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Approximations on the Aggregate MPEG Video Traffic and Their Impact on Admission Control

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Abstract

In this paper, we investigate the aggregate traffic approximations for the Motion Pictures Expert Group (MPEG) coded variable bit rate (VBR) video traffic and their impact on admission control at a desired Quality of Service (QoS) level. In order to generate the MPEG coded VBR video traffic, we use a novel source model that employs a mixture of two first-order autoregressive processes with lognormally distributed residuals (2LAR). The model parameters are found based on least square estimates to capture the marginal distribution and autocorrelation function as well as the single server queuing behavior of an MPEG coded empirical bitstream. We also present two candidate approximations to estimate the aggregate traffic: Gaussian and lognormal approximations, such that the former relies on the central limit theorem and the latter, which relies on the residual sequence of the 2LAR process, is further estimated based on moment expectations by a lognormal distribution. Finally, we show a set of Monte-Carlo simulation results for these approximations based on an admission control strategy that is specified by a QoS threshold determined by the value of the probability of aggregated traffic exceeding the link capacity.

Key Words: *MPEG video source model, aggregate traffic, quality of service, admission control*

1. Introduction

Motion Picture Expert Group (MPEG) coded video encoders generate variable bit rate (VBR) traffic that results from the fact that the bit rate (frame size) of the compressed video is not constant but rather a random process so that the picture quality is maintained at varying scene activity. Developing accurate and analytically tractable source models for video traffic will provide a basis for efficient multiplexing schemes to utilize the network resources (bandwidth, buffer, etc) at a desired Quality of Service (QoS) level. This paper proposes a new method to build a stochastic model for the MPEG coded VBR traffic that can then be used for admission control purposes for reservation based networks such as ATM or IP networks.

In general, VBR source models follow simulation-based autoregressive (AR) processes, analytic-based Markovian processes or a mixture of processes. One of the major concerns in traffic modeling is the assumptions upon which the model is based, and consequently, exhibition of the trade-off between the accuracy of the statistical multiplexing characteristics and its tractability of queuing analysis. For example, in teleconferencing video, where the characteristics of the subjects of videos can be limited to some degree, an AR(1) process may provide an analytic solution and easily simulate the multiplexing characteristics [1]. However, full-motion video traffic cannot be restricted, and thus a universal model for unrestricted video sources has not yet been established, especially for the aggregated (statistically multiplexed) video traffic. Some AR models proposed in the literature to represent VBR traffic are a p-th order AR (AR(p)) process [2], AR(1) with Gamma distributed residuals (GAR) process [3], and a mixture of two first-order AR (2-AR) processes [4, 5, 6].

While a mixture of m AR(p) with some residual distributions may be developed to achieve more accurate statistics, the modeling complexity becomes unmanageable. Therefore, we need models with a relatively simpler complexity yet which closely capture the statistics of the bitstream. Based on our examination of the empirical bitstream, we propose a new source model using a mixture of two first-order autoregressive processes with lognormally distributed residuals (2LAR), which closely captures the marginal distribution (PDF) and the autocorrelation function (ACF) as well as the single server queuing statistics of the bitstream.

In order to examine the aggregated traffic approximations, we first reproduce N bitstreams from the empirical bitstream by using the circular shifting technique with twenty-five minutes of separation time between each reproduced bitstream so that these bitstreams are assumed to represent iid VBR sources (or slightly correlated). We find the actual aggregate traffic by summing the bit rates of the reproduced bitstreams. In addition, we separately generate N bitstreams using the 2LAR source model, and the corresponding aggregated traffic is found by summing the bit rates of these bitstreams. Since the queuing analysis of the 2LAR model is intractable, we exhibit the trade-off by showing the performance of tractable distributions. In particular, we consider the two candidate approximations to represent the aggregate traffic: Gaussian and lognormal approximations. The former relies on the central limit theorem and the latter relies on the residual sequence of the 2LAR process. Although these two approximations are equal for very large numbers of aggregate traffic, the central limit theorem may not hold for small to moderate numbers of aggregate traffic. Unfortunately, for a finite number of random variables, each distributed lognormally, there is no exact distribution form that represents their sum [8]. We approximate this sum distribution based on the moment expectations by a lognormal distribution [14].

We use the Monte-Carlo simulation technique to estimate the loss performance of the network for varying numbers of bitstreams on a fixed link capacity and their impact based on the developed source model and the aggregate traffic approximations. The rest of the paper is organized as follows. Section 2 presents the individual MPEG VBR source model. Section 3 describes the aggregate traffic approximations and admission control concept. Section 4 presents the bitstream preparation and the performance results. Section 5 contains our conclusions.

2. MPEG Source Model

There are different degrees of fidelity that one can use to model MPEG video, namely, block/macroblock/slice/frame/GOP levels [7]. MPEG encoders generate a sequence of frames according to a cyclic frame pattern, which is referred to as a group of pictures (GOP). The size of each GOP pattern can be found simply by summing all the frame sizes belonging to that GOP. Since we are interested in the queuing behavior in a traffic mixture, we model the MPEG source on a GOP level using the following source model.

2LAR Model

We consider two first-order autoregressive (AR) processes, each denoted by $\{X_i(k);\ i=1,2\}$. Then we can obtain a new process called $\{Y(\mathrm{k})\}$ as follows:

$$\begin{aligned} X_i(k) &= a_i X(k-1) + b_i w_i(k) i = 1,2(1) \\ Y(k) &= \sum_{i=1}^{2} f_i X_i(k) \end{aligned} \tag{1}$$

where a_i, b_i, and f_is are proportion coefficients. The residual terms, $w_i(k)$, are usually considered as white noise sequences with mean m_i and variance s_i [8]. Thus, this process is denoted by a 2-AR process [4]. Unfortunately, the 2-AR process may generate negative bit rates, and it has been observed in [6] that this process may underestimate the loss probability by several orders of magnitude, for low probabilities. In [9] we observed similar loss probability when 2-AR is used for MPEG-1 coded "Starwars" movie bitstream.

Relying on the available empirical bitstreams that follow subexponentially distributed bit rate histograms, we speculated that one should employ these characteristics for the 2-AR model. Based on our extensive analysis on the subexponentially distributed residuals, we found that the "Starwars" bitstream can be better modeled when lognormally distributed residuals are used instead of Gaussian distributed residuals [10]. In this study, we also observed that our empirical bitstream (HBO Cable TV) can also be represented by a mixture of two AR processes with lognormally distributed residuals, and we denote this process as a 2LAR process. In this model, to obtain the number of bits that generated by an MPEG encoder for the k-th GOP, $\{Y(k)\}$, we use two first-order AR processes with lognormally distributed residuals, $\{X_i(k);\ i = 1,2\}$. One should note that the higher orders of mixture processes may provide better fitness at the expense of substantially increased modeling complexity.

The mean (M) and variance (D^2) of the mixture process can be found easily as follows:

$$E(Y) = M = \sum_{i=1}^{2} \frac{f_i b_i}{(1-a_i)} m_i\ , \quad D^2 = \sum_{i=1}^{2} \frac{f_i^2 b_i^2}{(1-a_i^2)} \tag{2}$$

where m_i is the mean of the lognormally distributed residuals (with variances equal to one) for the i-th process. Moreover, its autocovariance functions can be found as follows:

$$\rho_k = \sum_{l=1}^{2} \frac{a_i^k f_i^2 b_i^2}{(1-a_i^2)} \tag{3}$$

Corte [4] suggests a systematic way to determine the proportion coefficients to closely fit the empirical bitstreams. We performed least square estimation to fit the ACF of the test bitstream to the 2LAR model following their steps. Unfortunately, Corte's method did not provide a good estimate to simultaneously fit the PDF and the ACF. Therefore, we followed a simple search algorithm based on the information provided by [6] to determine the proportion coefficients to fit both the ACF and the PDF. The transformations between lognormal and Gaussian distributions are given in Section 3.

Autocorrelation Functions of Several Other Models

In what follows, we present the autocorrelation functions (ACF) of several processes given in [11] to compare them with our model:

1) In general, the ACF of p-th order autoregressive process AR(p) (with Gaussian distributed residuals) at lag k can be written as follows:

$$\rho_k = \sum_{l=1}^{p} a_l \rho_{k-l} \sim e^{-\beta.k} \tag{4}$$

2) The theoretical ACF of the FARIMA process is given as follows:

$$\rho_k = \frac{a(1+a).....(k-1+a)}{(1-a)(2-a)....(k-a)} \sim k^{-\beta}, \qquad k = 1,2,3......., \ 0 < a < \frac{1}{2} \tag{5}$$

3) The long range dependence (LRD) process has an ACF similar to (5)

4) The on-off source Markovian process has an ACF similar to (4)

5) The M/G/∞ process has an anACF, which is given below, that lies between (4) and (5).

$$\rho_k \sim e^{-\beta\sqrt{k}} \tag{6}$$

MPEG-2 Coded "HBO Cable TV" Test Bitstream

In this subsection, we compare the ACFs of the above models with that of the 2LAR model using the test bitstream, which is an MPEG-2 coded VBR bitstream with a GOP pattern of 15 frames. The test bitstream is encoded, on the basis of CCIR601 quality, for 24 hours from the "HBO Cable TV" program, for a typical Direct Broadcast Satellite (DBS) application. Table 1 presents the basic statistics of the bitstream.

Table 1. Basic statistics of MPEG-2 coded VBR test bitstream.

Length (frame)	Peak.GOP (kbits)	Ave.GOP (kbits)	Std.GOP(kbits)	Min.GOP(kbits)
2,589,300	13,777.02	3,212.90	861.92	1,306.14

Table 2 presents the parameters of the 2LAR model as well as the parameters of M/G/∞, On-off Markov and LRD models. The parameters of the 2LAR model are found as explained previously, whereas the parameters (β) for other models are obtained by the least square fitting, based on the ACF formula given above for that ACF. Figure 1 depicts the probability density functions (PDF) of the real HBO bitstream and that of the 2-AR and the 2LAR generated bitstreams (left) and a sample of GOP sizes from the real bitstream (right). We observe that the 2LAR model outperforms the 2-AR model in capturing the marginal distribution, while they have similar ACFs. Figure 2 depicts the short- and long- term ACFs of the real HBO bitstream, the 2LAR model, and the M/G/∞, On-off Markov and LRD models. We can observe that the LRD model can achieve a more accurate fit for the empirical bitstream (right). However, this model has $\vartheta(n^2)$ computational complexity for a sequence length of n, while most other models have complexity of $\vartheta(n)$. Moreover, the LRD model underestimates the strong short-term correlations as compared to the 2LAR model (left). As presented in [11], the ACF of the M/G/∞ model lies between that of the Markov and LRD models, yet this model misestimates both the short-term and the long-term dependencies. In short, the 2LAR model outperforms the M/G/∞ and Markov models, and behaves somewhat complementary to the LRD model, i.e., the long-term dependencies are better captured by the LRD, whereas the strong short-term dependencies are better captured by the 2LAR.

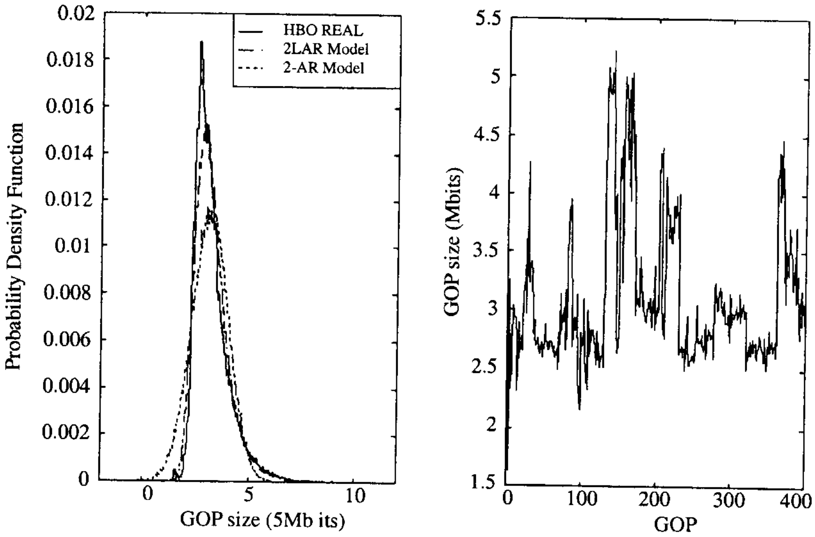

Figure 1. Probability density functions of GOP size histograms and a short sequence.

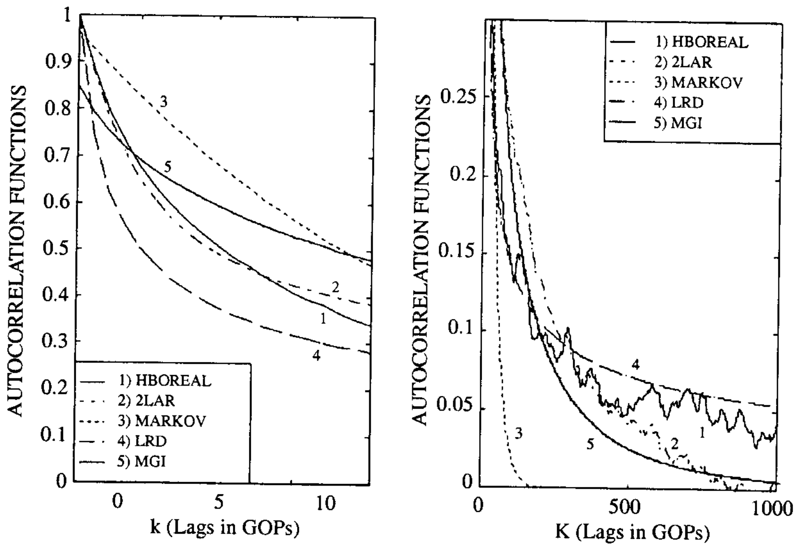

Figure 2. ACFs of the real HBO bitstream and the models.

Table 2. Model parameters based on least square estimates of the ACFs.

Least square parameter estimates	HBO Cable TV Bitstream
LRD (β)	0.424
Markov (β)	0.038
M/G/∞ (β)	0.164
2LAR (a_1, a_2, b_1, b_2, f_1, f_2)	0.9944, 0.7810, 0.0063, 0.2475, 0.5, 0.5

In addition to the marginal distribution and autocorrelation function statistics, the model should accurately estimate its queuing behavior. In order to perform the queuing behavior of these models we simulated a first-in-first-out (FIFO) single queue served by a high-speed DBS link (bit/sec). The real test bitstream as well as the generated bitstreams are packetized as described in [12]. In addition to the 2-AR and 2LAR models, we consider the average/peak rate combinations as an On-off Markov source model [13]. Let Wp and Wm be the peak and mean GOP rates of the real bitstream, respectively. This source either generates Wp bits (on) or idle (off) and the probability that the state is at "on" is given by $P_{on} = Wm/Wp$. Figure 3 depicts the average queue sizes in packets for the real bitstream and the on-off, 2-AR and 2LAR sources. The 2LAR model outperforms both the on-off model and the 2-AR model at all utilizations, while, 2-AR model may perform worse than a simple on-off source.

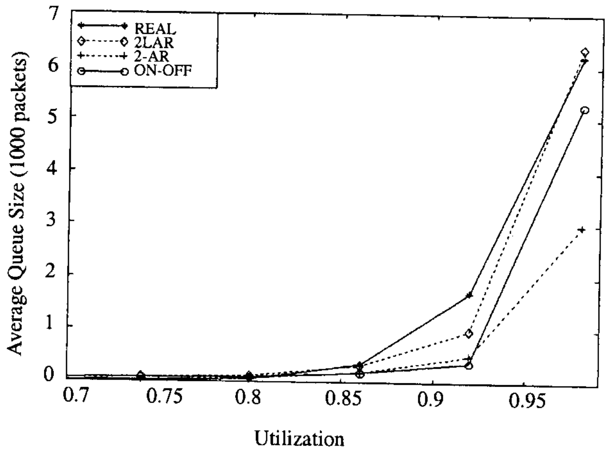

Figure 3. Average queue size in packets.

3. Admission Control & Aggregate Traffic Approximations

3.1. Admission Control

We formulate the admission control algorithm on the basis of a bandwidth assignment problem that may be given as follows: N sources, each generating bit rates with a finite mean and variance, will share a transmission link with a finite transmission capacity of C bps. Let α_i denote the bandwidth expansion factor of the i-th source, which is a measure of excess bandwidth (relative to the average) that must be assigned to the i-th incoming traffic for QoS guarantee such as a loss probability. Given these assumptions and definitions, we determine α_i such that the probability of the aggregate instantaneous rate exceeding the fraction of the capacity assigned to the admitted VBR services will not be greater than a specified QoS threshold γ:

$$\Pr\left\{\sum_{i=1}^{N} R_i \geq C\right\} = \int_{C}^{\infty} f_x(x)\, dx \leq \gamma \tag{7}$$

$$C = \sum_{i=1}^{N} \alpha_i R_i^m$$

where R_i is the instantaneous rate of the i-th admitted VBR service, R_i^m is the average rate of the $i-$th VBR service, and $f_x(x)$ is the probability density function of the aggregate traffic rate. For simplicity, we assume that all the sources are iid sources, and thus they all have the same bandwidth expansion factor. In the case of known $f_x(x)$, the allocation of resources may be optimum for a given γ. However, the distribution of the aggregate traffic cannot be found analytically, as we mentioned in the previous section.

3.2. Aggregate Traffic Approximations

3.2.1. Gaussian Approximation

This approximation relies on the central limit theorem. Accordingly, when very large numbers of randomly distributed sequences are summed, then the corresponding sequence of the sum distribution follows a Gaussian distribution. Thus, the aggregate traffic based on Gaussian approximation can be estimated in such a way that the *aggregate traffic mean* is equal to the sum of the individual traffic means and the *aggregate traffic variance* is equal to the sum of individual traffic variances. Therefore, Equation (7) for the Gaussian approximation can be written as follows:

$$\begin{aligned} &\Pr\left\{\sum_{i=1}^{N} R_i \geq C\right\} = \int_{C}^{\infty} f_x(x)\,dx = \int_{C}^{\infty} \frac{1}{\sqrt{2\pi\sigma_{agr}^2}} \exp\left(\frac{(x-\mu_{agr})^2}{2\sigma_{agr}^2}\right) dx \leq \gamma \\ &\mu_{agr} = \sum_{i=1}^{N} R_i^m \qquad \sigma_{agr}^2 = \sum_{i=1}^{N} \sigma_i^2 \end{aligned} \tag{8}$$

3.2.2. Lognormal Approximation

As presented in Section 2, an MPEG coded VBR source can be better modeled by using lognormal residuals. This suggests that the aggregate traffic may also be approximated by a lognormal distribution. Unfortunately, for a given finite number of random variables, each distributed lognormally, there is no exact distribution that represents the sum of these random variables. The sum distribution may be approximated by a lognormal distribution that has the same moments as the exact sum distribution [14].

The lognormal probability density and corresponding distribution function can be given as follows:

$$f(w) = \frac{1}{\sqrt{2\pi}\sigma w} \exp\left(-\frac{(\ln w - \mu)^2}{2\,\sigma^2}\right) \tag{9}$$

$$F(w) = \int_{z=0}^{w} f(z)dz = \int_{z=0}^{w} \frac{1}{\sqrt{2\pi}\sigma w} \exp\left(-\frac{(\ln z - \mu)^2}{2\sigma^2}\right) dz \tag{10}$$

The above lognormal distribution can be transformed from the Gaussian distribution

$F_0(v) = \int_{x=-\infty}^{v} f_0(x)dx = \int_{x=-\infty}^{v} \frac{1}{\sqrt{2\pi}\sigma} e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)} dx$ by substituting x = ln z and setting $f_0(x) = f(z)dz$

Note that in all the calculations, μ and σ^2 are the mean and the variance of the Gaussian distribution, and M and D^2 denote the mean and variance of the lognormal distribution. Therefore, based on the above definitions, $F_j(w)$ denotes the j-th component lognormal distribution with corresponding Gaussian parameters N(μ_j ,σ_j^2), and lognormal parameters of N(M_j ,D_j^2). In order to find the lognormal parameters

N(M_j , D_j^2) based on the first and second order statistics, the v-th moment α_v about the origin can be found for a lognormal distribution,

$$\alpha_v = \int_{z=o}^{\infty} z^v \frac{1}{\sqrt{2\pi}\sigma z} \exp\left(-\frac{(\ln z - \mu)^2}{2\sigma^2}\right) dz \quad (11)$$

By substituting $v = \frac{\ln z - \mu}{\sigma}$; $dv = \frac{dz}{\sigma z}$; the integral in (11) reduces to the characteristics function of the Gaussian distribution as given below:

$$\alpha_v = e^{\mu v} \int_{v=-\infty}^{\infty} e^{\sigma v \nu} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{v^2}{2}\right) dv \quad (12)$$

Thus, the moment about the origin reduces to the form

$$\alpha_v = e^{\mu v + \frac{\sigma^2}{2} v^2} \quad (13)$$

Using (13), we find the first (α_1) and second (α_2) moments,

$$\alpha_1 = e^{\mu + \frac{\sigma^2}{2}} \alpha_2 = e^{2(\mu+\sigma^2)} \quad (14)$$

The parameters of the component lognormal distribution, N(M_j , D_j^2) can be found as follows:

$$M_j = e^{\mu_j + \frac{\sigma_j^2}{2}}; D_j^2 = e^{2(\mu_j+\sigma_j^2)} - e^{2\mu_j+\sigma_j^2} \quad (15)$$

Once the component lognormal distribution parameters are determined as shown above, the mean (M_{sum}) and the variance (D_{sum}^2) for N of the sum-distribution can be approximated as follows

$$M_{sum} = M_1 + M_2 + \ldots + M_j + \ldots M_N; D_{sum}^2 = D_1^2 + D_2^2 + \ldots + D_j^2 + \ldots D_N^2 \quad (16)$$

Now the equivalent lognormal distribution, which has the same mean M_{sum} and variance D_{sum}^2 as the sum distribution, can be found as follows: the values μ and σ^2 (i.e., the mean and variances of the corresponding Gaussian distribution) of this equivalent distribution are related to M_{sum} and D_{sum}^2 as follows:

$$\mu = \ln\left(\frac{M_{sum}}{\sqrt{1 + \frac{D_{sum}^2}{M_{sum}^2}}}\right) \quad ; \qquad \sigma^2 = \ln\left(1 + \frac{D_{sum}^2}{M_{sum}^2}\right) \quad (17)$$

In order to improve the accuracy of the sum distribution, we can further approximate second and third order, and third and fourth order moments following [14].

4. Performance Results

4.1. Preparing Actual Bitstreams

We are interested in evaluating the multiplexing performance of a finite numbers of (iid) VBR bitstreams, i.e., the aggregate traffic resulting from the superposition of these sources. In fact, there is almost no chance of finding two or more actual VBR bitstreams that exhibit the same statistical characteristics due to different scene dynamics. Since our test bitstream is twenty-four hours long, we may obtain such iid bitstreams by using the circular-multiplexing technique: arrange the bitstreams as a circular list, start each bitstream randomly (or shifted by s units), and then proceed sequentially until the circle is completed. We consider uniformly distributed random starting times between the first and the last GOP intervals. As for the shifted sequences, we shift the original bitstream for different values of s. Table 3 presents the s values and the corresponding ACF values of the empirical bitstream.

Table 3. Autocorrelation function of the test bitstream at lag s.

$s\{.\}$	10	50	100	200	500	1000	2000	3000	Mean (*random*)
ACF	0.510	0.204	0.142	0.095	0.053	0.042	0.030	0.011	0.028

Figure 4 depicts the effect of s values on the corresponding aggregate bitstream as well as the randomly started sequences. The performance measure, probability, is found by using the Monte-Carlo simulation technique in which we examine the performance of Equation (7). Figure 4 suggests that the reproduced bitstreams achieved for smaller values of s $\{s$=10, 50, 100, 200$\}$ do not represent iid sources due to the high correlation (Table 3). Similarly, for $\{s$ =500, 1000, 2000$\}$, the probability trend goes down as expected, due to the decreased correlation. As for the randomly started sequences, denoted by {Random}, the average shifting time has a higher correlation compared to that of $\{s$=3000$\}$. Therefore, the reproduced bitstreams obtained by $\{s$=3000$\}$ should reasonably represent the iid video sources, and thus we further consider the aggregate traffic resulting from superposition of these reproduced bitstreams as the actual (real) aggregate traffic.

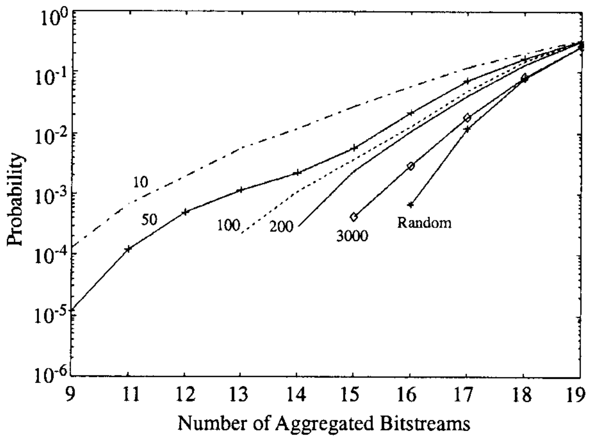

Figure 4. Performance of the aggregate bitstreams: shifted by fixed or random.

4.2. Performance of Aggregate Traffic

We examine the aggregate traffic results from the 2LAR model, Gaussian and lognormal approximations to estimate the real aggregate traffic. For each approximation we measure the performance of Equation (7) by using the Monte-Carlo simulation.

Figures 5-8 depict the simulation results for the link capacities of 40, 120, 200 and 260Mbps, respectively. From a few up to a moderate number of aggregate bitstreams (Figures 5-6), the 2LAR model very closely estimates the loss probability, while for higher numbers of aggregate bitstreams it does not provide good estimates (Figures 7-8). This suggests that the effect of the correlation statistics decreases as the number of aggregate sources increases. We can also observe from Figure 8 that the lognormal approximation closely predicts the real aggregate traffic for high numbers of aggregate bitstreams. However, for smaller numbers of aggregate bitstreams (Figure 5), the lognormal approximation underestimates the loss probability by two or more orders of magnitude. On the other hand, the Gaussian approximation severely underestimates (by several orders of magnitude) the loss probability for small to moderate numbers of aggregate bitstreams. While the Gaussian approximation still underestimates the loss probability for higher numbers of aggregate bitstreams, the gap between these approximations decreases due to the central limit theorem (Figure 8). In short, the lognormal approximation may be used to represent the aggregate video traffic, if some higher numbers of video bitstreams (say more than thirty) are multiplexed into the same link, whereas the 2LAR model is necessary for the representation of a smaller number of aggregate bitstreams.

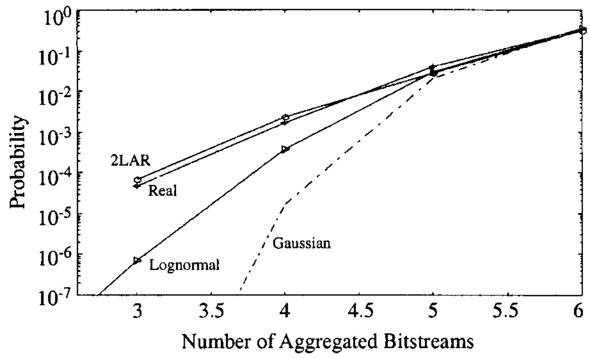

Figure 5. Performance of the aggregate traffic approximations (C= 40Mbps).

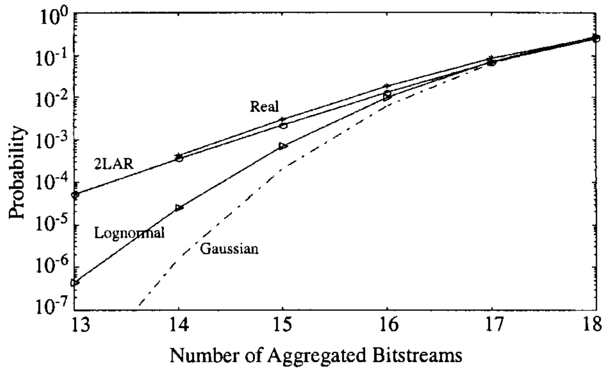

Figure 6. Performance of the aggregate traffic approximations (C= 120Mbps).

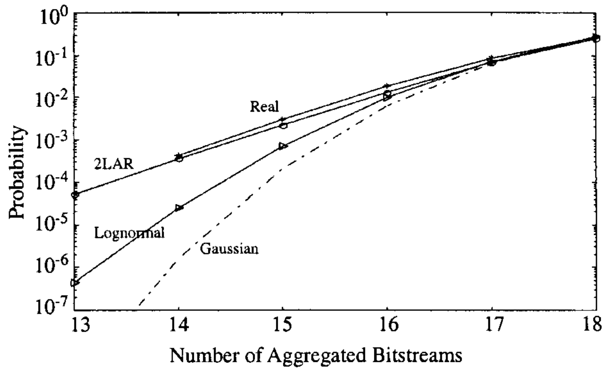

Figure 7. Performance of the aggregate traffic approximations (C= 200Mbps).

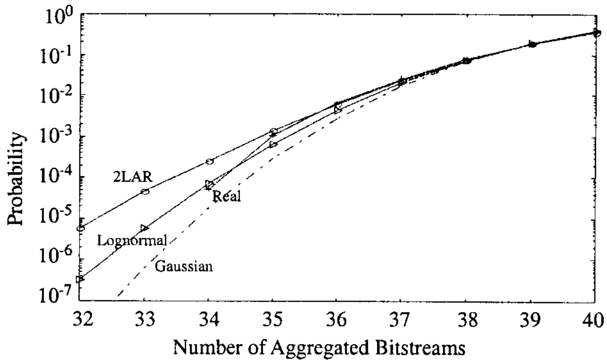

Figure 8. Performance of the aggregate traffic approximations (C= 260Mbps).

5. Conclusions

In this paper, we have investigated the aggregate variable bit rate (VBR) traffic approximations and their impact on the admission control, based on a newly introduced source model as well as well-known approximation methods. Relying on a twenty-four hour long MPEG coded empirical bitstream analysis, our observations are summarized as follows:

• The proposed 2LAR source model can closely represent the individual MPEG coded VBR sources, and corresponding aggregate VBR traffic approximation is accurate for small to moderate numbers of aggregate traffic,

• Gaussian approximation severely underestimates the loss probabilities, especially, when a few numbers of sources are statistically multiplexed into the same link,

• The lognormal approximation also underestimates the loss probabilities when several sources are statistically multiplexed into the same link, however, it maybe a promising approximation when some higher numbers (more than thirty) of MPEG coded VBR sources are aggregated.

Acknowledgments

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