EXTENDING THE CONCEPT OF EFFECTIVE BANDWIDTHS TO DIFFSERV NETWORKS

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Abstract

It is a challenging issue to provide guaranteed QoS for diverse network applications while still obtaining high network utilization in Diffserv networks. As a promising approach to achieve the tradeoff between network utilization and the provision of QoS, the concept of effective bandwidths has been widely accepted. We propose a traffic measurement-based adaptive effective bandwidth allocation algorithm aiming at overcoming the conservative nature of effective bandwidths. We study the performance of adaptive effective bandwidth allocation under dynamic weighted round robin scheduling instead of a FIFO queueing discipline, aiming at providing differentiated services to traffic flows. We quantify the statistical multiplexing gain among multiple traffic classes with a set of simulations.

Keywords: *Effective Bandwidth; QoS; Traffic Prediction.*

1. INTRODUCTION

During the last 30 years, numerous network applications have been created. For these diverse applications, the quality of service (QoS) requirements are quite different. Some applications, such as email, ftp and other data transfer applications, are delay-tolerant but very sensitive to data loss. While other applications, such as real-time audio/video applications, are loss-tolerant but have tight delay requirement. A recent so-called Diffserv (Differentiated Services) approach has been developed to provide service differentiation for heterogeneous application requirements. In Diffserv architecture, QoS may be defined as quantitative or statistical terms of throughput, delay, jitter, and/or loss [1]. In order to solve the scalability problem, Diffserv approach provides QoS on the traffic aggregate level. At the incoming edge of the network, arriving packets are classified and marked. Traffic meters are used to monitor the user's traffic. The incoming traffic flow is compared against the negotiated traffic profile and a packet is determined whether within the negotiated traffic profile or not. A meter then passes state information to other conditioning elements such as shapers and droppers to trigger a particular action for each packet. In the core of the network, routers forward packets based on the differentiated service code point (DSCP). However, the Diffserv architecture only provides the framework for performing packet marking and conditioning, it does not mandate any specific implementation for what marking and conditioning is actually to be done [2].

In this paper, we develop a framework of using effective bandwidths under dynamic weighted round robin (DWRR) scheduling to study the statistical QoS assurance issue in self-sizing networks supporting Diffserv. 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 same QoS requirement. Here, we consider the packet loss

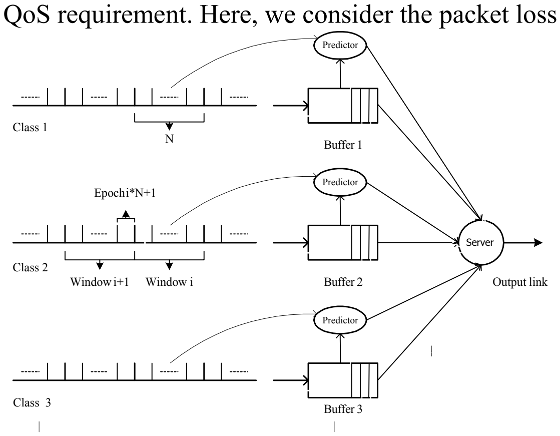

Fig.1 Effective bandwidths under DWRR

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probability as the QoS requirement of interest. We add the traffic prediction function into the meters since it is very difficult to get the exact traffic profiles in a real network environment. Thus, in self-sizing networks, a meter changes its role to be a predictor and the function of traffic conditioning is replaced by the function of dynamic link dimensioning, to some extent. 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 [3], we use the effective bandwidth estimated in the current time window to predict the bandwidth to be allocated in the next time window. According to the (sub) additive and independent properties [4] of effective bandwidths, we may wish to allocate the overall bandwidth according to the sum of effective bandwidth of individual classes. However, we will shortly see in section 3 and 4 that such pure effective bandwidth allocation is conservative, without taking into account the effect of multiplexing multiple classes together. This leads to a two-step adaptive effective bandwidth allocation approach: (1) we use the effective bandwidth as an approximation of the bandwidth to be allocated; (2) we adjust the bandwidth to be allocated according to the measured packet loss ratio. According to the buffer occupancy and the allocated bandwidth of each traffic class, the weights are adjusted dynamically.

The rest of this paper is organized as follows: In section 2, we describe the DWRR with AEBA. Then in section 3, we use homogeneous Poisson traffic sources as a special case to make a theoretical analysis of multiplexing gain. Next, in section 4, we evaluate the performance of our proposals with a set of simulations using Poisson and MMPP sources as input. Finally, in section 5, we draw the conclusion.

2. DWRR with AEBA

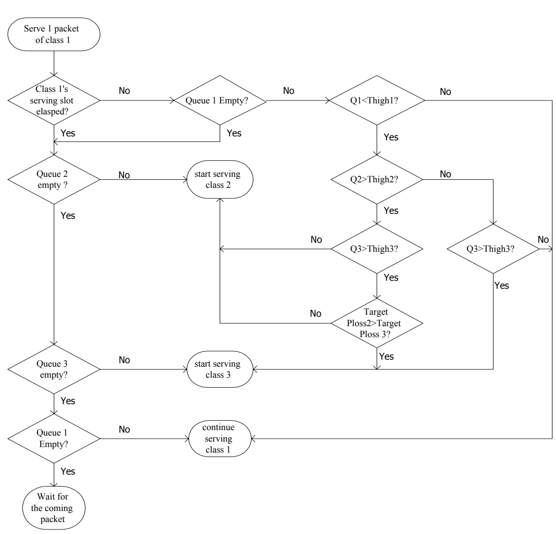

Fig.2 DWRR with buffer overflow preventive mechanism

2.1 Buffer Overflow Preventive Mechanism

While providing isolation among traffic classes, one traffic class can use only the amount of buffer that has been allocated to it. In particular, it can not utilize buffer capacity that is not currently being used by other traffic classes. It is therefore desirable to develop some mechanism to use buffer as efficiently as possible. To achieve that, we define a high threshold for each buffer, 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.

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 q2 and q3 exceeds the high threshold, the scheduler will start serving it. If both exceed the threshold, 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 Fig. 2. The similar procedure applies to class 2 and class 3.

2.2 Measurement-based Effective Bandwidths

In the literature, many effective bandwidth approaches have been proposed. Among them, a widely accepted mathematical framework for effective bandwidth of a stationary arrival process has been defined in [5]:

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

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.

It requires a full characterization of the underlying process to calculate (1), which is not trivial. Therefore, we use the measurement-based method to calculate the effective bandwidths. Our on-line measurement-based effective bandwidth calculation is based on the "block estimator" [6] method, which considers the non-overlapping blocks of arrivals over an interval of length t. By applying the block estimator method to (1), we can obtain the following equation:

$$\alpha(s,t)=\frac{1}{st}\log\frac{1}{N}\sum_{i=1}^{N} e^{sX[(i-1)t,\,it]} \tag{2}$$

where N is the window size. According to the large buffer asymptotic, s is approximated by

$$s=-\ln Ploss/B \tag{3}$$

where B is the buffer size, Ploss is the target packet loss probability.

2.3 AEBA

To exploit the statistical multiplexing gain, we develop the adaptive effective bandwidth allocation approach described in Fig. 3.

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

$$BW_{next} = \text{Min } \{\text{Max}\{EB(1-g), \text{average rate}\}, \text{peak rate}\} \quad (4)$$

where BW_{next} is the bandwidth to be allocated for the next window and EB is the effective bandwidth estimated in the current window. We define an upper threshold, *Thlosshigh*, and a lower threshold, *Thlosslow*, for measured packet loss ratio. We also define two step control parameters, *Ssmall* and *Slarge*, for adjusting the value of *g*. If the measured loss ratios are lower than *Thlosslow* in two successive windows, the over-allocation may have occurred. We increase the value of *g* by multiplying *Ssmall*, which will reduce the bandwidth allocation according to (4). 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 *Ssmall*. 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*.

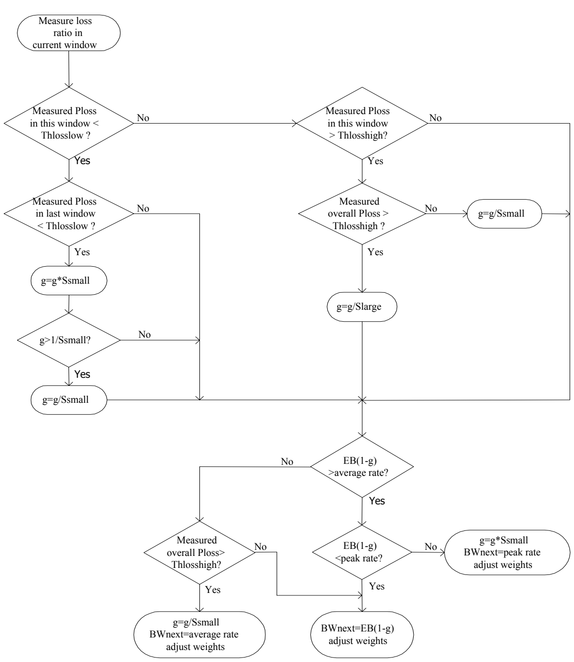

Fig.3 Adaptive effective bandwidth allocation

3. ANALYTICAL RESULT

To get an analytical result of multiplexing gain, we consider the following special case: Three classes of traffic sources in DWRR queueing system are all homogeneous Poisson traffic. They have the same arrival rate, for simplicity, assuming in an ATM network, λ=2000 cells/second. They also have the same cell loss ratio requirements, for example, Ploss=10^{-3}. And each class has the same buffer size: B=50 cells.

From (1), we can get the following effective bandwidth formula for Poisson traffic sources:

$$EB = \lambda \frac{e^{s} - 1}{s}. \quad (5)$$

Then, for each class, we calculate the effective bandwidth as follows:

$$EB_1 = EB_2 = EB_3 = 2144.74 \text{ cell/s}. \quad (6)$$

According to the additive property of effective bandwidths, we would wish to allocate the overall effective bandwidth with the sum of EB_1, EB2 and EB_3. However, such pure effective bandwidth allocation ignores the multiplexing gain among multiple classes. Due to statistical multiplexing, the bandwidth required to carry a set of classes with a certain QoS is less than the sum of the bandwidths that would be needed to carry each class separately with the same QoS. To calculate the multiplexing gain, consider a FIFO multiplexer with the buffer size of 3B fed by one Poisson traffic class with the arrival rate of 3 λ. With the same packet loss probability requirement, the effective bandwidth of this traffic flow will be

$$EB_{FIFO} = 6140.30 \text{ cell/s}. \quad (7)$$

As described in Fig.2, DWRR is work conserving and the buffer capacity is used efficiently. If we approximate the overall bandwidth in DWRR with (7), the overall packet loss in these two systems should be very close. Since all three traffic classes in DWRR are homogenous, the packet loss probability of each class should be the same with the overall packet loss probability. Through this way, we can estimate the multiplexing gain for this special case as follows:

$$\text{Gain} = (EB1+EB2+EB3- EB_{FIFO})/(EB1+EB2+EB3) = 0.04568 \quad (8)$$

4. SIMULATION RESULTS

We measure the traffic at the resolution of 50 milliseconds with the measurement window size set to 60. We set the initial value of *g*=0.05, upper loss ratio threshold *Thlosshigh*=0.98*target loss ratio, lower loss ratio threshold *Thlosslow*=0.6*target loss ratio, small step control parameter *Ssmall*=1.1 and large step control parameter *Slarge*=1.5.

4.1 Homogeneous Traffic Sources

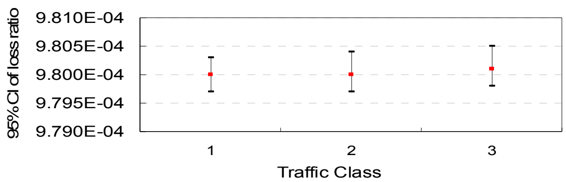

Fig. 4 95%CI of loss ratio with AEBA under DWRR

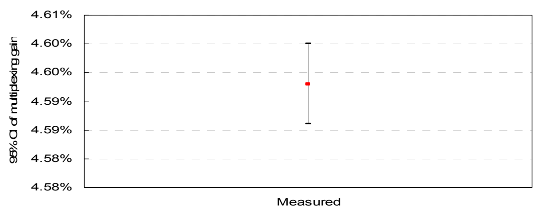

Fig. 5 95%CI of multiplexing gain with AEBA under DWRR

To evaluate the performance of DWRR with AEBA, We use three homogeneous traffic sources described in section 3 as input. The simulation results are given in Fig. 4 and Fig. 5.The simulation results show that the DWRR with AEBA approach can meet the QoS requirement of each traffic class while getting the statistical multiplexing gain of around 4.6% at the same time. The measured multiplexing gain is a little higher than the theoretical result in (8). The reason is that the effective bandwidth itself is conservative [7].

4.2 Heterogeneous Traffic Sources

In this scenario, we use three different two-state MMPP classes with different QoS requirements as input to evaluate the performance of DWRR with AEBA.

Table1 Traffic sources with different QoS requirements

Traffic sources	Class1	Class2	Class3
Target loss ratio	10^{-3}	10^{-2}	10^{-1}
Arrival rate in state 1 (cell/s)	1000	1000	200
State 1 lasting time(s)	200	600	300
Arrival rate in state 2 (cell/s)	2000	1500	300
State 2 lasting time(s)	200	600	300
Buffer size (Cell)	200	100	50

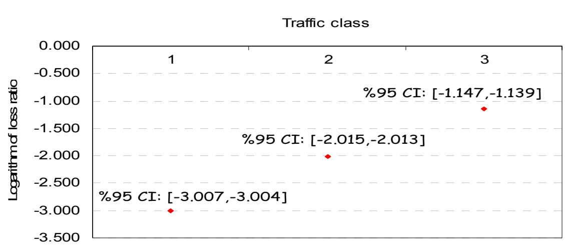

Fig. 6 Measured loss ratio for each class

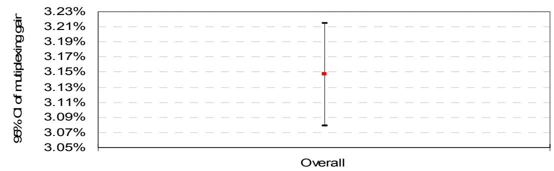

Fig. 7 95% CI of measured overall multiplexing gain

Table 1 lists the traffic source characteristics. Fig. 6 and Fig. 7 list the simulation results. The simulation results show that the different QoS requirements of all classes can be satisfied at the same time. Meanwhile, the overall statistical multiplexing gain of around 3.1% is achieved.

5. CONCLUSIONS

The analytical and simulation results show that DWRR with AEBA can exploit the multiplexing gain efficiently while satisfying the different QoS requirement of each class at the same time. AEBA can make more efficient bandwidth allocation than the pure effective bandwidth allocation.

References

[1] S. Blake, D. Black, M. Carlson, E. Davies, Z. Wang, and W. Weiss, "An Architecture for Differentiated Services," *RFC 2475*, December 1998

[2] J. Kurose and K. Ross, *COMPUTER NETWORKING: A TOP-DOWN APPROACH FEATURING THE INTERNET*, 2nd edition, Boston : Addison-Wesley, c2003

[3] I. Norros, "On the use of fractional Brownian motion in the theory of connectionless networks," *IEEE Journal on Selected Areas in Communications*, vol. 13, no.6, pp.953-962, August 1995

[4] J. Roberts, U. Mocci, and J. Virtamo(Eds.), *BROADBAND NETWORKS TELETRAFFIC: FINAL REPORT of ACTION COST 242*, Springer, 1996

[5] F. Kelly, "Notes on effective bandwidths," *STOCHASTIC NETWORKS: THEORY AND APPLICATIONS*, pp.141-168, ClarendonPress, Oxford, 1996

[6] N.G. Duffield, J.T. Lewis, N.O'Connell, R. Russell and F. Tomey, "Entropy of ATM streams: a tool for estimating QoS parameters," *IEEE Journal on Selected Areas in Communications*, vol. 13, no. 6, pp.981-990, August 1995

[7] M. Schwartz, *BROADBAND INTEGRATED NETWORKS*, Prentice-Hall, 1996