Machine-Learning-Assisted Optical Fiber Communication System

Xinyu Zhou

Department of Chemistry, University College London, London, UK

*Corresponding author: zccahoc@ucl.ac.uk

Abstract: With the development of software-defined networking and coherent transmission, to name only a couple of emerging technical and technological areas, optical networks have rapidly expanded during the past few years. To handle with the enormous increment, several sections of optical transmission networks have been addressed via machine learning. Techniques such as support vector machine and KNN algorithms are widely used in fiber-induced nonlinear mitigation, which can cause enormous financial loses if the problem is not solved properly. Optical performance monitoring is another essential area in optical networks, which often adopts multitasking, while failure management, where anomaly detection takes place, rely on both supervised and unsupervised learning methods. The overview includes a brief synopsis of four types of learning methods, including supervised learning, unsupervised learning, semi-supervised learning and reinforcement, as well as the most recent advancements in methodologies used in optical fibre communication. At the end of the analysis, it is demonstrated that ML algorithms are selected based on the challenges present and we have to consider multiple factors when choosing a suitable algorithm. The combination of the two fields brings prosperity to each other.

Keywords: Machine Learning, Optical Fiber Communication System.

1. Introduction

Telecommunication systems have evolved tremendously since 1850s. Over the upcoming ten years, optical telegraphy was gradually replaced by electrical telegraphy systems in most countries. In 1870, British physicist John Tyndall demonstrated that light follows a zig-zag path in water due to internal reflection, which became the basis of William Wheeler's idea after a decade: "piping light", an approach for light transmittance [1, 2]. Fiber optic communication flourished in the second half of the twentieth century [2]. About ten years later, the concept of machine learning (ML) was first introduced by Harvard psychology professor B. F. Skinner, who created a teaching machine [3,4]. As there is an increasing demand for high-speed information transmission, machine intelligence has become a vital solution to many fields of fiber-optic communication, which improves implementation efficiency, reliability, and quality.

Machine learning techniques can be roughly divided into four categories: supervised, unsupervised, semi-supervised, and reinforcement learning. The four subcategories has widespread applications to various aspects of optical fiber communication systems, including fiber-induced nonlinearity mitigation, optical performance monitoring (OPM), failure management [5].

This paper aims to explain the basic principles of the learning methods and review some of the applications of the four learning methods towards fiber-optic communication networks.

2. Principle Analysis of Machine learning methods adopted in optical networks and systems

2.1 Supervised Learning

Supervised machine learning algorithms are trained in a class of labeled input and target output data provided by trainer to seek functions that simulate the sample well [7]. The paired samples are independently and identically distributed from some distribution. The number of input attributes is a key factor that decides the time and space complexity of the function predicted and the training

algorithm, i.e., how much calculation we do and how much memory we need. Each observation encompasses numerical values or categorical values or both. During the process of mimicry, the algorithm generalizes new examples or classifies data based on the model suggested. As input data is fitted into the model, its weight parameters are adjusted until the model has been fitted appropriately to make the most accurate predictions on the set of data. The system measures its accuracy and learn over time. There are two subfields for supervised learning: classification and regression. Classification classifies discrete values, while regression predicts the trends and gives continuous values. In classification, a classifier assigns a class to an object [8]. An example of classification algorithms is the KNN algorithm. Regression can be further divided into linear regression and logistic regression. Supervised learning is ideal for support vector machine, decision trees, binary classification, multi-class classification, regression modeling and ensembling (ensemble methods).

2.2 Unsupervised Learning

Unsupervised learning is a field of practice that requires no trainer or training data. Untagged data is analyzed and clustered based on the machine's own experience, and the algorithm identify the data grouping and the underlying pattern of similar attributes. The models are utilized for three main tasks ---- clustering, association, and dimensionality reduction. Clustering involves grouping similar data in the dataset [9]. Commonalities among similar groups could be found in the dataset during clustering. One of the most popular clustering analysis techniques is k-means clustering, where k clusters are searched in the sample. Unsupervised learning is less commonly adopted than supervised learning. Unsupervised learning is less commonly used than supervised learning.

2.3 Semi-Supervised Learning

Halfway between supervised and unsupervised learning, semi-supervised learning is indeed a sort of partial supervision. The learning method incorporates the benefits of both supervised and unsupervised learning. There are numerous unlabeled data and a minimal number of labelled data from which labels can indeed be deduced. One of the key features of semi-supervised learning is proximity symmetry, which specifies that if the inputs are alike, the labels on the outputs should also be similar.

The following is a tenable hypothesis: The outputs y_1 and y_2 should be matching if two points, x_1 and x_2, in a dense area are close to one another. Semi-supervised learning is used in fiber non-linearity mitigation, optical spectrum analysis.

2.4 Reinforcement Learning

Reinforcement learning is a goal-directed learning, which works in accordance with the knowledge gained to guide individuals to make the optimal choices and maximising a concrete measure of success. An environment is constructed and a decision-maker known as the agent is placed in the environment. The environment is in a specific state at any instances. The state changes whenever the decision-maker executes a task. The solution to a task requires a sequence of actions, and we get feedback in the form of a reward. The feedback mechanism informs the agent whose behaviours result in success or failure, and the system is oriented on maximising a reward signal. During the process, the decision-making entity learns through trial and error.

When choices are made in a sequential manner and actions result in environment exploration, reinforcement learning is most effective. The learning approach has been widely used in the disciplines of control theory, autonomous systems, and other intelligent computation. It is simple to add the business's preferred measurements and optimises for long-term, multi-step benefits. The operators are not required to sample and fit offline because the algorithms actively seek out the best model. Credit assignment issues may result from reinforcement learning. It's possible for a reinforcement signal to be sporadic and delayed, not showing up right away after the behaviour that resulted in the reward.

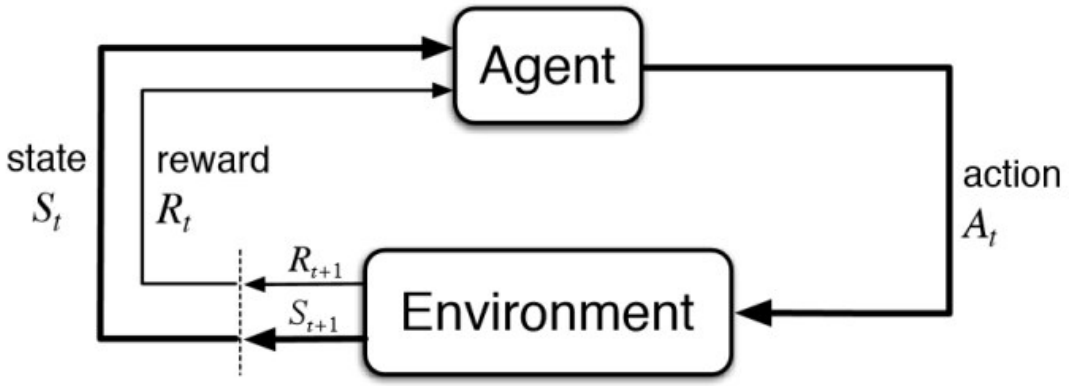


Figure 1. The schematic of Reinforcement Learning

3. Application of machine Learning in Optical Networks and Systems

3.1 Fiber-induced nonlinearity mitigation

Kerr nonlinearity is partially responsible for optical fibre channel nonlinearity in optical communication systems, which restricts high-speed internet's data capacity and transmission range. As a result, compensators are needed at the receiver and/or transmitter. These compensators could be implemented using high-speed DSP techniques [10].

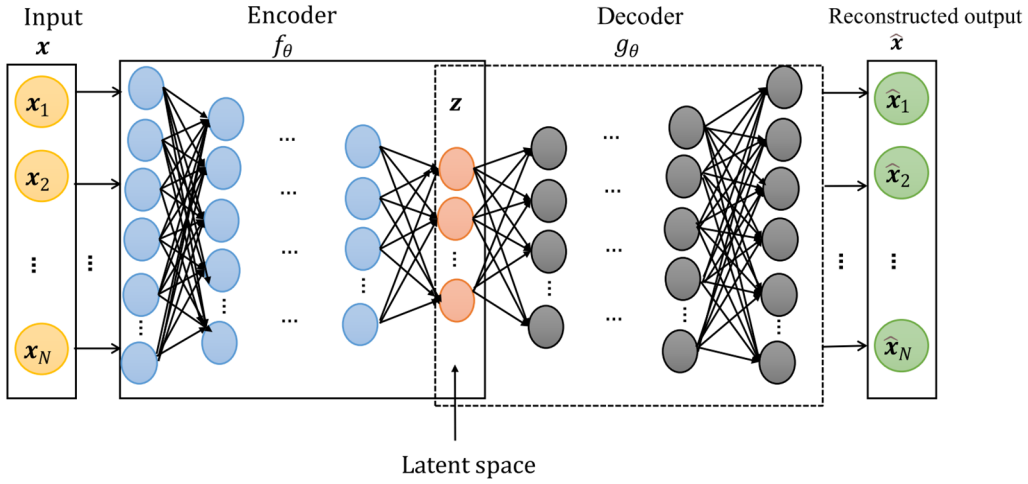


Figure 2. Fiber-induced nonlinearity mitigation process

Support vector machines (SVM) and artificial neural networks are two examples of the machine learning (ML) techniques that were used to forecast the ideal decision limits for the received constellations. A discriminative algorithm is one that generates decision boundaries and focuses on the differences between two classes. An example of such algorithm is SVM. SVM divides samples of various classes in each feature space. The functional margin can show whether a classification was made correctly, and the maximal margin hyper-plane can be used to find the decision function. There are two types of SVMs: linear and non-linear. The inputs are linearly transformed for linear SVMs, but they are not for non-linear SVMs.

Without any prior knowledge, SVM can learn and capture the connection attributes from the training data. SVM, a non-linear classifier, establishes the decision boundary to distinguish between the various constellations in order to prevent crosstalk and errors brought on by non-linear phase noise [11].

In PAM-N modulated optical connectivity systems, an ML detector based on SVM and utilising a complete binary tree structure may be used [12], which reduces the complexity of the whole system

while saving the cost of the implementation. Researchers are keen on doing more exploration on the area.

K-nearest neighbours (KNN) algorithms could be used to learn and capture the link attributes from just a tiny collection of training data [12]. For the unidentified testing data, the algorithms develop a function model that can forecast the class label. As a result, the testing data can be categorised using constellation points, each of which is made up of numerous data points, in accordance with the projected label [13]. To address the nonlinear distortion issue, KNN-based detectors have been added to the QAM-16 and CAP systems.

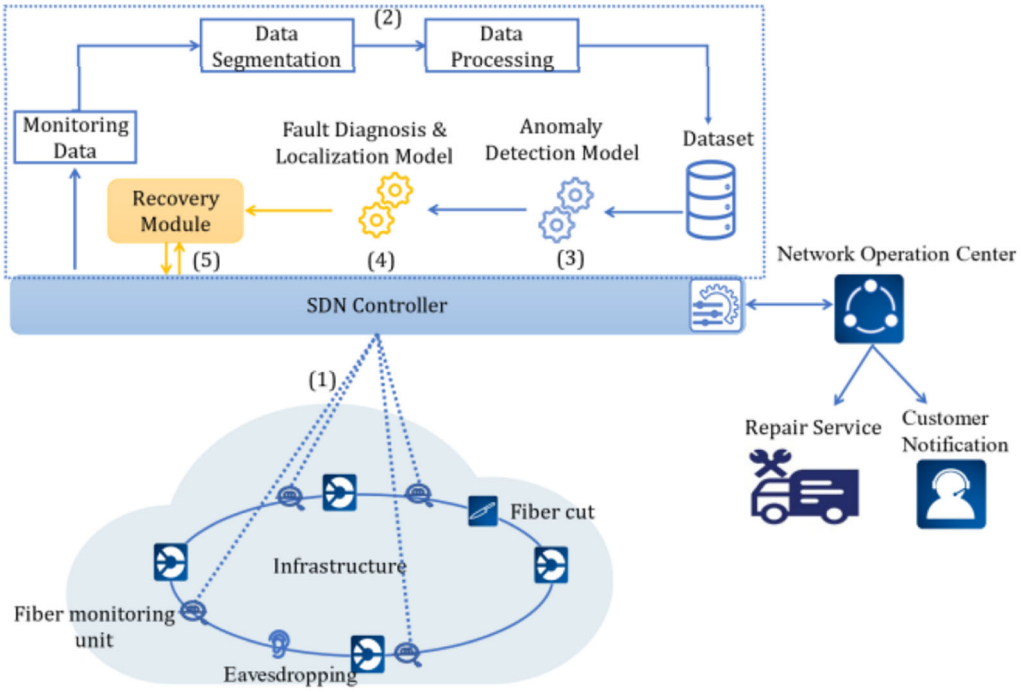


Figure 3. Overview of the ML-based fiber monitoring process

3.2 Optical performance monitoring (OPM)

Fibre monitoring discover anomalies in an optical layer. It was carried out via optical time-domain reflectometry (OTDR), a method based on Rayleigh backscattering that is frequently used for fibre defect localization and detection [14]. While challenges arise from the strong requirement for multiple training data for convergence, feature (representation) extraction requires pre-processing input data by human engineers, and guaranteeing operational ranges for trained models [15], machine learning is used to automatically find a methodology to achieve physical-layer monitors.

One method utilised to guarantee dynamic reconfigurability of the networks, which can address fault management control transmission, is optical performance monitoring. Dynamic reconfigurations add more complexity, which could necessitate sophisticated OPM to monitor the optical signal quality throughout the network.

The resulting fibre fault data is typically quite unbalanced (the instances of normal states are higher than the defective instances), which ultimately leads to problems with unbalanced class distributions. Obtaining data that precisely represents all errors or abnormalities produced for various circumstances or settings can also be unreasonably expensive and time-consuming. Unsupervised ML methods are commonly used, especially reconstruction-based anomaly detection methods.

A network automation schematic is shown in Figure 4. The traditional method of integrating several subsystems in accordance with their guaranteed worst-case specifications is different from this idea. Utilizing a closed-loop control system made up of an analytical component, a network control component, and a programmable optical network, this automation is made possible.

By learning numerous tasks simultaneously and sharing knowledge among them, multi-task learning can be used to enhance the overall performance of multiple activities [16]. The method can

be divided into two types of architectures: hard parameter sharing and soft parameter sharing. While maintaining task-specific output layers that were independently learned for each task, the hard parameter sharing method shares the hidden layers with various tasks (completely sharing the weights and the parameters between all tasks), whereas in soft parameter sharing, a model with its own parameters is learned for each task, and the distance between the model's parameters is regularised to encourage similarity among related parameters [17].

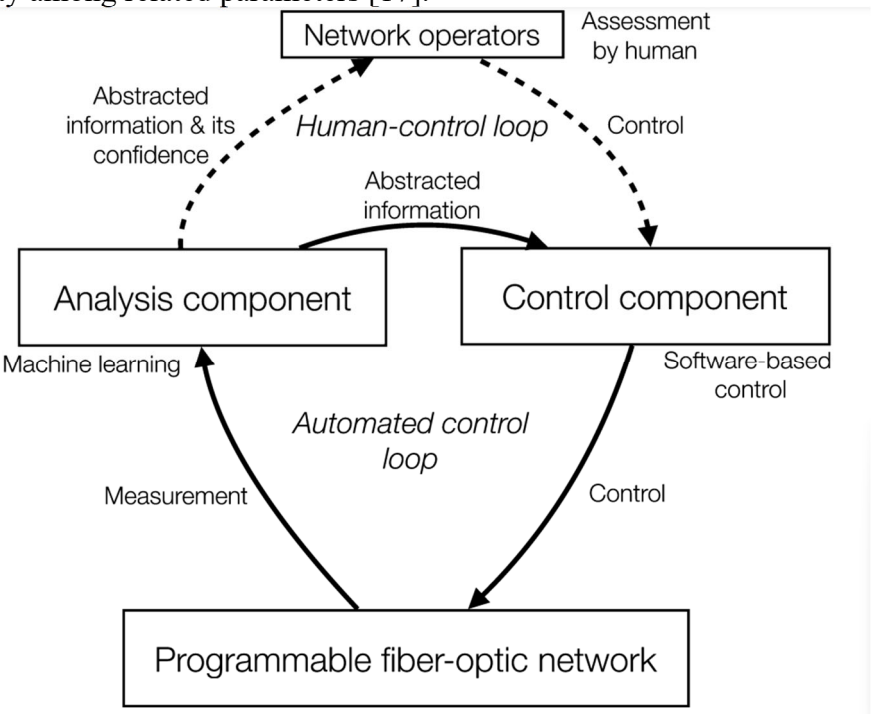


Figure 4. Concept of optical network automation with closed-loop control optimization

3.3 Failure Management

Large volumes of data are transported across the aggregated Internet, mobile backhaul, and core network using optical fibre, a crucial data transmission channel. Fiber cut, eavesdropping (fibre tapping), and other anomalies, including those caused by hard failures and hostile physical attacks, can affect optical fibre. Such abnormalities may disrupt the network, resulting in significant financial and data losses, compromise the availability and confidentiality of an optical network by allowing unwanted access to the data transported, or gradually deteriorate network operations [16]. As a result, fault management is crucial to ensuring proper operations. The common problems in commercial optical network systems are listed in Figure 5. Detection, categorization, isolation, repair, and resolution are common fault management duties. The availability and dependability of optical networks should be improved by implementing effective anomaly detection, diagnosis, and localisation techniques.

Fault Label	Description
I	Point abnormalities due to random flash events and may lead to abrupt device damage
II	Local abnormalities indicating potential flaws with potential long-term impact on service performance
III	Steady abnormalities due to preceding system configuration changes, and may lead to damage and/or consistent performance loss
IV	Ramp abnormalities representing gradual system and/or service distortion possibilities

Figure 5. Fault types typically encountered in commercial optical network systems

Scientists trained models with experimental data incorporating faults modeled using optical components such as connectors or reflectors, though the generalization and robustness capabilities of such models may severely degrade when tested with unseen data, including real induced faults with various patterns such as fiber bend events generated for different bending radius values.

Most of the ML-based anomaly detection and identification schemes employ supervised learning models relying on specific knowledge of abnormal network behaviors and large amount of anomaly data which are difficult to obtain in a real network scenario where anomalies occur infrequently. Since anomalies typically exhibit unique patterns deviating from normal network behaviors, unsupervised ML techniques that can learn patterns of data by directly analyzing the similarities among data instances become promising tools for identifying anomalies from huge volumes of monitoring data. Hence hybrid supervised, unsupervised learning is applied, and the processed data are input to an unsupervised DCM for pattern analysis. Then the learned patterns are transferred to train a supervised DRCM for online anomaly detection [18].

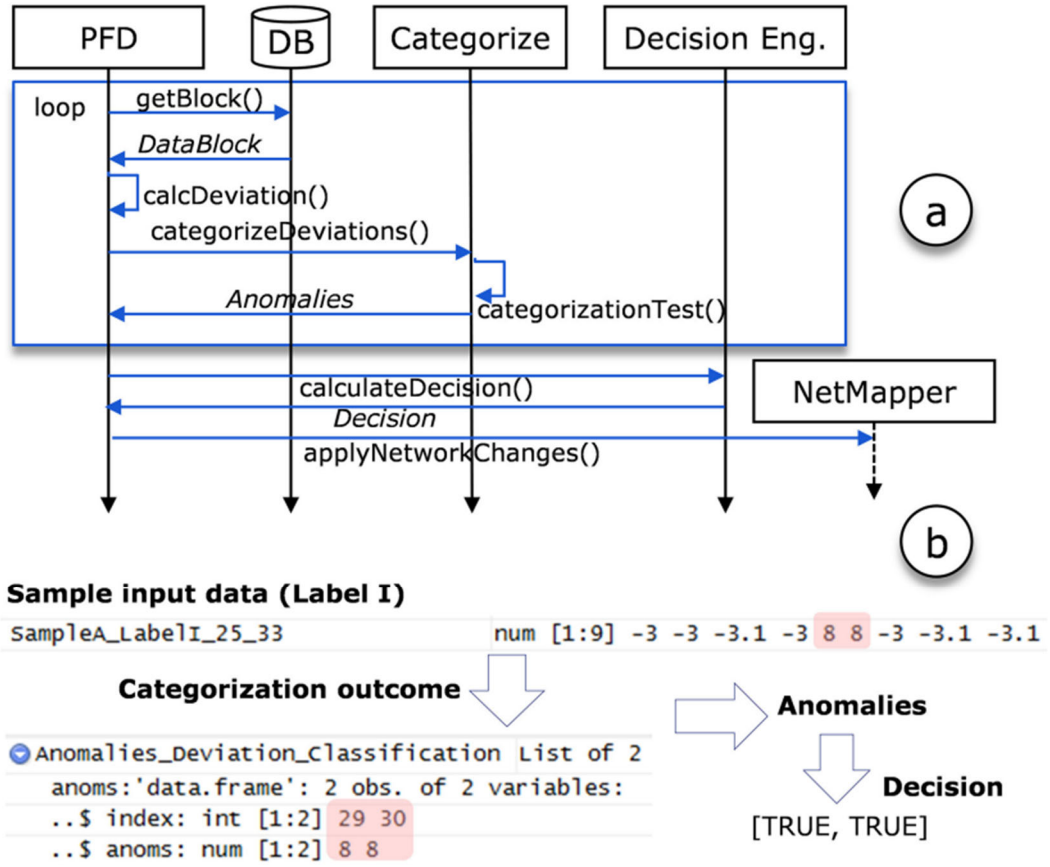


Figure 6. (a) Sequence flow, (b) Implementation snapshot

3.4 Other applications

In order to reduce fibre nonlinearity, scientists are focusing on nonlinear interference (NLI) noise and optical signal-to-noise ratio (OSNR) in long-haul optical systems. Machine learning algorithms (MLA) have been used in long-haul coherent optical orthogonal frequency division multiplexing (CO-OFDM) to primarily mitigate DSP-based fiber-induced nonlinearity.

When doing an optical spectrum analysis, machine learning is utilised to mimic the results. Based on principle component analysis (PCA) and SVM, an OSR approach was suggested. The goal of the ML algorithms is to predict values for fresh inputs by attempting to find a functional description of the given data.

3.5 Comparison of techniques

ML algorithms that are supervised and unsupervised are the two types of ML techniques suggested for OPM in optical networks.

While some machine learning (ML) algorithms are quite accurate, others are less computationally complex. As a result, the choice of ML algorithm depends on the issue at hand. The KNN algorithm, for instance, is the most straightforward algorithm in the supervised category and just a few parameters are needed to implement it. It is not advised for high-dimensional data, though. High dimensional issues in linearly separable spaces lend themselves well to the SVM. It is important to note that SVMs are non-linear learning algorithms due to the use of kernel, however choosing the right kernel function is not an easy operation.

Clustering and dimensionality reduction are best achieved with unsupervised ML-based methods. The k-means algorithm is quick and simple to use for clustering. However, hard-decision clustering is used, and the number of clusters must be pre-selected.

4. Conclusions

Machine learning plays an absolutely important role in optical communication systems. The development of intelligent software and high-performance hardware together lays a strong foundation for future breakthroughs in optical networking.

In order to learn from experience and make networks more adaptable and agile, advanced machine learning algorithms can leverage the vast amount of data made available by network monitoring components. Machine learning methods are already being applied by researchers to create smart optical networks. This essay provides an overview of some of the research that has been done.

Long-distance optical systems, optical monitoring, and optical spectrum analysis were the main topics of recent study. Still, there are numerous fields that cannot be dealed with and extensive researches should be conducted in the future.

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