The First Testbed Demonstration of Cognitive End-to-End Optical Service Provisioning with Hierarchical Learning across Multiple Autonomous Systems

Gengchen Liu[1], Kaiqi Zhang[1], Xiaoliang Chen[1], Hongbo Lu[1], Jiannan Guo[2], Jie Yin[2], Roberto Proietti[1], Zuqing Zhu[2], S. J. Ben Yoo[1]

1. University of California, Davis, CA 95616, USA

2. University of Science and Technology of China, Hefei, Anhui 230027, China

sbyoo@ucdavis.edu, zqzhu@ustc.edu.cn

Abstract: We demonstrate the first experimental testbed with a hierarchical machine-learning network management framework for impairment-aware end-to-end elastic optical RMSA service provisioning across multi autonomous domains with QoT estimation deviations below 10%.

OCIS codes: (060.4250) Networks; (060.2330) Fiber optics communications

1. Introduction

While software-defined elastic optical networking (SD-EON) is emerging as a promising solution for effectively supporting high-capacity and dynamic traffic demands, realizing the same effectiveness across multiple autonomous systems (ASes) [1] remains a challenge. In particular, guaranteeing the quality-of-transmission (QoT) of end-to-end lightpaths is non-trivial across optically transparent inter-domain networks. Due to administrative constraints, each AS manager (or domain manager - DM) will disclose only very limited intra-domain information, making the estimation the QoT of inter-domain lightpaths challenging. As a consequence, previous QoT estimation solutions based on analytical methods [2] or big data analytics [3-5] cannot be easily applied since they require full knowledge of the domains (i.e. topology, links characteristics, etc.). In this paper, we take advantage of a broker-based multi-domain SD-EON framework [6] and propose a hierarchical machine learning mechanism for inter-domain QoT-aware provisioning. In the proposed mechanism, DMs adopt a domain-level learning model with the full domain knowledge and performance monitoring data. The DMs negotiate market-driven relationships [7] with the broker plane with a set of agreements. Then, the DMs abstract local knowledge repository and pass it on to the broker plane which eventually learns the end-to-end path QoT across multiple domains. The broker plane makes use of the QoT estimator to calculate inter-domain lightpaths with appropriate performance margins or reconfigure in-service lightpaths with degraded QoT. By using a two-domain seven-node testbed with real-time optical performance monitoring (OPM) and a broker-based multi-domain SD-EON framework [6] (see Fig. 1(a)), we demonstrate the first hierarchical machine learning mechanism for inter-domain QoT-aware provisioning. By using artificial neural networks (ANN) with real-time OPM data, we demonstrate the proposed hierarchical framework with *Q*-factor estimation accuracy above 90% (e.g. less than 10% of deviation) for 40 Gb/s 16-QAM lightpaths.

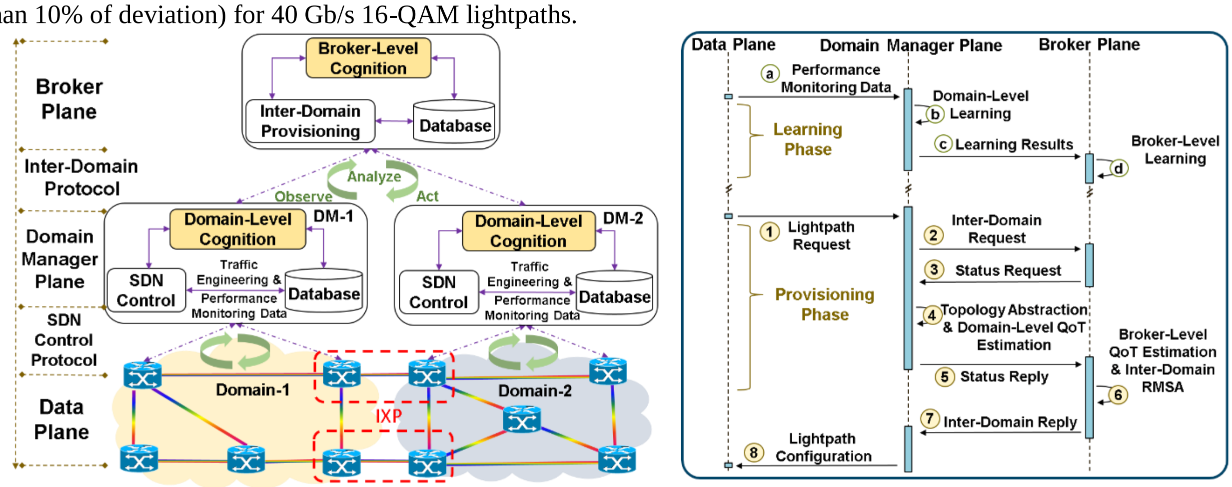

Fig. 1. (a) Multi-domain network architecture with hierarchical learning. IXP: internet-exchange point. (b) Proposed workflow.

2. Hierarchical learning assisted network architecture

Fig. 1(a) shows the broker-based multi-domain SD-EON architecture with the proposed hierarchical learning framework for QoT-aware inter-domain provisioning. Each DM manages service provisioning operations of its domain through the software-defined network (SDN) framework. It consecutively monitors and records the performance of intra-/inter-domain lightpaths and the status of the data plane equipment. With these data, each DM can train a domain-level QoT-estimator that can predict the QoT of lightpaths given the corresponding link configurations (e.g., modulation format, link loads, optical power, etc.). The broker plane coordinates DMs for inter-domain provisioning. DMs abstract their domains and submit virtual links together with the predicted QoT to the broker. Then, the broker can build a hierarchical learning model that makes use of the learned knowledge from each domain to predict the QoT of inter-domain lightpaths. By exploiting the domain-level and broker-level learning progressively, the proposed framework fully supports the autonomy of ASes. Fig. 1(b) shows the operation principle of the learning and the provisioning phases of the proposed framework. In the learning phase (steps *a-d*), DMs and the broker train reliable QoT estimators through the hierarchical learning method. Then, when a DM receives an inter-domain lightpath request (step *1*), it forwards the request to the broker for inter-domain services (step *2*). The broker sends out *Status_Request* messages (step *3*) to related DMs for the information of virtual links and the domain-level QoT predictions. After receiving the *Status_Reply* (step *5*), the broker constructs a multi-domain virtual topology and calculates a QoT constrained routing, modulation and spectrum allocation (RMSA) scheme with the assist of the hierarchical learning (step *6*). Finally, the broker informs the associated DMs with the desired resources allocation (step *7*), which in turn configure their domains to provision the requested the inter-domain lightpath (step *8*).

3. Experimental Testbed for datasets generation and training

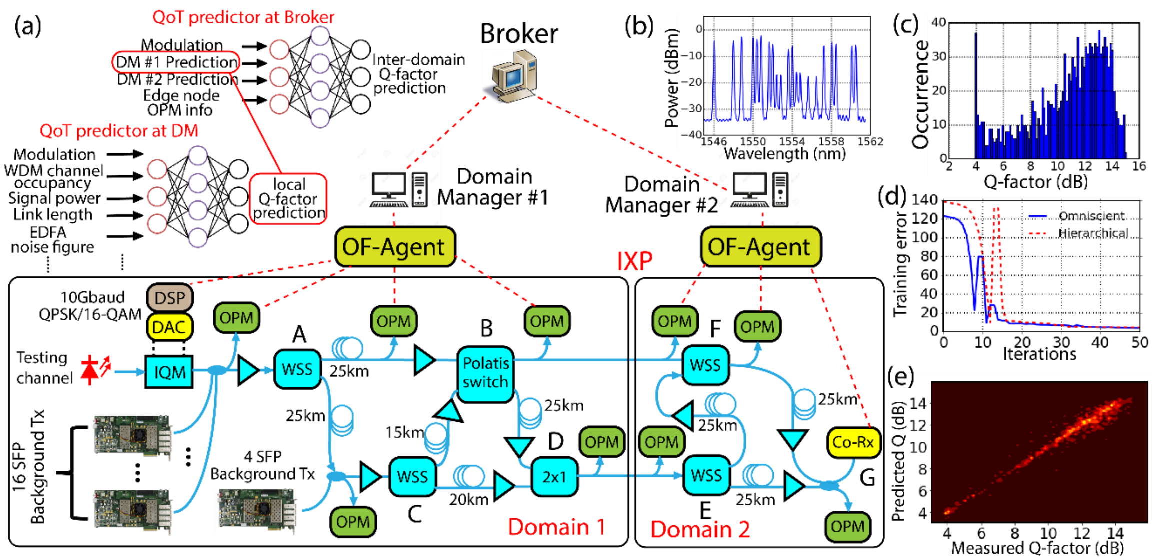

Fig. 2. (a) Multi-domain SDN testbed setup. (b) OPM reading at ingress of node A. (c) Histogram of the collected inter-domain dataset. (d) Convergence of the hierarchical ANNs and the omniscient ANN. (e) Histogram of the measured Q-factor versus predicted Q-factor.

Fig. 2(a) shows the experimental testbed, which consists of two domains and seven nodes. In the transmitter at the source node (node *A*), a 30 kHz linewidth external cavity laser (ECL) at 1551.75 nm is modulated with a 40 Gb/s 16-QAM signal using a $LiNbO_3$ phase-quadrature modulator. This signal is the testing channel. A standard coherent receiver is located at the destination node (node *G*) to receive the testing channel with a narrow band fiber-Bragg-grating (FBG) filter. Twenty 50GHz-spacing DWDM channels in the C-band act as background traffic. They are launched into the network at the input of node *A*, and node *C*. Four wavelength selective switches (WSSs) route, bypass, drop, or apply specific attenuation to any WDM channel in the network testbed. Amplified fiber spans of different length separate each node. We used an optical spectrum analyzer (OSA) as the OPM tool since it can provide information regarding DWDM channels location, optical signal to noise ratio (OSNR) and power. Fig. 2(b) shows the OPM reading (0.1 nm resolution) at the output of node *F*. The OPMs report their readings to a PC that serves as the OpenFlow (OF) agent, which processes the raw data obtained from the OPMs and send the collected information (total power, noise power, and channel occupancies) to the corresponding DMs (the same PC). The two DMs connected to a third PC which serves as the broker. We implemented the ANNs on the DMs and broker with *PyTorch*, where five and seven hidden-layers are employed for the DMs' and broker's ANNs, respectively. To collect training and testing datasets, we enumerated all the possible routing paths from node *A* to node *G* for the testing signal, while applying random routing paths with uniform distribution for each background signal and random attenuations with exponential distribution for all signals (including the testing signal) at each WSS. For each routing configuration, the actual *Q*-factor of the testing signal measured at node *G*, Q_{mes}, is recorded as the label of the training dataset. Fig. 2(c) presents a histogram of the collected inter-domain datasets with over 1400 elements. In addition, we also collected over 780 datasets for each domain individually by putting the coherent Tx or Rx at the IXP. For the domain-level ANN, we used 680 datasets for training and 100 datasets for evaluation. Once the domain-level ANN converged, we started training the broker-level ANN with 1200 elements. The absolute deviations between the broker-level ANN Q_{est} and the label Q_{mes}, defined as $|Q_{est} - Q_{mes}|/Q_{mes}$, is below 10%. Fig. 2(d) presents the convergence of the proposed hierarchical estimator as a function of training iterations. For comparison, we also included the training result example of an *omniscient* orchestrator, who has all information of domain *1* and *2*. The proposed framework shows slightly slower convergence speed and less robustness against the *omniscient* orchestrator since it relies on the predictions from the domain-level ANNs. Yet once it converges, our hierarchical model can achieve comparable accuracy as the *omniscient* orchestrator. Fig. 2(e) shows the result of inter-domain *Q*-factor estimation using the hierarchical learning approach. This result demonstrates that the hierarchical learning-based framework can estimate the QoT (using *Q*-factor as the metric) of an inter-domain optical link with satisfactory accuracies.

4. Use case and results: impairment-aware inter-domain service provisioning

Once we experimentally verified that the hierarchical learning-based QoT estimator performance is accurate, we now demonstrate an inter-domain lightpath service provisioning using the proposed framework. A network client located in domain *1* requests a lightpath between node *A* and node *G* (located in domain *2*). Fig. 3(a) shows the Wireshark captures from the DM *1*. First, the client submitted its request to the local DM (message *1*). Second, the DM initiated the RMSA process (message *2-7*) depicted in Fig. 1(b) and established a lightpath over node *A-B-F-G*, *as* shown in Fig. 3 (b). Fig. 3 (c) shows the detailed message about the report of intra-domain QoT prediction of a virtual link sent from DM 1. Once the connection was established, we purposely introduced a time-varying attenuation between node *A-B*, which resulted in an intra-domain link failure. The domain-level ANN detected the *Q*-factor degradation and triggered an intra-domain rerouting (node *A-C-B-F-G*) shown in Fig. 3 (b) within Domain *1* to re-provision the service. The measured *Q*-factor and the end-to-end *Q*-factor prediction (calculated every 30 seconds) are shown in Fig. 3(c). As the optical attenuation between node *A-B* increases, the measured and predicted *Q*-factors go down due to the increased noise level. When domain *1* triggers the intra-domain rerouting, the *Q*-factor of the lightpath resumes to 12 dB, and efficient impairment-aware service provisioning is realized.

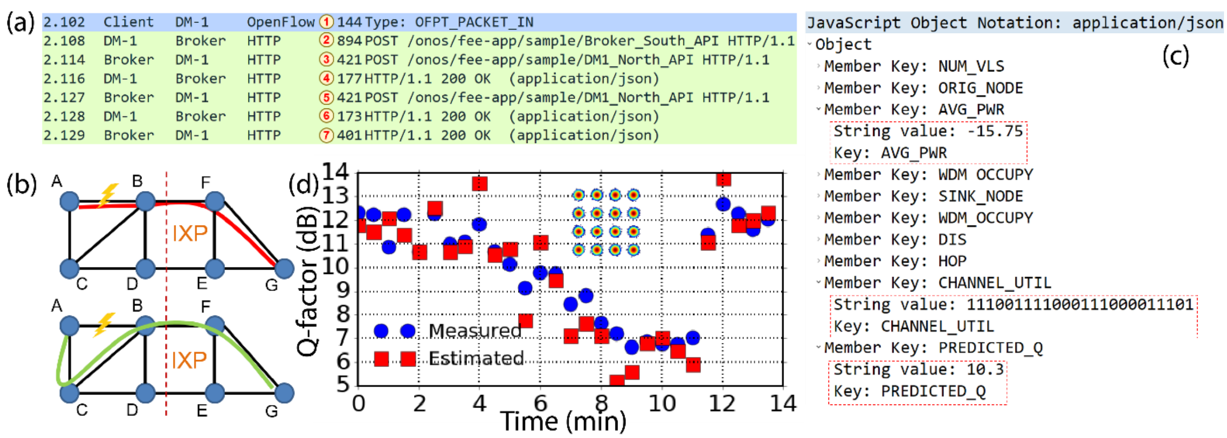

Fig. 3. (a) Wireshark captures at DM-1 during RMSA. (b) Illustration of the RMSA scenario; Top: original lightpath; Bottom: lightpath after rerouting. (c) Detail of selected message. (d) Q-factor over time with time-varying optical attenuation on link A-B. Inset shows the recovered constellation after the rerouting.

5. Conclusion

We experimentally demonstrated the first hierarchical learning framework that achieves end-to-end RMSA and impairment-aware service provisioning for elastic optical networks with autonomous domains. By using a hierarchical ANNs, the proposed framework effectively exploits the correlation between QoT and the monitored data from OPM units to provision end-to-end services across multi-domains while guaranteeing autonomy and privacy of each domain.

This work was supported in part by DoE DEFC02-13ER26154 and NSF CNS 1346688.

1. Zhu, Z., et al.,. Journal of Lightwave Technology, 2015. **33**(8): p. 1508-1514.
2. Sartzetakis, I., et al., Journal of Optical Communications and Networking, 2016. **8**(9): p. 676-688.
3. Yan, S., et al. in *43rd European Conference on Optical Communication (ECOC 2017) Th.PDP.b.4*. 2017.
4. Rottondi, C., et al., Journal of Optical Communications and Networking, 2018. **10**(2): p. A286-A297.
5. Oda, S., et al., Journal of Lightwave Technology, 2017. **35**(8): p. 1350-1356.
6. Castro, A., et al., Journal of Lightwave Technology, 2016. **34**(23): p. 5391-5400.
7. Yoo, S.J.B. in *European Conference and Exhibition on Optical Communication (ECOC)*. 2014. We.2.6.3.