Effective Bandwidths under Dynamic Weighted Round Robin Scheduling

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Abstract- We develop a framework of using effective bandwidths under dynamic weighted round robin scheduling to study the statistical quality of service assurance issue in self-sizing networks supporting differentiated service. A traffic measurement-based adaptive effective bandwidth allocation algorithm aiming at improving the performance of effective bandwidths is proposed. We evaluate our proposed mechanism with a set of simulations that use Poisson and Markov modulated Poisson process sources as input. The simulation results show that the adaptive effective bandwidth allocation allows different quality of service requirements to be satisfied at the same time while overcoming the conservative nature of the pure effective bandwidth allocation.

Keywords- Effective Bandwidth, QoS, Bandwidth Management

I. INTRODUCTION

As a promising approach to achieve the tradeoff between network utilization and the provision of QoS, the concept of effective bandwidth has been widely accepted. In the literature, there are many approaches to estimate the effective bandwidth of a bursty source. In general, we can categorize these approaches 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 for some traffic sources (such as Markov and fBm processes) can be obtained. There are rich researches about such approaches, see, for example, [1] [2] [3] [4] [5] [6] [7] etc. The second categorization is to use Kelly's mathematical definition to calculate the effective bandwidths for different kinds of traffic. Based on large deviation theory, Frank Kelly defined a mathematical framework [8] for the effective bandwidth of a stationary arrival process as follows:

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

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. In practice, there are two methods to calculate the operating point of s and t. One is the many sources asymptotic [9] approach, which assumes that as the number of independent input increases, the buffer size and service rate per input stay fixed; the other one is the large buffer asymptotic [6] [10] method, which is concerned with how buffer overflow probability decays as buffer size increases. In the many sources asymptotic, a *sup-inf* algorithm is used to calculate the s and t. Since the *sup-inf* calculation can be computationally intensive and needs the whole traffic trace beforehand, many sources asymptotic is only suitable for off-line effective bandwidth approximation. According to a large buffer asymptotic, s is approximated by

$$s=-\ln(Q>B)/B \tag{2}$$

where B is the buffer size. We may choose a suitable time interval for t for on-line measurement-based effective bandwidth estimation.

Note that (2) is a simplifying form of

$$P\,(Q>x) \approx Ce^{-sx} \qquad \text{as } x\to\infty \tag{3}$$

by assuming C=1, where C is an undetermined asymptotic constant. This simplification, as well as the additive property of effective bandwidths without considering the statistical multiplexing gain, may result in the conservatism of effective bandwidth allocation [2] [5] [11] [12]. In some cases, the effective bandwidth approximation may overestimate the target loss probabilities by several orders of magnitude [12]. To solve this problem: we develop the measurement-based adaptive effective bandwidth allocation (AEBA) approach: (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.

Section II describes the AEBA algorithm. We study the performance of AEBA under dynamic weighted round robin (DWRR) scheduling instead of a FIFO queueing discipline, aiming at providing differentiated services to traffic flows. Section III provides the simulation results. And Section IV states the conclusion.

II. EFFECIVE BANDWIDTHS UNDER DWRR

A. Measurement-based effective bandwidths

It requires a full characterization of the underlying process to calculate (2), which is not trivial. For practical purposes, we use the measurement-based method to calculate the effective bandwidths. The performance of different methods for measuring effective bandwidths such as the direct estimator, the block estimator, the Kulback-Leibler distance (KLD) estimator and the linear regression (LR) estimator is compared in [13]. Among them, the block estimator is the fastest one. Therefore, it is suitable for the calculation of effective bandwidths in the real-time self-sizing network environment.

The block estimator method was proposed by Duffield *et al.* in [14]. It considers the non-overlapping blocks of arrivals over an interval of length t. By applying the block estimator method to (2), we can obtain the following equation:

$$\alpha(s,t)=\frac{1}{st}\log\frac{1}{N}\sum_{i=1}^{N}e^{s\sum_{k=(i-1)t+1}^{it}X_k} \quad (4)$$

where N is the window size. The essential idea behind formula (4) is to transfer the calculation of ensemble average in (2) into time average calculation, by assuming that the underlying processes have ergodic characteristics.

B. AEBA under DWRR

As shown in Fig. 1, at the ingress points of the networks, the incoming traffic streams are classified into different classes. Each class of traffic has the similar traffic characteristics and QoS requirements and is isolated into its own separated buffer. 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 past [7]. 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 [15] of effective bandwidths, we may wish to allocate the overall bandwidth according to the sum of effective bandwidth of individual class and adjust the weight assigned to each class according to its effective bandwidth estimated in the current time window. However, such pure effective bandwidth allocation ignores the effect of multiplexing multiple classes together. 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 exploit the statistical multiplexing gain among multiple

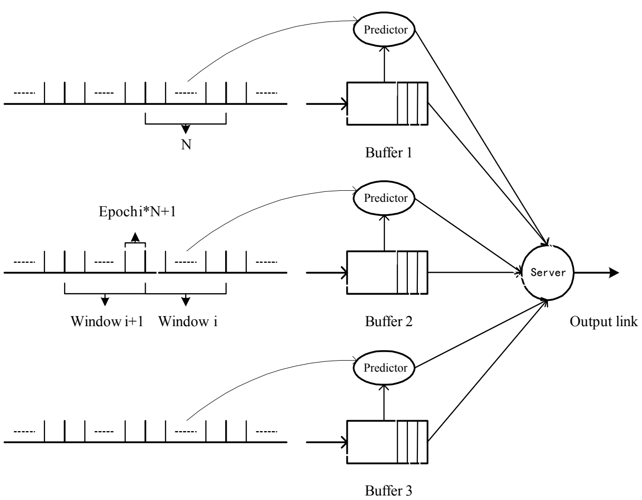

Fig.1 DWRR with traffic prediction in self-sizing networks

Fig. 2 Adaptive effective bandwidth allocation

classes, we develop the adaptive effective bandwidth allocation approach (AEBA) as described in Fig. 2.

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:

$$BW_{next}=\text{Min}\ \{\text{Max}\{EB(1\text{-}g), average\ rate\}, peak\ rate\} \quad (5)$$

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 a upper threshold, *Thlosshigh*, and a lower threshold, *Thlosslow*, for measured packet loss ratio:

$$0<Thlosslow<Thlosshigh<\ Target\ loss\ ratio \quad (6)$$

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

$$Slarge>Ssmall>1 \quad (7)$$

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 (5). 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*.

C. 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 Fig. 3.

We define two thresholds, *Thbw1* and *Thbw2*, for the measured arrival rates; and two parameters, *N1* and *N2*, for the measurement length.

$$Thbw1 > Thbw2 > BWnow \quad (8)$$

$$N2 > N1 >= 3 \quad (9)$$

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 a sustained burstiness occurs. If the measured loss ratio exceeds *Thlosshigh*, a bandwidth reallocation is needed.

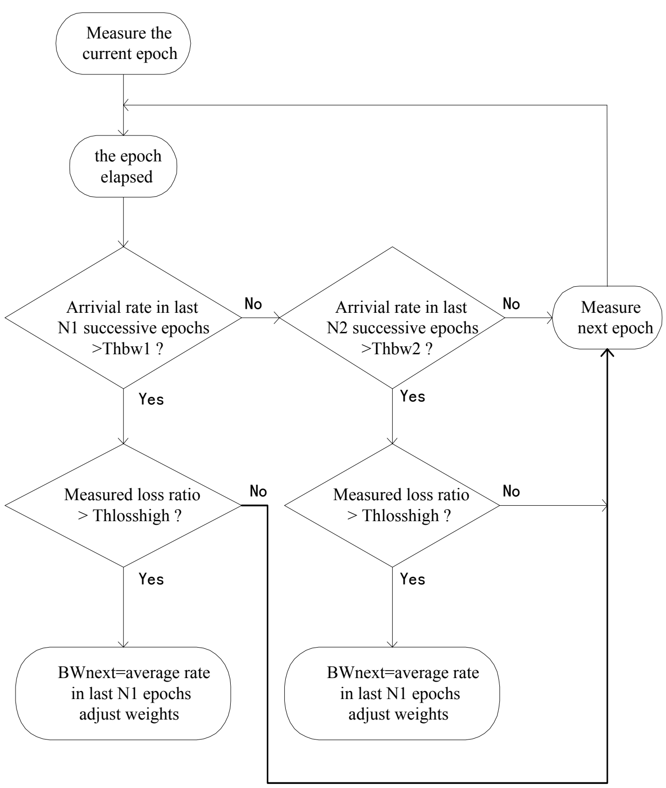

Fig. 3 Quick detection of sustained burstiness

III. Simulation Results

To evaluate the performance of our proposals, we perform the following simulations with Poisson traffic and MMPP traffic as input. In scenario 1, we use homogeneous Poisson traffic as input. In scenario 2, we use MMPP traffic as input.

A. Scenario 1

In this scenario, we evaluate the performance of AEBA under DWRR with three homogeneous classes of Poisson traffic as input. 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 measurement window size set to 60, i.e. each measurement epoch is 50 milliseconds long and each measurement window is 3 seconds long. We set the initial value of multiplexing gain factor *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.

Fig. 4 gives the measured loss ratio with pure effective bandwidth allocation under DWRR. Fig. 5 gives the measured loss ratio with AEBA under DWRR. Fig. 6 gives the measured overall multiplexing gain achieved with AEBA under DWRR. The measure multiplexing gain is calculated as follows:

$$Gain = (BWp - BWa)/BWp \quad (9)$$

where *BWp* is the overall bandwidth that would have been allocated with pure effective bandwidth allocation, BWa is the actual bandwidth that has been allocated with AEBA.

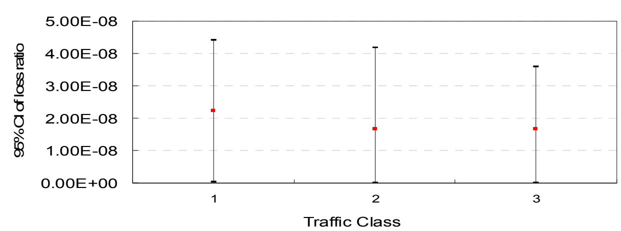

Fig. 4 95%CI of loss ratio using pure effective bandwidth allocation under DWRR

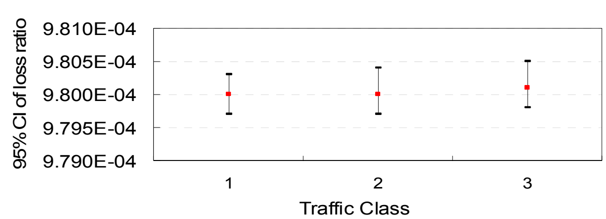

Fig. 5 95%CI of loss ratio with AEBA under DWRR

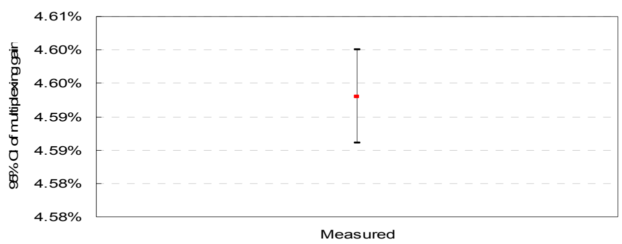

Fig. 6 95%CI of multiplexing gain with AEBA under DWRR

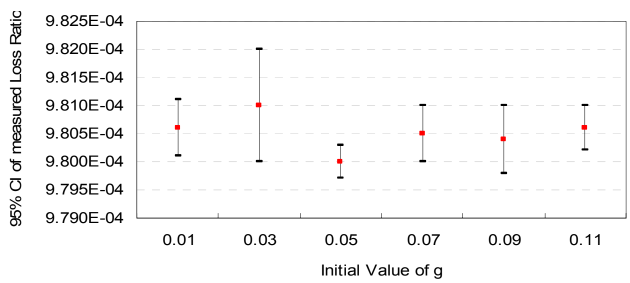

Fig. 7 Sensitivity of loss ratio (class 1) to initial value of *g*

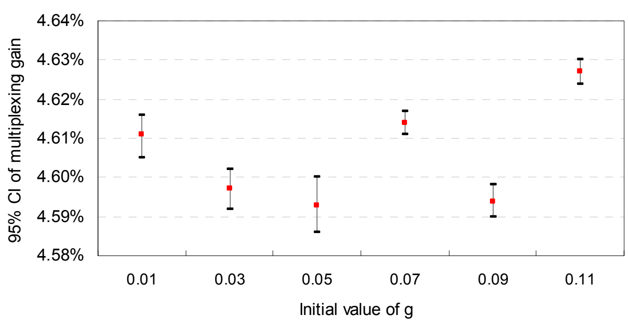

Fig. 8 Sensitivity of multiplexing gain to initial value of *g*

The simulation results show that the measured loss ratio is approximately 10^{-8} while the target loss ratio is 10^{-3}. So the pure effective bandwidth allocation is too conservative. 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.

The simulation results in Fig. 7 and Fig. 8 show that the measured loss ratio and the overall multiplexing gain are not sensitive to the initial value of *g* (using class 1 as an example in Fig.7, we obtain the corresponding simulation results for classes 2 and 3).

B. Scenario 2

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. We set the initial value of *g*=0.05, bandwidth thresholds *Thbw1*=1.5*current allocated bandwidth and *Thbw2*=1.2*current allocated bandwidth, time control parameters *N1*=3 and *N2*=5.

TABLE 1 Traffic sources with different QoS requirements

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

Table 1 lists the traffic source characteristics. Fig. 9 and Fig. 10 list the simulation results with window size=60. Table 2 and Fig. 11 give the simulation results with different window sizes. To obtain a better understanding of the performance of DWRR with AEBA and quick burstiness detection, a sample of how our approach adjusts the effective bandwidth allocation and tracks the traffic fluctuations during a period of three simulated minutes is given in Fig. 12.

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 approximately 3.1% is achieved.

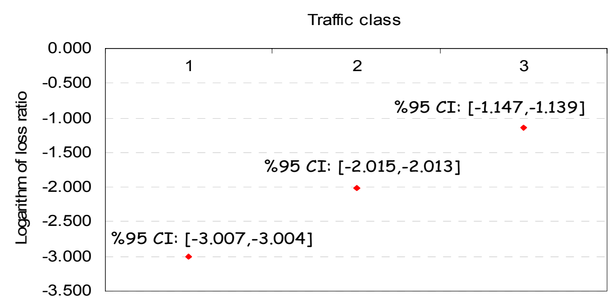

Fig. 9 Measured loss ratio for each class

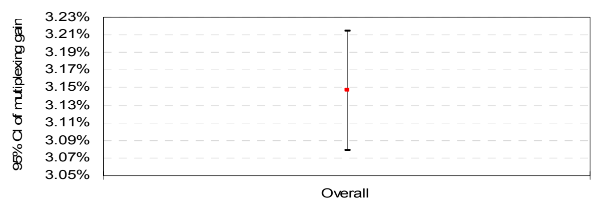

Fig. 10 95% CI of measured overall multiplexing gain

TABLE 2 Sensitivity of loss ratio to window size

Traffic sources	Window size	Measured loss ratio	95% CI
Class 1	60	9.867E-4	[9.830E-4, 9.904E-4]
	120	9.717E-4	[9.680E-4, 9.754E-4]
	180	9.658E-4	[9.627E-4, 9.689E-4]
	240	9.610E-4	[9.586E-4, 9.634E-4]
	300	9.722E-4	[9.574E-4, 9.870E-4]
Class 2	60	9.686E-3	[9.664E-3, 9.708E-3]
	120	9.604E-3	[9.572E-3, 9.636E-3]
	180	9.533E-3	[9.487E-3, 9.579E-3]
	240	9.450E-3	[9.365E-3, 9.535E-3]
	300	9.392E-3	[9.311E-3, 9.472E-3]
Class 3	60	7.198E-2	[7.129E-2, 7.267E-2]
	120	6.871E-2	[6.776E-2, 6.966E-2]
	180	6.622E-2	[6.549E-2, 6.659E-2]
	240	6.495E-2	[6.422E-2, 6.568E-2]
	300	6.908E-2	[6.804E-2, 7.012E-2]

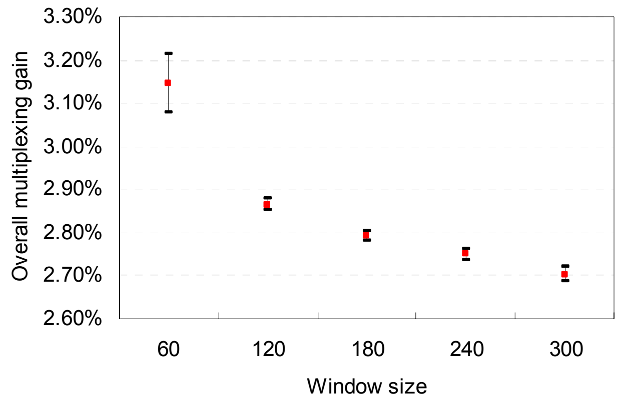

Fig. 11 Sensitivity of overall multiplexing gain to window size

The difference of the measured loss ratio of each class is very small for different measurement window sizes. The reason is that we use the fast detection approach to track sustained burstiness quickly. It seems that the measured overall gain decreases a little with the increase of measurement window size. The reason may be that: the decrease of the traffic is not detected in the sustained bursiness detection algorithm.

Fig. 12 gives a sample of the effective bandwidth, allocated bandwidth and measured traffic rate of class 3 during the simulated time period [3240, 3420]. We can see that the allocated bandwidth is lower than the effective bandwidth, i.e., there exists a multiplexing gain. There is also a big change of traffic rate at the time point of around 3320s, the allocated bandwidth tracks it well.

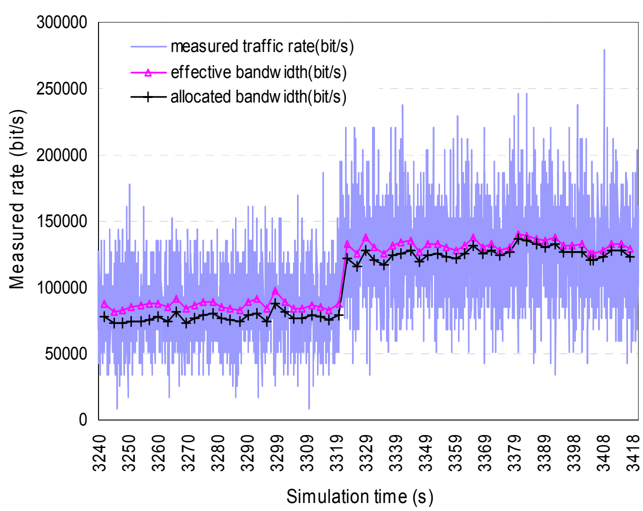

Fig. 12 Effective bandwidth vs. allocated bandwidth vs. traffic rate during the simulated period (54m, 57m)

IV. Conclusion

In this paper, we have quantified the statistical multiplexing gain obtained by using the AEBA approach under DWRR. We accomplished this with a set of simulations that use Poisson and MMPP traffic as input. The simulation results show that the adaptive effective bandwidth allocation algorithm can exploit the multiplexing gain efficiently. The persistent burstiness detection approach can track the traffic fluctuation quickly. Therefore, using AEBA under DWRR can allocate bandwidth more efficiently than the pure effective bandwidth allocation.

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