Ultra-fast Optical Network Throughput Prediction using Graph Neural Networks

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***Abstract*—One of the key performance metrics for optical networks is the maximum achievable throughput. Determining it however, is an NP-hard optimisation problem, often solved via computationally expensive integer linear programming (ILP) formulations. Heuristics, in conjunction with sequential loading, are scalable but non-exact. There is, thus, a need for ultra-fast performance evaluation of optical networks. For the first time, we propose message passing neural networks (MPNN), to learn the relationship between the structure and the maximum achievable throughput of optical networks. We demonstrate that MPNNs can accurately predict the maximum achievable throughput while reducing the computational time by 5-orders of magnitude compared to the ILP.**

***Keywords*—graph neural networks, throughput estimation**

I. Introduction

Multiwavelength optical networks underpin the global data communication network infrastructure and use the wavelength domain both for routing and the increase in point-to-point data transmission. To operate these networks, a routing and wavelength assignment (RWA) is solved to establish lightpaths between the different node pairs. This problem has been shown to be NP-hard and is, therefore, computationally difficult to solve optimally [1].

The overarching goal of physical network design is to maximise the performance, measured by throughput, latency and resilience, whilst minimising the cost and/or resource use, making them intelligent and adaptive [2]. This is an evolution from the previous goals of minimising the number of wavelengths needed to optically route data within the network [3], where the relationship between wavelength requirements and the physical topology is well understood [4]. However, due to growing number of wavelengths in fibres and the associated linear and nonlinear physical layer impairments, physical properties play a significant role in determining both routing and throughput, and must be taken into account in network design [5].

To measure the maximum throughput achievable in any given network, an optimal solution to the RWA problem needs to be found. Integer linear programming (ILP) formulations have been shown to solve the RWA problem optimally [6], however are computationally infeasible for networks larger than about 30 nodes, on average already taking 1000s of seconds for 15 node networks. Problem-agnostic optimisation frameworks, that aim at efficiently exploring the solution space, i.e. meta-heuristics, have been shown to give good solutions in this area, however have no guarantee of achieving a global optimum, whilst often still taking a long time to solve [7]. Heuristics are handcrafted algorithms for specific purposes, based on rules-of-thumb, which on the other hand are highly-scalable, however have shown limited success compared to ILP solutions [8]. The efficient and accurate measurement of the maximum achievable throughput of optical networks remains a considerable challenge.

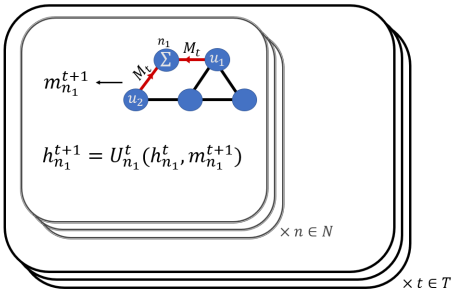

Fig. 1: Diagram demonstrating the process of message passing.

To make this task more computationally efficient, machine learning has been proposed to learn the relationship between the topology and performance parameters based on previously labelled datasets [9]. Traditional deep learning frameworks, such as artificial neural networks (ANN), operate on grid-style data, i.e. vector/matrix inputs. Therefore, when applying them to graph structured problems, suitable graph features need to be chosen, however the graph structure, i.e. how nodes are connected in the graph, is not utilised, thereby losing valuable features. Geometric deep learning, a collection of deep-learning frameworks designed for graph structured data, on the other hand incorporates the graph structure within the learning process. A collection of supervised learning methodologies, within geometric deep learning, are referred to as graph neural networks (GNN), where message passing neural networks (MPNN) are a specific formulation, shown to perform well for regression tasks [10].

In this paper we propose to use an MPNN architecture and apply it to model the throughput performance of optical networks, by learning the relationship between the topology, demand and the maximum achievable throughput. Initially this work focused on core networks. It uses a large dataset

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(about 80000 graphs) to train an MPNN model to generalise the relationship between the topology and the performance of optical networks. We demonstrate significant computational time gains (5 orders of magnitude less than ILP) made when using MPNNs to estimate network performance, thus enabling future topology optimisation including the maximum achievable throughput,and thereby making topology design more intelligent and efficient.

II. Message Passing Neural Networks

A set of digraphs, individually denoted as $G(N, E)$, where N and E represent the set of nodes and edges, respectively, are used to represent the data. All nodes and edges have a pre-determined set of node and edge features, x_n and e_{nu}, respectively, where $n, u \in N$ and $(n, u) \in E$. These node and edge features, are vectors with information relating to either nodes, i.e. degree, traffic, or for the edges, i.e. distance, signal-to-noise (SNR) ratio. In addition to these node and edge features, MPNNs use abstract vectors. An abstract vector is referred to as a node's hidden state, and is represented by h_n^t or for an edge h_{nu}^t, where t represents a message passing iteration. These hidden states are vectors that hold the embeddings for nodes and edges, i.e. for a specific node or edge, they capture the structural information from the rest of the graph. We define the set of node features as X_N and the set of hidden node states as H_N.

The MPNN is made up of three stages: (i) message passing (ii) update (iii) readout. In (i) each node in the graph requests information from its neighbourhood ($\mathcal{N}(n)$). This information is given by feeding in node and edge information into a message function ($M_t(h_n^t, h_u^t, e_{nu})$). To form the message of node n (m_n^{t+1}), the messages are summed from the neighbourhood of n, each given by $M_t(h_n^t, h_u^t, e_{nu})$. This is then, in stage (ii), fed to an update function defined as $U_t(h_n^t, m_n^{t+1})$, which updates the state (h_n^{t+1}) of each node. These two steps are illustrated in the inner block of the diagram shown in figure 1, where one can see that the process is repeated for each node (n) in nodeset (N). This procedure iteratively distributes the information of the graph to every node by collecting the messages and using these to update the new hidden vectors.

After T, normally chosen to be in the order of the diameter of the graphs, message passing rounds and update layers, shown by the outer blocks in figure 1, the hidden states are aggregated and used to create a graph level prediction y, represented by stage (iii). This process of aggregation and graph-level readout is summarised within the readout function $R(H_N, X_N)$, where H_N denotes the set of hidden states and X_N the set of node features. The readout function outputs a scalar value used for prediction. An advantage of this model is that the architecture is size agnostic, meaning that the model can be applied to graphs of different sizes. The message function consists of matrix and vector valued ANNs, the update of a gated recurrent unit (GRU) and the readout of an attention mechanism detailed in [11]. Using supervised learning we can train these three functions, end-to-end, to predict properties by learning on a large number of labelled graphs. The next section lays out how we generated the dataset of graphs and their maximum achievable throughput labels.

III. Data Generation

A dataset of 80000 unique graphs, with 10 to 15 nodes, were used to train the MPNN. The node locations were chosen uniform randomly over a grid that represents the size of the north-American continent, from which the graphs were then generated via the SNR-BA model [5]. These were labelled with their corresponding maximum achievable throughput. This was done by finding the RWA that maximises the throughput, using an ILP, given a uniform traffic distribution.

$$\sum_{w \in W} \sum_{k \in K} \delta_{w,k,z} = \lceil M \cdot T_z^c \rceil \quad \forall z \in Z \tag{1}$$

$$\sum_{z \in Z} \sum_{k \in K} \delta_{w,k,z} I(j \in k) \leq 1 \quad \forall j \in E \quad \forall w \in W \tag{2}$$

The ILP used for the labelling of the dataset, uses a decision variable defined as $\delta_{w,k,z}$, where $w \in W$, $k \in K$ and $z \in Z$, are the set of wavelengths, k-shortest paths and node-pairs, respectively. It is constrained to assigning a lightpath, subject to the normalised traffic matrix (T_z^c) and the objective M, defined as in Eq.(1). For this work all the training data was generated with uniform traffic. Here the objective is to maximise M. The wavelength continuity and edge-disjoint constraints of paths are defined in Eq.(2).

Using this ILP formulation, optimal RWAs were found for each of the graphs in the dataset. Next, their total throughput was calculated using a closed form Gaussian noise (GN) physical layer impairments (PLI) model [12] to estimate the SNR of the different lightpaths. A fully populated C-band (1530-70 nm) and 32 GBd Nyquist spaced channels, giving 156 possible wavelengths was assumed. All links were modelled as multiples of 80km standard single mode fibre spans, amplified with identical erbium-doped fibre amplifiers (noise figure of 4dB). They were interfaced with colourless, directionless and contentionless, reconfigurable optical add-drop multiplexers. After finding the SNR of lightpaths, the capacity was calculated with Shannon's formula and summed over all lightpaths. Using these throughput labels the MPNN was trained in a supervised manner and tested over an unseen dataset of graphs taken from the same distribution, the results of which are analysed in the next section.

IV. Results

For each of the 6000 graphs in the unseen test set, the performance was evaluated via ILP (used for the labels), MPNN, First-Fit k-Shortest-Path (FF-kSP), k-Shortest-Path First-Fit (kSP-FF) and plotted in figure 2a. The latter two are commonly used heuristics for the estimation of maximum achievable throughput [8]. To evaluate the performance of each method, the coefficient of determination (R^2) and the Pearson's correlation coefficient (ρ) were used as metrics. It can be seen that the kSP-FF and FF-kSP heuristics generally underperformed compared to the ILP, giving R^2 values of 0.10 and 0.74, respectively, compared to a value of 0.95 for

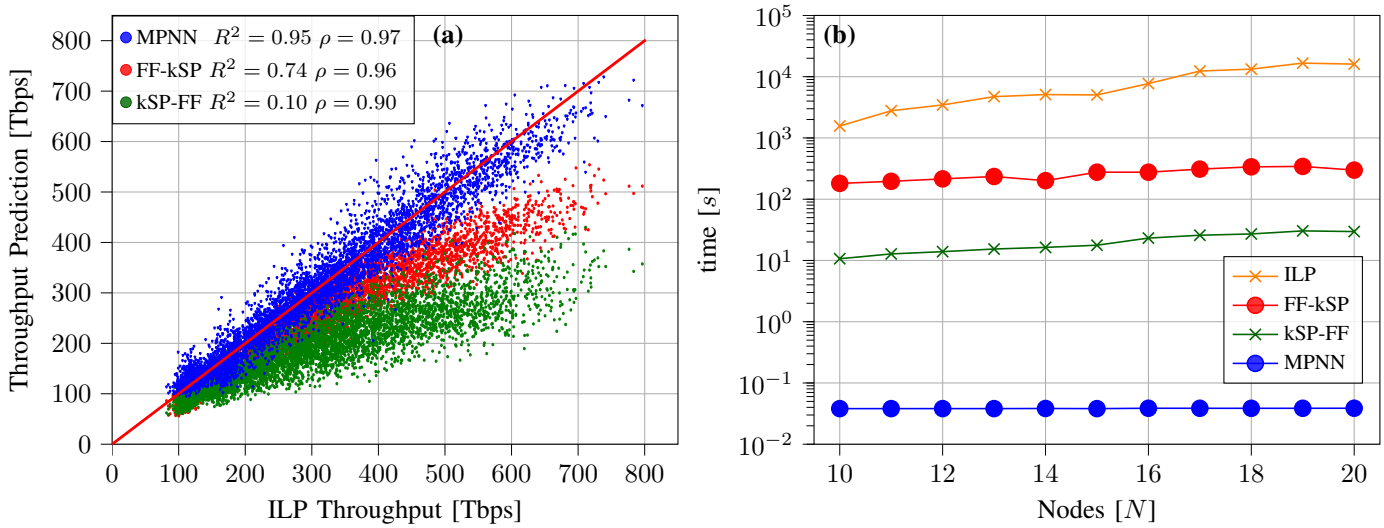

Fig. 2: (a) Residual plot showing the predicted maximum achievable throughput values compared to the true ILP calculated values. (b) Comparison of the computational time needed for ILP, FF-kSP, kSP-FF and MPNN.

the MPNN. This signifies poor predictive accuracy of the labels. The MPNN in comparison has learnt on a variety of graphs of these sizes and can more accurately predict the trend for throughput. The other metric, the Pearson's correlation coefficient (ρ), indicates how linearly correlated two quantities are, in this case the predicted throughput and the actual, with higher ρ values indicating higher linear correlation. It can be seen that the heuristics generally perform well, and the FF-kSP has a high linear correlation ($\rho = 0.96$) between the estimated throughput values and those calculated via the ILP. The MPNN, has the highest correlation ($\rho = 0.97$), meaning it predicts the relative throughput performance of networks the best. To quantify the computational benefits of using MPNNs to model optical networks, graphs with nodes varying from 10 to 20, were used to evaluate the ILP, FF-kSP, kSP-FF and MPNN time performance. For each graph, the respective methodologies were used to calculate the maximum achievable throughput and their computation times measured and plotted in figure 2b. The reduction in computation time for the MPNN model is clear and is in the range of 10s of ms, compared to 10s, 100s and 1000s of seconds for kSP-FF, FF-kSP and ILP respectively. The MPNN model is thus an accurate and fast method for evaluating performance metrics of graphs, which are generally computationally difficult to evaluate. The widespread use of MPNN would allow for the fast evaluation of a large number of graphs within any topology design process, enabling its use in a host of more complex optimisation algorithms.

V. Conclusion

We show that MPNNs can learn to predict with high accuracy, computationally expensive performance parameters such as the maximum achievable throughput of an optical network, whilst massively reducing the computational complexity (about 5 orders of magnitude less than ILP) of predicting this property, enabling its inclusion in future optical network design. Work is ongoing to expand the model to larger number of nodes, traffic asymmetry and explore its generalisability.

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