Origin of Critical Behavior in Ethernet Traffic

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Abstract

We perform a simplified Ethernet traffic simulation in order to clarify the physical mechanism of the phase transition behavior which has been experimentally observed in the flow density fluctuation of Internet traffic. In one phase traffics from nodes connected with an Ethernet cable are mixed, and in the other phase, the nodes alternately send bursts of packets. The competition of sending packets among nodes and the binary exponential back-off algorithm are revealed to play important roles in producing $1/f$ fluctuations at the critical point.

Key words: phase transition; Internet traffic; numerical simulation,

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1 Introduction

The Internet can be viewed as an autonomous system in which the nodes are heterogeneously connected without any central control. In the Internet, the

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unit of information is a packet, and many researchers have been investigating
the statistical properties of packet density fluctuations.

In 1994 Leland et. al analyzed the time series of packet flow density in the
Internet, and showed the existence of the $1/f$ type fluctuation[1]. Similar to
the packet flow fluctuation, Csabai reported that the time series of round
trip time (RTT) exhibits the self-similarity in certain path of the Internet
[2]. Following these pioneering works, many observations clearly demonstrate
that Internet traffic are characterized by the long-range dependency, and the
assumption of Poisson process, which had been a major traffic model in the
traditional traffic theory, has clearly lost its validity [3,4].

Takayasu et al. pointed out that the Internet traffic can be viewed as a phase
transition phenomenon between congested and sparse phases by both the RTT
experiment [5–7] and the packet flow density analysis[8–10]. Only at the criti-
cal point they found the $1/f$ type fluctuation consistent with the above results.
Namely, they clarified that the self-similarity cannot always be observed in the
Internet traffic, and the phase transition view is more general and adequate.

Although there are many observational evidences for this phase transition, we
still do not fully understand the physical explanation of the observed phenom-
ena. Takayasu et al. reported that a simple queue itself plays an important
role in phase transition phenomena in general [11]. We believe that the theory
is qualitatively correct, however, there are some quantitative differences
between the observation and the simple queueing theory. For example, the
congestion duration time is known to be characterized by the power law dis-
bistribution whose exponent is $-1.0$ at the critical point, while the simple queue
model can only reproduce the traffic characterized by the power law distri-
bution whose exponent is $-0.5$ at the critical point. Thus, we need to find a
mechanism that causes such difference in exponents.

In this paper, we focus on the effect of the Ethernet (CSMA/CD) mechanism
in order to give a more sophisticated physical explanation for the observation
facts. Ethernet has been mostly used in the local area network in the In-
ternet. Ethernet itself, however, has very complicated mechanisms to achieve
efficient communication, so it is difficult to clarify the role of each mechanism
in the phase transition. For this reason, we perform a simulation based on the
minimal mechanism of the Ethernet algorithm, especially focusing on the two
effects; the competition among nodes that intend to send their packets to the
shared media, and the exponential back-off algorithm in collision detection.

We review the observation facts in the following section. In section 3 we in-
troduce a model of Ethernet traffic with simplified algorithm for numerical
simulation. Simulation results are described in Section 4 which is divided into
four sub-sections. We discuss the cause of $1/f$ type fluctuations in section 5.
The final section is devoted to the summary.

2 Observation of Phase Transition Phenomena in Ethernet Traffic

2.1 Data Measurement Environment

In order to collect the raw data trace, we set up a FreeBSD PC connected to the 10Mbps Ethernet link between the WIDE (Widely Distributed Environment project) backbone and Keio University in Japan by a non-intelligent hub. There are no other hosts in this link, so the tapping host can capture all packets and the time stamps through this link by using the tcpdump command. From the measurements, we obtained 12 data traces, each 14440 seconds (about 4 hours) long between Nov. 1997 and Feb. 1998. Each trace is categorized into the three typical time periods, i.e. early morning, business hour, and evening. We reconstruct each original tcpdump trace into seven time sequences of the flow density fluctuation in bytes, whose sample size is 0.1 seconds.

2.2 Phase Transition Phenomena in Real Traffic

Figure 1 shows an example of packet flow density fluctuation of a 4-hour measurement. The abscissa shows the time in seconds and the ordinate is the corresponding flow density in bytes. The periods denoted by (a), (b), and (c) in the figure indicates three typical periods, namely, sparse, moderately-congested, and congested periods, respectively. The mean flow densities of the three periods are 150 kbyte/sec, 550 kbyte/sec, and 850 kbyte/sec, respectively. From the figure, it is clear that the flow density highly fluctuates in the moderately-congested periods (b) in Figure 1, though it roughly stays in lower or higher states in the other cases, (a) and (c), respectively.

Next we explain the data analysis method called as congestion duration length
Congestion duration length is a major index to characterize the statistical nature of a given time fluctuation. We first define a congestion state that the flow density has larger value than a threshold value. Then, the congestion duration length is defined as the sequential number of the congestion state multiplied by the bin size of the original time series. We are interested in the cumulative distribution of this congestion duration length. At the critical point, it is known that the congestion duration length distribution follows the power-law distribution with exponent $-1.0$. This slope is theoretically corresponding to the so-called $1/f$ power spectrum in the original time series.

Figure 2 shows the congestion duration length distribution in a log-log plot. The flow data traces of these three plots correspond to the three periods shown in (a), (b), and (c) in Figure 1. The plotted line clearly decays exponentially in the sparse period, and the distribution is approximated by a power law distribution with exponent $-1.0$ in the moderately-congested period. (The straight line in this figure represents the power law distribution with slope $-1.0$.) Thus, this observed power law distribution shows that the mean flow density in this period is close to the critical point. Moreover, above the critical point, the distribution deviates from the power law again due to large clusters of congestion.

From these figures we confirm the existence of the typical two phases, namely, the sparse and congested phases. Particularly in the intervals, which are close to this critical mean flow density, the congestion duration length distribution clearly shows the self-similarity. Also, it is reported that the tendency of divergence of the autocorrelation time the whole behaviors can be confirmed near this critical mean flow density in the same data traces[8,10]. Namely, the actual Ethernet traffic flow generally changes its statistical property, which
3 Simplified Ethernet Traffic Simulator

In this section, we focus on the dynamic aspect of the Ethernet mechanism, in order to clarify the physical mechanism of the observed phase transition phenomenon. Since the actual Ethernet dynamics consists of many complicated rules, it is difficult to extract the essence of the phase transition phenomenon directly from a real system. Therefore, we need to focus on a few basic properties of Ethernet rules by introducing a minimal network architecture model to check the occurrence of the phase transition. For this purpose, we consider the two most basic effects in the Ethernet mechanism; the competition of the nodes at packet transmission, and the binary exponential back-off algorithm. Also, to simplify the simulation, we assume a topology consisting of two nodes (to be called as nodes 1 and 2) sending packets randomly and one shared medium to connect them.

Figure 3 illustrates our simplified discrete simulation algorithm. In every discrete time step, each node probabilistically generates a fixed-size packet to be sent to the medium. Each node has an assigned input rate, and a packet is created randomly with this rate and injected into the finite-size output queue of this node. This input rate is given initially and it does not change during the simulation. As known directly from this rule of packet creation, there is no temporal correlation among the input traffic to the queue.

Fig. 3. Simplified Ethernet simulation algorithm

can be fully modeled by the phase transition view.
The maximum size of the output queue is 16384 (= 2^{14}) packets in this simulation. When a generated packet finds no room in the queue, it is simply discarded. If more than one packets are waiting in the queue, then the node tries to transmit a packet from the queue to the shared network medium. When only one node intends to send a packet to this network, this node successfully transmits one packet from the queue, and it takes one time step to finish its transmission. However, when more than one node try to send packets simultaneously, both nodes fail to transmit them, and the packets remain in their queues. Then, the nodes increase their back-off counters, which indicate the level of the back-off, by 1. Furthermore, they set their own waiting time $k$ chosen randomly from $[1, 2^n]$ where $n$ denotes the back-off counter. Each waiting time decreases one time step in every time step, and a waiting node tries to send a packet when its waiting time becomes zero. The successful node, conversely, resets its back-off counter to zero after transmission.

In our simulation the maximum level of the back-off counter is set to 14, i.e. the waiting time is chosen from a random number smaller than 16384 (= 2^{14}). Also, the back-off counter remains the maximum number even after the node fails to send a packet more than 14 times successively, while the actual Ethernet algorithm drops the packet when the back-off limit is larger than the maximum back-off number. It should be emphasized that new packets are stored in the queue corresponding to the input rate even when the node is in the waiting status.

4 Observation of Phase Transition Phenomenon

Here, we focus on the property of the total amount of packet traffic flow passing through the link based on our simplified Ethernet algorithm.

4.1 Two-node Case

In Figure 4 we plot macroscopic performance metrics (packet dropping rate, throughput, and reliability) in our simulation. The abscissa denotes the input rate of the nodes, where we set the same input rate for both nodes. From the definition of input rate, the input rate 50% statistically corresponds to the maximum link capacity. Here, the packet dropping rate is given by the ratio of the number of packets overflowing at either of the nodes divided by the total number of input packets. The throughput is defined as the number of packets normalized by the link capacity. The reliability shows the rate of successfully transmitted packets, which is given by 100% minus the packet dropping rate. Obviously, packet dropping rate suddenly takes non-zero values for input rate
above about 30%, which is to be called as the critical input rate.

Figures 5 (a), (b), and (c) show three typical packet flow fluctuations for input rates 15, 29.5, and 45%, respectively. Each figure consists of three sub figures, namely, the output flow fluctuations from node 1, from 2, and from 1 + 2 (the total traffic in this link). The abscissa shows the time step, and the ordinate indicates the number of output packets per every 16 time steps.

At the low input rate the two nodes randomly transmit their packets, and the total traffic seems to have spontaneous small bursts. Near the critical input rate, the total packet fluctuation consists of two typical types of fluctuations. One is a highly variable fluctuation observed around 28000 time steps, where the two nodes mutually send packets to the network with fine granularity, and the total traffic is nearly a superposition of such individual traffic flows. The other type is observed around 5000 time steps in which one node continuously sends packets until its buffer becomes empty. Thus, we can expect the sizes of the congestion to be distributed widely at the critical mean flow density.

In the case that the input rate is high, each node alternately sends bursts of roughly same size depending on the buffer size. The short fluctuations followed by the full bursts observed around 20000 time steps in node 1 are likely due to the imbalance of the buffer size and the maximum back-off waiting time. Comparing the figures, we found that the simulated packet flow captures the qualitative characteristics of the actual traffic flow.

Next, we show the result of the congestion duration length distribution in this two-nodes simulation in Figure 6. The original data trace is the total flow density fluctuations from the two nodes per 16 time steps, and the threshold value of congestion level is set to be two packets. The three lines in this figure represent the low (15%), the medium (29.5%), and the high input rates (40%)
Fig. 5. Simulated traffic flow. top (a): input rate = 15%, middle (b): input rate = 29.5%, bottom (c): input rate = 45%. The sub figures represent the traffic flow from node 1, from node 2, and the total flow through the link.
Fig. 6. Congestion duration length distribution (2 node). The straight line indicates the power law with exponent $-1.0$

in log-log scale. When the packet input rate is low, the congestion duration length follows the exponential distribution. Namely, the congestion duration has only short-range dependency. In the case of high input rate the distribution deviates from the power-law distribution due to the large clustered congestion. The decay of this plotted line at large $L$ is due to system size limitation (e.g., buffer size, simulation time, etc.). In the medium input rate case the plotted line is approximated by a power law distribution with exponent $-1.0$. This input rate is the same as the critical value at which a node begins dropping packets due to the buffer overflow in Figure 4.

From these results, we confirm that the simplified packet traffic model can reproduce the two typical phases and the critical point characteristics observed in real systems. The three types of distributions of the congestion duration lengths are consistent with the distributions obtained from the actual traffic measurement[8,10]. It should be noted that the packet input to the queue is based on purely random events of Poisson process, so, the self-similarity observed in the output fluctuation at the critical point is caused by the evolution dynamics based on the competition and the binary exponential back-off algorithm.

4.2 Three-node Case

The observed network introduced in Section 2 simply consists of only two nodes. In an ordinary network, however, there are generally many nodes connected to the shared media. Therefore, we need to consider the situation in
which more than two nodes participate. Here, we show the traffic fluctuations passing through a link connected to three nodes. Figure 7 represents the congestion duration length distributions in the aggregated traffic from the three nodes following the same simulation algorithm as in the preceding sub-section. Though the critical input rate (23%) is lower than the case of the two-node simulation (29.5%), the same three typical types of distributions are clearly observed also in this figure. Similarly, we found that the three performance metrics (packet dropping rate, reliability, and throughput) bend at this critical point. We also observed the same type of the phase transition in the four node simulation. The cases with more than four nodes give the same result in general. These results clearly show that the occurrence of the phase transition behavior is considered to be independent of the number of nodes connected to the link.

4.3 Asymmetric Case

In the previous simulations, we have assumed that all nodes had the same input rate. Here, we analyze an asymmetric case consisting of two nodes having different input rates.

Figure 8 depicts the phase diagram of the estimated critical point when the combination of the input rates of the two nodes changes. The abscissa and the ordinate represent the input rates of nodes 1 and 2, respectively. The point (30%, 30%) corresponds to the critical point in the previous symmetric case. The plotted line represents the set of critical points estimated by the
simulation, where self-similar traffic flows can be observed. We can divide this diagram into two regions separated by the critical line. The aggregated traffic belongs to the non-congested phase if the combination of input rates of the two nodes is in the lower-left region of this figure, and to the congested phase if it is in the upper-right region above the critical line. Their aggregated traffic fluctuations do not show self-similarity, and their congestion duration length distributions follow approximately an exponential distribution and a distribution with a plateau, respectively, as we saw in Figure 6.

It is found that the phase transition behavior disappears when the nodes connected to the link have extremely different input rates. This can be understood as follows. In the extremely asymmetric case, the probability of collision, which is proportional to the multiplication of the input rates of the two nodes, is relatively small. As a result, the back-off becomes less effective and the statistical property of the input process is likely to be preserved.

4.4 Dependence on Back-off Functions

In order to clarify the effect of the functional form of the back-off function, we performed the simulation with a different back-off rule. With the normal Ethernet algorithm, when collision is detected, the waiting time is chosen randomly in the interval between 1 and $2^n$, where $n$ is the back-off counter.

For comparison with this basic algorithm, we check the case of a linear back-off algorithm in this simulation, namely, the back-off time is selected from a random time between 1 and $n \times k$, where the coefficient $k$ is set to be 100 in
this simulation. We have confirmed that the following results are the same for 
$k$ between 10 and 1000.

Figure 9 shows the results of the congestion duration length analysis for the 
linear back-off algorithm. The plotted lines clearly follow exponential functions 
independent of the value of the input rate. Thus, neither the phase transition 
phenomenon nor the self-similarity can be observed in the resulting traffic. It 
is now clear that the binary exponential back-off algorithm plays an important 
role in generating self-similar traffics.

Similarly, we also check the case of ternary exponential back-off algorithm, that 
is, the waiting time $k$ is chosen randomly from $[1, 3^n]$ with $n$ being the back-off 
counter. By this simulation we find the power law distribution with the same 
slope $-1.0$ at the critical point while the critical point itself shifts from the 
value in the binary exponential back-off case. Therefore, the exponential type 
back-off function is expected to be the essence of the observed phase transition 
behaviors.

5 Discussion

We have found that our simplified Ethernet simulation based on both compe-
tition in transmission and the exponential back-off algorithm can reproduce 
esentially the same traffic behaviors as observed in real Ethernet traffic. When 
the total traffic flow rate is low, there are few collisions in the link, and the 
traffic statistics are dominated by the random input. The aggregated traffic 
is approximately consisted of superposition of the input traffic from the two
nodes. However, at the critical input rate, the number of collisions becomes
not negligible and the back-off mechanism works effectively, and the resulting
output traffic becomes correlated in long time scales. The traffic is hovering
about the two phases rather randomly causing large fluctuations showing self-
similarity. Above the critical input rate the traffic is dominated by clustered
congestion whose size depends both on the buffer size of the nodes and on
the maximum number of the back-off count. In this phase the traffic loses the
self-similarity.

In the single queue model the power law exponent for the congestion duration
length distribution is known to be $-0.5$ at the critical point\cite{5}. Our results
show that the network traffic behavior from more than two nodes following the
simplified back-off algorithm exhibits a power law distribution with exponent
$-1.0$. Thus, we conclude that the back-off delay due to competition among the
nodes is a key factor in generating the $1/f$ type fluctuation. In particular, it is
very important that the phase transition and resulting self-similarity appear
in the output traffic behavior even when the input traffic is purely random,
having no temporal correlation.

Moreover, our simulation demonstrates that the linearly incremental back-off
algorithm fails in realizing a phase transition. Thus, it is clear that the multi-
plicative form of the back-off function is an essential factor in characterizing
the statistical property of the Ethernet traffic behavior.

Finally, our simulation demonstrates that the critical point does not always
exist when the nodes have extremely different input rates. In the highly asym-
metric case packets have less chance to collide with other packets, and the
back-off value cannot become very large. For this reason the output traffic is
not much modified from superposition of input traffics. We can expect that
the critical behavior can be found in a wider region in the phase diagram if
the input traffic is temporally correlated because correlated packets generally
have more chance of collision with other packets than the case of independent
random inputs.

6 Conclusion

Our simulation is based on only two effects in the complicated Ethernet mech-
anism; the competition among the nodes at transmission process and the ex-
ponential back-off. The simplicity of the simulation algorithm enables us to
investigate detailed statistical properties of packet traffics.

Our results can be summarized as follows: (1) The simplified simulation can re-
produce the basic properties of the real traffic fluctuations especially in terms
of the phase transition between the sparse or mixed transmission phase and congested alternating transmission phase.  (2) At the critical flow density the output flow shows a self-similarity in its fluctuation even though the input is totally random without having any temporal correlation.  (3) Phase transition does not appear when the input rates of the nodes are extremely asymmetric. The approximate phase diagram in the parameter space is drawn with a critical curve.  (4) The occurrence of the phase transition is expected to be independent of the number of the nodes.  (5) The functional form of the back-off algorithm plays an essential role. The linear back-off function cannot realize a phase transition, while the exponential back-off always reproduce the $1/f$ type fluctuation at the critical point.

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References

[1] W.E. Leland, M.S. Taqqu, W. Willinger, D.V. Willson, *IEEE/ACM Trans. Networking* 2 (1994) 1.
[2] I. Csabai, *J.Phys. A* 27 (1994) 417.
[3] V. Paxson, S. Floyd, *IEEE/ACM Trans. Networking* 3 (1995) 226.
[4] M.E.Crovella, A.Bestavros, *IEEE/ACM Trans. Networking* 4 (1996) 209.
[5] M. Takayasu, H. Takayasu, T. Sato, *Physica A* 233 (1996) 924.
[6] K. Fukuda, H. Takayasu, M. Takayasu, *Adv. Performance Anal.* 2 (1999) 45.
[7] K. Fukuda, H. Takayasu, and M. Takayasu, *Fractals* 7 (1999) 23.
[8] M. Takayasu, H. Takayasu, K. Fukuda, *Physica A* 277 (2000) 248.
[9] M. Takayasu, K. Fukuda, H. Takayasu, *Physica A*, 274 (1999) 140.
[10] K. Fukuda, PhD thesis, Department of Computer Science, Keio University, Feb 1999. [http://www.t.onlab.ntt.co.jp/~fukuda/](http://www.t.onlab.ntt.co.jp/~fukuda/) research/thesis.ps.gz.
[11] M. Takayasu, A. Tretyakov, K. Fukuda, H. Takayasu, in D.E. Wolf (Ed.), *Traffic and Granular Flow '97*, Springer, Berlin, 1998, p.57.
[12] M. Takayasu, *Physica A* 197 (1993) 371.