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Leveraging Pointer Network for QoT-aware Routing and Spectrum Assignment in Elastic Optical Networks

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Abstract *We propose a pointer network-based QoT-aware routing and spectrum assignment scheme that can directly generate lightpaths with high OSNR, without pre-calculated candidates. Simulation results showed that the proposed scheme can significantly reduce the blocking probability while with a good guarantee of the lightpath QoT.* ©2022 The Author(s)

Introduction

Dynamic and adaptive service provisioning in current Elastic Optical Networks (EONs) enables flexible resource utilization, where efficient path selection and quality of transmission (QoT) guarantee are required.

To provide the required level of QoT, a fast and accurate QoT estimation is needed. Machine Learning (ML)-based approaches have been widely studied, owing to their outstanding predicting capability and good computational speed [1]. By utilizing either lightpath-based [2-4] or network-wide information [5, 6], ML models can achieve a considerable QoT-estimation accuracy. However, in the lightpath-provisioning phase, a large number of path-frequency slot (FS) pairs need to be evaluated for each single service request, especially in EONs, and thus may lead to high computational complexity.

Recently, ML and reinforcement learning-based approaches have been employed to turn the resource and spectrum allocation (RSA) problem into a classification problem [7], which have significantly reduced the computational complexity and achieved low blocking probability. For instance, DeepRMSA [8] can select one of the K-shortest paths (KSPs) based on artificial features, and MaskRSA [9] extends the action space to the path-FS pairs. However, pre-calculated KSPs were required for their path selections, which significantly reduced the network flexibility. Moreover, the QoT has not been guaranteed. Therefore, an efficient RSA scheme with a good QoT guarantee is required for EON.

In this paper, we proposed a pointer network-based QoT-aware RSA scheme that can determine the lightpath provisioning with low computational complexity. Given the network topology parameters, the states, and the service requests, the pointer network-based scheme can directly generate lightpaths with high end-to-end optical signal-to-noise ratio (OSNR) after being trained using the actor-critic algorithm. A low blocking probability is attained by leveraging the pointer network.

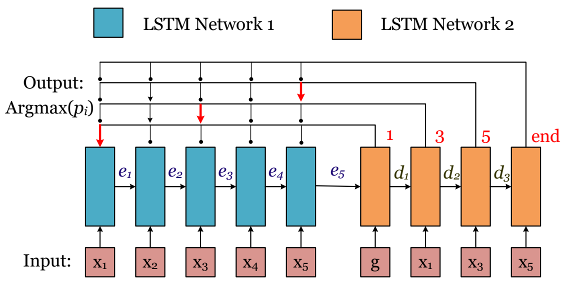

Fig. 1: A pointer network architecture and mechanism.

Pointer Network-based RSA

To eliminate the limitation of candidate paths, we employ the pointer network to generate node-based lightpaths. Fig. 1 illustrates the architecture and mechanism of the pointer network [10], which consists of two Long Short-Term Memory network (LSTM) modules, one as the encoder (LSTM Network1) and the other (LSTM Network2) as the decoder. Given an input sequence regarding to the node-based network topology, states, and service requests, it points to a specific position in the input sequence rather than predicting an index value from a fixed-size vocabulary and finally it gives the sequence of indexes of the input nodes.

The detailed procedures are introduced as follows. The node information is first transformed into a d-dimensional embedding of a two-dimensional point x_i via a linear transformation for all nodes before feeding into the pointer network. As shown in Fig. 1, the encoder network (LSTM Network1) sequentially reads and transforms the input information x_i into a sequence of latent memory states e_i. Once the encoding finishes, a d-dimensional vector g is fed into the decoder network (LSTM Network2) as a signal to trigger the decoding. Similarly, a sequence of latent memory states d_i are also maintained in the decoder network at each step i.

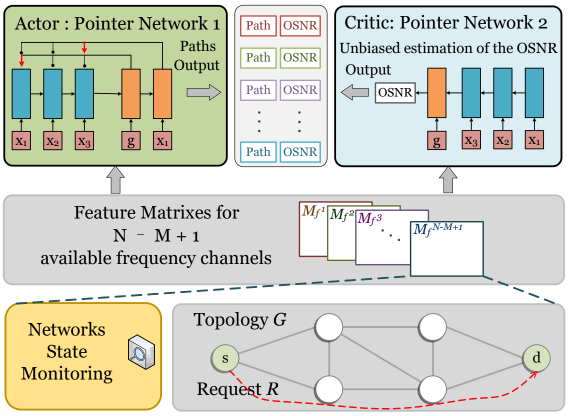

Fig. 2: Working principle of the pointer network-based RSA.

For each decoding step i, the attention mechanism produces a distribution u_i for the next node to select,

$$u_j^i = v^T \cdot \tanh\left(W_1 \cdot e_j + W_2 \cdot d_i\right) \quad j \in (1,2,\dots N)$$

where v, W_1, and W_2 are the learnable parameters of the pointer network.

A dual-mask scheme is applied to ensure the validity of the generated path. *Mask1* masks the unavailable nodes based on the topology matrix, while *mask2* disenables the past nodes. Then, the *softmax* function is employed to normalize the probability distribution p_i among the available nodes, which is expressed as

$$p_i = \mathrm{softmax}(u_i \cdot Mask1 \cdot Mask2)$$

Based on the probability distribution p_i, we can select the next node using the *argmax* function for sampling.

Fig. 2 illustrates the working principle of the pointer network-based RSA for EON, which includes three parts, i.e., input feature abstraction, pointer network training, and QoT guaranteed spectrum selection.

(1) Input Features:

The EON topology is denoted as $G(V,E,F)$, where V and E represent the sets of nodes and fiber links. $F = \{F_{e,f}|e,f\}$ contains the state of each frequency slot (FS) on each fiber link. The total number of frequency slots is N. The service request $R(s,d,M)$ arrives with the source-destination pair (s,d) and the number of demand frequency slots M.

Due to the frequency contiguity constraint, we can only assign the consecutive M frequency slots for a service request $R(s,d,M)$. In this case, only $N - M + 1$ choices of frequency channels exist to accommodate the service request $R(s,d,M)$ by EON $G(V,E,F)$. The pointer network is employed to generate the desired lightpath for each available frequency channel.

For each frequency channel, the node information is incorporated into a network feature matrix M_f of a dimension of $[N, 9N+2]$, expressed as

$$M_f = [M_T, M_{SL}, M_{SN}, M_{ASE}, M_{SCI}, M_{NC}, M_{sd}],$$

where M_T is the network topology matrix that $M_{i,j}^T = 1$ if there is a link between node i and node j; M_{SL} is the span length matrix, M_{SN} is the span number matrix, M_{ASE} is the ASE noise matrix, M_{SCI} is the self-channel interference (SCI) noise matrix, M_{NC} is the neighboring channel states matrix, and M_{sd} is the source-destination indicator matrix. Each row contains one node's information, and the network feature matrix is fed into the pointer network row by row.

As shown in Fig. 2, given the network graph G and service R, a total of $(N - M + 1)$ feature matrixes are formulated, and they are then fed into the pointer networks and executed in parallel.

(2) Training:

Inspired by using reinforcement learning to train the model [11], we optimize the parameters of the pointer network using the actor-critic algorithm (PtrNet-AC). Two pointer networks are established, one as the actor model and the other as the critic model. The actor model outputs the desired path π, while the critic model outputs an unbiased estimation of the OSNR.

The training objective of the actor model is to minimize the difference between the actor's lightpath OSNR and the critic's estimation OSNR; while the critic model is to reduce the difference between the estimated OSNR and the real OSNR. Therefore, the loss functions of the actor model and critic model are defined as

$$f_{\mathrm{loss-actor}} = \left(-L\left(\pi \mid M_f\right) + b\left(M_f\right)\right) \times p_\pi$$

$$f_{\mathrm{loss-critic}} = \| \, b\left(M_f\right) - L\left(\pi \mid M_f\right) \|$$

where $L(\pi \mid M_f)$ is the end-to-end OSNR of the lightpath π generated by the actor model, and $b(M_f)$ is the OSNR estimation from the critic model. $L(\pi \mid M_f)$ equals 0 if the lightpath is unavailable. The p_π is the factorized probability of the selected path π.

(3) Output and Spectrum Selection:

The network feature matrix M_f is fed into the actor and the critic models, separately, to obtain the lightpaths and the corresponding OSNR estimation for each frequency channel. In this paper, we select the path with the largest estimated OSNR and prioritize the frequency channels with a smaller index.

For a network with N nodes, the computation complexity of the pointer network-based RSA scheme is $O(N^2)$.

Simulation Results

Numerical simulations have been conducted with

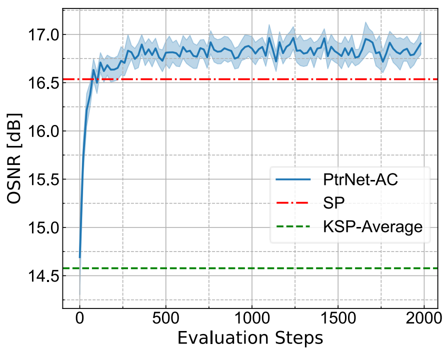

Fig. 3: OSNR [dB] versus training steps.

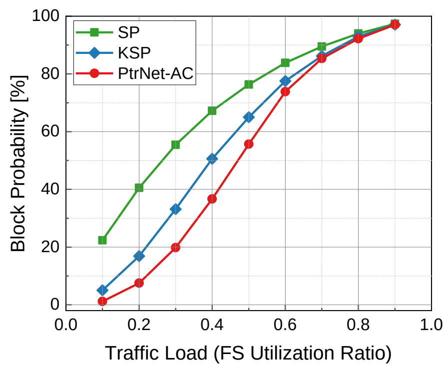

Fig. 5: Blocking probability versus traffic load.

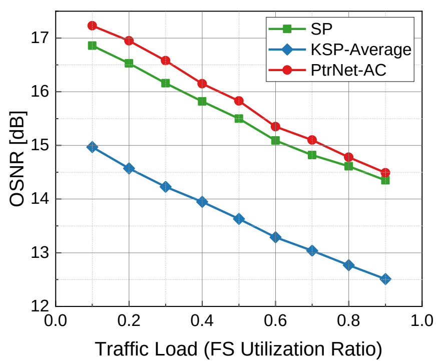

Fig. 4: OSNR [dB] versus traffic load.

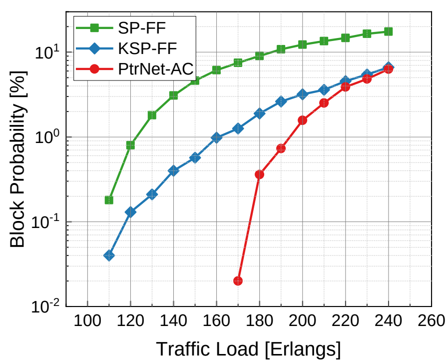

Fig. 6: Blocking probability versus dynamic traffic load.

the 14-node and 22-link NSF network to evaluate the efficiency of the proposed scheme in both single-channel and dynamic traffic scenarios. We assume 40 C-band channels with a fixed channel spacing of 37.5 GHz, anchored to 194 THz, on each link. All transmitted channels have a fixed launch power P of -3dBm and at the same symbol rate of 28 GBaud. The EGN model [5] is applied to construct the training and the evaluation environments. The embedding size and the hidden size of the pointer network are both set to be 256. The initial learning rate is set to be 1e-4, decaying by a factor of 0.8 for every 500 steps. The SP-FF and KSP-FF (K=3) schemes are applied as benchmarks.

Fig. 3 shows the average end-to-end OSNR of a single-FS channel with 10,240 randomly generated requests after certain training steps (each with a batch size of 512 samples), assuming a 20% traffic load (FS utilization ratio) in the neighborhood channels. We can see that PtrNet-AC can outperform SP in the average end-to-end OSNR of the generated path with a gain of up to 0.3 dB after about 150 training steps. Fig. 4 shows the end-to-end OSNR gain under different traffic load conditions. With the traffic load increase, the end-to-end OSNR gain decreases from 0.35 dB to 0.11 dB, owing to the similar the crosstalk interference noise among different links when approaching full load.

Figure 5 shows the blocking probability of the single-FS channel routing in the NSF network, under different traffic loads. We notice that a reduction of up to 14.3% in the blocking probability is achieved by PtrNet at 0.2-traffic load, compared with KSP, as the generated paths are not limited to the pre-calculated candidate paths. Such improvement in blocking probability reduces at traffic loads higher than 0.4.

We have also evaluated the performance of the PtrNet-AC scheme in a dynamic traffic scenario, where requests were generated following a Poisson process with a fixed average arrival rate of 10 and an average service duration of the range of [11,24], corresponding to a traffic load (in Erlangs) of the range of [110,240]. Fig. 6 shows the results in the case with 40 C-band channels in the NSF network. We can notice that PtrNet-AC can significantly reduce the blocking probability in comparison with SP-FF and KSP-FF. No blocking occurs at a traffic load below 170.

Conclusion

We proposed a pointer network-based QoT-aware routing and spectrum assignment scheme that can directly generate the end-to-end path with a high OSNR value instead of choosing from the pre-calculated candidates. Simulation results showed that the proposed scheme could achieve a better QoT and reduce the blocking probability by up to 14.3% compared with the benchmarks.

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