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OVERVIEW OF TRAFFIC FORECASTING METHODS IN OPTICAL NETWORKS

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Abstract: *An optical network is a data communication network that uses optical fiber technology for data transmission. This paper provides an overview of the key traffic parameters within optical networks, some of which are common to all communication networks while others are specific to optical networks. The paper describes in detail the techniques for monitoring and collecting traffic data that facilitate a deeper understanding of network performance and resource optimization. The research focuses on applying machine learning methods for predicting the variability of key traffic parameters, aiming to enhance the efficiency and adaptability of optical networks. The objective of the paper is to conduct a review analysis of practical applications of the selected traffic forecasting methods/techniques in optical networks through relevant available research.*

Key words*: Optical network, traffic parameters, data collection, machine learning, traffic forecasting*

1 Introduction

An optical network is a communication network built using optical fiber technology. Some types of optical networks include active optical networks, passive optical networks, and more modern elastic and software-defined optical networks. The implementations of optical networks refer to the way in which the optical fiber connects to the user's premises, such as Fiber to the Home (FTTH), Fiber to the Building (FTTB), Fiber to the Node (FTTN), Fiber to the Curb (FTTC), Fiber to the Desk (FTTD), etc. Optical networks have various features and parameters that affect the quality of transmission (QoT), with some of the more important ones being optical power, optical nonlinearity, optical signal-to-noise ratio (OSNR), traffic volume, blocking probability, bit error rate (BER), Q factor, bandwidth, etc. With growing complexity of the optical networks, traffic prediction becomes crucial for the implementation of adaptive adjustments, optimization, and improvement of user experience. Today, the capabilities of artificial intelligence and deep learning open revolutionary possibilities focusing on enhancing network efficiency and user experience.

The purpose of this paper is to present methods for predicting optical network traffic using modern machine learning techniques. The machine learning methods will be presented in categories, and the way in which each method works and what type of traffic it is most suitable for, will be analyzed. The goal of the paper is to conduct an overview analysis of the optical network traffic prediction methods/techniques.

In Chapter 2, the methods and techniques for measuring traffic parameters in optical networks are described. Chapter 3 describes the techniques that can be used for prediction of the traffic parameters in optical networks. Chapter 4 presents and describes the examples of the application of the methods mentioned in the previous chapter through past research. Chapter 5 presents the classification of the analyzed methods. In the Conclusion, all the collected information is synthesized, and a proposal for planning the future research is provided.

2 Methods of Data Collection in Optical Networks

Collecting data in optical networks is often very complex and most performed at the physical or network layer. [1], [2] There are direct detection systems, which are further divided into analog and digital ones. Analog techniques are used to gather information about channel impairments by analysing the waveform of the analog signal, and they are divided into Time domain, Frequency domain, and Polarization domain techniques.

Time domain monitoring techniques can be categorized into asynchronous and synchronized, depending on whether the data collection rate is synchronized with the symbol rate or not. Some examples of the asynchronous data collection techniques are asynchronous amplitude histograms (AAH), asynchronous delay-tap plots (ADTP), and others. The Eye diagram and Q-factor are examples of synchronized techniques. Frequency domain monitoring techniques can be divided into optical spectrum-based techniques and radio frequency spectrum-based techniques. Radio frequency spectrum-based techniques provide a better assessment of signal quality compared to optical spectrum-based techniques because they analyse the spectrum of the signal encoded onto the optical carrier. Polarization domain monitoring techniques use changes in the polarization characteristics of optical signals, caused by various channel degradations, to monitor network faults [3], [4].

Digital methods provide information about the overall signal quality degradation caused by network impairments, but their individual impact cannot be isolated. In digital coherent systems, the dispersion does not necessarily degrade transmission, if it is properly estimated. Therefore, transmission performance is primarily determined by the OSNR. [3]

3 Traffic Prediction Methods in Optical Networks

For this review analysis, five traffic prediction techniques have been examined. Neural Networks (NN) are machine learning algorithms used to solve problems by processing data in a manner like the functioning of brain cells in the human brain. These neurons send data to the hidden layers, which in turn send the final output data to the last output layer. The hidden layer itself can consist of multiple layers, and various algorithms can be used within it to process the data. Input data move through the network via a series of interconnected nodes, being weighted and recalculated with each node from the beginning.

Support Vector Machine (SVM) is a machine learning algorithm used for classifying unlabelled collected data into two labelled categories, effectively separating the dataset into distinct binary groups [5]. This method involves complex data transformation based on the selected kernel function, aiming to maximize the separation boundaries between data points according to predefined labels or classes.

The Principal Component Analysis (PCA) is a manipulation or reduction method that reduces the amount of observed data while minimizing the amount of lost information. The analysis is conducted in such a way that the initial variables are transformed into a new set of variables called principal components through an orthogonal transformation. The principal components are then ranked, resulting in the initial variables retaining most of the information.

Selection of the most appropriate statistical model depends on the specific characteristics of the traffic and network requirements. While statistical models can provide valuable insights, it is always important to combine them with detailed knowledge of the network infrastructure and the traffic patterns for the best results. Some of the more important models for this paper include the Markov model, Bayesian model, and Monte Carlo model.

Linear regression is a common technique used in statistical analysis to find and estimate the relationship between two or more sets of variables, regardless of their distribution. Variables for the regression analysis must contain the same number of observations, but they can be of any size or content. [6]

4 Analysis of Traffic Prediction Methods/Techniques

There is a substantial amount of research available that investigates the traffic prediction in communication networks using machine learning methods, which is described further in the paper.

4.1 Traffic Prediction using NN

Studies [7] and [8] propose the usage of the Long Short-Term Memory (LSTM) method for optical network traffic prediction. In study [7], LSTM is used to solve resource allocation in SDONs, and the blocking probability was predicted. Study [8] aims to achieve approximately 1 ms delay and energy efficiency in Optical Network Units (ONUs) by predicting the bandwidth. Simulation results show a 28.9% reduction in one-way packet delay, and a 73.7% reduction in energy consumption per bit for data transmission under 1 ms latency condition. Studies [9] and [10] propose the usage of a Backpropagation Neural Network (BPNN) for the prediction of various traffic parameters in EONs. In study [9], a BPNN is used to predict future connections in an EON to improve performance by increasing the bandwidth and reducing the blocking probability. The study has shown satisfactory results. Study [10] proposes a Power-

Aware Lightpath Management (PALM) algorithm to reduce energy consumption during the setup and reestablishment of optical paths in EONs. A traffic prediction module integrates BPNN with Particle Swarm Optimization (PSO) to determine the initial input values. Simulation results show a 31-36% improvement in energy reduction at an 80% utilization threshold compared to the Energy-Efficient Manycast (EEM) algorithm over a month. Studies [11] and [12] have proposed a Generative Adversarial Network (GAN) with Graph Convolution Network (GCN) for traffic prediction surges over short and long periods. GCN captures the network's topological state, and GAN predicts the future traffic spikes. Using real traffic data from Telus Fiber Network, the GCN-GAN model was more effective in predicting traffic surges compared to the LSTM model, showing lower mean squared error values and less traffic overestimation. In study [13], traffic prediction in a real optical network in western China is examined. The study uses a Graph Convolutional Network with Gated Recurrent Unit (GCN-GRU), where GCN learns node interdependencies and GRU collects traffic samples over a certain period. Evaluated with real datasets from the optical network backbone, the study achieved a prediction accuracy of 98%. In study [14], various RNN variants are evaluated for predicting the network traffic on the GEANT optical network backbone. LSTM performed best, but GRU and Identity Recurrent Neural Network (IRNN) were comparable in performance and had lower computational costs than LSTM. All RNN methods showed satisfactory traffic prediction accuracy. Studies [15] and [16] proposed optical network QoT prediction using different Artificial Neural Networks (ANNs) methods. Multiple tests were performed, and large sets of synthetic data were used. The results showed high prediction accuracy, with one test achieving a standard deviation error of 0.3 dB. Study [17] introduces an eye diagram analyzer to assess the Q factor and link length based on image processing, using various Convolutional Neural Networks (CNNs). CNN models tested on several modulation formats showed satisfactory prediction accuracy, with the best results achieving the mean square error of 0.00188 and 0.00036.

4.2 Traffic Prediction using SVM

Studies [18] and [19] use the SVM method to predict the transmission quality in optical networks. In [18], an off-network testing used data from the Deutsche Telekom optical network, and a quality estimator classified light paths based on a user-defined Q-factor threshold. The approach achieved 99.95% accuracy in the light path classification and significantly reduced the calculation time. Study [19] proposes a multi-functional optical spectral analysis technique based on four machine learning algorithms, including SVM. SVM achieved optimal accuracy of 100% and the shortest testing time, under 0.34 seconds. For practical application, the simultaneous variation of wavelength, OSNR, and bandwidth was also studied. SVM still maintained over 99.1% accuracy with a calculation time of 0.776 seconds. Study [20] proposes a failure prediction scheme in Software-Defined Optical Networks (SDONs) using LSTM and SVM methods. LSTM predicts optical network parameters, and SVM forecasts the network failures. The study shows a prediction accuracy of up to 90.63%. Study [21] proposes an SVM-based model for predicting and classifying optical network congestion levels. The SVM simulation used bandwidth data, simulating dynamic traffic on two optical network backbones. The simulation results showed a classification accuracy of 97.8%, demonstrating the model's effectiveness for network management, resource allocation, and quality of service improvement.

4.3 Traffic Prediction using PCA

In study [22], an ANN was used to evaluate the performance in wavelength-routed optical networks (WRON) and to provide a way to estimate the blocking probability in WRONs, considering physical impairments. Independent variables related to the physical layer and the topological properties of WRON were determined through PCA, conducted to generalize and identify variables that would facilitate model training and allow its use in different networks. The results showed that the neural network is an efficient way to estimate the blocking probability in cases where inadequate network training and execution time are required. In study [23], a complex fully connected neural network model based on complex PCA analysis is experimentally demonstrated on a coherent optical communication network system, 375 km long. The purpose of the research was to predict the Kerr nonlinear effect. PCA is used in combination with the neural network to further reduce the computational complexity and evaluation time. Results showed that PCA achieved a 40% reduction in calculation time and a 70% reduction in spatial complexity.

4.4 Traffic Prediction using Statistical Models

Studies [24] and [25] propose a Markov model for optical network traffic prediction. In [24] a simulation was conducted to test the blocking probability prediction for cloud service providers. The traffic prediction approach, although providing a higher-cost solution, resulted in a low percentage of blocking requests and more efficient use of network resources. In [25], a load balancing technique to improve QoS for lightpath establishment (LBIQLE) is proposed. The purpose of the research was to improve QoS by predicting the optical network traffic volume. The LBIQLE method shows a higher network utilization rate and a reduction in blocking probability and delay. Studies [26], [27], [28] and [29] propose the use of a Bayesian model for the prediction of various optical network traffic parameters. Study [26] proposes a node failure prediction mechanism for optical networks that does not disrupt network operation. The results of this study have shown that this mechanism demonstrates high accuracy in predicting node failures. Studies [27] and [28] proposed a prediction of the availability of optical network links. The data was collected over a specific period, and the model was tested through a series of simulation experiments. The results showed a 52% and 75% reduction of link availability prediction error. In [29], a model for optical network QoT estimation using OSNR measurement data is proposed. The test results showed that the Bayesian model improved the accuracy of QoT estimation by up to 1.78 dB. In study [30], the algorithms for wavelength sharing optimization are proposed to maximize the traffic throughput during peak traffic periods in elastic optical networks. The results showed that the wavelength sharing optimization can increase the overall traffic throughput in the network, assuming that the network traffic can be split. The proposed optimization technique is a viable solution for short-term peak traffic lasting from a few hours to several days. In study [31], an algorithm based on the Monte Carlo method is used to predict the traffic volume in elastic optical networks, and the results are compared with the predictions using neural networks. The results showed that the Monte Carlo model adapts better to traffic changes over a shorter period of time compared to neural networks.

4.5 Traffic Prediction using Linear Regression

In study [32], a machine learning regression model is proposed to obtain the best combination of fiber loads that minimize the network fragmentation. An algorithm aware of vertical and horizontal fragmentation has been developed, demonstrating that the proposed metric and allocated fiber loads reduce network fragmentation. The proposed solution enables a reduction in bandwidth blocking probability in the short term. Study [33] describes how linear regression can be used to assess the QoT of optical networks and in routing and resource distribution. It was concluded that linear regression is simple to execute, analyze, and standardize; however, it cannot accurately resolve nonlinear difficulties. Study [34] presents the concept of an optical network with an integrated linear regression method that tracks the network performance. BER data are collected, and the OSNR for future service requests are estimated using linear regression. The results showed satisfactory accuracy in estimating OSNR. Studies [35] and [36] describe the traffic volume prediction in optical networks, using several machine learning methods, including linear regression. In study [35], data sets for simulation are generated and they reflect the actual traffic from an internet exchange point in Seattle, while in study [36], the model was tested with synthetic traffic datasets tailored to simulate natural traffic behavior. Both studies showed satisfactory prediction results. It was also proven that a combined linear regression model provides more accurate results than individual regression models.

5 Classification of Analyzed Methods

Table 1 presents a classification of machine learning methods for traffic prediction in optical networks based on all previously described studies.

Table 1 – Classification of machine learning methods for optical network traffic prediction

Method	Type of method	Traffic parameter	Time classification	References
NN	LSTM	Blocking probability	Long-term	[7]
	BPNN	Blocking probability	Short-term	[9]
	GCN-GAN	Traffic volume	Long-term	[11], [12]
	GCN-GRU	Traffic volume	Short-term	[13]
	RNN	Traffic volume	Short-term	[14]
	ANN	QoT	Short-term	[15]
	CNN	Q factor	Short-term	[17]
SVM	SVM	QoT	Long-term	[18], [19]
	Hybrid model	Failure prediction	Short-term	[20]

PCA	PCA	Blocking probability	Short-term	[22]
Statistical models	Markov model	Blocking probability	Short-term	[24]
	Bayes model	Node failure prediction	Long-term	[26]
		Availability of optical	Long-term	[27], [28]
		QoT	Short-term	[29]
	Statistical	Traffic volume	Short-term	[30]
	Monte Carlo	Traffic volume	Short-term	[31]
Linear regression	Linear regression	Network fragmentation	Long-term	[32]
		QoT	Short-term	[33]
		OSNR	Long-term	[34]
		Traffic volume	Short-term	[35], [36]

In Table 1, traffic prediction methods are classified as "Short-term" and "Long-term". Short-term methods involve predictions over minutes, hours, or days, while long-term methods cover weeks, months, or years. Time-independent techniques are classified as long-term since they can be applied regardless of time.

6 Conclusion

Machine learning and artificial intelligence technologies are being introduced to better manage the high traffic volume situations and ensure quality of service in optical networks. The analysis determined that the neural network techniques are the most used tools for predicting traffic parameters, and they have the largest body of research (which is systemized in the work in Table 1). RNN are more effective for accurately predicting future network states due to their feedback mechanisms, which allow them to function as memory. They are followed by statistical models, while support vector methods and principal component analysis are somewhat less prevalent. Traffic volume and blocking probability have been the most common metrics for prediction in optical communication networks, and each of the mentioned techniques can be used for both short-term and long-term traffic prediction. Linear regression methods and SVM are more suitable for short-term predictions due to their quick data processing, while neural networks, PCA, and statistical models are better suited for long-term predictions as they can model more complex prediction patterns. The analyzed solutions (methods) should be easily maintainable, and their capabilities should be continuously updated with minimal human involvement, and without increasing complexity. Future research could explore the combination of multiple machine learning methods for optical network traffic prediction, aiming to enhance prediction accuracy and reduce computation time. Additionally, testing various types of modular neural networks presents another promising opportunity for further study.

Literature

[1] M.M Rad, K. Fouli, H.A. Fathallah, L.A. Rusch, M. Maier, “Passive optical network monitoring: Challenges and requirements”, *IEEE Communications Magazine*, Vol. 49, pp. 45–52, February 2011. DOI:10.1109/MCOM.2011.5706313

[2] S. Miladić-Tešić, G. Marković, V. Radojičić, “Traffic grooming technique for elastic optical networks: A survey”, *Optik*, Vol. 176, 2019, pp. 464-475, DOI: 10.1016/j.ijleo.2018.09.068.
[3] Z. Dong, F.N. Khan, S. Qi, K. Zhong, C. Lu, A. Lau, “Optical Performance Monitoring: A Review of Current and Future Technologies”, *Journal of Lightwave Technology*, vol. 34, pp. 525-543, January 2016. DOI:10.1109/JLT.2015.2480798
[4] D. C. Kilper, R. Bach, D. J. Blumenthal, D. Einstein, T. Landolsi, L. Ostar, M. Preiss, A. E. Willner, “Optical Performance Monitoring”, *Journal of Lightwave Technology*, Vol. 22, pp. 294-304, January 2004. DOI: 10.1109/JLT.2003.822154
[5] W. S. Noble, “What is a support vector machine?”, Nat. Biotechnol., Vol. 24, pp. 1565–1567, December 2006. DOI: 10.1038/nbt1206-1565
[6] A. Chen, J. Law, M. Aibin, “A Survey on Traffic Prediction Techniques Using Artificial Intelligence for Communication Networks”, *Telecom*, Vol. 2, pp. 518-535, December 2021. DOI: 10.3390/telecom2040029
[7] M. Aibin, “Deep Learning for Cloud Resources Allocation: Long-Short Term Memory in EONs”, in *Proceedings of the International Conference on Transparent Optical Networks*. July 2019.
[8] P. Li, Y. Lv, M. Bi, “Bandwidth Prediction Based Resource Allocation Scheme for Low-Latency and Energy-Efficient PONs with Heterogeneous ONU Propagation Delays”, *IEEE Photonics Journal*, Vol. 16, pp. 1-15, February 2024. DOI: 10.1109/JPHOT.2024.3356573
[9] W. B. Jia, Z. Q. Xu, Z. Ding, K. Wang, “An efficient routing and spectrum assignment algorithm using prediction for elastic optical networks”, *2016 International Conference on Information System and Artificial Intelligence*, 2016. pp. 89-93.
[10] Y. Xiong, J. Shi, Y. Lv, G. N. Rouskas, “Power-aware lightpath management for SDN-based elastic optical networks” *International Conference on Computer Communications and Networks*, 2017. pp. 1-9.
[11] M. Aibin, N. Chung, T. Gordon, L. Lyford, C. Vinchoff, “On Short-and Long-Term Traffic Prediction in Optical Networks Using Machine Learning”, *International Conference on Optical Network Design and Modelling*, July 2021.
[12] C. Vinchoff, N. Chung, T. Gordon, L. Lyford, M. Aibin, “Traffic Prediction in Optical Networks Using Graph Convolutional Generative Adversarial Networks”, In *Proceedings of the International Conference on Transparent Optical Networks*, 2020. pp. 1-4.
[13] Y. Gui, D. Wang, L. Guan, M. Zhang, “Optical Network Traffic Prediction Based on Graph Convolutional Neural Networks”, *Opto-Electronics and Communications Conference*, 2020. pp. 1-3.
[14] R. Vinayakumar, K. P. Soman, P. Prabaharan, “Applying Deep Learning Approaches for Network Traffic Prediction”, 2017 *International Conference on Advances in Computing, Communications and Informatics*, 2017. pp. 2353-2358.
[15] A. M. R. Brusin, A. Nespola, M. R. Zefrech, S. Piciaccia, P. Poggiolini, F. Forghieri, A. Carena, “ML-Based Spectral Power Profiles Prediction in Presence of ISRS for Ultra-Wideband Transmission”, *Journal of lightwave technology*, vol. 42, pp. 37-47, January 2024. DOI: 10.1109/JLT.2023.3301897
[16] Y. He, K. Chandramouli, Z. Zhai, S. Chen, L. Dou, C. Xie, C. Lu, A. Lau, “QoT Estimation for Large-scale Mixed-rate Disaggregated Metro DCI Networks by

Artificial Neural Networks” *2024 Optical Fiber Communications Conference and Exhibition*, 2024. pp. 1-3.
[17] S. A. Al-Shamayleh, A. Raza, Z. Ali, S. Malik, S. Iqbal, B. Raza, M. Iqbal, A. Etiah, “Performance Evalutaion of Optical Transmission Based on Link Estimation by Using Deep Learning Techniques”, *IEEE Access*, Vol. 12, pp. 64126-64139, May 2024.
[18] J. Mata, I. De Miguel, R. J. Durán, J. C. Aguado, N. Merayo, L. Ruiz, P. Fernández, R. M. Lorenzo, E. J. Abril, “A SVM approach for lightpath QoT estimation in optical transport networks. *2017 IEEE International Conference on Big Data*, 2017. pp. 4795-4797.
[19] D. Wang, M. Zhang, Z. Zhang, J. Li, H. Gao, F. Zhang, X. Chen, “Machine Learning-Based Multifunctional Optical Spectrum Analysis Technique”, *IEEE Access*, vol. 7, pp. 19726-19737, April 2019. DOI: 10.1007/s11432-022-3557-9
[20] P. Liu, W. Ji, Q. Liu, F. Liu, X. Xue, Y. Zhu, “Failure Prediction Based on LSTM and SVM under SDON Architecture*”, 2021 7th International Conference on Computer and Communications*, 2021. pp. 398-402.
[21] Q. Sun, H. Lan, X. Yang, “Prediction of Optical Network Congestion Based on SVM”, *2019 IEEE 7th International Conference on Computer Science and Network Technology*, 2019. pp. 13-16.
[22] D.R. De Araújo, C.J. Bastos-Filho, J.F. Martins-Filho, “Methodology to obtain a fast and accurate estimator for blocking probability of optical networks”, *Journal of Optical Communications and Networking*, Vol. 7, pp. 380–391, May 2015. DOI: 10.1364/JOCN.7.000380
[23] X. Huang, Y. Wang, C. Li, R. Gao, Q. Zhang, L. Han, X. Xin, “Complex principal component analysis-based complex-valued fully connected NN equalizer for optical fibre communications”, *Optics Express*, vol. 31, pp. 42310-42326, December 2023. DOI: 10.1364/OE.502294
[24] M. Aibin, K. Walkowiak, S. Haeri, L. Trajkovic, “Traffic Prediction for Inter-Data Center Cross-Stratum Optimization Problems”, *2018 International Conference on Computing, Networking and Communications*, 2018. pp. 393-398.
[25] K. Chitra, M. R. Senkumar, “Hidden Markov model based lightpath establishment technique for improving QoS in optical WDM networks”, *Second International Conference on Current Trends in Engineering and Technology*, 2014. pp. 53-62.
[26] D. Das, M. F. Imteyaz, J. Bapat, D. Das, “A Data Augmented Bayesian Network for Node Failure Prediction in Optical Networks” 2021 *International Conference on Artificial Intelligence in Information and Communication*, 2021. pp. 83-88.
[27] F. Christou, “Availability Estimation of Optical Network Links Using Multilevel Bayesian Modeling” 2023 *International Conference on Optical Network Design and Modeling,* 2023. pp. 1-6.
[28] F. Christou, “Availability estimation of optical network links using a Bayesian model”, *Journal of Optical Communications and Networking*, Vol. 16, pp. 1-15, February 2024. DOI:10.1364/JOCN.510726
[29] R. Ayassi, A. Triki, B. Guyader, F. Frank, T. Marcot, E. Rouzic, M. Laye, R. Minerva, N. Crespi, “Field Trial to Assess Bayesian Optimization for Improving QoT Estimation” *European Conference on Optical Communications*, 2023. pp. 389-392.

[30] Z. Zhong, N. Hua, M. Tornatore, J. Li, Y. Li, X. Zheng, B. Mukherjee, "Provisioning Short-Term Traffic Fluctuations in Elastic Optical Networks", *IEEE/ACM Transactions on Networking*, Vol. 27, pp. 1460-1473, August 2019. DOI:10.1109/TNET.2019.2925631

[31] M. Aibin, "Traffic prediction based on machine learning for elastic optical networks" *Optical Switching and Networking*, Vol. 30, pp. 33-39, June 2018. DOI: 10.1016/j.osn.2018.06.001

[32] P. Lechowicz, "Regression-based fragmentation metric and fragmentation-aware algorithm in spectrally-spatially flexible optical networks", *Computer Communications*, Vol. 175, pp. 156–176, July 2021. DOI: 10.1016/j.comcom.2021.05.012

[33] S. Rai, A. K. Garg," Analysis of RWA in WDM optical networks using machine learning for traffic prediction and pattern extraction" *Journal of Optics*, vol. 52, pp. 900-907, June 2021. DOI:10.1007/s12596-021-00735-6

[34] S. Oda, M. Miyabe, S. Yoshida, T. Katagiri, Y. Aoki, T. Hoshida, J. C. Rasmussen, M. Birk, K. Tse, "A learning living network with open ROADMS", *Journal of Lightwave Technology*, Vol. 35, pp. 1350–1356, January 2017. DOI: 10.1109/JLT.2017.2660540

[35] D. Szostak, A. Włodarczyk, K. Walkowiak, "Machine Learning Classification and Regression Approaches for Optical Network Traffic Prediction", *Electronics*, Vol. 10, pp. 1578, June 2021. DOI: 10.3390/electronics10131578

[36] B. Ulanowicz, D. Dopart, A. Knapinska, P. Lechowicz, K. Walkowiak, "Combining Random Forest and Linear Regression to Improve Network Traffic Prediction" *2023 23rd International Conference on Transparent Optical Networks*, 2023. pp. 1-4.

Sažetak: *Optička mreža je mreža za prenos podataka koja koristi tehnologiju optičkih vlakana za prenos podataka. Ovaj rad daje pregled ključnih parametara saobraćaja unutar optičkih mreža, od kojih su neki zajednički za sve komunikacione mreže, dok su drugi specifični za optičke mreže. U radu su detaljno opisane tehnike praćenja i prikupljanja podataka o saobraćaju koje omogućavaju dublje razumevanje performansi mreže i optimizacije resursa. Istraživanje se fokusira na primenu metoda mašinskog učenja za predviđanje varijabilnosti ključnih parametara saobraćaja, sa ciljem da se poboljša efikasnost i prilagodljivost optičkih mreža. Cilj rada je da se kroz relevantna dostupna istraživanja sprovede pregledna analiza praktične primene odabranih metoda/tehnika predviđanja saobraćaja u optičkim mrežama.*

Ključne reči: *Optička mreža, parametri saobraćaja, prikupljanje podataka, mašinsko učenje, predviđanje saobraćaja*

PREGLED METODA PREDVIĐANJA SAOBRAĆAJA U OPTIČKOJ MREŽI

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