Parameter Optimisation for Ultra-Wideband Optical Networks in the Presence of Stimulated Raman Scattering Effect

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***Abstract*—This paper studies the effects of channel launch power and topology parameters on performance for ultra-wideband optical networks in the presence of stimulated Raman scattering (SRS). Results exhibit significant throughput improvements for optimised per-channel launch power allocation over conventional uniform power allocation. Furthermore, the impact of network structural features on performance is investigated and a significant increase in throughput and a reduction in fibre installation cost are achieved by optimising network topology for two real world core networks.**

***Index Terms*—parameter optimisation, stimulated Raman scattering, network topology, launch power**

I. Introduction

Performance optimisation for optical networks is an interesting and challenging research topic. Several studies have been conducted using exact [1]–[6] and intelligent [7]–[9] methods considering different network parameters and performance metrics. It is vital to understand the effects from each parameter in order to improve the network performance given the flexibility and costs associated with setting these parameters. In a novel flexible ultra-wideband scenario, individual links can be populated with a variable number of channels with variable characteristics, and the problem of fast network reconfiguration and optimisation becomes critical.

Due to stimulated Raman scattering effects, the channel power optimisation problem becomes non-convex in ultra-wideband settings as presented in the work of Roberts et al. [2]. Therefore, conventional convex optimisation methods cannot be applied to this problem directly. Meta-heuristic optimisation methods such as Genetic Algorithms (GA) [10] have been successfully applied to solve a wide range of non-linear non-convex complex engineering optimisation problems [11], [12]. In this paper, a GA based approach is proposed to solve the network optimisation problem for a general real-world optical network considering a comprehensive set of parameters and performance metrics including throughput, resilience, latency and cost. This study presents network performance improvements by optimal setting of network parameters for ultra-wideband networks. Recent studies [3], [5] have observed improved network performance in $C+L$ bands by optimising uniform launch power allocation. We further extend this line of research by performing per-channel non-uniform launch power optimisation for SRS aware ultra-wideband networks. According to previous studies on C band systems [1], [13] only marginal throughput gains are achieved by per-channel launch power allocation over the uniform power allocation and therefore, optimising per-channel launch powers does not seem cost-effective for C band systems. This study exhibits throughput improvements in the range of $10\% - 13\%$ for optimised per-channel launch power allocation over uniform power allocation in ultra-wideband networks under both uniform and non-uniform traffic suggesting the cost effectiveness of optimised per-channel launch power allocation in ultra-wideband networks.

Recent study by Bayvel et al. [9] suggests that the network performance can be improved by generating network topology considering optical parameters over traditional topology generators that do not consider these parameters. Extending this approach we generate optimal topology by evolving existing topology using genetic algorithm considering optical parameters. Significant increase in throughput is achieved in the range of $39\% - 65\%$ by optimising network topology for two real world networks and for three traffic models. Also, a reduction in fibre installation cost is achieved in the range of $16\% - 29\%$.

The organisation of the rest of the paper is as follows. Section II discusses the state of the art of modelling SRS effect in optical networks. In Section III, the proposed performance optimisation framework is presented. Section IV describes the launch power optimisation simulations for three traffic matrices and for a real world network DTAG followed by Section V describing the topology optimisation simulations for two real world networks DTAG and GB. Finally, Section VI concludes the paper.

II. Stimulated Raman Scattering Aware Network Simulation for Ultra-Wide Bands

We employ GNPy, the Gaussian noise model based simulator proposed by Ferrari et. al [14] for network simulation. We extend GNPy with the closed form approximation for SRS aware generalised Gaussian noise (GGN) model by Semrau et al. [15]. Figure 1 depicts the GGN model outputs of nonlinear noise powers for sample uniform channel launch powers. Both fibre loss and inter-channel SRS gains are assumed to be entirely compensated and ideally equalised by EDFAs after each fibre span, respectively. Hence, the EDFA gain is defined

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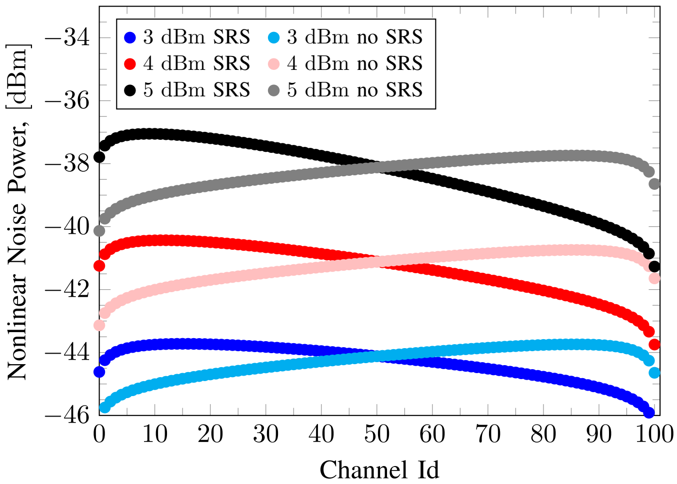


Fig. 1: Nonlinear noise powers based on GGN model [15] for a 101 channel, 100 GHz spacing, 2000 km (80 km, 25 spans) link for sample uniform launch powers 3 dBm, 4 dBm and 5 dBm with and without SRS effect.

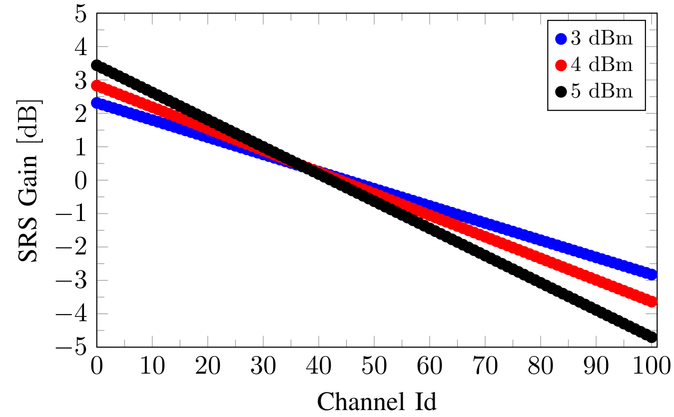


Fig. 2: SRS gain (Formula 1) for 3 dBm, 4 dBm and 5 dBm launch powers for a 2000 km link of 25, 80 km spans and for 101 channels and 100 GHz spacing.

as $G_{\text{EDFA}}(f_k) = e^{\alpha(f_k)L_s} G_{\text{SRS}}^{-1}(f_k)$, with $\alpha(f_k)$ being the fibre loss parameter corresponding to the centre frequency f_k of each $k-$channel [1], and L_s being the fibre span length. The inverse gain due to SRS can be expressed as [16]

$$G_{\text{SRS}}^{-1}(f_k) \approx \frac{\text{Sinhc}\left(\frac{C_r}{2}\,\text{BW}\, L_{\text{eff}}(f_k) \sum_k P(f_k)\right)}{\exp\left(-C_r\, f_k\, L_{\text{eff}}(f_k) \sum_k P(f_k)\right)}, \quad (1)$$

where BW stands for the total WDM bandwidth, C_r is the linear regression slope of the normalised (by the effective fibre mode area $A_{\text{eff}}(f_k)$) polarisation-averaged Raman gain, L_{eff} is the fibre effective length, and the function $\text{Sinhc} \triangleq \frac{\sinh(x)}{x}$. Figure 2 describes the gain profiles due to the inter-channel SRS assuming sample uniform launch powers, i.e., $P(f_k) = \text{const}, \forall k$ of a 101 channel system.

III. Framework for Performance Optimisation in Optical Networks

A. Optimisation Problem

The variables of the optimisation problem are the considered network parameters. We consider channel launch powers and topology parameters in this study. The objective function for the throughput optimisation can be formulated as follows:

$$\text{Find:} \quad \boldsymbol{X} = [x_1, x_2, \ldots, x_n], \quad (2a)$$

$$\text{Maximise:} \quad C_{\mathsf{T}}(\boldsymbol{X}) = \sum_{j=0}^{m} \mathsf{T}_{p_j}. \quad (2b)$$

In the above equation, $\boldsymbol{X}$ is a vector of decision variables containing the parameters for a network, n is the number of parameters, m is the number of light-paths, $C_{\mathsf{T}}(\cdot)$ represents the performance metric throughput T within the network for all the light-paths p_j for which the individual throughput for each light-path is represented by T_{p_j}. The per light-path throughput T_p is defined as follows:

$$\mathsf{T}_p = 2R_S \sum_k \log_2\left(1 + \text{SNR}\left[p(\lambda_k)\right]\right) \quad [\text{Tbps}], \quad (3)$$

where k denotes the channel index in the light-path p, R_S is the symbol rate, and $\text{SNR}\big[p(\lambda_k)\big]$ stands for the signal-to-noise ratio [2] at the receiver at the end of path p of the channel with λ_k channel centre wavelength.

B. Optimisation Algorithm

Algorithm 1: $(\mu + \lambda)$-EA: Evolutionary Algorithm

1) Initialise the population $\mathcal{P} = \{X_1, X_2, \ldots, X_{j-1}, X_j, X_{j+1}, \ldots, X_\mu\}$ with μ optical network parameter setting individuals $X_j = [x_1, x_2, \ldots, x_{i-1}, x_i, x_{i+1}, \ldots, x_n]$, i.e., a vector of optical network parameters x_i.
2) Select $\mathcal{O} \subseteq \mathcal{P}$, where $|\mathcal{O}| = \lambda$.
3) For each $\{I_1, I_2\} \in \mathcal{O}$, produce offspring I_1' I_2' by crossover and mutation. Add each offspring to $\mathcal{P}$.
4) Fitness evaluation of all $I \in \mathcal{P}$.
5) Select $\mathcal{S} \subseteq \mathcal{P}$ where $|\mathcal{S}| = \mu$.
6) $\mathcal{P} := \mathcal{S}$.
7) Repeat step 2 to 6 until termination criterion is reached.

The population $\mathcal{P} = \{X_1, X_2, \ldots, X_{j-1}, X_j, X_{j+1}, \ldots, X_\mu\}$ consists of a candidate solution named a GA individual. Such an individual is represented by a real valued vector $X_j = [x_1, x_2, \ldots, x_{i-1}, x_i, x_{i+1}, \ldots, x_n]$, where each GA gene [10] represents a network parameter x_i (1). Genetic operators crossover and mutation are applied on the

[1] k being the channel index relative to the centre bandwidth channel for which k = 0

TABLE I: System parameters

Parameter	Value	Units
Carrier wavelength	1550	nm
Symbol rate (R_S)	100	GBd
Channel spacing	100	GHz
Number of channels	101	–
EDFA noise figure	4.5	dB
Roll-off factor	0.001	%
Attenuation coefficient (α)	0.2	dB/km
CD coefficient	17	ps/nm/km
CD slope coefficient	0.067	ps/nm^2/km
Nonlinear coefficient	1.2	/W/km
Raman gain slope (C_r)	0.028	/W/km/THz

selected (2) GA individuals to create offsprings (3). The state-of-the-art uniform crossover and perturbation mutation operators [10] are employed. Each generation is "fitness tested" (4) to see whether its members are better or worse than the preceding, with the best going forward for the next generation (5). Algorithm 1 outlines the Genetic Algorithm (GA) optimisation process.

1) Fitness Function: The fitness value for throughput as described in Formula 2 is retrieved from the GNPy simulation [14] for a optical network parameter setting represented by a GA individual. We employ k shortest path routing [17] with the Dijkstra algorithm [18] to find the shortest paths, and the well-known first fit spectral assignment (FFSA) strategy [19] for spectral assignment. The considered simulation set-up and the traffic matrices are described in the Section IV-A.

IV. Launch Power Optimisation

A. Simulation Set-up

The objective and the constraints for the optimisation simulations are as defined in Section III-A. The optical parameters are kept fixed as presented in Table I for the simulation. TRx noise is assumed to be set to zero and system margins can be deemed entirely neglected.

1) Optimiser set-up: The GA hyper-parameters for the optimisation are chosen as follows: the population size of 10, the crossover and mutation probabilities of 0.8 and 0.1, respectively. The number of generations is set to 2000 or until the convergence is observed.

2) Demand simulation: Three traffic demand matrices based on state-of-the -art [1], [3], [20]–[24] are considered within this study: $\hat{T}_1$ and $\hat{T}_2$ representing non uniform traffic generated from a Pareto distribution [21], [24] representing traffic bursts and Poison distribution [20], [23] representing smoother traffic respectively, and $\hat{T}_3$ representing uniform all-to-all traffic: a matrix considered in the state-of-the-art [1], [3], [22]. For simplicity, we consider static traffic simulation similar to the studies of Ives et al. [22] and Virgillito et al. [3]. Let us consider a network graph $\mathscr{G} = (\mathcal{V}, \mathcal{E})$ with a set of nodes $\mathcal{V} = \{v_1, v_2, ..., v_n\}$ and set of edges $\mathcal{E}$, traffic matrix $\hat{T}_{nn}$, source nodes v_i, destination nodes v_j and $i \neq j$. Let us define the traffic demand as follows:

$$\hat{T}_1: \quad \forall \{v_i, v_j\} \in \mathcal{V}, \quad \hat{T}_{ij} = X \sim \mathrm{Pareto}\left(x_m, \alpha\right). \tag{4a}$$

$$\hat{T}_2: \quad \forall \{v_i, v_j\} \in \mathcal{V}, \quad \hat{T}_{ij} = X \sim \mathrm{Pois}\left(\lambda\right). \tag{4b}$$

$$\hat{T}_3: \quad \forall \{v_i, v_j\} \in \mathcal{V}, \quad \hat{T}_{ij} = \frac{c}{n\left(n-1\right)}. \tag{4c}$$

and $\hat{T}_{ij} = 0$ for the case of $i = j$. Figure 3 describes the respective traffic demand matrices for DTAG network with the number of nodes $n = 14$, the lower bound for the Pareto distribution Eq. (4a) $x_m = 250$, the shape parameter $\alpha = 2$, the expectation of the Poisson distribution $\lambda = 500$ (see, Eq. (4b)), and finally the constant $c = 91000$ in the case of the uniform matrix Eq. (4c). These scaling parameters are chosen to have the same expected value $\mathbb{E}\left[X\right]$ for the three traffic demand distributions.

B. Results

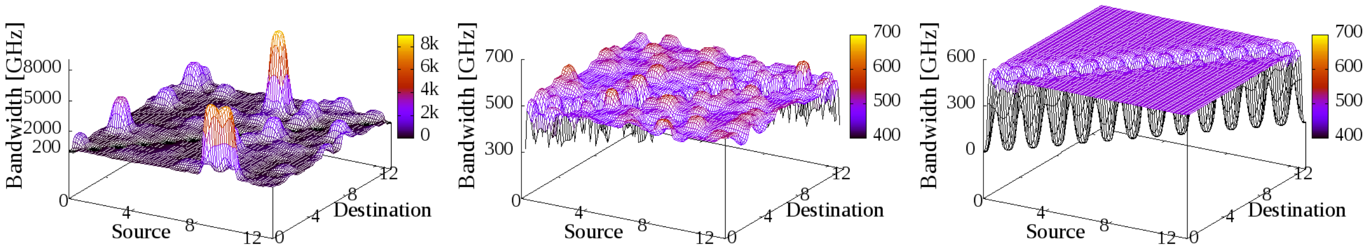
The optimisation simulation is performed for an ultra-wideband system with 101 channels considering the system parameters presented in Table I. Figure 4 presents the optimised launch powers obtained for traffic matrices $\hat{T}_1$, $\hat{T}_2$, and $\hat{T}_3$. For traffic matrix $\hat{T}_1$, the optimal non-uniform launch powers resulted in 63.1 Tbps, achieving a 12.7% gain over uniform launch powers. For traffic matrix $\hat{T}_2$, the resultant throughput is 65.3 Tbps achieving a 11.2% gain over uniform launch powers. Similar results are observed for traffic matrix $\hat{T}_3$, with a throughput of 66.6 Tbps and a throughput gain of 10.1% over uniform launch powers.

We further consider the performance for traffic matrices and networks with different graph densities in order understand the inter-dependencies between launch powers, traffic and network structure and their effects on throughput. Density D of graph $\mathscr{G} = (\mathcal{V}, \mathcal{E})$ with a set of nodes $\mathcal{V}$ and a set of edges $\mathcal{E}$ is defined as follows [25]:

$$\mathsf{D} \triangleq \frac{2\left|\mathcal{E}\right|}{\left|\mathcal{V}\right|\big(\left|\mathcal{V}\right|-1\big)}, \tag{5}$$

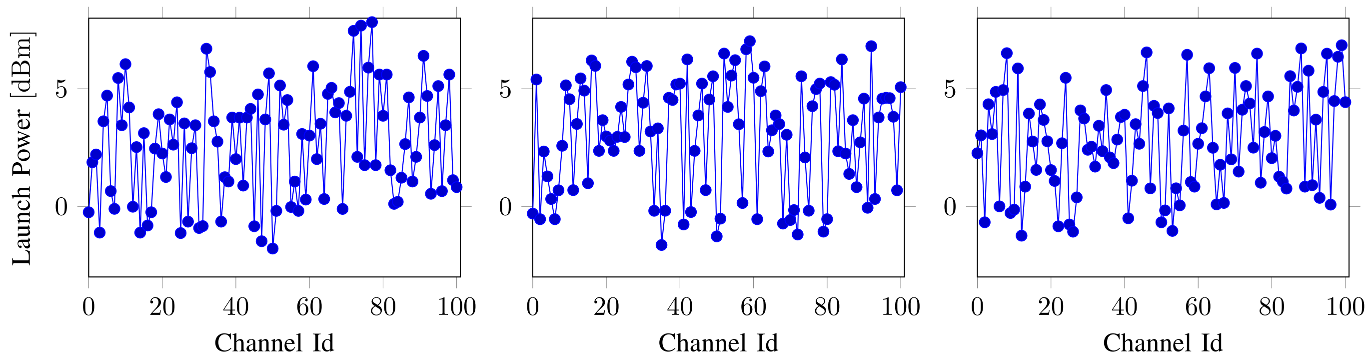
where $|\cdot|$ denotes the cardinality of a set.

In order to understand the sensitivity of throughput based on graph density, launch powers and traffic, 3 different density levels are considered for simulations. The density of the original graph of the DTAG network, a 25% reduction of the density and a 25% increase of the density. The original topology is modified by adding or deleting edges uniformly at random, adhering to a resilience constraint of minimum node degree of 2. Throughput is optimised for each topology by optimising channel launch powers. As observed in Figure 5 throughput is positively correlated with graph density. However, the amount of improvement seems to be affected by the underlying traffic matrix. This sheds light into the impact of network traffic and topology on network performance. Hence, we further investigate topology optimisation considering the traffic in the next section.



(a) $\hat{T}_1$ (b) $\hat{T}_2$ (c) $\hat{T}_3$

Fig. 3: Traffic demand matrices $\hat{T}_1$, $\hat{T}_2$, and $\hat{T}_3$ for DTAG network (topology presented in Fig 8 (a))



(a) $\hat{T}_1$ (b) $\hat{T}_2$ (c) $\hat{T}_3$

Fig. 4: Optimised channel launch powers for mesh network DTAG (topology presented in Fig 8 (a)), for 101 channels and for traffic matrices $\hat{T}_1$, $\hat{T}_2$, and $\hat{T}_3$ (as defined in Formula 4) resulting in 63.1 Tbps, 65.3 Tbps and 66.6 Tbps throughput and gains of 12.7 %, 11.2 % and 10.1 %, over uniform power allocation respectively.

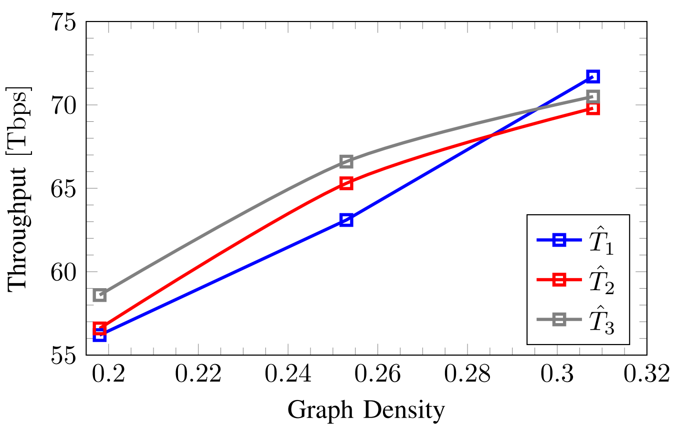


Fig. 5: Throughput variation over graph density (Formula 5) for 101 channels for DTAG network with traffic matrices $\hat{T}_1$, $\hat{T}_2$ and $\hat{T}_3$ (Formula 4).

V. Topology Optimisation

To understand the importance of the topology parameters on network optimisation, we conduct simulations. In practice, topology may be constrained by several real world constraints. Different from the previous optimisation, the standard genetic operators used for real valued vector of parameters cannot be applied to the new genetic individuals represented by a network topology. Therefore, we modify the optimisation algorithm discussed in Section III-B by introducing new mutation and crossover operators and new constraints.

A. Genetic Operators for Topology Generation

The network topology is represented by the respective adjacency matrix of the network graph. A GA individual is extended by a bit-wise vector representing the adjacencies. Bit-wise variation operators are employed including inversion mutation, where bit `1` is flipped to bit `0` and vise versa and the crossover operators inspired by bit-wise operators `OR`, `AND` and `XOR` as explained in the work by Lima et al. [26]. Moreover, we consider a problem specific mutation operator to speed up the optimisation process called 2-Opt mutation where two edges are deleted and two edges are added following the well-known 2-Opt operator [27] in the local search domain.

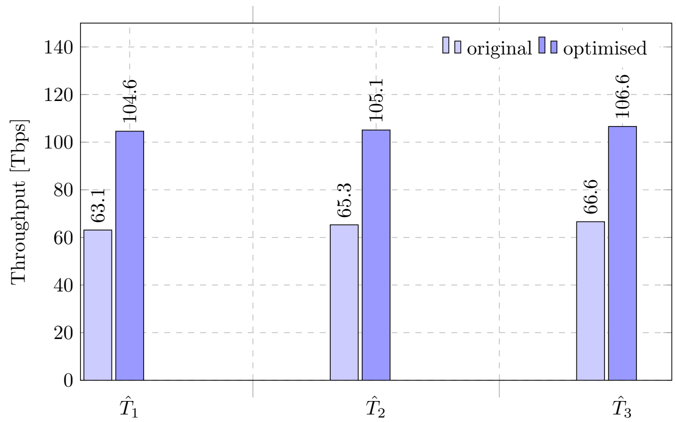


Fig. 6: Topology optimisation results showing original and optimised throughput values for DTAG network under 3 traffic matrices (Formula 4). System parameters are as defined in Table I and optimisation set up is as described in Section V-B.

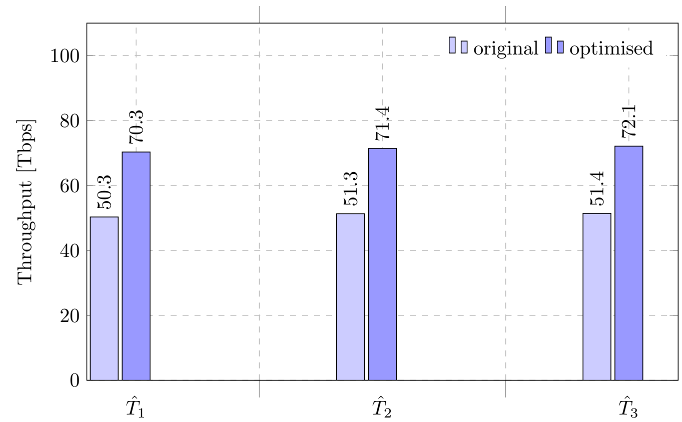


Fig. 7: Topology optimisation results showing original and optimised throughput values for GB network under 3 traffic matrices (Formula 4). System parameters are as defined in Table I and optimisation set up is as described in Section V-B.

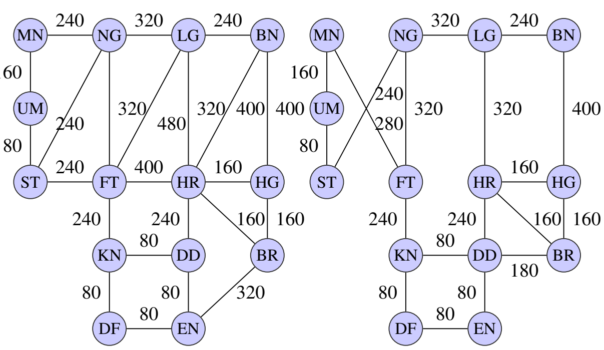
B. Simulation Set-up

The simulation set-up is as described in Section IV-A1 except for the mutation and crossover probabilities and the topology specific constraints. Here, we consider a lower crossover probability of 0.5 to compensate the effects from higher diversity introduced by the bit-wise crossover operators. Moreover, we consider a higher mutation probability of 0.5 to allow both mutation operators to contribute effectively. Within each mutation, either inversion mutation or 2-Opt mutation is chosen uniformly at random. The network physical parameters are kept fixed during the topology optimisation as described in Table I and launch power is kept fixed at the optimised values in Section IV. We consider additional constraints on the maximum total fibre length to be 80% of the complete mesh graph and the minimum node degree of 2 as a resilience constraint.

C. Results

Simulation results for DTAG network under the 3 traffic matrices $\hat{T}_1$, $\hat{T}_2$, and $\hat{T}_3$ are presented in Figure 6. For all three cases, significant throughput gains are observed in the range of $60\% - 65\%$. The simulation is repeated for another benchmark core network namely GB and the results are presented in Figure 7. Significant throughput gains are observed for the three traffic matrices in the range of $39\% - 40\%$. However, this performance gain comes at a cost of increased expenses due to fibre installation.

Moreover, the topology is optimised minimising the fibre installation cost as the objective with a specified minimum throughput constraint under traffic matrix $\hat{T}_3$. A 16% (64080 to 53800 km) reduction in the fibre installation cost is observed for GB (Figure 9) allowing a minimum throughput constraint of 51 Tbps. For DTAG, a cost reduction of 29.3% (5520 to 4240km) is achieved maintaining a 66 Tbps minimum throughput constraint respectively (Figure 8).

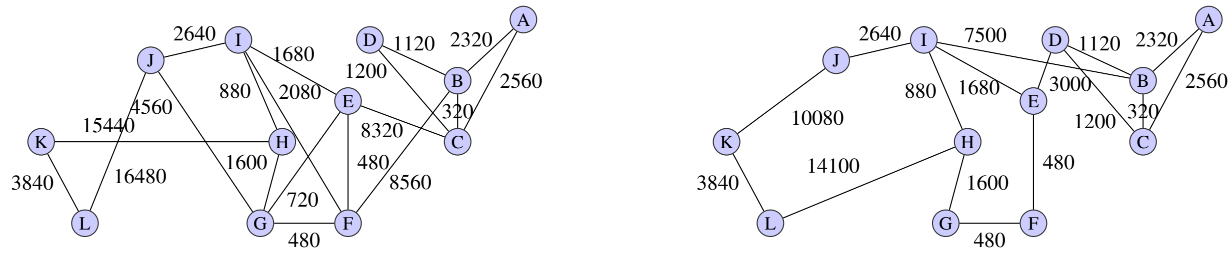


(a) Original DTAG topology (b) Optimised DTAG topology

Fig. 8: The topology before *(a)* and after *(b)* the optimisation achieving 29.3% reduction in the fibre installation cost for the DTAG network for a 66 Tbps throughput constraint. The edge weights of the graphs correspond to the distances in km.

VI. Conclusion and Future Work

The effects of optimised channel launch powers and network topology are studied for ultra-wideband optical networks in the presence of SRS effect. Significant improvements in throughput in the range of $10\% - 13\%$ are achieved by optimising per-channel launch powers in ultra-wideband systems compared to the marginal gain shown in the literature for C band systems. Considering the cost of optimising per-channel launch powers, it can still be cost effective for ultra-wideband systems. The impacts of traffic is investigated and the optimal launch powers exhibit dependency to the underlying traffic. Hence, in practice, re-optimising the launch powers at network operational stage is desirable with the changing network traffic. Furthermore, the throughput dependency on graph density is observed and therefore, optimisation is carried out to generate optimal topology. Significant performance improvements are achieved by optimising the topology in terms of throughput (in the range of $39\% - 65\%$) and fibre installation cost (in the range of



(a) Original GB topology

(b) Optimised GB topology

Fig. 9: The topology before *(a)* and after *(b)* the optimisation achieving 16% reduction in the fibre installation cost for the GB network for a 51 Tbps throughput constraint. The edge weights of the graphs correspond to the distances in km.

$16\% - 29\%$) for the considered core networks DTAG and GB and for the three considered traffic matrices highlighting the effects of network structural parameters on performance and the benefits of simulation based optimisation at network design and re-design stages. Future work will extend this approach to multi objective optimisation to generate network topology optimising throughput and cost simultaneously and dynamic launch power re-optimisation under dynamic traffic.

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