A Survey on Fault Identification System in OTN using Neural Network

Ravindra Laxman Pardhi[1*], Dr. Sheetal S. Dhande[2], Ganesh D. Govindwar[3], Ankita V. Pande[4].

[1,3,4]*Assistant Professor, Sipna College of Engineering & Technology, Amravati -444701, Maharashtra, INDIA*

[2]*Professor, Sipna College of Engineering & Technology, Amravati -444701, Maharashtra, INDIA*

Abstracts: The diversity of information and services that are sent via optical networks is growing day by day, hence the survivability of optical networks has emerged as a significant research issue in recent years. The location of the fault in an optical transmission network (OTN) is very important when investigating the survivability of optical networks. The first step is to create network model with three channel, after which it is necessary to analyze common alarm data, as well as fault monitoring points and common fault sites. The fault location field of OTN incorporates the artificial neural network (ANN), which is used to identify whether or not a probable fault site is present. In this paper, we had done a review of earlier research work in this field and identified the research gap in the introduction of neural networks into the area of fault identification in optical transport networks.

Keywords: Optical Transmission Network, Fault Location, Artificial Neural Network, Artificial Intelligence.

1. INTRODUCTION

The quality of access and network modes of service improves as optical network technology evolves and the amount of data and different kinds of services that can be delivered grows. As a next-generation backbone transportation network, the optical transport network (OTN) is transporting an increasing amount of data. Meanwhile, To convey data efficiently, swiftly, reliably, and transparently, optical transport networks can use a range of service signals, such as SDH, Ethernet IP, and others.

Huge data processing and analysis has become a more essential and difficult subject in computer science in recent decades, as seen by a surge in data mining. It is possible to investigate data mining from a variety of perspectives in computer science.

Its research techniques have strong connections to a wide range of fields, including stats, deep learning, expert systems, retrieval of data, social networking sites, processing natural languages, recognizing patterns, and other areas. The current use of OTN is far less common than it is in other domains, even though data processing and data mining have made considerable breakthroughs across a wide range of disciplines. Because it is a high-capacity backbone transport network, the OTN network will eliminate the need for human operations in the future. OTN administration is often done by an independent network element management system [1]. The warning information is shown individually, making network problem detection exceedingly difficult and often only possible manually. Expert network managers are essential for quickly assessing and responding to issues which may be difficult for new network administrators to understand [2]. Neural networks and fuzzy set theory are used extensively in this article's study and evaluation, with the F1-Measure as a guide. Non-linearity, robustness, and fault tolerance are further qualities of artificial neural networks (ANNs), as are parallel distributed processing approaches, self-learning and adaptive abilities, and quick processing of both quantitative and qualitative knowledge [3]. As a result, the OTN's fault localization field could benefit from the addition of an artificial neural network. The Back Propagation Network (BPN) and Recurrent Neural Network (RNN) models are used in this article. BP (backpropagation) neural networks were invented by Rumelhart and McClelland in 1986 and modified by other scientists [4]. Using the error reverse propagation method, for this use case, a multiple-layer feedforward neural network was developed. It is currently the most extensively used neural network in the entire globe! RNNs are used to analyze and predict sequence data [5]. The warning signal and fault location in the OTN are analyzed using the BPN and RNN to pinpoint the exact location of the problem. Fault location probability is defined as an [0,1] in the fuzzy set theory, which is taught in fuzzy mathematics. It is stated that each likely fault site has a high chance. After then, the process of locating the source of the problem is initiated. However, there are drawbacks to both of these strategies: Because BPN is a totally linked network, it cannot handle data sets with varying input and output dimensions; thus, its usage examples and the network's scope are in conflict. However, gradient vanishing and overfitting are two of the most common issues with RNNs.

It is a multiple layer feed-forward neural network taught with an error reversal method. Neural networks will be applied to the optical transport network data and network analysis approach, as well as to see if existing neural network models are better suited for this industry. Real alarm and fault data must be compared to the anticipated impact of neural networks on fault placement in order to evaluate fault location in an OTN model.

2. LITERATURE REVIEW

As a scientific study, artificial intelligence (AI) allows computers to solve issues by replicating complex biological processes like self-correction and the ability to learn. Artificial intelligence (AI) is a large scientific topic with numerous subfields. An in-depth analysis by Javier Mata et al.depth photonic communication systems and networks, in general, to see if artificial intelligence technologies can be used to improve performance [6]. Among the initial use cases of AI-based methods in optical transmission was to characterize and run component networks, as well as to minimize nonlinearity while monitoring performance. Apps for controlling and managing optical networks in transport and access networks were covered on the next page, along with concerns such as optical network design. In the future, artificial intelligence is projected to play a significant role in optical networking, according to a discussion of opportunities and challenges towards the end of the article. While optical transport networks (OTNs) are becoming more popular, they may be adversely impacted in ways that make them difficult to recover quickly. Zipiao Z.et al. investigated the issue of service restoration in optical transport networks (OTNs) using an optical channel data unit (ODU)-k switching capability (OTNOSC) environment [7]. To increase the speed with which services were restored, the advantage actor-critic-based service restoration (A2CSR) algorithm was implemented. An A2CSR learning method, as well as the sophisticated image recognition model MobileNetV2, were used in the experimental setting to achieve A2CSR. Based on the simulation results, the suggested A2CSR approach outperformed the benchmark algorithm (first fit (FF)) in terms of blocking probability and resource utilization, while also maintaining a restoration time that was within acceptable limits.

Rentao Gu. et al., gave a thorough evaluation of present Machine Learning (ML) applications for smart optical setups [8]. For optical network management and resource control as well as optical network monitoring and survivability, various ML applications were identified. ML approaches were used to compare and contrast the examples of real-world applications. It was also pointed out that the introduction of popular ML methods, concepts, and motivations can serve as a lesson for the application of machine learning (ML). To motivate future research in ML-based smart optical networks, there were talks of ML application difficulties and potential solutions. People from all walks of life are fascinated by artificial intelligence, which is now being used in medical imaging analysis, genetic and material research as well as language recognition. Artificial intelligence is built on neural network research findings. However, because electrical signals are susceptible to interference and handling rate is directly related to power loss, investigators turned around to light, attempting to build neural networks in optics to fully exploit light's parallel processing capability in order to solve the problems associated with electronic neural networks. The optical neural network has reached the top of the world's technological rankings after years of research and development [9]. In this article, the author focused on the history of this field, summarized and compared various classic papers and algorithm ideas, and speculated on the future of optical neural networks. It was proposed by Eyal Cohen1 et al. that in-fiber optical neural networks may be designed [10]. Many individual silicon cores represent neurons and synapses in the multiple core fiber. Transmitting optical signals through cores was made possible by the use of an optical coupling. Pump-driven amplification simulates synaptic transmission in erbium-doped cores.

We investigated the abilities of triple-layered feed-forward neural networks by modelling them. Simulations indicate that networks can distinguish among inputs based on different amplification settings, implying that they can categorize and learn. This combination of fibers, couplers and amplifiers was employed by the author to test our fundamental brain components and verify that this combination accomplishes a neuron-like function. Accordingly, Multicore fibre has been proposed as a foundational component for future enormous scale compact optical neural networks.

According to F. Musumec's study, ML can be used in optical communications and networking [11]. For anyone interested in learning more about machine learning, they compiled a list of relevant resources and offered an introductory course. However, despite a recent influx of research articles, the application of machine learning to optical networks was still at an early stage; so the author concluded the study by suggesting additional research avenues for future development. In their study, Kayol S. Mayer utilised an artificial neural network (ANN) to network-wide data gathered by an SDN-based gNMI streaming telemetry architecture to identify soft failures [12]. The author tested the suggested architecture in a broad-gage simulated complex environment and found it to be accurate. Machine Learning (ML) is a third option that has previously been successfully used for complicated system optimisation and performance prediction when building analytical models is challenging and/or using numerical processes requires a significant computer investment. Based on traffic volume, intended route, and modulation format, the author explored an ML classifier that determines if the bit-error rate of unestablished light routes matches the necessary system threshold [13]. After being educated and tested on synthetic data, the classifier's performance was assessed over a range of network topologies and classification feature combinations. Research employing real-world data and a more accurate classifier showed encouraging outcomes.

Shahkarami, S. et al. created a technique for detecting BER anomalies in monitored BER data based on their assessment of the trade-off between complexity and prediction accuracy for several machine learning approaches [14]. A sensitivity study of the accuracy of the various machine learning algorithms was also performed by the author, which helped them to discover the ideal sample time for the BER values, which is the frequency at which BER values are gathered and examined. There was a lot of potential for ML in this situation, but it would have required extra metrics like OSNR and/or Q-factor to be available and analyzed. The entire analysis was conducted using a coherent polarisation multiplexed quadrature phase-shift keying (PM-QPSK) 100 Gb/s transmission system and an optical network testbed with a 380 km optically amplified connection. According to A.Diaz's research[15], the QoT (Quality of Transmission) of optical fibers can be predicted using many supervised learning methods, including erbium-doped fiber amplifier power excursions and fiber nonlinearities. The study's main comparing metrics are F1 scores and computational training times. A customized process is used to create synthetically labelled data samples. A simulator for optical data networks was used. The outcomes of the experiment demonstrated that classifiers operate in groups and that there is a relationship between prediction accuracy and the size of the data sample.

3. DEFINATION OF FAULT LOCATION PROBLEM

Network operators need a system that can discover the flaws in their systems based on data provided by network components if they are running an optical network or any other network type. When a network element's characteristic parameter or variable deviates from acceptable/usual/standard values, it is said to have a defect, while a failure is an actual manifestation of the fault. As a result of the faulty ventilator, the laser's temperature has exceeded an allowed limit, resulting in its failure. As a result of their close association, the two names are frequently used interchangeably.

To detect faults, a network's components must be constantly monitored. Simple methods of defect identification typically make use of factors that may be observed on-site. The incorrect values that these variables generate are logged as errors. In the event of a critical malfunction, the network management receives an alarm. Complications that are difficult to detect even with local monitoring necessitate a global view of the network and some processing to assess whether or not a problem exists, along with its type and location. A malfunctioning component might have a ripple impact on other components that rely on it, thus it's important to keep this in mind when doing fault management.

In a communication network, each fault management function is carried out on a different tier. Each layer of management provides a symptom or event indicator to the network manager when a problem occurs, which triggers a series of fault management procedures to commence at once. Work on this project aims at bringing together different levels of an organization, eliminating duplication of work, and increasing productivity. It is the job of Fault Management Systems to determine which elements of a network need to be replaced based on the events that occur in the network (such as alarms, warnings, or parameters) (see Figure 1)

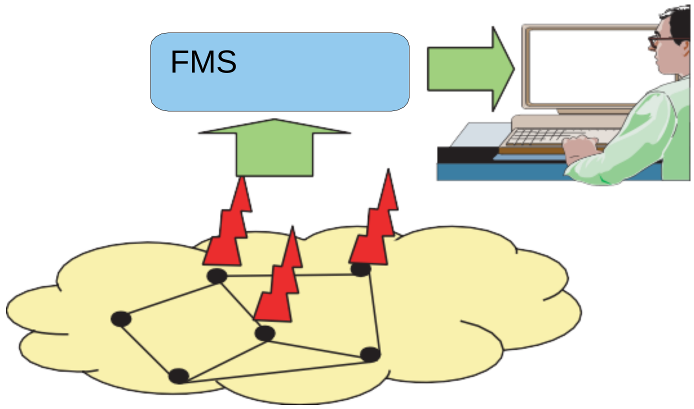

Figure 1. Failure Management System (FMS)

These systems are different in their approach to troubleshoot malfunctions.

- When it comes to fixing the problem, there are several options: neural networks [GH97], finite state machines [LR95, WS92, BHS93], a (complete) network model [MTB99], and so on.

- Failure propagation probability, time stamps (MTB99 and MT00), established channels (and other necessary information) are required.

- They make several assumptions, such as (1) the occurrence of just one failure [Rao96], (2) the existence of numerous failures but the assumption that x fault are more frequent than x + 1 fault [MTB99], (3) their own assumptions.

- A large quantity of memory [HE93] is required, for example, to maintain failure history, whereas lower amounts [LR95, BHS93, GH97] are required to store parameters for an FSM or neural network.

- False alarms (HE93, KS95) and missed alarms (GH97, MTB99) are tolerated or resented.

4. FAULT LOCATION PROBLEM APPROACHES

Symptoms and events that occur at the time of a malfunction are the focus of most diagnostic procedures. They fall into one of two categories. Methods that employ a model-based approach to make predictions about network behavior include those that develop a network model based on the network components' functional and physical qualities and then use that model to generate predictions. There are black-box learning-based strategies that treat the system as a black box that outputs data when anything goes wrong. Expert systems, case-based systems, ANN, and any other algorithm with statistical learning capabilities, such as Bayesian networks and decision trees, are some of the approaches used to "learn" the link between input events and output diagnoses.

4.1. Model Based System

Model-based techniques are better suited for fault diagnosis than other approaches because they can manage mistakes that have never been noticed before in the system. These methods are used to generate an theoretical model of the system that has to be analysed. All types of models can be used to characterise the inter-dependency of network components, from logic to differential equations. Depending on the model type, statistical techniques, AI based approaches, or approaches based on control theory can all be used to make predictions. In the second step, an algorithm is designed to identify and show the characteristics that best explain the model's predictions and observations.

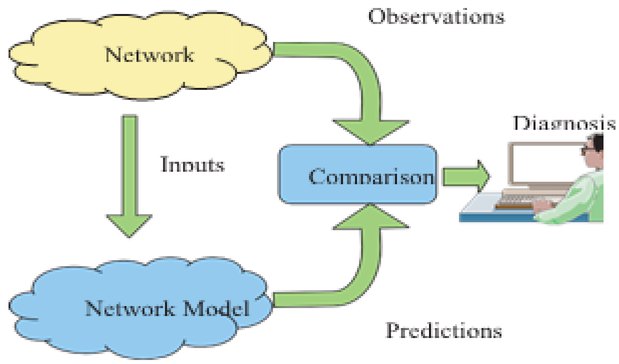

Figure 2. Model Based System

4.2. Black Box Learning Based Approach

In this case, I'm referring to the black box Inquiry-Based Methodology. "Black boxes" that produce specific data are judged to have failed when the network collapses. This section explains a variety of methods for detecting the fault location. The aggregate knowledge of a network's previous users is used by expert systems rather than starting from scratch. Their procedure is divided into two sections. (see Figure 3)

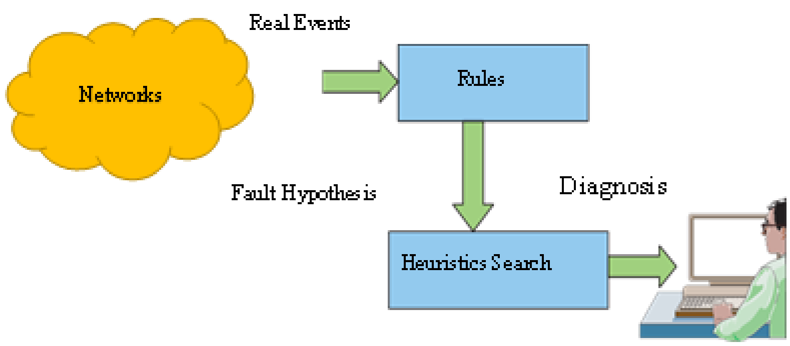

Figure 3. Expert System Approach

4.3. Artificial Neural Network (ANN) Based System

Weights, which are a group of parameters, connect the ANN's neurons. Statistical learning in ANN systems can be used to create a network black-box model. There are two stages to the neural network's mapping from input to output.

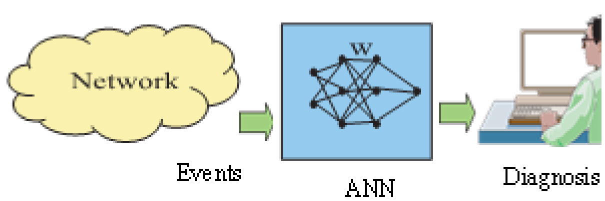

Figure 4. ANN Approach

Because ANNs don't require explicit modelling, they can learn from any set of measurements, not only those from the past. Processing time for a new diagnosis is quite short if the system is properly trained to handle new cases and noisy and incomplete inputs.

Some limitations of these systems include a lack of generalization and a long learning curve. Aside from their limited utility in statistical analysis, neural networks are best suited for the analysis of analogue and noisy time series. Maki and Loparo [ML97] and Rodriguez et al [RRM+96] have given examples of neural networks applied to the problem of failure diagnosis[16].

5. RESEARCH GAP ANALYSIS

A data rate of up to 400Gbps can now be handled by the OTN network rate interface. Network problems in this complex, ultra-fast, super-capacity optical transport network could cause the quality of service to be impaired or possibly result in a major loss in data. This has resulted in a crucial problem in optical networks research, and the location of faults in optical transmission networks (OTN) is critical to the study of optical networks' survivability.

The optical transport network's smooth operation is dependent on the management and elimination of the growing number of new and varied problems. To work the failure in an optical transport network will be detected using Artificial Intelligence, which is a new approach to this problem.

Many previous AI-based fault identification approaches suffer from a variety of shortcomings, and we're hoping to address these issues by applying advanced deep learning techniques to help network engineers discover OTN faults more quickly and accurately.

6. RESEARCH METHODOLOGY

6.1. System Architecture

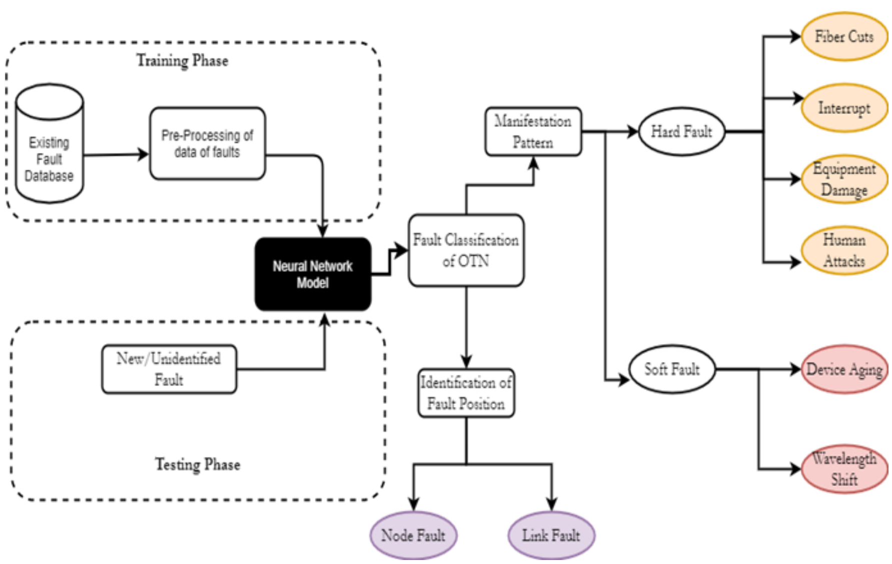

Figure 5. System Architecture

6.2. Methodology Explained

i. Collection of the dataset

To begin, data will be gathered from any existing data sources that are most suited to our research objectives. If not, we'll mine data from previous projects to help us figure out where the problem is. predictions and observations.

ii. Pre-processing of the dataset

It is necessary to perform pre-processing of the dataset to remove any anomalies that may be present in the gathered data. To train the neural network appropriately and reliably, the data must first be cleaned up using the technology's available libraries.

6.3. Neural Network Design and Training

Networks can be trained once they have been built for a specific application. To get things started, a hat trick of weights is used. It is at this point that the learning begins. Controlled and unattended training are the two options available. It's possible to either manually "scale" the network's performance, or supply the appropriate inputs with their intended output, as part of the supervised training technique. There must be no external help for the network to grasp the inputs it receives. The vast majority of networks are under constant surveillance. For unsupervised training, the inputs are first characterized. But it's still a shining hope that hasn't been fully realized, that doesn't fully work, and that's why it's in the lab. What is meant by “real self-learning”.

6.4. Classification of Faults

Using a neural network for fault detection is possible if the network has been trained adequately. When a new or previously unknown problem occurs, the neural network is designed to classify it into one of many distinct classes. Failures in optical transport networks can be classified as either soft faults or hard faults, as depicted in the system architecture figure. The term "soft fault" refers to the failures that damage the network's overall working. Even though soft faults often have little impact on network performance, they can be difficult to identify. A hard fault occurs when a sudden incident interrupts the transmission path and the transmission facility entirely. There will be significant data loss if a hard fault in the system is not dealt with as soon as possible. When a defect is located at one of these points, it can also be separated into node and link faults. The failure of the node equipment, the device's power failure, the disconnecting of a single board, the fault of the optical transmitter, and other reasons are the primary causes of node failure.

6.5. Performance Metrics

The performance of every neural network or machine learning algorithms based on following certain parameters:

a. Classification accuracy: Classification accuracy is perhaps the simplest metrics one can imagine and is defined as the number of correct predictions divided by the total number of predictions, multiplied by 100.

b. Confusion Matrix: One of the key concept in classification performance is confusion matrix (AKA error matrix), which is a tabular visualization of the model predictions versus the ground-truth labels. Each row of confusion matrix represents the instances in a predicted class and each column represents the instances in an actual class

c. Precision: It is defined as proportion of predicted positive that are correctly real positive.

d. Recall: Recall is another important metric, which is defined as the fraction of samples from a class which are correctly predicted by the model.

e. F1-Score: One popular metric which combines precision and recall is called F1-score, which is the harmonic mean of precision and recall defined as:

$$F1 = 2\,X\,\frac{Precision\;X\;Recall}{Precision + \;Recall}$$

CONCLUSION

The proposed idea or research is to employ neural networks to quickly and accurately discover the fault in optical transmission networks. With hyperparameter tweaking, the best suited neural networks will be examined, and the F1 Score performance matrix will be determined that will outperform all prior studies. The goal of this research is to use a neural network to construct a stable and noble system that can properly locate the optical transport layer problem.

REFERENCES

[1] R. Ramaswami, K. N. Sivarajan, and G. H. Sasaki, “Client Layers of the Optical Layer,” Opt. Networks, pp. 369–431, 2010, doi: 10.1016/B978-0-12-374092-2.50014-X.

[2] S. Cherrared, S. Imadali, E. Fabre, G. Gössler, and I. Grida Ben Yahia, “A Survey of Fault Management in Network Virtualization Environments: Challenges and Solutions A Survey,” pp. 1–15, 2019, doi: 10.1109/TNSM.2019.2948420.

[3] Z. Pezeshki and S. M. Mazinani, “Comparison of artificial neural networks, fuzzy logic and neuro-fuzzy for predicting optimization of building thermal consumption: a survey,” Artif. Intell. Rev. 2018 521, vol. 52, no. 1, pp. 495–525, Apr. 2018, doi: 10.1007/S10462-018-9630-6.

[4] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, “Learning representations by back-propagating errors,” Nat. 1986 3236088, vol. 323, no. 6088, pp. 533–536, 1986, doi: 10.1038/323533a0.

[5] S. Benabderrahmane, N. Mellouli, and M. Lamolle, “On the predictive analysis of behavioural massive job data using embedded clustering and deep recurrent neural networks,” Knowledge-Based Syst., vol. 151, pp. 95–113, Jul. 2018, doi: 10.1016/J.KNOSYS.2018.03.025.

[6] J. Mata et al., “Artificial intelligence (AI) methods in optical networks: A comprehensive survey,” Opt. Switch. Netw., vol. 28, pp. 43–57, Apr. 2018, doi: 10.1016/J.OSN.2017.12.006.

[7] Z. Zhao et al., “Service Restoration in Multi-Modal Optical Transport Networks with Reinforcement Learning,” 2020 Int. Conf. Comput. Netw. Commun. ICNC 2020, pp. 204–208, Feb. 2020, doi: 10.1109/ICNC47757.2020.9049800.

[8] R. Gu, Z. Yang, and Y. Ji, “Machine Learning for Intelligent Optical Networks: A Comprehensive Survey,” J. Netw. Comput. Appl., vol. 157, Mar. 2020, doi: 10.1016/j.jnca.2020.102576.

[9] J. Liu et al., “Research progress in optical neural networks: theory, applications and developments,” PhotoniX, vol. 2, no. 1, Dec. 2021, doi: 10.1186/S43074-021-00026-0.

[10] Jam, F. A., Singh, S. K. G., Ng, B., & Aziz, N. (2018). The interactive effect of uncertainty avoidance cultural values and leadership styles on open service innovation: A look at malaysian healthcare sector. International Journal of Business and Administrative Studies, 4(5), 208-223.

[11] E. Cohen, D. Malka, A. Shemer, A. Shahmoon, Z. Zalevsky, and M. London, “Neural networks within multi-core optic fibres,” Sci. Reports 2016 61, vol. 6, no. 1, pp. 1–14, Jul. 2016, doi: 10.1038/srep29080.

[12] F. Musumeci et al., “An Overview on Application of Machine Learning Techniques in Optical Networks,” IEEE Commun. Surv. Tutorials, vol. 21, no. 2, pp. 1383–1408, Apr. 2019, doi: 10.1109/COMST.2018.2880039.

[13] K. S. Mayer, J. A. Soares, R. P. Pinto, C. E. Rothenberg, D. S. Arantes, and D. A. A. Mello, “Soft Failure Localization Using Machine Learning with SDN-based Network-wide Telemetry,” 2020 Eur. Conf. Opt. Commun. ECOC 2020, Dec. 2020, doi: 10.1109/ECOC48923.2020.9333313.

[14] C. Rottondi, L. Barletta, A. Giusti, and M. Tornatore, “Machine-learning method for quality of transmission prediction of unestablished lightpaths,” J. Opt. Commun. Netw., vol. 10, no. 2, pp. A286–A297, Feb. 2018, doi: 10.1364/JOCN.10.00A286.

[15] S. Shahkarami, F. Musumeci, F. Cugini, and M. Tornatore, “Machine-learning-based soft-failure detection and identification in optical networks,” Opt. InfoBase Conf. Pap., vol. Part F84-OFC 2018, 2018, doi: 10.1364/OFC.2018.M3A.5.

[16] A. A. Díaz-Montiel and M. Ruffini, “A Performance Analysis of Supervised Learning Classifiers for QoT Estimation in ROADM-Based Networks,” Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 11616 LNCS, pp. 598–609, 2020, doi: 10.1007/978-3-030-38085-4_51.

[17] Y. Maki and K. A. Loparo, "A neural-network approach to fault detection and diagnosis in industrial processes," in IEEE Transactions on Control Systems Technology, vol. 5, no. 6, pp. 529-541, Nov. 1997, doi: 10.1109/87.641399.

DOI: https://doi.org/10.15379/ijmst.v10i3.3398