Live Demonstration of ML-based PON Characterization and Monitoring

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Abstract: We demonstrate a machine learning-based solution for optical time-domain reflectometry devices which can assist in the classification and monitoring of reflective events in a passive optical network.

1. Overview

Due to ever-increasing demand for bandwidth-hungry low-latency services, optical networks are being deployed at both commercial and residential end-user locations. For access network deployments, passive optical networks (PONs) have emerged as a commercially viable solution [1]. However, with such a widespread deployment, automated network characterization and monitoring solutions become essential for fast and cost-efficient maintenance [2].

Network operators use optical time-domain reflectometry (OTDR) based devices to monitor their fiber infrastructure and quickly detect and localize faults such as fiber cuts. OTDR traces are commonly post-processed using signal processing techniques. These traces are usually analyzed by experienced field engineers relying on optical reflectors [3] to identify reflective events of interest. While the detection and localization of faults in point-to-point links using OTDR is straightforward, the low signal power and overlaying reflections from multiple fibers make it difficult to detect and localize faults in PONs. Furthermore, the exact topology of the PON is often unknown to network operations engineers. This increases the difficulty of distinguishing between anomalous events that represent faults and reflective events that are created by the presence of network components.

The use of machine learning (ML) based solutions been recently proposed for event detection and localization on OTDR traces in optical networks [4]. Detection and localization of pre-determined failure types has also been demonstrated [5]. However, both solutions do not cater for overlaying events in PONs.

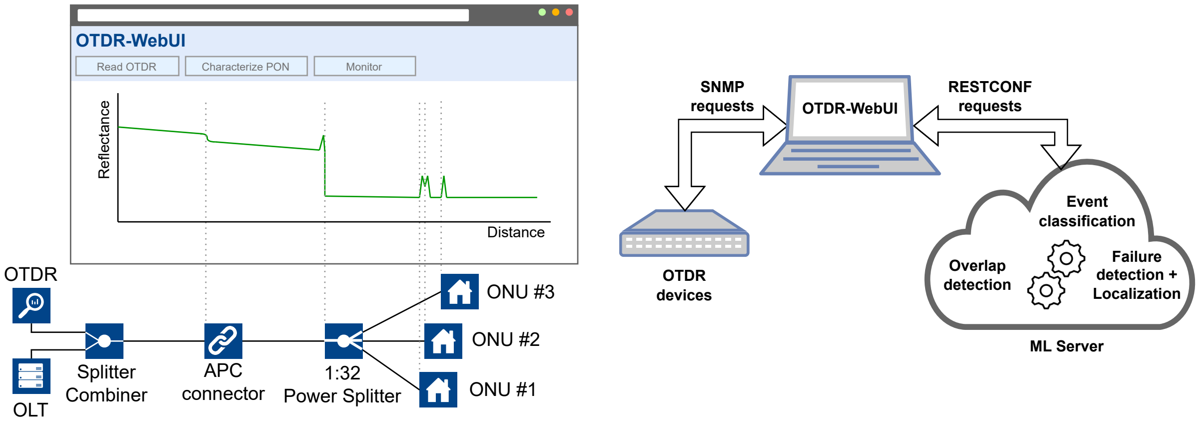
In this work, we demonstrate a unified approach of automated PON characterization and monitoring. Using OTDR traces, the PON is characterized through the classification of reflective events by a novel deep neural network (DNN) model optimized for classification and monitoring capabilities [6]. Two use-cases will be presented in this demonstration. In the first use-case, accurate characterizations will be demonstrated in the presence of overlapping reflective events in the OTDR trace. For the second use-case, the PON will be continuously monitored and trigger alarms related to fault type and location [5].

2. Innovation

In this work, a cloud-based ML solution is used to characterize PON topologies without the use of optical reflectors as shown in Fig. 1a on an example topology. Typical PON topologies consist of the optical-line terminal (OLT), a feeder-link, a $1:N$ power splitter and N distribution fibers connecting optical network units (ONUs) located near end-users [2].

Usually, due to lack of production network data, ML-based methodologies cannot guarantee accuracy of characterization results. To tackle this, a data set has been artificially extended by data augmentation techniques to represent a diverse set of PON topologies in a training data set, thereby increasing model generality. Using this approach, high accuracy is observed while characterizing PON topologies with overlayed reflection peaks.

In this demonstration, we present a DNN trained on an experimental data set which has been artificially extended by data augmentation techniques to represent a wide variety of PON topologies in a diverse training data set. A combination of using available information and logical restrictions with the DNN characterization model, accurate results in characterizing different PON topologies can be achieved. Specifically, a fully convolutional network (FCN) [7] is trained on the diversified training data set to classify reflective events in a PON. A second ML model, based on Gated Recurrent Units (GRUs) [8] is used to identify the number of ONUs in case of overlapping ONU reflections.



(a) Web-interface with PON topology

(b) Proposed setup

Fig. 1: (a) Web-interface with an example PON setup and (b) Proposed setup including the communication protocols used.

Finally, changes in the OTDR trace over time are monitored and combined with the results of the characterization for detecting and localizing faults.

3. OFC Relevance

This demonstration covers the topic categories of automated characterization of networks and the application of artificial intelligence (AI) and ML to optical networking, including autonomous network management and control.

4. Objectives and Configuration of the Demo

4.1. Experimental Setup

Different experimental PON setups can be selected in the web-interface shown in Fig. 1a. The PON topologies consists of commercially available optical line terminal (OLT) as well as an OTDR systems, combined in a splitter/combiner, entering feeder fibers of different lengths. The feeder fibers consist of multiple fibers connected through angled physical contact (APC) connectors. Each feeder fiber is connected to a $1:32$ power splitter used to connect multiple optical network units (ONUs) to the OLT. An OTDR measurement will be triggered from the web-interface to the OTDR device via Simple Network Management Protocol (SNMP [9]) as shown in Fig. 1b, thereby displaying the OTDR trace.

4.2. Characterization of PONs

We use a web server for mediating data flow as well as querying the devices as shown in Fig. 2. After the OTDR trace is displayed, the characterization of the PON setup can be triggered. As seen in Fig. 1b, the ML models are hosted on a cloud-based server and can be requested via RESTCONF protocol [10]. Accurate characterization will be demonstrated in challenging circumstances as we forgo the use of demarcation reflectors and showcase topologies where the difference in distance between the OLT and multiple ONUs is small, leading to the overlapping of reflective events in the OTDR trace.

4.3. Monitoring of PONs

Once characterized, periodical monitoring of the PON using OTDR can be triggered (Fig. 2). While this is commonly used for fiber fault detection and localization in point-to-point links, in PONs it is challenging to detect and localize faults occurring between the splitter and the ONUs as the reflections of multiple distribution fibers are overlayed in the OTDR trace. We will demonstrate the detection and localization of triggered faults, using a deep learning model and the information gained from the characterization of the PON.

5. How the demonstration will be physically set up

This demo will be composed of an experimental PON setup including an OTDR device as well as the mentioned server structure in Fig. 1b. The labeled OTDR trace as well as the monitoring data are displayed in a web-based dashboard. Each step can be triggered by using the buttons on the web interface.

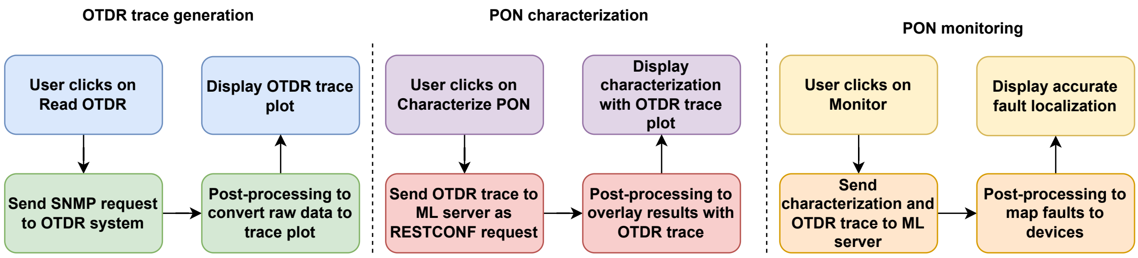


Fig. 2: Data workflow of the demonstrated use-cases

6. How the demo will be presented to the attendees

The web-based dashboard will show real-time characterization of different PON setups. Reflective events in OTDR traces will be labeled by the DNN. Continuous monitoring will allow for detection and localization of triggered faults in the network.

7. How attendees might be able to interact with the demonstration

Attendees will be able to choose one of multiple PON setups, triggering an OTDR measurement, the characterization of the network and fault monitoring using the web-based dashboard. Furthermore, faults may be triggered, showcasing the fault detection and localization capabilities.

Acknowledgements

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