Performance evaluation of slotted OPS switching fabrics under self-similar traffic

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***Abstract*—This paper evaluates the performance of slotted Optical Packet Switching (OPS) switching fabrics under self-similar traffic. The issue of how to synthesize a realistic self-similar traffic pattern for OPS networks is discussed. As a result, a methodology for designing self-similar *batch* sources suitable for OPS networks is proposed. Then, a buffering dimensioning study of the switching fabric is conducted under the proposed traffic model. Also, the variation in the self-similar traffic parameters suffered in the output process of the switch is evaluated and discussed.**

***Index Terms*—Optical Packet Switching, self-similar traffic, performance evaluation.**

I. Introduction

THE collapsing of the dot-com bubble occurred during 1995-2001 had a severe impact on the evolution of the optical backbone networks. The decline in the expectation of the revenues blocked the commercial deployment of novel switching technologies under research, aimed to cope with a larger and more dynamic traffic demands. Optical Packet Switching (OPS) is one of the cut alternatives that still stay in the research stage. Despite of this, it has been quoted in different forums as the most promising option for the midterm optical backbone [1].

In OPS networks, ingress traffic is assembled into optical packets that are optically buffered and switched across the network. The packet granularity implies the highest performance and traffic manageability benefits, but also the highest cost in photonic components. An OPS network may be synchronous or asynchronous. In synchronous OPS, packets are optically aligned at switch input ports to a slot boundary, in order to improve the contention resolution in the switching fabric. Asynchronous OPS does not require this type of optical alignment, but yields to higher packet delays and requires larger optical buffers. The European DAVID project [1] selected synchronous slotted OPS with packet duration in the order of ~1 μs as the most promising preference for the Wavelength Division Multiplexing (WDM) backbone network. In this paper, we consider slotted OPS networks, with fixed size packets that are aligned to slot boundaries at switch inputs.

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In order to assess the benefits of OPS networks in the backbone, a reasonable line of work is the performance evaluation of an OPS network when carrying a realistic traffic demand. Well-known analysis of Internet traffic confirms its self-similar properties. Also, the impact of self-similar traffic on queuing performance in electronic switches has been largely investigated [2]. It is recognized that traffic self-similarity is a crucial issue as far as network engineering is concerned. Nevertheless, the studies of the impact of self-similar traffic on OPS switches are still embryonic. This research line addresses two main questions: (i) to characterize the expected traffic of optical packets in the fiber links, as a result of the assembling and injection of optical packets, (ii) to evaluate the effect of the expected traffic on the queuing performance of OPS switching architectures.

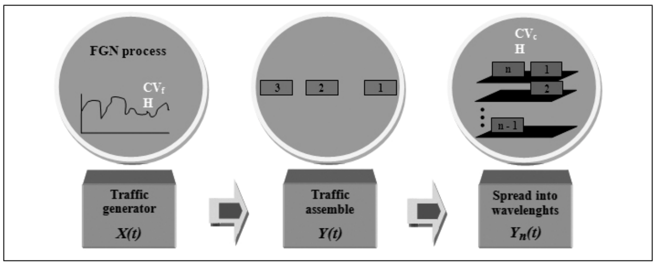

Fig. 1. OPS traffic synthesizing methodology.

Traffic characterization in OPS networks is affected by the particular way in which optical packets are spread across the wavelengths of a fiber. This is given by the Scattered Wavelength Path (SCWP) network control. In the OPS backbone network, traffic flows are provisioned to follow a fixed sequence of hops from ingress to egress nodes. The Scattered Wavelength Path (SCWP) operational mode [3] means that the packet transmission wavelength in each hop is not fixed. Therefore, when a packet arrives at a switching node, its destination fiber is given by the information stored in the packet header; but the packet output wavelength is undetermined and has to be chosen dynamically. Consequently, a degree of freedom exists for the SCWP switch schedulers to take a joint decision on the packet delay and packet output wavelength. This joint decision improves the statistical multiplexing effect, yielding lower delay and

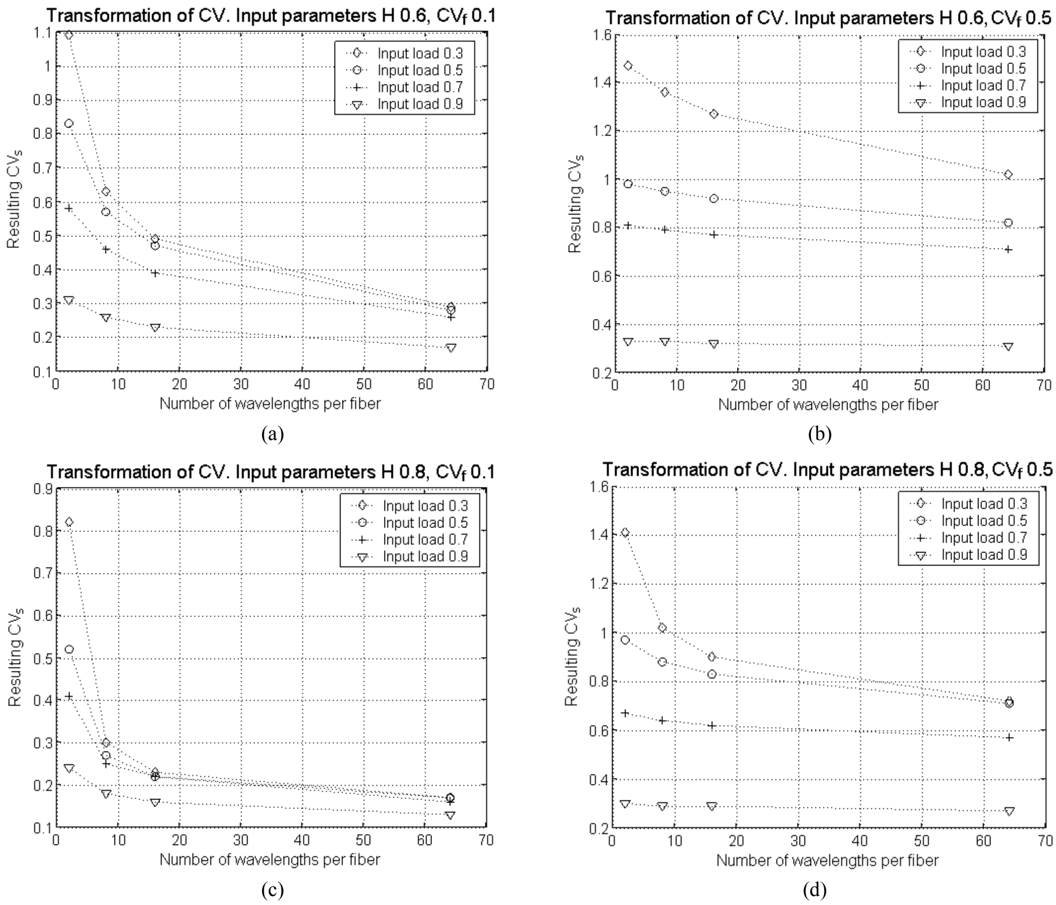

Fig. 2. Influence of the number of wavelengths per fiber and the input load over the CV_s parameter. Feeding traffic parameters: (a) H=0.6, CV_f=0.1, (b) H=0.6, CV_f=0.5, (c) H=0.8, CV_f=0.1, (d) H=0.8, CV_f=0.5.

lower buffer requirements. By nature, the reduction in buffer requirements is better in the Dense WDM (DWDM) scenario with a higher number of wavelengths per fiber.

The particular use of the wavelength dimension to multiplex the traffic implies that in OPS slotted networks, it is not possible to consider an input fiber with n wavelengths as n independent traffic sources, one per transmission wavelength. Despite of this, it should be modeled as one *batch* discrete source with up to n simultaneous arrivals. In this paper, the traffic model for OPS networks proposed in [4] is employed in order to capture this effect. Specially, this is useful to estimate how the consideration of a fiber as a batch source may vary the self-similar properties of a realistic traffic demand.

The traffic of optical packets synthesized from this model is employed to evaluate the buffering penalties that arise in OPS switching nodes. A synchronous OPS switch able to emulate output buffering is assumed in this paper. In this type of nodes, the switching fabric is able to switch input packets to the target output fibers with no additional constraint than the unavoidable output contention: no more than n packets can be transmitted simultaneously in any output fiber, being n the number of wavelengths in that fiber. Thus, output-buffered OPS switches provide the optimum throughput-delay performance. Examples of OPS switching architectures able to emulate output buffering can be found in references [5,6].

This paper is organized as follows. In section 2 the traffic model employed is described, which aims to capture its particular characteristics in OPS networks. Section 3 evaluates the buffering performance of the OPS switch under the presented traffic model. In section 4 the resulting output traffic of the node is analyzed in order to evaluate the hop-to-hop variation of the self-similar nature of the traffic. Finally, section 5 concludes the paper.

II. TRAFFIC MODEL

This section describes the traffic model employed in this paper. The model of the input traffic will be based on a Fractional Brownian Traffic (FBT) which has been shown to model accurately traffic from a LAN [14]

A traffic arrival process $A(t)$ is a continuous time random process giving the total arrival of bytes to a system up to time t. $A(t)$ is called self-similar if it has the same statistical structure regardless of the time scale it is analyzed. More precisely if its distribution is a scaled copy of itself at different time scales $A(t) =_d a^{-H}A(at)$ is called self-similar with parameter H. Usually it is more convenient to work on the process of traffic arrivals in fixed time intervals. We call $X_{\Delta t}(t)$ the process of bytes arrivals in slots of duration Δt (thus $X_{\Delta t}(t)=A(t)-A(t-\Delta t)$). For simplicity we will write just $X(t)$ when Δt is a choosen time unit. We assume this interval arrival process to be stationary. In this case the process $A(t)$ is called Hss.s.i (H-self-similar with stationary increments and presents a number of well known properties relating scaling behavior, long range dependence and heavy tail distribution (see [12]). An important property of $X(t)$ is that resampling at a larger time scale the distribution is scaled in a similar way to that of $A(t)$. Consider $X_{m\Delta t}(t)$ the sampling of $A(t)$ in intervals m times larger. Let's call $X^{(a)}_{m\Delta t}(t)$ the process sampled at intervals of duration $m\Delta t$ built by averaging m samples of $X_{\Delta t}(t)$. Due to $A(t)$ being H-ss.s.i. these two process are scaled versions of $X(t)$ with the following factors

$$X^{(a)}{}_{m\Delta t}(t) =_d m^{H-1} X_{\Delta t}(t) \quad (1)$$

$$X_{m\Delta t}(t) =_d m^{H} X_{\Delta t}(t) \quad (2)$$

Equation (1) implies that the variance of the process $X^{(a)}_{m\Delta t}(t)$ is given by

$$Var[X^{(a)}{}_{m\Delta t}(t)] = m^{2H-2} Var[X^{(a)}{}_{\Delta t}(t)] \quad (3)$$

This provides a simple method to estimate the H paramater of a process $X(t)$ by plotting the variance for different levels of aggregation in log-log and estimating the slope. See [13] for a full description of the method.

Related to this the process $X(t)$ has an autocorrelation function $\gamma(k)$ that falls with k^{2H-2} thus being not-sumable. That property is known as long-range dependence.

In practice such a process $A(t)$, $X(t)$ only makes sense as a traffic process for values $1/2 \le H < 1$. The case $H=1/2$ is the limit case that corresponds to a self-similar but not long-range dependent process. A well known mathematical process with these properties exists and is called Fractional Brownian Motion (FBM) or Fractional Gaussian Noise (FGN) if we refer to the increments process. A FGN has 0 mean and is characterized only by an H parameter and a variance value σ_0^2 (at a given time scale of sampling it will change if observed at another sampling scale according to equation (2)). There are algorithms for generating sample paths of an FGN. One of the most frequently used is the Random-Midpoint-Displacement algorithm [7] which was chosen to generate all the traces in this work.

A general traffic process will not have 0 mean but can be generated from an FGN as

$$X(t) = \mu + \sigma Z_H(t) = \mu\big(1 + CV Z_H(t)\big) \quad (4)$$

Where $Z_H(t)$ is a normalized FGN with 0 mean and variance 1. μ controls the average traffic generated in every time slot but the shape of the traffic is given only by H and CV. Notice also that this process has a different variance (and CV) depending on the scale it is sampled. We call σ_0^2 (and CV_0) the variance (or coefficient of variation) exhibited by the process $X(t)$ at a given time scale indicated by the width of the time slot $\Delta t=1$. The process $X_k(t)$ giving the amount of bytes arriving in slots of duration $k\Delta t$ has a variance of $\sigma_k^2=k^{2H}\sigma_0^2$ (equation (2)) and a coefficient of variation of $CV_k=k^{H-1}CV_0$. This traffic model is usually referred as Fractional Brownian Traffic (FBT)

An FBT is a good model for the arrival of bytes in a LAN but we are interested in generating the pattern of optical packets that will feed the ports of an OPS switch. The additional objective of this model is to provide a suitable tool for evaluation, which captures the main effects that appear in OPS networks. The method to create synthetic traces of OPS traffic is sketched in figure 1:

i) The starting point is synthesizing a trace of self-similar traffic. In our work we used RMD to generate sample traces of FBT. Of course, this traffic is usually measured in bytes, not in optical packets. These samples are employed to generate the amount of bytes arriving to the node every *100 ns* slot.
Sample traces for different H and CV values were generated. As the variance depends on the sampling scale, input traffic CV will be expressed in the reference scale of $\Delta t=1ms$ so it can be compared with previous works (i.e. Abilene-I data sets [8] show H values around *0.7* and values for CV near *0.3* measured in slots of duration $\Delta t=1ms$ as described in [9]).
The result at this stage is a continuous time byte arrival fluid process sampled at intervals of *100 ns* with shape characterized by two parameters H, CV and that can be rescaled to any μ value to control load (see figure 2).

ii) The volume of synthesized traffic is converted into a sequence of optical packets by means of the assembling process. The method employed for packet assembling is as follows: a value for the desired utilization factor is chosen (ρ). From this value the average time to fill an optical packet (t_{fill}) is derived from the relation $\rho = 1/t_{fill}$. From t_{fill} the μ parameter of FGN is selected in order to have $t_{fill} = s/\mu$, being s the size of the optical packet. The process generated in stage (i) is added and the time of generation of an optical packet is triggered every time s bytes are accumulated. From the series of times of packets generated it is decided if there is an optical packet present at every $1\mu s$ slot. In any slot where there is more than one packet generated extra packets are assigned to the next free slot.

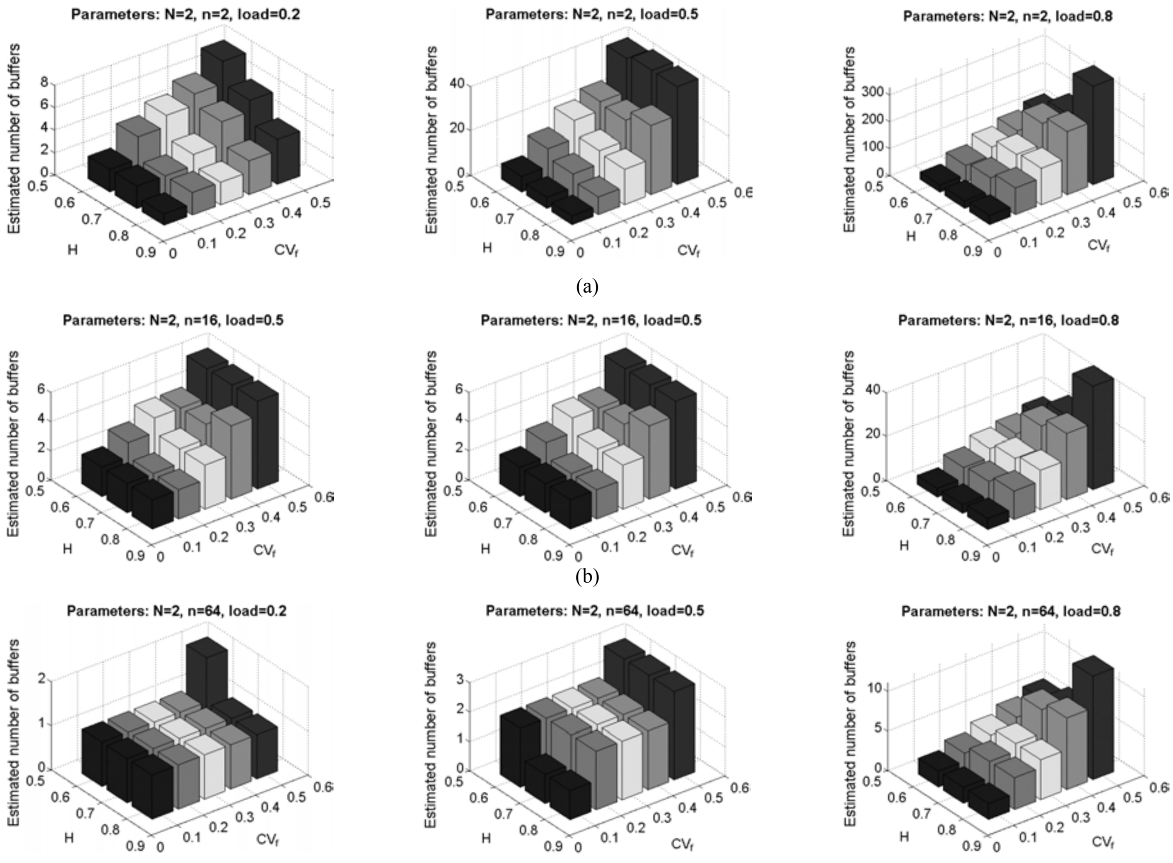

Fig. 3. Influence of CV_f, H, n and input load parameters over the number of buffers necessary to achieve PLP of 10^{-6}. (a) n=2, (b) n=16, (c) n=64.

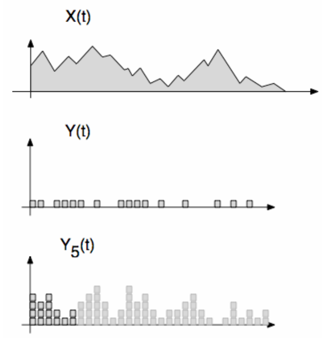

Fig. 2. OPS traffic synthesizing methodology.

iii) At the end of process (i) and (ii), a sequence of optical packets of fixed size is obtained ($Y(t)$ process). We call this source as the feeding source, which generates one optical packet every time slot. In order to emulate the batch source, the method employed in [4] is applied here. That means that a batch source of up to n packets per time slot is generated by sampling the feeding source n times faster. Thus, one time slot in the batch source occurs after n time slots in the feeding source, and a maximum of n packets are produced. This process characterizes the effect that in OPS networks, fibers are employed as a large tube with a capacity of up to n packets per time slot.

Traffic process from (ii) is a series $Y(t)$ taking values in $\{0,1\}$ indicating if an optical packet arrived or not during that time slot. The process $Y(t)$ retains the properties of the original FGN process. The expectation is the utilization factor $E[Y(t)]=\rho$ and the correlation structure and coefficient of variation are preserved at large timescales (i.e. if $Y(t)$ is aggregated to the scale of reference $\Delta t=1ms$, the process number of packets arriving during $1ms$ has the target CV).

TABLE I

ESTIMATED NUMBER OF BUFFERS TO ACHIEVE A PLP OF 10^{-6}. INPUT LOAD P=0.7, INPUT/OUTPUT FIBERS (N=2 / N=4 / N=8).

CV	Parameter of Hurst											
	0.6				0.7				0.8			
	Number of wavelengths				Number of wavelengths				Number of wavelengths			
	2	8	16	64	2	8	16	64	2	8	16	64
0.1	17/16/13	5/5/4	3/3/3	2/2/2	14/13/12	4/4/4	3/3/3	2/2/2	11/11/11	4/4/4	2/2/2	2/2/2
0.2	31/25/20	8/7/6	5/4/3	2/2/2	42/25/19	11/7/5	6/4/3	2/2/2	41/31/16	11/8/5	6/5/3	2/2/2
0.3	65/43/29	17/118/	9/6/4	3/2/2	85/37/27	22/10/7	12/6/4	4/2/2	74/44/26	19/12/7	10/6/4	4/3/2
0.4	63/59/34	16/16/9	9/8/5	3/3/2	114/52/35	29/14/10	15/7/5	5/3/2	113/81/32	29/21/9	15/11/5	5/4/2
0.5	85/57/45	22/15/12	11/8/6	4/3/3	119/82/43	31/21/11	16/11/6	5/4/2	148/117/53	38/30/14	19/16/8	6/5/3

The effect of sampling the feeding source n times faster in

(iii) is that the resulting $Y_n(t)$ has n times the expectation of $Y(t)$ and thus the normalized load (0...1) is the same. But due to the aggregation of several correlated samples the variability (CV) of $Y_n(t)$ is less than that of $Y(t)$. And in fact the behavior of process $Y_n(t)$ is equivalent to that of $Y(t)$ in n scales above.

Moreover, the re-scaling effect produces a modification of the variation coefficient of the batch source. In the following, we denote as CV_S the variation coefficient of the process $Y_n(t)$, and CV_f (or simply CV), the variation coefficient of the $Y(t)$ process.

III. Dimensioning the optical network

In this section the impact on the buffering requirements of the self-similar nature of the traffic is evaluated by means of computer simulation. The confidence intervals are of 95%. The input traffic consists of sample traces generated as explained in section 2. Different traces are used in different fibers, and different configurations of load, H and CV_f (the variation coefficient the feeding source shows at an aggregation scale of 1 ms). Feeding source traces have a length of 12×10^6 samples (each sample is 0 or 1 representing the absence or existence of a packet). Each time slot (1 µs), n samples are consumed for a fiber of n wavelengths. Then, the (up to n) packets obtained are simultaneously transmitted in the fiber. Therefore, $12/n$ seconds of real traffic are evaluated. In our tests, the packets are spread across the wavelengths according to the round-robin criteria described in [10]. Nevertheless, the particular set of wavelengths used each time slot is irrelevant for the performance evaluation of the *output buffered* switching fabrics under consideration.

The simulation parameters of the input traffic are input load ρ={0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9}, H={0.6,0.7,0.8}, and CV_f={0.1,0.2,0.3,0.4,0.5}. Figure 3 illustrates the variation of the CV_s parameter for different traffic configurations. Figures 2(a) and 2(b) with H=0.6 and CV_f ={0.1,0.5} respectively and figures 2(c) and 2(d) with H=0.8 and CV_f={0.1,0.5} respectively. The results show that an increase in the input load yields a decrease in the CV_s coefficient, for any value of the rest of the parameters. Also the resulting CV_s decreases when the number of wavelengths per fiber increases (Dense WDM links).

A set of tests has been conducted to illustrate the variation of the buffering requirements of an output buffered node with N={2,4,8} input and output fibers, and n={2,8,16,64} wavelengths per fiber, under different traffic parameters H, CV_f and input load. In order to estimate the buffer depth, we simulate a system with an infinite queue, and estimate the Packet Loss Probability (PLP) for a buffer of B Fiber Delay Lines (FDLs), to the probability of a packet suffering a delay higher than B time slots. Note that this is a pessimistic approximation. Figure 3 displays the results for a switch with N={2} input/output fibers and n={2,16,64} wavelengths per fiber. The other results obtained confirm our conclusions:

- In all the cases when the value of the CV_f increases, a higher number of FDLs are required to achieve the same target packet loss probability.
- Parameter H shows a more peculiar behavior. With low load, small values of H imply higher buffer requirements than with elevated values of H, but with high input load the opposite effect is observed.
- A higher number of wavelengths per fiber minimizes the negative effects of H and CV_f. With a low number of wavelengths per fiber and medium or high input load, high values of CV_f and H involve unfeasible FDL requirements.

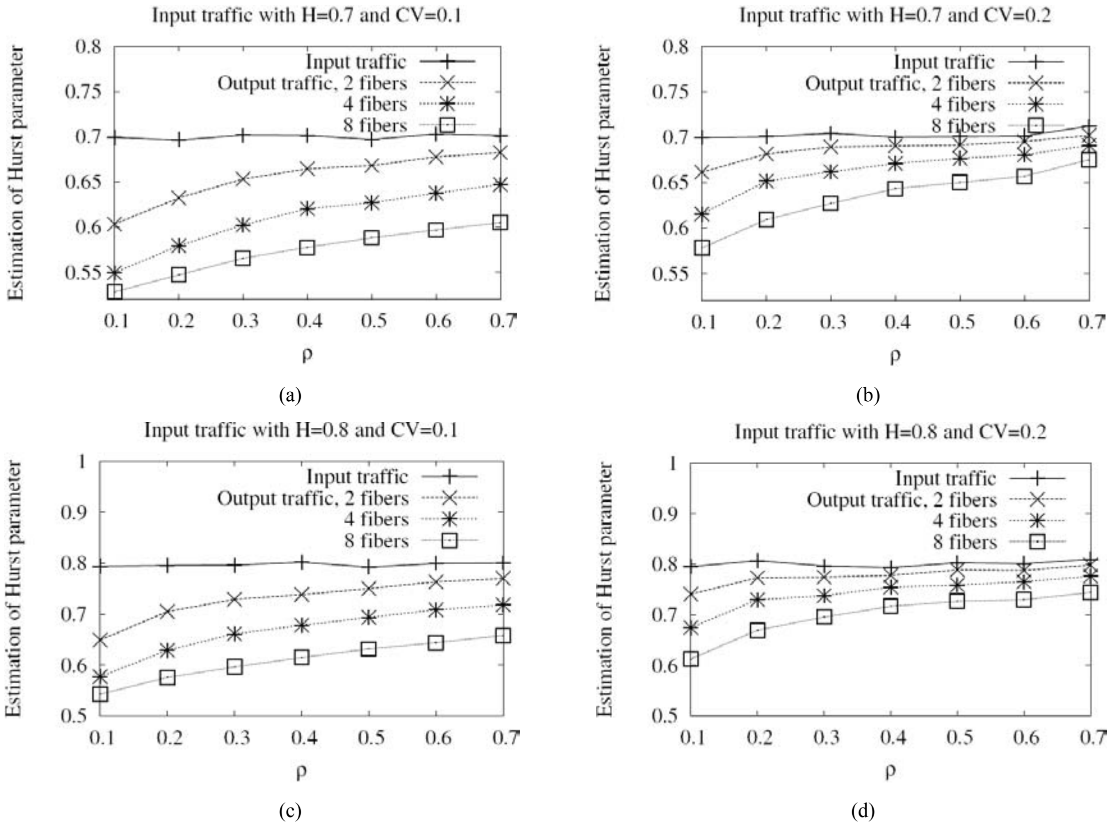

Fig. 4. Estimation of the Hurst parameter for the output traffic from one fiber of the switch. Input traffic with H=0.7 and CV_f=01 (a), H=0.7 and CV_f=0.2 (b), H=0.8 and CV_f=0.1 (c), H=0.8 and CV_f=0.2 (d).

Table 1 provides more complete results, by evaluating the required number of FDLs under different configurations, to achieve a target packet loss probability of 10^{-6}. It includes the effect of the number of input/output fibers N={2,4,8} in the buffer requirements. Not surprisingly, results show that an increase in the number of fibers per node implies a meaningful reduction of the necessary number of buffers. This is a well-known effect as the aggregation of a higher number of independent sources, yields to a more uncorrelated traffic. It is interesting to remark that in DWDM nodes (i.e. 64 wavelengths) a low PLP can be obtained with small buffering (i.e. 3 FDLs), under realistic traffic parameters.

IV. Output traffic analysis

In this section we compare the input and the output processes of an OPS switch, in order to evaluate the variation in the self-similar nature of the traffic traversing a node. Therefore, we estimate the Hurst parameter of the traffic in a target input and output fiber, using the slope in the log-log representation of the variance-aggregation-plot of the traffic [11]. It should be mentioned that the estimation of the input traffic H parameter has been used also as a validation of our synthesizing method.

Fig. 4 compares the estimated value of the Hurst parameter for the input and output traffic, under input traffic given by H={0.7,0.8}, different traffic loads, number of fibers in the switch and coefficients of variation CV_f={0.1, 0.2}. Due to the scaling nature of asymptotic self-similar traffic we have observed no significant effect of the number of wavelengths per fiber in the self-similar characteristics of the output traffic. This is because a different number of wavelengths $n1$ or $n2$ per fiber resamples the same process $Y(t)$ in $Y_{n1}(t)$ or $Y_{n2}(t)$ but both processes keep the scaling behavior of $Y(t)$. Hence, even if the CV of this process may change, the decay of variance with scale is the same than in $Y(t)$ and H is the same. The results obtained for different number of lambdas are similar (validating this analysis) and are not shown in this paper.

For all the scenarios in Fig. 4 we observe that as the number N of fibers in the switch increases, the Hurst parameter value of the output process gets reduced, and is always below the H parameter at the input. Again, this effect is caused by the statistical multiplexing of a greater number of independent flows. The ouput traffic at a given port $Y_{n,out}(t)$ studied is the sum of the contributions coming from each of the input ports (where the destination of every optical packet is choosen by a uniform random variable among the output ports). Thus $Y_{n,out}(t) = Y_{n,out}^{(1)}(t) + Y_{n,out}^{(2)}(t) + \ldots\ Y_{n,out}^{(N)}(t)$. (figure 3) Each of the $Y_{n,out}^{(k)}(t)$ process is self-similar and presents scaling behaviour with parameter H. But the sum of independent self-similar processes reduces its self-similarity and this effect is greater when the number of independent sources increases. For instance, Fig. 4a (H=0.7, CV_f =0.1) shows that for very low loads, output traffic self-similary gets close to H=0.5 (no long-range dependence) for a switch with 8 input/output fibers.

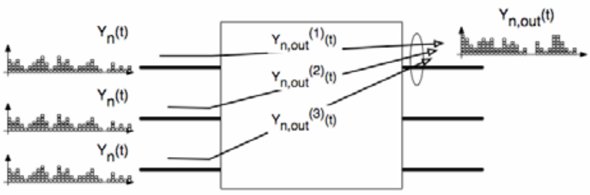

Fig. 3.Traffic contributions to output port.

In addition, we observe that as the switch load (ρ) increases the H parameter of the output traffic gets closer to the input one's. The reduction in self-similarity is better for lower utilization factors. Again, from Fig. 4a (ρ=0.7), the multiplexing obtained with 8 input/output fibers barely reduces the input traffic self-similarity from H=0.7 to H=0.6.

Finally, the reduction on self-similarity is greater as the input coefficient of variation CV_f decreases. As an example, Fig. 4b (H=0.7, CV_f=0.2) shows that a reduction from H=0.7 to H=0.6 is only obtained when the traffic load is below ρ=0.2 while for CV=0.1 (Fig. 4a) this reduction on H is obtained even for loads as high as ρ=0.7.

V. Conclusions and future work

This paper addresses the performance evaluation of output-buffered OPS switching fabrics under self-similar traffic. First, a traffic synthesizing method is proposed, which models a WDM fiber with n wavelengths as a discrete batch traffic source, capable of transmitting up to n packets per time slot. The model aims to capture the effects in the traffic that may appear because of the multiplexing usage of the wavelengths in a fiber. A more soften traffic is predicted in networks with a higher number of wavelengths per fiber. A buffering evaluation in the nodes is conducted for different traffic and switch configurations. Results reveal that in the DWDM scenario, a PLP target of 10^{-6} can be achieved with small amount of buffering. In addition, the self-similar parameters of the output traffic process are evaluated, to estimate the hop-by-hop variation of the network traffic. Results show that the variation of the self-similar parameters of the traffic is barely dependent on the number of wavelengths of the links. In addition, the expected reduction of the self-similar nature of the output process as the number of input sources increase, has been also evaluated in this scenario.

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