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A Review of Machine Learning Enabled Distributed Fiber Optic Sensors: Principles and Applications

[1, *] Kishore DAVARAPALLI, [2] Sonu KUMAR, [3] Ganesh SABBARAPU,
[4] Nageswara LALAM, [3] Lokesh VASKA, [1] Upendra PASALAPUDI,
[5] Persis VOOLA and [1] Hanumanthu JENNE
[1] Department of Electronics and Instrumentation Engineering, University College of Engineering,
Adikavi Nannaya University, Rajamahendravaram, Andhra Pradesh-533296, India
[2] Department of Electronics Engineering, Medi-Caps University, Indore,
Madhya Pradesh-453331, India
[3] Council of Scientific & Industrial Research (CSIR)-National Geophysical Research Institute
(NGRI), Uppal Road, Hyderabad, Telangana-500007, India
[4] National Energy Technology Laboratory, Cochrans Mill Road, Pittsburgh, PA-15236, USA
[5] Department of Computer Science, University College of Engineering, Adikavi Nannaya
University, Rajamahendravaram, Andrapradesh-533296, India
E-mail: kishore.eie@aknu.edu.in

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Abstract: Distributed fiber optic sensors have gained a lot of attention due to their numerous monitoring applications in aerospace, defense, security, civil engineering, and energy monitoring over the last three decades. These examples demonstrate how useful data can be gathered from huge structures with the help of a suitable distributed sensor system for the assessment and management of the monitored structures. Recently, the use of Machine learning (ML), Artificial Intelligence (AI) into the fiber optics for advanced analytics data, rapid data processing, high sensing precision and the ability to categorize the structural events has been demonstrated considerably. The rapid advancement of ML and AI techniques has revolutionized the field of distributed fiber optic sensors, enabling unprecedented capabilities and applications. This review paper provides a comprehensive analysis of machine learning-enabled distributed fiber optic sensors, focusing on their underlying principles and diverse range of applications. This paper reviews recent developments of ML and AI algorithms integration into distributed fiber optic sensors, discussing the advantages and challenges associated with this combination. Various techniques, such as supervised learning, unsupervised learning, and deep learning, are examined in the context of distributed fiber optic sensing. Moreover, the review addresses the key challenges and limitations associated with ma-chine learning-enabled distributed fiber optic sensors, including data preprocessing, feature ex-traction, model selection, and interpretability of results. Potential solutions and future research directions are also discussed to overcome these challenges and advance the field. This analysis also discusses Potential and Perspective game-changing directions for distributed fiber optical sensor technology development on industrial applications, particularly energy systems monitoring. Possible future outlooks that can be developed with more research have also been mentioned.

Keywords: Distributed fiber sensor, AI, Machine learning, Structural health monitoring, BOTDR.

1. Introduction

Since the first successful fiber manufacturing technique was developed in the 1970s, which lowered the attenuation in optical fibers to an acceptable level below 20 dB/km, optical fibers have received a great deal of interest. In the last few decades, optical fibers have seen extensive use in a variety of high-speed, long-distance communication, imaging optics, laser gain media, and illumination applications. As one example of its usefulness, optical fibers have attracted interest around the world for their usage as sensors due to their many advantages over conventional electronic alternatives. The optical fiber sensors can demonstrate high sensitivity to the changes in physical environment like temperature, acoustic vibration, strain, pressure, current etc.

Recent advancements in machine learning (ML) have further expanded the capabilities of distributed fiber optic sensors. ML models, such as artificial neural networks (ANNs) and support vector machines (SVMs), enable efficient data processing, pattern recognition, and predictive analytics for fiber optic sensing applications. ML-assisted DFOS has shown significant potential in infrastructure monitoring, particularly in strain and vibration sensing, where ANNs improve accuracy and CNNs enhance signal denoising for long-range applications [77]. These improvements significantly enhance sensor accuracy, event detection, and anomaly prediction, making Distributed fiber optic sensor (DFOS) more reliable for real-world industrial applications.

DFOS have emerged as a powerful and versatile technology for monitoring and measuring a wide range of physical parameters along the length of an optical fiber. With the ability to provide real-time, high-resolution measurements over long distances, these sensors have found applications in various industries, including civil engineering, energy, environmental monitoring, and biomedical fields. The integration of DFOS into composite pressure vessels enhances safety, reduces maintenance costs, and enables predictive structural health monitoring [78]. The distributed fiber optic sensors have many advantages [1, 2], including immunity to electromagnetic interference, resistance to corrosion, compact size, light weight, ease of installation, and the ability to function in difficult environments.

For instance, Karapanagiotis, et al. (2023) demonstrated the use of convolutional neural networks (CNNs) for Brillouin Optical Frequency Domain Analysis (BOFDA), reducing noise and improving measurement accuracy by more than nine times compared to traditional methods [64]. Similarly, Nordin et al. (2022) explored the application of Lorentzian curve fitting and generalized linear models (GLMs) for BFS detection, significantly enhancing precision under low signal-to-noise ratio (SNR) conditions. These studies highlight the growing impact of ML in optimizing distributed fiber optic sensing systems [82].

In distributed sensing, the optical fiber serves as both the sensing element and the communication medium. By employing different sensing mechanisms, such as intensity, phase, frequency or polarization modulation, the fiber can be used to measure a wide range of physical quantities, including temperature, strain, pressure, vibration, and acoustic signals. This spatially resolved sensing capability has significant advantages, particularly in applications where localized events or changes in the physical parameter of interest need to be detected and characterized. While distributed fiber optic sensors have shown immense promise, there are still challenges to overcome. These include data preprocessing, feature extraction, model selection, and interpretability of results when integrating machine learning techniques. Fiber optic sensors (FOS) offer long-distance, high-accuracy measurement capabilities, but challenges such as cross-sensitivity, large data volume, and signal degradation require advanced ML-based solutions for optimization [74]. Efforts are being made to address these challenges and develop robust and efficient algorithms that can handle the complexity and volume of data generated by distributed sensors. A typical spectrum of spontaneously scattered light is shown in Fig. 1.

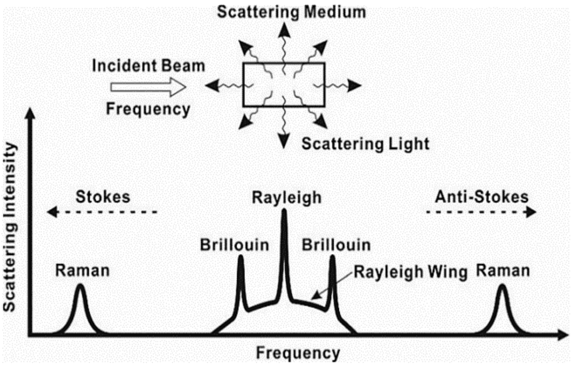

Fig. 1. Schematic representation of backscattered spectrum from the fiber under test [7].

The integration of machine learning techniques with distributed fiber optic sensors has further enhanced their capabilities and potential applications. Machine learning algorithms, such as neural networks, support vector machines, and clustering algorithms, can process and analyze the vast amount of data collected by distributed sensors in real time. Φ-OTDR has shown great potential for urban infrastructure monitoring, particularly in telecommunication networks, where CNN-based classification achieves up to 98.55 % accuracy in detecting structural events [79]. By extracting meaningful patterns and relationships from the sensor data, machine learning enables accurate predictions, anomaly detection, and intelligent decision-making. Recent advances in DFOS utilize Rayleigh, Brillouin, and Raman scattering mechanisms to enhance event classification, structural health monitoring, and environmental sensing. The integration of ML further refines event localization and real-time anomaly detection, expanding DFOS applications across geohazard monitoring and smart city infrastructure [83]. The combination of machine learning and distributed fiber optic sensors has led to significant advancements in various fields. In civil engineering, for example, these sensors are used for structural health monitoring of bridges, buildings, and pipelines, enabling early detection of potential failures and proactive maintenance. In the energy sector, distributed fiber optic sensors facilitate efficient monitoring of power grids, oil and gas pipelines, and wind turbine blades, ensuring safe and reliable operations. Additionally, in environmental monitoring, these sensors aid in detecting and mitigating pollution, tracking changes in soil conditions, and monitoring water resources. A machine learning-based approach using low-frequency DAS and DTS has demonstrated high accuracy in distributed pressure estimation, achieving an R^2 of 0.96. This technique enhances real-time monitoring in deep-well applications, optimizing gas injection and water circulation processes [85].

Shiloh et al. (2019) utilized generative adversarial networks (GANs) to generate synthetic training datasets for DAS-based event detection. Their approach significantly improved ANN performance in long-range fiber optic sensing applications, demonstrating the transformative role of ML in advancing DFOS technologies [81]. Additionally, Sun et al. (2024) introduced a Noise Adaptive Mask-Masked Autoencoder (NAM-MAE) for underwater acoustic monitoring, achieving 96.61 % classification accuracy in noisy environments [89].

This paper aims to provide a comprehensive review of machine learning-enabled distributed fiber optic sensors, exploring their principles, applications, and challenges, and highlighting the potential for future advancements in this exciting field.

2. Machine Learning Enabled Brillouin-based Distributed Fiber Sensors

Brillouin-based distributed fiber sensors have got a lot of attention recently because of its long sensing range (tens of kilometers) and excellent accuracy (accuracy within a few percent) for measuring both strain and temperature. These sensors use the pulse time-of-flight technique to pinpoint their location, simultaneously taking advantage of the linear dependence of Brillouin frequency shift (BFS) on strain and/or temperature along the fiber length. Brillouin optical time domain reflectometry (BOTDR) and Brillouin optical time-domain analysis (BOTDA) are two methods that have been studied extensively in relation to Brillouin-based distributed fiber sensors [3, 4]. It is easier to construct BOTDR, which only needs access to one end of the sensing fiber, than BOTDA, which has a far greater sensing range but requires knowledge of both ends of the fiber.

Karapanagiotis et al. (2023) introduced a CNN-based signal post-processing method for Brillouin Optical Frequency Domain Analysis (BOFDA). This method achieves over nine times faster temperature measurements compared to Lorentzian curve fitting, significantly enhancing real-time monitoringcapabilities. Their work demonstrates the potential of CNNs in reducing noise and improving measurement efficiency in Brillouin-based sensing systems [64].

Nordin et al. (2022) explored the sequential use of Lorentzian curve fitting, backward correlation techniques, and generalized linear models (GLMs) to improve BFS detection accuracy under low signal-to-noise ratio (SNR) conditions. Their approach significantly enhanced BFS measurement precision, particularly for structural health monitoring applications [82].

The BOTDR system is further hindered by polarization noise, which reduces its performance. To a large extent, the oscillations in the beat signal, and consequently the measurement inaccuracy, are affected by the polarization noise. The beat signal is strongest when the local oscillator (LO) signal and observed Brillouin signal have the same polarization state, and weakest when the polarization states are orthogonal to one another.

Pedraza et al. (2023) introduced deep neural networks (DNNs) to decouple temperature and strain measurements in Brillouin-based sensors. Their ML-based approach eliminates the need for specialized fibers and improves sensing accuracy, making it a viable solution for high-resolution distributed sensing [87]. Furthermore, Huynh et al. (2023) applied XGBoost algorithms for real-time seismic event detection in DAS data, demonstrating high accuracy in identifying low-magnitude earthquakes and quarry blasts [86].

A polarization scrambler, which randomizes the polarization states and, on average, covers all polarization states, is the most used tool for reducing polarization noise [5]. A polarization scrambler, on the other hand, is an active device that adds noise to the system and is quite pricey. The average polarization states must be covered by the scrambled polarization states, and this requires a sophisticated design. That's why, in this article, a cheap and easy passive depolarizer [6] to drastically reduce polarization noise.

If the medium's optical properties don't fluctuate throughout the operation, optical scattering is referred to as spontaneous. The intensity of the incident light is usually quite weak for spontaneous scattering to take place and is brought on by variations in the medium's optical, thermal, and quantum mechanical densities. When the optical characteristics of the medium are changed by contact with the incident light, optical scattering is considered to be stimulated scattering. As a result, stimulated light scattering typically takes place at greater intensities, where changes in material properties are brought on by the incident light itself. The value and performance resulting from the application of each of these scattering concepts in various energy-related domains will be examined. Scattering principles are distinct and helpful in distributed fiber optic sensing.

By leveraging machine learning, Pedraza et al. (2023) demonstrated the feasibility of decoupling temperature and strain using deep neural networks (DNNs) in Brillouin-based sensors. Their approach eliminates the need for specialized fibers, enhancing sensing accuracy and reliability in high-resolution distributed systems [87].

Shiloh et al. (2019) utilized generative adversarial networks (GANs) to generate training datasets for distributed acoustic sensing (DAS) systems. This innovative approach significantly enhanced the performance of artificial neural networks (ANNs) for event detection in long-range sensing applications, such as 20-km fiber setups [81].

Huynh et al. (2023) developed a real-time seismic event detection method using XGBoost and spatial features for DAS data. Their method successfully detected low-magnitude earthquakes and quarry blasts with minimal false alarms, demonstrating the potential of ML in enhancing the accuracy of distributed fiber optic sensors [86].

Recently, artificial intelligence (AI) and ML has become a major talking point in the tech world. AI is having a greater impact on the commercial sector than it is on our personal life. The goal of AI is to create computer programs with intelligence similar to that of a human being. Machine learning is an area of AI that focuses on problem-solving through data analysis. These solvers are data models that have been trained to learn from the data they are given. Probability theory and linear algebra are the sources of this data. Machine learning algorithms can use our data to learn and do predictive tasks automatically. Machine learning techniques can indeed be combined with Brillouin-based distributed fiber sensors to enhance their performance and enable advanced signal processing and data analysis. Brillouin-based distributed fiber sensors rely on the interaction between light waves and acoustic waves in an optical fiber to measure various physical parameters such as temperature and strain along the fiber length. By incorporating machine learning algorithms, these sensors can benefit from improved accuracy, higher sensitivity, and better noise reduction. Here are a few ways machine learning can be used in Brillouin-based distributed fiber sensors:

Signal processing: Machine learning algorithms can be employed to process the raw Brillouin scattering signals obtained from the optical fiber and extract useful information. These algorithms can learn complex patterns and relationships in the data, enabling more accurate parameter estimation and reducing measurement uncertainties.

Noise reduction: Brillouin-based distributed fiber sensors are susceptible to various sources of noise, such as optical and electronic noise. Machine learning techniques can be utilized to develop noise filtering and denoising algorithms that enhance the signal-to-noise ratio and improve the sensor's sensitivity and precision.

Calibration and calibration-free sensing: Machine learning algorithms can be used to develop calibration models for Brillouin-based sensors. These models can account for environmental factors, fiber characteristics, and other variables that affect sensor performance. Additionally, machine learning techniques can enable calibration-free sensing by learning the relationship between the measured Brillouin scattering signals and the target parameters without explicit calibration steps.

Event detection and localization: Machine learning algorithms can be trained to detect and localize specific events or disturbances along the fiber. By analyzing the temporal and spatial characteristics of the Brillouin scattering signals, these algorithms can identify and locate changes in temperature or strain with high accuracy.

Predictive maintenance: By analyzing historical sensor data using machine learning models, it is possible to predict potential faults or failures in the fiber infrastructure. This enables proactive maintenance and minimizes downtime.

Overall, integrating machine learning techniques with Brillouin-based distributed fiber sensors can enhance their performance, accuracy, and reliability. These advancements open up opportunities for a wide range of applications, including structural health monitoring, environmental monitoring, and smart infrastructure management.

Possible integration points for several ML applications include the pre-processing design phase, parameter optimization, and anomaly detection, in-situ monitoring and post-processing phases. Distributed fiber optic sensors (DFOS) with the help of machine learning have potential in the area of infrastructure monitoring. Road and rail traffic monitoring are two areas where dynamic DFOS applications using machine learning could be useful. The popular Brillouin optical frequency domain analysis (BOFDA) method is used alongside machine learning in static DFOS. In particular, CNN have demonstrated to be very tolerant to noisy spectra, and their inclusion contributes to greatly reduced measurement times. In addition, the well-known issue of cross-sensitivity that arises when measuring temperature and humidity simultaneously is addressed by employing several machine learning techniques (linear and polynomial regression, decision trees, ANNs). Improved, more cost-effective and dependable infrastructure monitoring may be possible with the help of DFOS powered by machine learning. These parameters can be measured using a distributed fiber optic network, with the difficulty of data processing taking into account the DS type and the parameter of interest. It is easier to process data for measuring flow temperature with DTS [8] than it is for measuring the speed of sound or flow velocity with DAS [9,10]. Feed-forward Neural Networks [11], Recurrent Neural Networks [12, 13], Support Vector Machines [14], Gradient Boosting Algorithms with Regression Trees [15], and Kalman Filters [13] are just some of the machine learning-based techniques that have been used to estimate multiphase flows and flow rates. The back propagation ANN architecture presented in [16] for fiber optic sensing is shown in Fig. 2. CNN model architecture presented in [17] for fiber optic sensing is shown in Fig. 3.

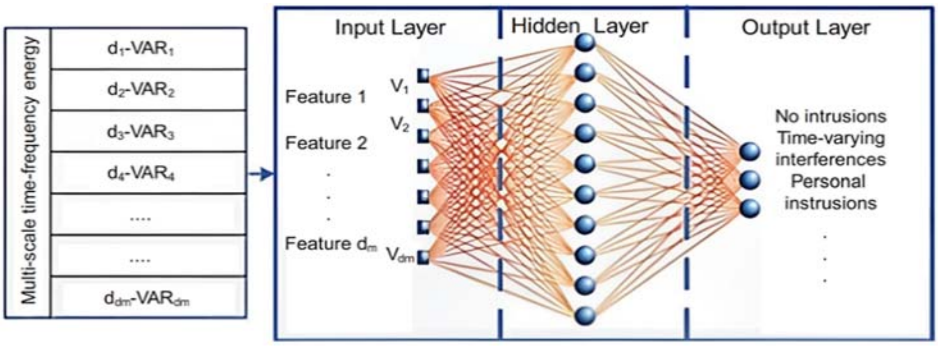

Fig. 2. Back-propagation artificial neural network architecture [16].

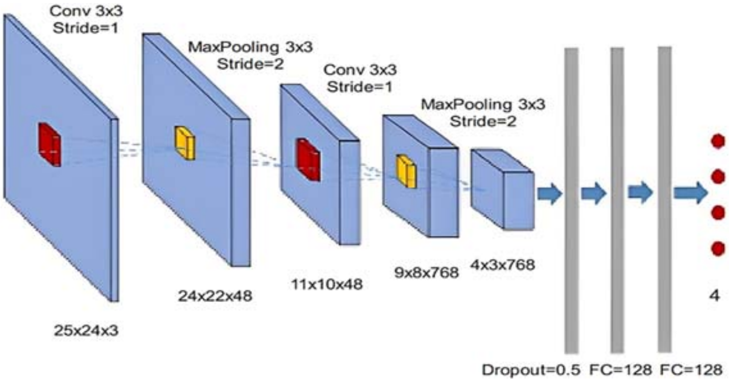

Fig. 3. Convolution neural network model architecture [17].

Several studies (Jalilianet al., [18], Silkina [19], and Vahabiet, et al., [20, 21]), among others, have investigated the feasibility of applying machine learning to the DS data in order to estimate flow rate and phase.

Zhang et al. (2024) developed an Attention-ResNet-AR-LSTM model for strain prediction in fiber optic sensors, achieving an R^2 above 98 %. This demonstrates the potential of hybrid deep learning models in complex sensing environments, particularly for improving multiphase flow analysis in distributed sensing networks [88].

More than 60 % of a data scientist's time is spent on the phase of data comprehension and pre-processing, as reported by Forbes [22]. The machine learning pipeline relies heavily on this step. Gathering, cleaning, slicing, and modifying the input data before sending it on for further processing are all part of the data pre-processing [19, 23].

Hu et al. (2024) introduced an event augmentation method for Φ-OTDR classification, enhancing data diversity and improving event detection accuracy from 76.4 % to 91.0 %. This highlights the importance of advanced data preprocessing techniques in improving the overall efficiency of machine learning applications in fiber optic sensing [84].

Some examples of useful machine learning techniques for characterizing multiphase flows are the Support Vector Machine [14, 24], several members of the Kalman Filter family (such as the Extended Kalman Filter (EKF) and Ensemble Kalman Filter (EnKF) [13, 25]), and the Neural Network families [14,26,27].

The details about different fiber optic sensor principle and applications are presented by various researchers in the literature, such as optical fiber sensors [28-30], distributed optical fiber sensors [28-30], optical time domain reflectometry [28, 31, 32], Brillouin optical time domain reflectometry [31-33], Brillouin optical time domain analysis [34-36], Brillouin optical frequency domain analysis [37], pulse pre pump-BOTDA [38-40], differential pulse pair-BOTDA [41], optical frequency domain reflectometry [28], optical backscattered reflectometer [42], distributed acoustic sensing [43, 44], distributed vibration sensing [43, 44], phase-OTDR [44, 45] and fiber Bragg grating [46-48].

2.1. Machine Learning Enabled Brillouin Based Distributed Fiber Sensors Using ANN

Fig. 4 depicts the experimental set-up of a BOTDR system [69] with a passive depolarizer. One example of a type of laser source is a DFB laser operating at 1550 nm. With a 50/50 coupler, the laser's output is split in two branches, one of which serves as the pump while the other serves as the local oscillator. Optical pulses with a high extinction ratio are created from the electrical pulses. High extinction ratio optical pulses are generated from the electrical pulses by a dual drive

MZM (DD-MZM) in the upper branch. In order to reduce the polarization noise, a passive depolarizer is used in the local oscillator. A photo detector (PD) receives the backscattered beat signal and processes it. Fig. 5 [70] depicts a typical experimental setup for the BOTDA system. Theory suggests a Lorentzian profile for the Brillouin gain spectrum, which can be written as [71].

$$g(\nu) = g_B \frac{(\Delta\nu_B/2)^2}{(\nu-\nu_B)^2 + (\Delta\nu_B/2)^2}$$

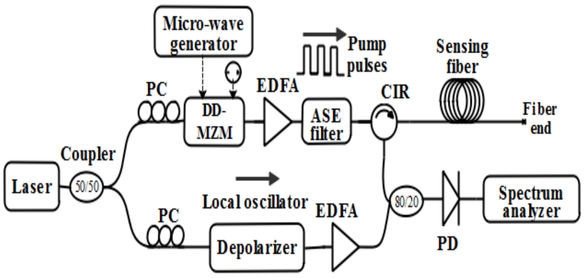

Fig. 4. The coherent Φ-OTDR experimental setup [7].

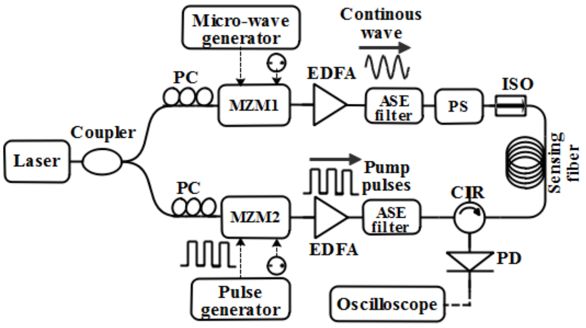

Fig. 5. Experimental setup of BOTDA system [70].

Constructing the BOTDR in an experimental setting. In this equation, g_B represents the Brillouin gain coefficient, Δvb the Half-maximal Brillouin line width at full width and vb the peak BFS. When the frequency of the continuous-wave probe is swept, the BGS spectrum can be reconstructed [72]. The strain and/or temperature information over the sensor fiber is determined by the peak BFS measurement. By employing ANN, we may bypass the time-consuming and error-prone process of estimating the BFS and instead retrieve strain and temperature data immediately along the full length of the sensor fiber. The ANN's adaptive learning, dispersed sociability, and nonlinear map ability are all advantages.

3. Machine Learning Enabled Rayleigh Based Distributed Fiber Sensors

Rayleigh-based distributed fiber sensors, also known as Rayleigh scattering-based sensors, rely on the analysis of Rayleigh scattering signals in an optical fiber to measure physical parameters such as temperature and strain along the fiber length. Machine learning techniques can be applied to enhance the performance of Rayleigh-based distributed fiber sensors in several ways:

Signal processing: Machine learning algorithms can be utilized to process and analyze the raw Rayleigh scattering signals acquired from the fiber. These algorithms can learn patterns and correlations in the data, enabling more accurate parameter estimation and improved signal-to-noise ratio. Advanced signal processing techniques such as noise reduction, feature extraction, and denoising can be implemented using machine learning algorithms.

Calibration and calibration-free sensing: Machine learning models can be developed to calibrate the Rayleigh-based sensors. These models can account for variations in the fiber characteristics, environmental factors, and other variables that affect the sensor's performance. Machine learning can also enable calibration-free sensing by learning the relationship between the acquired scattering signals and the target parameters without explicit calibration procedures.

Fault detection and localization: Machine learning algorithms can be trained to detect and localize faults or anomalies along the fiber. By analyzing the temporal and spatial characteristics of the Rayleigh scattering signals, these algorithms can identify deviations from normal conditions, such as the presence of hotspots or strain concentrations. This enables the early detection of potential failures or abnormalities in the monitored system.

Data fusion and multi-sensor integration: Machine learning can facilitate the fusion of data from multiple distributed fiber sensors, allowing for a comprehensive understanding of the monitored system. By combining information from different sensing points along the fiber, machine learning algorithms can provide a more accurate and detailed representation of the physical parameters under investigation.

Predictive maintenance and anomaly prediction: By analyzing historical sensor data using machine learning models, it is possible to predict future faults or anomalies in the fiber infrastructure. These models can learn from patterns and trends in the data to identify potential issues before they manifest. Predictive maintenance based on machine learning can optimize maintenance schedules, minimize downtime, and improve the overall reliability of the system.

Machine learning techniques, when applied to Rayleigh-based distributed fiber sensors, can significantly enhance their performance, sensitivity, and accuracy. These advancements can benefit various applications, including structural health monitoring, oil and gas pipeline monitoring, and smart grid management. A novel deconvolution method combining iterative algorithms with denoising neural networks significantly enhances spatial resolution in DOFS. This approach achieves a deconvolution gain of 15.8 dB, surpassing conventional iterative and end-to-end ML-based techniques in restoring high-resolution measurements [76].

3.1. Phase-OTDR (DAS)

Optical frequency domain reflectometry (OFDR) and phase-optical time-domain reflectometry (Ø-OTDR) are two popular Rayleigh-based distributed fiber sensors [7]. Lately, distributed fiber sensors have adopted the usage of an ANN for sophisticated data analytics, quick processing of data, precise sensing, and event categorization. Mathematicians Walter Pitts and Warren McCulloch first proposed the ANN operation principle in the 1940s, drawing inspiration from the functioning of the brain [49]. Since then, ANN technology has advanced significantly for a variety of applications using increasingly powerful computers and complex software platforms. The effectiveness of ANN is evaluated in comparison to traditional signal processing algorithms. The application of ANN in distributed fiber sensor systems has only recently come about, up until this point. In this study, we examined current advances in ANN-based signal processing techniques and results that apply to distributed fiber sensors, together with their underlying operational theories and experimental approaches. Fig. 6, represents a typical BGS resulted from a 25 m segment of a 30 km long optical fiber and how this is analyzed using both the conventional and the CNN approach in order to acquire the temperature value corresponding to that segment.

Ø-OTDR, which is based on Rayleigh backscattering and is sometimes referred to as a distributed acoustic sensor (DAS), is an exciting new method for high-sensitivity, high-dynamic-range vibration and acoustic monitoring in real time. Protection of pipelines, buildings, fences and wellbore integrity are just some of the many uses for the Ø-OTDR system, which is primarily designed for distributed acoustic sensing. In order to move the DAS technology forward, autonomous and effective methods for processing, detecting and classifying sensing data are essential. Since ANNs may be trained to extract the sensory features on their own, they are a particularly good option. To see the experimental configuration of the coherent Ø-OTDR system, refer to Fig. 4 [7] depicts to generate pulses and maintain a stable local oscillator frequency, a highly coherent laser with a short line width (1 kHz) is split in two. Using an AOM, we shifted the frequency of the pump pulses by 200 MHz then, an optical band pass filter is used to remove the ASE noise, and an EDFA is used to boost the signal to its optimal power level. An EDFA2 is used to boost the strength of the signal that has been backscattered, and a tunable fiber Bragg grating (TFBG) filter removes any noise that may have been present in the original signal. A balanced photodetector is then used to detect the signal and remove the DC component. After that, a band-pass filter and low-noise amplifier (LNA) are employed to condition the signal (BPF). An oscilloscope sampling at 1.25 GSa/s [7] examines the received signal for anomalies.

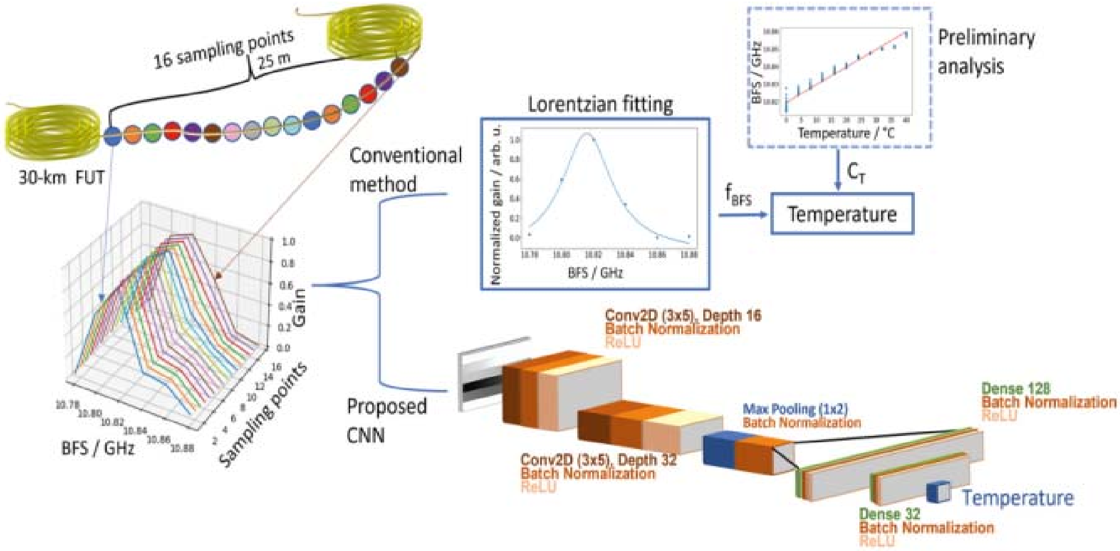

Fig. 6. Schematic representation of the conventional and the CNN-based approach [50].

Multiple methods, including OTDR [51-53] and fiber Bragg grating array [54] have been published for leakage detection or pipeline security. Ultra-violet (UV) exposure of the hydrogen-loaded single mode fiber [54, 55] and UV inscription of ultra-weak fiber Bragg gratings (FBGs) [56, 57] are two methods proposed to increase Rayleigh scattering in fiber and hence improve the signal-to-noise ratio (SNR) of -OTDR. These laser-induced Rayleigh scattering spots, unlike FBG, are wavelength-independent and stable at high temperatures, making them ideal for use in extreme environments [58-61].

The most crucial aspect of Ø-OTDR or DAS sensing technology is the development of effective algorithms to detect events of interest and classify them. The raw data was processed with ANN to enhance linearization of the laser's wavelength sweep, computing speed and precision of measurements. In a 2019 study by S. Liehr et al. [62] that used wavelength scanning coherent optical time-domain reflectometry (COTDR) to measure strain in real time over a 970 m long sensing fiber. When frequency drifts during a laser wavelength sweep with saw tooth laser current modulation, the sweep is not linear [63]. Here we show that a trained ANN network can outperform the standard least-mean-squares (LMS) correlation technique when it comes to nonlinear sweep correction with fast strain extraction. A comparison of the typical LMS correlation approach and the ANN method is given in terms of sensing performance, specifically with regards to sweep linearization and strain extraction time. Strain extraction using ANN is 268 times more accurate and linearization 272 times faster than the traditional LMS correlation-based technique.

The ANN has received more attention for its advanced data processing, pattern identification and category of vibrations event in the Φ-OTDR system than traditional deterministic methods. A number of Φ-OTDR systems using the ANN technique have been developed for tracking train location and speed as well as counting bogie numbers and classifying events like nearby construction and pedestrian traffic. In [63], the authors tracked the location, speed, and number of cars on a railway using a commercially available Helios DAS system. The train's speed is then determined in three distinct ways: from the train's perspective, from the rail's perspective, and by analyzing the clusters of wheels on the bogie cars. They trained a huge number of data sets using an ANN model applied to DAS sensing data. In comparison to the 300 seconds required by the traditional peak finding approach for filtering, processing, and localizing trains, the ANN model only needs 22 seconds. As a bonus, ANN allows for the processing of a wide variety of data sets at lightning speed. Q. Che et al. [65] showed that an ANN-based Φ-OTDR system can detect partial discharge (PD) in cross-linked polyethylene power cables in 2019. To boost the Rayleigh backscattering signal, a sensing fiber made of weak Bragg gratings (wFBGs) is used. A variety of events, such as internal PD, corona PD, surface PD, and noise, are all easily identifiable and classified using the suggested ANN algorithm. During experimentation, they found that using 1280 training samples and 832 test samples increased the accuracy, sensitivity, and specificity for each event to a maximum of 96.3 %, 96.4 %, and 98.7 %, respectively. Hence, ANN-based event recognition in DAS or -OTDR systems holds much promise. DL-TSD method, describing the learning process and the testing process, presented in [33] for fiber optic sensing is shown in Fig. 8.

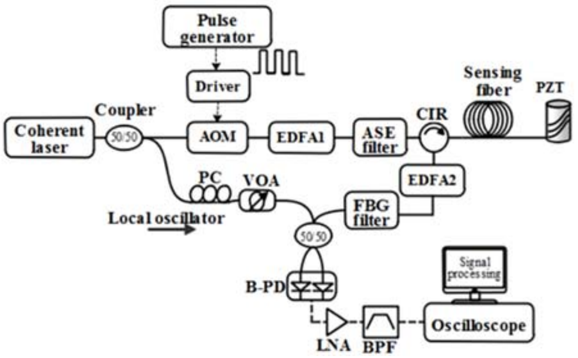

Fig. 7. The coherent Φ-OTDR experimental setup [7]. (FBGis the fiber Brag grating, PZTis the piezoelectric transducer, BPDis the balanced photo-detector, LNAis the low-noise amplifier, BPFis the band-pass filter, AOMis the acousto-optic modulator, EDFAis the Erbium-doped fiber amplifier, ASEis the amplified spontaneous emission, PC is the polarization controller, VOA is the variable optical attenuator).

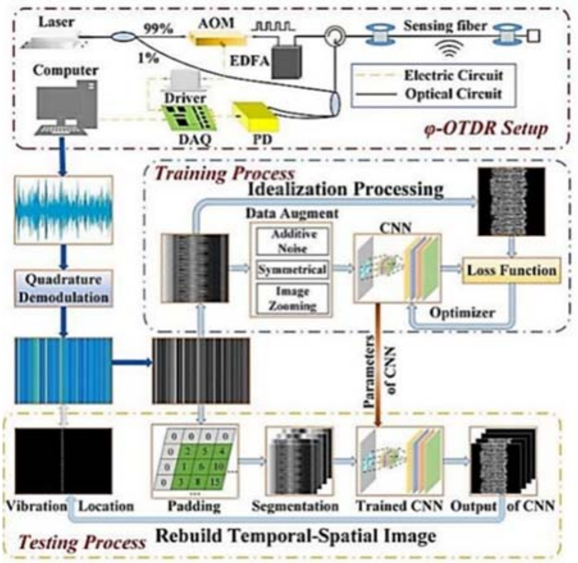

Fig. 8. DL-TSD method representing the learning process and the testing process [66].

With a neural network DAS system, the authors of [67] were able to successfully detect human movement and monitor pipeline degradation. When used in the sensing fiber, the wFBGs improve the SNR of the Rayleigh backscattered signal by 29 dB. Classifying human motion, such as walking, running, or a combination of the two, with an ANN is a breeze. Together with this, they categorized the sources of vibrational excitation, such as pipeline knocking by hammers made of steel, rubber, plastic and aluminum and created an ANN model for pipeline corrosion monitoring. Using a neural network method alongside the DAS improves pipeline corrosion detection accuracy to 94.29 %. Table 1 displays a summary of the development of the ANN-based DAS system. Distributed optical fiber sensor networks clearly benefit from ANN's use as a signal processing technique. Long-distance measurements with high spatial resolution, such as those used by BOTDR, OFDR, DAS, and BOTDA systems, are poised to benefit greatly from the application of artificial neural networks in the near future [68]. Table 1 represents recent developments related to Phase-OTDR (DAS) OFDR.

3.2. OFDR

The examination of optical light pathways and reflection characteristics in optical fibers and components is a specialized use of optical frequency domain reflectometry (OFDR). By operating in the frequency domain with continuous wave (CW) light sources, OFDR is able to achieve greater signal-to-noise ratios than its Optical Time Domain Reflectometry (OTDR) counterpart. The wavelength of a tunable laser source is swept across a range in an ordinary OFDR system (e.g. 1535nm – 1565nm). When the light reaches the fiber, it is brought into interference with the reference arm. The geographical distribution of the reflected light is then quantified by Fourier analysis of the resulting signal. The reflection might be caused by Rayleigh scattering inherent to the glass, or it can be amplified by continuously written, low reflecting, optical fiber Bragg gratings (FBG). Strain and temperature can be determined by monitoring shifts in the peaks and valleys of the Rayleigh or FBG reflection pattern. The enhanced signal-to-noise ratio that results from employing FBGs rather than Rayleigh allows for faster measuring times. Measure strain or temperature with sub-millimeter accuracy over distances of several tens of meters using OFDR technology.

4. Machine Learning Enabled Raman – Distributed Temperature Sensing

Given its potential for precise temperature readings over great distances, Raman Distributed Optical Fiber Temperature sensing (RDTS) has been the subject of extensive research for decades. The sensing range and precision of RDTS temperature readings are primarily constrained by the signal-to-noise ratio (SNR). To boost SNR in long-distance applications, we produce low water peak optical fiber (LWPF) with minimal transmission loss. In addition, we refine an existing denoising neural network approach to lower background noise and increase precision while measuring temperatures.

Table 1. Recent developments related to Phase-OTDR (DAS).

Sensing system	Classification Task	Accuracy	Computational time	Sensing fiber length	Spatial resolution
Commercial Helios DAS system	Position, speed, and number of bogies for 4 trains	±0.8 km/h (@160km/h train speed)	22 s	25 km	10 m
DAS assisted by wFBGs	Partially discharged power cables	96.3 %	Not stated	1.5 km	5 m
DAS	Moving forward by means of walking, digging, shoveling, and harrowing	93 %	Not stated	40 km	10 m
DAS	Earthquakes (footsteps, ambient noises)	94 %	0.5s	5 km	5 m
DAS	Signal from people walking and cars passing by	94 % for 5km fiber 89.3 % for 20km fiber	0.5s	5 km and 20 km	5.5 m for 5 km fiber, 10.3 m for 20 km fiber
DAS assisted by wFBGs	Human moment (one individual walk, one individual run, two individuals walk and one individual run)	90 %	1.25s	7 wFBGs in sensing fiber	n/a
DAS assisted by wFBGs	Diverse things (Al, plastic, rubber and steel) induced corrosion in pipelines.	94.29 %	Not stated	7 wFBGs in sensing fiber	n/a

Distributed temperature sensing (RDTS) based on Raman technology is commonly used for keeping tabs on the interior temperatures of vital facilities, and its accuracy extends to distances of tens of kilometers. In contrast to the pump pulse, the acquired spontaneous Raman scattering (SpRS) signals are typically roughly 60 dB weaker, greatly impact the accuracy of RDTS. This means that traditional RDTS setups based on single-mode fiber (SMF) function poorly. The employment of specialized optical fibers, pulse coding techniques, and denoising algorithms are just some of the strategies proposed to boost its functionality. These approaches, meanwhile, do have certain restrictions. Here, a novel, deep, one-dimensional convolutional denoiser is proposed and experimentally demonstrated. To train and improve the 1DDCNN, a simpler RDTS model is developed. The 1DDCNN has substantial advantages in practical applications over standard denoising algorithms, including no need for human parameter adjustment and independence from sampling rate.

We further believe that the suggested 1DDCNN, after being fine-tuned with suitable training data, can be used in various distributed optical fiber sensing systems.

5. Machine Learning Enabled Quasi-distributed Fiber Sensors

For sensing needs in extreme conditions where traditional electronic sensors fail, fiber optic sensor (FOS) technologies are a viable alternative. Several FOS methods have been developed for point, quasi-distributed, and distributed sensing to monitor mechanical, chemical, and thermal parameters (vibrations, temperature, gas species, etc.). A method of sensing and measuring using optical fibers has been considered for more than 25 years. Micro structured fibers, fiber Bragg gratings, long-period gratings and fiber ring lasers are just a few examples of the many different types of discrete fiber sensor structures that have been developed, whereas interferometric tools like multimode interference cavities, Mach-Zehnder interferometry and others, Fabry-Perot interferometers, Michelson interferometers, and Signac interferometers There has been a dramatic increase in the use of distributed fiber sensors during the past decade.

Machine learning enabled quasi-distributed fiber sensors combine the advancements in ML with fiber optic sensing techniques to create intelligent sensor systems. These sensors leverage the power of ML algorithms, particularly deep learning and neural networks, to analyze raw sensor data and extract meaningful information from noisy and sparse sensing tuned with fiber Bragg gratings (FBGs) mitigate side lobe interference in quasi-distributed sensing networks, enhancing temperature and strain differentiation. Machine learning models, such as ensemble classifiers and artificial neural networks, further improve measurement accuracy and cross-sensitivity reduction [80]. By utilizing computation and statistical learning tools in the design phase, these sensors can fundamentally change the hardware designs of traditional sensors, taking into account inherent sources of noise and variations in signal generation and decoding schemes. The integration of ML with fiber optic sensors offers benefits such as increased measurement speed, higher spatial resolution, and the ability to acquire multiple physical and chemical parameters from discretized local points along a single optical fiber. These advancements open up new possibilities for applications in strain- or temperature-sensing, fault detection, predictive maintenance, and other areas where quasi-distributed sensing is required [73-75].

Recent developments in machine learning-enabled quasi-distributed fiber sensors have seen significant advancements in the integration of ML techniques with fiber optic sensor technology. Fiber optic sensors are known for their ability to provide accurate and reliable measurements in various applications. The recent digital revolution, driven by advancements in ML and AI, has further enhanced the capabilities of fiber optic sensors. One of the key aspects of these recent developments is the utilization of deep learning, a subfield of ML that employs biologically inspired neural networks for learning tasks. Unlike conventional ML algorithms that rely on the selection of specific features, DNN automatically generate features as part of the learning process. This capability has enabled deep learning-based AI technologies to achieve performance levels comparable to humans in various practical tasks, such as image recognition, speech recognition, personalized recommendation, and machine translation.

In the context of quasi-distributed fiber sensors, these ML techniques are being used to integrate physics-based simulation models with data-driven ML models, creating hybrid predictive models for complex physical systems. This integration is achieved through the application of scientific machine learning (SciML) algorithms. SciML aims to leverage relevant scientific domain knowledge, such as physical conservation laws, symmetries, and computational simulations, along with available sensor data. By combining these approaches, hybrid models can be developed to monitor parameters of interest that cannot be directly measured by individual sensors. This collaborative behavior among the sensors enhances the overall sensing capabilities.

Additionally, recent developments have focused on the use of uncertainty quantification tools to determine the level of confidence in predictive models. These tools play a crucial role in certifying the reliability and accuracy of predictions made by the quasi-distributed fiber sensors. The combination of ML techniques, deep learning algorithms, and the integration of physics-based simulation models has opened up new possibilities for quasi-distributed fiber sensors. These sensors can now provide enhanced accuracy, predictive capabilities, and monitoring of parameters that were previously challenging to measure directly. These recent developments are instrumental in expanding the applications of fiber optic sensors in various industries, including industrial infrastructure, asset monitoring, fault detection, and predictive maintenance.

6. Conclusion

In conclusion, the integration of machine learning techniques with distributed fiber optic sensors has brought significant advancements in the field of sensing. This review has provided an overview of the principles and applications of machine learning-enabled distributed fiber optic sensors, focusing on Brillouin-based and Rayleigh-based sensing technologies. Machine learning algorithms have revolutionized the way to process, analyze, and interpret the vast amount of data generated by distributed fiber optic sensors. These algorithms excel at uncovering complex patterns, extracting valuable information, and improving the accuracy and reliability of sensor measurements. By leveraging machine learning, distributed fiber optic sensors can achieve enhanced performance, higher sensitivity, and improved noise reduction.

Moreover, machine learning algorithms have been utilized for event detection and localization, enabling the identification and localization of disturbances or anomalies along the fiber. These algorithms leverage the spatial and temporal characteristics of the sensor data to provide precise and timely information about changes in temperature, strain, or other physical parameters. The applications of machine learning-enabled distributed fiber optic sensors are diverse and far-reaching. Structural health monitoring, environmental monitoring, smart infrastructure management, and industrial process control are just a few examples of the areas where these sensors find practical use. The combination of distributed sensing capabilities and machine learning algorithms unlocks new opportunities for real-time monitoring, data-driven decision-making, and optimization of critical systems.

However, it is important to recognize that challenges remain in the field. The availability of high-quality training data, the development of robust algorithms that can handle complex and dynamic environments, and the integration of distributed sensor networks with existing infrastructure are some of the areas that require further research and development.

In summary, machine learning-enabled distributed fiber optic sensors hold immense potential for a wide range of applications. By harnessing the power of machine learning algorithms, these sensors can provide accurate, real-time, and actionable information about the physical world, contributing to improved efficiency, safety, and reliability across various industries and domains. Future advancements in machine learning techniques and sensor technologies will continue to drive the evolution of distributed fiber optic sensors, enabling even more sophisticated and intelligent sensing capabilities.

Optical fiber can be used for pipeline vibration monitoring in real-world monitoring applications. Optical fiber can be incorporated with a BOTDR sensor system utilizing a single 25 km optical fiber with two wavelengths. For further sensor system performance enhancement, the BOTDR sensor system can be integrated with other emerging techniques, such as Raman amplification, pump pulse coding, and wavelength diversity techniques. The capability of extract the BFS distribution over fiber distance both the BGS, and BPS spectra, and provides a pathway to enhance the BOTDA system performance. The combination of the FBG sensor-embedded smart helmet prototype with ML models significantly simplified the data analysis process; this benefit may provide accurate guidance for real-time diagnoses of blunt force impact events. Future research will concentrate on the use of multiple in-line FBG configurations to facilitate the three-dimensional sensing of impact locations with high temporo-spatial resolution. In this work a fiber optic distributed acoustic sensing system along with signal processing and machine learning, threat detection and classification techniques aimed at use with the proposed system were presented.

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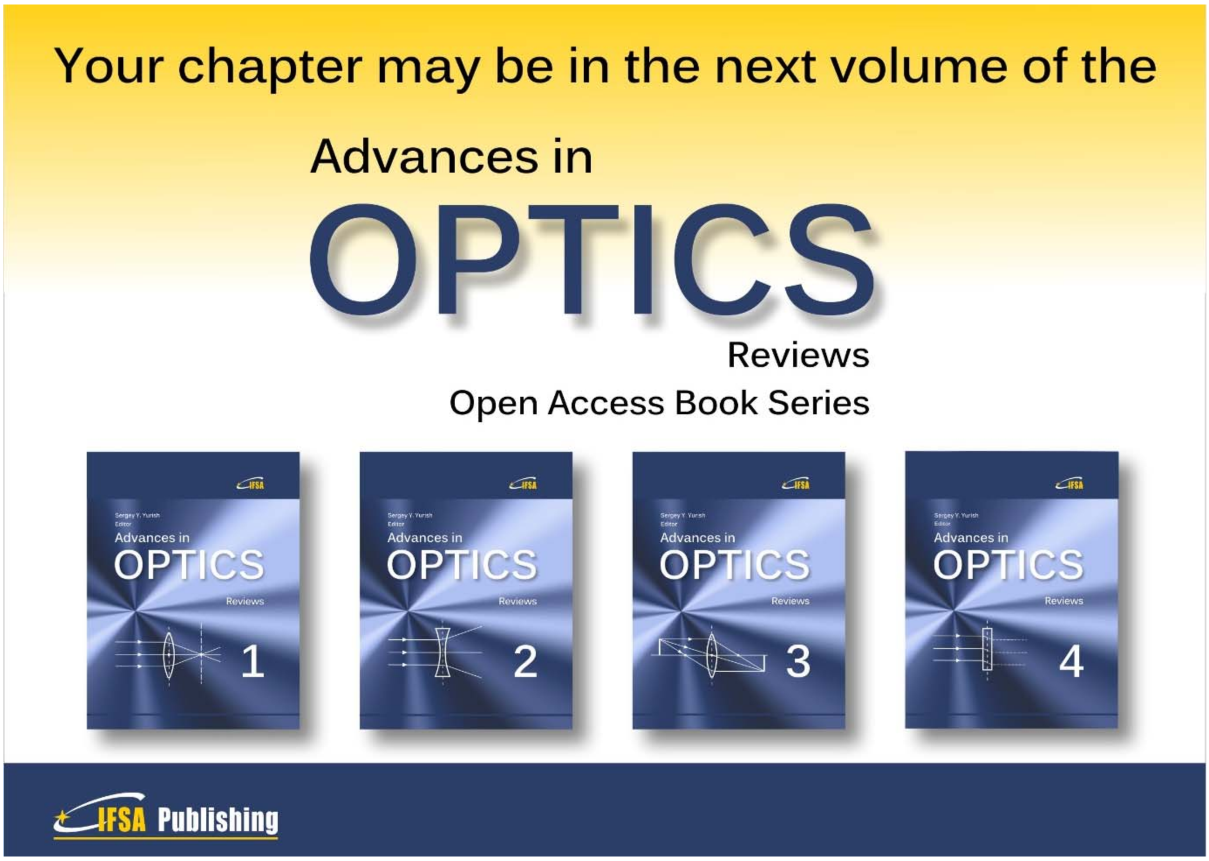

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