Hierarchical Learning for Cognitive End-to-End Service Provisioning in Multi-Domain Autonomous Optical Networks

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***Abstract*—This paper demonstrates, for the first time to our knowledge, hierarchical learning framework for inter-domain service provisioning in software-defined elastic optical networking (SD-EON). By using a broker-based hierarchical architecture, the broker collaborates with the domain managers to realize efficient global service provisioning without violating the privacy constrains of each domain. In the proposed hierarchical learning scheme, machine learning-based cognition agents exist in the domain managers as well as in the broker. The proposed system is experimentally demonstrated on a two-domain seven-node EON testbed for with real-time optical performance monitors (OPMs). By using over 42000 datasets collected from OPM units, the cognition agents can be trained to accurately infer the Q-factor of an unestablished or established lightpath, enabling an impairment-aware end-to-end service provisioning with an prediction Q-factor deviation less than 0.6 dB.**

***Index Terms*—Multi-domain networking, optical networks, modulations.**

I. Introduction

THE Internet traffic has been growing exponentially driven by explosive expansions of cloud-based multimedia applications, which now demand a high-throughput an agile cyber-infrastructure that can support such dynamic and high-capacity traffic [1]. While software-define elastic optical networking (SD-EON) can facilitate flexible optical-layer spectrum management in single-domain networks [2]–[4], effective end-to-end service provisioning across multiple autonomous systems (ASes) still remains challenging. Specifically, subjecting to administrative constraints, AS managers may keep the detailed traffic engineering information (e.g., network topology, spectrum utilization etc.) confidential, while disclosing only very limited amount of intra-domain information. Hence, performing the routing, modulation and spectrum assignment (RMSA) for inter-domain lightpaths in optically transparent multi-AS systems with guaranteed quality-of-transmission (QoT) is a non-trivial task [5], [6].

Current optical network operators usually guarantee the QoT of lightpaths by considering the worst link conditions and allocating large margins to account for the potential performance degradations during the lifetime of lightpaths. Thus, accurate QoT estimation models for unestablished lightpaths are essential for enhancing the efficiency of operating optical networks. Previous works have reported a number of theoretical models [7]–[11] for QoT estimation. For instance, in [10], [11], the authors monitored and predicted the optical signal-to-noise ratio (OSNR) across the optical networks as an indicator of the QoT. The downside of this approach is that it ignored other QoT degradation factors, such as dispersions and crosstalk. In fact, most theoretical models generally assume that there is only a single kind of impairment presented in the transmission system. However, many transmission impairments are non-orthogonal and are coupled to each other. That is to say, due to the highly complex nature of optical transmission systems and the implicit characteristics of practical networks (e.g., device conditions, crosstalk etc.), it is difficult to obtain a universal close-form analytical solution that correlates the QoT with various impairment, and as a result, the prediction accuracy of the theoretical models will be reduced. In that case, during the network planning stage, the network designer has to assign higher power/OSNR margin to combat the QoT uncertainty, which would ultimately lower the network capacity. On the other hand, recent breakthroughs in artificial intelligence have made it possible to represent high-dimensional data and approximate complex functions with machine learning tools, such as deep neural networks (DNNs). Mo *et al.* proposed an artificial neural network (ANN) based transfer learning system to predict the QoT by monitoring the channel power [12]. In [13], a cognitive tool with random forest (RF), support vector machine (SVM), and K-Nearest neighbor (KNN) is demonstrated for accurate QoT estimation. Other researchers have investigated cognitive QoT estimation using case-based reasoning (CBR), where the impairment parameters of an optical network are learned with training datasets to derive the QoT of a lightpath [14]. Nevertheless, these models cannot be directly applied to the multi-AS scenarios as they require access to the state of every optical component, which definitely violates the autonomy of ASes. In [15]–[17], we proposed a broker-based multi-domain SD-EON framework for hierarchical multi-AS management, where a broker plane was introduced to coordinate the operations of AS or domain managers through market-driven and incentive-driven interactions rather than superior-subordinate relation-

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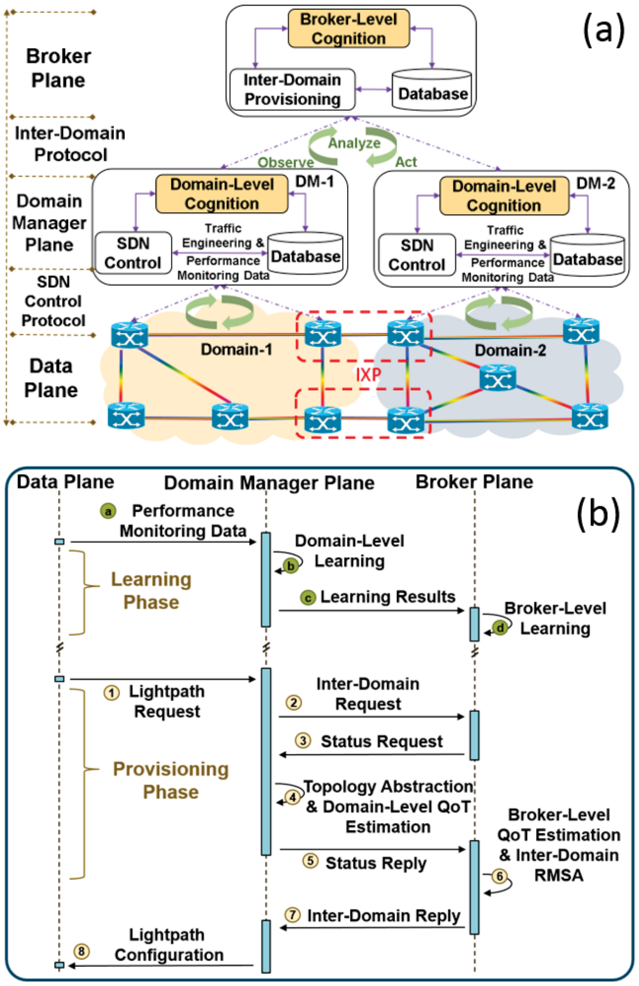

Fig. 1. (a) Broker-based multi-domain provisioning with Hierarchical Cognition. IXP: internet-exchange point; DM: domain managers; (b) Workflow of the proposed system.

ships. Compared with the previous distributed management mechanisms (i.e., peer-to-peer AS networking [18], [19]), the broker-based architecture can improve the efficiency of inter-domain service schemes with a semi-centralized provisioning scheme while also respecting the autonomy of ASes by working with them according the mutual service level agreements (SLAs). This architecture is especially beneficial for QoT estimation in multi-AS systems as it enables the design of unified multi-domain monitoring and learning frameworks with optimized inter-AS networking flows.

This paper extends our work in [20] by providing detailed descriptions and implementations of the proposed hierarchical learning framework and, more importantly, by presenting an entirely new set of improved results with QoT prediction accuracy $<$ 0.6 dB (Q-factor deviation) to support impairment-aware inter-domain service provisioning in multi-domain SD-EONs. The organization of the paper is as follows. Section II introduces the details of the proposed hierarchical architecture and framework. Section III covers the experiment demonstration, which includes testbed implementation, dataset generation, training of the neural networks, and the impairment aware service provisioning. Section IV concludes this work.

II. Architecture and Framework

A. Broker-based Multi-Domain Architecture

Fig. 1(a) shows the block diagram of the proposed broker-based multi-domain SD-EON with hierarchical cognitions in both the broker plane and the domain manager plane. In the proposed architecture, each domain manager is responsible for managing a subset of the global optical networks, providing services such as intra-domain service provisioning, performance monitoring, and traffic engineering. A broker plane lies above the domain manager plane to handle inter-domain service requests and global optimizations. Through different service level agreements (SLAs), each domain manager can provide the broker with an abstracted representation of its network as well as monitoring data, allowing the broker to realize global coordination and provisioning.

The operation principle of the proposed framework is summarized in Fig. 1(b). When a lightpath setup request arrives, the corresponding domain manager will first determine whether the destination node belongs to its own domain or another domain. For an intra-domain request, the domain manager first lists all available path segments between the source and destination nodes from its database. Then the domain manager inquires its cognition agent using the performance monitoring data to get a QoT prediction for each possible path available. Based on the prediction results, the domain manager then sets up the lightpath that yields the highest resource efficiency while satisfying the QoT. As for inter-domain requests, the domain managers will list all available path segments between the source/destination node and the border nodes at the Internet-exchange point (*IXP*) for the source/destination domain or among the border nodes for intermediate domains [11], [21], [22]. In the next step, each domain manager obtains the QoT predictions associated with the paths from the cognitive unit. Subsequently, the domain managers report the information of the path segments, including the spectrum utilization and QoT prediction values, to the broker. The broker can make use of the reported information as well as the monitoring data from the border nodes to realize the impairment-aware inter-domain service provisioning. Once the lightpath is established, the domain managers and the broker can continuously inquire their cognition unit to track the status of the lightpaths. In case of a link failure, the corresponding domain manager can re-initiate the process of service provisioning to recover lightpaths affected by the link failure.

Comparing with the conventional orchestrator-based approach, the proposed scheme shown in Fig. 1 does not require the detailed knowledge from the network, such as the network topology or the OPM data at each node, to realize the service provisioning. Instead, the broker requires only the abstracted information from the domain managers (*i.e.*, the source/sink node, the local Q-factor estimation, and available frequency slots). That is to say, each domain manager is seen as a black box that may provide certain requests and resources from the broker's point-of-view. Based on the provided resources, the

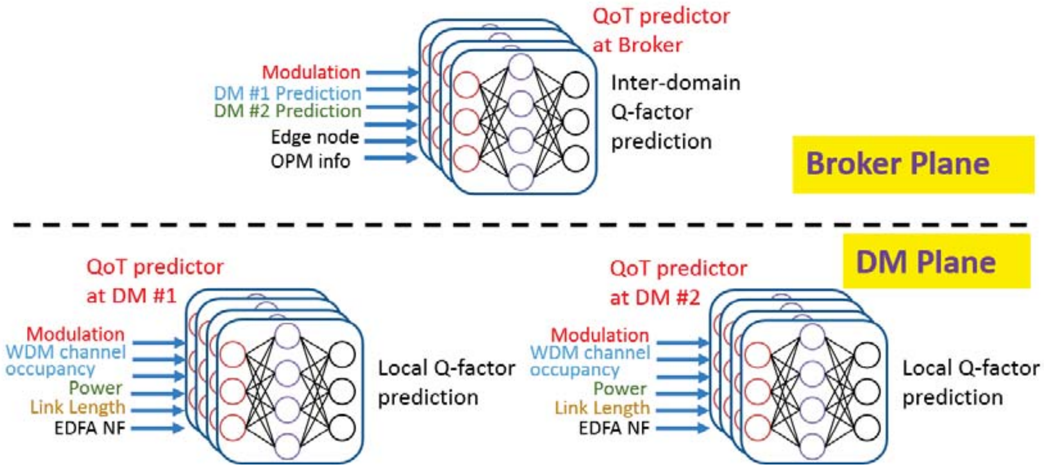

Fig. 2. Design of Hierarchical QoT predictor. The local Q-factor predictions from the DM plane are sent to the broker plane as the inputs of the Broker-level QoT predictor

broker can inquire its cognition unit to come up with the best provisioning plan for a new request. By using this approach, the broker does not need to know how the provided resources are implemented inside each domain manager and the privacy constraints are successfully satisfied.

B. Hierarchical Learning Framework for QoT prediction

Conventional ML-based QoT estimators generally require complete visibility on the OPM information, which is impractical to be implemented due to its violation of the privacy of each domain [12], [23]. Nevertheless, a good inter-domain QoT can always be guaranteed if two premises, which include a good local QoT for each domain and a good QoT at the *IXP*, were satisfied. Following this unique characteristic, we can divide the task of inter-domain QoT prediction into multiple hierarchical subtasks with the broker-based architecture. Considering the task of the cognitive unit (QoT predictions), we can use any supervised learning regressive model (or a multi-class classifier with logistic regression) as our learning model. Selection of ML models should base on various practical factors, such as the scale of the provisioned optical network, the number of accessible datasets, and the computational capability of the network controllers. For instance, if we are designing a QoT predictor for a complex optical network with abundant datasets available, it would be wise to choose a more powerful regressor (such as an deep neural networks) to obtain a better approximation. On the other hand, when the scale of the target optical network is relatively small, simpler ML methods such as artificial neural network (ANN) or support vector machine (SVM) should be given higher priorities to avoid overfitting. In this work, we used artificial neural network (ANN) as our ML block due to its strong capability to approximate complex nonlinear functions. As depicted in Fig. 2, the domain manager-level ANNs elaborate on the information provided by the optical performance monitors (OPMs) to obtain a list of local Q-factor prediction values. The input features are parameters that can precisely reflect the status of an optical link and impairments while still accessible through affordable OPMs, such as the modulation formats, the channel utilizations, power level, fiber span length, or the noise figure (NF) of the node's pump EDFA. The domain manager-level ANN then uploads the local Q-factor prediction list to the broker-level ANNs to calculate the inter-domain Q-factor predictions. To combat overfitting, we trained a distinct ANN for each lightpath configuration between a source and a destination node, forming an ANN-banks as our QoT predictor. By using this approach, we can significantly reduce the dimensions of input features and weighting parameters, which generally lower the probability of having overfitting according to Vapnik-Chervonenkis theory [24]. Note that it is also possible to use a single ANN to predict all the lightpath as shown in [20] because one can derive the routing paths from the OPM readings. The downside of using this approach is that the neural network would require too many samples to be trained properly in real-time.

III. EXPERIMENT

A. Experimental setup

Fig. 3 shows the two-domain seven-node SD-EON network testbed used to demonstrate the proposed hierarchical learning method. The first domain has a star-ring architecture that consists of four nodes, while the second domain has a three-node ring architecture. Each node is connected to other nodes by spools of single-mode fiber (SMF) or dispersion shifted fiber (DSF) of different lengths (15, 20, and 25 km). A 10 GBd 16-QAM coherent transmitter generates the testing signal used for data training and prediction. This signal is multiplexed with 20 50 GHz spacing 10 Gb/s dense wavelength division multiplexing (DWDM) on-off keying (OOK) signals, serving as the background traffic. The signal at the output of the multiplexer is injected into the testbed. The optical spectrum analyzer (OSA)-based OPMs are placed at the inputs of each node to monitor the optical power and the spectrum occupancy of background traffics. For measuring the QoT of the testing signal, we deployed a digital coherent receiver containing a local oscillator with 100-kHz linewidth, an optical hybrid, two balanced photodetectors, and one real-time oscilloscope operating at 50 GS/s. We adopted offline digital signal processing (DSP) algorithms, including timing recovery, chromatic dispersion compensation, adaptive equalization, carrier frequency and phase recovery, to demodulate the captured signal and calculate the Q-factor. A 0.2 nm bandwidth optical bandpass filter (BPF) rejects the power of background traffics before the digital coherent receiver. Four wavelength selective switches (WSSs) route, bypass, drop, and attenuate any DWDM signals with 50 GHz granularity at node A, C, E, and F. The fiber span losses between each node are compensated using erbium-doped fiber amplifiers (EDFAs) with constant output power. For the network control and management, we implemented the broker and the domain managers with the open network operating system (ONOS) platform [25] running on independent Linux Servers. The domain managers control the WSSs and the coherent transceiver in their territory through OpenFlow agents (OF-AGs, implemented with OpenvSwitches) that are co-located with the devices. The communications among the broker, domain managers and OF-AGs are realized with the RESTful API [26].

B. Dataset Collection and Training

The collection of training and evaluation datasets can be achieved by enumerating each of the possible routing paths for the testing signal from node A to node G. We applied random routing for the background traffic and random attenuations (0 dB - 7 dB for each WSS) for all the signals to purposely introduce perturbations to the network and allowing to sample the entire input space of the unknown target function that correlates the QoT and OPM readings. The launch power of each fiber span varies from -7 dBm to 12 dBm depending on the random applied attenuation and routing at each WSS node. At each run, we measured the actual Q-factor of the testing signal at Node G and record this value as the label of the current dataset. Then, we filtered out the testing signal using WSSs and recorded the outputs of the OPMs as the feature of the dataset. The OPM's reading contains a vector of 1024×1 data points from the OSA. It is of great importance to compress the dimensions of the input feature space to avoid overfitting [24]. We processed the OPM's raw data to obtain the number of background traffic channels and related optical

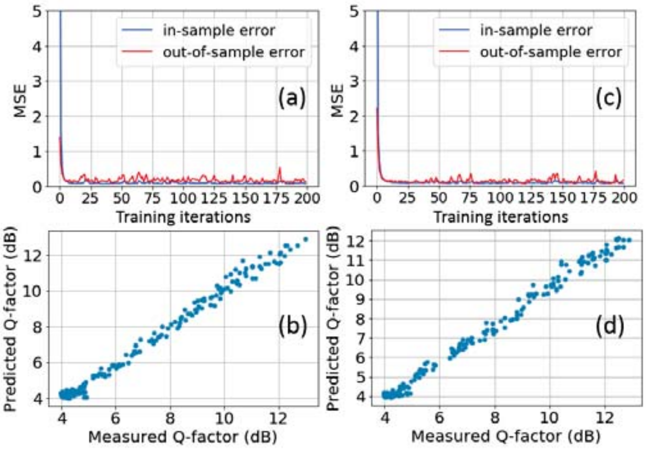

Fig. 4. Intra-domain learning performance. (a) MSE vs. training iterations for path A-C-B; (b) QoT prediction accuracy for path A-C-B; (c) MSE vs. training iterations for path E-F-G; (d) QoT prediction accuracy for path E-F-G.

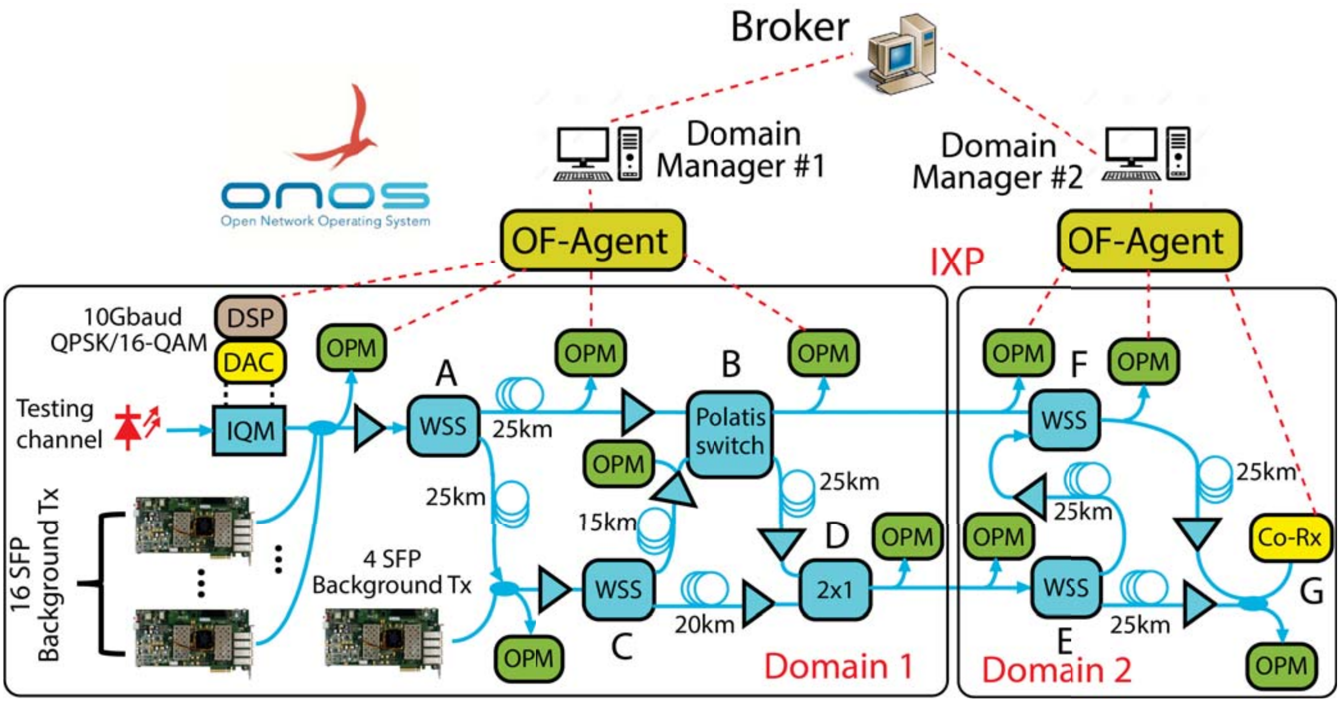

Fig. 3. Multi-domain testbed implementation. DSP: digital signal processing; DAC: digital-to-analog converter; IQM: I/Q modulator; OPM: optical performance monitor; OF-Agents: openflow agent; WSS: wavelength selective switch; Co-Rx: Coherent receiver; SFP: small-form factor pluggable.

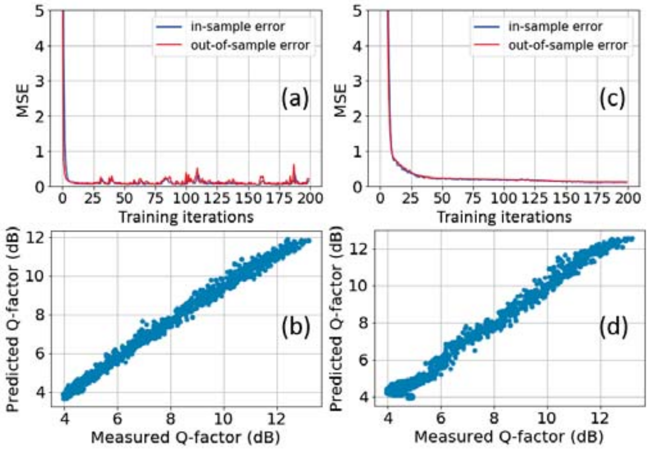

Fig. 5. Inter-domain learning performance for path A-C-D-E-F-G. (a) MSE vs. training interations for omniscient estimator; (b) QoT prediction accuracy for omniscient estimator; (c) MSE vs. training iterations for hierarchical estimator; (d) QoT prediction accuracy for hierarchical estimator.

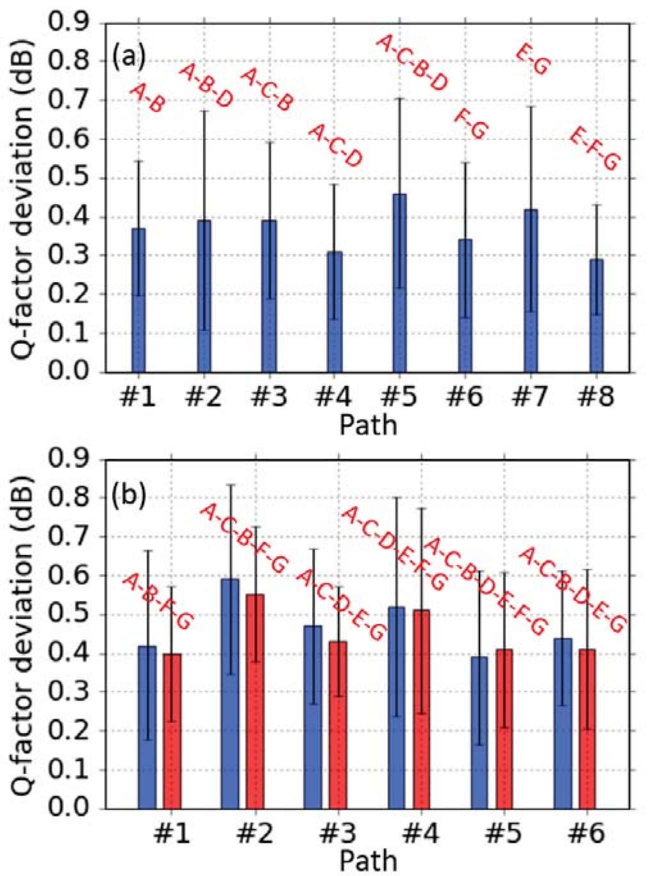

Fig. 6. Q-factor deviations of the evaluation sets for (a) domain manager-level ANN bank and (b) broker-level ANN bank. The blue and red bars correspond to hierarchical and omniscient QoT estimators.

power, the power level of the noise floor, and the power level of the testing signal (although it has been filtered out). This feature-engineering method reduces the size of the input feature space from 1024×1 to 4×1 for each OPM. Therefore, the input of the DM-level estimators consists of $N \times 4 \times 1$ samples, where N represents the number of OPMs reside in the inquired optical path. The broker-level estimators require $(4 + 2) \times 1$ input samples, which includes the two DM-level QoT estimation results as well as the processed OPM readings at the *IXP*. In the next step, we reinserted the testing signal and recorded a second set of OPM data that contains the testing signal. These data were used along with the first set of OPM data to train the neural network. The reason for using these two sets of OPM data is to make the learning model suitable for both prediction (of an unestablished lightpath) and monitoring (of an established lightpath) applications.

We implemented the domain manager-level ANNs and broker-level ANNs using *PyTorch* [27]. For benchmarking purpose, we also implemented an omniscient ANN that can access all the OPM data of the two domains. Obviously, the omniscient ANN bank violates the privacy and autonomy of each domain and its performance represents the upper bound of the proposed hierarchical estimator. Each neural network contains only a single fully-connected hidden layer with 25 nodes to reduce its complexities. The nonlinearities for the second layer is the *tanh* function [28].

We first collected 3,000 datasets (with and without the testing signal, 1500 for each) for each intra-domain provisioning path of domain #1 and domain #2. This collection was achieved by moving the coherent transmitter (for training domain #2) or the coherent receiver (for training domain #1) to the location of *IXP*. Due to the fact that the random attenuation applied on each WSS followed an exponential distribution, more samples have a Q-factor biased toward the forward error correction (FEC) threshold (8.5 dB, 7% HD-FEC). To overcome this dataset biasing, we applied higher weight on the less frequent samples and lower weight on the more frequent samples during the optimization process. 2400 samples have been used for training and the rest samples are used for evaluation purpose. During each training iteration, we randomly shuffled the entire dataset to select a new combination of training and evaluation datasets. Fig. 4(a) shows the in-sample error and out-of-sample error versus the number of training iterations for path A-C-B. The in-sample error is defined as the average squared deviations between the predicted and actual Q-factors within the training set, while out-of-sample error represents the average squared Q-factor deviations within the evaluation set. Note that as training iteration increases, the in-sample error and out-of-sample error closely align with each other, which indicates the absence of overfitting. Once the training is complete, we used the evaluation set to verify the Q-factor prediction performance for each estimator. Fig. 4(b) depicts the comparison between the predicted and measured Q-factors for path A-C-B. An averaged Q-factor deviation around 0.38 dB is obtained for the estimator. In this study we choose to use averaged Q-factor deviation as our evaluation metric as it is equivalent to the commonly used mean absolute error (MAE) for estimator evaluation [29]. Fig. 4(c) and (d) show the training and evaluation results for one of domain #2's estimators (path E-F-G), where an averaged Q-factor deviation around 0.29 dB is achieved. After the training and verification for intra-domain QoT estimators, we started

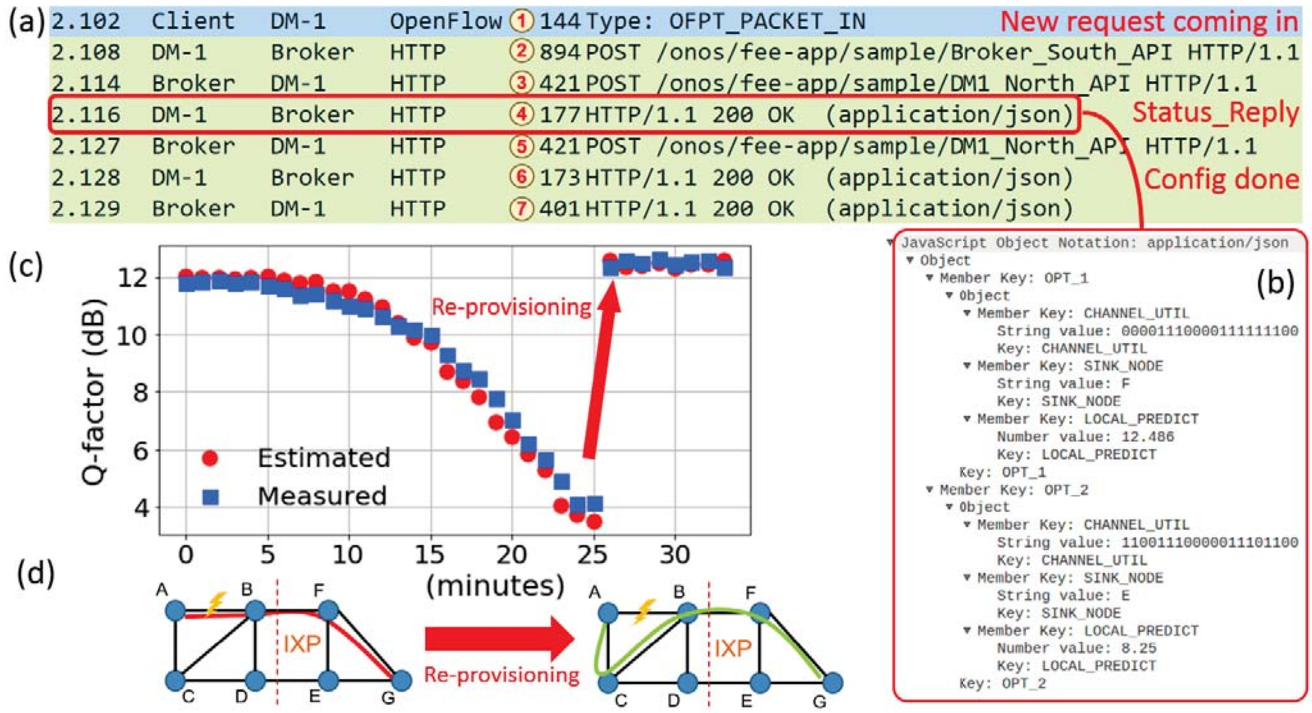

Fig. 7. (a) Wireshark captures of control signaling at Domain Manager #1 during the initial lightpath setup; (b) Detail of the selected message; (c) Evolution of Q-factor over time with time-varying attenuation on link A-B.

training the broker-level hierarchical and omniscient ANNs with 2400 samples per path. The input features of the broker-level hierarchical ANNs contain the two prediction values from the domain manager-level ANNs, as well as the OPM information from the IXP, forming a 6×1 vector. Fig. 5 shows the training and Q-factor prediction performance of the omniscient and hierarchical estimators for one of the routing path (A-C-D-E-F-G). Both ANNs converge properly without overfitting. The Q-factor deviations for the omniscient and hierarchical estimators are 0.5 and 0.52 dB, respectively. From Fig. 5 (a) and (b), the hierarchical estimator seems to have a slower convergence speed and slightly higher out-of-sample error against the omniscient ANN. These results indicate that the proposed hierarchical estimator can achieve nearly ideal QoT prediction performance (with a small penalty) while supporting the autonomy and privacy of each autonomous domain. Fig. 6 summarizes the performance of the intra- and inter-domain ANN banks in terms of absolute Q-factor deviations as well as their standard deviation. The blue and red bars in Fig. 6(b) correspond to the Q-factor deviations of the hierarchical and omniscient QoT estimators, respectively. It shows that the hierarchical learning based QoT predictor achieves less than 0.6 dB Q-factor deviation in the worst case scenario.

C. Impairment-aware Inter-Domain Service Provisioning

Once the performance of the hierarchical learning based QoT estimators has been verified, we integrated the proposed hierarchical ANN banks into the SDN controllers on the broker plane and the domain manager plane. Based on the acquired knowledge, we demonstrate a use case of impairment-aware inter-domain service provisioning where a network client located in domain #1 wants to establish a lightpath from node A to node G (located in domain #2). First, the client submits its request to the local domain manager. The domain manager then asks the broker to initiate the inter-domain RMSA process shown in Fig. 2(a) and set up a lightpath over node A-B-F-G. The launch power for the testing signal across the A-B link was set to -5 dBm by controlling the pump power of node A's input EDFA. Fig. 7(a) shows the Wireshark messages captured from domain manager #1 for the whole procedures of the provisioning process. The entire inter-domain RMSA process takes 27 *ms* to set up a new end-to-end lightpath (excluding the time taken to physically reconfigure the WSS). Fig. 7(b) presents the message of *Status_Reply* that are captured at domain manager #1. In this message, domain manager #1 is telling the broker that it has two routing candidates for the inter-domain lightpath request. The information about DWDM channel utilization, the domain-level Q-factor prediction, and the name of the sink node at IXP for each routing candidate is included in the message. To show the impairment awareness of the proposed provisioning scheme, we purposely introduced a time-varying attenuation from 0 dB to 20 dB with a rate of 1 dB per 60 seconds between node A and node B using the WSS, and recorded the measured Q-factor at node G. This attenuation ultimately results in an intra-domain link failure, which ultimately leads to an inter-domain link failure between node A and node G. During this process, the domain manager and broker-level ANN constantly monitor the intra- and inter-domain Q-factor prediction values and notice the

Q-factor degradation. We plot the evolution of the measured and predicted Q-factors on Fig. 7(c). It should be noted that the measured Q-factor only serves as the ground truth results to benchmark the proposed QoT estimator. As we increase the attenuation on link A-B, the measured and predicted Q-factors are reduced due to the presence of more amplified spontaneous emission (ASE) noise. After six consecutive low-value Q-factor predictions, the domain manager #1 triggers an intra-domain rerouting (node A-C-B-F-G) shown in Fig. 7(d) to re-provision the signal. After re-provisioning, the Q-factor of the lightpath resumes to 12 - 13 dB because the faulty link has been bypassed. The mean absolute error between the estimated Q-factors as well as measured Q-factors was found to be 0.6 dB, which further confirms the performance of the proposed hierarchical learning-based QoT estimator. In conclusion, efficient impairment-aware multi-domain service provisioning with low prediction error (<0.6 dB) is demonstrated by using the proposed hierarchical scheme.

IV. CONCLUSION

This paper investigates a hierarchical learning framework for impairment-aware service provisioning across multiple autonomous optical domains while respecting the autonomy and privacy of each domain. The proposed framework taking various transmission impairments, such as noise, crosstalk, and distortions into considerations during the provisioning process to ensure accurate QoT prediction. We implemented the proposed system on a multi-domain testbed, quantitatively verified the performance of the hierarchical learning based QoT estimator and demonstrated its application in a use case of impairment-aware inter-domain service provisioning.

While the proposed framework offers an efficient provisioning scheme, its scalability remains to be fully assessed. Since the broker-level ANN relies on the predictions from the domain manager-level ANNs as inputs, the prediction error from domain manager-level ANNs might accumulate at the broker-level ANN, potentially reducing the prediction accuracy of the inter-domain QoT. As the number of autonomous optical domains under single broker's coverage increases, the effect of error propagation might become more significant. Accuracy of predictions at each layer and each plane (physical layer measurements from OPM, predictions by agents in domain manager and broker plane) as well as efficient and accurate abstractions going from intra-domain information to inter-domain big-pictures are important for scalable and effective multi-domain network operation enhanced by machine learning. Fault-tolerant and error-tolerant hierarchical learning methods by spatio-temporal abstraction may play an important role [30]. Future research will include effective abstractions and hierarchical learning that mitigate error propagation effects, multi-broker multi-domain networking, and applications of game-theories to multi-agent networking.

REFERENCES

[1] P. Lu, L. Zhang, X. Liu, J. Yao, and Z. Zhu, "Highly-efficient data migration and backup for big data applications in elastic optical inter-datacenter networks," *IEEE Netw.*, vol. 29, pp. 36–42, Sept./Oct. 2015.

[2] C. Chen, X. Chen, M. Zhang, S. Ma, Y. Shao, S. Li, M. Suleiman, and Z. Zhu, "Demonstrations of efficient online spectrum defragmentation in software-defined elastic optical networks," *J. Lightw. Technol.*, vol. 32, no. 24, pp. 4701–4711, Dec 2014.

[3] Y. Yin, L. Liu, R. Proietti, and S. B. Yoo, "Software defined elastic optical networks for cloud computing," *IEEE Network*, vol. 31, no. 1, pp. 4–10, 2017.

[4] S. B. Yoo, L. Liu, R. Proietti, and R. P. Scott, "Software defined elastic optical networking in temporal, spectral, and spatial domains," *Photonic Network Communications*, vol. 28, no. 1, pp. 19–33, 2014.

[5] Z. Zhu, W. Lu, L. Zhang, and N. Ansari, "Dynamic service provisioning in elastic optical networks with hybrid single-/multi-path routing," *J. Lightw. Technol.*, vol. 31, no. 1, pp. 15–22, Jan 2013.

[6] B. Chatterjee, N. Sarma, and E. Oki, "Routing and spectrum allocation in elastic optical networks: A tutorial," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 3, pp. 1776–1800, thirdquarter 2015.

[7] N. Sambo, Y. Pointurier, F. Cugini, L. Valcarenghi, P. Castoldi, and I. Tomkos, "Lightpath establishment assisted by offline qot estimation in transparent optical networks," *Journal of Optical Communications and Networking*, vol. 2, no. 11, pp. 928–937, 2010.

[8] P. Poggiolini, G. Bosco, A. Carena, V. Curri, Y. Jiang, and F. Forghieri, "The gn-model of fiber non-linear propagation and its applications," *Journal of lightwave technology*, vol. 32, no. 4, pp. 694–721, 2014.

[9] I. Sartzetakis, K. Christodoulopoulos, C. Tsekrekos, D. Syvridis, and E. Varvarigos, "Quality of transmission estimation in wdm and elastic optical networks accounting for space–spectrum dependencies," *IEEE/OSA Journal of Optical Communications and Networking*, vol. 8, no. 9, pp. 676–688, 2016.

[10] S. Yan, F. N. Khan, A. Mavromatis, D. Gkounis, Q. Fan, F. Ntavou, K. Nikolovgenis, F. Meng, E. H. Salas, C. Guo *et al.*, "Field trial of machine-learning-assisted and sdn-based optical network planning with network-scale monitoring database," in *European Conf. and Exhibition on Optical Communication*, 2017, pp. Th–PDP.

[11] Y. Li, W. Mo, S. Zhu, Y. Shen, J. Yu, P. Samadi, K. Bergman, and D. C. Kilper, "tsdx: enabling impairment-aware all-optical inter-domain exchange," *Journal of Lightwave Technology*, vol. 36, no. 1, pp. 142–154, 2018.

[12] W. Mo, Y.-K. Huang, S. Zhang, E. Ip, D. C. Kilper, Y. Aono, and T. Tajima, "Ann-based transfer learning for qot prediction in real-time mixed line-rate systems," in *2018 Optical Fiber Communications Conference and Exposition (OFC)*. IEEE, 2018, pp. 1–3.

[13] S. Aladin and C. Tremblay, "Cognitive tool for estimating the qot of new lightpaths," in *Optical Fiber Communication Conference*. Optical Society of America, 2018, pp. M3A–3.

[14] A. Caballero, J. C. Aguado, R. Borkowski, S. Saldaña, T. Jiménez, I. de Miguel, V. Arlunno, R. J. Durán, D. Zibar, J. B. Jensen *et al.*, "Experimental demonstration of a cognitive quality of transmission estimator for optical communication systems," *Optics express*, vol. 20, no. 26, pp. B64–B70, 2012.

[15] S. J. B. Yoo, "Multi-domain cognitive optical software defined networks with market-driven brokers," in *Proc. of ECOC*, Sept. 2014, pp. 1–3.

[16] X. Chen, Z. Zhu, L. Sun, J. Yin, S. Zhu, A. Castro, and S. J. B. Yoo, "Incentive-driven bidding strategy for brokers to compete for service provisioning tasks in multi-domain SD-EONs," *J. Lightw. Technol.*, vol. 34, no. 16, pp. 3867–3876, 2016.

[17] A. Castro, L. Velasco, L. Gifre, C. Chen, J. Yin, Z. Zhu, R. Proietti, and S.-J. B. Yoo, "Brokered orchestration for end-to-end service provisioning across heterogeneous multi-operator (multi-as) optical networks," *Journal of Lightwave Technology*, vol. 34, no. 23, pp. 5391–5400, 2016.

[18] M. Chamania and A. Jukan, "A survey of inter-domain peering and provisioning solutions for the next generation optical networks," *IEEE Commun. Surveys Tuts.*, vol. 11, no. 1, pp. 33–51, First 2009.

[19] Z. Zhu, C. Chen, X. Chen, S. Ma, L. Liu, X. Feng, and S. J. B. Yoo, "Demonstration of cooperative resource allocation in an OpenFlow-controlled multidomain and multinational SD-EON testbed," *J. Lightw. Technol.*, vol. 33, no. 8, pp. 1508–1514, April 2015.

[20] G. Liu, K. Zhang, X. Chen, H. Lu, J. Guo, J. Yin, R. Proietti, Z. Zhu, and S. B. Yoo, "The first testbed demonstration of cognitive end-to-end optical service provisioning with hierarchical learning across multiple autonomous systems," in *Optical Fiber Communication Conference*. Optical Society of America, 2018, pp. Th4D–7.

[21] X. Chen, R. Proietti, H. Lu, A. Castro, and S. J. B. Yoo, "Knowledge-based autonomous service provisioning in multi-domain elastic optical networks," *IEEE Commun. Mag.*, in press.

[22] A. Gupta, L. Vanbever, M. Shahbaz, S. P. Donovan, B. Schlinker, N. Feamster, J. Rexford, S. Shenker, R. Clark, and E. Katz-Bassett, "Sdx:

A software defined internet exchange," *ACM SIGCOMM Computer Communication Review*, vol. 44, no. 4, pp. 551–562, 2015.
[23] M. Tornatore, "Data analytics and machine learning applied to transport layer," in *2018 Optical Fiber Communications Conference and Exposition (OFC)*. IEEE, 2018, pp. 1–71.
[24] A. Blumer, A. Ehrenfeucht, D. Haussler, and M. K. Warmuth, "Learnability and the vapnik-chervonenkis dimension," *Journal of the ACM (JACM)*, vol. 36, no. 4, pp. 929–965, 1989.
[25] "Onos mission." [Online]. Available: https://onosproject.org/mission/
[26] "What is rest?" [Online]. Available: https://www.restapitutorial.com/lessons/whatisrest.html
[27] "Pytorch get started." [Online]. Available: https://pytorch.org/about/
[28] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, 2010, pp. 249–256.
[29] T. Chai and R. R. Draxler, "Root mean square error (rmse) or mean absolute error (mae)?–arguments against avoiding rmse in the literature," *Geoscientific model development*, vol. 7, no. 3, pp. 1247–1250, 2014.
[30] J. A. Starzyk and H. He, "Spatio–temporal memories for machine learning: A long-term memory organization," *IEEE Transactions on Neural Networks*, vol. 20, no. 5, pp. 768–780, 2009.

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