Multi-Associated Parameters Aggregation-Based Routing and Resources Allocation in Multi-Core Elastic Optical Networks

Hui Yang, *Senior Member, IEEE*, Qiuyan Yao, *Member, IEEE*, Bowen Bao, Ao Yu, Jie Zhang, *Member, IEEE*, and Athanasios V. Vasilakos, *Senior Member, IEEE*

***Abstract*— Space division multiplexing (SDM), as a potential means of enhancing the capacity of optical transmission systems, has attracted widespread attention. However, the adoption of SDM technology has also additionally increased resource dimensions, introduced complex crosstalk, and made it difficult to integrate multi-dimensional fragments. These factors force the transmission constraints to be more complicated. Especially, some factors have a mutual restraint relationship, and excessive consideration of certain factors will cause the deterioration of other ones. Therefore, how to comprehensively consider the associated factors to achieve trade-offs and improve network performance is a problem worthy of study. This paper exploits the advantages of self-organizing feature mapping (SOFM) model to process multi-dimensional data with relevant features. Firstly, multiple constraints will be input into SOFM as mode vectors from the core level. Then, by judging the similarity between the competition layer neuron and the pattern vector, the position of the winning neuron is located, which determines the transmission level of each core. Finally, a routing, core, and spectrum allocation scheme is proposed by preferentially locating the core with higher transmission quality. Along the selected core, the available slots will be classified twice respectively by the number of adjacent cores and crosstalk direction to quickly find the spectrum blocks with relatively small crosstalk. Results indicate the scheme can reduce blocking probability and the resource fragmentation. Further, it can increase the resource utilization within tested network load.**

***Index Terms*— Elastic optical networks, crosstalk, multi-core fiber, routing and resource allocation, self-organizing feature mapping.**

I. Introduction

MASSIVE machine type communication (mMTC), ultra reliable and low latency communication (uRLLC), and enhanced mobile broadband (eMBB) are three typical service scenarios in 5G and beyond communications [1]. Especially in the eMBB scenario, high-definition video, VR games and other services with large bandwidth requirements will continue to emerge, which puts ultra-high bandwidth requirements on 5G and beyond networks [2]. As one of the most important bearer technologies for 5G and beyond, the expansion of optical network transmission capacity is also imminent [3], [4]. Space division multiplexing (SDM) related technologies have been seen as promising approaches to increase the transmission capacity of optical networks [5]–[7]. Multi-core fibers (MCFs) own multiple cores, proportionally expanding their transmission capacities, and their simpler design also makes them more practical in elastic optical networks (EONs) which are designed to realize flexible utilization on frequency slots [8]–[10].

A. Motivation

The introduction of SDM technology will lead to more complicated and diverse factors restricting service transmission. Besides some traditional factors, such as link length, available bandwidth, physical layer impairments, etc., two other additional factors involving complex crosstalk and multi-dimensional fragmentation should also be noted. The former has a serious impact on quality of service (QoS) during the service provisioning [11]. The latter is also a non-negligible factor which can make resource optimization more complicated and resource utilization more inefficient [12].

Related studies have considered some factors as independent constraints in the resource assignment process to improve network performance. Authors in [13], [14] proposed several different fragmentation metrics under the premise of considering crosstalk to reduce blocking probability. Works in [15] simplified the resource allocation to mitigate the crosstalk and spectrum fragments based on the traffic prediction exploiting deep learning method. Authors in [16] mainly considered the crosstalk, spectrum fragmentation, and load imbalance to enhance the QoS for requests with high priority. Additionally, a transfer learning-based spectrum defragmentation time prediction method was proposed in [17] where the number of blocked services, hops, and the services affected by crosstalk were taking into account.

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Hui Yang, Qiuyan Yao, Bowen Bao, Ao Yu, and Jie Zhang are with the State Key Laboratory of Information Photonics and Optical Communication, Beijing University of Posts and Telecommunications, Beijing 100876, China (e-mail: yanghui@bupt.edu.cn; yqy89716@bupt.edu.cn; baobowen@bupt.edu.cn; yuao@bupt.edu.cn; lgr24@bupt.edu.cn).

Athanasios V. Vasilakos is with the College of Mathematics and Computer Science, Fuzhou University, Fuzhou 350116, China, and also with the Center for AI Research (CAIR), University of Agder (UiA), 4898 Grimstad, Norway (e-mail: thanos.vasilakos@uia.no).

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However, we have captured that some influencing factors will change dynamically with the network operation. For each service arriving at the network, these constraints need to be evaluated in real time. In addition to this, there is a relationship of mutual restraint and trade-off among some factors, and such relationship will also change constantly. For example, in multi-core EONs (MC-EONs), two typical influencing factors are crosstalk and multi-dimensional fragmentation [18]. They are continuously changing, and we also find that if excessively searching for resources with small crosstalk values, there is a great possibility of increasing the fragments. Besides, if blindly avoiding fragments, it may cause services to be more severely affected by crosstalk, or even blocked. According to our analysis of the research status, most of the current work regards each constraint as an independent measure, does not consider the interrelationship between factors, or may ignore the influence of certain factors. While excessive consideration of certain factors will lead to the deterioration of others, unable to make a trade-off between them, resulting in degradation on network performance.

In short, while using SDM technology to improve the transmission capacity of optical networks, it also introduces additional complex influencing factors on service transmission, which poses severe challenges to the services' QoS guarantee. Thus, how to comprehensively evaluate and balance the impact of various parameters on the service provisioning is a key issue in MC-EONs, which is also the main driving force of this paper.

B. Contributions

This paper exploits SDM technology with multi-core fibers to focus on the ultra-high bandwidth provisioning with optical networks as the bearer. Moreover, the unsupervised self-organizing feature mapping model (SOFM) is used to aggregate and balance the influence relationship among various factors. This model can rapidly sort the cores in consideration of various factors with its competitive learning mechanism by quickly processing multidimensional data with associated features, which is consistent with our goal of comprehensively evaluating the influence of multiple parameters. Concretely, each influencing factor will be firstly taken as the input vector, and then the winning neuron can be determined through the similarity judgment between different input modes and neurons in the competition layer. Finally, the level of the corresponding input pattern vector is determined by the size of the Euclidean distance value.

This paper first presents a link quality assessment (LQA) method based on SOFM model from the core perspective. Multiple constraint values on each core are calculated to form a vector and used as the input mode of SOFM. By running its competitive self-learning mechanism, the similarity between the weight vector of the neurons in the competition layer and the input layer pattern is calculated to locate the winning neuron. After each input pattern finds the corresponding winning neuron, the level of the input pattern is determined by the relative distance between the winning neurons. The final output of SOFM model is the transmission level of each core after comprehensive consideration of multiple factors, thereby achieving a trade-off between them.

Then, a routing, core, and spectrum assignment algorithm using SOFM-based LQA (LQA-SOFM-RCSA) is proposed. During the core allocation, the one with higher rank will be preferentially selected along each link of each candidate path to guarantee the QoS. For the spectrum assignment, we classify the spectrum resources in the selected core twice respectively according to the number of adjacent cores and the direction of crosstalk. Specifically, the free slot blocks corresponding with the services' bandwidth will be first classified by the number of adjacent cores considering the different severity of crosstalk. Ulteriorly, given that the direction of signal transmission will cause crosstalk in different directions, in the class with relatively small crosstalk, the spectral blocks are further classified according to the direction of crosstalk.

Specifically, the main contributions of this work are summarized as follows.

- Due to the difficulty on comprehensively evaluating the mutual influence between complicated and diverse factors affecting service transmission, we put forward a multi-associated parameters aggregation and evaluation method based on SOFM model from the perspective of core level to realize the trade-off between these factors.
- We present a LQA-SOFM-RCSA scheme where the core with better transmission quality is preferentially selected, and the slot blocks in the core are classified twice according to the size and direction of crosstalk. Experimental results show that the presented algorithm can reduce the blocking and spectrum fragmentation as the network load increases. It can also improve the resource utilization.

The reminder of this paper is structured as follows. Section II reviews the related work. Multiple constraints on QoS are analyzed in detail in Section III. Section IV first gives the typical SOFM model, then it is used to evaluate the link quality, and finally a LQA-SOFM-RCSA scheme is presented. Section V shows the experimental results and analysis. Conclusions are drawn in Section VI.

II. Previous Works

The parameters affecting service transmission are complicated, making it difficult to evaluate the transmission quality of the links. In order to comprehensively estimate the link transmission quality and ensure the quality of service, many factors need to be considered when designing RCSA algorithms. This section studies some typical traditional and machine learning-based RCSA schemes, and analyzes their overall problems. Meanwhile, it also points out the importance of comprehensively evaluating the impact of various parameters.

A. Traditional Methods

Authors in [19] studied the problem of routing, modulation format, core, and spectrum assignment (RMCSA) in SDM-EONs. A path-based mixed-integer linear programming (MILP) scheme was proposed taking the contiguity, non-overlapping, crosstalk, and spectrum usage as independent constraints. By involving the spectrum allocation layout (SAL) variety and defining spectrum waste metric for each SAL, A. Ghadesi *et al.* mainly focused on the intentional spectrum waste approach during the resource assignment process [20].

Differently, authors in [21] presented a comprehensive model to address the resource allocation problem in SDM-EONs with few-mode multi-core fibers (FM-MCFs). Three physical dimensions including spectrum, mode, and core were concurrently considered as a three-dimension allocation model by investigating the effects of inter-core crosstalk, inter/intra-mode crosstalk, and also the traditional noise induced by the erbium-doped fiber amplifier (EDFA).

In [22], two active resource allocation algorithms were designed to alleviate the fragmentation problem in SDM scenarios. The spectrum assignment was determined by considering the status of spectrum fragments and also the possible bottleneck links as the constraints. Additionally, authors in [23] proposed a RCSA algorithm with fluctuating traffic by separately evaluating the crosstalk impact.

The above studies are based on traditional methods, and consider different constraints independently in the two stages of routing and resource assignment. In the SDM scenario with complex crosstalk effects, these methods may reduce the efficiency of RCSA process.

B. Machine Learning-Based Schemes

Recently, machine learning is regarded as one of the most promising approaches to perform network data analysis and enable network automation configuration [24]–[28]. A transfer learning model was used in [29] to predict the quality of transmission (QoT) in optical systems with different modulation formats. Authors in [30], [31] designed accurate QoT estimators by using machine learning approaches to monitor the QoT of existing connections in EONs. A classifier was trained in [32] with features indicating a lighpath, including lightpath length, longest link length, number of links, and traffic volume, etc. To realize autonomous resource allocation in EONs, a deep reinforcement learning based self-learning resource agent was proposed in [33]. The optimal RCSA policy can be learned based on the perception of network states, such as topology, spectrum utilization, and in-service lightpaths.

Against SDM-EONs scenario, authors in [34] used an Elman neural network to predict traffic demands and exploited a two-dimensional rectangular packing model to assign spectrum resources in order to decrease spectrum fragments. In SDM-EONs, there are many factors affecting service transmission, such as complex crosstalk and multi-dimensional resource fragments. It is much necessary to comprehensively evaluate these factors in the RCSA process to improve the RCSA efficiency. However, there is little work for this purpose from this point. To achieve efficient resource allocation, this paper presents a SOFM model-based RCSA algorithm which can quickly locate cores with better transmission quality and spectrum blocks with smaller crosstalk. Its innovations mainly lie in the following two aspects.

- Firstly, different from the existing machine learning-based methods only considering a few independent features, the SOFM competition mechanism is used to comprehensively evaluate the impact of multiple related parameters on transmission quality from a core perspective.
- Secondly, to locate the spectrum blocks with slight crosstalk, the available spectrum resources are classified twice respectively according to the number of adjacent cores and the number of adjacent cores transmitted in the same direction. This is different from the traditional method that only considers the number of adjacent cores for crosstalk evaluation.

III. Multiple Transmission Constraints Analysis in MC-EONs

In this section, we mainly take the assessment model on physical impairments, crosstalk, and multi-dimensional fragments into account. They will all be used as influencing factors to comprehensively evaluate the link transmission quality to ensure the services' QoS.

A. Physical Layer Impairments

In MC-EONs, complicated physical layer constraints will seriously affect the service transmission process. Especially, complex crosstalk is a non-negligible factor that affects service transmission quality in SDM optical networks. In particular, the difference in signal transmission direction will also interfere with the crosstalk evaluation model. It means that the crosstalk models of co-directional transmission and non-directional transmission are slightly different, since the power coefficients converted from the additional crosstalk are different. In this subsection, we first depict the crosstalk evaluation process, and then conduct the estimation model on traditional physical impairments.

1) Crosstalk Estimation Along Links: In MCFs, the typical crosstalk assessment can be expressed as (1) where n_c is the number of adjacent cores and L is transmission length. They are treated as two key parameters to estimate the crosstalk when the fiber type is determined. h denotes the average increase in crosstalk per unit length and can be given by (2) in [35]. k_cc, R_b, β, and w_c are the coupling coefficient, bend radius, propagation constant, and core-pitch.

$$XT = \frac{n_\mathrm{c} - n_\mathrm{c} \cdot \exp[-(n_\mathrm{c}+1)\cdot 2hL]}{1 + n_\mathrm{c} \cdot \exp[-(n_\mathrm{c}+1)\cdot 2hL]} \tag{1}$$

$$h = \frac{2{k_\mathrm{cc}}^2 R_\mathrm{b}}{\beta w_\mathrm{c}} \tag{2}$$

In (1), calculation for the key parameter n_c can be illustrated as Fig.1. Take C_j as the core number and j will be from the set {0,1,2,3,4,5,6}. For a service with two slots, if core C_0 is selected, the adjacent core set will be $\{C_1,\ C_5,\ C_6\}$. Along the selected C_0, if slots 0 and 1 are as the candidate, the value of n_c will be 3. This is because the slot 0, slots 0 and 1, slot 0 respectively along C_1, C_5, and C_6 are overlapped occupied, which can lead to serious crosstalk. Another case is that slots 4 and 5 are available, n_c will be 0 since slots 4 and 5 along C_1, C_5, and C_6 are not allocated for services.

In this paper, we focus on the XT estimation of trench-assisted MCF (TA-MCF) due to its low crosstalk level. For

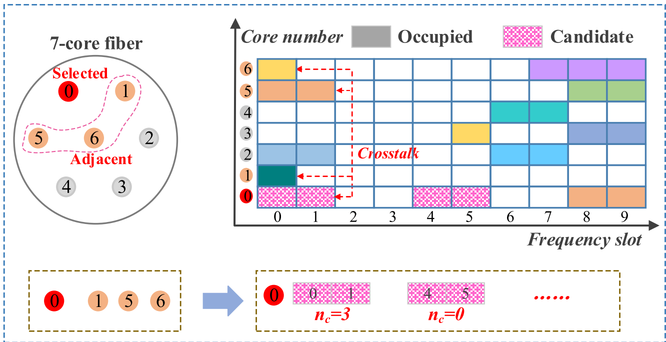

Fig. 1. Calculation for the number of adjacent cores.

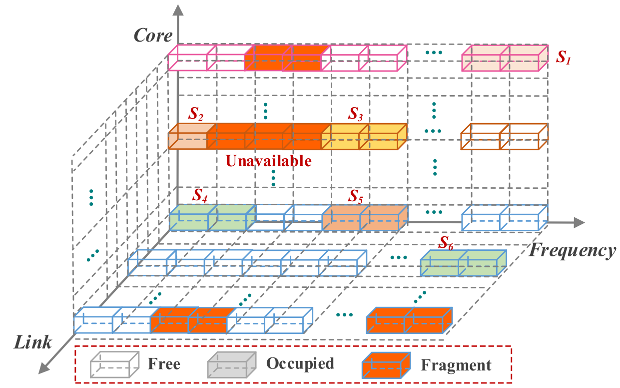

Fig. 2. Multi-dimensional fragmentation.

TA-MCF, h can be modified as (3) according to [36] where w_{t} and R_{c} are the trench width and core radius.

$$h' = h \cdot \frac{W_1}{[W_1 + (W_2 - W_1) \cdot \frac{w_{\mathrm{t}}}{w_{\mathrm{c}}}]} \cdot \exp[\frac{-4(W_2 - W_1) \cdot w_{\mathrm{t}}}{R_{\mathrm{c}}}] \tag{3}$$

W_1 and W_2 can be calculated by (4) where r_{clad} is the cladding refractive index. Δ_2 is the refractive index difference between trench and cladding. λ is the selected wavelength.

$$\begin{cases} W_1 = 1.1428V_1 - 0.996 \\ W_2 = \sqrt{V_2^2 + W_1^2} \\ V_2 = 2\pi R_{\mathrm{c}} r_{\mathrm{clad}} \cdot \sqrt{2\,|\Delta_2|}/\lambda \end{cases} \tag{4}$$

As the reference [36], for the bi-directional TA-MCF, the crosstalk can be estimated by (5) where P_1 is $10^{\Delta\mathrm{XT(dB)}/10}$ and P_2 is $10^{[\Delta\mathrm{XT(dB)}-\Delta\mathrm{XT(-dB)}]/10}$. Note that they are power coefficients converted from additional crosstalk. XT_1 and XT_2 are respectively the crosstalk from the same direction and the opposite direction. n_1 and n_2 are the number of adjacent cores from the same and opposite directions.

$$\begin{cases} XT_{\mathrm{total}} = XT_1 + XT_2 \\ \quad = \dfrac{(P_1 \cdot n_1 - P_1 \cdot n_1 \cdot \varepsilon) + (P_2 \cdot n_2 - P_2 \cdot n_2 \cdot \varepsilon)}{1 + P_1 \cdot n_1 \cdot \varepsilon + P_2 \cdot n_2 \cdot \varepsilon} \\ \varepsilon = \exp[-(n_{\mathrm{c}} + 1) \cdot 2h'L] \end{cases} \tag{5}$$

ΔXT_{dB} is the additional wavelength-dependent crosstalk contribution and can be expressed by (6) where r_{core} is the core refractive index and Δ_1 is the refractive index difference between cladding and core.

$$\begin{aligned} \Delta XT_{\mathrm{dB}} &= 10\log_{10}[1 - 0.001256(\lambda - \lambda_0)]^4 \\ &\quad + 19.85 r_{\mathrm{core}} \cdot \sqrt{2\Delta_1} \cdot [(\lambda - \lambda_0) \cdot w_{\mathrm{c}}/(\lambda \cdot \lambda_0)] \end{aligned} \tag{6}$$

In EONs, several continuous frequency slots will be assigned to the services. Thus, it needs to transform the frequency to be the wavelength according to (7) as [37] where C is the speed of light, f_0 is the starting frequency, and N_{slot} is the number of required slots for the service.

$$\lambda = \frac{C}{f} = \frac{C}{f_0 + 0.0125(N_{\mathrm{slot}} + 2)} \tag{7}$$

2) Physical Impairments Consideration: The signal transmission quality can be affected by other impairment factors, including linear and nonlinear impairments. In this paper, we will take the amplified spontaneous emission (ASE), cross-phase modulation (XPM), and four-wave mixing (FWM) into account, and the estimation models will be used as our previous work in [37].

Note that the Q-factor will be exploited to represent the quality of transmission since it is sensitive to the bit error rate (BER). Their relationship can be expressed by (8). For different modulation formats, the Q-factor evaluation method will be different. For OOK channels, the Q-factor is related with the receiver sensitivity and the signal-to noise ratio (SNR) per symbol. But for QPSK channels, the Q-factor estimation will be complex, and it is also closely related to the self-phase modulation (SPM) and XPM.

$$BER = \frac{1}{2} erfc(\frac{Q}{\sqrt{2}}) \approx \frac{1}{Q\sqrt{2\pi}} \cdot e^{-Q^2/2} \tag{8}$$

B. Multi-Dimensional Resource Fragmentation

In MC-EONs, the introduction of cores has led to the expansion of resource dimension. With the operation of the network and the continuous arrival and departure of services, multi-dimensional resources are continuously occupied and released, leaving the fragments to be multi-dimensional, which can limit the improvement of network performance. In view of this, we regard it as an important factor affecting the service provisioning. Multi-dimensional fragments at a certain moment can be illustrated as Fig.2 where S_i represents the service. Three dimensions called link, core, and frequency are considered. For a core on a certain link, if at a moment, some continuous spectrum blocks are unavailable due to severe transmission quality degradation or unable to meet bandwidth requirements, they will be treated as multi-dimensional fragments.

In order to further improve network performance and ensure the QoS, it is crucial to make evaluation on multi-dimensional fragments. In this paper, it can be represented by the fragmentation degree (FD) and calculated by (9) where FB_{fra} is the fragmented frequency block and FS_{total} is the total number of frequency slots in a core along a link. K denotes the number

TABLE I
SYMBOL DEFINITIONS AND DESCRIPTION FOR MULTIPLE CONSTRAINTS

Symbols	Definitions
n_c	The number of adjacent cores
k_{cc}	Coupling coefficient
R_b	Bend radius
β	Propagation constant
w_c	Core-pitch
w_t	The trench width
R_c	Core radius
r_{clad}	The cladding refractive index
Δ_2	The refractive index difference between trench and cladding
r_{core}	The core refractive index
Δ_1	The refractive index difference between cladding and core
λ	The selected wavelength
C	The speed of light
f_0	The starting frequency for the service
N_{slot}	The number of required slots for the service
S	Service
K	The number of fragmented spectral blocks in the core C_j of the link L_i
FB_{fra}	The fragmented spectrum block
FS_{total}	The total number of frequency slots in a core along a link
FD	Fragmentation degree

of fragmented spectral blocks in the core C_j of the link L_i. It should be noted that when consecutive free frequency slots are not enough to serve a service, it will be regarded as a fragmented spectrum block.

$$(FD)^{C_j,L_i} = \frac{\sum_{k=1}^{K} n_k \cdot (FB_{\text{fra}})_k^{C_j,L_i}}{(FS_{\text{total}})^{C_j,L_i}} \tag{9}$$

Symbols and definitions of parameters used throughout this section are given in Table I. In MC-EONs, from the perspective of the entire network, multiple constraints in different cores on different links have different impact on service transmission quality, and a certain constraint may become the dominant factor. For different services, the dominant factor in each core on each link along the selected path needs to be determined to achieve a trade-off between the factors. Thus, we will first model the evaluation method based on SOFM in next section.

IV. Routing, Core and Spectrum Assignment Based on SOFM Model

In this section, we will comprehensively consider multiple influencing factors from the core level to evaluate the link transmission quality. Then, a routing and spectrum assignment algorithm is proposed based on SOFM.

A. The Typical SOFM Model

Self-organizing feature mapping model adopts unsupervised learning method with neurons' competition. SOFM can learn the distribution of input samples and also recognize the topology of input vectors. The SOFM network has two layers and each neuron in the input layer collects external information to each neuron in the output layer through a fully connected weight layer. Its structure has been shown in Fig.3.

For the input layer, the neuron is labeled as $I_i (i = 1, 2, 3 \ldots, m)$ and its number is equal to the sample dimension.

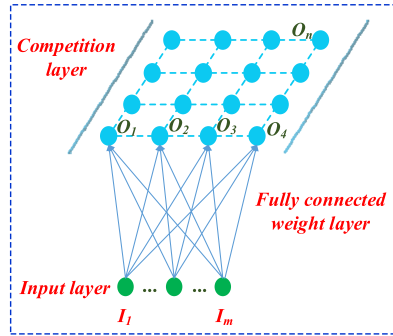

Fig. 3. SOFM model.

The most typical organization of the output layer is according to a two-dimensional plane. Each neuron is laterally connected to other neurons around it.

In the learning algorithm of SOFM, the winning neuron in the output layer and its surrounding neurons need to adjust the weight vector. The typical process for training is as follows. First, initialize parameters including weight vector, learning rate, an initial winning neighborhood etc. Then, input samples to find the winning neuron and update the weight vector. If the learning rate is zero, the training ends.

Based on the above analysis, SOFM model can transform any dimensional input into a two-dimensional discrete mapping. In MC-EONs, due to the variety of factors affecting the transmission quality of the link, each factor collected from the core level can be used as a dimension to be input into the SOFM model, and finally the reordered cores along each link will be output. The result can be exploited during the RCSA process.

B. Link Quality Assessment Based on SOFM From Core Level

We first present a link quality assessment method from the core level exploiting SOFM model as Fig.4 shows. The specific process can be described as following. First, the routing model will output k shortest paths for the new service. Evaluate the impact of multiple parameters in each core C_j along each link l_i of each path L_{p} on the transmission quality to form a core attribute set. (①②③) Then, this set will be input into the SOFM model to obtain the reordered core set along l_i of L_{p}. (④⑤) After that, this set will be used as a reference for resource allocation to obtain a CSA solution for each service. (⑥⑦)

TA-MCFs with 7 cores are deployed in the optical network. For the service, it can be expressed as $S(S_i, s, d, XT_{\text{threshold}}, N_{\text{slot}})$ where S_i, s, and d are the service index, the source node, and destination node. $XT_{\text{threshold}}$ is the crosstalk threshold which is determined by the selected modulation format since different modulation formats have different crosstalk tolerance limits. N_{slot} is defined as the number of slots consistent with the service bandwidth requirement. For the link, 8 dimensions will be considered as $L_{\text{att}}(L, C_j, N_{\text{ser}}, B_{\text{ava}}, R_{\text{uti}}, XT, Q, FD)$ where L represents the link length, C_j is the selected core, and N_{ser} denotes the number of services

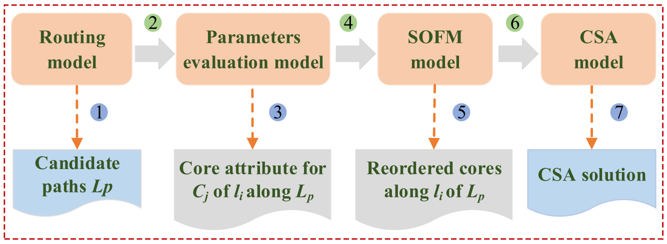

Fig. 4. LQA process based on SOFM.

carried in C_j. B_{ava}, R_{uti}, XT, Q, and FD are respectively the available bandwidth, the resource utilization, crosstalk and BER evaluation, and fragmentation degree along C_j of the link. Considering that the crosstalk is related to whether the relevant spectrum position in the adjacent cores carries services, the crosstalk along the core of each link can be roughly evaluated based on the total number of carrying services in the adjacent cores for a certain core. Thus, during the link quality assessment by using SOFM model, this method will be exploited.

C. RCSA Based on LQA-SOFM

The diversification of factors affecting the transmission quality of the link makes it extremely difficult to evaluate them comprehensively, which will further affect the service provisioning. From this point of view, we present the RCSA algorithm based on LQA-SOFM shown as Algorithm 1 and its detailed process is described as following.

Step1: is the routing process. When new services arrive at the network, calculate k shortest paths for S by exploiting the Floyd algorithm. (Lines 1-3)

Step2: is the core selection process. Multi-parameter evaluation is performed for each core C_j on each link L_i of each candidate path. The evaluation results will be transformed into a link attribute set $L_{i\text{-}att}$ with 8 dimensions and input into the SOFM model. Then, output the reordered core level for each link l_i through competitive learning. The core with the highest core level can be marked as $C_j{}'$. (Lines 4-11)

Step3: is the spectrum assignment process. Along each link l_i of each candidate path, the free slot blocks in $C_j{}'$ are classified in ascending order of the number of adjacent cores labeled as n_{c}. The slot block with the smallest n_{c} will be preferred. (Lines 12-14)

Then, reclassify the free slot blocks in the selected class with smaller n_{c} by the number of adjacent cores with the same and opposite directions indicated as n_1 and n_2, respectively. Select a spectrum block in ascending order of n_1, and calculate the actual crosstalk and Q values for the new service S. If they meet the requirement, the new service will be served successfully. If there are no available resource along all the candidate cores and links, block this service. (Lines 15-25)

The presented algorithm is designed for the core optical network where core cross-connect equipment (CXC) is deployed to achieve core switching ability. Core selection is not restricted by consistency constraint, which indicates that

Algorithm 1 RCSA Based on Link Quality Assessment by SOFM (LQA-SOFM-RCSA)

Input: Network $G\,(V, E)$, service $S\,(S_i, s, d, XT_{\text{threshold}}, N_{\text{slot}})$
Output: RCSA solution for S
1. Parameters initialization, including parameters for the network and SOFM model
2. Service S reaches the network and acquire its related parameters
3. Calculate k shortest paths for S by Floyd algorithm
4. for each candidate path $L_{\text{p}} \in \{1, 2, 3, \ldots, k\}$ **do**
5. for each core along each link of L_{p} **do**
6. Calculate multi-parameters in each core C_j of each link l_i
7. Calculated values are formed into a link feature as $L_{i\text{-}att}(L, C_j, N_{\text{ser}}, B_{\text{ava}}, R_{\text{uti}}, XT, Q, FD)$
8. Input $L_{i\text{-}att}$ into the SOFM model
9. Output reordered core level for each link l_i
10. Select the core with the highest rank marked as $C_j{}'$
11. end for
12. for each link l_i along L_{p} **do**
13. The idle slot blocks in $C_j{}'$ are classified according to the number of adjacent cores marked as n_{c}
14. Choose free slot block in the class by ascending order of n_{c}
15. Reclassify the idle slot blocks in the selected class according to the number of adjacent cores with the same direction n_1
16. Choose a spectrum block in ascending order of n_1
17. Calculate the crosstalk and Q value for S as XT_{actual} and Q_{actual}
18. if XT_{actual} and Q_{actual} meet the threshold requirement
19. S is served successfully
20. end if
21. end for
22. end for
23. if no available resources are found
24. S will be blocked
25.end if

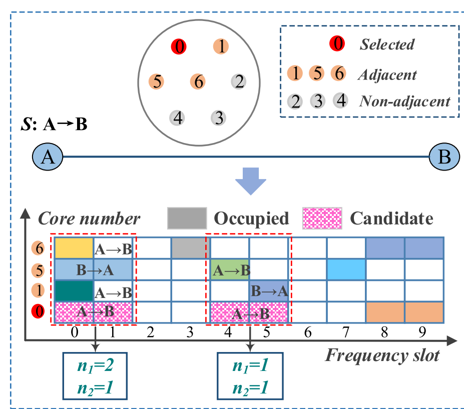

Fig. 5. Example on n_1 and n_2 calculation.

along the selected path, the cores allocated on different links may be different.

Note that for a service, the available spectrum blocks are first classified by the number of adjacent cores n_{c} since according to the theoretical analysis by (1), if the number of adjacent cores is larger, the crosstalk will be more serious. Additionally, the available slot blocks with relatively small crosstalk are selected for secondary classification based on the transmission direction of the signal, due to the fact that power coefficients characterizing transmissions in the same direction or in two opposite directions are different. Based on

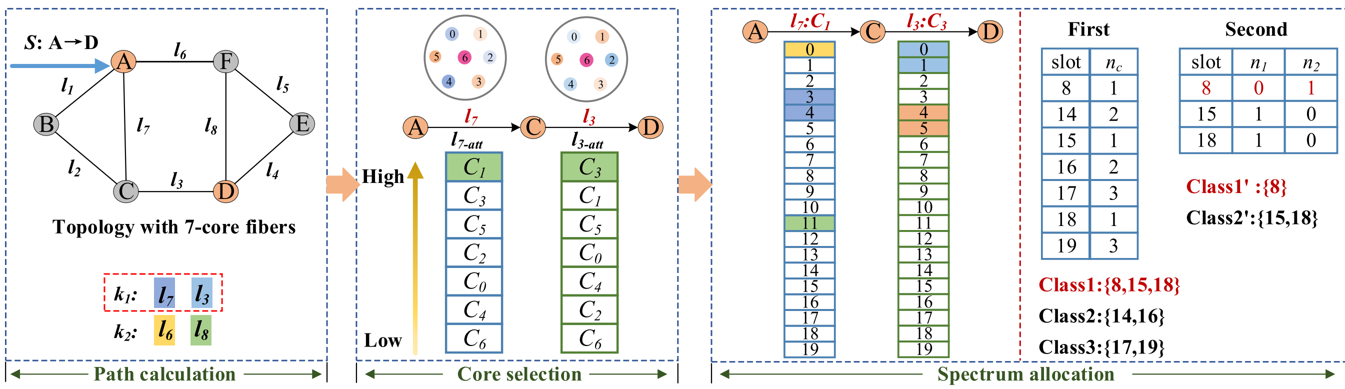

Fig. 6. An example for the proposed LQA-SOFM-RCSA.

the above analysis, when n_c is determined, the size of the crosstalk value will be related to the transmission direction of services in adjacent cores. The determination of the values of n_1 and n_2 is based on the transmission direction of the service currently arriving at the network. Their calculation is illustrated as Fig.5. If C_0 is selected, for two different spectrum blocks {0,1} and {4,5} along C_0, n_1 and n_2 are {2,1} and {1,1}, respectively.

We give a sample graph to illustrate the flow of proposed algorithm to make it clearer as Fig.6. The topology with 6 nodes and 8 links is used and the links are labeled as l_i ($\mathrm{i} = 1, 2, 3, \ldots, 8$). Suppose that at a certain moment, a new service with the source A and destination node D arrives at the network. Its required number of frequency slot is 1. First, Floyd algorithm is performed to calculate two candidate paths indicated as k_1 and k_2, which is the path calculation process.

Next, k_1 will be first selected to find the available resources. The transmission quality is evaluated for the 7 cores on the two links of l_7 and l_3 respectively. The calculated multi-parameters are input into the SOFM model to obtain the core sequence reordered by the core transmission quality. The core order of l_7 and l_3 is respectively $\{C_1, C_3, C_5, C_2, C_0, C_4, C_6\}$ and $\{C_3, C_1, C_5, C_0, C_4, C_2, C_6\}$. Finally, C_1 and C_3 are selected along l_7 and l_3 respectively. This process is about the core selection.

Then, find the available spectrum resources on the path by searching. Due to spectrum consistency constraint, the free frequency slots are {8, 14, 15, 16, 17, 18, 19}. The number of adjacent cores they correspond to are {1, 2, 1, 2, 3, 1, 3}. The available resources are classified for the first time by n_c as Class1 {8, 15, 18}, Class2 {14, 16}, and Class3 {17, 19} which are labeled in ascending order of n_c. The significance of this classification is to guide us to select the available slots in the corresponding class. Therefore, we will select the resources in Class 1 and then classify them for the second time as Class1′ {8} and Class2′ {15, 18} in ascending order of n_1. Note that Class1′ and Class2′ are a subset of Class1. Finally, slot 8 that meets the crosstalk requirements is selected to carry the new service. Remind that if n_c is equal to n_1 for a selected class, the second classification result will be the same as the selected class. If there are no available resources along k_1 and k_2, the service will be blocked. The whole process above is spectrum allocation.

To sum up, the standard for the first classification is based on the number of adjacent cores and the second classification is executed in a certain class selected from the first classification result. Therefore, as long as there are continuously available slots in the selected core along the path, it means that the first classification result is definitely not empty. Then, it can be inferred that the result of the second classification is also not empty, since it is a subset of a certain class in the result of the first classification.

V. Experimental Setup and Performance Verification

In this section, the feasibility and effectiveness of the presented LQA-SOFM-RCSA scheme is verified on our constructed experimental testbed with both control plane and data plane.

A. Experimental Setup

The feasibility of the proposed scheme is first verified by building an experimental platform shown as Fig.7. In the data plane, we construct a software defined core cross-connect (SD-CXC) node model based on the core selective switch (CSS) in [38] with our developed OpenFlow agent [39]. The other nodes are implemented by virtual machines and can be considered as real nodes. The virtual machines are realized by VMware ESXI V6.7 running on Dell R740 servers with 16 2.00 GHz Intel Xeon(R) Gold 6138 CPU cores and 1 Tesla v100 GPU core with 32G. All links are virtualized and equipped with 7-core fibers with available 358 slots for each core.

In the control plane, transport controller is developed by the Boron version of OpenDaylight. All nodes and links are virtualized to form the NSFNet and US nationwide network topologies which are used as emulation topologies to input into the presented LQA-SOFM-RCSA scheme [40]. The RCSA algorithm cooperates with the SOFM model to realize resource scheduling through the relationship between input and output. Note that the level of lightpath crosstalk will change over time during network operations including setup and teardown

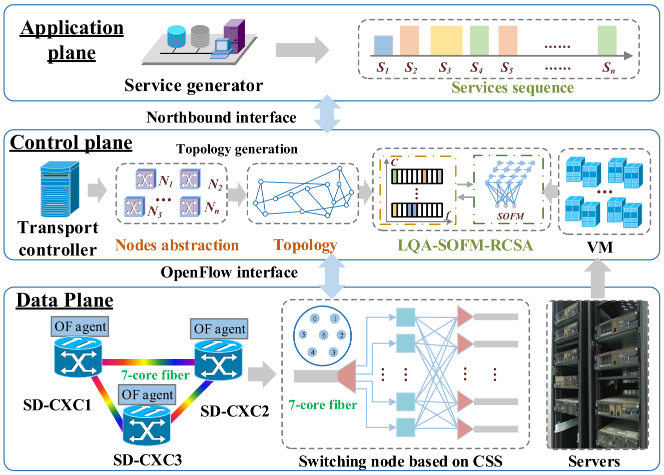

Fig. 7. Experimental testbed.

TABLE II
EMULATION PARAMETERS

	Symbols	Definitions	Values
XT related	k_{cc}	Coupling coefficient	0.06
	R_b	Bend radius	0.05m
	β	Propagation constant	$4*10^6(m^{-1})$
	w_c	Core-pitch	30μm
	R_c	Core radius	5.5μm
	r_{clad}	Cladding refractive index	1.448716
	Δ_1	The refractive index difference between cladding and core	0.35%
	Δ_2	The refractive index difference between trench and cladding	-0.35%
Service related	B	Bandwidth requirement	10/40Gb/s
	M	Modulation format	BPSK/QPSK
	$XT_{threshold}$	Crosstalk limitation	-21dB/-26dB [42]
	k	The number of candidate paths	2
SOFM training related	m	The number of neurons in the input layer	7
	n	Size of two-dimensional map	6
	T	The maximum number of trainings	200
	η_0	Initial value of learning rate	0.6
	R_0	Initial value of neighborhood radius	2

of channels or spatial channels transmitted through neighboring cores. This may lead to the fact that the accumulated crosstalk on some already established lightpaths may exceed the required threshold, resulting in service blocking. Therefore, during the simulation, an optical path performance monitor is established and triggered to assess whether the quality of the transmission channel for the deployed services still meets the requirements when allocating resources to the new services. If the crosstalk and BER thresholds of the existing services are exceeded, the currently evaluated spectrum block is considered to be unavailable.

In the application plane, the service generator dynamically generates service sequences with different bandwidth granularities including 10 or 40 Gb/s, following Poisson distribution with parameter λ_0. Meanwhile, the services' holding time is negative exponentially distributed with parameter μ. The network load is represented by λ_0/μ and varies in [100-1200] Erlang by setting $\mu = 0.2$ [41]. It should be noted that in order to ensure the credibility of the comparison results, the service bandwidth distribution of different algorithms will be consistent.

Then, we estimate the effectiveness of presented algorithm on the virtual machine. The related parameters are given in Table II. Note that for different modulation formats, the XT thresholds are also different. For BPSK and QPSK, they are respectively -21dB and -26dB. The evaluation result of crosstalk should be compared with its threshold, and the resources meeting the requirements should be selected.

For SOFM training, the number of neurons in the input layer indicated as m is the same as the size of the sample. In this paper, 8-dimensional link attributes are considered and seven cores on each link along the selected path need to be re-evaluated for the same service. Therefore, we set the SOFM model to 7-dimensional input, and each input contains 8-dimensional features. For core sorting, since only 6 cores except the center core are considered, the output layer parameter n is set to 6.

The initial winning neighborhood should be as large as possible. As the number of training increases, the winning neighborhood decreases, and the final radius is zero. The neighborhood radius can be in the form of an exponential change [43]. Thus, R_0 must be greater than 0, otherwise no neurons will be updated. But if R_0 is set too large, it means that with the winning node as the center, there are more nodes which require to update the weight, affecting the speed of model training. Since the size of two-dimensional map is 6, we set R_0 to 2 to balance training speed and performance.

Learning rate is generally a monotonic descent function of training time to ensure the convergence of the training algorithm. It ranges between [0,1] and will affect the convergence speed. At the beginning of training, we can set the learning rate to a larger value and then decrease it at a faster rate, which helps to quickly capture the rough structure of the input vector. Then the learning rate slowly drops from a small value to zero. In this way, the weight can be finely adjusted to conform to the sample distribution structure of the input space. Based on the above analysis, we first set the initial learning rate to 0.6.

The training dataset is obtained starting from an empty network. Services are generated dynamically following Poisson distribution the holding time is negative exponentially distributed, which is consistent with the simulation setting. For routing, Floyd algorithm is used to calculate the candidate paths. For the core and slots allocation, first fit method will be always used following the pre-defined number sequence. When the resource allocation process ends, the link attribution will be calculated. About 62,000 data records are input to the model to complete the training process. The trained model will be used in the resource allocation process to determine the core level on each link. The specific training process is referenced to [44].

TABLE III
COMPARED ALGORITHMS

	Routing	Core selection	Spectrum selection
KSP-FF	KSP	First fit	First fit
KSP-NC-FF	KSP	First fit and nonadjacent core first	First fit
RCSA in [45]	SOFM	First fit	First fit
KSP-SOFM-FF	KSP	SOFM	First fit
KSP-FF-SC	KSP	First fit	Spectrum classification twice; Minimum n_c and n_1
LQA-SOFM-RCSA in this paper	KSP	SOFM	Spectrum classification twice; Minimum n_c and n_1

B. Compared Algorithms

The difference of the comparison algorithms in routing, core selection, and spectrum selection is shown in Table III, which will be described in detail in the next section. Note that for the path selection, all the compared algorithms will use a first fit method in the paths set calculated by the KSP algorithm. Note that in the presented LQA-SOFM-RCSA algorithm, the adoption of SOFM model is to comprehensively evaluate the impact of multiple related parameters on transmission quality from a core perspective during the core selection process. The purpose of double spectrum classification is to locate spectrum resources with less crosstalk for services, which is applied in the spectrum resource allocation stage. Thus, SOFM and double spectrum classification respectively act on core selection and spectrum allocation. The performance of two additional comparison algorithms including KSP-SOFM-FF and KSP-FF-SC has been evaluated to decouple the effects of the adoption of SOFM and those due to double spectrum classification.

1) Routing: For all the algorithms except the RCSA scheme in [45], the routing method will exploit k shortest paths (KSP) algorithm. For the routing in [45], multiple parameters will be first measured from the link perspective. Then, use the SOFM model to output all link levels to form a weight matrix for the routing process.

2) Core Selection: For KSP-first fit (KSP-FF) algorithm and KSP-FF-spectrum classification (KSP-FF-SC), a core will be selected with the first fit manner. Specifically, arrange the core numbers in a certain order and select the core that meets the transmission requirements for the first time in this order. Reference [45] also uses this method to select core resources.

For KSP-nonadjacent core first-FF (KSP-NC-FF) scheme, the cores need to be logically numbered in the same way as KSP-FF first, and then check whether there are available resources in this order. If there is no spectrum resource meeting the transmission requirements on the selected core, the cores are judged in ascending order from the core set that is not adjacent to the selected core to search for available resources.

For the proposed LQA-SOFM-RCSA method in this paper, we first conduct a multi-parameter evaluation of all cores on each link in the selected path. Then, use the results as the input of the SOFM model to finally output the core levels which are used as the basis for core sorting. Available spectrum resources are checked according to the core level in descending order. The core selection of KSP-SOFM-FF is the same with LQA-SOFM-RCSA algorithm.

3) Spectrum Selection: For KSP-FF, KSP-NC-FF, RCSA in [45], and KSP-SOFM-FF, spectrum selection will be all performed in a first fit way. For the presented LQA-SOFM-RCSA scheme, the spectrum resources on the related path are classified twice according to the number of adjacent cores and the number of adjacent cores in the same direction, indicated as n_c and n_1, respectively. Always select the spectrum resource with the smallest of these two values, ensuring the crosstalk to be relatively minimized along the selected path. The spectrum allocation of KSP-FF-SC scheme is consistent with LQA-SOFM-RCSA algorithm.

4) Time Complexity Analysis: Table III clearly describes several algorithms, and it can be seen that only the routing of RCSA in [45] is different. Actually, it uses SOFM to update link weights, and then runs KSP algorithm which is the same with other compared algorithms. Therefore, the complexity for routing part by Floyd algorithm is O(V^3) where V denotes the number of nodes in the network. During the core and spectrum selection, KSP-FF, KSP-NC-FF, RCSA in [45], and KSP-FF-SC have the same upper bound of complexity for serving a lightpath request, expressed as $O(k \cdot N_C \cdot N_{slot})$. k is the number of candidate paths, N_C is the number of cores, and N_{slot} indicates the number of frequency slots along each core. Thus, the overall time complexity of these four algorithms can be $O(V^3 + k \cdot N_C \cdot N_{slot})$.

For KSP-SOFM-FF and the proposed LQA-SOFM-RCSA in this paper, the core selected on each hop along the located paths may be different since CXCs are assumed. Thus, for a lightpath request, their time complexity upper bound during CSA process can be $O(k \cdot N_l^2 \cdot N_c^2 \cdot N_{slot})$ where N_l is the number of links along the candidate paths. Therefore, the total complexity of these two algorithms is $O(V^3 + k \cdot N_l^2 \cdot N_c^2 \cdot N_{slot})$.

C. Results on SOFM Training

For a specific service deployed in NSFNet, we first evaluate the multiple parameter values of each core for each link along the relevant path, take the result as an input matrix, and use the mapping mechanism of the SOFM model to determine the rank of each core. It means that for the same service, the priority order of each core on different links along the path are also likely to be different. This is because each core on each link is relatively independent, and the number of services carried is also different, which results in significant differences in the transmission quality of different cores. We chose a specific service with source node 2 and destination node 10 as an example to illustrate this situation. The results on different cores along different links are shown as Fig.8 with different colors mapping. Along the selected shortest path 2→4→5→7→10,

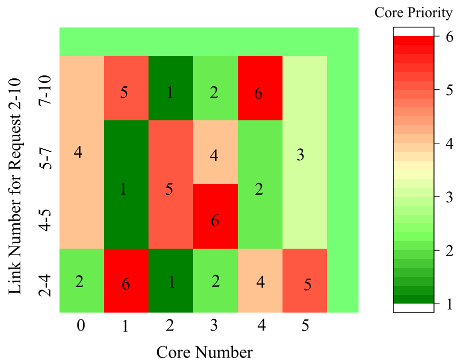

Fig. 8. Core priorities on different links for the same service.

TABLE IV
INFORMATION FOR THE SELECTED SERVICES SERVED IN NSFNET

	s	*d*	Selected path	The same link
S_1	8	13	8→9→13	link8-9
S_2	7	11	7→8→9→12→11	
S_3	13	1	13→9→8→1	

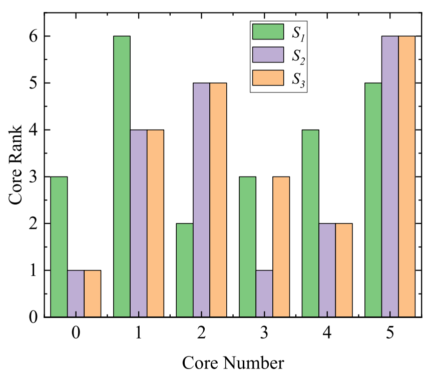

Fig. 9. Core ordering of different services on the same link.

core levels on link2-4, link4-5, link 5-7, and link7-10 are obviously different. Note that since the middle core will be affected by particularly serious crosstalk, we always take it as the last consideration.

Another case is that for different services, the selected path contains the same link, and the core levels on this link may also be different. This is because the multi-parameter metric is closely related to each core of each link along the path, especially the crosstalk which can be used to indirectly measure the QoS. We select three services, each of which contains link8-9 on their chosen shortest paths. Their specific parameters are given in Table IV, and the results are reported in Fig.9. It shows that the level of each core on the same link changes in real time, because each considered parameter value changes dynamically. When a new service arrives at the network, it is necessary to comprehensively reassess the impact of each parameter.

D. Network Performance Evaluation

In order to illustrate the advantages of the proposed scheme, we compared with other algorithms mainly in terms of blocking rate, fragmentation degree, and resource utilization.

1) Blocking Probability: The service blocking rate (SBR) is equal to the ratio of the number of blocked services to the total number of services in the network. The bandwidth blocking rate (BBR) can be represented by the ratio of the blocked service bandwidth to the total bandwidth of services carried on the network. When no resource meeting the service transmission requirements is found under the set constraints, the service will be blocked.

The results on different topologies are shown as Fig.10. They indicate that in the tested network load range, the SBR and BBR of the proposed method are relatively lower than compared algorithms. This is because before the core selection, the multiple influencing factors of each core on each link along the relevant path are comprehensively evaluated. It is always preferred to select a core with a higher rank to search for available resources. Along the selected core, the available spectrum resources are first classified by the number of adjacent cores, which can qualitatively locate the spectrum position with a smaller total crosstalk value to form a resource set. Then, in this set, the second classification is performed based on the number of cores transmitted in the same direction, so as to further reduce the impact of crosstalk. It can greatly improve the probability of finding available resources that meet the transmission requirements, decreasing the blocking.

2) Fragmentation Degree: With the arrival and departure of services, there are irregularities in the occupation and release of resources, which will cause the generation of resource fragments. If the fragmentation is left to flow, it will seriously affect the improvement of resource utilization. Taking this into consideration, it is regarded as a very important influencing factor in the scheme presented in this paper.

The results on the fragmentation degree with two topologies are respectively given as Fig.11 (a) and (b). It indicates that the proposed algorithm can decrease the fragmentation degree compared with other algorithms. This is because the resource selection and allocation process always considers the impact of fragmentation on service provisioning. By using the SOFM model to balance the relationship between fragments and other influencing factors, the fragments generation can be effectively reduced. Therefore, except for the proposed LQA-SOFM-RCSA, the spectrum fragmentation of KSP-SOFM-FF is lower than that of other comparison algorithms which do not consider the impact of fragmentation during the resource assignment.

3) Resource Utilization: Under the premise of rapid growth in service volume, it is critical to realize the maximum utilization of limited resources. Through comparison and verification with other algorithms, it fully illustrates the advantages of the proposed method in terms of resource utilization. The results for two topologies are respectively displayed as

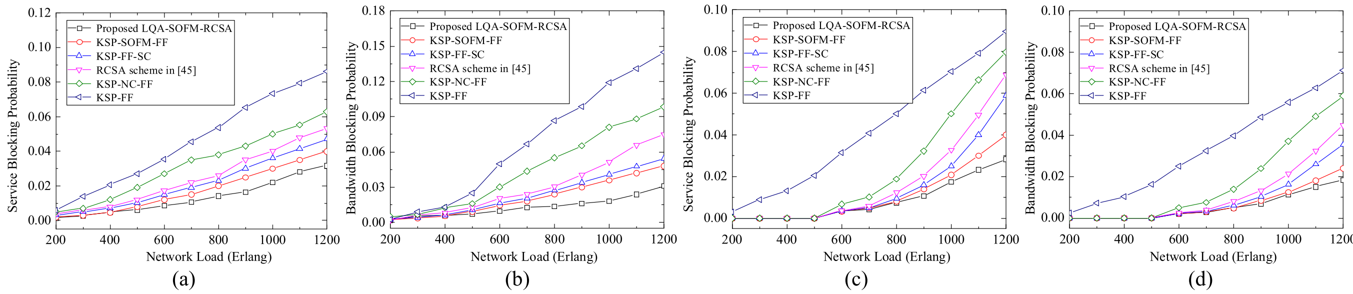

Fig. 10. Performance evaluation on blocking: (a) SBR (b) BBR under NSFNet (c) SBR (d) BBR under US nationwide network.

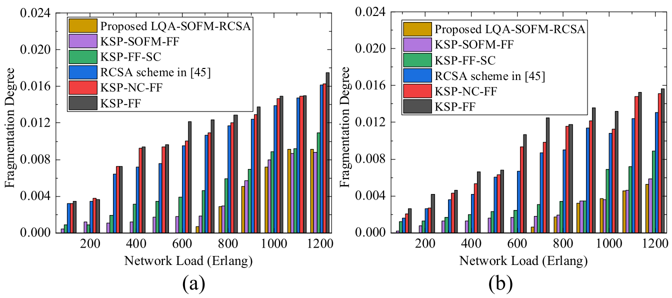

Fig. 11. Results on fragmentation: (a) NSFNet (b) US nationwide network.

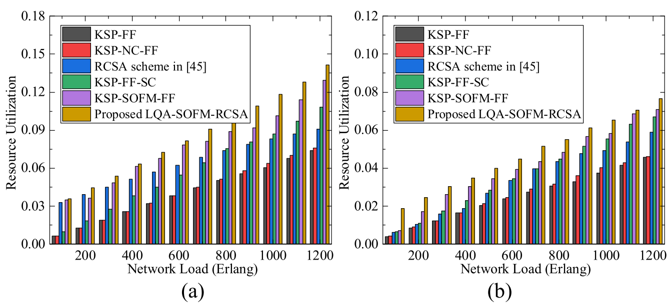

Fig. 12. Results on resource utilization: (a) NSFNet (b) US nationwide network.

Fig.12 (a) and (b). It testifies that the proposed scheme can increase the efficiency of resource utilization. In the proposed LQA-SOFM-RCSA algorithm, the competition mechanism of the SOFM model is used to comprehensively consider the restrictive relationship among multiple influencing factors. Finally, it outputs relatively high-quality transmission resources for services to improve resource utilization efficiency.

In summary, the proposed LQA-SOFM-RCSA algorithm accurately guarantees the quality of the final selected transmission channel from the two dimensions of core and spectrum. RCSA scheme in [45] only starts from the path dimension and selects the path with better transmission quality. KSP-SOFM-FF only selects cores with better transmission quality in the core dimension, but still exploits the FF method in the spectrum dimension. Although KSP-FF-SC uses secondary classification in the spectrum dimension, FF method is still used for core selection. The above three compared algorithms all search for available resources for the services from a single dimension, which will cause network performance degradation to a certain extent.

VI. Conclusion

This paper addressed the problem of how to comprehensively consider multiple factors to evaluate link transmission quality in MC-EONs. The unsupervised SOFM model was used for LQA process from the core level. Through the competitive mechanism of the SOFM model, reordered core sequences according to transmission quality on each link can be obtained along the selected candidate path. Then each link will select the core with better transmission quality to search for available spectrum resources. For the free slot block selection, the one with the smallest number of adjacent cores and the smallest number of services carried in the same direction will be finally selected. Experimental results demonstrate that our proposed method can greatly improve the network performance in terms of blocking, resource fragmentation degree, and resource utilization.

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Hui Yang (Senior Member, IEEE) is currently the Vice Dean and an Associate Professor at the Beijing University of Posts and Telecommunications (BUPT). He has authored or coauthored 150 papers in prestigious journals and conferences and is the first author of more than 70 of them. His research interests include SDN, AI, elastic optical networks, blockchain, and so on. He has received the Best Paper Award at IWCMC'19/NCCA'15 and the Young Scientist Award in IEEE ICOCN'17. He has served as the General Chair for ISAI'16. He has served as an Editor for IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS, *IEEE Communications Magazine*, and *China Communications*.

Qiuyan Yao (Member, IEEE) received the M.S. degree in computer science and technology from the Hebei University of Engineering, Handan, China, in 2015, and the Ph.D. degree from the Beijing University of Posts and Telecommunications (BUPT), Beijing, China, in 2020. She is currently working as a Post-Doctoral Researcher at BUPT. Her research mainly focuses on the AI driven routing and spectrum assignment strategy in elastic optical networks and space division multiplexing networks.

Bowen Bao received the M.S. degree in computer science and technology from the Hebei University of Engineering, Handan, China, in 2019. He is currently pursuing the Ph.D. degree in information and communication engineering with the Beijing University of Posts and Telecommunications (BUPT), Beijing, China. His research interests include elastic optical networks, spectrum assignment and routing, fragmentation, distance-adaptive transmission, and physical layer impairments.

Ao Yu received the B.S. degree from the China University of Petroleum (UPC), Shandong, China, in 2014. He is currently pursuing the Ph.D. degree in information and communication engineering with the Beijing University of Posts and Telecommunications (BUPT). His main research interests include cross stratum resource allocation, optical access networks, software defined networks, and radio over fiber.

Jie Zhang (Member, IEEE) is currently a Professor and the Dean of the Institute of Information Photonics and Optical Communications, BUPT. He is sponsored by more than ten projects of the Chinese government. He has published eight books and more than 100 articles. Seven patents have also been granted. His research focuses on optical transport networks, packet transport networks, and so on. He has served as a TPC Member for ACP 2009, PS 2009, ONDM 2010, and so on.

Athanasios V. Vasilakos (Senior Member, IEEE) is currently with the College of Mathematics and Computer Science, Fuzhou University, Fuzhou, China, and also with the Center for AI Research (CAIR), University of Agder (UiA), Grimstad, Norway. He has served or is serving as an Editor for many technical journals, such as the IEEE TRANSACTIONS ON NETWORK AND SERVICE MANAGEMENT, IEEE TRANSACTIONS ON CLOUD COMPUTING, IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, IEEE TRANSACTIONS ON CYBERNETICS, IEEE TRANSACTIONS ON NANOBIOSCIENCE, IEEE TRANSACTIONS ON INFORMATION TECHNOLOGY IN BIOMEDICINE, *ACM Transactions on Autonomous and Adaptive Systems*, and IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS.