A novel routing algorithm for optical networks based on ML methods

Paweł Krysztofik[1,3][0009−0001−0833−5222],
Paweł Cichosz[1][0000−0002−8049−7410],
Sławomir Sujecki[2][0000−0003−4588−6741], and
Stanisław Kozdrowski[1][0000−0001−6647−5189]

[1] Department of Computer Science,
Warsaw University of Technology, Nowowiejska 15/19,
[2] Telecommunications and Teleinformatics Department,
Wroclaw University of Science and Technology,
[3] pawel.krysztofik@pw.edu.pl

Abstract. Routing is essential to the seamless operation of an optical network. In this paper, we develop a novel routing algorithm specially tailored for optical networks. It uses machine learning methods to predict the feasibility of a particular route and depending on the prediction outcome makes the decision on whether to admit or reject the specific route. The machine learning model for feasibility prediction is created using data gathered via the control plane from a real telecoms network. The results obtained show the superiority of the proposed routing algorithm when compared with the standard approach.

Keywords: Optical network · Routing · Machine Learning.

1 Introduction

Optical networks have reshaped our society over the past two decades. High throughput backbone networks, based on optical technology, enabled the global availability of numerous services operating under an umbrella of the widely understood Internet.

Routing is essential to the correct operation of an optical network and its optimal long-term expansion planning and development. When considering the day-to-day operation of a network, correct routing is key to an effective deployment of optical path protection. Further, routing is at the heart of the Generalised Multiprotocol Label Switching (GMPLS), which is used widely in new-generation optical networks for optical path management. The day-to-day operation of an optical network routing becomes increasingly challenging due to an ever-increasing network flexibility resulting from the introduction of novel technologies. An eminent example here is the flex grid technology, which allows more efficient exploitation of the available bandwidth.

The current status of the routing in the day-to-day operation on a network is that a routing algorithm operating, for instance, within GMPLS will suggest an

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97554-7_3

admissible optical path for a realization of a specific demand but will not provide any reliable information on whether this path is feasible or not. Thus, the responsibility of checking the optical path feasibility is left to the network operator. As already mentioned, the other important aspect of a network operation is the long-term network expansion planning to increase the network capacity and coverage area. Here, the critical role play optical network optimization tools, which use routing algorithms to determine the optimization space. Errors introduced at this stage will propagate to incorrect predictions and reflect in increased capex and opex costs.

There is a very rich literature devoted to optical network optimization focusing on various aspects of the optimization process, including the impact of the specific network infrastructure, selection of the optimization algorithm, routing and wavelength assignment (RWA) [7], and routing and spectrum allocation (RSA) problems [15], which are at the heart of network optimization. However, for both the RWA and RSA the optimal routing requires reliable information about the performance of the optical channel, which takes into account physical phenomena in the network. The routing algorithms used so far do not provide any information on a particular path feasibility.

The reason why the routing algorithms used in networks usually do not perform optical path feasibility verification is primarily the fact that it is difficult to accurately verify the feasibility of a specific optical path in a network. So far, many authors have tried to solve this problem [2, 10]. In principle, two types of methods for an optical path feasibility assessment were considered. One of them consists of using models based on understanding of the main physical phenomena governing the light propagation in an optical fiber while the other approach consists in applying Machine Learning (ML) methods [14, 11, 5, 12]. Here, we decided to use the latter approach, i.e., ML algorithms. We thus incorporate ML algorithms directly into the routing algorithms. However, for the sake of completeness, it should be noted that there were also two ways in which ML was used to assess the feasibility of a particular optical path. One of them relied on the models assessing the path quality using ML in combination with physical models predicting the light propagation through an optical fiber. Thus, this approach is closely related to the methods mentioned above, which are based on the principle of studying optical propagation. The other approach relies on deciding on the feasibility of an optical path based on the knowledge about the network operation gathered directly from a network via the control plane. Here, we follow this latter approach and incorporate it directly into a routing algorithm.

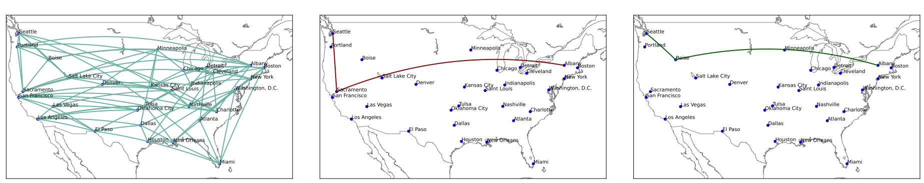
Considering the paper structure, we give a more detailed description of the proposed novel routing algorithm in the problem formulation section after the introduction. The 3rd Section describes how the ML model for route feasibility prediction is created and how it operates within the routing algorithm. In Section 4 for a selected optical network, we present and discuss the results of the proposed ML routing approach. Finally, Section 5 provides conclusions and future work.

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97554-7_3

2 Problem formulation

There is a constant demand for bandwidth on networks due to the ever-increasing level of resource-intensive services. Therefore, optical networks come to the rescue as the only medium that guarantees high bandwidth. This paper proposes a novel routing algorithm for next-generation optical networks. The novelty of the method consists of considering two crucial aspects, i.e., optimality concerning the value of the cost function and the quality of the optical channel as a whole, taking into account the physical phenomena occurring in the new-generation optical network.

As the introduction explains, effective routing is essential for many aspects of a DWDM network operation. Routing plays an important role in both day-to-day DWDM network management and in long-term planning. Here, we are more specifically focused on the latter problem and specifically discuss the importance of routing considered as a stage in a DWDM network optimization procedure. The importance of this problem comes from the fact that incorrectly predicted optimal structure of a DWDM network can result in an unnecessary increase of a DWDM network's opex and capex costs, which in turn is of significant concern to a network operator. In particular, we aim to avoid the presence of infeasible optical paths in the optimal solution predicted by a DWDM network optimization tool. For this purpose, we invoke within a routing algorithm another algorithm that asses the Quality of Transmission (QoT) of a specific path and classifies it as either a feasible or infeasible path. A machine learning model is used to obtain predictions of optical path feasibility. The model is created based on data gathered in a database by specially developed software that collects traffic-related data directly from the analyzed network. We explain this process in more detail below. For the purpose of the study, we performed the analysis on the American 30-vertex network from the sndlib database. We assumed that the degree of each of the vertices in the network is 6. The analyzed network is shown in Figure 1a



(a) Analyzed network. (b) Not feasible path. (c) Feasible path.

Fig. 1: An example of a no feasible and feasible optical channel on analyzed realistic network topology.

During the operation of a DWDM network, one can collect a significant amount of information on various aspects of optical transmission via the control plane, which can subsequently be used for many purposes. Of specific interest to this contribution is the assessment of the QoT. Knowledge of QoT is essential to correctly estimate the specific optical path's feasibility. Therefore, here

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97554-7_3

we have data from a real operating network and use it to create a database. The database contains 1000 optical paths, described by a set of a set of path attributes and labeled as feasible or infeasible depending of their OSNR value. By the very nature of the information-gathering process, the created database forms an unbalanced set whereby the number of set elements corresponding to feasible paths is much larger than the set of elements corresponding to infeasible paths. The next section explains how the data is used to create a path feasibility prediction model and then how the model is used within the the proposed routing algorithm.

3 Methods

This Section presents and describes the concept of optical channel classification using Machine Learning (ML) methods. The presentation of the proposed routing algorithms follows.

3.1 Path classification

The adopted approach to path (optical channel) classification is based on our previous work which investigated the utility of different classification algorithms [8, 9, 4], with some modifications necessary due to a partially different set of available path attributes.

Vector representation Path descriptions are transformed to a vector representation, to make it possible to apply machine learning algorithms for tabular data. This is accomplished using an aggregation-based feature engineering technique applied to path hops. It aggregates each of the available hop properties: `HopLength`, `NumOfPathsInHops`, `HopLosses`, `Amplifiers`, `PreAmpGaindB`, and `Nsp` over all hops in a path using the following aggregation functions: mean,standard deviation (assuming 0 for one-hope paths), minimum, maximum, median, first quartile, third quartile, linear correlation coefficient with the ordinal number of the hop in the path.

The transformation creates a vector representation containing 8 attributes for each of the 6 hop properties. With the additional 2 attributes describing the whole path rather than individual hops, `Length` and `NumberOfPaths`, this yields a total of 50 attributes available for model creation.

Model creation The random forest algorithm, found the most useful overall by prior studies, is used to create the path classification model. A random forest model consists of multiple decision trees, grown on multiple bootstrap samples from the training set, additionally diversified by split selection randomization [3]. Predictions are obtained by voting of individual trees, with vote distribution providing class probability predictions. The algorithm combines high predictive performance with resistance to overfitting and ease of use. The latter is primarily

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97554-7_3

due to its limited sensitivity to hyperparameter settings, making it capable of producing high quality models without excessive tuning.

The implementation provided by the `scikit-learn` Python library [13] is used, with the number of trees set to 500. Tuning other hyperparameters did not provide a substantial improvement in classification performance.

Model evaluation The verify the predictive performance of the model before using it as a component of the proposed optimization solution, the stratified 10×5-fold cross-validation procedure [1] was applied to obtain the ROC and precision-recall (PR) curves and calculate the corresponding area under curve (AUC) values. PR curves more reliably evaluate prediction quality with heavily imbalanced classes, being much more sensitive to false positives.

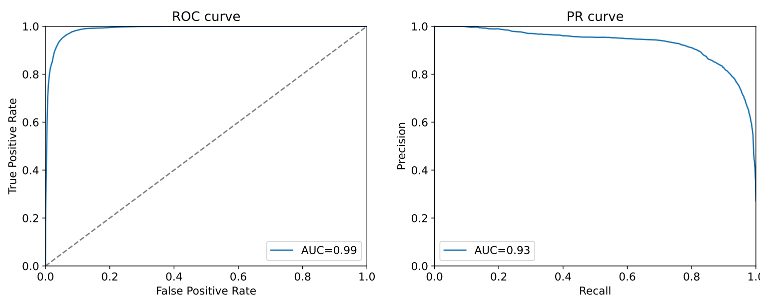


Fig. 2: Model evaluation results: the ROC and PR curves.

Figure 2 presents the ROC and precision-recall curves obtained using the model setup described above. The predictive performance level with ROC AUC of about 0.99 and PR AUC of about 0.93 was achieved, which indicates a very good level of predictive power.

3.2 Routing algorithms

In this paper, we compare two approaches to network routing. The first one consists in using the classic Dijkstra algorithm [6] to generate N shortest paths between a pair of cities. Then, one of these paths is selected to be used for data transmission. Paths generated in this way have no guarantee to meet the physical constraints imposed on them by the specifics of transmitting data via an optical fiber. To be certain that the path is feasible, it is necessary to calculate the Optical Signal to Noise Ratio (OSNR). Thus, when using a standard routing algorithm, there is a high risk that the selected path is infeasible. We therefore explore here, an approach which consists in combining the a standard routing algorithm with Machine Learning (ML). Machine learning algorithm uses a model trained on a dataset of paths for which OSNR was previously calculated and feasibility determined. So, in the proposed algorithm paths generated by the Dijkstra algorithm are sent to the ML model for feasibility prediction. The paths, which are classified by the ML algorithm as infeasible are rejected and are not used for routing. The operation of the proposed algorithm is presented in Algorithm 1 and in Fig. 3.

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97554-7_3

Algorithm 1 Routing + ML

1: **procedure** ML Routing
2: Load graph
3: Generate paths using Dijkstra's algorithm
4: Evaluate paths using ML
5: Remove not feasible paths
6: Choose a path from list
7: **return** *Path*
8: **end procedure**

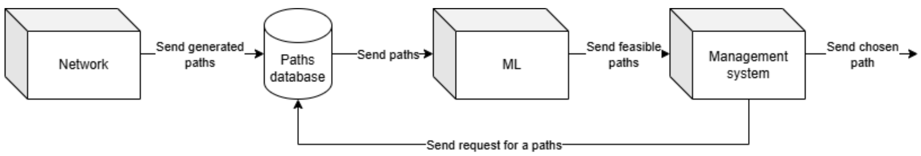


Fig. 3: Diagram illustrating path selection with the use of ML.

4 Early Results and Discussion

The calculations were prepared using a AMD Ryzen 7 4800H processor with 16 GB RAM running under the Windows 10 operating system. Table 1a summarizes the sets used by the routing procedures. N is the number of nodes in the network, and E is the number of edges (hops). D, denotes the number of considered demands (relations for which an optical path is created) in the network. Finally, P denotes the set of paths for a given relation. It was assumed that 200 randomly generated paths were already used in the network. 10 paths were created between each pair of cities. 1000 paths generated for 100 pairs were used as a training set used for model creation. The remaining 3350 paths for 335 pairs were treated as a test set.

Table 1: Parameters description and model results.

Set	**Set settings**
N, E	$N = 30$, $E = 90$
D	335 demands
P	10 per demand

(a) Network parameters.

Number of paths	3350
Correct predictions	3108
Incorrect predictions	242
Accuracy	92.8%

(b) ML results.

The path generation time for the analyzed network is negligible. It took less than a second to create 4350 paths. The effectiveness of the model can be assessed as very good. Out of 3350 predictions, 3108 were correct, which gives the accuracy of 92.8%. In the analyzed graph, on average out of 10 paths, there were 5.491 correct paths, while in the model assessment it was 5.836. The probability of selecting an infeasible path for randomly selected pair using ML is 8.3%, while without using ML it was 45.1%. For 32 pairs, only infeasible paths were generated. The model correctly detected the lack of a feasible path in 23 of them. The relevant results are summarized in Tables 1b and 2.

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97554-7_3

Table 2: Comparison of algorithms effectiveness.

Avg number of feasible paths per pair	5.491
Avg number of paths per pair selected by model	5.836
Prob. of choosing the wrong path for random selected pair with the model	8.3%
Prob. of choosing the wrong path for random selected pair without the model	45.1%

The chart presented in 4 shows the percentage of all pairs for which the model obtained accuracy at the level of X or higher. For 51% of the analyzed pairs, the model correctly classified all paths. The level of 90% or higher was achieved by 83% of pairs. This means that for the vast majority of the considered demands, the risk of selecting an infeasible path is 10% or less. Only for one pair accuracy went down to 60%. Thus A of 70% or higher was achieved for almost all pairs.

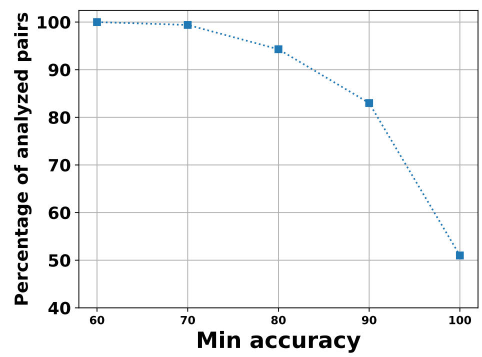


Fig. 4: Percentage of pairs for which the model was at least as accurate.

These results confirm the benefit of using the ML routing approach. The risk of selecting an infeasible path is significantly lower than in the case of using classical routing. Another benefit is the ability to detect pairs for which no feasible path has been created. This gives the network operator valuable information about the feasibility of new paths. The only potential disadvantage of using ML may be false negative results whereby a rejection of correct paths may happen. Out of 3350 classifications, we obtained only 63 such cases, which is 1.8%. On this basis, it can be concluded that the benefits of using ML outweigh the potential disadvantages.

5 Conclusions

In this paper, we have proposed a novel routing algorithm for optical networks. The novel algorithm uses an ML model to predict the feasibility of a particular route. The ML model makes an inference about a particular route feasibility based on the knowledge gathered from a real optical network via the management system. We have shown that the use of ML improves significantly routing in an optical network through elimination of unfeasible paths. The benefits of the novel approach can be exploited within a generalized multi-protocol label switching paradigm or in traffic allocation and network expansion planning. In the future, we plan to test the performance of the developed algorithm in a real optical network environment. We will also investigate how the use of the proposed routing algorithm affects the optical network optimization process for a range of network topologies relevant to real applications.

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97554-7_3

References

1. Arlot, S., Celisse, A.: A survey of cross-validation procedures for model selection. Statistics Surveys **4**, 40–79 (2010)
2. Barletta, L., Giusti, A., Rottondi, C., Tornatore, M.: Qot estimation for unestablished lighpaths using machine learning. In: 2017 Optical Fiber Communications Conference and Exhibition (OFC). pp. 1–3 (2017)
3. Breiman, L.: Random forests. Machine Learning **45**, 5–32 (2001)
4. Cichosz, P., Kozdrowski, S., Sujecki, S.: Learning to classify dwdm optical channels from tiny and imbalanced data. Entropy **23**(11) (2021). https://doi.org/10.3390/e23111504, https://www.mdpi.com/1099-4300/23/11/1504
5. Diaz-Montiel, A.A., Aladin, S., Tremblay, C., Ruffini, M.: Active wavelength load as a feature for qot estimation based on support vector machine. In: ICC 2019 - 2019 IEEE International Conference on Communications (ICC). pp. 1–6 (2019)
6. Dijkstra, E.W.: A note on two problems in connexion with graphs. Numerische mathematik **1**(1), 269–271 (1959)
7. Klinkowski, M., Żotkiewicz, M., Walkowiak, K., Pióro, M., Ruiz, M., Velasco, L.: Solving large instances of the RSA problem in flexgrid elastic optical networks. IEEE/OSA Journal of Optical Communications and Networking **8**(5), 320–330 (May 2016). https://doi.org/10.1364/JOCN.8.000320
8. Kozdrowski, S., Cichosz, P., Paziewski, P., Sujecki, S.: Machine learning algorithms for prediction of the quality of transmission in optical networks. Entropy (Basel, Switzerland) **23**(1) (January 2021). https://doi.org/10.3390/e23010007
9. Kozdrowski, S., Paziewski, P., Cichosz, P., Sujecki, S.: A comprehensive study of machine learning application to transmission quality assessment in optical networks. Applied Sciences **13**(8) (2023). https://doi.org/10.3390/app13084657, https://www.mdpi.com/2076-3417/13/8/4657
10. Mata, J., de Miguel, I., Durán, R.J., Aguado, J.C., Merayo, N., Ruiz, L., Fernández, P., Lorenzo, R.M., Abril, E.J.: A svm approach for lightpath qot estimation in optical transport networks. In: 2017 IEEE International Conference on Big Data (Big Data). pp. 4795–4797 (2017)
11. Morais, R.M., Pedro, J.: Machine learning models for estimating quality of transmission in dwdm networks. IEEE/OSA Journal of Optical Communications and Networking **10**(10), D84–D99 (2018)
12. Panayiotou, T., Manousakis, K., Chatzis, S.P., Ellinas, G.: A data-driven bandwidth allocation framework with qos considerations for eons. Journal of Lightwave Technology **37**(9), 1853–1864 (2019)
13. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E.: Scikit-learn: Machine learning in Python. Journal of Machine Learning Research **12**, 2825–2830 (2011), library version 1.1.3
14. Rottondi, C., Barletta, L., Giusti, A., Tornatore, M.: Machine-learning method for quality of transmission prediction of unestablished lightpaths. IEEE/OSA Journal of Optical Communications and Networking **10**(2), A286–A297 (2018)
15. Żotkiewicz, M., Ruiz, M., Klinkowski, M., Pióro, M., Velasco, L.: Reoptimization of dynamic flexgrid optical networks after link failure repairs. IEEE/OSA Journal of Optical Communications and Networking **7**(1), 49–61 (Jan 2015). https://doi.org/10.1364/JOCN.7.000049

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97554-7_3