986 km Field Trial of Cascaded ANN-based Link-Penalty Models for QoT Prediction

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Abstract: Cascaded ANN-based link penalty models are developed and demonstrated for QoT predictions over a 986-km field trial testbed, with precision of \pm 0.16 dB. Co-training of ANN models allows network-level QoT prediction feasible. © 2022 The Author(s)

1. Introduction

Quality of transmission (QoT) prediction, one of the essential technologies to enable low-margin automatic optical networks, has recently attracted increasing interest among researchers [1]. Analytical model-based QoT estimation, such as the GNPy software, provides system-level optimization for static operations [2]. However, in low-margin dynamic optical networks, QoTs should be predicted based on traffic payload, link configurations, and other parameters to obtain precise QoTs for dynamic configurations with further reduced link margins. In [3], a point-to-point multi-channel QoT prediction based on artificial neural networks(ANN) was proposed, however, lacking end-to-end solutions in terms of training and deployment. P. Safari, etc., developed a network-wide model for QoT classification based on a deep convolutional neural network (DCNN) model [4]. However, the complex DCNN model strongly depends on network typologies and requires a huge amount of data from the whole network, which makes it infeasible to train and deploy the model in a practical optical network.

In this paper, two cascaded multi-channel ANN models are developed, co-trained, and demonstrated to predict link penalties over a 986-km field-trial testbed consisting of two links and ROADMs. With the two-cascaded ANN setting, the QoT of a channel over the two links is predicted considering traffic payloads in two links with precision of \pm 0.16 dB. The co-training of the two cascaded penalty prediction models also provides a feasible solution to provide network-level QoT predictions.

2. Network-level QoT Prediction with Cascaded Traffic-aware ANN-based Penalty Models



Fig. 1: Performance degradation vs. count of neighbor channels

To scale up the point-to-point QoT models for network-level prediction, a link-level traffic-aware penalty prediction model is necessary. It should include features such as the Q-factors of the signal before propagation and its adjacent traffic payloads. To understand the impact of the adjacent channels, an optical channel with 32Gbaud PM-16QAM Nyquist signals is used to test the impact of the neighbour channels over two transmission links with different distances (493 km and 986 km). As shown in Fig. 1, the existence of the most adjacent 8 channels dominates the QoT performance due to nonlinear effects. So in our design, 8 neighbour channels are considered to achieve a channel-aware design. Figure 2(a) presents the designed multi-channel traffic-aware ANN-based penalty model for each link, which estimates the penalties from the optical fibre link and the ROADM. In the design, the ANN model consists of an input layer, an output layer, and two hidden layers. The input layer consists of 24

inputs, including neighbour channel availability and Q-factors of the input channels. Both hidden layers include 24 neurons. The output layer is of the dimension of 1×12 , with each element presenting the output Q-factors of the specific channel.

Similarly, the ANN-based penalty model for the second link can be designed with the same architecture. With the two penalty models and the input Q-factors, the performance of optical channels that transmit along the two links can be predicted by cascading the two ANN-based penalty models. In order to train the two models, Q-factors for all input and output signals should be measured. However, in the intermediate node, QoTs of the optical channels that transverse two links are impractical to obtain without dropping operation, which makes the training for the second ANN model cumbersome. So in this paper, a co-training mechanism is proposed to train the ANN model for the second link. The trained ANN model 1 is used to predict the intermediate QoT values of the channels, which are fed into the second link ANN model to train and inference the following ANN models, as shown in Fig. 2(b). With the two cascaded ANN penalty models, the penalty of a channel over two links can be predicted. The co-training of the cascaded models paves the way to train network-level ANN-based penalty models in practical networks.



Fig. 2: (a) Structure of the designed ANN models; (b) Two cascaded ANN-based penalty prediction model with inference of ANN1 as input for ANN2; (c) Experimental setup of the 986-km field-trial.

3. Field-trial Experimental Setup and Results

3.1. Testbed and field-trial setup

Figure 2(c) presents the 986-km field trial setup, which includes three nodes, and two optical links over part of the UK National Dark Fiber Facility (NDFF) that connects multiple sites with commercially available fibres and equipment. At node A, 12 optical channels with 32Gbaud real-time Nyquist PM-16QAM optical signals are generated with two Facebook Voyager transponders and two ADVA FSP3000 Teraflex platforms and then are aggregated into the same fibre via a wavelength selective switch (WSS). All signals are packed into a 50GHz grid with wavelengths ranging from 1546nm to 1551nm. At Node B, a two-degree route-and-select ROADM is deployed using two WSSs to switch, add and drop optical channels. In Node C, another WSS is deployed to separate WDM channels to individual receivers.

In Node B, by configuring the ROADM, some channels transmitting from Node A will be dropped according to the spectrum allocation, and then sent back to the corresponding receivers for detection and measurement. New optical channels will be added through the ROADM and join the remaining optical channels from Node A together, which will be sent to the second link. After 493 km fibre link, all signals are separated with the WSS and sent back to the transponders for Q-factor measurements at Node C. The two links used in the setup are part of the NDFF from the Bristol (UoB) to the Powergate bypassing Bradley Stoke, Froxfield, and Reading. As shown in the inset of Fig. 2.(c), two pairs of dark fibres with EDFAs provide connections between Node A to Node B, and from Node B to Node C. With this setup, all the transponders and the switching devices are located at Bristol for easy setup and configurations. All transponders and WSSs are controlled through centralized SDN controllers. Control agents are developed with the REST APIs to configure transponders and enquire about signal qualities. Through the control agents, spectrum allocations in both links can be dynamically configured.

In the experiments, the optical connections between devices, including transponders, four WSS, and the input/output ports of two NDFF optical links, are managed by a large-scale optical switch for reconfiguration. By configuring the optical switch, optical signals dropped at different nodes will be sent back to the corresponding transponder for BER measurements, which are converted to Q-factors during data processing. With this configuration, 1306 data samples with different channel payloads at both links, and Q-factors measured at three nodes have been collected from the field trial.

3.2. Experimental results of cascaded ANN-based penalty models and discussions

As shown in Fig. 2 (b), two ANN-based penalty models for the two links are required to provide end-to-end QoT predictions. In total 1306 data have been collected from the testbed, while 80% data were set as training and others as validation. Each model provides traffic-aware optical link penalties for all input channels, caused by transmission impairments (inc. nonlinear effects, link loss) and ROADM-based configurations. To generate the required data for training two ANN models, 12 input channels in both links are reconfigured with "On" and "Off" states to generate some combinations of different channel payloads.

Regarding the ANN1 for the first link, a similar training and optimization approach in [3] is adopted with the obtained data. The trained ANN1 model for link 1 is evaluated with three error metrics and high precision is obtained, as summarised in Table 1. In terms of ANN2 for the second link, two different datasets are used to train



Fig. 3: Results of the trained ANN-based penalty models: (a) learning curves of ANN2 model with individual training or co-training, (b) predicted Q-factor vs. the measured Q-factor for end-to-end performance with cascaded models, (c) predicted Q-factor vs the measured Q-factor for end-to-end performance, and (d) distribution of prediction errors for predictions with co-trained ANN2 model.

the model. The first dataset is obtained by dropping all optical channels from Node A for Q-factor measurements as the input of ANN2, which is referred to as individual training. The second dataset is to use the trained ANN1 to infer the Q-factors for all the optical channels from Node A. The training with this dataset is referred to as co-training. The co-training does not require intermediate Q-factors, and therefore, allows for practical deployment for end-to-end QoT predictions.

Figure 3 depicts the results of the ANN2 model for the second link. The learning curves of the ANN2 model training with different datasets, i.e., individual training with full measurements and co-training with inferences of ANN1 are presented in Fig. 3(a). Fig. 3(b) shows the comparison of the prediction Q-factors with the measurements of the two ANN models for both links. With the two ANN models for the two links, the end-to-end performance for optical channels transversing both links can be predicted by cascading the two models, as shown in Fig. 3(c). The prediction error of end-to-end is presented in the Fig. 3(d), which shows that all the prediction errors are within ± 0.16 dB, which is degraded from ± 0.13 dB for two individual ANN model. The performance degradation is caused by transferred errors from cascading. The error metrics of the two ANN models and the cascaded models are summarized in Table 1. It can be seen that the implemented ANN models perform with low mean square error (MSE) around 0.005, and mean absolute error (NAE) around 0.045. The high prediction accuracy up to 99% of R-square score (R2) validates the feasibility of ANN model cascading and the capability to be scaled up.

4. Conclusion

In this paper, cascaded ANN-based traffic-aware link penalty prediction models are proposed and demonstrated over the 986 km field trial to provide end-to-end QoT predictions with a prediction error within 0.16 dB. The proposed co-training methods use the trained penalty models for previous links to provide the required data that is impractical to obtain in practical networks for the following link, providing a possible way to train all link penalty models in a complex network topology. By cascading the link penalty models, network-level QoT prediction can be achieved.

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