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AI-Driven Proactive Fault Prediction and Restoration Leveraging Real-Time State-of-Polarization Telemetry in Live Optical Networks

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***Abstract*—Optical transport networks are evolving from communication-only infrastructures into distributed sensing platforms. Among the physical-layer observables available in coherent systems, the state of polarization (SOP) is highly sensitive to fiber perturbations caused by mechanical stress, vibrations, bending, and environmental events. These dynamics may appear before conventional quality-of-transmission indicators, such as pre-forward-error-correction bit-error rate (pre-FEC BER), received optical power, or Q-factor, exhibit service-affecting degradation. This paper proposes a closed-loop framework for proactive fault prediction and restoration based on real-time SOP telemetry. Building on a previously validated Kafka-based telemetry architecture for real-time optical sensing, the proposed workflow extends high-frequency telemetry ingestion toward ML-based perturbation detection, observability, and controller-facing restoration. The architecture combines SOP data acquisition, topic-based Kafka stream distribution, independent consumer groups, time-series storage, dashboard visualization, and an ML inference module that reads raw SOP telemetry directly from Kafka topics. The trained model classifies the temporal evolution of SOP measurements into three alarm levels associated with different degrees of mechanical perturbation severity. These compact alarms are then forwarded to the software-defined networking (SDN) control plane, which can update the network state and activate preventive restoration actions, such as rerouting over preconfigured backup paths, through standardized control interfaces. The proposed design targets disaggregated and multi-vendor optical networks, where telemetry scalability, interoperability, and low-latency decision making are essential requirements for autonomous operation.**

***Index Terms*—state of polarization, streaming telemetry, fault prediction, restoration, autonomous networking**

I. Introduction

Optical transport networks are progressively evolving beyond their traditional role as communication infrastructures. The same fiber links that carry high-capacity data traffic can also act as geographically distributed sensing media, because physical perturbations affecting the fiber leave measurable signatures on the propagated optical signal. This evolution is often framed within the broader vision of integrated sensing and communication, where optical networks are expected to support both connectivity and environmental awareness. Mechanical stress, vibrations, bending, seismic activity, and other external events can therefore become observable through physical-layer telemetry, opening new opportunities for infrastructure supervision, early-warning systems, network resilience, and autonomous control [1, 2]. This change requires a different role for optical telemetry. Conventional monitoring systems have mainly been designed for communication-oriented supervision, fault detection, and quality-of-transmission (QoT) assessment. They typically collect slowly varying parameters, such as received optical power, pre-forward-error-correction bit-error rate (pre-FEC BER), Q-factor, or optical signal-to-noise ratio, using polling-based or low-rate streaming mechanisms [3]. These approaches are sufficient for traditional network management, but they are not adequate when the network must also operate as a sensing infrastructure. Sensing-oriented telemetry may involve fast, time-dependent, and heterogeneous physical-layer streams that must be acquired close to the device, timestamped accurately, and made immediately available to analytics and control functions. A key challenge is therefore to transform physical-layer telemetry into actionable information for network operation. Different sensing observables can be exploited depending on the available equipment and on the target phenomenon, including optical phase, frequency variations, polarization-related quantities, or transmission impairments. Among them, the state of polarization (SOP) represents a practical and sensitive observable for experimental validation, because polarization dynamics react to mechanical perturbations affecting the fiber. In this paper, SOP is used as a representative sensing signal to demonstrate how real-time physical-layer telemetry can be connected to AI-based event prediction and controller-facing restoration. As shown in Fig. 1, physical-layer sensing telemetry and complementary QoT metrics are collected close to the optical layer, timestamped by a telemetry agent, and transported through a Kafka-based streaming backbone. The same raw stream is consumed in parallel by storage, visualization, AI/ML inference, and controller-facing alarm services through independent Kafka consumer groups. When the infer-

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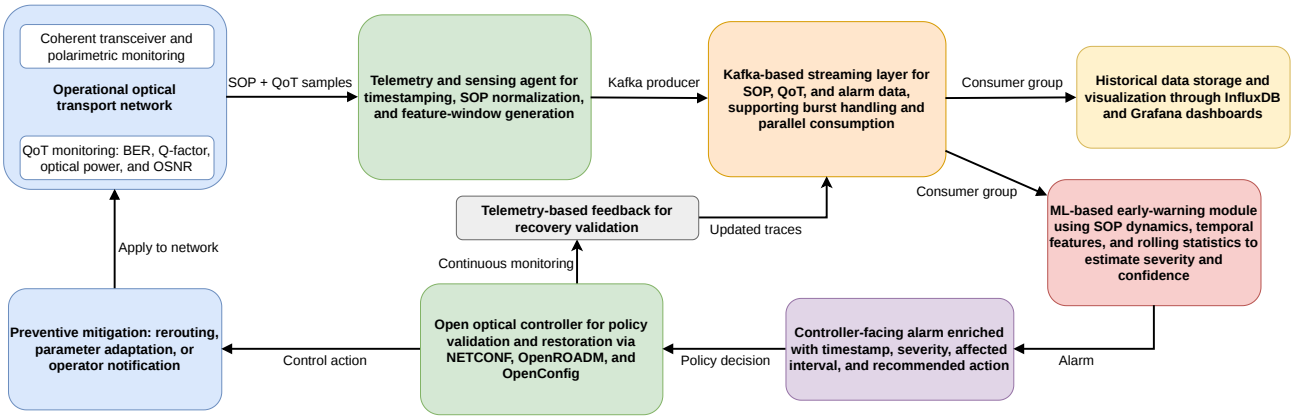

Fig. 1. Closed-loop workflow for SOP-based proactive fault prediction and restoration. High-frequency SOP/QoT telemetry is streamed through Kafka to storage, visualization, and ML inference. Detected anomalies are translated into controller-facing alarms that can trigger preventive restoration actions.

ence module detects a potentially harmful event, it produces an alarm with severity. The optical controller can then apply preventive actions, such as rerouting, before the perturbation becomes service-affecting. First, we define a telemetry-driven closed-loop workflow connecting high-frequency physical-layer sensing, Kafka-based stream distribution, AI inference, and controller-facing restoration. Second, we describe how the inference module consumes raw sensing telemetry directly from Kafka, avoiding database-centric polling in the critical decision path. Third, we experimentally demonstrate SOP-based optical-path restoration.

This work builds on our previous contributions on Kafka-based optical telemetry [4], SOP-based ML classification [5], and proactive restoration demonstration [6]. The present paper combines these elements into a unified closed-loop workflow and further details their end-to-end integration, including multi-consumer telemetry distribution, XGBoost-based perturbation classification, persistence-based alarm confirmation through five consecutive anomalous predictions, and orchestrator-driven restoration of live optical traffic over a multi-vendor reconfigurable optical add/drop multiplexer (ROADM).

II. Real-Time Telemetry and Control Workflow

The proposed workflow is organized around four functional planes: data acquisition, streaming transport, analytics, and control. The acquisition plane is implemented by a telemetry [7] agent connected either to the optical equipment or to an external sensing device. Its role is to collect physical-layer sensing measurements together with communication-oriented QoT indicators when available. In the experimental instance considered in this paper, the sensing stream is represented by SOP telemetry acquired from an optical polarimeter. A key requirement of the acquisition plane is accurate timestamping. Timestamps should be assigned as close as possible to the data generation point, before buffering, transport, or software-side processing can introduce additional uncertainty in the form of jitter.

The streaming transport plane is based on Apache Kafka [8], a distributed event-streaming platform designed to collect, buffer, and distribute high-throughput data streams. In Kafka, data are organized into *topics*, which can be interpreted as logical queues or append-only streams associated with a given class of events. A producer writes records to a topic, while one or more consumers read those records asynchronously. In the proposed workflow, the telemetry agent acts as Kafka producer and publishes raw timestamped measurements as soon as they are acquired from the optical device or sensing monitor. Each telemetry family can be mapped to a dedicated Kafka topic, for example SOP samples, QoT indicators, generated alarms, or controller events. A telemetry record contains the acquisition timestamp, source identifier, monitored link or span, and the corresponding measurement values. Once published, the same stream can be consumed by multiple independent applications without requiring repeated access to the sensing device. This is particularly important in optical sensing scenarios, where the acquisition interface should not be overloaded by concurrent requests from storage, visualization, inference, and control-facing services. Kafka also supports *consumer groups*, which allow independent services to read the same telemetry stream while maintaining separate consumption states. In this architecture, the time-series database writer, dashboard, AI/ML inference module, and alarm-forwarding service can therefore operate as separate Kafka consumers. Each service processes the stream at its own rate and maintains its own offset, so a delay in storage or visualization does not block the inference path. This decoupling enables the inference module to process recent telemetry directly from the Kafka topic, while the same raw data remain available for persistence, replay, post-event analysis, and model refinement.

Once raw SOP records are produced by the telemetry agent and written to the corresponding Kafka topic, they are no longer tied to a single downstream application. Instead, different consumers can subscribe to the same stream and process it according to their own objective, timing requirements, and computational constraints. The main consumer

considered in this paper is the ML inference module for mechanical-perturbation detection. This module reads SOP samples directly from the Kafka topic and groups them into short temporal windows. The trained model then analyzes the polarization evolution and classifies the observed event into one of three alarm levels, corresponding to different degrees of mechanical perturbation severity on the fiber. The inference module generates a compact controller-facing alarm including the timestamp, monitored link or span, predicted alarm level, confidence level, and event class. In this way, high-frequency SOP telemetry is transformed into actionable information for the control plane without requiring the controller to process the raw sensing stream. Other Kafka consumers can operate in parallel on the same telemetry topic. For example, in [4], a possible consumer is an ML-based data-compression module, which reads high-frequency sensing telemetry and reduces the amount of data to be stored or transmitted while preserving the relevant information content. This demonstrates that the Kafka-based architecture is not limited to a single analytics function, but can support multiple processing pipelines over the same raw telemetry stream. A further consumer is responsible for long-term data persistence. In the considered implementation, Telegraf reads the Kafka stream and forwards the measurements to InfluxDB, where they are stored as time-series data. This long-term storage enables offline analysis, post-event inspection, dashboard visualization, and the execution of additional algorithms on historical traces. Importantly, storage is not placed on the critical inference path: the ML perturbation detector can consume SOP samples directly from Kafka, while Telegraf independently handles persistence toward InfluxDB. This multi-consumer organization decouples real-time inference, compression, visualization, and storage. Each reader maintains its own consumption state and can operate at its own processing rate, so delays in one pipeline do not block the others. As a result, Kafka acts as a shared telemetry backbone that distributes the same raw SOP stream to the ML detector, compression modules, database connectors, and monitoring tools, enabling both low-latency event detection and long-term data exploitation.

The Kafka-based telemetry stream also supports observability functions. In the considered implementation, Telegraf forwards the acquired measurements to InfluxDB, where they are stored as time-series data and made available to visualization tools such as Grafana. This enables the creation of dashboards that correlate heterogeneous telemetry sources on a common time axis, including SOP measurements, received optical power, BER, Q-factor, generated alarms, and controller events. Such correlation is particularly useful for validating the sensing capability of SOP telemetry: mechanical perturbations on the fiber can be detected through polarization dynamics even when conventional optical indicators, such as received power or BER, remain almost unchanged. The same alarm information can also be used by the software-defined networking (SDN) control plane. In SDN, the controller maintains a global view of the network topology and of the lightpaths currently configured over each link. When an alarm associated with a specific fiber span is received, the controller can mark the corresponding link as degraded or unavailable in its internal topology representation. Since the controller also knows which services are routed through that link, it can identify the affected connections and activate the corresponding backup paths, which are typically preconfigured for protection or restoration purposes. This interaction can be supported through standardized southbound interfaces, which allow the controller to configure and monitor heterogeneous optical devices using common data models. In particular, OpenROADM provides a practical reference model for interoperable optical SDN control in disaggregated and multi-vendor environments [9]. In this way, SOP-based perturbation detection is connected to network-level resilience mechanisms without requiring the controller to process the high-frequency raw telemetry stream.

III. AI-Based Fault Prediction

The AI block used in the proposed workflow relies on a machine-learning model trained to detect mechanical perturbations on the fiber from the temporal evolution of the state of polarization. In this work, the prediction module is implemented using an XGBoost classifier. The input of the model is not a single SOP sample, but a short time window of polarization measurements acquired from the polarimeter at a sampling rate of 95.4 Hz. This input is aggregated over an effective observation window of $[10, 50]$ samples. In particular, the model exploits the Stokes parameters and the corresponding state-of-polarization angular speed (SOPAS) [2], which captures the rate of polarization rotation on the Poincaré sphere and is therefore highly sensitive to fiber vibrations, bending, and mechanical stress [5, 6]. The model is trained on labeled SOP traces generated under controlled mechanical perturbations. The dataset was divided into training and test subsets with a 70/30 split. These traces include different vibration regimes and perturbation intensities, allowing the classifier to learn the polarization fingerprints associated with different levels of fiber disturbance. The trained classifier achieved a test accuracy of 99.85% and a weighted F1-score of 0.9985 for the three alarm levels. Detailed per-class precision, recall, F1-score, and confusion-matrix results are reported in [5].

IV. Experimental Demonstration and Results

The experimental setup is hosted at the LINKS Foundation laboratories in Turin, Italy, and emulates a multi-vendor optical core network. It consists of three Adtran ROADMs connected through three bidirectional optical lines, forming a triangular topology. The corresponding spans have lengths of 520 km, 220 km, and 210 km. Real optical traffic is generated through pluggable transponders and transported over the configured lightpath.

Two service paths are available between the source and destination ROADMs. Under nominal conditions, traffic is carried over the direct one-hop path, while a two-hop path through the intermediate ROADM is pre-provisioned as a protection route. An optical polarimeter monitors the state of polarization of the transmitted signal. A robotic arm mechanically perturbs the

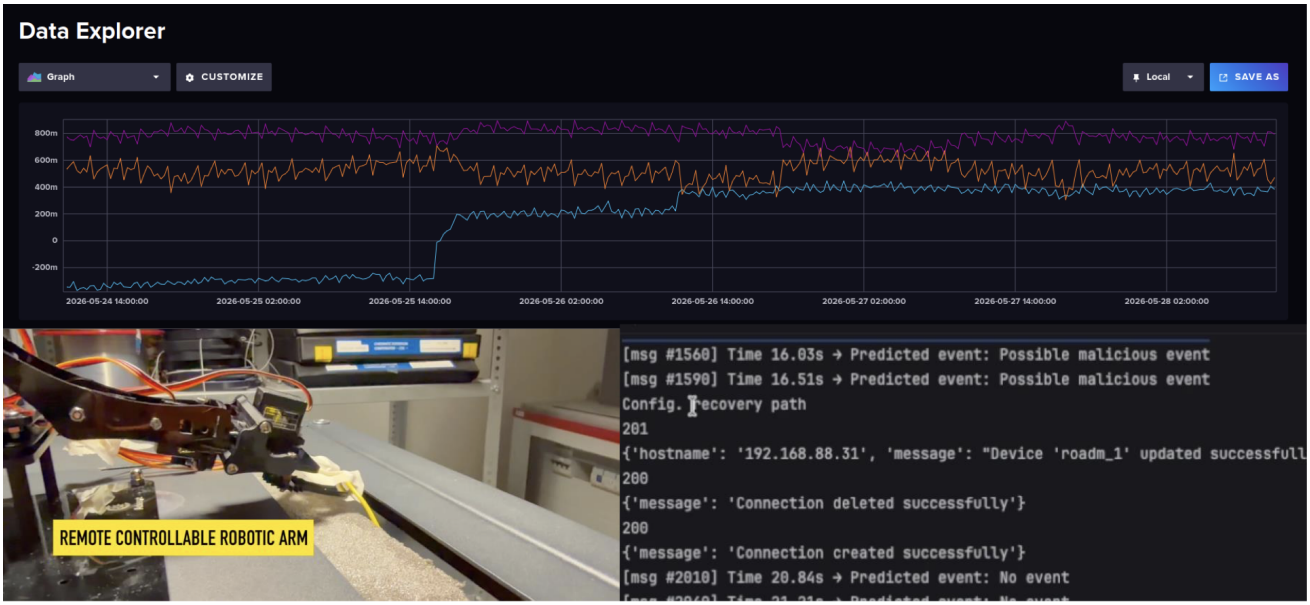

Fig. 2. Experimental demonstration of the SOP-based closed-loop telemetry and control workflow. The upper panel shows the temporal evolution of the polarimeter measurements acquired during the experiment. The lower-left panel shows the robotic arm used to introduce controlled mechanical perturbations on the fiber, while the right-hand panel reports the orechestrator logs generated during anomaly detection and restoration triggering.

monitored fiber by shaking it at variable frequencies, thereby producing controlled variations in the measured SOP.

During the demonstration, the previously described telemetry and inference pipeline continuously processed the SOP measurements acquired by the polarimeter. A single anomalous prediction is not sufficient to activate the restoration procedure. To reduce the impact of isolated false-positive classifications, the system requires five consecutive anomalous predictions before confirming the event. This persistence mechanism reduces the risk of unnecessary traffic rerouting, at the cost of an additional alarm-confirmation delay.

Fig. 2 shows the execution of the complete closed-loop procedure. The robotic arm introduces the controlled mechanical perturbation, while the polarimeter records the corresponding SOP variations. After five consecutive anomalous predictions, the alarm is forwarded to the network orchestrator. The orchestrator successfully removes the service from the affected direct path and reroutes the live optical traffic over the pre-provisioned two-hop protection path.

V. Conclusion

This paper presented a real-time SOP telemetry and AI-driven restoration workflow for autonomous optical networks. Building on a Kafka-based telemetry architecture previously validated for optical networks as distributed sensing platforms, the proposed workflow connects high-frequency SOP acquisition, multi-consumer stream distribution, machine-learning (ML)-based perturbation detection, observability, and SDN-based restoration. Future work will focus on validating the ML model over longer field traces and integrating policy-aware restoration in an open optical controller. Additional work will investigate replay-based post-event analysis, robustness against false alarms, and the trade-off between inference latency, alarm reliability, and restoration effectiveness.

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