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

Kayol S. Mayer(1,+), Jonathan A. Soares(1), Rossano P. Pinto(2), Christian E. Rothenberg(2), Dalton S. Arantes(1), and Darli A. A. Mello(1)

(1) DECOM, (2) DCA, University of Campinas, 400 Albert Einstein Ave., Campinas, 13083-852, SP, Brazil.
(+) kayol@decom.fee.unicamp.br

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.

Different approaches have been proposed for soft failure management. Barzegar et al.[5] monitor the performance of established lightpaths, detect anomalous behaviors, and look for correlations to localize the failure. Vela et al.[6] identify soft failures during commissioning testing and lightpath operation by monitoring optical spectrum analyzers and optical test channels. Lun et al.[7] propose a two-stage soft failure identification scheme based on a convolutional neural network and receiver DSP. Shahkarami et al.[8] identify soft failures in an experimental link by continuously monitoring the BER. Varughese et al.[9] identify the type of soft failure by applying support vector machines (SVM) to the weights of the DSP adaptive filter. Shu et al.[10] identify soft failures by monitoring the digital spectrum of connections. Wang et al.[11] and Rafique et al.[12] exploit time-series to predict soft failures.

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[14] process. Recent data-driven SDN-based optical networks[12],[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[18] 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.

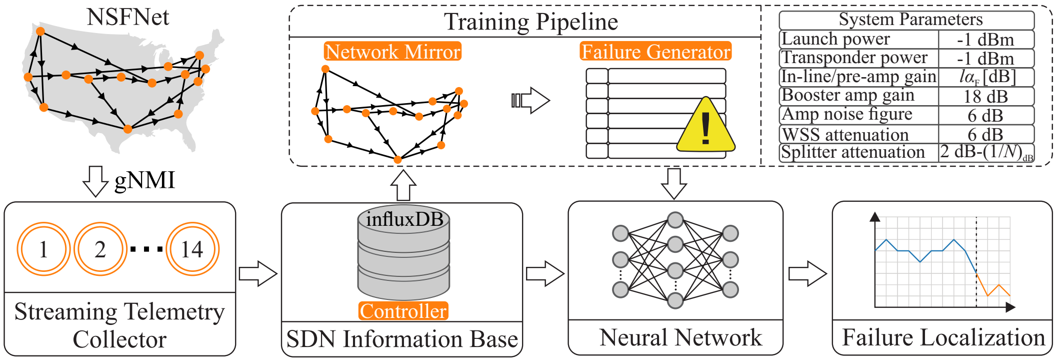

Fig. 1: Proposed network-wide soft failure localization framework.

Evaluation Setup

Topology and Traffic Generation. We evaluate the proposed soft failure localization mechanisms on the 14-node NSFNet[19], 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[20] performs routing, and wavelength assignment follows the first-fit algorithm[21]. 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 l 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[22]. 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[23] 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)[24] 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

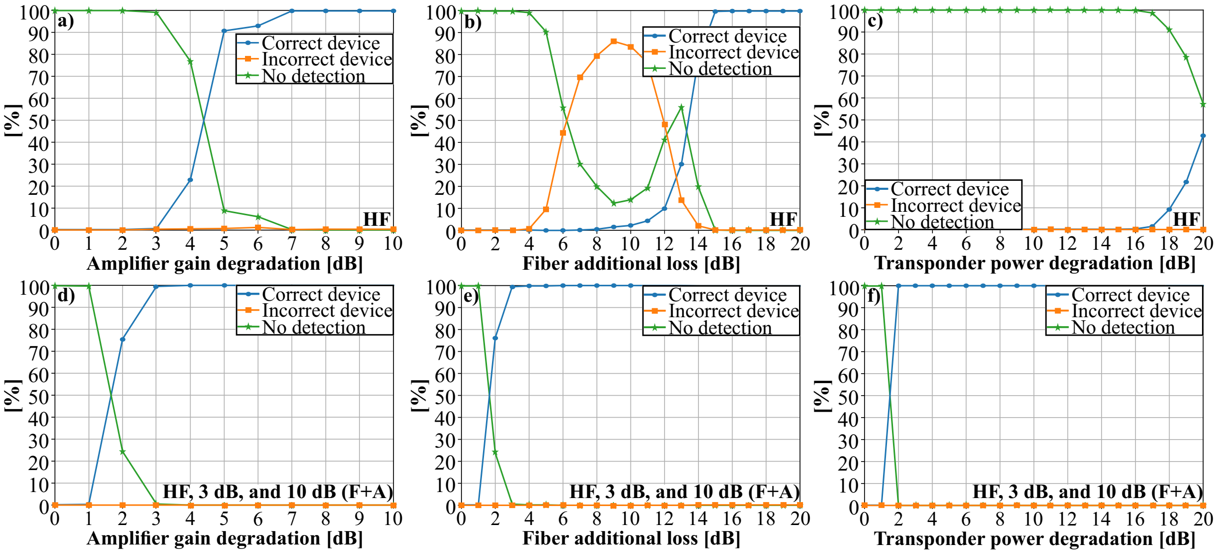

Fig. 2: Soft failure localization ANN performance (accuracy %) in amplifiers (A), fiber links (F) and transponders (T). In (a), (b), and (c), the ANN is trained only for hard failures (HF), and tested with soft failures, whereas in (d), (e), and (f), the ANN is also trained with soft failure scenarios (parameter degradation of 3 dB and 10 dB).

figures show three curves each, corresponding to the cases where the correct device is identified as faulty, the incorrect device is identified as faulty, and no failure is identified. Fig. 2a shows that, if the gain of the amplifier is degraded by more than 5 dB, the ANN is able to correctly recognize the faulty amplifier with a probability higher than 90%. The probability of incorrect device detection remains zero. Fig. 2b indicates that, upon a fiber link soft failure (e.g., additional 6 dB loss), failure in the wrong device is identified with high probability. Fig. 2c shows the results for a soft failure that reduces the output power of a transponder. Clearly, the ANN is only able to localize soft failures corresponding to high losses. Figs. 2b and 2c show that training an ANN to localize hard failures is not sufficient to localize soft failures.

Hard and soft failure training. To circumvent the observed limitations, we now train the ANN to localize some soft failure scenarios: (*i*) amplifier gain degradation of 3 dB and 10 dB, (*ii*) transponder power degradation of 3 dB, and (*iii*) fiber additional loss of 3 dB and 10 dB. Similarly, after 120 training epochs (80-min dataset generation and 6-min ANN training time), the ANN algorithm reaches a categorical accuracy of 99.59%. Figs. 2d, 2e, and 2f show the performance of the ANN trained for these soft failure scenarios. Fig. 2d shows that the ANN correctly localizes all soft failures in amplifier gains for degradations greater than 3 dB. Fig. 2e shows that it also localizes all soft failures in fiber links causing losses greater than 3 dB. Likewise, Fig. 2f shows that all transponders were correctly localized when their power reduction is greater than 2 dB.

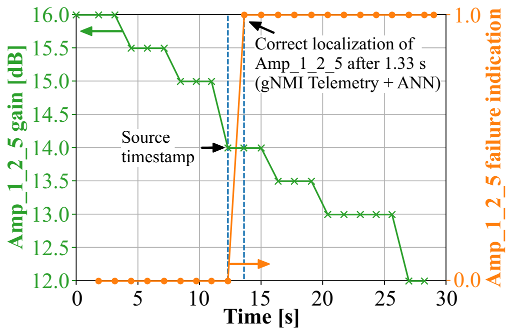

Fig. 3: Emulation results of a failure in Amp_1_2_5.

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 5^{th} 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.

Acknowledgements

This work was supported by Padtec S/A.

References

[1] F. N. Khan, Q. Fan, C. Lu, and A. P. T. Lau, “An optical communication’s perspective on machine learning and its applications”, *Journal of Lightwave Technology*, vol. 37, no. 2, pp. 493–516, 2019.

[2] F. Musumeci, C. Rottondi, A. Nag, I. Macaluso, D. Zibar, M. Ruffini, and M. Tornatore, “An overview on application of machine learning techniques in optical networks”, *IEEE Communications Surveys Tutorials*, vol. 21, no. 2, pp. 1383–1408, 2019.

[3] F. Musumeci, C. Rottondi, G. Corani, S. Shahkarami, F. Cugini, and M. Tornatore, “A tutorial on machine learning for failure management in optical networks”, *Journal of Lightwave Technology*, vol. 37, no. 16, pp. 4125–4139, 2019.

[4] N. Guo, L. Li, L. Xiang, S. K. Bose, and G. Shen, “What if AI fails: Protection against failure of AI-based QoT prediction”, in *2020 Optical Fiber Communications Conference and Exhibition (OFC)*, 2020, pp. 1–3.

[5] S. Barzegar, E. Virgillito, M. Ruiz, A. Ferrari, A. Napoli, V. Curri, and L. Velasco, “Soft-failure localization and device working parameters estimation in disaggregated scenarios”, in *2020 Optical Fiber Communications Conference and Exhibition (OFC)*, 2020, pp. 1–3.

[6] A. P. Vela, B. Shariati, M. Ruiz, F. Cugini, A. Castro, H. Lu, R. Proietti, J. Comellas, P. Castoldi, S. J. B. Yoo, and L. Velasco, “Soft failure localization during commissioning testing and lightpath operation”, *IEEE/OSA Journal of Optical Communications and Networking*, vol. 10, no. 1, A27–A36, 2018.

[7] H. Lun, M. Fu, X. Liu, Y. Wu, L. Yi, W. Hu, and Q. Zhuge, “Soft failure identification for long-haul optical communication systems based on one-dimensional convolutional neural network”, *Journal of Lightwave Technology*, vol. 38, no. 11, pp. 2992–2999, 2020.

[8] S. Shahkarami, F. Musumeci, F. Cugini, and M. Tornatore, “Machine-learning-based soft-failure detection and identification in optical networks”, in *2018 Optical Fiber Communications Conference and Exposition (OFC)*, 2018, pp. 1–3.

[9] S. Varughese, D. Lippiatt, T. Richter, S. Tibuleac, and S. E. Ralph, “Identification of soft failures in optical links using low complexity anomaly detection”, in *2019 Optical Fiber Communications Conference and Exhibition (OFC)*, 2019, pp. 1–3.

[10] L. Shu, Z. Yu, Z. Wan, J. Zhang, S. Hu, and K. Xu, “Dual-stage soft failure detection and identification for low-margin elastic optical network by exploiting digital spectrum information”, *Journal of Lightwave Technology*, vol. 38, no. 9, pp. 2669–2679, 2020.

[11] Z. Wang, M. Zhang, D. Wang, C. Song, M. Liu, J. Li, L. Lou, and Z. Liu, “Failure prediction using machine learning and time series in optical network”, *Opt. Express*, vol. 25, no. 16, pp. 18 553–18 565, Aug. 2017.

[12] D. Rafique, T. Szyrkowiec, H. Grießer, A. Autenrieth, and J. Elbers, “Cognitive assurance architecture for optical network fault management”, *Journal of Lightwave Technology*, vol. 36, no. 7, pp. 1443–1450, 2018.

[13] T. Panayiotou, S. P. Chatzis, and G. Ellinas, “Leveraging statistical machine learning to address failure localization in optical networks”, *IEEE/OSA Journal of Optical Communications and Networking*, vol. 10, no. 3, pp. 162–173, 2018.

[14] T. Pan, E. Song, C. Jia, W. Cao, T. Huang, and B. Liu, “Lightweight network-wide telemetry without explicitly using probe packets”, in *2020 INFOCOM*, 2020, pp. 2–3.

[15] A. S. Thyagaturu, A. Mercian, M. P. McGarry, M. Reisslein, and W. Kellerer, “Software defined optical networks (SDONs): A comprehensive survey”, *IEEE Communications Surveys & Tutorials*, vol. 18, no. 4, pp. 2738–2786, Oct. 2016.

[16] Y. Zhao, Y. Li, X. Zhang, G. Geng, W. Zhang, and Y. Sun, “A survey of networking applications applying the software defined networking concept based on machine learning”, *IEEE Access*, vol. 7, pp. 95 397–95 417, 2019.

[17] A. framework for machine learning in future networks including IMT-2020, ITU - International Telecommunication Union, Tech. Rep., 2019.

[18] A. Sadasivarao, S. Sayed, D. Panda, P. Gomes, R. Rao, J. Buset, L. Paraschis, J. Brar, and K. Raj, “Demonstration of extensible threshold-based streaming telemetry for open DWDM analytics and verification”, in *2020 Optical Fiber Communications Conference and Exhibition (OFC)*, 2020, pp. 7–9.

[19] H. Chen, Y. Zhao, J. Zhang, W. Wang, and R. Zhu, “Static routing and spectrum assignment for deadline-driven bulk-data transfer in elastic optical networks”, *IEEE Access*, vol. 5, pp. 13 645–13 653, Jul. 2017.

[20] I. Katib and D. Medhi, “IP/MPLS-over-OTN-over-DWDM multilayer networks: An integrated three-layer capacity optimization model, a heuristic, and a study”, *IEEE Transactions on Network and Service Management*, vol. 9, no. 3, pp. 240–253, Apr. 2012.

[21] Y. Xiao, J. Zhang, Z. Gao, and Y. Ji, “Service-oriented DU-CU placement using reinforcement learning in 5G/B5G converged wireless-optical networks”, in *2020 Optical Fiber Communications Conference and Exhibition (OFC)*, Mar. 2020, pp. 1–3.

[22] M. Soltanolkotabi, A. Javanmard, and J. D. Lee, “Theoretical insights into the optimization landscape of over-parameterized shallow neural networks”, *IEEE Transactions on Information Theory*, vol. 65, no. 2, pp. 742–769, Feb. 2019.

[23] A. Jain, K. Nandakumar, and A. Ross, “Score normalization in multimodal biometric systems”, *Pattern Recognition*, vol. 38, no. 12, pp. 2270–2285, Dec. 2005.

[24] D. P. Kingma and L. J. Ba, “Adam: A method for stochastic optimization”, in *International Conference on Learning Representations (ICLR) 2015*, May 2015, pp. 1–15.