

A Traffic Intensity Model for Flexgrid Optical Network Planning under Dynamic Traffic Operation

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Abstract: We obtain a model to estimate the highest traffic intensity that a flexgrid-based network can support in dynamic scenarios. A design problem is introduced to illustrate its application. Numerical results validate both accuracy and utility.

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1. Introduction

Future flexgrid optical networks need to be designed to support huge volumes of traffic in dynamic scenarios [1]. The flexibility provided by mixing connections of different bitrates is achieved by assigning different amount of frequency slots to each connection so to match bandwidth requirements. The actual number of such slots depends, among others, on the slot width (Δ_s) considered [2]. Dynamicity in the network is coped by means of a GMPLS or OpenFlow -based control plane [3] allowing automatic connections set-up and tear down.

The optimal design of flexgrid networks is crucial for network operators in order to reduce capital expenditures (CAPEX). Nonetheless, the deployment of new flexgrid-based optical networks can be done taking advantage of already deployed infrastructures. In this regard, the co-existence of flexgrid and fixed grid infrastructures can be managed up to the point of combining both technologies [4] where the optical spectrum can be shared in the network links.

Considering dynamic traffic in offline planning problems adds enormous complexity as a consequence of including probabilistic traffic distributions into mathematical programming formulations. Hence, static traffic matrices representing on-average traffic have been typically considered instead [5].

In this paper, we present a method that facilitates the design of flexgrid-based optical networks under dynamic traffic operation by means of a traffic intensity model, similarly to our previous work in [6] for fixed grid networks. To this aim, we firstly obtain a statistical model to predict the traffic intensity (I), also known as network offered load, i.e. the ratio between connection holding time and inter-arrival time, which can be dynamically served over a network at a given blocking probability. Specifically in flexgrid-based optical networks, connections of different bitrates can coexist; to specify the percentage of connections of each of the considered bitrates we use the concept of traffic profile (TP). After obtaining the statistical model, we introduce an offline network planning problem to design networks able to serve a required offered load in dynamic scenarios; we propose a method to solve the planning problem based on the intensity model.

2. Traffic intensity statistical model

To obtain a statistical model to estimate the traffic intensity, we follow the classical statistical procedure consisting in finding values for the *response variable* from a representative *sample set* and applying some statistical methodology to find the model with the highest fitness. Since the set of real backbone networks available in literature is too small, we generated random topologies to increase the size and diversity of the sample set thus improving the quality of our model.

The generation of random topologies was made according to two common characteristics of backbone networks: two-connectivity (at least) and nodes with a maximum nodal degree not greater than some given value (a value of 8 can be generally accepted when 1:9 WSSs are used to build optical nodes). In addition, we considered topologies with a number of nodes in the range [10, 40] and an average nodal degree in the range [2.5, 4]. Note that most of the reported real networks fit into these intervals.

Each topology was characterized by means of topology-dependent variables; these variables (used later as input model variables) can be grouped into three categories: (1) topology size variables, i.e. number of nodes, links, and nodal degrees (min, max, average); (2) topology distance variables, i.e. radius, diameter, several k-shortest path lengths (in hops), and node and link betweenness; and (3) topology connectivity variables, i.e. mean and standard deviation of clustering coefficient and algebraic connectivity. Several works provide definitions of the above variables (e.g. see [7]).

Taking advantage of our previous work in [6], we selected variables containing useful information such as nodal degree and average hop path length. Moreover, additional variables related to some important features for

core networks such as network robustness against failures were considered; this is the case of the algebraic connectivity, defined as the second eigenvalue of the network Laplacian matrix.

After generating thousands of random topologies, a diverse subset of them consisting in 144 topologies were eventually selected for modeling. To produce values for the response variables we used the routing and spectrum allocation algorithm in [2] on an ad-hoc event-driven simulator implemented in OMNeT++. Different traffic intensities were offered to each of the selected topologies for different spectrum width (sp), frequency slot width and TPs, and those intensities unleashing the objective blocking probability (PB_{max}) were stored. In this regard, we guarantee that PB_{max} is not exceeded for any of the bitrates considered. With the topologies and I values in hand, we applied statistical regression techniques based on generalized linear models [8] to find out a model depending exclusively on topology variables for each combination of sp and Δ_S . After evaluating all combinations of variables (and transformations of them) we concluded that the best model follows eq (1), where $|N|$ is the number of nodes, h the average shortest path length, κ the algebraic connectivity, a_i are the model parameters, and ε is the model error. Each a_i parameter can be expressed as a function of sp and Δ_S as illustrated in eq. (2). Note that the characteristics of the considered TPs are represented as b parameters.

$$I = |N| \cdot (a_1 \cdot h + a_2 \cdot \kappa + a_3) + \varepsilon \quad (1)$$

$$a_i = b_{i1} \cdot sp \cdot (\Delta_S)^{b_{i2}} + b_{i3} \cdot sp + b_{i4} \cdot (\Delta_S)^{b_{i2}} + b_{i5} \quad (2)$$

3. Network design with intensity models for dynamic traffic scenarios

To illustrate the application of the above-defined traffic intensity model let us define the following problem which consists in designing a network capable of serving a given traffic intensity.

Given: a) a network topology $G(N, E)$ defined as a set of nodes N and a set of links E ; b) an optical spectrum width sp and a slot width Δ_S ; c) a traffic profile TP defining the set of connection bitrates and the proportion of each of them; d) a requested traffic intensity I_{req} ; and e) a threshold blocking probability PB_{max} .

Find: a network topology $G^*(N, E^*)$, where $E^* \subseteq E$ and G^* is at least two-connected.

Objective: minimize the number of links in E^* so that the traffic intensity that the network can serve is higher or equal than I_{req} , without exceeding the given PB_{max} .

It is worth noting that by minimizing the number of used links we are in fact minimizing the network CAPEX. The above network design problem can be exactly solved using mathematical programming where those constraints ensuring I_{req} would include the statistical model defined in eq. (1) and (2). Notwithstanding, with the aim to reduce the complexity of the problem when facing real network instances, we propose an iterative algorithm (Table 1) consisting in solving a simpler sub-problem at each iteration (Table 2).

Table 1. Proposed iterative algorithm for offline network planning

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Initialize  $nlinks = |N|$  //Minimal two-connected topology
while ( $nlinks <= |E|$ )
  Obtain  $G^*$  by solving sub-problem in Table 2
  if feasible  $G^*$  is found and  $I >= I_{req}$  then
    return  $G^*$ 
   $nlinks++$ 
return Unfeasible

```

Table 2. Sub-problem definition

Given:

- an optical network $G(N, E)$
- a number of links $nlinks$

Find $G^*(N, E^*)$ such that:

- $E^* \subseteq E$, $|E^*| = nlinks$
- G^* at least two-connected

Objective: maximize I (eq. 1)

4. Illustrative numerical results

In our experiments, we assume that uniformly distributed connection requests arrive to the network following a Poisson distribution with a mean inter-arrival time (iat) and connections holding time is exponentially distributed with mean ht . To run simulations for different traffic intensities we fixed ht and modified accordingly iat to obtain the desired load (recall that $I = ht/iat$). To obtain a wide range of response variable values for each topology we performed simulations considering 3 sp values (800, 1600, and 3200 GHz), 3 Δ_S (12.5, 25, and 50 GHz), and 2 TPs mixing connections of 10, 40, 100, and 400 Gbps (Table 3). Moreover, we fixed PB_{max} to 1%.

Table 3. Traffic profiles considered

TP	Avg. conn. bitrate (Gbps)	10 Gbps	40 Gbps	100 Gbps	400 Gbps
TP-High	80	0%	66.7%	26.7%	6.7%
TP-Low	24.1	80%	13.4%	5.4%	1.3%

Table 4. Values for b_{ij} parameters

	TP-High					TP-Low				
	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
$i=1$	0.863	0.001	-0.867	-372.1	373.7	-0.011	-0.600	0.001	1.209	-0.031
$i=2$	-1.633	0.005	1.674	456.1	-467.1	0.220	-0.750	-0.002	-53.81	0.315
$i=3$	-0.004	0.300	0.016	2.321	-8.699	0.071	-0.750	-0.002	-20.55	0.132

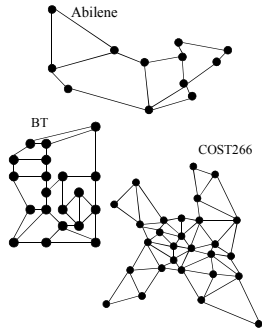


Fig. 1. Test Networks

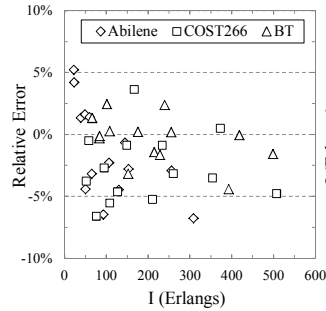


Fig. 2. Model Validation

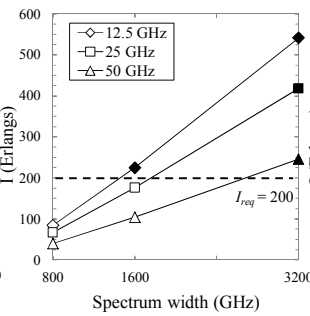


Fig. 3. Capacity dimensioning

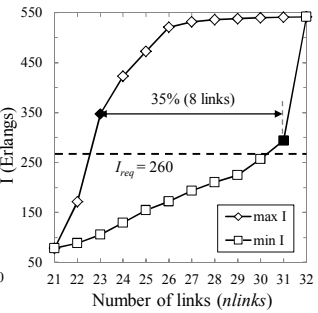


Fig. 4. Network Planning

Table 4 shows the values of the b_{ij} coefficients for both TPs. Once the a_i parameters have been computed from the b_{ij} values using eq. (2), we observe that all a_1 coefficients are negative whereas all a_2 ones are positive. This explains clearly eq. (1): the higher the connectivity (κ) and the lower the average shortest path (h), the higher the traffic intensity that a network can serve.

To illustrate the goodness-of-fit of the model, we computed the Pearson determination coefficient (R^2) [8] obtaining values as high as 96.98% and 95.87% for *TP-High* and *TP-Low*, respectively, which are better than the commonly accepted reference for validating the quality of a model ($R^2 \geq 95\%$). As a result, we can conclude that our model is accurate enough in the studied range.

As a final validation, we applied the traffic intensity model over 3 real backbone topologies (Fig. 1) (not belonging to the fitting set) of different sizes and compare the results obtained against simulations. To this end on-average relative error of the predicted I values against those obtained by simulation for different sp , Δ_S , and TPs values are illustrated in Fig. 2. In view of the obtained results, the accuracy of model can be completely validated since the relative error is within $\pm 5\%$ in the vast majority of cases.

After the model has been validated, let us illustrate the utility of the intensity model for network planning. To simplify the problem stated in Section 3, whose solution is out of the scope of this paper as a consequence of length limitations, let us assume an already deployed network. We are interested in finding the optimal values of sp and Δ_S to fit some requested I_{req} . Solving this problem could be of interest for network operators planning a migration of part of the network infrastructure from fixed grid to flexgrid, dedicating part of the available spectrum in each of the links to the flexgrid technology. Focused on the BT topology (Fig. 1) and under *TP-High*, Fig. 3 illustrates the predicted traffic intensity against the dedicated spectrum size (sp) for different Δ_S values. The CAPEX minimization problem can be solved by computing those $\{sp, \Delta_S\}$ pairs guaranteeing I_{req} (solid markers in Fig. 3) and choosing the best option in terms of objective cost.

Finally, to illustrate the utility of solving the problem described in Section 3 for the off-line network planning problem, in particular the sub-problem described in Table 2, we have computed near-optimal solutions of that sub-problem (*maxI* in Fig. 4) and bad-quality feasible i.e. low expected I , solutions (*minI* in Fig. 4) for the BT network under *TP-High*, considering $sp=3200$ GHz and $\Delta_S=12.5$ GHz. As we can observe, the difference between near-optimal and poor-quality solutions is remarkable (31-23=8 links in the example).

5. Conclusions

A traffic intensity statistical model for accurately estimating the supported offered load in flexgrid networks was presented. Then, an offline network planning problem was introduced with the aim to emphasize the role and utility of the model. Numerical results showed the accuracy of the model and allowed validating the quality of prediction. Finally, numerical results obtained for a reference network highlighted the application and usefulness of the model for network design problems under dynamic traffic operation.

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