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RESEARCH ARTICLE

Machine Learning Techniques in Optical Networks: A Systematic Mapping Study

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ABSTRACT During the last decade, optical networks have become ''smart networks''. Software-defined networks, software-defined optical networks, and elastic optical networks are some emerging technologies that provide a basis for promising innovations in the functioning and operation of optical networks. Machine learning algorithms are providing the possibility to develop this promising study area. Since machine learning can learn from a large amount of data available from the network elements. They can find a suitable solution for any environment and thus create more dynamic and flexible networks that improve the user experience. This paper performs a systematic mapping that provides an overview of machine learning in optical networks, identifies opportunities, and suggests future research lines. The study analyzed 96 papers from the 841 publications on this topic to find information about the use of machine learning techniques to solve problems related to the functioning and operation of optical networks. It is concluded that supervised machine learning techniques are mainly used for resource management, network monitoring, fault management, and traffic classification and prediction of an optical network. However, specific challenges need to be solved to successfully deploy this type of method in real communication systems since most of the research has been carried out in controlled experimental environments.

INDEX TERMS Optical networks, machine learning, systematic mapping.

I. INTRODUCTION

Currently, the large amount of heterogeneous data generated every day, the computational capacity available to the end user (mainly in terms of RAM and CPU), the access to different information types, and the implementation of the techniques (libraries) such as the gradient descent algorithm, have promoted that machine learning (ML) can be applied in different work areas. Systems trained with ML can now perform intellectual activities that were traditionally only solved by human beings, finding the solution to a specific problem in a short period [1].

The communications networks field has not been exempt from incorporating ML-based solutions for process performance optimization, such as quality estimation or traffic parameter prediction of a signal [2]. However, exploiting ML techniques and solutions in this field is still beginning. Therefore, through a systematic review of the literature, this paper seeks to contribute to the state-of-the-art regarding the use of ML for future studies or implementations in communication systems and networks, specifically in the optical networks area. Optical networks constitute the basic physical infrastructure of all the networks of large providers worldwide. This is due to its unique properties (*e.g.*, high capacity, low cost, etc.) and no signs of new technology appearing to replace it soon [1].

Promising results from using ML in optical networks have generated great research interest in this domain in recent years. Yet, such knowledge, published in different journals, conferences, symposia, and workshops, is scattered. Therefore, this survey aims to unify in a single study all those investigations that provide the possibility for the optical networks to respond in a better way to the changing conditions of the current world and the users' needs using ML.

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As a starting point, this research describes the motivation for applying ML in networking, specifically in optical networks, because there are various ways an artificial intelligence system can improve network management. An overview of ML and its categories is presented, including supervised, unsupervised, semi-supervised, and reinforced learning. After that, the different work areas in which ML techniques could be applied in optical networks are described in a general way. Finally, based on the systematic literature review, the use of ML techniques applied to solve problems related to the functioning and operation of optical networks are analyzed and classified (*e.g.*, resource management, network monitoring, data management, fault management, traffic classification, prediction, etc.). Moreover, this paper analyzes the maturity level of the reported ML techniques, identifies opportunities, and suggests future research lines. This study aims to be an academic reference for future contributions to communications systems and optical networks.

The rest of this survey is organized as illustrated in Fig. 1. Section II details the motivations for ML techniques application in optical networks. Additionally, it provides a background into ML techniques and challenges in optical networks solved with ML: resource management, network monitoring, traffic prediction, traffic classification, failure management, and QoT estimation, among others. These work areas have been taken as a reference of the papers [2], [3], [4], because it is evident that these fields are of the most significant study interest in the optical networks domain. Section III summarizes the existing work related to this area of study. Section IV presents the research method, *i.e.*, the underlying process of the flow and tasks of the systematic mapping study, including the research questions and classification scheme. Section V provides the mapping study results, responding to the research questions formulated. Section VI presents a trend analysis, discusses the results, and outlines the gaps observed. Section VII examines potential threats to construct, internal and external validity, and how they have been dealt with. Finally, conclusions are outlined in Section VIII.

II. BACKGROUND

This section provides a summary of the fundamental concepts for understanding this study. First, it briefly describes the motivation for applying machine learning in optical networks. Second, it represents the types and sub-types of ML techniques and a general definition of the challenges in optical networks solved with ML.

A. MOTIVATION

With the rapid development of the Internet, communications systems are becoming much more complex every day. Optical networks, which play an essential role in both the core and the access networks in a communication system, also face significant challenges of complexity and operation [2]. To overcome these limitations and address problems in the future, greater intelligence capacity needs to be implemented in optical systems, enabling both autonomous and flexible network operations [5]. It has been shown that AI and ML techniques can solve complex problems and optimize the efficiency of optical systems through better performance in spectrum allocation tasks, traffic prediction, traffic classification, and QoT, among other parameters. Based on [2], the four factors that drive the ML application in optical networks are described below, summarized in Fig. 2.

1) HISTORICAL DATA USE

Different types of statistical data on the management and control of an optical network can be collected in the systems. So, knowing the right way to manipulate this data to optimize network performance becomes an essential requirement. Traditional methods, such as Bayesian estimation or heuristic methods, usually only exploit the current state of the optical network as they do not use historical information, generating a modification of system performance when there is noise or errors in the samples used. If ML techniques are used, the model is trained with a data set that contains historical information, and it learns the existing relationship in the data set. As a result, the ML-based method achieves better performance against data noise, and it is not necessary to train the algorithm again when the network state undergoes slight changes [2].

2) COMPUTATION REQUIREMENTS REDUCTION

Due to the 5G networks development, data traffic has become increasingly dynamic and heterogeneous. Flexible reconfiguration is critical in future optical networks to meet different QoS levels. However, traditional (analytical and heuristic) methods use a large computational burden. Consequently, it generates excessive processing times when an extensive network reconfiguration is presented; therefore, these methods are not convenient for real-time network operations. Using a well-trained ML technique involves only linear and pseudo-linear computing, which enables complex task results with great time efficiency, thus optimizing the optical network's operation [2].

3) PROFESSIONAL KNOWLEDGE REQUIREMENTS REDUCTION

In specific tasks of optical networks, analytical methods have not been fully exploited. Therefore, it is unknown what information exists in those raw data. This causes a waste of human resources in data processing because feature engineering is not targeted [2]. Using deep learning (DL), the source data characteristics can be automatically obtained, simplifying the step of feature engineering and reducing the professional knowledge requirements [6]. For instance, in monitoring the Optical Signal to Noise Ratio (OSNR) with an eye diagram, there is no clear relationship between the pixels in the eye diagrams and the OSNR value. Hence, the capacity of the analytical method is limited. However, with DL, the raw data is fed into the neural network, and the

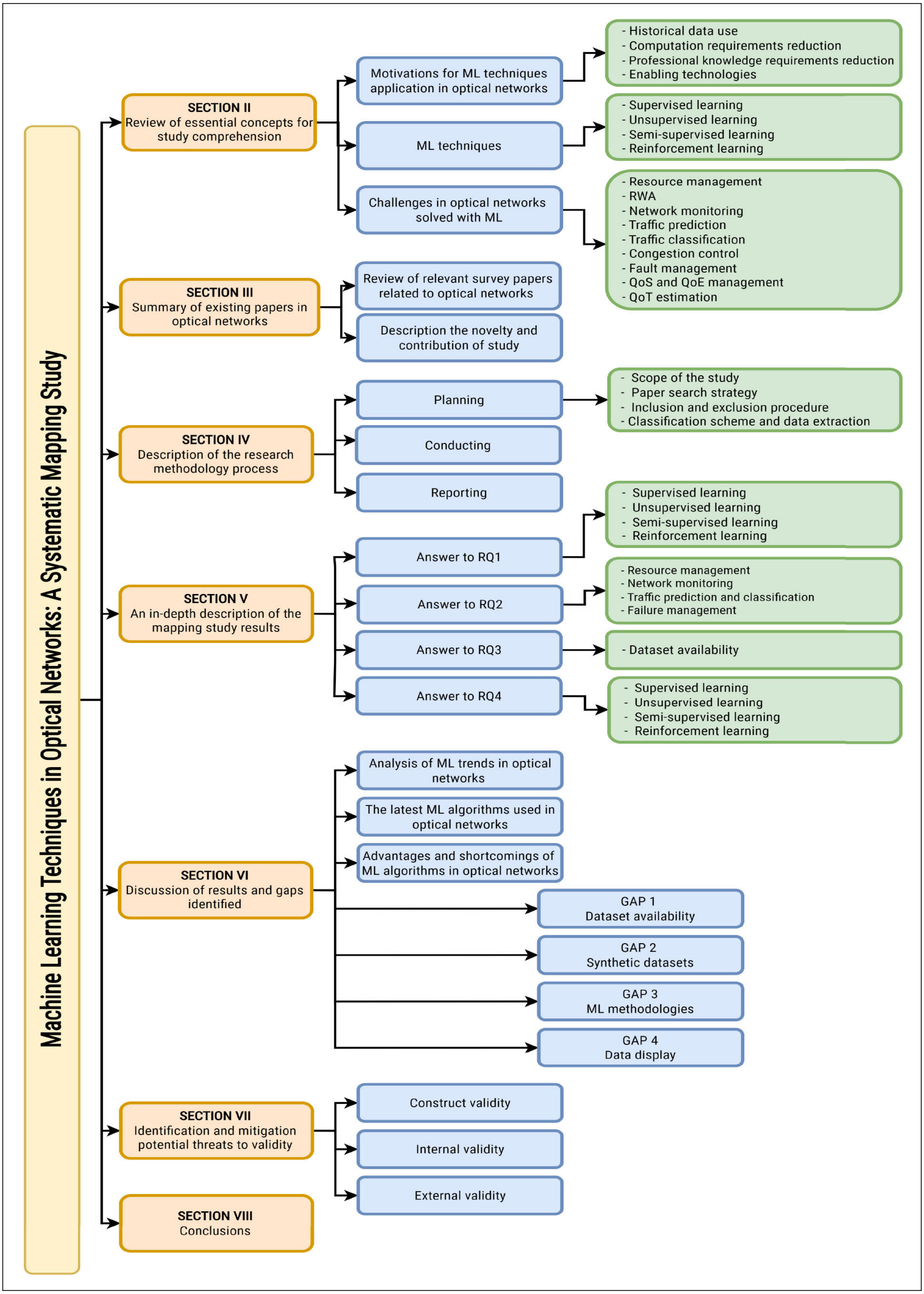


FIGURE 1. Structure of the survey.

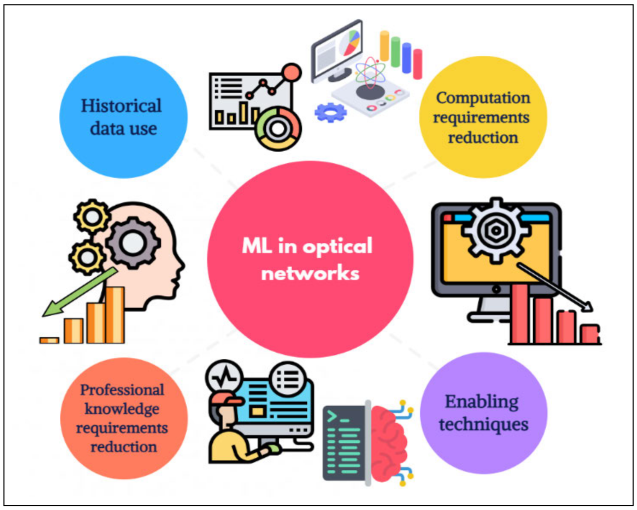


FIGURE 2. Motivation for ML application in optical networks.

TABLE 1. Regression algorithms.

Algorithms	Description
Linear regression	It is the simplest regression algorithm. It is used to identify the relationship between a dependent variable and one or more independent variables, allowing predictions about future results [11]. Linear regression models mathematically the unknown or dependent variable and the known or independent variable as a linear equation. It is coupled to a straight line or surface, minimizing the differences between the predicted and actual output values [14].
Polynomial regression	It is a regression algorithm in which the relationship between the independent variables and the dependent variables is modeled through a degree polynomial n. It is a special linear regression case, where the polynomial equation is fitted to the data with a curvilinear relationship between the dependent and independent variables [15]. This algorithm enriches the linear model by increasing additional predictors, which are obtained by raising each of the original predictors to a power [16].

found features are automatically extracted from the analyzed information [7].

4) ENABLING TECHNOLOGIES

In addition to the significant advantages that ML provides, some technologies cover aspects of network architecture, network management, and optical devices, which facilitate ML use in optical networks. From a network architecture point of view, Software Defined Optical Network (SDON) offers fully programmable and reconfigurable optical network capabilities that increase operational flexibility [8]. From network management and data collection, with the help of SDON network architecture, the monitored data and network configuration are transmitted in a north-south direction. Then, a management loop is formed in the optical network, which is important for ML applications [2]. Regarding optical devices, optical signal processing techniques are under development, allowing knowledge about these systems to be more efficient and accurate [9].

B. ML TECHNIQUES

ML is a research area that teaches machines to perform an activity like the human mind. Although their cognitive capacity is much more limited than human beings, they can process large amounts of information quickly and obtain helpful information [10]. Fig. 3 summarizes the most popular types and sub-types of machine learning techniques described below.

1) SUPERVISED LEARNING

Supervised learning is a sub-category of ML, which employs data sets labeled to train algorithms that classify information or predict results accurately. As input data enters the model, it adjusts its weights until the algorithm operates correctly [11]. Supervised machine learning is used if you know in advance what you want to teach a machine [10]. It requires exposing the algorithm to a large training data set, allowing the model to examine the output, and adjusting the parameters until the desired results are obtained. The algorithm measures its accuracy through a loss function, adjusting itself until the error has been sufficiently minimized. Finally, the trained machine is tested by allowing it to make predictions for a validation data set, *i.e.*, new unseen data [10], [11]. Supervised learning can be classified into two types of algorithms: regression and classification, as shown in Fig. 3.

- **Regression algorithms:** Regression methods are defined as a process to find the correlations between dependent and independent variables [12]. This algorithm is a statistical method that allows you to summarize and study relationships between two continuous quantitative variables [13]. It will enable predicting or explaining a particular numerical value based on previous data. Linear regression and Polynomial regression are the most popular algorithms of this type [11], which are described in Table 1.
- **Classification algorithms:** Classification algorithms can explain or predict a class value. In other words, they use an algorithm to assign the test data into specific categories [10]. The classification recognizes specific associations within the analyzed data set and attempts to conclude how those entities should be labeled and characterized. The most widely used example to understand classification algorithms is the spam or junk mail detector because these types of algorithms are the ones that decide if the message is an email or spam. Table 2 describes the common classification algorithms: linear classifiers, support vector machines (SVM), decision trees, k-nearest neighbors, random forest, neural networks, and naive Bayes.

2) UNSUPERVISED LEARNING

Unsupervised learning is a sub-category of ML that allows a machine to explore a data set without the need to monitor

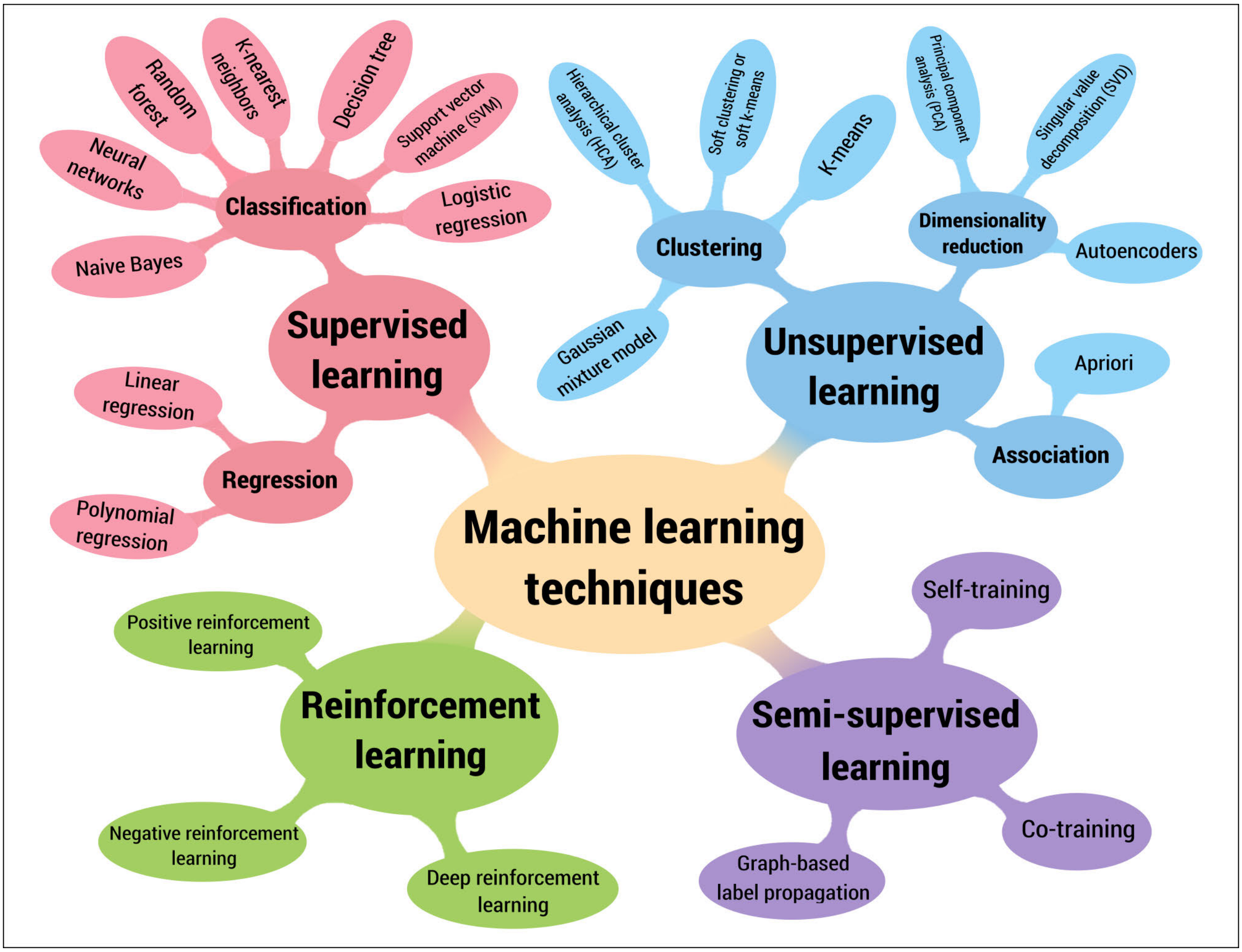


FIGURE 3. Types and sub-types of ML techniques.

the model. In other words, the training process is a data set without previously defined labels or classes [21]. After the initial data is scanned, the algorithm tries to identify patterns that relate different variables to discover hidden information that was not previously detected, based solely on statistical properties [10]. Unsupervised learning algorithms are divided into: clustering, association, and dimensionality reduction, as presented in Fig. 3.

- **Clustering algorithms:** Clustering is a technique that mainly tries to find a structure or pattern in an unlabeled collection of data, based on their similarities or differences [22]. The most common grouping algorithms are: k-means, soft clustering or soft k-means, hierarchical cluster analysis (HCA) and Gaussian mixture model, which are described in Table 3.
- **Association algorithms:** Association algorithms are rule-based techniques that allow finding non-obvious relationships between variables in a particular data set. So, it can be considered as a data analysis tool [22]. Apriori algorithm is the most used within this classification, which is described in Table 4.
- **Dimensionality reduction algorithms:** Although a greater amount of data allows you to generate much more accurate results, it can also affect the performance of ML's algorithms. Dimensionality reduction algorithms are techniques that are used when the number of features in a given data set is very high. During operation, these algorithms reduce the number of data entries to a suitable size while preserving the integrity of the data set [25]. Table 5 describe the most common dimensionality reduction algorithms: principal component analysis (PCA), singular value decomposition (SVD) and auto-encoders.

3) SEMI-SUPERVISED LEARNING

Semi-supervised learning is a subcategory of ML. During the training stage, instead of adding labels to the entire analyzed data set, only a small portion of the data is reviewed and hand-labeled to train a model. Finally, this trained model allows a correct classification of features of a larger unlabeled data set [27]. Semi-supervised learning combines unsupervised and supervised learning techniques. Unlike unsupervised

TABLE 2. Classification algorithms.

Algorithms	Description
Logistic regression	It is the most basic classification algorithm, it sounds like a regression method, but it is not. Logistic regression is used when the dependent variable has two outputs: "true" and "false" or "yes" and "no" [11]. It is helpful for cases where you want to predict the presence or absence of a feature or outcome based on the values of a set of predictors. It is similar to a linear regression model but adapted for models where the dependent variable is dichotomous [17].
Support vector machine (SVM)	It is a supervised learning model that builds a hyperplane, where the distance between two classes of data points is maximum. The hyperplane is known as the "decision limit" and separates the data point classes, on either side of the plane [11].
Decision tree	It is a supervised learning model in which the analyzed data is continuously distributed according to a determined parameter. The decision tree comprises two entities: decision nodes and leaves. The leaves are the final results. While the decision nodes are the point where data is divided [18].
K-nearest neighbor	This algorithm seeks to calculate the distance between data points, usually through the Euclidean distance. It is a supervised learning model that classifies data points based on their proximity and association with other available data. And then, assign a class based on the most frequent category or average [11].
Random forest	It is a supervised learning model used for both the classification and regression of data. The "forest" represents a collection of uncorrelated decision trees merged to reduce variance and create more accurate data predictions [11].
Neural networks	They are a type of ML (also known as classifiers) that use nodes or neurons interconnected in a layered structure resembling the human brain, mimicking how biological neurons send signals to each other. Neural networks can learn and model the relationships between non-linear input and output data, allowing complex problems to be solved with limited human assistance [19].
Naive Bayes	It is a particular class of ML based on a statistical classification technique called "Bayes' theorem". Naive Bayes is a simple probabilistic classifier with a strong independence assumption. It learns from the training data and then predicts the test instance class with the highest subsequent probability [20].

learning, semi-supervised learning works for a variety of classification, regression, clustering, and even association problems. Unlike supervised learning, semi-supervised learning employs small amounts of labeled data and large amounts of unlabeled data, which reduce computational capacity and shorten data preparation time [28]. Table 6 describes the commonly used semi-supervised learning techniques: self-training, co-training, and graph-based label propagation (see Fig. 3).

4) REINFORCEMENT LEARNING

Reinforcement learning is an ML subcategory that allows a machine to interact with an environment. An agent learns to behave in an environment, performing actions and seeing the results of actions. For every good action, the agent receives positive feedback; for every bad action, the agent

TABLE 3. Clustering algorithms.

Algorithms	Description
K-means	It is an algorithm that divides the analyzed data set into distinct non-overlapping subgroups (clusters) predefined by K, where each data point belongs to a single group. K-means tries to make the data points within the cluster as similar as possible, while at the same time trying to keep the clusters as different as possible [23].
Soft clustering or soft k-means	It is an algorithm like K-means. Its only difference is that instead of assigning a point exclusively to a single group (cluster), there may be some form of blurring or overlap between two or more groups [24]. In other words, data points can belong to multiple groups with varying degrees of membership [25].
Hierarchical cluster analysis (HCA)	It is an algorithm that aims to associate elements or records that are "close" to each other, forming hierarchical clusters. It can work in two ways: agglomerate or divisive. In an agglomerate cluster, the data points are initially isolated and then iteratively merged based on their similarity until a cluster is achieved. The divisive cluster can be defined as the opposite of an agglomerative cluster. In this case, a single data set is divided based on the differences between the analyzed data points [25].
Gaussian mixture model	It is an algorithm used to classify data into different categories according to the probability distribution. It assumes that all data points are generated from a combination of Gaussian distributions with unknown parameters [26].

TABLE 4. Association algorithms.

Algorithms	Description
Apriori Algorithm	It is a technique that follows a sequence of steps to find the most frequent set of elements in the given database. They are used within transactional data sets to identify frequent sets of items or collections of items. In other words, it determines the probability of consuming a product, given the consumption of another product [25].

TABLE 5. Dimensionality reduction algorithms.

Algorithms	Description
Principal component analysis (PCA)	It is an algorithm used to reduce redundancies and compress data sets through feature extraction. It uses linear transformations to create new data representations, generating sets of "principal components" [25].
Singular value decomposition (SVD)	It is an algorithm that factorizes a main array in three low-range arrays. It is commonly used to reduce noise and compress data, e.g., image files [25].
Auto-encoders	They are algorithms that take advantage of neural networks to compress data and then recreate a new representation of the original data input [25].

receives negative feedback or a penalty. The machine can eventually learn from its experience by repeating the process thousands of times [10]. Reinforcement learning differs from supervised learning in that in supervised learning; the training data holds the key to the answer. So, the model is trained with the correct solution. While, in reinforcement learning, there is no response, but the reinforcement agent decides what to do to respond or perform a certain task. Compared

TABLE 6. Semi-supervised algorithms.

Algorithms	Description
Self-training	It is one of the simplest semi-supervised learning techniques. You can choose any classification or regression supervised learning technique and modify it to work in a semi-supervised way. However, it should be emphasized that the performance of these algorithms can vary from one data set to another, and in many cases, it has lower performance compared to a supervised technique [28].
Co-training	It is a technique derived from auto-training algorithms. It is used when only a small set of labeled data is available. During its initial stage, two individual classifiers are trained based on two data views. Data views are different sets of features that provide additional information about each stage, which means they are independent given the class [28].
Graph-based label propagation	One of the most popular ways to employ semi-supervised learning is to represent labeled and unlabeled data graphically. To then apply a label propagation algorithm that spreads the information throughout all data network. The practical use of this method makes it possible to predict the interests of customers based on information about other customers [28].

TABLE 7. Reinforcement learning.

Algorithms	Description
Positive reinforcement learning	It is defined as an event that occurs due to a specific behavior. It increases the strength and frequency of the behavior and positively impacts the action the agent takes. This type of algorithm helps to maximize performance and maintain change over a long period. However, it can cause over-optimization of the state and affect the results [29].
Negative reinforcement learning	It is defined as behavior that occurs due to a negative condition, which should have been avoided or stopped. This type of algorithm helps determine the minimum performance standard. Negative reinforcement can be an effective tool when used correctly. However, its use may not consistently achieve the expected results since it can reinforce favorable or unfavorable behaviors [29].
Deep reinforcement learning	Deep reinforcement learning combines reinforcement learning and deep learning. It is a new generation of ML techniques characterized by trial-and-error decision-making, so a machine can learn to perform a specific task. Deep reinforcement learning is made up of an intelligent agent that learns to optimize a decision process. If the result of that decision is favorable, the agent will automatically repeat that decision. While if the result is detrimental, it will avoid making the same decision again [30].

to unsupervised learning, reinforcement learning is quite different regarding objectives [29]. Table 7 describes the three types of existing reinforcement learning algorithms: positive reinforcement learning, negative reinforcement learning, and deep reinforcement learning (see Fig. 3).

C. CHALLENGES IN OPTICAL NETWORKS

According to [2], [3], and [4], Fig. 4 summarizes the work areas with the most significant study interest in which ML techniques could be applied to solve problems related to

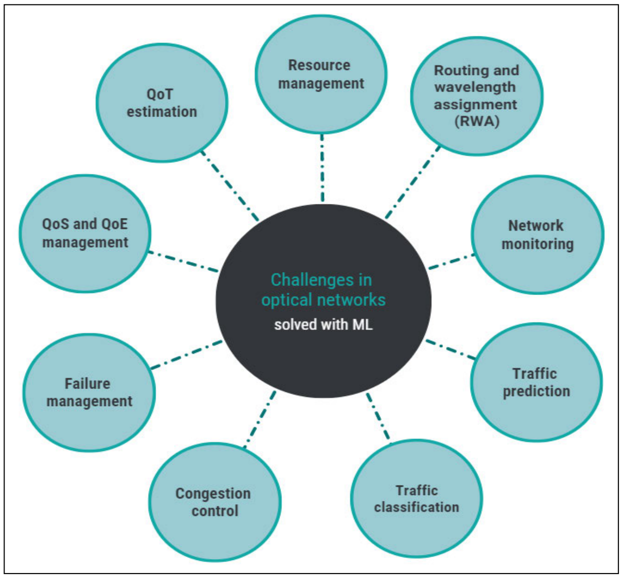


FIGURE 4. Challenges in optical networks solved with ML.

the functioning and operation of optical networks. These challenges are described below.

1) RESOURCE MANAGEMENT

Resource management allows you to create an effective method of analyzing the traffic that travels through a network. Thus, downtime, errors, and other problems that may arise are reduced, allowing the needs of users and devices to be met simultaneously. Network resource management is comparable to creating dedicated lanes for traffic. Resources can be assigned differently for each lane of the network. Configuring network lanes where resources are distributed according to actual need increases efficiency in processing network packets [31], [32].

2) ROUTING AND WAVELENGTH ASSIGNMENT (RWA)

The routing and wavelength assignment problem considers a network where requests (i.e., light paths) can be transported at different optical wavelengths through the network. Each accepted request is assigned a path from its source to its destination and a specific wavelength. Light paths routed over the same link must be assigned to different wavelengths. In contrast, light paths whose paths belong to separate links can use the same wavelength [33].

3) NETWORK MONITORING

Monitoring a network involves managing the links between devices, workstations, servers, virtual devices, and mobile devices to identify congestion and maximize and improve network performance for the user. Analysts can use automated network monitoring tools to collect data, identify, measure, perform performance assessments, and diagnose problems on a given network. Monitoring tools collect data from sources such as SNMP protocol, flow data, packet capture, and network infrastructure devices, so their performance and availability can be analyzed and maximized [34], [35].

4) TRAFFIC PREDICTION

Network traffic prediction uses previous network traffic data to predict subsequent traffic, which can serve as a proactive approach to network management, planning tasks, security processes, avoiding congestion, and increasing network speed. So now, it has now become an issue of interest to the computer community. Fast traffic prediction enables network administrators to take early action to control traffic load and avoid the congestion state of a network [36], [37].

5) TRAFFIC CLASSIFICATION

Traffic classification allows automatically recognizing the application that has generated a given packet flow based on direct and passive observation of individual packets or packet flow flowing in a network. Each identified traffic class could be treated differently, which is essential for a series of activities that interest operators, Internet service providers, and network administrators in general. Accurate traffic classification is paramount in network activities such as security monitoring, traffic engineering, fault detection, and network usage accounting [38], [39].

6) CONGESTION CONTROL

The term congestion control describes the efforts made by network nodes to prevent or respond to overload conditions. Because congestion is often a big problem, the fundamental goal of a network is to reduce or prevent congestion. This could be achieved by persuading some hosts to stop sending information packets on the network, thus improving the situation for all others. However, it is more common for congestion control mechanisms to be characterized as fair. In other words, try to share the overload conflict among all the users that belong to the network instead of causing a problem for a few. So many congestion control mechanisms have some resource allocation built into them [40].

7) FAULT MANAGEMENT

Fault management is an essential component in managing a network. Network fault management is finding, isolating, and fixing network errors in the shortest possible time. Resolving detected failures quickly minimizes downtime and prevents device setbacks, guaranteeing optimum network availability and decreasing business losses [41].

8) QoS AND QoE MANAGEMENT

It is necessary to clarify the difference between quality of service (QoS) and quality of experience (QoE). The first term is related to the network resource management process, such as packet loss reduction, latency, network instability, etc. QoS is responsible for allocating resources to the different types of data that transit through the network based on varying priority levels. The second term measures the general level of customer satisfaction with a network provider. Because QoE represents QoS from the user's point of view, QoE is a QoS extension. Due to the limitations that revolve around telecommunication networks, there are restrictions in network strategies for resource management, making it difficult to achieve the optimal level of QoE and QoS simultaneously [42].

9) QoT ESTIMATION

The nature of the medium is directly proportional to the quality of the transmission. In other words, if the bandwidth of the medium is high, good-quality signals will be transmitted. And if the quality of a signal is good, the transmission is smooth and successful. Currently, estimating the QoT of a light path before its deployment is a fundamentally important step for an optimized design of optical networks [43], [44].

III. RELATED WORK

ML techniques have been used as enablers of intelligence, adaptability, and efficiency in the functioning and operation of optical networks. Thus, various authors have been identified during this research who propose multiple innovative ML models to address challenges around optical networks. To give an example, Viljoen et al. [45] and Morales et al. [46] make use of ML techniques for the prediction and classification of traffic transmitted through optical networks. Salani et al. [47] and Guo et al. [48] employ ML techniques for resource management. Thrane et al. [49] and Morais and Pedro [50] make use of ML techniques to monitor an optical network, Gosselin et al. [51] and Das et al. [52] use ML for failure detection, among others.

Promising results from using ML in optical networks have generated a sustained increase in the body of knowledge in this domain. Yet, such knowledge, published in different journals, conferences, symposia and workshops, is scattered. A study that systematically organizes this body of knowledge is needed in this context.

In papers [2], [3], and [4], first efforts have been made to organize the knowledge of this domain. In [2], Gu et al. present a survey of the application of ML for intelligent optical networks. In that survey, ML is applied in two domains: (1) control and management of optical network resources and (2) monitoring and survivability of optical networks. Zhang et al. [3] present a study focused on routing and resource allocation in optical networks, which are highly relevant challenges to be addressed with ML techniques. Finally, in [4], Boutaba et al. performed a survey of the various ML techniques applied to fundamental problems in networks in general (not focused on optical networks), including traffic and classification prediction, routing and resource management, failure management, QoS and QoE management, and network security.

Our study builds upon previous works and follows a systematic mapping methodology to rigorously organize the knowledge on the use of ML techniques to solve problems related to the functioning and operation of optical networks. However, our study further determines the maturity level of the contributions presented and the availability of the data sets used in the different contributions. The maturity level determines those contributions that still require research efforts, while other researchers can exploit the available data sets to enhance their contributions. Furthermore, our study identifies a broader set of issues than the individual aforementioned studies, employs a more exhaustive classification of ML techniques (including semi-supervised and reinforcement algorithms), addresses a broader set of papers (as our study is more up-to-date), identifies the latest ML techniques used in optical networks, determines the main advantages and shortcomings of using ML techniques in optical networks, details opportunities, and suggests future lines of research.

IV. METHODOLOGY

This research follows the general guidelines for conducting a systematic mapping study (SMS) based on [53]. An SMS is a systematic approach that aims primarily to provide an overview of a research area of interest by showing quantitative evidence to identify trends. In other words, this paper seeks to provide an overview of ML techniques to solve problems related to the functioning and operation of optical networks. The methodology consists of three stages: planning, conducting, and reporting, whose processes flow and tasks developed throughout the investigation are presented in a general way in Fig. 5.

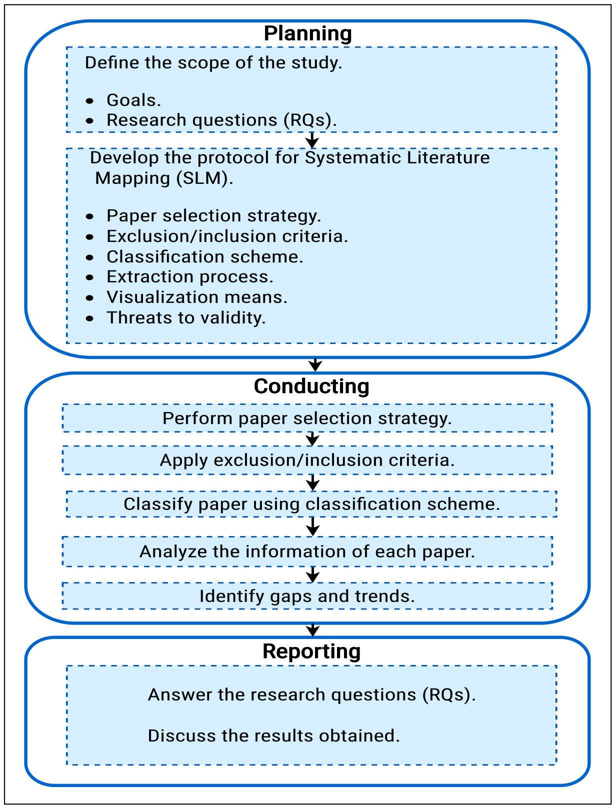


FIGURE 5. Process flow and tasks of the systematic mapping study, based on [53].

A. PLANNING

This paper adopts a quantitative approach, because its main objectives are to collect, classify and graphically represent information obtained about using ML techniques to solve problems related to the functioning and operation of optical networks. Five tasks have been developed during the planning stage, which are detailed below.

1) SCOPE OF THE STUDY

This task consists of two parts. The first part describes the background of the research to be carried out. In other words, issues related to the motivation for using ML in optical networks, ML concepts, and description of work areas in which ML techniques could be applied in optical networks are addressed, evidencing them in Section II. In the second part, the objectives of this study and the research questions (RQs) formulated to achieve these proposed objectives are defined.

- **Objective:** The objective of this study is twofold: i) identify and organize the state-of-the-art ML techniques systematically that can apply to solve problems related to the functioning and operation of optical networks, and ii) provide adequate bases to outline the gaps and trends in this field of research and, subsequently, the directions of possible research that help to fill them.
- **Research Questions (RQs):** In order to achieve this objective, the following research questions have been formulated:
  1) **RQ1. What are the ML techniques used to solve the problems reported in [2], [3], and [4] related to the functioning and operation of optical networks?** Knowing which ML techniques are used to solve the problems reported in [2], [3], and [4] related to the functioning and operation of optical networks is the cornerstone of this project. RQ1 allows us to provide an overview of this research area and identify its gaps.
  2) **RQ2. What challenges reported in [2], [3], and [4] have been mostly addressed by using the reported ML techniques?** The objective of the research is to obtain knowledge about the challenges reported in [2], [3], and [4] related to the functioning and operation of optical networks that have been mostly addressed through the identified ML techniques.
  3) **RQ3. Are the data sets that have been used by ML techniques in the reviewed papers available?** Knowing about the availability of information from the data sets used by ML techniques in the reviewed papers provides the possibility of creating a repository of data so that they can be used by people who need them in future research.

TITLE-ABS-KEY ((“Machine Learning”) AND (“Optical Communication” OR “Optical Network”))

FIGURE 6. **Defined search string.**

4) **RQ4. What is the maturity level of the identified ML techniques?** Using the existing literature, a level of maturity is assigned to the ML techniques identified in the study to recognize gaps and trends in this topic. The information obtained may be valuable for future research.

2) PAPER SEARCH STRATEGY

This task uses an information-gathering strategy using the Scopus database to find high-quality research literature. It was decided to use this platform because it indexes papers from the leading digital libraries used in the research area of interest for this work, including IEEE Xplore, Springer Link, Science Direct, or ACM [54]. Starting from Scopus, a search string is created that covers the most significant number of possibilities of topics related to the research carried out, in this case: “Machine Learning” and “Optical Networks”. Therefore, the final search string obtained is presented in Fig. 6:

With this search string, 841 contributions related to the subject of study were initially obtained. However, to ensure that the defined string is correct, that papers that may be of importance during the investigation are not being omitted, and to validate the integrity of the contributions provided by Scopus (Threats to validity), it is compiled independently a set of test papers related to this research topic. The test papers have as their primary objective their review within the list of papers extracted in Scopus. If most of them appear in the results obtained, the defined search string is correct. Otherwise, its redefinition is required as many times as necessary, based on specific characteristics (titles, keywords, etc.) of the papers that have not been found in the Scopus results, avoiding omitting contributions that can provide valuable information in research. In this work, the test papers with which the search string was validated obtained a high success rate in the first iteration (10/10), so modifying the search string initially proposed was unnecessary.

3) INCLUSION AND EXCLUSION PROCEDURE

In addition to creating the search string, it is necessary to identify the inclusion and exclusion criteria of papers in an automated and manual way, which allows a suitable collection of information. Inclusion and exclusion criteria exclude studies that are irrelevant to answer the research questions (RQs).

- **Automated inclusion and exclusion:** The automated inclusion and exclusion criteria are those filters that can be applied directly through online tools and functions that the platforms serving as a database have, in this case, Scopus. The criteria selected for this research have been defined from similar systematic mapping studies such as [53]. All inclusion criteria must be met for a paper to go through manual filtering. Table 8 describes these automated inclusion and exclusion criteria.
  In this paper, from the 841 contributions initially obtained, by applying the automated inclusion and exclusion criteria in the Scopus platform, the results were reduced to 831 papers.
- **Manual inclusion and exclusion criteria:** The manual inclusion and exclusion criteria are those filters applied by decisions taken by the study's researchers. A decision tree is made to clarify what types of criteria need to be taken into account at this stage. This tree can be visualized for this investigation in Fig. 7.
  Figure 7 describes the decision processes to be considered for the manual selection of papers analyzed in this study. Of the 831 contributions obtained from the

TABLE 8. **Automated inclusion and exclusion criteria.**

Parameters	Description
Document type	The contributions that are part of this study are conference documents and articles because they are those documents that can provide updated and relevant data regarding a research topic.
Language	The papers taken into account for this study must be written in English because this is the universal language used for transmitting and understanding new knowledge around the world.

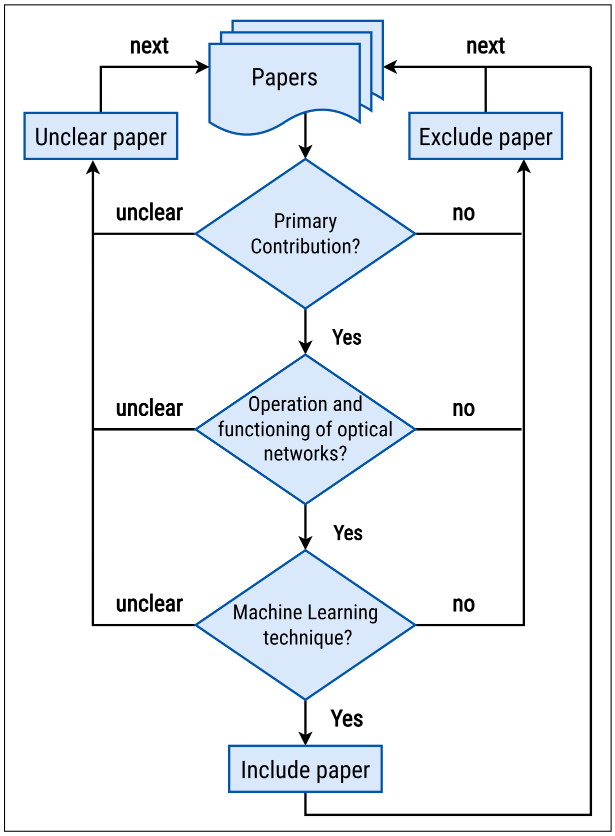


FIGURE 7. **Decision tree for manual paper selection, based on [53].**

TABLE 9. Automated inclusion and exclusion criteria.

Criteria	Description
Inclusion criteria	1) The paper is a primary contribution. 2) The contribution reported in the paper is related to the functioning and operation of optical networks. 3) The paper includes at least one contribution that proposes an ML technique applied to the resolution of a problem reported in [2], [3], [4].
Exclusion criteria	1) The paper reports a secondary or tertiary contribution. 2) The contribution does not focus on the functioning and operation of optical networks. 3) The reported contribution addresses some problem reported in [2], [3], [4], but does not employ an ML technique.

automated filtering process, it is required to determine if the papers are primary contributions, belong to the domain of optical networks, and are related to ML techniques. If the contribution complies with the three main features defined in the decision tree, it automatically becomes included for further coding. On the other hand, if the paper does not comply with any of the features of the decision tree, it is excluded. Finally, if there are doubts about screening any research paper, it can be marked as "Unclear". Thus, the paper can be analyzed later, and decide whether or not to include it in the paper group to be coded.

From the decision tree, the list of manual inclusion and exclusion criteria used to evaluate the papers during this investigation is included in Table 9. All criteria must be met for a paper to be included, but the contribution is excluded if any exclusion criteria are met.

Two phases of paper screening are carried out during this manual filtering stage. All these stages are done through CADIMA (https://www.cadima.info/). The first stage is known as the "pilot phase", whose objective is to align the criteria between researchers (coders). The pilot phase details are presented below.

- The pilot phase is an n-iterative process of screening papers, which is carried out until reaching a reliability coefficient of 0.8 (Krippendorff's alpha) between researchers (coders) [55].
- From a set of five randomized papers from the group of 831 contributions, researchers individually read the title and abstract sections of the papers and classified them as included, excluded, or unclear.
- If at the papers screening end, a reliability coefficient greater than or equal to 0.8 has not been obtained, the researchers discuss the results obtained to harmonize their classification criteria before the next iteration. In this investigation, it was possible to get a reliability coefficient of 0.94 after the third iteration.

The second phase is called the "main phase". The main phase consists of two stages of manual paper screening. In the first stage, contributions are selected based on their titles and abstracts. In the second stage, contributions based on their full-text are chosen. The main phase details are presented below.

- In the first stage, evaluators (researchers) work individually by reading paper titles and abstracts and marking them as included, excluded, or unclear. In this study, 167 contributions (20%) are reviewed by the three researchers in charge of the investigation. As there is more than one evaluator, it is possible to avoid the contributions exclusion that can provide relevant information to this study, improving the results in the papers screening. While two evaluators exclusively analyze the remaining 664 papers (80%), the divergences found in the paper's screening are discussed and resolved by the evaluators in scheduled meetings. At the end of this stage, there are 223 selected papers.
- In the second stage, the evaluators (researchers) read the papers selected in the first stage at a detailed level. In other words, the title is analyzed first, then the abstract, and finally, the conclusions. However, if this information is unclear, other parts of the paper may be considered (*e.g.*, introduction, section, and subsection titles). At this stage, the 223 papers can only be classified as included or excluded. Like the first stage, 45 contributions (20%) are reviewed by the three evaluators in charge of the research. While two evaluators exclusively analyze the remaining 178 papers (80%). The divergences found in the paper's screening are discussed and resolved by the evaluators in scheduled meetings.

After completing the manual inclusion and exclusion process, there are 96 papers for the coding process.

4) CLASSIFICATION SCHEME AND DATA EXTRACTION

The classification scheme is a tool that makes it possible to extract relevant information from each selected paper in an organized way, allowing answers to the research questions (RQs) raised above.

In this project, a part of the scheme is elaborated from existing classifications and described in Section II. For example, there are various types of previously established classifications of ML techniques and different areas of work (challenges) related to the functioning and operation of optical networks. These guides reduce the time spent on the scheme development because starting it from scratch is unnecessary. This scheme is then completed and refined by merging or adding new categories (*e.g.*, new ML techniques, combining optical networking work areas into a single challenge) or dividing categories into subcategories (*e.g.*, classification and subclassification of ML techniques). The main objective is obtaining the most significant amount

TABLE 10. Attributes of the maturity level dimension.

Type of research	Description
Evaluation research	"Techniques are implemented in practice, and the technique is evaluated. It is indicated how the technique is implemented in practice (solution implementation) and the consequences of the implementation in terms of benefits and drawbacks (implementation evaluation). This also includes identifying problems in the industry."
Validation research	"Techniques investigated are novel or significant updates and have not yet been implemented. Techniques used are, for example, experiments, *i.e.*, work done in the laboratory."
Solution proposal	"A solution for a problem is proposed; the solution can be either novel or a significant extension of an existing technique. The potential benefits and the applicability of the solution are shown by a small example or a good line of argumentation."
Philosophical papers	"These papers sketch a new way of looking at existing things by structuring the field in the form of a taxonomy or conceptual framework."
Opinion papers	"These papers express the personal opinion of somebody on whether a particular technique is good or bad or how things should be done. They do not rely on related work and research methodologies."
Experience papers	"Experience papers explain what and how something has been done in practice. It has to be the personal experience of the author."

of data possible from the papers that allow answering the research questions, not excluding important information for the study, and trying not to extract unnecessary data that does not provide relevant information. The classification scheme for this research is shown in Fig. 8.

Figure 8 presents the information to be extracted during the coding stage of the selected papers. Four main dimensions (light blue boxes) have been created: the research questions posed in the planning stage. In turn, each dimension has a certain number of attributes (green boxes), which are those data that need to be extracted from each paper. One or several attributes can be extracted from the same paper for a particular dimension. The attributes that allow us to respond to RQ1 and RQ2 have been described in Section II (ML techniques and areas of work or challenges in optical networks where ML could be applied). For RQ3, the possibility of finding the URL address or not of the data sets used in the paper is designated as an attribute. For RQ4, its attributes were obtained from Table 10, which allows us to differentiate the techniques of empirically proven ML (*i.e.*, evaluation and validation research) from those that are not empirically proven (*i.e.*, solution proposals, philosophical papers, opinion papers, or experiences). Finally, the maturity of the selected studies is analyzed based on the efforts made by their authors to validate them [53]. Precisely, the attributes of this dimension correspond to the research types proposed in [56].

B. CONDUCTING

Conducting is the path that helps answer the research questions posed in the planning stage. With this purpose in mind, the paper exploration in Scopus is carried out using the search string defined above. Then, the obtained results are filtered according to the previously proposed automatic and manual inclusion-exclusion criteria, and the remaining papers are coded using the designed classification scheme. Until July 26, 2022, 841 papers were obtained due to the original search string that had been defined. After applying the different automatic and manual filters, we finally worked with the 96 papers analysis in this project. Fig. 9 shows the number of contributions considered in each planning section process.

The 96 selected papers list is displayed in Table 14. Each contribution has been assigned a specific ID. With which the papers will be identified and cited in the results analysis description in Section V and Section VI of this paper. Fig. 10 presents an encoding file example made in CADIMA. From the 96 contributions, all the attributes that allow classifying the ML techniques used to solve a problem related to the functioning and operation of optical networks, the study data set availability are extracted, and a certain level of maturity is assigned to the research. After completing the data extraction process, CADIMA stores the information collected on the platform. To be viewed, it is necessary to download it from its website. The resulting file is a database in an Excel spreadsheet format, which can be seen in the replication package at http://dx.doi.org/10.17632/k66kr79wzg.1.

C. REPORTING

In this section, the answers to the four research questions posed above are presented: (1) ML techniques used to solve problems related to the functioning and operation of optical networks, (2) challenges related to the functioning and operation of optical networks that are mainly addressed with ML techniques, (3) the data set availability used in the investigations and (4) the level of maturity of the techniques developed in the studies. All this information is presented in graphic form so that it can be understood clearly and, while its respective description of results is made—additionally, the most relevant data obtained after the papers coding process is discussed. How promising this research area is, what topics are those with the greatest and least interest for study, and what the gaps still found within this research field? They are some of the most critical data detected during this project. This last stage is part of Section V and Section VI of this project.

V. RESULTS

After coding and analyzing the 96 selected papers, we answer the four research questions in Section IV.

In the following subsections, we respond to the research questions. Subsection V-A presents the results regarding the ML techniques used to solve problems related to the functioning and operation of optical networks (RQ1). The challenges related to the functioning and operation of optical networks that are mainly addressed with ML techniques are presented in Subsection V-B (RQ2). Subsection V-C instead

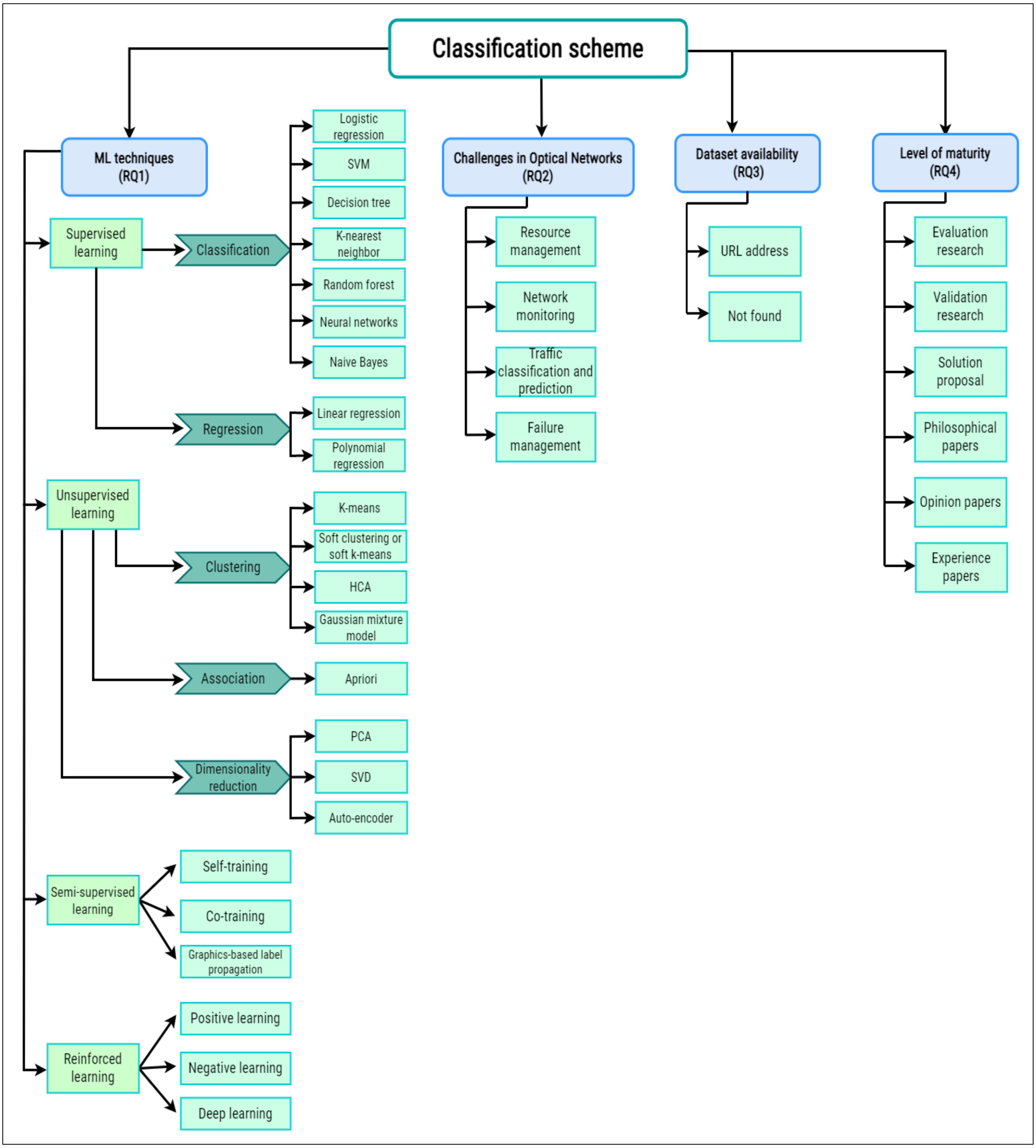


FIGURE 8. Classification scheme.

shows the results regarding the data set availability used in the investigations (RQ3). Finally, Subsection V-D presents the results relating to the level of maturity of the techniques developed in the studies (RQ4). Throughout this section, we refer to or cite the papers studied by the number ID of Table 14.

A. RQ1. WHAT ARE THE ML TECHNIQUES USED TO SOLVE THE PROBLEMS REPORTED IN [2], [3] and [4] RELATED TO THE FUNCTIONING AND OPERATION OF OPTICAL NETWORKS?

RQ1 seeks to provide data on which ML techniques have been used in previous research to solve the problems

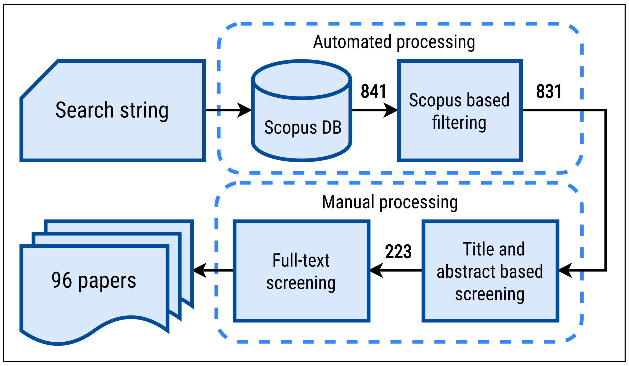


FIGURE 9. Scope of this study, based on [53].

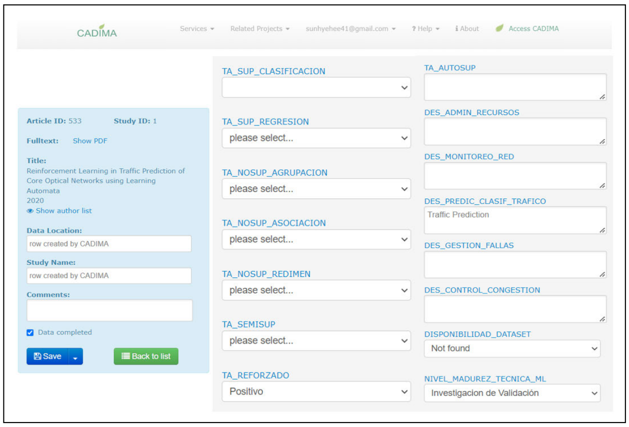


FIGURE 10. Data extraction area in CADIMA.

reported in [2], [3] and [4], which are related to the functioning and operation of optical networks. The results that allow answering this question are discussed below. As shown in Fig. 11, most of the analyzed contributions use supervised learning techniques (92 papers) to solve problems related to resource management, network monitoring, traffic classification and prediction, and failure management of an optical network.

These results are obtained because these supervised techniques, when working with labeled data where the system knows the output patterns, cause these learning algorithms to achieve much more precise results and thereby better solve the problems or challenges around the optical networks (ID156). On the other hand, a few contributions (6 papers) use semi-supervised learning techniques to address problems such as failure management and traffic classification and prediction. These results are derived because the answers provided by the iterations when applying this type of technique are unstable and unreliable, often generating unsuccessful results when trying to solve some problem (ID102).

It should be noted that although 96 papers have been worked on, more than one of them has used various ML techniques within the same research. Therefore, the sum of the papers for each ML technique exceeds the value of the total contributions analyzed.

1) SUPERVISED LEARNING TECHNIQUES

Of the 92 papers using supervised learning techniques (Fig. 12), 90.22% correspond to classification algorithms, and 9.78% use regression algorithms.

Among the classification algorithms, neural networks (34.78%) are the techniques most used to solve problems related to resource management, network monitoring, fault management, and traffic classification and prediction of an optical network. Because by trying to emulate how the human brain processes information, neural networks have multiple benefits with their use. For example, one of the most important features is that they can organize the learned data by themselves, reducing the algorithm complexity to solve a given problem (ID114).

In addition, they present a varied classification that covers multiple work areas, from the simplest to the most complex (ID72). During the analysis of the paper, it was identified that specific investigations make use of multilayer perceptron (ID43), artificial neural networks (ID72, ID114, ID129, ID172, ID174, ID228, ID256, ID262, ID275, ID283, ID478, ID581, ID697, ID726, ID736, ID787, ID820), convolutional neural networks (ID172, ID221, ID255, ID281, ID720), recurrent neural networks (ID151, ID242, ID464, ID827) and deep neural networks (ID139, ID648, ID787). Likewise, it is identified that around 26 papers (28.26%) make use of a combination of supervised learning techniques (SVM, logistic regression, k-nearest neighbor, etc.) to solve challenges related to resource management, network monitoring, fault management and traffic classification, and prediction of an optical network. The objective of this type of combinations is to try to use the best features of each algorithm to achieve much more accurate results.

2) UNSUPERVISED LEARNING TECHNIQUES

Of the eight papers that use unsupervised learning techniques (Fig. 13), 75% correspond to clustering algorithms, and 25% use dimensionality reduction algorithms. These results are because unsupervised algorithms work with unlabeled data sets, and the results they provide can be less precise, presenting difficulties when trying to solve problems or challenges related to optical networks (ID156).

In the clustering algorithms, four of the coded papers (50%) make use of unsupervised learning techniques different from the popular ones; among them, we find one-class SVM (ID331, ID452, ID608), isolation forest (ID608), one-class naive Bayes (ID608), linear autoregressive (ID778), linear support vector regression (ID778), which are unsupervised strategies based on architectures that employ supervised learning techniques (ID778). These unsupervised ML models tend mostly to try to solve problems related to fault management in an optical network.

After determining the location and cause of a failure (unsupervised algorithms), estimating the magnitude of the failure can provide additional information to understand its severity and possible solution (supervised algorithms)

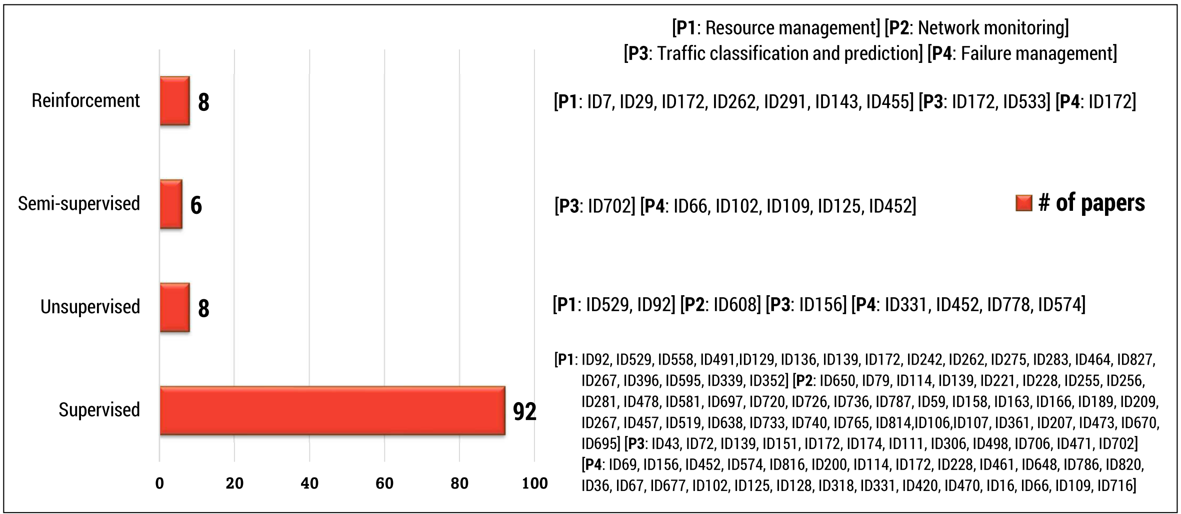


FIGURE 11. ML techniques reported with their respective papers ID.

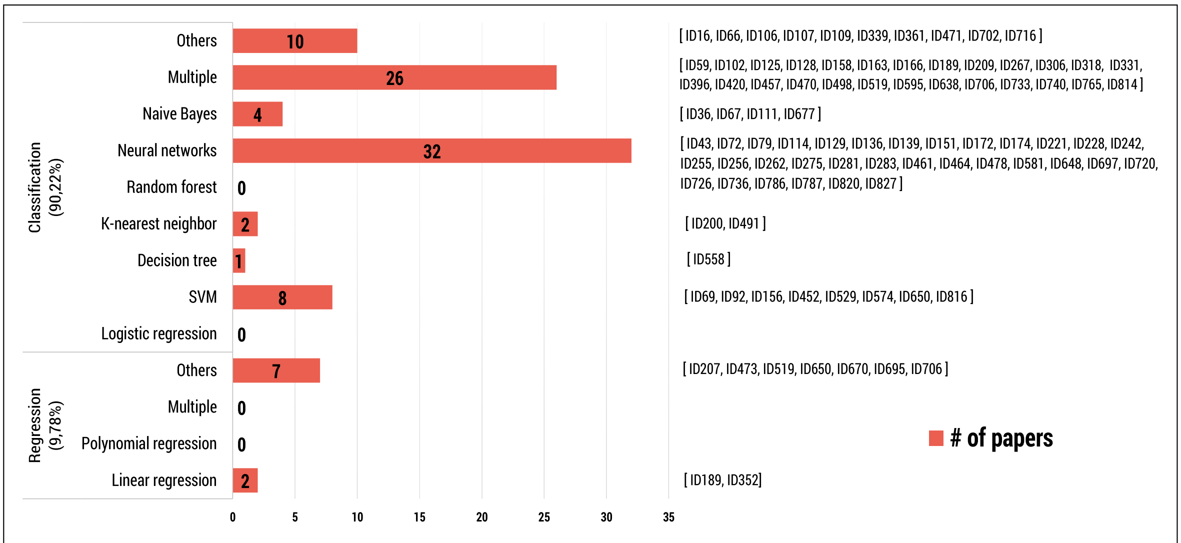


FIGURE 12. Papers that have contributed to resolving problems in optical networks with supervised learning techniques.

(ID331). By way of example, a network operator, after identifying a failure, can decide if a network reconfiguration is enough or if it is necessary to repair or even replace some system equipment using unsupervised and supervised techniques simultaneously (ID778).

3) SEMI-SUPERVISED AND REINFORCED LEARNING TECHNIQUES

Of the six papers that use semi-supervised learning techniques (Fig. 14), 100% correspond to learning algorithms different from those popularly used in this type of technique; among them, we find correlation graph model (ID66, ID109), binary support vector (ID102, ID125), semi-supervised one-class support vector machine (ID452), semi-supervised graphical convolutional network (ID702) and semi-supervised generative adversarial network (ID702). These algorithms are commonly used to solve problems related to fault management in an optical network. The main objective of this type of technique is to try to locate link failures by training data that describe the network state in current and past failure incidents through supervised and unsupervised processes simultaneously (ID102).

In addition, it is determined that eight of the analyzed papers use reinforcement learning techniques, focusing their research on the resource management of an optical network. This is a work area that includes issues related to the balanced allocation of resources (bandwidth, optical spectrum, etc.), routing, and wavelength assignment (RWA), among others, which are complicated challenges that require this type of technique to achieve its proper functioning within the network (ID291). Reinforcement learning achieves much more accurate and realistic results than any conventional technique. However, it requires complex processes for its proper functioning, this being a possible cause of the papers

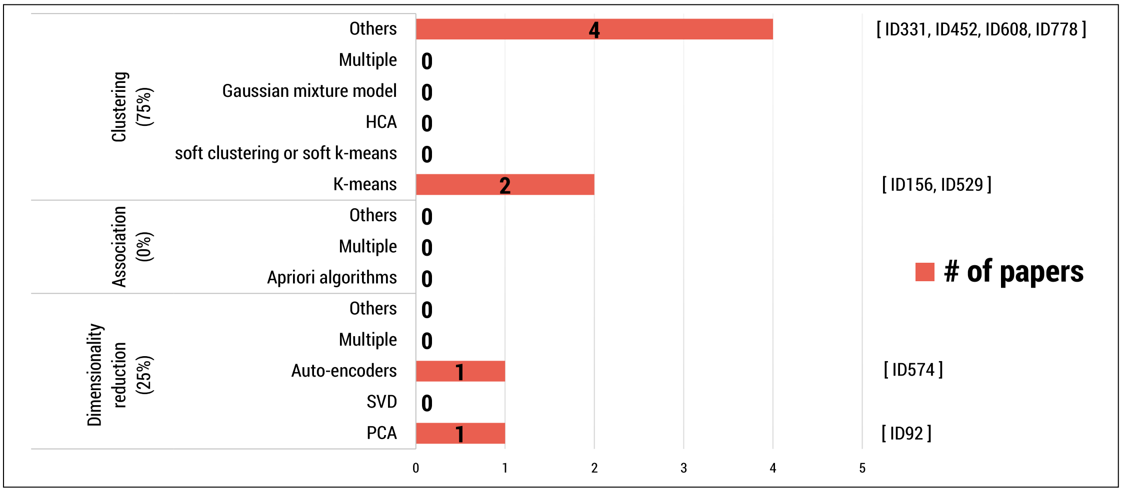


FIGURE 13. Papers that have contributed to resolving optical network challenges with unsupervised learning techniques.

lower number that makes use of reinforcement learning in the analyzed research.

B. RQ2. WHAT CHALLENGES REPORTED IN [2], [3] AND [4] HAVE BEEN MOSTLY ADDRESSED BY USING THE REPORTED ML TECHNIQUES?

RQ2 seeks to provide data on which challenges or problems related to the functioning and operation of optical networks have been addressed chiefly with ML techniques in previous research. The results that allow answering this question are discussed below.

As shown in Fig. 15, most of the contributions analyzed (41 papers) take optical network monitoring as their research area. These results are obtained because this challenge addresses issues related to monitoring the performance of an optical network, QoT estimation, QoE, and QoS management, among others, which are essential areas that need to be explored through ML to maximize and improve the performance of the network for the user (ID650).

Additionally, the second most relevant topic in the research focuses on managing failure in an optical network (37 papers). Failure detection and correction are essential in this type of system due to the enormous amount of traffic that optical connections support. By applying ML techniques, there is the possibility of identifying the problem cause as soon as possible so that the failed resources can be eliminated from the calculation of the restoration routes. Thus the communication network is not entirely affected (ID16). It should be noted that although 96 papers have been worked on, some address various challenges in optical networks within the same investigation. Therefore, the number of papers for each reported challenge exceeds the value of the total contribution that has been analyzed.

1) RESOURCE MANAGEMENT

Of the 96 papers coded in this project, 28 focus their research on resource management (see Table 11). A challenge, which in turn covers the following sub-problems:

- Allocation and management of optical resources.
- Resources balanced allocation.
- Routing and wavelength assignment (RWA).
- Routing and spectrum assignment (RSA).
- Dynamic adaptive allocation of wavelength and bandwidth.
- Bandwidth prediction, allocation, and monitoring.

Figure 16 shows that most research has taken supervised learning (67.86%) as the appropriate ML technique to address resource management in an optical network. These results are because the routing and resource allocation challenge can be seen as a classification problem (ID529). Therefore, 18 papers (64.29%) use classification algorithms, and only one paper (3.57%) employs regression algorithms. When a service arrives, it is required to route a light path and assign the resource in real-time according to the network's current state. In other words, each traffic demand has a corresponding routing and resource allocation solution.

By fitting the mathematical relationship between network states and routing and resource allocation solutions, the appropriate solution for a new request can be intelligently selected through supervised learning (ID275). However, achieving the optimization of this challenge is not a simple task because its theoretical analysis is complex, and employing conventional techniques is not very suitable for finding an adequate solution (ID143). Therefore, on certain occasions, support is required from other types of techniques, such as unsupervised learning (7.14%) and reinforced learning (25%), to address the challenge of Resource Management in optical networks. Especially, Deep Reinforcement Learning (DRL) is one technique currently under investigation to address the Routing, Modulation, and Spectrum Assignment (RMSA) problem in optical networks.

At present, the continuous deployment of cloud-edge computing and IoT has been simulating the boom of new advance reservation (AR) services, such as bulk data migration and virtual machine backup, driving the development of substrate

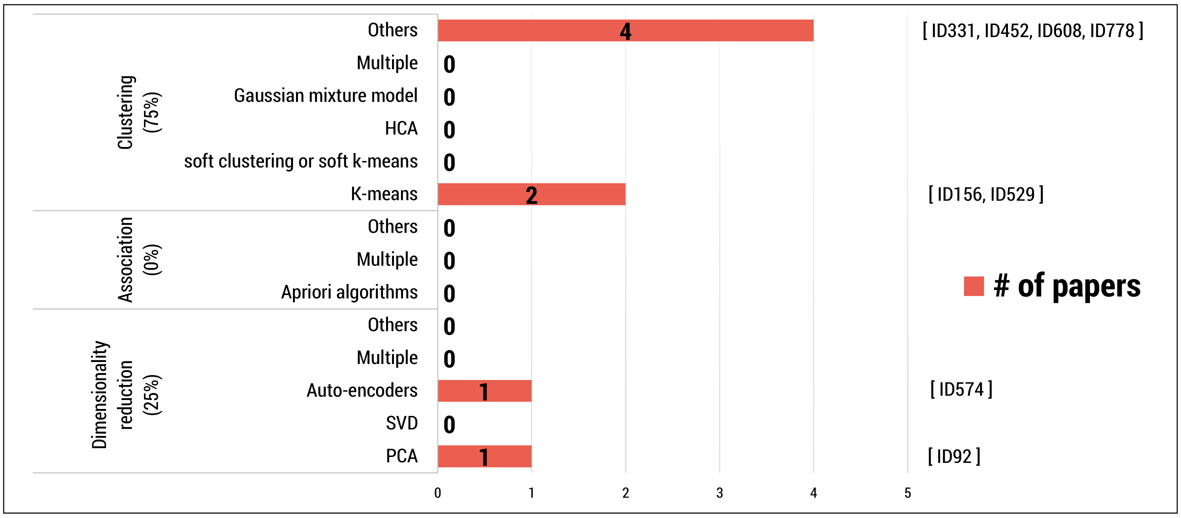


FIGURE 14. Papers that have contributed to resolving optical network challenges with semi-supervised and reinforcement learning techniques.

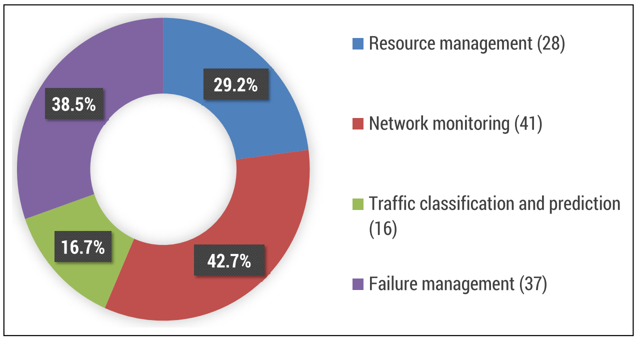


FIGURE 15. Contributions number that addresses a challenge related to optical networks and ML.

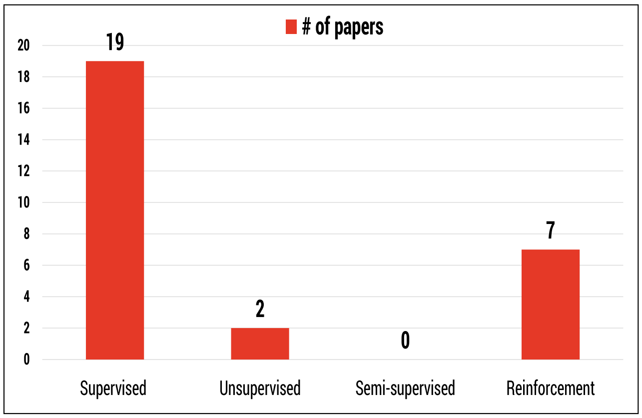


FIGURE 16. Contributions for the resource management problem addressed with ML.

elastic optical networks (EONs) [57]. These deadline-driven advance reservation (DDAR) service requests can tolerate certain initial delays if they can be completed before the deadline [58]. Therefore, effective routing, modulation, and spectrum assignment (RMSA) for these AR requests will provide the potential to decrease pressure on network resources and avoid network congestion. Thus, [57] proposes a Deep Reinforced Deadline-Driven Allocation (DRDA) algorithm to solve the AR resource allocation problem in an efficient way that conventional heuristic methods can't do, being the first work to take advantage of DRL to solve the AR resource allocation problem.

2) NETWORK MONITORING

Of the 96 coded papers, 41 focus their research on network monitoring (see Table 11). A challenge which, in turn, covers the following sub-problems:

- Optical performance monitoring
- QoT estimation, prediction, and evaluation.
- SNR and OSNR estimation.
- Quality of service (QoS) and quality of experience (QoE).

Figure 17 highlights that around 97.56% of the 41 papers have used supervised learning techniques to address this challenge. At the same time, 2.44% make use of unsupervised learning.

Optical performance monitoring (OPM) estimates, predicts, and acquires various critical physical parameters of transmitted optical signals and network elements (QoT, SNR, OSNR, and BER, among others). Therefore, its functionalities are essential for reliable and flexible network operation and for improving efficiency (ID59, ID650). For that reason, in recent years, supervised learning algorithms, especially neural networks (artificial, convolutional, and deep), have been successfully applied to address the cost-effective monitoring of multiple deficiencies in optical networks (ID255). OPM is also considered an enabling technology for Software Defined Networks (SDN). Through OPM, SDNs can know the network conditions in real-time, and later, they can adjust various parameters of the network elements (power, data speeds, modulation formats, etc.),

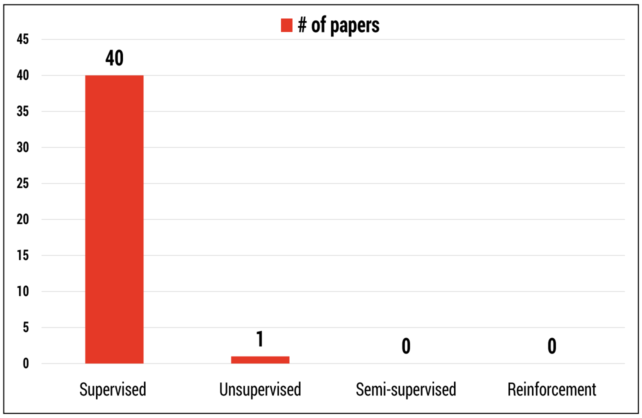


FIGURE 17. Contributions for the network monitoring problem addressed with ML.

allowing better optimization way the network transmission performance by using architectures based on supervised learning (ID209).

Until the selection date of the 96 papers in this study, the results showed that the supervised and unsupervised learning methods were the most used to improve the functioning and operation of optical networks. However, by 2023, in [59], a novel method based on Deep Reinforcement Learning (DRL) has been proposed to improve the quality of service (QoS) in elastic optical networks (EONs). With an effective service provisioning strategy based on Network Functions Virtualization (NFV), cloud-edge computing can improve QoS in EONs. NFV emerges as a promising technology that enables flexible services by orchestrating different virtual Network Function Chains (vNFC) [59]. However, its implementation process is complex because it involves two stages: (1) allocating diverse Virtual Network Functions (VNFs) onto different physical nodes and (2) routing suitable paths for Virtual Links (VLs), which with the methods heuristics and state-of-the-art DRL algorithms used for its operation have generated unsatisfactory performance. Thus, in [59], a Double-Agent Reinforced vNFC Deployment algorithm (DARD) is proposed to integrate the VNFs and VLs deployment stages by two cooperative DRL agents, improving the performance of vNFC.

3) TRAFFIC PREDICTION AND CLASSIFICATION

Of the 96 coded papers, 16 of them focus their research on the subject of traffic classification and prediction (see Table 11). A challenge that, in turn, covers the following sub-problems:

- Traffic flow estimation, classification, and prediction.
- Short and long-term traffic prediction.
- Congestion control.

Figure 18 shows that most research has taken supervised learning (81.25%) as the appropriate ML technique to address the challenge of traffic classification and prediction in optical networks. These results are because network traffic data is a time series data type [3], whose resolution can be considered a classification or regression problem (ID43). Therefore, 75% of the papers analyzed using supervised classification algorithms, and 6.25% employ regression algorithms.

The traffic distribution estimation of a network is an essential tool for evaluating the communications system's performance. By analyzing network traffic data and extracting its features, its rules and operating mechanisms can be explored (ID43). In optical networks, due to the change of the user's access location, there is a possibility of experiencing a "tidal traffic" phenomenon, in which the network traffic changes over a period. Because of this, the spectrum may be wasted when network resources cannot be flexibly scheduled in real-time [3]. Therefore, quickly estimating tidal traffic change and reasonably allocating network resources according to existing traffic are key challenges to solve using supervised learning (ID111). On the other hand, the semi-supervised (6.25%) and reinforced (12.5%) learning algorithms are used for network traffic prediction, an essential mechanism and much more complex to analyze and solve with conventional learning techniques. This potentially benefits improved optical network management since it serves as a base for resource allocation, short-term traffic re-routing long-term capacity planning, network design, and anomaly detection, thereby improving user service quality (ID702).

It should be noted that, in recent times, due to the development of 5G communication networks, deep reinforcement learning techniques are being used to address and optimize the challenge of traffic prediction and classification in optical networks. Cloud-fog computing emerges to satisfy the low latency and high computation requirements of IoT services [60], which cloud computing alone can't satisfy. Whereas, Elastic Optical Networks (EONs) have been defined as excellent substrate communication networks between fog datacenters and cloud datacenters [61]. With the development of 5G, virtual reality (VR), and other emerging services, EONs are currently characterized as networks carrying 5G services. However, the uneven traffic from massive cloud-fog services (mice traffic) incurs many spectrum fragments, leading to additional high-energy consumption within the network's operation [60]. The way to groom the mice traffic on the same channel to save spectrum resources and reduce energy consumption is extremely important to analyze in EON networks. So, to address this problem, in [60] an energy-efficient deep reinforced traffic grooming (EDTG) algorithm is proposed to generate the optimal traffic grooming strategy in EONs for cloud–fog computing using deep reinforcement learning techniques.

4) FAILURE MANAGEMENT

Of the 96 coded papers, 37 focus their research on failure management (see Table 11). A challenge that, in turn, covers the following sub-problems:

- Failure detection, identification, location, and management.
- Soft and hard failures detection, categorization, and localization.

TABLE 11. Challenges in optical networks vs. ML techniques reported.

Resource management (28)

Supervised learning (19)			
Classification (18)	SVM	2	ID92, ID529
	Decision tree	1	ID558
	K-nearest neighbor	1	ID491
	Neural networks	10	ID129, ID136 ,ID139, ID172, ID242, ID262, ID275, ID283, ID464, ID827
	Multiple	3	ID267, ID396, ID595
	Others	1	ID339
Regression (1)	Linear regression	1	ID352

Unsupervised learning (2)			
Clustering (1)	K-means	1	ID529
Dimensionality reduction (1)	PCA	1	ID92

Semi-supervised learning (0)
-

Reinforcement learning (7)		
Positive	5	ID7, ID29, ID172, ID262, ID291
Multiple	2	ID143, ID455

Network monitoring (41)

Supervised learning (40)			
Classification (33)	SVM	1	ID650
	Neural networks	15	ID79, ID114, ID139, ID221, ID228, ID255, ID256, ID281, ID478, ID581, ID697, ID720, ID726, ID736, ID787
	Multiple	14	ID59, ID158, ID163, ID166, ID189, ID209, ID267, ID457, ID519, ID638, ID733, ID740, ID765, ID814
	Others	3	ID106, ID107, ID361
Regression (7)	Linear regression	1	ID189
	Others	6	ID207, ID473, ID519, ID650, ID670, ID695

Unsupervised learning (1)			
Clustering (1)	Others	1	ID608
Dimensionality reduction (0)	-		

Semi-supervised learning (0)
-

Reinforcement learning (0)
-

Traffic classification and prediction (16)

Supervised learning (13)			
Classification (12)	Neural networks	6	ID43, ID72, ID139, ID151, ID172, ID174
	Naive Bayes	1	ID11
	Multiple	3	ID306, ID498, ID706
	Others	2	ID471, ID702
Regression (1)	Others	1	ID706

Unsupervised learning (0)
-

Semi-supervised learning (1)		
Others	1	ID702

Reinforcement learning (2)		
Positive	2	ID172, ID533

Failure management (37)

Supervised learning (27)			
Classification (27)	SVM	5	ID69, ID156, ID452, ID574, ID816
	K-nearest neighbor	1	ID200
	Neural networks	7	ID114, ID172, ID228, ID461, ID648, ID786, ID820
	Naive Bayes	3	ID36, ID67, ID677
	Multiple	7	ID102, ID125, ID128, ID318, ID331, ID420, ID470
	Others	4	ID16, ID66, ID109, ID716
Regression (0)	-		

Unsupervised learning (4)			
Clustering (3)	Others	3	ID331, ID452, ID778
Dimensionality reduction (1)	Auto-encoders	1	ID574

Semi-supervised learning (5)		
Others	5	ID66, ID102, ID109, ID125, ID452

Reinforcement learning (1)		
Positive	1	ID172

- Alarm analysis and failure prognosis.
- Proactive protection and restoration methods.
- Equipment failures detection and identification

Figure 19 highlights that around 72.97% of the 37 papers have used supervised learning techniques to address this issue because the approach to address this challenge is mainly based on a set of classifiers that make predictions using features extracted from the optical signal spectrum (ID331). Therefore, the 27 papers analyzed use supervised classification algorithms (SVM, K-nearest neighbor, neural networks).

Failure management is one of the most important challenges to address because failures can cause severe service interruption and loss of data transmission, thereby degrading transmission quality (ID716). Failures in optical network communication are two types: soft or minor failures and hard or severe failures (ID786). Severe failures immediately lead to loss of service and can be easily identified, *e.g.*, fiber bends, fiber cuts, among other problems. Minor faults slowly lead to signal quality degradation and reduced QoT due to signal overlap, laser deflection, filter switching, non-linear interference, noise, etc (ID786). Generally, ML techniques are used only to identify and estimate minor failures. Hence, the supervised, unsupervised (10.81%), semi-supervised (13.51%), and reinforced (2.7%) algorithms are providing effective solutions (early warning mechanisms, protection methods, and proactive optical network restoration) to this problem.

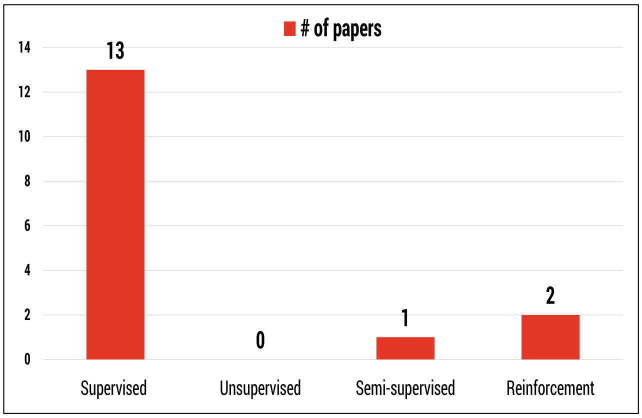


FIGURE 18. Contributions for the traffic classification and prediction problem addressed with ML.

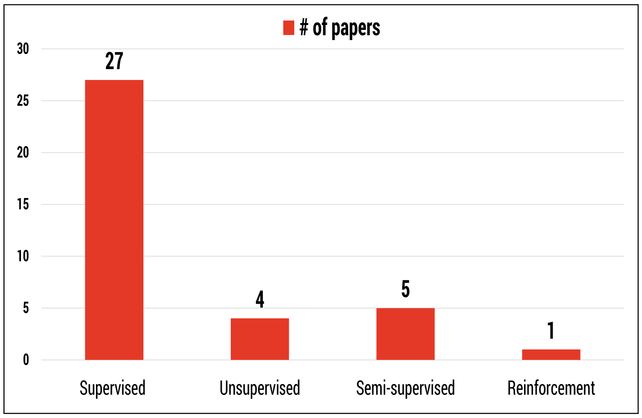


FIGURE 19. Contributions for the failure management problem addressed with ML.

C. RQ3. ARE THE DATA SETS THAT HAVE BEEN USED BY ML TECHNIQUES IN THE REVIEWED PAPERS AVAILABLE?

RQ3 seeks to provide data on which previous investigations provide information (URL addresses) of the data sets that have been used to carry out the training tests of the ML algorithms. The results that allow answering this question are described below.

Around 98.96% of the papers analyzed, they do not have any information about the data sets used for training the ML algorithms. Several of the papers mentioned that synthetic data has been worked on (e.g., ID158, ID166, ID473, ID773, ID740, ID786, etc.), and in other contributions data sets from real networks of different international locations have been used to achieve much more precise results (e.g., ID129, ID172, ID174, ID200, ID221, ID281, ID361, among others). But unfortunately, no information is provided about the location of these data so that they can be used in future research. Below, Table 12 presents details about the only data set (1.04%) that is available, which has been used to address the traffic classification and prediction challenge by supervised learning techniques.

TABLE 12. Data set information available.

Data set name	Description	Paper
SIX (Seattle Internet Exchange)	They provide inter-network traffic statistics data to the northwestern United States. **URL address:** https://www.seattleix.net	ID706

D. RQ4. WHAT IS THE MATURITY LEVEL OF THE IDENTIFIED ML TECHNIQUES?

RQ4 seeks to provide information about the level of maturity of the ML techniques identified to solve challenges related to optical networks based on the efforts made by their authors to evaluate their research. It should be mentioned that to qualify the maturity of the identified ML techniques, the types of research presented in Table 10 have been used, which establish for each paper a degree of maturity that goes from a minimum level when a paper is based solely on opinions (experience papers, opinion papers, philosophical papers, and solution proposals) to a maximum level when a paper has been empirically evaluated in real scenarios (validation research and evaluation research) [53]. The results that allow answering this question are discussed below.

1) SUPERVISED LEARNING TECHNIQUES

As shown in Fig. 20, most of the challenges addressed with supervised learning techniques (98.96%) have been empirically tested, while the remaining 1.04% have not. Additionally, of the papers evaluated empirically, only six papers (6.25%) have been evaluated in a real context (ID43, ID69, ID106, ID174, ID200, ID702), while most of them (92.71%) were only validated under a controlled simulation environment. On the other hand, among the techniques not empirically tested, we found only one solution proposal (ID156) and no philosophical or opinion paper. Consequently, these results suggest that contributions on supervised learning techniques to solve challenges or problems related to optical networks tend to be specific proposals rather than abstract or just general ideas because most of the papers try to evaluate the validity of their papers at least by an example to publicize the applicability of their solution.

Figure 20 also allows observing the level of maturity of the supervised learning techniques for each problem, highlighting that for the challenges of failure management, network monitoring, and traffic classification and prediction, there papers tested in a real environment (ID43, ID69, ID106, ID174, ID200, ID702) and evaluated under a controlled experimental setting. For the resource management challenge, only validation papers are presented. And additionally, for the failure management challenge, there is a solution proposal paper (ID156). Finally, it is concluded that the supervised learning algorithms applied in traffic classification and prediction emerge as the most mature techniques because their contributions have been empirically tested (13 papers). And in addition, they have the largest number of papers evaluated in a real context using supervised learning techniques (3 out of 6 papers).

2) UNSUPERVISED LEARNING TECHNIQUES

As shown in Fig. 21, all contributions that have used unsupervised learning algorithms to address some challenges related to optical networks have been empirically tested. However, none of the papers were evaluated realistically but were validated only under a controlled simulation environment. These results indicate that although the number of contributions that use unsupervised learning techniques to solve challenges or problems related to optical networks is low (7 papers), these tend to be specific proposals rather than just general ideas because most of the papers try to evaluate the validity of their papers at least by an example, to publicize the applicability of their solution.

Figure 21 also allows visualizing the level of maturity of the unsupervised learning techniques for each problem, highlighting as a primary characteristic that for the challenges of failure management, network monitoring, and resource management, there are papers evaluated under a controlled experimental environment. At the same time, the traffic classification and prediction challenge has not been solved by unsupervised techniques. Consequently, it is concluded that unsupervised learning algorithms applied to failure management emerge as the most mature techniques because their contributions have the largest number of papers empirically evaluated in a controlled environment (4 out of 7 papers).

3) SEMI-SUPERVISED LEARNING TECHNIQUES

As shown in Fig. 22, all the papers that have used semi-supervised learning algorithms to address some challenges related to optical networks have been empirically tested. Additionally, of the papers evaluated, only 16.67% have been evaluated in a real context (ID702), while most of them (83.33%) were validated only under a controlled simulation environment. These results show that although the number of paper that makes use of semi-supervised learning techniques to solve challenges or problems related to optical networks is low (6 papers), these tend to be specific proposals rather than just vague ideas because most of the papers try to evaluate the validity of their papers at least by an example, to publicize the applicability of their solution.

Figure 22 also allows determining the level of maturity of the semi-supervised learning techniques for each problem, highlighting that there is only one paper tested in a real environment for the traffic classification and prediction challenge. Five papers are evaluated under a controlled experimental environment that addresses the failure management challenge, and no paper reports semi-supervised techniques for network monitoring and resource management problems. Therefore, it is concluded that semi-supervised learning algorithms applied in traffic classification and prediction emerge as the most mature techniques because their contribution has been empirically evaluated in a real-world context (ID702).

4) REINFORCEMENT LEARNING TECHNIQUES

As shown in Fig. 23, most of the challenges addressed with reinforcement learning techniques (90%) have been empirically tested, while the remaining 10% have not. Additionally, none of the empirically evaluated papers have been evaluated in a real context, but all were validated only under a controlled simulation environment. On the other hand, we found only one solution proposal (ID7) and no philosophical or opinion paper among the techniques not empirically tested. Therefore, these results indicate that although the paper's number of contributions that use reinforcement learning techniques to solve challenges or problems related to optical networks is low (10 papers), these tend to be specific proposals rather than just vague ideas because most of the papers try to evaluate the validity of their papers at least by an example to publicize the applicability of their solution.

Figure 23 also allows observing the level of maturity of the reinforcement learning techniques for each problem, highlighting that for the challenges of failure management, resource management, and traffic classification and prediction, there are papers evaluated under a controlled experimental environment. A solution proposal paper is additionally presented for the resource management challenge, and no paper is addressed with reinforced network monitoring techniques. Accordingly, it is concluded that reinforcement learning algorithms applied to resource management emerge as the most mature techniques because it has the largest number of papers empirically evaluated in a controlled environment (6 out of 9 papers).

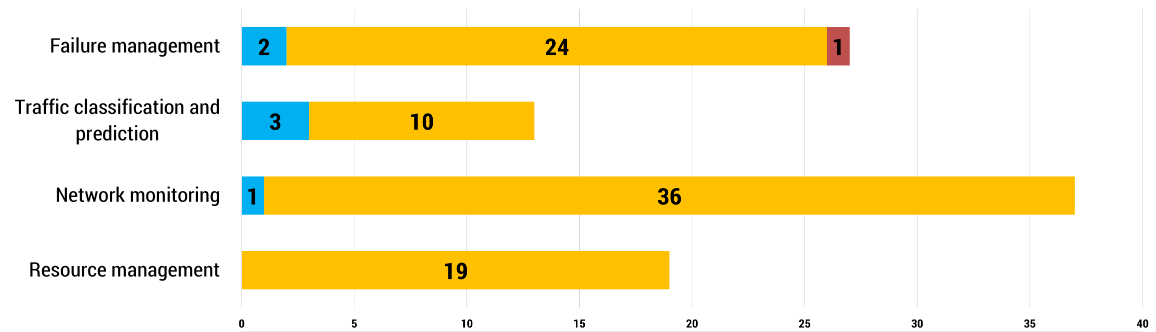
VI. DISCUSSION

Analysis of ML techniques to solve problems related to the functioning and operation of optical networks seems to be a promising research area. This result has been reached because we have worked with articles from 2009 (ID7); an increasing interest has been identified in this area, especially in the last five years, and additionally, it is seen that around two-thirds (87.5 %) of the papers coded in this work come from these last years, as shown in Fig. 24.

If we focus on analyzing the last three years' publications collected until July 26, 2022. It is determined that supervised learning algorithms are those ML techniques mainly used for the functioning and operating of optical networks today. Secondly, there are the reinforcement learning algorithms and the unsupervised and semi-supervised learning algorithms, as shown in Fig. 25.

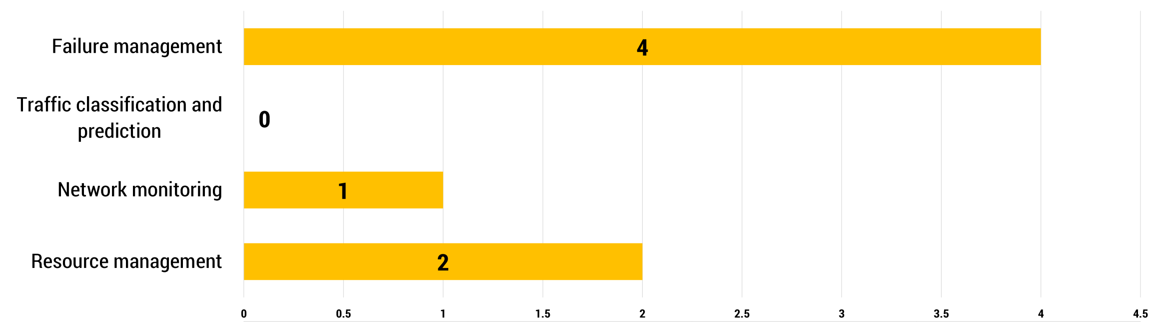
Within the supervised learning techniques, it has been detected that those algorithms that have greater use in optical networks are: SVM, decision tree, k-nearest neighbor, random forest, and mainly neural networks.

- The SVM, k-nearest neighbor, and random forest algorithms are mostly employed for classification tasks



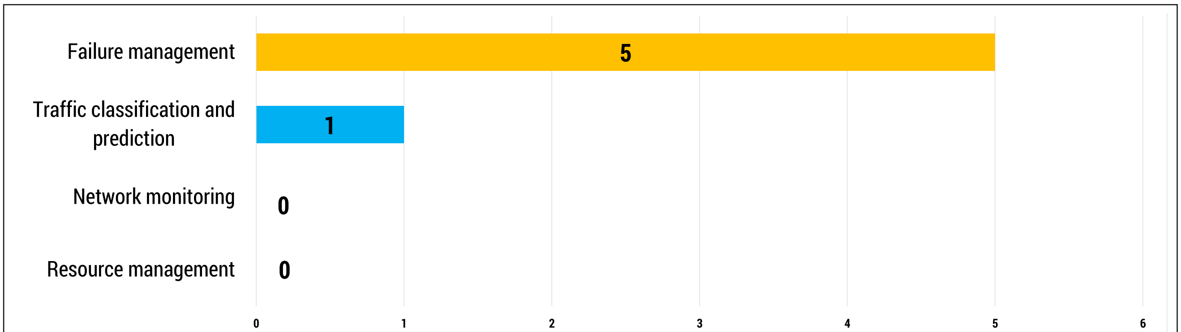
	Resource management	Network monitoring	Traffic classification and prediction	Failure management
Evaluation Research	0	1	3	2
Validation Research	19	36	10	24
Solution Proposal	0	0	0	1
Philosophical papers	0	0	0	0
Opinion papers	0	0	0	0
Experience papers	0	0	0	0

FIGURE 20. **Level of maturity of supervised learning techniques (papers number per problem).**



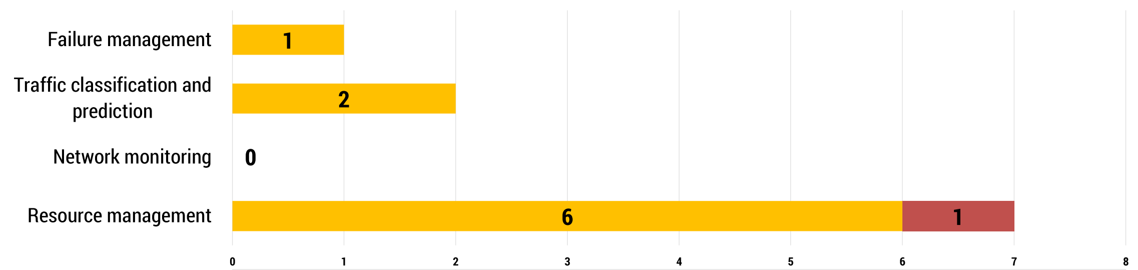
	Resource management	Network monitoring	Traffic classification and prediction	Failure management
Evaluation Research	0	0	0	0
Validation Research	2	1	0	4
Solution Proposal	0	0	0	0
Philosophical papers	0	0	0	0
Opinion papers	0	0	0	0
Experience papers	0	0	0	0

FIGURE 21. **Level of maturity of unsupervised learning techniques (papers number per problem).**



	Resource management	Network monitoring	Traffic classification and prediction	Failure management
Evaluation Research	0	0	1	0
Validation Research	0	0	0	5
Solution Proposal	0	0	0	0
Philosophical papers	0	0	0	0
Opinion papers	0	0	0	0
Experience papers	0	0	0	0

FIGURE 22. **Level of maturity of semi-supervised learning techniques (papers number per problem).**



	Resource management	Network monitoring	Traffic classification and prediction	Failure management
Evaluation Research	0	0	0	0
Validation Research	6	0	2	1
Solution Proposal	1	0	0	0
Philosophical papers	0	0	0	0
Opinion papers	0	0	0	0
Experience papers	0	0	0	0

FIGURE 23. Level of maturity of reinforcement learning techniques (papers number per problem).

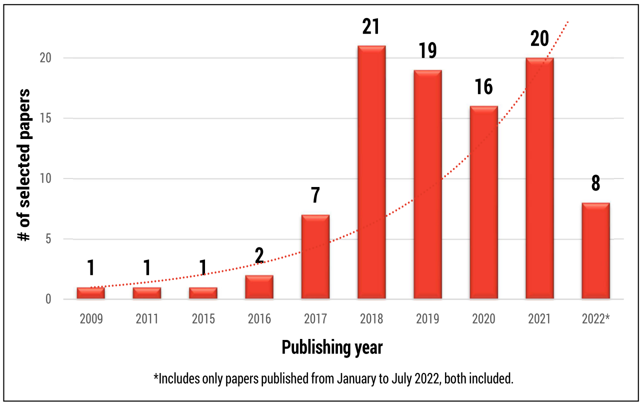


FIGURE 24. Distribution of selected papers by publishing year.

in optical networks. It has been identified that these algorithms are used in work areas such as resource management (ID529) (ID491), predicting the bandwidth requests (ID595), hierarchical classifications of transmission channel qualities (ID529), fault detection, and identification. (ID452) (ID574) (ID816) (ID470), optical performance monitoring (ID650), QoT estimation (ID457) (ID733) (ID704) (ID765) (ID814), and traffic forecasting (ID498).

On the other hand, due to the outstanding characteristics that neural networks have of being a model based on the functioning of the human brain and attempting to replicate it. They have become the fundamental pillar of AI and today of optical networks. We have identified that, in the last three years, most of the analyzed papers utilize different types of neural networks to provide optimized solutions related to the functioning and operation of optical networks. Some of the prominent algorithms that are used include:

- Artificial neural networks (ANNs): It is determined that ANNs are employed in optical networks to address challenges related to the lightpaths QoT estimation (ID765) (ID478) (ID726) (ID736), performance monitoring (ID581) (ID697), and fault detection (ID786) (ID820).
- Convolutional Neural Networks (CNNs): It has been shown that CNNs have been used for various tasks such as traffic flow classification (ID396), soft failure identification (ID461), and QoT prediction of unestablished lightpaths (ID720) in optical networks.
- Deep Neural Networks (DNNs): DNNs have been identified as being implemented in optical networks to address challenges such as traffic pattern recognition (ID396), QoT estimation (ID519) (ID787), and failure prediction (ID648) (ID677) (ID420).
- Recurrent Neural Networks (RNNs): RNNs, particularly long short-term memory networks (LSTM), are those algorithms that are being studied to solve problems related to the functioning and operation of optical networks. In the analyzed articles, LSTM-RNN is used to address challenges such as failure prediction (ID420), lightpaths performance forecasting (ID457), lightpath QoT estimation (ID814), and routing and spectrum allocation (ID464) (ID827).

Additionally, within unsupervised learning techniques, algorithms such as one-class SVM and autoencoder are used to address problems related to the functioning and operation of optical networks.

- One class SVM: This algorithm, together with supervised, semi-supervised, or reinforcement learning addresses challenges such as soft failure detection and identification (ID452), and QoT prediction (ID608).
- Autoencoder: This type of algorithm, in conjunction with supervised, semi-supervised, or reinforcement learning, is used to address challenges related to soft failure identification (ID574).

Similarly, reinforcement learning (RL) has proven to be a promising ML technique to address challenges related to optical networks. Several of the analyzed papers use an ML technique to solve some problems and perform a combination

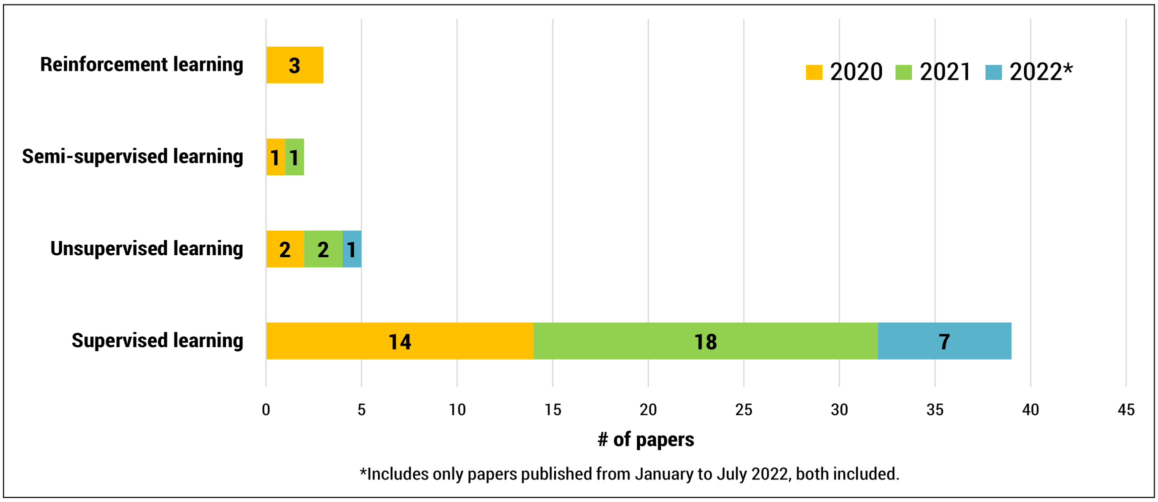


FIGURE 25. **Publications number in the last three years that used ML algorithms in optical networks.**

of algorithms, including RL. From the analysis studies, some challenges in optical networks in which RL is employed are self-adaptive bandwidth allocation (ID455) and traffic prediction (ID533).

However, it must be remembered that the ML field is dynamic, and there is a great possibility that new models and algorithms emerge after this study. By the year 2023, new research has been identified that proposes novel methods based on deep reinforcement learning (DRL), such as those reported in [57], [59] and [60] to address challenges related to optical networks. Undoubtedly, the ML algorithms used in the functioning and operation of optical networks are bringing unprecedented opportunities to this communication area, further improving its capacity and reliability for the user's benefit. During the paper's coding, it was identified that most of the contributions (42.7%) base their research on the monitoring area of an optical network. The growing demand for bandwidth is due to emerging services such as online gaming, streaming, and IPTV, forcing service providers to upgrade their networks to support these new services (ID695). An appropriate solution to this demand is to employ optical networks due to their multiple advantages (sizeable available bandwidth, approximately 100 THz) compared to other technologies such as RF. Therefore, in the not-too-distant future, optical networks will admit different modulation formats and speeds according to channel status and end customer demand (ID695), becoming increasingly heterogeneous systems. And to manage these types of networks will be essential to build network monitoring systems using ML. The models proposed in the analyzed papers suggest that these ML algorithms enable the possibility of acquiring information about the quality of the physical link (parameters such as QoT, SNR, OSNR, QoS, QoE, etc.) in real-time. So, the network will be aware of the existing physical deficiencies, perform its diagnosis, and comply with the end user's quality of service agreement dynamically and reliably (ID695).

Likewise, it has been identified that traffic classification and prediction in an optical network is the research area with the lowest number of papers (16.7%). According to Cisco, the Internet users number will grow from 3.9 in 2018 to 5.3 billion by 2023 [62] as a result of the increase in mobile devices (cell phones, computers, tablets, etc.), as well as the IoT emergence and the long-awaited 5G. The excessive growth of users translates into an increase in network traffic. Today, communication media used as backbone networks that allow the transport of a large amount of user data traffic are the optical networks (ID498). Having prior knowledge about network traffic can be a tremendous advantage for operators because network operating costs can be reduced due to efficient management of its resources (ID498). The small papers number that address this topic (16 out of 96 papers) is not because it is a research area that does not benefit the optical networks but because, as previously mentioned, any increase in users becomes traffic for the network. It needs to be controlled correctly to avoid mishaps for the users. The problem of papers' reduced number focuses on the fact that ML algorithms that can be used to forecast traffic with high accuracy require training data according to the real networks so that they can be reliable methods. But unfortunately, network providers and operators do not share this type of information (actual traffic flow) with third parties because it could contain their end users' sensitive data, making it difficult to develop methods to classify and predict network traffic. ML can model continuous, regular, time-changing traffic flows and use that data in training to predict future data flow from a network (ID471). Nevertheless, we can observe daily and weekly patterns of users' daily activities in a true network traffic data set. ML algorithms can forecast, find, analyze, and use that data to predict future network data flows according to the real world. As evidenced throughout the discussion of the results, optical networks have become an essential underlying technology in our interconnected world. As the amount of data and information grows, so does the demand for a faster, more reliable, and scalable communication infrastructure. And to achieve this, the use of ML algorithms has proven to be one of the best solutions for the functioning and operation of optical networks in recent years due to its multiple advantages. Nonetheless, applying ML techniques also finds deficiencies that must be solved over time to improve network performance. Table 13 describes the main advantages and shortcomings of using ML algorithms in optical networks.

Finally, we want to argue that although ML offers great benefits to improve the performance of optical networks, implementing ML-based methods in real communication networks is still very difficult. Because to successfully deploy ML techniques in optical networks, there are still many gaps to be solved. Below are some of the challenges identified during this project development and which are believed to require more attention in the coming years in future research to fully exploit ML's potential in optical networks.

1) DATA SET AVAILABILITY

While encoding the 96 analyzed papers, only information from one data set was available to address the traffic classification and prediction problem (ID706). This result is a cause of not successfully deploying ML-based methods in the functioning and operation of real optical networks. There is no possibility that data sets will be reused in new research, thus limiting this promising study area.

2) SYNTHETIC DATA SETS

It was identified that most papers use synthetic data sets to evaluate their developed ML method experimentally. Synthetic data is much less expensive but can be much more biased and less accurate than real-world data. The quality of the developed ML model depends on the training data source that is provided to it. When working with synthetic data, although the ML algorithm yields positive results during its testing phase, its results may vary if implemented in a real scenario because reproducing the scenario diversity of a real network in a laboratory environment is unlikely. Additionally, it can be mentioned that we work with synthetic data sets because it is difficult for providers and network operators to reveal an extensive collection of field data to test the practicality of any solution under study.

3) ML METHODOLOGIES

There are two types of methodologies: online and offline. Online ML takes place as data becomes available. In other words, the model can learn from new information in real-time as soon as it arrives. Offline ML is the opposite of online ML because the model cannot learn incrementally from a live data stream. Although online ML has been used, traditional machine learning is done offline [67].

During the paper's coding, it was identified that most of them use offline ML methods to develop their research. An assumption that may be far from reality in optical networks because this type of network constantly evolves due to traffic variations and changes in the optical components' behavior, among others [67]. Therefore, if the ML method is trained under a data set provided by a particular topology, this method may not work correctly if applied to a different or modified topology, limiting the successful deployment of ML-based solutions for real optical networks.

4) DATA DISPLAY

During the paper's coding, it was identified that there is little development of visualization tools that allow users to understand the information produced by the ML algorithms easily. Therefore, solving this challenge is critical for the perfect integration of ML methods in the functioning and operation of optical networks. Although an article that develops some research steps in this direction was identified (ID156), where the K-means algorithm is used to group the BER tracking data of light paths, this challenge requires much more research in the future.

VII. THREATS TO VALIDITY

This section discusses the potential threats to the validity of this SMS and the actions taken to mitigate or minimize them. Although the SMS process was carefully followed to reduce threats to the validity of the results and conclusions drawn in this paper, some threats were faced in the project's different stages that deserve further discussion.

A. CONSTRUCT VALIDITY

When formulating the strategy for paper selection, the study faced two threats concerning its integrity, *i.e.*, whether both (1) the database search strategy and (2) the search string enabled all relevant papers to be retrieved. On the one hand, the Scopus database was used for dealing with the former because it enables us to find the most relevant and complete high-quality refereed research literature for this research. As mentioned, Scopus indexes high-quality peer-reviewed papers from the most relevant digital libraries for communications science, including journal and conference papers from IEEE Xplore, Springer Link, Science Direct, and ACM. On the other hand, for dealing with validity threats regarding the search string (*i.e.*, missing keywords leading to the exclusion of relevant papers), (1) vocabulary that is well-known in the research field was used, and (2) validation of the defined search string was performed, comparing the results obtained with a set of 10 independent test papers provided by a senior optical network researcher. With this, successful results were obtained in the first iteration, as explained in Section IV-A.

Finally, despite the actions taken, we are aware that the study has limitations mainly related to coverage. The number of candidate papers may have been affected because (1) the search string might not be complete and require additional or alternative terms, and (2) only one search strategy was

TABLE 13. Advantages and shortcomings from using ML algorithms in optical networks.

Advantages	Shortcomings
Improved network efficiency: Since machine learning algorithms can adaptively allocate network resources in optical networks [63]. ML provides the ability to optimize the allocation of network resources, such as bandwidth and routing, ensuring efficient use of available resources and improving network efficiency.	**Your best-effort:** ML-based methods generally work on a best-effort basis and don't provide performance guarantees. However, optical networks have high transmission speeds and serve as the fundamental bear networks where a small performance degradation or crash can cause a large amount of traffic disruption (data loss) and consequently lead to decreased network performance [2].
Traffic prediction and optimization: Machine learning models can analyze historic traffic patterns and predict future demands in optical networks [36]. This capability allows network operators to proactively optimize network resources and avoid congestion, leading to improved performance and reduced latency.	**Training overhead:** Training ML models in optical networks might require substantial computational resources and time. Keeping the models up to date with the ever-changing network conditions can be a problem, especially in highly dynamic environments [64].
Failure prediction and prevention: ML models can analyze network data to identify potential failures before they cause service interruptions [65]. Machine learning improves network reliability and minimizes network downtime by predicting and preventing failures.	**Computational complexity:** ML algorithms can be computationally intensive, especially for large-scale optical networks with high data rates [2]. Implementing ML models in real-time scenarios may require powerful hardware and introduce additional latency.
Energy efficiency: By analyzing network data and traffic patterns in optical networks, machine learning can optimize the energy consumption of network devices and infrastructure [2]. This energy-efficient operation reduces operational costs and creates a more sustainable optical network.	**Lack of interpretability:** Many machine learning models, especially deep learning approaches, are known for their "black box" nature, making it difficult to interpret the decision-making process [66]. Understanding the reasons behind certain network decisions is crucial for troubleshooting and network management in optical networks.

used to select the candidate papers. It is recognized that these issues can be improved, for instance, by using thesauri or other search strategies such as snowballing, etc. However, considering the significant number of candidate papers (841), the results and findings are deemed valuable to providing researchers and practitioners with an overview of the state of the art of ML techniques used to solve challenges or problems related to the functioning and operation of optical networks.

B. INTERNAL VALIDITY

Individual researcher's bias in (1) deciding whether to include or exclude a candidate paper, (2) classifying it according to the built scheme, and (3) analyzing the results is an internal threat inherent in the study that could lead to biased or erroneous conclusions [53]. Two main steps were taken to minimize this threat: criteria were standardized across the research team to ensure similar understanding, 20% of papers were reviewed by three researchers, and the remaining 80% by two researchers.

Regarding applying the inclusion and exclusion criteria during the selection procedure, the research team (one senior optical network researcher and two optical network researchers) carried out an iterative pilot to validate the criteria and normalize their understanding. It only passed to the main screening after obtaining a high rate of Krippendorff's alpha coefficient (0.94). In addition, as explained in Section IV-A, in the selections based on title, abstract, and full-text, 20% of the papers were reviewed by at least three researchers, while two researchers examined the remaining 80%. The full-text screening consisted of a mandatory and adaptive approach (*i.e.*, title, abstract, introduction, and conclusions were compulsory, but other types of sections were also read, if necessary), thus striving to ensure adequate depth reading and preventing relevant papers from being mistakenly omitted and, inversely, some irrelevant ones being incorrectly included.

As for the classification procedure, a great effort was made to build a collectively exhaustive classification scheme to classify the 96 papers consistently. Therefore, this scheme was built using existing recognized classifications, refining them, discussing them in detail, and agreeing when divergences appeared among the research team.

Finally, to analyze the results and draw conclusions, we rely on the collective results of the research team rather than the individual researcher's interpretations. Therefore, the graphs were generated directly from the results of the paper classification, and the findings and conclusions were drawn from direct observations and trends. In this sense, the conclusions finally obtained can be correctly validated by other researchers based on all the processes developed against the threats to validity.

C. EXTERNAL VALIDITY

A lack of consensus, when researchers refer to the domain addressed in this study (*e.g.*, optical networks vs. optical communications) might lead to an erroneous generalization in our findings. The results and conclusions of this SMS are only valid for techniques that fall within the scope defined in Section IV-A, *i.e.*, ML techniques used to solve problems (challenges) related to the functioning and operation of optical networks. Much effort has gone into systematically configuring the SMS protocol—through a detailed definition

TABLE 14. List of studied papers.

Paper ID	References
ID7	IEE Alsarhan, A., Agarwal, A. (2009). Spectrum sharing in multi-service cognitive network using reinforcement learning. Proceedings - 2009 1st UK-India International Workshop on Cognitive Wireless Systems, UKIWCWS 2009. https://doi.org/10.1109/UKIWCWS.2009.5749427 [68].
ID16	Proactive restoration of optical links based on the classification of events | IEEE Conference Publication | IEEE Xplore. (n.d.). Retrieved January 5, 2023, from https://ieeexplore.ieee.org/document/5753394 [69].
ID29	Obaidat, M. S., Holzinger, A., Filipe, J. (Eds.). (2015). E-Business and Telecommunications (Vol. 554). https://doi.org/10.1007/978-3-319-25915-4 [70]
ID36	Informationstechnische Gesellschaft im VDE, Verband der Elektrotechnik, E., Institute of Electrical and Electronics Engineers. (n.d.). ECOC 2016; 42nd European Conference on Optical Communication: 18-22 Sept. 2016 [71].
ID43	Viljoen, N., Rastegarfar, H., Yang, M., Wissinger, J., Glick, M. (2016). Machine learning based adaptive flow classification for optically interconnected data centers. International Conference on Transparent Optical Networks, 2016-August. https://doi.org/10.1109/ICTON.2016.7550294 [45].
ID59	Thrane, J., Wass, J., Piels, M., Diniz, J. C. M., Jones, R., Zibar, D. (2017). Machine Learning Techniques for Optical Performance Monitoring from Directly Detected PDM-QAM Signals. Journal of Lightwave Technology, 35(4), 868–875. https://doi.org/10.1109/JLT.2016.2590989 [49].
ID66	Panayiotou, T., Chatzis, S. P., Ellinas, G. (2017). A probabilistic approach for failure localization. 2017 21st International Conference on Optical Network Design and Modeling, ONDM 2017 - Conference Proceedings. https://doi.org/10.23919/ONDM.2017.7958555 [72]
ID67	Gosselin, S., Courant, J. L., Tembo, S. R., Vaton, S. (2017). Application of probabilistic modeling and machine learning to the diagnosis of FTTH GPON networks. 2017 21st International Conference on Optical Network Design and Modeling, ONDM 2017 - Conference Proceedings. https://doi.org/10.23919/ONDM.2017.7958529 [51].
ID69	Wang, Z., Zhang, M., Wang, D., Song, C., Liu, M., Li, J., Lou, L., Liu, Z. (2017). Failure prediction using machine learning and time series in optical network. Optics Express, 25(16), 18553. https://doi.org/10.1364/oe.25.018553 [73].
ID72	Morales, F., Ruiz, M., Velasco, L. (2017). Data analytics-based origin-destination core traffic modelling. International Conference on Transparent Optical Networks. https://doi.org/10.1109/ICTON.2017.8024980 [46].
ID79	Samadi, P., Amar, D., Lepers, C., Lourdiane, M., Bergman, K. (2017). Quality of Transmission Prediction with Machine Learning for Dynamic Operation of Optical WDM Networks. European Conference on Optical Communication, ECOC, 2017-September, 1–3. https://doi.org/10.1109/ECOC.2017.8346216 [74].
ID92	Lu, H., Cui, S., Ke, C., Liu, D. (2017). Automatic reference optical spectrum retrieval method for ultra-high resolution optical spectrum distortion analysis utilizing integrated machine learning techniques References and links. http://aragonphotonics.com/bosa-100-400 [75].
ID102	Machine-Learning-Based Soft-Failure Detection and Identification in Optical Networks | IEEE Conference Publication | IEEE Xplore. (n.d.). Retrieved January 5, 2023, from https://ieeexplore.ieee.org/document/8385774 [76]
ID106	Seve, E., Pesic, J., Delezoide, C., Bigo, S., Pointurier, Y. (2018). Learning process for reducing uncertainties on network parameters and design margins. Journal of Optical Communications and Networking, 10(2), A298–A306. https://doi.org/10.1364/JOCN.10.00A298 [77].
ID107	Rottondi, C., Barletta, L., Giusti, A., Tornatore, M. (2018). Machine-learning method for quality of transmission prediction of unestablished lightpaths. Journal of Optical Communications and Networking, 10(2), A286–A297. https://doi.org/10.1364/JOCN.10.00A286 [78].
ID109	Panayiotou, T., Chatzis, S. P., Ellinas, G. (2018). Leveraging statistical machine learning to address failure localization in optical networks. Journal of Optical Communications and Networking, 10(3), 162–173. https://doi.org/10.1364/JOCN.10.000162 [79].
ID111	Wang, L., Wang, X., Tornatore, M., Kim, K. J., Kim, S. M., Kim, D. U., Han, K. E., Mukherjee, B. (2018). Scheduling with machine-learning-based flow detection for packet-switched optical data center networks. Journal of Optical Communications and Networking, 10(4), 365–375. https://doi.org/10.1364/JOCN.10.000365 [80].

TABLE 14. ***(Continued.)*** **List of studied papers.**

Paper ID	References
ID114	Rafique, D., Szyrkowiec, T., Grießer, H., Autenrieth, A., Elbers, J. P. (2018). Cognitive Assurance Architecture for Optical Network Fault Management. Journal of Lightwave Technology, 36(7), 1443–1450. https://doi.org/10.1109/JLT.2017.2781540 [81].
ID125	S. Shahkarami, F. Musumeci, F. Cugini, and M. Tornatore, "Machine-Learning-Based Soft-Failure Detection and Identification in Optical Networks," Optical Fiber Communication Conference (2018), paper M3A.5, vol. Part F84-OFC 2018, p. M3A.5, Mar. 2018, doi: 10.1364/OFC.2018.M3A.5 [82].
ID128	B. Shariati, A. P. Vela, M. Ruiz, and L. Velasco, "Monitoring and data analytics: Analyzing the optical spectrum for soft-failure detection and identification," 22nd Conference on Optical Network Design and Modelling, ONDM 2018 - Proceedings, pp. 260–265, Jun. 2018, doi: 10.23919/ONDM.2018.8396142 [83].
ID129	Frigui, N. E., Lemlouma, T., Gosselin, S., Radier, B., le Meur, R., Bonnin, J. M. (2018). Optimization of the upstream bandwidth allocation in passive optical networks using internet users' behavior forecast. 22nd Conference on Optical Network Design and Modelling, ONDM 2018 - Proceedings, 59–64. https://doi.org/10.23919/ONDM.2018.8396107 [84].
ID136	Ruan, L., Mondal, S., Wong, E. (2018). Machine learning based bandwidth prediction in tactile heterogeneous access networks. INFOCOM 2018 - IEEE Conference on Computer Communications Workshops, 1–2. https://doi.org/10.1109/INFCOMW.2018.8406834 [85].
ID139	Chen, X., Proietti, R., Lu, H., Castro, A., Yoo, S. J. B. (2018). Knowledge-based autonomous service provisioning in multi-domain elastic optical networks. IEEE Communications Magazine, 56(8), 152–158. https://doi.org/10.1109/MCOM.2018.1701191 [86].
ID143	Panayiotou, T., Ellinas, G. (2018). Data-Driven Bandwidth Allocation in EONs. Proceedings of the 2018 Photonics in Switching and Computing, PSC 2018. https://doi.org/10.1109/PS.2018.8751369 [87].
ID151	Troia, S., Alvizu, R., Zhou, Y., Maier, G., Pattavina, A. (2018). Deep Learning-Based Traffic Prediction for Network Optimization. International Conference on Transparent Optical Networks, 2018-July. https://doi.org/10.1109/ICTON.2018.8473978 [88].
ID156	Vela, A. P., Ruiz, M., Velasco, L. (2018). Examples of Machine Learning Algorithms for Optical Network Control and Management. International Conference on Transparent Optical Networks, 2018-July. https://doi.org/10.1109/ICTON.2018.8473900 [89].
ID158	Morais, R. M., Pedro, J. (2018). Evaluating Machine Learning Models for QoT Estimation. International Conference on Transparent Optical Networks, 2018-July. https://doi.org/10.1109/ICTON.2018.8473941 [50].
ID163	Mata, J., Miguel, I. de, Duran, R. J., Aguado, J. C., Merayo, N., Ruiz, L., Fernandez, P., Lorenzo, R. M., Abril, E. J., Tomkos, I. (2018). Supervised Machine Learning Techniques for Quality of Transmission Assessment in Optical Networks. International Conference on Transparent Optical Networks, 2018-July. https://doi.org/10.1109/ICTON.2018.8473819 [90].
ID166	Morais, R. M., Pedro, J. (2018). Machine learning models for estimating quality of transmission in DWDM networks. Journal of Optical Communications and Networking, 10(10), D84–D99. https://doi.org/10.1364/JOCN.10.000D84 [91].
ID172	Zhao, Y., Yan, B., Liu, D., He, Y., Wang, D., Zhang, J. (2018). SOON: self-optimizing optical networks with machine learning. Optics Express, 26(22), 28713. https://doi.org/10.1364/oe.26.028713 [63].
ID174	Aibin, M. (2018). Traffic prediction based on machine learning for elastic optical networks. Optical Switching and Networking, 30, 33–39. https://doi.org/10.1016/j.osn.2018.06.001 [92].
ID189	Sartzetakis, I., Christodoulopoulos, K., Varvarigos, E. (n.d.). Formulating QoT Estimation with Machine Learning. http://www.ciena.com/products/wavelogic/wavelogic-Ai/ [93].
ID200	Allogba, S., Tremblay, C. (2018). K-Nearest Neighbors Classifier for Field Bit Error Rate Data. Asia Communications and Photonics Conference, ACP, 2018-October. https://doi.org/10.1109/ACP.2018.8596133 [94].
ID207	Lippiatt, D., Varughese, S., Richter, T., Tibuleac, S., Ralph, S. E. (2019). Machine-learning-based optical performance monitoring using carrier phase recovery. IET Conference Publications, 2019(CP765). https://doi.org/10.1049/CP.2019.0955 [95].
ID209	Tremblay, C., Allogba, S., Aladin, S. (2019). Quality of transmission estimation and performance prediction of lightpaths using machine learning. IET Conference Publications, 2019(CP765). https://doi.org/10.1049/CP.2019.0757 [96].

TABLE 14. *(Continued.)* List of studied papers.

Paper ID	References
ID221	Panayiotou, T., Savva, G., Behnam, S., Tomkos, I., Ellinas, G. (2019). Machine Learning for QoT Estimation of Unseen Optical Network States; Machine Learning for QoT Estimation of Unseen Optical Network States. In *2019 Optical Fiber Communications Conference and Exhibition (OFC)* [97].
ID228	Rahouma, K. H., Ali, A. (2019). Applying Machine Learning Technology to Optimize the Operational Cost of the Egyptian Optical Network. *Procedia Computer Science*, *163*, 502–517. https://doi.org/10.1016/j.procs.2019.12.133 [98].
ID242	Hatem, J. A., Dhaini, A. R., Elbassuoni, S. (2019). Deep learning-based dynamic bandwidth allocation for future optical access networks. *IEEE Access*, *7*, 97307–97318. https://doi.org/10.1109/ACCESS.2019.2929480 [99].
ID255	Tanimura, T., Hoshida, T., Kato, T., Watanabe, S., Morikawa, H. (2019). Convolutional neural network-based optical performance monitoring for optical transport networks. *Journal of Optical Communications and Networking*, *11*(1), A52–A59. https://doi.org/10.1364/JOCN.11.000A52 [100].
ID256	Proietti, R., Chen, X., Zhang, K., Liu, G., Shamsabardeh, M., Castro, A., Velasco, L., Zhu, Z., ben Yoo, S. J. (2019). Experimental Demonstration of Machine-Learning-Aided QoT Estimation in Multi-Domain Elastic Optical Networks with Alien Wavelengths. Journal of Optical Communications and Networking, Vol. 11, Issue 1, Pp. A1-A10, 11(1), A1–A10. https://doi.org/10.1364/JOCN.11.0000A1 [101].
ID262	Yan, B., Zhao, Y., Li, Y., Yu, X., Zhang, J., Wang, Y., Yan, L., Rahman, S. (2019). Actor-Critic-Based Resource Allocation for Multi-Modal Optical Networks. 2018 IEEE Globecom Workshops, GC Wkshps 2018 - Proceedings. https://doi.org/10.1109/GLOCOMW.2018.8644190 [102]
ID267	Salani, M., Rottondi, C., Tornatore, M. (2019). Routing and Spectrum Assignment Integrating Machine-Learning-Based QoT Estimation in Elastic Optical Networks. Proceedings - IEEE INFOCOM, 2019-April, 1738–1746. https://doi.org/10.1109/INFOCOM.2019.8737413 [47].
ID275	Liu, B., Zhang, L., Wang, F., Liu, M., Mao, Y., Zhao, L., Sun, T., Xin, X. (2019). Adaptive dynamic wavelength and bandwidth allocation algorithm based on error-back-propagation neural network prediction. Optics Communications, 437, 276–284. https://doi.org/10.1016/j.optcom.2018.12.064 [103].
ID281	Panayiotou, T., Savva, G., Behnam, S., Tomkos, I., Ellinas, G. (n.d.). Machine Learning for QoT Estimation of Unseen Optical Network States [104].
ID283	Ruan, L., Dias, I., Wong, E. (2019). Machine intelligence in supervising bandwidth allocation for low-latency communications. IEEE International Conference on High Performance Switching and Routing, HPSR, 2019-May. https://doi.org/10.1109/HPSR.2019.8808127 [105].
ID291	Panayiotou, T., Manousakis, K., Chatzis, S. P., Ellinas, G. (2019). A Data-Driven Bandwidth Allocation Framework With QoS Considerations for EONs. Journal of Lightwave Technology, Vol. 37, Issue 9, Pp. 1853-1864, 37(9), 1853–1864. https://opg.optica.org/abstract.cfm?uri=jlt-37-9-1853 [106].
ID306	Szostak, D., Walkowiak, K. (2019). Machine learning methods for traffic prediction in dynamic optical networks with service chains. International Conference on Transparent Optical Networks, 2019-July. https://doi.org/10.1109/ICTON.2019.8840301 [107].
ID318	Zhang, M., Wang, D. (2019). Machine Learning Based Alarm Analysis and Failure Forecast in Optical Networks. OECC/PSC 2019 - 24th OptoElectronics and Communications Conference/International Conference Photonics in Switching and Computing 2019. https://doi.org/10.23919/PS.2019.8817991 [108].
ID331	Musumeci, F., Rottondi, C., Corani, G., Shahkarami, S., Cugini, F., Tornatore, M. (2019). A Tutorial on Machine Learning for Failure Management in Optical Networks. Journal of Lightwave Technology, 37(16), 4125–4139. https://doi.org/10.1109/JLT.2019.2922586 [65].
ID339	Martín, I., Troia, S., Hernández, J. A., Rodríguez, A., Musumeci, F., Maier, G., Alvizu, R., de Dios, Ó. G. (2019). Machine learning-based routing and wavelength assignment in software-defined optical networks. IEEE Transactions on Network and Service Management, 16(3). https://doi.org/10.1109/TNSM.2019.2927867 [109].
ID352	Butt, R. A., Faheem, M., Arfeen, A., Ashraf, M. W., Jawed, M. (2019). Machine learning based dynamic load balancing DWBA scheme for TWDM PON. Optical Fiber Technology, 52. https://doi.org/10.1016/j.yofte.2019.101964 [110].
ID361	Panayiotou, T., Savvas, G., Tomkos, I., Ellinas, G. (2019). Centralized and distributed machine learning-based QoT estimation for sliceable optical networks. 2019 IEEE Global Communications Conference, GLOBECOM 2019 - Proceedings. https://doi.org/10.1109/GLOBECOM38437.2019.9013962 [111].

TABLE 14. ***(Continued.)*** **List of studied papers.**

Paper ID	References
ID396	Guo, H., Wang, C., Tang, Y., Zhu, Y., Wu, J., Zuo, Y. (2020). Machine Learning Assisted Optical Network Resource Scheduling in Data Center Networks. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 11616 LNCS, 204–210. https://doi.org/10.1007/978-3-030-38085-4_18/COVER [48].
ID420	Xing, X., Zhao, Y., Li, Y., Zhang, J. (2020, March 1). Knowledge-Based Collective Self-learning for Alarm Prediction in Real Multi-Domain Autonomous Optical Networks. 2020 16th International Conference on the Design of Reliable Communication Networks, DRCN 2020. https://doi.org/10.1109/DRCN48652.2020.1570611066 [112].
ID452	Shu, L., Yu, Z., Wan, Z., Zhang, J., Hu, S., Xu, K. (2020). Dual-Stage Soft Failure Detection and Identification for Low-Margin Elastic Optical Network by Exploiting Digital Spectrum Information. Journal of Lightwave Technology, 38(9), 2669–2679. https://doi.org/10.1109/JLT.2019.2947562 [113].
ID455	Ruan, L., Dias, M. P. I., Wong, E. (2020). Towards self-adaptive bandwidth allocation for low-latency communications with reinforcement learning. Optical Switching and Networking, 37. https://doi.org/10.1016/j.osn.2020.100567 [114].
ID457	Aladin, S., Tran, A. V. S., Allogba, S., Tremblay, C. (2020). Quality of Transmission Estimation and Short-Term Performance Forecast of Lightpaths. Journal of Lightwave Technology, 38(10), 2806–2813. https://doi.org/10.1109/JLT.2020.2975179 [115].
ID461	Lun, H., Fu, M., Liu, X., Wu, Y., Yi, L., Hu, W., Zhuge, Q. (2020). Soft Failure Identification for Long-haul Optical Communication Systems Based on One-dimensional Convolutional Neural Network. Journal of Lightwave Technology, 38(11), 2992–2999. https://doi.org/10.1109/JLT.2020.2989153 [116].
ID464	Wang, Y., Cheng, B., Hang, C., Yu, J., Liu, S., Hu, Y., Shen, J. (2020). Routing Algorithm for Elastic Optical Network Based on Machine Learning assisted Traffic Prediction. Journal of Physics: Conference Series, 1550(3). https://doi.org/10.1088/1742-6596/1550/3/032123 [117].
ID470	Mitropoulou, K., Sartzetakis, I., Varvarigos, E. (2020). Soft failure detection, categorization and localization. International Conference on Transparent Optical Networks, 2020-July. https://doi.org/10.1109/ICTON51198.2020.9203373 [118].
ID471	Szostak, D., Walkowiak, K., Wlodarczyk, A. (2020). Short-term traffic forecasting in optical network using linear discriminant analysis machine learning classifier. International Conference on Transparent Optical Networks, 2020-July. https://doi.org/10.1109/ICTON51198.2020.9203040 [119].
ID473	Khan, I., Bilal, M., Curri, V. (2020). Advanced formulation of QoT-Estimation for un-established lightpaths using cross-train machine learning methods. International Conference on Transparent Optical Networks, 2020-July. https://doi.org/10.1109/ICTON51198.2020.9203334 [120].
ID478	Khan, I., Bilal, M., Siddiqui, M., Khan, M., Ahmad, A., Shahzad, M., Curri, V. (2020). QoT estimation for light-path provisioning in un-seen optical networks using machine learning. International Conference on Transparent Optical Networks, 2020-July. https://doi.org/10.1109/ICTON51198.2020.9203364 [121].
ID491	Pandya, R. J. (2020). Machine learning-oriented resource allocation in C + L + S bands extended SDM-EONs. IET Communications, 14(12), 1957–1967. https://doi.org/10.1049/iet-com.2019.1191 [122].
ID498	Szostak, D., Walkowiak, K. (2020). Application of Machine Learning Algorithms for Traffic Forecasting in Dynamic Optical Networks with Service Function Chains. Foundations of Computing and Decision Sciences, 45(3), 217–232. https://doi.org/10.2478/fcds-2020-0012 [123].
ID519	Khan, I., Bilal, M., Curri, V. (2020). Assessment of cross-train machine learning techniques for QoT-estimation in agnostic optical networks. OSA Continuum, 3(10), 2690. https://doi.org/10.1364/osac.399511 [124].
ID529	Zhi, C., Ji, W., Yin, R., Feng, J., Xu, H., Li, Z., Wang, Y. (2020). The flexible resource management in optical data center networks based on machine learning and SDON. Optical Switching and Networking, 39. https://doi.org/10.1016/j.osn.2020.100594 [125].
ID533	Valkanis, A., Beletsioti, G. A., Nicopolitidis, P., Papadimitriou, G., Varvarigos, E. (2020, November 3). Reinforcement Learning in Traffic Prediction of Core Optical Networks using Learning Automata. Proceedings of the 2020 IEEE International Conference on Communications, Computing, Cybersecurity, and Informatics, CCCI 2020. https://doi.org/10.1109/CCCI49893.2020.9256655 [126].

of the research questions, inclusion and exclusion criteria, and classification scheme— and applying it to ensure that general conclusions are valid irrespective of the lack of consensus highlighted.

TABLE 14. *(Continued.)* List of studied papers.

Paper ID	References
ID558	Andreoletti, D.;, Rottondi, C. E., Margherita, Bianco, A., Giordano, Silvia.-E. (2021). A Machine Learning Framework for Scalable Routing and Wavelength Assignment in Large Optical Networks ǀ IEEE Conference Publication ǀ IEEE Xplore. (n.d.). Retrieved January 5, 2023, from https://ieeexplore.ieee.org/document/9489780 [127]
ID574	Sun, K., Yu, Z., Shu, L., Wan, Z., Huang, H., Xu, K. (2021). Experimental Demonstration of Soft Failure Identification Based on Digital Residual Spectrum and Machine Learning. 2021 6th International Conference on UK-China Emerging Technologies, UCET 2021, 81–84. https://doi.org/10.1109/UCET54125.2021.9674951 [128].
ID581	Yao, C. C., Zheng, J. Y., Jou, J. J., Yang, C. L. (2021). Performance Monitoring of High-Speed NRZ Signals Using Machine Learning Techniques. ISPACS 2021 - International Symposium on Intelligent Signal Processing and Communication Systems: 5G Dream to Reality, Proceeding. https://doi.org/10.1109/ISPACS51563.2021.9650979 [129].
ID595	Gupta, G., Rai, A., Jha, V. (2021). Predicting the Bandwidth Requests in XG-PON System using Ensemble Learning. International Conference on ICT Convergence, 2021-October, 936–941. https://doi.org/10.1109/ICTC52510.2021.9620935 [130].
ID608	Cichosz, P., Kozdrowski, S., Sujecki, S. (2021). Application of ML algorithms for prediction of the QoT in optical networks with imbalanced and incomplete data. 2021 29th International Conference on Software, Telecommunications and Computer Networks, SoftCOM 2021.https://doi.org/10.23919/SOFTCOM52868.2021.9559095 [131].
ID638	Kozdrowski, S., Cichosz, P., Paziewski, P., Sujecki, S. (2021). Machine learning algorithms for prediction of the quality of transmission in optical networks. Entropy, 23(1), 1–18. https://doi.org/10.3390/e23010007 [132].
ID648	Das, D., Imteyaz, M. F., Bapat, J., Das, D. (2021). A Non-intrusive Failure Prediction Mechanism for Deployed Optical Networks. 2021 International Conference on COMmunication Systems and NETworkS, COMSNETS 2021, 24–28. https://doi.org/10.1109/COMSNETS51098.2021.9352868 [133].
ID650	Saif, W. S., Ragheb, A. M., Alshawi, T. A., Alshebeili, S. A. (2021). Optical Performance Monitoring in Mode Division Multiplexed Optical Networks. Journal of Lightwave Technology, 39(2), 491–504. https://doi.org/10.1109/JLT.2020.3027725 [134].
ID670	Ibrahimi, M., Abdollahi, H., Rottondi, C., Giusti, A., Ferrari, A., Curri, V., Tornatore, M. (2021). Machine learning regression for QoT estimation of unestablished lightpaths. Journal of Optical Communications and Networking, 13(4), B92–B101. https://doi.org/10.1364/JOCN.410694 [135].
ID677	Das, D., Imteyaz, M. F., Bapat, J., Das, D. (2021). A Data Augmented Bayesian Network for Node Failure Prediction in Optical Networks. 3rd International Conference on Artificial Intelligence in Information and Communication, ICAIIC 2021, 83–88. https://doi.org/10.1109/ICAIIC51459.2021.9415186 [52].
ID695	Esmail, M. A. (2021). Optical Wireless Performance Monitoring Using Asynchronous Amplitude Histograms. IEEE Photonics Journal, 13(3). https://doi.org/10.1109/JPHOT.2021.3080593 [136].
ID697	Paudyal, P., Shen, S., Yan, S., Simeonidou, D. (2021). Toward Deployments of ML Applications in Optical Networks. IEEE Photonics Technology Letters, 33(11), 537–540. https://doi.org/10.1109/LPT.2021.3074586 [137].
ID702	Aibin, M., Chung, N., Gordon, T., Lyford, L., Vinchoff, C. (2021, June 28). On Short-and Long-Term Traffic Prediction in Optical Networks Using Machine Learning. 25th International Conference on Optical Network Design and Modelling, ONDM 2021. https://doi.org/10.23919/ONDM51796.2021.9492437 [138].
ID706	Szostak, D., Włodarczyk, A., Walkowiak, K. (2021). Machine learning classification and regression approaches for optical network traffic prediction. *Electronics (Switzerland)*, *10*(13). https://doi.org/10.3390/electronics10131578 [139].
ID716	Zhang, C., Wang, D., Wang, L., Guan, L., Yang, H., Zhang, Z., Chen, X., Zhang, M. (2021). Cause-aware failure detection using an interpretable XGBoost for optical networks. *Optics Express*, *29*(20), 31974. https://doi.org/10.1364/oe.436293 [140].
ID720	Usmani, F., Khan, I., Masood, M. U., Ahmad, A., Shahzad, M., Curri, V. (2021). Convolutional neural network for quality of transmission prediction of unestablished lightpaths. *Microwave and Optical Technology Letters*, *63*(10), 2461–2469. https://doi.org/10.1002/mop.32996 [141].

VIII. CONCLUSION

This project coded 96 papers out of the 841 publications from the Scopus database to find relevant information to meet the objectives set out in work and answer the four research questions (RQs) defined during this study. After the research completion, it is concluded that the main result of this

TABLE 14. ***(Continued.)*** **List of studied papers.**

Paper ID	References
ID726	Lu, J., Fan, Q., Zhou, G., Lu, L., Yu, C., Lau, A. P. T., Lu, C. (2021). Automated training dataset collection system design for machine learning application in optical networks: An example of quality of transmission estimation. *Journal of Optical Communications and Networking*, *13*(11), 289–300. https://doi.org/10.1364/JOCN.431780 [142].
ID733	Usmani, F., Khan, I., Siddiqui, M., Khan, M., Bilal, M., Masood, M. U., Ahmad, A., Shahzad, M., Curri, V. (2021). Cross-feature trained machine learning models for QoT-estimation in optical networks. *Https://Doi.Org/10.1117/1.OE.60.12.125106*, *60*(12), 125106. https://doi.org/10.1117/1.OE.60.12.125106 [143].
ID736	Lonardi, M., Pesic, J., Zami, T., Seve, E., Rossi, N. (2021). Machine learning for quality of transmission: A picture of the benefits fairness when planning WDM networks. *Journal of Optical Communications and Networking*, *13*(12), 331–346. https://doi.org/10.1364/JOCN.433412 [144].
ID740	Fu, Y., Chen, J., Wu, W., Huang, Y., Hong, J., Chen, L., Li, Z. (2021). A QoT prediction technique based on machine learning and NLSE for QoS and new lightpaths in optical communication networks. *Frontiers of Optoelectronics*, *14*(4), 513–521. https://doi.org/10.1007/s12200-020-1079-y [145].
ID765	Ayoub, O., Bianco, A., Andreoletti, D., Troia, S., Giordano, S., Rottondi, C. (2022). On the Application of Explainable Artificial Intelligence to Lightpath QoT Estimation; | *IEEE Conference Publication* | *IEEE Xplore*. (n.d.). Retrieved January 5, 2023, from https://ieeexplore.ieee.org/document/9748572 [146].
ID778	Silva, M. F., Pacini, A., Sgambelluri, A., Valcarenghi, L. (2022). Learning Long-and Short-Term Temporal Patterns for ML-Driven Fault Management in Optical Communication Networks. *IEEE Transactions on Network and Service Management*, *19*(3), 2195–2206. https://doi.org/10.1109/TNSM.2022.3146869 [147].
ID786	Menaghapriya, B. R., Sangeetha, R. G. (2022). Failure Detection Using Artificial Neural Networks. *Lecture Notes in Electrical Engineering*, *792*, 655–661. https://doi.org/10.1007/978-981-16-4625-6_65 [148].
ID787	Khan, I., Bilal, M., Curri, V. (2022). Cross-Train: Machine Learning Assisted QoT-Estimation in Un-used Optical Networks. *Lecture Notes in Electrical Engineering*, *797 LNEE*, 78–87. https://doi.org/10.1007/978-981-16-5692-7_9/COVER [149].
ID814	Allogba, S., Aladin, S., Tremblay, C. (2022). Machine-Learning-Based Lightpath QoT Estimation and Forecasting. *Journal of Lightwave Technology*, *40*(10), 3115–3127. https://doi.org/10.1109/JLT.2022.3160379 [150].
ID816	Usman, A., Zulkifli, N., Salim, M. R., Khairi, K. (2022). Fault monitoring in passive optical network through the integration of machine learning and fiber sensors. *International Journal of Communication Systems*, *35*(9). https://doi.org/10.1002/dac.5134 [151].
ID820	Guo, N., Li, L., Mukherjee, B., Shen, G. (2022). Protection against failure of machine-learning-based QoT prediction. *Journal of Optical Communications and Networking, Vol. 14, Issue 7, Pp. 572-585*, *14*(7), 572–585. https://doi.org/10.1364/JOCN.457313 [152].
ID827	Cheng, L., Qiu, Y. (2022). Routing and spectrum assignment employing long short-term memory technique for elastic optical networks. *Optical Switching and Networking*, *45*. https://doi.org/10.1016/j.osn.2022.100684 [153].

systematic literature mapping is identifying and classifying existing ML techniques that address challenges related to the functioning and operation of optical networks. And the same time, the level of maturity of the different techniques is detailed, opportunities and gaps are identified, and future lines of research are suggested.

It is identified that most of the papers examined (95.8%) use supervised learning to address issues related to resource management, network monitoring, fault management, traffic classification, and prediction of an optical network. These results are because the solutions generated by the supervised methods are more accurate and reliable than those produced by the unsupervised and semi-supervised techniques. In addition, the training process of the supervised algorithms is less complex than when working with reinforcement learning algorithms. Because the latter requires much more computations, which can lead to an overload of states in the training process and a decrease in the accuracy of the desired results.

It is determined that the challenge to which the most significant research efforts have been devoted is network monitoring because it covers sub-problems related to OPM, QoT, SNR, OSNR, QoS, QoE, etc., parameters that are essential for a reliable and flexible network operation as well as to improve its efficiency. So, in recent years, supervised learning algorithms, especially neural networks (artificial, convolutional, and deep), have been successfully applied to address cost-effective multi-deficiency monitoring in optical networks.

Although the use of ML algorithms in the functioning and operation of optical networks provides unprecedented opportunities to this communication area, it can be identified that there are still gaps that prevent the possibility of applying these developed methods in real communication networks. The data set availability for future work, the use of real data instead of synthetic data, online machine learning in algorithm training, and improvement of data visualization for the end user are some identified challenges that need to be explored in the future. Thus, it is possible to improve the level of maturity of the techniques used in the different investigations related to this field. Since most of the papers tend to be validation research, in other words, the proposed models are only subjected to experimental tests in controlled environments and more not tested in real optical networks.

APPENDIX

See Table 14.

REFERENCES

[1] F. Musumeci, C. Rottondi, A. Nag, I. Macaluso, D. Zibar, M. Ruffini, and M. Tornatore, "An overview on application of machine learning techniques in optical networks," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 2, pp. 1383–1408, 2nd Quart., 2019.

[2] R. Gu, Z. Yang, and Y. Ji, "Machine learning for intelligent optical networks: A comprehensive survey," *J. Netw. Comput. Appl.*, vol. 157, May 2020, Art. no. 102576.

[3] Y. Zhang, J. Xin, X. Li, and S. Huang, "Overview on routing and resource allocation based machine learning in optical networks," *Opt. Fiber Technol.*, vol. 60, Dec. 2020, Art. no. 102355.

[4] R. Boutaba, M. A. Salahuddin, N. Limam, S. Ayoubi, N. Shahriar, F. Estrada-Solano, and O. M. Caicedo, "A comprehensive survey on machine learning for networking: Evolution, applications and research opportunities," *J. Internet Services Appl.*, vol. 9, no. 1, pp.1–99, Dec. 2018.

[5] J. Gordon, A. Battou, M. Majurski, D. Kilper, U. Celine, D. Zibar, M. Tornatore, J. Pedro, J. Simsarian, and J. Westdorp, "Summary: Workshop on machine learning for optical communication systems," Nat. Inst. Standards Technol., USA, Tech. Rep. 2100-04, Mar. 2020. [Online]. Available: https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.2100-04.pdf

[6] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, May 2015. [Online]. Available: https://www.nature.com/articles/nature14539

[7] D. Wang, M. Zhang, Z. Li, J. Li, C. Song, J. Li, and M. Wang, "Convolutional neural network-based deep learning for intelligent OSNR estimation on eye diagrams," in *Proc. Eur. Conf. Opt. Commun.*, 2017, pp. 1–3.

[8] R. Masoudi and A. Ghaffari, "Software defined networks: A survey," *J. Netw. Comput. Appl.*, vol. 67, pp. 1–25, May 2016.

[9] Y. Ji, H. Wang, J. Cui, M. Yu, Z. Yang, and L. Bai, "All-optical signal processing technologies in flexible optical networks," *Photonic Netw. Commun.*, vol. 38, no. 1, pp. 14–36, Aug. 2019, doi: 10.1007/s11107-019-00838-y.

[10] *Top 5 Machine Learning Algorithms for Bus. Applications*. Accessed: Mar. 10, 2022. [Online]. Available: https://mobidev.biz/blog/5-essential-machine-learning-techniques

[11] *What is Supervised Learning? | IBM*. Accessed: Mar. 10, 2022. [Online]. Available: https://www.ibm.com/cloud/learn/supervised-learning

[12] *Difference Between Classification and Regression in Machine Learning*. Accessed: Mar. 10, 2022. [Online]. Available: https://machinelearningmastery.com/classification-versus-regression-in-machine-learning

[13] *Regresión Lineal—TeorÍA—Aprende IA*. Accessed: Mar. 10, 2022. [Online]. Available: https://aprendeia.com/algoritmo-regresion-lineal-simple-machine-learning

[14] *Acerca De La Regresión Lineal—México | IBM*. Accessed: Mar. 10, 2022. [Online]. Available: https://www.ibm.com/mx-es/analytics/learn/linear-regression

[15] *Understanding Polynomial Regression!!! | by Abhigyan | Analytics Vidhya | Medium*," Accessed: Mar. 10, 2022. [Online]. Available: https://medium.com/analytics-vidhya/understanding-polynomial-regression-5ac25b970e18

[16] *Regresión Polinomial—Teoría—Aprende IA*. Accessed: Mar. 10, 2022. [Online]. Available: https://aprendeia.com/algoritmo-regresion-polinomial-machine-learning

[17] *Regresión Logística—Documentación de IBM*. Accessed: Mar. 10, 2022. [Online]. Available: https://www.ibm.com/docs/es/spss-statistics/saas?topic=regression-logistic

[18] *Decision Trees for Classification: A Machine Learning Algorithm*. Accessed: Mar. 10, 2022. [Online]. Available: https://www.xoriant.com/blog/product-engineering/decision-trees-machine-learning-algorithm.html

[19] *What is a Neural Network?—Artificial Neural Networks Explained—AWS*. Accessed: Dec. 21, 2022. [Online]. Available: https://aws.amazon.com/es/what-is/neural-network

[20] R. Mosquera, O. D. Castrillón, L. Parra, R. Mosquera, O. D. Castrillón, and L. Parra, "Máquinas de soporte vectorial, clasificador Naïve Bayes Y algoritmos genéticos para la predicción de riesgos psicosociales en docentes de colegios públicos colombianos," *Informacion Tecnologica*, vol. 29, pp. 153–162, Dec. 2018. [Online]. Available: https://www.scielo.cl/scielo.php?pid=S0718-07642018000600153script=sciabstract

[21] *Aprendizaje Supervisado Y no Supervisado—Healthdataminer.com*. Accessed: Mar. 15, 2022. [Online]. Available: https://healthdataminer.com/data-mining/aprendizaje-supervisado-y-no-supervisado

[22] *Unsupervised Machine Learning: Algorithms, Types With Example*. Accessed: Mar. 15, 2022. [Online]. Available: https://www.guru99.com/unsupervised-machine-learning.html

[23] *K-Means Clustering: Algorithm, Applications, Evaluation Methods, and Drawbacks | by Imad Dabbura | Towards Data Science*. Accessed: Mar. 15, 2022. [Online]. Available: https://towardsdatascience.com/k-means-clustering-algorithm-applications-evaluation-methods-and-drawbacks-aa03e644b48a

[24] *Fuzzy K-Means Clustering in Mahout*. Accessed: Mar. 15, 2022. [Online]. Available: https://www.edureka.co/blog/fuzzy k-means

[25] *What is Unsupervised Learning? | IBM*. Accessed: Mar. 15, 2022. [Online]. Available: https://www.ibm.com/cloud/learn/unsupervised-learning

[26] *Gaussian Mixture Models: What are They & When to Use?—Data Analytics*. Accessed: Mar. 15, 2022. [Online]. Available: https://vitalflux.com/gaussian-mixture-models-what-are-they-when-to-use

[27] *Qué es Machine Learning?—España | IBM*. Accessed: Mar. 15, 2022. [Online]. Available: https://www.ibm.com/es-es/cloud/learn/machine-learning

[28] *Semi-Supervised Learning, Explained | Altexsoft*. Accessed: Mar. 20, 2022. [Online]. Available: https://www.altexsoft.com/blog/semi-supervised-learning

[29] *What are the Types of Reinforcement Learning Algorithms?—Finsliq Blog*. Accessed: Mar. 22, 2022. [Online]. Available: https://www.finsliqblog.com/ai-and-machine-learning/what-are-the-types-of-reinforcement-learning-algorithms

[30] *Aprendizaje Profundo Por Refuerzo—IIC*. Accessed: Mar. 22, 2022. [Online]. Available: https://www.iic.uam.es/aprendizaje-profundo-por-refuerzo

[31] *Overview of Network Resource Management—Managing Network Virtualization and Network Resources in Oracle Solaris 11.2*. Accessed: Apr. 1, 2022. [Online]. Available: https://docs.oracle.com/cd/E3678401/html/E36813/gecki.html

[32] *What is Network Virtualization and Network Resource Management? —Managing Network Virtualization and Network Resources in Oracle Solaris 11.2*. Accessed: Apr. 1, 2022. [Online]. Available: https://docs.oracle.com/cd/E3678401/html/E36813/gndac.html

[33] O. Brun, S. Baraketi, O. Brun, and S. Baraketi. (2014). *Routing and Wavelength Assignment in Optical Networks*. [Online]. Available: https://hal.science/hal-01062321

[34] *What is Network Performance Monitoring?* Accessed: Apr. 8, 2022. [Online]. Available: https://www.techtarget.com/searchnetworking/definition/network-performance-monitoring

[35] *What is Network Performance Monitoring? Definition and FAQS | Heavy.AI*. Accessed: Apr. 8, 2022. [Online]. Available: https://www.heavy.ai/technical-glossary/network-performance-monitoring

[36] R. Vinayakumar, K. P. Soman, and P. Poornachandran, "Applying deep learning approaches for network traffic prediction," in *Proc. Int. Conf. Adv. Comput., Commun. Informat.*, 2017, pp. 2353–2358.

[37] *Overview of Traffic Prediction System and Its Impact on TMS Efficiency | Download Scientific Diagram*," Accessed: Apr. 8, 2022. [Online]. Available: https://www.researchgate.net/figure/Overview-of-traffic-prediction-system-and-its-impact-on-TMS-efficiencyfig5266673838

[38] M. M. Raikar, M. M. Mulla, N. S. Shetti, and M. Karanandi, "Data traffic classification in software defined networks (SDN) using supervised-learning," *Proc. Comput. Sci.*, vol. 171, pp. 2750–2759, Jan. 2020.

[39] S. Valenti, D. Rossi, A. Dainotti, A. Pescapè, A. Finamore, and M. Mellia, ''Reviewing traffic classification,'' in *Data Traffic Monitoring and Analysis*, (Lecture Notes in Computer Science), vol. 7754. USA: Springer, 2013, pp. 123–147, doi: 10.1007/978-3-642-36784-7_6.
[40] *Issues in Resource Allocation—Computer Networks: A Systems Approach Version 6.2-DEV Documentation*. Accessed: Apr. 12, 2022. [Online]. Available: https://book.systemsapproach.org/congestion/issues.html
[41] *Network Fault Management and Monitoring Tools—Manageengine Opmanager*. Accessed: Apr. 16, 2022. [Online]. Available: https://www.manageengine.com/network-monitoring/network-fault-management.html
[42] C. Z. Liu and M. Kavakli, ''Data-aware QoE-QoS management,'' in *Proc. IEEE 11th Conf. Ind. Electron. Appl. (ICIEA)*, Jun. 2016, pp. 1818–1823.
[43] *The Quality of Transmission Depends Upon*. Accessed: Apr. 20, 2022. [Online]. Available: https://www.toppr.com/ask/question/the-quality-of-transmission-depends-upon
[44] 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. 286–297, Feb. 2018. [Online]. Available: https://opg.optica.org/viewmedia.cfm?uri=jocn-10-2-A286&seq=0&html=true
[45] N. Viljoen, H. Rastegarfar, M. Yang, J. Wissinger, and M. Glick, ''Machine learning based adaptive flow classification for optically interconnected data centers,'' in *Proc. Int. Conf. Transparent Opt. Netw.*, Aug. 2016, pp. 1–4.
[46] F. Morales, M. Ruiz, and L. Velasco, ''Data analytics based origin-destination core traffic modelling,'' in *Proc. 19th Int. Conf. Transparent Opt. Netw. (ICTON)*, Jul. 2017, pp. 1–4.
[47] M. Salani, C. Rottondi, and M. Tornatore, ''Routing and spectrum assignment integrating machine-learning-based QoT estimation in elastic optical networks,'' in *Proc. IEEE INFOCOM Conf. Comput. Commun.*, Apr. 2019, pp. 1738–1746.
[48] H. Guo, C. Wang, Y. Tang, Y. Zhu, J. Wu, and Y. Zuo, ''Machine learning assisted optical network resource scheduling in data center networks,'' in *Optical Network Design and Modeling* (Lecture Notes in Computer Science), vol. 11616. USA: Springer, 2020, pp. 204–210, doi: 10.1007/978-3-030-38085-4_18.
[49] J. Thrane, J. Wass, M. Piels, J. C. M. Diniz, R. Jones, and D. Zibar, ''Machine learning techniques for optical performance monitoring from directly detected PDM-QAM signals,'' *J. Lightw. Technol.*, vol. 35, no. 4, pp. 868–875, Feb. 15, 2017.
[50] R. M. Morais and J. Pedro, ''Evaluating machine learning models for QoT estimation,'' in *Proc. Int. Conf. Transparent Opt. Netw.*, 2018, pp. 1–4.
[51] S. Gosselin, J. L. Courant, S. R. Tembo, and S. Vaton, ''Application of probabilistic modeling and machine learning to the diagnosis of FTTH GPON networks,'' in *Proc. 21st Int. Conf. Opt. Netw. Design Model.*, Jun. 2017, pp. 1–3.
[52] D. Das, M. F. Imteyaz, J. Bapat, and D. Das, ''A data augmented Bayesian network for node failure prediction in optical networks,'' in *Proc. 3rd Int. Conf. Artif. Intell. Inf. Commun.*, 2021, pp. 83–88.
[53] D. S. Guamán, J. M. D. Alamo, and J. C. Caiza, ''A systematic mapping study on software quality control techniques for assessing privacy in information systems,'' *IEEE Access*, vol. 8, pp. 74808–74833, 2020.
[54] P. Mongeon and A. Paul-Hus, ''The journal coverage of web of science and scopus: A comparative analysis,'' *Scientometrics*, vol. 106, no. 1, pp. 213–228, Jan. 2016, doi: 10.1007/s11192-015-1765-5.
[55] K. Krippendorff. (2004). *Reliability in Content Analysis: Some Common Misconceptions and Recommendations*. [Online]. Available: http://repository.upenn.edu/ascpapers/242
[56] R. Wieringa, N. Maiden, N. Mead, and C. Rolland, ''Requirements engineering paper classification and evaluation criteria: A proposal and a discussion,'' *Requirements Eng.*, vol. 11, no. 1, pp. 102–107, Mar. 2006. [Online]. Available: https://research.utwente.nl/en/publications/requirements-engineering-paper-classification-and-evaluation-crit
[57] R. Zhu, G. Li, P. Wang, M. Xu, and S. Yu, ''DRL-based deadline-driven advance reservation allocation in EONs for cloud-edge computing,'' *IEEE Internet Things J.*, vol. 9, no. 21, pp. 21444–21457, Nov. 2022.
[58] S. C. Nayak and C. Tripathy, ''Deadline sensitive lease scheduling in cloud computing environment using AHP,'' *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 30, no. 2, pp. 152–163, Apr. 2018.
[59] R. Zhu, P. Wang, Z. Geng, Y. Zhao, and S. Yu, ''Double-agent reinforced vNFC deployment in EONs for cloud-edge computing,'' *J. Lightw. Technol.*, vol. 41, no. 16, pp. 5193–5208, Aug. 15, 2023.
[60] R. Zhu, S. Li, P. Wang, M. Xu, and S. Yu, ''Energy-efficient deep reinforced traffic grooming in elastic optical networks for cloud-fog computing,'' *IEEE Internet Things J.*, vol. 8, no. 15, pp. 12410–12421, Aug. 2021.
[61] J. Yuan, R. Zhu, Y. Zhao, Q. Zhang, X. Li, D. Zhang, and A. Samuel, ''A spectrum assignment algorithm in elastic optical network with minimum sum of weighted resource reductions in all associated paths,'' *J. Lightw. Technol.*, vol. 37, no. 21, pp. 5583–5592, Nov. 1, 2019.
[62] *Cisco Annual Internet Report—Cisco Annual Internet Report (2018–2023) White Paper—Cisco*. Accessed: Dec. 14, 2022. [Online]. Available: https://www.cisco.com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/white-paper-c11-741490.html
[63] Y. Zhao, B. Yan, Y. He, D. Wang, D. Liu, and J. Zhang, ''Soon: Self-optimizing optical networks with machine learning,'' *Opt. Exp.*, vol. 26, pp. 28713–28726, Oct. 2018. [Online]. Available: https://opg.optica.org/viewmedia.cfm?uri=oe-26-22-28713&seq=0&html=true
[64] M. Hinrichs, B. Poddig, P. Hellwig, and V. Jungnickel, ''Reducing overhead for low-power optical wireless communications,'' in *Proc. 48th Annu. Conf. IEEE Ind. Electron. Soc.*, Oct. 2022, pp. 1–5.
[65] F. Musumeci, C. Rottondi, G. Corani, S. Shahkarami, F. Cugini, and M. Tornatore, ''A tutorial on machine learning for failure management in optical networks,'' *J. Lightw. Technol.*, vol. 37, no. 16, pp. 4125–4139, Aug. 15, 2019.
[66] S. Chakraborty, R. Tomsett, R. Raghavendra, D. Harborne, M. Alzantot, F. Cerutti, M. Srivastava, A. Preece, S. Julier, R. M. Rao, T. D. Kelley, D. Braines, M. Sensoy, C. J. Willis, and P. Gurram, ''Interpretability of deep learning models: A survey of results,'' in *Proc. IEEE SmartWorld, Ubiquitous Intell. Comput., Adv. Trusted Comput., Scalable Comput. Commun., Cloud Big Data Comput., Internet People Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, Aug. 2017, pp. 1–6.
[67] *Online vs Offline Machine Learning—What's the Difference? | Qwak's Blog*. Accessed: Dec. 16, 2022. [Online]. Available: https://www.qwak.com/post/online-vs-offline-machine-learning-whats-the-difference
[68] A. Alsarhan and A. Agarwal, ''Spectrum sharing in multi-service cognitive network using reinforcement learning,'' in *Proc. 1st U.K.-India Int. Workshop Cognit. Wireless Syst. (UKIWCWS)*, Dec. 2009, pp. 1–5.
[69] J. Pesic, E. Le Rouzic, N. Brochier, and L. Dupont, ''Proactive restoration of optical links based on the classification of events,'' in *Proc. 15th Int. Conf. Opt. Netw. Design Model.*, 2011, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/5753394
[70] P. Sarigiannidis, G. Papadimitriou, P. Nicopolitidis, V. Kakali, E. Varvarigos, and K. Yiannopoulos, ''ARES: An adaptive, resilient, estimation scheme for enforcing bandwidth allocation in XG-PON systems,'' *Commun. Comput. Inf. Sci.*, vol. 554, pp. 131–151, Aug. 2015, doi: 10.1007/978-3-319-25915-4_8.
[71] F. Fresi, A. P. Vela, G. Meloni, N. Sambo, F. Cugini, L. Poti, L. Velasco, P. Castoldi, and M. Ruiz, ''Service-triggered failure identification/localization through monitoring of multiple parameters,'' in *Proc. 42nd Eur. Conf. Opt. Commun.*, 2016, pp. 1–3. [Online]. Available: https://ieeexplore.ieee.org/document/7769406
[72] T. Panayiotou, S. P. Chatzis, and G. Ellinas, ''A probabilistic approach for failure localization,'' in *Proc. Int. Conf. Opt. Netw. Design Model. (ONDM)*, May 2017, pp. 1–6.
[73] Z. Wang, M. Zhang, D. Wang, C. Song, M. Liu, L. Lou, and Z. Liu, ''Failure prediction using machine learning and time series in optical network,'' *Opt. Exp.*, vol. 25, pp. 18553–18565, Aug. 2017. [Online]. Available: https://opg.optica.org/viewmedia.cfm?uri=oe-25-16-18553&seq=0&html=true
[74] P. Samadi, D. Amar, C. Lepers, M. Lourdiane, and K. Bergman, ''Quality of transmission prediction with machine learning for dynamic operation of optical WDM networks,'' in *Proc. Eur. Conf. Opt. Commun. (ECOC)*, Sep. 2017, pp. 1–3.
[75] S. Cui, D. Liu, C. Ke, and H. Lu, ''Automatic reference optical spectrum retrieval method for ultra-high resolution optical spectrum distortion analysis utilizing integrated machine learning techniques,'' *Opt. Exp.*, vol. 25, pp. 32491–32503, Dec. 2017. [Online]. Available: https://opg.optica.org/viewmedia.cfm?uri=oe-25-26-32491&seq=0&html=true
[76] S. Shahkarami, F. Musumeci, F. Cugini, and M. Tornatore, ''Machine-learning-based soft-failure detection and identification in optical networks,'' in *Proc. Opt. Fiber Commun. Conf. Expo.*, 2018, pp. 1–3. [Online]. Available: https://ieeexplore.ieee.org/document/8385774

[77] E. Seve, J. Pesic, C. Delezoide, S. Bigo, and Y. Pointurier, "Learning process for reducing uncertainties on network parameters and design margins," *J. Opt. Commun. Netw.*, vol. 10, no. 2, pp. 298–306, Feb. 2018.
[78] T. Panayiotou, S. P. Chatzis, and G. Ellinas, "Leveraging statistical machine learning to address failure localization in optical networks," *J. Opt. Commun. Netw.*, vol. 10, no. 3, pp. 162–173, Mar. 2018.
[79] L. Wang, X. Wang, M. Tornatore, K. J. Kim, S. M. Kim, D. U. Kim, K. E. Han, and B. Mukherjee, "Scheduling with machine-learning-based flow detection for packet-switched optical data center networks," *J. Opt. Commun. Netw.*, vol. 10, pp. 365–375, Apr. 2018.
[80] D. Rafique, T. Szyrkowiec, H. Grieser, A. Autenrieth, and J.-P. Elbers, "Cognitive assurance architecture for optical network fault management," *J. Lightw. Technol.*, vol. 36, no. 7, pp. 1443–1450, Apr. 1, 2018.
[81] B. Shariati, A. P. Vela, M. Ruiz, and L. Velasco, "Monitoring and data analytics: Analyzing the optical spectrum for soft-failure detection and identification," in *Proc. Int. Conf. Opt. Netw. Design Model. (ONDM)*, May 2018, pp. 260–265.
[82] N. E. Frigui, T. Lemlouma, S. Gosselin, B. Radier, R. L. Meur, and J. M. Bonnin, "Optimization of the upstream bandwidth allocation in passive optical networks using internet users' behavior forecast," in *Proc. 22nd Conf. Opt. Netw. Design Model.*, 2018, pp. 59–64.
[83] L. Ruan, S. Mondal, and E. Wong, "Machine learning based bandwidth prediction in tactile heterogeneous access networks," in *Proc. IEEE INFOCOM Conf. Comput. Commun. Workshops (INFOCOM WKSHPS)*, Apr. 2018, pp. 1–2.
[84] X. Chen, R. Proietti, H. Lu, A. Castro, and S. J. B. Yoo, "Knowledge-based autonomous service provisioning in multi-domain elastic optical networks," *IEEE Commun. Mag.*, vol. 56, no. 8, pp. 152–158, Aug. 2018.
[85] T. Panayiotou and G. Ellinas, "Data-driven bandwidth allocation in EONs," in *Proc. Photon. Switching Comput. (PSC)*, Sep. 2018, pp. 1–3.
[86] S. Troia, R. Alvizu, Y. Zhou, G. Maier, and A. Pattavina, "Deep learning-based traffic prediction for network optimization," in *Proc. 20th Int. Conf. Transparent Opt. Netw. (ICTON)*, Jul. 2018, pp. 1–4.
[87] A. P. Vela, M. Ruiz, and L. Velasco, "Examples of machine learning algorithms for optical network control and management," in *Proc. 20th Int. Conf. Transparent Opt. Netw. (ICTON)*, Jul. 2018, pp. 1–4.
[88] J. Mata, I. D. Miguel, R. J. Duran, J. C. Aguado, N. Merayo, L. Ruiz, P. Fernandez, R. M. Lorenzo, E. J. Abril, and I. Tomkos, "Supervised machine learning techniques for quality of transmission assessment in optical networks," in *Proc. Int. Conf. Transparent Opt. Netw.*, 2018, pp. 1–4.
[89] R. M. Morais and J. Pedro, "Machine learning models for estimating quality of transmission in DWDM networks," *J. Opt. Commun. Netw.*, vol. 10, no. 10, pp. 84–99, Oct. 2018.
[90] M. Aibin, "Traffic prediction based on machine learning for elastic optical networks," *Opt. Switching Netw.*, vol. 30, pp. 33–39, Nov. 2018.
[91] I. Sartzetakis, K. Christodoulopoulos, and E. Varvarigos, "Formulating QoT estimation with machine learning," in *Proc. Eur. Conf. Opt. Commun. (ECOC)*, Sep. 2018, pp. 1–3.
[92] S. Allogba and C. Tremblay, "K-nearest neighbors classifier for field bit error rate data," in *Proc. Asia Commun. Photon. Conf. (ACP)*, Oct. 2018, pp. 1–3.
[93] D. Lippiatt, S. Varughese, T. Richter, S. Tibuleac, and S. E. Ralph, "Machine-learning-based optical performance monitoring using carrier phase recovery," in *Proc. 45th Eur. Conf. Opt. Commun. (ECOC)*, Sep. 2019, pp. 1–4.
[94] C. Tremblay, S. Allogba, and S. Aladin, "Quality of transmission estimation and performance prediction of lightpaths using machine learning," in *Proc. 45th Eur. Conf. Opt. Commun. (ECOC)*, Sep. 2019, pp. 1–3.
[95] T. Panayiotou, G. Savva, B. Shariati, I. Tomkos, and G. Ellinas, "Machine learning for QoT estimation of unseen optical network states," in *Proc. Opt. Fiber Commun. Conf.*, 2019, pp. 1–3. [Online]. Available: https://ieeexplore.ieee.org/document/8696540
[96] K. H. Rahouma and A. Ali, "Applying machine learning technology to optimize the operational cost of the Egyptian optical network," *Proc. Comput. Sci.*, vol. 163, pp. 502–517, Jan. 2019.
[97] J. A. Hatem, A. R. Dhaini, and S. Elbassuoni, "Deep learning-based dynamic bandwidth allocation for future optical access networks," *IEEE Access*, vol. 7, pp. 97307–97318, 2019.
[98] T. Tanimura, T. Hoshida, T. Kato, S. Watanabe, and H. Morikawa, "Convolutional neural network-based optical performance monitoring for optical transport networks," *J. Opt. Commun. Netw.*, vol. 11, no. 1, pp. 52–59, Jan. 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8651197
[99] R. Proietti, X. Chen, K. Zhang, G. Liu, M. Shamsabardeh, A. Castro, L. Velasco, Z. Zhu, and S. J. B. Yoo, "Experimental demonstration of machine-learning-aided QoT estimation in multi-domain elastic optical networks with alien wavelengths," *J. Opt. Commun. Netw.*, vol. 11, no. 1, pp. 1–10, Jan. 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8651192
[100] B. Yan, Y. Zhao, Y. Li, X. Yu, J. Zhang, Y. Wang, L. Yan, and S. Rahman, "Actor-critic-based resource allocation for multi-modal optical networks," in *Proc. IEEE Globecom Workshops*, Dec. 2019, pp. 1–6.
[101] B. Liu, L. Zhang, F. Wang, M. Liu, Y. Mao, L. Zhao, T. Sun, and X. Xin, "Adaptive dynamic wavelength and bandwidth allocation algorithm based on error-back-propagation neural network prediction," *Opt. Commun.*, vol. 437, pp. 276–284, Apr. 2019.
[102] L. Ruan, I. Dias, and E. Wong, "Machine intelligence in supervising bandwidth allocation for low-latency communications," in *Proc. IEEE 20th Int. Conf. High Perform. Switching Routing (HPSR)*, May 2019, pp. 1–6.
[103] T. Panayiotou, K. Manousakis, S. P. Chatzis, and G. Ellinas, "A data-driven bandwidth allocation framework with QoS considerations for EONs," *J. Lightw. Technol.*, vol. 37, no. 9, pp. 1853–1864, May 1, 2019.
[104] D. Szostak and K. Walkowiak, "Machine learning methods for traffic prediction in dynamic optical networks with service chains," in *Proc. 21st Int. Conf. Transparent Opt. Netw. (ICTON)*, Jul. 2019, pp. 1–4.
[105] M. Zhang and D. Wang, "Machine learning based alarm analysis and failure forecast in optical networks," in *Proc. 24th OptoElectronics Commun. Conf. (OECC) Int. Conf. Photon. Switching Comput. (PSC)*, Jul. 2019, pp. 1–3.
[106] I. Martín, S. Troia, J. A. Hernández, A. Rodríguez, F. Musumeci, G. Maier, R. Alvizu, and de O. G. Dios, "Machine learning-based routing and wavelength assignment in software-defined optical networks," *IEEE Trans. Netw. Service Manag.*, vol. 16, no. 3, pp. 871–883, Sep. 2019.
[107] R. A. Butt, M. Faheem, A. Arfeen, M. W. Ashraf, and M. Jawed, "Machine learning based dynamic load balancing DWBA scheme for TWDM PON," *Opt. Fiber Technol.*, vol. 52, Nov. 2019, Art. no. 101964.
[108] T. Panayiotou, G. Savvas, I. Tomkos, and G. Ellinas, "Centralized and distributed machine learning-based QoT estimation for sliceable optical networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2019, pp. 1–7.
[109] X. Xing, Y. Zhao, Y. Li, and J. Zhang, "Knowledge-based collective self-learning for alarm prediction in real multi-domain autonomous optical networks," in *Proc. 16th Int. Conf. Design Reliable Commun. Netw.*, 2020, pp. 1–5.
[110] L. Shu, Z. Yu, Z. Wan, J. Zhang, S. Hu, and K. Xu, "Dual-stage soft failure detection and identification for low-margin elastic optical network by exploiting digital spectrum information," *J. Lightw. Technol.*, vol. 38, no. 9, pp. 2669–2679, May 1, 2020.
[111] L. Ruan, M. P. I. Dias, and E. Wong, "Towards self-adaptive bandwidth allocation for low-latency communications with reinforcement learning," *Opt. Switching Netw.*, vol. 37, May 2020, Art. no. 100567.
[112] S. Aladin, A. V. S. Tran, S. Allogba, and C. Tremblay, "Quality of transmission estimation and short-term performance forecast of lightpaths," *J. Lightwave Technol.*, vol. 38, no. 10, pp. 2806–2813, May 15, 2020.
[113] H. Lun, M. Fu, X. Liu, Y. Wu, L. Yi, W. Hu, and Q. Zhuge, "Soft failure identification for long-haul optical communication systems based on one-dimensional convolutional neural network," *J. Lightw. Technol.*, vol. 38, no. 11, pp. 2992–2999, Jun. 1, 2020.
[114] Y. Wang, B. Cheng, C. Hang, J. Yu, S. Liu, Y. Hu, and J. Shen, "Routing algorithm for elastic optical network based on machine learning assisted traffic prediction," *J. Phys., Conf.*, vol. 1550, no. 3, May 2020, Art. no. 032123. [Online]. Available: https://iopscience.iop.org/article/10.1088/1742-6596/1550/3/032123
[115] K. Mitropoulou, I. Sartzetakis, and E. Varvarigos, "Soft failure detection, categorization and localization," in *Proc. 22nd Int. Conf. Transparent Opt. Netw. (ICTON)*, Jul. 2020, pp. 1–4.

[116] D. Szostak, K. Walkowiak, and A. Wlodarczyk, "Short-term traffic forecasting in optical network using linear discriminant analysis machine learning classifier," in *Proc. 22nd Int. Conf. Transparent Opt. Netw. (ICTON)*, Jul. 2020, pp. 1–4.

[117] I. Khan, M. Bilal, and V. Curri, "Advanced formulation of QoT-estimation for un-established lightpaths using cross-train machine learning methods," in *Proc. 22nd Int. Conf. Transparent Opt. Netw. (ICTON)*, Jul. 2020, pp. 1–4.

[118] I. Khan, M. Bilal, M. Siddiqui, M. Khan, A. Ahmad, M. Shahzad, and V. Curri, "QoT estimation for light-path provisioning in un-seen optical networks using machine learning," in *Proc. 22nd Int. Conf. Transparent Opt. Netw. (ICTON)*, Jul. 2020, pp. 1–4.

[119] R. J. Pandya, "Machine learning-oriented resource allocation in C + L + S bands extended SDM–EONs," *IET Commun.*, vol. 14, no. 12, pp. 1957–1967, Jul. 2020.

[120] D. Szostak and K. Walkowiak, "Application of machine learning algorithms for traffic forecasting in dynamic optical networks with service function chains," *Found. Comput. Decis. Sci.*, vol. 45, no. 3, pp. 217–232, Sep. 2020.

[121] V. Curri, I. Khan, and M. Bilal, "Assessment of cross-train machine learning techniques for qot-estimation in agnostic optical networks," *OSA Continuum*, vol. 3, pp. 2690–2706, Oct. 2020. [Online]. Available: https://opg.optica.org/viewmedia.cfm?uri=osac-3-10-2690&seq=0&html=true

[122] C. Zhi, W. Ji, R. Yin, J. Feng, H. Xu, Z. Li, and Y. Wang, "The flexible resource management in optical data center networks based on machine learning and SDON," *Opt. Switching Netw.*, vol. 39, Nov. 2020, Art. no. 100594.

[123] A. Valkanis, G. A. Beletsioti, P. Nicopolitidis, G. Papadimitriou, and E. Varvarigos, "Reinforcement learning in traffic prediction of core optical networks using learning automata," in *Proc. Int. Conf. Commun., Comput., Cybersecurity, Informat. (CCCI)*, Nov. 2020, pp. 1–6.

[124] D. Andreoletti, C. Rottondi, A. Bianco, and S. Giordano, "A machine learning framework for scalable routing and wavelength assignment in large optical networks," in *Proc. Opt. Fiber Commun. Conf. Exhib. (OFC)*, Jun. 2021, pp. 1–3. [Online]. Available: https://ieeexplore.ieee.org/document/9489780

[125] K. Sun, Z. Yu, L. Shu, Z. Wan, H. Huang, and K. Xu, "Experimental demonstration of soft failure identification based on digital residual spectrum and machine learning," in *Proc. Int. Conf. U.K.-China Emerg. Technol. (UCET)*, Nov. 2021, pp. 81–84.

[126] C. C. Yao, J. Y. Zheng, J. J. Jou, and C. L. Yang, "Performance monitoring of high-speed NRZ signals using machine learning techniques," in *Proc. Int. Symp. Intell. Signal Process. Commun. Syst.*, 2021, pp. 1–2.

[127] G. Gupta, A. Rai, and V. Jha, "Predicting the bandwidth requests in XG-PON system using ensemble learning," in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, Oct. 2021, pp. 936–941.

[128] P. Cichosz, S. Kozdrowski, and S. Sujecki, "Application of ML algorithms for prediction of the QoT in optical networks with imbalanced and incomplete data," in *Proc. Int. Conf. Softw., Telecommun. Comput. Netw. (SoftCOM)*, Sep. 2021, pp. 1–6.

[129] S. Kozdrowski, P. Cichosz, P. Paziewski, and S. Sujecki, "Machine learning algorithms for prediction of the quality of transmission in optical networks," *Entropy*, vol. 23, no. 1, p. 7, Dec. 2020. [Online]. Available: https://www.mdpi.com/1099-4300/23/1/7/htm https://www.mdpi.com/1099-4300/23/1/7

[130] D. Das, M. F. Imteyaz, J. Bapat, and D. Das, "A non-intrusive failure prediction mechanism for deployed optical networks," in *Proc. Int. Conf. Commun. Syst. Netw.*, 2021, pp. 24–28.

[131] W. S. Saif, A. M. Ragheb, T. A. Alshawi, and S. A. Alshebeili, "Optical performance monitoring in mode division multiplexed optical networks," *J. Lightw. Technol.*, vol. 39, no. 2, pp. 491–504, Jan. 15, 2021.

[132] M. Ibrahimi, H. Abdollahi, C. Rottondi, A. Giusti, A. Ferrari, V. Curri, and M. Tornatore, "Machine learning regression for QoT estimation of unestablished lightpaths," *J. Opt. Commun. Netw.*, vol. 13, no. 4, pp. 92–101, Apr. 2021.

[133] M. A. Esmail, "Optical wireless performance monitoring using asynchronous amplitude histograms," *IEEE Photon. J.*, vol. 13, no. 3, pp. 1–9, Jun. 2021.

[134] P. Paudyal, S. Shen, S. Yan, and D. Simeonidou, "Toward deployments of ML applications in optical networks," *IEEE Photon. Technol. Lett.*, vol. 33, no. 11, pp. 537–540, Jun. 1, 2021.

[135] M. Aibin, N. Chung, T. Gordon, L. Lyford, and C. Vinchoff, "On short- and long-term traffic prediction in optical networks using machine learning," in *Proc. Int. Conf. Opt. Netw. Design Model. (ONDM)*, Jun. 2021, pp. 1–6.

[136] D. Szostak, A. Wlodarczyk, and K. Walkowiak, "Machine learning classification and regression approaches for optical network traffic prediction," *Electronics*, vol. 10, no. 13, p. 1578, Jun. 2021. [Online]. Available: https://www.researchgate.net/publication/352871242

[137] D. Wang, M. Zhang, L. Guan, C. Zhang, L. Wang, Z. Zhang, X. Chen, and H. Yang, "Cause-aware failure detection using an interpretable XGBoost for optical networks," *Opt. Exp.*, vol. 29, pp. 31974–31992, Sep. 2021. [Online]. Available: https://opg.optica.org/viewmedia.cfm?uri=oe-29-20-31974&seq=0&html=true

[138] F. Usmani, I. Khan, M. U. Masood, A. Ahmad, M. Shahzad, and V. Curri, "Convolutional neural network for quality of transmission prediction of unestablished lightpaths," *Microw. Opt. Technol. Lett.*, vol. 63, no. 10, pp. 2461–2469, Oct. 2021. [Online]. Available: https://onlinelibrary.wiley.com/doi/full/10.1002/mop.32996

[139] J. Lu, Q. Fan, G. Zhou, L. Lu, C. Yu, A. P. T. Lau, and C. Lu, "Automated training dataset collection system design for machine learning application in optical networks: An example of quality of transmission estimation," *J. Opt. Commun. Netw.*, vol. 13, no. 11, pp. 289–300, Nov. 2021.

[140] F. Usmani, I. Khan, M. Siddiqui, M. Khan, M. Bilal, M. U. Masood, A. Ahmad, M. Shahzad, and V. Curri, "Cross-feature trained machine learning models for QoT-estimation in optical networks," *Opt. Eng.*, vol. 60, no. 12, Dec. 2021, Art. no. 125106. [Online]. Available: https://www.spiedigitallibrary.org/journals/optical-engineering/volume-60/issue-12/125106/Cross-feature-trained-machine-learning-models-for-QoT-estimation-in/10.1117/1.OE.60.12.125106.full

[141] M. Lonardi, J. Pesic, T. Zami, E. Seve, and N. Rossi, "Machine learning for quality of transmission: A picture of the benefits fairness when planning WDM networks," *J. Opt. Commun. Netw.*, vol. 13, no. 12, pp. 331–346, Dec. 2021.

[142] Y. Fu, J. Chen, W. Wu, Y. Huang, J. Hong, L. Chen, and Z. Li, "A QoT prediction technique based on machine learning and NLSE for QoS and new lightpaths in optical communication networks," *Frontiers Optoelectron.*, vol. 14, no. 4, pp. 513–521, Dec. 2021, doi: 10.1007/s12200-020-1079-y.

[143] O. Ayoub, A. Bianco, D. Andreoletti, S. Troia, S. Giordano, and C. Rottondi, "On the application of explainable artificial intelligence to lightpath QoT estimation," in *Proc. Opt. Fiber Commun. Conf. (OFC)*. USA: Springer, 2022, pp. 1–3. [Online]. Available: https://ieeexplore.ieee.org/document/9748572

[144] M. F. Silva, A. Pacini, A. Sgambelluri, and L. Valcarenghi, "Learning long- and short-term temporal patterns for ML-driven fault management in optical communication networks," *IEEE Trans. Netw. Service Manag.*, vol. 19, no. 3, pp. 2195–2206, Sep. 2022.

[145] B. R. Menaghapriya and R. G. Sangeetha, "Failure detection using artificial neural networks," in *Futuristic Communication and Network Technologies* (Lecture Notes in Electrical Engineering), vol. 792. 2022, pp. 655–661, doi: 10.1007/978-981-16-4625-6_65.

[146] I. Khan, M. Bilal, and V. Curri, "Cross-train: Machine learning assisted QoT-estimation in un-used optical networks," in *Proc. Int. Conf. Telecommun. Commun. Eng.*, vol. 797, 2022, pp. 78–87, doi: 10.1007/978-981-16-5692-7_9.

[147] S. Allogba, S. Aladin, and C. Tremblay, "Machine-Learning-Based lightpath QoT estimation and forecasting," *J. Lightw. Technol.*, vol. 40, no. 10, pp. 3115–3127, May 15, 2022.

[148] A. Usman, N. Zulkifli, M. R. Salim, and K. Khairi, "Fault monitoring in passive optical network through the integration of machine learning and fiber sensors," *Int. J. Commun. Syst.*, vol. 35, no. 9, p. e5134, Jun. 2022. [Online]. Available: https://onlinelibrary.wiley.com/doi/full/10.1002/dac.5134

[149] N. Guo, L. Li, B. Mukherjee, and G. Shen, "Protection against failure of machine-learning-based QoT prediction," *J. Opt. Commun. Netw.*, vol. 14, no. 7, pp. 572–585, Jul. 2022.

[150] L. Cheng and Y. Qiu, "Routing and spectrum assignment employing long short-term memory technique for elastic optical networks," *Opt. Switching Netw.*, vol. 45, Sep. 2022, Art. no. 100684.

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