Multiresolution Analysis of Optical Burst Switching Traffic

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Abstract—**In this paper, a Multiresolution Analysis is conducted in order to study the self-similar features of Optical Burst Switching (OBS) traffic. The scenario consists of an OBS backbone with input traffic from a large number of Internet users, that generate Poisson-arriving heavy-tailed bursts. The results show that long-range dependence is preserved at timescales longer than the burst assembly timeout value while the traffic variability at short timescales is increased.**

Keywords: Optical networks, optical burst switching, self-similarity

I. Introduction and problem statement

The advent of terabit optical networks requires the use of an efficient transfer mode for IP packets. In fact, asynchronous transmission of IP packets, which have negligible transmission time, poses a number of challenges regarding synchronization and buffering in the all-optical routing elements. Alternatively, Optical Burst Switching (OBS) [1] is based on the principle of grouping several IP packets in a single burst, which can be handled more efficiently. Thus, OBS provides "coarse packet switching" service in the optical network, namely a transfer mode which is halfway between circuit switching and pure packet switching. First, a resource reservation message is sent along the path from source to destination, so that resources can be reserved for the incoming burst. Then, the data burst follows. As a result, OBS does not incur in the overhead of circuit setup but still resource reservation is performed on a per burst fashion, thus providing enhanced capabilities for QoS discrimination beyond pure packet switching. In fact, OBS offers scope for differentiated quality of service, (MPLS) traffic engineering and path protection and restoration [2].

Even though the concept of OBS has attracted considerable research attention there is scarce literature concerning practical implementations and impact in traffic engineering. In OBS networks, since incoming traffic comes in packets, burst assembly functionality is required at the edges. Ge et al. [3] have recently proposed a simple algorithm for burst assembly which can be explained with the aid of figure 1. Packets coming to the optical cloud are demultiplexed according to their destination in separate queues. A timer is started with the first packet in a queue and, upon timeout expiration, the burst is assembled and relayed to the transmission queue. As a result, the burst assembly time is kept within the timeout value independent of network load. In doing so, large packetization delays due to burst assembly are avoided, thus circumventing a major drawback of OBS. Furthermore, the fact that bursts are variable length is in accordance with the OBS paradigm [1].

The above mentioned algorithm provides a simple and efficient way to encapsulate packets in optical bursts and, following

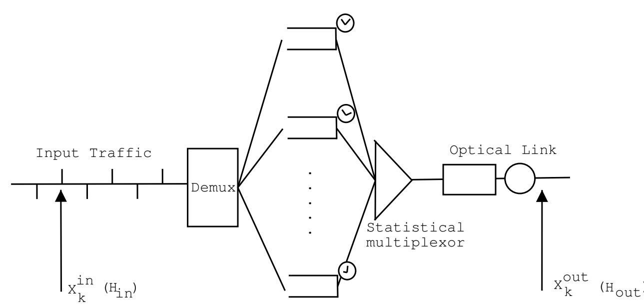

Fig. 1. Burst assembly algorithm

[3], the traffic self-similarity is reduced. Actually, the concept of self-similarity involves the definition of a timescale beyond which the traffic shows scaling behavior. In order to have a better understanding of this issue, let us first provide a brief introduction to self-similarity.

A. Self-similarity

Traffic self-similarity (or scaling) is defined as follows: Let $\{X(t), t > 0\}$ be the continuous process of number of bytes transmitted in the interval $[0, t)$ and let $X_k = \{X(k\delta) - X((k-1)\delta), k \geq 1\}$, being δ a measurement interval in milliseconds. Note that X_k denotes the (weakly stationary) discrete process of number of bytes per time interval δ. Now, consider the *aggregated* process

$$X_i^{(m)} = \frac{1}{m} \sum_{k=m(i-1)+1}^{mi} X_k, \qquad m > 1, i \geq 1 \tag{1}$$

and let $\rho^{(m)}(j)$ with $j \geq 1$ be the autocorrelation function of $X_k^{(m)}$. The process X_k is *asymptotically second-order self-similar with H parameter* if

$$\lim_{m \to \infty} \rho^{(m)}(j) = \frac{1}{2}((j+1)^{2H} - 2j^{2H} + (j-1)^{2H}) \tag{2}$$

where H is the Hurst (or self-similarity) parameter. For $1/2 < H < 1$ the autocorrelation function in equation 2 decays slowly, thus being not summable, and we call X_k *long-range dependent*. That is precisely the case for Internet traffic, which shows dependency in contrast to, for instance, a Poisson traffic.

On the other hand, note that m in equation 1 defines a traffic timescale. Furthermore, equation 2 states that self-similarity is an asymptotic property, namely, it only happens when $m \to \infty$. In practice, there is a cutoff timescale (δ) beyond which the traffic behaves as a stationary self-similar process with constant H parameter. However, for shorter timescales, the process may show complex, multifractal behavior. Most importantly, Grossglauser and Bolot [4] show that the queueing performance is determined by the "timescale of interest" which is related to the buffer size. For short buffer sizes, only the short timescales determine queueing performance. Actually, self-similarity is only relevant in the busy period timescales [5]. In fact, a queueing system is regenerated (reset) when the number of packets in the queue reaches null. Thus, only correlations in the timescale of the busy period are relevant. For short buffers or large buffers with low and intermediate utilization factors, the statistical features of Internet traffic at short timescales are responsible for queueing performance [6]. Thus, a comprenhensive analysis of self-similarity should also include the *timescales for which the traffic shows self-similarity*. Precisely, a multiresolution approach is adopted in this paper in order to determine such timescales, for the case of OBS traffic.

B. Contribution

For a thorough treatment of self-similarity in network traffic the reader is directed to [7]. In the remaining of the paper we will use the term "self-similar" for brevity to refer to "asymptotic second-order self-similar". The main contributions of this paper follow. First, we further analyze the implications of burst switching in self-similarity to conclude that the scaling behavior of the process is indeed preserved in timescales longer than the burst assembly timeout. In smaller timescales the traffic process is "whitened" due to burst sequencing and shuffling before the optical transmission queue. Secondly, and opposite to this beneficial effect, an increase in the marginal distribution coefficient of variation is observed. Therefore, the choice of the burst assembly timeout value becomes of fundamental importance in practical implementations of OBS networks.

II. Methodology

We performed extensive simulations of the burst assembly system depicted in figure 1, considering an input traffic process X_k^{in} which is generated by aggregation of Poisson-arriving heavy-tailed flows. Willinger et al. [8] show that the multiplex of on-off sources with heavy-tailed on-off periods turns out to have self-similar features. Furthermore, Tsybakov and Georganas [9] show that the resulting traffic multiplex is asymptotically second-order self-similar, as long as the on-period of the individual flows is heavy-tailed. A heavy-tailed random variable R has a distribution tail with the form

$$P(R > r) \sim \left(\frac{K}{r}\right)^{\alpha}, \qquad 1 < \alpha < 2 \tag{3}$$

If $1 < \alpha < 2$ then it turns out that $1/2 < H = (3-\alpha)/2 < 1$. In [10] such model is used to explain Internet traffic self-similarity. Both size (bytes) and duration of WWW connections can be modeled as heavy-tailed random variables (Pareto), with α values 1.15 for size and 1.2 for duration. Therefore, Internet traffic turns out to be asymptotically second-order self-similar, since an important part of it comes from a multiplex of WWW connections.

A traffic generator of this sort presents a key advantage for our analysis since it allows for two demultiplexing strategies: i) per-packet demultiplexing, which is performed by randomly routing packets to any of the burst assembly queues, as in [3]; and ii) per-flow demultiplexing, which is performed by routing packets considering that *packets belonging to the same flow have the same destination*. We note that the second strategy is more accurate than the first one, since usually a group of IP packets belong to the same file. Thus, the burst assembly queues are not fed by a random sampling of the incoming process but instead by Poisson arriving heavy-tailed flows. Assuming random destinations, the arrival rate is equal to the input traffic rate divided by the number of burst assembly queues.

On the other hand, a time interval of 1 ms. was selected to form the counting process of bytes per interval for both incoming and outgoing traffic, X_k^{in} and X_k^{out} in figure 1 respectively, whose self-similarity features are measured by means of the Abry-Veitch estimator [11]. Such estimator is based on a Multiresolution Analysis (MRA), which consists of decomposition of the process X_k in its details $d_x(j,k)$ and approximations $a_x(j,k)$ from the shortest to the longest time scale j, namely from $j = 1$ to $j = log_2(N)$, being N the total number of samples in X_k. The coefficient $|d_x(j,k)|^2$ provides the "energy per scale" or energy of the process about the time instant $2^j k$ and frequency $2^{-j} f_0$ where f_0 depends on the choice of the mother wavelet [11]. By plotting the energy per scale

$$V(j) = \frac{1}{n_j} \sum_k |d_x(j,k)|^2 \tag{4}$$

versus the scale j in log-linear scales (also known as scalegram or log-scale diagram) [1] we can determine the scaling behavior of X_k. More specifically, if the process X_k is self-similar it can be shown that

$$V(j) \sim (2H-1)j. \tag{5}$$

The use of the Abry-Veitch estimator is most convenient since it estimates not only the Hurst parameter but also the timescales for which the process shows scaling behavior [7, chapter 2].

III. Results and Discussion

Figure 2 shows the energy per scale of the traffic entering the optical network after OBS burst assembly, for an input traffic with $H_{in} = 0.898$ ($\alpha = 1.2$ in equation 3) and timeout values of 2, 4, 8 and 16 ms. The scale in the x-axis is translated to milliseconds for clarity. Results for per-flow and per-packet demultiplexing are identical. Thus, only one scalegram per timeout value is shown in figure 2. The process shows a scaling behavior (with $H_{out} \sim H_{in}$) but *only from a cutoff value which is in the vicinity of the timeout value* t_{out}. However, the original traffic X_k^{in} shows a scaling behavior from a much lower cutoff value (1 ms.), which is close to the packet interarrival time within a burst. Figure 2 (left) clearly indicates that the self-similarity of

[1] See [7, chapter 2] for a number of examples on the use of wavelets to detect scaling regions.

the process X_k^{in} is preserved *in timescales longer than the burst assembly timeout value*.

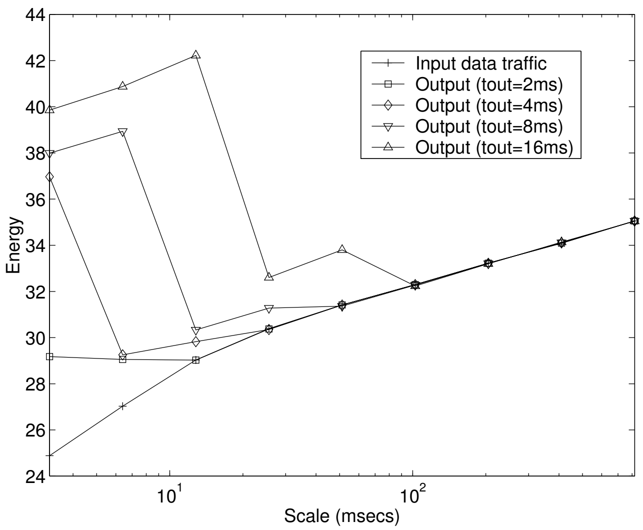

Fig. 2. Energy per scale

For further proof and clarity we show the R/S plot of X_k^{out} for the different timeout values in figure 3. The scale in the x-axis is also translated to milliseconds. The R/S plot is used in [3] as an estimator of the H parameter. For a self-similar process

$$log(R(n)/S(n)) \sim Hlog(n) \qquad (6)$$

where n is the number of samples in the rescaled sample variability or *adjusted range* R and sample variance S^2 [12]. Thus, for large n the slope of the least squares fitted line gives H. We note that for values of n larger than the corresponding timeout value the R/S plots have the same slope, thus indicating that the self-similarity of X_k^{in} is preserved in long timescales.

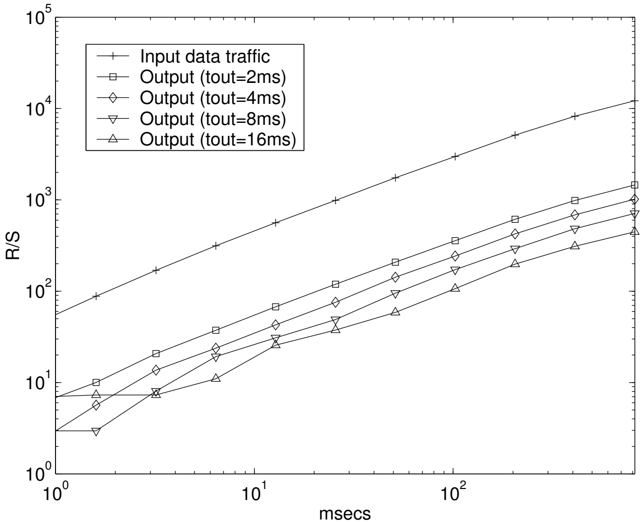

Fig. 3. R/S plot

The results can be explained as follows: On one hand, for timescales shorter than the timeout value, the original traffic process (X_k^{in}) is divided in chunks of data (optical bursts). We note that X_k^{in} shows scaling behavior at those short timescales (see figure 2). Such (optical) bursts are then transmitted sequentially and are possibly shuffled due to statistical multiplexing with other bursts. However, the self-similar features shown by Internet traffic are caused by the *concurrent* transmission of heavy-tailed traffic bursts, like in an $M/G/\infty$ system [8–10]. Thus, X_k^{out} cannot present self-similar features. On the other hand, for longer timescales, the output process X_k^{out} is not altered at all with respect to the original process X_k^{in} and the self-similarity is therefore preserved.

More precisely, let m' be the value of m such that $m'\delta > T_{out}$, where T_{out} is the timeout value. We note that m' is the first aggregation scale larger than the burst assembly timeout value. For timescales beyond $m'\delta$ the aggregated process $(X_i^{(m)})^{in}$ and $(X_i^{(m)})^{out}$ (equation 1) are approximately equal in distribution, but for negligible border effects. Therefore,

$$(X_i^{(m)})^{in} \cong_d (X_i^{(m)})^{out}, \qquad m > m', i \geq 1 \qquad (7)$$

where the equality is in distribution.

On the other hand, an *increase in the marginal distribution variability* at short timescales is observed. We choose a timescale of 1 ms, where the output traffic to the optical network X_k^{out} does not show scaling behavior. In such timescale, for timeout values of 2, 4, 8 and 16 ms the traffic coefficient of variation is equal to 0.0957, 0.306, 0.881, 3.906 respectively, the index for dispersion of counts (IDC) is equal to 181185.65, 518150.68, 1490057.08 and 8345361.24 respectively and the peak-to-mean ratio is equal to 2.13, 3.47, 5.54 and 13.67 respectively. For the original traffic process X_k^{in} the values of coefficient of variation, IDC and peak-to-mean ratio in the same timescale are 0.0053, 9430.11 and 1.24 respectively. We note that it is intuitively clear that the instantaneous burstiness is increased in short timescales due to the effect of grouping several packets in the same burst. As a conclusion, while the scaling region of the input traffic process X_k^{in} is shifted to longer timescales the instantaneous traffic variability is increased in shorter timescales, thus compensating for correlation decrease. Such variability increase may have a strong impact in queueing performance [13].

IV. Conclusions and future work

In this paper we provide an explanation of the apparent decrease in self-similarity due to optical burst switching. The burst assembly timeout becomes the lower cutoff value beyond which scaling behavior of the OBS traffic is observed. On the other hand, the higher the timeout value the higher the marginal distribution coefficient of variation in short timescales. In this way correlation decrease compensates with instantaneous variability increase. Since queueing delay increases with both correlation and instantaneous variability, our findings suggest that there may be a trade-off timeout value that maximizes performance, which is subject of our current research.

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