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Long-Term Traffic Forecasting in Optical Networks Using Machine Learning

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Abstract: Here, we lay forth the framework for the optical network traffic forecast issue. The next step is to develop a machine learning strategy for effective network building using Graph Convolutional Networks and Generative Adversarial Networks. Predicts future states. Identifying network peak traffic that could impact routing choices is the primary goal. We check our findings using actual networks supplied by the operator of the network as well as with pseudo realistic datasets created in a bespoke simulator.The results validate the efficacy of our method in optimising both the short-term routing decisions and the long-term network architecture choices.

Keywords: Convolutional Networks,Generative Adversarial Networks,pseudo realistic, Datasets

Introduction: Cloud computing's great fault tolerance and user-friendliness have attracted many businesses in recent years. Consequently, there is a rising need for high-data transmission [1]. Leading cloud service companies, such Tech giants like Google, Amazon, and Microsoft are always investing and competing for a larger slice of the market. Unfortunately, this increase in demand is beyond the capabilities of the existing Internet infrastructure. To deal with the surge in traffic, some have suggested using new technologies as Spectrally-Spatially Flexible Optical Networks (SS-FONs) [2]. Two parameters, the dynamic spectrum and the space assignment, define the 'elasticity' of an SS-FON. According to [3], SS-FON is the most recent iteration of DWDM, which stands for Dense Wavelength Division Multiplexing. With separate spectral and spatial fibre resource management, we can optimise space, bandwidth, and wavelength.

In order to increase transmission power as a whole, space-division multiplexing (SDM) and flexible wavelength allocation are the primary uses of the spatial dimension in fibres.

Furthermore, we will inevitably encounter physical limitations, regardless of how many new technology we use. The capacity crisis will be an issue for optical networks by 2030, according to studies [4]. We can explore more sophisticated ways to regulate it instead of trying to update the technology. The development of a cognitive network idea and the extraction of useful information from large datasets both need the use of these novel models [5]. Cognitive networks are a kind of network that use state-of-the-art analytical methods from several fields to address current issues in communication networks [6]. These fields include deep learning, data analytics, knowledge representation, telecommunication, and network administration. Cognitive optical networks are transport networks that use cognitive processes to understand the present state of the network, make decisions based on that perception, learn from past data, and predict what will happen next in order to accomplish end-to-end objectives.

Cognitive processes utilise different data analytics solutions, usually using machine learning methods, and learn from past data to enhance performance. Data analytics, ML, and deep learning are three potential methodological areas that might pave the way for cognitive network data analysis and, by extension, more sophisticated approaches to allocating resources. We seek to use cognitive approaches to enhance the following important performance parameters of optical networks: energy consumption, network resources, and capital and operational expenses (CAPEX and OPEX).

According to recent studies, the most effective use of optical resources is achieved via network resource provisioning algorithms like Monte Carlo Tree Search (MCTS) that use cognitive networks through traffic prediction. Regrettably, these methods are very vulnerable to variations in traffic load patterns, sometimes known as burst data [7]. Due to the random nature of MCTS's action selection, the accuracy of the network prediction method is proportional to the number of calculation cycles executed within the allotted computational budget. We anticipate a higher likelihood of discovering a workable route within the computational budget if we use data pattern sensitivity to reduce the selection space. Graph convolutional networks (GCNs) [8] and generative adversarial networks (GANs) [9], [10] will be used to achieve this goal. To be more precise, we will first collect the topological structural features of each individual graph snapshot using the GCN. The GAN class of machine learning systems will employ the studied network properties to compete with each other's neural networks. Our concept calls for a single network to act as a generator, sending out data packets in order to produce burst traffic. In order to reduce the Request Blocking Percentage (BP), the other network, known as the discriminator, will use the present state data to attempt to forecast the occurrence of future burst events and change the network's resource provisioning approach accordingly.

The impact of spontaneous peak network traffic occurrences, such as the FIFA World Cup or the Olympics, is a big problem for dynamic routing algorithms [11]. The impact of such peak occurrences grows in proportion to the growth in background network traffic since there are less resources available to handle the increased demand. It is the traffic prediction algorithms that determine how well a dynamic routing algorithm handles peak routing traffic (also known as "flash events"). Unusual peak data characteristics are inefficiently captured by routing algorithms that do not include traffic prediction based on the overall network condition. To reduce BP, we propose using a GCN-GAN model for traffic prediction, which would make network resource allocation more pattern sensitive.

The GCN-GAN approach, a deep learning methodology, is applied to the issue of short-term and long-term traffic prediction in actual optical networks, which is the major originality of this study.

The data given by TelusPureFibre allowed us to test our resource allocation strategy in dynamic routing in real-life settings, proving its efficacy. In this paper, we evaluate GCNGAN in comparison to Long-Short Term Memory. We employed GCN-GAN for traffic prediction in [12], and this article is a follow-up study of that work. A more extensive examination of scenarios with different traffic matrices; research into the network design phase, when our method may be used to pinpoint areas of the network that need updating or expansion; and confirmation of our findings using the actual optical networks in use are the key distinctions.

This study primarily contributes to the following areas.

• **Method:** The distribution of resources in optical networks is our area of research. Both real-world network simulations (based on PureFibre networks in Canada) and datasets derived from TelusPureFibre's historical data are used.

For the purpose of solving the aforementioned issue, we use the GCN-GAN approach. Afterwards, we evaluate it in relation to Long-Short Term Memory, an approach often used in literature. We are not comparing those two methods with other standard solutions like Shortest Path The first thing we did was show that our method is much better than the one in [13], as we have done in previous publications. Our approach is designed to be readily applied to real-time optical network operations due to its rapid calculation time and ability to learn about traffic in real-time.

• **Evaluation:** A pre-existing CEONS simulator is used to analyse our algorithms [14]. After that, we test our hypothesis by applying the algorithms to actual networks.

In other areas of network systems, including urban physical traffic, traffic prediction algorithms have gotten a lot of interest. It is common for deep learning models to

make imprecise predictions since it's hard to average all the potential future states of the issue, therefore they usually only look at the next iteration of states when making predictions, which doesn't take the spatial-temporal aspects of the data into account. More recent models use adversarial training to reduce fuzziness in multi-step traffic prediction and use graph convolution to produce future states that better represent spatial-temporal characteristics; these models outperform non-adversarial models in this field [15].

The authors of [16] suggest and assess a model for dealing with traffic variations using unsupervised learning termed Pattern-Sensitive Networks (PSNs).

All things considered, the authors come to the conclusion that PSNs are superior to other methods for lowering the training duration of the model and better capturing the patterns of variation inherent in past traffic flow. While LSTM-based models outperformed PSNs in severe situations, PSNs did somewhat worse in typical traffic.

The authors of [11] provide a method for handling traffic variations using a new light-splitting strategy in aeons. Despite decreased service delivery due to network congestion, the authors demonstrate that throughput may be significantly improved by dynamic bandwidth reconfiguration.

While discussing ways to optimise network resources, the authors also pointed out that optical route re-routing and wavelength defragmentation are the variables that prevent considerable performance improvement.

In our pursuit of optimal candidate route prediction, we shall shift our attention from the authors' emphasis on the latter to the former.

Graph Convolutional Network Generative Adversarial Network (GCN-GAN) is a non-linear model that can forecast the dynamics of weighted dynamic networks' temporal links; it is proposed and evaluated in [17]. To train a generative-adversarial model that can realistically generate future states, their approach integrates GCNs with Long Short-Term Memory (LSTM) networks to record changing patterns in subsequent graph time slices. Despite not having deployed it yet, the authors claim that the GCNGAN beats six rivals, including a generic LSTM, in particular in sparse-edge-weight networks. Though we examine a different scenario, our work employs a similar method. We want to forecast the "flash events" (to be described later in the article) so that network operators like Telus may reroute traffic to make better use of the resources they already have. In addition, we are assisting network operators in further expanding the network by using GCN-GAN to identify and address any current bottlenecks.

Authors suggest and assess the efficacy of using machine learning methods for traffic prediction in [13]. They examined AMRA, GA, and MNC in relation to their traffic prediction capabilities with and without MCTS and ANN. With medium to high traffic loads, the authors compared SPF. With lesser traffic loads, they compared IBM CPLEX Solver. According to the authors, MCTS is able to deal with traffic fluctuations more quickly.

In low-traffic situations, the GA+MCTS fared better than the AMRA+MCTS, while in high-traffic situations, the AMRA+MCTS performed better. Since there were so many choices to be made so quickly, they reasoned that this must be the explanation. AMRA+MCTS worked well across the board.

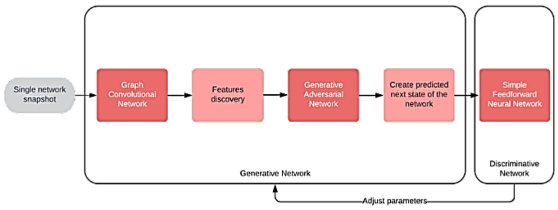

Figure 1: GCN-GAN flowchart

Conclusion

he GCN-GAN model can effectively solve the challenging optical traffic prediction problem by correctly representing edge weights' sparsity in each network snapshot. By allowing forecasting in the resource allocation process, we have accepted more traffic into the network and thereby reduced the network's operating expenditure (OPEX)

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