Demonstration of Machine-Intelligent Soft-Failure Localization Using SDN Telemetry

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Abstract: We demonstrate a soft-failure localization framework using SDN-based network-wide telemetry. Soft failures are generated in a small-scale laboratory environment and collected in an SDN architecture. Failure localization is accomplished by ML algorithms. © 2021 The Author(s)

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1. Overview

In optical transport networks, effective failure localization is an essential task to ensure proper network operation and avoid service disconnections. Failure localization has typically been carried out by correlating alarms generated in several network layers. Recent advances in telemetry features of software-defined networking (SDN) architectures enable a new range of functionalities, such as early anomaly detection and soft-failure localization [1–5]. Soft failures are network anomalies that affect the network parameters but are not severe enough to trigger alarms. The detection and localization of soft failures have the potential to speed up the failure repair and mitigate service interruptions. While soft-failure *detection* is a local process, soft-failure *localization* is a network-wide process, as failures in certain network elements can generate anomalies in network parameters distributed over the entire network. A possible solution to failure localization is to operate on the network telemetry and directly localize the root-cause using if-else rules based on a dependence tree. However, particularly in disaggregated scenarios, part of the telemetry data may not be available or may not be even implemented. This can impair failure localization and require the development of more complex if-else rules. Alternatively, ML algorithms can automatically learn the rules and interpolate missing data, re-adapting its parameters to the available telemetry data set [6].

In recent work, we have developed an ML-based soft-failure localization framework shown in Fig. 1 as presented in [7], where the proposed technique was evaluated through simulations and experiments in an emulated scenario. A telemetry collector retrieves telemetry data from network elements. The telemetry data is stored in an SDN information base and sent to an artificial neural network (ANN) that processes the data and eventually locates the failure. The proposed ANN architecture has three layers: input, output, and one hidden layer. The input layer corresponds to all telemetry data collected in the network, and the output layer corresponds to all network elements that may fail. The output layer has nonlinear neurons using the Softmax activation function [3, 8]. The outputs add to one, representing an indicator about the probability that an element has failed. The ANN is trained

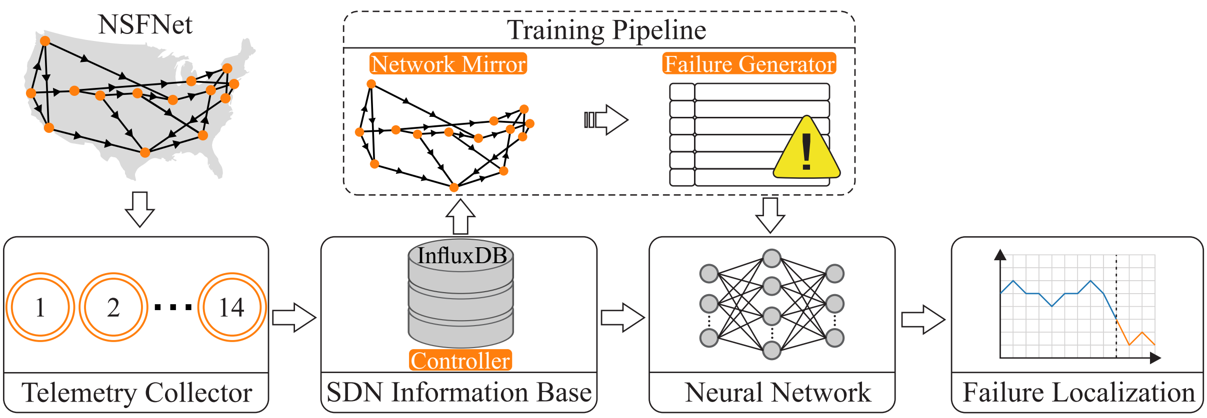


Fig. 1. ML-based soft-failure localization framework.

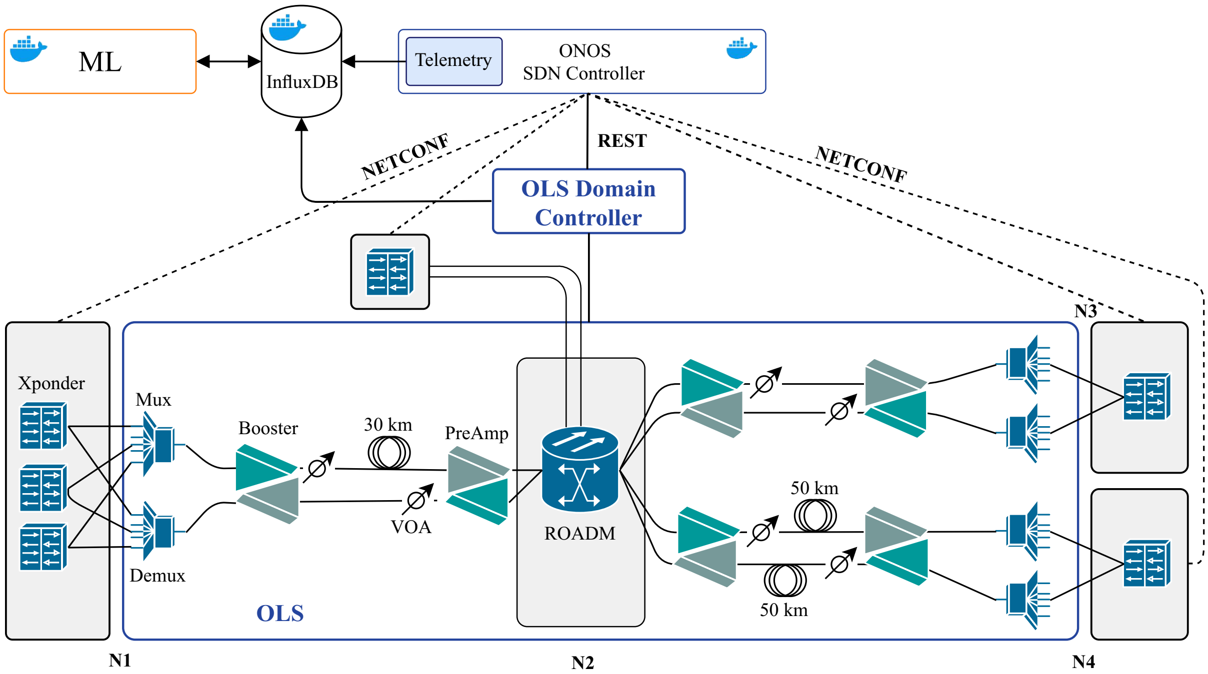


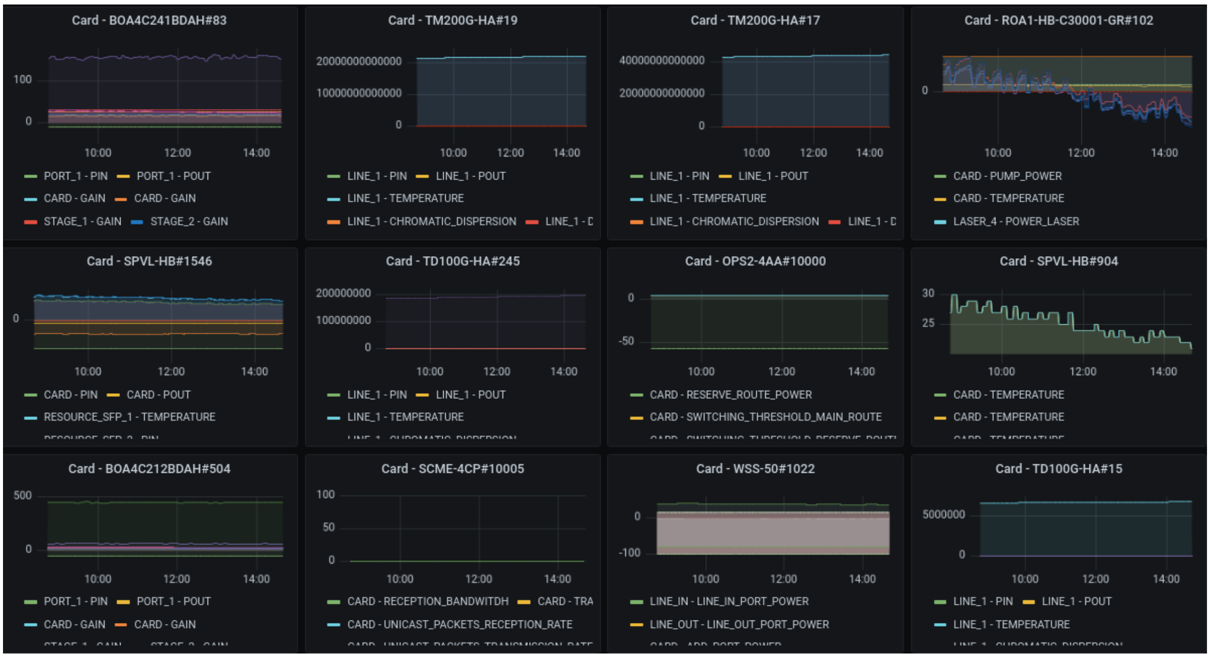
Fig. 2. OFC demonstration experimental setup for soft-failure generation and localization. SDN telemetry data retrieved from the physical testbed is stored in the time series InfluxDB database for ML-based soft-failure identification.

through a pipeline that constructs a mirror of the network. The mirror replicates the network topology, lightpaths, and telemetry data based on analytic models for power propagation. Although we use analytic models in our first studies, ML-based models for quality of transmission (QoT) estimation are also a promising approach.

Demonstration details. The focus of the demonstration is to showcase the proposed ML-based failure localization framework with SDN telemetry in a small-scale experimental network setup, as depicted in Fig. 2. The experimental testbed consists of four nodes (N1, N2, N3, and N4), three of them equipped with fixed optical add-drop multiplexers (N1, N3, and N4), and the fourth one equipped with a reconfigurable add-drop multiplexer (ROADM) with broadcast and select (B&S) architecture (N2). Nodes are interconnected by optical links with optical fibers and/or attenuators. The network is loaded with three bidirectional lightpaths, interconnecting nodes N1-N2, N1-N3, and N1-N4. Additional unmodulated unidirectional lightpaths are generated by a comb-generator in N1, with part of the lightpaths ending in N2, N3, and N4. The transponders are Padtec boards at 100 Gb/s and 200 Gb/s modulated with the QPSK, 8-QAM, and 16-QAM formats. Transponders are connected to the ONOS SDN controller by means of NETCONF/YANG interfaces. Amplifier and wavelength-selective switch (WSS) telemetry is carried out via an optical line system (OLS) domain controller. All telemetry data collected by the OLS Domain Controller and the ONOS SDN controller are stored in the InfluxDB time series database. Fig. 3 shows the telemetry time series collected from the InfluxDB and displayed with Grafana. In regular operation, both telemetry data retrieval and ML-based soft-failure localization are carried out continuously in real-time. For the OFC demonstration, we will store the telemetry data generated by the optical setup in an information base and replicate this telemetry data during the OFC demo. The demonstration will feature real-time retrieval of the stored telemetry data using SDN interfaces, the storage of the data in the InfluxDB database, and the ANN processing of the received telemetry data for soft-failure localization. Training of the ML application will run in a public cloud (Amazon Web Services). Soft and hard-failure generation will be carried out by attenuating segments of fiber, the transponder output power, and the gain of amplifiers. OFC demo attendees will be able to visualize the real-time operations of the different components (ONOS, InfluxDB, ML) by inspecting the available GUI, dashboards, and user terminals.

2. Innovation

The demonstration contains several innovative features. Firstly, we present a testbed experimental validation of a novel method for soft-failure localization leveraging state-of-the-art SDN telemetry. Secondly, we demonstrate how public cloud facilities can be used to run machine learning workloads using an ANN trained with analytic network propagation models. Thirdly, and probably most innovative, we verify the capabilities of an ML-based algorithm to localize failures not only in scenarios of full telemetry but also in the cases of partial telemetry, where certain network elements do not expose the full telemetry data.



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LOA4C211AYAHA#75	PreAmp_2_1	POUT:	1613754717073000000	19.300000
LOA4C211AYAH#2414	PreAmp_2_3	PIN:	1613754642194000000	-11.840000
LOA4C211AYAH#2414	PreAmp_2_3	POUT:	1613754642194000000	13.180000
EOA2-HA-E21211-GW#445	PreAmp_2_4	PIN (IN_LINE_IN_POWER):	1613754723886000000	-14.938000
EOA2-HA-E21211-GW#445	PreAmp_2_4	POUT (OUT_DATA_POWER):	1613754723886000000	7.037000
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LOA4C211AYAH#1480	PreAmp_1_2	POUT:	1613754415466000000	10.520000

Fig. 3. InfluxDB telemetry data displayed with Grafana (top). Data preparation to be inserted into ANN (bottom).

3. OFC Relevance

Machine intelligence and SDN-based telemetry are active discussion topics within the broader networking community and OFC specifically. Taming OPEX related to failure handling is paramount to any network operator. Our work contributes to the vision that the extensive analysis of telemetry data collected by programmatic interfaces will offer novel features beyond the current state of affairs in networks, such as, but not limited to, quality of transmission and advanced failure management. This demo represents a step forward to the applicability of machine learning to network-wide telemetry data for proactive failure handling by means of smart soft-failure localization. We expect that the demo will be of interest both to network operators and equipment manufacturers interested in exploring the possibilities of the combination of rich, up-to-date telemetry and data analytic techniques on their network to reduce OPEX and improve customer satisfaction. Academia and research-centric OFC participants will certainly value insights of our demonstration work and potentially trigger fruitful discussions to impact the OFC community roadmaps ahead.

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