Machine Learning-based Spectrum Resource Assignment and End-to-End Path Reconfiguration for Flexible Optical Networks

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ABSTRACT
Optical resource management and path reconfiguration have become increasingly paramount in the era of dynamic and flexible optical networks. This paper presents machine learning-based optical resource assignment for highly efficient resource utilization in Spatial Division Multiplexing (SDM) networks. We also demonstrate a network orchestration with a Whitebox-based optical network and failure prediction in an SDM network.
Keywords: flexible optical network, routing, spectrum assignment, failure management, orchestration

1. INTRODUCTION

In the B5G/6G era, in addition to the ever-increasing capacity, various network characteristics other than increased communication capacity, such as low-latency communication and multiple terminal connections, are required. To accommodate the ever-increasing traffic and to provide a communication infrastructure that can meet these new demands, it is essential that the optical network also has a further increase in capacity. To realize all-optical networks, in addition to developing various devices, research and development are also being conducted on technologies closely related to network control, such as super-channel switching, wavelength assignment, wavelength/waveband conversion, etc. In contrast to the conventional method, which sets the wavelength according to a fixed grid, which effectively sets an excessive margin, an approach represented [1], which adaptively assigns bandwidth of different widths according to the transmission distance and transmission rate, thereby reducing the frequency margin, has become generally considered. Furthermore, in recent years, multi-core and multi-mode fibers have attracted attention, and several studies report a large network capacity transmission using a single fiber of space division multiplexing (SDM) technology [2,3]. From a network perspective, SDM-based elastic optical networks (SDM-EONs) have become an active research topic.

In network control in SDM-EONs, when setting up each optical path, the transmission route, spatial channel (core or mode, etc.), modulation format, and assigned frequency slots are determined by some algorithms, and optical signals are transmitted using the assigned channel. In addition, if necessary, prior to actually transmitting optical signals, advance verification may be performed, such as estimating the Quality of Transmission (QoT) using GNPy [4]. To assign spectrum resources of various bandwidths to individual lightpaths while satisfying the continuity constraint, it is known that setting up lightpaths on demand sequentially results in the existence of narrow bands that do not meet the required bandwidth, leading to a decrease in the efficiency of frequency utilization. Many studies propose heuristic routing and spectrum assignment methods before machine learning becomes popular.

Recently, machine learning is commonly used in various systems. Since the emergence of AlphaGo and the significant improvement in image processing recognition performance, the application of machine learning, particularly deep learning, has been actively explored from various perspectives in the field of optical communication networks. This has drawn significant attention as one of the promising technologies. Key examples of machine learning applications in the optical network field include nonlinear compensation, QoT estimation, device parameter optimization, monitoring, resource allocation for high-frequency demands, traffic forecasting, fault detection and identification, equipment life estimation, automatic control, and orchestration. Additionally, to use optical networks themselves as optical reservoir computing is considered. Among them, network automation and failure management are expected solutions for future SDM networks. We experimentally demonstrate a closed-loop control of Whitebox-based optical network. In addition, we propose a machine learning model for failure prediction in SDM networks with crosstalk issues.

2. RELATED WORKS

In EONs, the spectrum can be flexibly set while considering the requirements of each optical path and physical factors such as optical reach, and the number of optical paths that can be accommodated in the entire network can be increased by allocating only the required frequency slots with low margin to each optical path. Various Routing and Spectrum Assignment (RSA) algorithms have been proposed, including those in the literature [5, 6], as research on the RSA problem in EONs. The authors have previously proposed a signaling and dynamic frequency resource allocation method for distributed EON and a frequency allocation method for reducing crosstalk in multi-core fiber [7, 8].

While research and development about SDM technology has been actively conducted in recent years, there is a physical limit to the number of signals that can be multiplexed, and it is difficult to increase the degree of multiplexing further. In addition, further study is required on relay node architecture to perform appropriate demultiplexing and multiplexing. Meanwhile, in recent years, the use of machine learning has been progressing in various fields to efficiently use of spectrum resources. The use of machine learning in optical network control has also been considered. The scope of its applicability is wide, including the RSA problem targeting dynamic traffic demand. In reference [9], deep learning determines which resources are best to allocate.

3. REINFORCEMENT LEARNING-BASED SPECTRUM RESOURCE ASSIGNMENT

In this study, we focus on multi-fiber SDM optical networks in which multiple optical fibers are connected in parallel in links between nodes, and propose a frequency resource allocation method that significantly reduces switching processing by performing fiber-based switching in addition to spatial and wavelength channel-based demultiplexing at relay nodes. Normally, relay nodes demultiplex each fiber into core channel units and then into frequency channels before switching processing, so an exchange node configuration is used with a number of ports corresponding to these. Assuming that switching processing is performed at the fiber granularity, it can be said that some of the core channel demultiplexing and other functions can be reduced, but for simplicity in this paper, we do not set a constraint on the number of fibers that can demultiplex core channels, and assume that inputs from all fibers can be demultiplexed by core and frequency units if necessary.

3.1. Direct Path Configuration

At the relay node, a direct fiber path is designed that can transmit to the desired destination node by only switching processing at the fiber level, without separating and multiplexing at the core channel or wavelength channel level. The direct fiber path is set as the shortest route to accommodate more traffic (light paths) between specific nodes. When a light path setting request arrives, it is confirmed whether an existing direct fiber path exists between the same transmitting and receiving nodes, and if not, it attempts to set up a direct fiber path as follows. Specifically, it is confirmed whether fiber switching is possible on the shortest route, and if it is possible at all relay nodes, an arbitrary fiber is selected at each link to construct a virtual direct fiber path. The input fiber and the output fiber at each relay node are directly connected at the fiber level, and thereafter, light path setting requests at the same transmitting and receiving nodes will preferentially use the resources of this direct fiber path. Note that only one direct fiber path can be set up between each transmitting and receiving node. This is to prevent a significant decrease in flexibly usable frequency resources by increasing the number of direct fiber paths themselves.

3.2. Machine Learning-based Optical Resource Assignment Method

Figure 1 shows an overview of the lightpath setting process in the proposed method. When setting up a lightpath on demand, first, fiber switching is set at the relay node, and it is confirmed whether there is a direct fiber path that can transmit to the destination node by fiber switching alone. If there is a direct fiber path, it is confirmed whether a channel is available to add a new lightpath to the direct fiber path, and if so, an arbitrary channel is assigned. On the other hand, if a direct fiber path is not available, the frequency resource allocation method using reinforcement learning is executed in the following procedure, and if a solution is found, the spatial and frequency channels are assigned. If no solution is found, the new lightpath is blocked.

The frequency resource allocation method using reinforcement learning is described below. As a pre-processing step for creating a reinforcement learning model, k candidate routes are calculated using the k-shortest path algorithm. Next, a Q value is set for each combination of transmitting node, receiving node, candidate route ID, spatial channel ID, and frequency slot ID. After that, when new request arrives, the Q value is updated, and the transmission route, spatial channel ID (fiber-core pair), frequency, etc. are selected. In addition, instead of making all frequency slots selectable for each route and spatial channel of a certain transmitting/receiving node pair, we assume that there is a virtual grid for each multiple of the number of required frequency slots determined by the transmission distance of the candidate route calculated in advance.

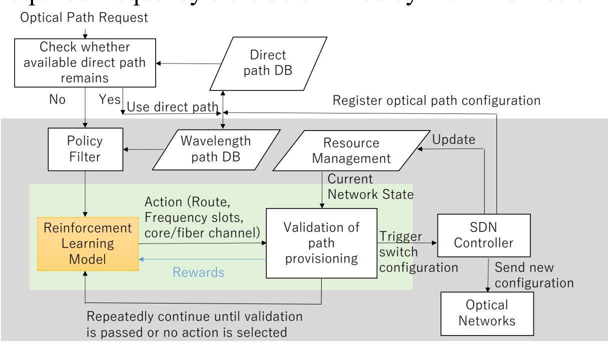

Fig. 1: Outline of proposed resource assignment

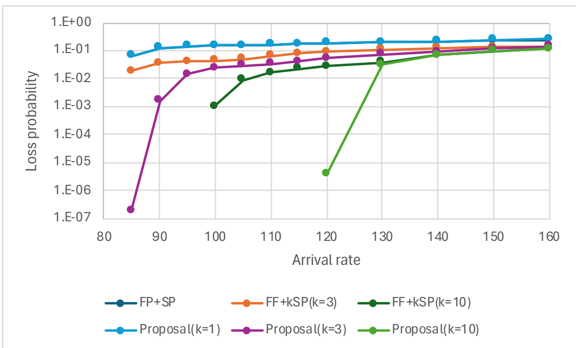

Fig. 2: Result of loss probability

3.3. Simulation Results

The JPN12 model (number of nodes N = 12, number of links L = 34) [10] was adopted as the target network topology in a multi-fiber SDM optical network. The evaluation was performed assuming that the links between each node are equipped with a maximum of $F = 25$ optical fibers in one direction. The number of frequencies per spatial channel was set to 80. The routes were calculated in advance using the k-shortest path algorithm and used as candidate routes. The first-fit allocation method was used for comparing frequency allocation. In this comparison method, first, an allocatable frequency slot is searched for by first-fit on the shortest route. If no allocatable frequency slot exists that satisfies the continuity constraint, the second shortest route among the candidate routes is searched for again. After that, the search continues until a solution is found (allocation successful) or the search for all candidates is completed (rejected). The reinforcement learning-related parameters in the proposed method are set as $\alpha = 0.9$, $\gamma = 0.1$, $\varepsilon = 0.01$. The positive reward given to the learning unit is the value obtained by multiplying $reward_{success} = 1.0$ by the number of input fibers for which demultiplexing/multiplexing is performed on a core-by-core basis. A uniform traffic model was adopted for the traffic between each lightpath's source and destination nodes. In the uniform traffic model, traffic was assumed to occur at intervals following an exponential distribution with an occurrence rate of $\lambda = 20560$ throughout the entire network, and the sending and receiving nodes of each traffic were assumed to be selected randomly. The average holding time per connection was assumed to be given by an exponential distribution with a mean of 1.0, and the results were obtained for 10^7 lightpaths (excluding transient states) for each trial. For comparison, we adopted a benchmark method that uses the shortest path or k-shortest path (k = 3, 10) for route selection and allocates frequency resources according to the first-fit policy.

Figure 2 shows the results of loss probability of optical paths. In the proposed reinforcement learning method, the performance is worse than that of the first-fit method because it actively distributes the load, but the performance difference is smaller than that of the shortest path only. By using direct fiber paths, about half of the traffic is transmitted over the direct fiber paths, which partially enables ideal resource utilization without the effects of fragmentation and reduces the loss probability. When the k-shortest path is used in the proposed reinforcement learning method, it is clear that a very low loss probability can be achieved.

4. MACHINE LEARNING-BASED CLOSED-LOOP CONTROL

Considering network automation and zero-touch operation, monitoring optical network information and closed-loop control using machine learning are essential functions for future optical network control systems. We constructed an experimental system using white-box transponders and demonstrated the closed-loop control functions, including the cooperation between the orchestrator and the ML server. Figure 3 shows the experimental system. Figure 4 shows the experimental results. Performance monitor data such as OSNR and Pre-FEC BER are acquired at the receiving side of the monitoring signal, and the results are stored in an orchestrator database. The stored data is periodically acquired by API access, and when further deterioration of signal quality is expected in the next time slot, a workflow is started to change the FXC connection by connecting to the orchestrator via API. When the signal quality improves, the FXC is changed back to the original connection configuration, and the operation of the closed-loop control was successfully verified.

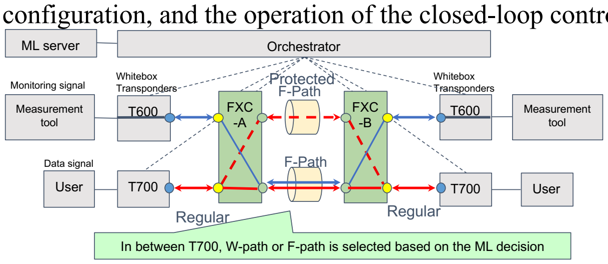

Fig. 3: Overview of experimental setup

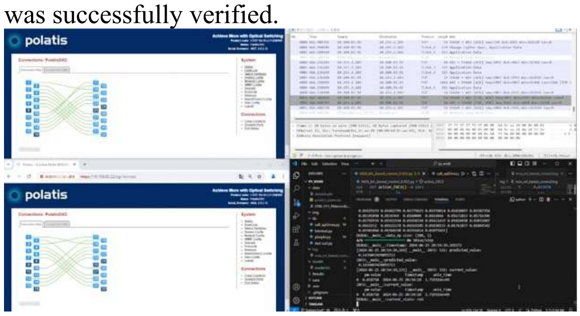

Fig. 4: Result of FXC closed-control

5. MACHINE LEARNING-BASED FAILURE PREDICTION IN MCF NETWORKS

In this section, we introduce a model for predicting transmission quality degradation using machine learning as a research topic related to the resiliency of optical networks. As the programmability of optical fiber networks improves due to disaggregation, fault management in optical networks is one of the most important issues. In recent years, various research and development efforts have been actively conducted on fault detection and fault location identification technologies using machine learning. However, these fault detection and identification technologies are mainly for single-core optical fibers, and there has been little research on multi-core fiber optical networks. In this paper, we focus on the degradation of transmission quality due to crosstalk from adjacent cores, which is unique to multi-core fibers, as an elemental technology for fault management in multi-core optical fiber networks, and propose a machine learning model that predicts instantaneous and temporary optical path outages due to changes in crosstalk over time. In this study, we construct multiple datasets using a small-scale experimental network and use these datasets to develop and evaluate machine learning models.

Figure 5 shows the experimental setup. A router tester for generating background traffic was connected to a commercial 100G transponder, which was then connected to a 32 km 4-core optical fiber. An optical path signal generated by ROADM-A was also inserted into the multi-core fiber, and a part of this optical path was cut off by the AOM switch in the middle stage to simulate a sudden decrease in the number of optical paths. Even if the network throughput keeps the same level immediately after the hardware failure, the transmission quality of the optical path deteriorates, and the optical path link becomes temporarily unavailable due to changes in the amount of crosstalk over time. The network throughput also decreases. To suppress this cascading failure of performance degradation in multicore fiber networks, we propose a machine learning model that predicts the occurrence of instantaneous and temporary link outages. Figure 6 shows the predicted status and actual state results of the proposed machine learning model. Using the information on OSNR and Pre-FEC BER measured in the throughput measurement experiment, it is predicted that a link failure may occur before a temporary link outage occurs. After the failure event, no link outage occurred until around time 3300, so the learning model determined that no failure would occur. On the other hand, due to QoT fluctuation, it can be seen that the proposed machine learning model outputs the possibility of a link failure as high when the Pre-FEC BER becomes relatively high.

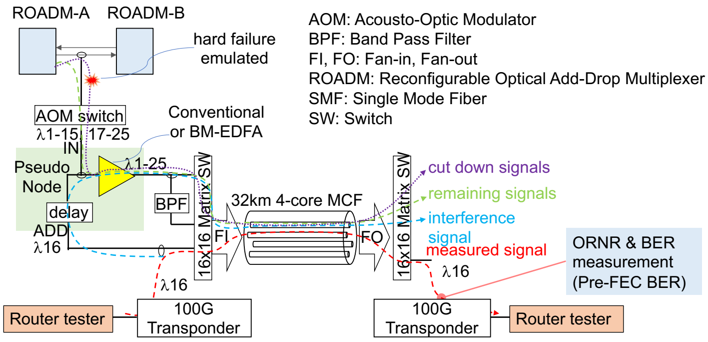

Fig. 5: Experimental setup for cascading failure

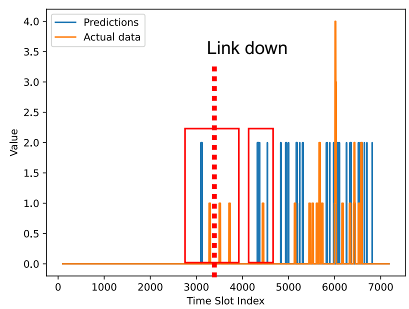

Fig. 6: Prediction result

6. CONCLUSIONS

While attempts are being made to transmit more information by increasing the degree of multiplexing in optical fibers, in this paper, we mainly focused on the multi-fiber optical networks and Whitebox-based networks. We proposed an optical resource assignment method using direct fiber paths that simplifies switching processing at relay nodes and confirmed its effectiveness through simulation. In addition, we experimentally demonstrate a machine learning-assisted closed-loop control in an optical network with Whitebox transponders and a machine learning model of failure prediction based on several performance monitor data of multi-core network datasets.

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