Demonstration of Autonomous Fault Diagnosis by Real-time Monitoring of Digital Coherent Optical Signals

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***Abstract*—We demonstrate autonomous fault diagnosis platform that performs data collection, analyzing, and inferring of the cause in photonic network with the help of machine learning. We successfully clarified the cause of failures by implementing workflows in StackStorm and real-time monitoring containers in WhiteBox packet transponder.**

Keywords—fault diagnosis, machine learning, digital coherent, disaggregation, WhiteBox

I. Introduction

In recent years, many online and mobile services including 5G have been developed and being penetrating into our society. Thus network traffic is still continuously expanding. In addition to that, virtualization in network such as 5G slices is also expected to be deployed widely. To meet these demands, optical network should be more cost-effective, power efficient and flexible. Starting with the data center network, disaggregation of optical transmission systems is now ongoing to make optical networks more open and flexible [1, 2] with the development of digital coherent optical systems [3]. WhiteBox equipment, open source software, and open interfaces are being deployed. Network disaggregation can reduce equipment cost by enabling more flexible configuration in optical network. Also it may accelerate development of both network software and hardware, since software and/or hardware can be developed independently. However, when we operate such network that consists of network components from various vendors, fault isolation or diagnosis could be a daunting task. To tackle these issues, machine learning and/or deep learning based approaches are expected [4]. In disaggregated architecture, we can easily install container based applications for information monitoring [2]. So we can realize real-time detection of optical filter shift in ROADM nodes and optical fiber bending by using machine learning techniques [5, 6]. In addition to that, various approaches for autonomous network control and management have been reported and summarized [7]. We have proposed novel autonomous network diagnosis platform that focus on autonomous fault isolation [8]. The CAT platform consists of three functional blocks: Collecting, Analyzing, and Control & Testing as shown in Fig. 1. The Collecting block collects information from devices and services in real network.

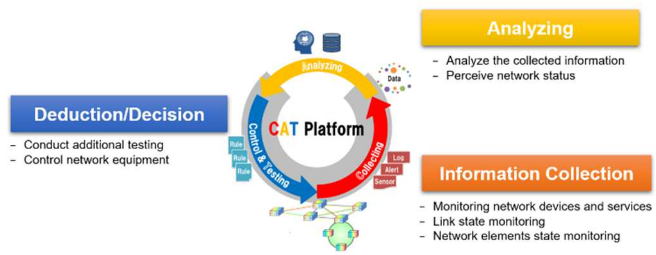

Fig. 1. CAT platform

The Analyzing block uses machine learning techniques to perceive network status by utilizing the information collected by the Collecting block. The Control & Testing block infers the current network status based on the result from analyzing block and then performs additional testing when needed. These three functional blocks forms a closed-loop for autonomous fault diagnosis. In the previous works, various fault diagnosis and/or fault predictions by using machine learning have been reported. However, there have been no report on autonomous fault diagnosis engine that utilize real-time data obtained from digital coherent LSI and clarify the cause of failure from multiple failure candidates.

In this paper, we present Proof of Concept (PoC) demonstration of the CAT platform, where we clarify various optical network failures including fiber bending [6] in transmission links, filter shift [5] in ROADM nodes, and transponder failures. In addition to that, we demonstrate autonomous recovery from the ROADM failure.

II. Network Diagnosis Platform

Figure 2 shows the system configuration of our network diagnosis platform. It consists of a disaggregated WhiteBox packet transponder Cassini [2] for real-time monitoring of digital coherent optical signals and a workstation for autonomous diagnosis of network failures. In the Cassini WhiteBox, following container applications are deployed as shown in Fig. 2:

i) Data capture container

ii) Fiber bend estimation container

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iii) Filter shift estimation container

iv) Database container

The Data capture container constantly captures constellation data (I/Q signals for X/Y polarizations) just after Analog-to-Digital Converters (ADCs), received optical power and bit error rate from the digital coherent LSI. It is very important to capture the constellation data just after the ADCs since the data contains various impacts from phenomena occurring in transmission link such as fiber bending. When we demodulated the constellation, such information from transmission link will disappear. The captured data is sent to and stored in database container. The Fiber bend estimation container and the Filter shift estimation container pull the constellation data of the received signals from the database container and estimate current status of optical network using CNN (resnet50). The estimation results are stored in the database container. In the Fiber bend estimation

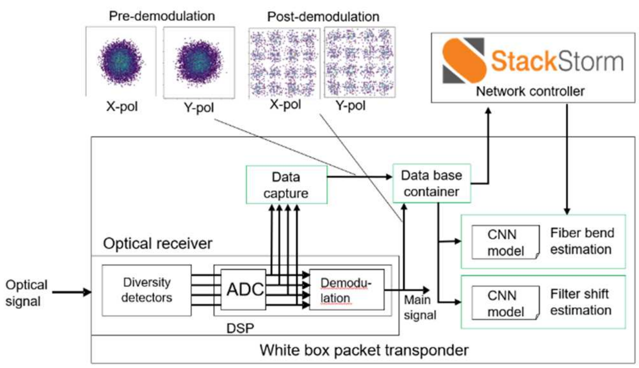

Fig. 2. Optical network diagnosis system

container, a pre-trained CNN model with pre- and post-demodulation data is used to estimate fiber bending. In the Filter shift estimation container, optical filter shift with its direction (positive or negative) from optimum position are estimated using a pre-trained CNN model with pre-demodulation data.

We implemented the network controller in a workstation PC. StackStorm [9], an event-driven workflow engine, is used as the autonomous fault diagnosis engine, which execute workflows for detecting network anomalies, identifying the causes of failures.

III. Demonstration and Results

The experimental configuration for autonomous network diagnosis is shown in Fig. 3. It consists of single-mode fibers, variable attenuators, an optical filter, optical fiber bending device and Erbium Doped Fiber Amplifier (EDFA). This configuration emulates two transmission lines, which has Reconfigurable Optical Add-Drop Multiplexer (ROADM) node in-between them. The transmitter generates 25 GBaud Dual Polarization (DP)-16QAM optical signal. The launched optical power is set at 1 dBm. The attenuation of variable attenuator ATT#1 is set at a value that gives Signal-to-Noise Ratio (SNR) of 20 dB in the output of the EDFA. The ATT#2 is set to the amount of attenuation that would result in a signal power of -9.65 dBm at the input to the receiver.

Figure 4 shows a workflow diagram and the implemented StackStorm codes for classifying the cause of the anomaly in optical network. This workflow classifies the cause of the anomaly by performing the following processes corresponding to each functional block of the CAT platform. First, the workflow fetches the BER from the database container and check if the value does not exceed the threshold value of 1.5 x 10^{-6}. Here, we check BER before Forward Error Correction (FEC). Therefore, when we found some errors before FEC, they can be corrected by FEC. So there is no service disruption at this moment. If the fetched BER before FEC is below the threshold, the autonomous fault diagnosis engine decide that the network is in a normal state and return to the start in the diagram. If the fetched BER is above the threshold, the autonomous engine activates the Fiber bend estimation container and the Filter shift estimation container to determine the cause of the detected anomaly. It then fetches the estimation results from the Fiber bend estimation container and the Filter shift estimation container stored in the database container in real-time. If the fiber bending estimation result shows "bend", the cause of the anomaly is determined to be "fiber bend" and output the decision. If the filter shift estimation result is not "normal," the cause of the anomaly is determined to be "optical filter shift," and the result is output.

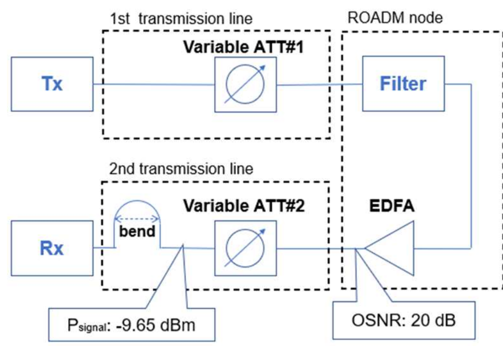

Fig. 3. Experimental configration

```
version: 1.0
description: A basic sequential workflow.
input:
  - threshold
vars:
  - diagnosis_result: null
output:
  - diagnosis_result: <% ctx().diagnosis_result %>
tasks:
  fetch_BER:
    action: default.fetch_data target="BER"
    next:
      - when: <% result().result.BER >= ctx().threshold %>
        do:
          - run_fiber_bend_container
          - run_filter_shift_container
      - when: <% result().result.BER < ctx().threshold %>
        publish: diagnosis_result="Nomal state"
        do: output_task
  run_fiber_bend_container:
    action: default.run_container target="fiber_bend_estimation"
    next:
      - when: <% succeeded() %>
        do: fetch_estimation_result
  run_filter_shift_container:
    action: default.run_container target="filter_shift_estimation"
    next:
      - when: <% succeeded() %>
        do: fetch_estimation_result
  fetch_estimation_result:
    action: default.fetch_data target="estimation_result"
    next:
      - when: <% (result().result.fiber_bend_estimation = "1") and (result().result.filter_shift_estimation = "0") %>
        publish: diagnosis_result="Fiber bend"
        do: output_task
      - when: <% (result().result.fiber_bend_estimation = "0") and (result().result.filter_shift_estimation = "1") %>
        publish: diagnosis_result="Filter shift"
        do: output_task
      - when: <% (result().result.fiber_bend_estimation = "0") and (result().result.filter_shift_estimation = "0") %>
        publish: diagnosis_result="Transceiver failure"
        do: output_task
  output_task:
    action: core.echo message=<% ctx().diagnosis_result %>
```

Fig. 4. a) StackStorm codes

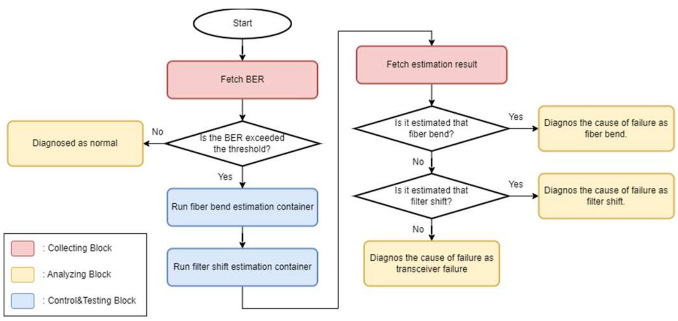

Fig. 4. b) Flow diagram

If the estimation results from both containers showed the normal state, the cause of the anomaly is diagnosed as "possible transceiver failure." The autonomous failure diagnosis engine periodically execute this workflow without human operators' intervention.

TABLE I. ANOMALIES AND EXPERIMENTAL OPERATION

Case	Cause of anomaly	Actual operation
1	Accidental fiber bending in 2nd transmission line	Bend fiber at 15 mm of diameter after the 2nd ATT
2	Optical filter failure in the ROADM node	Apply +53 GHz filter shift
3	Failure in a connector in the optical receiver	Increase attenuation of 2nd ATT

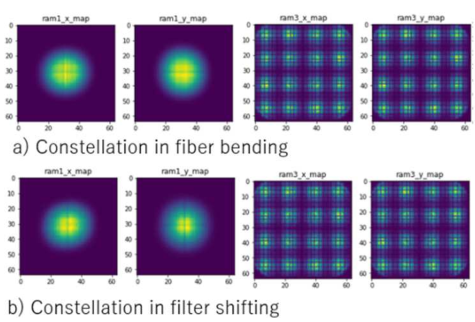

Fig. 5. Constellation data

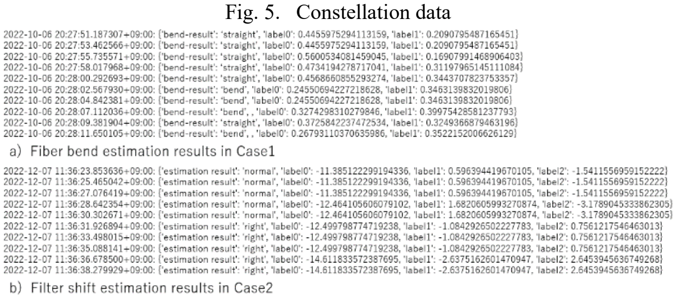

Fig. 6. Output from estimation containers

Fig. 7. Autonomous engine output

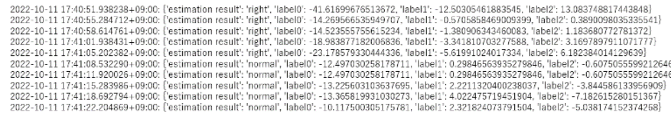

Fig. 8. Autonomous filter shift recovery results

In this demonstration, we have intentionally made anomalies by various means as shown in Table I.

Figure 5 a) and b) shows constellation diagram obtained from digital coherent LSI for optical fiber bending and optical filter shift, respectively. The left-hand and right-hand side show pre- and post-demodulation data, respectively. We can find slight tilt in pre-demodulation data for optical filter shift. Fig. 6 shows output from estimation containers. For each case, we have successfully clarified the cause of failure as show in Fig. 7.

Since the optical filter shift container can detect direction of filter shift, we can automatically recover the optimum position of the filter. Depending on the detected direction, the autonomous engine sent message to move counter direction. As shown in Fig. 8, the optical filter shift was recovered to its normal position.

IV. CONCLUSIONS

We present demonstration of novel autonomous network diagnostic platform using machine learning based on the data from digital coherent LSI. We successfully confirmed real-time classification of failure causes of fiber bending, optical filter shift, and transmitter failure using the implemented workflow in StackStorm. We also demonstrated autonomous optical filter failure recovery by using the estimated result. The proposed autonomous engine can support various failure scenarios by adding corresponding workflows.

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