

A Research on Routing and Spectrum Allocation Algorithm for Elastic Optical Networks Based on Deep Learning

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Abstract: Dynamic allocation request and spectrum release will lead to spectrum fragmentation, which will affect the allocation of subsequent services and spectrum resource utilization of elastic optical network. This paper proposes a new routing and spectrum allocation algorithm based on deep learning, which will find the best routing and spectrum allocation method for a specific network, so as to improve the overall network performance. Simulation results show that compared with the traditional resource allocation strategy, the neural network model used in this paper can improve the degree of spectrum fragmentation and reduce the network blocking probability.

Keywords: Elastic optical network, Deep learning, Route Spectrum allocation.

1. Introduction

With the rapid development of cloud technology including cloud computing, cloud storage and cloud services, data transmission services are no longer limited to simple text data transmission, while new services such as video, image and virtualization become the main part. With the increase of these data services, the demand of various businesses is also explosive growth. The traditional wavelength division multiplexing (WDM) network adopts a fixed spectrum division mechanism, which takes the wavelength as the smallest division unit, so it is difficult to adapt to the rapid growth of transmission rate. In order to improve the spectrum efficiency, elastic optical networks (eons) technology based on orthogonal frequency division multiplexing (OFDM) further divides the network resources into smaller spectral units, and has the advantages of flexible spectrum allocation [2]. Therefore, it is considered as one of the main research directions of next generation optical networks. In order to solve the RSA problem in eon, several RSA strategies have been reported to achieve better network transmission performance and resource utilization. Aiming at the problem of delay in multipath routing, Zhang et al. Proposed a dynamic cache cost saving multipath routing algorithm [3]. After a service is divided into several sub services, priority is given to the high delay path for transmission. Although the algorithm achieves the goal of reducing the blocking rate and cache overhead, it will lead to the increase of spectrum overhead. 50. Delvalle et al. Designed an algorithm simulator which can be used for comprehensive research of RSA problems. The simulator can compare the performance of different RSA algorithms. 10. Liu et al. Studied and proposed an improved algorithm based on shortest path tree and minimum spanning tree [4]. Ching Fang Hsu et al. RSA algorithm based on hierarchical graph uses spectral constrained path vector search (SPV), full path search algorithm and spectrum window routing algorithm to solve RSA problem in each hierarchical graph [5]. Considering the complexity of RSA problem in eon and the breakthrough of artificial intelligence (AI) technology, some new schemes based on machine learning or deep learning are proposed [6].

These schemes have been proved to be a good way for network operators to configure and manage network resources more intelligently. Autonomously, for example, Chen proposes a deep reinforcement learning algorithm deep rmsa based on self-learning rmsa agent, which is used to realize eon autonomous cognitive rmsa and shows significant performance improvement [7].

Up to now, the research of applying deep learning to routing and spectrum allocation algorithms in elastic optical networks is still relatively small. Considering that most of the traditional allocation is a relatively fixed solution, the strategy is neither flexible nor intelligent for the future network requirements. This paper proposes an eon strategy based on RSA, which is based on generative countermeasure network. The proposed strategy will consider the dynamic changes of arrival services, so as to route the optical path and allocate the spectrum in real time according to the current spectrum utilization rate in the network, so as to flexibly adopt the best strategy to reduce the possibility of network congestion.

2. The Network Modeling for the Proposed AR-ISA Algorithm

In the traditional method, routing algorithm is used to find the path, and then spectrum is allocated according to specific rules. However, in deep learning method, through neural network training, a large number of data including network state and RSA strategy are used to fit their mathematical relationship, so as to achieve accurate prediction.

2.1. Data Set Establishment

The data set contains some basic information, including network topology, frequency slot usage on the link, the amount of traffic arriving, and the source destination pairs of services. In order to identify different spectrum conditions on the link, "1" can be used to represent the occupied time slot, while "0" can be used to represent the unoccupied time slot. The "single hotspot" coding method is used to uniquely represent the source target pair.

2.2. Sample Marking

After the processing of feature data, it is necessary to mark

the prepared data. Firstly, the K shortest path algorithm is used to find the appropriate route, and then the multiple links of each route are combined to form a new equivalent link. For each equivalent link, the degree of spectrum fragmentation is used as an evaluation index, and the best allocation method is selected by traversing the label search. The spectrum fragmentation index F_{ext} is expressed as follows:

$$F_{ext} = 1 - \frac{FS_{max}}{N_{fre}} \quad (1)$$

FS_{Max} is the frequency slot number of the largest free spectrum block. N_{fre} is the total number of idle slots. The closer FS_{Max} is to 1, the higher the degree of spectrum fragmentation in the link.

A combination of routing and spectrum allocation strategy is proposed to mark the feature representation of each sample, which will help to improve the performance of RSA strategy:

$$L = [R | A] \quad (2)$$

L is the vector representation of the label. It represents the k -dimensional sparse matrix used to represent the routing method, and a is the matrix used to represent the spectrum allocation position containing "0" and "1". Through this feature combination method, the prediction results of the proposed model will contain both routing and spectrum allocation information.

Finally, the reserved method is used to divide the data set into training set and test set.

2.3. Neural Network Design

In this paper, eight layer neural network is used to select RSA strategy. The first layer is the input layer, which inputs the elements of the training set. The second layer to the seventh layer is the hidden layer, and leaky relu is used as the activation function. The eighth layer is the output layer, and the softmax function is used as the activation function of classification. The label for each example in the training set is a category. The input characteristic of each sample is $X_i = [Li_1, Li_2, \dots, s, D, b]$, where Li represents the state of the link, s represents the source node, D represents the destination node, and B is the size of the service. Leaky relu can be expressed as follows:

$$y_i = \begin{cases} x_i, & \text{if } x_i \geq 0 \\ \frac{x_i}{k}, & \text{if } x_i < 0 \end{cases} \quad (3)$$

The six hidden layers are all full junction layers, and the positive propagation process between neurons in full junction layer is as follows:

$$\begin{aligned} z_i &= w_i * x_i + b \\ a_i &= g(z_i) \end{aligned} \quad (4)$$

G is the leaky relu function, and I is the result calculated on the neurons of the fully connected layer. The softmax function used in the final output layer can be expressed as follows:

$$S_i = \frac{e^i}{\sum_j e^j} \quad (5)$$

I is the vector representation of the sample feature after

passing through the fully connected layer. The probability that the output result is of a certain class can be obtained by softmax function, and the output result is the one with the highest probability. The neural network loss function used in this model is cross entropy loss function, which can be expressed as follows:

$$Loss = -\frac{1}{n} \sum \log s_i \quad (6)$$

The gradient descent algorithm is used for back propagation and the correct fitting of input samples is realized.

3. Simulation and Discussion

3.1. Simulation Parameters

The network topology used for simulation is NSFNET (14 nodes, 21 links). The total spectrum bandwidth of each link is 4000 GHz. Each slot on the link is set to 12.5 GHz. Each link has 320 frequency slots with protection bandwidth. In the simulation, the average transmission rate of network services is between 10-400 GB / s. A total of 30000 samples were collected in the data set. 22000 samples were used as the training set, and the remaining 8000 samples were used as the test set by the retention method. In order to speed up the training, the mini batch optimization model is used, and the gradient descent method optimized by Adam is used to speed up the gradient descent [8]. The size of micro batch is 256, and the number of neural units in DNN input layer is equal to the dimension of characteristic matrix X . Both fully connected layers use leaked relu as the activation function. Finally, the output layer has neural units equal to the number of categories, and uses softmax function to predict all categories.

3.2. Results and Discussion

The training effect of the training set is shown in Figure 1. The figure shows that after 5000 steps of calculation, the loss function of DNN is below 0.1, which can be well fitted. The performance of the proposed DNN model is verified in the test set, and the accuracy is shown in Figure 2. We can find that after 5000 steps of calculation, the accuracy of the model in the test set has reached 0.9 or higher, which means that the prediction results of the model are quite accurate.

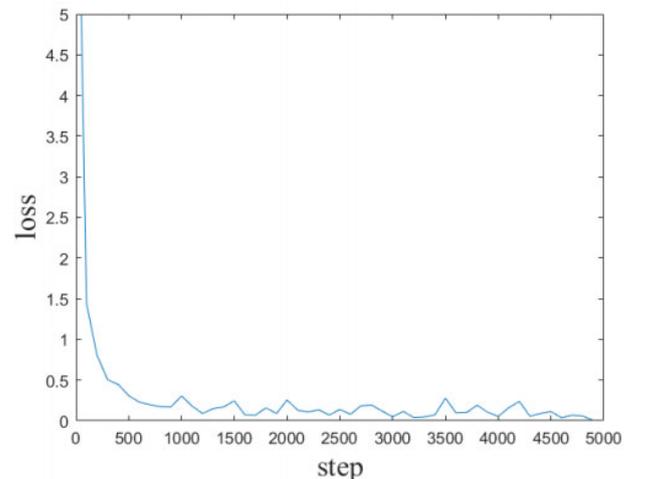


Figure 1. DNN loss function performance

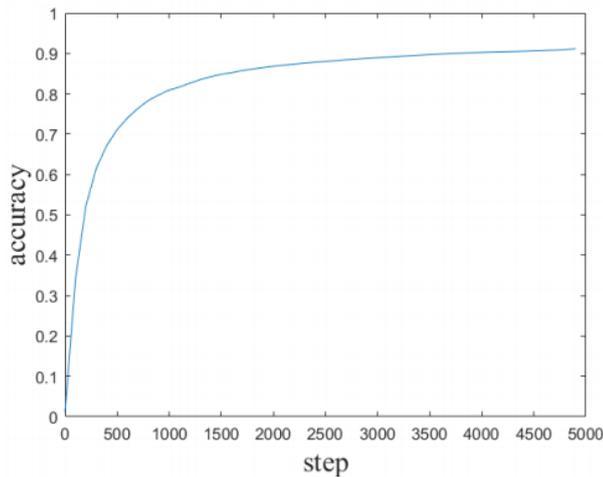


Figure 2. Model Accuracy Simulation Result

In order to verify the superiority of the proposed DNN model, compared with the first hit spectrum allocation algorithm and the accurate hit spectrum allocation algorithm using K shortest path (FF + KSP) strategy, the spectrum fragmentation and bandwidth blocking probability of the algorithm using KSP (EF + KSP) strategy are evaluated. First, figure 3 shows a comparison of the three algorithms. This shows that the spectrum fragmentation degree of RSA strategy using DNN method is better than the other two RSA strategies. We can see that the spectrum fragmentation of DNN is 3.1% lower than KSP + FF and 2.1% lower than KSP + EF when the service reaches 200Gbit / s. In addition, the blocking probabilities of the three methods are calculated and compared under different traffic loads. As shown in Figure 4, the blocking probability of RSA strategy based on DNN method is significantly lower than KSP + FF and KSP + EF methods. When the traffic load is up to 400 Erlang, the bandwidth blocking probability of the proposed method is about 5.7% lower than KSP + FF and 4.4% lower than KSP + EF, respectively.

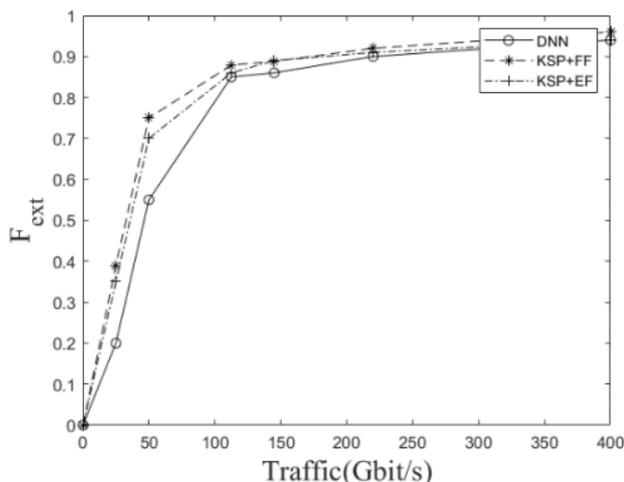


Figure 3. Spectrum Fragmentation Degree Comparison

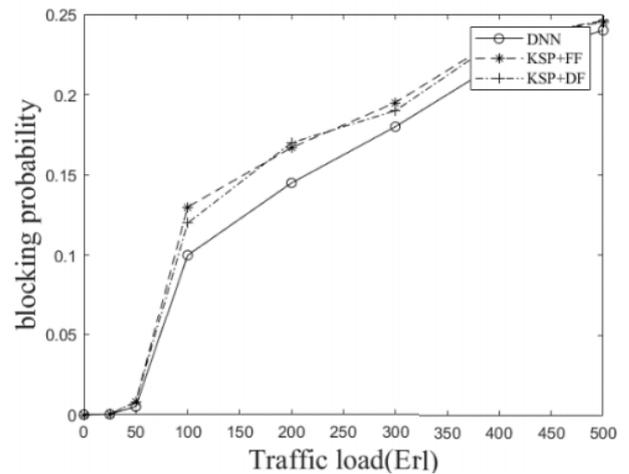


Figure 4. Bandwidth Blocking Probability Comparison

4. Conclusion

This paper proposes an RSA strategy based on deep learning con. Firstly, the feature representation of routing and spectrum allocation strategy is proposed to label each sample, which helps to simplify RSA strategy. Then the proposed DNN model is used to train and predict RSA strategy. Simulation results show that the proposed strategy based on deep learning has better spectrum fragmentation performance and bandwidth blocking probability.

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References

- [1] Zuqing Zhu, Wei Lu, Liang Zhang, Ansari N. Dynamic service provisioning in elastic optical networks with hybrid single-/multi-path routing[J]. Lightwave Technology, IEEE, 2012, 31(1): 15-22.
- [2] C. F. Hsu, Y. C. Chang, and S. C. Sie, "Graph-model-based dynamic routing and spectrum assignment in elastic optical networks", IEEE/OSA Journal of Optical Communications and Networking, Vol. 8, No. 7, pp. 507-520, 2016.
- [3] Yu E S, Chen C Y R. Traffic prediction using neural networks[C]. Proceedings of GLOBECOM '93. IEEE Global Telecommunications Conference. IEEE, 1993: 991-995.
- [4] Liu X, Gong L, Zhu Z. Design integrated RSA for multicast in elastic optical networks with a layered approach[C]// Global Communications Conference. IEEE, 2014:2346-2351
- [5] X. Liu, L. Gong, and Z. Zhu, "Design integrated RSA for multicast in elastic optical networks with a layered approach", IEEE Global Communications Conference (GLOBECOM), pp. 2346-2351, 2013.
- [6] Chen D, Feng Hai-liang, Lin Qing-jia, Chen Chun-xiao. Multi-scale Internet Traffic Prediction Using Wavelet Neural Network Combined Model [C]. International Conference on Communications and Networking in China, IEEE, 2006: 1-5.
- [7] Xiaoliang Chen, Jiannan Guo, Zuqing Zhu, et. "Deep-RMSA: A Deep-Reinforcement-Learning Routing, Modulation and Spectrum Assignment Agent for Elastic Optical Networks," OFC 2018 © OSA 2018.
- [8] Kingma D P, Ba J. "Adam: A Method for Stochastic Optimization," Computer Science, 2014.