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Dynamic Abstraction of Optical Networks with Machine Learning Technologies^{*}

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Abstract. The emerging 5G network will bring a huge amount of network traffic with big variations to optical transport networks. Software-defined optical networks and network function virtualization contribute to the vision for future programmable, disaggregated, and dynamic optical networks. Future optical networks will be more dynamic in network functions and network services, with high-frequency network re-configurations. Optical connections will last shorter than that of the static optical networks. It's straightforward that Programmable optical hardware will require a reduced link margin to improve the hardware utilization. To configure network dynamically, real-time network abstractions are required for both current links and available-for-deploy links. The former abstraction guarantees the established links not be interfered by the newly established link while the latter abstraction provides information for intelligent network planning. In this talk, we use machine-learning technologies to process the collected monitoring data in a field-trial testbed to abstract performances of multiple optical channels. Based on the abstract information, a new channel can be established with maximum performance and minimized interference on the current signals. We demonstrated the dynamic network abstraction over a 563.4-km field-trial testbed for 8 dynamic optical channels with 32 Gbaud Nyquist PM-16QAM signals. The work can be further extended to support complex optical networks.

Keywords: Machine Learning · Network Abstraction · Low-Margin Networks.

1 Introduction

Optical networks have becoming the essential infrastructure for the future fifth generation (5G) networks. 5G transport networks, including fronthaul, middle-haul and backhaul networks, rely on optical network infrastructure [19]. Optical

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and wireless converged network architecture was proposed to support operational network and end-user services [20]. In addition, the emerging 5G applications, such as augmented reality applications, require more interactions with computing resource that located either in the cloud or in the edge. Compared to the previous mobile networks, an increased proportion of mobile traffic will be sent to metro and core networks. The successful deployments of 5G networks require lot of innovations to be made in optical networks. In 5G networks, a peak data rate up to 20 Gbit/s is provided for per user [12], which is comparable to optical channel capacities in optical networks providing 100G Ethernet standard still dominates the market [6]. Therefore, dynamic network traffic with big variations in 5G networks need to be supported by a flexible and dynamic optical network.

On the other side, optical networks are continuously evolving to be more flexible and dynamic. Software-defined optical networks (SDN) decouple the control plane and data plane, allowing the independent developments of both technologies [3]. Network function virtualization (NFV) brings flexibility of network functions to be configured, migrated or terminated in optical networks. End-to-end network service orchestration can deploy network services over multiple network domains [1, 22]. In the perspective of optical hardware, hardware-programmable network functions have been developed to deliver node functions in an on-demand way [14].

In dynamic optical networks, network services or connections will serve in a short time and high-frequency network re-configurations will be expected in optical networks. From the perspective of network operators or network controllers, it is straightforward that optical networks should be planned at short timescales rather than the end of life (EoL) of network facilities. Network margins part of which were reserved for aging can be eliminated by considering the service life period [17].

Dynamic optical networks with reduced network margins raise many challenges for network operations. One of the key challenges is that network controllers need up-to-date information about dynamic networks to dynamic configure optical networks with a reduced margin. Network abstraction that abstracts information of network states assists network controllers to deploy services according to the current network states. In addition, the abstract process needs to evaluate the impact of the new established services or links on the previous services or links. The latter abstraction function guarantees the established links not be interfered by the newly established link. In margin-reduced networks, the dynamic abstraction becomes more critical. Due to the fast-frequency network re-configurations, the dynamic abstraction need to be continually updated after each reconfiguration with a fast response time.

In optical networks, one of the key information regarding per link is the link impairment, which is affected by operation parameters of network facility and network configurations. Static network abstraction can be achieved by testing link performance in advance [4]. However, the static network abstraction neglects the dynamics in network payloads and other physical parameters. In margin-reduced dynamic optical networks, it is of vital importance to abstract optical

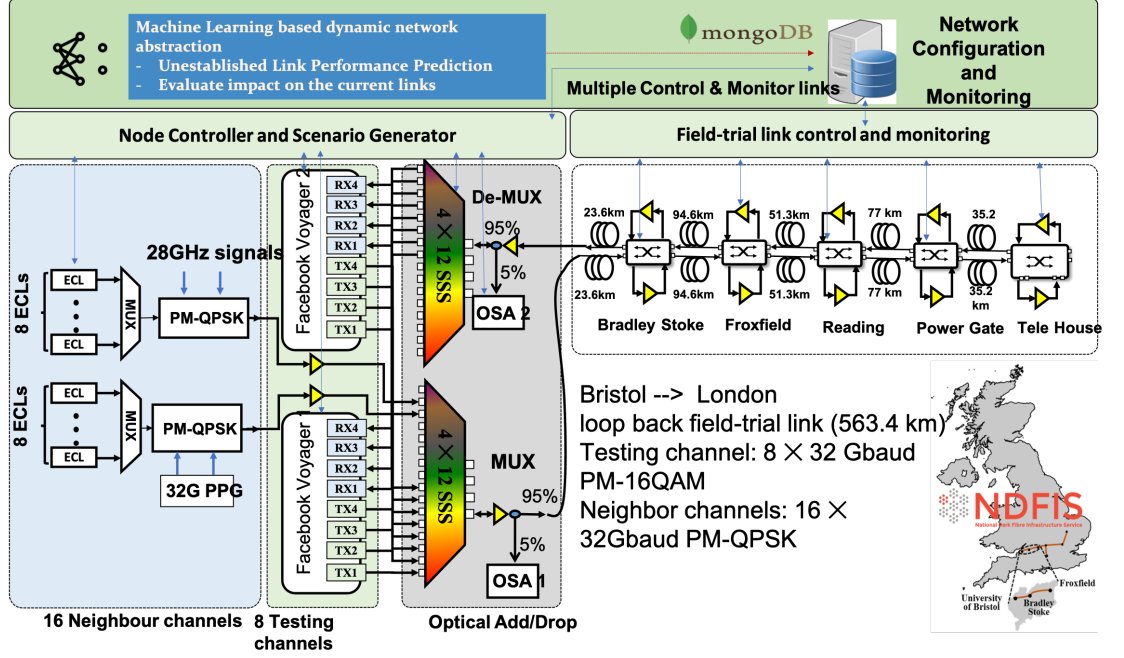


Fig. 1. Field-trial demonstration over a 560-km link between Bristol and London.

network impairments dynamically. Therefore, time-consuming link optimization can be eliminated to support high-frequency network reconfigurations.

In this paper, we explored machine-learning technologies to process the collected optical performance monitoring data and operation data of the key equipment in a field-trial testbed to dynamically abstract qualities of transmission (QoTs) of multiple optical channels. For the first time, we developed machine-learning (ML) based dynamic network abstraction using Random forest regression. The developed ML-based dynamic network abstraction is able to predict the transmission quality, i.e., BERs of the un-established optical channels and to evaluate the impact on the previously established channels. The ML-based predictor can predict the link performance up to 8 channels simultaneously. The evaluation of the current link is essential for a low-margin network. In the demonstration, a field-trial link between Bristol and London is setup with 24 optical channels transmitting over 564 km. A network-scale cloud network configuration and monitoring database (CMDDB) is implemented over the field-trial link based on [15], with extensions to include parameters of EDFA pump lasers, such as pump laser current and temperature. The central 8- channel signals, generated by eight real-time PM-16QAM transponders, are configured dynamically with real-time BER (Bit Error Rate) measurements. Random forest regression based network abstraction algorithm is developed to abstract all the eight channels by the transmission performance. With 4324 training data sets, the developed net-

work abstraction algorithm can predict the performance of the un-established channels based on the current network states. The algorithm can also evaluate the impacts on the previous established channels. The experimental results show the developed network abstraction algorithm could abstract network performance with a high precision. The dynamic network abstraction can assist network controller to deploy new services based on link performance while minimize the disturbance on current services. The work will be one of the potential enabling technologies for a reliable margin-reduced network.

2 Literature review of network abstraction with machine learning technologies

To abstract optical network impairments, multiple technologies have been explored. Gaussian-noise (GN) model has been developed extensively to provide a relatively simple and sufficiently-reliable tool for performance predictions [9, 10]. Considering the complexity in dynamic optical networks, the complex calculation in GN-model prohibits its deployment in practical networks for network planning. Some simplified analytical models have been developed to reduce the complexity in [2, 11]. Such analytical models could be used for general analysis to support network design. Nokia bell labs also reported a similar system design tool to facilitate the design of the terrestrial transmission systems with high-order modulation formats and coherent detection technologies [7]. In [5], an open source QoT estimator was developed with the capability to predict performance with an accuracy of $\pm 0.75\text{db}$. This kind of analytical models can't provide precision predictions to reflect the impairments, especially the dynamic impairments in optical networks. Therefore, these tools were mainly used at the network design phase. In margin-reduced networks, more precise QoT estimation with a short computation time is required. The QoT prediction needs to be done for each operation.

Thanks to the advance of machine learning technologies, many researchers started to explore network dynamics in optical networks with advanced machine learning technologies. Artificial neural network based QoT prediction algorithms have been developed to predict the performance of the un-established optical channels [8, 13, 15]. Most of the previous works use network configurations, such as modulation formats, link distance, fiber parameters, to predict the QoT of the unestablished channels. In such case, the QoT-prediction actually neglects the dynamics in optical devices, especially the active devices, whose operation parameters affect the transmission performance significantly. The developed QoT prediction algorithm worked well in the collected data in a short time. However, failure to handle dynamics in optical device will lead to inaccuracy of QoT estimations in long term. In [15, 16, 21], we built a cloud network configuration and optical performance monitoring database to collect the physical parameters over the whole network. ANN-based QoT prediction was developed to predict a single channel. Combining with network configurations, the developed ANN-based QoT prediction algorithm is able to handle the dynamics in optical networks,

which could be reflected in the operation parameters in optical devices. In this paper, we further developed the concept to dynamic optical network with multiple channels.

3 Field-trial demonstration of dynamic network abstraction

Figure 1 shows experimental setup of the field-trial testbed. Total 24-channel optical signals are generated with three sets of transmitters in our lab. Eight external cavity lasers (ECLs) are combined together and then modulated with a dual-polarization IQ modulator to generate 8×28 Gbaud PM-QPSK signals. The IQ modulator is driven by four 28 Gbaud electrical signals, which are generated by a high-performance FPGA. In a similar way, 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. Another 8-channel real-time Nyquist PM-16QAM signals are generated by two Facebook Voyager transponders, which also provide BER measurements of per channels. The total 24 channel optical signals are multiplexed together by a 4×20 Wavelength Selective Switches (WSSs). After auto equalization, the combined 24-channel signal is launched to the 563.4-km fiber link between Bristol and London. The optical spectrum of the 24-channel optical signal is shown in Fig. 2. In this paper, the developed dynamic network abstraction will focus on the dynamic channels as indicated in Fig. 2. The node controller and scenario generator controls the three transmitter sets and WSSs. It can generate any combination with different channel slot "on". By configuring the three transmitter sets, various network scenarios with different channel distribution can be configured.

The used link which is part of the national dark fiber infrastructure (NDFIS) includes five intermediate nodes. Each intermediate node includes EDFA, DCM and a Polaris fiber switch to allow remote reconfiguration and monitoring of the fibers and amplifiers. The fiber switch monitors the launch power of each span. The operation parameters of the EDFAs are sent back to the cloud monitoring database. The launch power for each span was estimated using incoherent GN model. After transmission over the field-trial link, the signals are demultiplexed by another 4×20 WSS. Then the BER measurements will be carried out for each channel. The BER measurements of the 8-channel PM-16QAM signals are also collected and sent to the cloud monitoring database.

3.1 Cloud Monitoring Database

To dynamic configure a margin-reduced network, network controller requires up-to-date network state information. In addition to the dynamic network payloads (spectrum allocations), operation states of the key infrastructure in the link can provide in-depth information to abstract link impairments. The EDFAs in the link contribute to the most OSNR penalties. On the other hand, optical powers

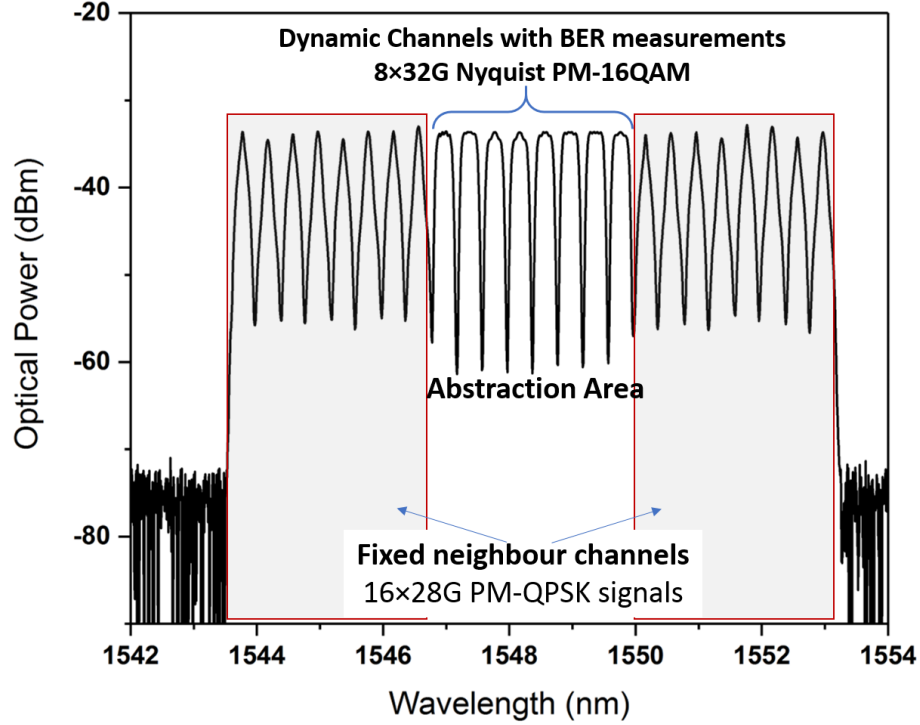


Fig. 2. Optical Spectrum of the 24-channel optical signal. The dynamic abstraction focuses on the 8x32 Gbaud PM-16QAM signals.

play a significant role for nonlinear effects, which limit the maximum transmission distance. Thus, a cloud monitoring database (CMDB) is implemented to collect network configuration information, operation information of key infrastructure, and the quality of transmission per links. The database creates the relationship between network configurations and the corresponding transmission performance. The design of the cloud monitoring database enables reusing of the local monitoring data. The separation of database from the SDN controller allows the possibility to deploy high-performance computing resource to analysis collected data and implement powerful machine-learning algorithms to serve the SDN controller as a network abstraction service.

The proposed CMDB is implemented over the field-trial testbed as shown in Fig. 1. The CMDB collects network configuration information from the SDN controller, such as channel configurations, wavelength, modulations, link lengths. The optical link monitoring information in the CMDB includes optical launch power monitored at each span, operation parameters of all EDFAs, and optical spectrum information at the transmitters and receivers. Regarding EDFAs, the CMDB collects operation information from each EDFA, include temperature

and bias of the pump laser, optical power of the input and output ports, and the noise figure.

3.2 Machine learning based network abstraction

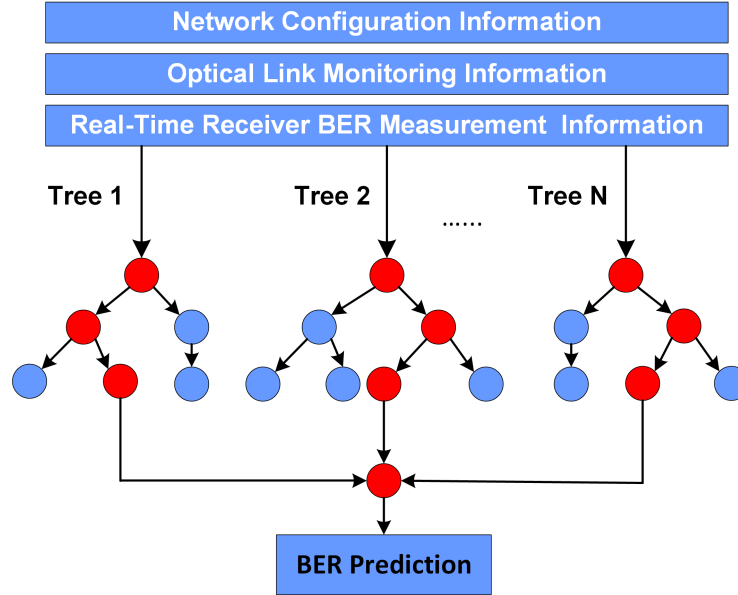


Fig. 3. Structure of BER prediction algorithm based on random forest regression.

Considering that the data contains a lot of features, Random Forest Regression is chosen as a Machine Learning algorithm to predict link performance and evaluate the impact on the current channels. Random Forest is one of the most effective ensemble learning algorithms, which includes N random decision Trees. Its final prediction result is combined from a set of base models, which improve its performance compared with a single model[18]. Furthermore, it handles thousands of features efficiently and runs on big data bases. Figure 3 shows the structure of BER prediction algorithm based on monitoring data from the CMDDB. Monitoring data include three parts: network configuration information, optical link monitoring information and the BER measurements from the 8-channel real-time transponders. In order to improve the accuracy of prediction, the interrelationship of established channels is characterized by One-Hot coding.

In order to generalize the network state, the node controller and scenario generator as shown in Fig. 1 configures the transmitter sets to generate different scenarios of the 8 dynamic channels. We collected 4324 data to train the model. Each data include information about the transmitters, optical links, and receiver-side BER measurements.

3.3 Results of dynamic network abstraction

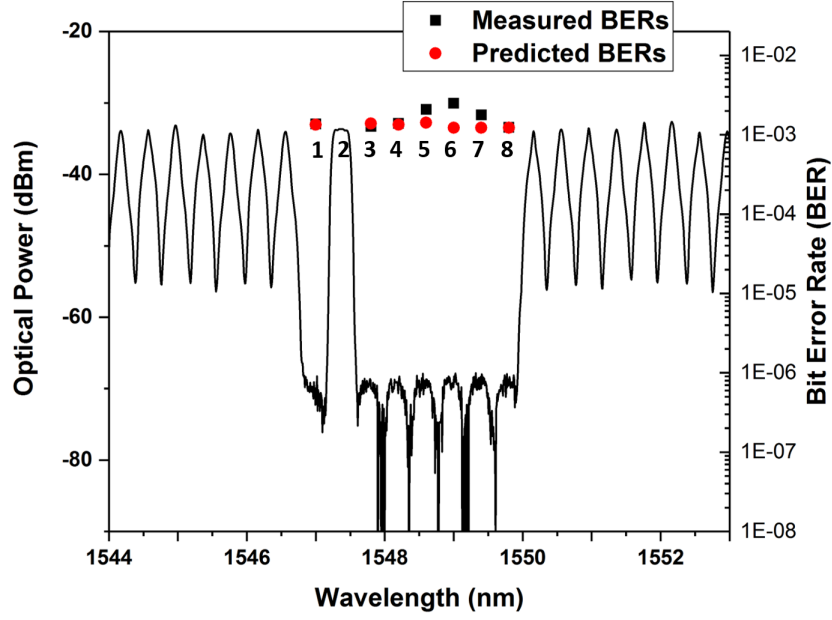


Fig. 4. Predicted BERs vs. Real BERs for all the available channel slots in the chosed scenario.

To verify proposed network abstraction algorithm, one scenario with only channel 2 "on" is considered. To deploy new link, the network abstraction algorithm will predict the BER performance of all the available channel slots and evaluate the corresponding impact on the Channel 2. Figure 4 shows the comparison of the predicted and actual BERs for un-established channel when only channel 2 is established. The developed network abstraction algorithm predicted the BER of all the available channels (Channel 1,3,4,5,6,7,8). As show in the Fig. 4, the implemented network abstraction algorithm predicted the link BERs of the un-established channel with a high precision. The maximum error occurs at Channel 5. The different performances for channel 5 and other channels contribute to the difference. The predicted performance for all the available channel slots can help network controller to deploy optical links intelligently. In the future work, the transmitter performance will be also included in the prediction model.

In the margin-reduced dynamic network, another challenge is to ensure the established channels not to be disturbed by the new deploy channels. Therefore, in the phase of network planning, the proposed network abstraction algorithm can evaluate the impact of the establishing links on the current channels. The

evaluation will prohibit the failure of current channels. In the same scenario, the network abstraction algorithm predicts BERs of the channel 2 when the new established channel is deployed in the available channel slots, such as Channel 1, 3, 4, 5, 6, 7, 8. Figure 5 shows the comparison of predicted BERs and the actual BER for existed channel 2 when channel 1,3,4,5,6,7,8 is switched on respectively. We can see the prediction is very accurate, and the performance of existed optical path almost remains unchanged as the experiment platform is very stable. By adding another channel, the impact on the current channel is very limited.

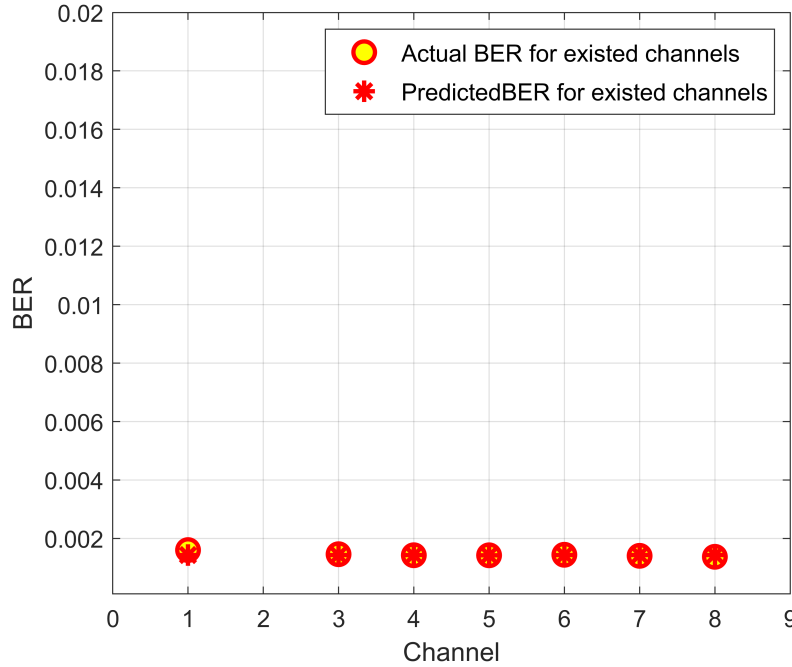


Fig. 5. Evaluation of the impacts on the current link by choosing different wavelength slots to establish a new link. The channel number is the choosed wavelength slot. The corresponding BER is the predicted BER performance of the previous link when the new link is established.

3.4 Scalabilities of the cloud monitoring database and Machine-learning based QoT predictor

In this paper, we extended the previous work to dynamically abstract the QoTs of multiple channels. The experimental demonstration shows the ML-based QoT prediction can help the SDN controller plan the network efficiently, i.e., to maximize the link capacity by reducing link margins with precise QoT predictions and minimize the interference on the current established channels. The QoT

prediction relies on the collected massive network operation data from both the SDN controller and the optical performance monitoring. In current demonstration, the OSNR penalties of the multiple paths connected several optical nodes can be predicted with the implemented cloud monitoring database. To deploy the ML-based QoT predictor in the future optical networks, scalabilities of both cloud monitoring database and the ML-based QoT predictor need to be considered.

Regarding the cloud monitoring database, i.e., NCMDB, each physical transmitter is used with the event time together to generate the record ID. All the other information is linked to the record ID. In such approach, the whole network activities can be recorded and linked to each transmitter. Therefore, the scale of the NCMDB depends on the deployed transmitters in the link. Especially in core networks, there are limited numbers of nodes and links. The NCMDB can be easily scaled up to store more network information. The centralized monitoring data hub collects the monitoring information through dedicated links. The dedicated link could provide enough bandwidth to allow the NCMDB to collect raw data. Therefore, the data can be re-used by multiple network analytic applications. The network analytic applications that run on top of the NCMDB also provides an interface for the SDN controller to access the processed monitoring information. Therefore, the developed network abstraction application is deployed as a service. In such way, the centralized network information hub simplifies the work-flow of SDN controller to use the monitoring information. The design of the NCMDB provides good scalability for future big networks.

As far as the scalability of the ML-based QoT prediction technique is concerned, an increase in network size will definitely result in an increase in the number of links parameters (e.g. number of EDFAs' parameters) which are in fact used by our ML model for OSNR monitoring. This implies that the computational resources/time required for the training of ML will also increase significantly in this case. However, we would like to emphasize that the training procedure of ML model is conducted completely offline and prior to actual deployment in an SDN. Once the parameters of an ML are optimized offline, the actual OSNR monitoring process in SDNs employing trained ML model involves few simple matrix multiplications. Therefore, we believe that the computational complexity and processing time will keep at a low level and possible provide real-time network abstractions.

4 Conclusion

In this paper, random forest regression based network impairment abstraction algorithm is developed to analyze the implemented cloud monitoring and configuration database (CMDB). The network abstraction algorithm predicts the performance of all the available channel slots and also evaluate the impact on the current links when any available slot is selected to deploy new links. We demonstrated the network impairment abstraction up to 8-channels over a 564-km field-trial link. The implemented algorithm could predict the channel perfor-

mance with a high precision to support margin-reduced optical network. The dynamic network abstraction could be integrated with the SDN controller to achieve low-margin dynamic optical networks. The introduced CMDDB and the network analytic applications open new possibilities for future dynamic optical networks.

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