ADMIRE: Demonstration of Collaborative Data-Driven and Model-Driven Intelligent Routing Engine for IP/Optical Cross-Layer Optimization in X-Haul Networks

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Abstract: We first demonstrate a collaborative data-driven (using deep reinforcement learning) and model-driven (using experience knowledge) routing engine for cross-layer optimization in a real X-Haul testbed with a real dataset, which achieves 23% wavelength saving. © 2022 The Author(s)

1. Introduction

In the 5G and beyond era, massive connections and mobility of user terminals have reinforced the dynamicity of optical networks, which poses a great challenge on network operators to make an optimal network decision (e.g., routing). Three approaches for making a network decision are shown in Fig. 1(a). Conventional network optimization is based on a model-driven approach, where the "model" is usually built upon the physical mechanisms and mathematical principles of optical networks. Model-driven approach is outstanding in simplifying the complicated network problem by establishing a rigorous and logical mathematical model. However, the problem of the model-driven approach lies in the difficulty in accurately modeling for a dynamic network scenario, for which the predetermined model designment is incompetent for variable traffic load and unexpected network events (e.g., network failure). Recently, data-driven approach enabled by deep reinforcement learning (DRL) shows its potential on optical network optimization [1, 2]. It learns the underlying mapping mechanism between the state and action of DRL by extracting knowledge from historical data. Moreover, it has self-evolution ability and can make a proper decision for the current network condition. However, in a real complex network circumstance, DRL may hold a large action space which is difficulty in convergence, and the arbitrary decision made by inexperienced DRL may result in poor network performance. Collaborative data-driven and model-driven approach was proposed to overcome the issues of two individual approaches but leverage their advantages [3]. Model-driven can take advantage of the knowledge-based mathematical model to compress the action space of DRL, while data-driven can modify some inaccurate parameters of the model to be suitable for the current network condition.

In this paper, we propose a coll**A**borative **D**ata-driven and **M**odel-driven **I**ntelligent **R**outing **E**ngine (**ADMIRE**) for IP/optical cross-layer optimization in 5G X-Haul networks. As shown in Fig. 1(b), we exploit a classical auxiliary graph (AG) [4] to modelling cross-layer routing problem and use DRL to train accurate auxiliary graph edge weights (AGEW) in AG. The optimized AGEW is assigned to an auxiliary graph topology (AGT) to make a routing decision. We compare the performance of ADMIRE with legacy AG using manually defined weights from experience [4]. The experimental results show that ADMIRE can achieve 23% wavelength reduction than a legacy algorithm and show good performance on latency. In addition, ADMIRE is proved to have a strong generalization ability.

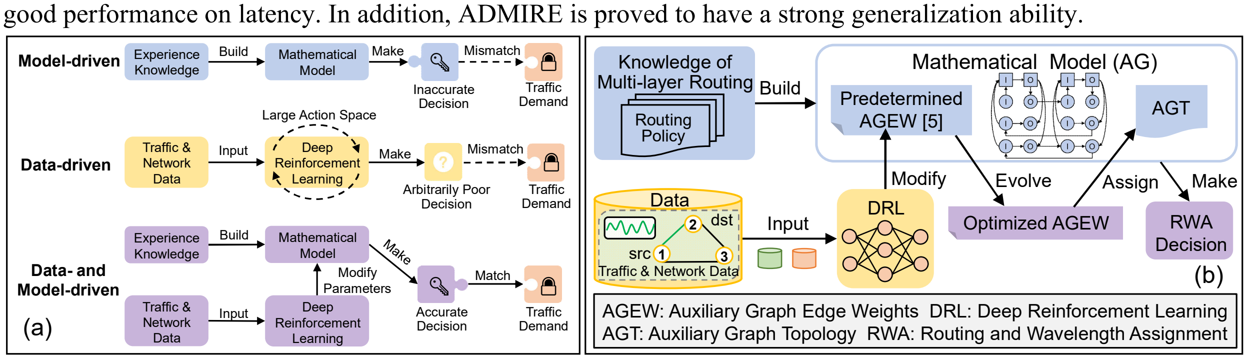

Fig. 1. (a) Three approaches for making a network decision; (b) Framework of ADMIRE for IP/optical cross-layer routing.

2. ADMIRE for Cross-Layer Routing Decision in X-Haul Networks

2.1. Cross-layer routing in IP over WDM network with Auxiliary Graph

The X-Haul aims at integrating fronthaul, midhaul and backhaul in a flexible transport network that consists of two layers, i.e., IP layer and optical layer. Routing on a multi-layer network is a complicated combinatorial optimization

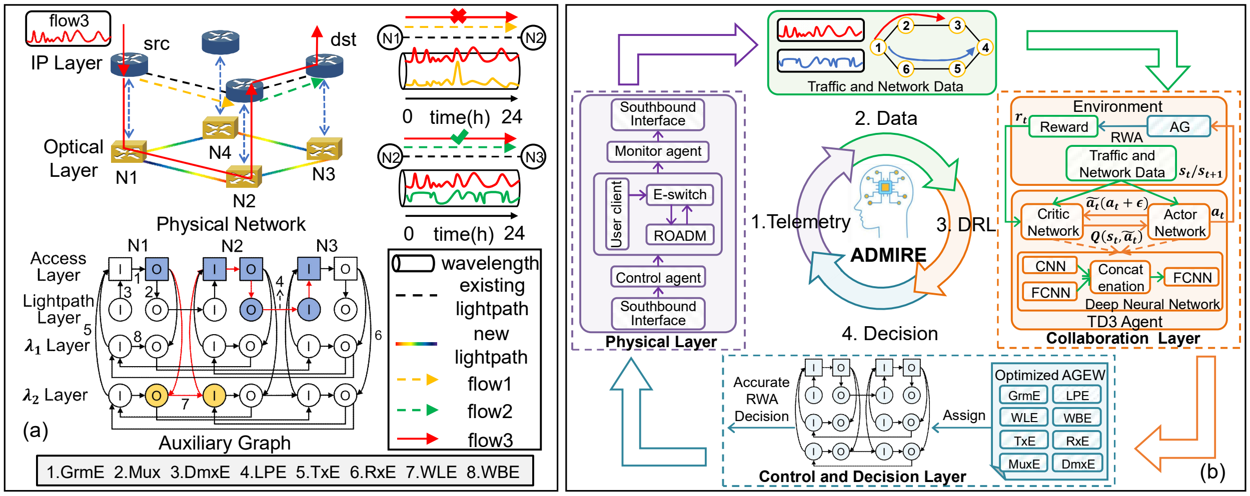

Fig. 2. (a) Auxiliary graph based cross-layer routing in IP over WDM network; (b) The operation mechanism of ADMIRE.

issue. It can be divided into two sub-problems: how to determine routing on a virtual topology (IP layer), which is composed of a set of existing lightpaths; and, how to determine routing and wavelength assignment (RWA) in optical layer. A traditional model for solving this problem is AG, which is based on the graph theory. Fig. 2 (a) illustrates an AG example for a 3-node physical network. There are three layers in AG, which are access layer, lightpath layer and multiple wavelength layers. The nodes in AG are linked by eight kinds of directed edges: GrmE, Mux, DmxE, LPE, TxE, RxE, WLE and WBE. Different routing policies can be achieved by assigning different edge weights. An AG is constructed each time a new connection request (flow) arrives, and edges appearing in the AG should satisfy the flow's bandwidth requirement. In this paper, we consider the bandwidth of a flow in 24 hours, which can be discretized into 24 time periods. Each period represents one-hour traffic which remains unchanged. The remaining capacity of selected lightpaths for each flow should satisfy its traffic demand during all 24 time periods. For example, flow3 can be routed in the existing lightpath between N2 and N3 rather than the one between N1 and N2.

2.2. Cross-layer routing decision enabled by ADMIRE

Different routing policies can be achieved as long as the relationship of edge weights satisfies the policy requirements. For instance, to minimize the number of used wavelengths, the weight of WLE should be much larger than the weight of LPE [4]. However, the pre-defined and unchanged AGEW can hardly adapt to dynamic networks. Therefore, we propose ADMIRE to obtain an appropriate AGEW for the current network situation. The detailed operation mechanism of AMDIRE is shown in Fig. 2(b). Firstly, at time-step t, ADMIRE telemeters traffic and network data from user, electrical and optical domains using the monitor agent. Secondly, these data are filtered and processed, then transmitted to collaboration layer as the input of DRL algorithm. Thirdly, DRL algorithm observes the received data (state s_t), then outputs an AGEW (action a_t) for current flow and delivers it to the control and decision layer. Finally, the optimized AGEW is assigned to AGT, and the RWA decision is deployed to the physical network via the control agent. At next time-step $t+1$, the data of the following flow and updated network are transmitted to DRL as state s_{t+1}, and the reward r_t is obtained. Through continuously perceiving the network condition and modifying the AGEW, ADMIRE can eventually obtain an accurate RWA decision. One of the key components of ADMIRE is DRL, where the twin delayed deep deterministic policy gradient (TD3) algorithm [5] is adapted. TD3 is an actor-critic algorithm, in which the actor outputs the action and the critic analyzes the action's quality. The actor and the critic share the deep neural network including convolutional neural network (CNN) layers and fully connected neural network (FCNN) layers, and we concatenate the output of CNN layers and FCNN layers as the input of additional FCNN layers. The state, action and reward of TD3 are defined as follows. 1) State: The state is a combination of matrices of residual capacity of each wavelength in all links and a vector of flow information (i.e., source, destination, 24-hour traffic), which are the input of CNN and FCNN respectively. 2) Action: The action describes the weight of each kind of edge in AG, which is represented as a vector of several continuous variables. 3) Reward: The reward is defined as $r_t = -W$, where W denotes the number of newly activated wavelengths, which is the number of used wavelengths in s_{t+1} minus the number of used wavelengths in s_t.

3. Experimental Setup and Results

The X-Haul testbed contains nine hybrid optical-electrical switching nodes, as shown in Fig. 3(a). We deploy three wavelengths in a fiber, and each of them works at 10Gbps. The fiber length between the nodes is 20km. Each electrical switch (E-Switch) is connected to a line card of the Spirent traffic generator and analyzer (TGA), which is responsible for generating variable traffic flows and analyze their performance. The 24-hour traffic data of 50 base stations (BSs) are collected from nine geo-distributed areas (see Fig. 3(b)) in Shenzhen, during Sep. 14th and Oct. 14th in 2020. We emulate 50 bidirectional fronthaul, midhaul and backhaul flows, and their bandwidth can be calculated according to [6]. We choose the data of BSs in 22 days to compose a traffic dataset for ADMIRE, and each subset contains the traffic of 50 BSs in one day. On one hand, the dataset is loaded into TGA to generate 50 bidirectional flows. On the other hand, connection requests are input into the network management system (NMS) and are sent to the software-defined network (SDN) controller to automatically setup and tear down connections. The detailed procedure of ADMIRE is shown in Fig. 3(a), and the experimental testbed is shown in Fig. 3(c).

We compare ADMIRE with a model-driven approach that tries to minimize the number of wavelength-links (MinWL) [4]. Fig. 3(d) shows the trend of reward against training episodes for ADMIRE. The reward starts with a low value for random exploration strategy, then increases quickly for improving strategy, and finally stabilizes at -20. This means that good convergence performance of ADMIRE is achieved. We use ADMIRE and MinWL to determine the routing of 100 unidirectional flows (i.e., 50 bidirectional flows) respectively, and measure the activated wavelengths using the optical spectrum analyzer. Firstly, we select one subset (traffic of 50 BSs in one day) for training and the same subset for testing. The result is shown in Fig. 3(e), where ADMIRE achieves 23% wavelength reduction than MinWL. This is because ADMIRE can perceive the traffic and network condition and obtain the optimized AGEW for each single flow, while MinWL applies the same AGEW to all flows without considering the influence of the dynamic network condition. We also observe that ADMIRE activates more wavelengths than MinWL when the number of flows is between 37 and 40. The reason is that MinWL prefers to select existing lightpaths, which leads to temporary optimization result, while ADMIRE chooses to establish new lightpaths in advance, aiming to minimize the global wavelength usage. Secondly, we select one subset (i.e., subset 0) for training and the other 21 subsets for testing. The results of Fig. 3(f) demonstrate that ADMIRE shows a strong generalization ability in other subsets in terms of wavelength usage. Despite the number of used wavelengths, we also evaluate the end-to-end latency. Each boxplot in Fig. 3(g) shows the maximum, average and minimum latency of 50 bidirectional flows. We can see that ADMIRE achieves lower latency than MinWL. This is because MinWL prefers to select existing longer lightpaths, which results in a longer propagation latency.

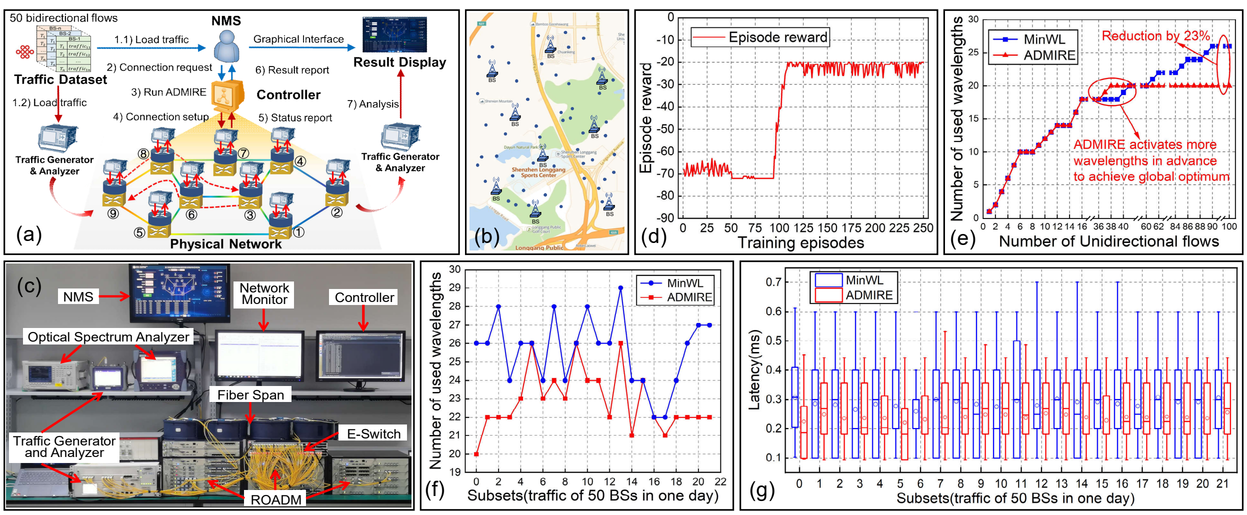

Fig. 3. (a) Cooperation procedures of ADMIRE; (b) Geographical distribution of BSs; (c) ADMIRE testbed; (d) Convergence property of ADMIRE; (e) No. of wavelengths vs. No. of unidirectional flows; (f) No. of wavelengths vs. different subsets; (g) Latency vs. different subsets.

4. Conclusions

We proposed and demonstrated ADMIRE for IP/optical cross-layer optimization in X-Haul. We verified its feasibility for improving network performance, such as wavelength usage and latency, and proved its strong generalization ability.

Acknowledgement

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