Real-time Detection of Optical Cross-talk for Autonomous Network Diagnosis

Mirei Onodera and Akira Hirano
Information and Communication Engineering, Tokyo Denki University
5 Senjuasahi-cho, Adachi-ku, Tokyo 120-8851, Japan
22kmc06@ms.dendai.ac.jp

Abstract*— *We have experimentally confirmed real-time detection of optical cross talk noise in photonic network for autonomous network diagnosis by applying machine learning to tapped raw optical signal data obtained from digital coherent LSI for the first time. We have achieved above 98% of accuracy by using 200 G bit/s DP-16QAM optical signal.

Keywords*—*machine learning, digital coherent transmission

I. INTRODUCTION

Data traffic has been expanding rapidly so far, and this trend is expected to continue to support traffic demands for upcoming novel services, including video and mobile data. In addition to that, in the 5G and beyond 5G era, virtualization in network on top of physical layer will be needed to achieve various Key Performance Indicators (KPIs) required for 5G or future 6G networks. Moreover, various virtual network operators, including Mobile Virtual Network Operators (MVNOs), will provide novel services and applications by using such virtualized networks. Accordingly, future network will become more data intensive and complex in operation.

On the other hand, by making full advantage of Software Defined Networking (SDN) and Network Functions Virtualization (NFV), future networks will acquire higher levels of flexibility and programmability in terms of management and service provisioning. So, we can say that future networks will have larger capacity, become more complex, and need to be more flexible and programmable. In such networks, many different types of network slices will run on a layered network infrastructure and will be operated by different types of network service and/or content providers. Therefore, complexity, heterogeneity, and scale of networks may exceed the limits of human-based operation and maintenance.

To tackle such issues, there is a strong trend toward automation in network operation and management. Rapid advances in artificial intelligence (AI), machine learning (ML), and deep learning (DL) are already paving the way toward autonomous operation and management. Various use cases in which AI-based techniques are effective in optical network operation are summarized [1]. Extensive surveys on how ML works in optical network management are provided in [2]. They also discuss several network management architectures that make use of ML in automation for optical networks. The authors in [3] propose and demonstrate a monitoring and data analytics framework and discuss tools that recognize network status in detail by collecting huge amounts of data from many devices. For autonomous network diagnosis, we have proposed CAT platform for autonomous network diagnosis as shown in Fig. 1 [4-8].

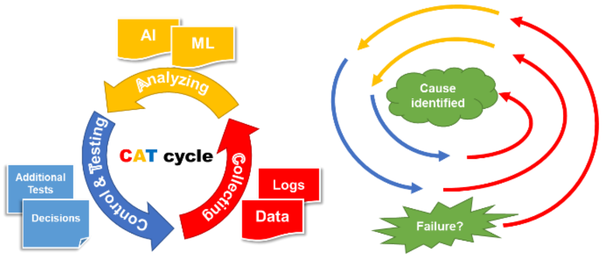


Fig. 1. CAT platform

In usual network maintenance operations, we need multiple types/times of test measurements to find a root cause of failures. We can implement such network diagnosis algorithms in the CAT platform which is realized by open-source software StackStorm [5]. It runs such diagnosing procedures automatically by repeating various network tests to find a final cause of failures. The procedures are written in Yet Another Markup Language (YAML) in the algorithms.

In recent years, there has been a demand for higher capacity in the metro/access network domain in preparation for beyond 5G and 6G network. Digital coherent transmission technologies have been deployed widely in core/metro networks and its extension into metro/access domain is being considered, i.e. in the design of a 5G metro/access network called Centralized Radio Access Network (CRAN) [9].

As of 2015, thousands of 100G+ digital coherent optical equipment ports have been deployed for the metro and access applications [10]. In addition, with the rapid miniaturization of digital coherent transceiver components, expectations for simplified digital coherent technology have increased rapidly. WhiteBox optical transceivers using these simplified digital coherent technologies could be suitable for low-complexity optical access systems. As a result, more compact optical transceivers based on digital coherent technology in WhiteBox are expected to be deployed in metro access networks in the near future [11].

Optical cross talk noise comes from incomplete fiber connection and/or fusion splices in optical fiber links as shown in Fig. 2. Almost all optical signal transmits through optical amplifiers such as Erbium Doped Fiber Amplifiers (EDFAs), optical connectors, optical fiber links, and Reconfigurable Optical Add Drop Multiplexers (ROADMs) as shown in Fig. 2. However, very small portion of the signal may be reflected backward at a connector as shown in this figure. When we have another reflection point (in this example, before the ROADM), the reflected signal will be

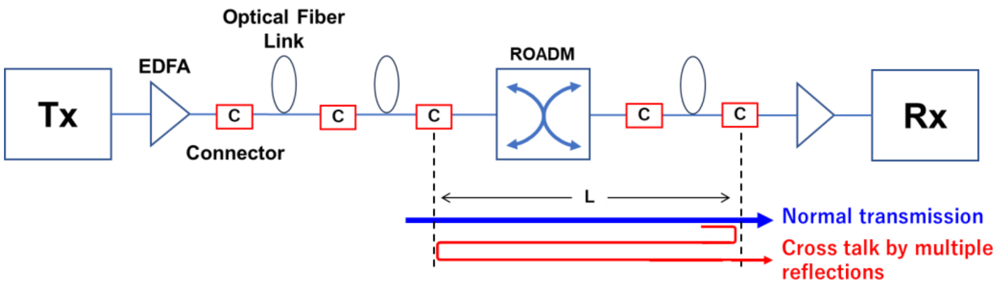


Fig. 2. Optical cross talk noise in photonic network

reflected again in forward direction. This component will arrive at the receiver with some amount of temporal delay. Thus, it will interfere with the normal signal without reflections. This is the cross-talk noise that will degrade quality of the optical signal. Depending on the linewidth of the laser diode in the transmitter and the difference in transmission distance between the normal and the reflected components, it will cause coherent/incoherent cross talk, leading to degradation of optical signals [12]. It has also been reported that coherent cross talk can generate a large power penalty at the optical cross-connects (OXC) in dense wavelength division multiplexer (WDM) based optical networks [13]. It also comes from inter-core cross talk in Multi Core Fibers (MCFs) which will be installed in optical network in the near future. To date, various works have been reported on the effects of optical cross-talk based on IMDD transmission systems. However, there has been little work on its real-time detection.

Real-time detection of such noise will be essential to reduce operational workload for fault diagnosis. If we could clarify the cause of degradation instantly by machine-learning of received optical signals among various kinds of cause candidates, it will greatly reduce OPEX for fault diagnosis. Moreover, the number of digital coherent transceivers is expected to increase towards 5G/6G. Metro/access networks have aggregation functions to accumulate and switch mobile data traffic from huge number of base stations. Therefore, they generally have large number of connection points including optical connectors, optical couplers, and fusion splices. So, frequency of incomplete connections or slices may increase in these network domains. Therefore, real-time detection of optical cross talk noise could contribute to improve reliability of metro/access network and to simplify maintenance operations. To the best of our knowledge, there have been no reports on real-time detection of cross talk noise by applying machine learning to the data tapped from digital coherent LSIs.

We propose novel cross talk detection approach where we tap digital data just after the Analogue-to-Digital Converters (ADCs) in digital coherent LSIs and use them for machine learning to train models to detect cross talk noise. We trained convolutional neural network for detection of cross-talk noise. By applying the approach in DP-16QAM optical signals, we have successfully detected cross talk noise ranging from -30 to -50dB experimentally. We have implemented detection software as one of the sensing modules (Docker containers) in the CAT platform. Thus, it will work with other detection modules in the platform to realize autonomous network diagnosis.

II. Cross Talk Detection

A. Our approach

We have proposed novel network monitoring approach which is Tapped Raw Digital Signal (TRDS) monitoring in digital coherent optical receivers. Optical signal transmitted through optical transmission links experiences various impairments including chromatic dispersion, polarization mode dispersion, optical losses in connection points, optical fiber bending, noise from optical amplifiers, and optical spectrum deformation induced by optical filter shift in intermediate optical filters in optical add-drop multiplexers. Therefore, there will be some information on these impairments in the optical signal received in digital-coherent receivers. In conventional optical receivers, we use various powerful signal processing to compensate such impairments as shown in Fig. 3.

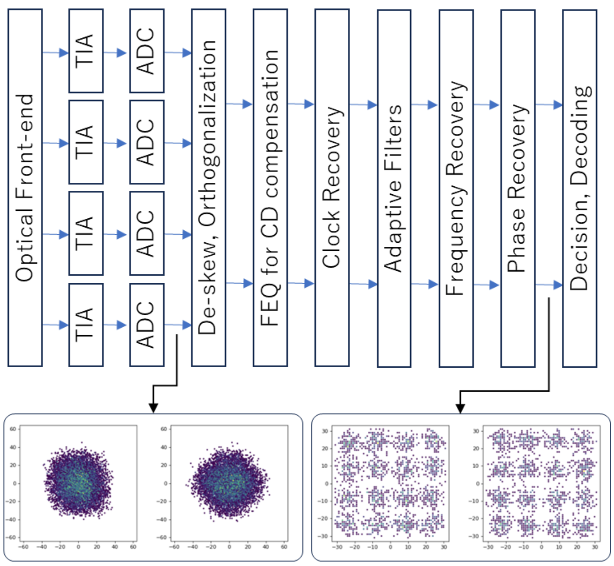


Fig. 3. Block diagram of coherent receiver

For example, chromatic dispersion can be compensated by using finite impulse response (FIR) filters in time domain or frequency domain. Polarization mode dispersion can be compensated by some butterfly type adaptive filters where dynamic update of tap coefficients occurs. From the viewpoint of detection of various impairments, such strong signal processing may be harmful since they can mask or erase the information in the received optical signals. Thus, we propose novel approach where we tap digital signals just after Analog-to-Digital Converters (ADCs) in optical receivers. When we got digital signal at the final stage in the block diagram, we could observe clear constellation diagram as shown in the bottom right in Fig. 3. On the other hand, when we got digital signal just after the ADCs, we got spherical diagram as you can see in the bottom left in Fig. 3. This is because we do not recover any impairments and/or phase/clock information.

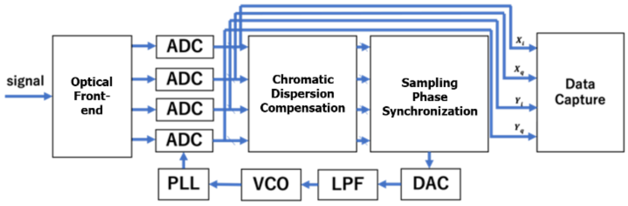


Fig. 4. Tapped Raw Digital Signal (TRDS)

Actual configuration for TRDS is shown in Fig. 4. Sampling phase is synchronized with symbol rate of optical signal by the Phase Lock Loop (PLL) circuit as shown in the figure. To enhance accuracy of synchronization, we compensated known impairment of chromatic dispersion of optical transmission links. The tapped raw digital signals can have information on various impairments as they are. Therefore, we can expect to detect such impairments by analyzing the TRDS signals. We used symbol synchronized sampling in TRDS. Asynchronized sampling approaches have been proposed to detect Optical Signal to Noise Ratio (OSNR) of optical signal [14]. However, such asynchronized approach may lose information in optical signals by averaging over time domain. Our approach can preserve time-dependent variations. So we can expect to get more information on impairment.

We have already succeeded in detection of optical fiber bending in optical transmission links and optical filter shift (de-tuning from optimum position) in optical add-drop multiplexers by using the data obtained from TRDS to train machine learning models [15-18]. Thus, we apply our approach for detection of optical cross-talk noise.

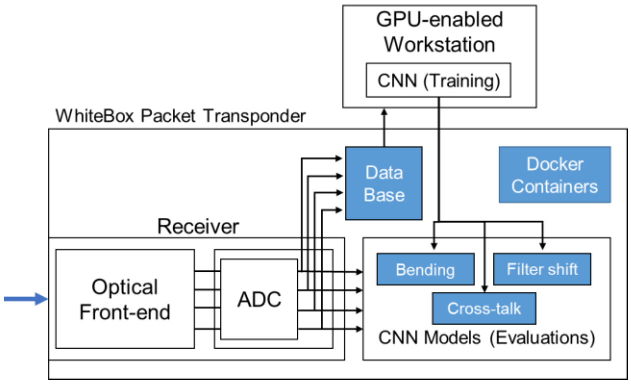


Fig. 5. Sensing system configuration

Figure 5 shows our sensing system configuration where we employed a WhiteBox packet transponder called Cassini [19] to acquire/store constellation data and to test trained CNN models. The Cassini WhiteBox can be used to install a variety of container-based applications for different purposes, such as data collection and information monitoring [19]. A tapping port has been implemented on a digital coherent receiver LSI to capture TRDS data. Dual Polarization 16 Quadrature Amplitude Modulation (DP-16QAM) was used in the experiment. Therefore, we can get four lanes of digital data (I/Q components for X/Y polarizations) as shown in Fig. 5. The captured data is sent to a Redis database container and stored in the container. The TRDS data is retrieved from the database and used to train CNN models in GPU-installed workstation server. Labels (0 and 1) for states with and without cross-talk noise are assigned to both the training and evaluation data. Fig. 6 shows software stack of our WhiteBox transponder system. We have implemented network diagnosing containers on top of the Kubernetes orchestrator. As you can see, we can easily add new sensing, diagnosing, and testing applications as we need in this platform.

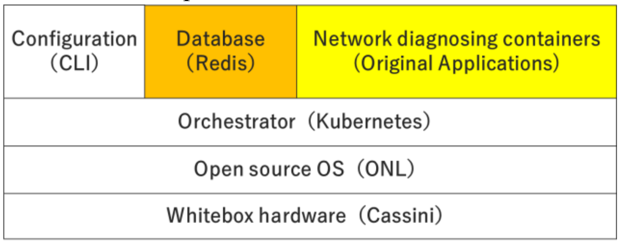


Fig. 6. Software Stack of our WhiteBox

B. Experimental setup for evaluation

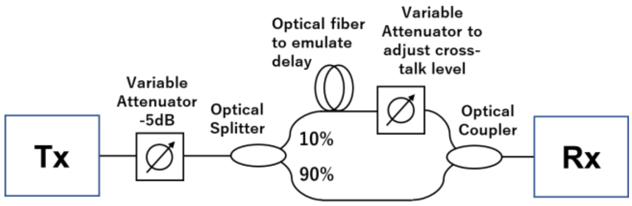


Fig. 7. Experimental setup

Figure 7 shows the experimental setup for cross-talk noise detection. A CFP2-ACO transceiver installed in Cassini WhiteBox is used as the optical source. The transmitter wavelength and corresponding linewidth of the CFP2-ACO transceiver are 1550 nm and 300 kHz, respectively. Thus, its coherent length can be estimated as approximately 300 meters. The output of the transmitter is divided into two branches by the optical splitter with branching ratio of 1:9 to simulate the effects of cross-talk. The optical signal in the upper arm is launched into a fiber link that consists of G.652 standard Single Mode Fiber (SMF) and an optical variable Attenuator (ATT) and then combined by the optical coupler. The G.652 fibers emulate optical delay that reflected signal will suffer. The ATT emulates level of reflection. Since we have used polarization multiplexed signal, we omit polarization controller. The signal in the upper/lower arm works as reflected/normal signal component, respectively. The Angled PC (APC) connectors are used at the connection points to avoid residual reflections. By controlling the ATT, we set relative residual reflection levels of -30 dB, -40 dB, and -50 dB at the output of the coupler. Four different lengths of fiber links are used: 5 m, 2 km, 5 km, and 7 km to check the effect of coherent length of 300 m. In total, 12 different datasets (3 x 4) were captured, varying the residual reflection level and the fiber link length. For optical cross talk detection, the captured data with the same fiber link length and residual reflection level were used for the training/evaluation data. Fig. 8 shows block diagram of data processing for model training.

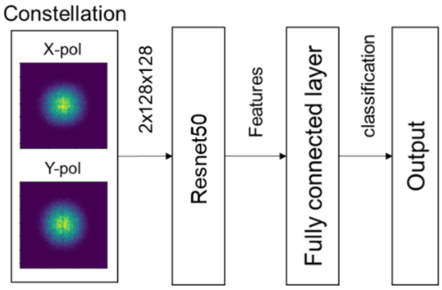


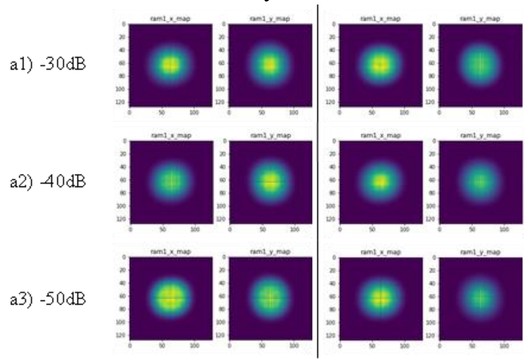
Fig. 8. Block diagram of data processing

We used polarization multiplexed 16QAM signal for evaluation. So it has two polarization components of X and Y. Each component has 128x128 resolution in complex plane. There, the size of the input layer of Resnet50 is 2x128x128 as shown in Fig. 8. The extracted feature is then input to fully-connected layer for classification output of label "0" (cross talk detected) and "1" (normal).

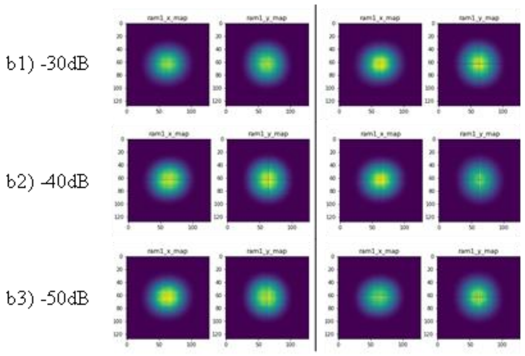
III. RESULT AND DISCUSSION

A. *Cross talk detection with trained models*

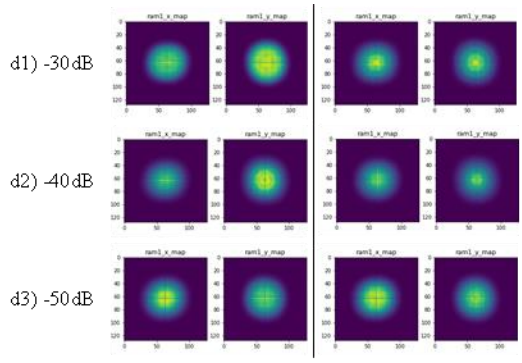
We used Resnet50 to classify whether there was cross-talk noise or not. For training and evaluation, the data of labels "0" and "1" were split by 1:1 for all 12 datasets. As a result, we prepared and obtained 12 trained models in total. Each trained model was tested with evaluation data which was collected under the same conditions but at different timeframe. The size of the dataset was 1240 for all the conditions. Thus, the size of training/evaluation datasets was 620. The 128x128 constellation generated from the TRDS data for each condition is shown in Figure 9 a), b), c), and d). We observed slight variations that reflected cross-talk noise in these constellations. The corresponding evaluation results for cross-talk detection for all the evaluations are shown in Figure 10. For evaluation, we adopted the scores of accuracy.



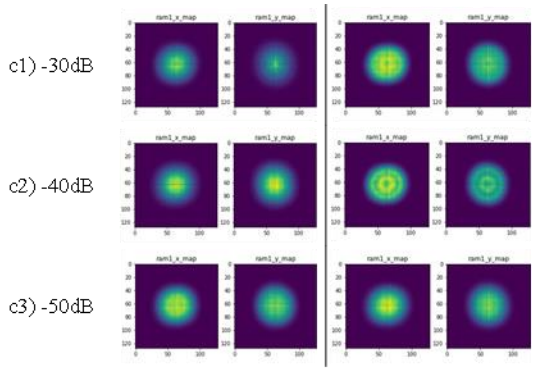
a) SMF length of 5 m



b) SMF length of 2 km



c) SMF length of 5 km



d) SMF length of 7 km

Fig. 9. Constellation from TRDS data
(Left: w/, right: w/o cross talk noise)

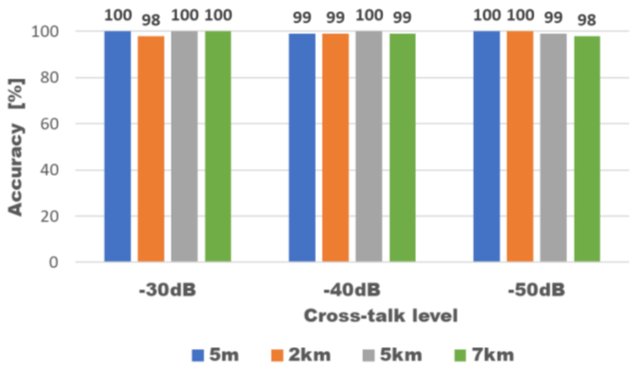


Fig. 10. Cross talk detection accuracy (%)

We tried 18 times of evaluation tests for different combinations of models and datasets. All of which gave stable and high accuracy. The values in Fig. 10 show the averaged values over 18 times of trials. These results indicate successful learning of cross talk noise for each test condition. Especially, we have succeeded in cross talk noise detection at down to -50 dB level. Usually, power penalty resulted from cross talk noise can occur around as small as -50dB [10], therefore we can say that our proposed approach showed sufficient sensitivity for actual applications. In this work, we have used a specific condition of optical signals. Further experiments with different network conditions and optical signals will be needed to verify this study.

B. *Generality of machine learning models*

We have carried out further experiments to test generality of the trained models whether they can be applied to different cross talk levels or not. Datasets collected at different cross talk levels were used to evaluate the trained models. For example, a model trained with dataset at cross talk level of -30dB was used to evaluate data obtained at -40dB and -50dB. This specific experiment was performed over the SMF fiber link length of 7 km.

Table 1. Results of model generality tests

cross talk level of trained model	cross talk level of evaluation data	Accuracy [%]
-30dB	-40dB	90
	-50dB	100
-40dB	-30dB	100
	-50dB	93
-50dB	-30dB	100
	-40dB	95

These results showed a high accuracy of 90-100% as shown in Table 1. We have confirmed generality of the trained models for different cross talk levels at the SMF fiber link length of 7 km. Looking at the results, we can achieve high detection accuracy for cross talk levels of -30 and -40dB, if we used models trained at cross talk level of -50dB. Accordingly, we can expect to reduce the number of models for detection. For actual application to metro/access network, the number of required models should be minimized to reduce workload and/or cost of model training, so further reduction and/or sophistication of machine learning models will be needed and will be for further study. In our work, we supposed the simplest case where cross talk noise comes from two reflection points. In actual network operation, frequency of incomplete and problematic connections will be very low, so the model we used in this work seems to cover almost all the cases of cross-talk noise.

IV. CONCLUSION

We have successfully confirmed real-time detection of cross-talk noise by applying TRDS data to machine learning in dual polarization 16QAM optical signal. The detection accuracy above 98% has been achieved for all experimental conditions ranging from -30 to -50dB of relative cross-talk level. We observed no significant impact of coherent length on the detection accuracy. Thus, our approach could be applicable to both coherent and incoherent cross-talk. Our approach is based on usual configuration of digital coherent receivers. We only need to insert tapping interface and add the software component for detection. Thus, the cost for practical implementation will be relatively small. The successful result of cross-talk detection contributes the enhancement of sensing/detection functions in CAT platform in addition to optical fiber bending detection and optical filter shift detection. Moreover, such cross-talk can occur in MCFs which will be installed in the near future. Thus, cross-talk detection by TRDS will help to reduce OPEX in future large capacity photonic networks.

REFERENCES

[1] J. Mata, I. Miguel, R. J. Durán, N. Merayo, S. K. Singh, A. Jukan, and M. Chamania, “Artificial intelligence (AI) methods in optical networks: a comprehensive survey,” Optical Switching and Networking, Vol. 28, pp. 43–57 (2018).

[2] D. Rafique and L. Velasco, “Machine learning for network automation: overview, architecture, and applications,” Journal of Optical Communication and Networking, Vol. 10, no. 10, pp. D126-D143 (2018).

[3] A. P. Vela, L. Gifre, O. González De Dios, M. Ruiz, and L. Velasco, “CASTOR: a monitoring and data analytics framework to help operators understand what is going on in their networks,” 44th European Conference on Optical Communications, TuDS.1, Rome, Italy (2018).

[4] T. Tanaka, A. Hirano, S. Kobayashi, T. Oda, S. Kuwabara, A. Lord, P. Gunning, O. González de Dios, V. Lopez, A. Mayoral Lopez de Lerma and A. Manzalini, “Autonomous network diagnosis from the carrier perspective,” OSA Journal of Optical Communications and Networking, Vol. 12, No.1, pp. A9-A17, 2020.

[5] F. Inuzuka, T. Oda, T. Tanaka, K. Kitamura, S. Kuwabara, A. Hirano, M. Tomizawa, “Demonstration of a novel framework for proactive maintenance using failure prediction and bit lossless protection,” IEEE Journal of Lightwave Technology, Vol. 38, Issue 9, pp. 2695-2702, 2020.

[6] A. Hirano, S. Kobayashi, T. Oda, T. Tanaka, S. Kuwabara and H. Nishizawa, "CAT platform: Challenges Toward Autonomous Network Diagnosis," 24th Opto-Electronics and Communications Conference (OECC), 2019.

[7] A. Hirano, "Autonomous Network Diagnosis with AI," 2019 Optical Fiber Communications Conference and Exhibition (OFC), 2019.

[8] T. Yoshioka, S. Nishijima, Y. Nishikawa and A. Hirano, "Demonstration of Autonomous Fault Diagnosis by Real-time Monitoring of Digital Coherent Optical Signals," IEEE International Conference on Optical Network Design and Modeling (ONDM), 2023.

[9] Ciena 5G White paper, “New Network Design for Transporting 5G Converged Traffic, ” pp.1-6 (2021).

[10] X. Pang, O. Ozolins, J. Rodrigo Navarro, A. Udalcovs, A. Kakkar, R. Lin, R. Schatz, M. Tang, S. Fu, D. Liu, G. Jacobsen, S. Popov, J. Chen, “Low-Complexity Digital Signal Processing Techniques to Enable Coherent Optical Systems for Metro and Access networks,” The 23rd OptoElectronics and Communications Conference (OECC), 2018.

[11] Naoki Suzuki, Hiroshi Miura, Keita Mochizuki, Keisuke Matsuda, “Simplified digital coherent-based beyond-100G optical access systems for B5G/6G [Invited],” OSA Journal of Optical Communications and Networking, pp. A1-A10, Vol. 14, No. 1, January 2022.

[12] James L. Gimlett et al., “Effects of Phase-to-Intensity Noise Conversion by Multiple Reflections on Gigabit-per-Second DFB Laser Transmission Systems,” IEEE Journal of Lightwave Technology, pp.888-895, June 1989.

[13] Yunfeng Shen, Kejie Lu, Wanyi Gu, “Coherent and Incoherent Cross talk in WDM Optical Networks,” IEEE Journal of Lightwave Technology, pp.759-764, Vol. 17, No. 5, May 1999.

[14] T. Tanimura et al., "OSNR monitoring by deep neural networks trained with asynchronously sampled data, " Opto-Electronics and Communications Conference (OECC), TuB3-5, 2016.

[15] Yuichiro Nishikawa, Shota Nishijima and Akira Hirano, “Real-time Detection of Fiber Bending and/or Optical Filter Shift by Machine-learning of Tapped Raw Digital Coherent Optical Signals,” IEICE Transaction of Communications, Vol. E106-B, No.11, Nov. 2023. (Accepted)

[16] T. Tanaka, W. Kawakami, S. Kuwabara, S. Kobayashi and A. Hirano, "Intelligent Monitoring of Optical Fiber Bend Using Artificial Neural Networks Trained with Constellation Data," IEEE Networking Letters, vol. 1, no. 2, pp. 60-62, June 2019.

[17] Y. Nishikawa and A. Hirano, "Enhanced Accuracy in Optical Fiber Bending Detection with Machine Learning against Accumulated ASE Noise," Opto-Electronics and Communications Conference (OECC), 2022.

[18] S. Nishijima and A. Hirano, "Real-time Optical Filter Shift Detection without Demodulation Processes with Machine Learning," International Conference on Photonics in Switching and Computing (PSC), 2022.

[19] Hideki Nishizawa et al., "Open whitebox architecture for smart integration of optical networking and data center technology," OSA Journal of Optical Communications and Networking, vol. 13, no. 1, pp. A78-A87, January 2021.