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Collaborative Learning in Multi-Domain Optical Networks

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Abstract: This paper presents a collaborative learning framework for multi-domain optical networks to empower cognitive end-to-end networking while guaranteeing the autonomy of each administrative domain.

1. Introduction

To meet the ever-increasing capacity and latency requirements imposed by emerging networking applications (e.g., the Internet of Things), it is essential that the next-generation optical transport networks can not only optimize the operations of the local administrative domains but also realize effective inter-domain networking [1]. Software-defined networking (SDN) enables to revolutionize the network control and management (NC&M) of legacy networks toward a softwarized and programmable paradigm by decoupling the data and control planes. The merit of SDN has inspired several novel multi-domain NC&M architecture designs, where SDN-based domain managers (DMs) work in a peer-to-peer mechanism (flat architectures) or under the coordination of third-party resource brokers [2] (hierarchical architectures). While these architectures offer unprecedented flexibility to the NC&M layer, optimizing inter-domain networking is still a nontrivial task because of the domain autonomy constraint. Previous works mostly rely on rule-based heuristic approaches that exploit the limited domain information advertised for service provisioning in multi-domain optical networks (MD-ONs) [3], which can result in suboptimal resource utilization.

Recently, machine learning (ML) has received a surge of research interests from the optical communication and networking community. ML makes it possible to learn complex network rules directly from big data and thereby can facilitate knowledge-based cognitive networking. A number of successful ML applications in optical networks, for instance, lightpath quality-of-transmission (QoT) estimation [4], soft failure detection [5], and routing, modulation and spectrum assignment (RMSA) [6], have been reported lately. However, most of the existing works consider a single-domain scenario, which can hardly be applied to MD-ONs where employing a unified learning function possessing global network state data is infeasible. In this paper, we present a collaborative learning framework for empowering cognitive inter-domain networking in MD-ONs. The proposed framework leverages a broker-based NC&M architecture and makes use of broker plane and local ML functions learning cooperatively to exploit full network state data while securing the privacy of each domain. Case studies with inter-domain QoT estimation and RMSA verify the effectiveness of the proposed framework.

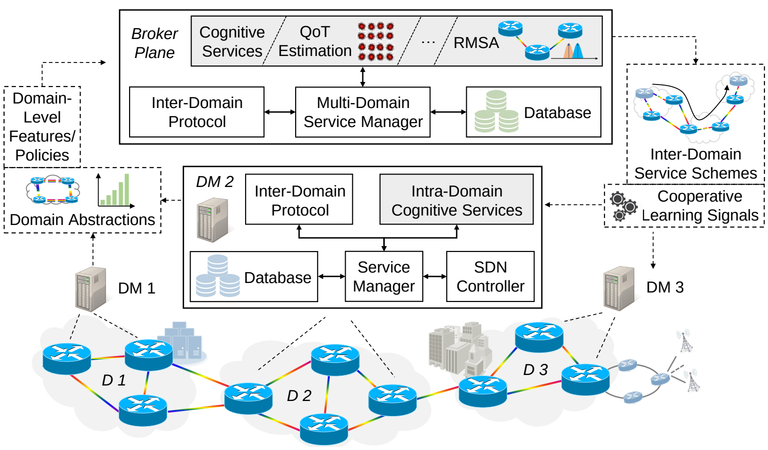


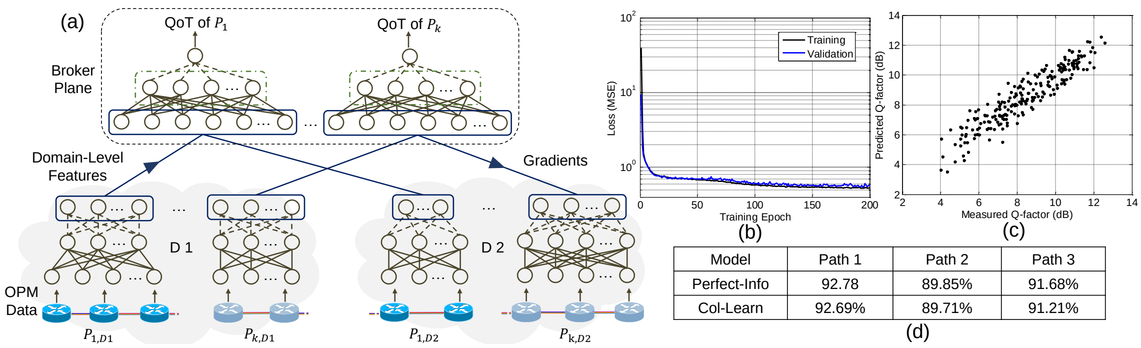
Fig. 1. Proposed collaborative learning framework for MD-ONs.

2. Principle and Case Studies

Fig. 1 shows the proposed collaborative learning framework adopting a broker-based hierarchical MD-ON architecture. Each DM controls its intra-domain operations with an SDN paradigm while subscribing to the broker plane services for inter-domain networking. The broker plane receives domain abstractions (e.g., virtual links among domain border nodes [7]) from DMs according to the mutual service level agreements. To facilitate cognitive inter-domain networking, the collaborative learning framework employs ML functions in both the broker plane and DMs. The ML functions in DMs aim at learning domain-level features or local provisioning policies from the raw network state data. The broker plane ML functions aggregate the outputs of the local ML functions and take necessary domain abstractions to generate end-to-end learning results. Each time the broker plane ML functions are updated, the broker plane distributes learning signals to DMs, such as gradients [8] or rewards [6], to assist in training the local ML functions. The proposed framework essentially decomposes an intact ML model into multiple submodels distributed in different administrative entities. These submodels, as an ensemble, allow to exploit the full multi-domain state data while securing the privacy of each domain by exchanging only high-level features and learning signals. Next, we discuss the designs of inter-domain QoT estimation and RMSA as case studies of the collaborative learning framework.

2.1. QoT Estimation

Fig. 2(a) illustrates the principle of a collaborative learning-based inter-domain QoT estimator design in a two-domain scenario [8]. The broker plane and DMs employ separate ML functions (e.g., neural network blocks) for different inter-domain lightpaths P_k as they can be composed of different numbers of nodes. The local ML functions take as input the optical performance monitoring (OPM) data collected at each node along the intra-domain segments (e.g., $P_{1,D1}$), including the measured channel utilization, signal power, and noise floor. The broker plane ML functions combine the domain-level features related to each P_k to compute the end-to-end QoT estimation. With the measured QoT values as labels, the broker plane can train its ML functions using a gradient-based approach that minimizes the prediction errors (i.e., losses). The broker plane can further distribute the gradients of the loss functions regarding its input-layer weights, with which the DMs can train the local ML functions according to the chain rule [8]. Note that, as the QoT estimation tasks for different P_k can share certain similarities, transfer learning can be applied to enhance the performance of the QoT estimators while significantly reducing the amount of OPM data required [9].



Model	Path 1	Path 2	Path 3
Perfect-Info	92.78	89.85%	91.68%
Col-Learn	92.69%	89.71%	91.21%

(d)

Fig. 2. (a) Collaborative learning-based inter-domain QoT estimator design, (b) losses in training, (c) comparison between measured and predicted QoT, and (d) comparison of prediction accuracy between the collaborative learning-based approach and the perfect-information baseline [8].

We evaluated the performance of the inter-domain QoT estimator design using the experimental data collected from a two-domain testbed [8]. Specifically, the data set covers three inter-domain lightpaths with various link load scenarios (different numbers of channels injected) and emulated equipment conditions (channel-specific attenuation introduced at the intermediate optical switches). Each local ML function was implemented with a two-layer neural network outputting four domain-level features, whereas a three-layer neural network architecture ($[8,8,1]$) was used for the broker plane ML functions. Fig. 2(b) shows the evolution of losses in training the QoT estimator for path 1. The results show that the ML functions fit well as the validation losses always stick closely to the training losses. We visualize the performance of the trained QoT estimator for path 1 in Fig. 2(c) by showing the comparison between the predicted and measured QoT (i.e., Q-factors). Finally, we compare the proposed design (denoted as Col-Learn) with a perfect-information baseline (denoted as Perfect-Info) which, hypothetically, reduces the inter-domain tasks into intra-domain ones by having full domain visibility. Thus, Perfect-Info can be seen as providing the performance upper bounds. Fig. 2(d) summarizes the results of prediction accuracy for the three paths, suggesting that the proposed approach can achieve performance very close to that of Perfect-Info.

2.2. *RMSA*

Our previous work in [6] demonstrated a deep reinforcement learning agent (i.e., DeepRMSA) which can autonomically learn effective RMSA policies from repeated operation experiences. We adapt the DeepRMSA design to the collaborative learning framework for autonomic inter-domain RMSA as follows. The broker plane and DMs each employs a DeepRMSA agent. We denote an inter-domain lightpath request by $R(s,d,b,\tau)$, where s and d are the source and destination nodes, b represents the requested bandwidth, and τ is the service period. Upon receiving R, the local agent of each DM takes as input the request's information and the spectrum utilization state within the domain to recommend a set of intra-domain path segments (abstracted as virtual links) to be reported to the broker plane. In particular, the path segments of the source, destination, and intermediate domains include the routing paths from s to every domain egress node, from every domain ingress node to d, and between every ingress and egress node pair, respectively. The broker plane constructs a virtual topology with the received virtual links (see the example in Fig. 1) and invoke its DeepRMSA agent to decide an end-to-end RMSA scheme. Afterward, the involved DMs map the decision by the broker plane to the path segments selected and attempt to configure the data plane accordingly. With the feedback from DMs, the broker plane evaluates the overall performance of the decisions made (by all the agents) and computes a team reward r. For instance, r can be a positive value if R is correctly provisioned, otherwise, r takes a negative value. The provision experience, including the agent-specific network states, actions, and r, is recorded by each agent. Every time L experience samples are collected, the agents perform concurrent training, by reinforcing actions resulting in higher cumulative rewards [6]. Note that, during the provisioning of R, a local agent can be executed multiple times, each for determining the path segment between specific end nodes. The agent will only adopt the sample incorporated in the end-to-end scheme for training as the other samples do not directly reflect the performance of its policy. Eventually, with a large number of trial and error, the broker plane and local agents can potentially converge to cooperative RMSA policies maximizing the long-term multi-domain throughput [10].

3. Summary

In this paper, we presented a collaborative learning framework for cognitive inter-domain networking in MD-ONs. The application of the proposed framework in inter-domain QoT estimation and RMSA were then discussed.

Acknowledgments

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