Generalizability of ML-Based Classification of State of Polarization Signatures Across Different Bands and Links

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Abstract *We evaluate the Machine Learning (ML) model generalization for State of Polarization (SOP)-based event classification across spectral bands and links. Results show strong intra-system accuracy of up to 98.6% but limited cross-system generalizability, whereas multi-system training improves performance, highlighting the need for specific system-level knowledge.*

Introduction

Fiber optic networks, essential to modern communications for high-speed, long-distance data transmission, are increasingly used for sensing and security monitoring applications[1]. Optical fiber sensors enable high-precision monitoring by leveraging scattering, interferometric effects, and light propagation changes to detect environmental perturbations[2]. The State of Polarization (SOP) is particularly sensitive to such perturbations, making it a valuable metric for network monitoring purposes, i.e., detecting external events and anomalies that affect the physical layer in the Open Systems Interconnection (OSI) model, thereby impacting the higher layers involved in data transmission through the fibers[3].

The interest in SOP-based sensing has grown significantly in recent years, largely due to the fact that coherent receivers inherently capture polarization-resolved optical field information. This enables software-based estimation of the SOP, making SOP-based network monitoring a promising and cost-effective approach[4]. Despite this advantage, effectively interpreting SOP signatures remains a challenge. Traditional monitoring systems that rely on rules and thresholds often fail to capture the complexity of real-world fiber events, particularly those that introduce subtle or transient SOP changes[5].

To address these limitations, recent studies explored the potential of Machine Learning (ML) for detecting SOP variations caused by various disturbances, enabling more robust and intelligent sensing capabilities[6]. For instance, in our prior work, we developed approaches based on Supervised Learning (SL)[7]–[9] and Deep Learning (DL)[10] for SOP analysis to detect fiber eavesdropping and mechanical vibrations from the incurred SOP alterations on a channel using the O-band. Other studies investigated the application of ML to enhance event detection and classification in the C-band using SOP features[11]–[14]. In general, existing efforts are confined to SOP data collected from a single spectral band and link. It is however interesting to analyze how an ML model trained on a given link and band behaves when tested on a different setup.

Polarization dynamics in optical fibers is influenced by wavelength-dependent physical-layer effects such as birefringence, Polarization Mode Dispersion (PMD), and varying modal coupling characteristics. These effects can cause the SOP to evolve differently across spectral bands. Hence, knowledge about SOP features extracted in one system may not directly translate to another, raising concerns about the transferability of ML models trained on data in a specific band and link. There is a lack of studies that examine the generalization of ML model performance when they are trained on one band and fiber link and applied to a different link on a different band. This raises a fundamental question: *even if similar physical events produce qualitatively comparable SOP signatures, do ML models for event detection generalize across bands and fiber links without retraining or adaptation?* We address this question by analyzing the generalization capabilities of an ML model, eXtreme Gradient Boosting (XGBoost), in classifying SOP-based signatures across two different fiber links using two spectral bands. We collect three distinct signatures from a real-world, noisy environment of the HEAnet live metro network (which operates in the C-band)[15] and compare the results with those obtained from a field dark fiber in the O-band. XGBoost was selected due to its consistent performance in our prior SOP-based studies[7]–[9] and its superior accuracy during preliminary testing. We train one XGBoost model per system and assess their performance when tested either on the same system or on a different one. We compare the performance to a multi-band model trained on an aggregate of both systems. Our study provides the first empirical evidence of band and link dependency of the ML classifier performance, indicating that polarization-based features learned in one system may not be directly transferable to another.

Experimental setup

The experimental setup used in this study is illustrated in Fig. 1, which depicts two distinct systems designed to investigate the generalization ability of SOP-based event detection. The first system setup (labeled *System1*), operating in the O-band, consists of a 21 km (round-trip) dark fiber link accessed via the OpenIreland testbed. A Continuous Wave Distributed Feedback (CW-DFB) laser is used as the source, and the fiber under test is a standard Single Mode (SM) G.652 fiber. We used a field fiber rather than a lab spool in order to consider a more realistic noisy environment. The second system setup (labeled *System2*), operating in the C-band, is implemented over a live production metro network in the Dublin area, operated by Ireland's National Education and Research Network HEAnet[15]. Access to this network is provided via the OpenIreland laboratory at Trinity College Dublin through a dedicated dark fiber connection. The HEAnet metro ring comprises six Reconfigurable Optical Add-Drop Multiplexer (ROADM) nodes and spans a total fiber length of 77 km, and an External Cavity Laser (ELS) is used as the source. For our experiments, a 400 GHz spectral window ranging from 192.8 to 193.2 THz was allocated as a *Spectrum-as-a-Service* slice. To capture polarization signatures resulting from physical disturbances on the transmission line, we adopt the experimental setup from[10] at a wavelength in the C-band.

The transmission line is subjected to various actions that emulate real-world tampering and eavesdropping scenarios capable of inducing measurable changes in the SOP of the transmitted signal. To extract signatures for each specific event, we use the methodology from[10]. For each signature and band, SOP samples are captured every 0.5 ms over a 20-minute interval, yielding 2.4 million samples per event. Numerical Polarization State Variation (NPSV) values are computed as distances between consecutive points on the Poincaré sphere and segmented into 500-sample windows. Each segment undergoes Fast Fourier Transform (FFT) analysis with 512 frequency bins using a Hamming window[16], resulting in a power spectrum dataset with 4,800 time slots (samples) and 512 frequency bins (features). This process generates two datasets, one for each band, which serve as the input for ML-based classification.

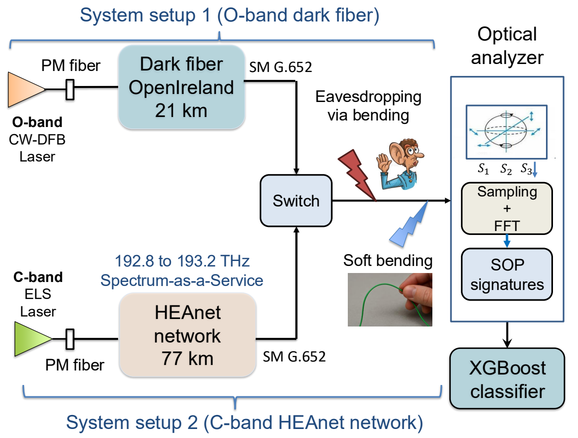


Fig. 1: A schematic of the two experimental systems used in the study. System 1 (top) shows the O-band setup and system 2 (bottom) illustrates the C-band deployment.

Collected signatures and ML pre-processing

The ML analysis is based on one dataset per band, containing three distinct event signatures: relaxed (*rlx*), eavesdropping (*eav*), and soft bending (*sbd*). *rlx* represents the baseline state of the fiber, with only background environmental noise and no intentional disturbances. *sbd* simulates non-harmful physical handling during routine maintenance where the fiber is gently bent to a radius of approximately 2 cm at 10-second intervals, mimicking typical patch-panel manipulation. *eav* models a malicious eavesdropping attempt, where the fiber is bent using a specialized coupler with a 4 mm radius and a 25-degree angle, resulting in approximately 0.3 dB attenuation and 3% signal coupling, as described in[17].

The C-band dataset from the HEAnet network contains three collected signatures denoted as rlx_2, eav_2, and sbd_2, each initially comprising 4,800 samples, resulting in a total of 14,400 data points. We applied a post-processing filtering step to the eav_2 and sbd_2 classes to remove samples collected between two consecutive events, i.e., samples that represented the fiber in a relaxed state. As a result, the filtered dataset contains 644 samples for eav_2 and 773 samples for sbd_2. An 80/20 train-test split was applied across all classes, resulting in a total of 4,973 training and 1,244 testing samples.

The O-band dataset contains the same three event signatures, denoted as rlx_1, eav_1, and sbd_1, with 4,800 samples per class, totaling 14,400 data points. This dataset did not require any filtering, as its signatures were collected with clearly separated event intervals, resulting in inherently clean and well-isolated samples. Using the same 80/20 split, this dataset yields 11,520 training and 2,880 testing samples overall.

These datasets are structured for a supervised ML classification task, where each sample is labeled according to its corresponding event class.

Tab. 1: Classification accuracy (Acc) for the different training/testing scenarios.

Scenario	Training	Testing	Acc.
S_1	System1	System1	88.85%
S_2	System2	System2	98.63%
S_3	System1	System2	8.11%
S_4	System2	System1	60.59%
S_5	System1+2	System1+2	91.11%

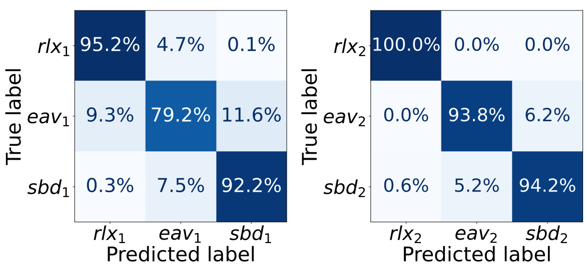
Results

We initially evaluated the performance of ten different ML classifiers from the Scikit-Learn library to identify the most suitable model for SOP-based event classification. Among them, the XGBoost classifier demonstrated superior accuracy across both O-band and C-band datasets. Thus, we limit the scope of this analysis to XGBoost.

We test XGBoost on five scenarios: S_1 (training and testing both in System1), S_2 (training and testing both in System2), S_3 (training on System1 and testing on System2), S_4 (training on System2 and testing on System1), and S_5 (training and testing on a combined dataset from both System1 and System2). Table 1 reports the classification accuracy for each scenario, with confusion matrices shown in Figs. 2 - 4.

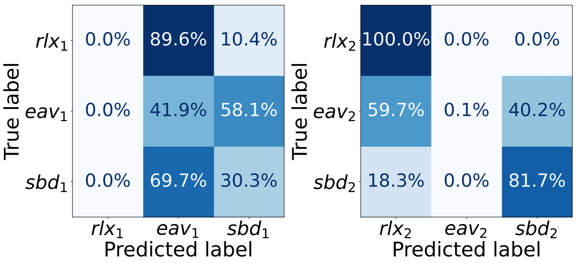
1) Intra-system classification (S_1 and S_2): The performance of the model in intra-system scenarios S_1 and S_2 is illustrated in Fig. 2. The model achieves high classification accuracy for both systems, i.e., 88.85% in System1 and 98.63% in System2 (see Table 1). In S_1 (System1), the model correctly classifies most samples, although some confusion occurs between the *eav* and the other two classes. Nonetheless, the diagonal dominance of the matrix confirms that the event classes can be distinguished by the model. In S_2 (System2), the model achieves near-perfect classification, with 100% accuracy for *rlx*, i.e., no false positives, and over 93% accuracy for *eav* and *sbd*.

2) Cross-system generalization (S_3 and S_4): The performance of the model in cross-system scenarios S_3 and S_4 is illustrated in Fig. 3. In S_3 (System1 training $\rightarrow$ System2 testing), the classifier's accuracy drops dramatically to only 8.11% (see Table 1). This performance is worse than a naive classifier, which could theoretically achieve 33.3% accuracy by random guessing. The confusion matrix in Fig. 3(a) shows that the model fails to correctly classify most of the events, assigning the majority of test samples to the class *eav*$_1$. This indicates that the SOP signatures learned by the model from System1 do not apply to System2 data. In contrast, scenario S_4 (System2 training $\rightarrow$ System1 testing) yields an accuracy of 60.59% (see Table 1), suggesting partial generalization, i.e., higher accuracy than a naive classifier. Notably, in both cross-system scenarios, one class is completely misclassified: *rlx*$_1$ in S_3 and *eav*$_2$ in S_4, which indicates a higher susceptibility of certain event signatures to misclassification when transitioning between systems. These results suggest that optical network monitoring based on SOP signatures and ML exhibits a substantial degree of system sensitivity.



(a) System1 (S_1) **(b)** System2 (S_2)

Fig. 2: Confusion matrices for intra-system classification



(a) System1 $\rightarrow$ System2 (S_3) **(b)** System2 $\rightarrow$ System1 (S_4)

Fig. 3: Confusion matrices for cross-system generalization

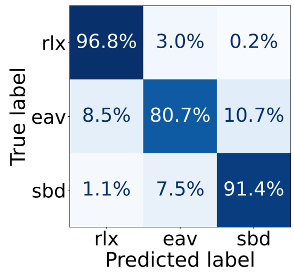


Fig. 4: Confusion matrix for multi-system classification

3) Multi-system classification (S_5): The confusion matrix in Fig. 4 illustrates strong per-class performance of the model trained and tested on a combined System1 and System2 dataset, achieving an overall accuracy of 91.11%. Despite some misclassifications, particularly between the *eav* and other classes, these results indicate that multi-system training significantly improves robustness and generalization, effectively mitigating the limitations observed in cross-system scenarios.

Conclusion

Our study on the generalization capability of ML models for SOP-based event detection indicates high accuracy (up to 98.63%) in intra-system classification, a dramatic performance drop and asymmetric generalization in cross-system, and a beneficial trade-off (91.11%) in multi-system training scenarios. To refine generalizability, in our future work we will investigate domain adaptation and transfer learning strategies.

Acknowledgements

This work was supported by the Swedish Research Council (2023–05249), the European Commission's Digital Europe Programme (101127973) through the 5G-TACTIC project, the European Union's Horizon Europe research and innovation program (10113933) through the ECO-eNET project, and by the Research Ireland grant 18/RI/5721.

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