DRL-assisted Light-tree Reconfiguration for Dynamic Multicast in Elastic Optical Networks

Xiaojian Tian[1], Baojia Li[1], and Zuqing Zhu[1]

1. University of Science and Technology of China, Hefei, Anhui 230027, China, Email: zqzhu@ieee.org

Abstract: We propose an approach based on deep reinforcement learning (DRL) to reconfigure light-tree dynamically for multicast sessions in Elastic Optical Networks (EONs).

1. Introduction

The rising of cloud services, especially the surge in demand for video conferencing and online classroom services during the epidemic since 2020, has made multicast services increasingly popular in the Internet. This puts Internet infrastructures and service provisioning over them under tremendous pressure [1, 2]. Because of the abundant bandwidth on optical fibers, optical networks can enable high-throughput and long distance transmission economically and efficiently. Furthermore, the advances on the flexible-grid elastic optical networks (EONs) have enhanced the flexibility and effectiveness of optical networks [3, 4]. Therefore, a lot of studies have been done on enabling multicast in EONs, and many algorithms have been proposed [5–7]. At the same time, the dynamic nature of multicast services further increases the complexity of the problem. As members can join and leave dynamically during the life-time of a multicast service, its light-tree can gradually lose the optimality if it is not reconfigured regularly [8].

The problem of light-tree reconfiguration for dynamic multicast in EONs has been explored in [8], in which the authors divided it into two sub-problems, *i.e.*, light-tree selection and light-tree reconfiguration, and put forward corresponding algorithms to solve them. They proposed D-/Q-value based algorithms for the light-tree selection and developed full/partial rearrangement algorithms to solve the light-tree reconfiguration. Ideally, people would like to achieve a lower blocking probability with as few reconfiguration operations as possible, which is the most important tradeoff for evaluating the performance of light-tree reconfiguration. However, due to the complexity of dynamic EONs, the algorithms developed in [8] can hardly optimize this tradeoff. Hence, we revisited the sub-problem of light-tree selection with a deep reinforcement learning (DRL) based approach [9]. Specifically, we proposed a DRL model based on graph neural networks (GNNs) [10], which can obtain statistically optimal solutions for the light-tree selection sub-problem. GNNs enable our proposal to directly process graph-structured data, which overcomes the limitations of conventional neural networks and avoids the loss of the information about light-tree structures.

2. Network Model and Algorithm Design

The topology of an EON can be represented as $G(V,E)$, where V and E are the sets of nodes and fiber links, respectively. Each node $v \in V$ uses a multicast-incapable (MI) bandwidth-variable optical switch for cost-saving [8]. Each fiber link $e \in E$ contains F frequency slots (FS'), each of which has a bandwidth of 12.5 GHz. We represent each multicast session as $MR(s,D,b,t)$, where s, D, b and t denote the source, the set of destinations, the bandwidth demand in Gbps and its life-time, respectively. We use the spectrum-flexible member-only relay (SFMOR) algorithm [7] to build a logic light-tree for each newly-arrived multicast session, *i.e.*, the lightpaths in the light-tree can only start and end at the member nodes of the multicast session (*i.e.*, $s \cup D$). Since the $d \in D$ can join and leave dynamically during the life-time of MR, the light-tree will be updated constantly and thus can lose its optimality. Hence, we propose to reconfigure the light-tree from time to time with a graph-aware DRL model [9], whose basic elements are as follows.

Agent: As shown in Fig. 1(a), our DRL agent uses the asynchronous advantage actor-critic (A3C) framework [11], which leverages multiple pairs of actor GNN (A-GNN) and critic GNN (C-GNN) for multi-threaded parallel online training. Here, A-GNN selects proper actions according to the state, while C-GNN evaluates the action from A-GNN.

State: With the GNNs, we can use graph-structured data $\mathscr{G}(V,\tilde{V},E,\tilde{E})$ to denote the state information of an EON and the light-trees in it. Here, $\tilde{V}$ and $\tilde{E}$ are the features of V and E, respectively, which are for the categories of nodes and the spectrum usages of links. Each lightpath in the light-trees is set up with the fragmentation-aware scheme [12].

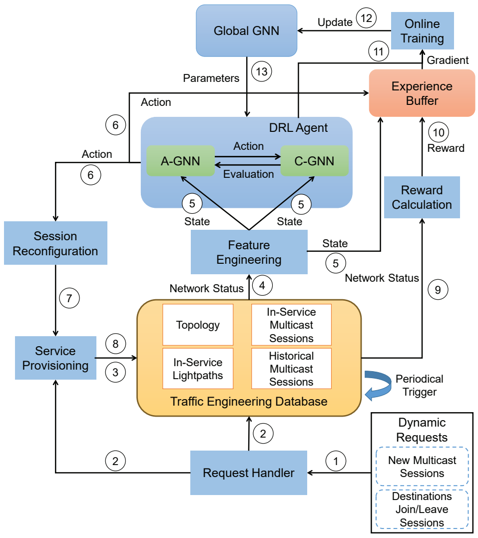
Action: The action a is a Boolean variable, which equals 1 if a light-tree should be reconfigured, and 0, otherwise.

Reward: The reward r can be expressed as the weighted sum of the number of reconfiguration operations and the spectrum resources saved by the reconfiguration. The weight of the former is negative, because we want to reduce the number of reconfiguration operations. Meanwhile, the weight of the latter is positive such that the more spectrum resources can be saved by a reconfiguration operation, the greater the reward r is.

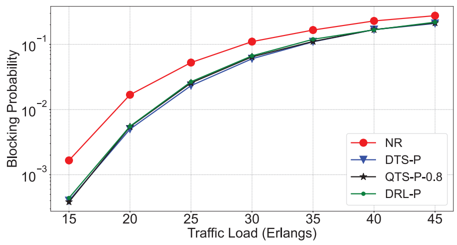
Fig. 1(a) shows the system architecture and operation principle of our graph-aware DRL (one of its threads). The service provisioning will build a light-tree for each newly-arrived multicast session MR, and update the light-tree when the members in its multicast group have changed. Specifically, multicast session reconfiguration is triggered periodically, and in each reconfiguration, the feature engineering module collects the current state s of the EON and the light-tree for each multicast session MR_i, and sends it to the local DRL agent. The session reconfiguration module decides whether to reconfigure the MR_i based on the output of the local DRL agent, and updates the light-tree for MR_i if it needs to be reconfigured. The reward calculation module then calculates the reward r after the reconfiguration. The tuple $< s, a, r >$ will be stored in the experience buffer as a training sample. When there are enough training samples, online training will be triggered to update the global GNN, which will then synchronize the parameters to local GNNs.

3. Performance Evaluation

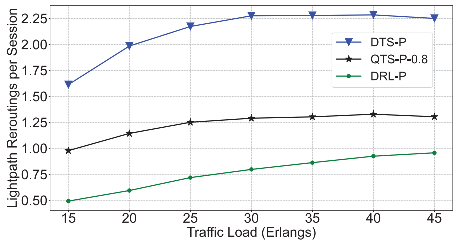
Our simulations use the NSFNET topology [1], and the capacity of each fiber link is set to be $F = 100$ FS'. Each multicast session $MR(s, D, b, t)$ arrives dynamically following the Poisson traffic model, and b is uniformly distributed within $[50, 200]$ Gbps, while t follows the exponential distribution with an average of 500 time-units. For each MR_i, the service time of each $d \in D$ follows the exponential distribution, and new destinations are generated according to the Poisson model. The DTS and QTS algorithm in [8] are used as the benchmarks. Due to the page limit, we only show the results when partial rearrangement is used for light-tree reconfiguration, in Figs. 1(b) and 1(c). Here, "NR" denotes the case without any light-tree reconfiguration. Compared with the benchmarks, our DRL model significantly reduces the number of reconfiguration operations while maintaining almost the same blocking probability.



(a) Architecture and operation principle of our DRL.



(b) Overall blocking probability



(c) Average number of lightpath reroutings per session

Fig. 1. System architecture and simulation results (NSFNET, partial rearrangement) (adapted from [9]).

4. Summary

We proposed a graph-aware DRL model to reconfigure the light-trees of dynamic multicast sessions in an EON. The results showed that our proposal reconfigures light-trees more efficiently than the existing deterministic algorithms.

References

[1] L. Gong *et al.*, "Virtual optical network embedding (VONE) over elastic optical networks," *J. Lightw. Technol.*, vol. 32, pp. 450-460, Feb. 2014.
[2] Y. Wang *et al.*, "Cost-efficient virtual network function graph (vNFG) provisioning in multidomain elastic optical networks," *J. Lightw. Technol.*, vol. 35, pp. 2712-2723, Jul. 2017.
[3] P. Lu *et al.*, "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.
[4] Z. Zhu *et al.*, "Dynamic service provisioning in elastic optical networks with hybrid single-/multi-path routing," *J. Lightw. Technol.*, vol. 31, pp. 15-22, Jan. 2013.
[5] Q. Wang, *et al.*, "Performance analysis of multicast traffic over spectrum elastic optical networks," *in Proc. of OFC 2012*, paper OTh3B.7, Mar. 2012.
[6] L. Gong *et al.*, "Efficient resource allocation for all-optical multicasting over spectrum-sliced elastic optical networks," *J. Opt. Commun. Netw.*, vol. 5, pp. 836-847, Aug. 2013.
[7] X. Liu *et al.*, "On the spectrum-efficient overlay multicast in elastic optical networks built with multicast-incapable switches," *IEEE Commun. Lett.*, vol. 17, pp. 1860-1863, Sept. 2013.
[8] M. Zeng *et al.*, "Control plane innovations to realize dynamic formulation of multicast sessions in inter-DC software-defined elastic optical networks," *Opt. Switch. Netw.*, vol. 23, pp. 259-269, Jan. 2017.
[9] X. Tian *et al.*, "Reconfiguring multicast sessions in elastic optical networks adaptively with graph-aware deep reinforcement learning," *J. Opt. Commun. Netw.*, in Press, 2021.
[10] F. Scarselli *et al.*, "The graph neural network model," *IEEE Trans. Neur. Net.*, vol.20, pp. 61–80, Jan. 2009.
[11] V. Mnih *et al.*, "Asynchronous methods for deep reinforcement learning," *in Proc. of ICML 2016*, pp. 1928-1937, Jun. 2016.
[12] Y. Yin *et al.*, "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.