Optical Networks

Nolen Belle Bryant, Kwong Keung Chung, Jie Feng, Sommer Harris, Kristine Umeh

I. INTRODUCTION

Optical networks refer to network communication used to exchange information through an optical fiber cable. It uses signals encoded in light to transmit various types of information from the sender node to the receiver node.

It is almost guaranteed that this paper is being read on a device with internet access. By 2023, 66% of the global population will be Internet users, an increase of 15% from 2018 [1]. The currently projected growth of traffic demands would cause significant bandwidth bottlenecks within the conventional optical network technology [2]. This rapidly increasing demand on bandwidth is pushing the evolution of more flexible, efficient, and scalable optical networks. The traditional wavelength division multiplexing (WDM) networks are limited by their fixed wavelength assignment which leads to underutilized spectrum. One solution to this problem and the main candidate for the future of optical transmission technology is elastic optical networks (EON) [3].

This paper is an implementation of a machine learning algorithm to optimize the handling of traffic requests within a simulated EON through considering the factors of the Routing, modulation, and spectrum assignment (RMSA) problem.

A. Importance of Elastic Optical Networks

Many of the parameters which had to be constants in the WDM networks, such as modulation format and wavelength space between channels, can now be dynamically changed based on the demands of the systems. The newer optical orthogonal frequency-driven multiplexing (O-OFDM) technology allows for greater bandwidth efficiency by allocating spectrum into multiple, narrow slices according to the request.

However, the increase in the elasticity of these networks requires more sophisticated and dynamic algorithms which can utilize the new flexible spectrum technologies to handle high traffic without violating the constraints of the system [4]:

- ***Spectrum contiguity, spectrum continuity and slice opacity:*** the required spectrum slots must be adjacent, they must be available in all the links of the route, and until the assignment is finished, they cannot be reallocated [5]

To meet all of those challenges, researchers are implementing RMSA algorithms.

B. The RMSA Problem

Routing, modulation, and spectrum assignment (RMSA) are the features that the algorithm will choose for each request.

A route is the path the light travels on from source to destination. When a route is static, the route from source to destination can be set before the light has started traveling through the network, while with a dynamic route, the route may be adjusted in path, depending on the resources available [4].

Modulation is how the light wave carrying data through the optical fiber is altered. The data that is coded and sent through the beam is not changed in modulation, but the beam itself is altered. We can think of this as similar to refracting light or changing the amplification of a wavelength. There are six modulation formats that we will consider in the scope of this project: BPSK, QPSK, 8-QAM, 16-QAM, 32-QAM, and 64-QAM. Each modulation has benefits or tradeoffs to consider for each signal, depending on the path length, bit rate, and Optical Signal to Noise Ratio (OSNR) [3].

Spectrum assignment is how we allocate segments of the signal spectrum to carry client requests, avoiding frequency overlapping. There are different kinds of allocation policies- or 'fits' for assigning connection requests to spectrum segments [3].

C. Reinforcement Learning Strategy

Reinforcement learning is a type of machine learning which is well suited for sequential decision making due to the action-value learning cycle which defines 'good' behavior incrementally [7]. Reinforcement learning can provide strong, adaptive, and economical solutions to complicated and large-scale challenges.

Q-learning is an off policy reinforcement learning algorithm as it learns from acts outside the existing policy by doing all possible actions. In particular, q-learning is about learning a strategy which maximizes the overall reward. So by trying all actions in all states repeatedly, it learns which are best overall, judged by long-term discounted reward [8]. Reinforcement Learning can provide strong, adaptive, and economical solutions to complicated and large-scale challenges. Different algorithms with specific structures were suitable for different problems and specialized in different data types.

II. RELATED WORKS

Different methods for optimizing just the spectrum assignment portion of RMSA have been researched. Some of the most common methods include: First Fit provides lower call blocking probability and computation complexity [3]. Random Fit is good for reducing the possibility of multiple connections being allocated to the same spectrum [3]. First-Last Fit is expected to provide more contiguous aligned segments than Random and First Fit [6]. It is also the most efficient with the least blocking [6], and that Exact Fit is a good way to reduce the fragmentation problem in optical networks [3].

Other papers focus specifically on the routing and or the modulation [9][10]. Savory prioritized shortest route paths which avoid the links with highest spectral usage [11].

Many researchers who are proposing entire RMSA solutions, as opposed to those focusing on one portion, are doing it with machine learning. Zhou et al demonstrate an adaptive genetic algorithm [12].

Machine learning algorithms are being used in numerous areas, such as traffic prediction [13], and regenerator placement optimisation [18]. Though there are a few optical network papers specifically using Q-learning algorithms, all the ones we found have either been using deep Q-learning [14] and or are applying the q-learning algorithm to different areas of optical networks such as edge scheduling [15], policy determination [16], or optimizing WDMA wireless optical networks [17].

We therefore believe that the application of a q-learning algorithm to the RMSA problem with the optimization goal of lowering the overall Blocking Proportion of the requests is novel. We will implement our Q-learning algorithm within the CEONS simulator [19].

III. Problem Statement

Our goal is to find the most efficient path [fig 1] from source node to destination node for each request such that the overall blocking percentage (BP) is minimized for the full set of requests. As traffic requests and content demand increases globally, networks will require more intelligent routing algorithms, and Q-learning is a potential fit for this environment.

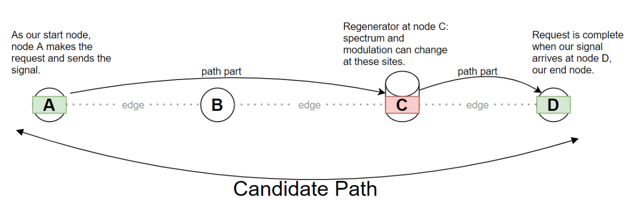

Fig. 1. Path Structure and Definitions: A candidate path is shown here. Note that the path parts will be combined to complete the request from source to end nodes (green). Path parts begin at source node or at a node with a regenerator (red) and end at end node or node with a regenerator. Paths may use different modulations.

A. Network Model Notation

We will use the same network notation as other papers operating within CEONS [4][18][19]. The optical network is represented as a graph $G(V, E, B, L)$ where V is the set of nodes, E is the set of fiber links (directed edges), B the maximum number of frequency slices that each fiber link can

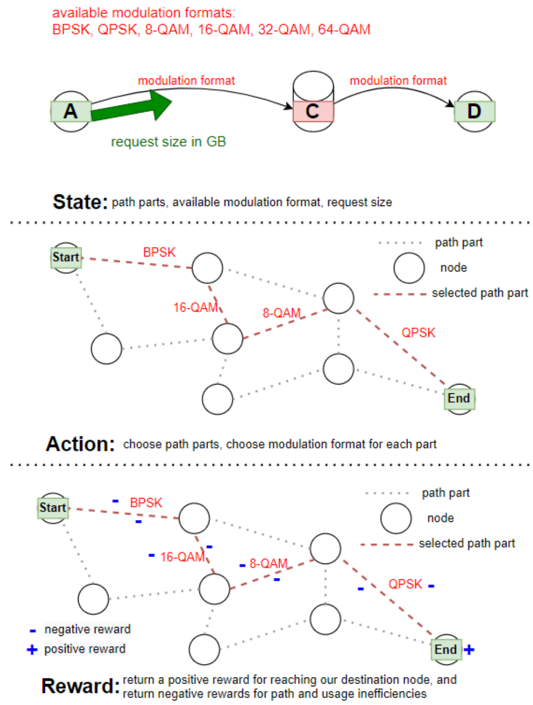

Fig. 2. State, Action, and Reward: Our state is defined as path parts with available modulation formats, and the request size. Our action is defined as choosing the path parts for the request, from source to terminal node, and choosing modulation formats for each of those parts. Our reward will be calculated by taking into account factors such as distance, slices occupied, regenerators used, spectrum used up, regenerators used up, request blocked and destination reached. Our algorithm will give a negative reward for each additional path part, and when modulations are chosen, there are negative rewards for modulation inefficiencies.

accommodate, and L is the fiber link lengths for each $e \in E$. There are six modulation formats that we will consider for each network: $BPSK$, $QPSK$, $8-QAM$, $16-QAM$, $32-QAM$, and $64-QAM$. The set of modulation formats is denoted by M. For each $m \in M$, we have the maximum distance which is supported by that modulation given as $dist(m)$.

During the simulations, a set D of requests is created with each point in time indicated by $t \in T$. The bit rate of each request $c(d)$ is used to calculate the number of slices needed $n(c(d), m)$ for a modulation m. We will exclude the first 50k requests from our results calculations as we have chosen that to be our train stage. The blocked requests included in set Dbl will be used to calculate the final Blocking Percentage of the simulation run.

B. Optimization Problem

Fundamentally, we are hoping to optimize the traffic handling in the optical network through considering the routing, modulation, and spectral assignment to find the most efficient candidate path which therefore reduces the total Volume Blocking Percentage [Eq. 1]. Requests could be blocked due to modulations which cannot make the distance to the next node or required frequency slices of spectrum which is unavailable in the path edge.

$$BP = (SpectrumBlockedVolume + RegeneratorBlockedVolume + LinkFailureBlockedVolume)/TotalVolume \quad (1)$$

Our q-learning algorithm will train it's q-table with the first 50k requests from D by exploring and rewarding possible actions included in set A from the states included in set S within the requested paths [fig 2]. The Q-table contains the "quality" score of the action a from the state s. The score $Q(s, a)$ is the maximum expected future reward expected from taking that action at that state.

During training, the Q-table is updated iteratively through exploration and calculated using the Bellman Equation [Eq 2].

$$\Delta Q(s, a) = Q(s, a) + \alpha * TD$$
$$TD = r + \gamma(maxQ(s', a') - Q(s, a)) \quad (2)$$

In the equations above, α is the learning rate ($0 < \alpha \leq 1$), the factor determining exploration v exploitation by weighting the importance of newly acquired scores. r is the reward calculated from R reward function. γ is the discount factor ($0 < \gamma \leq 1$) the factor weighting the importance of future rewards.

The rewards will be calculated with the function R(distance, slices, regenerators, usedUpSpectrum, usedUpRegenerators) with the reward scoring detail per factor summarized in figure 3. If a candidate path is allocated successfully,

Factor	Reward Impact
Distance	Shorter distance = slightly higher reward
Slices occupied	Fewer slices occupied = higher reward
Regenerators used	Fewer regenerators used = higher reward
Spectrum used up	If true = significantly lower reward
Regenerators used up	If true = significantly lower reward

Fig. 3. The relationship between action results and reward scoring.

$$R = 100 * (1 - MaxPathOccupiedSlices\%),$$

else,

$$R = -1800$$

then for each part of the path,

$$R = (RAbove * PartLength)/SupportedModulationLengthForThatVolume$$

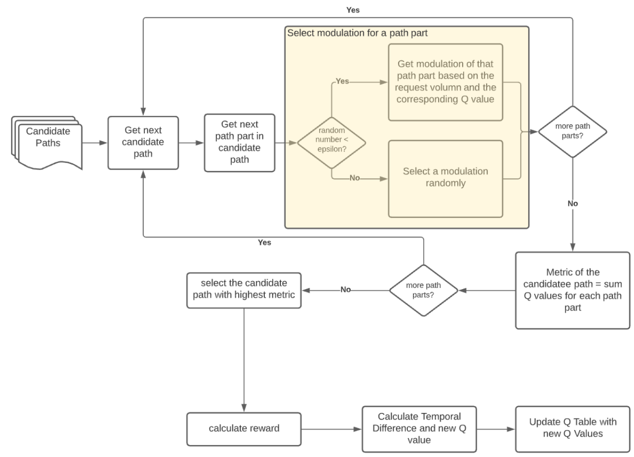

Fig. 4. Q-learning algorithm flow chart

After adapting our Q-learning algorithm to this problem [fig 4], We can assess Q-learning's potential by running simulations and comparing the results with those of other algorithms. In our simulations, we will compare our Q-learning results with results from a Shortest Path First (SPF) algorithm and an Adaptive Modulation and Regenerator-Aware (AMRA) dynamic routing algorithm.

IV. Simulation

A. Network topologies

This study uses the CEONS simulator and its topologies: US26 and Euro28, shown in [fig 5]. US26 has 26 network nodes while Euro28 has 28 network nodes.

Regenerators are used for amplifying the signals or changing modulation format in path. All of our AMRA and SPF simulations ran on topologies that had net 100 regenerators. We collected data for our Q-learning algorithm (QL) on topologies with net 100 regenerators.

Fig. 5. Euro28 (top), US26(bottom)

B. Dynamic Routing

We divided the simulations up by number of candidate paths: 2, 3, 5, 10, and 30. Then within each of those categories we divided the runs up by Erlang values (traffic intensity): 300, 400, 500, 600, 700, 800 and 900. For each candidate path and Erlang pair, we ran a simulation for the SPF and AMRA algorithms on a map with net 100 regenerators. We ran a simulation for each configuration, for example: US26, QL, Erlang at 600, and candidate paths at 30. The number of requests was set at 100000 for all of our simulations [fig 6].

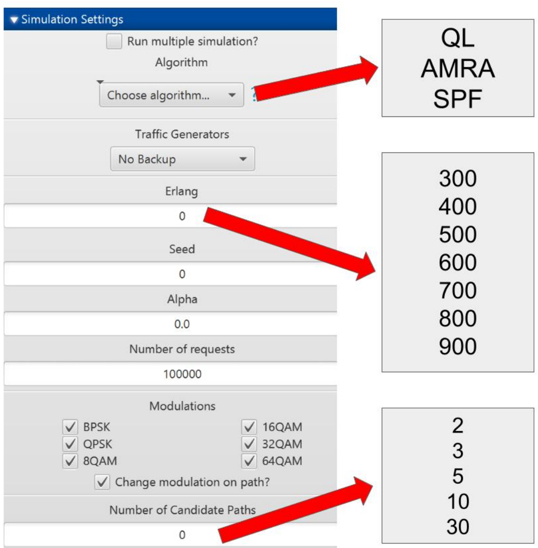

Fig. 6. Simulation Settings Summary

V. Results

Our main measure of algorithm efficiency is the total blocking volume percentage (BP). The BP results of our q-learning algorithm compared to the AMRA SPF algorithms in the Euro28 network are presented in figure 7, and the BP results from the US26 network are presented in figure 8. Q-learning significantly out performs SPF though the BP does increase quickly from 700 - 900 Erlangs. It performs at it's worst at erlangs 700 and higher and at candidate paths 10 30. Those simulations result in q-learning BP of around 15% greater than AMRA and 40% less than SPF.

We then separately analyzed the individual components calculated in the total blocking volume percentage (BP). Link failure spectrum blockage was 0% in all simulations and is therefore ignored here. The spectrum blocking percentage of all simulations in the EURO28 network and the US26 network are represented in figure 9 and 10 respectively. The regenerator blocking percentage of all simulations in the EURO28 network and the US26 network are represented in figure 11 and 12 respectively.

Of all three algorithms, q-learning performs the worst in regards to spectrum assignment, especially at Erlangs of 700 and higher.

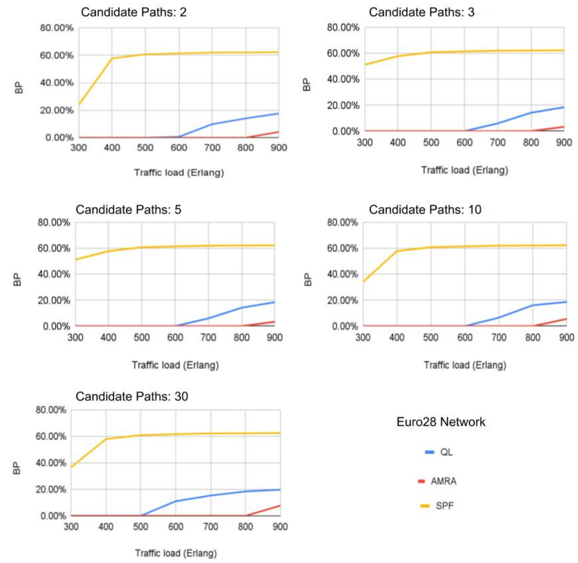

Fig. 7. Total volume blocking percentage (BP) at each traffic load in the Euro28 network

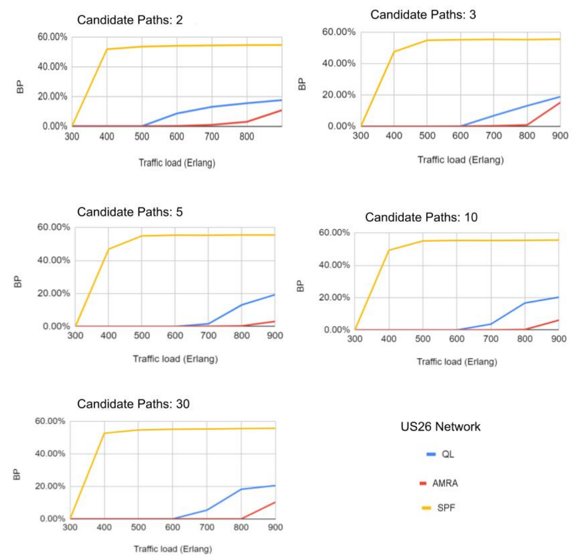

Fig. 8. Total volume blocking percentage (BP) at each traffic load in the US26 network

AMRA and q-learning perform almost identically in the regenerator blocked percentage, and the SPF values are consistently high.

VI. Discussion

We have shown here that q-learning algorithms are clearly capable of being adapted to facilitate RMSA assignment within Elastic Optical Networks. Though our BP was not as low as AMRA, we are confident that this study proves proof of the potential. Future work on this algorithm could include training on a significantly larger volume and reworking the Qvalue reward system to lower the spectrum blocked percentage.

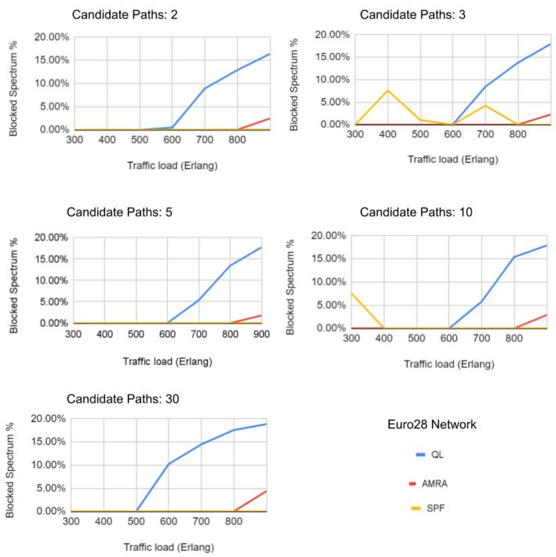

Fig. 9. Spectrum blocked volume percentage at each traffic load in the Euro28 network

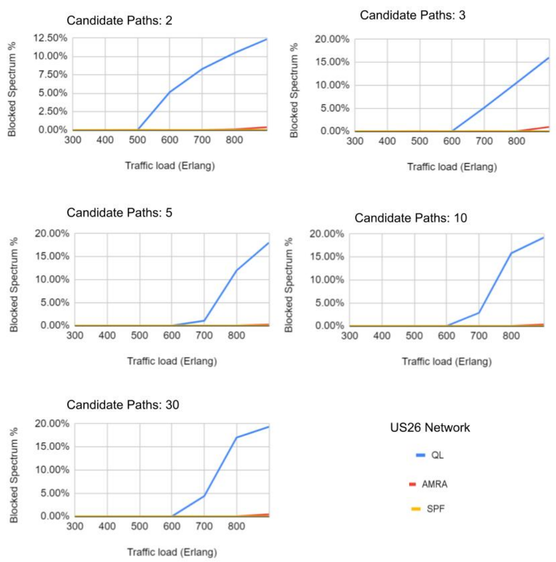

Fig. 10. Spectrum blocked volume percentage at each traffic load in the US26 network

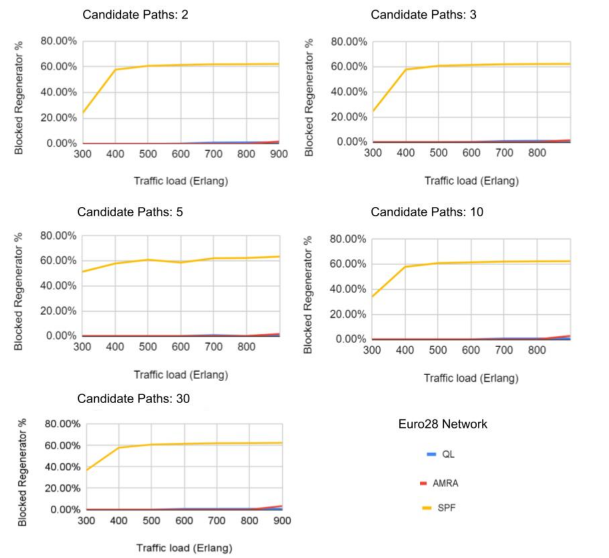

Fig. 11. Regenerator blocked volume percentage at each traffic load in the Euro28 network

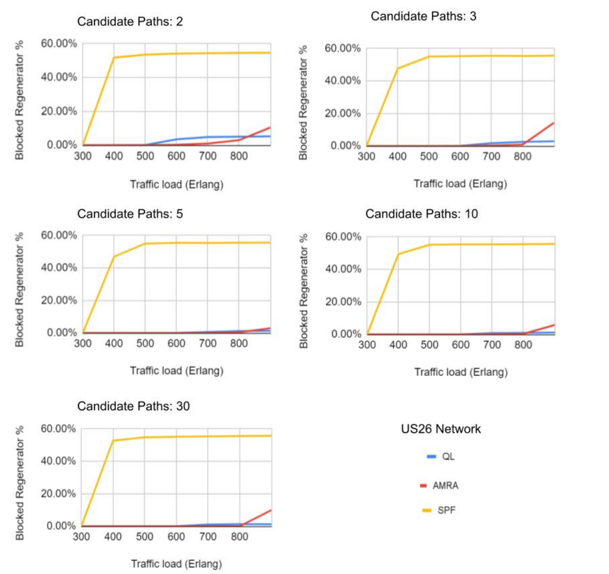

Fig. 12. Regenerator blocked volume percentage at each traffic load in the US26 network

REFERENCES

[1] Cisco Annual Internet Report: Executive Summary, (2018 - 2023).

[2] M. Jinno et al., "Spectrum-efficient and scalable elastic optical path network: Architecture, benefits, and enabling technologies," IEEE Commun. Mag., vol. 47, no. 11, pp. 66–73, Nov. 2009.

[3] Chand Chatterjee, B., Sarma, N., & Oki, E. (2015). Routing and Spectrum Allocation in Elastic Optical Networks: A Tutorial. IEEE COMMUNICATION SURVEYS TUTORIALS, VOL. 17(NO. 3), THIRD QUARTER 2015.

[4] Aibin, Michal. (2017). Dynamic Routing Algorithms for Cloud-Ready Elastic Optical Networks. 10.13140/RG.2.2.26460.80000.

[5] Xavier, A., Almeida Jr., R., Martins-Filho, J., Chaves, D., & Bastos-Filho, C. (2017). Spectrum Continuity and Contiguity based Dedicated Protection for Flexible Optical Networks. Journal Of Microwaves, Optoelectronics And Electromagnetic Applications, 16(2), 481-493.

[6] Yuan, J., Ren, Z., Zhu, R., Zhang, Q., Li, X., Fu, Y. (2018). A RMSA algorithm for elastic optical network with a tradeoff between consumed resources and distance to boundary. Optical Fiber Technology, 46, 238-247. doi: 10.1016/j.yofte.2018.10.020

[7] Vincent François-Lavet, Peter Henderson, Riashat Islam, Marc G. Bellemare and Joelle Pineau (2018), "An Introduction to Deep Reinforcement Learning", Foundations and Trends in Machine Learning: Vol. 11, No. 3-4. DOI: 10.1561/2200000071.

[8] Watkins, Christopher JCH, and Peter Dayan. "Q-learning." Machine learning 8.3-4 (1992): 279-292.

[9] M. Jinno et al., "Distance-adaptive spectrum resource allocation in spectrum-sliced elastic optical path network [topics in optical communications]", IEEE Commun. Mag., vol. 48, no. 8, pp. 138-145, Aug. 2010.

[10] J. Jue and G. Xiao, "An adaptive routing algorithm for wavelength-routed optical networks with a distributed control scheme", Proc. IEEE 9th ICCCN, pp. 192-197, 2002.

[11] S. J. Savory, "Congestion Aware Routing in Nonlinear Elastic Optical Networks," in IEEE Photonics Technology Letters, vol. 26, no. 10, pp.

1057-1060, May15, 2014, doi: 10.1109/LPT.2014.2314438.

[12] X. Zhou, W. Lu, L. Gong, and Z. Zhu, “Dynamic RMSA in elastic optical networks with an adaptive genetic algorithm,” in Proc. IEEE GLOBECOM, 2012, pp. 2912–2917

[13] Michal Aibin, “Traffic prediction based on machine learning for elastic optical networks, Optical Switching and Networking”,Volume 30, 2018, pp. 33-39, ISSN 1573-4277

[14] Abrahão, D., Vieira, F. (2016). Resource allocation algorithm for LTE networks using fuzzy based adaptive priority and effective bandwidth estimation. Wireless Networks, 24(2), 423-437. doi: 10.1007/s11276-016-1344-6

[15] Q. Zhang, M. Lin, L. T. Yang, Z. Chen, S. U. Khan and P. Li, ”A Double Deep Q-Learning Model for Energy-Efficient Edge Scheduling,” in IEEE Transactions on Services Computing, vol. 12, no. 5, pp. 739-749, 1 Sept.-Oct. 2019, doi: 10.1109/TSC.2018.2867482.

[16] K. Zhan, H. Yang, J. Li, G. Zhao, B. Wang and J. Zhang, ”Demonstration of Intent Defined Optical Network: Toward Artificial Intelligence-Based Optical Network Automation,” 2020 International Wireless Communications and Mobile Computing (IWCMC), 2020, pp. 874-877, doi: 10.1109/IWCMC48107.2020.9148441.

[17] Abrahão, D., Vieira, F. (2016). Resource allocation algorithm for LTE networks using fuzzy based adaptive priority and effective bandwidth estimation. Wireless Networks, 24(2), 423-437. doi: 10.1007/s11276-016-1344-6

[18] Michal Aibin, Stephen Cheng, David Xiao, Aldrich Huang, (2020) “Optimization of Regenerator Placement in Optical Networks Using Deep Tensor Neural Network”.

[19] M. Aibin and M. Blazejewski, ”Complex Elastic Optical Network Simulator (CEONS),” 2015 17th International Conference on Transparent Optical Networks (ICTON), 2015, pp. 1-4, doi: 10.1109/ICTON.2015.7193519.