Adaptive Effective Bandwidth Allocation Schemes

by

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Abstract

As a promising approach to achieve the trade-off between the high network utilization and the provision of quality of service (QoS), the concept of effective bandwidth has been widely accepted.

However, it is well known that pure effective bandwidth allocation is conservative. To overcome this issue, we develop a traffic measurement-based *adaptive effective bandwidth allocation* (AEBA) algorithm. We develop a framework of using *dynamic weighted round robin* (DWRR) scheduling with measurement-based AEBA approach to study the statistical QoS assurance issue for self-sizing networks supporting service differentiation.

We evaluate our algorithms with both theoretical analysis and simulation experiments. We develop a set of simulations using both traditional Poisson traffic and self-similar traffic as input. The simulation results show that our approach allows different QoS requirements to be satisfied while effectively exploiting the statistical multiplexing gain occurring among multiple traffic classes at the same time. The simulation results also show that our approach is robust in that it does not need any assumptions about the underlying traffic and it is insensitive to the system parameters.

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To my family

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List of Acronyms

AEBA	Adaptive Effective Bandwidth Allocation
CAC	Connection Admission Control
DTMW	Double Threshold Moving Window
DWRR	Dynamic Weighted Round Robin
FIFO	First in First out
GPS	Generalized Processor Sharing
LRD	Long-range dependence
MMP	Markov Modulated Process
MMPP	Markov Modulated Poisson Process
MSA	Many Sources Asymptotic
QoS	Quality of Service
SRD	Short-range dependence

List of Notations

α	Effective bandwidth of a stationary process
$1/\beta$	Mean length of time of state 2
$1/\mu$	Mean length of time of state 1
ε	Buffer overflow probability
σ	variance coefficient
B	Buffer size
C	Channel capability
$E\{X\}$	Expectation of X
g	Multiplexing Gain Parameter
H	Hurst parameter
P_{loss}	Packet loss probability
s	Space-scale parameter
t	Time-scale parameter
$X[0,t]$	Amount of data that arrives from a source during the interval of length t

1 Introduction

1.1 Background

Effective bandwidth, or its synonyms, equivalent bandwidth or equivalent capacity, has been the subject of intense research activities since the idea was proposed by Hui in the seminal paper [23] in 1988. Afterward, many researchers have contributed to develop the appropriate notion of effective bandwidth by investigating different traffic models.

The original idea of effective bandwidth has been proposed in the context of connection admission control (CAC) for ATM networks. Typically, a large number of traffic streams with a wide variety of traffic statistics and quality of service (QoS) requirements are integrated into such networks. The effective bandwidth is a measure of resource usage, which adequately represents the trade-off between traffic streams of different types, taking proper account of their varying statistical characteristics and QoS requirements [25].

The general notion of effective bandwidth is that: given the system parameters such as the buffer space B and channel capability C , we wish to know how to estimate the required bandwidth, say α_j , for a set of traffic sources with the QoS requirement in terms of buffer overflow probability ε , such that $P\{\text{queue length} \geq B\} \leq \varepsilon$ if

$$\sum_j \alpha_j M_j \leq C, \quad (1.1)$$

where α_j is the effective bandwidth of source type j and M_j is the number of sources of type j [15] [25] [27] [47].

From CAC's perspective, effective bandwidth can be defined for an arbitrary collection of traffic sources as the minimum bandwidth needed at the multiplexer to support these sources together without violating the QoS requirements [36].

From a practical standpoint, two essential characteristics of effective bandwidths are defined in [16] [37]:

- Independence property: the effective bandwidth of a traffic stream is independent of the other streams with which it is mixed, it is only a function of the traffic stream's parameters.
- Additive property: Effective bandwidths are additive, that is, the sum of the effective bandwidths of a set of independent traffic streams is equal to the effective bandwidth of their superposition.

If these two requirements hold, determining whether a given collection of traffic sources can be accommodated without violating their QoS requirements simplifies to comparing the sum of the effective bandwidth of individual sources in that collection to the link bandwidth, as shown in (1.1).

In the literature, there are many approaches to estimate the effective bandwidth for a bursty source. In general, we can categorize them into two classes: the first one includes the analytic approaches based on traditional queueing theory. By hypothesizing the traffic models, an explicit expression for the effective bandwidths of some traffic sources (such as Markov and fBm processes) can be obtained. There is a rich literature about such approaches, see, for example, [8] [12] [15] [18] [25] [33] [47] etc. In Chapter 2, we will give a brief review of some typical ones.

The second categorization is to use Kelly's definition to calculate the effective bandwidth of the arriving traffic. Based on large deviation theory, Frank Kelly defined a mathematical framework [25] for the effective bandwidth of a stationary arrival process as follows:

$$\alpha(s, t) = \frac{1}{st} \log E[e^{sX[0, t]}] \quad 0 < s, t < \infty, \quad (1.2)$$

where s is the space-scale parameter and t is the time-scale parameter, $X[0, t]$ denotes the amount of data that arrives from a source during the interval of length t . Here, the arrival process can be an individual traffic flow or an aggregate traffic stream. For the latter, $X[0, t]$ can be expressed as:

$$X[0, t] = \sum_{j=1}^J \sum_{i=1}^{M_j} X_{ji}[0, t], \quad (1.3)$$

where $X_{ji}[0, t]$ are independent processes with stationary increments whose distributions depend on j but not on i . M_j is the number of sources of type j . Depending on whether the arrival process is modeled as a single aggregate traffic stream, or it is broken down into individual flows, the effective bandwidth can be calculated for the aggregate, $\alpha(s, t)$, or for

each flow separately, $\alpha_j(s,t)$. Provided that the flows are independent of each other, according to the additive property, the following relationship between $\alpha(s,t)$ and $\alpha_j(s,t)$ holds:

$$\alpha(s,t) = \sum_{j=1}^J M_j \alpha_j(s,t) . \quad (1.4)$$

We will prove this equation in the next chapter.

Nowadays, besides CAC, the concept of effective bandwidth has also been applied to resource management, network dimensioning and optimal charging.

1.2 Motivation

In this thesis, we develop a framework for using on-line measurement-based *adaptive effective bandwidth approach* (AEBA) under *dynamic weighted round robin* (DWRR) scheduling to study the statistical QoS assurance issue in self-sizing networks supporting differentiated services. Our motivation comes mainly from the following two aspects.

The first one arises from the fact that most research on effective bandwidths is based on First in First out (FIFO) queueing discipline. They require all traffic sources to be at the same priority and have the same QoS requirements [40]. In real networks, different classes of traffic will have different QoS demands. Some researchers have done the research on effective bandwidths under Generalized Processor Sharing (GPS) [46][48] scheduling, however, their approaches departed from the additive and independence

requirements of the effective bandwidth method, that is to say, the effective bandwidth of a source depends not only on the traffic characteristic and QoS requirement of that source, but also on the other sources sharing the link, which makes the concept of effective bandwidth lose its original goal and not practically useful [48].

The second one is that the current effective bandwidth methods may turn out to provide conservative estimates of the bandwidth requirements [9] [18] [36] [40] [44], especially when the buffer size is small and moderate. Our simulation results in Chapter 4 also support this conclusion.

Realizing the conservative nature of the effective bandwidth approaches in which there may exist significant potential statistical multiplexing gain to exploit, we develop the adaptive effective bandwidth allocation scheme. Our aim is to provide differentiated statistical QoS guarantees to different traffic classes while exploiting the statistical multiplexing gain occurring among multi traffic classes without losing the independence and additive properties of the effective bandwidth. We focus our work at the edge of the network.

1.3 Contributions

We address the conservative nature of effective bandwidths by developing the AEBA algorithm. Applying AEBA to DWRR scheduling, we provide the service differentiation

to different traffic classes. We quantify the statistical multiplexing gain among multi traffic classes by means of both theoretical analysis and simulation experiments [30].

We develop a bandwidth reallocation control mechanism to reduce the bandwidth reallocation frequency and the buffer overflow preventive mechanism to improve the buffer utilization. We also develop a quick sustained burstiness detection algorithm to make our on-line measurement AEBA algorithm insensitive to the measurement window size [31].

We advocate a *unified on-line AEBA approach* to bypass modeling the underlying traffic, and prove its feasibility through simulations with both long-range dependent (LRD) and short-range dependent (SRD) traffic as input.

1.4 Outline

The rest of this thesis is organized as follows: In Chapter 2, we briefly review some typical effective bandwidth methods and prove some important properties of effective bandwidth defined by (1.2). After that, we discuss the common issues of effective bandwidths in more detail. Then in Chapter 3, we propose our solutions to solve these issues. We will describe the dynamic weighted round robin scheduling, adaptive effective bandwidth allocation scheme, buffer overflow preventive mechanism, sustained burstiness detection method and the bandwidth reallocation frequency control algorithm. Next in Chapter 4, with the help of the concept of virtual FIFO queueing system, we analyze the potential statistical multiplexing gain occurring among multi traffic classes

under DWRR. We also give the simulation results to validate our proposals and analysis. Finally, in chapter 5, we state the conclusions and give the recommendations for future study.

2 Development of Effective Bandwidth Theory

The effective bandwidth of one source is determined by its traffic characteristic and the associated QoS requirement. Since the notion of effective bandwidth was originally introduced to simplify the call admission procedure in packet-switched networks, a lot of researchers have shown the existence of effective bandwidths for a large class of traffic models.

2.1 ON-OFF Model

By an ON-OFF source, we mean a traffic source that alternates between the exponentially distributed active (ON) and silent [OFF] periods, with the transmission rate being constant during the ON period [3]. This is often a good abstraction of a data communication terminal [37]. The ON-OFF model is also the most popular model for voice sources [1].

Let the ON and OFF periods of a traffic source be exponentially distributed with means $1/\mu$ and $1/\beta$ respectively. When the source is ON, it produces information at a constant rate γ . Gibbens and Hunt [15] derived the effective bandwidth of a single ON-OFF source i as

$$\alpha_i(s) = \frac{s\gamma - \mu - \beta + \sqrt{(s\gamma - \mu + \beta)^2 + 4\beta\mu}}{2s}, \quad (2.1)$$

where s is related to the loss probability requirement P_{loss} and can be approximated as $-\log(P_{loss})/B$.

In this framework, the overall effective bandwidth of a set of i.i.d. ON-OFF sources is equal to the sum of the effective bandwidth of individual sources in that set. However, this method is generally conservative because it does not take into account the interaction between individual traffic streams. To capture the effect of multiplexing, Guérin et al. proposed a Gaussian approximation method as a refinement of the ON-OFF model.

2.2 Refinement of ON-OFF Model with Gaussian Approximation

In [18], a hybrid approach of effective bandwidth was proposed. Firstly, a flow approximation that is similar to the above ON-OFF effective bandwidth model is used. The effective bandwidth of a single ON-OFF source, which is characterized by the peak rate γ , utilization ρ , and mean burst period b , is obtained as:

$$\alpha_i(s) = \frac{sb(1-\rho)\gamma - 1 + \sqrt{[sb(1-\rho)\gamma - 1]^2 + 4sb\rho(1-\rho)\gamma}}{2sb(1-\rho)}, \quad (2.2)$$

where $s = -\log(P_{loss})/B$.

Note that formula (2.1) is identical to formula (2.2) by substituting μ and β with $1/b$ and $\frac{\rho}{b(1-\rho)}$ in formula (2.1) respectively.

Secondly, considering multiple sources, a Gaussian approximation is adopted. Assuming that the distribution of the aggregate bit rate of a set of traffic streams can be accurately approximated by a Gaussian distribution, the effective bandwidth for the aggregate stationary bit rate is derived as:

$$C = m + \sigma \sqrt{-2 \ln(P_{loss}) - \ln(2\pi)} \quad (2.3)$$

where m is the mean aggregate bit rate, σ is the standard deviation of the aggregate bit rate. The Gaussian approximation is based on a bufferless model, formula (2.3) is obtained from the approximation for the inverse of Gaussian distribution of the aggregate bit rate, of which the cumulative tail probability beyond C does not exceed P_{loss} . Thus, C is an upper bound on the actual bandwidth required for the aggregate traffic to have a loss probability of less than or equal to P_{loss} . Due to the fact that the buffer size is not taken into consideration in the calculation of C , C may significantly overstate the required bandwidth for the aggregate traffic when buffer exists, which is often the case in the realistic networks.

Finally, the flow approximation and the Gaussian approximation are combined together. The total effective bandwidth for the M multiplexing streams is taken as the minimum of Gaussian approximation and the sum of the individual flow approximation:

$$\alpha = \min \{ C, \sum_{i=1}^M \alpha_i \} \quad (2.4)$$

The flow and Gaussian approximation complement each other over the different ranges of sources. For small numbers of sources, the flow approximation tracks the required bandwidth better. As the number of sources increases, the Gaussian approximation performs better.

2.3 General Markov Model

Elwalid and Mitra extended the results of ON-OFF model to the general Markov model in [12]. And Kesidis *et al.* also obtained similar results in [27].

A random process $Y(t)$ is called a Markov process [2] if the future of the process given the present is independent of the past, that is, if for arbitrary times $t_1 < t_2 < \dots < t_k < t_{k+1}$,

$$P[Y(t_{k+1})=y_{k+1} \mid Y(t_k)=y_k, \dots, Y(t_1)=y_1] = P[Y(t_{k+1})=y_{k+1} \mid Y(t_k)=y_k]$$

if $Y(t)$ is discrete-valued, and

$$P[a < Y(t_{k+1}) \leq b \mid Y(t_k)=y_k, \dots, Y(t_1)=y_1] = P[a < Y(t_{k+1}) \leq b \mid Y(t_k)=y_k]$$

if $Y(t)$ is continuous-valued.

By introducing an explicit notion of state into the description of a traffic stream, a Markov modulated process, also called a doubly stochastic process, uses an auxiliary Markov process in which the current state of the Markov process control the probability distribution of the traffic [1][13]. For example, let $x(t)$ be a discrete-time homogeneous Markov process on the states $\{1, 2, \dots, M\}$ with transition matrix r , i.e., r_{ij} is the transition probability from state i to state j . Also let $\{Y_i(t), t = 1, 2, \dots\}$, $i=1, 2, \dots, M$, be a sequence of M i.i.d. random variables. The process $Z(t) = Y_{x(t)}(t)$ is then a Markov Modulated Process (MMP) with modulating process $x(t)$ [7]. Two typical modulated processes are the fluid model and the Poisson model.

The fluid model characterizes the traffic as a continuous stream with a parameterized flow rate. A fluid model is called the Markov modulated fluid model if the flow rate is determined by the current state of the underlying Markov process.

The Markov modulated Poisson process uses Poisson process as the modulated mechanism. In this model, while in state k , the arrivals are Poisson process with intensity λ_k . As the state changes, the rate changes accordingly.

In [12], the authors have shown the existence of the effective bandwidth for a general Markov source. It has been proved to be the maximal real eigenvalue of a matrix, which is derived from the QoS requirements, traffic parameters and network capacities, with dimension equal to the number of source states. Two sets of results are obtained: one for the model of statistical multiplexing with Markov modulated fluid sources and the other for queues in which arrival traffic flows are Markov modulated Poisson processes (MMPP).

For a two-state Markov-modulated fluid source with $1/\mu$ and $1/\beta$ as the mean lengths of time, λ_1 and λ_2 as the rates of the fluid at state1 and state 2 respectively, a close expression for its effective bandwidth is obtained as

$$\alpha(s) = \frac{1}{2s} [(\lambda_1 + \lambda_2)s - \beta - \mu] + \frac{1}{2s} \sqrt{[(\lambda_1 + \lambda_2)s - \beta - \mu]^2 - 4(\lambda_1\lambda_2s^2 - s\beta\lambda_1 - s\mu\lambda_2)} . \quad (2.5)$$

If the rate of one state is set to zero, the same result will be obtained as that in formula (2.1). For example, by setting $\lambda_1 = \gamma$, $\lambda_2=0$, formula (2.5) becomes

$$\alpha(s) = \frac{1}{2s}[\gamma s - \beta - \mu] + \frac{1}{2s}\sqrt{[\gamma s - \beta - \mu]^2 + 4s\beta\gamma}$$

$$= \frac{s\gamma - \mu - \beta + \sqrt{(s\gamma - \mu + \beta)^2 + 4\beta\mu}}{2s},$$

which is exactly the same as formula (2.1).

The effective bandwidth for a two-state MMPP source is derived as

$$\alpha(s) = \frac{1}{2} \left[\frac{\lambda_1 + \lambda_2}{-s} - \frac{\mu + \beta}{1+s} \right] - \frac{1}{2} \sqrt{\left(\frac{\lambda_1 + \lambda_2}{s} + \frac{\mu + \beta}{1+s} \right)^2 - 4 \left(\frac{\lambda_1 \lambda_2}{s^2} + \frac{\mu \lambda_2 + \beta \lambda_1}{s(1+s)} \right)}, \quad (2.6)$$

where λ_1 and λ_2 are Poisson arrival rates at state1 and state2 respectively.

2.4 fBm Model (Norros Formula)

The aforementioned effective bandwidth methods are primarily based on Markov traffic models. However, extensive studies of traffic measurement have shown that scale-invariant burstiness or self-similarity is a ubiquitous phenomenon found in diverse contexts, from LAN and WAN to IP and ATM protocol stacks to copper and fiber optic transmission media [34]. Markov models cannot generally capture such characteristics. For example, in [29], it has been shown that the generally accepted argument for the “Poisson-like” nature of aggregate traffic has very little to do with the Ethernet LAN traffic under study. Ethernet LAN traffic is statistically self-similar. In [35], it has been shown that Poisson processes are only valid for modeling the arrival of user sessions (Telnet connections, FTP control connections) and they fail as accurate models for other WAN arrival processes. Wide area traffic is much burstier than Poisson models predict,

over many time scales. The distribution of the number of bytes in each burst has a very heavy upper tail. Thus, WAN packet arrival processes appeared better modeled using self-similar processes.

A basic traffic model that can capture the effect of long-range dependence with the self-similar processes is the fractional Brownian motion (fBm) model. The fractional Brownian motion is a Gaussian self-similar process with self-similarity parameter $H \in [1/2, 1]$. A stochastic process $Z_t, t \in (-\infty, \infty)$, is a normalized fractional Brownian motion with Hurst parameter $H \in [1/2, 1)$ if it satisfies the following characteristics [33] [37]:

- (1) Z_t has stationary increments;
- (2) $Z_0=0$, and $E\{Z_t\}=0$ for all t ;
- (3) $E\{Z_t^2\}=|t|^{2H}$ for all t ;
- (4) Z_t has continuous sample paths;
- (5) Z_t is Gaussian, i.e., all its finite-dimensional marginal distributions are Gaussian.

The process $A_t = mt + \sqrt{\sigma m} Z_t$ is called the fractional Brownian traffic, where $m > 0$ is the mean arrival rate, $\sigma > 0$ is the variance coefficient. If $H=1/2$, it is the standard Brownian motion. Many features of fractional Brownian motions with $H > 1/2$ are different from those of most stochastic processes usually appearing in traffic models. They are not Markov processes.

In [33], Norros modeled aggregated connectionless traffic as fractional Brownian motion traffic and approximated the buffer occupancy distribution as a Weibull distribution:

$$P(Q>B) \sim \exp \left[-\frac{(C-m)^{2H}}{2kH^2am} x^{2-2H} \right]. \quad (2.7)$$

Solving (2.7) for C , the effective bandwidth for fBm traffic is obtained as follows:

$$\alpha = m + \left(k(H) \sqrt{-2 \ln(Ploss)} \right)^{1/H} \sigma^{1/(2H)} B^{-(1-H)/H} m^{1/(2H)} \quad (2.8)$$

where m is the mean bit rate of the traffic stream, H is the Hurst parameter of the stream, σ is the variance coefficient, B is the queue size and $k(H) = H^H (1-H)^{(1-H)}$. $Ploss=P(Q>B)$ is achieved approximately.

Although the fBm model is able to capture the effect of long-range dependence, fractional Brownian traffic does not model well traffic where the local rate, averaged on seconds, is far from Gaussian [33]. In addition, we need to measure H and a , which is a nontrivial job. The Norros formula overestimates the bandwidth needed by short-range dependent or weakly self-similar traffic if the total mean rate is relatively high [4].

2.5 Kelly's Definition

Kelly's mathematical framework in (1.2) is defined based on the logarithmic moment generating function of $X[0,t]$.

Definition: Moment Generating function [6]

The moment generating function of X is defined as

$$M(s) := E \{ e^{sX} \} \quad (2.9)$$

2.5.1 Some Important Properties of Kelly's Effective Bandwidth Formula

(1) **Additive property** [25]: if $X[0, t] = \sum_i X_i[0, t]$, where $X_i[0, t]$ are independent, then

$$\alpha(s, t) = \sum_i \alpha_i(s, t) \quad (2.10)$$

Proof

$$\begin{aligned} \alpha(s, t) &= \frac{1}{st} \log E \left[e^{s \sum_i X_i[0, t]} \right] \\ &= \frac{1}{st} \log E \left[\prod_i e^{s X_i[0, t]} \right] \\ &= \frac{1}{st} \log \prod_i E[e^{s X_i[0, t]}] \\ &= \sum_i \frac{1}{st} \log E[e^{s X_i[0, t]}] \\ &= \sum_i \alpha_i(s, t) \end{aligned}$$

(2) For any fixed value of t , $\alpha(s, t)$ lies between the mean and peak of the arrival rate measured over an interval of length t [25]: that is

$$\frac{EX[0, t]}{t} \leq \alpha(s, t) \leq \frac{\hat{X}[0, t]}{t}, \quad (2.11)$$

where $\hat{X}[0, t]$ is the (possible infinite) essential supremum

$$\hat{X}[0, t] = \sup \{x : P\{X[0, t] > x\} > 0\}. \quad (2.12)$$

Firstly, we prove that $\alpha(s, t) \leq \frac{\hat{X}[0, t]}{t}$:

Proof

Let Φ be the probability density function of $X[0, t]$, then,

$$E[e^{sX[0,t]}] = \int_0^\infty e^{sx} \phi(x) dx$$

From (2.12):

$$\begin{aligned} 0 &\leq E[e^{sX[0,t]}] \leq e^{s\hat{X}[0,t]} \quad \text{for } 0 < s < \infty \\ \Rightarrow \quad \frac{1}{st} \log E[e^{sX[0,t]}] &\leq \frac{1}{st} \log e^{s\hat{X}[0,t]} \\ \Rightarrow \quad \alpha(s,t) &\leq \frac{\hat{X}[0,t]}{t} \end{aligned} \tag{2.13}$$

To prove $\alpha(s,t) \geq \frac{EX[0,t]}{t}$, we need to introduce the concept of convexity and Jensen's inequality beforehand.

Definition: Convex sets and functions [6]

A subset S of R^d is said to be convex if for every x and y in S and $0 < \lambda < 1$, $\lambda x + (1-\lambda)y$ is in S . A function is convex on a subset S of R^d if S is convex, $f(x)$ is finite for at least one $x \in S$, f does not take the value $-\infty$, and

$$f(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)f(y) \tag{2.14}$$

for all x and y in S and for $0 < \lambda < 1$.

Test for convexity: f is convex on S if

- (1) f is a twice differentiable function on C ;
- (2) $f''(x) \geq 0$ for $x \in S$.

Theorem 1: Jensen's Inequality [6]

Let f be a finite convex function on an open interval A of $\mathbf{R}$. Let X be a random variable such that $P\{X \in A\} = 1$. Then if $E\{X\}$ is finite,

$$f(E\{X\}) \leq E\{f(X)\}. \quad (2.15)$$

Lemma the exponential function $f(x) = a^x$ is convex on $\mathbf{R}$ for $a > 0$.

Proof

$$f'(x) = \log(a) a^x$$

$$f''(x) = \log^2(a) a^x > 0$$

Hence, $f(x) = a^x$ is convex.

Thus, from (2.15), assume $E[X[0, t]] < \infty$

$$e^{E[sX[0, t]]} \leq E[e^{sX[0, t]}] \quad \text{for } 0 < s < \infty$$

$$\Rightarrow \log e^{E[sX[0, t]]} \leq \log E[e^{sX[0, t]}]$$

$$\Rightarrow \frac{1}{st} E[sX[0, t]] \leq \frac{1}{st} \log E[e^{sX[0, t]}]$$

$$\Rightarrow \frac{E[X[0, t]]}{t} \leq \alpha(s, t) \quad (2.16)$$

Hence, from (2.13) and (2.16), we get $\frac{EX[0, t]}{t} \leq \alpha(s, t) \leq \frac{\hat{X}[0, t]}{t}$.

2.5.2 Derivation of Effective Bandwidth for Poisson Traffic

Poisson models are the oldest traffic models. If the inter-arrival times between individual arrivals being observed have identical exponential distributions then the input process is

modeled as a Poisson process. In traffic applications that physically comprise a large number of independent traffic streams, each of which may be quite general, as the number of streams grows, if the individual rates decrease so as to keep the aggregate rate constant, then the multiplexed streams approach a Poisson process [13].

Let $X(t)$ be a Poisson process with average arrival rate of λ events (fixed size packets) per second. We therefore know that the number of arrivals in the interval $[0, t]$ has a Poisson distribution with parameter λt :

$$P(X[0, t] = n) = \frac{(\lambda t)^n e^{-\lambda t}}{n!} \quad n=0, 1, 2, \dots \quad (2.17)$$

2.5.2.1 Moment generating function of $X[0, t]$

$$\begin{aligned} & E \{ e^{sX[0, t]} \} \\ &= \sum_{n=0}^{\infty} e^{sn} \frac{(\lambda t)^n e^{-\lambda t}}{n!} \\ &= e^{-\lambda t} \sum_{n=0}^{\infty} \frac{(e^s \lambda t)^n}{n!} \\ &= e^{-\lambda t} e^{e^s \lambda t} \\ &= e^{\lambda t (e^s - 1)} \end{aligned} \quad (2.18)$$

2.5.2.2 Effective Bandwidth of Poisson Model

According to (1.2) and (2.18),

$$EB_{Poisson} = \frac{1}{st} \log E[e^{sX[0, t]}]$$

$$\begin{aligned}
&= \frac{1}{st} \log e^{\lambda t (e^s - 1)} \\
&= \frac{\lambda t (e^s - 1)}{st} \\
&= \lambda \frac{e^s - 1}{s}
\end{aligned} \tag{2.19}$$

This formula is in accordance with the result in [27]. We can see that the effective bandwidth of a Poisson process does not depend on the time scale parameter. Indeed, if $X[0,t]$ has independent increments, then its effective bandwidth does not depend on t [25].

2.5.3 Calculation of the Operating Point

Kelly's mathematical framework of effective bandwidth has been the most widely accepted effective bandwidth definition nowadays. The problem with respect to its practical usage is to find the appropriate values for s and t (link operating point).

In general, there are two methods to calculate the operating point. One is the many sources asymptotic (MSA) [10] method, which assumes that as the number of independent arriving streams increases, the buffer size and service rate per stream stay fixed; the other one is the large buffer asymptotic, which is concerned with how buffer overflow probability decays as buffer size increases.

The MSA method works with a queueing model where the arrival process is the superposition of M independent flows of J types feeding a buffered link with buffer size $B=Mb$ and transmission capacity $C=Mc$, where M is the number of combined sources

entering the link, b, c are the buffer and capacity per source, respectively. Let $M_j = Mn_j$ be the number of sources of type j , $P(\text{overflow})$ denotes the probability that the queue length is above the threshold Mb , the following sup-inf formula is used to estimate the values of s and t :

$$\lim_{M \rightarrow \infty} \frac{1}{M} \log Q(Mc, Mb, Mn) = \sup_t \inf_s \left[st \sum_{j=1}^J n_j \alpha_j(s, t) - s(b + ct) \right] = -I, \quad (2.20)$$

where I is called the asymptotic rate function. According to the above equation, the overflow probability can be written as $P(\text{overflow}) = e^{-MI - o(M)}$. When M is large, $o(M)$ goes to 0 and the probability of overflow is

$$P(\text{overflow}) \approx e^{-MI} \quad (2.21)$$

The sup-inf formula involves two optimization procedures [20]:

- The minimization with respect to s (*inf s*): For a fixed value of t , the *inf s* is found using a golden section search starting from an initial uncertainty interval which contains the minimum. The search procedure decreases the uncertainty interval in successive steps, and stops when the width of the uncertainty interval is less than some small number.
- The maximization with respect to t (*sup t*): *sup t* is found by linear searching a range of values for t , in steps equal to the epoch of the trace file. The range of t that is searched is determined heuristically and depends, among other things, on the buffer size.

Once the parameters s and t are computed from the sup-inf formula, the effective bandwidth can be calculated with formula (1.2). The physical interpretation for s and t obtained with this method is as follows:

- The time-parameter t corresponds to the most probable duration of the buffer busy period prior to overflow.
- The space-parameter s is an indication of the degree of multiplexing and depends, among others, on the size of the peak rates of the multiplexed sources relative to the link capacity.

Note three important facts about MSA method. Firstly, the calculation of s and t depends both on the link resources (capacity and buffer) and on the traffic mix (percentage and characteristics of the different source types). This in turn make the calculation of the effective bandwidth of one source depend not only on the statistical characteristics and QoS requirements of that source itself, but also on the statistical properties of other traffic sources with which it is mixed. Secondly, to estimate the effective bandwidth of one traffic stream, the whole trace of the traffic source is needed beforehand. Thirdly, the sup-inf calculation can be very computationally intensive, particularly with long traffic traces. For example, when the trace files contain 40,000 epochs and 50 values of t are searched, it will take around 23 seconds to get the solution on an ULTRA-1 workstation with one UltraSPARC processor at 170 MHz [10]. Due to these three reasons, the MSA method is only suitable for off-line effective bandwidth estimation.

In large buffer asymptotic, originally, the effective bandwidth is calculated as the time parameter t tends to be infinite [7] [8] [27] [26] [37]. In practice, especially for the on-line measurement-based effective bandwidth estimation, we can choose a suitable time interval for t . The space parameter s is calculated as follows:

$$s = -\log(Q > B)/B, \quad (2.22)$$

where B is the buffer size.

2.6 Effective Bandwidths under Generalized Processor Sharing

While most research on effective bandwidths is based on FIFO scheduling, less attention has been paid to multi-queue systems. In [48], Zhang applied Large deviations theory to GPS systems to study the asymptotic decay rate of backlog tail distribution. The upper bounds on the asymptotic decay rate of the backlog tail distribution of each session are derived through the following theorem:

Theorem 2 [48]. Assume that there are n independent sessions sharing a single GPS server with a given GPS assignment, $\{\phi_i\}_{1 \leq i \leq n}$. For session i ,

$\alpha_i(s) = \limsup_{t \rightarrow \infty} \frac{1}{st} \sup_{\tau \geq 0} \log E[e^{sA_i(\tau, t+\tau)}]$ is the effective bandwidth function of its arrival

process $A_i(t)$. Let r be the service rate of the GPS server. Assume that the sum of the long-term average arrival rates of all the sessions is less than r . Let $N = \{1, 2, \dots, n\}$. Then, for each session i , the following bounds hold,

$$\limsup_{q \rightarrow \infty} \frac{1}{q} \log \Pr\{Q_i(t) \geq q\} \leq -s_i^*, \quad (2.23)$$

where

$$s_i^* = \max_{F \subseteq \mathcal{N} \setminus \{i\}} \sup \left\{ s \geq 0 : \alpha_i(s) < \frac{\phi_i}{\sum_{j \in F} \phi_j} \left(r - \sum_{j \in F} \alpha_j(s) \right) \right\}. \quad (2.24)$$

We can see that the calculation of s_i^* for session i is very complicated, which depends not only on session i itself but also on other sessions. De Veciana and Kesidis got a similar result in [46], in which the calculation of the effective bandwidth of one session depends not only on that session but also on other sessions. For practical purposes, independence and additivity are two essential requirements for the definition of the effective bandwidth. It will be hard to apply those effective bandwidth approaches that don't meet these two demands in realistic networks.

2.7 Issues of the Effective Bandwidth Methods

As a promising approach to achieve the trade-off between the network utilization and the provision of QoS, the concept of effective bandwidth has been widely accepted. However, three main issues are raised to apply the effective bandwidth methods to the realistic networks.

The first one arises from the fact that effective bandwidth approximation is not always accurate. It is generally conservative [9] [18] [36] [40] [44]. In some cases, the effective

bandwidth approximation may overestimate the target loss probabilities by several orders of magnitude [9]. Such conservative results stem from three aspects.

(1) In most mathematical analyses, the packet loss probability is assumed to be identical to the buffer overflow probability, which in turn is approximated by the probability of exceeding the level corresponding to the actual buffer size in an infinite buffer system. Simulations with various traffic models combined with different buffer sizes and link capacities have shown that the buffer overflow probability is normally larger than the corresponding packet loss probability [36].

(2) Formula (2.22) in large buffer asymptotic is a simplifying form of

$$P(Q > B) \approx Ae^{-sB} \quad \text{as } B \rightarrow \infty, \quad (2.25)$$

by assuming $A=1$, where A is an undetermined asymptotic constant. However, in general, A is not equal to 1. In [9], to better approximate the loss probability, Choudhury et al. further refined (2.25) by introducing more parameters. Instead of using loss probability, the waiting time probability is given as:

$$P(W > B) \approx \beta e^{-n\gamma} e^{-\eta B}. \quad (2.26)$$

Although (2.26) might be more accurate than (2.25) and (2.22), it increases the computational complexity. And it is only suitable when there are large numbers of similar sources.

(3) The additive property of effective bandwidths is obtained at the price of neglecting the multiplexing gain. The Gaussian approximation is one remedial method aiming at

solving this problem. However, even formula (2.4) takes the minimum of the values from flow approximation and Gaussian approximation, it still overestimates the required bandwidth [18]. The MSA method is another refinement for this problem, but this method departs from the independence property of effective bandwidths in that it depends not only on the statistical characteristics and QoS requirement of one source, but also on the other traffic sources with which it is multiplexed.

The second issue of effective bandwidths is that the accuracy of effective bandwidth methods depends greatly on the statistical characterization of the underlying sources. However, it is often not feasible to get reliable traffic models that can capture the statistical characteristics of the actual traffic, and the assumptions made about the traffic in effective bandwidth approach may not be in agreement with the actual traffic. Recent research on statistical QoS has attempted to estimate the required bandwidth without assuming a specific traffic model [5]. For example, in [21] [22], the DTMW method is proposed to predict the traffic and reallocate the resource according to the queue occupancy and the increasing rate of the buffer occupancy.

Finally, the effective bandwidth methods based on FIFO are not suitable for Diffserv networks. It can be argued that the research results from effective bandwidths under GPS can solve this problem. It is true that some theoretical bounds on the asymptotic decay rate of the backlog tail distribution under GPS have been achieved with the help of large deviation theory. But these bounds are not practically useful since it is very difficult, if not impossible, to compute them [48].

To solve the above issues, we develop a framework of using on-line measurement based AEBA under DWRR scheduling to study the statistical QoS assurance issue in self-sizing networks, which aims at both keeping the independence and additive properties of effective bandwidth and overcoming its conservative nature. To bypass the traffic modeling problem, we propose the unified AEBA approach and prove its feasibility with concrete simulation results.

3 AEBA under DWRR

3.1 Self-sizing Networks

The concept of self-sizing networks was originally proposed for ATM network operations [32]. Self-sizing means the automatic adjustment of virtual-path (VP) bandwidth based on traffic conditions observed in real time [43]. Recent research results [41] [42] have extended a similar concept to MPLS networks.

3.2 Measurement-based Effective Bandwidth Approach

No matter which effective bandwidth method is used, it requires some exact traffic descriptors of the underlying traffic sources. For example, to use (2.1) and (2.2) the traffic parameters such as mean ON/OFF periods and peak rate are needed, to use (2.3) and (2.4), additional parameters such as mean and variance of the traffic rates are needed. To calculate (1.2) requires a full characterization of the underlying process, which is not trivial, if not impossible. For practical purposes, we use the measurement-based method to estimate the effective bandwidth. The performances of different methods for measuring the effective bandwidth such as the direct estimator, the block estimator, the Kulback-Leibler distance (KLD) estimator and the linear regression (LR) estimator were compared in [45]. Among these measurement methods, the direct estimator proposed by Gibbens in [14] and the block estimator proposed by Duffield in [11] are based on

equation (1.2). And the block estimator is the fastest one. Therefore it is suitable to be applied to calculate the effective bandwidths in the real time self-sizing network environment.

Figure 3.1 Block estimator under FIFO queueing system in self-sizing networks

The block estimator considers the non-overlapping blocks of arrivals over an interval of length t . When applying the block estimator method to (1.2), we can obtain the following formula:

$$\alpha(s, t) = \frac{1}{st} \log \frac{1}{N} \sum_{i=1}^N e^{sX[(i-1)t, it]}, \quad (3.1)$$

where N is the window size. The essential idea behind (3.1) is to transfer the calculation of ensemble average in (1.2) into a time average calculation, by assuming the underlying processes having the ergodic characteristic.

3.3 Dynamic Weighted Round Robin Scheduling

Figure 3.2 Effective bandwidths under DWRR queueing system

We consider a class-based dynamic weighted round robin scheduler where packets of different classes are scheduled according to their measured arrival rates.

At the incoming edge of the network, the incoming traffic streams are classified into different classes and isolated into separate buffers. Each class of traffic has the similar traffic characteristics and the same QoS requirement. Here, we consider the packet loss probability as the QoS requirement of interest. It is difficult to achieve *a priori* link

dimensioning in self-sizing networks, so a traffic prediction method is required. Noting that the most effective way to predict the traffic is to use the latest second to predict the next second, the latest minute to predict the next minute, there is not too much benefit to increase the number or lengths of the accounted time intervals in the past [33]. We use the effective bandwidth estimated in the current time window to predict the bandwidth to be allocated in the next time window. As mentioned previously, the accuracy and applicability of the various effective bandwidth methods greatly depend on the traffic characteristics under which they were derived. As shown in [19], for different statistical characteristics of the underlying traffic and buffer size, the different effective bandwidth approaches will have different performance. Since the traffic of different applications will exhibit different statistical characteristics, for example, some exhibit SRD characteristic and others exhibit LRD characteristic, we may use different effective bandwidth approaches for different classes of traffic to get better performance. According to the additive and independence properties [37] of effective bandwidths, we may wish to allocate the overall bandwidth according to the sum of the effective bandwidth of individual classes and adjust the weights assigned to each class according to its effective bandwidth estimated in the current time window. The scheduler visits each queue in a weighted round-robin fashion. According to the buffer occupancy and the allocated bandwidth of each traffic class, the weights are adjusted dynamically.

3.4 Buffer Overflow Preventive Mechanism

One of the principles underlying the provision of QoS is that it is desirable to use resources (e.g. link bandwidth and buffers) as efficiently as possible [28].

While providing isolation among traffic flows, a flow can only use the amount of buffer that has been allocated to it. In particular, it cannot utilize buffer capacity that is not currently being used by other traffic classes. As an example of such inefficient buffer utilization, consider the following example where buffer 2 is full while the

Figure 3.3 An example of inefficient buffer utilization

scheduler is serving Buffer 1. When a packet from class 2 enters the system, even though buffer 1 and buffer 3 have available capacity, this packet is still dropped.

It is therefore desirable to develop some mechanism to use buffers as efficiently as possible. To achieve that, we define a high threshold for each buffer, and DWRR checks if there is some queue whose occupancy is above the high threshold after serving one packet. If so, the queue with higher QoS demand will start its serving slot if the queue currently being served has low buffer occupancy.

Figure 3.4 DWRR with buffer overflow preventive mechanism

Take class 1 as an example: after serving one packet of class 1, if queue 1 has high buffer occupancy, the scheduler will continue serving queue 1. Otherwise, if either of queue 2 and queue 3 exceeds the high threshold, the scheduler will start serving it. If both exceed the thresholds, the scheduler will serve the one with higher QoS requirement. If no buffer exceeds its high threshold or all buffers exceed their high thresholds, the scheduler will take turns to serve each class according to the weight assigned to it. The detailed algorithm is described in Figure 3.4. A similar procedure applies to class 2 and class 3.

3.5 Adaptive Effective Bandwidth Allocation

The conservative nature of the pure effective bandwidth allocation under DWRR comes from two reasons. The first one is that the large buffer asymptotic effective bandwidth approach itself is conservative, which has been discussed in Chapter 2. The second one is that, in order to keep the additive nature of effective bandwidths, the effective bandwidth for each traffic class is calculated independently as a function of the required loss probability and buffer size of that class. However, when using the sum of per-class effective bandwidth as the overall bandwidth requirement, we impose a linear relationship on the effective bandwidth allocation under DWRR scheduling where such linearity does not hold. Due to the effect of statistically multiplexing multiple classes together, the bandwidth required to carry a set of classes with a certain QoS demand might be less than the sum of the bandwidths that would be needed to carry each class separately with the same QoS requirement. However, due to the coupled interactions among different classes, it is very difficult to calculate the multiplexing gain. To exploit

the statistical multiplexing gain, we develop the adaptive effective bandwidth allocation approach as follows:

Figure 3.5 Adaptive effective bandwidth allocation

It is a two-step bandwidth allocation procedure: (1) we use the effective bandwidth as a rough approximation of the bandwidth to be allocated; (2) we adjust the bandwidth to be allocated according to the measured QoS.

According to the measured loss ratio in each window and the measured overall loss ratio, we adjust the value of the multiplexing gain factor g , which adjusts the bandwidth to be allocated for the next window in the following way:

$$BW_{next} = \text{Min} \{ \text{Max} \{ EB (1-g), \text{average rate} \}, \text{peak rate} \}, \quad (3.2)$$

where BW_{next} is the bandwidth to be allocated for the next window and EB is the effective bandwidth estimated in the current window.

There are two important thresholds related to the AEBA operation, which characterize each class: $Thlosshigh$, the upper threshold of the packet loss ratio for each class; and $Thlosslow$, the lower threshold of the packet loss ratio for each class.

$$0 < Thlosslow < Thlosshigh < \text{Target loss ratio} \quad (3.3)$$

We also define two step control parameters, $Ssmall$ and $Slarge$, for adjusting the value of g :

$$Slarge > Ssmall > 1 \quad (3.4)$$

If the measured loss ratios are lower than $Thlosslow$ in two successive windows, then over-allocation may have occurred. We increase the value of g by multiplying $Ssmall$, which will reduce the bandwidth allocation according to (3.2). If the measured loss ratio in the current window is higher than $Thlosshigh$, with high probability, g is too large. We

reduce the value of g to the former value by dividing S_{small} . If the measured overall ratio is higher than $Thlosshigh$ at the same time, we need to reduce the loss ratio in the next several windows to reduce the overall loss ratio to the target loss ratio. To achieve this goal, we reduce the value of g by dividing $Slarge$. If the measured loss ratio in one window falls between $[Thlosslow, Thlosshigh]$, we don't change the value of g . In this way, we can measure the multiplexing gain:

$$Gain = \frac{MeasuredEffectiveBandwidth - ActuallyAllocatedBandwidth}{MeasuredEffectiveBandwidth}. \quad (3.5)$$

3.6 Quick Detection of Sustained Burstiness

For traffic exhibiting short-term burstiness characteristics, the limited buffer size acts well as a smoothing mechanism. For traffic sources exhibiting burstiness over multiple time scales, it will be difficult to control the loss ratio under a fixed measurement time window. For example, there are episodes where a persistent peak of 5 times the long-term average rate lasts over 10 seconds in an MPEG-1 compressed version of Star Wars movie [17]. In such cases, the overflow in a single window would cause a significant increase of overall loss ratio.

Figure 3.6 Quick detection of sustained burstiness

To improve the performance of AEBA under DWRR for the traffic sources exhibiting burstiness over multiple time scales, we develop the quick persistent burstiness detection mechanism described in Figure 3.6.

We define three thresholds, $Thbw1$, $Thbw2$ and $Tlbw$ for the measured arrival rates; and three parameters, $N1$, $N2$ and $N3$, for the measurement length.

$$Thbw1 > Thbw2 > BWnow > Tlbw \quad (3.6)$$

$$N3 > N2 > N1 \geq 3 \quad (3.7)$$

We monitor the traffic in each measured epoch. If the measured traffic rate is higher than $Thbw1$ for $N1$ successive epochs or higher than $Thbw2$ for $N2$ successive epochs, we assume that, with high probability, sustained burstiness is occurring. If the measured loss ratio exceeds $Thlosshigh$, a bandwidth reallocation is needed. We also monitor the decrease of the arrival traffic. If the measured traffic rate is lower than $Tlbw$ for $N3$ successive epochs and the measured loss ratio is lower than $Thlosshigh$, the bandwidth should be reallocated to save resources.

3.7 Bandwidth reallocation frequency control

Figure 3.7 Bandwidth reallocation frequency control

From a traffic engineering viewpoint, the less frequently the bandwidth is reallocated the better. To reduce the bandwidth reallocation frequency, we examine the difference between the overall bandwidth to be allocated for the next window (*NextOne*) and the overall bandwidth that has been allocated for the current window (*CurrentOne*). We define a bandwidth reallocation control parameter R , and use

$$P=R* \text{ (the most stringent packet loss ratio requirement)} \quad (3.8)$$

as the measure of the degree to which the bandwidth allocation procedure can tolerate without violating the QoS requirements.

If

$$\left| \frac{NextOne - CurrentOne}{CurrentOne} \right| \leq P * CurrentOne \quad (3.9)$$

and for each traffic class,

$$Thlosslow \leq Measured \text{ loss ratio} \leq Thlosshigh2, \quad (3.10)$$

the bandwidth will not be reallocated. By adjusting the value of the parameter R , we control the bandwidth reallocation frequency under some fixed window size.

4 Performance Analysis

We evaluate the performance of our proposals through both theoretical analysis and simulation experiments.

4.1 Theoretical Analysis

Because of the complex bandwidth sharing dynamics among different sessions, where the service rate of one session depends on other sessions at any moment, it is very difficult to analyze a general DWRR system. We restrict ourselves to the simplest case of using three homogeneous Poisson traffic classes as input in an ATM network, which will be tractable for analysis.

We assume that the three classes of traffic in the DWRR queueing system are homogeneous Poisson traffic. They have the same arrival rates, $\lambda=2000$ cell/second. They also have the same cell loss ratio requirements, for example, $P_{loss}=10^{-3}$. And each class has the same buffer size, $B=50$ cells.

From the effective bandwidth equation for Poisson traffic given in formula (2.19), for each class, we calculate the effective bandwidth as follows:

$$EB1=EB2=EB3=2144.74 \text{ cell/s.} \quad (4.1)$$

According to the additive requirement of effective bandwidths, we would wish to allocate the overall effective bandwidth with the sum of $EB1$, $EB2$ and $EB3$. However, such pure effective bandwidth allocation ignores the multiplexing gain among multi classes.

To calculate the multiplexing gain, let us consider the following scenario where we consider the DWRR scheduling scheme as a black box.

Figure 4.1 Virtual FIFO queueing system

Since the superposition of the Poisson processes is again a Poisson process and DWRR is work conserving, we then can reconsider the black box as a virtual FIFO queueing system fed by one Poisson traffic class with the arrival rate of 3λ .

As described in Section 3.4, when using the buffer overflow preventive mechanism, ideally, no packet will be dropped before all three buffers exceed their high thresholds

and one of them is full. Assuming the high buffer threshold is set equal to 90% of buffer capacity, Figure 4.2 shows such improvement of the buffer utilization visually:

Figure 4.2 Improvement of buffer utilization

The arrival traffic rate is $3 \times 2000 = 6000$ cell/s, the effective buffer capacity of this virtual FIFO queueing system ranges between $[2 \times 45 + 50, 3 \times 50] = [140, 150]$.

Let us also set the overall loss ratio requirement of the aggregate traffic of three Poisson traffic classes to 10^{-3} , in the most optimistic case (effective buffer size=150), the effective bandwidth of aggregate traffic will be

$$EB_{FIFO} = 6140.301 \text{ cell/s}, \quad (4.2)$$

And in the worst case (effective buffer size=140), the effective bandwidth of aggregate traffic will be:

$$EB_{FIFOw} = 6150.488 \text{ cell/s.} \quad (4.3)$$

Since all three individual traffic classes are homogeneous, when the overall loss ratio requirement of the aggregate traffic can be satisfied in the virtual FIFO queueing system, the loss ratio requirement of each class should also be satisfied. Therefore, the actual bandwidth requirement to satisfy the QoS demand is EB_{FIFO} . Substituting the “Measured Effective Bandwidth” with $EB1+EB2+EB3$ and “Actually Allocated Bandwidth” with EB_{FIFO} in (3.5), we can calculate the multiplexing gain for this special case as follows:

$$Gain = (EB1+EB2+EB3 - EB_{FIFO}) / (EB1+EB2+EB3). \quad (4.4)$$

In the most optimistic case, the multiplexing gain is

$$Gain_{upper} = 4.568\% . \quad (4.5)$$

In the worst case, the multiplexing gain is

$$Gain_{lower} = 4.410\% . \quad (4.6)$$

4.2 Simulation Results

We implement our algorithms in the simulation tool OPNET 9.0. A batch simulation approach is used. The simulation time is divided into 51 segments, each lasting 30 simulated minutes. The results collected in the first “warm-up” segment are discarded.

To compare with the analytical results, firstly, we run the simulations with 3 homogeneous Poisson traffic streams as input. To obtain the generic results, we perform simulations with heterogeneous traffic as input.

4.2.1 Homogeneous Poisson Traffic Sources

In accordance with the scenario discussed in 4.1, we evaluate the performance of our algorithms with three homogeneous classes of Poisson traffic as input in the ATM network. Each class has the same arrival rate of 2000 cell/s, same buffer size of 50 cells and same loss ratio requirement of 10^{-3} . We measure the traffic at the resolution of 50 milliseconds with the measurement window size set to 60, i.e., each measurement epoch is 50 milliseconds long and each measurement window is 3 seconds long.

4.2.1.1 Pure Effective Bandwidth Allocation

To illustrate the conservative nature of the effective bandwidth methods, we start with the simulations using pure effective bandwidth allocation method. The effective bandwidth calculated in the current window is used as the bandwidth demand for the next window. The scheduler then drains the buffers with the new drain rate, which is set according to the new allocated bandwidth. In consideration of the calculation and setup latency, the new drain rate will come into effect one epoch after the calculation of the new bandwidth to be allocated.

We do simulations under DWRR scheduling with and without protection against avoidable buffer overflow respectively. The high buffer threshold is set to 90 percent of the buffer capacity. The simulation results are shown as follows:

Figure 4.3 95% CI of logarithm of measured loss ratio using pure effective bandwidth allocation under DWRR without protection against avoidable buffer overflow

Figure 4.4 95% CI of logarithm of measured loss ratio using pure effective bandwidth allocation under DWRR with protection against avoidable buffer overflow

There are two observations from the simulation results. One is that DWRR with protection against avoidable buffer overflow mechanism has better performance than that without it. As shown in Figure 4.3 and Figure 4.4, with the same traffic arrivals and the same service rate, the measured packet loss ratio is around 10^{-5} without the buffer overflow preventive mechanism while it is reduced to 10^{-8} with the buffer overflow preventive mechanism. The other one is that the pure effective bandwidth allocation is conservative.

4.2.1.2 Adaptive Effective Bandwidth Allocation

We set the initial value of the multiplexing gain factor $g=0.05$, upper loss ratio threshold $Thloshigh=0.98*target\ loss\ ratio$, lower loss ratio threshold $Thlosslow=0.8*target\ loss\ ratio$, small step control parameter $Ssmall=1.1$ and large step control parameter $Slarge=1.3$.

Figure 4.5 95% CI of logarithm of measured loss ratio with AEBA under DWRR ($g=0.05$)

Figure 4.6 95% CI of measured multiplexing gain with AEBA under DWRR ($g=0.05$)

As shown in Figure in Figures 4.5 and 4.6, using AEBA under DWRR, the QoS requirement of each traffic class in terms of loss ratio can be satisfied while a statistical multiplexing gain of around 4.6% can be achieved at the same time.

4.2.1.3 Comparison of the Analytical and Simulation Results

Figure 4.7 Comparison of the analytical and simulation results

Figure 4.7 shows that the measured multiplexing gain is a little higher than the analytical results (the analytical results shown in Figure 4.7 is the range of the theoretical results). The reason is that the effective bandwidth itself is conservative as mentioned in chapter 2. To illustrate it, we perform the following simulation: We apply the AEBA algorithm to the FIFO queueing system with buffer size = 150, arrival rate = 6000 cell/s. The target loss ratio is also set to 10^{-3} .

Table 4.1 Simulation results with AEBA under FIFO

Target loss ratio		10^{-3}
Measured loss ratio	Average	9.84×10^{-4}
	95% CI	$[9.80 \times 10^{-4}, 9.88 \times 10^{-4}]$
Theoretical effective bandwidth (cell/s)		6140.301
Measured effective bandwidth (cell/s)	Average	6140.467
	95% CI	[6139.699, 6141.235]
Actually allocated bandwidth (cell/s)	Average	6074.646
	95% CI	[6073.574, 6075.718]

Table 4.1 shows that the measured effective bandwidth is very close to the theoretical effective bandwidth. However, the target QoS loss ratio can be satisfied when the actually allocated bandwidth is around 6074.646 cell/s, which is a little lower than the value of effective bandwidth. If we substitute the theoretical effective bandwidth with the actually allocated bandwidth in formula (4.4), the upper bound on the gain will become:

$$Gain_{upperbound} = 5.589\%, \quad (4.7)$$

which is higher than the measured gain.

4.2.1.4 Sensitivity of System Performance to Multiplexing Gain Parameter g

To test how sensitive the system performance will be with respect to various initial values of multiplexing gain factor g , we get the following simulation results with different initial values of g .

Figure 4.8 95% CI of logarithm of measured loss ratio of class 1 with AEBA under DWRR with different initial values of g

Figure 4.9 95% CI of measured multiplexing gain with AEBA under DWRR

The simulation results in Figures 4.8 and 4.9 show that the measured loss ratio and the overall multiplexing gain are not very sensitive to the initial value of g (using class 1 as an example in Figure 4.5, we also obtain the corresponding simulation results for classes 2 and 3).

In the following simulations, we will use $g=0.05$.

4.2.1.5 Sensitivity of System Performance to Packet Size

So far, we have performed simulations with a fixed cell size, assuming ATM networks. In the following simulations, we will do simulations with variable packet size to get the general results. In this scenario, we assume that packet size is Poisson distributed with mean size equal to 750 bytes. The simulation results are given as follows:

Figure 4.10 95% CI of logarithm of loss ratio with AEBA under DWRR (variable packet size)

Compared with Figure 4.5, the measured loss ratios in the two scenarios are very close to each other.

Figure 4.11 95% CI of multiplexing gain with AEBA under DWRR (variable packet size)

Figure 4.11 shows that the measured multiplexing gains in two situations are also very close. Therefore, our algorithms work well for both fixed cell size and variable packet size.

4.2.2 Simulation with Heterogeneous Traffic Sources

To obtain general results, we do simulations with heterogeneous traffic as input. We use both SRD traffic and LRD traffic as input.

4.2.2.1 Traffic profiles

Table 4.2 gives the traffic profiles for each class. Without loss of generality, we use the Poisson traffic source, the superposition of the Fractal Renewal Point Process (Sup_FRP) [38] [39] and the superposition of ON-OFF sources to generate packet-based traffic.

Table 4.2 Traffic profiles

Traffic Sources		Class 1	Class 2	Class 3
Target loss ratio		0.001	0.01	0.05
Traffic models		Poisson	Sup_FRP (H=0.7)	ON-OFF (50) ON: 0.362s OFF: 0.65s
Arrival rate (packet/s)		1000	1000	50 when ON
Buffer size (Packet)		50	100	20
Packet size (Byte)		Poisson (100)		
Effective Bandwidth Method	Dedicated	Poisson	Block Estimator	Gaussian Approximation
	Unified	Block Estimator		

According to the traffic characteristics of each class, we may apply different effective bandwidth approaches to each class. We call this method the dedicated AEBA approach in the following discussion. We may also use the block estimator as a unified AEBA approach for all classes. We will do simulations to compare the performance of these two methods.

4.2.2.2 Simulation Results with Dedicated AEBA approach

We set bandwidth thresholds $Thbw1=1.5*\text{current allocated bandwidth}$, $Thbw2=1.2*\text{current allocated bandwidth}$ and $Tlbw=0.5*\text{current allocated bandwidth}$, time control parameters $N1=3$, $N2=5$ and $N3=10$.

Table 4.3 %95 CI of measured loss ratio with dedicated effective bandwidth approach

Traffic sources	Target loss ratio	Measured loss ratio	95% CI
Class1	10^{-3}	0.0009824	[0.0009796,0.09851]
Class2	10^{-2}	0.009742	[0.009728,0.009757]
Class3	0.05	0.04490	[0.04452,0.04529]

Figure 4.12 95% CI of logarithm of Measured loss ratio with dedicated effective bandwidth approach

The simulation results in Table 4.3 and Figure 4.12 show that the different QoS requirements of all classes can be satisfied at the same time. For class one, the measured loss ratio is around 0.0009824 while the target one is 0.001. For class two, the measured loss ratio is 0.009742 while the target one is 0.01. And for class three, the measured loss ratio is about 0.0449 while the target one is 0.05.

Table 4.4 95 CI of measured multiplexing gain with dedicated AEBA approach

Traffic sources	Measured multiplexing gain	95% CI
Class1	4.754%	[4.685%,4.824%]
Class2	7.680%	[7.636%,7.725%]
Class3	16.574%	[16.467%,16.681%]
Overall	9.855%	[9.820%,9.890%]

Figure 4.13 95% CI of measured multiplexing gain with dedicated AEBA approach

Meanwhile, the overall multiplexing gain of around 9.85% is achieved. As shown in Table 4.4 and Figure 4.13, for class 1, the multiplexing gain is around 4.75%, for class 2, it is around 7.68%, and for class 3, it is around 16.57%.

4.2.2.3 A Unified AEBA approach

It is difficult to know the traffic characteristics *a priori*. We wish to use a unified AEBA approach, which would bypass modeling the underlying traffic. To do that, we try to

apply the block estimator effective bandwidth approach to all classes, and we do simulations with the same traffic sources described in Table 4.2 to verify the feasibility of this approach.

Table 4.5 95% CI of measured loss ratio with unified AEBA approach

Traffic sources	Target loss ratio	Measured loss ratio	95% CI
Class1	10^{-3}	0.0009822	[0.0009793,0.09851]
Class2	10^{-2}	0.009741	[0.009729,0.009753]
Class3	0.05	0.04463	[0.04423,0.04503]

Figure 4.14 %95 CI of logarithm of measured loss ratio with unified AEBA approach

The simulation results in Table 4.5 and Figure 4.14 show that the different QoS requirements of all classes can also be satisfied with the unified AEBA approach. For class one, the measured loss ratio is around 0.0009822 while the target one is 0.001. For

class two, the measured loss ratio is 0.009741 while the target one is 0.01. And for class there, the measured loss ration is about 0.04463 while the target one is 0.05.

Table 4.6 95% CI of measured multiplexing gain with unified AEBA approach

Traffic sources	Measured multiplexing gain	95% CI
Class1	4.254%	[4.167%,4.340%]
Class2	7.773%	[7.726%,7.821%]
Class3	4.711%	[4.594%,4.828%]
Overall	5.563%	[5.526%,5.601%]

Figure 4.15 95% CI of measured multiplexing gain with unified AEBA approach

Meanwhile, as shown in Table 4.6 and Figure 4.15, the overall statistical multiplexing gain of around 5.56% is achieved. For class 1, the multiplexing gain is around 4.25%, for class 2, it is around 7.77%, and for class 3, it is around 5.56%.

4.2.2.4 Comparison of Dedicated and Unified AEBA Approaches

Figure 4.16 Comparison of the measured overall multiplexing gain of two approaches

As shown in Figure 4.16, there is a significant difference of the overall multiplexing gains between these two approaches. To find the reason, we examine the calculated effective bandwidth and the actually allocated bandwidth in two cases.

Figure 4.17 Comparison of the calculated effective bandwidth of two approaches

Figure 4.18 Comparison of the actually allocated bandwidth of two approaches

We can see that the actually allocated bandwidths are almost the same with the two approaches, while the calculated effective bandwidth with the unified AEBA approach is smaller than the one with the dedicated AEBA approach. Therefore, the overall multiplexing gain with the unified AEBA approach is smaller than the one with the dedicated AEBA approach. Next, we would examine which class mainly contributes to such a difference.

Figure 4.19 Comparison of the measured multiplexing gain of class 1 of two approaches

Figure 4.20 Comparison of the measured multiplexing gain of class 2 of two approaches

Figure 4.21 Comparison of the measured multiplexing gain of class 3 of two approaches

Comparing the simulation results shown in figures 4.19, 4.20 and 4.21, we observe that, the difference between the multiplexing gains achieved by these two approaches is mainly caused by class 3. The reason is that, the Gaussian approximation does not fully exploit the amount of statistical gain that can be achieved since it does not take into account the effect of buffer. Since the buffer will absorb some of the traffic fluctuations, the actual allocated bandwidth could be much less than the upper bound calculated by Gaussian approximation. Together with the effect of multiplexing between three traffic

classes, the actual allocated bandwidth is around 17% lower than the one calculated with the Gaussian approximation.

Since the unified AEBA approach consumes the same network resources as the dedicated effective bandwidth approach, and the unified AEBA approach does not need any assumptions about the traffic characteristics of the underlying traffic, the unified AEBA approach is preferable. We use the unified AEBA approach in the following simulations.

4.2.2.5 Sensitivity of System Performance to Bandwidth Reallocation Control Parameter R

$Th_{losshigh2}$ is set to be $0.99 \times \text{Target loss ratio}$.

Figure 4.22 Bandwidth reallocation frequency with different values of the bandwidth reallocation control parameter R

By increasing the value of the bandwidth reallocation control parameter R from 0 to 60, the bandwidth reallocation frequency can be reduced from around 0.34 1/s to 0.16 1/s. However, when we continue to increase the value of R beyond 60, the bandwidth reallocation frequency can not be reduced any more. This is caused by the fact that, in general, the packet loss ratio of each class increases with the increase of the value of R , which is shown in Figures 4.23, 4.24 and 4.25.

Figure 4.23 95% CI of logarithm of measured loss ratio of Class 1 with different values of the bandwidth reallocation control parameter R

Figure 4.24 95% CI of logarithm of measured loss ratio of Class 2 with different values of the bandwidth reallocation control parameter R

Figure 4.25 95% CI of measured loss ratio of Class 3 with different values of bandwidth reallocation control parameter R

As shown in Figures 4.23, 4.24 and 4.25, in general, the packet loss ratio will increase with the increase of the value of R . And the simulation results in Figure 4.23 show that the packet loss ratio of class one will be higher than the target one when R reaches 80. According to the algorithm described in Figure 3.7, the bandwidth reallocation frequency cannot be reduced any more after the measured loss ratio of any one class exceeds the target one.

Figure 4.26 Measured multiplexing gain with different values of bandwidth reallocation control parameter R

As shown in Figure 4.26, the measured multiplexing gain does not change much with the different values of R .

4.2.2.6 Sensitivity of System Performance to Window Size

In the previous simulations, we use window size =60. Even with the help of the bandwidth reallocation frequency control mechanism, the bandwidth reallocation frequency could only be reduced to around 0.16 1/s. To continue to reduce the bandwidth reallocation frequency, we try to increase the window size.

Figure 4.27 Bandwidth reallocation frequency with different window sizes

The simulation results show that the bandwidth reallocation frequency can be significantly reduced with the increase of the window size. When the window size is 60, the bandwidth reallocation frequency is around 0.335 1/s, while it is reduced to 0.035 1/s when the window size is increased to 600. Next, we examine how the increase of window size will affect the system performance.

Figure 4.28 95 % CI of logarithm of measured loss ratio of class 1 with different window sizes

Figure 4.29 95 % CI of logarithm of measured loss ratio of class 2 with different window sizes

Figure 4.30 95 % CI of logarithm of measured loss ratio of class 3 with different window sizes

As shown in Figures 4.28, 4.29 and 4.30, the packet loss ratio of each class decreases a little with the increase of the window size.

Figure 4.31 95% CI of measured average overall allocated bandwidth with different window sizes

At the same time, as shown in Figure 4.31, the average overall allocated bandwidth also decreases a little with the increase of window size. This may be caused by the fact that the overall multiplexing gain increases with the increase of the window size, which is shown in Figure 4.32.

Figure 4.32 95 % CI of measured overall multiplexing gain with different window sizes

It might be the following two factors that contribute to the increase of the multiplexing gain with the increase of the window size.

Figure 4.33 95% CI of measured average effective bandwidth with different window sizes

One is that, the measured effective bandwidths with different window sizes are different. As shown in Figure 4.33, the measured average effective bandwidth increases with the increase of the window size. The other reason may come from that, with a smaller window size, the allocated bandwidth is adjusted more frequently than it is with a larger window size. According to the algorithm described in Figure 3.5, the value of g of each individual class will be increased if the loss ratio in two consecutive windows is lower than the lower threshold, it will be decreased if the loss ratio of that class in one window is higher than the upper threshold. The smaller the window size is, the more it is possible that the loss ratio will oscillate around the target one, which will prevent the value of g from increasing. To envision how the algorithm works, we show the packet loss ratio of class 3 in each measurement window during a fraction of the length of two simulated

minutes in Figure 4.34 and the associated adjustment of the value of g in Figure 4.35 as an illustration. Without loss of generality, the simulation traces from window size =600 and window size =300 are compared.

Figure 4.34 The measured packet loss ratio of Class 3 in each window during a fraction of the simulation period

Figure 4.35 The adjustment of the value of g of class 3 in each window during a fraction of the simulated period

In Figure 4.34, there are eight measurement windows in the trace with window size=300, namely, *W31*, *W32*, *W33*, *W34*, *W35*, *W36*, *W37* and *W38*. There are four measurement windows in the trace with window size=600, namely, *W61*, *W62*, *W63* and *W64*. For the trace with window size=300, in *W31*, the measured loss ratio is around 5.2% and g is around 0.055. In *W32*, the loss ratio is around 0.9%, since the measured loss ratio in *W31* is higher than target one, the value of g will stay the same. And the measured loss ratios in *W33* and *W34* are successively lower than the lower threshold, so the value of g is increased to around 0.067 in *W34*. However, due to the increase of the value of g , the allocated bandwidth is decreased accordingly. In *W35*, the measured loss ratio exceeds the upper threshold. Thus the value of g is reduced to around 0.061. And since the measured loss ratios are lower than the lower threshold in both *W36* and *W37*, the value of g is increased again to 0.067 in *W37*. But the measured ratio exceeds the upper threshold again in *W38*, so the value of g is decreased to 0.061 accordingly.

Compared with the trace with window size = 300, the value of g is adjusted less frequently in the trace with window size = 600. The measured loss ratios are between the low threshold and high threshold in *W61* and *W62*, and lower than the lower threshold in *W63* and *W64*, so the multiplexing gain parameter g holds the same value of 0.067 in these four windows.

Of course, the above example is only a short fraction taken from the whole simulation trace to simplify the explanation. In all the traces, for both window size =300 and window size =600, the value of g will be adjusted in each window according to the

measured loss ratios. Combined with the fluctuation nature of the arrival traffic, a natural consequence is that the allocated bandwidth will be adjusted in each window accordingly. Using window size=300 and window size=600 as the example, Figures 4.36 and 4.37 show how our algorithms track the traffic fluctuations more explicitly.

Figure 4.36 Effective bandwidth vs. allocated bandwidth vs. traffic rate of class 3 during the simulation period [2000s, 3000s] with window size = 300

Figure 4.37 Effective bandwidth vs. allocated bandwidth vs. traffic rate of class 3 during the simulation period [2000s, 3000s] with window size = 300

We can see that, in both cases, the allocated bandwidth can track the traffic fluctuation. But in the case with window size = 600, the bandwidth for class 3 is reallocated less frequently and is smoother than that with window size = 300. The same conclusion also applies to the overall bandwidth allocation, which is shown in Figure 4.38.

Figure 4.38 Overall bandwidth allocations during the simulation period [2000s, 3000s] with window size = 300 and window size =600

This observation will explain why the loss ratio of each class decreases a little while the actually overall allocated bandwidth also decreases with the increase of the window size. Using window size =300 and 600 as the example, from Figure 4.34, we can see that the trace of the overall allocated bandwidth with window size =300 oscillates around that with window size =600. For most of the time, the trace of the overall allocated bandwidth with window size =300 is above that with the window size =600, so the overall allocated bandwidth with window size=300 will be larger than that with window size =600. Occasionally, the trace of the overall allocated bandwidth with window size =300 is below that with the window size =600, such oscillation might make the loss ratio with window size =300 be higher than that with window size =600.

It seems that the larger the window size, the better the system performance will be. However, we should note that the above simulation results are long-run measures of performance of the system. Next, we examine how the window size will affect the length of the transient time of the system. Here, the transient time of the system refers to the length of the simulation period during which the measured packet loss ratio of each class has not stabilized.

Figure 4.39 95% CI of transient time with window size =120 and window size =300

Using window size =120 and 300 as an example, Figure 4.39 gives the comparison of the transient time with these two window sizes. Compared with *window size* = 120, it takes a longer time for the system to equilibrate toward the steady state with *window size* =300.

In consideration of the long transient time with large window size, we can not reduce the bandwidth reallocation frequency by increasing the window size arbitrarily. With an adequate window size, to further reduce the bandwidth allocation frequency, we may apply the bandwidth allocation frequency control mechanism. Next, we investigate how

the bandwidth allocation frequency control mechanism affects the system performance with a large window size. Using window size =300 as an example, we get the following simulation results with bandwidth reallocation control parameter $R=0$ and $R=40$.

Figure 4.40 95% CI of bandwidth reallocation frequency with $R=0$ and $R=40$

Figure 4.40 shows that the bandwidth reallocation frequency can be reduced effectively with the combination of choosing the adequate window size and the value of bandwidth allocation control parameter R .

Figure 4.41 95% CI of measured packet loss ratio of class 1 with $R=0$ vs. $R=40$

Figure 4.42 95% CI of measured packet loss ratio of class 2 with $R=0$ vs. $R=40$

Figure 4.43 95% CI of measured packet loss ratio of class 1 with $R=0$ vs. $R=40$

The simulation results in Figures 4.41, 4.42 and 4.43 show that the measured loss ratio of each class is a little higher with $R=40$ than that with $R=0$. But all are below the target ones.

Figure 4.44 95% CI of measured overall multiplexing gain with $R=0$ vs. $R=40$

Figure 4.45 95% CI of measured overall allocated bandwidth with $R=0$ vs. $R=40$

Furthermore, as shown in Figure 4.44, the measured multiplexing gain with $R=40$ is a little lower than that with $R=0$. As a natural consequence, the average allocated bandwidth with $R=40$ is a little larger than that with $R=0$, which is shown in Figure 4.45.

The simulation results show that the bandwidth allocation frequency mechanism works well with window size as large as 300.

4.3 Discussion on setting the parameters

As discussed above, we need to adjust the parameters to tune the system performance. Among the different parameters, window size, *Thloshigh* and *Slarge* are particularly important to the system performance. If the traffic trace is long, we may set a large window size, through which a low bandwidth allocation frequency can be achieved. If the traffic trace is short, we need to set a small window size, which will make the system

equilibrate toward the steady state soon. By decreasing *Thlosshigh*, it would be easier to satisfy the QoS requirement, however, the multiplexing gain might decrease a little. By increasing *Slarge*, it would be quicker to make the measured loss ratio below the target one when it exceeds the target one, which might also reduce the multiplexing gain.

5 Conclusions and Future Work

The simulation results show that the *adaptive effective bandwidth allocation* algorithm can exploit the multiplexing gain among multiple traffic classes effectively, thus making the bandwidth allocation more efficient than the pure effective bandwidth approach. The buffer overflow preventive mechanism can improve buffer utilization, thus reducing the loss ratio. The long-term burstiness detection approach can track traffic fluctuations quickly, which makes the bandwidth allocation procedure insensitive to the measurement window size. The bandwidth reallocation control mechanism can also help decrease the bandwidth reallocation frequency greatly.

We have quantified the statistical multiplexing gain occurring among multiple classes by means of both theoretical analysis and simulation experiments. To compare the simulation results with the analytical results, we performed simulations with homogeneous Poisson traffic as input. The simulation results show that our AEBA approach can fully exploit the amount of multiplex gain that can be achieved without violating the QoS requirements.

We have evaluated the performance of the dedicated AEBA approach and the unified AEBA approach with heterogeneous traffic combined with both LRD and SRD traffic as input. The simulation results show that the unified AEBA approach can also allow the

different QoS requirements to be satisfied with almost the same network resources consumed by the dedicated AEBA method.

The unified AEBA approach is robust in that it is not sensitive to the system parameters such as the initial values of the multiplexing gain parameter g and the measurement window size. Furthermore, it does not require the *a priori* knowledge about the underlying traffic, which makes it more practically useful than the dedicated AEBA approach. Thus, the unified approach is preferable.

So far, we have focused our work at the edge of the network. We have investigated the performance of using AEBA schemes in the ingress node by means of both theoretical analysis and simulation experiments. How to extend these results to arbitrary topology network with multiple nodes is left for future study.

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