Soft Failure Localization Using Machine Learning with SDN-based Network-wide Telemetry

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Abstract Targeting soft failure localization, we present a machine learning approach using SDN streaming telemetry of network-wide parameters. The artificial neural network only requires a few training scenarios to achieve adequate interpolation performance. The framework implementation is validated using gNMI telemetry in an emulated NSFNet topology.

Introduction

Machine-learning (ML) techniques are being increasingly investigated to address several problems in optical networking[1][2]. Among them, failure management is one of the most promising targets[3][4]. Recently, tackling soft failures has become an active research topic. Soft failures are degradations that cause identifiable variations on network parameters, but not severe enough to cause alarms and disrupt the service. Eventually, soft failures may evolve into hard failures. Therefore, early detection, identification, and localization of soft failures contribute to avoiding service disruptions and improve faulty device repairs.


Although several works are dedicated to soft failure detection and identification, few works address the problem of localization[13]. A soft failure (e.g., an amplifier with degrading gain) may eventually trigger anomalies in several parameters of the network, and localizing the failure is a network-wide process. Recent data-driven SDN-based optical networks[14][15] are able to collect monitoring parameters generated by a potentially vast number of network elements, such as transponders and amplifiers, and process large volumes of monitoring data with ML pipelines[16][17].

In this paper, we propose an approach to localize soft failures by means of an artificial neural network (ANN) applied to network-wide parameters collected by an SDN-based gNMI streaming telemetry architecture. We experimentally validate the proposed framework in a large-scale emulated network scenario.

Network-wide Soft Failure Localization

Figure 1 presents the proposed framework. The failure localization workflow starts by creating a snapshot mirror of the current SDN information base, including network status, physical topology, routed lightpaths, and telemetry data (TD). This information is sent to a failure generation simulator, which produces synthetic TD for all scenarios considering any possible failure in the network as inputs to train the ANN used for failure localization. This training phase must be carried out whenever there is a change in the network lightpath topology. Network elements send TD to an SDN controller streaming telemetry collector (STC) using the gNMI protocol, a gRPC based service. The STC processes and stores the collected data into an InfluxDB time-series database. The ANN module is continuously fed with the TD from InfluxDB to localize potential network failures effectively and timely. Standardized OpenConfig/YANG models are used to exchange messages and maintain the SDN information base.
Evaluation Setup

**Topology and Traffic Generation.** We evaluate the proposed soft failure localization mechanisms on the 14-node NSFNet, assuming a static traffic scenario. We assume a 4.8-THz optical link spectrum, corresponding to 96 50-GHz frequency slots (FS). We generate 1,000 demands with uniformly distributed source-destination pairs and bandwidth uniformly distributed between 1 to 4 FSs. The Dijkstra’s algorithm performs routing, and wavelength assignment follows the first-fit algorithm. From the 1,000 demands, a total of 386 demands are accepted. We assume 80-km spans with 0.2 dB/km attenuation, except for the last one, which can be shorter to yield the desired total span length. The final topology has 580 unidirectional fiber spans, with 536 in-line amplifiers, 44 pre-amplifiers, and 44 booster amplifiers. We assume broadcast and select (B&S) reconfigurable add-drop multiplexers (ROADMs) equipped with a per-channel power control loop implemented with optical channel monitors (OCMs) and wavelength selective switches (WSSs). The control loop ensures a launch power of −1 dBm per channel. The accepted 386 demands are supported by 772 transponders, implementing bidirectional connectivity. The simulated system parameters are summarized in Fig. 1 in which N is the node degree, and i is the fiber length per span.

**Monitoring Data.** The simulated traffic generation scenario features 3,564 monitoring parameters. In amplifiers, we monitor 1,248 input and output power values. In transponders, we monitor 2,316 parameters of the optical signal to noise ratio (OSNR), input power, and output power. We assume that OSNRs can be estimated from the pre-forward error correction (FEC) bit error rate (BER). We consider 1,978 devices that may fail, including 772 transponders, 624 amplifiers (pre-booster, and in-line amplifiers), and 580 unidirectional fiber spans.

**Telemetry Setup.** We assume that the downstream network node collects TD from amplifiers via an optical supervisory channel. Thus, transponder and amplifier monitoring data are streamed by a single telemetry server per node. Acting as gNMI servers, each of the 14 emulated NSFNet nodes streams every second the TD to the STC which updates the SDN information base embodied in InfluxDB. Finally, the ANN module processes the updated TD to eventually localize a faulty device.

**Failure Localization Results**

**ANN Design and Training.** Failure localization is carried out by a shallow ANN composed of three layers. The first layer has 3,564 inputs (corresponding to all collected TD), the hidden-layer has 1,000 linear neurons, and the output-layer has 1,978 nonlinear neurons with the softmax activation function, corresponding to all network elements that may fail. Z-score normalization is applied at the input to accelerate the training process and improve numerical stability. The outputs add to one, representing a probability level that the corresponding element has failed. We use a categorical cross-entropy loss function to address the ANN output error. The adaptive moment estimation of infinite order (Adamax) is applied to the backpropagation process. A network element is identified as faulty if its output exceeds 0.5. Training is performed in an x86 server (Intel(R) Xeon(R) Silver 411 CPU at 2.20 GHz, 46-GB RAM and 10 physical cores).

**Hard failure training.** We first train the ANN algorithm only considering hard failures, i.e., a transponder power equals 0 W, the attenuation of a fiber link goes to infinity, or an amplifier gain equals 0 dB. After 120 training epochs (30-min dataset generation and 2-min ANN training time), the ANN algorithm reaches a categorical accuracy of 99.75%. After the training phase, we test the ability of the ANN to localize soft failures. The results are presented in Figs. 2a, 2b, and 2c. The
Fig. 2: Soft failure localization ANN performance (accuracy %) in amplifiers (A), fiber links (F) and transponders (T). In (a), (b), and (c), the ANN is trained only for hard failures (HF), and tested with soft failures, whereas in (d), (e), and (f), the ANN is also trained with soft failure scenarios (parameter degradation of 3 dB and 10 dB).

Emulation results. Fig. 3 presents the results from the complete soft failure localization framework implementation in the emulated environment. We emulate a gain degradation in the 5th transponder in the link interconnecting NSFNet nodes 1 and 2 (Amp_1_2_5) with nominal value of 16 dB and neglecting propagation latency. The green curve with crosses shows the relative time in which the TD in Amp_1_2_5 gain degradation is generated at all NSFNet nodes. The orange line with circles shows the output of the ANN, after streaming telemetry and database processing. The ANN failure localization is triggered when the amplifier gain reaches 14 dB. The entire process of streaming telemetry, database processing, and ANN processing takes less than 1.4 seconds.

Conclusions. The obtained results demonstrate a suitable performance in soft failure localization after training an ANN with few hard and soft failure scenarios. Performance insights from the emulated environments indicate appropriate real-time performance.

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References


