Queue Length Behavior of Bottleneck Link under Bursty Self-similar TCP Traffic

Takuo Nakashima†
†*School of Industrial Engineering, Tokai University*
9-1-1 Toroku, Kumamoto, Japan
taku@ktmail.tokai-u.jp

Abstract

The aims of this research are to expand the observation of queueing behavior to explore managing queueing activity for self-similar traffic using the network simulator, and to clarify the causes of different features focusing on the bottleneck link. We attached the Pareto on/off traffic over TCP on ns-2 simulator and observed temporal queue length of the bottleneck link and the congestion window size of TCP on the source node, from which certain properties were extracted. Self-similar property is preserved on the no-restricted bottleneck link even if the congestion window on TCP is consumed on the source node for long-range dependent input. On the other hand, the bursty TCP traffic creates the same consuming pattern for efficient queue resource regardless of the generation of the long-range dependent traffics.

1 Introduction

Since the seminal study of Leland, et al. [1], the scale-invariant burstiness, otherwise known as self-similarity has been found in real network. Currently, self-similarity of network traffic has been widely adopted in the modeling and analysis of network performance. In their research into simulation-based modeling, Park et. al. [2] conducted the simulation to evaluate network performances of self-similar traffic by varying network resources such as bottleneck bandwidth and buffer capacity. In an environment with fully equipped buffer size, Park et. al. [2] observed a gradual increase in the packet loss rate as α approaches to 1, meaning that performance declines drastically as self-similarity is increased, as measured by packet loss rate in UDP-based non-flow-controlled environment. We discovered that packet loss rate gradually increases as α approaches 1 just before the bottleneck restrainment causes the larger packet loss rate in both TCP and UDP heavy-tailed traffics. In addition, our simulation showed that throughput also increases gradually as α approaches 1, which means that throughput performance improves for self-similar traffic on both the TCP and UDP transport layer[3] as self-similarity is increased. This paper aims to explore the dependable network parameters for long-range dependent traffics focusing on the queueing activity on the bottleneck link.

The mathematical model tends to be adapted in the field of the queueing analysis due to the formalized theory. In addition, queueing analysis plays an important part in the establishment of basic performance boundaries, which are found by investigating queueing behavior. Primary performance analysis results for self-similar traffic were also derived from the queueing analysis with self-similar input[4][5]. This queueing analysis has given us fundamental insights into the performance impact of long-range dependence, from which we established the basic fact that the queue length distribution decays slower-than-exponential vis-a-vis the exponential decay associated with Markovian input. The queueing-based performance analysis explored the resource dimensioning paradigm which states that buffer capacity at routers should be kept small while link bandwidth is to be increased. Putting it another way, the paradigm states that the marginal utility of buffer capacity has diminished significantly compared to that of bandwidth. Observations showed that when long-rang correlation structure is weak, the mean queue length saturates in some level if buffer capacity is sufficient. On the other hand, when long-range correlation structure is strong, an increase in buffer capacity is accompanied by a corresponding increase in buffer occupancy, i.e. the mean queue length.

Our queueing analysis contributes toward providing the basic concept of resource provisioning, especially from the viewpoint of upper and lower queue length boundary for long-range dependent and short-range dependent traffics for TCP. Network performance is defined and described by the network parameters such as node and link parameters. Link parameters such as bandwidth and queue size play an important role in network performance. These properties of queue size variation lead to the basis of queue management. In this paper, we intend to focus on the relation between queue size and the long-range dependent traffics on the bottleneck link focusing on the correlation between queue length and congestion window size.

This paper is organized as follows. Firstly, heavy-tailed distribution is defined in Section 2. The network model and a simulation environment is laid out in Section 3. Based on the results of these simulations, we discuss the results of queueing properties for self-similar traffic in Section 4. Section 5 gives the summary and discussion for future work.

2 Heavy-tailed Distribution

Self-similarity and long-range dependence are not equivalent in general. In the case of asymptotic second-order self-similarity, however, by the restriction $1/2 < H < 1$ in the definition, self-similarity implies long-range dependence, and vice versa. On the other hand, heavy tails lead to predictability, and for a related reason, they lead to long-range dependence in network traffic. We will shortly introduce the basic concepts relating to heavy-tailed distribution. A more detailed explanation can be found in Park, et al.[6] and Abry, et al.[7].

A random variable Z has a heavy-tailed distribution for some positive constant c, if

$$P[Z > x] \sim cx^{-\alpha}, \quad 0 < \alpha < 2, \tag{1}$$

where $a(x) \sim b(x)$ means $\lim_{x\to\infty} a(x)/b(x) = 1$, and α is called the tail index or shape parameter. Regardless of the behavior of the distribution for small values of the random variable, it is heavy-tailed if the tail of the distribution asymptotically decays in a manner shown in a power law. If $P[Z > x]$ is heavy tailed then Z shows very high variability. Moreover, Z has infinite variance for $0 < \alpha < 2$, and, if $0 < \alpha \leq 1$, Z has infinite mean. In the networking context, we will be primarily interested in the case $1 < \alpha < 2$.

The simplest heavy-tailed distribution is the Pareto distribution. The Pareto distribution is a power law governing its entire range of value; its probability density function is given by

$$p(x) = \alpha k^{\alpha} x^{-\alpha-1}, \quad \alpha, k > 0, \quad x \geq k, \tag{2}$$

and its cumulative distribution function is given as

$$F(x) = P[Z \leq x] = 1 - (k/x)^{\alpha}. \tag{3}$$

The parameter k represents the smallest possible value of the random variable, and is called the location parameter.

3 Network Model and Simulation

3.1 Network Model

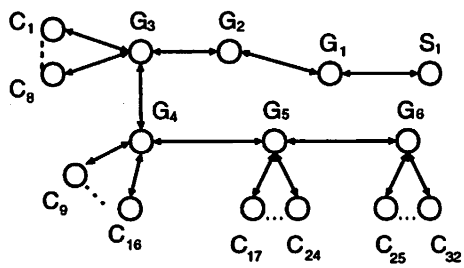


Figure 1: Network configuration.

The network is constructed by nodes and links. Each link has its own buffer, bandwidth, and latency. Figure 1 shows 1-server, 32-client network configuration. These clients are organized in a caterpillar graph with 4 articulation points (gateways G_3, G_4, G_5, G_6), each containing 8 clients. The link between gateway G_1 and G_2 forms a bottleneck link, with traffic volume intensifying as we progress from gateway G_6 to G_2 due to the increased multiplexing effect. We will refer to the traffic from G_1 to G_2 as downstream traffic and the one from G_2 to G_1 as upstream traffic, and measure the downstream traffic from G_1 to G_2.

The value of bottleneck bandwidth is set smaller than other link bandwidth emulating traffic restrainments. The bottleneck link is assumed to have a bandwidth of 10, 7 and 5 Mbps with a delay of 15 msec The bandwidths of non-bottleneck links are all set at 10 Mbps bandwidth and 15 msec latency.

3.2 Simulation Setup

We adopted the LBNL network simulator (ns) [8] to evaluate queueing properties on the bottleneck link with respect to self-similar traffic. The ns is a piece of software commonly used for simulating advanced TCP/IP algorithms and protocols.

Pareto distribution is adopted to reveal the self-similar traffic or exponential traffic by altering the shape parameter to various values between 1 and 2. Client node $c_i (i = 1, \cdots, 32)$ independently accesses the server using TCP. We generate traffic flows with Pareto distribution between client and server over TCP indicating that the server has the multiple flows for each client. Network parameter sets are discussed in detail in the following section.

3.2.1 On/off Traffic

We created multiple TCP connection flows between 8 to 32 clients and server on the topology in Figure 1. The traffic flows obey the Pareto on/off source based on the on/off model formally introduced by Willinger et al.[9]. On-times correspond to the transmission durations of individual traffics and off-times correspond to the intervals between transmissions. On/off model established that the superposition of a large number of independent on/off sources with heavy-tailed on and off periods leads to self-similarity in the aggregated process - a fractional Gaussian noise process - whose long-range dependent is determined by the heavy tailedness of on/off periods. To measure the queue activity on the bottleneck link, we concretely set the value to TCP between each client and the server, to measure the queue size by varying the maximum queue capacity.

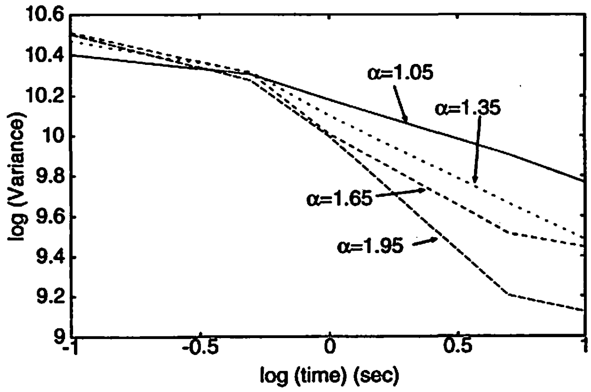
4 Queueing Properties

4.1 Traffic types

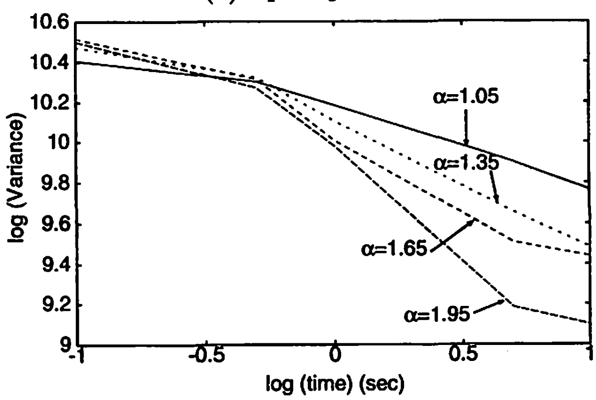
The definition of traffic types can be explained in association with our variable experimental parameters such as the number of traffic flows and the bandwidth. These two parameters influence the following three types to characterize the traffic on the bottleneck link in this paper. The first traffic type, called "no-queue-buffering", indicates the condition that queue resource on the bottleneck link is not consumed, which occurs when very few traffic flows are transferred or there is no restricted bandwidth on the path of flows meaning that there is no bottleneck link. In this condition, there is no buffering on the bottleneck queue and a few buffering on the source node when the transport layer is serviced by TCP.

In an ideal condition, queue buffering starts when the bandwidth is fully consumed. The queue buffering, however, starts before the bandwidth is totally used. The second traffic type, called "queue-buffering with no full use of bandwidth", indicates the condition that queue resource on the bottleneck link is consumed and that the entire bandwidth is not fully consumed. This condition occurs when comparatively small amount of traffic flow on the restricted bottleneck. The queue management on the start edge of bottleneck link is activated; however the queue resource is not fully consumed, meaning that there are no packet losses on the start edge of bottleneck link. In this condition, the bottleneck bandwidth is not fully consumed and two buffering systems, queue buffering and source node buffering for TCP layer, are activated, and then bottleneck bandwidth reaches the full consumption.

The third traffic type, called "queue-buffering with full use of bandwidth", occurs when large amount of traffic flow on the restricted bandwidth. Large queue resource is consumed in this condition causing the packet loss on the start edge of bottleneck link and source node, and finally queue resource is fully used. The packet losses on the start edge node of bottleneck link is created without failure when the full queue resource is consumed. If the queue resource is enlarged, the consumption pattern of queue resource is changed depending on the traffic pattern.



(a) S_1 - G_1 link

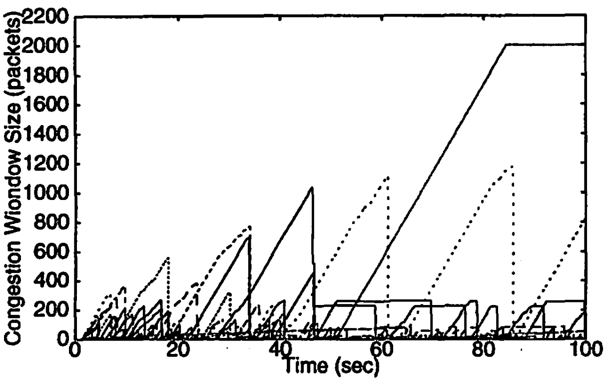


(b) Bottleneck link

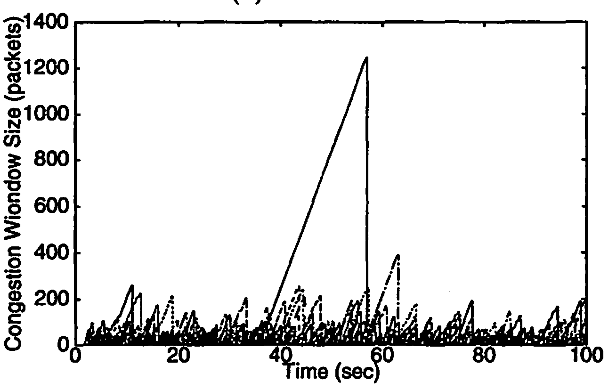
Figure 2: The variance-time plot for TCP throughput on non-restricted bandwidth.

4.2 Queueing activity of genereted traffic

Firstly, we verified the correctness for the long-range dependent traffic based on the on/off traffic generated by the ns-2 simulator. To verify the long-range dependent property, we adopted the variance-time plot with log − log order and measured the output traffics from the start edge of bottleneck link. Figure 2 shows the variance-time plot for the throughput of TCP traffics on non-bottleneck bandwidth (10 Mbps). Figure 2 (a) and (b) show the throughput on the S_1 - G_1 link and on the bottleneck link respectively. This traffic consists of the 3 client/server communication on TCP, and each client has 10 TCP connection flows. Each descending pattern for each α in Figure 2 (a) and (b) represents the property of the long-range dependence meaning that the "no-queue-buffering" traffic hold the property of Pareto distribution.



(a) $\alpha = 1.05$



(b) $\alpha = 1.95$

Figure 3: Fluctuations of congestion widow size for 10 flows of client 1.

In this case, queue resources of both links are not consumed yet. On the other hand, the congestion window of TCP is activated by traffic flows. Figure 3 shows fluctuations of congestion window size for 10 flows of client 1. Figure 3 (a) and (b) correspond to the case of $\alpha = 1.05$ and $\alpha = 1.95$ respectively. Each Figure shows that the variation of $\alpha = 1.05$ is more fluctuating than that of $\alpha = 1.95$. The size of congestion window of $\alpha = 1.05$ reaches at 1000 a few times. On the contrary, that of $\alpha = 1.95$ reaches once at 1000. This means that long-range dependent traffic tends to be required more congestion window on TCP than short-range dependent traffic even if the traffic is "no-queue-buffering" type.

4.3 Queueing activity of large amount of traffics with bandwidth restriction

4.3.1 Average queue length Behavior

Actual traffic in the Internet is considered to have a huge amount of flows and is multiplexed to each other. We investigated the behavior of average queue length for the large amount of traffics.

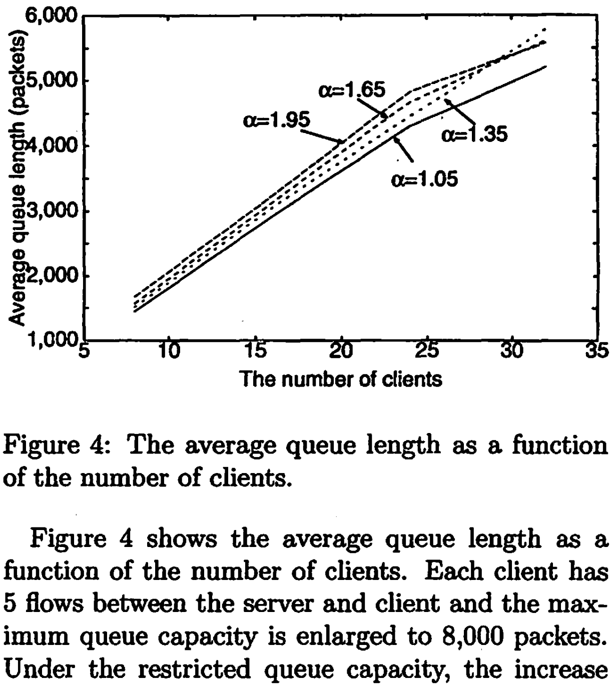
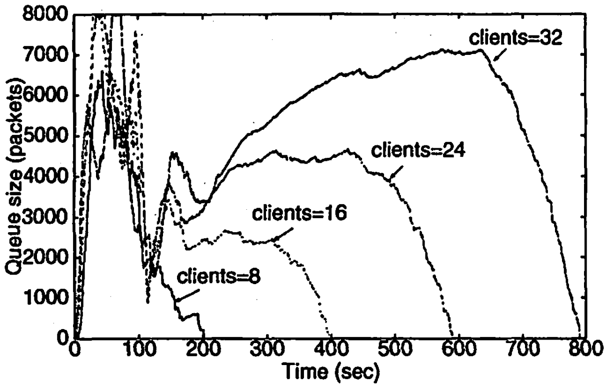


Figure 4: The average queue length as a function of the number of clients.

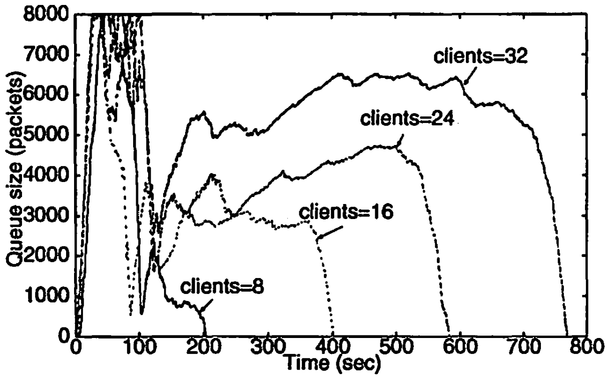
Figure 4 shows the average queue length as a function of the number of clients. Each client has 5 flows between the server and client and the maximum queue capacity is enlarged to 8,000 packets. Under the restricted queue capacity, the increase of the average queue length is proportional to the increase of the number of clients, and the increase pattern showed no significant difference in terms of the different αs. The result means that the consumption of queue mainly depends on the traffic flow controlled by TCP, and suppresses the features of different αs under the restricted bandwidth.

4.4 Time sequence of queue length for large queue resource

Figure 5 (a) and (b) show the time sequence of queue length with large queue resource queue-limit=8000 for $\alpha = 1.05$ and $\alpha = 1.95$ respectively. Each figure includes fluctuations of four different of the number of clients. We found in Figure 4 that long-range dependent traffics consumed less queue resource in average. The reason, however, mainly depends on the initial consuming activity for queue



(a) $\alpha = 1.05$



(b) $\alpha = 1.95$

Figure 5: Time sequence of queue length for different number of clients.

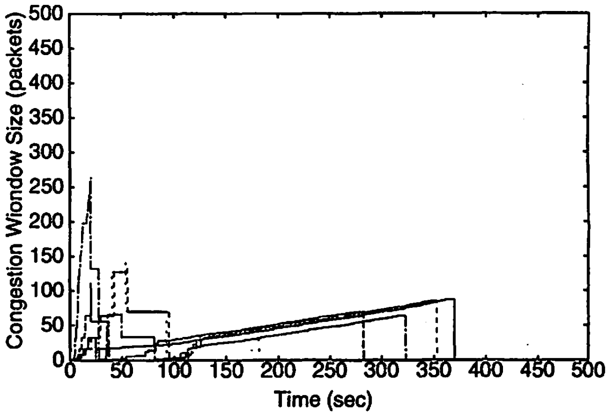


Figure 6: Time sequence of congestion window size for 5 flows of client 1 with $\alpha = 1.05$ traffic.

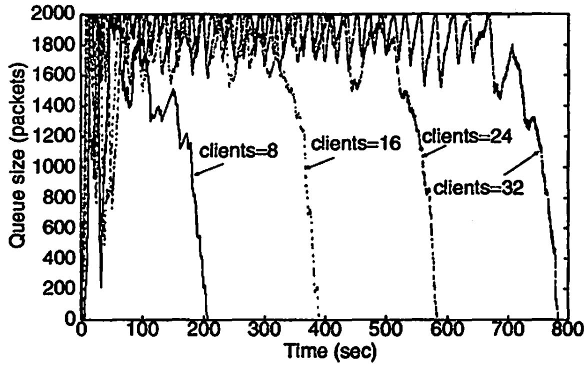


Figure 7: Time sequence of the queue length for $\alpha = 1.05$.

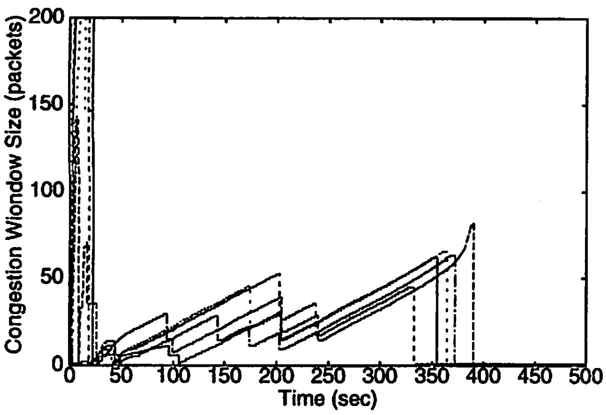
resource depicting in Figure 5. The stationary trend of both (a) and (b) in Figure 5 does not represent the significant differences meaning that burstiness of traffic disappear the property of short-range dependence. In addition, well-known results that short-range dependent traffic consumes more queue resource than long-range dependent traffic in efficient queue resource condition were not measured in our simulations.

Figure 6 illustrates the time sequence of the congestion window size for 5 flows of client 1 on the source node for 16 client with $\alpha = 1.05$ traffics. The fluctuation of start time in simulation is caused by the random start for each flow. One linear ascending pattern appeared for each flow meaning that traffic flows are mainly controlled in one congestion avoidance mode. The same ascending pattern appears in the other clients and αs.

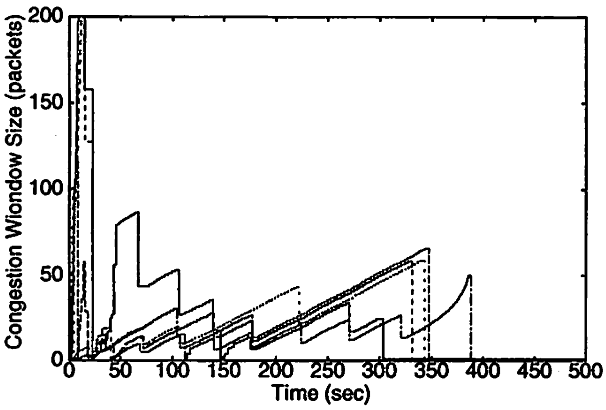
4.5 Time sequence of queue length for small queue resource

Figure 7 illustrates the time sequence of queue length with small queue resource queue-limit=2000 for $\alpha = 1.05$. The cases of four different clients are included in this figure. Except for the initial fluctuations, cyclic fluctuations up to maximum queue limit continued over total simulation time. These cyclic fluctuations synchronize to the cyclic fluctuations of the congestion window size on the source node. In addition, the case with other different αs has no significant differences.

Figure 8 (a) and (b) illustrate the time sequence of the congestion window size for 5 flows of client 1 for $\alpha = 1.05$ and $\alpha = 1.95$ respectively. These traffics consist of 16 clients with 5 flows for each client, and the bandwidth queue limit is restricted to 2000. Both Figure (a) and (b) are typical examples for the congestion window size on one client. Compared to the case of the large queue resource in Figure 6, the continuous time of the liner ascending pattern is apparently short caused by the packet loss in the restricted bandwidth queue size. Figure 8 (a) and (b) have no significantly differences, however, the cyclic continuous time for $\alpha = 1.05$ is slightly shorter than that for $\alpha = 1.95$.



(a) $\alpha = 1.05$



(b) $\alpha = 1.95$

Figure 8: Time sequence of congestion window size for 5 flows of client 1.

5 Conclusion

In this paper, we have investigated queueing properties for self-similar traffic using a network simulator. We attached the Pareto on/off traffic over the TCP on ns-2 simulator and observed temporal queue length and other network parameters, from which certain properties were extracted. Self-similar property is preserved on the no-restricted bottleneck link even if the congestion window on TCP is consumed on the source node for long-range dependent input. On the other hand, the bursty TCP traffic creates the same consuming pattern for efficient queue resource regardless of the generation of the long-range dependent traffics.

In the next step, real Internet traffic data will be analyzed to investigate the accuracy of the assumption.

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