Connection Admission Management for Self-Similar Traffic

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Abstract

In this paper, we investigate connection admission management for connections which generate self-similar traffic. We present a simple mathematical framework which does not require restrictive assumptions about the network behaviour. We show how this framework can be used to derive connection admission policies.

I) Introduction

Several studies [1]-[4] have claimed that different types of network traffic, *e.g*. local area network traffic (LAN), can be accurately modeled by a self-similar process. A self-similar process is able to capture the long-range dependence (LRD) phenomenon exhibited by this traffic. Moreover, series of simulation and analytical studies [2]-[3] have demonstrated that this phenomenon might have a pervasive effect on queueing performance. In fact, there is clear evidence that it can potentially cause massive cell losses in Asynchronous Transfer Mode (ATM) networks. Actually, the buffer overflow probability for an ATM queueing system with fractional Brownian arrivals follows a Weibull distribution. Furthermore, this queueing system suffers from the buffer inefficacy phenomenon [3], [7]. By just increasing the buffer size we are not able to significantly decrease the buffer overflow probability. Although several works have analyzed the self-similar nature of traffic, control mechanisms for self-similar traffic have not yet been fully investigated.

One of the key ideas behind Asynchronous Transfer Mode is the statistical multiplexing of heterogeneous packetized streams. The concept of Effective Bandwidth is intimately connected with admission management and associated service requirement [4]. The equivalent bandwidth of a connection (source) is a characterization of the demanded bandwidth of the connection such that its QoS requirements are provided in a network based on statistical multiplexing. Designers have gravitated towards the concept of equivalent bandwidth because it promises to bridge to familiar circuit-switched network design. Although connection admission management is crucial to transport providers, very little is know about the admission of heterogeneous connections with long-range dependencies. Few results based on the Theory of Large Deviation are available [4]-[8]. Nonetheless, these results require assumptions which may not correspond to the behaviour of real networks. In this paper, we derive expressions for the management of heterogeneous self-similar sources using very simple assumptions about the network. Moreover, we show how these expressions can be used to define connection admission procedures.

Actually, results shown in this paper are built on the top of a framework previously defined by ourselves [9]-[13]. In [9] we proposed a new traffic model called a fractional Brownian motion (fBm) envelope process which characterizes LRD sources. We also derived a new framework for computing probabilistic delay bounds for a deterministic queuing system, as a model of an ATM network, driven by this source. We showed that the delay bounds agree with known results obtained by large deviation theory. This new traffic characterization made possible a more intuitive understanding of the dynamics of the queuing system. We also derive three time-scales that completely characterize the queuing system behaviour [10]. Moreover, we analyzed different buffer management policies for providing diverse loss requirements to self-similar sources in overflow situations [11]-[13].

This paper is organized as follow. In section II we show an envelope process for a fractal Brownian motion process. In section III we introduce the time scale of interest for a queuing system fed by a self-similar process. In section IV we study the management of heterogeneous self-similar sources. Finally, conclusions are drawn in section V.

II) A Fractal Brownian Motion Envelope Process

It is well known that for a Brownian motion (Bm) process *A(t)* with mean $\bar{a}$ and variance σ^2, the envelope process $\hat{A}(t)$ can be defined by [14]:

$$\hat{A}(t) \stackrel{def}{=} \bar{a}t + k\sqrt{\sigma^2 t} = \bar{a}t + k\sigma t^{1/2}$$

The parameter *k* determines the probability that *A(t)* will exceed $\hat{A}(t)$ at time *t.* Since *A(t)* is a Brownian motion process we can write:

$$P\left(\frac{A(t) - \bar{a}t}{\sigma t^H} > k\right) = \Phi(k)$$

where Φ(y) is the residual distribution function of the standard Gaussian distribution. Using the approximation $\Phi(y) \approx (2\pi)^{-1/2}(1 + y)^{-1}\exp((-y^2/2) \approx \exp(-y^2/2))$ we find *k* such that $\Phi(k) \le \varepsilon$. Hence, *k* is given by $k = \sqrt{-2\ln\varepsilon}$.

We claim that $P(A(t) > \hat{A}(t)) \approx \varepsilon$, where $k = \sqrt{-2\ln\varepsilon}$. This approach can be extended to deal with LRD traffic. Let $A_H(t)$ be a fractional Brownian motion process with mean $\bar{a}$. Hurst's law states that the variance of the increment of this process is given by $Var[A_H(t + s) - A_H(t)] = \sigma^2 s^{2H}$ where $H \in [1/2, 1)$ is the Hurst parameter. Thus, we can also define a fBm envelope process by:

$$\hat{A}_H(t) \stackrel{def}{=} \bar{a}t + k\sqrt{\sigma^2 t^{2H}} = \bar{a}t + k\sigma t^H \quad (1)$$

The Brownian motion envelope process is just the special case of *H* = 1/2. Similarly, *k* determines the probability that $A_H(t)$ will exceed $\hat{A}_H(t)$. In addition, since the process exhibits LRD, if $A_H(t)$ exceeds $\hat{A}_H(t)$ at time *t*, it is possible that it will stay above it for a long period of time.

We should note that the source does not necessarily need to be self-similar in order to match this characterization, as long as it matches the behaviour of the envelope process over the time-scale of interest. We investigate the accuracy of the fBm envelope process representation by inspecting how well it can model the worst-case behaviour of real network traffic. Assume that the input traffic is characterized by trace with N sample points, defined by $A(t)$, where $A(t)$ represents the cumulative number of cell arrivals up to time t, $t \in [1,2\ldots,N]$. We propose a very simple method for computing the fBm envelope process parameters for this trace, by computing the trace's optimal envelope process. The advantage of this approach relies on the fact that we do not need to accurately estimate the trace's Hurst parameter. The optimal envelope process (the worst-case sample path) for this trace is defined by $Y(t-s) = max_{s<t}(A(t)-A(s))$. We assume that the process is stationary so that $Y(\tau)$, $\tau = t - s$ defines the maximum number of cell arrivals in an interval of size τ. Therefore, we can choose the fBm envelope process's parameters $\hat{A}_H$ (.) so that it matches the behaviour of Y(.).

We compare the envelope process representation to Bellcore's LAN trace. We compute the sample average arrival rate and the sample variance for this trace and substitute for $\bar{a}$ and σ^2 in Equation 1. We compute the optimal envelope process, i.e Y(.), and choose H so that $\hat{A}_H(.)$ matches the behaviour of Y(.). Results indicate that the proposed process is an accurate traffic model [10].

We extensively validated the effectiveness of the fractal Brownian motion envelope process by utilizing synthetic traces generated by Mandelbort's procedure [15]. For every trace used, we verified if the mean, the variance and the Hurst parameter were in agreement with the specified values. We investigate the accuracy of the envelope process by varying the traffic parameter in the following range: $\bar{a} \in [0.5,1.0]$, $\sigma^2 \in [0.01,0.7]$, $H \in [0.5,1.0]$, $\varepsilon \in [10^{-3},10^{-9}]$, where the mean and the variance are normalized to the channel capacity. Results indicate that the fBm envelope process is a close upperbound for a fBm process. Moreover, the fBm envelope process is highly accurate in all mentioned ranges.

The fBm envelope presents several advantages:

• It is parsimonious, i.e. only three parameters are required in order to completely characterize a source;

• It can represent SRD and LRD, i.e, the source does not necessarily need to be LRD. We need only to choose the parameters for the fBm envelope process so that it matches the source's optimal envelope process over the appropriate time-scale;

• The input parameters $\bar{a}$, σ, and H can be provided by the source or estimated in real-time from the incoming traffic sample by estimating its optimal envelope process;

• It provides very accurate delay bounds with minimal computational complexity.

III) Time Scale of Interest

In this section, we show the time until a queue reaches its maximum occupancy, in a probabilistic sense. The queue size at this time gives us a simple delay bound [9]. A rigorous mathematical derivation of the delay bound can be found in [10]. Here, we introduce an heuristic derivation in order to preserve the intuition behind the framework presented in this paper. Consider a continuous-time queuing system, with deterministic service given by c. The cumulative arrival process is given by $A_H(t)$ ($A_H(0) = 0$). Let $\hat{A}_H(t)$, continuous and differentiable, be the probabilistic envelope process of $A(t)$ such that $P(A_H(t) > \hat{A}_H(t)) \leq \varepsilon$

During a busy period which starts at time 0, the number of cells in the system at time t is given by $q(t)$. Thus, $q(t) = A_H(t) - ct \geq 0$.

By defining $\hat{q}(t)$ as

$$\hat{q}(t) = \hat{A}_H(t) - ct \geq 0 \quad (2)$$

We can see that $P(q(t) > \hat{q}(t)) = P(A_H(t) > \hat{A}_H(t)) \leq \varepsilon$

The maximum delay in a FIFO queuing system is given by the maximum number of cells in the queue during the busy period. We define

$$q_{max} \overset{def}{=} max(\hat{q}(t)) \qquad t \geq 0$$

Therefore, $P(q(t) > q_{max}) \leq P(q(t) > \hat{q}(t)) \leq \varepsilon$ and $P(q(t) > q_{max}) \approx \varepsilon$

We can say that the queue length at time t $q(t)$ will only exceed the maximum queue length q_{max} with probability e. In other words, only when the arrival process exceeds the envelope process, will the maximum number of cells in the system exceed its estimated value. Intuitively, by bounding the behaviour of the arrival process we are able to transform the problem of obtaining a probabilistic bound of the stochastic system defined by $q(t) = A_H(t) - ct \geq 0$ into an easier problem of finding the maximum of a deterministic system described by $\hat{q}(t) = \hat{A}_H(t) - ct \geq 0$.

For the case of the fBm process, we substitute the envelope process defined previously into Equation 2 which gives

$$\hat{q}(t) = \hat{A}_H(t) - ct = \bar{a}t + k\sigma t^H - ct \qquad (3)$$

In order to compute q_{max} we need to find t^* such that

$$\frac{d\hat{q}(t^*)}{dt} = 0$$

or equivalently,

$$\frac{d\hat{A}_H(t^*)}{dt} = c \quad (4)$$

Hence, t^* is given by

$$t^* = \left[\frac{k\sigma H}{(c - \bar{a})}\right]^{\frac{1}{1-H}}$$

The time-scale of interest is defined by the time until a queue size reaches its peak, i.e., t^*. We call it the Maximum Time-Scale (MaxTS), and it defines the point in time where the unfinished work in the queuing system achieves its maximum in a probabilistic sense. It means that the average arrival rate just dropped below the link capacity so that the queue size starts decreasing. The average arrival rate converges to the source's mean arrival rate by the law of large numbers. Consequently, we need to worry only about the time scale for which the source's rate still exceeds the link capacity, in a probabilistic sense. In other words, after a period of time, the probability that the average arrival rate exceeds the link capacity is negligible, so that the arrival model does not need to reproduce the source's behaviour for those time-scales. This is the most important time-scale in terms of traffic modelling. As a rule of thumb to choose the parameters of an input source in order to match the fBm envelope process, we need to find MaxTS analytically, and to choose the parameters of the fBm process, so that it matches the source's optimal envelope process at MaxTS.

Substituting t^* back into Equation 2, we conclude that:

$$q_{max} = \hat{A}_H(t^*) - ct^* \quad (5)$$

$$q_{max} = (c - \bar{a})^{\frac{H}{H-1}} (k\sigma)^{\frac{1}{1-H}} H^{\frac{H}{1-H}} (1-H)$$

Since the fBm process does not exceed $\hat{A}_H(t)$ with probability 1 - ε, the maximum number of cells will be bounded by q_{max} with the same probability. We find $\hat{c}$ so that q_{max} is equal to K. In other words, a buffer of size K will overflow with probability e if the link capacity is $\hat{c}$. Therefore, $\hat{c}$ is given by $\hat{c} = a + K^{\frac{H-1}{H}} (k\sigma)^{1/H} H(1-H)^{\frac{H-1}{H}}$

This result was also obtained by Norros [6] and Duffield [7]. In summary, our framework allow us to compute delay bounds with little computational effort yet achieve the same accuracy of the results predicted by large deviation theory. We have also reduced the sensitivity of the estimation process by using a bound rather than attempting to directly estimate the parameters from the full trace.

IV) Statistical Multiplexing of Self-Similar Sources

In this section, we use MaxTS to derive expressions for predicting the equivalent bandwidth and buffer requirements of an aggregate of self-similar sources. Essentially, we propose a way to compute the demanded bandwidth to support requirements of buffer overflow as well as a maximum probabilistic delay for an aggregate of sources with diverse traffic parameters. The problem we study in this section can be stated as:

Given a set of sources with mean $\bar{a}_i$, standard deviation σ_i and Hurst parameter H_i, what is the link capacity needed so that the maximum queue size will be bounded by q_{max} with probability ε?

Assume that we have N independent sources $A_H^i(t)$ defined by the following parameters: mean $\bar{a}_i$, standard deviation σ_i and Hurst parameter H_i for $i \in [1,N]$. Let the aggregate traffic be denoted by $A_H(t) = \sum_{i=1}^{N} A_H^i(t)$. The envelope process of each source is given by $\hat{A}_H^i(t)$, and the envelope process of the aggregate traffic is provided by $\hat{A}_H(t)$. We can compute q_{max} of a queue with heterogeneous sources by finding t^* for the envelope process of the aggregate stream.

The mean of the aggregate traffic is given by the sum of the mean of individual sources. Similarly, since the sources are independent, the variance of the aggregate traffic is also given by the sum of the variance of individual sources. Hence, the envelope process of the aggregate traffic is defined by:

$$\hat{A}_H(t) = \sum_{i=1}^{N} \bar{a}_i t + k\left(\sum_{i=1}^{N} \sigma_i^2 t^{2H_i}\right)^{1/2}$$

By substituting $\hat{A}_H(t)$ in equation 4, we have:

$$k\frac{1}{2}\left(\sum_{i=1}^{N} \sigma_i^2 t^{2H_i}\right)^{-1/2}\left(\sum_{i=1}^{N} \sigma_i^2 \; 2H_i \; t^{2H_i - 1}\right) = c - \sum_{i=1}^{N} \bar{a}_i \qquad (6)$$

We can solve equation 6 numerically in order to find t^* and then substitute t^* into Equation 5 to compute q_{max}.

Moreover, by combining Equations 4 and 5, we have:

$$k\frac{1}{2}\left(\sum_{i=1}^{N} \sigma_i^2 t^{2H_i}\right)^{-1/2}\left(\sum_{i=1}^{N} \sigma_i^2 2H_i t^{2H_i - 1}\right) - k\left(\sum_{i=1}^{N} \sigma_i^2 t^{2H_i - 2}\right)^{1/2} + \frac{q_{max}}{t} = 0 \qquad (7)$$

By using Equations 6 and 7 we can answer the fundamental question posed in the beginning of this section.

For the special case of multiplexing N identical sources, the envelope process is given by $\hat{A}_H(t) = N\bar{a}t + \sqrt{N}k\sigma t^H$ insofar as the Hurst parameter is preserved when aggregating N identical sources. In this case Equation 6 is, reduced to:

$$\frac{k}{2}\frac{(N\sigma^2 2Ht^{2H-1})}{(\sqrt{N}\sigma t^H)} = N(c - \bar{a})$$

Using the previous approach, we can find t^* and q_{max}:

$$t^* = \left[\frac{\sqrt{N}k\sigma H}{N(c - \bar{a})}\right]^{\frac{1}{1-H}} = N^{\frac{1}{2(H-1)}} t_i^*$$

$$q_{max} = N(\bar{a} - c)N^{\frac{1}{2(H-1)}} t_i^* + N^{\frac{H}{2(H-1)}} N^{1/2} k\sigma (t_i^*)^H = N^{\frac{(H-1/2)}{H-1}} \hat{q}_{max}$$

$$t_i^* = \left[\frac{k\sigma H}{(c - \bar{a})}\right]^{\frac{1}{1-H}} \qquad \hat{q}_{max} = \hat{A}_H(t^*) - ct_i^*$$

where t_i^* and $\hat{q}_{max}$ corresponds to a queueing system fed by just one source.

To evaluate the effectiveness of the equivalent bandwidth expressions (Equations 6/7), we define multiplexing gain as the ratio between N times the equivalent bandwidth of a single source and the equivalent bandwidth of N identical sources. We realize that a significant multiplexing gain can be achieved when multiplexing homogeneous sources. In Figure 1 we plot the gain for a link capacity of 150 Mbits and sources with mean arrival rate 1.1Mbps for different Hurst parameter. Figure 1.a displays the multiplexing gain for sources with $\sigma^2 = 0.01$ whereas Figure 1.b considers sources with $\sigma^2 = 0.3$. We observe that the gain for streams with moderate to high variance ($\sigma^2 = 0.3$) is significantly higher than for streams with low variance ($\sigma^2 = 0.01$). While for streams with $H = 0.9$ and low variance the gain is 1.25, it is almost 2.5 for streams with moderate to high variance.

The multiplexing gain also increases with the Hurst parameter, specially for streams with moderate to high variance. This can be understood by the fact that Equations 6/7 take into consideration the existence of long periods with no arrivals in streams with high Hurst parameters. As a consequence we have a lower bandwidth demand when multiplexing several sources than a no-multiplexing approach.

In Figure 2 we display the accuracy of the overflow probability computed by Equations 6/7 as a function of the buffer size. We consider an aggregate of sources with diverse traffic parameters (Table 1). As it can be seen, Equations 6/7 predict overflow probability which is in fair agreement with simulation outcomes. The larger the buffer the more accurate are our results. For small buffer sizes the difference between the overflow probability computed via our analytical model and via simulation is less than an order of magnitude.

We can use Equations 6/7 to derive admissible regions for scenarios with heterogeneous sources. In Figure 3 we illustrate the admission region for two classes of sources, different buffer sizes and for overflow probability of 10^{-6}. The definition of such region can be used to achieve a desired revenue/utilization ratio. Note that as the variance increases we considerably decrease the number of accepted sources. Moreover, the impact of the variance on the number of admitted sources is stronger for smaller buffer sizes.

The aim of every transport provider is to maximize revenue. Each connection brings a certain network demand, as well as a certain revenue. In addition, the revenue depends on the adopted pricing policies. A common pricing policy is based on the duration of the connection as well as the amount of the carried traffic [16]. In other words, the price of a connection can be defined as $price = a\,T + b\,V$ where a and b are constant, T is the duration of a connection and V is the carried traffic volume. In Figure 4, we show an example with two types of connections described in Table 2. Connections arrive according to a Poisson process and their durations are normally distributed. We consider $a = 1$ profit units and $b = 1.5\,a$. In Figure 4.a we show the revenue when both type of connections have the same duration ($\mu = 700$ ATM time slots) and different mean interarrival time [16]. Note that as the network utilization increases we admit a lower number of more demanding connections, and consequently decreases the revenue given by this class. In Figure 4.b both classes have the same arrival rate and the less stringent class (Class A) has the highest connection duration. Note that since class A holds the channel for longer period of time. We admit a lower number of class B connections than in the previous example.

V) Conclusions

Since the publication of findings about the self-similar nature of network traffic [1], there has been a great interest in traffic management mechanisms for this type of traffic. If on one hand, connection admission is crucial to transport providers. On the other hand, very little is known about connection admission for self-similar sources. The only available results use assumptions which may not correspond to real network behaviour. In this paper, we introduced a framework for defining connection admission procedures. By using this framework, admission as well as pricing policies can be defined to achieve a desired network revenue.

VI) References

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Table 1: Traffic Parameters for Figure 2

Sources	$\bar{a}$	σ	H
A	0.13	0.10	0.63
B	0.11	0.07	0.72
C	0.13	0.07	0.78
D	0.12	0.07	0.86
E	0.11	0.04	0.90

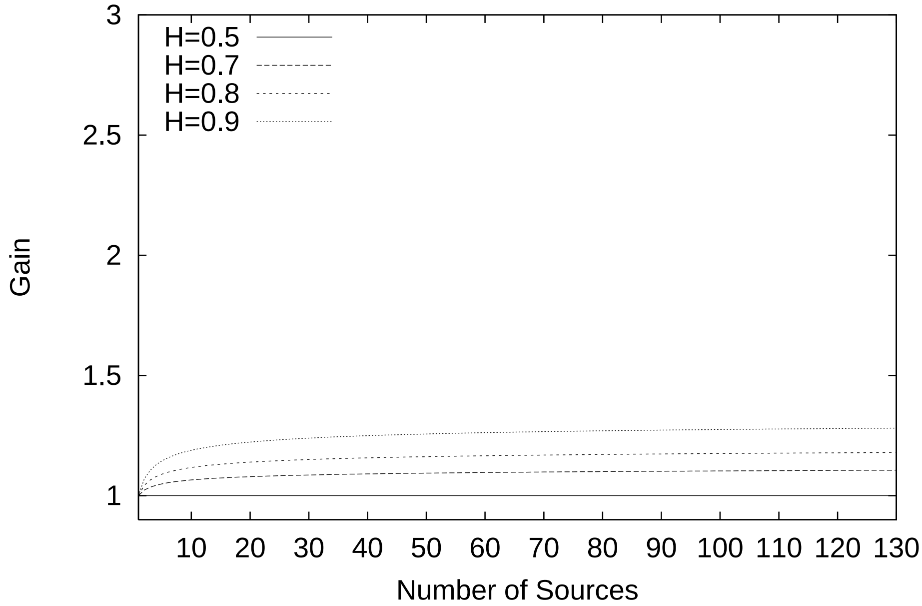

Figure 1a: Streams with Low Variance

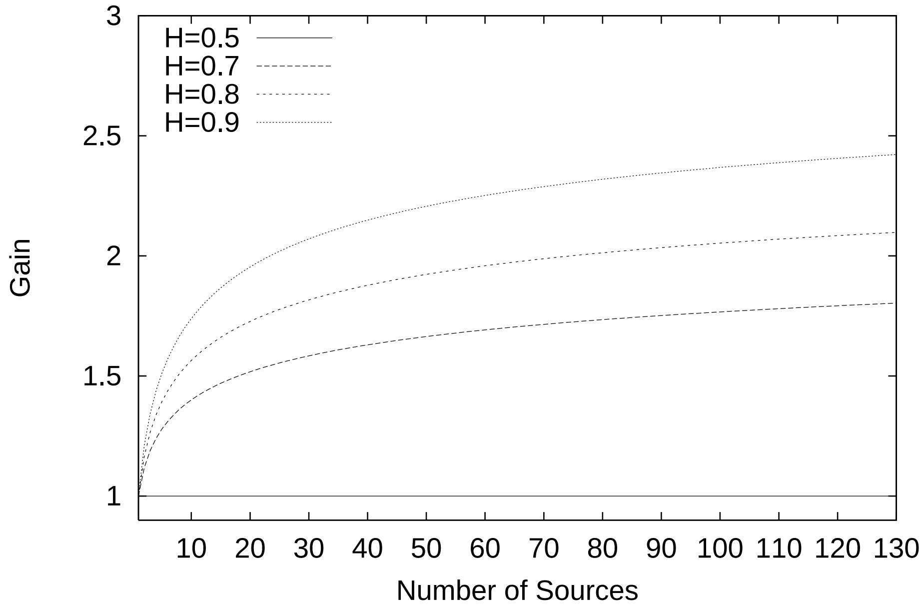

Figure 1.b: Stream with Moderate to High Variance

Figure 1: Multiplexing Gain for Streams with Different Hurst Paramete

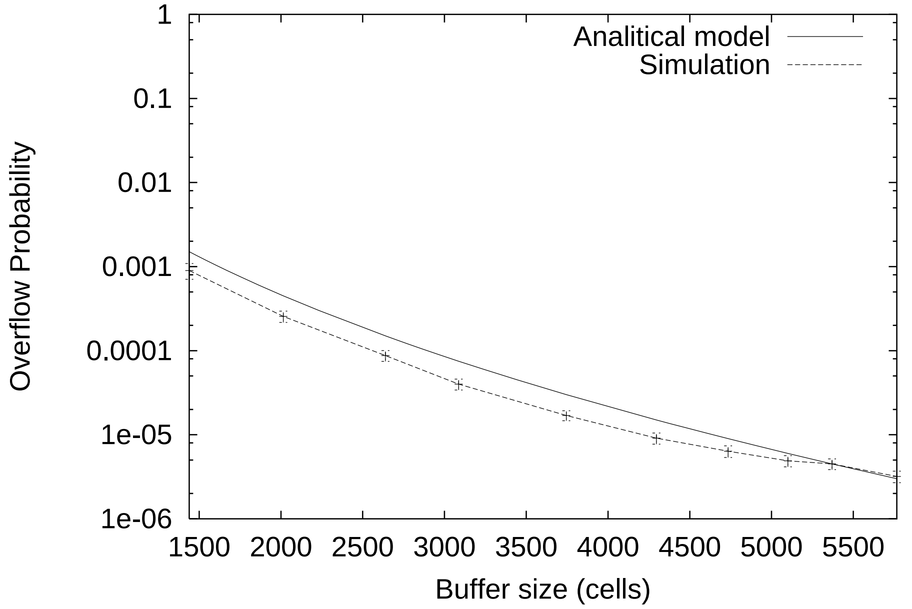

Figure 2: Overflow probability x Buffer Size for Heterogeneous Sources

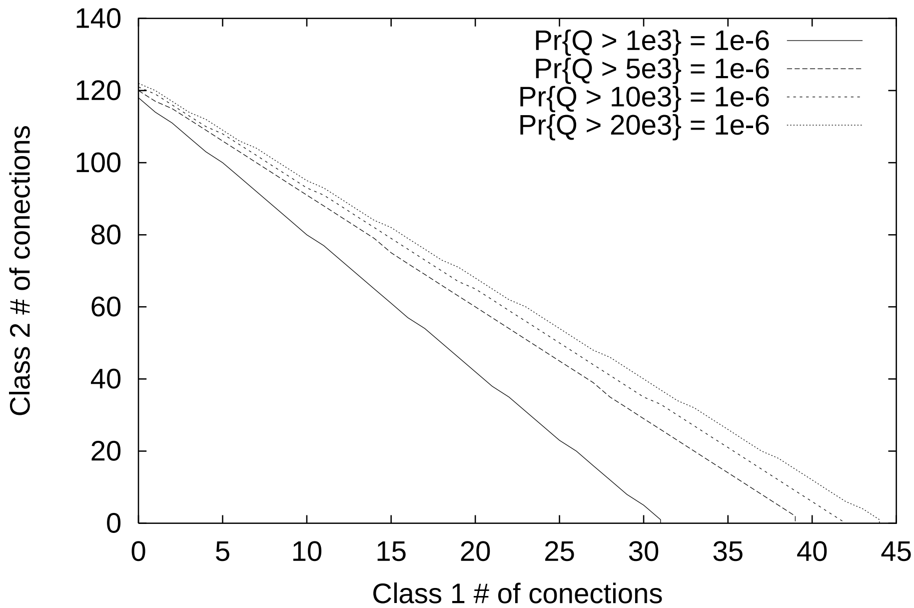

Figure 3.a: Streams with Low Variance

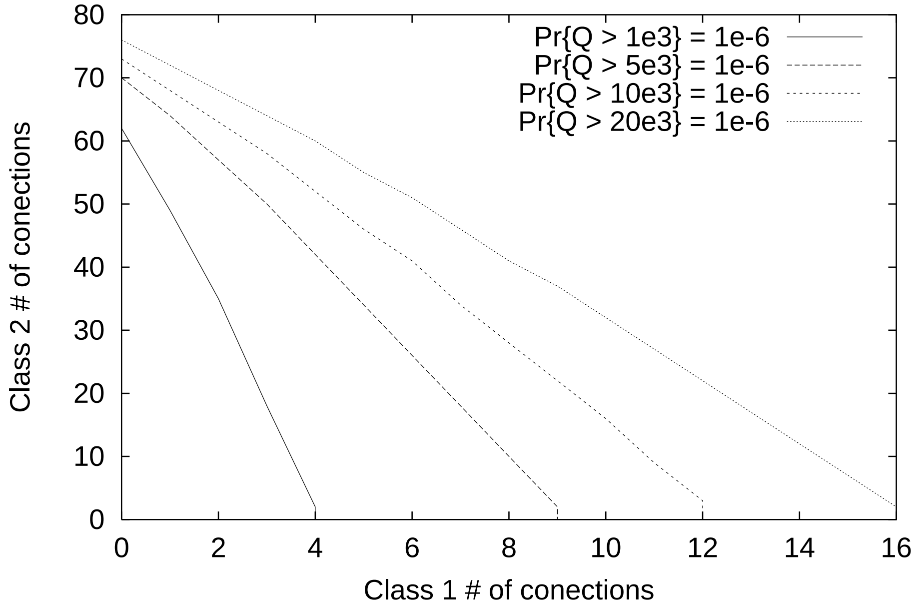

Figure 3.b: Stream with High Variance

Figure 3: Admission Regions for two Different Classes of Sources

Table 2: Traffic parameter for Figure 4

	$\bar{a}$	σ	H
Class A	2.84×10^{-4}	2.25×10^{-4}	0.63
Class B	2.2×10^{-3}	1.63×10^{-4}	0.8

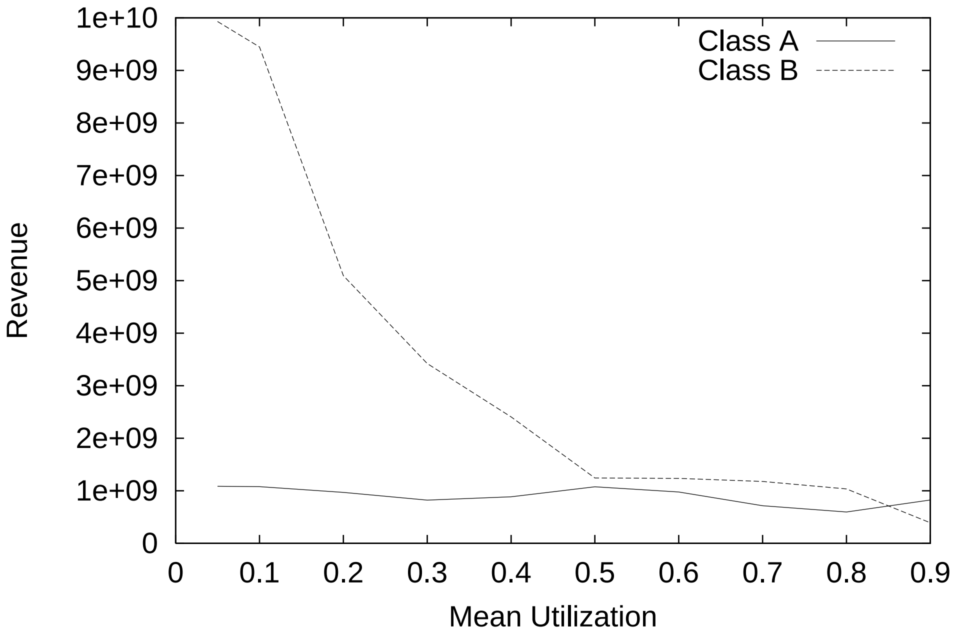

Figure 4.a: Class A and Class B interarrival time are respectively 200 and 100 slots and the mean connection duration is 700 ATM slots

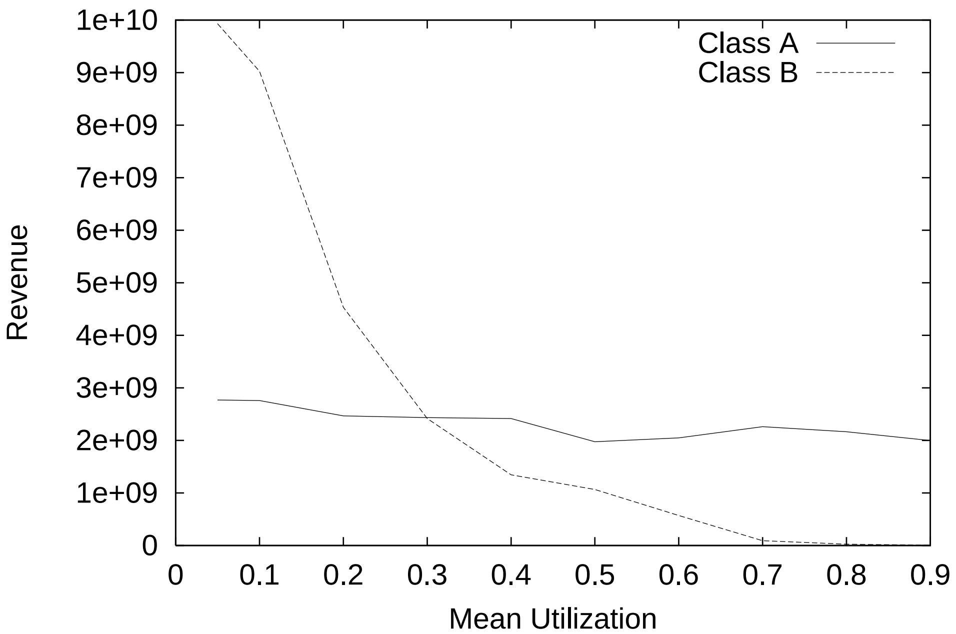

Figure 4.b: Both classes have mean intearrival time of 100 slots. Class A and Class B connection duration time are 900 and 700 slots, respectively.

Figure 4: revenue per class as a function of the network utilization