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Authors: H. Yang

Beijing University of Posts and Telecommunications

K. Zhan

Beijing University of Posts and Telecommunications

A. Yu

Beijing University of Posts and Telecommunications

Q. Yao

Beijing University of Posts and Telecommunications

J. Zhang

Beijing University of Posts and Telecommunications

Multiple Layer Resource Optimization for Optical as a Service

Abstract

We have established a neural network model optimized by adaptive artificial fish swarm algorithm. Then we propose a novel multi-path pre-reserved resource allocation strategy to increase resource utilization. The results prove the effectiveness of our method.

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Table of Contents

- [1. Introduction](#)
 - [1.1. Conventions Used in This Document](#)
- [2. PREDICTION STRATEGY](#)
 - [2.1. Artificial neural network model](#)
 - [2.2. Adaptive artificial fish swarm artificial neural networks \(AAFS-ANN \)](#)
- [3. MULTI-PATH PRE-RESERVED RESOURCE ALLOCATION](#)
 - [3.1. Reconfiguration time calculation](#)
 - [3.2. Multi-path pre-reserved resource allocation\(MP-RA\)](#)
- [4. Experimental evaluation and results analysis](#)
- [5. CONCLUSION](#)
- [6. ACKNOWLEDGMENT](#)
- [7. References](#)
 - [7.1. Normative References](#)
 - [7.2. Informative References](#)
- [Authors' Addresses](#)

1. Introduction

With the rapid growth of cloud computing, 5G services, and the periodicity of people's activities, traffic load has exhibited periodicity in both time and space domains, namely tidal traffic [1]. The number of people using optical metropolitan networks is enormous and unevenly distributed. In addition, the separation of work areas and residential areas is an important cause of tidal traffic. Generally, tidal traffic will reduce the performance of networks during to following two reasons: firstly, the network traffic will be blocked due to the sharp increase in traffic in the high-traffic area; secondly, network nodes may be idle and waste resources in the low-traffic areas. The static configuration resources will intensify both network and service congestion during traffic peak hours, as well as low resource utilization during low-traffic times and regions. In the future, global mobile Internet traffic will increase by 10 times [2], urbanization is rapidly advancing, the scope and severity of space and time domains affected by tidal traffic are increasing as communication need and network technologies developing. Tidal traffic will further affect the

optical access network and the optical core network, making it essential issue for network operators. Therefore, a more reasonable and efficient resource allocation scheme is urgently needed to solve the congestion and resource waste caused by the tidal traffic.

Known from the above, tidal traffic prediction becomes the core process of network optimization decision-making. Currently, there are several prediction methods, like support vector machine (SVM) and multi-layer perceptron (MLP). Literature [3] proposes a deep-learning-based prediction strategy to implement traffic assessment of data center optical networks. At the same time, a deep-learning-based global evaluation factor resource allocation algorithm is suggested to achieve lower blocking rate of the network. Compared with the traditional algorithm, deep learning can improve the accuracy of prediction, but it cannot identify the tidal traffic in specific festivals. In addition, the lower priority service will be discarded to reduce the network blocking rate. This method does not make good use of idle resources of other nodes, and some traffic requests cannot be executed normally. So we propose multi-path pre-reserved resource allocation based on traffic prediction.

In this paper, we establish an adaptive artificial fish-group neural network model to predict traffic, then use the predicted traffic demand to optimize the network at different times. Meanwhile, we propose multi-path pre-reserved resource allocation to adapt to the resource requirements of different nodes. Simulation results demonstrate that our strategy achieves a lower network blocking rate and higher resource utilization.

1.1. Conventions Used in This Document

The key words "MUST", "MUST NOT", "REQUIRED", "SHALL", "SHALL NOT", "SHOULD", "SHOULD NOT", "RECOMMENDED", "MAY", and "OPTIONAL" in this document are to be interpreted as described in [[RFC2119](#)].

2. PREDICTION STRATEGY

Before presenting the resource allocation algorithm, we provide an introduction to traffic prediction model. We establish a neural network of adaptive artificial fish algorithm to predict traffic request. The key resides in the construction of the artificial fish individual model. The optimal variables of the neural network are two weight matrices and two threshold variables $_io, v_o$.

2.1. Artificial neural network model

We build the neural network structure as shown in figure 1. The input is composed of six entries, $i_s(1)$ is the hour of the day, $i_s(2)$ is the day of the week, $i_s(3)$ is a flag for holiday/weekend, $i_s(4)$ is the previous days average load, $i_s(5)$ is the

load from the same hour of the previous day, and $i_{(s,6)}$ is the load from the same hour and same day from the previous week. The result of the output node $Y_{(s,1)}$ represents the traffic request that we want to predict[1]. Training sample set $A=\{(X^i, Y^i) | i=1,2,\dots,n\}$ X^i is the i -th group training data input, and Y^i is the i -th group input corresponding expected output. We define the error function as follows:

where O^i is the actual output of the i -th.

2.2. Adaptive artificial fish swarm artificial neural networks (AAFS-ANN)

In the artificial fish swarm algorithm, we introduce adaptive step size and visible range to improve convergence accuracy and speed. Generate initial artificial fish population N , namely N group $\{\omega_{ij}, \nu_{io}, \omega_{io}, \nu_{o}\}$. Every artificial fish is a neural network. The food concentration is defined as $FC=1/E$. X_i is the state of current location state, X_j is random state of the search, d_{ij} is the distance between X_i and X_j , $\omega_{ij}(i), \omega_{ij}(j)$ and $\omega_{ij}(i+1)$ respectively are X_i, X_j next state $X_{(i+1)}$ matrix ω_{ij} element of i -th row j -th column, "Rand(Step)" represents a random number between $[0, \text{Step}]$.

Let X_0 be the current artificial fish, its position is C , X_1 is the current optimal fish, X_2 is the nearest fish, Then we set two visible fields $\text{visual}_1=d_01, \text{visual}_2=d_02$. Two target positions A, B are randomly determined in the range of visual_1 and visual_2 respectively, then compare FC_A, FC_B, FC_C ,

If FC_A, FC_B

If FC_A, FC_B

$\omega_{ij}(i+1)=\omega_{ij}(i)+\text{Rand}(\text{step})$

If one or both of them are better than C , Then advance to the best point, and execute formula (3)

$\omega_{ij}(i+1)=\omega_{ij}(i)+\text{Rand}(\text{step})(\omega_{ij}(j)-\omega_{ij}(i))/d_{ij}$

Go for A with $\text{visual}_1 \text{Rand}()$ as the step size, to B with $\text{visual}_2 \alpha \text{Rand}()$, where α , which equal to 1 or slightly less than 1, is the visual factor. The other three optimization variables are similarly.

3. MULTI-PATH PRE-RESERVED RESOURCE ALLOCATION

The resource allocation method bases on the AAFS-ANN described above, and we propose a multi-path pre-reserved resource allocation

way to optimize optical network. We uses the predicted result to perform configuration time calculation and estimate the future network resource demand to pre-reserve resource for traffic request.

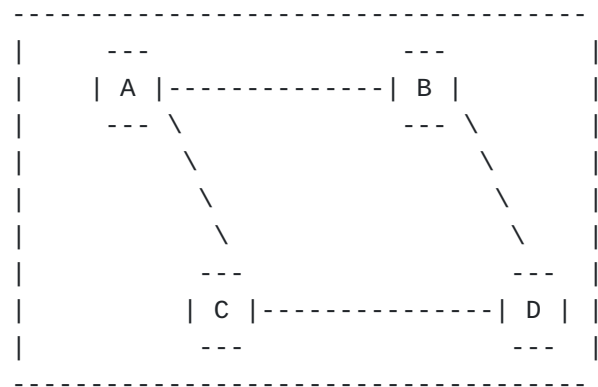


Figure 1: Fig.1(a) Sample network

T4										

T3			*		*					

T2			*		*					

T1										

T0										

	S0	S1	S2	S3	S4					

Figure 2: Fig.1(b) Requested resources

T4										

T3		#		*		#		#		#

T2		#		*		#		#		#

T1		#				#		#		

T0		#				#		#		

	S0	S1	S2	S3	S4					

Figure 3: Fig.1(c) Requested resources

	S0	S1	S2	S3	S4
T4					
T3	#	#	*	#	#
T2	#	#	*	#	#
T1	#		#		
T0	#				

Figure 4: Fig.1(d) Requested resources

3.1. Reconfiguration time calculation

Frequent reconfiguration can result in service interruption and unstable of distributed routing algorithm, so we need to predict the next 24-hour traffic demand D^{24} for the next configuration time point calculation. Algorithm 1 is the calculation process of the reconfiguration time point.

3.2. Multi-path pre-reserved resource allocation(MP-RA)

We reserve network resources for the predicted traffic. This type of service request is called Advance Reservation Service (AR). As the optical link is continuously established and removed, fragments are easily generated in both the time domain and the spectrum domain. The application of the Sliceable Bandwidth Variable Transceiver (S-BVT) [4] further enhances the flexibility of EON. The S-BVT has a slicing capability, i.e. it can provide multiple optical carriers for carrying optical links to different destinations. In order to reduce time and spectral fragmentation (referred to as two-dimensional fragmentation) and to solve the problem of insufficient resources, we propose cutting the request into multiple parts, and transfer on multiple paths.

The underlying optical network can be modeled as $G_s=(L_s,N_s,R_{st},D_s)$ { L_s : link set, N_s : optical node set, R_{st} : resource status of optical nodes and optical links at time t , D_s : distance of each pair of nodes in the set of nodes N in the network topology}. $R_A=(s,d,w,b,h)$ denotes a predicted service request, where s and d represent the source and destination nodes of the service, b is the time of service starts, h is the duration of the AR service, and w is the service start time b , and the duration h

period required link rate. $P_((s,d))$ represents the path set of the source node to the destination node.

If there are not enough spectrum resources available in the link for the incoming request, we will attempt to cut the request into different parts and assign those parts to different frequency bands. For a simple example, as shown in Figure 3(a), in order to reflect the state of the spectral resources in the time domain, we use a two-dimensional time spectrum resource model and assume that each time slot has the same time period. The network diagram is illustrated in the figure 3(a). Now there was an AR request, from node A to node D. The request requires two spectrum slots, lasting from T2 to T3, as shown in figure 2(b). Figure 2(c) and Figure 2(d) show the spectrum states of path A-C-D and path A-B-D, respectively. The black slot represents the occupied spectrum slot, the white slot represents the spectrum slot available for the spectrum resource, and the blue slot represents the spectrum slot occupied by the AR request. Before splitting the AR request, the two paths do not have enough resources to allocate. However, after we split the request into two parts, we can distribute them to two spectrum segments to implement AR-requested service provision. The MP-RA is as shown in Algorithm 2.

4. Experimental evaluation and results analysis

In this paper, we present the results of the AAFS-ANN prediction. Our goal is to demonstrate the accuracy and network performance of AAFS-ANN in different network environments. To fully reflect the changes in the network environment, we use WIDE data from 96h traffic data from April 6th to 9th, 2017, to train and verify. Figure 3(a) is the comparison between the actual traffic and the prediction results, which verify the effectiveness of our method. As shown in Figure 3(a), the prediction results of AAFS-ANN are significantly better than the traditional predictions. This is because the introduction of the adaptive step size and the visible field, making the artificial fish compares the FC in the large field of view. Our method enhances the global convergence and the optimization precision. The prediction error occurs because the traffic is directly affected by many non-linear sudden factors such as hot events, user movement patterns. Therefore, many traffic cannot be accurately predicted.

We also compare MP-RA with several state-of-the-art resource allocation techniques including evolutionary algorithms(EA) and artificial neural networks (ANN). From figure 3(b), we can see that MP-RA performs well among the three optimization resource allocation method, MP-RA greatly improves resource utilization.

According to the prediction results, the MP-RA can allocate resources to traffic more reasonably. This is because the algorithm considers the traffic that will be reached at each point in time and the resources it needs. Then re-plans the resources at the configuration time. As can be observed in the results shown in Figure 3(c), MP-RA can greatly reduce the probability of traffic blocking.

Resource utilization rate				
Traffic load	MP-RA	ANN	EA	
40	0.254	0.242	0.251	
70	0.263	0.253	0.272	
95	0.273	0.275	0.300	
120	0.332	0.29	0.420	
145	0.389	0.325	0.504	
170	0.457	0.356	0.583	
200	0.52	0.403	0.723	

Figure 5: Tab.1 Network blocking probability of four strategies

Network blocking probability				
Traffic load	MP-RA	ANN	EA	
50	0.008	0.0075	0.0078	
70	0.009	0.010	0.012	
100	0.0095	0.025	0.029	
125	0.01	0.06	0.074	
150	0.0108	0.08	0.10	
175	0.025	0.115	0.129	
200	0.06	0.15	0.20	

Figure 6: Tab.2 Average hop of four strategies

5. CONCLUSION

In the tidal traffic scenario, we propose AAFS-ANN model and MP-RA strategy. We use AAFS-ANN model to predict traffic and MP-RA to optimize metropolitan optical network. Results demonstrate that AAFS-ANN and MP-RA successfully increase prediction accuracy and resource utilization, as well as reduce the traffic blocking rate.

6. ACKNOWLEDGMENT

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Authors' Addresses

Hui Yang
Beijing University of Posts and Telecommunications
No.10, Xitucheng Road, Haidian District
Beijing

Phone: [+8613466774108](tel:+8613466774108)
Email: yang.hui.y@126.com
URI: <http://www.bupt.edu.cn/>

Kaixuan Zhan
Beijing University of Posts and Telecommunications
No.10, Xitucheng Road, Haidian District
Beijing

Phone: [+8618401695826](tel:+8618401695826)
Email: zhankai@bupt.edu.cn
URI: <http://www.bupt.edu.cn/>

Ao Yu
Beijing University of Posts and Telecommunications
No.10,Xitucheng Road,Haidian District
Beijing

Email: yua@bupt.edu.cn
URI: <http://www.bupt.edu.cn/>

Qiuyan Yao
Beijing University of Posts and Telecommunications
No.10,Xitucheng Road,Haidian District
Beijing

Email: yqy89716@bupt.edu.cn
URI: <http://www.bupt.edu.cn/>

Jie Zhang
Beijing University of Posts and Telecommunications
No.10,Xitucheng Road,Haidian District
Beijing

Phone: [+8613911060930](tel:+8613911060930)
Email: lqr@bupt.edu.cn
URI: <http://www.bupt.edu.cn/>