Analysis of Network Traffic and its Application to Design of High–Speed Routers

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Abstract: A rapid growth of the Internet and proliferation of new multimedia applications lead to demands of high speed and broadband network technologies. Routers are also necessary to follow up the growth of link bandwidths. From this reason, there have been many researches on high speed routers having switching capabilities. To have an expected effect, however, a control parameters set based on traffic characteristics are necesssary. In this paper, we analyze the network traffic using the network traffic monitor and investigate the Internet traffic characteristics through a statistical analysis. We then show the application of our analytical results to parameter settings of high speed switching routers.

1. Introduction

A rapid growth of the Internet and proliferation of new multimedia applications lead to demands of high speed and broadband network technologies. Accordingly, the capacity of the bandwidth has been increased rapidly. In Japan, for example, several ISPs (Internet Service Provider) increase the backbone bandwidth from 1.5 Mbps to 155 Mbps in last two years. A packet processing capability of routers are also necessary to follow up the growth of link bandwidths. From this reason, several techniques have been proposed for high speed routers. For example, IETF is now standardizing MPLS (Multi Protocol Label Switching) [1], which combines the flexibility of layer-3 routing with the high capacity of layer-2 switching. In MPLS, the router identifies a *flow* by IP addresses and applications (i.e., port number) of packets, and forwards them through faster switching paths.

However, its performance must be strongly affected by the control parameters set as well as hardware limitations of routers. To choose the appropriate control parameters set, we need to know the characteristics of the Internet traffic in order to obtain an expected performance of switching routers. For this purpose, we first investigate the characteristics of the actual Internet traffic using the traffic monitor called OC12MON developed by MCI [2]. Of course, the study on the characterization of the Internet traffic is not new. Traffic monitoring and its statistical analysis have already been studied in the literature [3, 4, 5, 2]. Our main contribution in this paper is that results of the statistical analysis are applied to determination of control parameters necessary in high speed switching routers.

In this paper, we first give analytical results of the network traffic, which are gathered by the traffic monitor OC12MON at our university. Our approach and results are summarized in Section 2. We then proceed to investigate the application to high speed IP switching techniques in Section 3. Finally, we conclude our work with future research topics in Section 4.

2. Analysis of Traced Data

2.1 Analysis Approach

In this subsection, we introduce our analytic approach. We follow the statistical approach described in [3] where the approach was applied to the analysis of `telnet` and `ftp` traffics. The analysis of WWW traffic was also analyzed by the same approach in [4]. In this approach, we first enumerate several probability distributions, and determine parameters of those distribution functions based on traced data. In this paper, we have chosen following distributions; an exponential distribution, an extreme distribution, a normal distribution.

We further consider a log–normal distribution and a log–extreme distribution. If the random variable $Y = \log X$ has a normal or extreme distribution respectively, then X is said to have a log–normal or log–extreme distribution. Namely, those distribution are defined as

$$F(x) = \int_0^x \frac{1}{\sqrt{2\pi}\sigma y} exp\left[\frac{-(\log y - \zeta)^2}{2\sigma^2}\right] dy, \quad (1)$$

and

$$F(x) = exp\left[-exp\left(-\frac{\log x - \alpha}{\beta}\right)\right]. \quad (2)$$

Those distributions are considered since they can cover a large range of values. We also consider a Pareto distribution which is defined as

$$F(x) = 1 - \left(\frac{k}{x}\right)^\alpha, \quad x \geq k, \quad (3)$$

Note that it is oftern used for modeling the self–similar traffics [6, 5].

We then test the goodness–of–fit of each model to select the most appropriate distribution via chi–squared examination. We use a criterion $\hat{\lambda}_2$ to choose the best model from probability distributions. The criterion $\hat{\lambda}_2$ of each model is derived as follows. Suppose that we have observed n instances of random variables. We partition the range of those instance into N bins. Each bin has a probability p_i which is the proportion of the distribution falling into the ith bin . Let Y_i the number of observation falling into the ith bin. Then $\hat{\lambda}_2$ is defined as

$$\hat{\lambda^2} = \frac{X^2 - K - N + 1}{n - 1}, \quad (4)$$

Table 1: Summary of Traced Data

No	Time	Duration (hours)	# of Packets	Transmission in MBytes
1	99.2.2 17:45	6	22,077,118	10,581
2	99.2.3 0:35	8	9,182,052	4,703
4	99.2.3 9:20	4	23,303,624	11,169
3	99.2.3 13:30	6	26,574,308	12,737

where

$$X^2 = \sum_{i=1}^{N} \frac{(Y_i - np_i)^2}{np_i}, \qquad K = \sum_{i=1}^{N} \frac{Y_i - np_i}{np_i}. \qquad (5)$$

Finally, we choose the distribution with the smallest value of $\hat{\lambda}_2$ as a most accurate one.

2.2 Analytical Results

In this subsection, we give analytical results of the network traffic, which are gathered by the traffic monitor OC12MON. The monitor is placed at the gateway of Osaka University (see Figure 1), i.e., our results reflect the characteristics of the traffic between the Internet backbone and the large–scale local network.

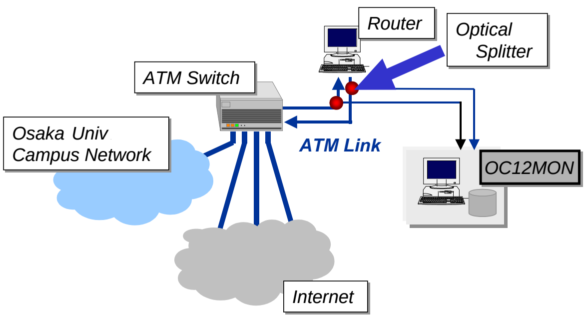

Figure 1: Configuration of OC12MON

Summary of the traced data collected by OC12MON is shown in Table 1. We monitored the gateway during a one day. (Traced data is divided into four parts due to its file volume.) As shown in Table 1, the number of packets was 81,767,103 and the total transmission size was about 43.1 GBytes. Table 2 summarizes several statistics dependent on the application. We identified the packet stream having the same source address, destination address and application (port number) as an individual *flow*. As shown in the table, the ratio of HTTP traffic is very high and the volume of major three applications (HTTP, FTP, and NNTP) becomes over 90% of all traffic in bytes. It coincides recent trends of the network traffic reported in the literature. We can also see the statistical difference among applications. For example, the flow of FTP contains 15 packets in average while the DNS flow does only two packets.

Based on the statistical analysis approach described in the previous subsections, we now present the results.

Table 2: Statistics Dependent on Applications (ratio)

application	# of pkts.	# of bytes (Mbytes)	# of flows
HTTP	40,440,520 (49.5%)	20,336 (51.9%)	4,067,691 (63.1%)
FTP data	11,361,570 (13.9%)	8,830 (22.5%)	59,641 (0.9%)
NNTP	12,080,756 (14.8%)	6,166 (15.7%)	67,269 (1.0%)
DNS	2,839,998 (3.5%)	394.4 (0.9%)	1,212,246 (18.8%)
SMTP	2,322,079 (2.8%)	541.2 (1.4%)	155,068 (2.4%)
FTP	611,559 (0.7%)	61.3 (0.2%)	33,968 (0.5%)
TELNET	1,010,214 (1.2%)	91.2 (0.2%)	50,895 (0.8%)
POP3	559,684 (0.7%)	119.6 (0.3%)	27,139 (0.4%)
others	10,540,732 (12.9%)	2,694 (6.9%)	770,370 (12.0%)

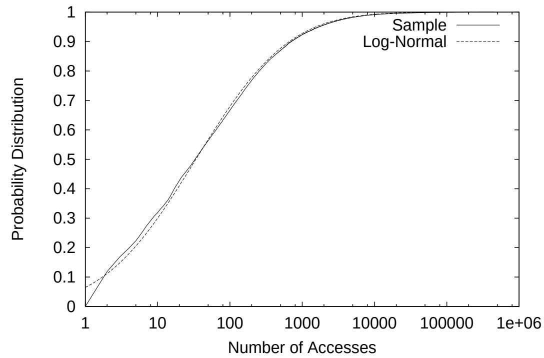

Figure 2: The Distribution of Access Frequencies of IP Address

- The distribution of IP address access frequencies

  We first show the distribution of access frequencies of IP addresses in Figure 2. The best model was a log–normal distribution. We can observe that the most of addresses are accessed at least twice, and that most frequently accessed WWW sites have more than 10,000 accesses.

- The distribution of the number of packets in the flow

  We next show the analytic results of the distribution of the number of packets contained in each flow. Figure 3 shows the result. The best one was a log–normal distribution which has a long–tail. However, if we fo-

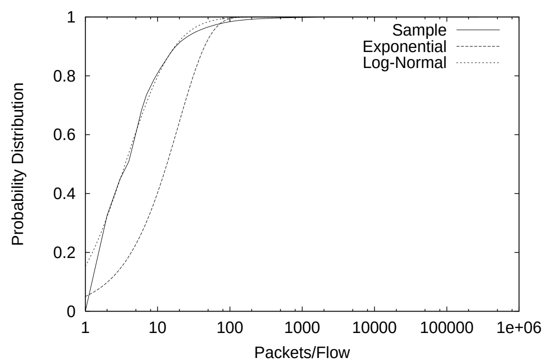

Figure 3: Distribution of the Number of Packets in Flow

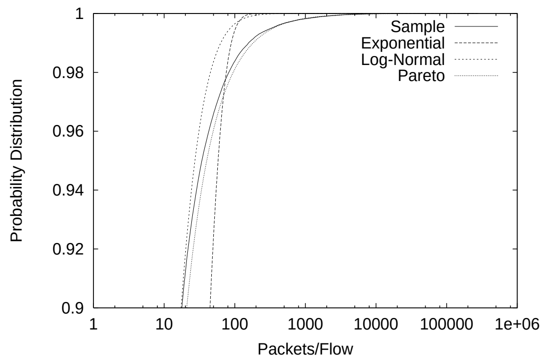

Figure 4: Distribution of the Number of Packets in Flow (Tail Distribution)

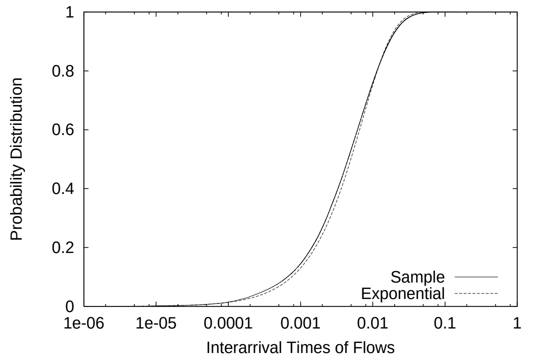

Figure 5: Distribution of Flow Arrival Intervals

cus on the tail of the distribution, the log–normal distribution cannot follow the traced lines [5]. Figure 4 shows the tail part of the distribution. As shown in the figure, a more suitable model is the Pareto distribution, which is known as a class of the heavy–tailed distribution decaying very slowly in its tail. It coincides recent studies on the traffic characterization. However, we should note that the heavy-tailed distribution well fits only in its tail. If we consider the entire distribution, the log–normal distribution is best. Henceforth, we will consider the log–normal distribution for parameterizing the traffic flow in the next section.

- The distribution of flow duration

  The best model of the distribution of flow durations is a log–normal distribution for the entire distribution, and a Pareto distribution for the tail. That is, the characteristics are same as the distribution of the number of packets in the flow described above. We omit the result due to space limitation.

- The distribution of flow intervals

  We finally show the interarrival distributions of flows in Figure 5. The best model is an exponential distribution.

3. Application to High Speed IP Switching

In this section we investigate the application of analytical results to determination of control parameters necessary in high speed switching routers. One important example is MPLS applied to ATM, where the VC (virtual circuit) setting is activated by the predefined number X of packets contained in the flow. More specifically, when the number X of packets from the same flow are processed by the MPLS switch, the flow is recognized to need to set up VC so that the faster hardware switching is performed. Thus, the performance of MPLS is affected by the parameter X, which depends on the traffic characteristics of flows. If the parameter X is small, many VC assignments would be required not only for long–term flows (including the large number of packets in the flow) but also for short–term flows, which results in the failure of setting more VCs for the long–term flows newly arriving at the switch. On the other hand, if the parameter X is large, the utilization of VC space becomes low, and the switch performance is degraded. Determining a parameter X in MPLS have been studied in [7, 8], but those studies did not take account of traffic characteristics.

To determine the appropriate parameter X, we first derive the mean flow processing time Y based on our statistical analysis. The mean flow processing time Y is derived as

$$\begin{aligned} Y &= F(X)\delta E_U(X) \\ &\quad +(1-F(X))\{\delta X + \gamma(E_L(X) - X)\}, \quad (6) \end{aligned}$$

where $F(x)$ is the distribution function of the number of packets in flows (i.e., log–normal distribution) given by

$$F(x) = \int_0^x \frac{1}{\sqrt{2\pi}\sigma y} exp\left[\frac{-(\log y - \zeta)^2}{2\sigma^2}\right] dy. \quad (7)$$

Furthermore, $E_U(X)$ is the mean number of packets of flows which contain less than X packets, and the mean processing time of the packet by "software" is denoted as δ. Similarly, $E_L(X)$ is the mean number of packets of flows having larger than or equal to X packets, and γ shows the packet processing delays in "hardware" switching.

Equation (6) shows that the router can process $1/Y$ flows in unit time. To process all flows without any losses, Y is required to satisfy $Y < 1/\lambda$ where λ is arriving rate of flows. We then determine the value of X based on hardware specifications. From our traced data, we found that $X = 6$ was most appropriate. However, such a "static approach" does not take account of the fluctuation of the traffic load. The adaptive control method is thus necessary to effectively utilize the line capacity dependent on the traffic load. The approach of our adaptive control is as follows.

We first introduce the time interval t_a. For each t_a, the switch observes the traffic load (the number of newly arriving flows), and changes the threshold value $X(t)$ adaptively. Then, we expect that the number of assigned VCs for every t_a is around the target value B. The target value B may be set by the static result, i.e.,

$$B = V_{max} - \lambda t_a (1 - F(X)). \quad (8)$$

We then determine the next $X(t+t_a)$ by balancing in and out flows for time interval t_a. For this, we introduce $V_d(t)$ as the variation caused by changing the parameter $X(t)$. We define $V_d(t)$ as

$$\begin{aligned} V_d(t) &= t_a\lambda'(t)(1 - 2F(X(t_1)) + F(X(t))) \\ &\quad -V(t)R(t_a), \end{aligned} \tag{9}$$

where $R(t_a)$ gives the ratio of the long–term flows which ceases its connection within t_a. It is derived from the residual time for given distribution, i.e.,

$$R(t_a) = \frac{1}{\mu}\int^{t_a}(1 - F(X(t)))dt, \tag{10}$$

Then, the adequate threshold value for next t_a is determined by taking account of $V_d(t)$. That is, we calculate the smallest value of $X(t+t_a)$ satisfying

$$V_d(t) \leq B - V(X(t)). \tag{11}$$

Figure 6 shows the results of trace–drive simulation to compare the static and adaptive control methods. In simulation, the maximum number of VCs, V_{max}, is set to be 5000, and t_a is 2 sec. In the adaptive control, we set $B = 4,900$. As can be seen in the figure, VCs are highly utilized and its usage is stable around the threshold $B = 4,900$. Figure 7 shows the comparison of the mean packet pro-

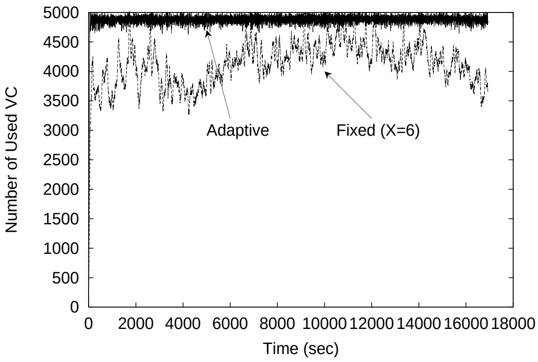

Figure 6: Comparison of VC Assignments Dependent on Time

cessing times dependent on time. As shown in this figure, the benefit of highly utilized VCs leads to reduction of the packet processing time (230 μsec to 205 μsec).

4. Concluding Remarks

In this paper, we first give analytical results of the network traffic, which are gathered by the traffic monitor. Through the statistical analysis, we found that most statistics, including the number of packets in the flow and active flow durations, follow the log–normal distributions. We next investigate the application to parameter settings in high speed routers. From simulation results, VCs are highly utilized and its usage is stable by applying the result of analysis for parameter settings. For future research topics, we need to consider the detection mechanism of VC release, which also affects the switch performance.

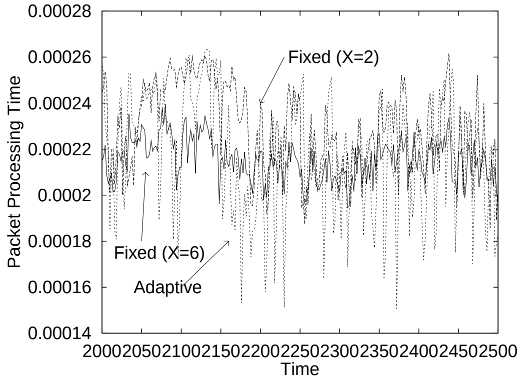

Figure 7: Comparison of Mean Packet Processing Times Dependent on Time

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