International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Elastic Optical Networks Based Optimization Using Machine Learning: State-Of-Art Review

[1]Ruchi G. Dave, [2]Dr. Dolly Thankachan

Submitted: 03/11/2022 **Accepted:** 01/02/2023

Abstract: To address the issues and difficulties relating to network capacity, elastic optical networks have been developed. Elastic optical networks have been regarded as being primarily enabled by software and hardware resource optimization (EONs). Several Tb/s long-distance data transmission lines can benefit from elastic optical networks' improved spectral efficiency. Elastic optical networks now use machine learning (ML) approaches to facilitate automated processes and unlock more physical layer capacity. One drawback is that training environment—such as traffic pattern or structure of optical network—has a significant impact on how much is learned. Retraining is therefore necessary in cases of network topology or traffic pattern changes, which requires a lot of processing power and time. We examine and debate several ML applications in connection modelling, provisioning, and network control.

Keywords: *Elastic optical networks, data transmission line, link monitoring, Machine learning, link provisioning*

1. Introduction

Space division multiplexed elastic optical networks (SDM-EONs) can meet the recent increases in bandwidth needs brought on by cloud-based services, 5G and 6G communications, high resolution game streaming, and data centre networks [1]. The ability to adjust transmission parameters and boost spectral efficiency has been made possible by developments in coherent optical transmission. Across the use of distance adaptive multicarrier transmission, SDM-EON permits the parallel transmission of optical signals through multicore fibres (MCFs). However, intercore crosstalk (XT) between weakly linked cores causes quality of transmission (QoT) of signals sent through MCF to deteriorate [2]. With a collection of continuous and contiguous frequency slices, light streams are routed through cores on the links of the route in SDM-EON (FSs). Theoretically, if the physical characteristics and core geometry are identical, a multifiber connection and an MCF link have the same capacity for transmission. However, due to the compact structure of weakly linked cores and the degradation in QoT caused by XT, the signal transmission in MCF differs from that in multifiber links. The impact of XT must therefore be addressed, and it must be handled properly. XT levels are impacted by the choice of multiefficient modulation forms (MFs). Optical networks that carry bulk of data traffic are expected to offer a range of bandwidth resources to accommodate current traffic demands. Effective network management allots resources in the best way possible, minimises resource waste, and boosts actual network throughput [3].

ruchi13nagar@gmail.com[1]
drdolly2709@gmail.com[2]

Even though the traffic request has a low bit rate, WDM networks require a full wavelength, which limits the utilisation of the spectrum. However, the lowest resource granularity in conventional wavelength division multiplexing (WDM) networks is fixed-sized spectrum grids. The problem is addressed by suggesting an elastic optical network (EON) based on orthogonal frequency division multiplexing (OFDM). The available spectrum is split up by EON into slots with a bandwidth of 12.5GHz or less. Lower bit rate traffic might be given smaller spectrum slots, maximising the use of the available spectrum. In order to reduce expense of wavelength conversion devices, data transferred between source node and destination node in EON must utilise same spectrum slots, sometimes referred to as spectral continuity restriction. Routing and spectrum allocation (RSA) thus becomes the main issue in EON, where lightpath is defined as a mix of routing path as well as spectrum slots granted to traffic request.

Because they are more adaptable than WDM optical networks in terms of SA and grid layout, elastic optical networks are favoured over WDM networks. While EON uses a collection of frequency slots with finer bandwidths to partition the spectrum, WDM optical networks have fixed bandwidths of 50GHz or 100GHz. ML methods are applied in EONs to automate processes and harvest additional volume from physical layer. Application of ML in EON is primary subject of this essay. As seen in Fig. 1, real-time monitoring capabilities, accurate link methods, and potent network management as well as control methods are necessary for an intelligent as well as automated optical network [4].

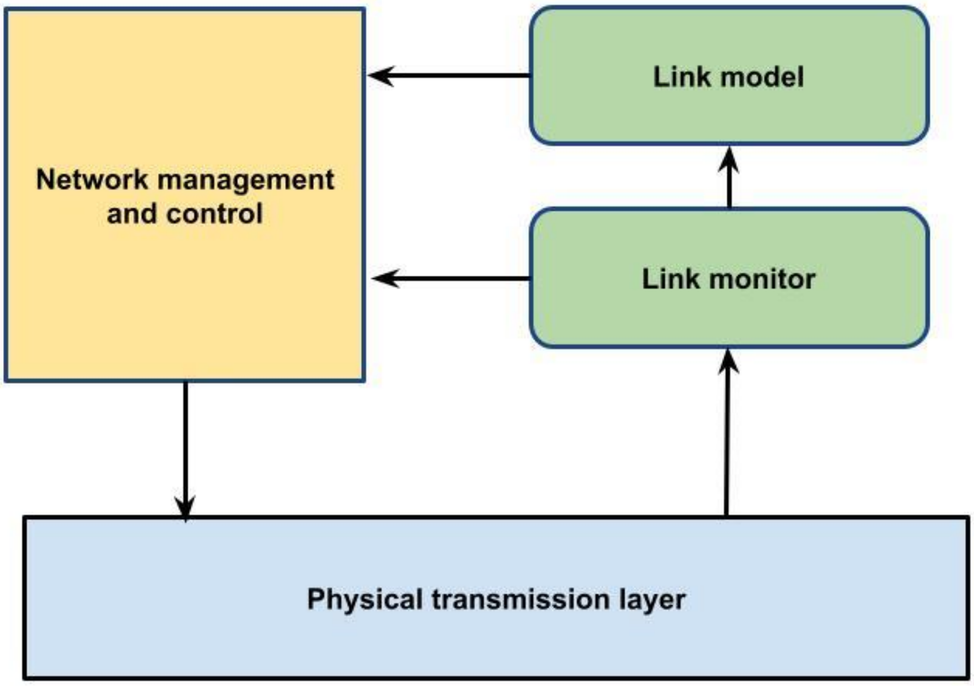

Fig. 1: Intelligent and automated optical network.

2. Routing Approach in EON

There is a wavelength-selective BV switch installed in cross-connect. During add or delete function, filter the signal. Planned research Numerous scholars have looked on spectrum assignment (RSA) in the past. The act of selecting an executable path for data transfer is known as routing, and the process of allocating spectrum to meet traffic demand is known as spectrum mapping. There are various sorts of spectral assignments, all of which must adhere to spectral constraints [5]. Data transfer is the act of moving data from a single source to numerous destinations. transmission of data using multicast. Applications for multicast are common. Video lectures are among the multicast applications. A little distance learning, online meetings, IPTV, etc. Broadcast and selection mechanisms support multicast transmission. Additionally prohibited are BV transponders and undesired broadcasts. BV wavelengths are linked. All fibre optic connections are a part of optical path, which is an optical data transmission link in optical network. This route always has same frequency range assigned to it. Light tree also provides an uninterrupted spectral path to every target.

3. Protection Approach of EON

The multicast data type implements a light tree, whereas data transfer implements a write path for a unicast data type. The two types of network protection technologies are exclusive protection and common protection. Shared protection include protective capacity, which may be shared. Dedicated protection is what you get when the protection cannot be shared. working with particular protective systems It is safeguarded by a specific backup capability. Multiple traffic requests may share one protection capacity when using common protection schemes. Each job path fails independently. shared defence In comparison to dedicated protection, it is more capacity efficient.

4. Machine Learning Approach in EON

Machine learning has three primary phases. I The model receives data as input. The model trains on the data in steps II and III, and some operations are carried out on output of trained data. Supervised learning, unsupervised learning, and reinforcement learning are three categories of ML. Algorithms are used in supervised learning, which is based on known outcomes and existing patterns and information. The output is sent to a computer, which analyses the data for patterns and applies training tasks to create a method that generates the intended outcomes in a fresh collection of data. In supervised learning, having enough data to cover all data alternatives is the main challenge. A huge data set should have data randomly selected from it. Otherwise, bias might manifest. Decision trees, nearest neighbours, regression analysis, SVMs, and ANNs are a few common supervised learning algorithms. Some variables in unsupervised learning are unidentified and unclassified. Unseen patterns are found by machines, which then form groups based on them. Analysis of the patterns is possible as more are found [6]. K-means clustering, association analysis, dimensionality reduction methods, and social network analysis are examples of unsupervised algorithms. Reinforcement learning is one of the most sophisticated subcategories of ML. In reinforcement learning, a model is improved by an algorithm that runs a series of random trials and errors and integrates feedback from the process. The model is trained by algorithms using ongoing learning. With reinforcement learning, a specific outcome is sought after through trial and error using a variety of input combinations. Results from the standard model are assessed using a set of performance measures. In comparison to conventional high density division multiplexing, elastic optical networks (EONs) have improved spectrum efficiency thanks to the employment of techniques like flexible spectral grids, OFDM, DWDM. Now you can utilise it. In elastic optical networks, machine learning (ML) technology enables automated operations and increases physical layer capacity. There are numerous uses for ML, including connection modelling, preparation, monitoring, and network administration [7].

5. Monitoring based on EON

Optical networks need to make greater use of network resources if they want to operate at high capacity. In many situations, a large design margin is necessary to account for the discrepancy between the anticipated metrics and the actual value in order to assure optimal network functioning because a planning tool cannot reliably forecast QoT. A large margin may cause the spectrum resources to be underutilised. On the other hand, controllers should be able to receive real-time status of networks to improve dependability of optical networks and avoid major system degradation. Advanced OPM approaches are necessary to enable necessary functionality to monitor QoT as well as impairments in order to do this. The monitoring techniques should be able to locate, identify, and recognise optical network faults if they do occur. In conclusion, the important components of the next generation EON are modelling and monitoring methodologies. Figure 2 [8] depicts the fundamental architecture of the modelling and monitoring techniques.

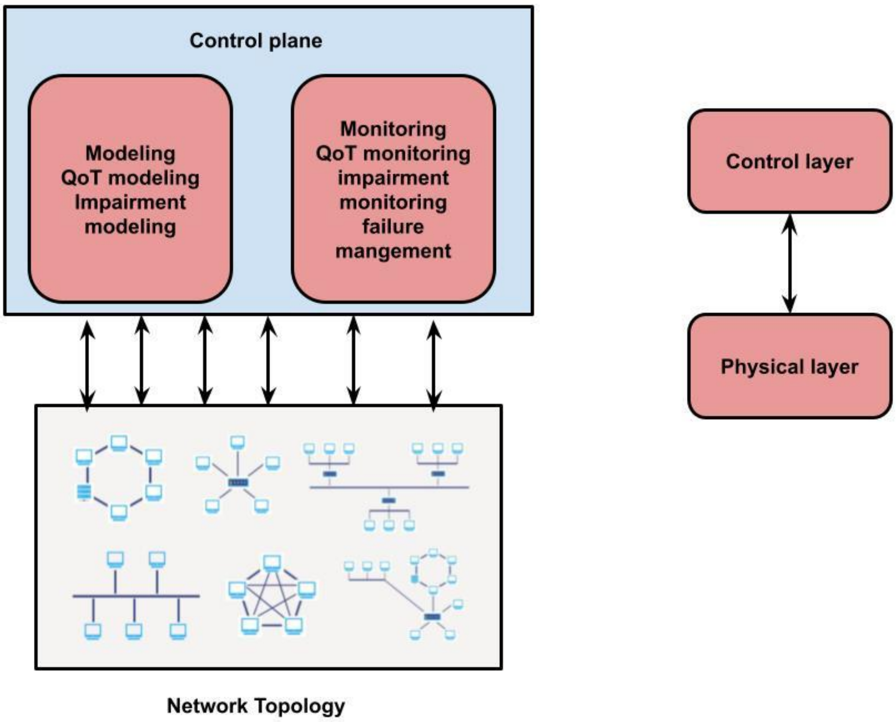

Fig. 2. Applications of modeling and monitoring methods in optical networks.

A few models are used in the modelling process to determine whether a lightpath satisfies the QoT criteria for establishment. Some are used to calculate a specific impairment or QoT value. There are some difficulties with EON for conventional analytical models. First of all, accuracy and complexity are frequently tradeoffs. Although the complexity of some complicated analytical models, such as the split-step Fourier technique (SSFM), which may capture many impairments with high precision, may be prohibitively large. It is possible to quickly construct some approximate methods, such as GN method, but accuracy must be increased, particularly for heterogeneous and dynamic networks. Moreover, it is challenging to find a single model that fits all cases due to the variability of EON. For some cases, estimation results of the methods may appear to have a significant variance in this case [9].

6. State of the Art ML Methods Applied to EON

To examine a current issue in EON, researchers have used several machine learning approaches, including supervised, reinforcement, and ANNs. The current machine learning methods used in optical networks can be roughly categorised into the following categories: I determining or forecasting transmission quality, ii) predicting failures, iii) predicting traffic, and others.

6.1 Assessing or predicting QoS

The authors of [10] suggested a data-driven methodology for EON bandwidth distribution that takes the network's quality-of-service (QoS) requirements into account. The bandwidth allocation issue is solved through reinforcement learning (RL). The network's quality-of-service needs can be met by this structure, which is adaptable to rising network traffic. Bandwidth allocation (BA) issue is represented as a Markov decision process with imperfect observation (POMDP). The architecture is made scalable utilizing POMDP and RL, and a central controller keeps track of how well the joint PBA model is performing in meeting quality-of-service standards. In the event that QoS criteria are not met, the model is modified using a reward function. PBA method output is taken into consideration as input to RSA method, which is utilised to do network re-optimization, for each reward optimization function. Results of an ILP formulation method and heuristic technique show that the network bandwidth could be effectively employed if reward function could be adjusted.

6.2 Surviability

In [11], authors use DRL to investigate challenge of network performance optimization while taking EON survivability into account. Goal is to increase network's cost effectiveness while simultaneously offering a solution for survival. The use of two agents—one to offer a functional scheme and the other to provide a protection scheme—in a DRL approach is suggested as a way to provide resilient routing, modulation, and spectrum assignment policies. The reward collection function is implemented into this strategy to boost cost efficiency. The simulation results demonstrate that the network's overall performance is maximised with a reasonable blockage rate and that there are viable options for situation of a single link failure. In [12], authors create and experimentally test a multi-layer software-defined IP over EON restoration method. A congestion-aware rerouting solution uses the restoration process, which may quickly restore failed traffic. This study makes use of DL that is based on a NN or short-term memory.

6.3 Traffic prediction

For estimating traffic in cloud data centre networks, the author of [13] suggests a Monte Carlo Tree Search method. This search method determined most suitable cloud data centre as well as candidate path-pair combination utilized for routing requests for a specific request. Monte Carlo sampling is used to implement selection when creating a sparse tree. The proposed methodology demonstrated higher performance in terms of flexibility and time when results of this method were compared to those of ANN-based technique. Goal was to forecast traffic and evaluate a traffic prediction system using dynamic routing algorithms. The method for predicting traffic could be used with various frameworks. Compared to other EON algorithms, the suggested traffic prediction method outperformed them. The authors of [14] proposed a framework for multi-domain SD-EON and used DL to attain knowledge-based autonomous service provisioning. A broker aircraft, which included a tool for predicting traffic based on deep learning, supported this framework. An integrated RMSA and DNN traffic prediction tool was used to execute autonomous traffic engineering based on the traffic predictions that were made. Reduced blockage and precise traffic prediction were the outcomes. An integrated RMSA as well as DNN traffic prediction tool was used to execute autonomous traffic engineering based on the traffic predictions that were made. Reduced blockage and precise traffic prediction were the outcomes.

6.4 Others

The authors of [15] suggested a DRL-based method for EON. Using dynamic network functions, this agent implemented self-learning and picked up useful policies. To realise cognitive and autonomous RMSA in EON was goal of designing such a model. The authors learned RMSA policies taking connectivity, spectrum utilisation, and traffic requests in EON into account using a CNN, often known as a Q network. An additional important component was the deployment of the target action-value. Six-node standard network was utilised for simulation, and results revealed that suggested method performed better than traditional methods. Authors of [16] created a framework for reconfiguring virtual networks without using a traffic demand matrix. The likelihood of taking into account a VN that was appropriate for a traffic condition and based on pre-specified traffic situations was inferred using a Bayesian inference method. The authors contrasted the suggested framework with a noise-induced VN reconfiguration method. Suggested framework did not alter a virtual network unless it performed poorly, in contrast to noise produced method. The suggested method's performance evaluation could identify traffic situations using edge router traffic rather than a traffic demand matrix, and it required less VN reconfigurations to get right VN for the situation.

7. Discussion

EON, during the network planning phase, several programmable characteristics like modulation format, symbol rate, and physical path in ON affect how accurate QoT and impairment models are. The estimations of QoT may deviate from the actual value if these factors are not precise [17]. In this instance, a high design margin is required due to the inaccuracy of the planning tools, and networks are overutilized to prevent network degradation until EoL. As a result, more accurate QoT methods are preferred, and impairment method can provide light on contributions made by every unique impairment to improve the performance of QoT estimators. Some conventional techniques can estimate an optical link's performance in terms of SNR, pre-forward error correction (FEC), bit error rate (BER), OSNR, and other metrics for QoT modelling. Traditional techniques may estimate certain significant physical layer effects for impairment modelling, including fibre nonlinearity, optical filtering effect, and amplified spontaneous emission (ASE) noise [18].

8. Conclusion:

This study provides a concise overview of recent advances in EON utilising machine learning approaches and presents cutting-edge methods. Planning techniques with greater precision are needed to increase optical networks' capacity. Accurate optical performance monitoring is also sought to increase optical networks' dependability. In this research, we evaluate numerous prior efforts on modelling and monitoring methods supported by machine learning (ML) in elastic optical networks. First, we looked at QoT and impairment modelling requirements. The benefits of using ML approaches for this work are then examined after analysing numerous ML-based modelling strategies. Then, we examine and discuss a number of studies on ML-based monitoring strategies for estimating QoT/impairment and managing failures. ML techniques offer a promising option to construct a dependable optical network with a smaller margin. Reviewing earlier publications that utilised machine learning techniques for modelling and monitoring, we found that ML performed better than many conventional approaches in terms of scalability, efficiency, and robustness. Future ML research will focus more on creating an effective, dependable, and self-sufficient optical network.

Reference

[1] Aibin, M. (2018). Traffic prediction based on machine learning for elastic optical networks. Optical Switching and Networking, 30, 33-39.

[2] Luo, X., Shi, C., Wang, L., Chen, X., Li, Y., & Yang, T. (2019). Leveraging double-agent-based deep reinforcement learning to global optimization of elastic optical networks with enhanced survivability. Optics express, 27(6), 7896-7911.

[3] Salani, M., Rottondi, C., Ceré, L., & Tornatore, M. (2022). Dual-Stage Planning for Elastic Optical Networks Integrating Machine-Learning-Assisted QoT Estimation. IEEE/ACM Transactions on Networking.

[4] Liu, X., Lun, H., Fu, M., Fan, Y., Yi, L., Hu, W., & Zhuge, Q. (2020). AI-based modeling and monitoring techniques for future intelligent elastic optical networks. Applied Sciences, 10(1), 363.

[5] Tian, X., Li, B., Gu, R., & Zhu, Z. (2021). Reconfiguring multicast sessions in elastic optical networks adaptively with graph-aware deep reinforcement learning. Journal of Optical Communications and Networking, 13(11), 253-265.

[6] Tang, B., Huang, Y. C., Xue, Y., & Zhou, W. (2022). Deep Reinforcement Learning-Based RMSA Policy Distillation for Elastic Optical Networks. Mathematics, 10(18), 3293.

[7] Zhang, J., Qian, F., & Yang, J. (2022). Online routing and spectrum allocation in elastic optical networks based on dueling Deep Q-network. Computers & Industrial Engineering, 173, 108663.

[8] Tang, B., Huang, Y. C., Xue, Y., & Zhou, W. (2022). Heuristic reward design for deep reinforcement learning-based routing, modulation and spectrum assignment of elastic optical networks. IEEE Communications Letters, 26(11), 2675-2679.

[9] Pinto-Ríos, J., Calderón, F., Leiva, A., Hermosilla, G., Beghelli, A., Bórquez-Paredes, D., ... & Saavedra, G. (2022). Resource Allocation in Multicore Elastic Optical Networks: A Deep Reinforcement Learning Approach. arXiv preprint arXiv:2207.02074.

[10] Mukherjee, A., & Choudhury, P. D. (2022). Recent Developments on Elastic Optical Networks: A brief

Survey. American Journal of Electronics & Communication, 3(2), 16-20.

[11] Trindade, S., Torres, R. D. S., Zhu, Z., & Fonseca, N. L. D. (2021). Cognitive control-loop for elastic optical networks with space-division multiplexing. Sensors, 21(23), 7821.

[12] Agarwal, A., Misra, G., & Agarwal, K. (2022). A Review and Analysis on Elastic Optical Networks (EONs): Concepts, Recent Developments and Research Challenges. Journal of The Institution of Engineers (India): Series B, 1-6.

[13] Zhu, R., Samuel, A., Wang, P., Li, S., Oun, B. K., Li, L., ... & Yu, S. (2021). Protected resource allocation in space division multiplexing-elastic optical networks with fluctuating traffic. Journal of Network and Computer Applications, 174, 102887.

[14] Li, R., Gu, R., Jin, W., & Ji, Y. (2021). Learning-based cognitive hitless spectrum defragmentation for dynamic provisioning in elastic optical networks. IEEE Communications Letters, 25(5), 1600-1604.

[15] Tang, F., Shen, G., & Rouskas, G. N. (2021). Crosstalk-aware shared backup path protection in multi-core fiber elastic optical networks. Journal of Lightwave Technology, 39(10), 3025-3036.

[16] Aibin, M., & Walkowiak, K. (2018, August). Monte Carlo tree search for cross-stratum optimization of survivable inter-data center elastic optical network. In 2018 10th International Workshop on Resilient Networks Design and Modeling (RNDM) (pp. 1-7). IEEE.

[17] Zhu, R., Li, S., Wang, P., & Yuan, J. (2020). Time and spectrum fragmentation-aware virtual optical network embedding in elastic optical networks. Optical Fiber Technology, 54, 102117.

[18] Yao, Q., Yang, H., Bao, B., Yu, A., Zhang, J., & Cheriet, M. (2021). Core and spectrum allocation based on association rules mining in spectrally and spatially elastic optical networks. IEEE Transactions on Communications, 69(8), 5299-5311.