Adapting Spectrum Resources using Predicted IP Traffic in Optical Networks

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Abstract: Elastic optical networks provide the advantage of elaborate resource utilisation for achieving a wide range of performance goals. Cross-layer optimisation is feasible by exploiting high layer IP traffic prediction for achieving efficient lightpath establishment at the lower layer. Swarm Intelligence can provide a tool to adaptively allocate spectrum resources according to traffic analytics from the IP layer. A new algorithm is designed and evaluated that exploits these analytics using particle swarm optimisation to allocate spectrum.

1 INTRODUCTION

Optical backbone networks reliably cover a wide range of current and possibly future connectivity needs. Intelligent resource allocation in this field undergoes ongoing research efforts from the community. Performance increases when resources are allocated in an on-line fashion while the network is operating (Kyriakopoulos et al., 2018), considering as input the current traffic demand and adapting to available spectrum resources facilitating it efficiently.

Various types of technology are enabled at the optical layer. Elastic optical network (EON) (Jinno, 2016) platforms offer flexibility for configuring, since the usage of variable-rate transponders can provide the right amount of resources on demand. Orthogonal frequency division multiplexing (OFDM) (Chatterjee et al., 2017), (Zhang et al., 2012a) is adequate to provide support for variable-rate light connections. This is achieved by utilising many subcarriers for data transfers. The overlapping of spectra between these subcarriers facilitates the compactness of available resources due to their orthogonal modulation. This design increases the overall efficiency. Bandwidth-variable transponders (BVTs) (Moreolo et al., 2016) embed the enabling technologies for achieving these goals.

In a cross-layer network design (Sartzetakis et al., 2018), a relation is formed between the physical and network layers. This is a push-pull design where both layers facilitate each other for achieving important performance goals. Traffic conditions taking place at the IP layer may be exploited for efficiently establishing lightpaths at the physical layer. As an example, connectivity between data centres follows specific traffic patterns. Predicting the state and variation of these patterns, useful analytics can be provided to the physical layer for establishing lightpaths having the right amount of spectrum resources for improving performance. In the opposite direction, impairments in the physical layer are estimated (Bouda et al., 2018), (Fludger and Kupfer, 2016), (Beletsioti et al., 2018) and considered for creating connections from the above layers.

An adaptive tool that solves many optimisation problems and is capable of exploiting higher layer analytics for improving its performance is particle swarm optimisation (PSO) (Mohemmed et al., 2008), (Zhang et al., 2015b). Its applications include neural network training, pattern classification and function optimisation, among others. The main focus is the emulation of animals' social behaviour including insects or birds. The main trait is that the individuals inside a group cooperate to find food. Each member in

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the swarm repositions itself by keeping track of past movements, either its own or from its neighbourhood. This type of social behaviour is standardised and can be used to solve difficult computational problems. For example, in a network graph topology, a population is able to find paths with specific traits like short distances, or any other metric that replaces the weight of an edge in the graph. Complexity decreases when this logic is applied to large topologies.

A popular tool for usage in network traffic prediction is linear regression (Mata et al., 2018). It is used to fit a predictive model to a set of values, e.g., in a Cartesian system. This way, when more values are collected in the x-axis, the corresponding values in the y-axis are predicted. It is used to detect the strength of the response and explanatory variables. Models of the regression are fitted by exploiting the least squares method.

In related research (Morales et al., 2017) of this field, a virtual topology reconfiguration mechanism is proposed based on data analytics for traffic prediction. It uses a machine learning algorithm that relies on an artificial neural network (ANN) for providing adaptive traffic models. Data from traffic prediction are used in the reconfiguration model and the problem is solved utilising a heuristic method.

In this work, higher layer analytics are collected by applying a linear regression method to predict future traffic demand. These analytics are provided to a PSO method for allocating the appropriate amount of spectrum resources in an online fashion. Performance is improved since the found paths carry spare bandwidth that can facilitate future traffic demand. At the same time, highly congested paths are avoided since the PSO core adapts to those providing more spare bandwidth to accommodate future demand. According to results, there is reduction in transponder numbers which leads to less power consumption. Also, The percentage of valid paths to allocate resources to is high and optical grooming is dominant at lower rates. At the same time, path elongation is minor.

The rest of the text is organised as follows. Section 2 describes the proposed Metis algorithm and Section 3 presents the network environment that is used to evaluate performance. Finally, in Section 4 simulation results are presented.

2 METIS ALGORITHM

Metis (a mythical titaness - mother of wisdom and deep thought) relies on analytics from the IP layer to establish lightpaths. Traffic requests between node pairs arrive sequentially. A history log of previous values is maintained and a window of these is used to predict the next arrival rate for every node pair. The predicted value comprises a parameter for the edge weight that the PSO core will use to calculate the appropriate path when establishing lightpaths.

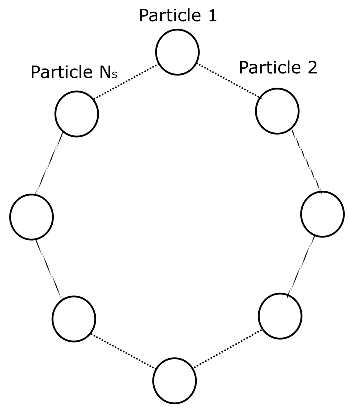

Figure 1: Ring particle neighbourhood.

The PSO core uses the physical topology connections with modified weights. This way, it tries to find paths avoiding routes where the load is predicted to increase. The resulting resource allocation is more balanced with low blocking probability, in comparison to the corresponding shortest path replacement. Adaptivity to future load is a trait that renders Metis suitable for online execution while network runtime conditions vary.

PSO is a stochastic optimisation method (Zhang et al., 2015b) that mimics the social behaviour of a bird flock, etc. The algorithmic flow initiates with a set of particles whose positions represent possible solutions in the search space. The search for optimal positions leads to a solution by updating their velocities in an iterative fashion. The fitness of each particle is calculated, and the one having the highest value provides the best solution in the search space. Each particle's velocity depends on the current and best position it had so far. Also, it depends on the best neighbour position. After a number of iterations, the solution is provided by the particle that converged faster.

Particle population is organised in a ring topology (Figure 1). The number of particles affects the percentage of valid paths to find. A larger number of particles, in relation to large iteration number, provides more accurate results (using the appropriate fitness function) but increases the computational complexity. This is due to more fitness function evaluations and candidate path constructions per particle. Every particle alters its velocity and hence its position according to the state of its neighbours.

Every incoming request is served by Metis which is described in Algorithm 1. The first preprocess-

Algorithm 1: Metis Abstract Pseudo Code.

```
New incoming spectrum allocation request
For every topology edge, use analytics as weight
Feed PSO core with the updated topology
direct ← false
path = psoRouter(src, dest)
if path.size() > 0 then
    for all edge ∈ pathEdges do
        optical ← false
        if optical = optGrooming(edge) ≠ 0 then
            continue
        else
            direct = directLP(edge)
        end if
    end for
else
    // Enter failsafe mode
    Get shortest path from 'src' to 'dest'
    for all edge ∈ pathEdges do
        direct = directLP(edge)
    end for
end if
```

ing event relates to the use of Equation 1's result as weight for every topology's edge (connection). Multiple data transfers exist between node-pairs. For example, if the third request is to be served, the previous two comprise the prediction window. If the first two are 10 and 20 Gbps, the predicted value for the next is 30 Gbps. The actual weight value to provide to PSO core from Formula 1 is 35.

Next, the updated topology becomes PSO core's input for finding the appropriate path from initial node to destination. If it succeeds, for every edge of the path, optical grooming is attempted (Zhang et al., 2012b). In this case, available transponder slices at both ends of the edge comprise a newly established lightpath (Kyriakopoulos et al., 2019). If no available slice(s) exist, one (or two) new transponder(s) are used for creating the light connection.

It is possible for the PSO core not to find a valid path. This happens if the number of iterations or the population size is not large enough. The failsafe mode initiates, where direct lightpaths (using two new transponders) are established upon every edge of the shortest path between end nodes.

$$Weight = \begin{cases} \frac{rate_n + rat\hat{e}_{n+1}}{2}, & rat\hat{e}_{n+1} > rate_n \\ rate_n, & otherwise \end{cases} \tag{1}$$

$$y = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + \cdots + a_n x^n + \varepsilon \tag{2}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^m \\ 1 & x_2 & x_2^2 & \cdots & x_2^m \\ 1 & x_3 & x_3^2 & \cdots & x_3^m \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & x_n & x_n^2 & \cdots & x_n^m \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ \vdots \\ a_m \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{bmatrix} \tag{3}$$

$$\overrightarrow{y} = X\overrightarrow{a} + \overrightarrow{\varepsilon} \tag{4}$$

$$\overrightarrow{a} = \left(X^T X\right)^{-1} X^T \overrightarrow{y} \tag{5}$$

In Equation 2, y represents $rat\hat{e}_{n+1}$ which is the predicted edge bandwidth. The previous values from $rate_1$ to $rate_n$ comprise the prediction window. Providing to x the slot $n+1$, y is calculated (Seber and Lee, 2012). Values between $y_1 \dots y_n$ comprise the window of previous rates. Values between $x_1 \dots x_n$ comprise the window of previous slots. A new representation for the equation is in Formula 3 with the purpose of finding the array of coefficients $\overrightarrow{a}$. In vector form is the Equation 4. Coefficients are calculated from Equation 5 by using ordinary least mean square estimation. The result is used in Equation 2 to calculate the next rate value which is the predicted value. The ε values represent possible minor errors which are ignored and the result is named an estimated value.

3 NETWORK ENVIRONMENT

The purpose is to allocate spectrum resources while incoming requests arrive one-by-one. The problem is formally described and follows next.

- A directed graph is used to describe the topology of the elastic network, i.e., *G(V, E)*. Specifically, V is the set of nodes and E is the set of links.
- A set of frequency slices F are used for transponder end-point connections for each link $\in E$. $F = \{f_1, f_2, \cdots, f_n\}$, where n is the ceiling of connections per fibre.
- A set of available modulation formats $M = \{m_1, m_2, \cdots, m_n\}$, where n is their maximum number. Each format is described by a pair $m = \langle f, r \rangle$, where f is the lightpath spectrum and r is the optical reach.
- A set of traffic demands D that reside in a matrix. Each entry is described by a tuple $d = \langle s, d, b \rangle$, where s is the request's source, d the destination and b represents the bitrate.

20 interconnected nodes comprise a topology to use for evaluating Metis' performance. Figure 2 depicts the connections and the corresponding weights.

Modulation is based on the available choices of Table 1. These choices are input to the modulation policy when light connections are established using available transponder slices. Distance is a factor that limits the subcarrier capacity and is obeyed for every new request's bitrate. To choose the appropriate

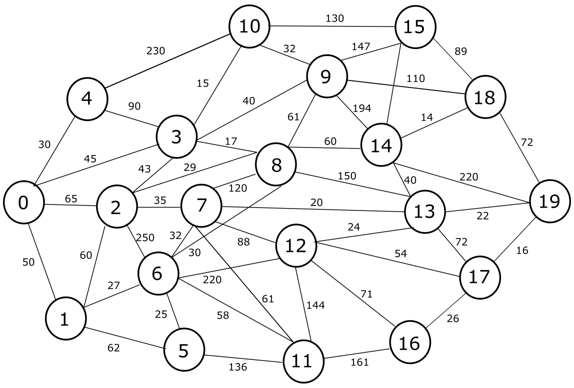

Figure 2: 20-node topology (Mohemmed et al., 2008).

Table 1: Modulation Formats.

Format	*Subcarrier Capacity (Gbps)*	*Distance (km)*
BPSK	12.5	4000
QPSK	25	2000
8QAM	37.5	1000
16QAM	50	500
32QAM	62.5	250
64QAM	75	125

format, all these are sorted in descending order. The value that is ceiling to incoming request's rate is kept by the policy.

Figure 3 contains the low level details of establishing the new lightpath λ_3 when λ_1 and λ_2 are already established. A prerequisite is the existence of available transponder slices at source (left) and destination (right) nodes. The intermediate node consists of a transmitter and a receiver.

4 RESULTS

The simulating environment consists of specific parameters that follow next. Variable-rate transponders utilise up to 10 lightpath connections. Two adjacent frequency slots comprise a guardband. Available modulation formats are in Table 1 and each of them has its own spectrum range. A table of spectrum values according to data rates is found in Reference (Zhang et al., 2015a).

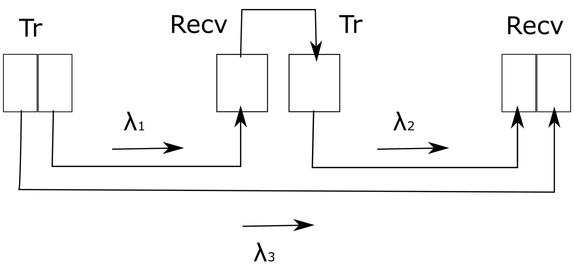

Figure 3: Optical grooming.

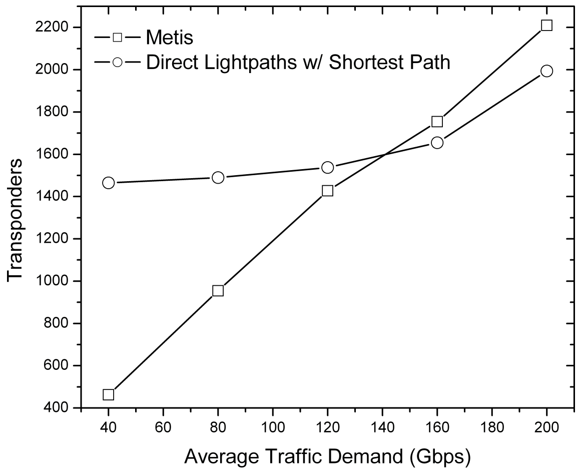

Figure 4: Transponders according to increased traffic demand.

Traffic demand values are generated by a random function in the range $[40, 2X-40]$ Gbps, using steps of 40 Gbps. Variable $X \in \{40, 80, 120, 160, 200\}$. 500 requests are established between uniformly selected node-pairs. Past values of a node-pair comprise the prediction window.

The PSO core relies on 750 iterations and population size of 40, unless otherwise noted. The linear regression prediction method uses a window of 5 previous traffic values between each node-pair.

The simulating environment is designed and implemented in Modern C++ with the Clang/LLVM 10 compiler, the aid of Boost graph library 1.67 and Armadillo linear algebra library 9, on x64 Debian 10.

In Figure 4, the number of utilised transponders increases according to traffic demand. When its average value reaches 200 Gbps, there are many requests that exceed the upper transponder limit of 400 Gbps, so optical grooming is not feasible in this case. This is the reason for the high performance of Metis at lower rates. Its slight path elongation results in more transponder usage at higher bitrates, in comparison to the direct lightpath establishment that relies on the shortest path between end nodes. When the average rate reaches 200 Gbps, some values are close to the maximum supported transponder rate which is 400 Gbps. So, optical grooming on existing transponders is not feasible and new ones must be utilised on paths not being shorter.

In Figure 5, the percentage of valid paths found by the embedded PSO mechanism in Metis, is depicted according to the particle population size increase. When the population is low, particles may not

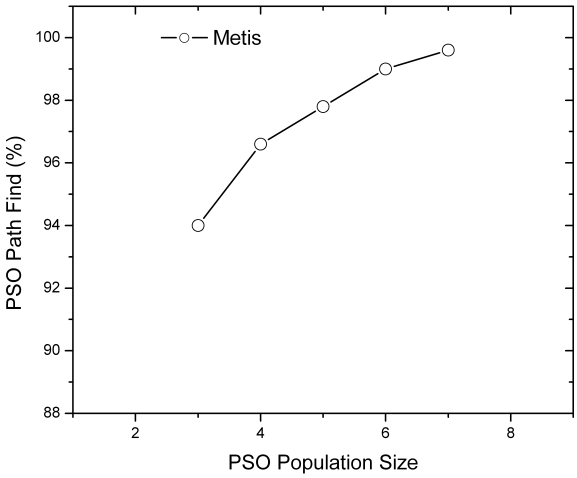

Figure 5: PSO valid path percentage according to population size.

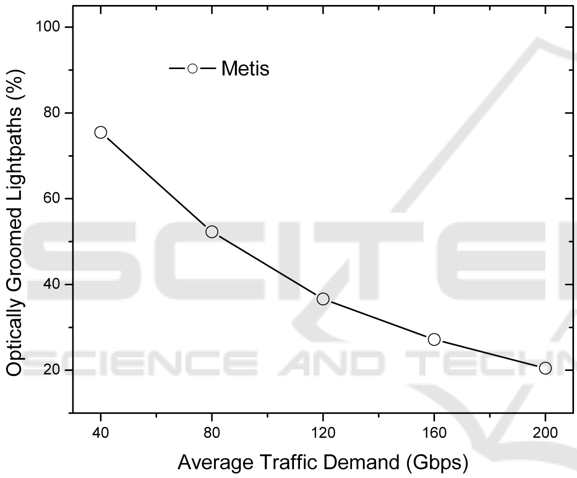

Figure 6: Optical grooming ratio according to traffic.

converge to a valid solution. At higher values (x axis), almost every execution returns valid paths, so the percentage (y axis) reaches the value of 100%. The average request rate is 80 Gbps with 10 iterations between particles. The percentage of failures for PSO to find paths can be considered as blocking probability for the PSO core, since it then enters the failsafe mode (Algorithm 1).

In Figure 6, the percentage of optically groomed lightpaths is depicted according to the increasing average traffic demand value. Since the availability of optical grooming at values above 400 Gbps is nonexistent, the percentage keeps decreasing. Metis' performance is high between low and mid-range traffic values. From the grooming perspective, the percentage of direct lightpaths can be considered as blocking probability.

In Figure 7, the effect of not utilising the short-

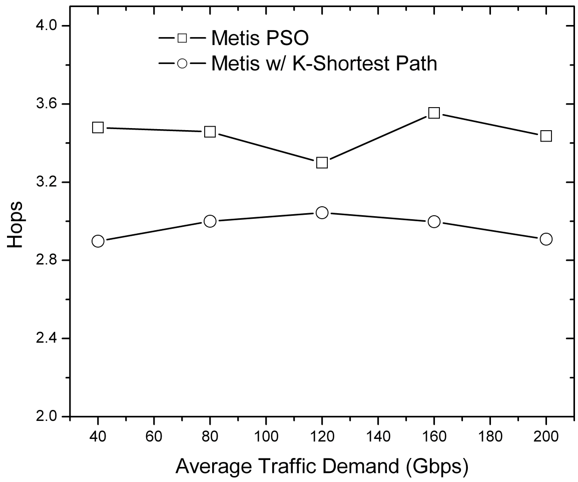

Figure 7: Hop-count according to increased traffic demand.

est path between request end nodes is depicted. This compensates due to the higher performance as described in the previous graphs. Also, longer paths are established for accommodating the prediction of IP layer's future traffic demand.

5 CONCLUSIONS

Higher layer analytics are exploited for improving the efficiency of the lightpath establishment procedures at the lower layer. The particle swarm optimisation core exploits the predicted future traffic demand and finds paths with higher available spectrum resources. The adaptivity to future IP traffic leads to higher overall performance, in relation intelligent spectrum allocation.

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