Deep Neural Network-enabled Fast and Large-Scale QoT Estimation for Dynamic C+L-Band Mesh Networks

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Abstract: A fast and accurate QoT estimation scheme using deep neural network is proposed for dynamic C+L-band large-scale mesh networks. The calculation time is decreased dramatically and it is applied to measure the fiber broken case.

1. Introduction

Estimating the Quality of Transmission (QoT) of a lightpath is crucial in network planning and service provisioning, where the performance of an existing or candidate lightpath should be evaluated based on its characteristics and the network configuration before the practical network deployment. Ferrari et. al [1] built a Gaussian noise simulation tool in Python (GNPy) based on Gaussian Noise (GN) model [2], which provided an end-to-end physical simulation environment. Most of the existing GN-based schemes focused on end-to-end modeling [3], in which the complex effects of all associated links have been ignored in the practical mesh optical networks. In large-scale optical mesh networks, physical layer is supposed to consider the fluctuant traffic demands and dynamic network states. Recently, with the gradual maturity of C+L-band transmission system and constant expansion of optical network scale, it is urgently desired to develop fast and large-scale QoT estimation for dynamic wideband optical mesh networks.

The complex calculation on inter-channel nonlinear interference (NLI) is the main difficulty of QoT estimation in wideband mesh network which is caused by dynamic cases in a wide spectral range (e.g., cross connection, services add/drop, and fiber broken). In addition, stimulated Raman scattering (SRS) effects transferring power from higher to lower frequencies interact with Kerr effect, resulting in frequency dependence of NLI and more complex inter-channel NLI in wideband scenarios [4]. The main motivation of deploying C+L network is to fully utilize optical fiber resources for capacity expansion. However, it also enormously increases the difficulty on the modeling and simulation for such large-scale mesh networks. In other words, the traditional QoT estimation methods (no matter Split-Step Fourier method (SSFM) or GN models), are very difficult to achieve fast and accurate calculation at the cost of huge computation. In addition, the research on machine learning (ML) based QoT estimation has attracted increasingly attention instead of the widely used GN model. For example, convolutional neural networks (CNN) [5] and graph convolution networks (GCN) [6] were adopted for QoT estimation, but with limited specific services and under static conditions in only C-band or small-scale networks. However, for a multi-band optical mesh network, a more powerful ML with larger neural network structure is required to calculate the real-time and dynamic interaction among massive services simultaneously, which can help the network to make comprehensive programme. If so, a series of functions can be realized at once, including service establishment, routing wavelength spectrum allocation (RWSA), QoT estimation, link fault monitoring and optimization.

In this paper, we realize an on-the-fly programmatically configurable C+L-band optical network simulator with large numbers of coupled connections in a mesh network. Given the continuous growth of the network traffic and the ability of the equipment parameters configuration, the physical network resources of bandwidth and power can be used more efficiently. A deep neural network (DNN)-based QoT estimator has been established to predict and evaluate the real-time network state with accurate and dynamic response according to the received power per lightpath and generalized signal-to-noise ratio (GSNR) per channel. Simulation verification demonstrates that the proposed DNN-based tool achieves high estimation accuracy, and low absolute error of GSNR (< 0.2 dB). In addition, we also study a fiber broken case to reflect the practicality and robustness of the DNN-based tool. The results verified that it has the ability of reliable and accurate prediction, and its calculation speed is much faster than those of the GN-based model.

2. Scenarios Description and Principle

The network physical topologies in two different scales are displayed in Fig. 1(a) and (b), which are 17-node German topology and 77-node CORONET Continental United States (CONUS) topology [7]. The detailed information of two topologies are listed in Table. 1. Note that to realize bi-directional transmission, each connection

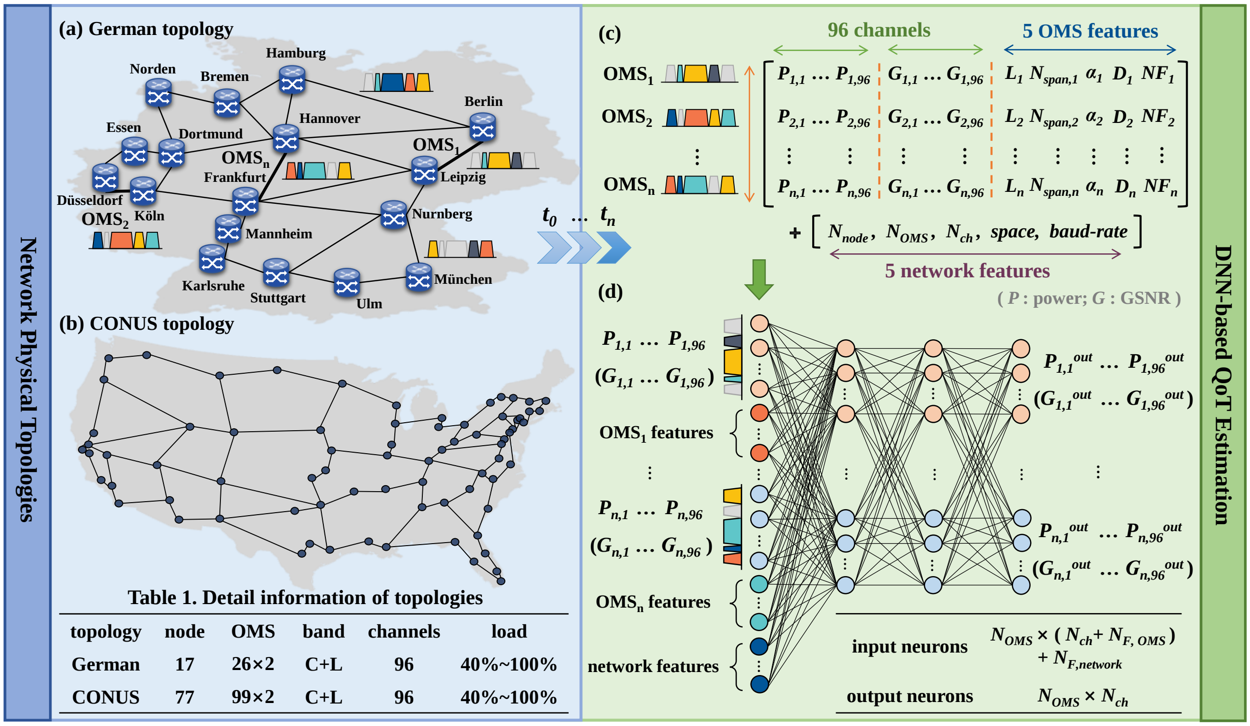

Table 1. Detail information of topologies

topology	node	OMS	band	channels	load
German	17	26×2	C+L	96	40%~100%
CONUS	77	99×2	C+L	96	40%~100%

Fig. 1. Framework of QoT estimation tools for mesh network: (a) German topology, as an example of dynamic services transmission; (b) CORONET CONUS topology [7]; (c) input features expressed as a matrix; (Optical Multiplex Sections (OMS) features: total length L, number of spans N_{span}, attenuation α and dispersion D of fibers, and noise figure NF of erbium doped fiber amplifier (EDFA); network features: number of nodes N_{node}, OMSs N_{OMS} and channels N_{ch}, transmission space and baud-rate.) (d) DNN-based QoT estimation model.

between two nodes consists of two Optical Multiplex Sections (OMSs) representing the part between two adjacent optical multiplexing terminal function blocks. First, we build a GN-based simulation tool to implement C+L-band calculation by modifying and enhancing GNPy. In the dynamic mesh physical layer, the networks are filled with randomly generated traffic across all 96 channels covering the whole C+L-band, as shown in German topology in Fig. 1(a). Routing and wavelength assignments are performed with shortest path and First Fit algorithm [8]. In order to minimize the impact of SRS effects, services are allocated from C-band low frequency to high frequency, and then on L-band in reverse. All the uploading services are satisfied to set the launch power using LOGO algorithm [9] and identical initial GSNR. Most importantly, the physical layer network is constantly running, accompanied by frequent add/drops and states updates. The inter-channel NLI leads to the fact that when the network spectrum utilization is more than 50%, one signal's variation makes the entire network state to be updated. For the GN-based tool, this means the simulation accuracy is guaranteed, while sacrificing the calculation time and memory.

In the DNN-based QoT estimation layer, network state matrices represent all the services' information in the mesh network at any given moment t_n in Fig. 1(c). The input matrix is composed of the launch power/GSNR profiles of 96 channels and physical parameter features, including five features of each OMS and five features of the network. The output matrix correspondingly includes the output power/GSNR profiles. Additional input features can help DNN import physical related descriptions and improve the input structure. The system simulation and data generation are implemented by dynamic GN-based tool as described above. Then, the network state matrices are transferred into the DNN-based tool in Fig. 1(d), whose input layer with $N_{OMS} \times (N_{ch} + N_{F,\,OMS}) + N_{F,network}$ neurons, and output layer with $N_{OMS} \times N_{ch}$ neurons. We collect more than 10000 sets of network state data for training for each network topology, with the traffic changes between 40% and almost 100% of the total bandwidth. The services are completely random, that is, all channels of all OMSs can be filled and participate in the entire dataset, ensuring the ergodicity of the services distribution in the whole mesh network.

3. Results and Conclusion

First, to demonstrate the accuracy and generalization performance of DNN-based model, all the collected samples for testing are not involved in training dataset, and the estimated power/GSNR by DNN against the actual power/GSNR of both German and CONUS network topologies are displayed in Fig. 2 (a) and Fig. 2 (b), respectively. It can be seen that compared with the baseline of the GN-based model, the estimation of power is accurate, and the GSNR has high reliability in a large range of 10 to 40 dB. Besides, for the empty channels without

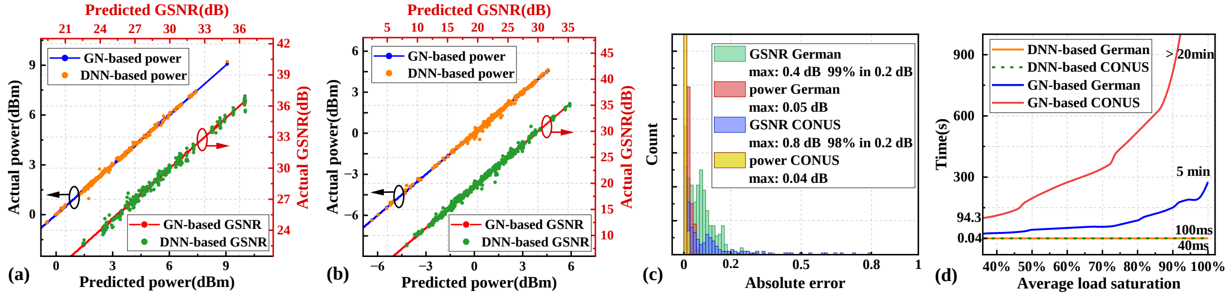

Fig. 2. (a) Predicted power/GSNR by the DNN-based model for the German network over actual power/GSNR (4992 samples); (b) Predicted power/GSNR by DNN-based model for the CONUS network over actual power/GSNR(19008 samples); (c) Probability density function (PDF) for absolute error of the DNN-based model; (d) Time comparison of each tool for different load cases on two topologies.

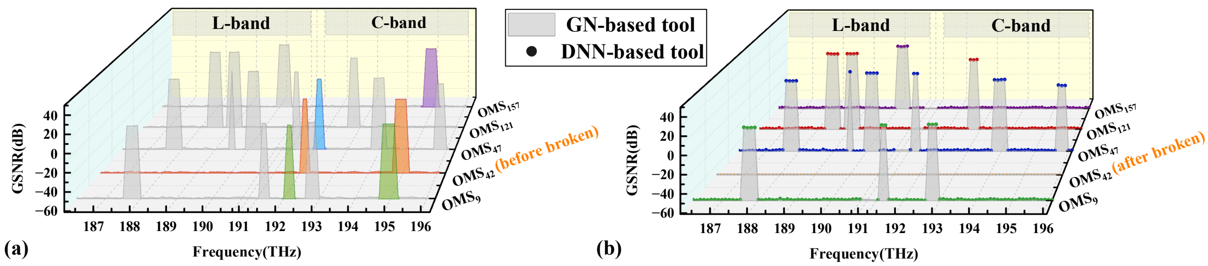

Fig. 3. The service states before and after the fiber broken in CONUS network and the performance of DNN-based model; Take the GSNR of services on five OMSs for example, and OMS_{42} is the broken fiber: (a) Before broken, color padding services indicate they will be affected; (b) After broken, services on OMS_{42} and related are disconnected, color dots are the GSNRs estimated by DNN-based model.

transmission services, the DNN-based model also gives accurate decisions. The probability density function (PDF) of power/GSNR estimation errors are shown in Fig. 2(c). Under CONUS topology as a large-scale mesh network, about 98 percent of estimated GSNR absolute errors are within 0.2 dB, almost 0.5% relative error. The GSNR estimation errors of German network are smaller, and the absolute errors of power estimation in two networks are both < 0.05 dB. Calculation time of the two models for different load cases are measured, as shown in Fig. 2(d). With the continuous improvement of topology complexity and spectrum utilization, the time penalty of GN-based model increases rapidly, reaching tens of minutes in large-scale networks. While for the trained DNN model, the calculation time only needs 40 - 100 ms for different scenarios owing to its fully parallel computation and matrix manipulation.

Next, we study one potential application of this model for measurement of fiber broken scenarios, as shown in Fig. 3. We take the GSNR of services on five OMSs as example, where the fiber of unidirectional OMS_{42} is broken. When the CONUS network running under a certain state, the GN-based model has to spend 20 minutes even more time to update all service calculations for the huge fluctuation caused by the sudden OMS_{42} broken, and thus cannot reflect the fiber cut-caused severe results in time. It is seen from Fig. 3(a) to (b), when the fiber is cut, the DNN-based model can perfectly fit the referenced results and update the network states immediately (< 100 ms), which is significant for real-time network monitoring and fast fault repair. It is enough to prove that when the actual large-scale mesh network is filled with massive traffic, DNN-based model that responds in real time and provides sufficient accuracy and robustness can deal with changes caused by service fluctuations or link failure.

In conclusion, we proposed a fast and accurate QoT estimation scheme based on DNN for evaluating the real-time network state in C+L-band large-scale mesh networks. The DNN-based model greatly decreases the calculation time from tens of mins to 100 ms and has extensive application scenarios, such as the fiber broken case.

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4. References

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