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Bandwidth Allocation for Broadband Transport Network

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Abstract**—**This paper proposes a bandwidth allocation process for a single broadband network traffic source. In recent years, broadband traffic source has been proved that it has self-similarity and self-similar model that is well fit to the broadband network traffic sources. The bandwidth allocation problem is very important in network planning. The network planning problems such as call admission control and route selection have to consider the required bandwidth of network traffic. We use the equivalent bandwidth of two-state fluid-flow model and self-similar model to estimate the bandwidth of the traffic traces. The traffic traces are generated from the Poisson model and the self-similar model. In order to efficiently utilize the network resources, we analyze those traffic sources and bandwidth estimations, which are suitable for different network conditions as well as the influence of buffer sizes on different bandwidth estimations.

Keywords**—**Bandwidth Allocation; Self-Similar Model; B-ISDN; Quality of Service

1. INTRODUCTION

The Broadband Integrated Services Digital Network (B-ISDN) based on the Asynchronous Transfer Mode (ATM) technology provides the multimedia (e.g., voice, video, data) services and the flexibility of bandwidth adjustment and supports a wide range of applications with different quality of service (QoS) requirements in a flexible and cost-effective manner. The ATM provides the required flexibility for supporting diverse services in a B-ISDN environment and becomes an emerging standard for transport in it.

Since the user requirements for using network services are continuously increasing and changing, the issues users focus on are the type and quality of services provided by the network service providers. The future trends of network services are to provide an integrated multimedia information network to meet the diverse requirements of users in any circumstance. In order to satisfy the various requirements, the telecommunication companies are trying to provide users with enough resources, such as bandwidth, to make more other users pay attention to them and increase their competition ability. Under the limitation of bandwidth resource, one of the most important issues is to effectively allocate proper bandwidth to the user's requests, so that the link utilization can be increased and more users' requirements can be achieved.

The growing needs of the Internet and the broadband services have created the demand for higher bandwidth from telecommunication networks. The bandwidth of the current networking equipment is not enough. Except from extending the new networking equipments, it is necessary to develop a good planning approach to effectively utilize the limited bandwidth. The traffic of broadband network becomes more complicated and hard to model than the traditional networking infrastructure and traffic model since it is difficult to describe the traffic characteristics, estimate the traffic parameters, and to allocate the bandwidth. The bandwidth allocation acts as an important mechanism in network planning and is considered in both route selection and call admission control. This paper proposes a bandwidth allocation process and applies it to the different traffic models and different self-similar parameters under different buffer sizes in order to allocate the bandwidth efficiently.

This paper is organized as follows. In Section 2, the models and generations of traffic and the bandwidth estimations are individually presented. Section 3 describes the proposed bandwidth allocation process. The experiments and results are presented in Section 4. Conclusions are made in Section 5.

2. TRAFFIC MODELS AND BANDWIDTH ESTIMATION

Traffic model is the core of evaluating the performance of telecommunication networks. Traffic models must be able to accurately capture the statistical characteristics of an actual traffic. If the traffic models do not accurately represent the actual traffic, one may overestimate or underestimate network performance which causes the waste of network resources or the loss of cells.

Traffic models in telecommunication networks include stationary or nonstationary models (Adas, 1997). Stationary traffic models can be divided into two classes: short-range and long-range dependent. Short-range dependent models include Markov processes and Regression models. Long-range dependent models include Fractional Autoregressive Integrated Moving Average (F-ARIMA) and Fractional Brownian motion (FBM).

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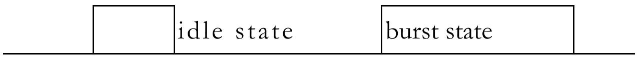

Figure 1. The two-state traffic.

2.1 Poisson model

Poisson traffic model is suitable to be used in modeling the voice traffic. In application, the traffic of traditional telephone is essentially of this kind. The model uses Poisson process as the modulated mechanism. Given a random process $\{N(t),\ t \geq 0\}$ is a Poisson process, where $N(t)$ is the number of arrival cells at time t, the properties of Poisson process are:

(1) The number of arrival cells during each unit interval is equal to 1;
(2) $N(t+s)-N(t)$ is independent of $\{N(u),\ 0 \leq u \leq t\}$; and
(3) The distribution of $N(t+s)-N(t)$ is independent of t for all $t,\ s \geq 0$.

The property (2) describing the number of arrival cells during any interval depends only on the length of that interval and not on the endpoints. According to the Poisson process, the traffic arrival process follows the Poisson distribution with mean rate λ and its service time follows the exponential distribution with mean rate $1/\lambda$.

2.2 Fluid-flow model

In order to characterize the effective bit rate of a connection, a two-state fluid-flow model is adopted to capture the basic behavior of the traffic source associated with a connection, where a source is either in an "idle state", transmitting at zero bit rate, or in a "burst state", transmitting at its peak rate (Guerin et al., 1994). Such a source model as shown in Figure 1 has the advantage of being simple and flexible.

Based on this two-state fluid-flow model, idle and burst periods are defined to be those during which the source is idle or active, respectively. Assuming independent identical distribution burst and idle period, the peak rate of a connection and distributions of idle and burst periods completely identify the traffic statistics of a connection. Assuming that the parameters of a connection are stationary, its peak cell rate (PCR) and utilization coefficient, ρ, i.e., fraction of time the source is active, completely identify other quantities such as mean m and variance σ^2 of the bit rate. For exponentially distributed burst and idle periods, the source is further completely characterized only by three parameters, namely PCR, ρ, and b, where b is the mean of the burst period (Guerin et al., 1994).

2.3 Self-similar model

Recent traffic measurements in corporate LANs, Variable-bit-rate video, WAN, and other communication systems show traffic behavior of self-similar nature (Beran et al., 1995). Using self-similar model to characterize actual traffic in broadband networks can describe significant variance (burstiness) across a wide range of time scales and the long-range dependence of traffic. The traditional Markovian or Poisson models have been proven to be unable to predict network performance in the case of self-similar traffic since they do not take into account the inherently burst nature of traffic.

A few mathematical models can be used to present the random process of self-similarity. Such models include fractional Gaussian noise (FGN), fractional autoregressive integrated moving-average (F-ARIMA) process, and Pareto process (Leland et al., 1994). Fractional Brownian motion (FBM) is a continuous zero-mean Gaussian process. It has stationary increments and is self-similar with the self-similarity parameter H. The increment process of FBM is called FGN. The FGN $X = (X_k:\ k \geq 0)$ with parameter $H \in (0,\ 1)$ is a stationary Gaussian process with mean μ, variance σ^2, and autocorrelation function $r(k) = (|k+1|^{2H} - |k|^{2H} + |k-1|^{2H}),\ k > 0$. The FGN is exactly second-order self-similar with self-similarity parameter H, as long as $1/2 < H < 1$. The F-ARMIA $(p,\ d,\ q)$ processes are asymptotically second-order self-similar with self-similarity parameter $H = d + 1/2$, as long as $0 < d < 1/2$. p and q are the integer 0 or 1. The F-ARMIA process is a long-range dependent self-similar process when $0.5 < H < 1$. The arrival process of self-similar packet is usually the distribution of heavy-tailed or power-law interarrival time. The random variable T has "heavy-tails" property when $P[T \geq t] \sim t^{-\eta},\ \ \eta > 0,\ \ t \to \infty$. Pareto distribution is one of the simplest power-law distributions and can be represented as $P[T \geq t] = 1 - F(t) = \beta^{\alpha} / (\beta + t)^{\alpha},\ \ \alpha,\ \beta > 0$ with the probability distribution function $f(t) = \alpha\beta^{\alpha} / (\beta + t)^{\alpha+1}$. Pareto distribution is a heavy-tailed distribution when $1 < \alpha < 2$ and is a traditional queue behavior when $\alpha > 2$. The distribution of interarrival time with parameter $0 < \alpha < 1$ and $1 < \alpha < 2$ satisfies the self-similar arrival process and has the fractional effect (Huang et al., 1996; Paxson and Sally, 1995).

The characteristics of self-similarity include slowly decreasing variance, long-range dependence, and noise. The random self-similar process is still self-similar after being divided. The sum of independent self-similar processes is also self-similar. Based on the self-similar model to characterize traffic, the real traffic behavior can be described and the network planning and control mechanisms, such as call admission control and route selection, can be developed to precisely control the network performance.

2.4 Traffic generation methods

Two models that yield elegant representations of the self-similar phenomena are FGN and F-ARMIA. The LAN traffic can be successfully modeled using FGN process. The F-ARMIA processes seem to describe the variable bit rate video traffic reasonably accurately (Garrett and Willingerm, 1994). However, the difficulty is that the queuing theory behind these models is still under development. There are very few analytical results available. Therefore, generating long traces of self-similar processes as input traffic becomes increasingly important and is essential for gaining better understanding of the queuing behavior and network-related performance issues. In order to acquire the general traffic data, we adopt the Successive Random Addition (SRA) algorithm, derived from the Random Midpoint Displacement (RMD) algorithm, to generate the self-similar input traffic source.

Assume we want to generate an FBM trace in time interval $[0,\ T]$. The basic idea of the RMD algorithm is to work inward, subdividing the interval $[0,\ T]$ recursively and constructing the values of the process at the midpoints from the value at the endpoints. In constructing the values $Z\big((a+b)/2\big)$ at the midpoints of an interval $[a,\ b]$ from the values $Z[a]$ and $Z(b)$ at the endpoint, if Z were FBM, then the midpoint displacement $Z\big((a+b)/2\big)-\big(Z(a)+Z(b)\big)/2$ would have a zero-mean Gaussian distribution. Let s_k be the standard deviation used in generating the midpoint at step k with σ_0 being the standard deviation of the displacement at the time scale T, then $\sigma_0 = T^{2H}$. We also assume $T = 2^n$. By the scaling properties of FBM, we have

$$s_k = (1/2^k)^H \sqrt{1-2^{2H-2}}\sigma_0 \tag{1}$$

$$s_k = \left(1/2^H\right)\ s_{k-1} \tag{2}$$

and it is convenient to define the initial value $s_0 = \sqrt{1-2^{2H-2}}$ (Lau et al., 1995).

The approximate FBM $\big(Z(t)\big)$ trace generated by the RMD algorithm can be interpreted as the cumulative arrival process $A(t)$ (Lau et al., 1995):

$$A(t) = Mt + \sqrt{aM}Z(t) \tag{3}$$

where M is the mean rate, a is the peakedness factor which is defined as the ratio of variance to the mean of the number of cells in a unit time interval. The increment from time t to $t+1$ is then

$$\tilde{A}(t) = M + \sqrt{aM}[Z(t+1)-Z(t)] \tag{4}$$

Although in the SRA algorithm, the midpoints are interpolated the same way as in the RMD algorithm, a displacement of a suitable variance is added to all the points at each stage of recursive subdivision. The SRA algorithm can generate self-similar traffic traces in very short instances and the results generated for $H < 0.9$ are very satisfactory (Prased et al.,1996).

2.5 Bandwidth estimation

As presented previously, the diverse traffic models describe the characteristics of traffic with their specific parameters, so that the traffic behavior can be represented. Based on these traffic models, the bandwidth estimation equations are developed to allocate an adequate bandwidth to traffic in order to meet the desired QoS.

According to the two-state fluid-flow model and its associated parameters, the equivalent capacity (EC) associated with a single connection in isolation for the desired overflow probability ε is then taken to be (Guerin et al., 1994):

$$\begin{aligned} EC \cong & \Big[\tau b(1-\rho)PCR - x \\ & + \sqrt{[\tau b(1-\rho)PCR - x]^2 + 4x\tau b\rho(1-\rho)PCR}\Big] \\ & / 2\tau b(1-\rho) \end{aligned} \tag{5}$$

where $\tau = \ln(1/\varepsilon)$ and x means a finite buffer size.

Recent traffic measurements have indicated that traffic behavior is of self-similar nature. The FBM model uses three parameters m, a, and H where m is the mean input rate, a is a variance coefficient, and H is the Hurst parameter to describe the self-similarity of traffic. Based on this self-similar model, the equivalent capacity for the desired overflow probability ε is (Norros, 1995):

$$EC \cong m + \left(k(H)\sqrt{-2\ln\varepsilon}\right)^{1/H} a^{1/(2H)} x^{-(1-H)/H} m^{1/(2H)} \tag{6}$$

where $k(H) = H^H\left(1-H\right)^{1-H}$.

2.6 Estimation of hurst parameter

Hurst parameter is a very important parameter in describing the long-rang dependence or the self-similarity of traffic. It is necessary to investigate the presence of self-similarity in a generating empirical input traffic trace. We will adopt Rescaled-Adjusted Range Statistics (R/S statistic) coupled with linear regression analysis to estimate the Hurst parameter H in this study. The main process is as follows:

Given a random process X_i at time i and the cumulative bit rate $Y_j = \sum_{i=1}^{j} X_i$, then the expression:

$$\begin{aligned} R(t,\ k) = & \max_{0\le i\le k}[Y_{t+i} - Y_t - (i/k)(Y_{t+k} - Y_t) \\ & - \min_{0\le i\le k}[Y_{t+i} - Y_t - (i/k)(Y_{t+k} - Y_t)] \end{aligned} \tag{7}$$

is called the adjusted range. In order to study the properties, $R(t,\ k)$ is standardized by:

$$S(t,\ k) = \sqrt{k^{-1}\sum_{i=t+1}^{t+k}(X_i - \bar{X}_{t,\ k})^2} \tag{8}$$

where $\bar{X}_{t,k} = k^{-1}\sum_{i=t+1}^{t+k} X_i$ is the sample mean and $S^2(t, k)$ is the sample variance. The ratio:

$$R/S = R(t, k)/S(t, k) \tag{9}$$

is called the rescaled adjusted range or R/S-statistic. According to Hurst's work for large values of k, $\log \mathrm{R/S}$ is scattered around a straight line with a slope that exceeds $1/2$. In probabilistic terminology this means that for large k,

$$\log E[R/S] \sim a + H \times \log k \tag{10}$$

The coefficients a and H can be estimated by the linear regression equation or any similar method (Garrett and Willingerm, 1994). Therefore, the self-similarity parameter, H, can then be estimated.

3. BANDWIDTH ALLOCATION PROCESS

When there is traffic, we first estimate the required bandwidth meeting the desired QoS and the current network conditions for the traffic. Then based on the required bandwidth and the network states, traffic is accepted or rejected by the decision of call admission control mechanism. After traffic is accepted, it is transmitted on the specific route decided by the route selection mechanism. In those decisions, bandwidth allocation plays an important role.

We proposed a bandwidth allocation process model shown in Figure 2 to investigate the relationship between the bandwidth estimation equations and the characteristics of traffic parameters. In Figure 2, Poisson model and SRA algorithm are used to generate the traditional traffic traces and the self-similar traffic traces, respectively. The R/S-statistic coupled with linear regression equation is used to estimate the Hurst parameter. The bandwidth estimation equations based on both the two-state fluid flow and the self-similar models are compared to find out the better one, which allocates the required bandwidth as low as possible to meet the requirement of cell-loss-rate (CLR). Then the high utilization rate of network resources and more accepted traffic can be expected.

The generation of long traces of self-similar processes is essential for gaining better understanding of the queuing behavior and network-related performance issues. By implementing the SRA algorithm with $M = 30$, $a = 5$, and $t = 1000$, four traffic traces are generated for $H = 0.5$, 0.7, 0.8, and 0.9 as shown in Figure 3. In Figure 3, the traces for $H = 0.9$ have stronger similarity and more obvious wave than the traces for $H = 0.5$ and have no large fluctuation between any two adjacent time points. It implies that the self-similarity of traffic is in positive correlation with the Hurst parameter, i.e., the larger the Hurst parameter, the stronger the self-similarity of traffic. From the above observations, the Hurst parameter is capable of characterizing the self-similarity of traffic. Therefore, we will first generate the traffic traces on the base of the input value of Hurst parameter and estimate the traffic parameters and Hurst parameters from the traffic traces. Then the required bandwidth to traffic can be allocated by applying traffic parameters in the bandwidth estimation equations. We can investigate the relationships among the bandwidth estimation equations, buffer sizes, and Hurst parameters from the allocation process.

In order to implement this experiment, the generation of traffic traces is necessary. Figure 4 illustrates the process of generating the traffic traces. Assume a random number in [*a*, *b*] is chosen as the input Hurst parameter to SRA algorithm. Traffic traces are generated by means of an SRA algorithm, and the Hurst parameter of generated traffic traces is estimated by the R/S-statistic and linear regression equation. If the estimated value of Hurst parameter was not in [*a*, *b*], the generated traffic traces should not be suitable. Otherwise, the generated traffic traces are suitable. The estimated value of Hurst parameter from suitably generated traffic traces can accurately describe the behavior of traffic and can be used in the bandwidth estimation equations to allocate the proper bandwidth.

According to equation (10), H is the slope of equation. Hurst parameters of four traffic traces shown in Figure 3 are estimated by R/S-statistic, and their R/S-statistic plots are presented in Figure 5. The two straight lines in Figure 5 have slopes 0.5 and 1, respectively. The larger the Hurst parameter, the closer the R/S-statistic plot next to the straight line with slope 1.

After the traffic-related parameters are estimated from the input traffic traces, they are used to calculate the required bandwidth by using equations (5) and (6). The results are compared to demonstrate the one which is better to allocate an adequate bandwidth without violating the desired cell loss rate (CLR) and wasting bandwidth to decrease the utilization rate of network resources.

The calculation of CLR has different forms of equation in different traffic models. In this paper, we assume that a switch completely transmits the whole traffic data in the buffer within the two adjacent unit interval times, so that the buffer is empty when the traffic comes in the next unit interval time. The major volume used to transmit the traffic will be the sum of buffer size plus the allocated bandwidth under the above assumption. As shown in Figure 6, the condition of cell loss only takes place when the traffic data is greater than the sum of buffer size plus the allocated bandwidth during the unit interval time.

The equation of CLR can then be represented as:

$$\mathrm{CLR} = \text{Number of cell loss} \,/\, \text{Total number of cells} \tag{11}$$

where the number of cell loss means the number of traffic data over the sum of buffer size plus the allocated bandwidth, and total number of cells means the total number of arrival traffic data.

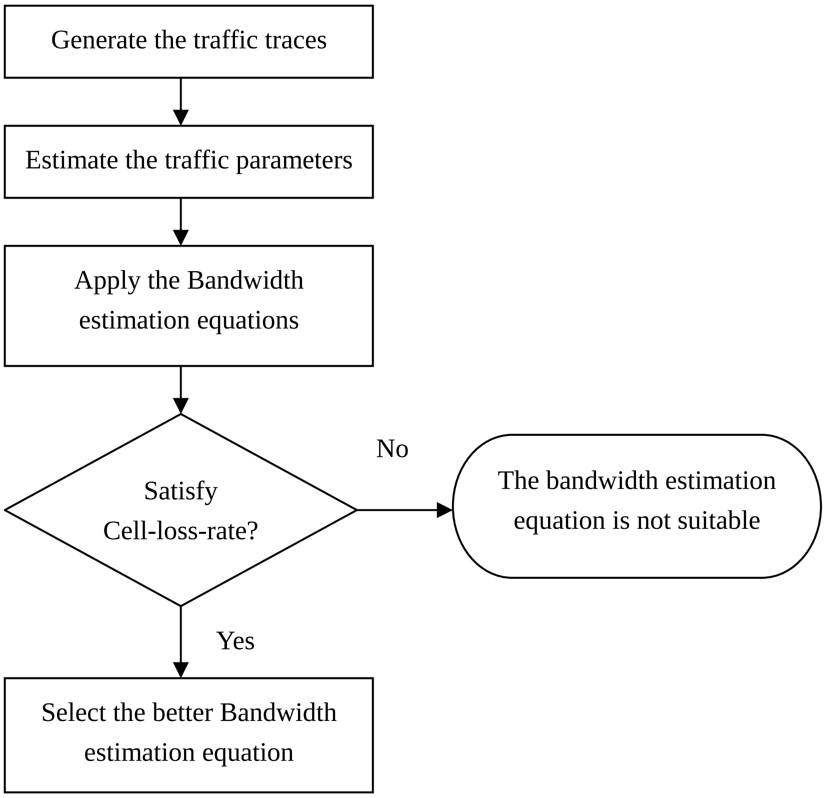

Figure 2. The bandwidth allocation process model.

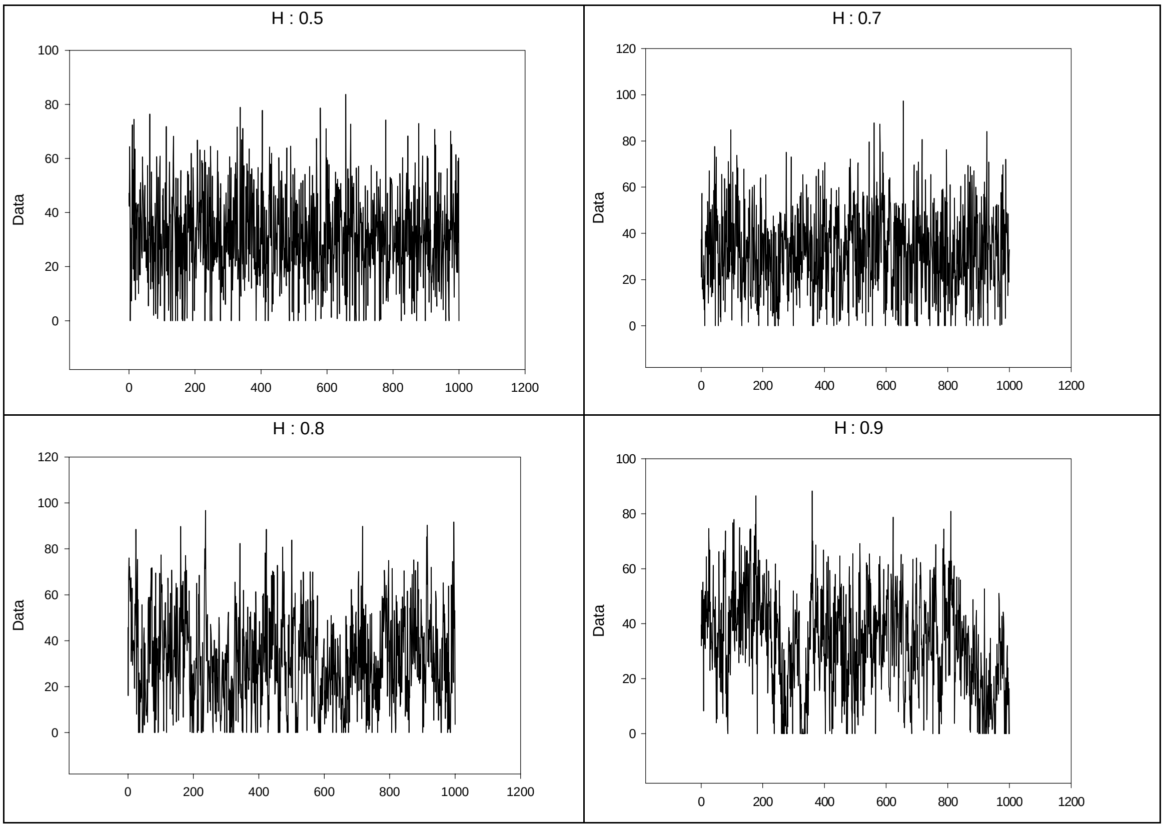

Figure 3. The traffic traces.

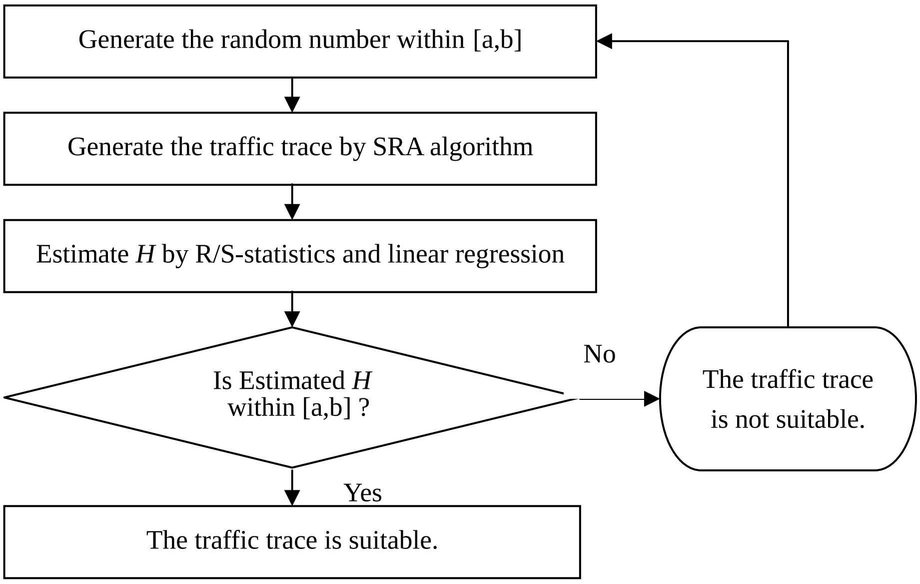

Figure 4. The process of generating traffic traces.

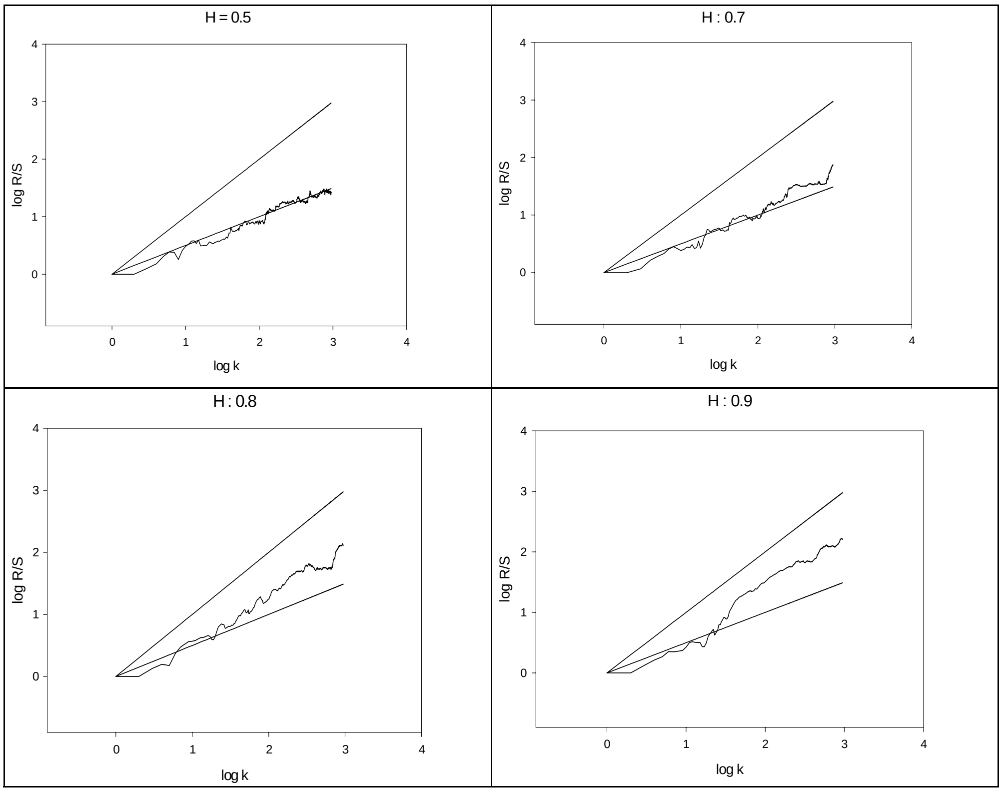

Figure 5. The R/S-statistic plots.

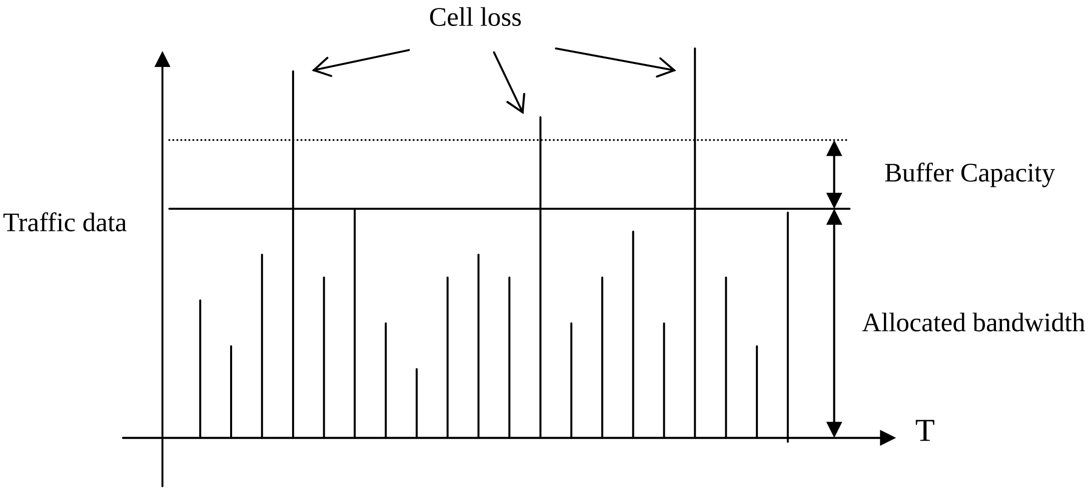

Figure 6. The situation of cell loss.

4. EXPERIMENTS AND RESULTS

The purpose of experiments is to investigate the relationships among the bandwidth estimation equations, buffer sizes, and Hurst parameters under both the Poisson and the self-similar traffic models by applying the proposed bandwidth allocation process. The proposed bandwidth allocation process is coded in C language. In this study, we use the traffic parameters of video telephony, which are given in Table 1 and are used to be the basic known parameters in the proposed bandwidth allocation process. Here, we assume that the utilization ρ is 0.99.

The experiments include two stages. The first stage is to study the relationships between bandwidth estimation equations and buffer sizes under both the Poisson and the self-similar traffic models when H is within 0.5 and 0.6. The SRA algorithm is used as the self-similar traffic model to generate the self-similar traffic traces. The reasons for taking the value of H within 0.5 and 0.6 are that the Poisson traffic model can not represent the long-range dependence of real traffic and the traffic data generated by Poisson model is independent of each other without self-similarity. The second stage including four groups of self-similarity is to compare the results of equation (5) named *EXP mode* and equation (6) named *Self-similar mode* in the condition of buffer size from 10 cells to 100 cells when H is 0.6~0.7, 0.7~0.8, 0.8~0.9, and 0.9~1.0, respectively. The estimates of H will change slightly in accordance with the conditions of networks. Moving from the busier hours to the less busy hours, the estimates of H seem to decline (Crovella and Bestavros, 1997). It is reasonable to use the traffic parameters of video telephony in the SRA algorithm to generate the traffic traces with H from 0.5 to 1.0.

For each buffer size, the experiment is run ten times under the random generated values in the range of H. Tables 2 and 3 present the average results of the allocated bandwidth by Poisson model and self-similar model, respectively, when H is within [0.5,0.6]. The allocated bandwidth of Poisson traffic model is relatively smaller than the self-similar traffic model. The reason is that the self-similar traffic has the burstness but the traffic of Poisson model has not. Furthermore, the *Self-similar mode* requires the smaller bandwidth than the *EXP mode* under both the Poisson and self-similar traffic models. The results show that the performance of *Self-similar mode* is significantly better than the *EXP mode*.

Tables 4 ~7 represent the allocated bandwidth results of self-similar traffic model for H within [0.6,0.7], [0.7,0.8], [0.8,0.9], and [0.9,1.0], respectively. Comparing the results, the *Self-similar mode* requires the smaller bandwidth than the *EXP mode* under the diverse ranges of H. However, the overflow of CLR, which is greater than 0.000155, will happen in the *Self-similar mode* when buffer size is between 10 cells and 30 cells as shown by the shadowed areas. Those cases do not meet the requirement of desired CLR and cause the *Self-similar mode* to be the unacceptable bandwidth allocation estimation.

Table 1. Traffic parameters of video telephony (Dzion, 1997; Sun and Lee, 1996)

Service Type	Mean rate (cell/sec.)	CLR(10^{-6})	Mean burst period (sec.)
Video Telephony	38.642	154.566	1

Table 2. Bandwidth of Poisson traffic for H = 0.5~0.6

Buffer	*EXP mode*		*Self-similar mode*		Buffer	*EXP mode*		*Self-similar mode*	
Size	Bandwidth	CLR	Bandwidth	CLR	Size	Bandwidth	CLR	Bandwidth	CLR
10	61.3986	0	57.1112	0	60	61.6295	0	45.5805	0
20	61.4127	0	51.8260	0	70	61.0279	0	44.5406	0
30	61.2760	0	47.8572	0	80	62.9060	0	42.6468	0
40	59.1716	0	45.7602	0	90	61.2169	0	42.1018	0
50	59.4567	0	46.3124	0	100	61.6099	0	44.8527	0

Table 3. Bandwidth of Self-similar traffic for H = 0.5~0.6

Buffer	*EXP mode*		*Self-similar mode*		Buffer	*EXP mode*		*Self-similar mode*	
Size	Bandwidth	CLR	Bandwidth	CLR	Size	Bandwidth	CLR	Bandwidth	CLR
10	109.1063	0	92.4179	0.000097	60	109.5333	0	61.0504	0
20	103.2921	0	78.2416	0.000118	70	99.9418	0	61.2899	0
30	100.9456	0	70.1929	0.000055	80	104.5317	0	59.0925	0
40	98.3400	0	67.6095	0.000052	90	104.9125	0	56.2890	0
50	107.0654	0	65.6795	0	100	101.5753	0	56.9871	0

Table 4. Bandwidth of Self-similar traffic for H = 0.6~0.7

Buffer	*EXP mode*		*Self-similar mode*		Buffer	*EXP mode*		*Self-similar mode*	
Size	Bandwidth	CLR	Bandwidth	CLR	Size	Bandwidth	CLR	Bandwidth	CLR
10	106.7225	0	91.6588	0.000225	60	110.3172	0	67.5559	0
20	106.1662	0	79.1408	0.000265	70	107.7139	0	65.5947	0
30	107.8574	0	73.7854	0.000322	80	109.1281	0	61.1104	0
40	107.1239	0	72.8254	0.000019	90	108.6097	0	66.8518	0
50	109.4130	0	68.4870	0.000044	100	100.7761	0	64.0556	0

Table 5. Bandwidth of Self-similar traffic for H = 0.7~0.8

Buffer	*EXP mode*		*Self-similar mode*		Buffer	*EXP mode*		*Self-similar mode*	
Size	Bandwidth	CLR	Bandwidth	CLR	Size	Bandwidth	CLR	Bandwidth	CLR
10	112.0782	0	89.8168	0.000279	60	106.2905	0	76.6231	0
20	117.2258	0	81.2526	0.000212	70	105.6379	0	71.9529	0
30	107.1915	0	78.0204	0.000077	80	112.2464	0	68.5668	0
40	113.2374	0	73.8871	0.000018	90	111.6642	0	67.0496	0
50	108.8001	0	75.6291	0	100	113.9489	0	65.5915	0

Table 6. Bandwidth of Self-similar traffic for H = 0.8~0.9

Buffer	*EXP mode*		*Self-similar mode*		Buffer	*EXP mode*		*Self-similar mode*	
Size	Bandwidth	CLR	Bandwidth	CLR	Size	Bandwidth	CLR	Bandwidth	CLR
10	107.8920	0.000041	90.3032	0.000648	60	111.8472	0	77.9245	0
20	103.8109	0	83.3318	0.000562	70	111.1094	0	76.1157	0
30	107.2456	0	83.0976	0.000139	80	109.1324	0	75.7775	0
40	107.3780	0	79.0972	0.000043	90	112.4863	0	76.0469	0
50	113.7856	0	78.3251	0.000035	100	109.9077	0	69.9354	0

Table 7. Bandwidth of Self-similar traffic for H = 0.9~1.0

Buffer	*EXP mode*		*Self-similar mode*		Buffer	*EXP mode*		*Self-similar mode*	
Size	Bandwidth	CLR	Bandwidth	CLR	Size	Bandwidth	CLR	Bandwidth	CLR
10	103.3283	0	90.8573	0.000349	60	98.0676	0	77.9508	0
20	99.6348	0	87.0696	0.000014	70	101.2545	0	81.3086	0
30	108.8584	0	84.4637	0.000031	80	99.6308	0	79.4993	0
40	97.7144	0	81.1528	0	90	94.0271	0	81.5865	0
50	100.3552	0	85.1461	0	100	92.1910	0	79.6777	0

Table 8. The differences of allocated bandwidth

Hurst	0.5-0.6	0.6-0.7	0.7-0.8	0.8-0.9	0.9-1.0
Difference (buffer size 10-buffer size 100)	35.4308	27.6032	24.2253	20.3679	11.1796

From the experimental results, the following conclusions are drawn. The *EXP mode* has the tendency of over-allocating the bandwidth. Consequently, the values of CLR in most of the cases are zero. In addition, the allocated bandwidth estimated by the *EXP mode* will not obviously change with the different buffer sizes. Contrarily, the allocated bandwidth estimated by *Self-similar mode* is sensitive to the various buffer sizes. For the *Self-similar mode*, the differences of the allocated bandwidth between buffer sizes 10 and 100 cells are shown in Table 8. The difference is getting smaller when H is increasing. It implies that the allocated bandwidth estimated by *Self-similar mode* becomes more stable when H increases. In all cases, the *Self-similar mode* has the better performance than the *EXP mode* because the former allocated smaller bandwidth to the traffic. However, the phenomena of violating the requirements of CLR may happen under the *Self-similar mode* with less buffer size. When the *Self-similar mode* is used to allocate the bandwidth, larger buffer size will be necessary in order to satisfy the requirements of CLR.

5. CONCLUSIONS

The bandwidth allocation acts as an important mechanism in network planning and is considered in both route selection and connection admission control. This paper proposes a bandwidth allocation process and applies the proposed process to the different traffic models and the different self-similar parameters under different buffer sizes to investigate the relationship between the bandwidth estimation equation and the characteristics of traffic parameters and to find out the superior bandwidth estimation method.

Traffic traces are generated by means of Poisson model and SRA algorithm. The Hurst parameter of generated traffic traces is estimated by the R/S-statistic and linear regression equation. According to the two-state fluid-flow and self-similar model and their associated parameters, the bandwidth estimation equations are used to calculate the required bandwidth. Comparing the allocated bandwidth, the *Self-similar mode* has smaller bandwidth than the *EXP mode* under both the Poisson and self-similar traffic model. Furthermore, the allocated bandwidth estimated by *Self-similar mode* becomes more stable when H increases. In conclusion, this paper has demonstrated that the self-similar traffic model can characterize real traffic in broadband networks. However, the bandwidth estimation model without violating the requirement of CLR should be further investigated.

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