Towards Self-Driving Optical Networking with Reinforcement Learning and Knowledge Transferring

(Invited)

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***Abstract*—This paper presents a self-driving networking paradigm exploiting the state-of-the-art reinforcement learning and transfer learning algorithms for highly resource-efficient, scalable, and adaptive next-generation optical networks. The proposed design makes use of learning agents to constantly learn and optimize service provisioning policies through an observe-analyze-act cycle in dynamic operations. Case studies on routing and spectrum assignment tasks show significant advantages of the proposed design over traditional heuristic algorithms.**

***Index Terms*—next-generation optical networks, reinforcement learning, transfer learning, routing and spectrum assignment**

I. Introduction

The fast evolution of emerging networking paradigms and applications, such as 5G networks and edge computing, has been imposing stringent capacity and quality-of-service requirements on the underlying optical transport networks [1]. To meet such requirements, advanced optical networking architectures supporting high degrees of network automation and intelligence are desired. While software-defined networking (SDN) has been shown to enable automated and programmable control and management of optical networks [2], most of the existing service provisioning designs still rely on artificial and fixed policies. Due to the lack of the cognition of rules of optical networks, these policies often have poor adaptability and can lead to sub-optimal resource utilization.

Recent breakthroughs in machine learning (ML) have made it possible to realize knowledge-based optical networking by developing ML models to learn network rules automatically from big data [3]. Previous studies have reported the benefits of a number of ML-aided cognitive designs for optical networks, but mostly focusing on quality-of-transmission (QoT) modeling [4], traffic prediction [3], and fault management [5]. Nevertheless, to realize effective service provisioning, artificial policies that can take advantage of the outputs of these ML designs are still required. For instance, after accurate QoT estimators are obtained, margin-aware provisioning strategies should be studied for reduced provisioning margins [6].

In this paper, we leverage the recent advances in deep reinforcement learning (DRL) [7] and transfer learning (TL) [8] to present a self-driving networking paradigm for optical networks. The proposed paradigm makes use of DRL agents to learn effective service provisioning policies autonomically from network operation experiences, and thus can constantly reoptimize and readapt. Meanwhile, the DRL agents can transfer knowledge mutually to pursue reduced learning costs (e.g., time) and better scalability. We perform case studies on the proposed design with the routing, modulation, and spectrum assignment (RMSA) application and the simulation results verify the effectiveness of our proposal.

The remainder of the paper is organized as follows. In Section II, we present the architecture and operation principle of the proposed self-driving network framework. In Section III, we detail the DRL-based RMSA design and the knowledge transferring mechanism and show the related performance evaluations. Finally, we summarize the paper in Section IV.

II. Network Architecture

Fig. 1(a) shows the architecture of a self-driving optical network. A centralized SDN control plane controls the operations of the optical data plane carrying the traffic aggregated from metro/access networks and datacenters. The SDN controller interacts with local SDN agents attached to the data plane equipment (e.g., switches, optical performance

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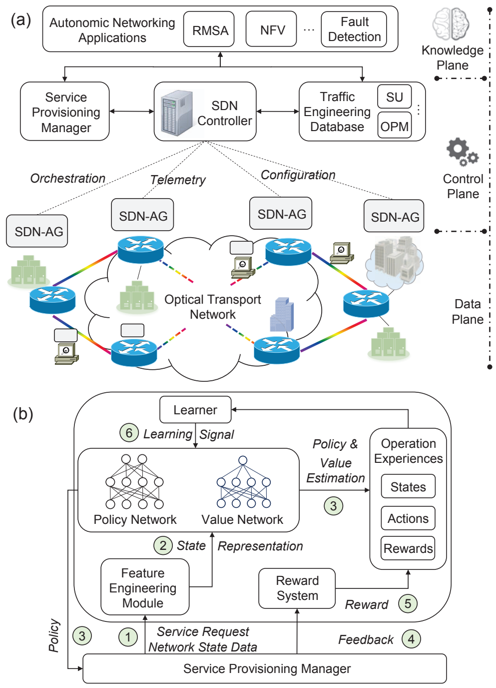

Fig. 1. (a) Self-driving networking architecture, and (b) operation principle of an autonomic networking application. OPM: optical performance monitoring, AG: agent, SU: spectrum utilization.

monitoring devices) to collect network state data and distribute configuration commands. The knowledge plane consisting of multiple DRL-based autonomic networking applications, such as RMSA and network function virtualization (NFV), acts as the key enabler for realizing self-driving networking operations. The operation principle of an autonomic networking application is depicted in Fig. 1(b). Upon receiving a service request from the service provisioning manager, the feature engineering module of the application acquires the related network state data and generates a state representation that can be recognized by the deep neural networks (DNNs). In a typical DRL setting [7], a policy and a value DNN are employed to parameterize the service policy and the reward estimation, respectively. The policy DNN processes the state representation and outputs a probability distribution over an action space or a service scheme directly, while the value DNN evaluates the performance of the current policy. Next, the service provisioning manager applies the service scheme recommended by the policy DNN and returns feedback. The reward system translates the feedback into a numerical reward as a function of the performance of the action taken. The operation experience is then stored, whereafter, the learner periodically produces learning signals from the experience samples to update the DNNs by reinforcing actions leading to higher long-term rewards. Overall, following such observe-analyze-act-based cycles, the autonomic applications can constantly learn and optimize the service provisioning policies and thereby realize self-driving networking operations. Meanwhile, as different applications in optical networks can share certain similarities, TL techniques can be applied to enable more prompt service deployment for enhanced network scalability.

III. Case Studies

RMSA is one of the most fundamental applications in elastic optical networks (EONs) [9]. In this section, we present a DRL-based autonomic RMSA design, namely, DeepRMSA [10], and a multi-task learning (MTL) aided TL approach for knowledge transferring between DeepRMSA agents as case studies of the proposed self-driving networking paradigm.

A. Autonomic RMSA Design

Given an EON represented by $G(V, E)$, where V and E are the node and link sets and each link $e \in E$ has F available frequency slots (FS's), DeepRMSA reads the EON state and determines an RMSA scheme for each dynamic lightpath request $\mathcal{R}(o, d, b, \tau)$. Wherein, o and d are the origin and destination nodes of the request, b is the requested data rate and τ is the service period. The state, action and reward formulations and the training procedures are as follows.

State representation: DeepRMSA reads state information consisting of $\mathcal{R}$ and the spectrum utilization on a set of precalculated candidate routing paths for $\mathcal{R}$.

Action space: The action space is composed of K routing options, while the first-fit spectrum allocation scheme is always applied.

Reward function: A DeepRMSA agent receives a reward of 1 if $\mathcal{R}$ is successfully provisioned, and -1 otherwise.

DNN architecture: Both the policy and value DNNs adopt fully-connected architectures of five hidden layers (128 neurons each layer).

Training: We train DeepRMSA agents with the DeepRMSA-FlX algorithm [10], which updates the policy and value DNNs with samples related to N requests every training step. Specifically, DeepRMSA-FlX attempts to increase the probabilities of actions with larger advantages (the differences between the real collected and the estimated rewards) and to minimize the overall reward estimation errors.

We evaluated the performance of DeepRMSA with simulations using two topologies, namely, the 14-node NSFNET and the 11-node Cost239 topologies. We generated dynamic and uniformly distributed lightpath requests following Poisson processes. The other parameters used in the simulations can be found in [11]. We select the K-shortest path routing and first-fit spectrum assignment (KSP-FF) ($K = 5$) [12] and the SP-FF (equivalent to the case of $K = 1$ for KSP-FF) algorithms as the baselines. Figs. 2(c) and (d) show the results of request blocking probability. We can see that the performance of DeepRMSA improves quickly with training and that DeepRMSA can successfully beat the baselines after training of $30,000$ and $50,000$ for the two topologies, respectively. Eventually, DeepRMSA can reduce the blocking probability by $\sim 46\%$ and $\sim 41\%$. The results clearly demonstrate the feasibility and benefits of the proposed self-driving networking paradigm.

B. Knowledge Transferring between RMSA Agents

Training a DeepRMSA agent is a non-trivial task, which can restrict the applicability of DeepRMSA when new agents need to be trained promptly in the case of significant changes

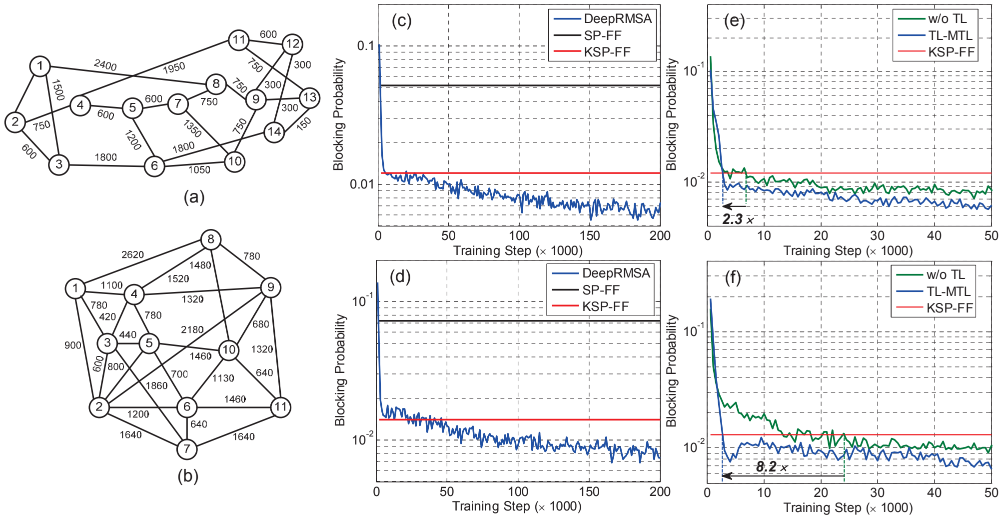

Fig. 2. (a) NSFNET topology, and (b) Cost239 topology. (c)-(d) Evolutions of blocking probablity in training basic DeepRMSA models for (c) the NSFNET topology and (d) the Cost239 topology. (e)-(f) comparison of differernt TL models under (e) the NSFNET topology and (f) the Cost239 topology.

in network conditions (e.g., due to disasters) or when operators provision network slices with various topologies [13]. Therefore, we propose an MTL-aided TL approach [14] to facilitate the training of DeepRMSA agents.

Let $\mathbb{M}_s$ denote a set of source tasks for which DeepRMSA agents have been trained and M_t denote a target task. We first train an MTL agent that can master all the tasks in $\mathbb{M}_s$. To this end, a large number of experience samples are generated with every agent for $\mathbb{M}_s$. We train the MTL agent with the generated samples using a supervised learning scheme, that is, to make the MTL agent mimic the policy and value functions of the agents for the multiple source tasks simultaneously. Then, we initialize the DNNs for M_t by copying the corresponding weights from the MTL agent, whereafter, a classic training algorithm can be applied. This way, we can exploit multiple source tasks and transfer better-generalized knowledge.

We trained the DeepRMSA agents for a six-node and a 14-node topology as two source tasks and evaluated the performance of the proposed TL design on the NSFNET and Cost239 topologies. For training the MTL agent, $100,000$ samples were generated from each source task. Figs. 2(e) and (f) show the evolutions of blocking probability in training. We can see that the proposed design (TL-MTL) can effectively expedite the learning process compared with the model without TL (w/o TL), i.e., reducing the number of training steps required to reach the performance of KSP-FF by $2.3\times$ and $8.2\times$, respectively. Meanwhile, TL-MTL helps to further reduce the ultimate blocking probability by $\sim 20\%$.

IV. Summary

We presented a self-driving networking paradigm for pursuing highly resource-efficient, scalable, and adaptive next-generation optical networks. A DeepRMSA design and an MTL-aided TL approach were studied as two use cases. Evaluation results verify the benefits of our proposed approach.

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-data-center networks," IEEE Netw., vol. 29, pp. 36–42, Sept./Oct. 2015.

[2] N. Cvijetic, A. Tanaka, P. N. Ji, K. Sethuraman, S. Murakami, and T. Wang, "SDN and OpenFlow for dynamic flex-grid optical access and aggregation networks," J. Lightw. Technol., vol. 32, pp. 864–870, Feb. 2014.

[3] 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., vol. 56, pp. 152–158, Aug. 2018.

[4] N. Cvijetic, A. Tanaka, P. N. Ji, K. Sethuraman, S. Murakami, and T. Wang, "Machine-learning method for quality of transmission prediction of unestablished lightpaths," J. Opt. Commun. Netw., vol. 10, pp. A286–A297, Feb. 2018.

[5] N. Cvijetic, A. Tanaka, P. N. Ji, K. Sethuraman, S. Murakami, and T. Wang, "BER degradation detection and failure identification in elastic optical networks," J. Lightw. Technol., vol. 35, pp. 4595–4604, Nov. 2017.

[6] D. Moniz, J. Pedro, and J. Pires, "Design and operation strategies for optical transport networks with reduced margins service-provisioning," in Proc. IEEE/OSA Opt. Fiber Commun. Conf., 2020, paper M4D.1.

[7] V. Mnih, A. Badia, M. Mirza, A. Graves, T. Harley, T. Lillicrap, D. Silver, and K. Kavukcuoglu, "Asynchronous methods for deep reinforcement learning," in Proc. Int. Conf. Mach. Learn., 2019, pp. 1928–1937.

[8] E. Parisotto, J. Ba, and R. Salakhutdinov, "Actor-mimic: Deep multitask and transfer reinforcement learning," 2015, arXiv:1511.06342.

[9] 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, pp. 15–22, Jan. 2013.

[10] X. Chen, B. Li, R. Proietti, H. Lu, Z. Zhu, and S. J. B. Yoo, "DeepRMSA: A deep reinforcement learning framework for routing, modulation and spectrum assignment in elastic optical networks," J. Lightw. Technol., vol. 37, pp. 4155–4163, Aug. 2019.

[11] X. Chen, R. Proietti, and S. J. B. Yoo, "Building autonomic elastic optical networks with deep reinforcement learning," IEEE Commun. Mag., vol. 57, pp. 20–26, Oct. 2019.

[12] Y. Yin, H. Zhang, M. Zhang, M. Xia, Z. Zhu, S. Dahlfort, and S. J. B. Yoo, "Spectral and spatial 2D fragmentation-aware routing and spectrum assignment algorithms in elastic optical networks," J. Opt. Commun. Netw., vol. 5, pp. A100–A106, Oct. 2013.

[13] L. Gong and Z. Zhu, "Virtual optical network embedding (VONE) over elastic optical networks," J. Lightw. Technol., vol. 32, pp. 450–460, Feb. 2014.

[14] X. Chen, , R. Proietti, C. Liu, Z. Zhu, and S. J. B. Yoo, "Exploiting multi-task learning to achieve effective transfer deep reinforcement learning in elastic optical networks," in Proc. IEEE/OSA Opt. Fiber Commun. Conf., 2020, paper M1B.3.