AI-Based OTDR Event Detection, Classification and Assignment to ODN Branches in Passive Optical Networks

Michael Straub(1), Tarek Saier(2), Johannes Reber(2), Robert Borkowski(3), Shi Li(4), André Richter(4), Michael Färber(2), Tobias Käfer(2) and René Bonk(1)

(1) Nokia Bell Labs, Magirusstr. 8, Stuttgart, Germany, michael.straub@nokia-bell-labs.com
(2) AIFB, Karlsruhe Institute of Technology, Kaiserstr 8, Karlsruhe, Germany, tarek.saier@kit.edu
(3) Nokia Bell Labs, 600 Mountain Ave, Murray Hill, NJ, USA
(4) VPIphotonics, Carnotstr. 6, Berlin, Germany, shi.li@vpiphotonics.com

Abstract: *An AI-supported monitoring concept is demonstrated allowing detection and classification of events on OTDR traces with high precision and recall for application on a PON optical distribution network. We can also associate events with ODN branches by using deployment data of the PON topology. ©2023 The Author(s)*

Network Monitoring and Fault Detection

Event detection and classification are important features for the fiber plant of passive optical networks (PON) especially in converged architectures for residential, mobile, and business customers. Optical time domain reflectometry (OTDR) is a well-known diagnostic technique to obtain a spatially resolved attenuation profile of the fiber and to identify catastrophic fiber events, e.g., location of a fiber break. In PONs, however, the optical distribution network (ODN) can be realized as a point-to-multipoint tree-like topology. The optical line terminal (OLT), located at the operator's central office, is connected to optical power splitters in the field (feeder section). Each optical network unit (ONU) is then connected over a separate fiber connection originating at this splitter (drop section). Thus, although OTDR works well in the feeder section where only one fiber is analyzed, the part of the OTDR trace corresponding to the drop section comprises superposed signals produced by back-scattered and back-reflected light from all drop-section fibers. This superposition creates ambiguity, which cannot be decomposed to isolate individual traces of each fiber drop section without additional means. In the literature, investigations for reflective event detection and overlaid reflective event resolution have been recently reported [1, 2], but without addressing event classification along the PON ODN and event assignment to ODN branches.

Thus, in this paper we introduce a concept for OTDR trace analysis and demonstrate that we can use artificial intelligence (AI) algorithms to detect and classify events with a high precision of 98 % and recall of 95 % and that we can associate ODN branches to those events by using deployment data of the PON topology.

AI-based OTDR Event Diagnostics

The combination of an AI-supported OTDR trace monitoring with PON-specific system or topology information enables the association of events and their nature with a certain probability to ODN branches, see Fig. 1. Firstly, we use AI methods to classify each OTDR data point of an OTDR trace into an event category and, this way, associate an ODN location with an event, e.g. reflection or attenuation. Secondly, system or network information are acquired, like:

- deployment data of the ODN topology including the number of splitter stages and their split ratios and the fiber length in the drop sections,
- ranging delay for ONUs corresponding directly to approximations of the distance of the ONU from the OLT location,
- diagnostic data from all transmitters within the PON, such as transmitted and received optical power levels.

These parameters can be stored in a knowledge base to generate a reference that can either be collected over the PON lifetime or based on an abstract mathematical model that is refined using accessible information.

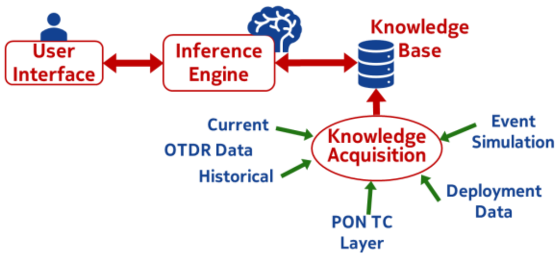

Fig. 1: Conceptual idea to combining an artificial intelligence supported OTDR trace monitoring and analysis with accessible PON-specific system data to enable associating probabilities for events and their nature to individual ODN branches of a PON.

A twofold operation of the system can be envisioned:

Instantaneous analysis: a trace (or multiple traces) collected within a short observation window is analyzed with the goal of event assignment to specific splitter branches and/or ONUs; based on deployment data and other prior information, events can be, with a certain probability, assigned to specific branches. Based on the geographical location of connected ONUs as well as deployment maps, events may be then localized topographically. Depending on what kind of OTDR measurement is possible and how much prior information is available, splitter branches where no ONU is connected, or even unused splitter branches could be identified.

Meta-analysis: tracking the evolution of instantaneous analysis / reinterpreting past observations over extended periods of time enables uncovering events that otherwise may be misinterpreted, wrongly classified, or considered improbable by a one-off instantaneous analysis due to insufficient prior knowledge. For example, a fiber break in a drop section where no ONU is connected may not be discovered by the instantaneous analysis if no deployment data was fed into the knowledge base. However, by comparing instantaneous analysis from before and after the break, a conclusion can be drawn that the observed change is an anomaly.

The knowledge base should also contain reference information on how a fiber impairment or fault, like bending, cracks, connectors, typically looks like in an OTDR trace. This way, the knowledge base is used to enable an advanced OTDR trace analysis by applying expectations and attempting to find patterns in the OTDR traces using AI techniques. The goal is the separation of the superposed events for individual optical fiber lines and the identification of changes or faults in the fiber infrastructure in the longer term.

We will demonstrate the benefits of AI here for two different reasons: in the first case (separation of traces), the AI algorithms will help to solve the mathematical problem of an underdetermined set of equations: with the OTDR measurement from OLT, one has only access to a single trace, but this signal comprises superpositions from *N* splitter branches. In the second case (identify anomalies in fiber plant), AI will help identify patterns or changes over time and the reasoning.

The inference engine can be implemented using different approaches. It can utilize probabilistic approaches, backtracking, opportunistic reasoning (backward or forward chaining), and other AI-powered approaches.

The system is trained over its lifetime, starting with a reference PON infrastructure architecture, including scenarios with different configurations like the number of splitter stages and splitting ratios. Prior knowledge and expectations on how optical fiber and PON splitters, but even more fiber breaks/cuts, reflection, open connectors, and aging/watering effects will translate into OTDR trace data, are the underlying basis for the AI training. Updates over time with detailed information about the transmission system like physical medium dependent (PMD), transmission container (TC), and media access control (MAC) can be passed to the system continuously from OLT, which acts as a master and knows all about the system. Periodic OTDR measurements over time and changes inside the PON-related data will show characteristic patterns and enable isolation of OTDR events inside the drop section of the ODN and correlate to a dedicated fiber.

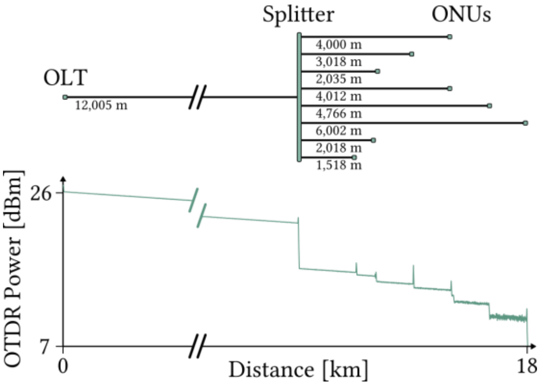

Fig. 2: Reference ODN (top) and OTDR trace (bottom).

Proof-of-Concept for Instantaneous Analysis

To demonstrate the viability of our AI-supported OTDR traces analysis system, we studied OTDR traces of a reference ODN, shown in Fig. 2. This 1:8 reference ODN fiber setup is used to acquire a total of 180 OTDR measurements with varying parameters (wavelength, pulse duration, and measurement time). These are the basis for evaluating our methods—i.e., the OTDR traces are used as model input and the events as expected model output. We pre-process the trace data by first linearizing its values and then determining the value changes between subsequent time steps. The change values are used as model input in our evaluation.

To investigate the feasibility of utilizing AI approaches, we model the task of OTDR event detection as a classification problem. A model is tasked to assign event classes (reflection, attenuation, or no event) to each point in time in an OTDR trace. This is followed by

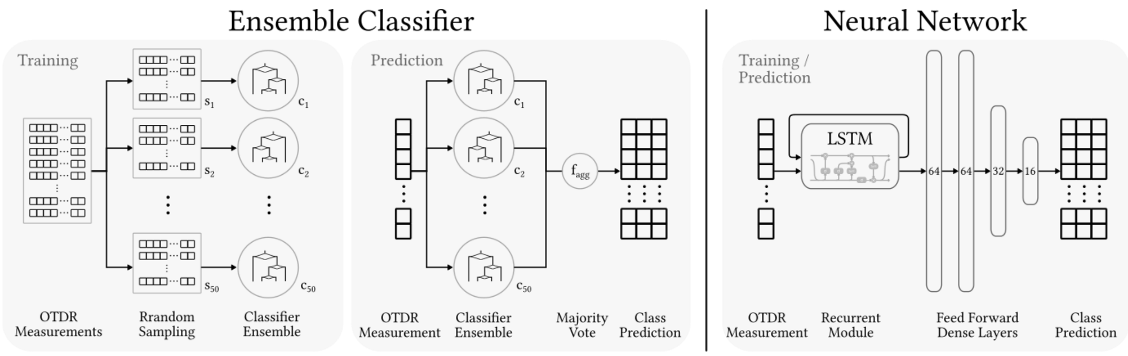

Fig. 3: AI-based methods for event detection and classification: a) ensemble classifier, b) neural network.

probabilistically assigning events to drop fibers based on deployment data.

We evaluate the performance of: (a) a simple baseline model that assigns classes based on heuristically determined rules, and (b) two machine learning (ML) models, shown in Fig. 3. The first model is an ensemble classifier, a model that learns and aggregates over multiple classifiers to improve stability. Specifically, we use a random forest [3] with an ensemble of 50 decision tree classifiers. Our second model is a neural network based on a Long Short Term Memory [4] (LSTM), an architecture that sequentially processes data while keeping a memory of previously seen inputs. To the LSTM we append a set of dense layers with decreasing dimensionality.

Evaluating all three models on our 180 OTDR traces, we measure precision and recall scores [5] as shown in Table 1. We note that the best ensemble classifier achieves the best performance, closely followed by the neural network.

Table. 1: Performance of our models at detecting and classifying events in OTDR traces. Precision and recall values are reported as the macro average over all classes.

	Precision	Recall
Baseline	52%	69%
Ensemble	98%	95%
Neural Net	96%	88%

We combine the OTDR trace event classification results of our ensemble classifier with deployment data about the knowledge of fiber length. This allows us to obtain an OTDR trace as shown in Fig. 4 in which all OTDR data points are categorized into one of the three event classes (indicated with different colors) and events can be associated with splitter location or ends of branches to single out ODN fiber connections contributing to an event.

For implementation in the field later, we envision training the AI model on large quantities of OTDR traces generated from realistic optical link simulations, while using our measurements from real PON architectures for validation and testing.

Conclusions

We have introduced and demonstrated an AI-based OTDR event detection and classification concept that if combined with PON deployment data allows to associate these events with PON ODN branches. In our proof-of-concept, we show a high precision of 98% and high recall of 95% using an ensemble classifier on measured OTDR traces and a successful mapping to ODN branches or groups of branches.

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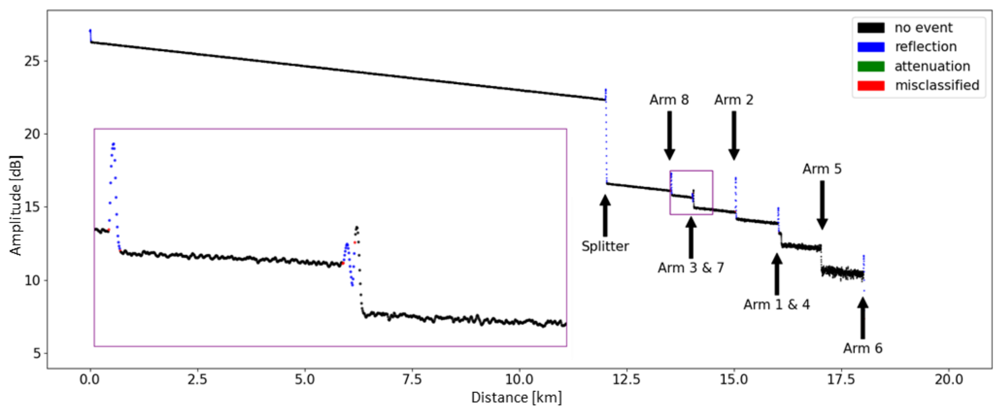

Fig. 4: OTDR traces with AI-based event classification for each OTDR data point (fiber attenuation, reflection, no event) and ODN branch probabilistic resolution using non-AI PON topology data.

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