



Article TDTS: Three-Dimensional Traffic Scheduling in Optical Fronthaul Networks with Conv-LSTM

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Abstract: Given the more intensive deployments of emerging Internet of Things applications with beyond-fifth-generation communication, the access network becomes bandwidth-hungry to support more kinds of services, requiring higher resource utilization of the optical fronthaul network. To enhance resource utilization, this study novelly proposed a three-dimensional traffic scheduling (TDTS) scheme in the optical fronthaul network. Specifically, large and mixed traffic data with multiple different requirements were firstly divided according to three-dimensions parameters of traffic requests, i.e., arriving time, transmission tolerance delay, and bandwidth requirements, forming eight types of traffic model. Then, historical traffic data with division results were put into convolutional-long short-term memory (Conv-LSTM) strategy for traffic prediction, obtaining a clear traffic pattern. Next, the traffic processing order was supported by a priority evaluation factor that was measured by traffic status of the link and network characteristics comprehensively. Finally, following the priority, the proposed TDTS scheme assigned the resource to traffic requests according to their results of traffic division, prediction, and processing order with the shortest path routing and first-fit spectrum allocation policies. Simulation results demonstrated that the proposed TDTS scheme, on the premise of accurate traffic prediction, could outperform conventional resource-allocation schemes in terms of blocking probability and resource utilization.

Keywords: optical fronthaul networks; Conv-LSTM; traffic scheduling; traffic priority

1. Introduction

With the evolution of the fifth generation (5G) or even beyond 5G (B5G) of mobile communication, the number of machine-to-machine (M2M) applications is growing within world-wide IoT development, which contributes to the increase in device-access connections in an exponential way in a network [1–3]. According to the Ericsson Mobility Reports, the number of mobile terminals in the world will reach 8.3 billion by 2024, and 45% of cellular traffics in this case are expected to be created by Internet of Things (IoT) devices [4–6], with the penetration of IoT applications and services in our daily life, as well as in industrial scenarios [7,8]. In this case, it is a significant situation that the access traffics from various devices naturally form diverse traffic types with different requirements, where various connection services spring up with the requirement of delay, bandwidth, high-speed access, and so on [9–11]. However, given the situation with more intensive deployments [12], even B5G would find it hard to support current bandwidth-hungry network scenarios if there is not flexible resource allocation for services to avoid spectrum wastage.

To cope with the flexibility of B5G traffic, access networks evolve to a new fronthaul network architecture including a centralized unit (CU), distributed unit (DU), and active antenna unit (AAU) [13–15]. In this architecture, the traditional BBU baseband portion is split into two logical network elements, i.e., the CU and DU, and part of the baseband



Citation: Bao, B.; Xu, Z.; Li, C.; Sun, Z.; Liu, S.; Li, Y. TDTS: Three-Dimensional Traffic Scheduling in Optical Fronthaul Networks with Conv-LSTM. *Photonics* **2021**, *8*, 451. https://doi.org/10.3390/ photonics8100451

Received: 17 September 2021 Accepted: 11 October 2021 Published: 18 October 2021

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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). physical layer underlying functions and antennas form the AAU. To realize efficient response of fronthaul network traffic, several studies have intensively researched fronthaul network traffic prediction and resource allocation. The authors of [16] proposed a dynamic network routing and resource-allocation scheme based on prediction of services in future time. The authors of [17] focused on resource utilization in 5G networks, where it is more rewarding to opt for an energy-awareness approach in resource allocation while targeting satisfaction of user Quality of Service (QoS) requirements. A resource-allocation scheme with high accurate prediction of traffic load was proposed in [18], where the resources were allocated according to a bin-packing algorithm based on neural-network predicted traffic. Although conventional traffic prediction can forecast the characteristics of traffic for a period of future time in advance, it cannot effectively divide fronthaul network traffic.

As artificial intelligence is increasing rapidly, some existing studies further focus on traffic classification and prediction to obtain better resource-allocation performance, as convolutional neural networks (CNN) and long short-term memory networks (LSTM) are widely used. Literature [19] summarized the differences between the standard LSTM and its eight variants. The authors of [20] proposed a multiple time-interval-based featurelearning network to handle the challenging task of one-step long-term traffic prediction. It extracted the long-term traffic features at different times to output a result of future traffic to allocate resources. However, the timing characteristics were solely concerned with the above research areas without taking a spatial correlation into consideration. To avoid this dilemma, the authors of [21] proposed a novel convolutional LSTM (Conv-LSTM) network for precipitation nowcasting. They formulated precipitation nowcasting as a spatiotemporal sequence-forecasting problem that can be solved by stacking multiple Conv-LSTM layers.

Benefiting from huge bandwidth and low latency, the optical network becomes a promising traffic-scheduling-supporting infrastructure for the fronthaul network. With the help of a finer frequency grid, the elastic optical network (EON) outperforms the traditional wavelength-division multiplexing network to improve resource utilization in the B5G scenario, since EON can flexibly set up bandwidth-variable super-channels and adaptively select modulation formats according to the quality of transmission of lightpaths [22–25]. As the main way to realize flexible resource allocation in EON, several routing, modulation, and spectrum assignment (RMSA) schemes are widely investigated and researched [26,27]. Integer linear programming (ILP) models for solving static RMSA problems have been proposed and have provided optimal solutions to static RMSA problems [28]. However, optimizing dynamic RMSA problems is more challenging and more realistic for the B5G fronthaul network, since the dynamic arrivals and departures of traffic requests, as well as the uncertainty of future traffic, may dramatically destroy the EON state. Therefore, several studies have proposed some algorithms as complements to the normal RMSA algorithm. The authors of [29] showed a multi-features weighted scheme including path lengths, link-spectrum utilization, and other features. The authors of [30–33] focused on fragmentation in the spectrum to optimize RMSA, where perceptible fragmentation and defragmentation can usefully reduce spectrum fragmentation. However, the above works were unable to achieve real-time RMSA allocation because they only apply fixed RMSA strategies without considering comprehensive perceptions of the EON state. To fill this gap, RMSA strategies with traffic prediction are required, particularly for resource allocation based on traffic division in the optical fronthaul network.

In this study, for the sake of high traffic-processing efficiency, we proposed a threedimensional traffic scheduling (TDTS) scheme for fronthaul networks with the improvement of blocking probability and resource utilization. In this scheme, we first presented a three-dimensional traffic division defined as extracting traffic features to classify traffic requests, where large and mixed traffic data with multiple different requirements from AAUs were combed according to three-dimensional characters, i.e., arriving time, transmission tolerance delay, and bandwidth requirements. In the traffic division progress, the character of arriving time determining the required resources of traffic was allocated to this traffic immediately or reserved, and delay-sensitive traffics were processed in DUs while CUs were selected to serve delay-tolerable traffics. Then, historical traffic data with division results were put into an artificial neural network, i.e., Conv-LSTM strategy, for traffic prediction to obtain a clear traffic pattern in the TDTS scheme. Based on this, the routing and spectrum assignment of TDTS was processed according to a priority-evaluation factor, which measured comprehensively the current status of link and traffic characteristics with the shortest path routing and first-fit spectrum allocation policies. Simulation results indicated that the proposed TDTS scheme could provide lower blocking probability and higher resource utilization, compared with conventional resource-allocation schemes.

This paper is organized as follows. Section 2 introduces the B5G fronthaul network and artificial-intelligence traffic prediction approach. In Section 3, The three-dimensional traffic scheduling scheme is proposed with the three-dimensional traffic division and traffic priority definition. The results of simulation and discussion are presented in Section 4. Finally, we conclude the paper in Section 5.

2. System Model Design

This section introduces the system model and artificial-intelligence traffic prediction approach that were used in this study.

2.1. Fronthaul Network Architecture Design

The new access network, architecture for the fronthaul network, consisted of three stand-alone devices, i.e., AAU, DU, and CU [13]. The distributed DU unit and centralized CU pool had several DUs and CUs. Each DU could control one or more AAUs and the CU pool was responsible for one or more DUs. This separate deployment architecture is more adaptable to future network needs as the DU is responsible for completing protocol stack-processing functions with high real-time requirements, and the CU is responsible for completing the protocol stack-processing functions with low real-time requirements [34,35].

Figure 1 shows the architecture of the fronthaul network. The access network system contained the centralized CU pool, distributed DU unit, and locally deployed AAUs. Each AAU has a logic connection with DUs, and multiple DU connects with a CU. As shown in Figure 1, DUs are responsible for dealing with high real-time requirements while CUs are responsible for completing low real-time requirements. Apart from default signaling intercommunication and data transmission between DUs and AAUs, some signaling messages need encapsulating and sending to CUs. In our study, the proposed TDTS scheme focused on complicated traffic processing, and different traffic flows were sent to DUs or CUs instead of sending all traffic to DUs. In this way, the fronthaul network was simplified, and network processing efficiency was increased.



Figure 1. Fronthaul network structure with CUs, DUs, and AAUs.

2.2. Conv-LSTM Approach

For general sequence modeling, CNN and LSTM, as traditional deep-learning methods, have been applied [21,36]. CNN is a non-linear activation function applied to the results of convolutional operation, where a full connection layer is used after the pooling operation for classification [37]. The core of convolutional operation is called filtering, i.e., kernel function, which completes feature extraction by sliding from top to bottom and from left to right in the original matrix. LSTM is a special recurrent neural network (RNN) structure that is stable and powerful for natural language processing tasks. Given the door mechanism and cell state for information storage, LSTM consists of three gates, i.e., forget gate, input gate, and output gate. The forget gate decides the information deleted from the cell state and the input gate inputs information to update the cell state. Then, the output gate decides the final output.

Conv-LSTM is the combination of CNN and LSTM, the core essence of which is similar to LSTM, taking the output of the previous layer as the input of the next layer. Note that to extract the feature of inter-relationship among the trained data, a data-convolution process is required, and, hence, the CNN was adopted in this study to capture the data-correlation character. However, after introducing the convolution operation, Conv-LSTM could not only obtain the temporal data relationship, but also extract the spatial features of traffic, such as the convolution layer, at the same time. In this way, the interaction between each state pair in Conv-LSTM was replaced by convolution operation, where the Conv-LSTM process is shown as Equations (1)–(5).

$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} \odot C_{t-1} + b_i),$$
(1)

$$f_t = \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} \odot C_{t-1} + b_f),$$
(2)

$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_{cf} \odot C_{t-1} + b_f), \tag{3}$$

$$o_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} \odot C_t + b_o),$$
(4)

$$H_t = o_t \odot \tanh(C_t), \tag{5}$$

where σ is the Sigmoid activation function, * is convolution operation, and \odot is the Hadamard product. i_t , f_t , and o_t , are the input gate, forget gate, and output gate, respectively. c_t is the storage unit, which could accumulate the unit status and update the status in real time.

3. Three-Dimensional Traffic Scheduling Scheme

For complicated traffic processing and resource allocation for traffic, this study proposed the three-dimensional traffic scheduling (TDTS) scheme to analyze the characteristics of different traffics and allocate resources for traffic. Figure 2 shows the supporting network structure of the proposed TDTS scheme. An internal switch could redirect traffic from AAUs, the processor could conduct three-dimensional traffic division, and the centralized controller could schedule network resources according to three-dimensional traffic-division results [38]. We assumed that the traffic from AAUs was sent separately to different DUs or CUs after three-dimensional traffic division. As DUs and CUs can synchronously process different types of traffic, the resource-allocation efficiency and connection response latency could be improved by using the proposed TDTS scheme.



Figure 2. Supporting network structure of the proposed TDTS scheme.

3.1. Three-Dimensional Traffic Division

In our proposed TDTS scheme, a large amount of traffic was divided into eight types with three-dimensional parameters including arriving time, delay, and spectrum consumption. In terms of arriving time, we classified the traffic via two patterns as traffic that arrives immediately and the other that arrives after a while. In this case, resources were determined to allocate resources immediately or reserve resources according to the arriving time of traffic. Generally, different traffics have different tolerances to processing delay such as video, text, and satellite remote sensing. Therefore, the second characteristic of traffic was the tolerance difference on transmission delay, and the traffic was classified as delay-sensitive traffic or delay-tolerant traffic. In this case, traffic could be processed in DUs or CUs according to sensitivity, as DUs handle traffic that is sensitive to latency while CUs handle traffic tolerant to delay. The third characteristic was bandwidth requirements of traffic, where different traffic requires different sizes of spectrum resource. Figure 3 depicts the traffic division with three-dimension parameters for eight types of traffic.



Figure 3. Traffic division with three-dimension parameters for eight types of traffic.

3.2. Conv-LSTM Based Traffic Prediction

In the proposed TDTS scheme, the main content of prediction included the processing of raw data, the segmenting of training data, the training of the model, and the prediction of future traffic. For the sake of a high accurate prediction, the convolutional layer and LSTM were combined to generate a Conv-LSTM model for sequence modeling, which could fully fuse the temporal characteristics and the spatial characteristics of traffic flow in the adjacent region of the prediction point [21]. The applied Conv-LSTM model is shown in Figure 4, where a long period of historical traffic with the parameter of access node, arriving time, transmission tolerance delay, and bandwidth requirements was the input of the Conv-LSTM traffic prediction model, and the forecasting traffic feature for the next period was the output of this model. In this case, it was sufficient to obtain the timing relationship, and it was also possible to extract features including delay and spectrum like a convolutional layer. To optimize the Conv-LSTM model, the Adam algorithm was adopted in the TDTS scheme, which could adjust the learning rate adaptively based on the first-moment mean value and make full use of the second-order-moment mean of the gradient.



Figure 4. The applied Conv-LSTM mode.

First, a long period of historical traffic $\{x_t\}$, t = 1, 2, ..., N needed to be transformed into a series of operable values for the Conv-LSTM model, where the process can be depicted as shown in Equations (6) and (7).

$$S = \frac{1}{N} \sum_{t=1}^{N} x_t,$$
 (6)

$$\{x_i\}_{treated} = \left\{\frac{x_i}{S}\right\}, i = 1, 2, \cdots,$$
(7)

If there is no special explanation, all $\{x_i\}_{treated}$ in the following part of this paper are simplified as $\{x_i\}$. Then, in the process of prediction, both training sequence forward and backward were two independent Conv-LSTMs that were connected to an output layer, which jointly provided complete past- and future-context information as an input sequence for each point in the output layer.

The proposed TDTS was to predict the mean value of traffic in the next period of time, which had the length of *T*. Assuming that previous traffic within the length of $D \times T$, the total traffic needed to be segmented to *D* traffic data sections, $S_j = \{x_j, x_{j+T}, ..., x_{j+D\times T}\}$, j = 1, 2, ..., T. In Conv-LSTM, O_j represents the output value of the network for the *j*th pair of samples, and $x_{j+D\times T}$ represents the actual value of previous traffic. Taking the input value S_j and O_j derived the prediction of future value $x_{j+(D+1)\times T}$. Finally, the accurate value of *T* was taken to obtain a predicted sequence, calculated by Equation (8).

$$S_T = \left\{ x_{1+(D+1)\times T}, x_{2+(D+1)\times T}, \cdots, x_{T+(D+1)\times T} \right\},$$
(8)

where the average of S_T was regarded as the prediction, denoted by P, for the mean value of the traffic within the next period, which was calculated by Equation (9).

$$P = \frac{1}{T} \sum_{j=1}^{T} O_j, \tag{9}$$

In the prediction process, the latest data were added to continue training the Conv-LSTM model, and in this case, it could meet the real-time requirements of the network.

3.3. Three-Dimensional Traffic Scheduling (TDTS) Scheme

3.3.1. Priority Model for Traffic Request

In the resource-allocation process, as a new request arrived, the proposed TDTS scheme established a connection and assigned a proper amount of resource for traffic with the priority of different types of traffic to improve resource utilization and reduce the blocking probability.

In terms of the traffic order of waiting requests, we novelly defined a concept of a request queue priority (RQP) model to represent the urgent degree of traffic, including two features as a link-request queue priority (LRQP) and network-request queue priority (NRQP). The NRQP of predicted traffic decided the order of the traffic entering the link, while the LRQP of traffic in the network link decided processing order. Table 1 presents all notations and definitions for LRQP and NRQP in this paper.

Table 1. Notations and definitions for LRQP and NRQP.

Notations	Definitions
Q(V, E)	A network topology is presented by $Q(V, E)$, V presents the node set in the
	network topology, and <i>E</i> presents the link set.
М	The number of links in the network.
λ_{max} , λ_{min}	The maximum occupied wavelength and minimum occupied wavelength in
	the link, of which ID = <i>i</i> is presented by λ_{max}^{i} , λ_{min}^{i} , respectively.
K	The number of network requests which exist between spectrum blocks being
	occupied by services in the selected link, of which ID = i is presented by K_i .
B_j, H_j	The connection of which ID = <i>j</i> occupies B_i spectral resources, and contains H_i
	links, respectively.
Ν	The number of connections that exist in the network at the moment.
t_1, t_2	The arriving time and leaving time of request.
t_s	The time sensitivity of the request.
p	The spectrum resources required to process the request.
$\alpha_{LRQP}, \alpha_{NRQP}$	The values of LRQP and NRQP, respectively.

Based on the above notation, the value of LRQP (α_{LRQP}) and NRQP (α_{NRQP}) can be calculated by Equations (10) and (11), respectively.

$$\alpha_{\text{LRQP}} = \frac{\lambda_{max} - \lambda_{min} + 1}{\sum_{j=1}^{N} B_j} \times \frac{1}{K} \times \frac{t_s}{(t_2 - t_1) \times \log_2^P},$$
(10)

$$\alpha_{\text{NRQP}} = \frac{\sum_{i=1}^{M} \left(\lambda_{max} - \lambda_{min} + 1\right)}{\sum_{i=1}^{N} B_j \times H_j} \times \frac{M}{\sum_{i=1}^{M} K_i} \times \frac{t_s}{(t_2 - t_1) \times \log_2^P},\tag{11}$$

Note that the values of α_{LRQP} and α_{NRQP} presented the priorities of requests in the waiting line, where a larger value meant greater priority of traffic request in the waiting line. The traffic request needed to be processed when the value of either LRQP or NRQP exceeded that of another request or a pre-determined threshold (TH) in the network, where the threshold was determined by the average value of ROP among the requests processed in CU in historical and future traffic via the prediction result. For example, if LRQP was larger than the others or a concerted threshold, the request would be processed in DU later; otherwise, it would be processed in CU. Figure 5 shows an outline of the whole procedure.



Figure 5. The procedure of the priority model for traffic requests.

In the process of responding to the request with priority, connections were ordered according to a priority level. Connections with top priority were the first to be checked if they could be shifted to another wavelength, and the bottom-priority connections were the last to be checked. The priority was decided by either bandwidth or path length. In the priority process, we needed to make sure that any existing request had one and only one chance to be checked if it could be shifted to another wavelength. In this way, the cost of calculation remained the same as common processes.

3.3.2. Priority Model for Traffic Request

In fronthaul networks, connections between AAUs and DUs have some fixed statistical properties. In terms of latency sensitivity of traffic, the service volume and traffic request sensitivity of each area are typically constant. In terms of time, it is the probability contribution of holding time and arriving interval time of connections. In terms of wavelength, the probability contributions are not likely to be fluctuated. Therefore, it was practical that we died some work with these properties of connections of the networks. Despite the complexity of networks that makes direct evaluation of the result of priority opaque for traffic prediction, we focused on the general statistical results that some networks with connections of certain properties yield, i.e., resource utilization and network blocking probability.

The proposed TDTS scheme took advantage of centralized and automated control and management of the EON data plane, where DUs and CUs interacted to obtain realtime messages of network-state, and required resource allocation. As shown in Figure 6, DUs and CUs collected traffic-requests messages from AAUs, and path lengths, linkspectrum utilization, and other features were measured to execute the TDTS scheme. For traffic from AAUs, DUs and CUs collected information on traffic priority, resource utilization, and topology abstraction to generate state-data for the centralized network controller. Then, according to traffic priority, as shown in Figure 6, T1, T3, T5, and T7 were sent to DUs, while T2, T4, T6, and T8 were sent to CUs. Traffics with a solid line, meaning traffic requests, were processed immediately, while traffics with a dotted line meant reserved resources for traffic request.



Figure 6. Priority-based proposed TDTS scheme.

The proposed TDTS scheme took path lengths, link-spectrum utilization, and other features into account to realize dynamic RMSA strategy with the shortest path routing and first-fit spectrum allocation (SPFF). The procedure of the proposed priority-based TDTS scheme is given in Algorithm 1. The complexity to search the shortest path for all requested traffics, assuming adopting the common Dijkstra's algorithm, was $O(|N| \cdot |V| \cdot \log |V| + |N| \cdot |E|)$, where the *V* and *E* are the set of the node link in network, respectively, and *N* is the set of all requested traffics. Then, the complexity to check whether sufficient resource was available for the requested traffic in the shortest path was $O(|N| \cdot |C| \cdot |V| \cdot \log |V| + |N| \cdot |C| \cdot |E|)$, where *C* is the set of usable resource in each link. The complexity to divide traffic into different types was O(|D|), where *D* is the set of traffic division-type candidates. The complexity of the proposed resource-allocation strategy was $O(|N| \cdot |C| \cdot |N|^3 \cdot \log |V| + |E| \cdot |C| \cdot |T| \cdot |N|^3)$. According to the probability of solution, the centralized network controller set up the corresponding lightpaths for corresponding traffic.

Algorithm 1: Priority-based TDTS Algorithm. **Input:** Traffic data of fronthaul network $\{x_t\}$ Output: Resource allocation with DUs and CUs decision 1. Divide traffic data $\{x_t\}$ according to three-dimensional parameters. Train Conv-LSTM model based on three-dimensional division result. 3. For new divided traffic in network do Search the shortest path for $\{x_t\}_1$. 4. 5. If there are enough resources in the path then 6. If priority of $\{x_t\}_1$ is greater than $\{x_t\}_2$ then 7. 3D dividing $\{x_t\}_1$ for getting traffic type of $\{x_t\}_1$. 8. Calculate remaining capacity of DU. 9. Place the traffic request $\{x_t\}_1$ into DU. 10. Else 11. Place the traffic request $\{x_t\}_1$ into CU. 12. End if 13. Find available resource with the first-fit policy for resource allocation. 14. Else 15. Block or reject $\{x_t\}_1$. 16. End if 17. End for

4. Simulation and Result Analysis

This section estimates the effectiveness of traffic prediction by using different neural networks for traffic prediction, including the common CNN, LSTM, CNN-LSTM, and the presented Conv-LSTM. Then, the performances of the proposed TDTS scheme are evaluated in terms of blocking probability and resource utilization, compared with the conventional DNN-RMSA [39], shortest path routing, and first-fit RMSA (SPFF-RMSA) [26], and Knapsack [40]. The experiment platform was a multi-core server with 122.5 GHz Intel Core i5-7200U CPU cores, two NVIDA TITAN GPU cores, and 32 GB RAM to guarantee meeting the high requirements of the network. We ran Ubuntu 16.04 and code in the Theano framework using Python 3.5.

4.1. Traffic Prediction Verification

For traffic prediction, we used a Conv-LSTM model to achieve our object of 3D traffic combing and traffic prediction, where the data were collected by the State Key Laboratory data center in Beijing China [41,42]. We experimented the Conv-LSTM module with other neural networks, i.e., CNN, LSTM, and CNN-LSTM, in traffic prediction, as shown in Figure 7. All traffic prediction models were trained with 200 epochs, where 1, 1.13, 0.94, 0.89 were the execution time with normalization when using the Conv-LSTM, CNN-LSTM, LSTM, and CNN, respectively. CNN has the ability to represent learning and can perform shift-invariant classification on input traffics according to their hierarchical structure. LSTM shows good performance in solving long-term dependence problems. However, CNN and LSTM are one-sided for our research questions. CNN-LSTM comprises two divided modules to extract the temporal feature and spatial feature. Conv-LSTM is a combined module to extract temporal–spatial features of traffic-flow data. Figure 7 compares results of root mean square error (RMSE) and mean absolute error (MSE), showing that our applied Conv-LSTM was better than others in traffic prediction.



Figure 7. Comparison of Conv-LSTM, CNN-LSTM, LSTM, and CNN.

4.2. Performance Comparisons of the Proposed TDTS Scheme in a Static Network Scenario

For a fixed number of traffic requests in resource-allocation strategy, we compared the performance of the proposed TDTS scheme with other RMSA schemes based on DNN strategy and SPFF-RMSA strategy, where NSFNET was adopted as the simulated network topology [43], as shown in Figure 8. Besides, traffic request, resource occupation, and link information are known in advance. RMSA based on DNN can perceive complex system status. By accumulating operational experience from repeated interactions with the target system, and by enhancing operations that bring higher returns, DNN can learn successful strategies. The SPFF-RMSA calculates resource allocation for all traffic requests with the shortest length of path with the first available spectrum resource in each used link, which are contiguous and continuous in links.



Figure 8. Simulated NSFNET network topology.

We simulated these three schemes and compared their performance in terms of blocking probability that indicates the probability of traffic blocking on the link, as shown in Figure 9. We can see that the proposed TDTS scheme and the conventional DNN-based RMSA scheme performed similarly at the beginning of simulation. The benchmark SPFF-RMSA scheme may easily be blocked due to limited resources by using inefficient resource allocation, while the proposed TDTS scheme and the conventional DNN-based RMSA scheme could more effectively access resource-utilization state and allocate resources due to their adaptability. Obviously, the intelligent schemes, i.e., TDTS and DNN-RMSA, were not suitable for static resource-allocation strategies due to its static characteristics when the number of traffic requests was small. This is because a certain amount of data is required to train the prediction model in the beginning of the simulation. After that, as much of the available spectrum resources as possible will be left for subsequent service requests when adopting the two intelligent schemes. Based on this, more traffic requests will be effectively allocated. When the number of traffic requests exceeded 500,000, the proposed TDTS scheme was better than the conventional DNN-RMSA scheme and they were both better than benchmark SPFF-RMSA scheme with traffic requests rising. This is because the proposed TDTS scheme had a more accurate prediction in resource allocation than that of the conventional DNN-RMSA scheme.



Figure 9. Blocking probability of TDTS, DNN-RMSA, and SPFF-RMSA.

Furthermore, we compared the resource utilization of two intelligent schemes, i.e., the proposed TDTS and the conventional DNN-based RMSA. According to Figure 10, it is evident that the proposed TDTS scheme outperformed the conventional DNN-RMSA scheme in the aspect of resource utilization. As RNN was used in the proposed TDTS

scheme, it could reserve resources for traffic with low delay tolerance, which was more suitable in our situation. In resource allocation, spectrum resources were divided into smaller spectrum blocks, and when traffic requests were combing, time and spectrum resources could be more fully utilized, and more traffic could be allocated according to combing results in the network.



Figure 10. Resource utilization of TDTS, DNN-RMSA, and SPFF-RMSA.

4.3. Performance Comparisons of the Proposed TDTS Scheme in a Dynamic Network Scenario

For dynamic-network resource allocation in fronthaul networks, we compared the performances of the proposed TDTS scheme with two other benchmark schemes. The first one was based on a Knapsack formulation to model the resource-assignment problem without traffic prediction, which used a mixed-integer linear problem (MILP) for real-time fluctuating traffic of mobile users. The second one was the SPFF-RMSA scheme. Based on this, the performances of the proposed TDTS scheme were evaluated in terms of blocking probability and resource utilization, shown in Figures 11 and 12, respectively.



Figure 11. Blocking probability of TDTS, SPFF-RMSA, and Knapsack.



Figure 12. Resource utilization of TDTS, SPFF-RMSA, and Knapsack.

We observe in Figure 11 that the proposed TDTS scheme always provided the lowest blocking probability compared with the benchmarks, i.e., Knapsack and SPFF-RMSA. This was because, in the fronthaul network, our TDTS could effectively predict traffic requests to reserve resources for future incoming traffic requests dynamically. Unfortunately, the SPFF-RMSA scheme reconfigures and virtualizes DU, and includes a centralized controller taking network change into account, presenting a comprehensive but complex study on the optimization problem. The Knapsack-based scheme is based on the result of a mixed-linear integer problem to allocate resources without virtualizing resources. In this case, the two involved benchmark resource-allocation schemes, i.e., Knapsack and SPFF-RMSA, had a higher blocking probability, since the resources with traffic features were out of consideration in resource allocation. On the contrary, during the virtual optical network mapping process, the proposed TDTS scheme considered both time and spectrum features of traffic requests. The blocking of links was minimized when allocating resources according to traffic type and link state. If the link was blocking, the centralized controller responded to traffic requests with other available link resources. Thus, the proposed TDTS scheme could reserve as many resources as possible for future incoming requests, which could effectively decrease blocking probability.

We also compared the performance in terms of resource utilization, as shown in Figure 12. It is obvious that the highest resource utilization was obtained when the proposed TDTS scheme was adopted. This resulted from the fact that resource reservation for future incoming traffic requests could efficiently use the available but limited spectrum resource in the network. A simple and untargeted resource allocation, such as Knapsack and SPFF-RMSA, causes a deterioration for spectrum usage efficiency.

5. Conclusions

To enhance resource utilization in the B5G scenario, this study proposed a threedimensional traffic scheduling (TDTS) scheme for the optical fronthaul network, which was based on future-traffic data prediction and traffic division. In this scheme, large and mixed traffic data were firstly divided into eight types according to three-dimensional parameters including arriving time, transmission tolerance delay, and bandwidth requirements. Then, historical traffic data with division results were put into an artificial neural network for traffic prediction to obtain a clear traffic pattern, where convolutional-long short-term memory strategy was adopted. Next, based on the traffic division result, the future traffic processing order was supported by a priority-evaluation factor, which was measured by the current traffic status of link and network characteristics comprehensively. Finally, the proposed TDTS scheme assigned spectrum resource to traffic requests according to their results of traffic division, prediction, and processing priority. Simulation results demonstrated that the proposed TDTS scheme provided a lower blocking probability and higher resource utilization in the fronthaul network compared with conventional resource-allocation schemes.

Author Contributions: Conceptualization, B.B. and Y.L.; data curation, Y.L.; formal analysis, Y.L.; investigation, S.L.; methodology, Z.X.; resources, S.L.; software, Z.X. and C.L.; validation, Z.S. and S.L.; writing—original draft, B.B.; writing—review and editing, Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the NSFC project (62122015, 61871056), Beijing Natural Science Foundation (4202050), and Fund of SKL of IPOC (BUPT) (IPOC2021ZT04, IPOC2020A004).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

- 1. Hellaoui, H.; Koudil, M.; Bouabdallah, A. Energy efficiency in security of 5G-based IoT: An end-to-end adaptive approach. *IEEE Internet Things* **2020**, *7*, 6589–6602. [CrossRef]
- 2. Yang, H.; Yuan, J.; Li, C.; Zhao, G.; Sun, Z.; Yao, Q.; Bao, B.; Vasilakos, A.; Zhang, J. BrainIoT: Brain-like productive services provisioning with federated learning in industrial IoT. *IEEE Internet Things* **2021**. [CrossRef]
- Liu, Y.; Peng, M.; Shou, G.; Chen, Y.; Chen, S. Toward edge intelligence: Multiaccess edge computing for 5G and Internet of things. *IEEE Internet Things* 2020, 7, 6722–6747. [CrossRef]
- Yang, H.; Yu, A.; Zhang, J.; Nan, J.; Bao, B.; Yao, Q.; Cheriet, M. Data-driven network slicing from core to ran for 5G broadcasting services. *IEEE Trans. Broadcast* 2021, 67, 23–32. [CrossRef]
- Ericsson Mobility Report. Available online: https://www.ericsson.com/en/mobility-report/reports/june-2019 (accessed on 11 October 2021).
- 6. Sarrigiannis, I.; Ramantas, K.; Kartsakli, E.; Mekikis, P.; Antonopoulos, A.; Verikoukis, C. Online VNF lifecycle management in an MEC-enabled 5G IoT architecture. *IEEE Internet Things* **2020**, *7*, 4183–4194. [CrossRef]
- Yang, H.; Yuan, J.; Yao, H.; Yao, Q.; Yu, A.; Zhang, J. Blockchain-based hierarchical trust networking for JointCloud. *IEEE Internet Things* 2020, 7, 1667–1677. [CrossRef]
- 8. Yang, H.; Bao, B.; Li, C.; Yao, Q.; Yu, A.; Zhang, J.; Ji, Y. Blockchain-enabled tripartite anonymous identification trusted service provisioning in industrial IoT. *IEEE Internet Things* **2021**. [CrossRef]
- 9. He, D.; Ai, B.; Guan, K.; Wang, L.; Zhong, Z.; Kürner, T. The design and applications of high-performance ray-tracing simulation platform for 5G and beyond wireless communications: A tutorial. *IEEE Commun. Surv. Tutor.* **2019**, *21*, 10–27. [CrossRef]
- 10. Zhang, J.; Björnson, E.; Matthaiou, M.; Ng, D.; Yang, H.; Love, D. Prospective multiple antenna technologies for beyond 5G. *IEEE J. Sel. Area Comm.* **2020**, *38*, 1637–1660. [CrossRef]
- 11. Yang, H.; Wang, B.; Yao, Q.; Yu, A.; Zhang, J. Efficient hybrid multi-faults location based on hopfield neural network in 5G coexisting radio and optical wireless networks. *IEEE Tran. Cogn. Commun. Netw.* **2019**, *5*, 1218–1228. [CrossRef]
- 12. Lu, X.; Petrov, V.; Moltchanov, D.; Andreev, S.; Mahmoodi, T.; Dohler, M. 5G-U: Conceptualizing integrated utilization of licensed and unlicensed spectrum for future IoT. *IEEE Commun. Mag.* 2019, *57*, 92–98. [CrossRef]
- 13. Xiao, Y.; Zhang, J.; Ji, Y. Can fine-grained functional split benefit to the converged optical-wireless access networks in 5G and beyond? *IEEE Trans. Netw. Serv. Manag.* 2020, 17, 1774–1787. [CrossRef]
- 14. Yang, H.; Liang, Y.; Yuan, J.; Yao, Q.; Yu, A.; Zhang, J. Distributed blockchain-based trusted multidomain collaboration for mobile edge computing in 5G and beyond. *IEEE Trans. Ind. Inform.* **2020**, *16*, 7094–7104. [CrossRef]
- 15. Giglio, A.; Pagano, A. Scenarios and economic analysis of fronthaul in 5G optical networks. *IEEE J. Lightwave Technol.* **2019**, 37, 585–591. [CrossRef]
- Mo, W.; Gutterman, C.; Li, Y.; Zussman, G.; Kilper, D. Deep neural network based dynamic resource reallocation of BBU pools in 5G C-RAN ROADM networks. In Proceedings of the Optical Fiber Communications Conference and Exposition (OFC), San Diego, CA, USA, 11–15 March 2018.
- 17. Papavassiliou, S.; Tsiropoulou, E.E.; Promponas, P.; Vamvakas, P. A paradigm shift toward satisfaction, realism and efficiency in wireless networks resource sharing. *IEEE Netw.* **2021**, *35*, 348–355. [CrossRef]

- Tian, B.; Zhang, Q.; Xin, X.; Tian, Q.; Wu, X.; Tao, Y.; Shen, Y.; Cao, G.; Liu, N. Recursive neural network based RRH to BBU resource allocation in 5G fronthaul network. In Proceedings of the Asia Communications and Photonics Conference (ACP), Hangzhou, China, 26–29 October 2018.
- 19. Greff, K.; Srivastava, R.; Koutník, J.; Steunebrink, B.; Schmidhuber, J. LSTM: A search space odyssey. *IEEE Trans. Neural Netw. Learn. Syst.* 2017, 28, 2222–2232. [CrossRef] [PubMed]
- Yu, A.; Yang, H.; Yao, Q.; Li, Y.; Guo, H.; Peng, T.; Li, H.; Zhang, J. Scheduling with flow prediction based on time and frequency 2D classification for hybrid electrical/optical intra-datacenter networks. In Proceedings of the Optical Fiber Communications Conference and Exhibition (OFC), San Diego, CA, USA, 3–7 March 2019.
- 21. Zheng, H.; Lin, F.; Feng, X.; Chen, Y. A hybrid deep learning model with attention-based conv-LSTM networks for short-term traffic flow prediction. *IEEE Trans. Intell. Transp.* 2020. [CrossRef]
- 22. Zhao, J.; Bao, B.; Yang, H.; Oki, E.; Chatterjee, B. Holding-time- and impairment-aware shared spectrum allocation in mixed-linerate elastic optical networks. *IEEE J. Opt. Commun. Netw.* **2019**, *11*, 322–332. [CrossRef]
- 23. Yang, H.; Yao, Q.; Yu, A.; Lee, Y.; Zhang, J. Resource assignment based on dynamic fuzzy clustering in elastic optical networks with multi-core fibers. *IEEE Trans. Commun.* **2019**, *67*, 3457–3469. [CrossRef]
- 24. Yang, H.; Zhang, J.; Zhao, Y.; Ji, Y.; Han, J.; Lian, Y.; Lee, Y. CSO: Cross stratum optimization for optical as a service. *IEEE Commun. Mag.* 2015, *53*, 130–139. [CrossRef]
- 25. Zhao, J.; Bao, B.; Chatterjee, B.; Oki, E.; Hu, J.; Ren, D. Dispersion based highest-modulation-first last-fit spectrum allocation scheme for elastic optical networks. *IEEE Access* 2018, *6*, 59907–59916. [CrossRef]
- 26. Yao, Q.; Yang, H.; Bao, B.; Yu, A.; Zhang, J.; Cheriet, M. Core and spectrum allocation based on association rules mining in spectrally and spatially elastic optical networks. *IEEE Trans. Commun.* **2021**. [CrossRef]
- 27. Yang, H.; Zhang, J.; Ji, Y.; Lee, Y. C-RoFN: Multi-stratum resources optimization for cloud-based radio over optical fiber networks. *IEEE Commun. Mag.* 2016, 54, 118–125. [CrossRef]
- 28. Christodoulopoulos, K.; Tomkos, I.; Varvarigos, E. Elastic bandwidth allocation in flexible OFDM-based optical networks. *J. Lightwave Technol.* **2011**, *29*, 1354–1366. [CrossRef]
- 29. Zhu, Z.; Lu, W.; Zhang, L.; Ansari, N. Dynamic service provisioning in elastic optical networks with hybrid single-/multi-path routing. *J. Lightwave Technol.* 2013, *31*, 15–22. [CrossRef]
- Lechowicz, P.; Tornatore, M.; Włodarczyk, A.; Walkowiak, K. Fragmentation metrics and fragmentation-aware algorithm for spectrally/spatially flexible optical networks. *IEEE/OSA J. Opt. Commun. Netw.* 2020, 12, 133–145. [CrossRef]
- 31. Zhang, J.; Bao, B.; Yao, Q.; Ren, D.; Hu, J.; Zhao, J. 3D fragmentation metric and RCSA scheme for space division multiplexing elastic optical networks. *IEEE Access* 2020, *8*, 201595–201605. [CrossRef]
- 32. Yao, Q.; Yang, H.; Yu, A.; Zhang, J. Transductive transfer learning-based spectrum optimization for resource reservation in seven-core elastic optical networks. *J. Lightwave Technol.* **2019**, *37*, 4164–4172. [CrossRef]
- 33. Bao, B.; Yang, H.; Yao, Q.; Yu, A.; Chatterjee, B.C.; Oki, E.; Zhang, J. SDFA: A service-driven fragmentation-aware resource allocation in elastic optical networks. *IEEE Trans. Netw. Serv. Manag.* 2021. [CrossRef]
- 34. Assimakopoulos, P.; Zhou, J.; Habei, K.; Elbers, J.; Jungnickel, V.; Gomes, N. A converged evolved ethernet fronthaul for the 5G Era. *IEEE J. Sel. Area Commun.* 2018, *36*, 2528–2537. [CrossRef]
- 35. Sung, M.; Kim, J.; Kim, E.; Cho, S.; Won, Y.; Lim, B.; Pyun, S.; Lee, H.; Lee, J.; Lee, J. RoF-based radio access network for 5G mobile communication systems in 28 GHz millimeter-wave. *J. Lightwave Technol.* **2020**, *38*, 409–420. [CrossRef]
- 36. Yang, H.; Zhan, K.; Kadoch, M.; Liang, Y.; Cheriet, M. BLCS: Brain-like distributed control security in cyber physical systems. *IEEE Netw.* **2020**, *34*, 8–15. [CrossRef]
- 37. Yang, H.; Zhao, X.; Yao, Q.; Yu, A.; Zhang, J.; Ji, Y. Accurate fault location using deep neural evolution network in cloud data center interconnection. *IEEE Trans. Cloud Comput.* **2020**. [CrossRef]
- 38. Alimi, I.; Teixeira, A.; Monteiro, P. Toward an efficient C-RAN optical fronthaul for the future networks: A tutorial on technologies, requirements, challenges, and solutions. *IEEE Commun. Surv. Tutor.* **2018**, *20*, 708–769. [CrossRef]
- Chen, X.; Li, B.; Proietti, R.; Lu, H.; Zhu, Z.; Yoo, S. DeepRMSA: A deep reinforcement learning framework for routing, modulation and spectrum assignment in elastic optical networks. J. Lightwave Technol. 2019, 37, 4155–4163. [CrossRef]
- 40. Hasan, M.; Farahmand, F.; Jue, J.; Zhu, Z. Knapsack-based drop-and-continue traffic grooming for power and resource efficiency. In Proceedings of the Optical Fiber Communications Conference and Exposition (OFC), Los Angeles, CA, USA, 4–8 March 2012.
- 41. Yu, A.; Yang, H.; Nguyen, K.; Zhang, J.; Cheriet, M. Burst traffic scheduling for hybrid E/O switching DCN: An error feedback spiking neural network approach. *IEEE Trans. Netw. Serv. Manag.* **2021**, *18*, 882–893. [CrossRef]
- 42. Yang, H.; Zhan, K.; Bao, B.; Yao, Q.; Zhang, J.; Cheriet, M. Automatic guarantee scheme for intent-driven network slicing and reconfiguration. J. Netw. Comput. Appl. 2021, 190, 103163. [CrossRef]
- 43. Zhu, R.; Li, S.; Wang, P.; Xu, M.; Yu, S. Energy-efficient deep reinforced traffic grooming in elastic optical networks for cloud–fog computing. *IEEE Internet Things* **2021**, *8*, 12410–12421. [CrossRef]