American Journal of Electronics & Communication

Aparajita Mukherjee et. al., American Journal of Electronics & Communication, Vol. III (2), 16-20

Recent Developments on Elastic Optical Networks: A brief Survey

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***Abstract* — Elastic optical networks provide flexible bandwidth allocation which helps to optimize overall bandwidth usage in a network. Though the study in this field is more than a decade long, some recent developments like inclusion of machine learning tools and new protection based approaches have emerged. In this paper, we review some of the recent developments in elastic optical networks using machine learning, different routing schemes and protection approaches. We have pointed out future research scope and challenges in this area of work.**

Keyword* — *Elastic optical network, machine learning,routing, protection approach.

I. INTRODUCTION

Today the main concern of Internet Service Providers (ISPs) is to meet the wide bandwidth requirements of traffic demand. Over the last decade, the number of Internet users has increased significantly. One of the main reasons for this is Internet applications such as multimedia communication, high resolution IPTV and cloud services. Data transfer technology having advanced preparation is required to cope with the increasing Internet which supports traffic in the speed range from Gbps to Tbps. Like that, advances in optical backbone transport networks are flexible networks in the elastic optical network domain. At conventional wavelengths Time Division Multiplexing (WDM) Optical Network, Fixed Network Architecture, spectral was wasted due to the total capacity of one wavelength. Channels cannot be used efficiently and in these optical networks it was not possible to meet the huge bandwidth needs of the traffic. Therefore, researchers have switched from traditional WDM optical networks. A more scalable and flexible paradigm for optical networks are elastic optical networks, which are high-speed optical networks. It provides flexible bandwidth allocation and follows Spectrum Sliced Elastic Optical Path Network (SLICE) architecture and spectrum allocation. It allocates resources to the traffic demand as much as it needs. The whole spectrum grid is divided into frequency slots and the bandwidth is converted to the number of slots required for each traffic demand. SLICE architecture supports sub-wavelength, super-wavelength, and multiple data rates services. The main advantages of Elastic Optical Networks (EON) are resource utilization, flexible spectral allocation and support for different data rates. It also contributes to low energy consumption. And low network setup cost.

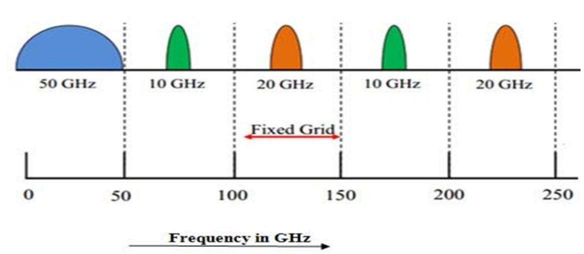

Fig.1. Spectrum allocation in conventional WDM network [14]

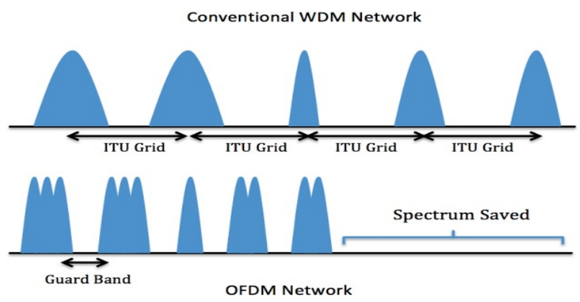

Fig. 2. Spectrum allocation OFDM network and conventional WDM network and along the frequency domain [13]

Variable Bandwidth (BV) Transponder Adjustable to work with variable data rate and optical BV switching Supported by BV wavelength cross-connect bandwidth variable.

Elastic optical Networks are preferred over WDM networks, because they are more flexible than the WDM optical networks in terms of spectrum allocation and grid architecture. WDM optical networks have fixed bandwidth of 50GHz or 100 GHz while in EON the spectrum is divided into a set of frequency slots with finer bandwidth. Benefits of EON are the flexible-grid architecture and elastic spectral allocation and its support for high-speed traffic demands. Other benefits are low signal attenuation, low signal distortion, low power requirement, small space requirement and low cost.

In elastic optical networks, machine learning (ML) techniques have been used to automate activities and fetch more volume from the physical layer. This paper focuses on some research directions in the application of ML in EON.

II. ROUTING APPROACH

The cross-connect is equipped with a wavelength-selective BV switch Filter the signal during the add or remove function. Routing research Spectrum assignment (RSA) has been studied by many researchers in the past. Choosing an executable path to transfer data called the routing process and the method of allocating spectra the traffic demand (or frequency slot (FS)) is known as the spectrum mapping process. Spectral assignments can be divided into several categories and must follow spectral constraints [12]. Data transfer from a single source to multiple destinations is called data transfer. Multicast type data transmission. Multicast applications are popular. Some of the multicast applications are video lectures. Some distance education, video conferences, IPTV, etc. Multicast Transmission is supported by broadcast and selection mechanisms BV transponders and unwanted signals are also excluded BV wavelengths are interconnected. In the optical network, the optical path is an optical data transmission link and all fiber optic connections are part of it. The same frequency range is continuously assigned to this route. Similarly, the light tree has a continuous spectral path to each target.

III. PROTECTION APPROACH

A light tree is implemented in the multicast data type, while a unicast type write path is implemented by data transfer. Network protection technologies fall into two categories, exclusive Protection and common protection. Protective capacity (or Spectral) can be shared and falls under shared protection. If the protection cannot be shared, it is called dedicated protection. Ability to work for special protection systems It is protected by a dedicated backup capacity. Common protection Schemes, multiple traffic requests can share one protection capacity in those cases Each work path does not fail together. Shared protection It is more capacity efficient than dedicated protection.

IV. MACHINE LEARNING APPROACH

There are three main stages in machine learning. i) Data is provided as input to the model. ii) the model performs training on the data and iii)some operations are performed on the output of the trained data. Machine learning (ML) can be divided into supervised learning, unsupervised learning and reinforcement learning. In supervised learning, algorithms use existing patterns and knowledge based on known outcomes. The output is sent to a computer to find patterns in the data and apply training tasks to build a model that produces the desired results in a new data set. The main challenge in supervised learning is to have enough data to cover all data options. Data should be randomly selected from a large data set. Otherwise, bias may occur. Some popular supervised learning algorithms are decision trees, nearest neighbors, regression analysis, support vector machines (SVMs), and artificial neural networks (ANNs). In unsupervised learning, some variables are unknown and unclassified. Machines discover unseen patterns and create groups based on them. As additional patterns are recognized, they can be analyzed. Unsupervised algorithms include k-means clustering, association analysis, dimensionality reduction algorithms, and social network analysis.

One of the most advanced categories of machine learning is reinforcement learning. In reinforcement learning, an algorithm performs a random trial and error procedure and incorporates feedback information from the procedure to improve the model. Algorithms train the model through continuous learning. The goal of reinforcement learning is to achieve a specific result through trial and error with various combinations of inputs. The standard model has a set of performance metrics by which results are measured. Elastic Optical Networks (EONs) use techniques such as flexible spectral grids, orthogonal frequency division multiplexing (OFDM), distance adaptive factors, and modulation to achieve higher spectral efficiency than traditional high density division multiplexing (DWDM). You can now use it. Machine learning (ML) technology is used in elastic optical networks to enable automated operations and extract more capacity from the physical layer. ML has many applications such as connection monitoring, connection modeling, connection preparation, and network management.

V. TECHNIQUES APPLIED TO ELASTIC OPTICAL NETWORKS

In elastic optical networks Machine Learning (ML) techniques have been adopted by enabling automated operations and extracting more capacity from the physical layer. In [1], the authors reviewed and discussed various ML applications for channel monitoring, channel modeling, channel provisioning, and network management. According to the authors of [2], fiber nonlinear interference (NLI) modeling and monitoring is a key building block supporting elastic optical networks. Previously, it was developed and studied separately. The accuracy of the previously proposed method still needs to be improved for heterogeneous dynamic optical networks. The authors presented applications of machine learning (ML) in NLI modeling and monitoring. In particular, we first propose the use of a machine learning approach to correct for errors in the current fiber nonlinearity model. The Gasceanna model is used as an exemplary example, and significant improvements are demonstrated using artificial neural networks. It also uses ML to combine modeling and monitoring methods to provide better estimates for NLI deviations.

According to the paper [3], the residential optical network (alternately) researchers have investigated various issues in the simulation and transmission of Eon for almost 10 years. EON is equipped with a flexible grid architecture created through transmitter and bandwidth. One of these technologies that helps to analyze EON is to analyze performance and manage traffic, and failure is to use approaches to mechanical research. Q-Learning algorithms fall into the category of reinforcement learning. Machine learning techniques can be applied to EON for data analysis, network performance monitoring, and many other important issues in EON. Various machine learning applications in telecommunication networks include intrusion detection, error management, anomaly detection, and network performance analysis.

Researchers have applied a variety of machine learning techniques such as monitoring, reinforcement learning, and artificial neural networks to study EON's existing problems. Existing machine learning technologies applied to optical networks can be broadly classified as follows. i) Transmission quality evaluation or prediction, [4] [7], ii) Error prediction [8] [9], ii) Traffic prediction [10] [11] Others. Evaluate or predict quality of service.

- Assessing or predicting the quality of service

In [10], the author proposed a data-driven framework for bandwidth allocation at EON, taking into account the quality of service (QoS) requirements of the network. Reinforcement learning (RL) is used to solve bandwidth allocation problems. This framework can adapt to increasing network loads to take into account the quality of service requirements of the network. Bandwidth allocation (BA) problems are mapped as partially observable Markov decision processes (POMDP). The framework will be scalable using POMDP and RL. The central controller monitors the achievement of quality of service requirements by assessing the performance of common PBA models. If the QoS requirements are not met, use the reward function to modify the model. For each reward optimization function, the output of the PBA model is considered as input to the RSA model used as a network reoptimization. An ILP formulation model and heuristic approach are used, and the results show that network bandwidth can be used efficiently if the reward function can be modified appropriately.

- Survivability

In [11], the author uses deep reinforcement learning to study the problem of optimizing overall network performance for viability in EON. The goal is to optimize the cost efficiency of the network and provide a viability solution. A Deep Reinforcement Learning (DRL) approach has been proposed. In this approach, one agent is used to provide the working schema and another agent is used to provide the protection schema, and the two are combined to provide a viable routing, modulation, and spectrum allocation policy solution. This approach is built into the reward collection feature to make it more cost effective. Simulation results show that the overall performance of the network is optimized with an acceptable blocking rate and that there is a solution that can survive a single link failure. In [12], the author designs and experimentally explores AI-assisted recovery schemes based on a multi-layered design of software-defined IP on elastic optical networks. The recovery process is used in a congestion-aware redirection approach to quickly restore failed traffic. This study uses deep learning based on a neural short-term memory network.

- Traffic forecast

In [8], the author proposes a Monte Carlo tree search approach for predicting data traffic in cloud data center networks. For a particular request, this search technique identified the most appropriate combination of cloud data center and candidate path pairs used to route the request. A sparse tree is built and the selection is implemented by Monte Carlo sampling. The results of this approach were compared with the results of an artificial neural network-based method, and the proposed approach showed excellent performance in terms of adaptability and time. The purpose was to predict traffic and use dynamic routing algorithms to test the traffic prediction mechanism. This traffic forecasting method can be applied to other frameworks. The proposed traffic prediction mechanism performed better than EON's other heuristics. In [9], the author used deep learning to enable knowledge-based autonomous service delivery and proposed a multi-domain SDEON framework. This framework was supported by a broker plane consisting of deep learning-based traffic forecasting tools. Autonomous traffic engineering was performed according to the forecasted traffic captured by the integrated RMSA and deep neural network based traffic forecasting tools. The results showed reduced congestion and accurate traffic forecasts.

- Other applications

In [13], the author proposed an EON approach based on deep reinforcement learning. This agent implemented self-learning from dynamic network capabilities and learned fertile policies. The purpose of developing such a model was to realize cognitive and autonomous RMSA in elastic optical networks. The author used a convolutional neural network, also known as Q-net, to learn RMSA policies that take into account EON connectivity, spectral usage, and traffic requirements. During the training phase of the Q network, empirical response is the key to improving training performance and reducing training distribution. Also, one such key factor was to provide target action values. A standard 6-node network was used for simulation purposes and the results showed that the proposed method performed better than the standard approach. In [14], the author developed a framework for virtual network reconstruction that does not use the traffic demand matrix. We used Bayesian inference to derive the probability of considering a suitable virtual network for a particular traffic situation. The authors integrated the method of reconstructing a noisy virtual network and compared the proposed framework with it. Unlike the noise-induced method, the proposed framework did not change the virtual network unless it degraded performance. In the performance evaluation of the proposed method, you can use the traffic from the edge router to identify the traffic. Alternative situations and procedures to use the traffic demand matrix have reduced the number of virtual networks. Reconfiguration to get a virtual network that suits the traffic situation.

VI. FUTURE SCOPE

EON, including machine learning algorithms, can improve network performance. Obviously many optical network researchers are introducing tools to study machines for existing problems of EON, and these tasks can scale these tasks by applying more ways to educate machines. This section emphasizes several ways to teach potential areas and applicable machines in EON.

- Statistical Training Application

Statistical training belongs to many tools used to understand data. Locate the forecasting features based on data. Some of the statistical training may be applied to solve important issues in the elastic optical network domain. One of these areas that statistical training can be applied to is an issue that is not limited. The probability of failure is estimated based on current and past. It may not be possible to mention failure in accordance with a particular event.

- Semi Value Training Application

The obtained learning is also configured as an inscription and not noted data to classify some unresolved data using a labeled data set. In the optical network domain, the obtained learning can not only monitor the optical properties on the network, but also in the case of failure prediction.

- Neural Network Application

Neural networks are one of the most widely used machine learning tools used in optical networks.
Researchers predict traffic based on previous data. Few researchers have applied this method in the field of elastic optical networks. Using neural networks for traffic prediction in EON can reduce spectral fragmentation and crosstalk problems in EON.

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