Yan, S., Khan, F. N., Mavromatis, A., Fan, Q., Frank, H., Nejabati, R., Lau, A. P. T., & Simeonidou, D. (2019). Field Trial of Machine-Learning-Assisted and SDN-Based Optical Network Management. In *2019 Optical Fiber Communications Conference and Exhibition, OFC 2019 - Proceedings* [8696730] (2019 Optical Fiber Communications Conference and Exhibition, OFC 2019 - Proceedings). Optical Society of America (OSA). <https://doi.org/10.1364/OFC.2019.M2E.1>

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Field Trial of Machine-Learning-Assisted and SDN-Based Optical Network Management

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Abstract: In this paper, we reported machine-learning based network dynamic abstraction over a field-trial testbed. The implemented network-scale NCMDDB allows the ML-based quality-of-transmission predictor abstract dynamic link parameters for further network planning.

OCIS codes: 060.4256, 060.2330.

1. Introduction

Recent emerging network applications require future optical networks to be more dynamic with fast, highly frequent, and automatic network reconfigurations. Especially, the visioned fifth network (5G) requires network resource in multiple network domains to be provided and allocated in an end-to-end approach, to support the heterogeneous 5G traffic with increasing mobility and volume. The dynamic optical network could reduce margins of optical links, by planning the optical networks in a short timescale rather than the life period of the optical links. The reduced link margins could improve network throughput significantly with a better resource utilization [1].

Software-defined networks SDN have been researched extensively to automate optical networks with network function virtualization, network slicing, and network orchestrations. However, dynamically reconfigured optical networks raises challenges for network reliability and stability. Therefore, the traditional optical performance monitoring data need to be accessed by the centralized SDN controller. Therefore, the monitoring data scattered in different optical nodes can be processed jointly to provide a global view of network states and offer proactive information to support automated network operations. Thus, machine learning technologies could play a pivot role to dynamically abstract network states by analyzing all the information from network monitoring and network operations.

In this paper, machine learning technology is explored over a network-scale network configuration and monitoring database (NCMDDB) which is implemented and running on a field-trial testbed based on UK national dark fiber facility (NDFIS), with extended works from [3]. The field-trial testbed connects Bristol and Froxfield with a 336.4 km fiber link. The implemented NCMDDB stores network configurations, all the related optical performance monitoring data, and the facility operation data over the link. To reflect the dynamics of optical networks, for the first time, the NCMDDB linked physical parameters from transmitters, EDFAs, and receivers, to network operations. Machine-learning based network abstraction application is developed to predict link performance based on current network operation parameters, therefore, to achieve dynamic network abstraction.

2. Field-trial testbed implementation

Figure 1 shows experimental setup of the field-trial testbed. It consists of parts of the national dark fiber infrastructure service (NDFIS) from Bristol to Froxfield, and several extra nodes in the lab. The programmable transmitter sets are located in the lab. Two sets of PM-QPSK transmitters are used to generate multiple-channel PM-QPSK signals. The IQ modulator is driven by four 28 Gbaud electrical signals, which are generated by a high-performance FPGA. Another eight ECLs are modulated by another IQ modulator driven by a 32 Gbaud pulse pattern generator (PPG), to generate 32 Gbaud PM-QPSK signals. The testing channel is the implemented probabilistic-shaping based spectral efficiency (SE) tunable transmitter (PS-BVT) with a dual-channel arbitrary waveform generator (AWG). The PS-BVT is operated at 28 Gbaud with a spectral efficiency adjustable between 2-4 bit/s/Hz per polarization. The spectral efficiency can be configured as 2.8, 3.2, 3.6 and 4 bits per polarization. The PS-BVT signal is located in the center while other 16 channels of optical signals act as the neighbor signals. All the generated optical signals are combined

Fig. 1: Field-trial testbed for machine-learning applications

by a 4×16 spectrum selective switch (SSS). An optical spectrum analyzer (OSA) measures the optical spectrum of the multiplexed optical signal to assist the SSS for automatic gain equalization.

Then the signal is launched into a 50-km fiber link in the lab. After the 50-km transmission, the signal is sent to the NDFIS link. As shown in Fig. 1, the NDFIS link consists two nodes with loop-back configuration at the Froxfield node. Each node includes an 8×8 fiber switch which enables port switching and manages node functions in the architecture-on-demand approach. After the NDFIS loop-back link, the signal was sent to another 50-km fiber link in the lab. The link distances of the two links in the NDFIS are 23.6 km and 94.6 km. The length of the link over multiple nodes is 336.4km. After the link transmission, the testing channel is demultiplexed by another SSS for coherent detection. A polarization-diversity coherent receiver detects the optical signal. Then, the electrical signals are sampled for analog-to-digital (A/D) conversion using a real-time oscilloscope and processed offline to perform the normal digital signal processing operations.

Fig. 2: (a) Spectra of optical signals in selected scenarios; (b) Sample data of the EDFA in Node Froxfield.

3. Data collection in NCMDB

The NCMDB is designed to store the whole network states, including both the network configurations and network performance monitoring data. The NCMDB is deployed as a centralized information hub to collect all the information related to network configurations and to expose the collected data to the network analytics applications and the SDN controller. The implementation of the database is comprised of three collections for each connection, (1) Transmitter information, (2) Optical path information, (3) Receiver information.

The lab controller as shown in Fig. 1 controls all the device and facilities through variable communication protocols. The ECLs, modulators, SSSs, and coherent receivers can be configured by the lab controller. To generate a big amount data, the scenario generator will generate different network scenarios with different allocations of the neighbor channels. The different scenarios allow the NCMDB to collect more data to train the ML-based QoT predictor. Some optical spectra of the launch signals in different scenarios are shown in Fig. 2a. Figure 2b showed the collected the input power and oputput power of one EDFA in the link for different scenarios.

4. Machine-learning based dynamic network abstraction

With the implemented NCMDDB, novel network applications can be developed to use both the historical and current network information. In this paper, dynamic network abstraction is achieved by exploiting various link and signal parameters stored in the NCMDDB.

The ML model used in our work is a multi-layer perceptron (MLP) artificial neural network (ANN) comprising of an input layer, one hidden layer and an output layer as shown in [2]. We selected tangent-sigmoid and linear activation functions for the hidden and output layer neurons, respectively. For the offline training, we first generated a data set of 20 vectors p comprising of different link/signal parameters (as mentioned above) by using the monitoring database. Each data set includes all the recordings for each network scenario. The OSNR is calculated based on the uploaded spectral data that measured in different nodes, as indicated in Fig. 1. For ANN training, we make use of a supervised learning method called Levenberg-Marquardt (LM) backpropagation (BP), whereby vectors p are applied at the input of ANN while OSNRs are used as targets, as shown in Fig. 3(a). Different ANN parameters are then optimized such that the mean-squared error (MSE) between the ANN outputs y and targets, i.e. $\|y - \tilde{o}\|^2$, is minimized over the whole training data set. After training, the ANN-based model is able to predict the performance (in terms of OSNR) of various unestablished paths in the network. To test that, an independent data set comprising of 14 vectors p is applied at the input of trained ANN and the corresponding outputs y then provide OSNR estimates for the unestablished lightpaths.

Figure 3(b) shows the results of OSNR monitoring for the 14 test cases. It is clear that OSNR estimates are quite accurate and the mean estimation error is < 1 dB. In addition, we investigated the mean OSNR estimation error with an increase in training data set size. Figure 3(c) shows mean error saturates at around 0.5 dB for training data set sizes in excess of 22. The average computation time required for a single OSNR prediction is determined to be 0.5 ms. The above results clearly demonstrate that the proposed ML-based OSNR monitor predictor can be used as a reliable and effective tool to abstract network impairments in SDNs.

Fig. 3: (a)MLP-ANN model with link/signal parameters vectors p as inputs and estimated OSNRs y as outputs; (b)True vs. estimated OSNRs using the proposed technique. The true OSNRs are obtained using an optical spectrum analyzer (OSA) for comparison purposes; (c)Mean OSNR estimation error for different training data set sizes using the proposed approach.

5. Conclusion

Machine-learning based network abstraction provides an effective tool to handle the dynamic characteristics in software defined networks. Over the field-trial testbed, the ML-based QoT predictor could abstract network impairments with a reasonable precision.

6. Acknowledgements

The authors acknowledge funding support from the UK EPSRC (INSIGHT (EP/L026155/2) and TOUCAN (EP/L020009/1)), the EU H2020 project(Metro-Haul,761727), and from Hong Kong Government General Research Fund (PolyU 152757/16E).

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