Intelligent design of optical networks: which topology features help maximise throughput in the nonlinear regime?

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Abstract *The overarching goal in intelligent network design is to deliver capacity when and where it is needed. The key to this is to understand which network topology characteristics impact the achievable network throughput. This is explored through the use of a new generative network model, taking into account physical layer network characteristics.*

Introduction

Multiwavelength optical fibre networks underpin the infrastructure of the Internet and enable a multitude of cloud services. Growing data demands and range of application require the network to be intelligent, able to adapt to the application demands, bandwidth or delay constraints, and deliver capacity when and where it is needed. Early work on wavelength routing focused on calculating wavelength requirements in arbitrarily connected mesh networks[1], without taking physical fibre characteristics into account. However, network throughput is a function of fibre parameters, link distances and lightpath configurations, and networks can not solely be characterised by randomly connected network topologies, defined by a set of vertices and edges[2]. It is the combination of network structure and physical properties, which will provide insights on how to design optimum topology and wavelength routing algorithms and make more intelligent use of deployed networks. Most papers on routing and resource allocation use specific (and typically a very small number) of published network topologies as benchmarks and, thus, the results are difficult to compare or to generalise into a set of parameterisable network design rules[3]–[8].

Large numbers of synthetic graphs have been analysed using generative models[9]–[12], however mostly without including spatial information or physical properties of optical networks. Known as non-geometric generative models, the Erdos-Renyi (ER)[13] and Barabasi-Albert (BA)[14] models are amongst the most widespread of these.

To understand the relationship between network topology and network performance, we describe a new generative graph model that takes spatial information into account, by incorporating the average signal-to-noise ratio into the BA

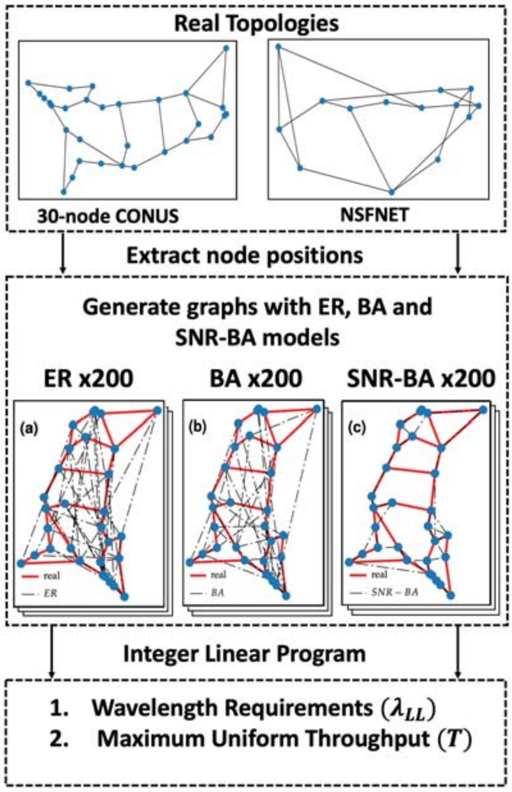

Fig. 1: Process of graph generation and optical network performance analysis.

model. The results are analysed in terms of wavelength requirements and overall network throughput and are compared to the NSFNET[15] and CONUS[16] topologies, representing large North American networks, frequently used in optical network studies.

Generative Graph Models

To account for distance-dependant transmission penalties in optical networks, we include the signal-to-noise ratio (SNR) in the probabilities of choosing edges when generating the graphs. Since geometric generative models capture the grid-like behaviour of real optical networks[17], yet fail at modelling local hubs, we use the conventional BA model[14], known for creating highly connected hubs, as the base. The new model, termed SNR-BA, has probability weights given by:

$$P_{\text{SNR-BA}}(i,j) = \left(\frac{\text{SNR}(i,j)}{\sum_{k \in N} \text{SNR}(i,k)} \right)^{\beta} \cdot \frac{\delta_j}{\sum_{k \in N} \delta_k}, \quad (1)$$

where SNR(i,j) is the SNR of the link between nodes i and j. The SNR includes nonlinear distortion caused by the optical Kerr effect, which can be approximated as noise, as well as amplified spontaneous emission noise from optical amplifiers. To decouple the accumulation of noise across multiple fibre spans[18], the nonlinear interference can be considered to accumulate incoherently. Assuming a similar (eg the average) SNR for each span, with the number of spans given by $n = \left\lfloor \frac{D(i,j)}{L} \right\rceil$, where L is the span length and $\lfloor x \rceil$ denotes rounding to the nearest integer, the SNR of a lightpath between node i and j is

$$\text{SNR}(i,j) = \text{SNR}_1 \cdot \left\lfloor \frac{L}{D(i,j)} \right\rceil, \quad (2)$$

where SNR$_1$ is the SNR after a single span. Substituting (2) in (1) yields the proposed probability weights:

$$P_{\text{SNR-BA}}(i,j) \approx \frac{1}{\left(\sum_{k \in N} \frac{D(i,j)}{D(i,k)} \right)^{\beta}} \cdot \frac{\delta_j}{\sum_{k \in N} \delta_k}, \quad (3)$$

where the approximation is introduced by dropping the rounding operation. Derivation of (3) assumed that the network spans are identical; while this is not always satisfied in practice, (3) still describes the *average* SNR scaling with distance.

Methodology

The performance metrics used to investigate the impact of structural and physical distance properties are (i) the lowest number of wavelengths needed to route all-to-all demands (λ_{LL})[19] and (ii) the maximum network throughput given zero blocking and uniform traffic. As shown in 1, starting with the CONUS and NSFNET node positions, 200 graphs were generated by ER, BA and SNR-BA, respectively, with a total 600 graphs per topology. The constraints imposed on the generated topologies were (i) a minimum degree of 2 and that (ii) no graph could be cut in two by removal of a single edge. The dramatically different network topologies, generated from the same set of CONUS nodes by different generative models, are seen in figure 1. As the CONUS topology is very sparse (connectivity, defined in[1] of 0.082), the ER and BA graphs struggled to satisfy the resilience constraint, creating graphs with 25% and 19% more edges than the original network. Exact edge numbers for all generative models based on the NSFNET node locations were achieved due to its high connectivity of 0.23.

For the exact calculation of wavelength requirements (λ_{LL}) and throughput, an integer linear program (ILP) was used. We assumed a fully populated C-band (1530-70 nm) and 16 GBd Nyquist spaced channels (channel spacing of 0.128nm), giving 312 possible wavelengths. All links were assumed to be multiples of 80km standard single mode fibre spans with $\beta = 0.2\frac{dB}{km}$,$D = 18\frac{ps}{mm \cdot km}$ and $\gamma = 1.2\frac{1}{W \cdot km}$, amplified by identical erbium-doped fibre amplifiers, (noise figure of 4dB). They were interfaced with colourless, directionless and contentionless, reconfigurable optical add-drop multiplexers (CDC-ROADM). The ILP computed λ_{LL} for all the 1200 of the ER, BA and SNR-BA graphs, to compare these with the λ_{LL} value, calculated for the CONUS and NSFNET actual topologies (with the exact link distances).

The maximum throughput (T) for the generated graphs was calculated via another ILP formulation[3] and a closed form Gaussian noise (GN) physical layer impairments (PLI) model[20] to estimate the SNR of the different lightpaths, to compare real and generated networks. For both ILP formulations only shortest paths were considered when calculating both λ_{LL} and T.

Results

The ILP yielded the minimum wavelength requirement, that is the minimum number of wavelengths needed to route the $N(N-1)/2$ demands between all node pairs, for the CONUS network as 122, for the NSFNET this number as 13, same as[1]. These are shown in the box-plots of figure 2, together with the values for the ER, BA and SNR-BA graphs. The box-plot shows the distribution of the data together with the median, interquartile range and the minimum and maximum values.

Figure 2a shows that the CONUS-based ER and BA graphs have 52% and 51% lower wavelength requirements than the SNR-BA graphs.

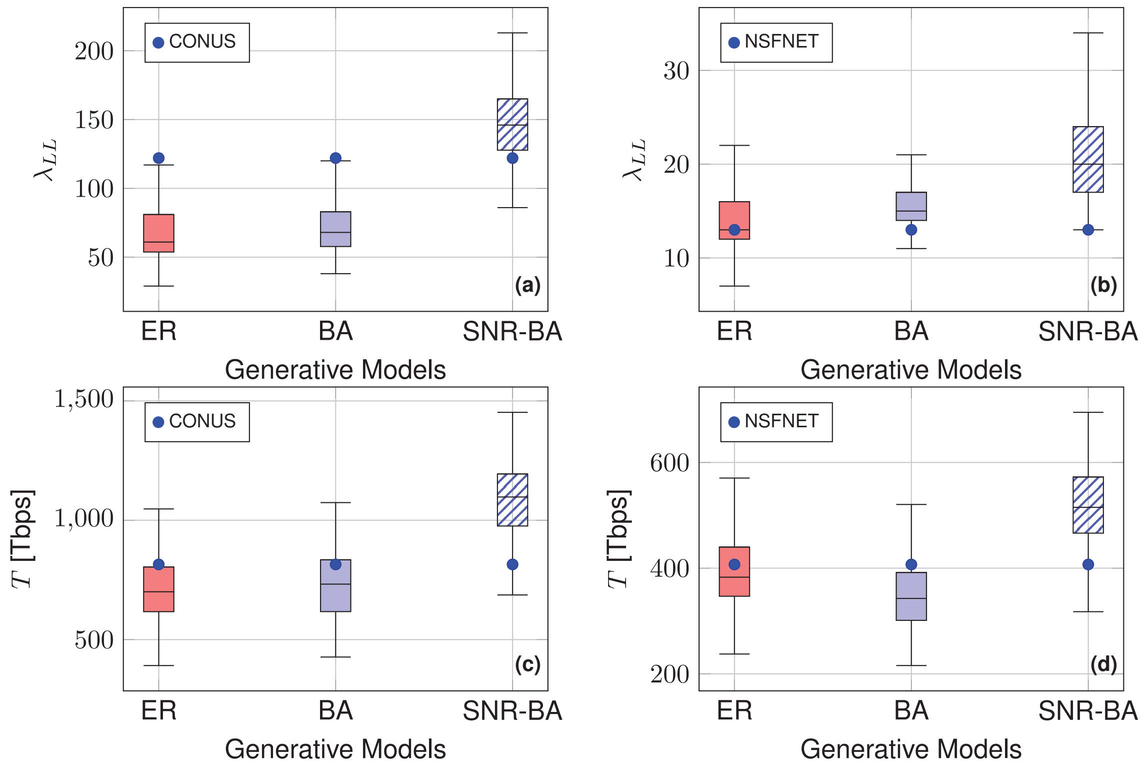

Fig. 2: Minimum number of wavelengths (λ_{LL}) for the ER, BA and SNR-BA graphs based on (a) CONUS and (b) NSFNET node-positions. Maximum uniform bandwidth throughput (T) for ER, BA and SNR-BA graphs based on (c) CONUS and (d) NSFNET node-positions.

Similarly, NSFNET-based ER and BA graphs (figure 2b) have 31% and 23% lower wavelength requirements, than the SNR-BA graphs. The ER and BA graphs appear to have a structural advantage, in terms of wavelength requirements, over the SNR-BA graphs, having smaller diameters and edges connecting larger part of the graph. However, given the overarching goal of maximising the network throughput, we must now consider physical properties, in conjunction with the structural properties.

The maximum uniform throughput (T) of the ER, BA and SNR-BA graphs based on the CONUS and NSFNET topologies was calculated and is shown in figure 2c and d. It can be seen that it is now the SNR-BA graphs that, on average, perform 48% better than the ER graphs and 43% better than the BA graphs for the graphs based on the CONUS topology, despite the greater number of edges in the ER and BA graphs. For the NSFNET-based graphs, the SNR-BA graphs, on average, outperformed the BA and ER graphs by 46% and 27%, respectively. Therefore, it is clear that the ER and BA graphs, on average, perform worse than the SNR-BA graphs for both example networks. This drop in performance between the ER and BA graphs compared to the SNR-BA graphs is the result of longer path lengths. The paths in the CONUS-based ER and BA graphs are on average 215% and 187%, respectively, longer than those taken over the SNR-BA graphs. For the NSFNET-based graphs, although shorter, the signals travels 95% and 98% further over the ER and BA graphs compared to the SNR-BA graphs. This difference in distances, and the associated transmission penalties, dominate the achievable throughput, and at these distances the structural advantages of the ER and BA graphs do not translate into larger throughputs.

In conclusion, the study of structural and physical properties of optical networks, using generative models highlights that the structural advantage of lower minimum wavelength requirements in ER and BA graphs, does not equate to higher throughputs due to the increased path lengths, and associated transmission penalties. The proposed model of SNR-BA, however, chooses shorter edges, minimising path lengths throughout the graph and therefore, helping to maximise throughput when the distance dominates the achievable throughput in the network. Work is ongoing to quantify the impact of demand variation, wavelength requirements, distance scaling and throughput for the different graph models.

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References

[1] S. Baroni and P. Bayvel, "Wavelength requirements in arbitrarily connected wavelength-routed optical networks", *Journal of Lightwave Technology*, vol. 15, no. 2, pp. 242–251, Feb. 1997.

[2] D. Semrau, S. Durrani, G. Zervas, R. I. Killey, and P. Bayvel, "On the Relationship Between Network Topology and Throughput in Mesh Optical Networks", *arXiv:2008.06708 [cs, eess]*, Aug. 2020.

[3] D. J. Ives, P. Bayvel, and S. J. Savory, "Routing, modulation, spectrum and launch power assignment to maximize the traffic throughput of a nonlinear optical mesh network", en, *Photonic Network Communications*, vol. 29, no. 3, pp. 244–256, Jun. 2015.

[4] R. J. Vincent, D. J. Ives, and S. J. Savory, "Scalable Capacity Estimation for Nonlinear Elastic All-Optical Core Networks", *Journal of Lightwave Technology*, vol. 37, no. 21, pp. 5380–5391, Nov. 2019.

[5] X. Wan, N. Hua, and X. Zheng, "Dynamic Routing and Spectrum Assignment in Spectrum-Flexible Transparent Optical Networks", EN, *Journal of Optical Communications and Networking*, vol. 4, no. 8, pp. 603–613, Aug. 2012.

[6] I. Martin, S. Troia, J. A. Hernandez, A. Rodriguez, F. Musumeci, G. Maier, R. Alvizu, and Ã. GonzÃ¡lez de Dios, "Machine Learning-Based Routing and Wavelength Assignment in Software-Defined Optical Networks", *IEEE Transactions on Network and Service Management*, vol. 16, no. 3, pp. 871–883, Sep. 2019.

[7] X. Chen, B. Li, R. Proietti, H. Lu, Z. Zhu, and S. J. B. Yoo, "DeepRMSA: A Deep Reinforcement Learning Framework for Routing, Modulation and Spectrum Assignment in Elastic Optical Networks", *Journal of Lightwave Technology*, vol. 37, no. 16, pp. 4155–4163, Aug. 2019.

[8] F. Shirin Abkenar and A. Ghaffarpour Rahbar, "Study and Analysis of Routing and Spectrum Allocation (RSA) and Routing, Modulation and Spectrum Allocation (RMSA) Algorithms in Elastic Optical Networks (EONs)", en, *Optical Switching and Networking*, vol. 23, pp. 5–39, Jan. 2017.

[9] H. Wu, F. Zhou, Z. Zhu, and Y. Chen, "Interference-and-security-aware distance spectrum assignment in Elastic Optical Networks", in *2016 21st European Conference on Networks and Optical Communications (NOC)*, Jun. 2016, pp. 100–105.

[10] M. W. Ashraf, S. M. Idrus, F. Iqbal, and R. A. Butt, "On spatially disjoint lightpaths in optical networks", en, *Photonic Network Communications*, vol. 36, no. 1, pp. 11–25, Aug. 2018.

[11] A. Pages, J. Perello, S. Spadaro, and G. Junyent, "Strategies for Virtual Optical Network Allocation", *IEEE Communications Letters*, vol. 16, no. 2, pp. 268–271, Feb. 2012.

[12] D. B. Depizzol, J. Montalvao, F. de Oliveira Lima, M. H. M. Paiva, and M. E. V. Segatto, "Feature selection for optical network design via a new mutual information estimator", *Expert Systems with Applications*, vol. 107, pp. 72–88, 2018.

[13] P. Erdos and A. Renyi, "On the Evolution of Random Graphs", in *Publication of the Mathematical Institute of the Hungarian Academy of Sciences*, 1960, pp. 17–61.

[14] A.-L. Barabasi and R. Albert, "Emergence of scaling in random networks", *Science*, vol. 286, no. 5439, pp. 509–512, Oct. 1999.

[15] N. M. Garcia, M. Pereira, M. M. Freire, P. P. Monteiro, and P. Lenkiewicz, "Performance of Optical Burst Switched Networks for Grid Applications", en, in *International Conference on Networking and Services (ICNS '07)*, Athens, Greece: IEEE, Jun. 2007, pp. 120–120.

[16] J. M. Simmons, *Optical Network Design and Planning*, en, ser. Optical Networks. Cham: Springer International Publishing, 2014.

[17] E. K. Cetinkaya, M. J. F. Alenazi, Y. Cheng, A. M. Peck, and J. P. G. Sterbenz, "A comparative analysis of geometric graph models for modelling backbone networks", *Optical Switching and Networking*, Special Issue on RNDM 2013, vol. 14, pp. 95–106, Aug. 2014.

[18] P. Poggiolini, G. Bosco, A. Carena, V. Curri, Y. Jiang, and F. Forghieri, "The GN-Model of Fiber Non-Linear Propagation and its Applications", *Journal of Lightwave Technology*, vol. 32, no. 4, pp. 694–721, Feb. 2014.

[19] S. Baroni, R. J. Gibbens, and P. Bayvel, "On the number of wavelengths in arbitrarily-connected wavelength-routed optical networks", en, in *Optical Networks and Their Applications*, Washington D. C.: OSA, 1998, MN2.

[20] D. Semrau, R. I. Killey, and P. Bayvel, "A Closed-Form Approximation of the Gaussian Noise Model in the Presence of Inter-Channel Stimulated Raman Scattering", *Journal of Lightwave Technology*, vol. 37, no. 9, pp. 1924–1936, May 2019.