Field trial of Machine-Learning-assisted and SDN-based Optical Network Planning with Network-Scale Monitoring Database

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Abstract An SDN based network planning framework utilizing machine-learning techniques and a network-scale monitoring database is implemented over an optical field-trial testbed comprised of 436.4-km fibre. Adaption of the spectral efficiency utilising probabilistic-shaping BVT based on link performance prediction is demonstrated.

Introduction

Software-defined optical networking (SDN)[1,2] enables centralization of control, provides a network-wide view and eases network programmability. As such, SDN facilitates the implementation of user-defined and application-specific complex data collection, monitoring techniques and the employment of emerging data analytics and machine-learning (ML) techniques on top for network management.

In this paper, for the first time we demonstrate in a field trial a novel network planning framework for optical networks. The proposed framework utilises an SDN controller and a novel elastic data based platform, designed for big data, to collect real- time optical network monitoring information from various points across network and network configuration information. The framework also incorporates a ML-based performance prediction mechanism and an SDN controller to control probabilistic-shaping-based bandwidth variable transmitter (PS-BVTs) and network switching elements in order to adaptively maximize network capacity.

An SDN-based network planning over the 436.4km-field trail testbed is demonstrated with the ML-based OSNR predictor. The developed PS-BVT provides a fine spectral-efficiency granularity, to maximize link capacity based on the predicted link performance. The centralized network-scale database opens new possibilities for big data analytics for optical networks.

Field trial demonstration and key enabling technologies

Figure 1 shows the SDN testbed with a total 436.4km optical path over the national dark fibre facility (NDFIS) in the UK. The test data plane includes five nodes, of which three nodes are located in the NDFIS field trial testbed. The Node A and Node E are located in our lab and connected to NDFIS by two 50km fibres. A developed SDN controller dynamically monitors and configures the data plane. A scalable and integrated database is used to store all the network configuration information from the control plane and monitoring information from the data plane device through optical performance monitoring. Machine learning applications, running on top of the database retrieve monitoring data from the database, to predict link performance. The SDN controller interfaces with the database to push information about the network paths that configures and to query the

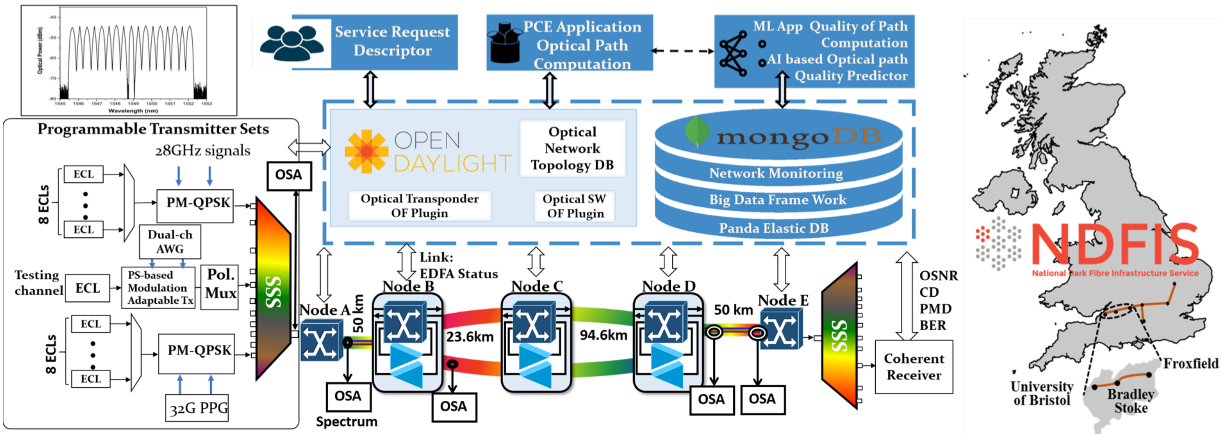

Fig. 1: Field trial demonstration of SDN-based network planning based on machine-learning network abstraction.

database for predictions on network information.

In node A, programmable transmitter sets are deployed. 16 external cavity lasers are modulated by three IQ modulators to obtain 28/32 Gbaud PM-QPSK signals. The testing channel is implemented with a two-channel 50Gs/s arbitrary waveform generator. Probabilistic shaping technology is used to obtain different spectral efficiency. To shape the input distribution, we start with the family of Maxwell - Boltzmann distributions and iteratively optimize the parameters to obtain 16QAM distributions with entropies 2.8, 3.2, 3.6 and 4 bits per polarization. Thus, the PS-BVT could be configured to adapt the spectral efficiency according to the OSNR budget of the link. All these signals are multiplexed together by a spectrum selective switching (SSS), which also equalizes all the channels automatically. The spectrum of the equalized signal is shown in the inset of the Fig.1.

As shown in Fig.1, Node A is connected to node E through node B, C, and D. For each node, a fibre switch (Polatis) is used to configure the cross-connection and deploy an EDFA to boost signal power. At the receiver node, the signal is firstly demultiplexed by a 4×1 SSS, then received by an intradyne coherent receiver.

Network configuration and monitoring database (CMDB)

The CMDB is designed to record all the information linked to each transmitter. To assess and provide scalability to the field trials information, a schema free NoSQL MongoDB database has been designed and developed implemented over the aforementioned SDN test-bed. The MongoDB has a hierarchical document-based data model design using JavaScript Object Notation (JSON) as the file format for recording real time information. This is a solution capable to support the complex data structures recorded throughout the experiments and therefore being stored to the respective database collections.

All the network configurations from the SDN controller will be pushed to the CMDB. In addition, the CMDB is connected to all the available optical performance monitors, including optical power, optical spectrum, and other parameters. In principle, all the stored information includes the current and previous information about the whole network.

In our experiments, CMDB stores each transmitter's capability (modulation adaptability), previous configurations, and characteristics. The link information, which is linked to transmitters, includes input/output powers of deployed EDFAs, noise figures, and other link parameters. At the receiver side, DSP-based monitoring information are recorded. In addition, the spectrum information at some nodes are also be stored. On top of the database, multiple data analytics applications can run in real- time[3].

Machine-learning based network abstraction

OSNR have been used as an indicator for QoT. In this paper, a ML-based OSNR monitor/predict is developed to estimate link performance and predict link performance for better network planning.

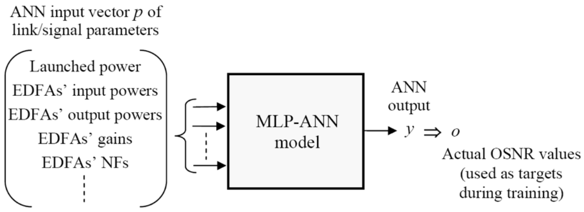

Fig. 2: MLP-ANN model with link/signal parameters vectors p as inputs and estimated OSNRs y as outputs.

For OSNR monitoring at a given node, we make use of a multilayer perceptron (MLP) artificial neural network (ANN) trained using various link and signal parameters extracted from the monitoring database. A supervised learning method i.e. Levenberg-Marquardt (LM) backpropagation (BP) is used for the offline training of ANN. During the training process, vectors p comprising of different link/signal parameters (such as launched power, EDFAs' gains, EDFAs' input and output powers, EDFAs' noise figures (NF) etc.) are applied at the input of ANN while the known OSNR values o at a given node corresponding to these parameters are used as targets, as shown in Fig. 2. All the link parameters are retrieved from the CMDB. Different ANN parameters like number of hidden layer neurons, biases for the neurons, and weights of interconnections between adjacent layers neurons etc. are then optimized such that the mean-squared error (MSE) between the ANN outputs y and targets o, i.e. ||y – o||2, is minimized over the whole training data set. After training, the ANN is used to predict the unknown OSNR values y at a given node by applying the relevant

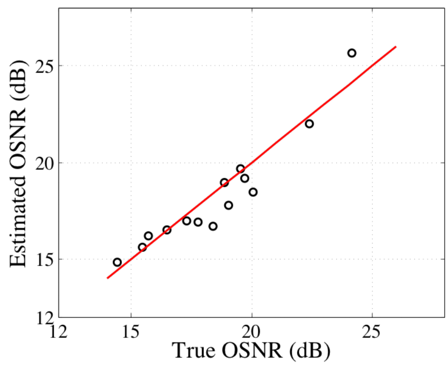

Fig. 3: True OSNR versus estimated OSNRs using the proposed approach. The true OSNRs are determined using an optical spectrum analyzer (OSA) for comparison purpose.

vectors p of link/signal parameters at its input. Figure 3 shows the results for OSNR monitoring at a given node using the proposed approach. The results demonstrate that the ANN-based monitor can estimate OSNRs with reasonably good accuracies. For the unestablished path, the OSNR could be predicted for network planning.

Probabilistic-shaping based BVT

Spectral-efficiency (SE) adaptable transmitter is one of the key technology for link optimization. For a given link budget, a fine-granularity SE adaptable transmitter can maximize the link capacity. In this paper, a probabilistic-shaping information variable transmitter is developed to provide a fine SE adaptability. To shape the input distribution, we start with the family of Maxwell - Boltzmann distributions and iteratively optimize the parameters to obtain 16QAM distributions with entropies 2.8, 3.2, 3.6 and 4 bits per polarization. Thus, the PS-BVT could offer three spectral efficiency between QPSK and 16QAM.

SDN demonstration with ML and PS-BVT

The setup of the demonstration is depicted on Fig. 1. User requests are emulated and submitted to the SDN controller. Each user requests from the SDN controller to connect a source to a destination at a particular bandwidth. The SDN controller leverages the path computation application to calculate a suitable path for the user request and then finds a set of available wavelengths for the transmission. The ML application is then queried to provide a prediction on the link bandwidth and the modulation to use across the path for the different available wavelengths. The first available wavelength that meets the user bandwidth requirements is chosen for the transmission. The SDN controller then configures appropriately the optical switches using OpenFlow, the Wireshark logs are shown in Fig. 4 and the transmitter's wavelength and modulation using a custom protocol and informs the user about the request acceptance. The SDN controller also notifies the user in case its request cannot be served due to unavailable path, wavelength or bandwidth. The workflow of the demonstration is depicted in Fig. 5(a)

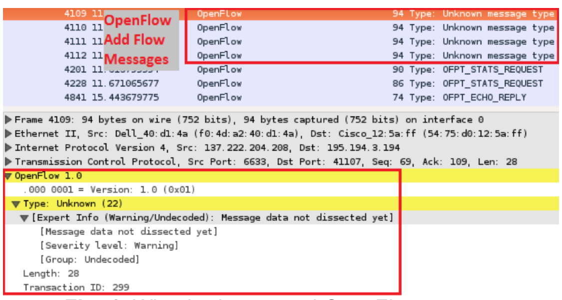

Fig. 4: Wireshark captured OpenFlow messages

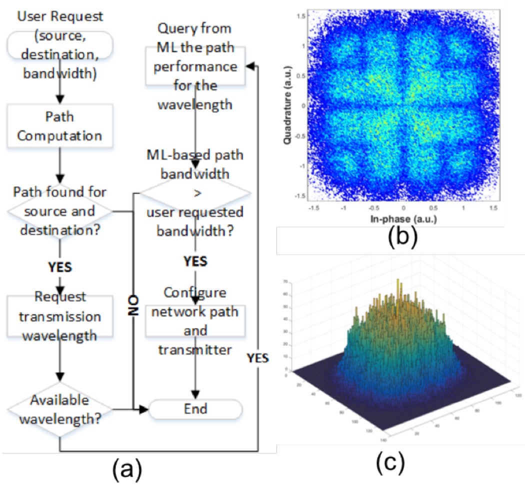

Fig. 5: (a) Workflow of the SDN demonstration; (b) Recovered constellation diagram after392-km transmission; (c) The received constellation distribution.

In the demonstration, the ML algorithm predicts the link performance and return the OSNR at the receiver side around 21 dB and the suggested spectral efficiency is 3.9987. Then the PS-BVT is adapted to shaping then entry of 16QAM to obtained the required spectral efficiency. Figure 5(b) shows the recovered constellations after 436.4-km fibre transmission.

Conclusion

In this paper, we demonstrate the planning of an SDN-based optical network, utilising machine learning mechanisms able to predict link performance in correlation with the OSNR. A monitoring database assess the decision making of configuring a probabilistic shaping based BVT in order to adapt the spectral efficiency accordingly, therefore maximising the link capacity.

Acknowledgements

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References

[1] M. Channegowda et al., "Software-Defined Optical Networks Technology and Infrastructure: Enabling Software-Defined Optical Network Operations [Invited]," *J. Opt. Commun. Netw.*, vol. **5**, no. 10, p. A274(2013).

[2] Y. Li *et al.*, "Transparent software-defined exchange (tSDX) with real-time OSNR-based impairment-aware wavelength path provisioning across multi-domain optical networks," Proc. *OFC*,Th5A.2, Los Angeles (2017).

[3] S. Yan, et al., "Multi-Layer Network Analytics with SDN-based Monitoring Framework [Invited]," *J. Opt. Commun. Netw.*, vol. 9, no. 2, p. A271(2017)