SDN Automation for Optical Networks Based on Open APIs and Streaming Telemetry

Jelena Pesic
Nokia Nozay, France
jelena.pesic@nokia.com

Marina Curtol
Nokia Nozay, France
marina.curtol@nokia.com

Lahcen Abnaou
Nokia Nozay, France
lahcen.abnaou@nokia.com

Abdelali El Imadi
Nokia Nozay, France
abdelali.el_imadi@nokia.com

Stefano Morganti
Nokia Vimercate, Italy
stefano.morganti@nokia.com

***Abstract*— This paper provides an overview of the missing pieces currently preventing effective application of machine learning in the field. We discuss access to field data and we perform a proof of concept for the two SDN automation use cases based on programmable hardware, open APIs and streaming telemetry. The automation workflow with its performance evaluations is also presented**

***Keywords*— optical networks, field data, SDN, streaming telemetry, API.**

I. Introduction

In the last few years, the application of machine learning (ML) in the domain of optical WDM networks gained a lot of interest within the research community. In addition to multiple regular contributions, several JOCN (journal of optical communications and networking) special editions are devoted to ML [2,3], workshops [4-6], tutorials [7,8] and surveys [9-14].

Despite a huge effort from the research community, there are still some missing pieces currently preventing the application of machine learning in the field. The goal of this paper is not to provide an extensive survey but rather to highlight these missing pieces, with the goal of putting the accent on solving them in the future and to present our recent advances in the Software Defined Networking (SDN) automation process based on Application Programming Interfaces (APIs) and streaming telemetry.

II. Field Data

Machine learning is a method which completely relies on data sets. The data set can be created artificially, using simulations, generated in the lab, or retrieved from the field. Due to limited access to field data, most up to date research studies use artificial (synthetic data sets) or a combination of artificial and data from the lab. Synthetic data sets offer a vast amount of options, no limits in terms of quantity and even the possibility of simulating rare events in meaningful quantities, which is often needed for ML. The problem with these is that they are not real and insight into actual field data may give a notably different picture. One solution in the case of limited access to the data sets is the transfer learning method. On the other hand, transfer learning can be counterproductive when pre-training and testing data sets do not have enough overlapping cases in feature selections [15, 16].

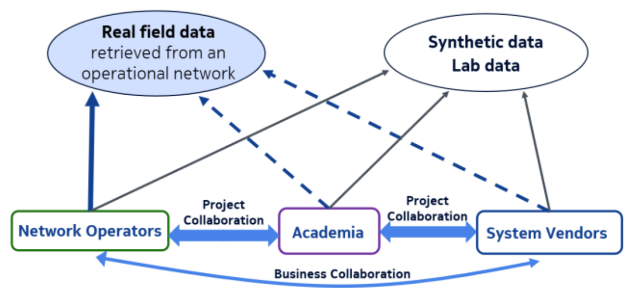

Fig. 1. Access to field data between network operators, academia, and system vendors

One question continues to appear during various workshops: “Who owns the field data and how do we obtain it?” Network operators (owners of network physical infrastructure) are data owners. Some operators, e.g., GAFAM (Google, Apple, Facebook, Amazon, Microsoft) prefer to retrieve their own data, while others team up with system and equipment vendors to retrieve data from their network, in order to create a data lake, which can be used for various purposes, like analytics, data correlation, root cause analysis, etc. Data is most often retrieved using an OpenAgent installed on optical equipment, using NETCONF/gNMI protocols.

Another challenge is that certain physical data is not monitored and therefore not retrieved from the field. All the physical parameters that have meaningful influence on (Quality of Transmission) QoT estimation should ideally be monitored. We can monitor accumulated polarization mode dispersion (PMD), accumulated chromatic dispersion (CD), signal to noise ratio (SNR), etc., notably via coherent receivers. However, despite some related studies and proposals in the research domain, methods for accurate measurement of amplifier noise figures, in-band crosstalk, filtering effects and polarization dependent loss (PDL) are today still not well-established. Besides, some of these impairments are even harder to evaluate as their harmfulness is a function of the steering state of the wavelength routing optical nodes and of the presence/absence of adjacent channels in the spectral vicinity along the light path crossed by the tested signal in transparent WDM networks.

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Another important and unsolved aspect is data confidentiality. Once gathered from the network, in order to be shared within the research community, it needs to be in a form with which operators would feel comfortable. The information needs to be untraceable on the network itself.

There were several attempts [4] to build a common data set which can be used by a large optical community for advancing research but up to now, only Microsoft has published a data set for random 4000 channels across random 115 optical paths, pulling optical signal Q-factor; transmit power; CD; and PMD, every 15 minutes [17]. Unfortunately, this data set is not complete for performing deeper analysis but represents a first step towards open data access sharing.

Another way to get access to generic field data sets for academia is via collaboration with network operators and system vendors, for instance through EU projects (Fig.1).

Field data has become synonymous with gold. Without refining it (cleaning the data set from non-usable data and putting it in a usable format) its value is not high. This requires a huge amount of work to determine which are the important parameters to measure, with which frequency and in which format.

III. SDN AUTOMATION

The importance of automating networks was summarized well in the report from STL Partners, conducted between December 2020 and February 2021, comprising a survey of 100 telecoms execs about their automation journeys [18]. The report concludes that network and service operations are the critical domains for operators to consider automating. For the average sized communication service provider (CSP), the saving from automating are equivalent to 5.7% of its total annual revenues, or $850 million, from revenue uplift, CapEx and OpEx savings (Fig. 2).

And since optical networks play such a fundamental role for many networks, automating them to support service optimization and minimal network Total Cost of Ownership will likely be key components to help unlock the benefits of broader automation initiatives.

Network operations teams often have a long list of method of procedures (MOPs), manual processes and scripts that have evolved over time. Existing automation artifacts, such as scripts, are often originally developed to address a specific pain point and are set up to run on legacy infrastructure. They may not support the long-term outcome-based business goal for automation and special care must be taken in assessing whether legacy processes and assets can be integrated into automation strategies.

In the previous work [1], we provided an overview of the missing pieces currently preventing effective application of machine learning to QoT estimation in the field. In this work, we go one step further by developing two SDN automation, proof of concept use cases, using streaming telemetry. Streaming telemetry is real-time data collection in which devices push data to a centralized location. Unlike legacy monitoring platforms such as SNMP, streaming telemetry does not only rely on collectors to continuously pull data from the network elements. Instead, network devices push and stream data continuously to collectors based on subscriptions. Both use cases are built on top of the open Application Programming Interfaces of the SDN applications. We have been using Nokia hardware for retrieving streaming telemetry, open APIs and open source automation platform Camunda [19].

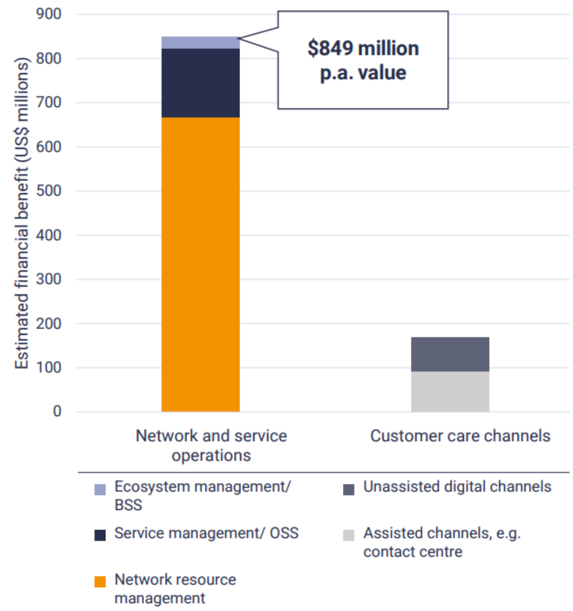

Fig. 2. Taken from STL Partners report [18] showing estimated benefits for network operators using the automation services.

The first use case of service optimization is triggered upon a detection of Q-drops using streaming telemetry while the second one is detection of span loss, using the streaming telemetry and triggering an Optical Time Domain Reflectometer (OTDR) scan for precise detection, identification and pinpointing the localization of the span loss. These are just two examples, but with the automation workflows and open APIs the possibilities become endless.

IV. THREE MAIN ELEMENTS OF SDN AUTOMATION

Hardware, programmable best in class. The success of building a software application using APIs depends on the variety and types of data that can be accessed and interpreted to perform the various tasks required by the operator. The hardware should have features and capabilities to provide a wide set of data points for software applications, which leverage the wide spectrum of collected data points.

API (Application Programming Interface). In this work, we are using SDN applications based on APIs. Development APIs based on RESTCONF and NETCONF protocols were built to be sessionless and very light on IT resources. Standard commands and procedures are sent to the network elements and a reply with requested data is sent back over short-lived interactivity sessions which do not require heavy IT resources. More details on the existing protocols and their comparison can be found in [20].

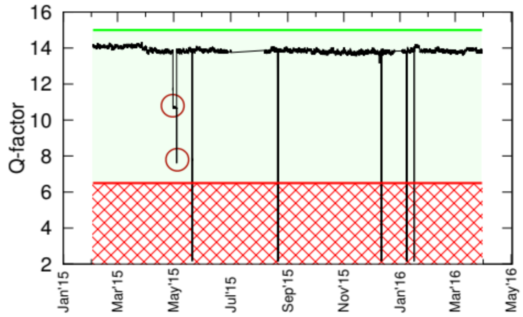

Fig. 3. Taken from [21], representing Q-factor variation of an optical channel over time. The graph is divided into healthy (solid green) and unhealthy (hashed red) areas. The circled areas are called Q-drops.

Workflows. A workflow is a system for managing processes and tasks which occur in a particular order. Automated workflow can be standardized or custom-based. We are using the Camunda, open-source platform for automating workflows. The beauty of automated workflows is that the workflow can be totally custom based.

When talking about the main elements of SDN automation it is also noteworthy to mention the considered SDN architecture. We consider a southbound interface which is the interface between SDN applications and programmable hardware and the northbound interface between SDN applications and a workflow.

V. USE CASES

A. Use case: Detection of Q-drops and service optimization

Microsoft performed an analysis based on 14 months of data, from February 2015 to April 2016, by pulling the aggregation devices for the optical signal Quality factor (Q-factor) for all 100Gbps channels taken from their optical backbone in North America [21]. The Q-factor measures the quality of an analog signal in terms of its signal-to-noise ratio (SNR). It takes into account physical impairments to the signal (e.g., noise, chromatic dispersion) which can degrade the signal and ultimately cause bit errors. Fig. 3 illustrates the Q-factor of a sample 100 Gbps channel over time. In this channel, the Q-factor is mostly stable with mean 13.8 and variance 0.3. Occasionally, the Q-factor drops to smaller values, indicating a complete loss of light or low SNR on the channel. The two circled areas in the figure mark when the Q-factor has dropped from its stable value but is still above the recovery threshold. Those events are called Q-drops. During such events, the channel is still available, and the degradation is not visible at the IP layer.

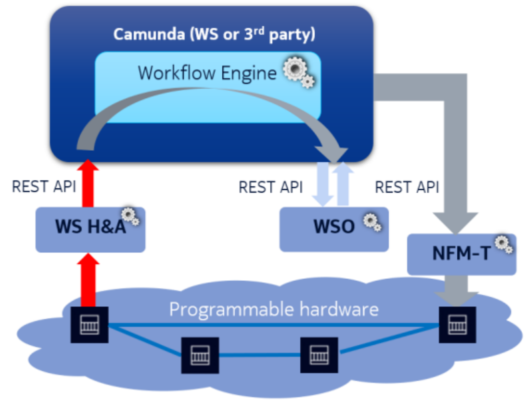

Fig. 4 Building blocks of the automation optimization use case

It has been shown that Q-drops can predict channel-level outages: if there has been a Q-drop event in the past, there is a significant jump in outage probability [21]. For example, for a window of 7 days, the probability of outage occurrence increases to 70% if there has been a Q-drop event within that week. This means Q-drop events are strong predictors of future outages.

This was one of the motivations for the work that is being presented here, with the note that we are not limited solely to Q-factor monitoring. The possibilities are endless, including detection of span loss, degradation of optical signal-to-noise ratio (OSNR) or any kind of physical degradation that might cause channel unavailability.

For this automation use case we use Nokia WaveSuite SDN applications (WaveSuite Health and Analytics, WaveSuite Optimizer and Network Functions Manager – Transport) and on

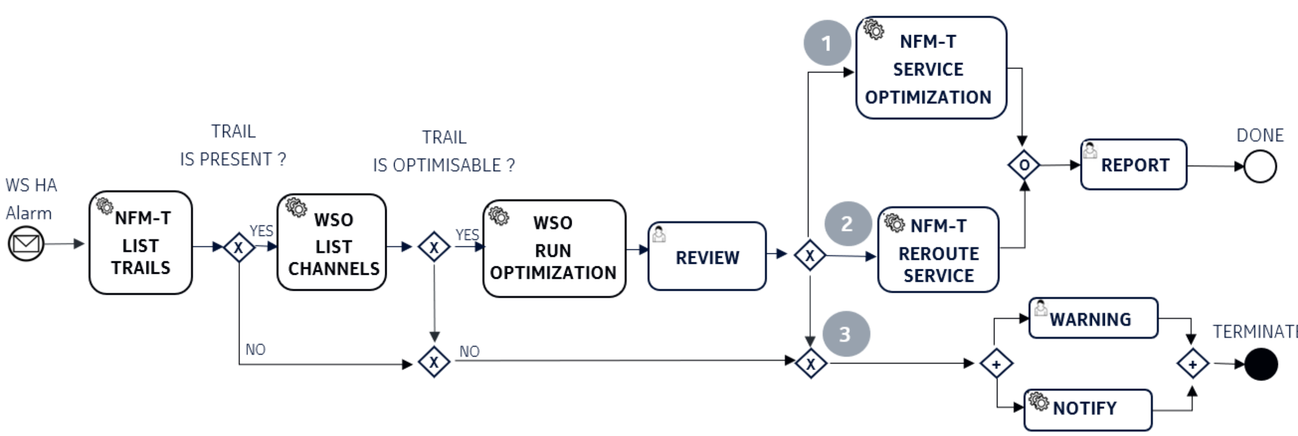

Fig. 5. Automated workflow for the optimization use case upon Q-drop detection

top of those applications we create the automated workflows for different use cases, triggered by alarms (TCA -Threshold Crossing Alarms). Since no two optical networks are the same, we developed standardized and custom-built artifacts to meet unique operator requirements. Due to geographical position, optical fibers are exposed to different impacts from the environment (next to highways, railways, higher exposure to lightning and temperature changes…).

The Nokia WaveSuite Health and Analytics (WS H&A) application helps optical network operators visualize, correlate, and learn from data. The application WS H&A, similar to other WaveSuite applications, is based on the Application Programming Interfaces (APIs), main enablers of open concepts, to build software tools and applications tailored around the operator's specific needs. We use this application for streaming telemetry directly from network elements and to orchestrate the Nokia WaveSuite SDN applications via a workflow engine. In Tab. 3 and 4 we list all the currently monitored KPIs.

The Nokia WaveSuite Optimizer (WSO) is the application which provides service connection optimization control for optical networks. The WS Optimizer enables the adjustment of programmable network capabilities. It supports adjustments based on measured transmission parameters and past wavelength performance rather than designing the network with traditional end-of-life parameters.

For this use case, the Nokia Network Functions Manager-Transport (NFM-T) enables a service to be established, deleted, and/or rerouted (all based on APIs). Description of the use case is presented in the Fig.4.

The automated workflows are based on the Camunda [19] open source automation platform. It can be also realized using any 3rd party automation platform. Graphical representation of the automation workflow for the service optimization use case is shown in Fig.5.

In general, a workflow consists of boxes which represent:

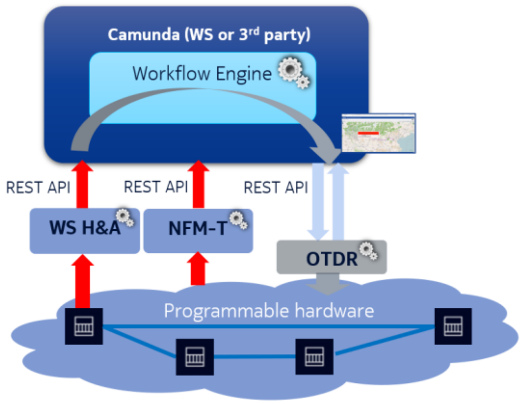

Fig 6. Building blocks of the OTDR span loss automation use case

- services tasks (boxes with circles in left upper corner),
- user tasks (boxes with human image), and
- gateways.

Service tasks represent an execution of the predefined application APIs, based on the specific use case. We use Python/Java for coding the service tasks. On the other hand, user tasks require an input from the end-user (operator) in order to proceed with the workflow. The end-user has its own allocated Camunda task list to approve or reject the recommended action(s). It is noteworthy that the automation workflow can be also designed without any user task. This would imply having a full automation and zero touch decisions to make. This process is similar to autonomous driving. Until we feel reassured, we keep our hands on "the steering wheel, even if the car is capable of self-driving". When the end-user (operator) feels reassured, we remove the human interaction. Some operators prefer to be a part of the decision process while others are ready to let go the steering wheel and benefit from a completely automated

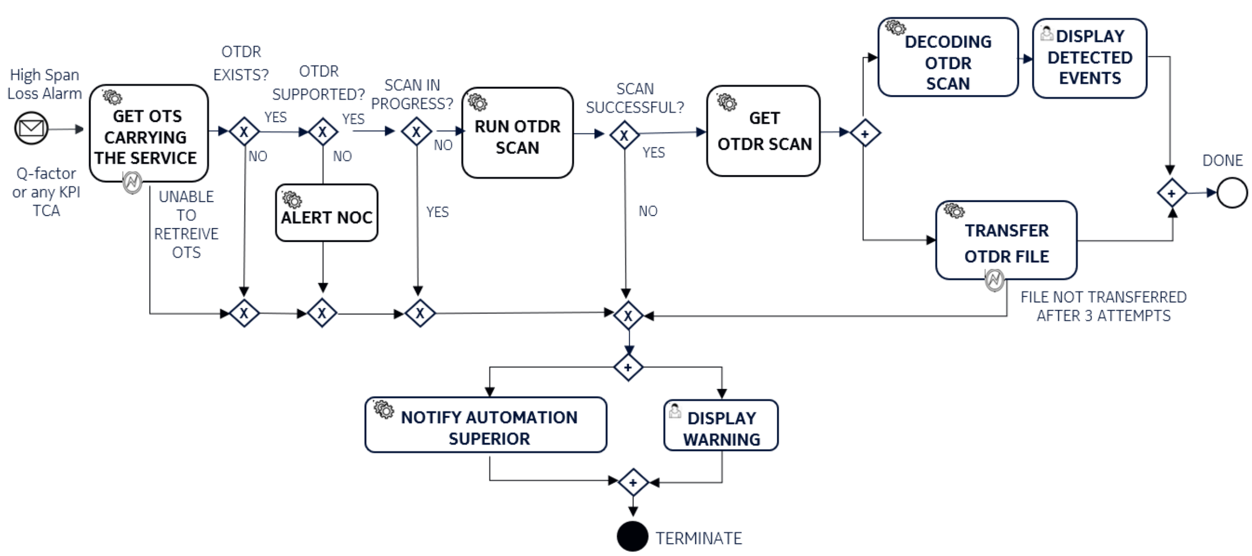

Fig. 7. Building blocks of the automation span loss detection triggering an OTDR scan use case

process. Gateways are simple logic functions such as “and”, “or” and “xor” which allow the information to flow in the diagram.

The Q-factor is retrieved every 10 seconds, directly from network elements using gNMI protocol. The gNMI protocol is an RPC-based Network Management Interface that Google created. gNMI sits on top of gRPC (Google Remote Procedure Call) open source framework messaging protocol, which acts as a transport protocol. When the signal Q-factor is detected falling below predefined custom based threshold, the workflow engine receives an alarm from the WS H&A application. We verify if the impacted service is being managed by the NFM-T.

If the trail is present in the NFM-T data base, we are checking whether the service is being supported by the WSO application.

If the impacted service is not being managed by the NFM-T, or not being supported by the WSO application, we are informing the end-user of the Q-factor drop on the given service without the possibility of performing any automated action in the network. Further actions are determined by the end-user.

If the impacted service is being supported by NFM-T and WSO, the workflow triggers optimization using the WSO application. The optimization application returns 3 possibilities (corresponding to the REVIEW box in Fig. 5). The network operator has visibility of all presented options and can chose the best one.

If the impacted service is running on the elastic transponders capable of changing modulation format/data net rate/Baud rate/FEC, the workflow offers the possibility to the end-customer of downgrading the modulation format and increasing the margin, making it more resilient to degradations.

On the other hand, if the impacted service is running on fixed transponders, the workflow offers the possibility to an end-user of rerouting the traffic, without any change of modulation format/data net rate/ Baud rate/FEC.

A service optimization report with a summary, is issued with an automatic email notification.

As mentioned, this proof-of-concept use case is based on the Q-factor streaming telemetry monitoring, but we have the possibility to perform actions on any other key performance indicator (KPI) TCA crossing. All the above-mentioned actions are performed using the Camunda platform workflow and APIs without human intervention. The only human intervention is during the decision process, although this process can be also automated, for example by using ML. If ML detects that in previous similar events, in the given circumstances, the end-user decision was to reroute the traffic, ML will learn the pattern and in the next event mimic this decision.

B. Use case: Span loss detection and triggering an OTDR scan for precise identification and localization of the problem.

Span loss is one of the parameters which directly impacts the physical performance of the channel. Dirty connectors, fiber ageing over time, or any unexpected additional attenuation, may impact the service. We believe that span loss is not a fast-varying parameter like Q-factor, Pre FEC BER or Post FEC BER and therefore we decide to monitor every span loss in the network, every 15 min. For this use case, we are using the WS H&A and the NFM-T applications together with the integrated OTDR cards. In general, the OTDR scans are being used on the fiber cut. The goal of performing the OTDR scan is to find the location of the fiber cut, to help the field team to pinpoint the fiber cut and repair it as soon as possible.

In this use case we want to benefit from the OTDR scans, not only in case of a fiber cut, but also for detection of any change of the span loss. On detection of span loss exceeding a predefined threshold, the WS H&A triggers an alarm and the workflow will try to retrieve the optical transmission section (OTS) trail of that service and perform the verification if there is an integrated OTDR (Fig. 6).

In the event of nonexistence of the OTDR cart, the workflow will inform the end-user of increased span loss on the impacted link and further investigation will be carried out by the user. If there is an OTDR, the OTDR is being triggered and (.sor) scan files retrieved from the network element. Baseline scan (.sor) is carrying the information on the span loss before detected event and is being compared with the troubleshot scan (.sor). By comparing fiber loss by section, attenuation due to splices, connectors we identify the problem and pinpoint its location. The information is presented to the end-user.

VI. PERFORMANCE EVALUATION

The performance is highly dependent on the use case implementation. For the first use case, based on the Q-factor degradation detection (Table 1), if the degradation is slowly progressive in time, the operator has enough time to plan the next steps during the prescheduled maintenance windows. On the other hand, if the Q-factor degradation is sudden, the importance of execution time from early detection to the optimization (adaptation of the modulation/data net rate/ Baud rate/FEC or rerouting) becomes important.

For the second use case, based on the increased fiber span loss detection, we consider a wider time frame (compared to the Q-factor drop), with the accent on automatic identification and localization of the problem.

Our test bed consists of eight 1830 PSS Reconfigurable Optical Add/Drop Multiplexers (ROADM) CDC-F (Colorless Directionless Contentionless with flex grid, with GMPLS enabled on the L0. We use transponders with configurable line rates (D5X500, S4X400, 2UC400, etc...) but other transponders with configurable line rates, controllable by APIs, can be equally used. The integrated OTDR card is plugged into 1830 shelf. We use the OTDR profile of 80km (Table 2) but it is noteworthy that the OTDR card has a range of profiles from 80km to 260km on 1610nm. We run the Camunda platform on the virtual machine (8 vCPU 16G RAM and 100Gb HDD) in the lab.

Table 1. Streaming Telemetry

Parameter	Protocol	Frequency
Q-factor, Pre FEC BER, Post FEC BER, Temperature, etc..	gNMI/gRPC	10s (configurable)
Span loss	SNMPv2/v3	15min (configurable)

Table 2. OTDR characteristics

Profile	Scan Time	Scan Resolution
80km	3min17s	2.5m

Table 3. KPI monitoring (native parameters)

Parameter	Protocol
Amplifier Input Power (avg)	SNMPv2/v3
Amplifier Output Power (avg)	SNMPv2/v3
Chromatic Dispersion (avg)	SNMPv2/v3
Cycle Slip Ratio (avg)	gNMI/gRPC
Differential Group Delay Received (avg)	SNMPv2/v3
Ethernet Tx BER	SNMPv2/v3
Ethernet Rx BER	SNMPv2/v3
Input Current	gNMI/gRPC
Input Voltage	gNMI/gRPC
Polarization Dependent Loss (avg)	gNMI/gRPC
Post-FEC BER (avg)	gNMI/gRPC
Pre-FEC BER (avg)	gNMI/gRPC
Q Margin (avg)	SNMPv2/v3
State of Polarization (avg)	gNMI/gRPC
Temperature (card)	gNMI/gRPC
Transponder Tx Power (avg)	SNMPv2/v3
Transponder Rx Power (avg)	SNMPv2/v3
ODU Background Block Errors	SNMPv2/v3
ODU Errored Seconds	SNMPv2/v3
ODU Severely Errored Seconds	SNMPv2/v3
ODU Unavailable Seconds	SNMPv2/v3
OTU Background Block Errors	SNMPv2/v3
OTU Errored Seconds	SNMPv2/v3
OTU Severely Errored Seconds	SNMPv2/v3
OTU Unavailable Seconds	SNMPv2/v3

Table 4. KPI monitoring (derived parameters)

Parameter	Protocol
Aging Coefficient	gNMI/gRPC
Availability	SNMPv2/v3
ESNR (avg)	gNMI/gRPC
ESNR Margin (avg)	gNMI/gRPC
ESNR Minimum Margin	SNMPv2/v3
Input Wattage	gNMI/gRPC
Q^2 Factor (avg)	gNMI/gRPC
Span Loss (avg)	SNMPv2/v3
Transponder Tx Power Deviation	gNMI/gRPC

We measure the time needed to perform the two use cases, from detection of the alarms (Q-factor drop, span loss or any other KPI TCA crossing) until the workflow termination. The optimization (first) use case can be divided into two parts: the first one until the user task box (report presented to the end-user and waiting for the human decision) and the second one from the user task decision until the workflow termination. With the current implementation, the first part is performed in 4min53s while for the second part, where the service is being optimized (from QPSK into SP-QPSK) without rerouting, 2min4s is needed. In the second part the following actions are included: delete service, delete trail, recreate trail with a new modulation format, recreate service. In case of performing the automation without any human intervention, by taking away the user task box, the total time needed would be the sum of two parts.

The total execution time for the second use case, from the detection of TCA crossing until the workflow termination takes on average 5min. This average is achieved through verification of whether the OTDR scan is ready and available every 30s. The OTDR characteristics are given in Table 2.

VII. CONCLUSION

Most legacy optical networks are still working in the "set and forget" regime. This regime applies high margins to assure non-obstructed work for a 10-year period with no, or seldom modifications. Those modifications are most often performed manually using scripts, prone to human error. These scripts are often obsolete following equipment updates. This limitation comes from legacy equipment which does not support the APIs.

New programmable infrastructure takes away that limitation, offering unlimited possibilities. In this work, we presented two automation proof of concept use cases based on the SDN network and open APIs. The goal of this study is to show some of the possibilities of the automation. Also, it can be considered as a first step toward machine learning deployment, where data is being retrieved from the field to form a data lake and predict a potential loss of service [22].

REFERENCES

[1] J. Pesic, "Missing Pieces Currently Preventing Effective Application of Machine Learning to QoT Estimation in the Field" OFC2021, M3E.5.

[2] JOCN featured edition "Machine Learning and Data Analytics for Optical Communications and Networking" 1 October 2018, Volume 10, Issue 10

[3] JOCN featured edition "Machine Leaning Applied to QoT Estimation in Optical Networks" Vol. 13, Iss. 4 -- April 1, 2021.

[4] J. Gordon et al.;: "Summary: Workshop on Machine Learning for Optical Communication Systems, "NIST SP 2100-04 (2020).

[5] "The Role of Machine Learning for the Next-generation of Optical Communication Systems and Networks," M3E, M4E at OFC2020

[6] "AI-based Optics," ACP 2020, workshop 1.

[7] R. Morais, "Machine Learning in Multi-Layer Optical Networks: Why and How," Optical Fiber Communication Conference (OFC), San Diego, CA, 2020, paper M1B.1.

[8] F. N. Khan et al.,, "Applications of Machine Learning in Optical Communications and Networks," OFC2020, paper M1G.5

[9] J. Mata et al., "Artificial Intelligence (AI) Methods in Optical Networks: A Comprehensive Survey," Opt. Switching Netw.28, 43–57 (2018).

[10] D. Rafique and L. Velasco, "Machine Learning for Network Automation: Overview, Architecture and Applications," JOCN10, D126–D143 (2018).

[11] F. Musumeci et al., "An Overview on Application of Machine Learning Techniques in Optical Networks," IEEE Commun. Surv. Tutorials 21,1383–1408 (2019).

[12] M. A. Amirabadi, "A Survey on Machine Learning for Optical Communication [machine learning view]," arXiv:1909.05148;2019

[13] R. Gao et al.,, "An Overview of ML-based Applications for Next Generation Optical Networks," Sci. China Inf. Sci.63, 160302 (2020).

[14] X. Liu et al., "AI-based Modeling and Monitoring Techniques for Future Intelligent Elastic Optical Networks," Appl. Sci.10, 363 (2020).

[15] J. Pesic et al., "Transfer Learning Using ANN for G-OSNR Estimation in WDM Network Topologies," in APC 2020.

[16] J. Pesic et al.,, "Transfer Learning from Unbiased Training Data Sets for QoT Estimation in WDM Networks" ECOC2020.

[17] https://www.microsoft.com/en-us/research/project/microsofts-wide-area-optical-backbone/

[18] Report : Prioritising Telco Network and Service Automation - Building Block Strategy (stlpartners.com)

[19] Camunda automation platform (https://camunda.com/)

[20] Ricard Vilalta et al., "Experimental evaluation of control and monitoring protocols for optical SDN networks and equipment"JOCN2021

[21] Ghobadi, Monia and Ratul Mahajan. "Optical Layer Failures in a Large Backbone." 2016 Internet Measurement Conference (2016)

[22] W. Du et al., "Forecasting loss of signal in optical networks with machine learning," in IEEE/OSA JOCN vol. 13, no. 10, pp. E109-E121, Oct.2021