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Application of Machine Learning Methods in provisioning of DWDM channels

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ABSTRACT

Complexity and size of modern optic-fiber networks start to challenge the traditional methods of managing them and yet majority of telecommunication companies still report rapid growth of their optical networks. One of essential problems in managing optic-fiber networks is calculating the Quality of Transmission (QoT) of given path in network. The unit responsible for this task is Optical Performance Unit (OPU) which communicates with Network Management System (NMS). OPU's task is to determine whether it is possible to transmit signal through a given path. Modern OPUs are still operating based on traditional algorithms e.g. these systems take into consideration known physics rules and information about the network parameters, calculating transmission losses for each path. Main parameter that determines the OPUs result is Optical Signal to Noise Ratio (OSNR). However, measuring its value from NMS level is often not practical. An alternative solution to this problem might prove the application of Machine Learning (ML) algorithms for the estimation of OSNR. In this contribution an application of Artificial Neural Network (ANN) to an evaluation of OSNR in an optical Dense Wavelength Division Multiplexing (DWDM) network is investigated.

Keywords: WDM optical networks, Quality of transmission, Machine learning, Artificial neural networks.

1. INTRODUCTION

In the last decade, due to the demand for high network throughput, the number of optical channels has increased rapidly. Therefore, it is important to increase the quality of transmission[1] along with the increase of the bit rate in the transmission networks.[2,3] Optical Signal-to-Noise Ratio (OSNR) is used as one of the main metrics to evaluate the quality of transmission for DWDM (Dense Wavelength Division Multiplexing) channels.[4] The knowledge of OSNR is very valuable since it helps estimating the BER (Bit Error Ratio) level.

DWDM channels information capacity is strongly limited by ASE (Amplified Spontaneous Emission). ASE is generated by optical amplifiers. When it comes to DWDM channels the main source of ASE are signal boosters, in-line and pre- amplifiers, which are placed in various places in optical network. ASE from all optical amplifiers accumulates along an optical path and may make the OSNR value too low, for reliable transmission of information.

Experimental measurement of OSNR is usually performed using an optical spectrum analyzer. However, such approach is often not practical in an operating DWDM network. Instead one can try to apply Machine Learning Algorithms (MLA) e.g. Artificial Neural Networks (ANN), Support Vector Machines (SVM) or Linear Regression (LR)[5 6 7] to estimate OSNR.

In this contribution a specific focus is given to ANN. MLAs based on ANNs proved effective in recognizing patterns and data classification. An ANN is build from neurons, which are connected to each other. Usually, neurons are organized in layers while a particular neuron is connected with all neurons in previous layer. In an ANN one can distinguish input layer (which holds the input data), the output layer (which holds the result of

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the calculation) and a number of hidden layers. There are many types of neural networks for example: feed-forward neural networks, in which information travels in only one direction, from input to output, recurrent neural networks, in which neuron connections may form loops and cycles, convolutional neural networks, which are a class of deep neural networks which have similar structure to feed-forward networks but are designed for image analysis. In a neural network single neuron holds a float value between 0 and 1. The learning process of the neural network consists in adjusting the weights of each neuron, so that the last layer of the neural network returns the results.[8] ML, in particular ANN, is being proposed for lightpath quality of transmission (QoS) estimation in the literature.[9,10]

This work describes and studies the application of ANN to the estimation of OSNR in DWDM networks.

2. PROBLEM FORMULATION

The simulations are performed for two optical networks, Polish network and German one. In order to evaluate the robustness of the ML method the data base was generated using realistic DWDM networks. Figure 1 shows the network topology for networks studied, which include cities and optic connections between cities.

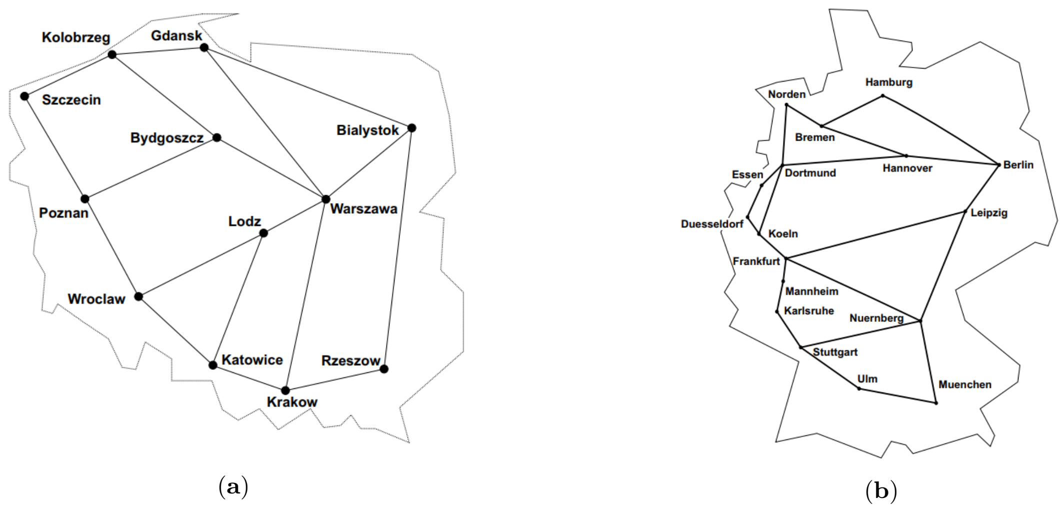

Figure 1: Analyzed network topologies: (a) Polish, (b) German national transmission optical backbone network.

Polish network has 12 cities, 18 connections which gives 2457 paths. German one has 17 cities, 23 connections and 4527 paths. Every connection has defined length which equals to real distance between given cities. In our model, every optic connection has signal boosters placed approximately every 70km (exact value depends on connection length). Boosters compensate for signal loss between the network but also act as source of noise in the transmission. Loss between boosters depends on the distance between them. OSNR value of a particular path is calculated based on total noise from all boosters in the path.

The developed software used python library called mxnet to implement feed-forward neural network and learning process. Input data for ANN is an array with integer values that represent the path in the optical DWDM network. Each integer represents the city (its value equals the city identifier). The order of identifiers corresponds to the occurrences of cities on the path. The length of every input array was fixed and equal to the longest path in a network. The input array was filled with path nodes identifiers and if particular path was shorter than the longest path, the end of array was filed with value -1.The output of ANN was an integer value in the range 0 - 3. Every output value corresponds to the specific range of OSNR values. The boundary values of OSNR ranges, which divide paths into 4 categories, were designated in such a way, that number of paths in each category was similar. For German network the ranges were defined as: less then 20.78, between 20.78 and 25.09, between 25.09 and 31.81 and greater then 31.81 while for Polish network: less then 19.01, between 19.01 and 22.97, between 22.97 and 29.73 and greater then 29.73. The exemplary sets of OSNR values and corresponding to them estimated categories are shown in 2. At the beginning a list of input arrays and list of corresponding

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correct outputs was prepared. Obviously, the order of paths in the list was randomized. Then this data was divided into training and test data.

Polish network		German network	
OSNR value	ANN output	OSNR value	ANN output
48.87	3	17.36	0
22.94	2	18.83	0
16.83	0	22.96	1
17.71	0	34.63	3
19.99	1	17.33	0
27.19	2	143.88	3
25.86	2	31.74	3
29.72	2	21.17	1
32.33	3	18.52	0
16.23	0	35.47	3

Figure 2: OSNR values for example paths in the both, Polish and German, networks and estimated by ANN category for each of them. Red color indicates a wrong estimation.

The considered ANN consists of two hidden layers (128 and 64 neurons), input layer and output layer. All layers are fully connected with layers before them. Figure 3 presents a diagram of an artificial neural network used in the paper.

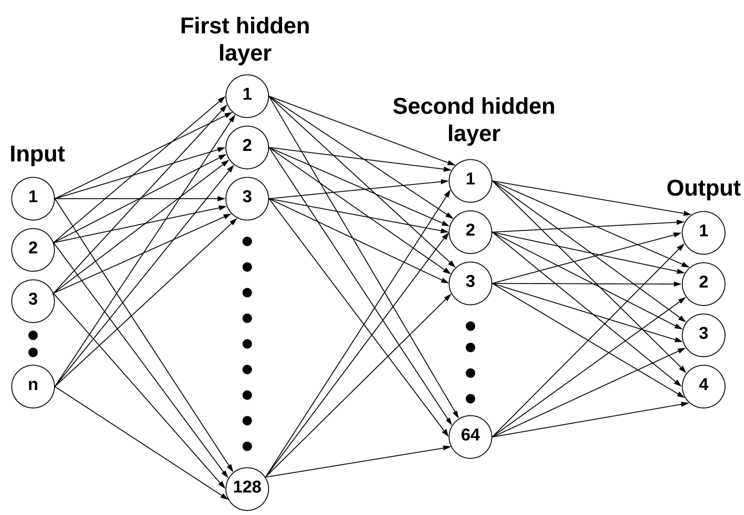

Figure 3: Diagram of the artificial neural network ANN used in the article; n (in the input layer) corresponds to the longest path in the optical network.

In the learning process training data was divided into batches of 15 input paths. Training process is divided into iterations, in the performed simulations the number of iterations equaled 300. In every iteration the whole training data was processed, one batch at the time. Network parameters were updated after processing single batch. After a defined number of iterations is completed one can start testing the network on data it has not seen before.

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3. RESULTS AND DISCUSSION

There are two parameters that are used to estimate quality of the ANN results. First one is the train accuracy which shows how good the network is at training data classification. This parameter only shows the network performance in classifying data that it is training on. However, its high value shows that neural network is complex enough to keep information about the optical network. The other parameter is validation accuracy. This parameter estimates how the network works with data that it has not seen before, and thus with a real data network. Its value equals to ratio between correctly estimated validation examples (examples that were not used while training) and all validation examples. Validation accuracy is usually calculated after the learning process. Because of that, it is hard to tell how good the machine learning model actually is until its validation accuracy is calculated on new data.[11]

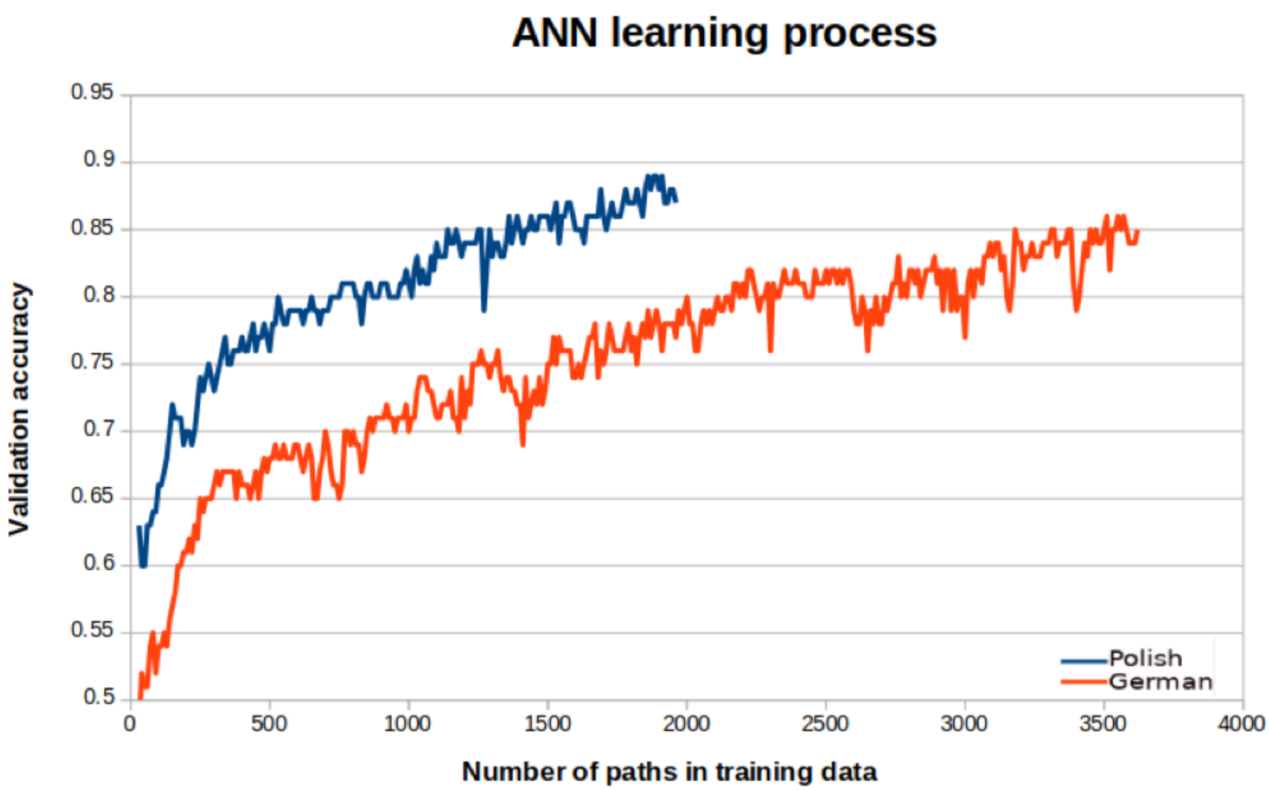

Figure 4: Dependence of validation accuracy on number of example paths in data base of both, Polish and German, networks.

In order to model training in real time we trained the neural network with increasing amounts of training data, starting from very low number of examples. Figure 4 shows relationship between validation accuracy and number of example paths in data base for both networks. These results show that neural network achieves high accuracy in classifying new input data when given enough training examples. In order to properly estimate OSNR of test paths, network has to accumulate information about distances between cities. Figure 4 suggest that even low number of examples, approximately 25% of all possible paths, enables gathering such information. The factor that might prevent network from achieving validation accuracy close to 1.0 is a random additional part in signal loss of an optical fiber.

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4. CONCLUSION

One of the key problems for network operators of a self-driving optical network is the automatic provisioning of lightpath in DWDM networks. In the paper, ANN was applied for estimating OSNR values in a simulation of DWDM network. The numerical results demonstrate the potential of artificial neural networks in estimating the quality of transmission.

REFERENCES

[1] Behnam Shariati, Antonia Mastropaolo, N.-P. D. J. M. R.-M. D. K. I. T., "Physical-layer aware performance evaluation of sdm networks based on smf bundles, mcfs, and fmfs," *International Journal of Optical Communications and Networking* (August 2018).

[2] Kozdrowski, S., Żotkiewicz, M., and Sujecki, S., "Resource optimization in fully flexible optical node architectures," in [*20th International Conference on Transparent Optical Networks (ICTON)*], (July 2018).

[3] Kozdrowski, S., Żotkiewicz, M., and Sujecki, S., "Optimization of optical networks based on cdc-roadm technology," *Applied Sciences* **9**, 4648–4658 (Jan 2019).

[4] Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., and Teller, E., "Evaluating machine learning models for qot estimation," *In Proceedings of the 20th International Conference on Transparent Optical Networks (ICTON).* (15 July 2018.).

[5] F. Musumeci, C. Rottondi, A. N. I. M. D. Z.-M. R. M. T., "An overview on application of machine learning techniques in optical networks," *IEEE Communications Surveys Tutorials* (08 November 2018).

[6] Faisal Nadeem Khan, C. L. and Lau, A. P. T., "Machine learning methods for optical communication systems," (2427 July 2017).

[7] L. Peshkin, V. S., "Reinforcement learning for adaptive routing," (12-17 May 2002).

[8] Wawrzyński, P., [*Podstawy Sztucznej inteligencji*], Oficyna Wydawnicza Politechniki Warszawskiej (2015.).

[9] Jimnez, T., Aguado, J. C., de Miguel, I., Durn, R. J., Angelou, M., Merayo, N., Fernndez, P., Lorenzo, R. M., Tomkos, I., and Abril, E. J., "A cognitive quality of transmission estimator for core optical networks," *Journal of Lightwave Technology* **31**(6), 942–951 (2013).

[10] Barletta, L., Giusti, A., Rottondi, C., and Tornatore, M., "Qot estimation for unestablished lighpaths using machine learning," *Optical Fiber Communication Conference* (Los Angeles, California United States, 1923 March, 2017).

[11] Cichosz, P., [*Data Mining Algorithms: Explained Using R*], Wiley (2014).

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