IP Packet Level vBNS Traffic Analysis and Modeling

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Abstract

In order to ensure continued availability of high-performance network for the nation's research and education community and to continue supporting the development of new high performance Internet capabilities, the National Science Foundation (NSF) established the very-high-speed Backbone Network Service (vBNS) through a cooperative agreement with MCI telecommunications Corporation. To ensure quality of service (QoS) provided by vBNS, an important task is to understand characteristics of vBNS traffic. In this paper we show that vBNS traffic has long-range-dependent (LRD) properties, which have been observed in LAN, WAN, WWW, and VBR video traffic traces. However, we also show that the burstiness of vBNS traffic varies from trace to trace, indicating considerable spatial variations of traffic features, and cannot be characterized by the Hurst parameter. We develop a generalized multifractal model for vBNS traffic. The model contains two parameters, is easy to construct, and generates short-range-dependent processes and ideal multiplicative multifractal processes as special cases. The power of the proposed process in modeling the vBNS traffic is demonstrated.

Key Words: vBNS traffic, burstiness of network traffic, long-range-dependence, generalized multifractal model, queueing performance.

1 Introduction

The very-high-performance Backbone Network Service (vBNS) is a leading-edge high-speed backbone network for research and education. Sponsored by the National Science Foundation (NSF) and implemented by MCI as an IP over ATM network, the vBNS was first set up as an OC3 backbone in early 1995 to interconnect the NSF-supported five supercomputer centers (SCCs) and four network access points. In the late 90's, it was upgraded to an OC12 backbone and was expanded to reach over 100 institutions. It is also connected to other research networks, both within the United States and abroad.

The primary goal of NSF in establishing the vBNS is to support NSF-supported SCCs, directly connected research institutions, and research institutions that are served by other networks, and to provide a test environment for early deployment and evaluation of new internetworking technologies. To ensure quality of service (QoS) provided by vBNS, an important task is to understand characteristics of vBNS traffic. The general statistical behavior of vBNS traffic, including packet sizes, flow duration, volume, and percentage composition, on 1-day and 7-day time scales was studied by Thompson et al. [1]. A recent pressing topic in traffic engineering is whether the traffic under study has long-range-dependent (LRD) properties [2-5], and how the LRD nature of network traffic may impact the performance of a network. Thus it is natural for us to ask whether vBNS traffic has LRD property, and if it has, how its LRD nature may impact the performance of vBNS, and how can this type of traffic be sufficiently accurately modeled.

To answer the above questions, we analyze in this paper a number of traffic traces collected by the National Laboratory for Applied Network Research (NLANR) measurement and analysis group passive monitors at the San Diego Supercomputer Center (SDSC) at a number of high-performance-connection (HPC) sites. The measurement durations of these traffic traces range from 0.5 to several minutes, with half million to several million arrivals.

Specifically, we shall show that like LAN [2], WAN [3], VBR video [4], and WWW [5] traffic, the vBNS traffic traces also have the LRD properties. However, we also show that the burstiness of vBNS traffic varies from trace to trace, indicating considerable spatial variations of traffic features, and cannot be characterized by the Hurst parameter. To parsimoniously and accurately model the vBNS traffic, we develop a generalized multifractal traffic model. The model contains two parameters, is easy to construct, and generates short-range-dependent processes and ideal multiplicative multifractal processes as special cases.

The rest of the paper is organized as follows. In Sec. 2, we show vBNS traffic to have the LRD property. In Sec. 3, we study the burstiness of vBNS traffic. In Sec. 4, we develop a simple generalized multifractal traffic model for vBNS traffic and evaluate the power of the model. Finally, we conclude in Sec. 5.

2 LRD features of vBNS traffic

Recent analysis of high–quality traffic measurements have revealed the prevalence of long-range-dependent (LRD) features in traffic processes in packet switching communications networks. Included are local area networks (LANs) [2], wide area networks (WANs) [3], variable-bit-rate (VBR) video traffic [4], and world wide web (WWW) traffic [5]. In this section, we show that vBNS traffic processes also have the LRD property.

Intuitively speaking, LRD property refers to the behavior that a burst group consists of a random number of subsequent burst periods, while the number of periods can be unbounded. The formal definition is as follows [2,4]: Given a time series $X = \{X_i : i = 0, 1, 2, \ldots\}$, for each $m = 1, 2, 3, \ldots$, one constructs a new time series, $X^{(m)} = \{X_i^{(m)} : i = 1, 2, 3, \ldots\}$, with $X_i^{(m)} = (X_{im-m+1} + \cdots + X_{im})/m, \quad i \geq 1$. In other words, $X^{(m)}$ is obtained by forming non-overlapping running means of X of length m. LRD means $X^{(m)}$ has the same statistical properties as those of X. The self-similarity feature refers to the behavior that effectively, no smoothing takes place for $X^{(m)}$ with large m values. The LRD feature refers to the behavior that the autocorrelation function $R(k)$ scales with time lag k in a power-law manner, $R(k) \sim k^{2H-2}$, with $1/2 < H < 1$, so that $\sum_k R(k) = \infty$.

H is called the Hurst parameter. It is considered one of the most important parameters for the study of LRD traffic. A number of estimators have been proposed to estimate H. One popular method is to employ the following variance-time relation [2,4]:

$$var(X^{(m)}) \sim m^{2H-2}, \quad 1/2 < H < 1 \tag{1}$$

That is, in a log-log plot of $var(X^{(m)})$ vs. m, one observes a more or less straight line with slope $2H - 2$. Note a process is called short-range-dependent when $H = 1/2$.

Fig. 1 shows four examples of variance-time plots for vBNS traffic traces (a) OSU (Ohio State University), (b) ANL (Argonne National Laboratory to STARTAP), (c) COS (Colorado State University), and (d) MRT (Michigan universities), respectively. We note that the line denoted by "Reference" corresponds to $H = 1/2$. A flat horizontal line corresponds to $H = 1$. Hence, all four lines, for OSU, ANL, COS and MRT, have their H values in between 1/2 and 1, meaning that all the traffic streams have the LRD property.

The Hurst parameter measures the persistence of correlations in a traffic process. It is even interpreted as the most important indicator of the burstiness of network traffic [2]. This is indeed true for certain type of LRD traffic models such as heavy-tailed ON/OFF model [6]. If this viewpoint is correct for the vBNS traffic, then we would expect that traffic trace COS is at least as bursty as OSU, since the Hurst parameter for COS is at least as large as that for OSU. The latter is a consequence of the variance-time plot for COS being curved to be more and more flat for large m. However, as we shall observe in the next section, traffic trace OSU is way more bursty than traffic trace COS. This suggests that new type of LRD models other than more conventional LRD traffic processes such as heavy-tailed ON/OFF processes are needed to accurately model vBNS traffic. We note that the contradictory

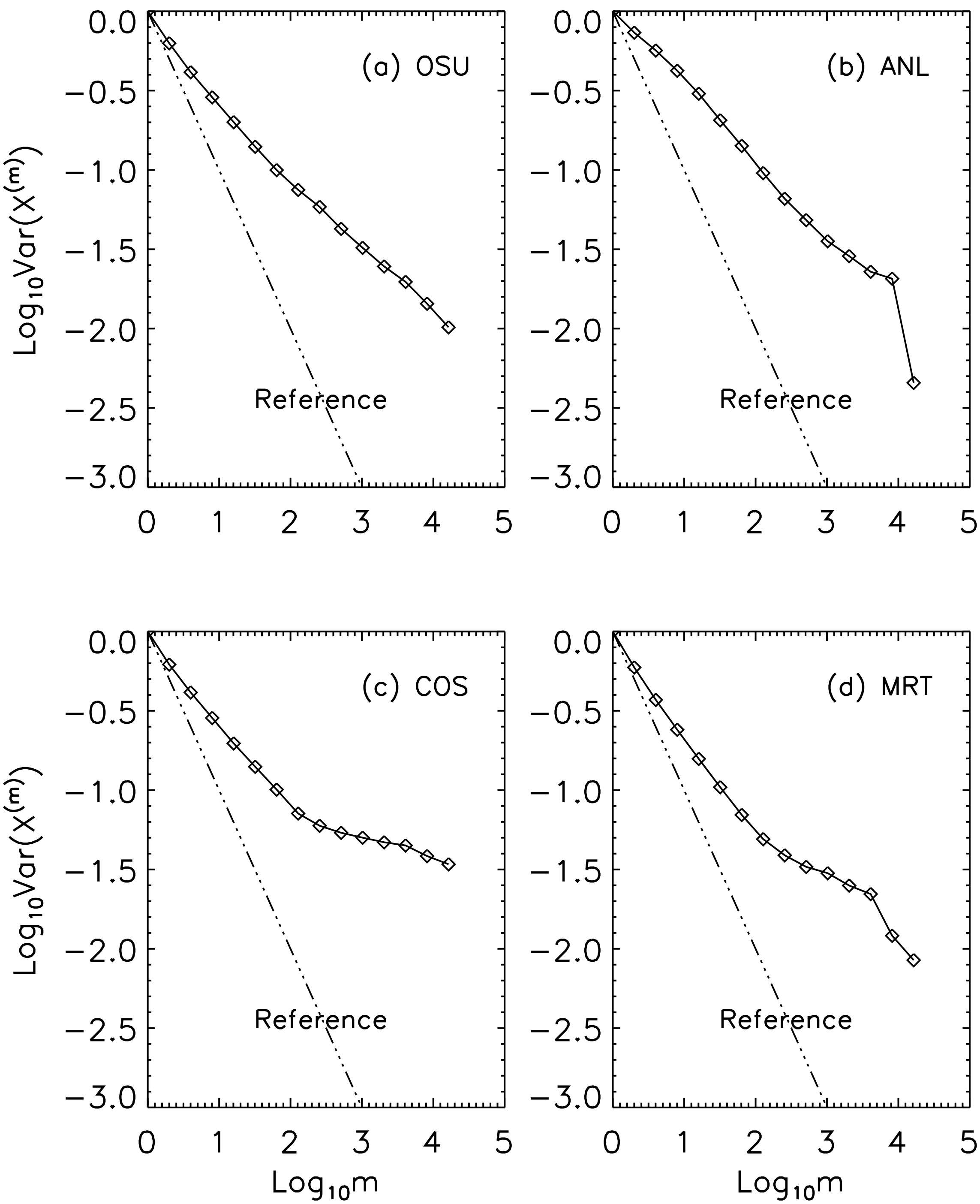

Figure 1: Variance-time plots for traffic traces (a) OSU, (b) ANL, (c) COS, and (d) MRT.

relation between the burstiness of network traffic and the Hurst parameter has also been observed in other type of measured LRD traffic streams [7].

3 Burstiness of vBNS traffic

We define the burstiness of network traffic by the following operation. Consider a single server first-in-first-out (FIFO) queueing system, with an infinite buffer. It is driven by two traffic processes A and B. Process A is said to be more bursty than process B, if a queueing system yields a longer system size tail distribution when the process A is used to drive the queueing system. Note that when the buffer size is of finite size X^*, then the system-size tail probability $P(X > X^*)$ estimates the packet loss probability. On the other hand, the packet delay time statistics can be readily computed by normalizing the system-size tail distributions by the service rate.

Figs. 2(a) and (d) show the system-size tail distributions when traffic trace data OSU and COS are used to drive a queueing system. The four curves, from bottom to top, correspond to utilization levels $\rho = 0.3$, 0.5, 0.7, and 0.9, respectively. To compare the burstiness between OSU and COS, we have re-plotted the $\rho = 0.9$ curve from Figs. 2(d) in Figs. 2(a). We thus observe that traffic trace OSU is much more bursty than traffic trace COS. Recall that the Hurst parameter for COS is actually larger than that for OSU (Sec. 2), hence, we have a contradictory relation between the Hurst parameter and the burstiness of traffic here. This contradictory relation in turn implies that more conventional LRD models are not sufficient for the modeling of vBNS traffic.

Next we examine how well a short-range-dependent model, such as a Poisson model represents the measured trace COS and OSU. For this purpose, we construct from the measured traffic trace data a process with exponentially distributed interarrival times and packet length sequences, with the mean interarrival time and mean packet length the same as

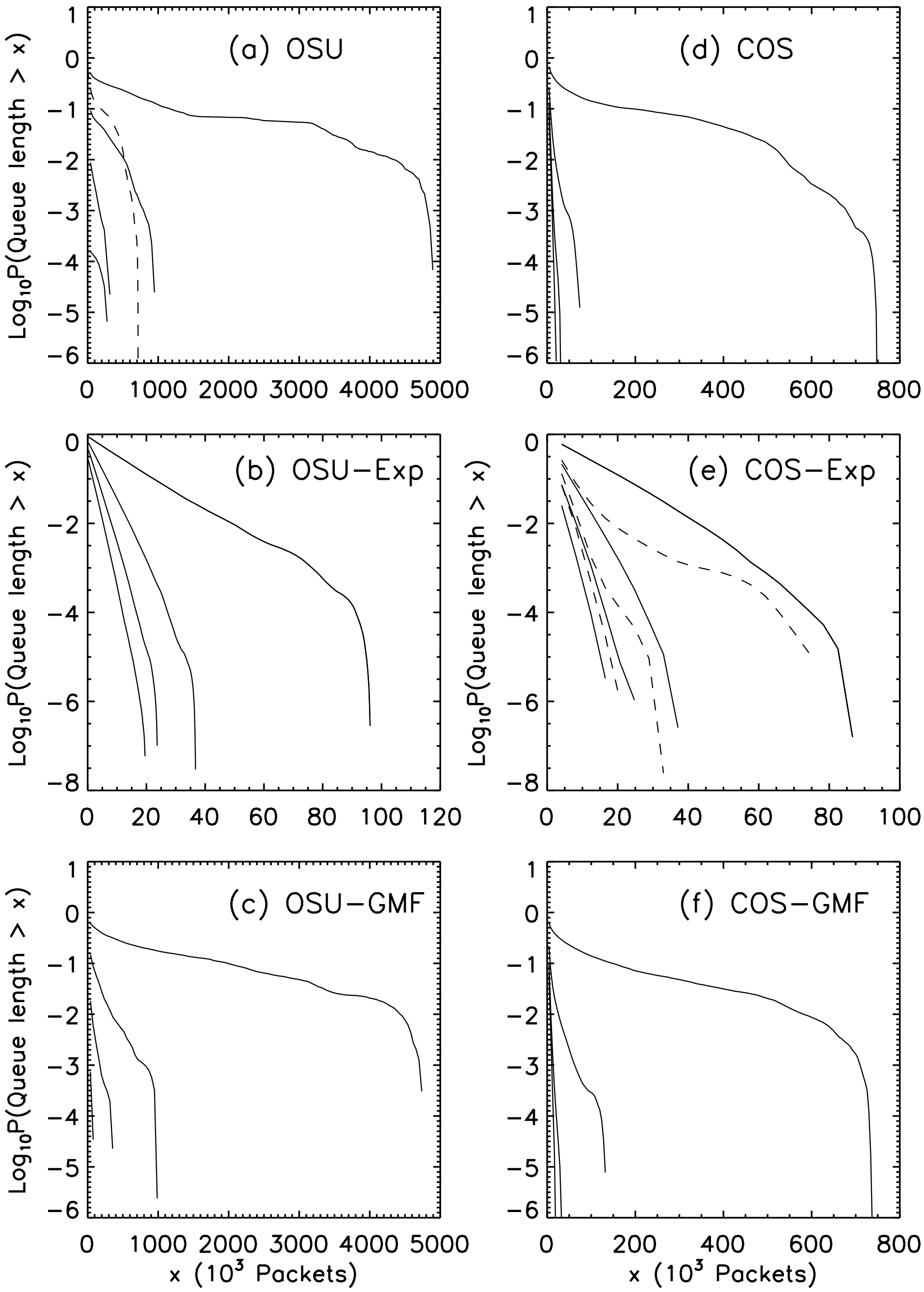

Figure 2: System-size tail distributions for a queueing system driven by trace data (a) OSU and (d) COS; Poisson model for (b) OSU and (e) COS; and generalized multifractal model for (c) OSU and (f) COS (see Sec. 4). The four solid curves, from bottom to top, correspond to utilization levels $\rho = 0.3$, 0.5, 0.7, and 0.9, respectively. The dashed line in Fig. 2(a) is a re-plot of the $\rho = 0.9$ curve from Fig. 2(b), while the three dashed curves in Fig. 2(e) are re-plots of the three low utilization level tail distribution curves from Fig. 2(d).

those of the measured traffic trace. Then we drive a queueing system using the constructed process. Such a queueing system is called an M/M/1 queueing system, where "M" denotes exponentially distributed interarrival times and packet length sequences. The system-size tail distributions for these queueing systems are shown in Figs. 2(b) and (e), respectively, where four curves, from bottom to top, again represent the four utilization levels, $\rho = 0.3$, 0.5, 0.7, and 0.9. We note that the two Poisson models themselves are of similar burstiness, though OSU is much more bursty than COS. For better appreciation of how good or bad the M/M/1 queueing system represents the behavior of a queueing system driven by an actual traffic trace, we have re-plotted the three low-utilization level curves from Fig. 2(d) in Fig. 2(e) as dashed curves. We thus notice that for not too high utilization levels, the Poisson model is actually quite good for COS. However, for high utilization level such as $\rho = 0.9$, even for COS, the Poisson model underestimates the packet loss probability and delay time by one order of magnitude. For OSU, the Poisson model simply underestimates the packet loss probability and delay time more than one order of magnitude for all the utilization levels.

We note that the traffic trace ANL is of similar burstiness to OSU, while MRT is similar to COS. The variations in the burstiness of vBNS traffic from trace to trace indicate considerable spatial variations of traffic features, and demand new type of models to accurately characterize vBNS traffic, especially the burstiness of vBNS traffic.

4 Generalized multifractal model for vBNS traffic

Multifractal analysis and modeling of LRD features of network traffic has been a hot research topic recently [8-10]. Gao and Rubin have developed two types of multiplicative multifractal models [7,11-15]. One type involves modeling the interarrival time series and packet length sequences of network traffic separately using two multifractals [11]. Another type involves

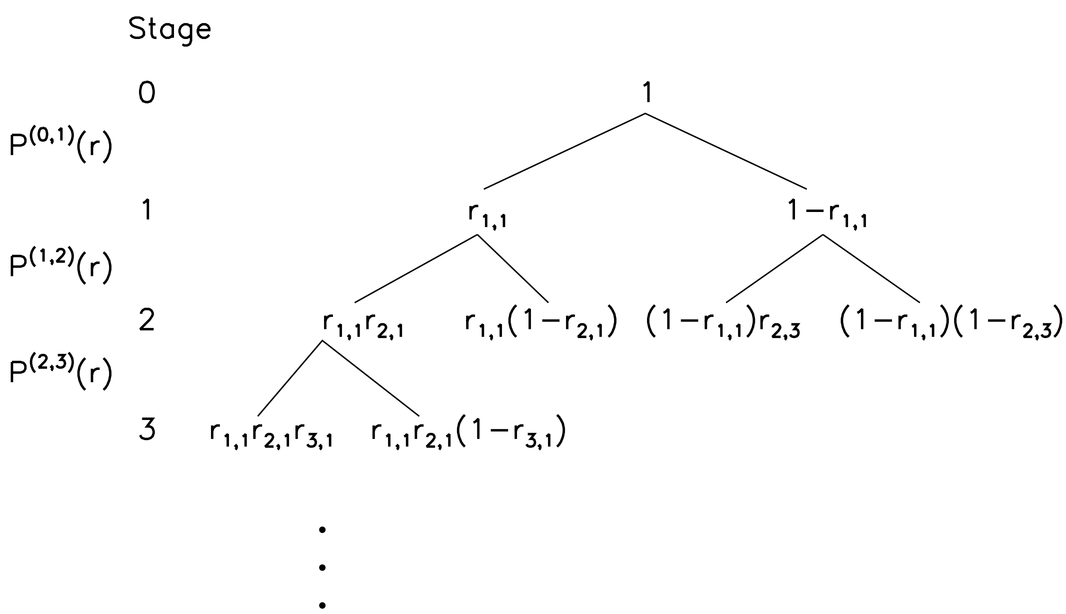

Figure 3: Schematic illustrating the construction rule of the model.

modeling the associated counting process (i.e., aggregated traffic) by a multifractal [7,12]. Both types of models only contain one or two parameters, very easy to construct, and provide amazingly good fit to the system size tail distributions obtained when measured traffic trace data, including LAN, WAN, WWW, and VBR video, are used to drive the queueing system. Unfortunately, those ideal multiplicative multifractal traffic models are not very suitable for the modeling of vBNS traffic. In this section, we propose a generalized multifractal traffic model for the vBNS traffic.

4.1 Stage-dependent multiplicative process traffic model

The stage-dependent multiplicative process is best described in a recursive manner (see the schematic of Fig. 3).

- **Step 1**: At stage 0, we have a unit interval and a unit mass (or weight). We divide the unit interval into two (say, left and right) segments of equal length, and partition the mass into two fractions, $r_{1,1}$ and $1-r_{1,1}$, and assign them to the left and right segments, respectively. The first subscript "1" means stage 1. The parameter $r_{1,1}$, called the multiplier, is a random variable governed by a probability density function (PDF) $P^{(0,1)}(r)$, $0 \leq r \leq 1$, where the superscript "(0,1)" means transition from stage 0 to stage 1. $P^{(0,1)}(r)$ is assumed to be symmetric about $r = 1/2$, so that $1 - r_{11}$ also has the distribution $P^{(0,1)}(r)$.

- **Step 2**: Divide each interval in stage i into two segments of equal length. Also partition each weight, say $r_{i,1}$, at stage i, into two fractions, $r_{i,1}r_{i+1,1}$ and $r_{i,1}(1 - r_{i+1,1})$, where $r_{i+1,1}$ is a random variable governed by a PDF $P^{(i,i+1)}(r)$, $0 \leq r \leq 1$, which is also symmetric about $r = 1/2$.

- **Step 3**: Assume $P^{(i,i+1)}(r)$ to be Gaussian

$$P^{(i,i+1)}(r) \sim \exp^{-\frac{(r-1/2)^2}{\sigma^2_{(i,i+1)}}} \tag{2}$$

  where its variance $\sigma^2_{(i,i+1)}$ varies from one stage to its next in a simple manner:

$$\sigma^2_{(i,i+1)} = a \cdot \sigma^2_{(i-1,i)} \tag{3}$$

  where $1 \leq a \leq 2$ is a constant scaling factor.

- **Step 4**: Interpret the weights at stage N as the time series of interest. For example, the weights at stage N can be used to model the interarrival time series, the packet length sequences, and the counting processes (aggregated traffic). When the counting process model is adopted, then the initial unit time interval is the total time span T of interest, and the initial unit mass is the total traffic loading in that time span. Each weight at stage N is the total traffic loading to a time slot of length $2^{-N}T$.

First we note that when $a = 1$, the multiplier distribution functions $P^{(i,i+1)}(r)$ become stage-independent, and the process reduces to the ideal multiplicative multifractal traffic model [7,11-15]. Among the most interesting properties of such processes are [7,13]:

- $M_q(\epsilon) = E(\sum_{n=1}^{2^N}(w_n(N))^q) \sim \epsilon^{\tau(q)}$, where $w_n(N)$ is a weight at stage N, $\epsilon = 2^{-N}$, and $\tau(q) = -\ln(2\mu_q)/\ln 2$. This property says that ideal multiplicative processes are multifractals. When $a \neq 1$, our generalized multifractal processes do not possess such a nice property.

- The weights at stage N have a log-normal distribution. For our generalized multifractal processes, when a is close to 1, this property is still approximately preserved. We note that among the four different types of distributions, normal, lognormal, exponential, and Weibull distributions, the lognormal distribution is found to be the best in describing certain features of WWW traffic such as page size, page request frequency, and user's think time [16].

- Ideal multiplicative multifractals have the LTD property, with the Hurst parameter given by $1/2 < H \leq -\frac{1}{2}\log_2 \mu_2 < 1$.

Second, we note that the variance parameter $\sigma^2_{(i,i+1)}$ describes the burstiness of the process at the particular time scale $2^{-(i+1)}T$, where T is the total time span. Hence, when $a = 1$, the burstiness level keeps unchanged for all time scales. We shall show below that when $1 < a < 2$, the process still has the LRD property. This is the case for the vBNS traffic. We shall also show below that when $a = 2$, the process reduces to the short-range-dependent processes such as Poisson processes.

4.2 Analysis of network traffic

Analysis of network traffic basically reverses the construction procedure for the model. Assume there are 2^N counting states, $\{X_i, i = 1, \cdots, 2^N\}$. We interpret them as the weight sequence at stage N. The weights at stage N−1, $\{X_i^{(2^1)}, i = 1, \cdots, 2^{N-1}\}$, can be obtained by simply adding the consecutive weights at stage N over non-overlapping blocks of size 2, i.e., $X_i^{(2^1)} = X_{2i-1} + X_{2i}$, for $i = 1, \cdots, 2^{N-1}$, where the superscript 2^1 for $X_i^{(2^1)}$ is used to

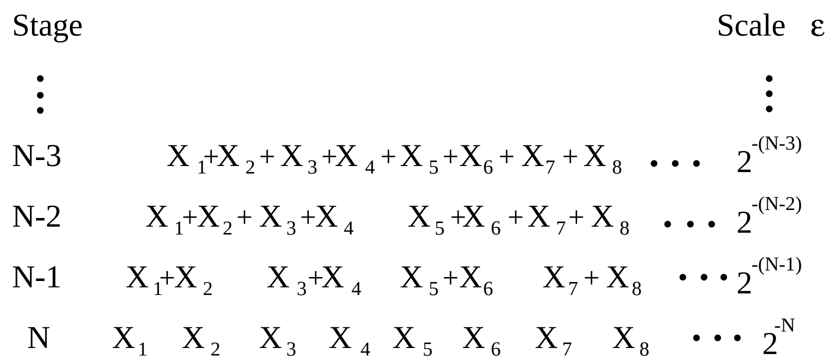

Figure 4: A schematic showing the weights at the last several stages for the analysis procedure described in the text.

indicate that the block size used for the involved summation at stage N$-$1 is 2^1. Associated with this stage is the scale $\epsilon = 2^{-(N-1)}$. This procedure is carried out recursively. That is, given the weights at stage j+1, $\{X_i^{(2^{N-j-1})}, i = 1, \cdots, 2^{j+1}\}$, we obtain the weights at stage j, $\{X_i^{(2^{N-j})}, i = 1, \cdots, 2^j\}$, by adding consecutive weights at stage j+1 over non-overlapping blocks of size 2, i.e.,

$$X_i^{(2^{N-j})} = X_{2i-1}^{(2^{N-j-1})} + X_{2i}^{(2^{N-j-1})} \tag{4}$$

for $i = 1, \cdots, 2^j$. Here the superscript 2^{N-j} for $X_i^{(2^{N-j})}$ is used to indicate that the weights at stage j can be equivalently obtained by adding consecutive weights at stage N over non-overlapping blocks of size 2^{N-j}. Associated with stage j is the scale $\epsilon = 2^{-j}$. This procedure stops at stage 0, where we have a single unit weight, $\sum_{i=1}^{2^N} X_i$, and $\epsilon = 2^0$. The latter is the largest time scale associated with the measured traffic data. Fig. 4 schematically shows this procedure.

Next, we explain how to compute the multipliers at different stages. From stage j to j+1, the multipliers are defined by the following equation, based on Eq. (4):

$$r_i^{(j)} = \frac{X_{2i-1}^{(2^{N-j-1})}}{X_i^{(2^{N-j})}} \tag{5}$$

for $i = 1, \cdots, 2^j$. We view $\{r_i^{(j)}, i = 1, \cdots, 2^j\}$ as sampling points of the multiplier distribution $P^{(i,j)}(r), 0 \le r \le 1$. After $r_i^{(j)}$ is obtained, we can easily estimate the variance of these multipliers, and even estimate the distribution $P^{(i,j)}(r)$ by forming the histograms of $r_i^{(j)}$.

To illustrate the above procedure, we first analyze two i.i.d time series with exponential distribution and uniform distribution. Figs. 5(a,b) plots the variation of the variance (in logarithmic scale) with the stage number. Clearly we observe that the variance doubles from one stage to its next. In other words, the scaling coefficient $a = 2$ in both cases.

Next we analyze the vBNS traffic OSU and COS. The variation of the variance (in logarithmic scale) with the stage number is shown in Figs. 5(c,d), respectively, where we again observe two straight lines with the slopes in between 0 and 1, indicating the scaling coefficient a is in between 1 and 2. Hence, our generalized multifractal model excellently describes the measured vBNS traffic data.

Now we are ready to understand why OSU is more bursty than COS. It is simply because the variance for the multipliers for OSU is always larger at any stage than that for COS.

4.3 Modeling of vBNS traffic

It is an easy matter to model the vBNS traffic after we have obtained the scaling coefficient a and the variance at, say, stage N or stage 1. Figs. 2(c,f) show the system-size tail distributions for queueing systems driven by our generalized multifractal traffic models for OSU and COS, respectively. The four lines, from bottom to top, correspond to the utilization levels $\rho = 0.3$, 0.5, 0.7, and 0.9. Comparing them with Figs. 2(a,b), we observe that overall the model is excellent in fitting the system-size tail distributions. One can make the model more sophisticated by adding, for example, one or two parameters, and then the model certainly will yield even better simulations to the system-size tail distributions. Such additional parameter(s) may indicate, for example, at which stage the curves in Figs. 5(c,d) become flat.

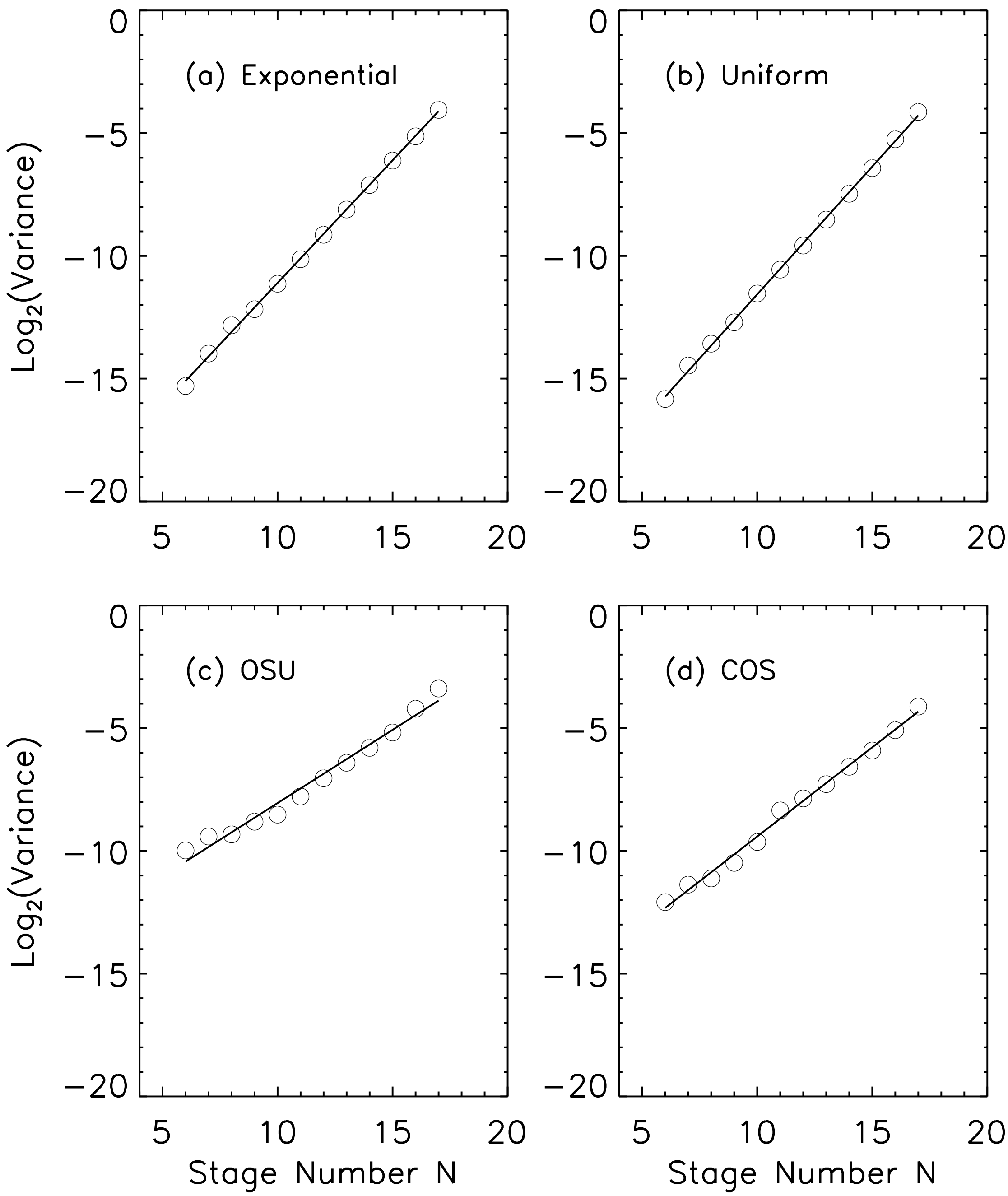

Figure 5: The variance (in logarithmic scale) vs. the stage number N for (a) exponentially distribution random variables, (b) uniformly distributed random variables, (c) vBNS traffic trace OSU, and (d) vBNS traffic trace COS.

5 Conclusions

In this paper, we have analyzed a number of IP packet level vBNS traffic traces. We have found that, similar to LAN, WAN, WWW, and VBR video traffic, vBNS traffic also has the LRD property. However, the burstiness of vBNS traffic is not well characterized by the Hurst parameter. We have developed a simple two-parameter generalized multifractal traffic model. The model includes short-range-dependent processes such as Poisson processes and ideal multiplicative multifractal processes as special cases. It is shown that the model is capable of accurately simulating the performance of a queueing system driven by measured vBNS traffic traces, even though these measured traffic traces may have wide variations in their burstiness levels. Being more general than the ideal multiplicative multifractal traffic model, this new model should be able to give a better description of other types of measured traffic such as LAN, WAN, WWW, and VBR video traffic.

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References

[1] K. Thompson, G. Miller, & R. Wilder, Wide-area Internet traffic patterns and characteristics. *IEEE Network*, vol.11, (no.6):10-23 (1997).

[2] W.E. Leland, M.S. Taqqu, W. Willinger, and D.V. Wilson, On the self-similar nature of Ethernet traffic (extended version). *IEEE/ACM Trans. on Networking*, **2**, 1–15 (1994).

[3] V. Paxson and S. Floyd, Wide Area Traffic—-The failure of Poisson modeling. *IEEE/ACM Trans. on Networking*, **3** 226–244 (1995).

[4] J. Beran, R. Sherman, M.S. Taqqu, and W. Willinger, Long-range-dependence in variable-bit-rate video traffic. *IEEE Trans. on Commun*, **43** 1566–1579 (1995).

[5] M.E. Crovella and A. Bestavros, Self-similarity in World Wide Web Traffic: Evidence and Possible Causes. *IEEE/ACM Trans. on Networking*, **5**, 835–846 (1997).

[6] K.H. Park, G. Kim, and M. Crovella: On the Effect of Traffic Self-Similarity on Network Performance. In *Proceedings of the SPIE International Conference on Performance and Control of Network Systems*, pages 296-310, November 1997.

[7] J.B. Gao and I. Rubin, Multifractal modeling of counting processes of Long-Range-Dependent network Traffic, *Computer Communications*, in press.

[8] M.S. Taqqu, V. Teverovsky, and W. Willinger, Is network traffic self-similar or multifractal? *Fractals* **5** 63-73 (1997).

[9] A. Feldmann, A.C. Gilbert, and W. Willinger, Data networks as cascades: investigating the multifractal nature of Internet WAN traffic. *ACM SIGCOMM'98 Conference.* Vancouver, BC, Canada.

[10] R.H. Riedi, M.S. Crouse, V.J. Ribeiro, and R.G. Baraniuk, A multifractal wavelet model with application to network traffic. *IEEE Trans. on Info. Theory*, **45**, 992-1018 (1999).

[11] J.B. Gao and I. Rubin, Multiplicative Multifractal Modeling of Long-Range-Dependent Traffic. *Proceedings ICC'99*, Vancouver, Canada.

[12] J.B. Gao and I. Rubin, Multifractal modeling of counting processes of Long-Range Dependent network traffic. *Proceedings SCS Advanced Simulation Technologies Conference*,San Diego, CA, 1999.

[13] J.B. Gao and I. Rubin, "Multiplicative Multifractal Modeling of Long-Range-Dependent (LRD) Traffic in Computer Communications Networks". World Congress of Nonlinear Analysts, July, 2000, Catonia, Sicily, Italy.

[14] J.B. Gao and I. Rubin, Statistical Properties of Multiplicative Multifractal Processes in Modeling Telecommunications Traffic Streams. *Electronics Lett.* **36**, 101-102 (2000).

[15] J.B. Gao and I. Rubin, Multifractal analysis and modeling of VBR video traffic. *Electronics Lett.* **36**, 278-279 (2000).

[16] M. Molina, P. Castelli, and G. Foddis, Web traffic modeling exploiting TCP connections' temporal clustering through HTML-REDUCE. *IEEE Network*, vol.14, (no.3):46-55 (2000).