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# Edge computing oriented virtual optical network mapping scheme based on fragmentation prediction①

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**Abstract**

As edge computing services soar, the problem of resource fragmentation situation is greatly worsened in elastic optical networks (EON). Aimed to solve this problem, this article proposes the fragmentation prediction model that makes full use of the gate recurrent unit (GRU) algorithm. Based on the fragmentation prediction model, one virtual optical network mapping scheme is presented for edge computing driven EON. With the minimum of fragmentation degree all over the whole EON, the virtual network mapping can be successively conducted. Test results show that the proposed approach can reduce blocking rate, and the supporting ability for virtual optical network services is greatly improved.

**Key words**: elastic optical networks, virtual optical network, fragmentation self-awareness, edge computing

## 0 Introduction

Rapid development of edge computing services has brought increasingly serious challenge to current elastic optical networks (EON) [1-2]. The emergence of edge computing and virtual optical network has become a new trend of resource schedule and service strategy for elastic optical network [3-4].

As the virtual network mapping is one of key issues for edge computing services driven elastic optical networks, multiple factors must be taken into consideration, including the spectrum consistence, the continuity constraints and the resource fragmentation [5-6]. Moreover, the frequent change of edge computing services will worsen the spectrum fragmentation problem of the elastic optical network, which may lead to poor network performance, in terms of service blocking rate and utilization of elastic optical resources.

To deal with the fragmentation problem, great effort has been made during recent years. Solutions of this problem can be divided into two categories: defragmentation methods and the fragmentation awareness based ones [7-8]. These defragmentation methods are often realized by reallocating optical resources, while the others are usually used by the optical resources pre-allocation to provide more available resources before service requests arrive[9-10]. Ref. [11] presented a multi-path aware routing algorithm by selecting the minimized free resources block, but it is limited by routing result. Ref. [12] fully considered frequency and time fragmentations to choose proper free resource for service requests. Ref. [13] presented fragmentation another algorithm by allocating path with the minimized fragmentation degree during the route computing. Ref. [14] combined time factor and frequency factor to reduce fragments in virtual network circumstances. Ref. [15] evenly take service sustained time into defragmentation algorithm. However, these approaches fail to be aware actively of fragmentation caused by edge computing services.

To solve this problem, this paper proposes a fragmentation prediction enabled virtual optical network mapping (FP-VNM) scheme in EON driven by edge computing. Firstly, a gate recurrent unit (GRU) enabled fragmentation prediction model is defined, which can dynamically be aware of the fragmentation condition of all optical links and nodes in advance. Based on this dynamic fragmentation prediction model, a virtual optical network mapping method is also presented for edge computing services oriented EON. Test results and analysis show that the proposed FP-VNM can achieve better edge computing services performance.

The rests of this article are organized as the fol-

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lowing. Section 1 discusses the edge computing optical virtual network systems. Then, the fragmentation indicator model is presented in Section 2, followed by the fragmentation prediction using the GRU algorithm in Section 3. And the virtual network mapping scheme based on the fragmentation prediction is also proposed in Section 4. Performance evaluation of the proposed scheme is illustrated and analyzed with comparisons in Section 5. Finally, Section 6 draws to the conclusions.

## 1 Virtual network of edge computing

For decades, the cloud computing is carried out by optical network, but the edge computing technology has greatly changed the tradition architecture of cloud computing over optical network. In the edge computing oriented elastic optical network system, original data can be distributed and be storied in several edge servers. When the service request arrives, the nearest edge server is chosen as edge data centre. And original data is processed locally in these edge servers. After that, data processing results are sent to the edge data server through the virtual optical network technology.

The virtual network architecture of edge computing oriented EON is illustrated in Fig. 1, which includes the virtual network layer and the physical network layer. The elastic optical network in the physical network layer works as the carrier to support various edge computing services in virtual network layer.

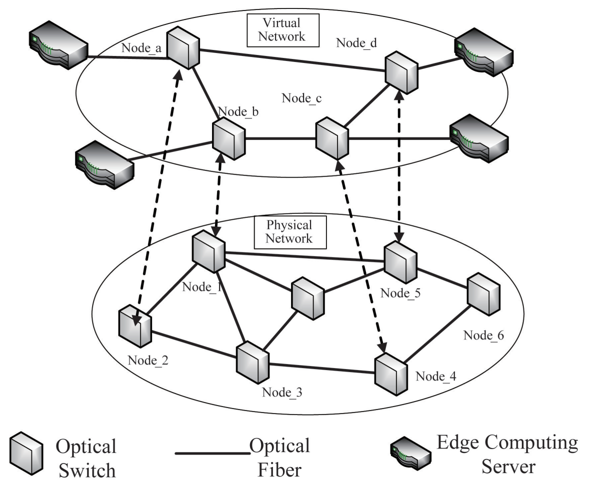


**Fig. 1** Typical architecture of edge computing virtual network

In the edge computing oriented EON, edge computing servers need to be connected through high efficient virtual network among them. As one of key principles, each virtual network of virtual optical networks is independent logically from each other and each virtual node can only be mapped into only one physical optical node. But one physical node is allowed to contain several virtual nodes. Therefore, one elastic optical network is able to support several virtual networks for edge computing services.

## 2 Fragmentation indicator model

This article makes full use of gap statistic algorithm and K-means algorithm to conduct fragmentation clustering, fragmentation indicator computing to obtain the fragmentation sample tags [16-17].

### 2.1 Fragmentation clustering method

To describe accurately the optical link fragmentation condition, the optical link fragmentation rate (LFR) is defined as $R_{link\_i}$ as shown in Eq. (1).

$$R_{link\_i} = \frac{\sum_{m=1}^{M} F_{frag\_m}}{S_{spec\_sum}} \tag{1}$$

where, $F_{frag\_m}$ and $S_{spec\_sum}$ represent number of frequency slots of the fragment $m$ and sum of spectrum slots, and $M$ is the number of fragments in $link\_i$.

The clustering number of fragmentation is determined by the gap statistic algorithm, which is depicted as follows.

**Step 1** Compute the distance $d_{mm'}$, between each pair of specimens $R_{link\_i}$ and $R'_{link\_i}$.

$$d_{mm'} = \| R_{link\_m} - R_{link\_m'} \|^2 \tag{2}$$

**Step 2** Assume that there are $K$ classes of $R_{link\_i}$ specimens and compute the sum of distances of $K$ classes.

$$D_k = \sum_{m=1}^{K} \sum_{m'=1}^{K} d_{mm'} \tag{3}$$

Thus, the average sum $W_k$ of all specimens can be gained.

$$W_K = \sum_{k=1}^{K} \frac{D_k}{2 \mid C_k \mid} \tag{4}$$

**Step 3** Take the logarithm of $W_k$ and compare it with the expected value using Monte Carlo simulation.

$$Gap(K) = E^*(lb(W_K)) - lb(W_K) \tag{5}$$

where $E^*(lb(W_K))$ is the expectation of $(lb(W_K))$ using the Monte Carlo simulation.

**Step 4** Compute the minimal $K$ value as the best clustering number.

$$\begin{cases} Gap(K) - Gap(K+1) + s_{K+1} \geqslant 0 \\ s_{K+1} = s'_{K+1} \sqrt{1 + 1/B} \end{cases} \tag{6}$$

where, $s_{K+1}$ is the standard deviation, $B$ is the number of data sets in Monte Carlo simulation.

### 2.2 Fragmentation indicator

Based on the gap statistic algorithm, the classes *number K* is determined. Then, the fragmentation indicator $F_{link\_i}$ can be got using K-means algorithm.

**Step 1** Select one specimen as the first initial clustering center from SFR specimens set.

**Step 2** Compute the Euclidean distance $D(p_m)$ of the nearest clustering center.

$$D(p_m) = \sqrt{(p_m - p)^2} \tag{7}$$

**Step 3** Compute the probability $Q(p_m)$ of each specimen to become the next clustering center.

$$Q(p_m) = \frac{D\ (p_m)^2}{\sum_{m=1}^{N} D\ (p_m)^2} \tag{8}$$

**Step 4** Repeat Step 2 and Step 3, until $K$ clustering centers are all obtained.

**Step 5** Put each specimen into the fragmentation class of its nearest clustering center.

**Step 6** Re-compute the average value of each cluster, and make this average value as the new cluster center.

**Step 7** Repeat Step 5 and Step 6, until the cluster center do not change any more.

Thus, the fragmentation indicator $F_{link\_i}$ of each specimen is finally determined. And the link fragmentation rate is well prepared to be transformed into its fragmentation indicator.

## 3 Fragmentation prediction model

As the fragmentation condition has strong time relation feature, this article proposes a GRU based fragmentation prediction model to be aware of the fragmentation indicator [18].

Benefitting from the outstanding ability to process and predict sequential data, the GRU is adopted to realize the fragmentation prediction (GRU-FP) function of elastic optical networks. And the GRU-FP model structure is depicted as shown in Fig. 2 .

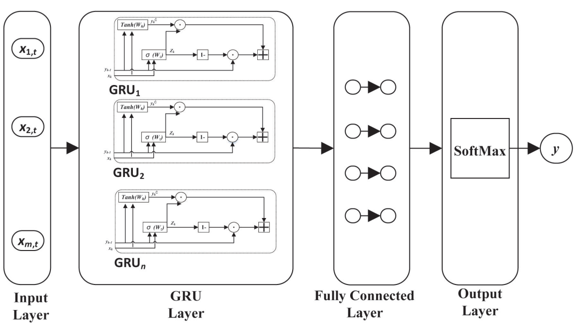


**Fig. 2** GRU-FP model structure

This GRU-FP model structure consists of input layer, GRU layer, full connected layer and output layer. In this model, the sequence of LFP values is inputted into the first layer, and the fragmentation degree value can be predicted through GRU layer and the SoftMax equation. Thus, the optical link fragmentation prediction can be realized. Moreover, the detailed GRU structure is composed of several GRU modules, as shown in Fig. 3.

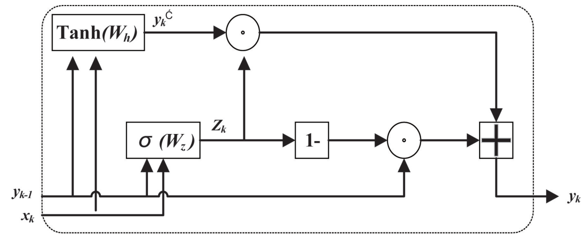


**Fig. 3** GRU model

The GRU model is also given by Eq. (9).

$$\begin{cases} z_k = \sigma(U_z y_{k-1} + W_z x_k + b_z) \\ y_k' = \tanh(U_z y_{k-1} + W_z x_k + b_z) \\ y_k = (1 - z_k) \odot y_{k-1} + z_k \odot y_k' \end{cases} \tag{9}$$

where, $y_k$ is the output result from hidden layer of the current GRU, and $x_k$ is the corresponding input value of link fragmentation. And $z$ is the updating gate of GRU and $W$ is the weight of each gate.

According to the Fig. 2, the input fragmentation indicators sequence is $\{F_{link\_i,1}, F_{link\_i,2}, \cdots, F_{link\_i,m}\}$, and the time sequency feature is obtained through the GRU learning and the full connection layer computing. Later, the final predicted value $F_{link\_i}$ of the next time slot can be gained using the SoftMax equation and the fragmentation prediction of each optical link can be finished using this GRU-FP model.

## 4 Virtual optical network mapping scheme

The virtual optical network mapping scheme is also presented based on this fragmentation prediction mentioned above.

### 4.1 Virtual node mapping

As the mapping operation includes both of node mapping and link mapping, some limitation must be followed. Firstly, every virtual node can only be mapped into one physical node with enough computation ability. Secondly, the spectrum of each virtual link must satisfy limits of both consistency and continuation.

Generally, the virtual node mapping can directly determine whether the virtual link mapping will be successive or not. In this paper, the fragmentation condition around the physical optical node is also taken into consideration. Based on the link fragmentation, the node fragmentation indicator is also defined as $F_{\mathrm{node}}$.

$$F_{\mathrm{node}} = \frac{\sum_{j=1}^{M} F_{link\_j}}{M} \quad (10)$$

where, $M$ is the number of direct optical link connected to the node. And this node fragmentation indicator is used in the virtual node mapping stage as the key factor.

On receiving newly arrived edge computing service, the node fragmentation indicator $F_{\mathrm{node}}$ of each optical node is computed according to Eq. (10). Then, all optical nodes are sorted by their $F_{\mathrm{node}}$ values and each virtual node is mapped into corresponding optical node in order with $F_{\mathrm{node}}$ value. Thus, the virtual nodes mapping operation is completed.

### 4.2 Virtual links mapping

After the node mapping operation is finished, the virtual link mapping is also performed. And the virtual link will be mapped into the physical path that minimizes the fragmentation degree.

The virtual link mapping procedure is also given as follows.

**Step 1** Choose all available links with enough bandwidth all over the elastic optical network.

**Step 2** Compute the fragmentation indicator value using the fragmentation prediction model for each physical optical link.

**Step 3** Make use of the shortest path algorithm to generate several physical paths with the lowest average fragmentation indicator for the virtual link.

**Step 4** Record the virtual link mapping relation of the virtual link and this physical path.

**Step 5** Refresh resources allocation results of all links belonging to this physical path.

**Step 6** Repeat Step 1 to Step 4, until all virtual links are mapped successively; otherwise, this virtual network mapping request is rejected.

This proposed FP-VNM scheme is aimed to improve the fragmentation situation for the EON system to perform virtual network mapping for edge computing services, by predicting fragmentation indicator of all related physical optical links and nodes.

## 5 Test results and analysis

To evaluate the proposed approach of this article, the simulation is conducted in this section, where the simulation environment is constructed by Python software tools, where the NSF-Net topology is adopted. This simulated elastic optical network mainly consists of 14 nodes and 21 fiber links with spectrum range of 4 THz, where each link contains 150 slots and each physical node has 750 units of computing capacity. Each virtual network request arrives randomly with the number of nodes within [3, 5] and the computing capacity within [1, 10] units. Moreover, the connection probability of each pair of virtual nodes is set to be 50%.

Simulation analysis is made in terms of blocking rate of virtual optical network mapping, the resources utilization rate, and the time delay of virtual network mapping operation. The comparison is made among the largest computing resources requirement versus the largest computing resources provisioning (LCLC) [19], the fragmentation awareness virtual netword mapping (FA-VNM) [20] and the proposed FP-VNM in this article. Finally, these testing results are given in Figs 4 – 6.

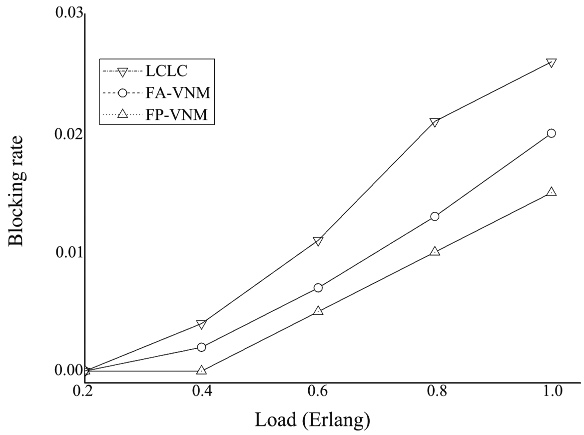


**Fig. 4** Comparison of the blocking rate

The comparison result of the blocking rate is given in Fig. 4. Under the same traffic burden, the proposed FP-VNM scheme can achieve lower blocking rate than the others. LCLC scheme shows the worst blocking rate, and the FA-VNM scheme has worse performance that FP-VNM. That is because the LCLC neglects the frequency fragment produced during virtual link mapping. Moreover, both LCLC and FA-VNM schemes may results in low continuity of free resources with higher blocking rate. In comparison, the proposed FP-VNM can predict fragmentation condition of the whole optical network with higher accuracy, so the blocking rate of network mapping is obviously reduced.

As shown in Fig. 5, the proposed FP-VNM has the best resources utilization rate, because this FP-VNM can improve the fragmentation condition when conducting virtual network mapping with better traffic balance. Benefitting from the fragmentation prediction of FP-VNM, newly arrived services requests will gain more available resources in advance. That means optical network resources can avoid being wasted by reducing fragmentation. Therefore, the utilization rate of optical network resources can be greatly improved by this proposed scheme.

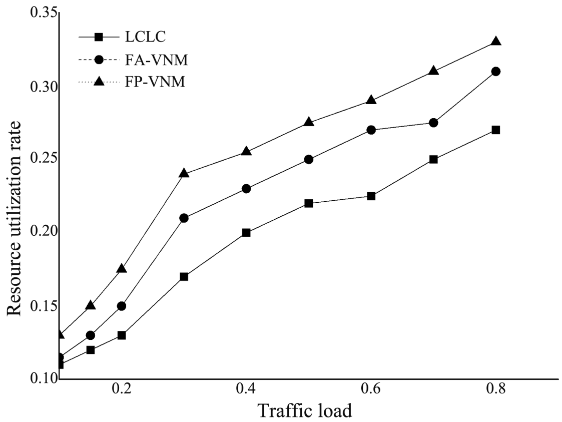


**Fig. 5** Comparison of the network utilization rate

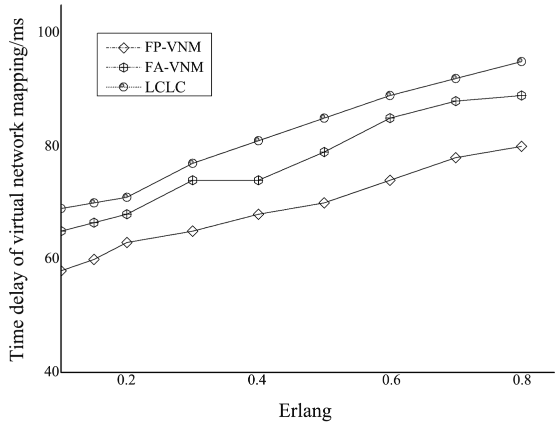


**Fig. 6** Comparison of the time delay

Comparison of average performance is given by Table 1. The FP-VNM has better blocking and utilization performances. Moreover, its delay time is also better than LCLC and FA-VNM. That is because the FP-VNM can in advance be aware of fragmentation condition of the whole EON.

Table 1 Performance comparison

| Scheme | Average blocking/% | Average utilization/% | Average time delay/ms |
|---|---|---|---|
| LCLC | 1.41 | 18 | 96 |
| FA-VNM | 1.28 | 21 | 75 |
| FP-VNM | 0.85 | 23 | 73 |

The time delay of virtual network mapping is compared in the Fig. 6. It is obviously that the proposed FP-VNM achieves the best performance and takes the shortest time among these methods, because edge computing ability can deal with part of processing task of virtual network service requests and greatly reduce fragments all over the EON.

## 6 Conclusions

With edge computing service development, the resource fragmentation problem brought serous challenges for EON to provide virtual networks. To overcome this problem, FP-VNM is proposed in this paper for EON system. With the fragmentation prediction ability, fragmentation indicators of optical links and nodes are presented using the GRU model. Test results suggest that the FP-VNM scheme could improve the supporting ability to virtual optical networks for edge computing services in terms of blocking rate, resource utilization rate and time delay.

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