Optimal Allocation of Fibre Delay Lines in Optical Burst Switched Networks

Daniele Tafani
The Rince Institute
School of Electronic Engineering
Dublin City University
Glasnevin, Dublin 9
Email: tafanid@eeng.dcu.ie

Conor McArdle
The Rince Institute
School of Electronic Engineering
Dublin City University
Glasnevin, Dublin 9
Email: mcardlec@eeng.dcu.ie

Liam P. Barry
The Rince Institute
School of Electronic Engineering
Dublin City University
Glasnevin, Dublin 9
Email: barryl@eeng.dcu.ie

***Abstract*—The realisation of cost-efficient Optical Burst Switching (OBS) networks can be greatly facilitated from minimising the number of contention resolution resources required at congested network nodes. In this paper we present a Fibre Delay Line (FDL) optimal allocation scheme where the total cost associated to the employment of FDLs is minimised subject to performance requirements defined in terms of maximum tolerable end-to-end blocking probability. The optimal buffer configuration is achieved by means of a constraint-handling genetic algorithm. We additionally increase the accuracy of our analysis by considering the non-Poissonian traffic characteristics of the OBS network under study. Results show that our method permits to identify an optimal FDL configuration that minimises the total buffer installation cost and simultaneously satisfies the network blocking probability requirements.**

***Keywords*-Optical Burst Switching; Fibre Delay Lines; Genetic Algorithms; Optimisation;**

I. INTRODUCTION

In recent years substantial research effort has been devoted to the performance evaluation of network architectures employing Optical Burst Switching [1], one of the most promising switching strategies for the deployment of next generation optical networks. A major drawback in OBS is due to burst loss which occurs when two packets (*bursts*) are contending for the same wavelength channel on a common output fibre link. This issue can be addressed with the employment of Fibre Delay Lines (FDLs) [1], [2]. An FDL can be considered as a buffer in the time domain and is capable of preventing burst loss by delaying the transmission of one of the contending bursts. It has been demonstrated that FDLs can be very effective in reducing burst loss of several orders of magnitude as shown in works such as [2], [3] and [4], where performance evaluations of buffered OBS architectures have been conducted. The overall performance of an FDL-buffered OBS network might vary considerably depending on how many FDLs are employed and their allocation in the network. In non-uniform network topologies some links of the network may be congested more than others even under uniform end-to-end traffic demands. This means that some links may require more buffering resources than others resulting in a non-uniform allocation of FDLs in the network, however, the problem can not be solved by simply adding FDL buffers to bottleneck links. In fact, the employment of an FDL might shift the traffic load from a congested link to the next link over the same path, thus potentially shifting the "congestion problem".

In this paper we address this issue by proposing a method to find an optimal FDL allocation that minimises the cost associated to the buffers employment and, at the same time, satisfies a maximum tolerable end-to-end blocking probability. We solve this problem by means of genetic algorithms [5], a branch of evolutionary algorithms that have been already successfully used to solve different optimisation problems for photonic switched networks. For example, in [6] the authors develop a genetic algorithm to jointly solve a Routing and Wavelength Assignment (RWA) problem for optical networks. A similar method has been derived in [7], where the authors solve an RWA problem for Optical Packet Switching (OPS) networks with load balancing. Yang et al. propose in [8] a multi-objective genetic algorithm to simultaneously minimise the delay while maximising the throughput for metro optical networks. Differently from these works, our main contribution is in applying a genetic algorithm to solve a cost minimisation problem where the decision variables define the *allocation of the FDL wavelength channels*. Castro et al. focus on a similar problem in [9] where they derive a method to find an optimal placement of the FDLs in OBS networks with Tabu Search, however, differently from [9], we decide to use a different OBS node buffered architecture [3] and a more realistic and accurate network model as proposed in [10]. The rest of the paper is organised as follows: in Section II, we briefly describe the architecture and the analytic model of the OBS network under study. In Section III, we define a cost minimisation problem for the OBS network in question and in Section IV we describe the genetic algorithm used to solve it. Results and conclusions are respectively given in Section V and VI.

II. THE OBS NETWORK UNDER STUDY

We consider the Tune And Select with Shared feedback FDL (TAS-shFDL) OBS node architecture analysed in [3] and illustrated in Figure 1(a). The switch is equipped with

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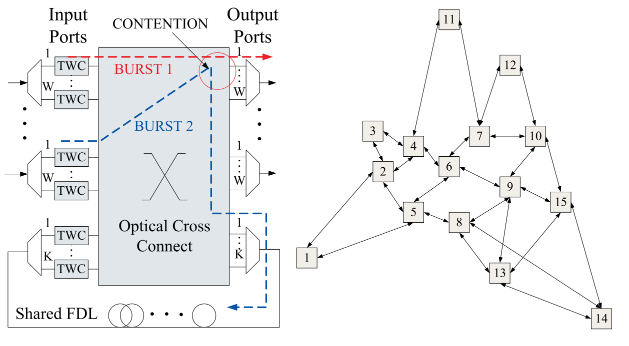

Figure 1. The architecture of the buffered OBS node (a) and the OBS European Optical Network (EON) topology under study (b).

P input/output ports, each one connected to an optical fibre link comprising W wavelength channels. We assume full wavelength conversion, that is each channel is supported by a Tunable Wavelength Converter (TWC) for burst contention resolution. Additionally, an extra input/output port is dedicated to an FDL comprising K wavelength channels. We refer to these channels as *virtual buffers* as described in [2]. The FDL is shared between the output links connected to the node in a feedback configuration [3]. This means that a contention between two bursts will be resolved by directing one of the bursts to a free virtual buffer of the FDL and then re-offering it to a free wavelength channel of the output port. If this is not possible, the burst will be dropped and consequently lost from the system.

We consider an OBS network of such switches described by a graph $\mathcal{G}(N, L, R)$, where N is the number of nodes, L is the number of links and R is the number of paths of the network. All links comprise the same number of wavelength channels W. Each path r is offered with burst traffic of load ρ_r (in Erlang). We further define $\boldsymbol{\rho}= [\rho_1, \rho_2, \ldots, \rho_R]$ as the vector comprising the burst traffic loads offered to each path. We characterise the burst traffic as a non-Poisson process by assuming generally distributed burst interarrival times and exponentially distributed burst lengths. We attempt to model the traffic characteristics with the BPP two-moment matching technique [11] by considering the additional contribution of the traffic *peakedness* Z. The peakedness quantifies the deviation of the burst traffic from being Poisson and is defined as the ratio between the variance and the load of the burst traffic. The traffic is said to be *peaked* or *smooth* whether Z is greater or less than one. If $Z = 1$ the traffic is Poisson. This analysis allows us to approximately match the expected OBS traffic characteristics, which are largely determined by the burst aggregation process [12]. Further results on the impact of traffic burstiness in optical packet switching networks can be found in [13]. Under these premises, we model the OBS network with the approximate method proposed by the present authors in [10]. The model is used to evaluate end-to-end burst blocking probabilities and can generally be summarised as a non linear function whose output is the vector $\boldsymbol{\mathcal{P}}= [\mathcal{P}_1, \ldots \mathcal{P}_R]$, where $\mathcal{P}_r$ is the end-to-end blocking probability of path r. Namely,

$$\boldsymbol{\mathcal{P}} = \boldsymbol{\mathcal{P}}(N, L, R, W, \mathbf{K}, \boldsymbol{\rho}, \mathbf{Z}), \tag{1}$$

where we have indicated with $\mathbf{Z} = [Z_1, \ldots Z_R]$ the vector of the burst traffic peakednesses offered to each path and with $\mathbf{K} = [K_1, \ldots, K_N]$ the vector comprising the number of virtual buffers allocated to each node in the network. For space constraints we can not provide a description of the method in this paper. The reader will find a detailed mathematical analysis and the validation of our method in [10], however we show here some additional new results in Figures 2 and 3. Particularly, the average end-to-end burst blocking probability obtained with our analytic model is compared with the one obtained from a discrete-event simulation of the OBS European Optical Network (EON) topology depicted in Figure 1(b). The network comprises $N = 15$ nodes, $L = 25$ bidirectional links and $R = 18$ source-destination pairs whose shortest paths are indicated in Table I. The FDL allocation is uniform, thus all nodes are equipped with the same number of virtual buffers. The traffic demands are uniform as well, that is each path is offered with the same traffic load and peakedness. As we can see from the graphs the accuracy of the analytic model compares favourably with the simulation data for a broad range of end-to-end blocking probability, a feature that convinces us to adopt our model for the definition and the solution of the cost minimisation problem.

III. Definition of the Optimisation Problem

We first start by introducing the cost function that will be used to define the objective of the optimisation problem. Our goal is to determine an estimate of the cost introduced by the employment of a shared FDL in a node of the network. Following the analysis presented in [3] on the

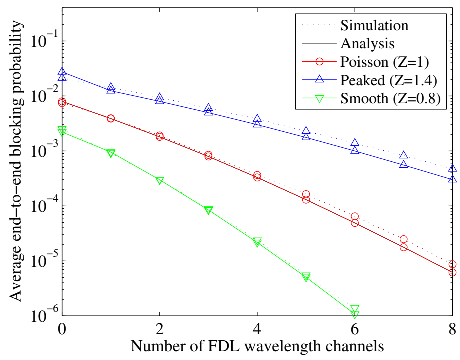

Figure 2. Average end-to-end blocking probability vs. number of FDL channels for the EON topology. The number of wavelength channels per link is $W = 16$ and the normalised load per path is $\rho_r = 0.25$ Erlang.

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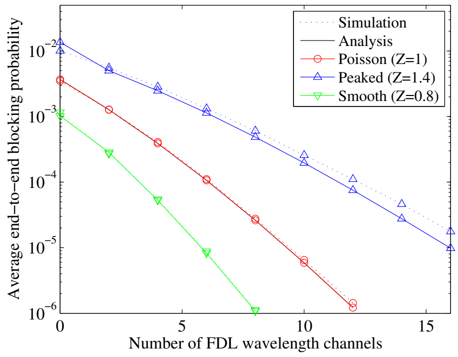

Figure 3. Average end-to-end blocking probability vs. number of FDL channels for the EON topology. The number of wavelength channels per link is $W = 32$ and the normalised load per path is $\rho_r = 0.3$ Erlang.

TAS-shFDL architecture, we note that the installation of an extra input/output port dedicated to the FDL requires one additional Erbium Doped Fibre Amplifier (EDFA). Furthermore, since we are assuming full wavelength conversion, each wavelength channel of the FDL must employ a TWC, for a total of K_n TWCs. Finally, in order to allow the transmission of burst packets to the FDL, each wavelength channel on each output port must be equipped with an additional Semiconductor Optical Amplifier (SOA), for a total of $P_n \cdot W$ SOAs, where we have indicated with P_n the number of output ports of node n. Similarly, in order to send packets to the output ports, each wavelength channel of the FDL requires P_n SOAs for a total of $P_n \cdot K_n$ SOAs. Under these premises, we define the total cost associated with an FDL to node n as follows,

$$C_n = h_E + h_T K_n + h_S P_n (W + K_n), \tag{2}$$

where we have denoted with h_E, h_T and h_S respectively the unit cost of an EDFA, of a TWC and of a SOA. Finally, the total cost arising from the employment of FDLs in the network can be expressed as

$$C(\mathbf{K}) = \sum_{n=1}^{N} C_n = \sum_{n=1}^{N} \left[h_E + h_T K_n + h_S P_n (W + K_n) \right], \tag{3}$$

Table I
PATHS OF THE EUROPEAN OPTICAL NETWORK TOPOLOGY.

Path	Path hops	Path	Path Hops
1	$1 \to 2 \to 4 \to 6 \to 7 \to 10$	10	$11 \to 7 \to 12$
2	$3 \to 4 \to 6$	11	$12 \to 10 \to 15 \to 14$
3	$13 \to 15 \to 10 \to 12$	12	$10 \to 7 \to 11$
4	$12 \to 7 \to 6 \to 4 \to 2$	13	$13 \to 9 \to 6 \to 4 \to 11$
5	$2 \to 4 \to 11$	14	$8 \to 5 \to 2 \to 3$
6	$11 \to 7 \to 6 \to 5 \to 8$	15	$4 \to 2 \to 1$
7	$12 \to 10 \to 9 \to 13$	16	$7 \to 10 \to 15$
8	$5 \to 8 \to 13 \to 14$	17	$13 \to 8 \to 5 \to 1$
9	$1 \to 5 \to 6 \to 7$	18	$14 \to 15 \to 10 \to 7 \to 11$

where $\mathbf{K} = [K_1, \dots K_N]$ is a vector representing the FDLs allocation in the network. We are now ready to define the following problem:

Given an OBS network defined by graph $\mathcal{G}(N, L, R)$ where each link comprises the same number of channels W and where the traffic demands for each path are quantified by vectors $\boldsymbol{\rho}$ and $\mathbf{Z}$, we want to minimise the cost function C as follows,

$$\begin{aligned} &\underset{\mathbf{K}}{\text{minimise}} && C(\mathbf{K}) && \\ &\text{subject to} && \mathcal{P}_r(\mathbf{K}) \le \mathcal{P}_{max}, && r = 1, \dots, R, \\ & && K_n \le K_{max}, \;\; K_n \in \mathbb{N}, && n = 1, \dots, N, \end{aligned} \tag{4}$$

where we have indicated with $\mathcal{P}_{max}$ the maximum tolerable end-to-end blocking probability and with K_{max} the maximum number of virtual buffers that can be allocated in a node of the network. Furthermore, we force the number of virtual buffers to be positive integers. We solve the above defined problem with the use of a genetic algorithm as described in the next section.

IV. GENETIC ALGORITHM

Genetic algorithms (GAs) [5] are a branch of *evolutionary* algorithms, a family of search heuristics that mimics the process of evolution to find near-optimal solutions for optimisation problems. In a GA, each potential solution corresponds to a string of decision variables called an *individual* (or *chromosome*) where each decision variable represents a *gene*. The algorithm starts by generating an initial random population of individuals. A set of individuals is selected from the population to form a new generation on the basis on "how suitable" they are as solutions of the optimisation problem. The "goodness" of the selected individuals is evaluated by a specific *fitness* function which is typically defined as a combination of the objective functions of the optimisation problem in question. In this way, the better individuals have more chances to "reproduce" and transfer their "good" genes to their children (*offspring*) that will form a better new generation, mimicking the evolution process. The algorithm normally ends when a user-defined maximum number of generations is reached or when some conditions on the improvement achieved by the best individuals are met.

A. Initial Population and Encoding

In our problem, each individual corresponds to a specific allocation of FDLs $\mathbf{K}$. Each element of $\mathbf{K}$ is the number of wavelength channels of an FDL at a given node and represents a gene of the individual. All the individuals are encoded directly into strings of integer numbers with values in the range $[0, K_{max}]$. Note that the encoding process forces the potential solutions to be integrals and within the interval $[0, K_{max}]$. Therefore, the constraints $K_n \le K_{max}$ and $K_n \in \mathbb{N}$ for $n = 1, \dots, N$ are already satisfied by the process of encoding of the individuals.

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B. Fitness function and Selection

The fitness function evaluates the "goodness" of an individual. The greater is the fitness value of an individual, the higher is the probability that the individual will be selected for "reproduction". Generally, in constrained optimisation problems, the fitness function of each individual is modified by introducing a non-zero *penalty function* for the solutions that are *unfeasible*, that is the solutions that do not satisfy the constraints of the optimisation problem. We adopt a simple yet very efficient method inspired by the work of Deb in [14]. Particularly, the fitness function f of an individual $\mathbf{K}$ can be written as

$$f(\mathbf{K}) = \begin{cases} -C(\mathbf{K}) & \text{if } \mathbf{K} \text{ is feasible,} \\ -C(\mathbf{K}^-) - |\mathcal{P}_r(\mathbf{K}) - \mathcal{P}_{max}| & \text{if } \mathbf{K} \text{ is unfeasible,} \end{cases} \tag{5}$$

where we have indicated with $\mathbf{K}^-$ the feasible FDL allocation with the lowest fitness in the population and with $|\mathcal{P}_r(\mathbf{K}) - \mathcal{P}_{max}|$ the *constraint violation* of individual $\mathbf{K}$ representing the penalty function for $r = 1, \ldots, R$. At each generation, the fitness of all individuals is evaluated and a set of "good" candidate solutions are selected to "reproduce". The *selection* process is a key operation in genetic algorithms and there are several mechanisms to perform it. We decide to select individuals with the *roulette wheel technique* [5] where the fittest individuals have more chances to be chosen for reproduction. Particularly we first normalise the fitness value of all the individuals of the population as

$$f_i^* = f_i / \sum_{i=1}^{I} f_i \qquad i = 1, \ldots, I, \tag{6}$$

where I is the number of individuals in the population and f_i is the fitness of individual i. Then, we sort the fitness values in ascending order (denoting them with t_i^*) and we generate a random number ϵ uniformly distributed within the interval [0,1]. If $\epsilon < t_1^*$, we select individual 1 as a parent for reproduction. If $\epsilon > t_1^*$, we calculate the cumulative sum $s_1 = t_1^* + t_2^*$ and we compare again ϵ with s_1. At this point, if $\epsilon < s_1$, we select individual 2 otherwise we recursively re-calculate the cumulative sum $s_2 = s_1 + t_3^*$ and proceed with the next comparison in a similar manner until two individuals will be selected as parents.

C. Crossover, Mutation and Elitism

Once the individuals have been selected, they reproduce to generate a new offspring. This step of the algorithm is called *crossover* and is performed with a user-defined probability $Prob_c$. We choose to perform a *two-point crossover* where the new offspring inherits genes from the parents on the basis of two random crossover points as illustrated in Figure 4.

Once the new children are generated, we *mutate* them by randomly changing one of their genes with a predefined mutation probability $Prob_m$. The mutation is an essential step in GAs that helps preserving the diversity in the population and prevents the GA to get stuck in a local minimum.

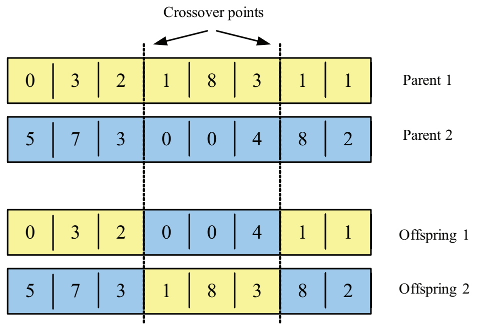

Figure 4. Example of crossover. In this case each individual is encoded as a string of 8 integers.

In the final step of the algorithm, once the new generation is obtained, we select a specific number of individuals E with the highest values of fitness and we include them in the new generation. This final step is known as *elitism* and the set of chosen individuals is called the *elite*. This procedure permits us to keep the best E individuals in the population as the algorithm continues its search for fitter solutions.

V. Results

We test our method on the same network topology of Figure 1(b). The configuration settings for the genetic algorithm are shown in Table II. The values of $Prob_c$ and $Prob_m$ are proved to generally work well for different optimisation problems. The estimation of the hardware unit costs h_S, h_E and h_T is quite difficult as real costs for these devices vary considerably on the basis of their manufacturer and their specifications. Based on the study proposed in papers such as [15] and [16] we decided that it may be reasonable to relate all unit costs to the one of a SOA, being the SOA a device less expensive than an EDFA and a TWC. Thus, we set the unit cost of a SOA as h_S = 1 and we decide to fix the unit cost of an EDFA at $3h_S$ and the unit cost of a TWC at $15h_S$. We stop the genetic algorithm after 300 generations. Table III and Table IV illustrate the benefits introduced by the optimisation in terms of cost savings subject to different values of $\mathcal{P}_{max}$ for different values of traffic load and peakedness. We first note how

Table II
Genetic Algorithm parameters configuration

Population Size	80
Elite Size (E)	16
Selection	Roulette Wheel
Crossover	Two-point
$Prob_c$	0.9
$Prob_m$	0.05

Table III
COST COMPARISON BETWEEN OPTIMAL (OPT) AND UNIFORM (UNI) VIRTUAL BUFFER ALLOCATION FOR $K_{max} = 8$ BUFFERS, $W = 16$, $\rho = 0.3$ ERLANG FOR EACH PATH. 'NF' STANDS FOR 'NOT FEASIBLE'.

	$\mathcal{P}_{max}$	10^{-1}	10^{-2}	10^{-3}	10^{-4}	10^{-5}
Z = 0.8	C_{OPT}	0	601	1209	1620	NF
	C_{UNI}	0	1179	1968	2757	NF
Z = 1	C_{OPT}	0	1020	1620	NF	NF
	C_{UNI}	0	1705	2757	NF	NF
Z = 1.4	C_{OPT}	87	1540	NF	NF	NF
	C_{UNI}	1179	2757	NF	NF	NF

Table IV
COST COMPARISON BETWEEN OPTIMAL (OPT) AND UNIFORM (UNI) VIRTUAL BUFFER ALLOCATION FOR $K_{max} = 16$ BUFFERS, $W = 32$, $\rho = 0.35$ ERLANG FOR EACH PATH. 'NF' STANDS FOR 'NOT FEASIBLE'.

	$\mathcal{P}_{max}$	10^{-1}	10^{-2}	10^{-3}	10^{-4}	10^{-5}
Z = 0.8	C_{OPT}	0	731	1937	2617	3065
	C_{UNI}	0	2313	3365	4154	4680
Z = 1	C_{OPT}	0	1536	2477	3210	NF
	C_{UNI}	0	3102	3891	4943	NF
Z = 1.4	C_{OPT}	0	2178	3479	NF	NF
	C_{UNI}	0	3891	5469	NF	NF

the cost varies considerably with Z, an occurence that, we believe, justifies the choice of modelling the OBS network with the analytic method proposed in [10]. We compare the total FDL cost resulting from our optimisation method (C_{OPT}) with the total cost resulting from the minimum uniform allocation of the virtual buffers that satisfies the requirements in terms of $\mathcal{P}_{max}$ (C_{UNI}). For example, in Table IV, to reach a maximum target blocking probability $\mathcal{P}_{max}$ of 10^{-2} on all paths for $Z = 1.4$, the optimal numbers of FDLs are found to be $\mathbf{K}_{opt}$=[0 8 0 10 4 6 10 4 0 10 10 4 0 0 4], resulting in a total cost of $C_{OPT} = 2178$. The same performance requirements can be satisfied with a uniform allocation of no less than 10 buffers in each node, for a total cost of $C_{UNI} = 3891$. Thus, for this particular scenario, the optimisation process yields a 44% reduction in cost of the extra hardware added by the employment of FDLs compared to a uniform FDL allocation. Furthermore, following [3], we can also estimate the achieved reduction in the total hardware cost of the network with the same optimal buffer allocation. In fact, in the bufferless TAS OBS node architecture (that is, without considering the extra hardware added by the FDL), a node n is equipped with $2P_n$ EDFAs, $W \cdot P_n$ TWCs and $W \cdot P_n^2$ SOAs. If we consider the cost of this additional hardware in the OBS network under study for all nodes of the same scenario above mentioned, we obtain a total hardware network cost of $C_{OPT} = 24294$ for the optimal allocation $\mathbf{K}_{opt}$ and $C_{UNI} = 26007$ for the uniform allocation of 10 buffers per node, resulting in an approximate total hardware cost saving percentage of 6.6%. We also note that for some scenarios it is not possible to find an optimal (and uniform) allocation of the FDLs (e.g., Table III for $Z = 1.4$ and $\mathcal{P}_{max} = 10^{-3}$). This is because all the solutions found are unfeasible, that is there is no FDL allocation that can satisfy the performance requirements given by $\mathcal{P}_r(\mathbf{K}) \leq \mathcal{P}_{max}$ for $r = 1, \ldots, R$ with $K_n \leq K_{max}$ for all nodes of the network.

Figure 5 illustrates an example of the distribution of the FDL virtual buffers in the OBS network. We observe that the FDL distribution changes considerably with Z, since congestion at nodes increases when traffic becomes peaked. Note that some nodes are not assigned with FDLs, regardless of the peakedness of their offered traffic demands. Thus, the genetic algorithm is able to identify the nodes of the network for which adding an FDL does not add any contribution in lowering the end-to-end blocking probability value. In this regard we want to remark that, although the offered load may be generally considered low in all the cases of study (0.3-0.35 Erlang), this is not the case for congested links in the core network, where it can reach normalised values of 0.6 Erlang. The algorithm allows to determine the optimal number of FDL buffers required for nodes with such congested links, a number that is higher than the one determined for the less congested links at the edges of the network. This feature may consent to considerably decrease the FDL cost compared to an uniform allocation as shown in the example of Figure 6. In this particular case, to satisfy the performance requirements, at least 4 FDL buffers must be employed to node 7. This means that, in an uniform allocation, we must employ at least 4 FDL buffers for each node of the network, resulting in an increased FDL cost per network node compared to the optimal scenario.

Finally, end-to-end blocking probabilities for each path are shown in Figure 7. We observe that the analytic method provides a quite accurate estimate of the blocking probability at the optimal point compared to simulation data. The graph

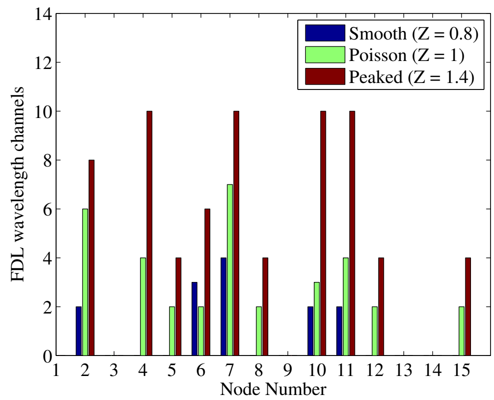

Figure 5. Allocation of the FDLs in the network for $W = 32, \rho = 0.35$ Erlang and $\mathcal{P}_{max} = 10^{-2}$. Note that nodes 1,3,9,13 and 14 do not contribute in lowering the blocking if equipped with FDLs, thus they are not assigned with FDLs.

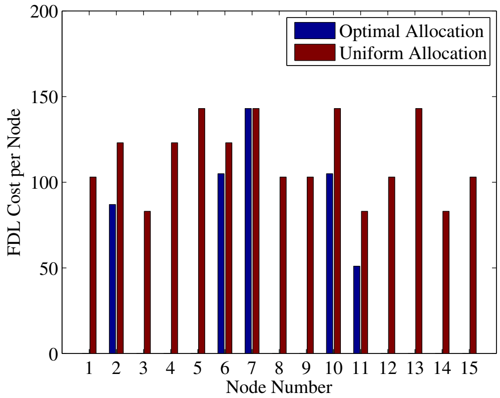

Figure 6. Comparison of the FDL cost per node between optimal and uniform FDL allocation for $W = 32$,$\rho = 0.35$ Erlang and $Z = 0.8$ and $\mathcal{P}_{max} = 10^{-2}$. The optimal FDL allocation is found to be **K**=[0 2 0 0 0 3 4 0 0 2 2 0 0 0 0]. The uniform allocation forces each node to employ at least 4 FDL buffers, that is the required minimum number of FDL buffers to satisfy the performance constraints at node 7.

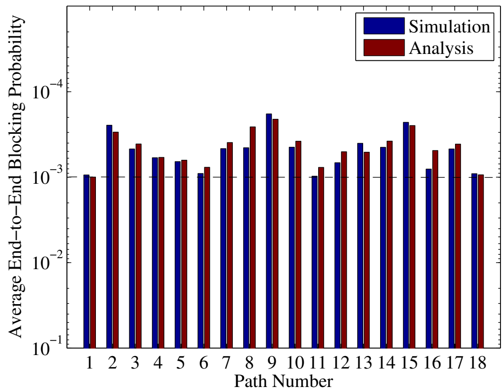

Figure 7. Path blocking probabilities for $W = 16$,$\rho = 0.3$ Erlang and $Z = 1$. Note that all blocking values compare favourably with simulation results and they are all below the required performance level given by $\mathcal{P}_{max} = 10^{-3}$. The optimal FDL allocation for this particular scenario is found to be **K**=[0 6 0 7 6 7 8 6 0 6 6 6 0 0 6].

additionally shows that each path blocking is below the maximum tolerable value given by $\mathcal{P}_{max}$, thus satisfying the performance constraint of our optimisation problem.

VI. Conclusions

We have proposed a method to find an optimal allocation of FDLs in an OBS network that minimises the cost associated with the employment of FDL-buffers and satisfies performance requirements in terms of maximum tolerable end-to-end blocking probability. Our results illustrate the potential equipment cost savings achieved when FDL allocation is optimised as opposed to uniformly distributing the number of buffers in the network. Future works will deal with the definition of multi-objective optimisation problems for OBS networks where conflicting objectives such as throughput maximisation and cost minimisation will be taken into consideration.

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