OMS_n and channel λ and line 10 sets launch power $P_n(\lambda)$ to:

$$\begin{cases} P_{n,optim}(\lambda), & \text{if } \left|P_{n,optim}(\lambda) - P_n(\lambda)\right| < \delta \\ P_n(\lambda) + \delta \cdot \operatorname{sign}\left(P_{n,optim}(\lambda) - P_n(\lambda)\right), & \text{otherwise} \end{cases}$$



(a) Workflow (b) Experimental Setup

Fig. 1: Workflow and experimental setup.

Pseudocode K_m-step lookahead prediction

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Definition N_OMS: OMS number, K_update: DT update iteration number, K_m: lookahead step, δ: power adjustment step size
while not optimized for all OMS
    Update DT
    Find the optimum launch power per OMS
    for k = 1, ..., K_update
        for m = 1, ..., K_m
            for all candidate steps
                for n = 1, ..., N_OMS
                    for λ = 1, ..., N_CH(n)
                        Adjust booster P_n(λ) in DT
                    Power propagation in DT
                    QoT prediction in DT
            Update candidate steps' list
        Find the best K_m steps
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It is important to note that the time complexity of this algorithm to generate the next step is $\mathcal{O}\left(\frac{1}{K_m} N_{OMS}^{K_m}\right)$, hence, the trade-off between K_m and computation power also needs to be considered during commissioning. For a network with N_{OMS} where OMS_n has $N_{span}(n)$ spans, the upper bound for simulation time t_{sim} in Eq. (3) is:

$$t_{sim} \leq \frac{1}{K_m}\left(\sum_{n}^{N_{OMS}} N_{span}(n)\right)^{K_m} t_{sim,span} \qquad (5)$$

where $t_{sim,span}$ is average simulation time per span. If any of the K_m step results in a significant degradation of the SNR, no further simulation of this step will be performed, hence Eq. (5) is indeed an upper bound.

Without considering any parallel data collection for updating DT, the update time t_{update} in Eq. (2) can be written as:

$$\begin{aligned} t_{update} &= \sum_{n}^{N_{OMS}} t_{update}(n) \\ &= \sum_{n}^{N_{OMS}} 2t_{OCM} + \left(N_{span}(n)+1\right)t_{OA} \end{aligned} \qquad (6)$$

where t_{OCM} is time to get power profile by an OCM, t_{OA} is time to collect data from an OA. The parameters refinement [6] technique can be used to estimate the OA gain profile and lumped losses so that power monitoring is only needed for the first and the last OA of each OMS.

If monitoring data for all OMSs is collected in parallel, Eq. (6) becomes:

$$t_{update} = \max_n \left(t_{update}(n) + t_{delay}(n)\right) \qquad (7)$$

where t_{delay} is the communication time between the controller and equipment on OMS_n.

Normally, $t_{update}(n)$ is in the order of seconds while $t_{sim,span}$ is in the order of ms, then $t_{update} \gg t_{sim}$ for $K_m = 1$ and any N_{OMS}. However, it may be not true in some scenarios if $K_m \geq 2$ with a large N_{OMS}.

Compared with [3], our proposed method can reduce N_{op} (thereby reducing T_{update}, T_{sim} and T_{op} and thus total commissioning time) in two aspects: 1. Reduce the risk of falling into a local optimum state; 2. Unlike [3] multi-step lookahead enables parallel OMS optimization while still ensuring SNR of any service does not degrade during intermediate steps, such that the number of steps can be divided by K_m: $N_{op} \rightarrow N_{op}/K_m$.

Experimental Setup

The commercial products-based testbed has a meshed network topology, as shown in Fig. 1(b). The OMSs are heterogeneous, containing heterogeneous fiber spans, and different types of amplifiers. The QoT measurements are performed by a real-time 400 Gb/s (PDM-PCS16QAM) transponder. The WSS grid is set to 100 GHz channel spacing within the 6 THz C-band. 95 services are loaded in the network with a non-optimized state, which has a power fluctuation (emulated following [7] as a Gaussian distribution with 0 dB mean and 1dB standard deviation) due to the channel add/drop process.

The testbed is automated with our software-defined networking (SDN) framework named AI-

Light [8]. The SDN controller collects the data from the physical layer and implements the DT to perform the proposed algorithm. The parameters of the algorithm are: $K_{update} = 2$ (update the DT every 2 steps), $\delta = 1\ dB$ (power adjustment step size). We compare the following 3 scenarios:

- $K_m = 1$ (baseline [7]);
- $K_m = 2$ (2-step lookahead);
- $K_m = 2$ (2-step lookahead) + parallel.

The parallel configuration is carried out by simultaneously adjusting the launch power of K_m OMS given by K_m-step lookahead prediction. As it is impossible to guarantee that all K_m OMS are adjusted simultaneously, the DT checks the impact on SNR for all $K_m!$ possible adjustment orderings.

Simulation and Experimental Results

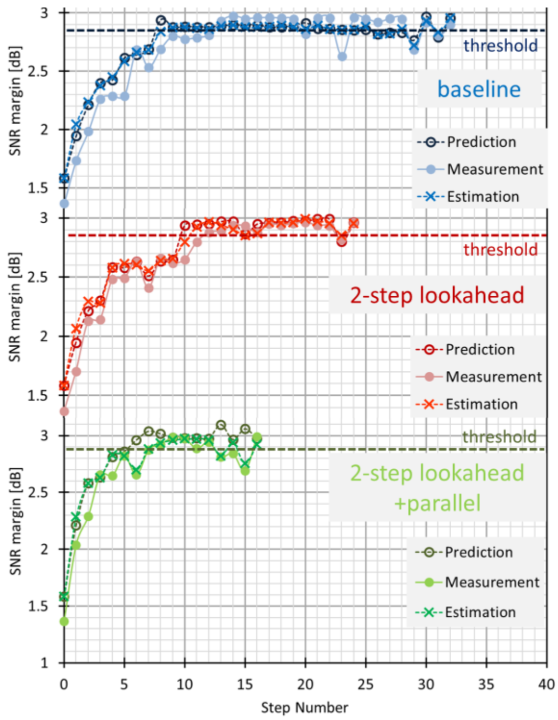
The objective of the optimization is to first improve the system margin SNR_{margin} and secondarily to maximize the overall SNR or total capacity $C = \text{sum}(\log_2(1 + SNR))$. Hence, the metric to evaluate the convergence speed is the maximum number of steps for both SNR_{margin} and total capacity to converge (line 2) i.e., $SNR_{margin}(s) > SNR_{margin,th} = SNR_{margin,DT} - \varepsilon_1$ and $C(s) > C_{th} = C_{DT} - \varepsilon_2$ for step s where $SNR_{margin,th}$ and C_{th} are threshold values, $SNR_{margin,DT}$ and C_{DT} are optimized target values computed by the DT and ε_1, ε_2 are predefined error tolerances.

As shown in Fig. 2(a), SNR_{margin} has been improved by ~1.5dB through power optimization. The plots include DT predicted value before operation (empty circle), measured value after operation (plain circle), and also the DT estimated value after operation (cross). It shows good alignment between results from DT and measurements. The SNR_{margin} converges in only ~10 steps for all strategies (Fig. 2(a)), however, total capacity converges more slowly (Fig. 2(b)). We then evaluate the convergence speed of the proposed algorithm: as seen on Fig. 2(b), baseline takes 32 steps, 2-step lookahead algorithm takes 24 steps without parallelization, and 16 steps with parallelization.

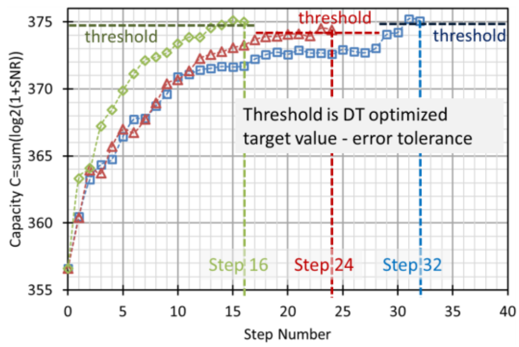
Then, the total commissioning time is re-calculated by applying Eq. (1)-(6). Data collection is not parallel here. The results are shown in Fig. 2(c), normalized to the baseline commissioning time (set to 100 for convenience). Compared with baseline, the proposed algorithm can save 22%/46% of T_{tot} with/without parallelization, respectively. The pie chart reveals that the major cost of T_{tot} is DT updates, indicating that increasing K_{update} to reduce update times could further save time.

Conclusion

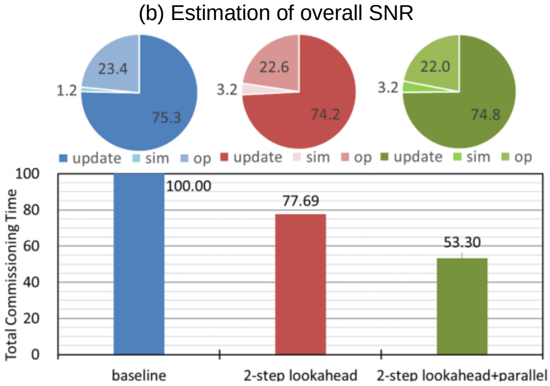
We propose and experimentally validate a DT-based multi-step lookahead prediction algorithm to reduce the total steps of operation N_{op} needed for network optimization. Consequently, the total commissioning time T_{tot} is significantly reduced. Moreover, the time contribution of T_{tot} is also evaluated so that other methods to reduce T_{tot} can be performed.



(a) SNR_{margin} variation during commissioning



(b) Estimation of overall SNR



(c) Total commissioning time (normallized)

Fig. 2: Simulation and experimental results.

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