Machine Learning Based Fiber Monitoring for Passive Optical Network

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ABSTRACT

In this paper, we present a machine learning-based approach for monitoring a failure in an optical fiber link for a passive optical network utilizing an optical mirror. A trained support vector machine (SVM) model is intended to detect and identify optical links with problems in an optical distribution network. The method is based on the optical reflected signal acquired from the optical reflectors, which is then processed using the SVM algorithm in MATLAB. A simulated 1x4 Gigabit passive optical network with a monitoring power of -4.16 dBm across a distance of 20 kilometres provides the training and testing dataset for the proposed model. Optimal SVM parameters are selected through cross-validation, resulting in an optimized non-linear decision boundary. The suggested technique is evaluated on a range of datasets produced from optical reflectors and indicates that the model achieves a high detection accuracy (97%-99%) when compared to the observed optical reflected spectra from the mirrors using an optical spectrum analyzer. The proposed technique is significant in that it may identify a failure in an optical channel using monitoring data supplied by multiple reflectors rather than an expensive optical spectrum analyzer or optical testing channel modules.

Keywords: *Passive Optical Network· Machine Learning· Optical Mirrors·*

1. Introduction

PON has become a significant broadband access network globally due to its increased bandwidth, long distance, passive architecture, ease of maintenance, and future upgradeability to higher rates [57]. PON generally provides high-speed internet access services to both residential and corporate users. In actuality, numerous service providers can currently provide their home consumers up to 1 Gbps connectivity [58]. Given the historical patterns in the expansion of optical communication networks, it was also assumed that 100 Gbps of service will be required by 2030 [59]. PON has been regarded by network operators as the most competitive and cost-effective solution to access network convergence.

Demand for high-speed internet services is expanding, and as the spread of fiber-based broadband networks rises, so does the number of network infrastructure. The number of optical fiber cables tends to expand with the number of passive optical network (PON) subscribers; nevertheless, with this development, unexpected defects have developed. Faults in the physical layer of PON are frequently caused by fiber bend and fiber breakage induced by animal exposure, such as rodents, insects, and birds [1]. Fiber breakage can also be caused by excavation damage and failure related to faulty fiber optic connectors and splices [2]. Therefore, PON necessitates the deployment of an excellent physical layer monitoring equipment that can provide maximum monitoring capabilities from the central office (CO) without deploying the technician to the field for the detection and localization of faults in the distribution fiber (DF) network.

The conventional optical time domain reflectometry (OTDR) method is the most often used technique in point-to-point (P2P) technology for fault detection and localization [3-5]. It is often used in P2P networks to remotely track and diagnose defects in optical links. It also computes metrics like splice faults, bit error rate, optical connection losses, and so on. However, the system has inherent limitations in point-to-multipoint (P2MP) technologies, where all back-reflected signals are merged together at the power splitter (PSC) in the optical distribution network (ODN) [6]. As a result, distinguishing a fiber branch from a number of other branches is challenging.

A centralized PON monitoring system, such as the modified OTDR, on the other hand, enables real-time defect detection and localization in the P2MP optical connection with certain modifications to the OTDR's capability. To increase the detectability of fiber impairments, one approach employing tunable OTDR (T-OTDR) [7, 8] employs a chaotic laser and a wavelength selective optical reflector at the end of each fiber branch. However, the technology has the disadvantage of requiring the use of an expensive tunable laser.

Another approach used to monitor optical links in a branch network, such as PON, is optical coding [9, 10]. The optical coding technology uses signal coding techniques inspired by optical code division multiplexing (OCDM) to control and manage passive encoders installed at each DF channel. To identify a given fiber branch in a PON, the encoders reflect the monitoring signal with a unique code. The approach used a distinct wavelength for data and monitoring signals, as well as passive components that do not require field power and are less costly. Although the approach may ensure a cost-effective monitoring solution, it still confronts certain obstacles in fault localization for P2MP networks, and there is a possibility of erroneous detection when there is interference across codes [11].

Brillouin optical sensors and fiber Bragg grating (FBG) sensors are gaining popularity in the scientific community for use in multipoint sensor networks. The Brillouin optical sensor-based technology is an effective monitoring solution for P2MP PON networks [12], but it necessitates a complete overhaul of the existing PON structure, which raises the implementation cost.

The PON fault management system necessitates early warning and increased automation of failure detection and localization. In light of this, machine learning (ML) based on artificial intelligence (AI) provides a possible path for automating PON fault management operations. Recently, ML applications have been used in the domains of optical communication and networking, including applications such as optical network failure management systems, failure detection, and equipment failure type identification [13-17]. The ability of ML tools to learn impairments from observed network data and extract information from given data based on some defining aspects to develop a probabilistic model of the impairments has been a significant advantage [18]. By proposing an automated way of detecting, identifying, and localizing network impairments, ML application in PON will transform traditional techniques to tackling failure management in PON.

- ✓ The main contribution of this study is that it uses machine learning to give an improved optical fiber monitoring system for passive optical networks.
- ✓ The technology detects various DF link failures in the ODN using optical reflectors (optical mirrors), and the reflected signals from the mirrors are evaluated in the central office using enhanced data analysis in the machine learning (ML) technique to discover fiber faults in the network's various DFs.
- ✓ Instead of using the Optical Spectrum Analyzer (OSA) or optical testing channel modules, the suggested SVM-based technique may be utilized to identify a failure in an optical link using monitoring information provided by various reflectors. As a result, the cost of monitoring is reduced.

The ML methodology is presented in Section 2, the simulations and outcomes are discussed in Section 3, and the paper is concluded in Section 4.

LIST OF SYMBOLS & ABBREVIATIONS

ASE	-	Amplified spontaneous emission
CIR	-	Optical circulator
CO	-	Central office
CV	-	Cross-validation
DF	-	Distribution fiber
GPON	-	Gigabit passive optical network
XG-PON	-	Next-Generation PON
OCDM	-	Optical code division multiplexing
ODN	-	Optical distribution network
OLT	-	Optical line terminal
ONU	-	Optical network unit
OSA	-	Optical spectrum analyzer
OTDR	-	Optical time domain reflectometer
PON	-	Passive optical network
P2P	-	Point to point
P2MP	-	Point-to-multipoint
PSC	-	Power splitter/combiner
ML	-	Machine Learning
SVM	-	Support Vector Machine
TDMA	-	Time-division multiple Access
TWDM	-	Time and wavelength division multiplexing
Gb/s	-	Gigabit per second
%	-	Percentage
nm	-	Nano meter
dBm	-	Decibel milliwatts

2. Machine Learning Technique for Fiber Monitoring in PON

ML is a branch of artificial intelligence that allows computers to adapt or adjust their activities in order to control or make decisions on a data set in order to make specific operations more effective. A substantial quantity of data is required to train the decision model in a conventional ML. Having a large amount of data helps the controller to give high computational abilities since it has a large amount of storage space. However, in a real network, several optical mirrors display the state of each optical link in the ODN. The controller would be severely overwhelmed if it had to forecast the condition of each mirror in the network on that scale. As a result, it is important to find an efficient ML technique that takes a small quantity of data to train an accurate model. In this regard, the support vector machine (SVM) is excellent for fewer than 5,000 sample training data with high precision, which is applicable to our dataset [19]. The flowchart of the proposed monitoring technique based on the SVM algorithm is shown in Figure 1. This is divided into four primary stages: data retrieval, training parameter configuration, data training and cross-validation (CV), and fault analysis.

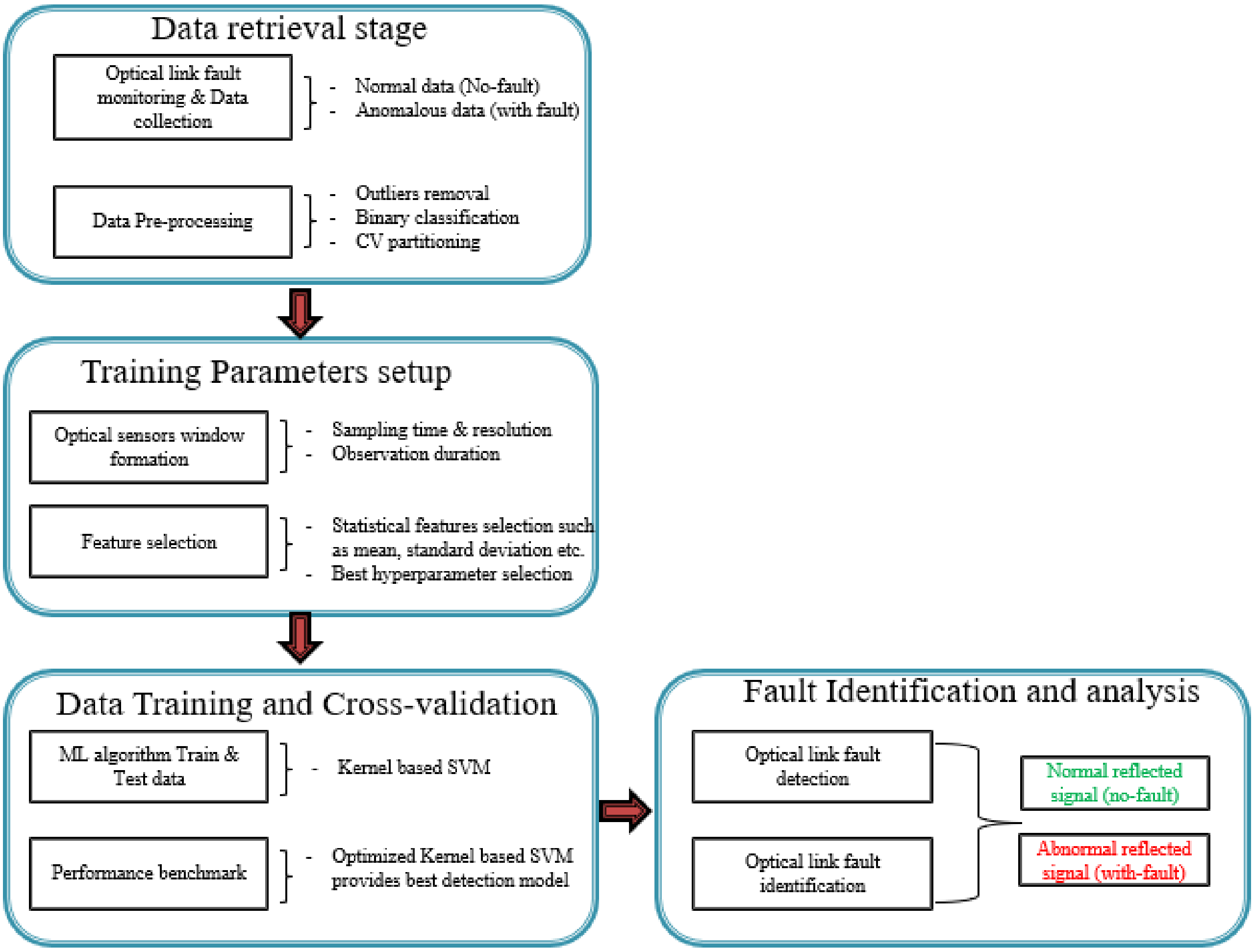

Figure 1. Flow Chart for the Proposed Machine Learning Based Fiber Monitoring System

The optical link is monitored by the optical reflectors located in the ODN, as seen in Figure 2. The reflectance and wavelengths of used optical mirrors vary. For normal and abnormal real-time traces in datasets, samples from these optical mirrors are retrieved from the CO. The SVM pre-processing of the data was done to remove outliers where the dataset is split into 70% training, a test set of 15% and a 15% CV. Upon specifying the training parameters, the SVM algorithm uses a selection of features to shape a vector *x* in each dataset after preparing the datasets. It is important to remember that these characteristics are the values obtained from our reflectors, and that multiple characteristics could result from each of them. Features should be connected to the optical link status to distinguish between link loss and regular service, based on the SVM principles. Therefore, it is important that the most appropriate metrics are chosen to ensure better model efficiency and to ensure the consistency of the final outcome. A 5-fold CV is used in data training to assess the classification precision of the qualified model. The precision of the classification is trained by a dataset created from a single optical mirror and used to obtain the relationship between the mirror's reflected signal obtained and the failure of the link. The loss of the link would obviously have an effect on the condition of the received reflected signal from the mirror. Because of the close association between the optical mirrors and the connection failure, a high classification accuracy would be determined. In this method, the learnt SVM model is utilized to identify the condition of many DF connections and find the optical mirror in the network with and without failure.

3. Simulation and Results

To achieve the results of our measurements, we use Optisystem software to deploy a 4-branched Gigabit-capable Passive Optical Network (GPON) in Time Division Multiple Access (TDMA) with a bit rate of

1.25 Gb/s upstream and 2.5 Gb/s downstream at a distance of 20 km from the CO to the user distribution unit. At the network's last mile, optical link reflectors are strategically placed, and the unmodulated Amplified Spontaneous Emission (ASE) C-band detection signal is multiplexed with the data signal and delivered to the network through the optical circulator (CIR). The OLT sends data at 1490 nm DS and 1310 nm US, while the ASE source sends monitoring data in the C-band between 1530 nm and 1565 nm. At a distance of 20 km, the two signals, data and monitoring, are linked by an ideal MUX and transferred over the FF through a bi-directional CIR. Both signals will co-promote across the feeder fiber and will be power separated through each DF using a PSC. A reflector with a distinct Bragg wavelength is installed at each DF. Depending on the Bragg condition, the monitoring source would be reflected by the sensors. Table 3.1 describes the simulation parameters for the proposed PON monitoring system.

Table 3.1 Simulation parameters for PON equipped with Optical Mirrors [20, 21]

No.	**Name**		**Specification**	
1	OLT module type		GPON - Class B	
2	ONU module type		GPON - Class B	
3	Split ratio of the PSC		1x4	
4	FF Length		20 km	
5	DF length		3.1 km	
No.	**Name**	**Type**	**Value**	**Units**
1	Wavelength	DS	1490	nm
		US	1310	
2	Mean launched power	DS	3	dBm
		US	2	
3	Receiver min. sensitivity	DS	-28	
		US	-21	
4	Bitrate	DS	2.5	Gbps
		US	1.25	
5	Launched Power	ASE	5.6	dBm
6	EDFA	Fiber length	10	m
7	Dual port WDM	WDM analyzer	1500-1620	nm
8	Modulation	DS/US	NRZ	-
9	Linewidth		10	MHz
10	Responsivity	PD	1	A/W
11	Dark current		10	nA
12	Thermal noise		4e-022	W/Hz
13	CW-Laser	Laser	1530/1565	nm
14	CW-Laser	Laser	-48/-44.3	dBm

15	Pump laser	Laser	1480	nm
16	Pump laser	Laser	7.94328	mW
17	Optical Mirror	Bragg wavelengths	1530-1565	nm
		Reflectivity	≤ 90	%
		Bandwidth	1	nm
PON link attenuation				
No.	**Name**	**Type**	**Attenuation (dB/km)**	**Specification**
1	Optical attenuation	DS	0.22	23.1 km
		US	0.35	23.1 km
2	Connecting point	Fusion splicing	0.1	2
		Connector	0.3	6
3	CIR	Optical circulator	0.8	1
4	PSC	PSC insertion loss	7	1
5	Safety margin	Fiber ≤ 5 km	1	
		5 km< Fiber <10 km	2	
		Fiber ≥10 km	3	√

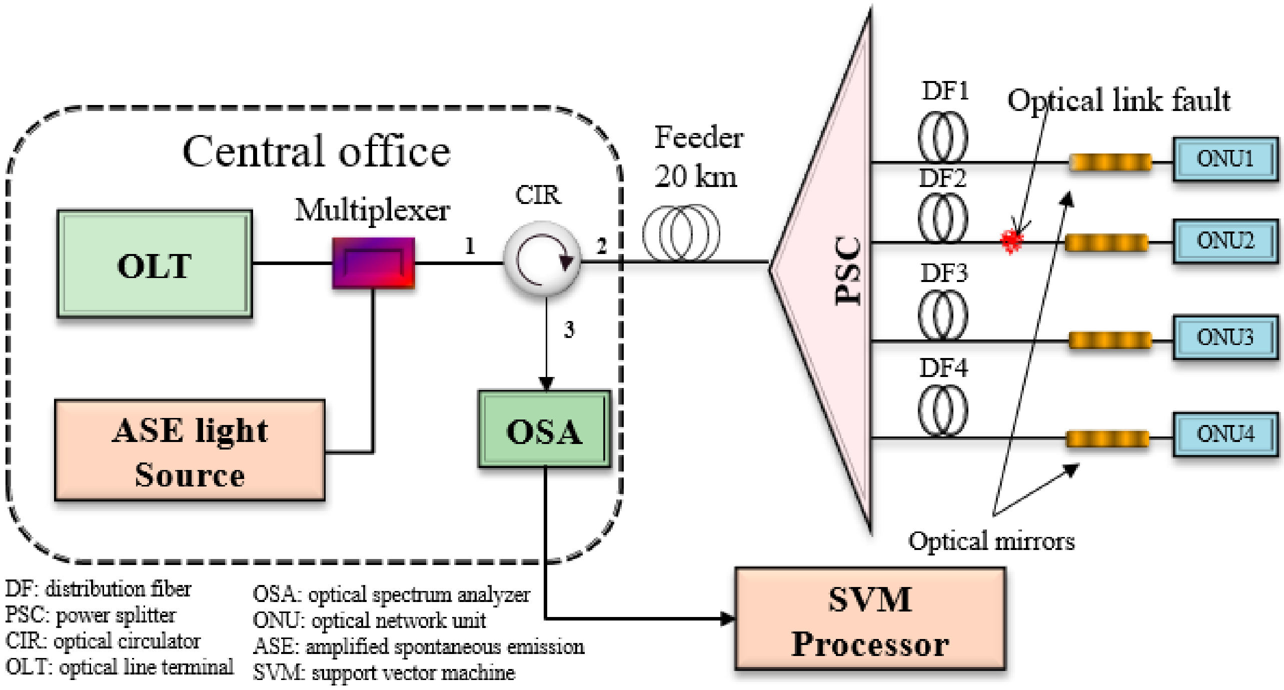

Figure 2. The Proposed Machine Learning Fiber Monitoring Network

The wavelengths of the optical mirrors are 1540.219, 1543.619, 1549.87 and 1553.27 nm respectively, with the reflectivity of all wavelengths exceeding 90%. The SVM was assigned the task of capturing the behaviors of the reflected probe signal collected from the optical reflectors at their Bragg wavelengths, where any changes in the received optical signal could be noticed. When a result, as an optical line nears failure, the reflected optical power signal begins to drop. As a result, the proposed SVM is appropriate for detecting the link with a significant drop in the received optical reflected signal and locating the defective reflector unit.

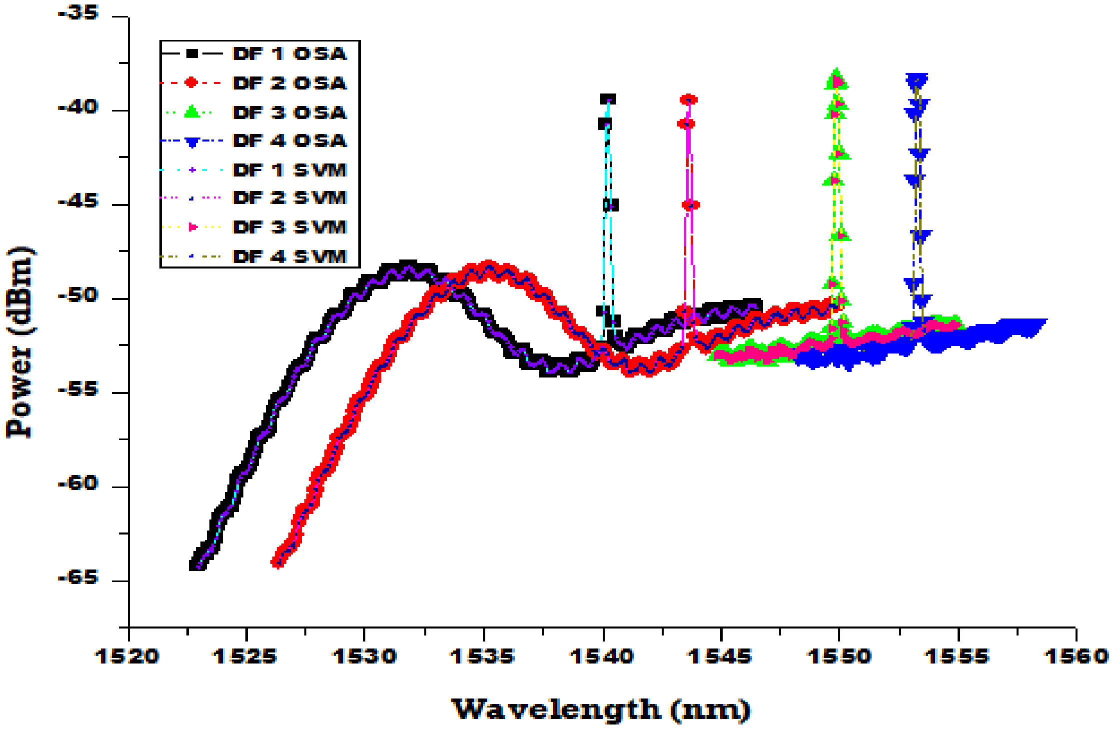

Figure 3. The detected monitoring signals from the reflectors without any fault

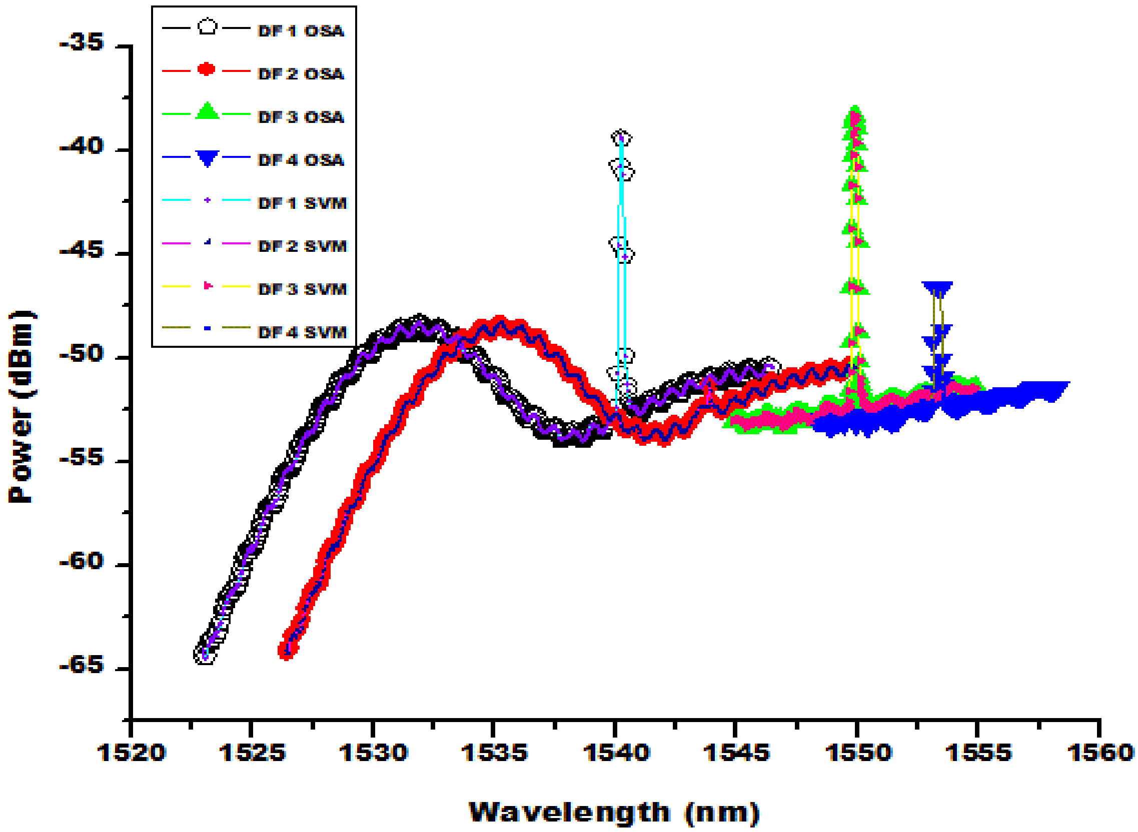

Figure 4. The detected monitoring signals from the reflectors with fault

In the absence of optical link fault, Figure 3 depicts the difference between the reflected mirror probe signals assessed using OSA and the anticipated SVM models. The results demonstrate that the suggested SVM model completely observes and detects all signal spectra from the 1x4 GPON branches, with optical powers ranging from -38 to -39 dBm. However, in the case of fiber branch faults at DF links 2 and 4, major decreases in the optical reflected signal can be detected, indicating an optical link power loss, as seen in Figure 4. The decreased optical power obtained will result in numerous fault events such as fiber bending, connector misalignment or splicing error, while a complete lost reflected spectrum shows fiber break along the optical link. When the optical reflected power collected dropped below a certain level in the optical path, the proposed SVM may also become part of an early warning mechanism by raising alarms for network operators.

In comparison to the typical OTDR system, the suggested approach displayed significant improvements in the detection of many failure scenarios concurrently in the fiber optic connection for the P2MP network. Defects in the DF following the PSC can be detected in the OTDR system by sequentially introducing OTDR pulses into the upstream system. This causes maintenance operations to be delayed. However, in the proposed solution, autonomous end-to-end defect monitoring from the CO may be offered in real time without the need for human involvement. The presented monitoring approach is far less sophisticated and requires less hardware than the solution provided in [22].

The PON splitting ratio employed in this study was only 1x4, although GPON may be expanded up to 1x64 utilizing reach extenders. As a result, the monitoring system may be expanded to monitor up to 64 DF lines. The monitoring and mirror's reflected signals, however, would be significantly attenuated due to significant optical power loss at the PSC. As a result, the monitoring signal source will need to be improved, as will a very high reflectivity Fiber Bragg Grating.

4. Conclusion

This study describes a centralized monitoring system for characterizing the optical link in a PON network. The kernel-based SVM method was trained using data collected from several network reflectors. Mirrors are installed in the ODN at the DF connection to function as monitoring components, reflecting monitoring signals under normal and abnormal situations. The trained SVM model will be used to identify the fiber optic link associated with the network failure automatically. The observed reflected FBG spectra will detect a defective fiber connection, whereas the completely received FBG spectrum shows a good fiber link and the partly reflecting spectrum discloses a flaw in the fiber link. The proposed SVM approach was evaluated on a range of data sets obtained from various DF links, and its ability to detect defective fiber branching was shown. The suggested approach's findings were compared to the results of the Optisystem simulation. When compared to the Optisystem simulation, the proposed SVM model has a maximum detection accuracy of 97 - 99%. The application of the ML approach for optical link monitoring in PON was limited to GPON in this work. It has the benefit of supporting both XG-PON and TWDM-PON. Improvements to the monitoring signal and optical mirrors would also be required. Furthermore, a large number of datasets with a high splitting ratio may be required, therefore SVM may be combined with other ML approaches, such as Deep Neural Network or double exponential smoothing, to improve failure identification features.

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