# Probabilistic Burstiness-Curve-Based Connection Control for Real-Time Multimedia Services in ATM Networks

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Abstract-In this paper we present a method to establish realtime connections with guaranteed quality of service (QOS), based on a per-session probabilistic burstiness curve (PBC). Under two distinctive service disciplines, rate proportional processor sharing and fixed rate processor sharing, we derive useful probabilistic bounds on per-session end-to-end loss which is caused by either buffer overflow in the path or excessive delay to the destination. One remarkable feature of the bounding solutions is that they are solely determined by the PBC of each session itself, independent of the network environment and other connections. To improve network resource utilization, our method is extended to allow statistical sharing of buffer resources. The admission control scheme presented in this paper has a great flexibility in connection management since bandwidth and buffer allocations can be adaptively adjusted among incoming and existing sessions according to present network resource availability. We also present a novel method to compute the PBC of multimedia traffic based on the measurement of two important statistics (rate histogram and power spectrum). Our study of MPEG/JPEG video sequences reveals the fundamental interrelationship among the PBC, the traffic statistics, and the QOS guarantee, and also provides many engineering aspects of the PBC approach to real-time multimedia services in ATM networks.

Index Terms—ATM networks, call admission control, end-toend performance bounds, traffic characterization, VBR video.

## I. INTRODUCTION

NE OF THE MOST challenging issues in supporting real-time multimedia communications in a high-speed network is to provide quality-of-service (QOS) guarantees to sessions. The QOS requirements of multimedia services are typically stringent, and differ depending on media and applications. The function of admission control is to determine whether or not an incoming session can be accepted at its requested QOS without violating QOS guarantees of ongoing sessions. In ATM networks, the QOS is mainly measured by end-to-end cell delay and loss performance.

In this paper, each session connection is defined by  $(\sigma, \rho)$  where  $\sigma$  and  $\rho$  represent, respectively, buffer space and transmission bandwidth allocated for the session at each switching

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node in the route. Obviously, the determination of  $(\sigma, \rho)$  strongly depends on the traffic characteristics and QOS requirement of the session. In allocating network resources, there exists a tradeoff between  $\sigma$  and  $\rho$ . For instance, reduction of buffer space can be achieved by increase of transmission bandwidth, and vice versa, as long as QOS is not violated.

The burstiness curve of a session can be defined either deterministically or probabilistically. In the deterministic definition, the traffic of each session is viewed as a deterministic rate function x(t) of finite duration. Then, the deterministic burstiness curve (DBC) is defined by

$$\sigma = \max_{0 \le s \le t} \left[ \int_{s}^{t} x(\tau) \, d\tau - \rho(t - s) \right], \qquad \rho \in (a, p] \quad (1)$$

where a and p are the average and peak rates of each session. Such a deterministic traffic description has been used in [2]–[6]. Similarly, we introduce a probabilistic burstiness curve (PBC) to allow stochastic traffic which is modeled by a stationary random process. Applying this random input process to a single-queue, single-server work-conserving system (WCS) with transmission bandwidth  $\rho$  and infinite/finite buffer capacity, one can get the following steady-state queue distribution as a function of  $\rho$ :

$$\Pr[q \ge \sigma | \rho], \qquad \rho \in (a, p] \tag{2}$$

where the random variable q denotes the queue length. We call this function a PBC of an input process. Many approaches [8]–[10], [12], [13] have been developed to upper bound the tail distribution of queue. Particularly in [8], Chang considered an arrival process whose moment-generating function is upper bounded by a linear envelope process, which is viewed as a stochastic version of (1), and derived an exponential bound of the tail distribution of queue. In addition, [8] proved the equivalence between well-known effective bandwidth [12], [13] and the minimum envelope rate of feasible linear envelope processes. Given  $\rho$ , the theory of effective bandwidth [12], [13] also gives an upper bound of the tail distribution of a queue in a regime where  $\sigma$  is very large and the tail probability is very small. In summary, the PBC is not those asymptotic bounds above which could be looser and sometimes even lower [8], [14], but the exact queue distribution function which is computed via a method in Section III.

One important feature of the burstiness curve is that it is determined by the queueing analysis of a single-queue, single-server WCS for a given deterministic rate function or a stochastic model of session. The computation of DBC is

straightforward from (1), once the rate function x(t) of each session is known. The computation of PBC requires stochastic traffic modeling and queueing analysis. In stochastic traffic modeling, there are two important statistical functions to be measured: rate histogram f(x) and power spectrum  $P(\omega)$ (equivalently, autocorrelation). The former describes traffic first-order statistics, and the latter captures traffic secondorder statistics. It is shown that the PBC in (2) is essentially determined by f(x) and  $P(\omega)$  of each session, whereas the higher order statistics of session can be neglected to a certain extent. Recently in [20], Li has developed an approach to the construction of a Markov-modulated Poisson process (MMPP) to match a wide range of f(x) and  $P(\omega)$ . The same approach is applied here in traffic modeling to reflect various statistical properties of real multimedia traffic (e.g., MPEG/JPEG video and PCM voice). Based on this Markovian traffic modeling, the numerical solution of PBC is readily obtained by using an advanced queueing solution technique in Section III. Our study of MPEG/JPEG video sequences reveals the fundamental interrelationship among the burstiness curve, the f(x) and  $P(\omega)$  (particularly, the scene-to-scene autocorrelation), and the QOS guarantee, and also reveals the limit of traffic smoothing for real-time video services.

Once network resources are allocated to each session according to its burstiness curve, one can bound per-session end-to-end delay/loss performance. For sessions with DBC, the QOS is measured by the deterministic guarantee of zero loss and bounded end-to-end delay. For sessions with PBC, the QOS is measured by the probabilistic guarantee of bounded end-to-end loss which is caused by either buffer overflow in the route or excessive delay to the destination. Obviously, the per-session performance bounds depend on the type of service discipline implemented at each switching node. Methodologies have been proposed to compute per-session performance bounds under various service disciplines; [2], [3], and [5]–[7] studied deterministic bounds, and [8], [9], and [11] derived probabilistic bounds. In this paper, we consider two distinctive service disciplines, rate proportional processor sharing (RPPS) [2], [15] and fixed rate processor sharing (FRPS) [3], [4], both of which can provide tighter per-session end-to-end performance bounds than FIFO service discipline. The only difference between RPPS and FRPS is that the former allows statistical multiplexing of different sessions, whereas the latter allocates a fixed transmission bandwidth to each session. The bound analysis found in [2] and [3] were based on DBC assuming RPPS or FRPS discipline. In [2], DBC was used to describe a leaky-bucket constrained session, whereas in [3], DBC was used to directly describe a session as in this paper. We generalize the deterministic bounding approach in [2] and [3] to a probabilistic bounding approach based on PBC to allow probabilistic guarantee of both end-to-end loss and delay.

An admission control scheme can be implemented based on PBC. Since the statistical functions f(x) and  $P(\omega)$  can be collected from representative traffic streams, the PBC of each possible type of incoming sessions can be computed and stored in advance by the network traffic manager. When a new session arrives, the admission controller examines the corresponding PBC, and identifies the *admissible set* Z of

 $(\sigma,\rho)$  pairs satisfying the session QOS constraints which is put by the session QOS requests. The concept of admissible set is to introduce a great flexibility to resource allocation between buffer space and transmission bandwidth at the connection setup stage. According to present network-wide resource availability, the admission controller selects a proper pair of  $(\sigma,\rho)$  in Z and reserves the corresponding resources. The QOS of the session is then guaranteed once the connection is set up. The arriving session is blocked if none of the  $(\sigma,\rho)$ s in Z can be ensured by the network.

Another advantage of PBC-based connection control is that it naturally allows us to take into account the buffer-sharing effect in allocating network resources. Instead of allocating a segregate buffer to each connection at a link, all of the interacting connections can statistically share a common buffer. It will be shown that the aggregate buffer space requirement can be substantially reduced by buffer sharing without violating the probabilistic QOS guarantee of each individual connection.

The paper is organized as follows. In Section II, we define deterministic and probabilistic burstiness curves, and derive bounds on per-session end-to-end delay/loss performance under both RPPS and FRPS service disciplines. In Section III, we introduce a novel traffic modeling technique to construct a MMPP session model from the measured f(x) and  $P(\omega)$ , and an efficient queueing solution technique to obtain the PBC from the MMPP model. Also, in Section III, these techniques are applied to MPEG/JPEG video sequences, and the relationship between the video statistics and the PBC is examined. The work is then extended in Section IV to admission control design with improvement of network resource utilization by buffer sharing and traffic aggregation. The paper is concluded in Section V.

## II. PER-SESSION END-TO-END PERFORMANCE

Consider an ATM network where routing is performed on a per-session basis. Each switching node in the network is assumed to be an output-buffered switch. Both RPPS and FRPS service disciplines are considered. A connection of session i is defined by a set of connection parameters, denoted by  $\{(\phi_i^m, \psi_i^m) | m \in R_i\}$  where  $R_i$  represents a set of links in the route, and  $\phi_i^m$  and  $\psi_i^m$ , respectively, denote bandwidth and buffer allocations at link m. To represent the same connection, we also use the notation  $\{(\phi_i^{(k)}, \psi_i^{(k)})|k=1,2,\cdots,N_i\}$  where the superscript (k) represents the kth link in the route and  $N_i$ is defined as the cardinality of the set  $R_i$ , i.e.,  $N_i = |R_i|$ [see Fig. 1(a)]. The total transmission bandwidth and buffer capacity at link m are denoted by  $C^m$  and  $B^m$ , respectively. In addition to such reservation-based connections, we assume that the network also supports best effort traffic which is either connectionless or connection-oriented without resource reservation requirement. Separate buffer space is assumed at each link to temporarily store the aggregate best effort traffic.

Let  $g_i^m(t)$  denote the departure rate of session i at link m at time t. The RPPS service discipline ensures that if connection

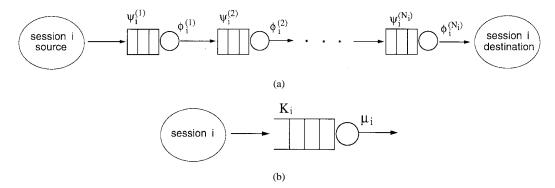


Fig. 1. (a) RPPS/FRPS connection of session i defined by  $\{(\phi_i^{(k)},\psi_i^{(k)})|k=1,2,\cdots,N_i\}$ . (b) Single-queue, single-server work-conserving system transmitting session i with transmission bandwidth  $\mu_i$  and buffer capacity  $K_i$ .

i is busy at link m

$$g_i^m(t) = \frac{\phi_i^m}{\sum_{j \in Q^m} \phi_j^m} C^m \tag{3}$$

otherwise,  $g_i^m(t)=0$ .  $Q^m$  denotes the set of all connections "currently" being busy at link m, including i. Note that the RPPS is work conserving among all reservation-based connections. The background best effort traffic streams are transmitted only when all the reservation-based connections are simultaneously idle. In contrast, the FRPS discipline ensures that if connection i is busy at link m

$$g_i^m(t) = \phi_i^m \tag{4}$$

regardless of the other connections. Otherwise,  $g_i^m(t)=0$ , and the unused bandwidth  $\phi_i^m$  is taken by best effort traffic instead of other reservation-based connections. Note that the FRPS is nonwork conserving among reservation-based connections.

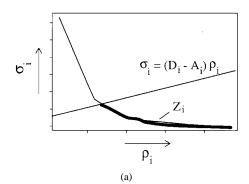
We start by reviewing the deterministic per-session performance bounds of an RPPS/FRPS connection [2], [3]. In [2], the DBC (1) is used to describe a leaky-bucket constrained session, whereas in [3], it is used to directly characterize a session on which no access control is imposed. Since the former approach cannot upper bound "actual" end-to-end performance which must include the queueing performance at the leaky-bucket device, we take the latter approach. The analysis in the paper assume that traffic is infinitely divisible, and hence viewed as fluid flow.

Let  $x_i(t)$  be the deterministic rate function of session i with finite duration. When the session is transmitted through a single-queue, single-server WCS with transmission bandwidth  $\mu_i = \rho_i$  and buffer capacity  $K_i = \infty$  [see Fig. 1(b)], the queue backlog at time t is described by

$$q_i(t) = \max_{s \in [0,t]} \left[ \int_s^t x_i(\tau) d\tau - \rho_i(t-s) \right]. \tag{5}$$

Then, the buffer space requirement  $\sigma_i$  of session i at each given  $\rho_i$  is equal to the maximum backlog which is expressed by

$$\sigma_i = \max_t [q_i(t)] = \max_{0 \le s \le t} \left[ \int_s^t x_i(\tau) d\tau - \rho_i(t-s) \right]. \quad (6)$$



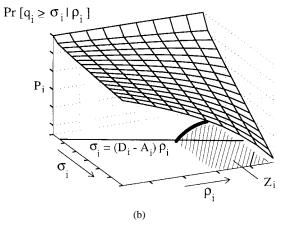


Fig. 2. Burstiness curve. (a) DBC. (b) PBC.

The set of such  $(\sigma_i, \rho_i)$  pairs for  $\rho_i \in (a_i, p_i]$  is the deterministic burstiness curve, and a typical DBC is shown in Fig. 2(a). Clearly,  $\sigma_i$  is a decreasing function of  $\rho_i$ .

Let  $\tilde{q}_i^{\text{worst}}$  and  $\tilde{d}_i^{\text{worst}}$ , respectively, denote the worst case end-to-end backlog and queueing delay of session i. We use the accent  $\tilde{\phantom{a}}$  in the notation to represent an *end-to-end* measurement. Define  $J^m$  to be the set of all of the connections on link m when a new session i requests its connection. If an RPPS connection of session i is set up with  $(\phi_i^m, \psi_i^m) = (\rho_i, \sigma_i), m \in R_i$ , subject to  $\phi_i^m + \Sigma_{j \in J^m} \phi_j^m < C^m, m \in R_i$ , then [2]

$$\tilde{q}_i^{\text{worst}} \le \sigma_i, \quad \tilde{d}_i^{\text{worst}} \le \frac{\sigma_i}{\rho_i}.$$
 (7)

If an FRPS connection of session i is set up with  $(\phi_i^{(1)},\psi_i^{(1)})=$ 

$$(\rho_i, \sigma_i), (\phi_i^{(k)}, \psi_i^{(k)}) = (\rho_i, 0), \ k \neq 1, \text{ subject to } \phi_i^m + \sum_{j \in J^m} \phi_j^m < C^m, m \in R_i, \text{ then [3]}$$

$$\tilde{q}_i^{\text{worst}} = \sigma_i, \qquad \tilde{d}_i^{\text{worst}} = \frac{\sigma_i}{\rho_i}.$$
 (8)

For the FRPS connection, no backlog ever occurs in the route except at the first node since the bandwidth assigned at each node for the connection is fixed and identical. Furthermore, both RPPS and FRPS connections have zero loss because the buffers never overflow. The bounds (7) and (8) are derived by fluid-flow queueing analysis which is acceptable for a high-speed network with small-size cells. The practical cell-based implementation of RPPS/FRPS connections requires small additional buffer space at each link to absorb cell-level dynamics [2], [15].

In general, a user end-to-end delay consists of queueing delay, propagation delay, nodal processing delay, media compression/decompression delay, and so on. Let  $D_i$  be the user end-to-end delay constraint of session i, and assume that the overall nonqueueing delay is bounded by  $A_i$ . For deterministic QOS guarantee, i.e.,  $\tilde{d}_i^{\text{worst}} \leq D_i - A_i$ , we must choose  $(\sigma_i, \rho_i)$  subject to  $(\sigma_i/\rho_i) \leq D_i - A_i$ , which leads to the following admissible set for session i:

$$Z_i = \{ (\sigma_i, \rho_i) | \sigma_i \le (D_i - A_i)\rho_i \}$$
(9)

as illustrated by the thickened curve in Fig. 2(a). Upon arrival of session i, the network traffic manager is responsible to choose a proper  $(\sigma_i, \rho_i) \in Z_i$  according to present networkwide resource availability, and the specific algorithm will differ depending on service provider's policies such as pricing and resource management strategies.

Let us now consider a stochastic session i whose arrival rate  $x_i(t)$  is represented by a stationary random process. Applying  $x_i(t)$  to the WCS with  $\mu_i = \rho_i$  and  $K_i$ , we define a PBC of session i by the following steady-state queue distribution function:

$$\Pr[q_i \ge \sigma_i | \mu_i = \rho_i, K_i], \quad \rho_i \in (a_i, p_i], \quad \sigma_i \in [0, K_i] \quad (10)$$

which is decreasing with respect to  $\sigma_i$  and  $\rho_i$ , as a typical PBC is illustrated in Fig. 2(b). The PBC of a session also varies by  $K_i$  as summarized in the following proposition.

*Proposition 1:* For all  $\sigma_i, \rho_i$ 

$$\Pr[q_i = \sigma_i | \mu_i = \rho_i, K_i = \sigma_i]$$

$$\leq \Pr[q_i \geq \sigma_i | \mu_i = \rho_i, \sigma_i \leq K_i < \infty]$$

$$\leq \Pr[q_i \geq \sigma_i | \mu_i = \rho_i, K_i = \infty].$$

The proof is omitted since it is straightforward.

The PBC is the tail distribution of queue parameterized by the bandwidth allocation  $\rho_i$ . Many approaches [8]–[10], [12], [13] have been proposed to upper bound the tail distribution of queue with/without a parameterization associated with  $\rho_i$  assuming  $K_i = \infty$ . Particularly [8] considered an arrival process whose moment-generating function is upper bounded by a linear envelope process, which is viewed as a stochastic version of (6), and derived an exponential bound of the tail distribution of queue. In addition, [8] proved the equivalence between well-known effective bandwidth [12], [13] and the

minimum envelope rate of feasible linear envelope processes. Given  $\rho_i$ , the theory of effective bandwidth [12], [13] also gives an upper bound of the PBC in a regime where  $\sigma_i$  is very large and the tail probability is very small. In summary, the PBC is not those asymptotic bounds above which could be looser and sometimes even lower [8], [14], but the exact queue distribution function which will be computed via a method in Section III.

Unlike the deterministic session whose QOS is measured by a hard delay bound with zero loss, the QOS of a stochastic session is measured by a probabilistic loss bound. Loss can occur either in the route by buffer overflow or at destination by excessive delay (i.e., end-to-end delay greater than  $D_i - A_i$ ). Denote the end-to-end loss probability of connection i in the route by  $\tilde{P}^i_{\text{blocking}}$  and at the destination by  $\tilde{P}^i_{\text{delay}}$ . Then, the overall end-to-end loss probability  $\tilde{P}^i_{\text{loss}}$  is defined by  $\tilde{P}^i_{\text{loss}} = \tilde{P}^i_{\text{blocking}} + \tilde{P}^i_{\text{delay}}$ . Let  $P_i$  be the user-specified QOS requirement of session i on the overall end-to-end loss probability. Then, the QOS of session i is guaranteed by ensuring

$$\tilde{P}_{\text{loss}}^{i} = \tilde{P}_{\text{blocking}}^{i} + \tilde{P}_{\text{delay}}^{i} \le P_{i}. \tag{11}$$

The following proposition states the end-to-end loss performance bounds for RPPS connections.

Proposition 2: If an RPPS connection of session i is set up with  $(\phi_i^m, \psi_i^m) = (\rho_i, \sigma_i)$  and  $\phi_i^m + \sum_{j \in J^m} \phi_j^m < C^m, m \in R_i$ , then

$$\tilde{P}_{\text{loss}}^{i} \le \Pr\left[q_{i} \ge \min\left\{\sigma_{i}, (D_{i} - A_{i})\rho_{i}\right\} \middle| \mu_{i} = \rho_{i}, K_{i} = \infty\right]$$
(12)

$$\tilde{P}_{\text{blocking}}^{i} \le \Pr\left[q_i \ge \sigma_i \middle| \mu_i = \rho_i, K_i = \infty\right]$$
 (13)

and

$$\tilde{P}_{\text{delay}}^{i} \leq \begin{cases}
\Pr\left[q_{i} \geq (D_{i} - A_{i})\rho_{i} \middle| \mu_{i} = \rho_{i}, K_{i} = \infty\right], \\
\text{if } (D_{i} - A_{i})\rho_{i} \leq N_{i}\sigma_{i} \\
0, \quad \text{if } (D_{i} - A_{i})\rho_{i} > N_{i}\sigma_{i}
\end{cases} (14)$$

where the value of  $\min \{\sigma_i, (D_i - A_i)\rho_i\}$  is  $\sigma_i$  if  $\sigma_i \leq (D_i - A_i)\rho_i$ , otherwise,  $(D_i - A_i)\rho_i$ . The proof is provided in the Appendix.

The significance of this result is that the end-to-end loss performance of a RPPS connection is upper bounded by its PBC which is determined *a priori* by an isolated single-queue, single-server WCS analysis, independent of the network environment and other connections. According to (12), the admissible set  $Z_i$  for RPPS session i to satisfy the QOS constraint (11) is defined by

$$Z_i = \{(\sigma_i, \rho_i) | \Pr\left[q_i \ge \min\left\{\sigma_i, (D_i - A_i)\rho_i\right\} \middle| \mu_i = \rho_i, K_i = \infty\right] < P_i \}$$
(15)

and this set is illustrated by the shadowed region in Fig. 2(b). Note that the subset of  $Z_i$  stressed by the thickened curve includes  $(\sigma_i, \rho_i)$  pairs which minimize the buffer allocation for a given bandwidth selection. In this subset, the reduction of buffer space  $\sigma_i$  can be achieved by an increase of transmission bandwidth  $\rho_i$ , and vice versa, without violating QOS. This feature allows a flexible design of an admission control

exploiting tradeoffs between buffer and bandwidth allocations. For the selection of a  $(\sigma_i, \rho_i)$  pair for a session in the admissible set, various resource allocation algorithms can be considered depending on the service provider's policies such as pricing and resource management strategies. An example of the optimal service provisioning algorithm is found in [4] for the deterministic service case.

On the other hand, the individual bounds (13) and (14) can be applied when  $\tilde{P}^i_{ ext{blocking}}$  and  $\tilde{P}^i_{ ext{delay}}$  are separately controlled. Similarly, the following proposition states the end-to-end loss performance bounds for FRPS connections.

Proposition 3: If an FRPS connection of session i is set up with  $(\phi_i^{(1)}, \psi_i^{(1)}) = (\rho_i, \sigma_i), (\phi_i^{(k)}, \psi_i^{(k)}) = (\rho_i, 0), k \neq 1$ , and  $\phi_i^m + \sum_{j \in J^m} \phi_j^m < C^m, m \in R_i$ , then

$$\begin{split} \tilde{P}_{\text{loss}}^{i} &\leq \Pr\left[q_{i} \geq \min\left\{\sigma_{i}, (D_{i} - A_{i})\rho_{i}\right\} \middle| \mu_{i} = \rho_{i}, \\ K_{i} &= \sigma_{i}\right] \\ \tilde{P}_{\text{blocking}}^{i} &\leq \Pr\left[q_{i} = \sigma_{i} \middle| \mu_{i} = \rho_{i}, K_{i} = \sigma_{i}\right] \end{split} \tag{16}$$

$$\tilde{P}_{\text{blocking}}^{i} \le \Pr\left[q_i = \sigma_i \middle| \mu_i = \rho_i, K_i = \sigma_i\right]$$
 (17)

$$\tilde{P}_{\text{delay}}^{i} \leq \begin{cases}
\Pr\left[q_{i} \geq (D_{i} - A_{i})\rho_{i} \middle| \mu_{i} = \rho_{i}, K_{i} = \sigma_{i}\right] \\
\text{if } (D_{i} - A_{i})\rho_{i} \leq \sigma_{i} \\
0 \quad \text{if } (D_{i} - A_{i})\rho_{i} > \sigma_{i}.
\end{cases}$$
(18)

The proof is provided in the Appendix.

Similar to RPPS, the admissible set for FRPS session i is given by

$$Z_{i} = \{(\sigma_{i}, \rho_{i}) | \Pr\left[q_{i} \ge \min\left\{\sigma_{i}, (D_{i} - A_{i})\rho_{i}\right\} | \mu_{i} = \rho_{i}, K_{i} = \sigma_{i}\right] \le P_{i}\}.$$

$$(19)$$

Compared to the RPPS discipline, the FRPS discipline has the following three advantages. First, for the same  $(\sigma_i, \rho_i)$ , the FRPS connection has tighter loss performance bounds than the RPPS connection. This is because the bounds for FRPS are derived from the queueing analysis of a finite-buffer WCS  $(K_i = \sigma_i)$ , whereas the bounds for RPPS are from that of an infinite-buffer WCS  $(K_i = \infty)$  (refer to Proposition 1). Second, the FRPS connection requires  $\sigma_i$  amount of buffer space only at the first node, whereas the RPPS connection requires the same buffer space at every node in the route. Third, best effort traffic will achieve better performance under the FRPS discipline. This is because any unused bandwidth of each individual FRPS connection will be instantaneously taken by best effort traffic, whereas best effort traffic under the RPPS discipline can be transmitted if and only if all of the connections are simultaneously idle. In other words, the RPPS connections always have high priority to transmit over best effort traffic, which is not true with the FRPS connections. For the same reason, the actual performance of the RPPS connections (i.e., not the bound performance) should be better than that of the FRPS connections, even though the two disciplines provide similar bound performance.

## III. PROBABILISTIC BURSTINESS CURVE OF MULTIMEDIA TRAFFIC

Although DBC has been used to describe either an original session [3] or a leaky-bucket constrained session [2], the actual

relationship between DBC and real traffic characteristics has not been studied extensively, and only a limited number of works are available [6], [16]. The emphasis in this section is placed on the burstiness-curve characterization of a set of representative multimedia traffic including MPEG/JPEG video and PCM voice. Recall that the burstiness-curve characterization of each individual session requires the only analysis of a single-queue, single-server WCS of its own session, completely separate from the network environment and any other sessions.

For the computation of DBC, the rate function  $x_i(t)$  of session should be deterministic and known. When  $x_i(t)$  is applied to an infinite-buffer WCS with transmission bandwidth  $\rho_i$ , the queueing process is also deterministic, and the computation of DBC is straightforward from (6). For the practical case of cellbased transmission, one way to model the queueing process in discrete time with time unit  $(1/\rho_i)$  is

$$q_i \left( t + \frac{1}{\rho_i} \right) = [q_i(t) - 1]^+ + \int_t^{t + (1/\rho_i)} x_i(\tau) d\tau.$$
 (20)

Based on this, one can obtain DBC by taking  $\sigma_i = \max_t [q_i(t)]$ for all  $\rho_i \in (a_i, p_i]$ . Notice that stored media applications such as video-on-demand (VOD) is suitable for this DBC characterization since their rate function  $x_i(t)$  is deterministic and known.

For the PBC computation of stochastic traffic, we need a different approach which is based on traffic statistics since only representative statistics are available through measurement and classification. It is argued that the best way to characterize live media applications such as interactive video and videoconferencing is a statistics-based approach.

#### A. Computation of PBC

The computation of PBC involves stochastic traffic modeling and single-queue analysis. Based on statistical measurement and classification, each multimedia traffic can be represented by two statistical functions: rate histogram f(x)and power spectrum  $P(\omega)$ . We say these two statistical functions to be important statistics for queueing analysis since, in [18], Li showed that the queueing performance such as mean queue, queue variation, and cell loss is essentially determined by f(x) and  $P(\omega)$  of the input traffic, whereas the influence of higher order input statistics such as bispectrum and trispectrum is negligible. In a recent work [19], Hajek also studied the queue response for input statistics, particularly with input mean and autocorrelation, and showed that for a subclass of randomly filtered white noise processes, the mean queue length is determined by the input mean and autocorrelation, whereas for two-state MMPP's and periodic-sequence modulated processes, the input mean and autocorrelation are not sufficient to completely determine the mean queue length. This conclusion is consistent with Li's conclusion above. That is, for the subclass of randomly filtered white noise processes with fixed mean and autocorrelation, f(x) is naturally fixed as a Gaussian distribution, and thus the mean queue length is fixed. In contrast, for the other two types of arrival processes, fixing mean and autocorrelation is not sufficient to fix f(x), and

thus the mean queue length can vary according to variations in f(x).

For Markovian traffic modeling, we use a novel statistical matching technique in [20]. Using this technique, one can construct a special form of multistate MMPP, the *circulant modulated Poisson process* (CMPP), whose statistical functions match with measured f(x) and  $P(\omega)$ . As demonstrated in [20], a multistate CMPP can cover a wide range of the statistical functions f(x) and  $P(\omega)$ . In contrast, for the superposition of two-state MMPP's, which is commonly adopted in traffic modeling,  $P(\omega)$  always has to be a monotone function of  $|\omega|$  and f(x) is limited to a convolution of mixed-rate binomial functions.

Consider a general N-state MMPP defined by  $\{Q,\vec{\gamma}\}$  where  $Q=[q_{ij}]$  is the state transition rate matrix of a continuous-time discrete-state Markov chain, and  $\vec{\gamma}=[\gamma_0,\gamma_1,\cdots,\gamma_{N-1}]$  is an input rate vector for the Poisson arrival rate in each state. By spectral decomposition, assuming that Q is diagonalizable,  $Q=\sum_{\underline{l}=0}^{N-1}\lambda_{l}\vec{g}_{l}\vec{h}_{l}$  where  $\lambda_{l}$  is the lth eigenvalue of Q and  $\vec{g}_{l}$  and  $\vec{h}_{l}$  are the right column and left row eigenvectors with respect to  $\lambda_{l}$ . Then, the power spectrum of the MMPP, denoted by  $P_{c}(\omega)$ , is obtained by taking the Fourier transform of the autocorrelation function

$$P_c(\omega) = \overline{\gamma} + 2\pi \overline{\gamma}^2 \delta(\omega) + \sum_{l=0}^{N-1} \frac{-2\psi_l \lambda_l}{\lambda_l^2 + \omega^2}.$$
 (21)

The first component in (21),  $\overline{\gamma}$ , is the white-noise term attributed to Poisson dynamics in each input state. The second component,  $2\pi\overline{\gamma}^2\delta(\omega)$ , is the dc term attributed to the average input rate. Note that each eigenvalue of Q contributes a bell-shaped component to the power spectrum.

An N-state CMPP is a special case of N-state MMPP where Q is a circulant matrix in which each row circulates one element to the right to form the next row. Hence, the whole matrix is fully characterized by the first row vector, say,  $\vec{a} = [a_0, a_1, \cdots, a_{N-1}]$ . Then, the cumulative distribution function (cdf) of the CMPP, denoted by  $F_c(x)$ , is given by

$$F_c(x) = \frac{m_x}{N} \tag{22}$$

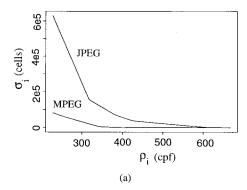
where  $m_x$  is the number of input rates  $\gamma_i$  in  $\vec{\gamma}$  which is less than or equal to x.

The first step to compute PBC for given f(x) and  $P(\omega)$  is to find  $\{N, \vec{a}, \vec{\gamma}\}$ , and hence construct a CMPP model such that

$$P_c(\omega) \approx P(\omega), \quad F_c(x) \approx F(x)$$
 (23)

where F(x) is the cdf of f(x). To do this, we use a programming approach proposed by Li in [20]. The construction of an N-state CMPP is much simpler than that of a general N-state MMPP since fewer parameters need to be determined due to the cyclic repetition of transition rates. Recent development of a faster algorithm for this CMPP modeling is reported in [26].

Once a CMPP model is obtained, the next step is to compute PBC by solving a single-queue, single-server WCS fed by the Markovian model. This queueing system, the MMPP/M/1/K queue, can be modeled by a quasi-birth-death (QBD) process



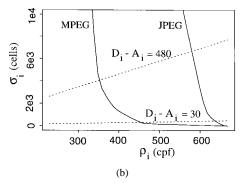


Fig. 3. (a) DBC of MPEG/JPEG video. (b) End-to-end queueing delay constraints imposed on DBC.

[21], and the transition rate matrix, denoted by G, is then given by

where  $Q' = Q - \rho_i I - \Gamma$ ,  $Q'_0 = Q - \Gamma$ ,  $Q'_1 = Q - \rho_i I$ ,  $\Gamma = \operatorname{diag}[\gamma_k]$ , and I is an identity matrix. The Poisson assumption of the service process has a negligible impact on the queueing solution as long as the MMPP input possesses high burst-level correlation, which is a typical characteristic of multimedia traffic [22].

In this paper, we use the so-called QBD folding algorithm [22] to solve the QBD matrix G, and hence obtain the PBC, i.e.,  $\Pr[q_i \geq \sigma_i | \mu_i = \rho_i, K_i]$ . Since  $K_i$  should be finite in the folding algorithm, in the numerical study, we take  $K_i$  sufficiently large to approximate an infinite-buffer WCS as necessary. Other queueing solution techniques such as the matrix-geometric solution approach [21] can be applied to solve such QBD processes.

#### B. MPEG/JPEG Video Traffic

Take a 3.5-min segment of the movie *Star Wars*, which is encoded into MPEG and JPEG video sequences [23]. Both sequences are recorded in cells per frame (cpf), and there are 24 frames/s. In the MPEG coding, we use predictive motion compensation only, and take the ratio of number of I frames to P frames equal to 15. The average rate of the MPEG

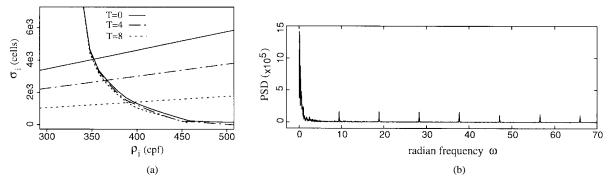


Fig. 4. (a) Effect of traffic smoothing on DBC of MPEG video. (b) Power spectrum of MPEG video.

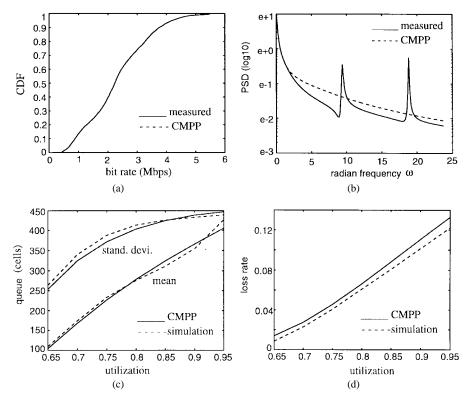


Fig. 5. MPEG Star Wars modeling by CMPP and queueing performance. (a) Rate cumulative distribution. (b) Power spectrum. (c) Mean and standard deviation of queue. (d) Loss rate.

sequence is 227.7 cpf (2.3 Mbit/s) and that of the JPEG sequence is 345.3 cpf (3.5 Mbit/s). Fig. 3(a) compares the DBC of the two video sequences, which is computed from (20). Given at the same bandwidth allocation  $\rho_i$ , the JPEG video obviously requires substantially more buffer allocation  $\sigma_i$  than the MPEG video in order to avoid any cell loss, except at higher bandwidth allocation.

The end-to-end delay constraint  $D_i=20$  for video services is typically in the range of 50–500 ms, depending on applications [24]. Assuming  $A_i=$  ms, the end-to-end queueing delay constraint is given by  $D_i-A_i=30$ –480 ms. The dotted lines in Fig. 3(b) show such constraints imposed on the DBC of MPEG/JPEG video. Taking the maximum queueing delay constraint  $D_i-A_i=480$  ms, for example, the bandwidth requirement  $\rho_i$  is minimized at 350 cpf (3.6 Mbits/s) for the MPEG video and at 580 cpf (5.9 Mbits/s) for the JPEG video. The corresponding buffer space requirement  $\sigma_i$  is about 4000 and 6000 cells, respectively. By comparison, the MPEG coding

with motion compensation can save considerable transmission bandwidth and buffer space in video transmission. A similar comparison can be made in Fig. 3(b) for the stringent delay constraint  $D_i - A_i = 30$  ms, except that more bandwidth is required to trade for less buffer space as  $D_i - A_i$  reduces.

The reason for the MPEG video to require fewer network resources is well explained from the statistics of the two video sequences. First, we compare the steady-state statistics (rate histogram) of the two sequences by plotting the corresponding cdf in Figs. 5(a) and 6(a). Obviously, the MPEG cdf concentrates more on lower input rate than the JPEG cdf. Second, we inspect the second-order statistics (power spectrum) of the two sequences in Figs. 5(b) and 6(b). It is clear that the MPEG video has much less power in the low-frequency band than the JPEG video. The less the low-frequency power, the better the queueing performance will be since the low-frequency power is equivalent to long-term correlations in the time domain [18].

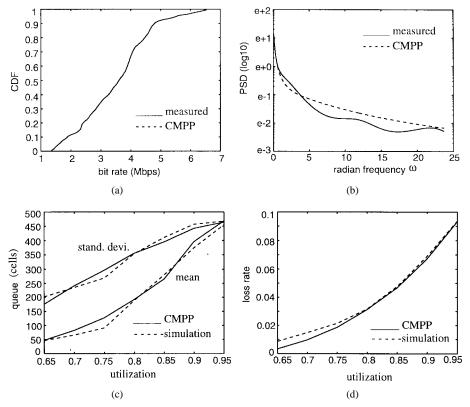


Fig. 6. JPEG Star Wars modeling by CMPP and queueing performance. (a) Rate cumulative distribution. (b) Power spectrum. (c) Mean and standard deviation of queue. (d) Loss rate.

Next, we study the effect of traffic smoothing on the DBC of MPEG video. In general, the I frame appears periodically in an MPEG video stream, such as at every interval of 16 frames in our example. Also, because of motion compensation, Band P frames, which appear adjacent to I frames, consist of many fewer cells than I frames. As a result, the generation of I frames corresponds to periodic burst arrivals in an MPEG video stream. To prevent nodal congestion due to such bursty arrivals, protocols have been proposed to smooth traffic streams at the user network interface (UNI). Naturally, adding a traffic-smoothing device will introduce extra queueing delay at the source and/or at the destination during playback. For example, consider a simple averaging device for smoothing [25]. Define the averaging time interval by T. The device holds cells arriving in the time interval [(n-1)T, nT) at a smoothing buffer, computes their average arrival rate, and then releases them to the network during the next time interval [nT, (n+1)T] at that average rate. The average queueing delay introduced by this device is approximately T. Fig. 4(a) shows the impact of smoothing on the DBC of the MPEG video. The solid curve is for no smoothing, i.e., T = 0, the nonuniformly broken curve is for smoothing at T = 4 frames, and the dotted curve is for smoothing at T=8 frames. Obviously, the DBC of MPEG video is basically unchanged by smoothing (unless T is unreasonably large). In other words, the network resource saving by traffic smoothing for MPEG video is insignificant! Moreover, such a smoothing introduces an extra delay of 167 ms at T=4 frames or 333 ms at T=8 frames. Due to this extra delay, the end-to-end network queueing delay constraint  $D_i - A_i$  becomes much more stringent with

increasing T, as illustrated in Fig. 4(a). In consequence, the minimum bandwidth allocation for a QOS guarantee needs to be substantially increased with T. The admissible set  $Z_i$  also becomes smaller as T increases.

The ineffectiveness of smoothing at T = 4.8 frames can be explained from the MPEG video power spectrum in Fig. 4(b). The spectral spikes appearing at harmonic radian frequencies  $(24/16) \times 2\pi k, k = 1, 2, \cdots$ , are attributed to the periodicity of the I frames. Yet, a large amount of video power, which is attributed to the scene-to-scene autocorrelation, is located in a well-founded low-frequency band (typically  $\omega < 2\pi$  rad). In a signal processing context, smoothing at T seconds is somewhat equivalent to a low-pass filtering at cutoff frequency  $\omega_c$  =  $(2\pi/T)$  rad. Obviously, the low-frequency video power cannot be filtered out by smoothing unless T can be much longer than a second. On the other hand, the queueing performance of the MPEG video is mainly determined by the video statistics in the low-frequency band (i.e., the slow time variation of scene changes). This is why the DBC of MPEG video is basically unaffected by the smoothing in Fig. 4(a).

For the computation of PBC of MPEG/JPEG video, we use the technique in Section III-A to construct a 101-state CMPP model to accurately represent important statistics of the 3.5-min MPEG/JPEG video sequences. Fig. 5(a) and (b) shows the comparison of cdf and power spectrum between the CMPP model and the real MPEG video sequence. The cdf of the CMPP model exactly matches that of the real sequence, and a large number of states, i.e., 101 states, was necessary for this matching. In power spectrum matching, emphasis is placed on the low-frequency band to which the scene-to-

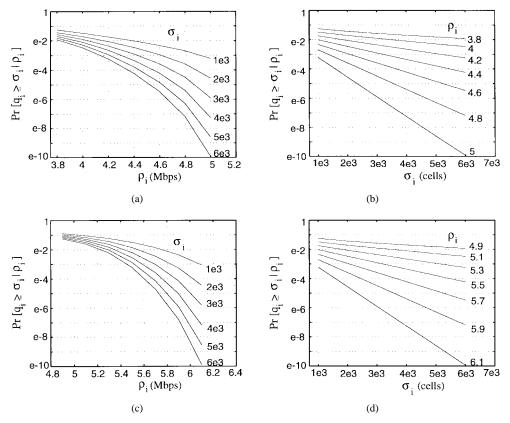


Fig. 7. PBC of Star Wars. (a) and (b) MPEG case. (c) and (d) JPEG case.

scene autocorrelation contributes, whereas the spectral spikes, which are attributed to periodic bursty I frames, were ignored because the queueing performance is mainly affected by the low-frequency power. Note that the logarithmic scale was used in Fig. 5(b). To check the validity of the model, we compare the analytical queueing solution of the CMPP, which is obtained by the QBD technique, to the simulated queueing solution of the real MPEG video sequence. The solutions of mean queue length, queue standard deviation, and average loss rate are compared in Fig. 5(c) and (d) assuming a buffer capacity of 1000 cells. As one can see, the model-based analytical queueing solutions are sufficiently close to the simulated queueing solutions at different utilizations. Similarly, we constructed a 101-state CMPP model for the JPEG video, and the results are shown in Fig. 6.

Using the above two CMPP models, one can compute the PBC of the MPEG/JPEG Star Wars via the QBD queueing technique, and the results are plotted in Fig. 7. An inspection of Fig. 7(a) and (c) indicates that, for each given  $\rho_i$ , the solution  $\Pr\left[q_i \geq \sigma_i \middle| \mu_i = \rho_i, K_i = \infty\right]$  of the MPEG video is much less than that of the JPEG video at each given  $\sigma_i$ . It implies that the MPEG video requires much less buffer space than the JPEG video at each given bandwidth. Similarly, as shown in Fig. 7(b) and (d), the MPEG video requires much less bandwidth than the JPEG video at each given buffer space. Another interesting observation is that the PBC decreases exponentially with respect to  $\sigma_i$  at each given  $\rho_i$ . In contrast, it decreases faster than exponential with respect to  $\rho_i$  at each given  $\sigma_i$ .

One might question whether or not the MMPP modeling above is necessary for the estimation of the PBC. Of course, the PBC can be directly calculated from the raw data traces by simulating a single-queue, single-server WCS with different  $(\sigma_i, \rho_i)$  pairs as in the DBC case. However, estimating a very small tail probability through the simulation is not practically feasible, and the duration of a session is often too short to estimate such a small probability. In addition, by using two important statistics above, traffic classification is greatly simplified, i.e., a set of different data traces can be represented by a pair of  $(f(x), P(\omega))$ , and thus one can create a PBC database indexed by a certain representation of  $(f(x), P(\omega))$ . An other alternative is to estimate the PBC directly from  $(f(x), P(\omega))$ , which is a topic for future research.

The computational complexity involved in the statistical matching and evaluation of the PBC prohibits the approach from being applied to real-time situations. Note that we are not proposing an on-line measurement-based connection control. In other words, we collect sufficient statistics to derive the PBC. Refer to [20] and [26] for the complexity of the matching procedure, and to [22] for the complexity of PBC computation. More examples of the CMPP modeling with longer video sequences and other values of buffer capacity (other than 1000 cells) can be found in [20], [26], and [27].

## C. Voice Traffic

A two-state MMPP, alternating between the ON and OFF states, is typically used to model a voice traffic. Define a two-state MMPP by

$$Q = \begin{bmatrix} -\beta & \beta \\ \alpha & -\alpha \end{bmatrix}, \quad \vec{\gamma} = [0, \gamma_{\text{on}}] \tag{25}$$

where  $\gamma_{on}$  is the Poisson rate while in the ON state. Then,  $\epsilon = (\beta/\beta + \alpha)$  is the steady-state probability of the ON state and  $\overline{\gamma} = \epsilon \gamma_{\text{on}}$  is the average rate. Consider a 64 kbit/s PCM voice source where the average silent and talkspurt periods are equal to 0.6 and 0.4 s, respectively [28]. Based on the ATM cell packetization, we get  $(\gamma_{on}, \alpha^{-1}, \beta^{-1}) = (151 \text{ cells/s}, 0.6)$ s, 0.4 s), and so  $\epsilon = 0.4$  and  $\overline{\gamma} = 60.4$  cells/s. The PBC of each voice source is plotted in Fig. 8(a). The end-to-end cell loss constraint  $P_i$  for voice services is dependent on the coding and priority packetization techniques. For the plain PCM coding without priority packetization, one can choose  $P_i = 10^{-2}$ [24]. Let us also bound the end-to-end delay of voice by 50 ms, and so  $D_i - A_i = 30$  ms. In Fig. 8(a), one may find an empty admissible set  $Z_i$  if the bandwidth is limited by  $\rho_i \leq 62$ kbits/s. In other words, under the condition of  $D_i - A_i = 30$ ms and  $P_i = 10^{-2}$ , there will be no solution  $(\sigma_i, \rho_i)$  to satisfy  $\Pr[q_i \ge \min\{\sigma_i, (D_i - A_i)\rho_i\} | \mu_i = \rho_i, K_i = \infty] \le P_i,$ if  $\rho_i \leq 62$  kbits/s. Note that the maximum voice bandwidth is only 64 kbits/s at which we can have  $\sigma_i = 0$  as in the circuit-switched case. Thus, virtually no improvement can be achieved by packet switching over circuit switching for voice transmission! This problem is essentially caused by the "narrow" bandwidth of voice and its "stringent" delay constraint. Obviously, even holding a few cells in the buffer would result in delay exceeding 30 ms in a voice connection with bandwidth less than 62 kbit/s. This is an inherent problem with the burstiness curve since the analysis of WCS is based on each individual session at its own transmission bandwidth, no matter how many sessions are multiplexed and how large the aggregate transmission bandwidth is on each link. One possible solution is to group a large number of small sessions into a "super" session, as will be discussed in Section IV.

We now examine the impact of voice ON/OFF periods on the PBC. Let the average ON and OFF periods be simultaneously scaled, which will change the voice power spectrum but not its rate distribution [17]. When  $(\alpha^{-1}, \beta^{-1})$  is increased to (1.2 s, 0.8 s), more voice power concentrates on the low-frequency band, and so the queueing performance deteriorates, and vice versa when  $(\alpha^{-1}, \beta^{-1})$  is reduced to (0.3 s, 0.2 s). Fig. 8(b) shows the corresponding PBC's as a function of  $\rho_i$  at  $\sigma_i = 200$  cells. Obviously, the voice transmission bandwidth  $\rho_i$  must be increased with the length of the ON and OFF periods for the same value of  $\Pr[q_i \geq \sigma_i | \mu_i = \rho_i, K_i = \infty]$ .

#### IV. ADMISSION CONTROL AND RESOURCE SHARING

When a deterministic session i arrives, its DBC and end-to-end delay constraint  $D_i$  will be provided to the network. When a probabilistic session i arrives, its traffic type, delay constraint  $D_i$ , and loss constraint  $P_i$  will be provided to the network. For each given traffic type, the corresponding PBC can be identified from the network database. As discussed in Section III-A, building such a database in advance is feasible once representative statistical functions f(x) and  $P(\omega)$  are collected and classified. The function of admission control is first to determine the admissible set  $Z_i$ , and then to select a proper  $(\sigma_i, \rho_i) \in Z_i$  according to present network-wide

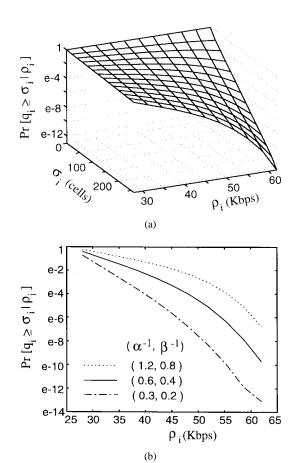


Fig. 8. PBC of voice traffic. (a) When  $(\gamma_{\rm on}, \alpha^{-1}, \beta^{-1}) = (151 \text{ cells/s}, 0.6 \text{ s}, 0.4 \text{ s})$ . (b) Impact of ON/OFF period changes at  $\sigma_i = 200$  (cells).

resource availability. If none of the  $(\sigma_i, \rho_i)$ 's in  $Z_i$  can be ensured by the network, the arriving session will be blocked.

The admission rule for RPPS connections is defined as follows. When session i requests connection setup, if the network traffic manager can identify a  $(\sigma_i, \rho_i) \in Z_i$  and find a route  $R_i$  such that

$$\sigma_i + \sum_{j \in J^m} \psi_j^m \le B^m \quad \text{and}$$

$$\rho_i + \sum_{j \in J^m} \phi_j^m < C^m, \qquad m \in R_i$$
(26)

the connection will be established with  $(\psi_i^m, \phi_i^m) = (\sigma_i, \rho_i), m \in R_i$ . The tradeoff between buffer and bandwidth allocations is examined in the identification of  $(\sigma_i, \rho_i)$  to comply with present network resource conditions. The admission rule is equally applied to deterministic and probabilistic connections. Once probabilistic session i is admitted under the rule, its QOS is guaranteed without violating the QOS guarantees of ongoing sessions (refer to Proposition 2).

On the other hand, if session i requests an FRPS connection, it is sufficient to examine the buffer space condition in (26) for the first node in route  $R_i$ . The QOS of each probabilistic FRPS connection is thus guaranteed from Proposition 3.

The importance of the admissible set  $Z_i$  is to provide a great flexibility in connection management. According to present network-wide resource availability, the network traffic

manager can adaptively adjust the  $(\sigma, \rho)$  allocation of all sessions as long as the  $(\sigma, \rho)$  of each connection is selected from its own admissible set. This capability plays an important role in resolving *network resource fragmentation*. When a new session cannot be accepted because of resource fragmentation, the network can selectively renegotiate the  $(\sigma, \rho)$  allocation of ongoing sessions to "create" resources for the new session.

## A. Buffer Sharing

One deficiency of the above admission rule is that resource sharing is completely neglected. The buffer allocation policy in (26) assumes that a separate buffer space  $\sigma_i$  is dedicated to each connection at every node. Similarly, the bandwidth allocation policy in (26) does not take advantage of statistical multiplexing gain, i.e., the direct sum of bandwidth allocations at each node never exceeds the link capacity. This is also why the end-to-end per-session performance bound can be determined from the queueing analysis of an "isolated" WCS, independent of the network environment and other connections. The number of connections that can be supported in a network can be substantially reduced by the admission rule (26).

For the probabilistic connections with PBC, however, one can take advantage of the *buffer sharing* effect in the design of admission control. Instead of dedicating a segregate buffer space to each connection, one can make the overall buffer space at each node to be statistically shared by all of the connections routed to the node. It will be shown that the total buffer space requirement can be substantially reduced by buffer sharing without violating the QOS guarantee of each individual connection.

Let  $x_i^m(t)$  be the arrival rate of session i at time t on link  $m \in R_i$ . The aggregate arrival rate on link m is denoted by  $x^m(t)$ . When the buffer of link m is full, the aggregate loss rate is equal to  $l^m(t) = [x^m(t) - C^m]^+$  under the assumption of fluid flow. The amount  $l^m(t)$  can be arbitrarily distributed among all the arrival rates  $x_i^m(t), \forall i$ , through the implementation of cell selective discarding. In our case, we assume rate proportional (RP) loss distribution. Denote the loss rate of session i at time t on link m by  $l_i^m(t)$ . The RP loss distribution ensures that when the buffer of link m is full

$$l_i^m(t) = \frac{x_i^m(t)}{x^m(t)} l^m(t), \qquad \forall i \in I^m$$
 (27)

where  $I^m$  denotes the set of all the connections on link m. Then, the instantaneous loss ratio of session i on link m during the buffer blocking period is given by

$$\frac{l_i^m(t)}{x_i^m(t)} = \frac{[x^m(t) - C^m]^+}{x^m(t)}$$
 (28)

which is identical for all of the sessions on link m. Define the steady-state loss probability of session i on link m,  $L_i^m$ , by the expectation of its instantaneous loss ratio. From (28), we get  $L_i^m = L_j^m, i, j \in I^m$ , i.e., the loss probability of each session on link m must be identical under the RP loss distribution. In practice, the RP loss distribution can be accomplished with selective cell discarding [29].

The following proposition states the end-to-end loss performance bounds for RPPS connections with buffer sharing.

Proposition 4: Suppose that an RPPS connection i is set up with  $\phi_i^m = \rho_i$  and  $\sum_{j \in I^m} \phi_j^m < C^m, m \in R_i$ , and the buffer at each node in the route is statistically shared by other connections on the node. Then, under RP loss distribution

$$\tilde{P}_{\text{blocking}}^{i} \le 1 - \prod_{m \in R_{i}} \left( 1 - \int_{B^{m}}^{\infty} [\otimes_{j \in I^{m}} h_{j}(q_{j}, \rho_{j})] dq^{m} \right)$$
(29)

and

$$\tilde{P}_{\text{delay}}^{i} \leq \begin{cases}
\Pr\left[q_{i} \geq (D_{i} - A_{i})\rho_{i} \middle| \mu_{i} = \rho_{i}, K_{i} = \infty\right], \\
\text{if } (D_{i} - A_{i})\rho_{i} \leq \sum_{m \in R_{i}} B^{m} \\
0, \quad \text{if } (D_{i} - A_{i})\rho_{i} > \sum_{m \in R_{i}} B^{m}
\end{cases}$$
(30)

where  $\otimes$  is a convolution operator and  $q^m = \sum_{j \in I^m} q_j$  is the aggregate queue length at the buffer of link m.  $h_i(q_i, \rho_i)$  is the probability density function (pdf) of  $q_i$  when session i is applied to an "isolated" WCS with  $\mu_i = \rho_i$  and  $K_i = \infty$ . By definition,  $h_i(q_i, \rho_i) = (d/dq_i) \Pr{q_i \geq \sigma_i | \mu_i = \rho_i, K_i = \infty}$ . The proof is provided in the Appendix.

The bound on  $\tilde{P}_{\text{delay}}^{i}$  is solely determined by the PBC of session i, whereas the bound on  $\tilde{P}_{\text{blocking}}^{i}$  requires the PBC's of all of the interacting connections in the route.

In practice, with the discrete queue state, once the PBC is known,  $h_i(q_i=a,\rho_i)$  can be easily obtained by  $\Pr[q_i \geq a | \mu_i = \rho_i, K_i] - \Pr[q_i \geq a+1 | \mu_i = \rho_i, K_i]$ . Alternatively, one can keep the PBC as an exponential function with respect to  $\sigma_i$  where both the prefactor and decrease rate are functions of  $\rho_i$ , as observed in Fig. 7(b) and (d). Then,  $h_i(q_i,\rho_i)$  can also be given as an analytical function.

For convenience, denote  $\otimes_{j\in J^m} h_j(q_j,\rho_j)$  and  $\int_{B^m}^\infty [\otimes_{j\in J^m} h_j(q_j,\rho_j)] dq^m$  by  $h^m$  and  $\mathrm{BLK}^m$ , respectively. Assume that the network traffic manager keeps the present information of  $h^m$  and  $\mathrm{BLK}^m$  for all shared buffers in the network. Also, it keeps the present bound on  $\tilde{P}^j_{\mathrm{delay}}$ , denoted by  $\mathrm{DLY}_j$ , for all connections in the network. The admission control for RPPS connections with buffer sharing is defined as follows. When session i requests an RPPS connection, the network traffic manager first selects  $\rho_i$  and  $R_i$  candidates, and updates  $h^m$  and  $\mathrm{BLK}^m, \forall m \in R_i$ , by  $h^m = h^m \otimes h_i(q_i, \rho_i)$  and  $\mathrm{BLK}^m = \int_{B^m}^\infty [h^m \otimes h_i(q_i, \rho_i)] d(q^m + q_i)$ . Then, if the following conditions are satisfied, the connection setup of session i with the candidates is accepted. Otherwise, the same steps are repeated

$$\rho_i + \sum_{j \in I^m} \phi_j^m < C^m, \qquad \forall m \in R_i \tag{31}$$

see (32), shown at the bottom of the next page, and

$$1 - \prod_{m \in R_j} (1 - BLK^m) + DLY_j \le P_j, \quad \forall j \in \Omega_i \quad (33)$$

where  $\Omega_i$  is the set of all of the RPPS connections interacting with the new connection i, which is defined by

 $\Omega_i = \{j | R_j \cap R_i \neq \emptyset\}$ . Equation (31) examines the bandwidth availability along the route for the arriving session i, (32) ensures  $\tilde{P}^i_{\text{blocking}} + \tilde{P}^i_{\text{delay}} \leq P_i$  for the arriving session i, and (33) guarantees  $\tilde{P}^j_{\text{blocking}} + \tilde{P}^j_{\text{delay}} \leq P_j, j \in \Omega_i$ .

Similarly, the following proposition states the end-to-end loss performance bounds for FRPS connections with buffer sharing.

Proposition 5: Suppose that an FRPS connection i is set up with  $\phi_i^{(k)} = \rho_i$  and  $\sum_{j \in I^{(k)}} \phi_j^{(k)} < C^{(k)}, (k) \in R_i$ , and the buffer space at each node in the route is statistically shared by other connections on the node. Then, under RP loss distribution

$$\tilde{P}_{\text{blocking}}^{i} \le \int_{B^{(1)}}^{\infty} \left[ \bigotimes_{j \in I^{(1)}} h_j(q_j, \rho_j) \right] dq^{(1)} \tag{34}$$

and

$$\tilde{P}_{\text{delay}}^{i} \leq \begin{cases}
\Pr\left[q_{i} \geq (D_{i} - A_{i})\rho_{i} \middle| \mu_{i} = \rho_{i}, K_{i} = \infty\right], \\
\text{if } (D_{i} - A_{i})\rho_{i} \leq B^{(1)} \\
0, \quad \text{if } (D_{i} - A_{i})\rho_{i} > B^{(1)}.
\end{cases}$$
(35)

The proof is provided in the Appendix.

Compared to RPPS, FRPS provides a tighter bound on  $\tilde{P}^i_{\text{blocking}}$  since buffer sharing is required only at the first node in  $R_i$ . Similar admission control can be implemented for FRPS connections. It is sufficient to examine the conditions (31)–(33) at the first node.

The admission control with buffer sharing will greatly improve buffer resource utilization, yet it requires a considerable increase of computational overhead for connection management, i.e., upon arrival and departure of a session, a convolution and a deconvolution are necessary, respectively. This is because the PBC's of all of the interacting connections must be taken into account for the evaluation of the per-session loss performance bound. By taking the Laplace transform of  $h_j(q_j, \rho_j)$ , the convolution and deconvolution can be simplified to a multiplication and a division, but an inverse Laplace transform may still be troublesome.

A practical approach to circumvent this difficulty for the RPPS case is to use a leaky-bucket policer at the UNI with token generation rate equal to  $\rho_j$ . Then, irrespective of the token pool size, the per-session end-to-end delay will still satisfy (30) since the leaky-bucket policer can be viewed as another hop. On the other hand, the worst case pattern of the departure process of the leaky-bucket policer can be readily modeled as a deterministic ON-OFF source whose parameters are determined by the policer parameters [30]. Then, the overflow probability estimate on link  $m \in R_j$ , i.e.,  $\int_{B^m}^{\infty} \left[ \bigotimes_{j \in I^m} h_j(q_j, \rho_j) \right] dq^m$ , can be replaced by the overflow probability estimate in a single FIFO queue with the same buffer and transmission capacities fed by ON-OFF sessions, i.e.,  $\forall j \in I^m$ , since both RPPS and FIFO disciplines are

work conserving, and thus should give the same overflow probability. The analysis of a FIFO queue fed by multiple ON–OFF sources is a standard problem in current ATM research and we argue that this will provide a much simpler solution for the loss computation with buffer sharing.

Let us investigate the reduction of the buffer space requirement by buffer sharing. For simplicity, consider N sessions of i.i.d. MPEG/JPEG video sources which are routed to a common network link. In terms of bandwidth allocation, each session requires the same amount of bandwidth  $\rho_i$ , and the aggregate bandwidth  $N \times \rho_i$  must be less than the link capacity. Without buffer sharing, each session requires a separate buffer allocation  $\sigma_i$ , and the aggregate buffer space requirement is  $N \times \sigma_i$ . For instance, take the loss probability bound  $\Pr[q_i \geq \sigma_i | \mu_i = \rho_i, K_i = \infty] = 10^{-6} \text{ in (13)}.$  One can then get  $\sigma_i = 4689$  cells at  $\rho_i = 4.8$  Mbits/s for each MPEG video session in Fig. 7(b) and  $\sigma_i = 5106$  cells at  $\rho_i = 5.9$ Mbits/s for each JPEG video session in Fig. 7(d). When the buffer sharing is considered by the admission control, denote the aggregate buffer space requirement by  $\sigma_{\text{sharing}}$ , subject to the same loss probability bound 10<sup>-6</sup> per session under the RP loss distribution. Taking the N-fold convolution of the video PBC, one can find  $\sigma_{\text{sharing}}$  from the bound solution in (29). Fig. 9(a) shows the ratio of  $N\sigma_i$  to  $\sigma_{\text{sharing}}$  as a function of N. At N = 50, only less than 5% of total buffer capacity is required by sharing for the aggregate MPEG/JPEG video using the same transmission bandwidth! Obviously, sharing can save a substantial amount of buffer space. In the admission control, one can always trade more buffer resource  $\sigma_{
m sharing}$ for less bandwidth  $\rho_i$  since the shared buffer space will not be significantly increased by the individual connections.

## B. Traffic Aggregation

In this subsection, we investigate the effect of traffic aggregation on bandwidth saving. In practice, when several sessions share a common route, they can be grouped into a "super" session. Such a grouping has the same effect as statistical multiplexing on bandwidth efficiency. For example, consider the existence of a large number of voice sessions between two distant local switching centers which are interconnected via a backbone ATM network. Instead of frequently setting up each individual voice connection on a per-session basis, one can infrequently set up a "super" connection such as VP provisioning between the two switching centers to transport multiple voice sessions together. For simplicity, assume that each voice session is a 64 kbit/s PCM voice with silence detection, which is modeled by the two-state MMPP in Section III-C. As previously discussed in Section III, under the constraints  $D_i - A_i = 30$  ms and  $P_i = 10^{-2}$ , the transmission bandwidth of each voice connection without grouping must

$$\begin{cases}
1 - \prod_{m \in R_i} (1 - \text{BLK}^m) + \Pr\left[q_i \ge (D_i - A_i)\rho_i | \mu_i = \rho_i, K_i = \infty\right] \le P_i, & \text{if } (D_i - A_i)\rho_i \le \sum_{m \in R_i} B^m \\
1 - \prod_{m \in R_i} (1 - \text{BLK}^m) \le P_i, & \text{if } (D_i - A_i)\rho_i > \sum_{m \in R_i} B^m
\end{cases}$$
(32)

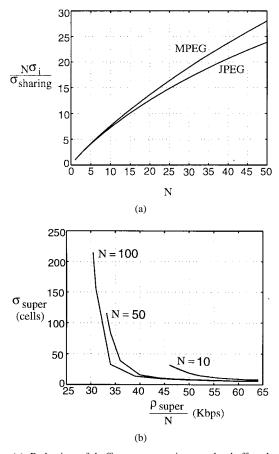


Fig. 9. (a) Reduction of buffer space requirement by buffer sharing in MPEG/JPEG video transmission. (b) Reduction of bandwidth requirement by traffic aggregation in PCM voice transmission.

be greater than 62 kbits/s. Therefore, for N voice sessions, if each session is set up as a separate connection, the total amount of bandwidth must be greater than  $N \times 62$  kbit/s. In contrast, when all of the N voice sessions are grouped into a "super" connection, the aggregate bandwidth requirement can be substantially reduced as indicated in Fig. 9(b). The curves represent the set of admissible ( $\sigma_{\text{super}}, \rho_{\text{super}}$ )'s for the "super" connection with respect to N=10, 50, 100 subject to  $D_i-A_i=30$  ms and  $P_i=10^{-2}$ . The ( $\sigma_{\text{super}}, \rho_{\text{super}}$ ) represents the buffer space and bandwidth requirement for the "super" connection. The bandwidth per voice session is measured by ( $\rho_{\text{super}}/N$ ), which can be greatly reduced as N increases.

This gain by grouping is closely related to statistical multiplexing gain. As discussed in Section III, for a single voice transmission with the loss and delay constraints above, there exists no  $(\sigma_i, \rho_i)$  pair to satisfy  $\Pr[q_i \geq \min{\{\sigma_i, (D_i - A_i)\rho_i\}}|\mu_i = \rho_i, K_i = \infty] \leq P_i$  if  $\rho_i \leq$  62 kbit/s. In other words, the maximum allowable backlog  $(D_i - A_i)\rho_i$  is so small that the loss requirement  $P_i = 10^{-2}$  cannot be met unless  $\rho_i$  reaches 62 kbit/s. In contrast, by grouping more voice sources into a super session, one can have larger maximum allowable backlog, i.e., larger  $(D_i - A_i)\rho_{\text{super}}$  since  $\rho_{\text{super}}$  will increase. For example, if  $\rho_{\text{super}}$  is 6.2 Mbit/s, the maximum allowable backlog  $(D_i - A_i)\rho_{\text{super}}$  is as large as 439 cells. On the other hand, statistical multiplexing takes effect as the

number of multiplexed sources increases. Hence, for a super session with N=100 and  $\rho_{\rm super}=6.2$  Mbit/s, the actual buffer requirement  $\sigma_{\rm super}$  to meet the  $10^{-2}$  loss constraint is only about ten cells, as shown in Fig. 9(b). This implies that for 6.2 Mbit/s transmission bandwidth, one can allow a backlog as large as 439 cells, and for 6.2 Mbit/s transmission bandwidth and a 439 cell buffer one, can accept much more than 100 voice sessions without violating the QOS guarantee. In comparison, without grouping, one can only accept 100 voice sessions for the same bandwidth and buffer space.

## V. CONCLUSION

This paper has presented a method to establish real-time multimedia connections with guaranteed QOS. A multimedia session has been viewed as a stochastic process of which only two important statistics (rate histogram and power spectrum) are measurable. Based on these statistics, the traffic characteristics of the multimedia session have been represented by the probabilistic burstiness curve. For the computation of PBC from the statistics, a traffic modeling and queueing analysis technique has been introduced, and the novelty has been demonstrated with applications to MPEG/JPEG video sequences.

Once network resources are allocated to each session according to its PBC, one can probabilistically bound persession end-to-end delay/loss performance under RPPS and FRPS service disciplines. The bounding solutions are solely determined by the PBC's of the sessions. Upon arrival of a new session, the network traffic manager determines the admissible set  $Z_i$  based on its PBC and QOS requirement, and selects a proper resource allocation pair  $(\sigma_i, \rho_i) \in Z_i$  according to present network-wide resource availability. In order to improve network resource utilization, we have also studied the admission control policy which allows statistical sharing of buffer resources, subject to the same QOS guarantee of each connection.

Our study of MPEG/JPEG video sequences has revealed the fundamental interrelationship among the burstiness curve, the QOS guarantee, and the video statistics (rate histogram and power spectrum, particularly in the low-frequency band, to which the scene-to-scene autocorrelation contributes). Also, we have provided many engineering aspects of the PBC approach to real-time multimedia services, including the video smoothing issue where its ineffectiveness for real-time applications has been pointed out.

#### **APPENDIX**

Proof of Proposition 2: Let us apply the same realization  $x_i(t)$  of session i to an RPPS connection with  $(\phi_i^m, \psi_i^m) = (\rho_i, \sigma_i), m \in R_i$ , as well as to an "isolated" WCS with  $\mu_i = \rho_i$  and  $K_i = \infty$ . The two queueing processes are compared. One can view the RPPS connection as a "virtual" queueing system with arrival rate  $x_i(t)$  from the source, departure rate  $g_i^{(N_i)}(t)$  at the last node, and overall loss rate  $\tilde{l}_i(t)$  due to buffer overflow at intermediate links. Let  $q_i^{(k)}(t)$  denote the backlog of session i on the kth node in the route at time t. Let  $\tilde{q}_i(t)$  be the end-to-end backlog of session i at time

t. The time interval of  $\tilde{q}_i(t)>0$  is called the *connection busy period* of session i. Without loss of generality, consider a connection busy period  $[\tilde{s},\tilde{e}]$ , during which we can write  $\tilde{q}_i(t)=\int_{\tilde{s}}^t x_i(\tau)\,d\tau-\int_{\tilde{s}}^t g_i^{(N_i)}(\tau)\,d\tau-\int_{\tilde{s}}^t \tilde{l}_i(\tau)\,d\tau$ . Note that, under the assumption of fluid flow and zero propagation delay, for  $t\in [\tilde{s},\tilde{e}],g_i^{(N_i)}(t)=g_i^{(k)}(t)\geq \phi_i^{(k)}=\rho_i$  for some  $(k)\in R_i$ . So, we get  $\tilde{q}_i(t)\leq \int_{\tilde{s}}^t x_i(\tau)\,d\tau-\rho_i(t-\tilde{s}),t\in [\tilde{s},\tilde{e}]$ . In contrast, in the "isolated" WCS with infinite buffer,  $q_i(t)\geq \int_s^t x_i(\tau)\,d\tau-\rho_i(t-s)$  for all  $0\leq s< t$  from (5). Therefore, we conclude that  $\tilde{q}_i(t)\leq q_i(t), \forall t\in [\tilde{s},\tilde{e}],$  which in steady state yields

$$\Pr\left[\tilde{q}_i \ge \sigma_i\right] \le \Pr\left[q_i \ge \sigma_i \middle| \mu_i = \rho_i, K_i = \infty\right]. \tag{36}$$

Now, we prove (12). Define  $\vec{q}^m(t), m \in R_i$ , to be a random vector whose elements are random variables  $q_i^m(t)$  and  $q_j^m(t), j \in J^m$ . Also, define  $\vec{q}_{R_i}(t)$  to be a random vector whose elements are random vectors  $\vec{q}^m(t), m \in R_i$ . We add the superscript  $\bullet$  in the notation to denote the value of a random variable/vector. Obviously, a sufficient condition for session i at time t to experience no blocking in the route and no overdelay at the destination is that  $\tilde{q}_i(t) < \min \{\sigma_i, (D_i - A_i)\rho_i\}$ . Define a set  $\Gamma_i = \{\vec{q}_{R_i}(t)^{\bullet}|\Sigma_{m\in R_i}q_i^m(t)^{\bullet}(=\tilde{q}_i(t)^{\bullet}) < B_i\}$  with  $B_i = \min\{\sigma_i, (D_i - A_i)\rho_i\}$ . One can then use the sufficient condition to lower bound the steady-state survival probability of session i

$$1 - \tilde{P}_{loss}^{i} \ge \lim_{t \to \infty} \int_{\vec{q}_{R_{i}}(t)^{\bullet} \in \Gamma_{i}} f(\vec{q}_{R_{i}}(t)^{\bullet}) d\vec{q}_{R_{i}}(t)^{\bullet}$$

$$= \lim_{t \to \infty} \int_{\tilde{q}_{i}(t)^{\bullet} < B_{i}} f(\tilde{q}_{i}(t)^{\bullet}) d\tilde{q}_{i}(t)^{\bullet}$$

$$= 1 - \Pr\left[\tilde{q}_{i} \ge B_{i}\right]$$

$$\ge 1 - \Pr\left[q_{i} \ge B_{i}\right] \mu_{i} = \rho_{i}, K_{i} = \infty$$

where  $f(\cdot)$  denotes the probability density function and the last inequality holds by (36). Hence, (12) is true. The same steps can be taken to prove (13) and (14), except to replace  $B_i$  by  $\sigma_i$  and  $(D_i - A_i)\rho_i$ , respectively. This is because the sufficient condition for session i at time t to experience no blocking is given by  $\tilde{q}_i(t) < \sigma_i$ , and the sufficient condition for session i at time t to experience no overdelay is given by  $\tilde{q}_i(t) < (D_i - A_i)\rho_i$ . Since  $\tilde{q}_i(t)$  must be upper bounded by the connection i's total buffer space in the route, i.e.,  $N_i\sigma_i$ , it is clear that if  $(D_i - A_i)\rho_i > N_i\sigma_i$ ,  $\tilde{P}^i_{\text{delay}} = 0$ .

Proof of Proposition 3: For the FRPS connection with  $\phi_i^{(k)} = \rho_i, \forall k$ , the first node is always the bottleneck. Therefore,  $\tilde{q}_i(t) = q_i^{(1)}(t), \forall t$ , for any realization  $x_i(t)$ . The loss occurs only at the first buffer. We first prove (16). Since the sufficient condition for session i at time t to experience no blocking and no overdelay is  $q_i^{(1)}(t) < B_i, 1 - \tilde{P}_{loss}^i \geq \lim_{t \to \infty} \int_{q_i^{(1)}(t)^{\bullet} < B_i} f(q_i^{(1)}(t)^{\bullet}) dq_i^{(1)}(t)^{\bullet} = 1 - \Pr[q_i^{(1)} \geq B_i] = 1 - \Pr[q_i \geq B_i | \mu_i = \rho_i, K_i = \sigma_i]$ . The last equality holds because the queueing process of the first buffer in the FRPS connection is identical to the queueing process of a WCS transmitting the same session with  $\mu_i = \rho_i$  and  $K_i = \sigma_i$ . Hence, (16) is true.

We next prove (17). The loss can occur only at the first buffer when  $q_i^{(1)}(t) = \sigma_i$ , and the instantaneous loss ratio is

given by  $([x_i(t) - \rho_i]^+/x_i(t))$ . Therefore, we get

$$\tilde{P}_{\text{blocking}}^{i} = \lim_{t \to \infty} \int \frac{[x_{i}(t)^{\bullet} - \rho_{i}]^{+}}{x_{i}(t)^{\bullet}} f(x_{i}(t)^{\bullet},$$

$$q_{i}^{(1)}(t) = \sigma_{i}) dx_{i}(t)^{\bullet}$$

$$\leq \lim_{t \to \infty} \int f(x_{i}(t)^{\bullet}, q_{i}^{(1)}(t) = \sigma_{i}) dx_{i}(t)^{\bullet}$$

$$= \Pr[q_{i}^{(1)} = \sigma_{i}] = \Pr[q_{i} = \sigma_{i} | \mu_{i} = \rho_{i}, K_{i} = \sigma_{i}]$$

where the symbol  $[\cdot]^+$  denotes  $\max[0, \cdot]$  and the inequality holds because  $0 \le [x_i(t)^{\bullet} - \rho_i]^+ \le x_i(t)^{\bullet}$ . The proof of (18) is similar to that of of (16), except that the sufficient condition for session i at time t to experience no overdelay is  $q_i^{(1)}(t) < (D_i - A_i)\rho_i$ .

Proof of Proposition 4: First, we derive the bound on  $\tilde{P}^i_{\mathrm{blocking}}$ . Let  $q^m(t)$  be the aggregate backlog in the shared buffer of link  $m \in R_i$ , defined by  $q^m(t) = \sum_{j \in I^m} q^m_j(t)$ . Let  $L^m_i$  be the loss probability of the session i stream at the buffer of link m. Define  $\vec{x}^m(t)$  to be a vector whose elements are  $x^m_j(t), j \in I^m$ , including  $x^m_i(t)$ . Then, under the RP loss distribution,  $L^m_i$  can be written by

$$L_i^m = \lim_{t \to \infty} \int \frac{[x^m(t)^{\bullet} - C^m]^+}{x^m(t)^{\bullet}} \cdot f(\vec{x}^m(t)^{\bullet}, q^m(t) = B^m) d\vec{x}^m(t)^{\bullet}$$
$$\leq \lim_{t \to \infty} \int f(\vec{x}^m(t)^{\bullet}, q^m(t) = B^m) d\vec{x}^m(t)^{\bullet}$$
$$= \Pr[q^m = B^m].$$

From the following two arguments, one can show that  $q^m(t) \leq \sum_{j \in I^m} \tilde{q}_j(t) \leq \sum_{j \in I^m} q_j(t), \forall t$ , for any realization of  $x_j(t)$ , where  $q_j(t)$  is the backlog at time t when the same realization  $x_j(t)$  is applied to a WCS with  $\mu_j = \rho_j$  and  $K_j = \infty$ . First, since  $q_j^m(t) \leq \tilde{q}_j(t)$ , we have  $q^m(t) \leq \sum_{j \in I^m} \tilde{q}_j(t), \forall t$ . Second, as in the proof of Proposition 2, one can obtain  $\tilde{q}_j(t) \leq q_j(t), \forall t$ . Hence, in steady state, we get  $L_i^m \leq \Pr[q^m = B^m] \leq \Pr[\sum_{j \in I^m} q_j \geq B^m]$ . Notice that  $q_j(t), j \in I^m$ , are independent, whereas  $q_j^m(t), j \in I^m$ , are dependent on each other. Because of this independence, the probability density function of  $\sum_{j \in I^m} q_j$  is given by  $\bigotimes_{j \in I^m} h_j(q_j, \rho_j)$  and so  $\Pr[\sum_{j \in I^m} q_j \geq B^m] = \int_{B^m}^{\infty} [\bigotimes_{j \in I^m} h_j(q_j, \rho_j)] dq^m$ . Therefore, we conclude that  $L_i^m \leq \int_{B^m}^{\infty} [\bigotimes_{j \in I^m} h_j(q_j, \rho_j)] dq^m$ . One can then derive (29) using  $\tilde{P}_{blocking}^i = 1 - \prod_{m \in R_i} (1 - L_i^m)$ . The proof of (30) is similar to that of (14) in Proposition 2.

Proof of Proposition 5: Recall that in the FRPS connection with  $\phi_i^{(k)} = \rho_i, (k) \in R_i$ , we have  $\tilde{q}_i(t) = q_i^{(1)}(t), \forall t$ , and  $L_i^{(k)} = 0$  for  $k \neq 1$ . Define  $\bar{q}^{(1)}(t)$  to be a vector whose elements are  $q_j^{(1)}(t), j \in I^{(1)}$ , including  $q_i^{(1)}(t)$ . Let  $G^{(1)}(t)$  be the aggregate departure rate of all of the FRPS connections at the first buffer. Unlike the RPPS discipline,  $G^{(1)}(t)$  is dependent on  $\bar{q}^{(1)}(t)$  since FRPS is a nonwork-conserving discipline. Therefore, under the RP loss distribution,  $\tilde{P}_{\text{blocking}}^i$  can be written by

$$\tilde{P}_{\text{blocking}}^{i} = L_{i}^{(1)} = \lim_{t \to \infty} \int_{\vec{q}^{(1)}(t)^{\bullet} \in \Lambda} \int \frac{[x^{(1)}(t)^{\bullet} - G^{(1)}(t)^{\bullet}]^{+}}{x^{(1)}(t)^{\bullet}} \cdot f(\vec{x}^{(1)}(t)^{\bullet}, \vec{q}^{(1)}(t)^{\bullet}) d\vec{x}^{(1)}(t)^{\bullet} d\vec{q}^{(1)}(t)^{\bullet}$$

with  $\Lambda=\{\vec{q}^{(1)}(t)^{\bullet}|q^{(1)}(t)^{\bullet}=B^{(1)}\}.$  Since  $0\leq [x^{(1)}(t)^{\bullet}-G^{(1)}(t)^{\bullet}]^{+}\leq x^{(1)}(t)^{\bullet},\ \tilde{P}^{i}_{\text{blocking}}\leq \lim_{t\to\infty}\int_{\vec{q}^{(1)}(t)^{\bullet}\in\Lambda}\int f(\vec{x}^{(1)}(t)^{\bullet},\ \vec{q}^{(1)}(t)^{\bullet})d\vec{x}^{(1)}(t)^{\bullet}d\vec{q}^{(1)}(t)^{\bullet}=\Pr[q^{(1)}=B^{(1)}].$  Next, we show that  $q_{j}^{(1)}(t)\leq q_{j}(t),\forall t,$  for any realization  $x_{j}(t).$  Again,  $q_{j}(t)$  is the backlog at time t in a WCS with  $\mu_{j}=\rho_{j}$  and  $K_{j}=\infty.$  Consider a busy period [s,e] of  $q_{j}^{(1)}(t).$  Then,  $q_{j}^{(1)}(t)=\int_{s}^{t}x_{j}(\tau)d\tau-\rho_{j}(t-s)-\int_{s}^{t}l_{j}^{(1)}(\tau)d\tau\leq\int_{s}^{t}x_{j}(\tau)d\tau-\rho_{j}(t-s)\leq q_{j}(t)$  where the last inequality holds by (5). Therefore,  $q^{(1)}(t)\leq \Sigma_{j\in I^{(1)}}q_{j}(t),\forall t,$  which leads to  $\Pr[q^{(1)}=B^{(1)}]\leq \Pr[\Sigma_{j\in I^{(1)}}q_{j}\geq B^{(1)}]$  in steady state. Thus,  $\tilde{P}^{i}_{\text{blocking}}\leq \Pr[\Sigma_{j\in I^{(1)}}q_{j}\geq B^{(1)}].$  Furthermore, since  $q_{j}(t),j\in I^{(1)},$  are independent of each other, we get  $\Pr[\Sigma_{j\in I^{(1)}}q_{j}\geq B^{(1)}]=\int_{B^{(1)}}^{\infty}[\otimes_{j\in I^{(1)}}h_{j}(q_{j},\rho_{j})]dq^{(1)}.$  The proof of (35) is similar to that of (18) in Proposition 3.

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