Bandwidth control and its applicability based on queue length monitoring

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1 Introduction

In [10], Shioda and Saito presented a method for estimating the cell loss ratio in real time, and applied it to VP bandwidth estimation and call admission control. They utilized the large deviation result of Glynn and Whitt [6], that the cell loss ratio (CLR) decays exponentially as the buffer size increases. In this case the CLR is characterised by two parameters, the asymptotic constant β and the asymptotic decay rate η [4]. As a result, an algorithm for estimating these coefficients on an on-line basis from the buffer measurement was proposed. Our objective now is to develop an algorithm (by reformulating the method proposed in [10] and applying the CLR estimation procedure presented in [8]) for real time VP bandwidth estimation, which works also in the case of long range dependent traffic.

2 VP bandwidth control

The simplest realization of VP bandwidth control is to replace the VP bandwidth by the estimated effective bandwidth of the cell stream transferred in the VP. Our aim is to estimate the effective bandwidth of the traffic using real time traffic measurements. To do this, we can proceed as follows.

In [8] a very simple approximation of the CLR in a single server queue with buffer size K has been developed under the assumption that the arrival process does not possess long range dependence. We rewrite it below in a form that is convenient for us:

$$\frac{1-\rho}{\rho} \approx d \log p_K, \tag{1}$$

where p_K is an approximation (upper bound) of the CLR, ρ is the VP utilization and d is an appropriate coefficient depending on the variance of the arrival process. Once we know the coefficient d, based on Eq.(1) the effective bandwidth (α) of the source can be estimated as

$$\alpha(\eta_{obj}) = A(1 + d \log CLR_{obj}), \tag{2}$$

where A is the mean arrival rate and CLR_{obj} is the target cell loss ratio. To do this, according to Eq.(1) we only need to measure the link utilization ρ and the probability p_K.

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3 Bayesian regression analysis and real time buffer measurement

Denote the identifier of the actual measurement epoch by n, $n = 0, 1, 2, \ldots$. By monitoring $\rho(n)$ and $\log p_K(n)$ somehow, we can observe $d(n)$ through Eq.(1). Actually, assume the following relation:

$$\frac{1-\rho(n)}{\rho(n)\log p_K(n)} = d(n) + \sigma(n), \tag{3}$$

where $\sigma(n)$ is Gaussian white noise with mean 0, representing the measurement error. To take into account traffic pattern variation and to ensure the convergence of the bandwidth to the objective, *even when the traffic is such that the effective bandwidth formula Eq.(2) is not valid* (e.g., the traffic is long range dependent), suppose that the coefficient d (system characteristic) can change with time according to the following equation:

$$d(n) = d(n-1) + \omega(n), \tag{4}$$

where $\omega(n)$ is also a Gaussian white noise with mean 0.

In the terminology of the control system Eq.(3) and Eq.(4) are called the "state space representation" of our single server queue, and the variable d is called the state variable of the system. Bayesian regression analysis can be applied to estimate the state variable d. The state variable can be recursively estimated at the end of every measurement epoch by a Kalman Filter formulation.

In case of long range dependent traffic the tail asymptotics of the queue length distributions are Weibullian [4, 8, 9]:

$$p_k = \beta e^{-\eta k^{\gamma}}, \quad \gamma \in (0,1]. \tag{5}$$

Based on this, in [8] a three-point measurement method is proposed that can be used for estimating $\log p_K(n)$. If we combine this estimate with the effective bandwidth result, VP bandwidth control can be expected to be performed through the following control equation for both short range and long range dependent traffic:

$$C(n) = A(1 + \hat{d}(n)\log CLR_{obj}). \tag{6}$$

The problem is that the notion of effective bandwidth can not be applied for long range dependent traffic because Eq.(2) was derived under the assumption of short range dependence. What we can do is to show that the proposed Kalman Filter formulation with the three-point measurement method works well, despite the fact that we are lack of the equations leading us to the direct solution. To do this, we can rewrite Eq.(1) as

$$d(C, p_K(C)) \approx \frac{C-A}{A\log p_K(C)}. \tag{7}$$

Here, the notation $d(C, p_K)$ emphasizes that (for the given traffic A_t) d is the function of the bandwidth C and the probability p_K, which probability also depends on C. For a given CLR_{obj} to be satisfied, Eq.(2) gives us the required VP bandwidth (C_{obj}). From Eq.(2), we get

$$d(C, CLR_{obj}) = \frac{C-A}{A\log CLR_{obj}}. \tag{8}$$

For the short range dependent case (where Eq.(2) is valid), assuming that the error of approximations on the way to get Eq.(1) is negligible, $d(C, p_K(C))$ *does not* depend on C and remains constant for various bandwidths. Therefore, once we can evaluate d by using Eq.(7) for a given initial bandwidth, d is used in Eq.(8) and we can derive C_{obj}, which is the bandwidth to be determined (see Figure 1). In this case, C_{obj} is at the point where $d(C, p_k(C))$ meshes $d(C, CLR_{obj})$ and it can be calculated *in one step.*

When the traffic is long range dependent (the notion of effective bandwidth can not be derived), or the errors of the approximations are non-negligible, $d(C, p_K(C))$ becomes dependent on C (see Figure 2 for an example). Our algoritm works as previously. Calculate $d(C, p_K(C))$ for C_0 and set the bandwidth to C_1 such that $d(C_1, CLR_{obj}) = d(C_0, p_K(C_0))$. Measuring p_K at C_1 gives $d(C_1, p_K(C_1))$, different from $d(C_0, p_K(C_0))$, and that is the point why the parameter $\omega(n)$ was introduced to the state equation Eq.(4) in the Kalman Filter. This parameter makes it possible for $\hat{d}$ to change its value successively. Next, the VP bandwidth is adjusted appropriatelly and the same step is repeated again. For such an iterative method the question of convergence emerges. The sufficient condition for that—assuming accurate measurements—is that the slope of $d(C, p_K(C))$ can not exceed the slope of $d(C, CLR_{obj})$.

Figure 3 shows the simulated curve of $d(C, p_K(C))$ for long range dependent traffic trace with Hurst parameter $H = 0.7$ and $A = 10$ Mbps (see Section 4.2 for more details) In this example, the sufficient condition of convergence is satisfied around C_{obj}. Note, that in practice, because of the Kalman Filter, the sequence of the determined bandwidth C_i, $(i = 0, 1, \ldots)$ can approach C_{obj}, even if the condition of the convergence does not hold.

4 Simulation

Here we describe simulation experiments when the VP bandwidth control using the proposed three-point measurement was applied.

4.1 Short range dependent traffic

Consider N identical but independent on-off sources (VCs). In the on-states, cells were offered from the VC at a constant rate (peak rate), while in the off-states the source remained silent. The duration of each on-state and each off-state were exponentially distributed. The cells from the multiplexed on-off sources arrived at the output buffer of 128 cells dedicated to the VP.

The simulation conditions were as follows: the VP bandwidth was initially 1.2 Mbps. 10 sources were multiplexed, the peak rate of each VC was 1 Mbps and the average rate of each VC was 0.1 Mbps. The mean duration of the on-state was 1 ms in the 'non-bursty' case (Figure 5), and 5.43 ms in the 'bursty case' (Figure 6). Every 20 minutes at three different thresholds (5, 10, 20), the frequencies in which the number of cells in the buffer was greater than or equal to the thresholds were measured, the unknown parameter, d, in Eq.(3) was estimated, and the VP bandwidth was adjusted by the proposed formula (Eq.(6)). The CLR objective was 10^{-8}.

The actually required VP bandwidth was calculated through an analytical method [1, 5], given complete information about the cell arrival process.

Figure 5 and Figure 6 show the dynamic behaviour of the VP bandwidth under the proposed control. In the case of 'non-bursty sources', β is close to 1, and therefore only η determines the shape of the queue length distribution. Parameter γ in the Weibullian distribution (Eq.(5)) becomes $\simeq 1$, and the fitted distribution is close to the real one. Our method works well, and finds slightly higher bandwidth than the theoretical required value.

In the case of 'bursty sources', β is in the order of 10^{-2}, and therefore the queue length distribution slowly approaches its asymptote. Although the tail asymptotics for the distribution *are* exponential, because of the small asymptotic constant, monitoring the queue at two points and estimating the queue length distribution by an exponential distribution is not appropriate here, the CLR is underestimated by several orders of magnitude. The three-point measurement method works better in this case in spite the fact that the asymptotics are *not* Weibullian. The fitted Weibullian distribution slightly overestimates the CLR, that results in larger VP bandwidth than theoretically required (Figure 6).

4.2 Long range dependent traffic

Markovian source models are only capable of generating short range dependent traffic. If we want to generate long range dependent traffic, we need to find an appropriate method to do that. For our simulator the on-off model originally proposed by [7] was suitable.

To introduce long range dependence into the on-off model, assume a heavy tail for the distribution of the activity periods T_{on} [2]. In the limit of a large number of such sources and high load, it is shown in [7] that the aggregated traffic, properly normalized, converges to an exactly self-similar Gaussian process, and in [2] Brichet *et al.* showed that the tail of the queue length distribution is Weibullian. In our numerical example the number of sources was set to 100. The mean duration of the on period was set to 0.1 ms to assure the high load, and the parameters of the Pareto distribution were set with Hurst parameter $H = 0.7$ for each source. Further discussions on this source model can be found in [8]. The VP bandwidth was initially set to 12 Mbps, and all the other parameters were kept as they had been in the previous example.

The simulation result is shown in Figure 4. What we can see is that the estimated VP bandwidth reaches a certain value and (except in the initial phase) no cell loss occurs during the simulation time. (Since we gave up the Markovian property in our source model, the actually required bandwidth can not be calculated). To verify the results, we rejected the assumption of Weibullian queue length distribution, and using only the first and third thresholds and fitting an exponential curve, reran the simulation. As can be seen from Figure 4, the estimated VP bandwidth is smaller by a few Mbps than previously, and the experienced CLR is in the order of 10^{-4}–10^{-5}. This means that our proposed control shows good CLR performance and its derived bandwidth is not excessive. At most the excessive bandwidth is less than a few Mbps.

While our simulation results with a short buffer size (128 cells) are shown, the VP bandwidth with a larger buffer size are easier to control in our simulation, so we omit the results here.

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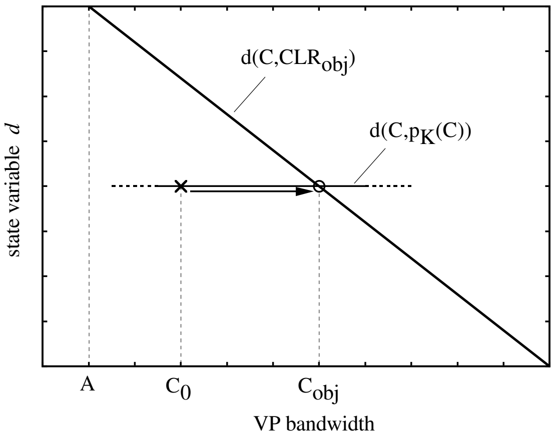
state variable d
d(C,CLR_obj)
d(C,p_K(C))
A
C0
Cobj
VP bandwidth

Figure 1: Transient behaviour of our algorithm for the short range dependent case.

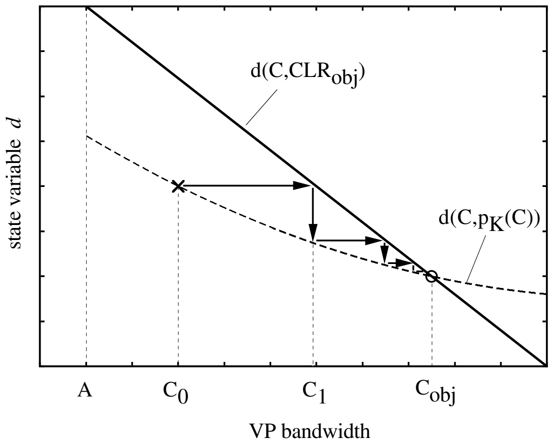
state variable d
d(C,CLR_obj)
d(C,p_K(C))
A
C0
C1
Cobj
VP bandwidth

Figure 2: Transient behaviour of the VP bandwidth control algorithm in general case.

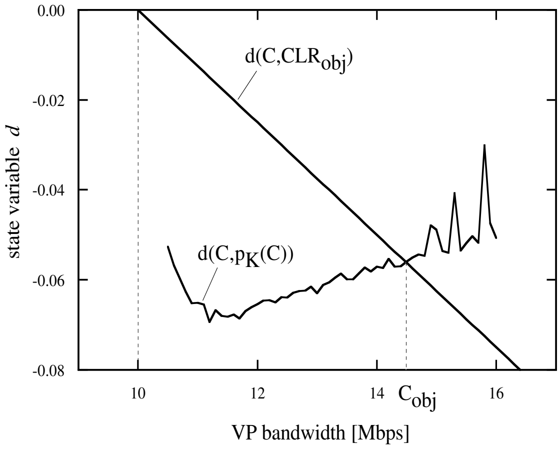

Figure 3: Simulated plot of $d(C, p_K(C))$ for long range dependent traffic.

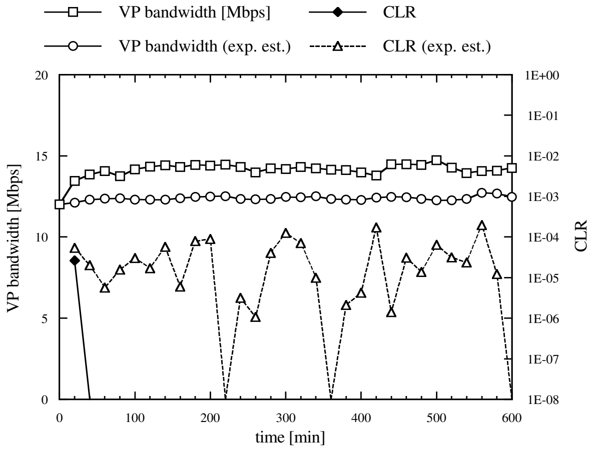

Figure 4: VP bandwidth control for Pareto-type sources with different estimate methods.

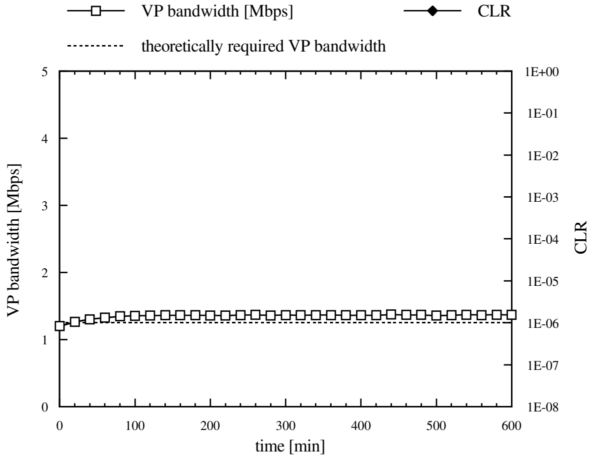

Figure 5: Sample path of VP bandwidth under the proposed control (non-bursty case).

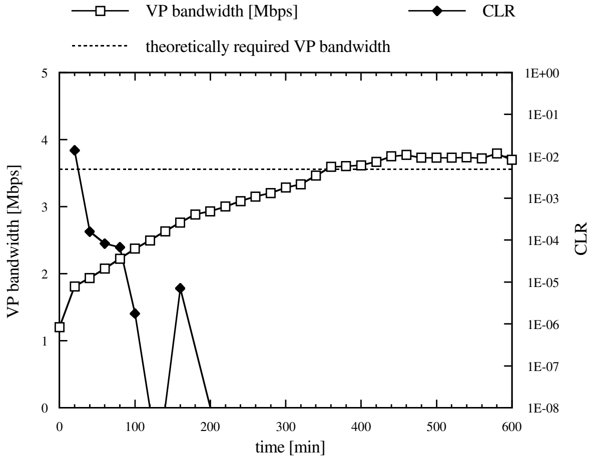

Figure 6: Sample path of VP bandwidth under the proposed control (bursty on-off sources).