Assessment of a Latency-aware Routing and Spectrum Assignment Mechanism Based on Deep Reinforcement Learning

C. Hernández-Chulde(1), R. Casellas(1), R. Martínez(1), R. Vilalta(1), R. Muñoz(1),

(1) Centre Tecnològic de Telecomunicacions de Catalunya (CTTC/CERCA), chernandez@cttc.es

Abstract *We present a solution based on deep reinforcement learning (DRL) that jointly addresses spectrum allocation and latency constraint in EONs. The results show that using a simple network representation, this strategy outperforms typical K-Shortest Path heuristic approach and previous DRL-based approaches.*

Introduction

The massive use of cloud services along with the emerging 5G network and its vertical applications lead to notably increase the data traffic carried over optical transport networks. Additionally, such services/applications impose stringent bandwidth and latency requirements that need to be continuously fulfilled. Thus, it is essential to improve the optical network control from traditional rule-based methods towards a more flexible and autonomous network systems and operations.

Elastic Optical Networks (EONs) emerged to attain a more efficient use of the optical fiber spectrum by flexibly allocating variable-sized frequency slots tailored to accommodate heterogeneous bandwidth connection demands. The provisioning of lightpaths in EONs is traditionally tackled by the Routing and Spectrum Allocation (RSA) algorithms[1]. The output of the RSA algorithms is made up of a spatial path (i.e., nodes and links) and the optical spectrum (i.e., frequency slots) fulfilling the continuity and contiguity constraints for an end-to-end connection. Additionally, optical connection services impose specific end-to-end QoS (i.e., guaranteed bandwidth and maximum tolerated latency) requirements. Therefore, the RSA algorithms are required to meet such requirements while attaining determined objective functions such as efficient use of the network resources (i.e., optical spectrum).

The application of Machine Learning (ML) in optical networking is a growing trend. In this regard, several works have been produced[2]–[4] adopting ML solutions for heterogeneous use cases: optical performance monitoring, lightpath quality of transmission (QoT) estimation, fault management, traffic prediction, resource allocation and routing optimisation[2]. Typically, network prediction and monitoring are modeled as regression and classification problems; hence, they are solved with supervised and unsupervised ML algorithms. On the other hand, resource allocation and routing problems are considered decision-making tasks that can be addressed with reinforcement learning (RL)[5].

With the recent breakthroughs in Deep Neural Networks (DNN) and its combination with RL, Deep Reinforcement Learning (DRL) has shown an outstanding performance in solving decision-making problems. Some works show the potential application and advantages of DRL for routing optimisation. In[6],[7], DRL is applied to routing connections over hierarchical channels/signals defined in the standard Optical Transport Network (OTN). To this end, these works rely on a a careful representation of network state. In[8], the authors propose a DRL agent to solve the RSA problem in EONs. Regarding the consideration of latency in routing,[7] is aware of the delays in the network paths, but routing is tackled in the electrical domain, assuming that lightpaths are already provisioned. On the other hand, in[8] routing, modulation and spectrum allocation only consider the current spectrum utilisation.

This paper proposes a DRL-based RSA solution for EONs that includes latency information in path calculation. To the best of our knowledge, this is the first time that a DRL agent jointly considers optical fiber spectrum constraints and required service latency. Moreover, our solution is benchmarked against the results of the k-shortest path routing and first-fit spectrum allocation (kSP-FF) algorithm and another DRL-based solution.

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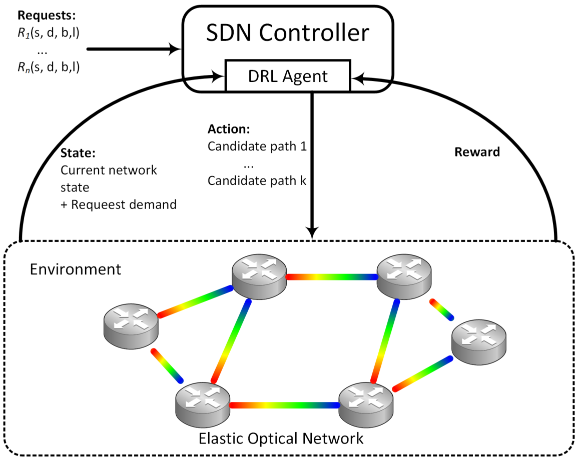

Fig. 1: Operation principle of proposed DRL-based RSA solution

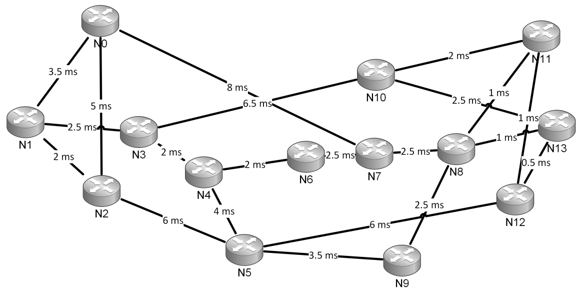

Fig. 2: NSFNET topology with optical link delays

Proposed DRL-based RSA Strategy

The EON is modelled as a graph $G(V, E)$, where V is the set of nodes (i.e., optical switches) and E represents the set of optical fiber links. Each $e \in E$ is defined by link attributes such as the available optical spectrum and propagation delay bound to the fiber distance. An optical connection request from s to d $(s, d \in V)$ is modeled as $R(s, d, b, l)$, where b and l denote the bandwidth and latency requirements, respectively. In this work, the targeted problem is to devise a routing strategy that for each incoming optical connection jointly meet the bandwidth and latency demands. To this end, the strategy seeks for the solution aiming at maximizing the spectrum utilisation whilst the accumulated end-to-end latency requirement is satisfied.

We propose a DRL agent to make the route decisions. Leveraging the Software Defined Networking (SDN) architecture, we assume that the DRL agent resides in the SDN controller and has the network state information (i.e., topology and resource utilisation). Upon receiving a new request, the DRL agent retrieves the current network state information. With this information, the DRL agent generates a state representation, which is the input for the DNNs of the agent. This state representation includes the current network information and the optical connection requirements. The output of the DNNs will be an action consisting of the selection of a path (i.e., nodes, links and frequency slots) for the request. The controller attempts to establish the selected path (i.e., allocating the computed resources) by configuring the involved underlying network devices and elements along the path. If the path establishment succeeds, the agent receives a positive feedback, otherwise the feedback is negative.

In the following, we present the network state, action space and reward representation for DRL agent. The network *state* representation leverages the proposal of[8] and includes delay information of the k candidate paths that connect the source and destination, satisfying the requested demand. Therefore, for each candidate path the network status comprises the current spectrum utilisation in terms of: available frequency slots (FSs), required amount of FS for the request, average FS block size and position of the first available FS block, as well as the required latency and the end-to-end delay. The *action* space includes a set of discrete actions, as the DRL agent selects one of the k candidate paths. Regarding the *reward*, to maximize the total bandwidth allocated in the network while satisfying the latency requirement, we defined an immediate reward proportional to bandwidth demand if the request is properly allocated; otherwise, the reward is -10. Fig. 1 shows the operation principle of the proposed solution.

Performance Evaluation

We conducted numerous simulations to evaluate the performance of the DRL agent. Dynamic requests were generated with a random selection of s and d nodes, and their bandwidth demands were evenly distributed between [2 - 4] FSs. The arrival of requests follows a Poisson process with inter-arrival time λ, and connection holding time follows an exponential distribution with an average μ. Tests were performed on the 14-node NSFNET topology shown in Fig. 2, where optical fiber links can accommodate 100 FSs.

For the scenario described above, we first analyzed the bandwidth blocking ratio (BBR) under certain traffic loads using the commonly used kSP-FF algorithm. The number of candidate paths for kSP-FF was set to 4 $(k = 4)$. The BBR represents the ratio of the total requested bandwidth that cannot be allocated. The results are shown in Fig. 3. From these results, a traffic load of 200 Erlang was chosen to benchmark the pro-

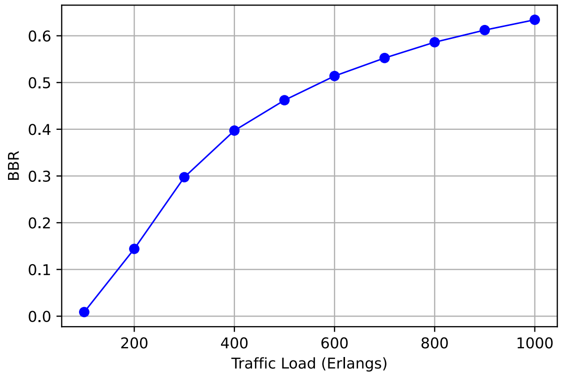

Fig. 3: Bandwidth blocking probability on NSFNET

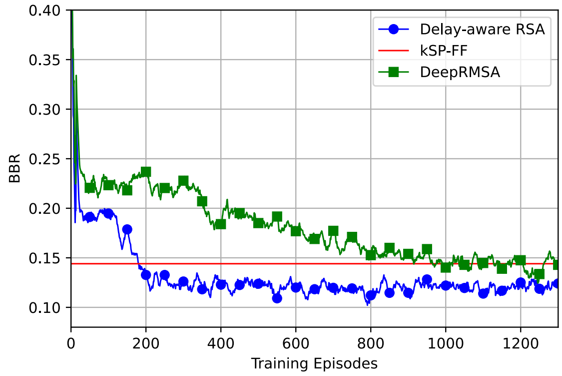

Fig. 4: Performance benchmarking of kSP-FF, DeepRMSA and Delay-aware RSA

posed DRL agent against both kSP-FF and DeepRMSA[8]. Under this traffic load, about 14 % of the requested bandwidth is not successfully allocated, so the agent's learning process can be observed.

The DRL agent was implemented based on the Asynchronous Advantage Actor Critic (A3C) algorithm[8]. A3C improves the agent learning speed by instantiating multiple agent threads in parallel. Each instance interacts with its own copy of the environment and updates a global policy. The DRL agent was trained in 1300 episodes. An episode consists of 10000 requests. The agent features neural networks with five fully connected hidden layers, 52 neurons in the input layer, and four neurons in the policy network's output layer, meaning the agent will choose one of the four candidate paths. The 52 input neurons consist of source and destination in a one-hot format and the six features of each of the four candidate paths. Adam optimizer was used in training. The learning rate and the discount factor were adjusted to 10^{-4} and 0.95, respectively.

To assess the robustness of the proposed latency-aware RSA, we compared its performance with that of the DeepRMSA and the baseline kSP-FF algorithm. Fig. 4 depicts the evolution of the BBR for the three approaches under a traffic load of 200 Erlangs. One can see that our latency-aware RSA clearly outperforms kSP-FF and DeepRMSA. Regarding kSP-FF, it reduces the BBR by 21.08 % (from 14.40 x 10^{-2} to 11.36 x 10^{-2}). This reduction was achieved after 200 training episodes, meaning that 2 x 10^{6} requests were simulated.

Furthermore, it can also be remarked that the proposed latency-aware RSA shows a faster convergence compared to DeepRMSA. Indeed, DeepRMSA achieves a comparable performance to kSP-FF only after 1000 training episodes. Therefore, it can be argued that when increasing the complexity of the RSA task by taking into account the spectrum utilisation and the delay of the requested service, DRL-based solutions offer even higher performance.

It should be noted that although DRL-based solutions show improved performance compared to traditional approaches such as kSP-FF, they require a learning phase. This learning phase involves an offline training process, where the parameters of the DRL agent are adjusted until the convergence is achieved. Once the parameters are optimised, the agent can be used to perform online provisioning of requests. Simultaneously to the online provisioning, the agent needs to continuously learn to adapt to the network's dynamic behaviour by executing online training.

Conclusions

This paper presents a DRL-based RSA solution for EONs. To the best of our knowledge, we propose for the first time a DRL-based RSA solution that jointly considers the spectrum utilisation of the optical links and the delay constraint of the service requesting the optical connection.

Simulation results demonstrate that the proposed latency-aware agent can efficiently learn from a straightforward representation of the network state. On the one hand, it outperforms the heuristic kSP-FF algorithm by keeping the BBR to a minimum. On the other hand, it accelerates its convergence compared to another DRL-based solution. Therefore, RL techniques are a promising solution to be exploited for solving the RSA problem at the expenses of requiring a necessary training time.

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