Delay–Throughput Curves for Timer-Based OBS Burstifiers With Light Load

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***Abstract*—The optical burst switching (OBS) burstifier delay–throughput curves are analyzed in this paper. The burstifier incorporates a timer-based scheme with minimum burst size, i.e., bursts are subject to padding in light-load scenarios. Precisely, due to this padding effect, the burstifier normalized throughput may not be equal to unity. Conversely, in a high-load scenario, padding will seldom occur. For the interesting light-load scenario, the throughput–delay curves are derived and the obtained results are assessed against those obtained by trace-driven simulation. The influence of long-range dependence and instantaneous variability is analyzed to conclude that there is a threshold timeout value that makes the throughput curves flatten out to unity. This result motivates the introduction of adaptive burstification algorithms, which provide a timeout value that minimizes delay, yet keeps the throughput very close to unity. The dependence of such optimum timeout value with traffic long-range dependence and instantaneous burstiness is discussed. Finally, three different adaptive timeout algorithms are proposed, which trade off complexity versus accuracy.**

***Index Terms*—Burstification algorithms, performance evaluation of OBS networks.**

I. Introduction and Problem Statement

Optical burst switching (OBS) is a transfer mode that is halfway between circuit switching and packet switching, thus, providing intermediate switching granularity. It is based on unconfirmed resource reservation for the optical burst, which is composed by several Internet protocol (IP) packets. Due to the fact that an optical burst is significantly larger than a single packet, the technological requirements at the optical switches are less stringent. For example, receiver synchronization is easier to achieve for a burst (milliseconds of transmission time) than for a packet (nanoseconds of transmission time). The same applies to switching time requirements.

The functional unit in charge of producing optical bursts out of packets is denoted as burstifier. Precisely, a number of burstification algorithms have been proposed and analyzed [1]–[6]. In [5], three categories are identified, namely 1) time-based algorithms; 2) burst-length-based algorithms; and 3) mixed time-/burst-length-based algorithms. Time-based algorithms take a fixed assembly time as a primary criterion to create a burst, whereas burst-length-based algorithms take the burst length instead. The third category corresponds to hybrid schemes that consider both time and burst length, whichever is fulfilled first. In a light-load scenario, a burst-length-based algorithm results in a high packetization delay due to the time it takes to collect a sufficient number of packets to create a burst [5]. For such scenario, time-based schemes are significantly more efficient, since the packetization delay is given by the assembly time. In this paper, we will focus on light-load scenarios and time-based schemes. The case with no padding has been considered elsewhere [7]. On the other hand, in [8], the latency and mean burst size are derived for an OBS network with acknowledgments. In those references, padding is not considered, and the packet arrival process is assumed to be Poisson, hence not long-range dependent.

The burstification algorithm under consideration is stated as follows: The incoming packet stream is demultiplexed per destination in separate queues. A timer is started with the first packet arrival in a queue. Then, upon timer expiration, the optical burst is formed and relayed to the optical core. On the other hand, it should be noted that bursts cannot be arbitrarily small due to the optical switches technological constraints (for example, minimum switching time). Thus, there is a lower bound to the optical burst size $b_{\min}$, and padding will be required for some of the bursts.

In this paper, we study the impact of burst padding on the optical network throughput. We choose the delay–throughput curve as the performance metric. As the timeout value increases, more packets are allowed to be transported onto the same optical burst, and padding will be less frequent. However, as the timeout value increases, so does the burstification delay. The findings of this paper allow the selection of a burstifier operating point that minimizes burstification delay, yet keep throughput at a reasonable value. On the other hand, the impact of long-range dependence and instantaneous variability on the throughput–delay curve will be analyzed. Finally, we propose an adaptive timeout algorithm that minimizes delay while keeping throughput beyond a given threshold.

A. Assumptions

In a medium to heavily loaded OBS network, padding is not likely to occur and the impact on throughput will be negligible in practice. However, a light-load scenario will potentially produce many bursts with a number of packets below the minimum burst size, and padding will be necessary. Even in highly loaded networks, load fluctuations do happen, for instance, during

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weekends, and light-load epochs will be observed.[1] For our analysis, the light-load assumption will imply that the lightpath bandwidth is very large compared to the incoming traffic average. When the timer expires, all packets awaiting transmission in the burst assembly queue are transmitted.

Secondly, the incoming traffic model (bytes per interval) will be modeled by a fractional Gaussian noise (FGN), which has been shown to model accurately traffic from a local area network (LAN) [9]. While recent studies show that highly multiplexed core traffic may be modeled as a nonhomogeneous Poisson process [10], note that the burstifier demultiplexes traffic on a per-destination basis. On the other hand, burstifiers will be placed at the edges of the optical network and not at the core. As a result, the expected multiplex level is not as large. Furthermore, note that in order to calculate the throughput, only the number of information bytes per burst matters and not the packet arrival dynamics, which may have multifractal behavior for low multiplex levels [11]. Precisely, the FGN is a fluid-flow model that provides the number of bytes per time interval only. While the small timescale traffic fluctuations are not captured by the model, the long-range dependence from interval to interval is indeed accurately portrayed. In this paper, we wish to analyze the impact of such dependence in the OBS throughput. Finally, our analytical results will be compared to trace-driven simulations, and the traffic model assumptions will be verified using a real-world scenario.

II. Analysis

According to our previous results in [12], for a timer-based burstifier, it turns out that the traffic arriving per time interval T_0 is a Gaussian random variable with mean $\mu = \mu' T_0$ and standard deviation $\sigma = \sigma' T_0^H$. Let us denote such random variable by X, with T_0 being the timeout value, H being the Hurst parameter, μ' and σ' being the mean and standard deviation of the marginal distribution of the traffic arriving in a given time unit (in this paper, it will represent bytes arriving in a 1-ms interval).

A. Delay–Throughput Curve

Let us assume that the minimum burst size is $b_{\min}$. The throughput will be defined as the ratio between the information bits and the total bits transmitted. Thus, the throughput will equal unity whenever $X > b_{\min}$ and $E[X]/b_{\min}$ if $X < b_{\min}$, where $E[X]$ denotes the expected value of the random variable X. For convenience, let us define the random variable Y as a function of X

$$Y = \begin{cases} X, & X \le b_{\min} \\ b_{\min}, & X > b_{\min} \end{cases} \tag{1}$$

then the throughput is equal to

$$\rho = \frac{E[Y]}{b_{\min}}. \tag{2}$$

[1] See, for instance, http://loadrunner.uits.iu.edu/weathermaps/abilene/ for daily variation of traffic in an Internet backbone.

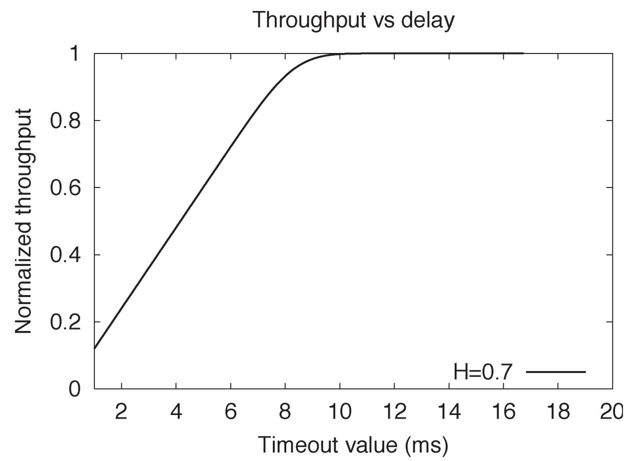

Fig. 1. Delay–throughput curve (parameters $b_{\min} = 500$ kB, $T_0 = 1, \ldots, 20$, byte arrivals per millisecond with $\mu' = 60\,162.88$ B, $\sigma' = 15\,038.2$ B, $H = 0.73$).

Note that the definition of Y implies that the throughput is equal to 1 if padding is not necessary ($Y = b_{\min}$). As a result, Y is a truncated Gaussian random variable in the range $[0, b_{\min}]$. Let $\phi(x) = (1/\sqrt{2\pi}) \exp((-1/2)x^2)$ and $\Phi(x) = \int_{-\infty}^{x} \phi(t)\, dt$. Then

$$P(Y \le y) = \begin{cases} \Phi\left(\frac{y-\mu}{\sigma}\right), & y < b_{\min} \\ 1, & y \ge b_{\min} \end{cases} \tag{3}$$

and

$$E[Y] = E[Y|Y < b_{\min}]P(Y < b_{\min}) + E[Y|Y = b_{\min}]P(Y = b_{\min}). \tag{4}$$

In order to derive the conditional expectation $E[Y|Y < b_{\min}]$, we use the moment generating function (MGF), written as

$$M_Y(t) = E[e^{tY}|Y < b_{\min}] = e^{\mu t + \frac{\sigma^2 t^2}{2}} \frac{\phi\left(\frac{b_{\min}-\mu}{\sigma} - \sigma t\right)}{\phi\left(\frac{b_{\min}-\mu}{\sigma}\right)} \tag{5}$$

yielding

$$E[Y|Y < b_{\min}] = M_Y'(0) = \mu - \sigma \frac{\phi(\alpha)}{\Phi(\alpha)} \tag{6}$$

with $\alpha = (b_{\min} - \mu)/\sigma$. Let us define the hazard function[2] as $\lambda(\alpha) = \phi(\alpha)/(1 - \Phi(\alpha))$. Then

$$E[Y|Y < b_{\min}] = M_Y'(0) = \mu - \sigma\lambda(-\alpha) \tag{7}$$

and using (4)

$$E[Y] = (\mu - \sigma\lambda(-\alpha))\,\Phi(\alpha) + b_{\min}\,(1 - \Phi(\alpha)). \tag{8}$$

Now, use (2) to obtain the throughput expression. Fig. 1 shows an example of throughput curve.

[2] Or inverse Mills ratio.

As expected, an increase in the timeout value results in a better throughput, since more packets can be accommodated per burst. One may argue that the average delay that a packet will experience is not the timeout value but actually half the timeout value. However, and without loss of generality, we will consider the maximum delay. Thus, the delay in the x-axis will be equal to the timeout value.

B. Generated Load

In this section, we derive an expression for the generated traffic to the OBS network. Due to padding, the burstifier traffic is larger than or equal to the input IP traffic. Let Z be the random variable that denotes the bits per second generated by the burstifier. Then

$$Z = \begin{cases} b_{\min}, & X \leq b_{\min} \\ X, & X > b_{\min} \end{cases} \tag{9}$$

and

$$P(Z \leq z) = \begin{cases} 0, & z < b_{\min} \\ \Phi\left(\frac{z-\mu}{\sigma}\right), & z \geq b_{\min} \end{cases} \tag{10}$$

i.e., Z is a truncated Gaussian variable from below. Now, we use the following MGF:

$$M_Z(t) = E[e^{tZ} | Z > b_{\min}] = e^{\mu t + \frac{\sigma^2 t^2}{2}} \frac{1 - \phi\left(\frac{b_{\min}-\mu}{\sigma} - \sigma t\right)}{1 - \phi\left(\frac{b_{\min}-\mu}{\sigma}\right)} \tag{11}$$

and, thus

$$E[Z | Z > b_{\min}] = M'_Z(0) = \mu + \sigma\lambda(\alpha). \tag{12}$$

Finally

$$\begin{aligned} E[Z] &= E[Z | Z = b_{\min}] P(Z = b_{\min}) \\ &\quad + E[Z | Z > b_{\min}] P(Z > b_{\min}) \\ &= b_{\min}\phi(\alpha) + (\mu + \sigma\lambda(\alpha))(1 - \phi(\alpha)) \end{aligned} \tag{13}$$

and $E[Z]/T_0$ represents the rate in bits per second.

C. Validation

In this section, we perform a trace-driven simulation to validate the analytical results. We used the Abilene-I data set provided by NLANR.[3] The Abilene-I data set traces contain traffic from two OC-48 links, which were collected at the Indianapolis router node. Traces are 2 h long, each of them comprises 12 files (10 min each) that contain the pair (arrival time, packet size) for every packet in the link. We use 10 min worth of traffic from a 2.5-Gb/s link as a real-world traffic source for the burstifier. The Abilene-I trace selected shows an average traffic rate around 480 Mb/s, which, assuming a 10-Gb/s wavelength in the OBS port, makes the utilization factor approximately equal to 0.05. Fig. 2 shows one of the Abilene traces (10 min). The trace characteristics are summarized in Table I.[4]

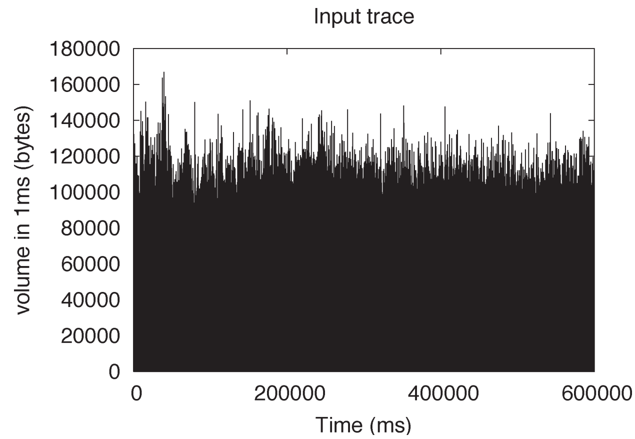

Fig. 2. Abilene-I trace.

TABLE I
TRACE CHARACTERISTICS

μ' (bytes in $1ms$)	σ' (bytes in $1ms$)	H
60162.8786	15038.2	0.73

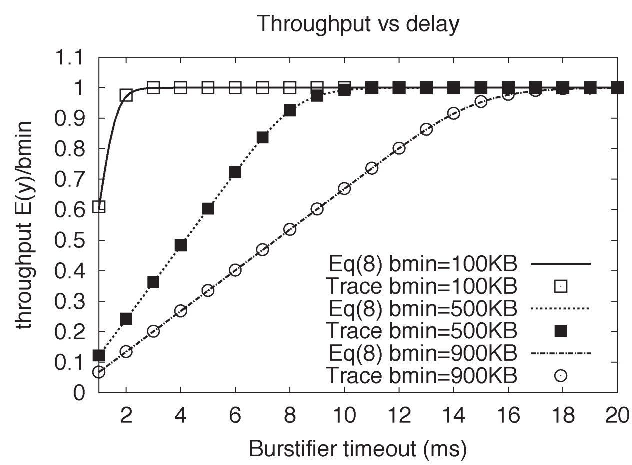

Fig. 3. Throughput–delay curve for the Abilene-I trace.

From the packet arrival process, the burst arrival process is generated through simulation of a timer-based burstifier. Simulation is performed with a set of timeouts varying from 1 to 20 ms and several values of $b_{\min} = \{100, 500, 900\}$ kB. The obtained throughput $E[Y]/b_{\min}$ is plotted in Fig. 3, along with the theoretical results from (8).

Note that the theoretical curve matches very well the simulation values, thus, validating the model and suggesting that Abilene-I traces are very well modeled by an FGN process, at least in the millisecond scale. This is a timescale that is relevant for a burstifier with timeout values of milliseconds. Smaller timescales do not really matter, since the aggregation performed at the burstifier is not affected by the packet arrival dynamics below the timeout value timescale.

[3][Online]. Available: http://pma.nlanr.net/Traces/long/ipls1.html

[4]Packets were taken from the Illinois to Cleveland link (IPLS-CLEV-20020814-102000-1), on August 14, 2002, from 10:20 to 10:30 AM.

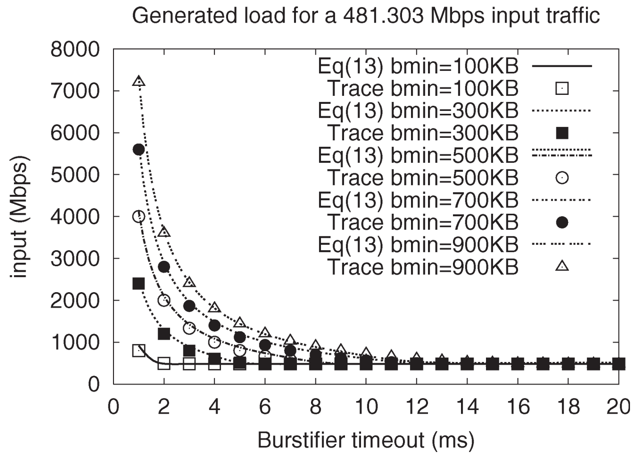

Fig. 4. Input traffic to the OBS network.

As the minimum burst size ($b_{\min}$) increases, the throughput decreases. For each value of $b_{\min}$, a cutoff timeout value exists, which makes the throughput curves flatten out to unity.

On the other hand, Fig. 4 shows the generated load to the OBS network, showing that the analytical expressions match closely the trace-driven simulation results. The y-axis shows the traffic generated by the burstifier and the x-axis the timeout value, for different minimum burst sizes. Interestingly, note that the joint effect of low burstifier timeout and large minimum burst size can amplify the input traffic to 6 Gb/s, more than ten times the average input traffic (480 Mb/s). As a result, it turns out that $b_{\min}$ and T_{out} should be carefully selected. The throughput–delay expressions provided in the previous section serve to select a burstifier operating point that actually minimizes the padding effect (i.e., throughput values close to 1). Such operating point also guarantees that the burstifier offered rate to the OBS network is close to the input traffic rate.

III. Results and Discussion

In this section, we evaluate the impact of the incoming traffic parameters on the OBS throughput. First, the influence of long-range dependence on the throughput–delay features of the OBS burstifier will be analyzed. Then the influence of the incoming traffic coefficient of variation will be studied. Finally, we will discuss whether dynamic burstification algorithms may serve to adaptively tune the burstifier timeout value in order to sustain throughput above a certain threshold.

A. Influence of Long-Range Dependence on Delay–Throughput Curves

The Hurst parameter H provides a measure of the traffic correlation structure. A value of $H = 0.5$ indicates no correlation (independent increments). As H increases, the traffic correlation also increases. Long-range dependence occurs whenever $1/2 < H < 1$. Fig. 5 shows the delay–throughput curves derived in the previous section for different values of H and two extreme cases of minimum burst size, i.e., $b_{\min} = 100$ kB and $b_{\min} = 900$ kB.

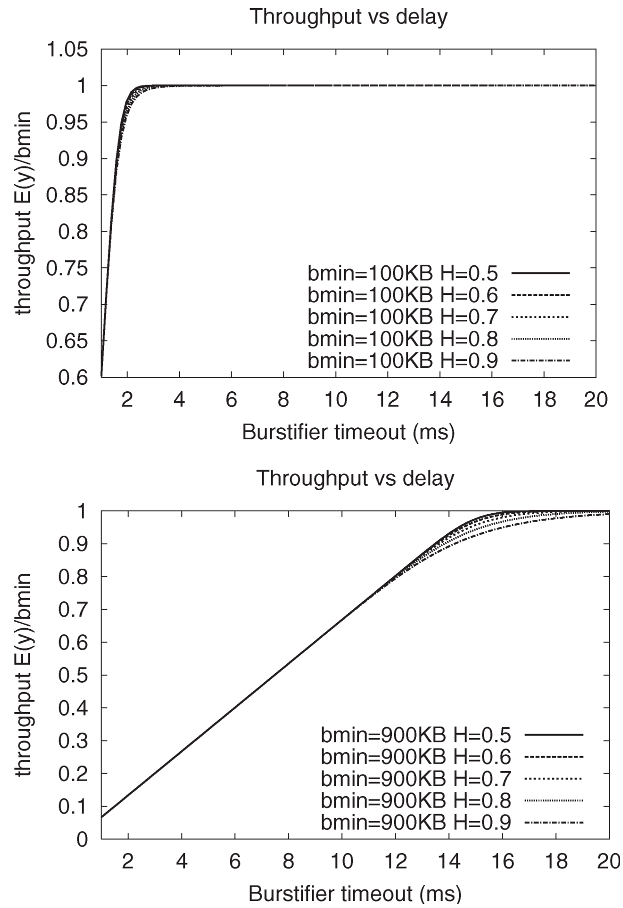

Fig. 5. Delay–throughput curves for different values of H (top: $b_{\min} = 100$; bottom: $b_{\min} = 900$).

As long-range dependence increases, the throughput decreases for a given delay value. On the other hand, the impact of long-range dependence on throughput is larger as the minimum burst size $b_{\min}$ increases. If the minimum burst size is large, padding will be performed more frequently. Overall, if the timeout value is larger than a certain threshold, the effect of long-range dependence is negligible. This threshold is approximately equal to 20 ms in the worst case of $b_{\min} = 900$ kB. Below this timeout value, the dependence on the value of H is higher, but it is marginal compared with the dependence on the timeout value.

B. Influence of Coefficient of Variation on Delay–Throughput Curves

The coefficient of variation ($c_v = \sigma/\mu$) provides a measure of the instantaneous variability of traffic. Note that this is "orthogonal" to the correlation. While long-range dependence serves to characterize the traffic behavior with time, the coefficient of variation is an instantaneous measure. Note also that the coefficient of variation depends on the scale of aggregation of the traffic process.

A sensitivity analysis of the throughput–delay curves versus the coefficient of variation is presented in this section. Fig. 6 shows the delay–throughput curves for different values of c_v

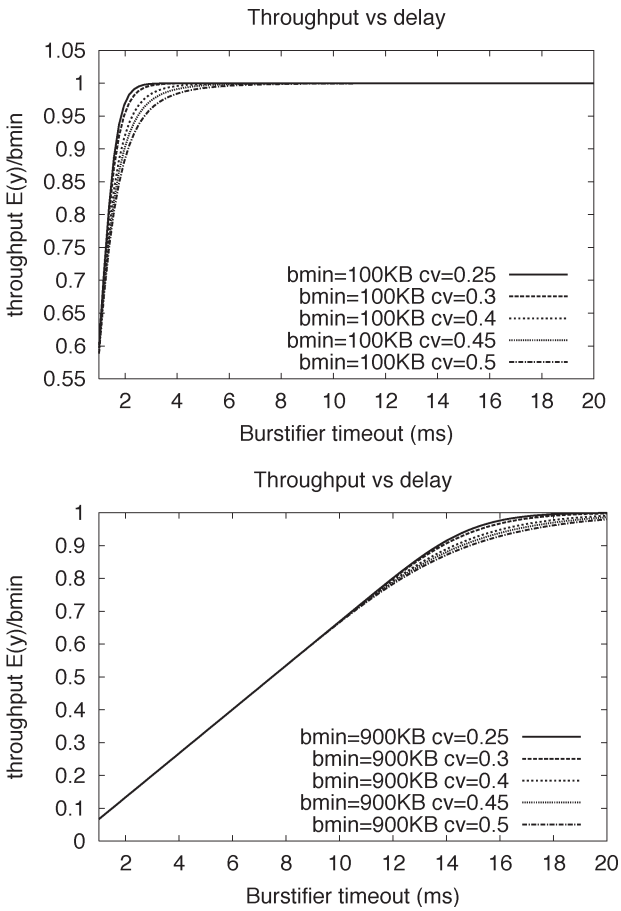

Fig. 6. Delay–throughput curves for different values of c_v (top: $b_{\min} = 100$; bottom: $b_{\min} = 900$).

and two extreme cases of minimum burst size, i.e., $b_{\min} = 100$ kB and $b_{\min} = 900$ kB.

It turns out that larger values of c_v have a negative influence on the throughput. The influence is worse when the minimum burst size value is larger. As with long-range dependence, the impact of instantaneous variability on throughput is negligible beyond a certain timeout value. For the worst case of $b_{\min} = 900$ kB, this threshold is also approximately equal to 20 ms.

C. Dynamic Adaptation of the Timeout Value

The results of the previous section show a negative gradient of the throughput with both the coefficient of variation (instantaneous variability) and Hurst parameter (long-range dependence). However, there is a timeout value that makes such gradient equal to zero. Such timeout value depends on the minimum burst size, the traffic load, and, to a lesser extent, the long-range dependence parameter H and the coefficient of variation c_v.

The above observation leads us to seek for an expression that provides the timeout value for which the delay throughout curves flatten out to unity. Not only is this beneficial to maximize the throughput at the minimum delay cost but also to decrease the network load. For the Abilene-I trace considered in Section II-C, recall that the increased traffic load due to padding

TABLE II
BURSTIFIER TIMEOUT (IN MILLISECONDS) FOR 95% THROUGHPUT

bmin=100KB					
	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	1.8	1.9	2.1	2.2	2.4
H=0.6	1.8	2.0	2.1	2.3	2.5
H=0.7	1.9	2.0	2.2	2.5	2.7
H=0.8	1.9	2.1	2.4	2.7	3.0
H=0.9	1.9	2.2	2.5	3.0	3.7
bmin=500KB					
	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	8.1	8.3	8.4	8.6	8.7
H=0.6	8.2	8.4	8.7	8.9	9.2
H=0.7	8.4	8.7	9.1	9.5	9.8
H=0.8	8.7	9.1	9.7	10.4	11.1
H=0.9	9.1	9.8	10.9	12.2	13.8
bmin=900KB					
	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	14.4	14.5	14.7	14.9	15.1
H=0.6	14.6	14.8	15.1	15.4	15.7
H=0.7	14.8	15.2	15.7	16.2	16.7
H=0.8	15.3	15.9	16.8	17.7	18.6
H=0.9	16.1	17.3	19.0	20.9	23.2

is shown in Fig. 4. The effect of choosing a wrong timeout value is very significant not only for the throughput but also for the generated load to the OBS network.

Table II shows the threshold timeout value that provides a throughput equal to 95%. Our backbone traffic trace has a coefficient of variation equal to 0.25 for an aggregation interval of 1 ms. The same trace gives a $c_v = 0.054$ using intervals of 1 s due to the decay of the variance with aggregation. In [9], the variance coefficient is equal to 0.34 (aggregation 1 s) for a LAN traffic trace (trace pOCT.TL), showing higher variability in comparison with our trace. Actually, as the input traffic multiplex level increases, the coefficient of variation decreases. Note that OBS networks are expected to carry traffic from a large number of hosts.

The figures in Table II show that for small values of the coefficient of variation, H has only a slight incremental influence on the timeout value, whereas for large values of the coefficient of variation, the influence is much stronger. Thus, if input traffic has a small coefficient of variation, then only the estimation of the first and second moments is necessary. As the coefficient of variation increases, one needs to take into account the influence of long-range dependence.

The fact that the delay–throughput curves are sensitive to both instantaneous burstiness and long-range dependence only with large coefficient of variation is very significant and useful for practical engineering purposes. Our findings show that if c_v is low, only the traffic first and second moments need to be estimated in order to derive an optimal timeout value.

Concerning the change rate of the traffic moments, other proposals based on link state estimation assume that the network load remains stable in timescales of minutes [13]. If that is the case, one could devise an adaptive burstifier that would offer minimum delay and maximum throughput for any given input traffic stream. The timeout value rate of change would be in the scale of minutes, which seems reasonable from a practical implementation standpoint.

IV. Adaptive Timeout Algorithm for Long-Range-Dependent Traffic

In this section, we propose three different adaptive timeout algorithms and compare them for different values of the Hurst parameter H and coefficient of variation c_v. The proposed algorithms trade off complexity versus accuracy.

A. Load Estimate (L-Estimate)

The load-based estimate T_0^L is based on the traffic first moment only, i.e.,

$$T_0^L = \frac{b_{\min}}{\hat{\mu}'} \tag{14}$$

where $\hat{\mu}'$ is the input traffic rate estimate in bits per second. The basic assumption is that the influence of the second moment and H parameter is negligible.

B. Load–Variance Estimate (LV-Estimate)

The load–variance estimate T_0^{LV} is based on the first and second moments. It is obtained as the solution of the nonlinear program written as

$$\begin{aligned} &\text{Minimize} && T_0 \\ &\text{subject to} && \rho(\hat{\mu}, \hat{\sigma}_{0.5}, \hat{\alpha}_{0.5}) > 0.95 \end{aligned} \tag{15}$$

where $\hat{\mu} = \hat{\mu}' T_0$, $\hat{\sigma}_{0.5} = \hat{\sigma}' T_0^{0.5}$, and $\hat{\alpha}_{0.5} = (b_{\min} - \hat{\mu})/\hat{\sigma}_{0.5}$. The throughput $\rho(\hat{\mu}, \hat{\sigma}_{0.5}, \hat{\alpha}_{0.5}) = E[Y]/b_{\min}$ can be obtained using (8). The LV-estimate neglects the influence of self-similarity (i.e., $H = 0.5$). Details for solving this problem and for parameter estimation with long-range dependence are given in the Appendix.

C. Load–Variance–H Estimate (LVH-Estimate)

The load–variance–H estimate T_0^{LV} is based on the first and second moments and the H parameter. It is obtained as the solution of the nonlinear program written as

$$\begin{aligned} &\text{Minimize} && T_0 \\ &\text{subject to} && \rho(\hat{\mu}, \hat{\sigma}_{\hat{H}}, \hat{\alpha}_{\hat{H}}) > 0.95 \end{aligned} \tag{16}$$

where $\hat{\mu} = \hat{\mu}' T_0$, $\hat{\sigma}_{\hat{H}} = \hat{\sigma}' T_0^{\hat{H}}$, and $\hat{\alpha}_{\hat{H}} = (b_{\min} - \hat{\mu})/\hat{\sigma}_{\hat{H}}$. Details for solving this problem are given in the Appendix. This algorithm provides the best timeout value in comparison to the L-estimate and LV-estimate algorithms. However, this is at a cost of higher complexity in parameter estimation.

D. Evaluation

The proposed algorithms will be evaluated for input traffic with different dependence (H parameter) and instantaneous burstiness (coefficient of variation). The evaluation is performed under ideal conditions, i.e., it will be assumed that there is no estimation error in computing the parameters $\hat{\mu}'$ and $\hat{\sigma}'$.

TABLE III
Relative Deviation (Percentage) of the L-Estimate Timeout ν^L (ms) With Respect to the Optimum Value (LVH-Estimate) for a 95% Throughput

	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
bmin=100KB					
H=0.5	7.7%	12.5%	20.8%	24.4%	30.7%
H=0.6	7.7%	16.9%	20.8%	27.7%	33.5%
H=0.7	12.5%	16.9%	24.4%	33.5%	38.4%
H=0.8	12.5%	20.8%	30.7%	38.4%	44.6%
H=0.9	12.5%	24.4%	33.5%	44.6%	55.1%
bmin=500KB					
H=0.5	2.6%	0.1%	1.1%	3.4%	4.5%
H=0.6	1.4%	1.1%	4.5%	6.6%	9.7%
H=0.7	1.1%	4.5%	8.7%	12.5%	15.2%
H=0.8	4.5%	8.7%	14.3%	20.1%	25.1%
H=0.9	8.7%	15.2%	23.8%	31.9%	39.8%
bmin=900KB					
H=0.5	3.9%	3.2%	1.8%	0.4%	0.9%
H=0.6	2.5%	1.1%	0.9%	2.9%	4.7%
H=0.7	1.1%	1.6%	4.7%	7.7%	10.4%
H=0.8	2.2%	5.9%	11.0%	15.5%	19.6%
H=0.9	7.1%	13.5%	21.3%	28.4%	35.5%

In what follows, we will focus on obtaining the minimum T_0 value that yields a throughput greater than 95%.

Note that Table II already shows the T_0 values corresponding to the LVH-estimate algorithm, with no estimation error. We take that table as a reference and calculate the following performance figures. First, the relative deviation from the optimum value of the L-estimate and LV-estimate is evaluated. Such relative deviation is defined as

$$\nu^x = \frac{\left|T_0^x - T_0^{LVH}\right|}{T_0^{LVH}} \tag{17}$$

where $x \in \{L, LV\}$ for the L-estimate and LV-estimate, respectively. Second, the actual throughput that is obtained with both the L-estimate and the LV-estimate is calculated. Even though the target throughput is 95%, note that this will only be attained with the LVH estimate. Tables III and IV show the relative deviation ν^x for the L-estimate and LV-estimate.

Tables V and VI show the throughput obtained by a burstifier using either L-estimate or LV-estimate. With LV-estimate, the throughput does not fall below 85% even if the coefficient of variation is doubled from that of the original traffic. This holds true for the whole range of variation of H. On the other hand, the lowest attained throughput with a simpler L-estimate is 80%. This suggests that a simple estimate can drive a variable timeout burstifier to adapt the timeout so as to maintain a reasonably high throughput.

The tables show that for small coefficient of variation, the L-estimate and LV-estimate produce timeout values that are very close to the theoretical optimal value. Since OBS networks are expected to multiplex traffic from a large number of sources, this is actually the case. In order to verify this conclusion, we extensively analyze the Abilene-I data set. Table VII shows the H and c_v values (on the millisecond scale) for every trace in the Abilene-I data set. Note that all of them have a small coefficient

TABLE IV
RELATIVE DEVIATION (PERCENTAGE) OF THE LV-ESTIMATE TIMEOUT ν^{LV} (ms) WITH RESPECT TO THE OPTIMUM VALUE (LVH-ESTIMATE) FOR A 95% THROUGHPUT

bmin=100KB	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	0.0%	0.0%	0.0%	0.0%	0.0%
H=0.6	0.0%	5.0%	0.0%	4.3%	4.0%
H=0.7	5.3%	5.0%	4.5%	12.0%	11.1%
H=0.8	5.3%	9.5%	12.5%	18.5%	20.0%
H=0.9	5.3%	13.6%	16.0%	26.7%	35.1%

bmin=500KB	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	0.0%	0.0%	0.0%	0.0%	0.0%
H=0.6	1.2%	1.2%	3.4%	3.4%	5.4%
H=0.7	3.6%	4.6%	7.7%	9.5%	11.2%
H=0.8	6.9%	8.8%	13.4%	17.3%	21.6%
H=0.9	11.0%	15.3%	22.9%	29.5%	37.0%

bmin=900KB	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	0.0%	0.0%	0.0%	0.0%	0.0%
H=0.6	1.4%	2.0%	2.6%	3.2%	3.8%
H=0.7	2.7%	4.6%	6.4%	8.0%	9.6%
H=0.8	5.9%	8.8%	12.5%	15.8%	18.8%
H=0.9	10.6%	16.2%	22.6%	28.7%	34.9%

TABLE V
THROUGHPUT OBTAINED USING THE L-ESTIMATE ALGORITHM FOR A 95% TARGET THROUGHPUT

bmin=100KB	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	92.3%	90.2%	88.0%	86.2%	84.5%
H=0.6	91.9%	89.7%	87.4%	85.4%	83.7%
H=0.7	91.5%	89.2%	86.7%	84.7%	82.9%
H=0.8	91.0%	88.6%	86.0%	83.9%	82.0%
H=0.9	90.6%	88.0%	85.3%	83.0%	81.0%

bmin=500KB	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	96.6%	95.6%	94.6%	93.8%	93.1%
H=0.6	95.7%	94.6%	93.4%	92.4%	91.4%
H=0.7	94.7%	93.3%	91.8%	90.5%	89.4%
H=0.8	93.5%	91.7%	89.9%	88.3%	86.9%
H=0.9	92.0%	89.8%	87.5%	85.6%	83.9%

bmin=900KB	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	97.4%	96.7%	96.0%	95.4%	94.8%
H=0.6	96.6%	95.7%	94.8%	94.0%	93.2%
H=0.7	95.6%	94.4%	93.1%	92.1%	91.1%
H=0.8	94.2%	92.7%	91.0%	89.6%	88.4%
H=0.9	92.4%	90.4%	88.2%	86.4%	84.8%

TABLE VI
THROUGHPUT OBTAINED USING THE L-ESTIMATE ALGORITHM FOR A 95% TARGET THROUGHPUT

bmin=100KB	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	95.5%	95.2%	95.8%	95.3%	95.8%
H=0.6	95.0%	94.6%	95.0%	94.3%	94.6%
H=0.7	94.5%	93.9%	94.1%	93.2%	93.3%
H=0.8	94.0%	93.2%	93.2%	92.0%	91.8%
H=0.9	93.5%	92.4%	92.1%	90.6%	90.1%

bmin=500KB	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	95.2%	95.6%	95.1%	95.3%	95.0%
H=0.6	94.4%	94.5%	93.9%	93.8%	93.4%
H=0.7	93.5%	93.3%	92.3%	92.0%	91.3%
H=0.8	92.3%	91.7%	90.3%	89.7%	88.7%
H=0.9	90.8%	89.7%	87.9%	86.8%	85.4%

bmin=900KB	cv=0.25	cv=0.32	cv=0.39	cv=0.45	cv=0.50
H=0.5	95.2%	95.0%	95.1%	95.2%	95.3%
H=0.6	94.5%	94.1%	93.9%	93.8%	93.7%
H=0.7	93.6%	92.8%	92.3%	91.9%	91.5%
H=0.8	92.3%	91.2%	90.2%	89.4%	88.8%
H=0.9	90.7%	89.0%	87.5%	86.2%	85.1%

TABLE VII
H AND c_v (MILLISECOND TIMESCALE) FOR ABILENE-I TRACES (EACH FILE COMPRISES 10 MIN WORTH OF TRAFFIC)

Abilene trace file name	H	c_v
IPLS-CLEV-20020814-090000-0.gz	0.68	0.28
IPLS-CLEV-20020814-091000-0.gz	0.74	0.32
IPLS-CLEV-20020814-092000-0.gz	0.76	0.32
IPLS-CLEV-20020814-093000-0.gz	0.75	0.31
IPLS-CLEV-20020814-094000-0.gz	0.75	0.29
IPLS-CLEV-20020814-095000-0.gz	0.72	0.29
IPLS-CLEV-20020814-100000-0.gz	0.74	0.29
IPLS-CLEV-20020814-101000-0.gz	0.75	0.28
IPLS-CLEV-20020814-102000-0.gz	0.71	0.27
IPLS-CLEV-20020814-103000-0.gz	0.73	0.29
IPLS-CLEV-20020814-104000-0.gz	0.73	0.31
IPLS-CLEV-20020814-105000-0.gz	0.68	0.29
IPLS-CLEV-20020814-090000-1.gz	0.78	0.28
IPLS-CLEV-20020814-091000-1.gz	0.75	0.26
IPLS-CLEV-20020814-092000-1.gz	0.73	0.25
IPLS-CLEV-20020814-093000-1.gz	0.80	0.26
IPLS-CLEV-20020814-094000-1.gz	0.73	0.25
IPLS-CLEV-20020814-095000-1.gz	0.73	0.25
IPLS-CLEV-20020814-100000-1.gz	0.72	0.25
IPLS-CLEV-20020814-101000-1.gz	0.76	0.27
IPLS-CLEV-20020814-102000-1.gz	0.74	0.25
IPLS-CLEV-20020814-103000-1.gz	0.73	0.25
IPLS-CLEV-20020814-104000-1.gz	0.75	0.26
IPLS-CLEV-20020814-105000-1.gz	0.71	0.25

of variation (c_v), which is usually below 0.3. On the other hand, the Hurst parameter (H) takes on values in the vicinity of 0.7. For $c_v = 0.25$ and $H = 0.7$, the timeout value that achieves a 95% throughput with minimum burst size $b_{\min} = 500$ kB is equal to 8.4 ms. To derive such value, one needs to solve the LVH-estimate program (16), which requires knowledge of first and second moments and Hurst parameter. The L-estimate provides a timeout equal to 8.5 ms and 94.7% throughput, whereas for the LV-estimate the timeout is equal to 9 ms and the throughput is 93.5%. Even though the burstification delay is slightly increased and the throughput is a little less than 95%, note that only the first moment estimation is needed for the L-estimate and first and second moment estimates are needed for the LV-estimate. Furthermore, the timeout value is straightforward to calculate with the L-estimate algorithm (14).

V. CONCLUSION

In this paper, we have derived the throughput–delay curve for a timer-based burstifier with minimum burst size. A threshold timeout value exists, which makes the normalized throughput value equal to unity. Such threshold value depends on the instantaneous traffic burstiness and long-range dependence to a much lesser extent than on the traffic load and minimum burst size. On the other hand, a bad choice of timeout value results in a severe increase of network load (see Fig. 4).

Three adaptive timeout algorithms have been proposed, which trade off accuracy versus complexity. Our trace-driven analysis of the Abilene backbone shows that for most cases of real Internet traffic, a first moment estimation is enough to provide a timeout value very close to the optimum. Thus, an adaptive timeout algorithm can be easily incorporated to timer-based burstifiers, with a significant benefit in burstification delay and throughput.

APPENDIX

A. Solving the Nonlinear Programs (15) and (16)

It can be easily shown that the constraint function in both programs (15) and (16) is increasing and concave. Let us denote the constraint function by f. The value of T_0 can be approximated by the single zero of the function $f - 0.95$. Such zero can be found using a search method (for instance, Fibonacci search).

B. Moment and Hurst Parameter Estimation With Long-Range-Dependent Traffic

Note that programs (15) and (16) require estimation of the input traffic mean, variance, and Hurst parameter [only for program (16)]. Let $(X_1, \ldots, X_n)$ be n traffic samples. Since traffic shows long-range dependence, the correlation function can be approximated by $\rho(k) \sim k^{2H-2}$. The well-known variance estimator $s^2 = 1/(n-1)\sum_{i=1}^{n}(X_i - \overline{X})^2$, where $\overline{X} = (1/n)\sum_{i=1}^{n} X_i$ is biased due to the covariance terms involved in the calculation.

A variance estimate has been proposed by the authors in [14], which provides a confidence interval on the variance estimate. Such estimator is defined as

$$s'^2 = \frac{1}{\frac{n}{r} - 1}\sum_{i=1}^{n/r}\left(X_{ri} - \overline{X'(n,r)}\right)^2 \tag{18}$$

where r is a parameter, and $\overline{X'(n,r)}$ is the r-decimated mean $\overline{X'(n,r)} = (1/(n/r))\sum_{i=1}^{n/r} X_{ri}$. This estimator allows confidence intervals on the sample variance for small values of r $(r > 4)$.

For online estimation of the traffic average, in the presence of long-range dependence, see [15]. Percival shows that if one is interested in estimating the mean in a given time frame, this can be achieved by decimation at a moderate decrease in efficiency. Finally, a wavelets-based on-line Hurst parameter estimation has been proposed in [16].

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