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Developments in Optical Fiber Network Fault Detection Methods: An Extensive Analysis

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Abstract: The rapid development of transmissions media in computer networks has set optical fiber at the very front because of their high data transmission abilities and low constriction. However, guaranteeing the dependability and usefulness of optical fiber networks stays a critical test, particularly in recognizing and tending to issues expeditiously. This paper gives a careful examination of shortcoming discovery strategies in optical fiber networks, beginning with an investigation of issue types in view of the information from a neighborhood stations which are called Network Operations Centers, NOCs. It examines the meaning of issue identification, order, and their effect on network execution. Moreover, the paper investigates conventional shortcoming recognition techniques like Optical Time Area Reflectometer (OTDR) and their restrictions in pinpointing issue areas precisely. To overcome these difficulties, the paper investigates the coordination of AI (ML) procedures for issue of fault location and expectation in optical networks. Different utilizations of ML in issue discovery, including shortcoming area, prescient upkeep, oddity location, and enhancement of sign quality, are examined exhaustively. Also, late examination endeavors and their commitments to the field of issue location and characterization in optical networks are dissected. The paper finishes up by underscoring the capability of ML-based ways to deal with improve issue discovery effectiveness, further develop network dependability, and decrease margin time in optical fiber networks

Keywords: Optical fiber networks, Fault detection, Machine Learning, Optical Time Domain Reflectometer (OTDR), Predictive maintenance.

1. Introduction

The quick improvement of communication networks has moved optical fiber to the very front as the essential part, on account of their low lessening and high transmission capacity abilities. Optical fiber networks, presented in the mid-1970s, are essential for fast, dependable, and secure information transmission over significant distances, making them ideal for gigabit and past transmission [1].

However, there are decisive challenges facing optical fiber networks represented in the reliable detection of malfunctions and location, as any malfunction can lead to service interruption and data loss, in addition to possible social effects[2]. Shortcomings can arise from different sources, such as the improper installation of cables, poor quality cables, signal inactivity, or due to external factors such as marine activities that cause damage to the under the sea or ground accidents, such as construction work or storms that cause damage to the cables Along the actual infrastructure such as roads and electricity lines.[3].

To address these challenges, an effective supervision system is essential to detect and identify faults with the aim of minimizing service interruptions. Most optical networks are designed with protection systems that can quickly switch data to backup fiber paths within 50 milliseconds to ensure uninterrupted service. [4].

One strategy for fault recognition in fiber optic networks is through Rayleigh scattering-based control networks, where the Optical Time Domain Reflectometer (OTDR) is a prominent procedure. OTDR allows the measurement of test pulses scattered along the fiber, providing an understanding of the integrity of the fiber without the need for controllers at each node of the

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network. [5]. High-quality OTDRs offer superior spatial resolution (less than 20 meters) and long-range capabilities (more than 200 km), enabling efficient monitoring of entire fiber networks. [6].

However; using the ODTR device has a number of drawbacks, such as its inability to locate faults precisely and notice them, particularly within the restricted range of distance measurement. In other words, its accuracy in measuring distances is limited to a specific threshold. Because of the nature of the technology employed in OTDRs, measurements lose precision with increasing distance, and eventually the reflections become too faint to be reliably detected and processed. This implies that OTDRs might not be the best tool for testing and debugging long-haul fiber optic networks that cover hundreds or thousands of kilometers.

Another disadvantage of using an OTDR tool is the high cost and complexity of the equipment. The high cost of OTDR equipment can be a major drawback for small businesses or individuals who need to perform fiber optic testing. The price of an OTDR can range from several thousand to tens of thousands of dollars, depending on the features and capabilities of the device. In addition, novice users may find it difficult to handle the intricacy of using an OTDR. To acquire reliable readings, OTDRs require proper configuration of a wide variety of settings and parameters. For individuals who are unfamiliar with fiber optic testing, it might be intimidating to interpret the findings and comprehend the numerous factors.

Machine Learning (ML) is progressively used in optical correspondences and systems administration, especially in nonlinear transmission networks, optical transmission enhancement, uninvolved optical execution observing, and cross-layer network advancements for programming characterized networks [7]. ML methods have been used to address different difficulties in optical correspondences foundation, empowering exact expectation of networks execution and improving complex networks the board, shortcoming recognition, recognizable proof of Bit Error Rate (BER), transmission of transmission (QoT), and signal enhancement [8].

Nonetheless, while critical headway has been made in using ML strategies for shortcoming location in optical networks, especially in long stretch underground optical networks, challenges continue following hard disappointments in underground optical links [9]. Customary techniques like optical time-domain reflectometer (OTDR) estimations give the distance of the fiber link covered in the earth yet miss the mark in pinpointing the specific spot of a link cut [10].

The profundity of the channels where fiber optic cables (FOCs) are laid presents a critical obstruction in issue following, prompting postponements and income misfortune for media transmission networks. Regardless of the accuracy of OTDR in assessing shortcoming distances, its failure to precisely find fiber cuts on the world's surface outcomes in extra expenses and asset assignment [11].

To address these difficulties, research proposes utilizing ML displaying to foresee the genuine issue area when a fiber link cut happens in underground optical foundation. By consolidating ML methods, irregularities between OTDR estimations and genuine issue distances can be alleviated, lessening delays, asset wastage, and financial misfortunes for telecom networks [12].

Past exploration endeavors have zeroed in on shortcoming following utilizing OTDR and different strategies yet have not completely settled the issue of precisely pinpointing shortcoming areas. By taking into account the distance of the FOC as well as the Euclidean distance on the world's surface, ML-based approaches mean to give more exact shortcoming area forecasts, limiting misfortunes in the FOC networks [13].

In rundown, the combination of ML strategies offers a promising answer for the difficulties of issue following in underground optical networks, possibly diminishing expenses and further developing effectiveness for telecom networks [14].

The paper investigates fault discovery procedures for optical strands, starting with a conversation on issue types in view of a difficult situation ticket information from neighborhood networks in the earlier year. This investigation includes characterizing deficiencies as per type, main driver, and their effect on administrations.

2. Optical Fiber Cable

Optical fiber cable can be defined as the backbone that is constitutive of the fiber optic communication system where it encompasses a very thin, extended structure that strictly transports light signals produced by the transmitter in tremendous efficiency. These can be of diverse types, with either glass or plastic and are designed to transmit light signals up to certain distance with least attenuation. There are two primary types of optical fibers used in communication systems, each with unique properties that determine their suitability for different applications: There are two primary types of optical fibers used in communication systems, each with unique properties that determine their suitability for different applications [15]:

A. Single-mode Fiber

1. Core Size: Single-mode fibers have quite a small core diameter, around 9 micrometers (μm) depending on the type. This results in the core being unusually narrow and the fiber only allowing for one type of light wave transmission, in other words,

light within the fiber merely travels through a singular pathway in the fiber core [16].

2. Light Propagation and Signal Distortion: This makes it possible for the narrow core to contain the light in an upright column along a straight-line keeping signal distortion as resulting from multiple reflections of light at different angles (as which is the case in multi-mode fibers). This leads to better quality of signal transmission and for SMFs they can transmit signals and data over long distances more than the MMFs can [17].

B. Multi-mode Fiber

1. Core Size: Multi-mode fibers have a relatively large core diameter, which is normally in the range of 50 – 100 m. This is because the larger core diameter allows the fiber to have multiple modes of transporting the light [18].
2. Light Propagation and Signal Distortion: Multi-mode fibers allow the propagation of light rays in different ways, or modes and exist in two types close and long. Some rays go through the core at once not reflecting off the interface of the cladding and core at various angles of incidence. This feature in turn has the potential of distorting the received signal especially when the transmission path is long since it takes light beams with different numbers of reflections to get to the receiver at a given time [19].
3. Advantages and Trade-offs: Even though the signal might be affected by the reflections, multi-mode fibers can have several benefits, including easier coupling with the light source and detector chips; this makes the installation easier and possibly less costly. However, their signal vulnerable to distortion results in the smaller transmission range compared to the single-mode fibers [20].

3. Optical Fiber Characteristics

A. Attenuation

Signal power in optical fiber line decreases over distance due to attenuation, it is the weakening of the light signal. Attenuation is important as it set the level of signal strength seen by the receiver so that it is able to correctly distinguish the sent signal. Therefore, it becomes essential to determine the maximum distance up which the signal can propagate given the sensitivity of the recipient and the strength of the source. Absorption, scattering and geometric losses take a part in decrease of signal next to attenuation. Expressed commonly in decibels per unit length (dB/km), attenuation is determined by the following [21].

$$a_{dB} = \frac{10\,log_{10}\frac{P_i}{P_o}}{l} \quad (1)$$

Where: represents the signal attenuation, stands for the input optical power inserted to a fiber, refers to the output optical power which is received from the fiber, and stands symbolically for the length of the fiber [22]. This logarithmic unit has the advantage of solving such equations in terms of addition and subtraction or multiplication and division as well as powers and roots (Figure 1).

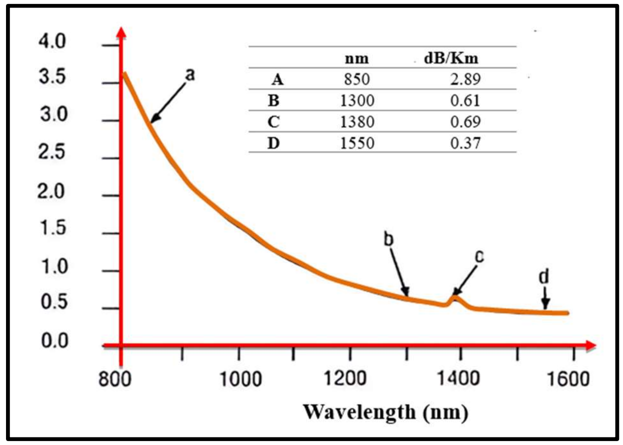

Figure 1: Attenuation Profile for Single Model Fiber

However, addition and subtraction require a conversion to numerical values, which may be accomplished using the following relationship: However, addition and subtraction require a conversion to numerical values, which may be accomplished using the following relationship: Where: is for the attenuation of signal, is for the input optical power that is launched into the fiber, and is for the output optical power that is received from the fiber; stands for the fiber length [23].

This logarithmic unit has the advantage of bringing into equation the multiplication and division operations and also the powers and root of the numbers by the use of addition and subtraction. However, addition and subtraction require a conversion to numerical values, which may be accomplished using the following relationship [23].

B. Chromatic Dispersion

The last thing is chromatic dispersion which is one of the greatest problems towards longer distances and accurate representation of single signals. In optic fiber communications, chromatic dispersion occurs due to the difference in the velocity with which the light signal travels through the fiber at different frequencies. There is accumulation within the optical network that leads to pulse widening and ultimately increased interference between symbols for this reason, the SNR will also reduce at the judgment circuit. As a result, in order to maintain the operational functionality of the system, more power must be provided at the receiver as is illustrated in figure (2)[24].

It is the product of two factors: MD (material dispersion) and Waveguide dispersion (WD). Since each source of light has a particular spectral band, a laser or LED source expands as it passes through the form of an optical waveguide- fiber. In the same shown waveguide, every dispersed spectral request propagates at unique band velocity. This is so because phase velocity changes with the material and the wavelength of the wave.

The first source is nuclear energy, while the other five are renewable energies. This is because, by the time the pulse reaches the receiver, the spectral components have separated from each other due to the different travel times and hence the pulse broadens. This is known as material dispersion Material dispersion occurs when the material through which the wave is travelling affects the relationships between the wavelengths of the outgoing waves, particularly when the frequency is being altered. Using incident wavelength λ0, the dispersion coefficient for MD using the following equation (1). Using incident wavelength λ0, the dispersion coefficient for MD using the following equation (2) [25].

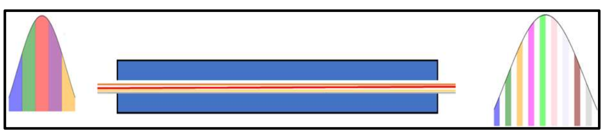

Figure 2: Chromatic dispersion

1) 3.3 Dispersion Compensation Fiber (DCF)

One of the major advantages of dispersion compensating fiber is that it can easily integrate with single-mode fiber networks [26]. Dispersion compensating fibers or fibers that can compensate the dispersion caused by the transmission fiber or the strand of fiber-optic cables used are known as DCFs. They derive this through a negative dispersion value which is expected to range between -300ps/nm/km.

These actions act as the counteraction mechanisms and help in minimizing signal distortion with the objective of enhancing system performance. Dispersion, Kerr nonlinearity and increased SE noise are the main issues that can affect the performance of optical WDM systems. But these are problems that can be avoided if DCFs are adopted and implemented consistently. It is possible to mount it before, after or side by side to the transmission fiber and each positioning has its unique merits depending on the system requirements. Key to enhancing the design of DCF is the need to minimize insertion loss, find ways of lowest possible PMD, minimize optical nonlinearity, and have ways of improving the chromatic dispersion coefficient. Since the signal quality is a critical factor in any optical communications system, DCF (Dispersion Compensation Fiber) is important for achieving reliable systems [27]. This is due to the consideration of the Value of Discounted Cash Flow in the Dispersions equations as displayed in the Figure (3).

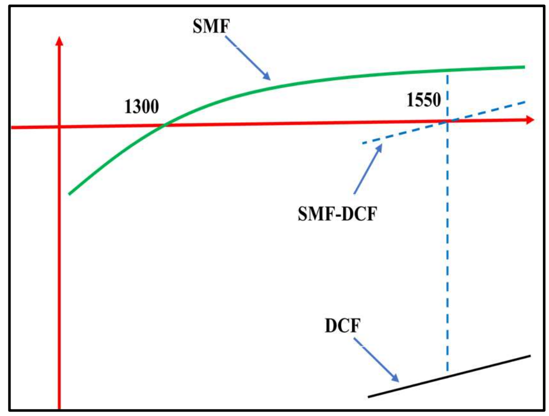

Figure 3: Dispersion compensation by DCF

C. Polarization Mode Dispersion

PMD arises as a result of internal parameters and external conditions in fiber. A number of events happening through the manufacturing of fibers, the presence of flaws in the fibers, variations in the inside tensions, and so on, come under intrinsic factors leading to birefringence between the fiber and cladding. External factors are sources and influences which exert pressure and force, and change the shape, curvature, and aging of fiber optics. On account of these two factors, the two polarization modes travel with different velocities, and the transmission time to reach the receiving end is not equals [28]. Polarization mode dispersion is actually a type of dispersion which relates to the differential group delay of two polarization modes. The totally circular cross-sectional geometry is the ideal fiber geometry, which also has circular symmetric refractive index [28].

This is in stark contrast to the two quadrature polarization modes of a single-mode fiber which are two-degrees orthogonal. The differential group delay distortion between the two polarization modes during transmission is basically due to material, geometrical and stress anisotropy. This is referred to as polarization mode dispersion as shown in Figure (3-9) [28].

PMD is caused by the following factors: dam fiber, that is the geometric size of the optical fiber which is randomly manufactured in its geometry size and the residual stress in it; the refractive index distribution of an optical fiber is anisotropic; the optical cable, during its laying an in use, under external extrusion, torsion or changes in the environmental temperature or else, polarization mode coupling occurs [29].

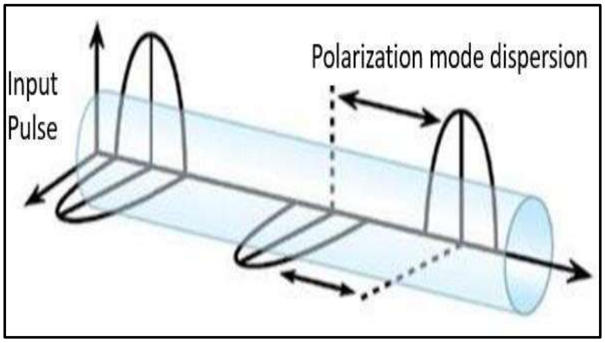

Figure 4: Polarization mode Dispersion in optical Fiber

4. Faults in Optical Fibers

To detect faults in optical fiber networks, it's essential to perceive the likely sorts of deficiencies that might happen. In optical fiber networks, two fundamental sorts of shortcomings are regularly experienced: fiber link property flaws and fiber cuts [30]. Fiber link property shortcomings allude to issues with the qualities or properties of the fiber link itself, like imperfections in the material or assembling process. Then again, fiber cuts happen when the actual progression of the fiber is disturbed, frequently because of outside factors like unplanned harm or conscious damage. Distinguishing and tending to these flaws are fundamental for keeping up with the respectability and usefulness of optical fiber networks [31].

A. 4.1 Fiber cable attribute faults

While evaluating the suitability of optical fibers for communications networks, the disadvantages of fiber cable characteristics come first. Basic transmission characteristics to consider include bandwidth, which is affected by dispersion and attenuation levels [16]. Dispersion refers to the spread of signals over time or distance, while attenuation refers to the loss of signal strength. These properties are affected by various factors, including radiation, absorption and scattering. Ensuring optimum levels of dispersion and attenuation is vital to maintaining reliable and efficient communications over fiber optic networks. [32].

B. Dispersion

In digital communications systems that use optical fibers, data is encoded in light pulses that are sent from the sender to the receiver. However, while traveling through the fiber, these pulses undergo scattering, leading to various types of signal degradation. [33]. Scattering causes the pulses to spread over time or distance, leading to phenomena such as cross-talk, where the overlapping pulses become blurred to the receiver. Dispersion in optical fibers can be classified into two main types: multiple dispersion, which occurs in multimode fibers due to differences in mode lengths and velocities, and internal dispersion, which prevails in single-mode fibers at high data rates, causing broadening of the pulses. Managing dispersion is important to maintain the integrity and performance of optical communications networks, and ensure reliable data transmission over long distances. [30].

C. Fiber cable cut

The occurrence of a break in an active fiber optic cable due to work carried out at the cable site is called the “fiber break phenomenon”. The extent of the outage depends on the location and number of active fiber optic cables affected by the outage. This phenomenon poses significant risks to the telecommunications industry, affecting network availability, operation, maintenance, and revenue margins.[34]. Optical fiber, with its superior advantages over traditional transmission media, is increasingly replacing microwave transmission networks in telecommunication networks. However, ensuring the reliability and smooth operation of fiber optic networks, which typically transmit large amounts of data traffic, remains a major challenge.[30].

Persistent fiber cuts represent a major challenge for telecom operators, as evidenced by domestic fiber optic network statistics in 2018. Faults are classified based on their impact on system parts and services and root causes. In backbone networks, where fiber cable lengths are much longer than in metropolitan networks and the number of nodes is higher, protecting the cable length is vital due to the higher failure rate.[34].

5. Fault Detection in Underground Optical Networks

Failures in optical networks mainly appear in the form of losses, which significantly affect the quality of transmission (NoT) and overall quality of service. These faults are usually classified into two main categories: hard faults and soft faults. Hard faults are sudden events such as fiber cuts or outages, while soft faults involve gradual degradation, often due to equipment failure or channel misalignment [32]. Multiple sources contribute to failures in optical networks, including channel misalignment, booster failure, and fiber kinking. Soft faults, in particular, can lead to signal degradation and bit error rate (BER) variations at the receiver, which can lead to packet losses or service interruptions [32**].**

While soft malfunctions are usually treated using specialized detection techniques, difficult faults in the underground networks, such as cutting and sprains in fiber cables, are usually followed and usually determined by using OTDR. However, the use of OTDR is accompanied by a set of problems as we mentioned earlier, causing difficulties for the cable repair teams to determine the exact location of the malfunctions in the optical fiber cable. This situation prolongs the period of disruption of the service, increases revenue losses and losing communication services for users [35].

A. OTDR

An Optical Domain Time Reflector (OTDR) is a pivotal device for tracking faults in optical cables. Its working principle is based on the use of Rayleigh scattering and Fresnel reflection techniques to accurately measure fault distances. In addition, OTDR is used to check for loss of links, measure cable length, and identify faults in optical cables, especially during initial installation.[36].

When an OTDR sends a high-power optical pulse through a fiber, Rayleigh scattering occurs, producing a feedback signal that reflects faults in the cable and returns to the device. This returned light is detected by a sensitive photoreceptor, converted into digital form, and the signal is averaged to improve the signal-to-noise ratio. The resulting data is displayed as a graph, providing a visual representation of backscatter activity, including cuts, link losses, bends, attenuation, and fault distances in the optical network.[37].

Fresnel reflection, another technique used by OTDR, detects discrete reflections caused by changes in refractive index elements, such as air gaps or particles that obstruct the flow of light. These reflections show fault locations, and by analyzing Fresnel reflection data, OTDR can predict both soft and hard faults in grid infrastructure[38].

In addition to Rayleigh scattering and Fresnel reflection, OTDR can use other analytical principles such as Raman scattering, Mie scattering, and Brillouin scattering to trace faults in optical networks. These principles allow OTDR to accurately measure underground fiber cable distances, enhancing fault detection capabilities under various conditions.[30].

B. Tracing Optical Network Faults

Fiber optic network troubleshooting is a critical activity as it helps identify flaws with the aim of enhancing the stability of these networks. It is often initiated by detected signs that include poor performance, signal attenuation, and so on. There are different methods of identifying faults, such as OTDR – which involves the transmission of light pulses along the fiber and whose reflections indicates the presence of faults; and VFL which uses visible lasers to indicate faults and breaks or bends in the fiber. Optical Power Meters and Optical Spectrum Analyzers (OSA) are instruments that respectively measure the signal power deviation and variations of the signal spectrum. Other fault isolation techniques such as the sectional and loopback testing aid in making a narrowing down of the fault. NMS continuously monitor alarms and performance to distinguish early signs of problems hence are important in the network. Once a fault is realized, then instruments such as the OTDR can be used to measure distance to the slash and mapping of the topology assists in figuring out the exact physical placement of the slash. Analyzing repair and maintenance, some of them consist of splicing of damaged or cut fibers, cleaning or replacement of connectors, and replacement of any bad networking part. The post-repair tests guarantee that faults found have been corrected while monitoring as continued helps in keeping a check on the efficient network [38].

C. 5.3 Shortcomings in the current Fault Tracing Techniques

Despite the advancement of current technologies applied in fault tracing techniques for optical networks, one can identify certain weaknesses. OTDR and OSAs are expensive tools which are not easily affordable by many firms especially those that operate in narrow fields; they require keen training to be used on the field. Also, while OTDR is good at fault identification, it may not be as accurate when it comes to determining the exact location of the fault, particularly when the network is highly branch or geographically entangled; also may provide insufficient data resolution in case of short fiber segments. Another weakness of some fault tracing tools is that they are selective in the types of faults that they can detect; for example, while OTDR works best when the breakage or severe bending of the fiber is present, it may not be able to recognize minor signs such as the wear and tear of the connectors as well as alignment problems with the fibers. Some forms of tests like loop back test may be invasive and can cause interruption in the network services and this is un desirable in heavily reliant applications or systems that run 24/7 [39].

There is also often manual intervention required in fault tracing processes, and this may take a long time in writing and can also involve human error. Due to the character of the sensor data, numerous external disturbances like temperature variations and mechanical vibrations may influence the precise detection of the fault. The major challenge with legacy fault tracing methods is that the existing techniques may become resource-intensive and time-consuming with increasing network size and complexity of optical networks, thus resulting in extended detection and repair times. Secondly, the integration of fault tracing tools with the existing network management platforms can be cumbersome and whose integration offers operational complications with the systems. Thus, the further development and improvement of fault tracing techniques pinpointed their current weaknesses and the need for their elaboration to suit today's characteristics of optical networks [40].

6. Application of Machine Learning in Optical-Network Failures

Machine learning (ML) is progressively being applied to address difficulties connected with optical network disappointments. Here are a few key applications:

1. Fault Location and Classification: ML calculations can investigate information gathered from optical networks, including OTDR follows, to recognize and arrange various sorts of deficiencies, for example, fiber cuts, twists, and sign corruption. Via preparing models on verifiable information, ML can distinguish designs demonstrative of explicit kinds of disappointments, empowering proactive support and quicker issue goal [41].
2. Predictive Maintenance: ML models can foresee expected disappointments in optical networks by breaking down different boundaries like sign strength, lessening, and natural circumstances. By checking these elements continuously and contrasting them and authentic information, ML calculations can gauge when and where disappointments are probably going to happen, permitting administrators to make preventive moves before issues heighten [42].
3. Anomaly Detection: ML procedures, for example, unaided learning can recognize oddities in optical network conduct that might demonstrate looming disappointments or strange circumstances. By ceaselessly checking network execution measurements, ML calculations can recognize deviations from typical activity and trigger cautions for additional examination [43].
4. Optical Signal Quality Optimization: ML calculations can upgrade optical sign quality by changing boundaries, for example, power levels, regulation arrangements, and scattering pay settings because of changing network conditions. By gaining from past execution information, ML models can powerfully adjust network setups to amplify signal quality and limit the gamble of disappointments [44].
5. Dynamic Steering and Asset Allocation: ML-based traffic designing calculations can upgrade directing choices and asset allotment in optical networks to moderate the effect of disappointments and guarantee productive utilization of network assets. By dissecting traffic examples and network geography, ML models can powerfully reroute traffic around bombed connections or hubs to keep up with administration progression and limit clog [45].
6. Performance Forecast and Limit Planning: ML models can anticipate future network execution and limit prerequisites in light of verifiable information and projected development patterns. By estimating traffic interest, transmission capacity usage, and asset accessibility, ML calculations can assist administrators with arranging network overhauls and extensions to forestall bottlenecks and oblige expanding request [46].

In general, the utilization of ML in optical-network disappointments holds extraordinary potential to improve network dependability, effectiveness, and execution by empowering proactive shortcoming discovery, prescient upkeep, and canny asset the executives.

7. Advantages of ML techniques in Fault Detection and Classification in Optical Networks

- Detecting and classifying errors in fiber optic networks using artificial intelligence techniques achieves many unique advantages, including:
- High accuracy: AI algorithms have the ability to detect and classify errors with high accuracy, reducing false positives and negatives.
- Real-time monitoring: AI-based systems can continuously monitor fiber optic networks in real-time, allowing immediate detection and response to faults.
- Scalability: AI algorithms can scale to analyze large amounts of data from complex fiber-optic networks, making them suitable for deployment in diverse environments.
- Adaptive learning: AI systems can adapt and learn from new data and experiences, improving error detection and classification capabilities over time. As Bill Gates once observed, "The progress of technology depends on making it so convenient that you don't really notice it, so part of everyday life." AI-based fault detection and classification is seamlessly integrated into existing network management workflows, enhancing overall operational efficiency [35][47]

7. Related Works Analysis

Fault detection and order assume a critical part in guaranteeing the unwavering quality and proficiency of different networks across various spaces. Table 1 gives a thorough outline of ongoing exploration endeavors pointed toward addressing different difficulties connected with issue identification and order. The examinations cover many applications, including optical networks, sensor networks, modern cycles, and Web of Things (IoT) conditions.

The table sorts the exploration concentrates on in light of the analysts, issue tended to, techniques utilized, results acquired, qualities of the methodologies, and impediments recognized. Each review offers one of a kind bit of knowledge and commitments to the field of issue location and characterization, using different strategies, for example, AI calculations, model-based techniques, profound learning approaches, and time-series examination.

From issue identification in optical fiber networks to prescient support for machine disappointments and wellbeing status expectation of electronic sensors in independent vehicles, the table features the variety and meaning of examination endeavors pointed toward upgrading framework unwavering quality, execution, and security through successful shortcoming location and characterization procedures.

Specialists and experts can involve this table as a significant asset to acquire bits of knowledge into the most recent headways, strategies, and difficulties in shortcoming discovery and grouping across various application spaces.

TABLE 1. Summary of Fault Detection and Classification Research Studies

Reference	Problem	Method	Results	Strength Points	Limitations
Ali [3]	Fault detection in optical fibers	Review of published papers, white papers, and articles	Identification of common faults: fiber cut, high attenuation, dispersion	Comprehensive overview of fault detection techniques	Limited to existing literature; may not cover all emerging methods
Khan et al. [7]	Lack of understanding regarding the applicability of ML techniques in optical communications and networking	Review of ML concepts from communication theory and signal processing perspectives	Description of mathematical foundations of basic ML techniques	Provides insights into potential ML applications in optical communications and networking	Limited to theoretical understanding; may not cover practical implementation aspects
Abdelli et al. [48]	Distortion of OTDR traces due to noise	Combination of denoising convolutional autoencoder (DCAE) and bidirectional long short-term memory (BiLSTM)	- DCAE efficiently removes noise from OTDR traces, outperforming other deep learning techniques and conventional methods , BiLSTM achieves high detection and diagnostic accuracy of 96.7% , Improvement of 13.74% compared to model trained with noisy OTDR signals	Effective denoising and fault detection in OTDR signals	Limited to experimental results, may not address all potential noise scenarios in real-world applications
Patri et al. [49]	Detection and identification of failures in Optical Spectrum-as-a-Service (OSaaS) networks	Evaluation of Machine Learning (ML) based algorithms using telemetry data from Flex-BVTs	- Utilization of Artificial Neural Network (ANN) model with dynamic threshold calculation and One-Class Support Vector Machine (OCSVM) model	Efficient failure detection and identification using telemetry data from end Flex-BVTs	Limited to evaluation of ML algorithms on a specific network configuration and duration
Liu et al. [50]	Efficient fault location mechanism for high-density interconnection scenarios in data centers	Application of customized AI module to OTDR device combined with optical power monitoring module	- AI-assisted optical network fault location mechanism implemented , Utilization of AI module for predicting potential failure in optical links , Significant improvement in fault detection efficiency	Improved fault detection efficiency using AI module	Limited to specific scenario of high-density interconnection in data centers

			by 98.41%		
Goni et al. [51]	Detection and classification of faults in transmission lines (TLs) to ensure stability and continuous power supply	Development of a spontaneous fault detection (FD) and fault classification (FC) system based on Machine Learning (ML)	- Utilization of MATLAB Simulink for simulation and data generation , Extreme Learning Machine (ELM) algorithm used as classifier , Achieved high fault classification and detection accuracies	Relatively shorter processing time and reduced computational complexity compared to traditional Artificial Neural Network (ANN) model	Limited to simulation-based study; may require further validation on real-world TLs
Villa et al. [52]	Utilizing machine learning algorithms to enhance the functioning and operation of optical networks	Systematic mapping analysis of 96 papers out of 841 publications to identify the use of machine learning techniques in solving optical network problems	- Supervised machine learning techniques predominantly used for resource management, network monitoring, fault management, and traffic classification and prediction , Identified opportunities and future research directions in the field	Provides an overview of machine learning applications in optical networks	Most research conducted in controlled experimental environments, highlighting the need for further validation in real-world communication systems
Kruse et al. [53]	Improving fault management in increasingly complex optical networks to enhance network assurance	Experimental comparison of performance of soft-failure management using different machine learning algorithms	- Introduction of a machine-learning based soft-failure management framework utilizing a variation auto encoder based generative adversarial network (VAE-GAN) , Outperformance of VAE-GAN in identification tasks with limited training data	Offers a novel approach to fault management in optical networks using machine learning	Limited to experimental comparison and may require validation in real-world scenarios
Lindström et al. [54]	Improving pulp testing in the pulp and paper industry through automated image analysis and machine learning (ML)	Application of four supervised ML techniques—Lasso regression, support vector machine (SVM), feed-forward neural networks (FFNN), and recurrent neural networks (RNN)—to fiber data obtained from fiber suspension micrographs	- Maximum accuracy achieved with FFNN algorithm with Yeo–Johnson preprocessing: 81% using commercial fiber analyzer software	- Offers a consistent, fast, and cost-efficient alternative to labor-intensive pulp testing	- Limitation to specific techniques and software used may affect generalizability - Potential need for further validation and optimization in real-world industrial settings
Singh et al. [55]	Predicting distributed denial-of-service (DDoS) attacks in fiber-optical networks using innovative SL-FLSTM strategy	Development of Sea Lion fine-tuned Long Short-Term Memory (SL-FLSTM) strategy to predict DDoS attacks	- Recall: 98.1% , Precision: 98.2% , F1 score: 98.3% , Accuracy: 98.4% , Outperformed other existing approaches in predicting DDoS attacks in fiber-optical networks	- Incorporates insights from Sea Lion (SL) behavior to improve sequential data processing , Integrates bio-inspired modifications into the LSTM architecture, enhancing long-term dependency modeling , Achieves high performance metrics in recall, precision, F1 score, and accuracy	- Limited to prediction of DDoS attacks in fiber-optical networks; may not generalize to other types of cyber attacks

Manzoni et al. [56]	Continuous Glucose Monitoring (CGM) sensor fault detection in an artificial pancreas	Model-based fault detection using Kalman predictor	Large inconsistencies between measured and predicted values suggest faults	Model-based approach, accounts for system dynamics	Requires a well-defined model, relies on accurate predictions
Jihani et al. [57]	Fault detection and isolation in Wireless Sensor Networks (WSN)	Parity space approach based on mathematical models	Significant differences between measured and predicted values indicate faults	Utilizes redundancy in sensor measurements	Requires prior knowledge for model construction
Hashimoto et al. [58]	Fault detection and diagnosis of internal sensor in mobile robots	Multimodal approach using Kalman filters	Fault decision based on mode probabilities estimated from sensor gain	Handles multiple failure modes	Assumes accurate estimation from Kalman filters
He et al. [59]	Optical fiber sensor fault detection in aero-engine system	Model-based method considering disturbances and uncertainties	Demonstrated performance on a gas turbine model	Accounts for system uncertainties	Requires accurate modeling of system dynamics
Yan et al. [60]	Minor soft faults detection in air conditioning sensors	Model using KPCA-DL-BiLSTM	Higher detection rate compared to individual methods	Utilizes advanced machine learning techniques	Performance may vary with different fault types
Alwan et al. [61]	Long-segmental faults detection in sensor nodes	Time-series clustering technique	Efficient detection of long-segmental outliers	Provides alternative to predictive analysis	Depends on the quality and representativeness of data
Zhao et al. [62]	Incipient faults detection in industrial processes	Sliding window approach with control limits	Detects constant bias and precision degradation	Utilizes empirical control limits	Limited to specific types of faults and processes
Uppal et al. [63]	Early fault prediction in IoT environment	Machine learning algorithms including Random Forest	High classification accuracy of 94.25%	Demonstrates effectiveness of ML in fault prediction	Performance may vary with different datasets and algorithms
Wahid et al. [65]	Predictive maintenance for machine failures	CNN-LSTM model for time-series analysis	Provides reliable and accurate prediction	Utilizes advanced neural network architectures	Performance may depend on the quality and quantity of data
Uppal et al. [66]	Fault classification in office appliances connected via IoT	Machine learning algorithms	Provides monitoring and classification of faults	Utilizes IoT data for fault detection	Performance may vary depending on appliance complexity
Safavi et al. [67]	Health status prediction of electronic sensors in autonomous vehicles	Feature extraction and multi-class DNN	Identifies faulty sensors and types of faults	Utilizes advanced machine learning for fault recognition	Requires accurate feature extraction and labeling of faults

8. CONCLUSIONS

To sum up, the incorporation of machine learning methods presents encouraging ways to tackle the difficulties related to defect detection in optical fiber networks. Operators may anticipate possible failures, proactively detect and categories errors, and improve network performance by utilizing ML algorithms. To evaluate the efficacy of ML models in practical settings and to solve particular issues like network complexity and noise in OTDR traces, more research is necessary. All things considered, ML-based fault detection techniques have the power to completely transform optical network fault management, resulting in improved performance, efficiency, and dependability.

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