Experimental Validation on Using Optical Network-as-a-Sensor for Earthquake Early Warning

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***Abstract*—Polarized optical signals traveling through optical networks are sensitive to environmental changes, making them suitable for capturing valuable data about their surroundings. This enables the entire optical infrastructure to function as a sensing and localization grid for earthquake early detection. In this paper, we experimentally validate the co-existence of a sensing detector with WDM traffic generators, making the proposed approach both practical and robust for real-world applications. Offline data post-processing and fine-tuning of a pre-trained machine learning method are employed to identify the pattern of polarization changes caused by the primary earthquake wave, which precedes the destructive wave by tens of seconds. To assess the system's effectiveness, we replicate, in a laboratory setup, the dynamics of a real M4.3 earthquake as a function of strain, propagating along 38 km of deployed fiber in a ring topology. The system captures two different earthquake-induced polarization datasets, showcasing that the machine learning model, pre-trained on one modality, successfully adapts to another. The model still achieves high accuracy in detecting the primary earthquake wave despite propagation challenges, demonstrating the potential for real-world integration of optical fiber networks as both high-speed communication channels and smart environmental sensors.**

***Index Terms*—Earthquakes, Early-Warning, Sensing, Optical-Networks, Machine-Learning, Polarization**

I. Introduction

In modern society, the ever-growing demand for information is driven by the increasing reliance on data for future predictions and decision-making. Optical fiber networks serve as the backbone of this information-driven society, enabling real-time analytics, predictive modeling, and automation. Beyond their conventional role in data transmission and by leveraging their sensitivity to environmental changes, optical fibers are emerging as a versatile array of sensors capable of detecting external events [1]–[4]. The integration of sensing functionality with data transmission offers a promising opportunity for cost-effective dual purpose WDM optical networks. In [5], we explored the concept of using the whole terrestrial optical network, in the form of interconnected mesh networks, as a distributed sensing and epicenter localization grid through computer-based simulations and analysis. By leveraging real M4.3 earthquake ground displacement data and a Waveplate-based polarization model integrated with a Machine Learning (ML) algorithm, the approach achieved 98% accuracy in detecting the primary earthquake wave (P-wave), and provided an early warning time window of 21 to 57 seconds for urban areas near the epicenter, with increasing lead time for locations further away, based on a triangulation method applied to locate the earthquake epicenter. Building on these findings, we replicate, in a laboratory-based setup, the State of Polarization (SoP) evolution induced by the aforementioned seismic event and allow it to propagate over 38 km of deployed fiber link in Turin, Italy. At the end of the fiber, a sensing card captures power differences in polarization components, while a polarimeter records the SoP, which is then converted into polarization angular speed. The strong correlation between power difference variations and angular speed allows the machine learning model, initially trained on angular speed data, to successfully generalize to power difference measurements. This paper demonstrates the feasibility of integrating sensing capabilities into real fiber networks, showcasing the potential of optical networks to serve as dual-purpose systems for both high-communications and smart environmental sensing despite propagation challenges. The following section presents the

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network architecture and demonstrates how a sensing card can be integrated into real networks to mimic real-world deployment. Section III details the replication of SoP evolution and card testing in a lab environment connected to the 38 km deployed fiber. Section IV focuses on the ML model and related results with performance evaluation in detecting the P-wave, while Section V concludes the discussion.

II. Network As A Sensor

To manage the rapidly changing traffic patterns, optical networks are transitioning toward dynamically reconfigurable and autonomous systems managed by a centralized intelligence - the Optical Network Controller (ONC). The ONC orchestrates network functions and communicates with network elements by means of Application Programming Interfaces (APIs), leveraging streaming telemetry for real-time network management. This approach enables the ONC to collect and analyze various metrics from network nodes, such as power levels, temperature variations from devices like amplifiers and Re-Configurable Add/Drop Multiplexers (ROADMs), and SoP changes from coherent transceivers (TRX) [6]. Beyond optimizing network management, this architecture can enable optical networks to serve as large-scale distributed sensing systems. The proposed system architecture, shown in Fig. 1, integrates several key building blocks to enable real-time environmental sensing and event detection.

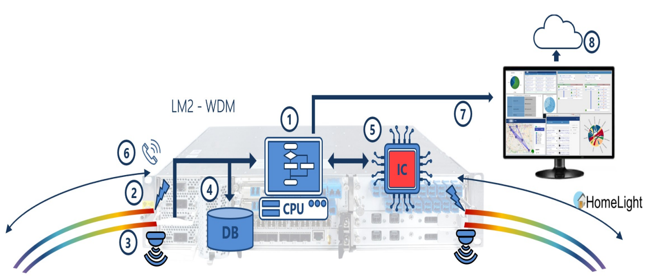

Fig. 1. Network Architecture

The system involves a powerful microprocessor for algorithm execution, a generator producing the monitored signal, a data sampling system, a database for data storage, a dedicated hardware accelerator for quick and massive data mining, a communication channel for intra-node communication, a communication channel between the Network Management System (NMS) and network elements for sensor coordination, and a north bound interface to interconnect the NMS with external applications. These components collectively create a robust framework for real-time sensing and data processing in optical networks. This system architecture reflects the envisioned future integration within optical networks. As shown in Fig. 2, the sensing card, a central component of this system, is installed in optical nodes at the edges of optical links. These optical nodes, equipped with these cards, monitor in real-time the SoP time evolution of a received polarized traffic signal. The sensing cards operate in pass-through mode, allowing the main traffic signal to continue along its optical path without significant interruption or modification, while splitting a small percentage of the signal for measurement. Each card separates the optical signal into two orthogonal polarization components and measures the power levels along the polarization axes at each time instance using two photodiodes. Additionally, each card uses another photodiode to measure the total input power logarithmically as a reference. The acquired data is temporarily stored and periodically transmitted from all six cards, as shown in the example figure, to an external server for post-processing. Processed data will be available via the NMS. Post-processing, based on edge computing, detects and classifies different seismic patterns using a pre-trained ML algorithm. Multiple nodes enable epicenter localization and correlated measurements to minimize false positive alarms. The sensing infrastructure is managed by the NMS or a domain controller within a Software-Defined Network (SDN) architecture, facilitating remote monitoring, configuration, and alarm notification. The sensing system is designed to coexist with WDM traffic-carrying optical fibers, ensuring no data security issues and no interference with communications services. Building on this framework, we aim to exploit the entire terrestrial traffic-carrying existing optical network as a distributed sensing grid for real-time environmental monitoring, particularly for early earthquake detection. Furthermore, we aim to employ a triangulation method used by the ONC to pinpoint the earthquake's epicenter and then determine each network-epicenter distance and prioritize early warning to areas close to the epicenter and progress to those further away [5].

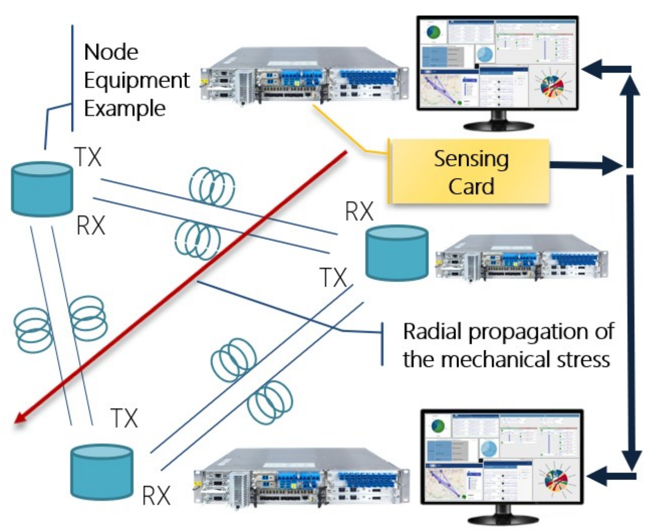

Fig. 2. Sensing Card Integration

III. Laboratory-Based Experiment

On the 23rd of May, 2012, an M4.3 earthquake struck the Modena region of Italy according to the Italian National Institute of Geophysics and Volcanology (INGV) [7]. The red circle shown in Fig. 3 marks the earthquake epicenter, while the triangles indicate the seismic stations that recorded the event. In a controlled laboratory environment, we replicate the dynamics of the M4.3 earthquake by emulating the impact of the earthquake's induced ground displacement values on light's polarization [8]. This setup involves using a tunable laser operating at an output power of 6 dbm and a wavelength of 1550 nm, an optical scrambler and a polarimeter. The optical scrambler is composed of seven waveplates with random oriented polarization axes. These orientations are adjusted according to voltages applied to each plate to match the target SoP, initially provided to the scrambler.

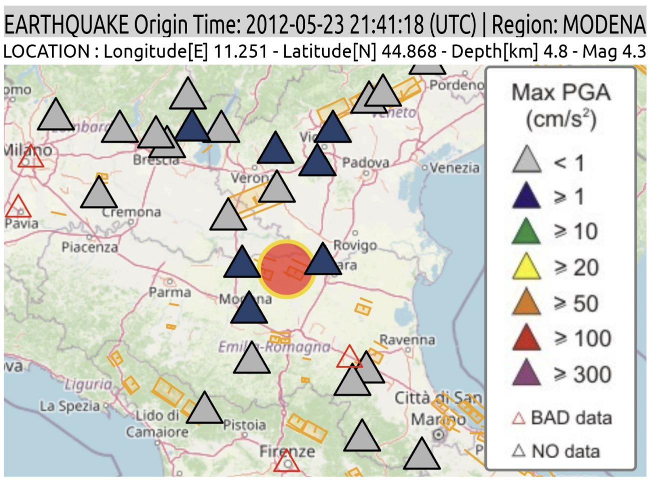

Fig. 3. M4.3 Modena Earthquake

A polarimeter captures the scrambled signal, indicating the difference between the measured and target SoPs using a feedback loop. The scrambler then adjusts new plates' orientations iteratively, applying a minimization function to gradually align the output SoP with the target. This configuration is referred to as the Back-to-Back (B2B) setup. The comparison between the set of B2B emulated SoP time evolution with the simulated ones, previously generated using the computer-based Waveplate model [9], demonstrated close alignment and exhibited strong correlation. For less complex computation, State of Polarization Angular Speed (SOPAS) was derived as a single parameter to represent the B2B polarization dynamics [10], thus dealing with one parameter instead of three. Building on these findings, we propagated the emulated SoP through a 38 km fiber ring deployed in Turin, Italy. Even though there was some discrepancy between the simulated and the propagated B2B stokes due to propagation challenges, as shown in Fig. 4, the SOPASs time evolution still fit exactly with high correlation. This ensures that the propagated SOPAS still hold earthquake information. In its current form, a sensing card acting as a datalogger and storing acquired data on internal storage for subsequent offline analysis, was placed in an optical node at the edge of the deployed optical link. Unlike the B2B setup which provides SoP stokes parameters (S1, S2, S3), the card's output consisted of measuring the power levels along polarization components over time. Additionally, we derive over time the output power differences from the output captured by the card to get the rate of change. Fig. 5 demonstrates an example of the comparison between a propagated SOPAS time evolution, recorded by a polarimeter, and the rate of change of power difference over time, captured by the card, highlighting their perfect alignment and high correlation despite propagation challenges. This alignment ensures that the ML model, pre-trained on SOPAS data, can seamlessly adapt to identify alterations in the power difference captured by the sensing card.

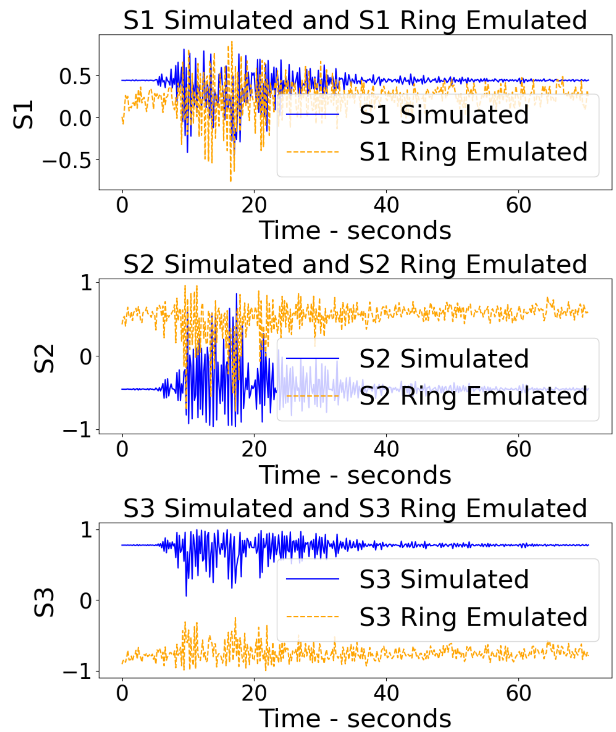

Fig. 4. Comparison of Simulated Stokes and propagated B2B Stokes

Furthermore, it maintains its ability to accurately detect the primary wave, enabling reliable early earthquake detection even when transitioning from SOPAS-based input to power difference data and from computer-based simulations to laboratory-based setup.

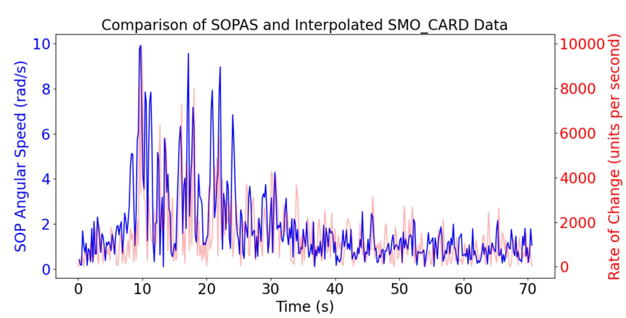

Fig. 5. Comparison of SOPAS and Card Rate of Change Data

The successful implementation of the sensing card in this experiment demonstrates its critical role in integrating sensing capabilities within optical networks. This experimental implementation provides the foundation for the future integration of real-time processing capabilities as described in Section II.

IV. Machine Learning Model and Results

We employ a deep learning-based pre-trained model to process sequential data using a stacked Long Short-Term Memory (LSTM) architecture with an attention mechanism to enhance its focus on important temporal SOPAS [11] [12]. The model begins with an input layer accepting sequences of shape (120, 1). In stacked LSTM layers, the First LSTM Layer with 64-units processes the input sequences, generating intermediate representations while maintaining sequential dependencies. A Second LSTM Layer with 128-units is used to refine the learned temporal features from the previous layer, outputting sequences for further processing. The Third LSTM Layer with 64-units is used to distill the temporal information, maintaining the sequential nature of the data. In attention mechanism, the output of the final LSTM layer is passed through a TimeDistributed Dense Layer with ReLU activation, producing attention weights for each time step. These weights are normalized using a softmax activation to calculate the importance of each step. The model computes a weighted sum of the LSTM outputs based on the attention weights, focusing on the most relevant time steps. Then, the weighted features are flattened and passed to a fully connected layer with 4 output neurons, employing a softmax activation to generate class probabilities for No Earthquake, P-wave, S-wave which is the Secondary wave, and Surface wave classification. In this study, we employ transfer learning by utilizing a pre-trained model on simulated SOPAS and an emulated B2B SOPAS dataset, and fine-tuning it on a smaller emulated B2B SOPAS dataset, which was propagated over 38 km of fiber and captured by a polarimeter, along with the rate of change of power difference dataset, which was captured by the sensing card.

This approach allows the model to adapt to real-world conditions with minimal additional training. Fine-tuning enables the model to adjust to the specific characteristics of the propagated dataset while retaining the knowledge acquired from the larger previous dataset. This transfer learning methodology enhances the model's performance and significantly reduces the reliance on extensive labeled data for training.

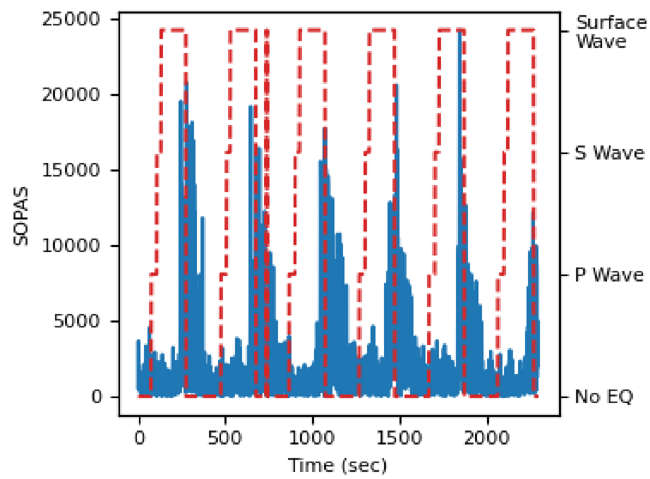

Fig. 7. Predictions on SOPAS Propagated Dataset

The study highlights how transfer learning facilitates the adaptation of a pre-trained model to new data, effectively bridging the gap between emulated SOPAS B2B and emulated rate of change of power difference dataset despite propagation challenges. Our transfer learning-based model achieves 98% accuracy, 98% precision, 98% recall and also 98% F1 score in detecting P-wave on the SOPAS propagated B2B dataset.

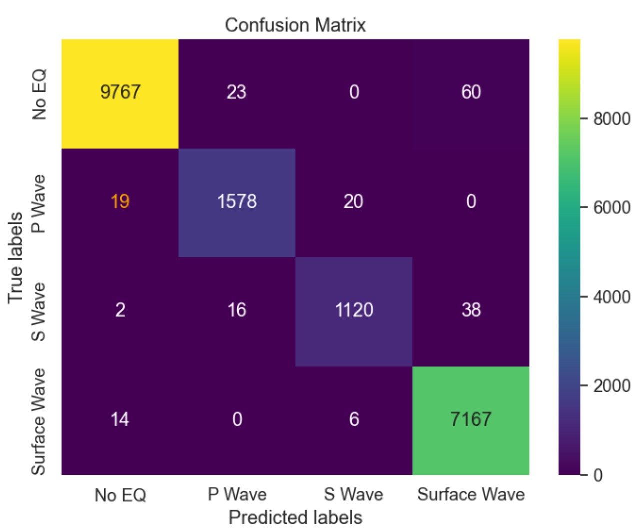

Fig. 6. Confusion Matrix for SOPAS Propagated Dataset

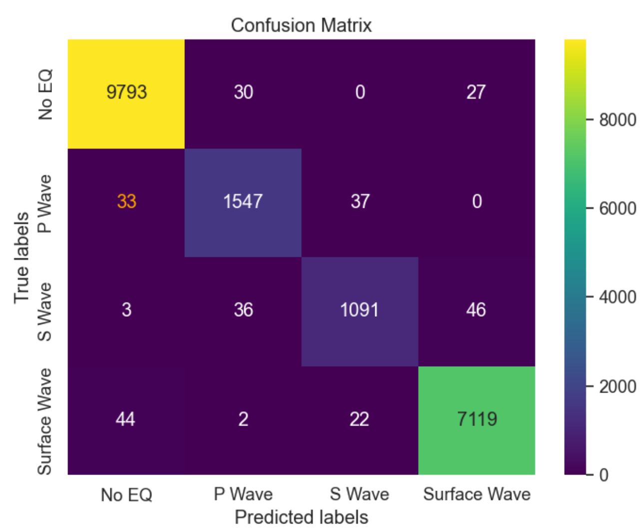

Fig. 8. Confusion Matrix for Power Propagated Dataset

The confusion matrix for SOPAS propagated B2B dataset is illustrated in Fig.6 demonstrates the model's strong performance in accurately identifying different wave types, such as "No Earthquake (No EQ)," "Primary Wave (P-Wave)," "Secondary Wave (S-Wave)," and "Surface Wave (Surface Wave)." Among 1617 primary wave events, the model successfully detected 1578, with only minor errors: 19 instances were mistakenly classified as No Earthquake, and 20 were incorrectly identified as Secondary Waves. Furthermore, Fig.7 demonstrates the model's ability to detect different seismic events predictions. Our proposed model achieves 96% accuracy, 96% precision, 96% recall and also 96% F1 score in detecting P-wave on the power difference measurements of the propagated B2B dataset as demonstrated in confusion matrix of Fig.8. Fig9 further demonstrates our model's ability to detect and classify different seismic waves. Fig. 7 and Fig. 9 show the performance of our model in detecting all events. The blue lines represent emulated B2B SOPAS data samples, Fig. 7, and rate of change of power difference measurements, Fig. 9, derived from the polarimeter and the card respectively, after the propagation over the deployed fiber. The red dashed lines indicate the model's classification output for all events, i.e., P-wave, S-wave, Surface Wave, and No EQ.

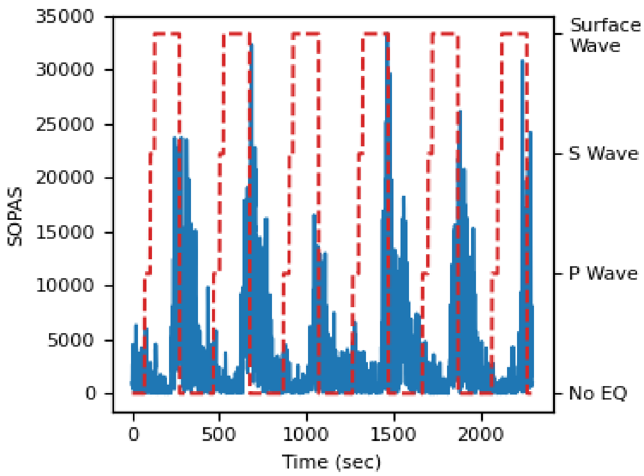

Fig. 9. Predictions on Power propagated dataset

It is important to note that the SOPAS and power difference datasets are inherently different, and the red dashed lines reflect the classification results corresponding to each dataset individually, rather than a direct overlay. This visual representation is consistent with the findings from the confusion matrices in Fig. 6 and Fig.8. These results highlight the effectiveness of our transfer learning-based approach, which achieves exceptional performance on the B2B propagated dataset and demonstrates robust adaptability when integrated with the sensing card that captures power difference fluctuations.

V. Conclusion

We demonstrate the feasibility of transforming optical networks into intelligent sensing platforms without interfering with communication services. After successfully emulating earthquake-induced state of polarization angular speed variations, the paper experimentally validates the integration of a sensing card at the edge of a deployed optical link. The card captures power differences in polarization components propagated over a deployed fiber link, confirming a strong correlation with the propagated polarization angular speed. The results highlight the potential of a pre-trained machine learning model applied to a large set of polarization data and fine-tuned on the rate of change of power difference to identify patterns corresponding to the arrival of primary earthquake wave in both datasets. The model achieved high accuracy in the early detection of a real seismic event, demonstrating its ability to generalize across different sensing modalities.

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References

[1] P. Boffi, "Sensing applications in deployed telecommunication fiber infrastructures," in *European Conference on Optical Communication (ECOC)*, J. Leuthold, C. Harder, B. Offrein, and H. Limberger, Eds., Technical Digest Series (Optica Publishing Group), pp. Mo4A.4, 2022.

[2] A. Mecozzi *et al.*, "Use of optical coherent detection for environmental sensing," Journal of Lightwave Technology, vol. 41, pp. 3350-3357, 2023.

[3] H. Awad *et al.*, "Environmental sensing and localization via SOP monitoring of IM-DD optical data channels," in *Optica Sensing Congress*, Technical Digest Series (Optica Publishing Group), pp. JTu4A.8, 2023.

[4] M. Mazur *et al.*, "Continuous fiber sensing over field-deployed metro link using real-time coherent transceiver and DAS," in *European Conference on Optical Communication (ECOC)*, pp. 1-4, 2022.

[5] H. Awad *et al.*, "Environmental surveillance through machine learning-empowered utilization of optical networks," Journal of Sensors, vol. 24, pp. 3041, 2024.

[6] H. Awad *et al.*, "A machine learning-driven smart optical network grid for earthquake early warning," in *International Conference on Transparent Optical Networks (ICTON)*, pp. 1–6, 2024

[7] Italian National Institute of Geophysics and Volcanology, "INGV," [Online]. Available:http://ismd.mi.ingv.it/ismd.php?tipo=lista. [Accessed: Apr. 20, 2024].

[8] H. Awad *et al.*, "Experimental earthquake early detection through polarization changes in intelligent optical networks," in *SPIE Photonics West* (SPIE), Proc. SPIE 13310, Optical Fibers and Sensors for Medical Diagnostics, Treatment, and Environmental Applications XXV, 133100L ,2025.

[9] F. Curti, B. Daino, G. D. Marchis, and F. Matera, "Statistical treatment of the evolution of the principal states of polarization in single-mode fibers," Journal of Lightwave Technology, vol. 8, pp. 1162–1166, 1990.

[10] S. Pellegrini, G. Rizzelli, M. Barla, and R. Gaudino, "Algorithm optimization for rockfalls alarm system based on fiber polarization sensing," IEEE Photonics Journal, vol. 15, pp. 1–9, 2023.

[11] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Computation, vol. 9, pp. 1735–1780, 1997.

[12] Y. Jia, "Attention mechanism in machine translation," J. Phys. Conf. Ser., vol. 1314, p. 012186, 2019.