PAPER

Dynamics of Feedback-induced Packet Delay in ISP Router-level Topologies

Takahiro HIRAYAMA[†a)], ***Nonmember***, **Shin'ichi ARAKAWA**[†b)], ***Member***, **Ken-ichi ARAI**[††c)], ***Nonmember***, ***and*** **Masayuki MURATA**[†d)], ***Fellow***

SUMMARY Internet behavior is becoming more complex due to ever-changing networking technologies and applications. Thus, understanding and controlling the complex behavior of the Internet are important for designing future networks. One of the complex behaviors of the Internet is traffic dynamics. Previous studies revealed that flow control in the transport layer affects the traffic dynamics of the Internet. However, it is not clear how the topological structure impacts traffic dynamics. In this paper, we investigate packet delay dynamics and traffic fluctuation in ISP router-level topologies where the degree distribution exhibits a power-law nature, and the nodes interact via end-to-end feedback control functionality. We show the packet delay dynamics of the BA topologies generated by the Barabási-Albert (BA) model and the ISP router-level topologies. Simulation results show that the end-to-end delay distributions exhibit a heavy tail in the TCP model. Moreover, the number of links with highly fluctuating queue length increases dramatically compared to that in the stop-and-wait model. Even in this case, the high-modularity structures of the ISP topologies reduce the number of highly fluctuating links compared with the BA topologies.

key words: *Power-law degree distribution, ISP router-level topology, Traffic dynamics, TCP*

1. Introduction

Dynamic interactions among various network-related protocols as a result of functional partitioning make the Internet a complicated system whose details are difficult to confirm because of its large-scale, heterogeneous structure. One of the complex behaviors of the Internet is traffic dynamics. For example, flow control and congestion control of TCP can cause short-range and long-range dependence of traffic [1]. Ever-changing networking technologies and applications make the behavior of the Internet more complex [2]; thus, understanding and controlling the complex behavior of the Internet are important for designing future networks.

Although the statistical properties of network traffic are hard to capture, studies have revealed that the degree distribution of the Internet topology follows a power law. That is, the probability that nodes having k links exist is proportional to $k^{-\gamma}$ (γ is constant). Barabási et al. proposed the Barabási-Albert (BA) model to generate power-law topologies having power-law degree distributions [3]. Li et al. showed several topologies that have different structures but have the same degree distribution [4, 5]. They pointed out that differences in structures lead to differences in the amount of traffic that the network accommodates. Moreover, the structures of power-law topologies also affect the performance of networking mechanisms, such as routing mechanisms [6]. These studies indicate that the power-law degree distribution alone does not determine network-level performance. That is, topological structure properties other than the degree distribution are essential to discuss the performance of networks [4, 7].

In previous studies, the relationship between the statistical properties of Internet traffic and end-to-end flow control has been discussed. In Refs. [8, 9], it is revealed that Internet traffic exhibits long-range dependence (LRD), where traffic fluctuation appears to be independent of measurement time scale. Various studies have investigated the reasons for LRD. One of the reasons is flow control in the transport layer, such as TCP [10–12]. However, these studies deal with small, simple topologies.

It has been revealed that end-to-end flow control functionality of TCP sessions affects traffic dynamics through an interaction at a single link. In large-scale topologies, TCP sessions interact with each other over all links. Nevertheless, previous studies on design and performance evaluation of a large-scale topology [13, 14] have not considered the end-to-end feedback control functionality provided by transport layer. We therefore investigate the traffic dynamics in large-scale topologies where the topological structure greatly affects the network performance. More specifically, we investigate traffic dynamics on ISP router-level topologies (ISP topologies) where the degree distributions exhibit a power-law nature, and the nodes interact via end-to-end feedback flow control functionality. First, we show the packet delay dynamics and compare the results against the BA topologies generated by the BA model and the ISP topologies. We then discuss how the interaction between the structures of topologies and the flow controls affects the end-to-end delay distribution and the appearance of LRD in the queue length for each link. The results show that the TCP flow control makes the queue length of links in the network fluctuate because TCP tries to use available bandwidth. However, we show that the queue length of many links does not fluctuate regardless of TCP in the ISP topologies. This phenomenon is due to the high-modularity structure of the ISP topologies. We investigate the relationship between the modularity of topologies and queue fluctua-

[†]Graduate School of Information Science and Technology, Osaka University, 1-5 Yamadaoka Suita-shi, Osaka, 565-0871, Japan
[††]NTT Communication Science Laboratories, NTT Corporation, 2-4 Hikaridai Seika-cho Soraku-gun, Kyoto, 619-0237, Japan
a) E-mail: t-hirayama@ist.osaka-u.ac.jp
b) E-mail: arakawa@ist.osaka-u.ac.jp
c) E-mail: ken@cslab.kecl.ntt.co.jp
d) E-mail: murata@ist.osaka-u.ac.jp
DOI: 10.1587/trans.E0.??.1

tion. We find that topologies with high-modularity structures have a lower number of highly fluctuating links.

This paper is organized as follows. We introduce related work in Section 2. In Section 3, we show the network model that we used for the simulations. In Section 4, we evaluate the influence of the power-law topologies and TCP flow control. Finally, in Section 5, we conclude this paper and mention future work.

2. Related Work

2.1 Structural Properties of Power-law Networks

Recently, there have been a considerable number of studies investigating power-law networks whose degree distribution follows a power law. Barabási et al. introduced the BA model as a method for generating a power-law topology in Ref. [3]. The BA model generates a power-law topology based on two rules: one is incremental growth, and the other is preferential attachment. The resulting power-law networks have two main characteristics. First, many nodes have a few links, and a few nodes, so-called hub nodes, have many links. Second, the average length of the shortest paths between nodes is small. Many studies have investigated topological properties appearing in the BA model or its variants. However, when router-level topologies are concerned, the BA model, where links are attached based on a preferential probability, does not emulate the structure of ISP topologies. We have compared the structural differences of the AT&T topology measured using the Rocketfuel tool [15] and the topology generated by the BA model [16]. The results indicate that the design principles of networks greatly affect the structure of the ISP topologies: Design principles determine the node functionality, which in turn determines the connectivity of nodes.

In [17], Guimerà et al. proposed a classification method of node functions. In this method, a network is divided into multiple modules, and the within-module degree, Z_i, and the participation coefficient, P_i, are defined for each node. Assuming that the node i belongs to a module s_i, the within-module degree Z_i of node i is defined as

$$Z_i = \frac{k_i - \langle k_{s_i} \rangle}{\sigma_{s_i}}, \qquad (1)$$

where k_i is the degree of the node, $\langle k_{s_i} \rangle$ represents the average degree in module s_i, and σ_{s_i} is the variance of the degree distribution of nodes in module s_i. We consider hub nodes as the nodes with Z_i greater than or equal to 2.58. That is, when we assume the standard normal distribution for Z_i, top 0.5% nodes are hub nodes and the remaining nodes are non-hub nodes. Note that the distribution of Z_i is not always the normal distribution. However, we use 2.58 to distinguish hub nodes having a much larger number of out-going links in the module and non-hub nodes.

The participation coefficient P_i of node i is defined as

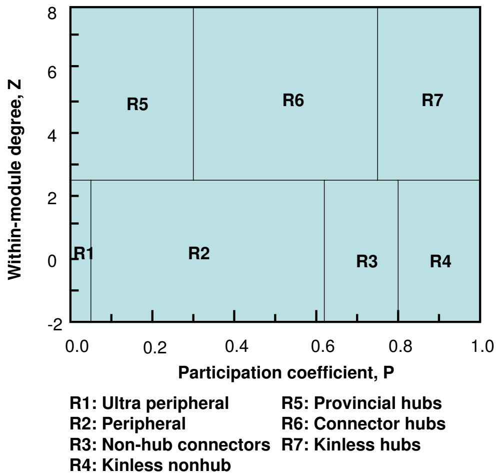


Fig. 1 Classification of node function by participation coefficient and within-module degree

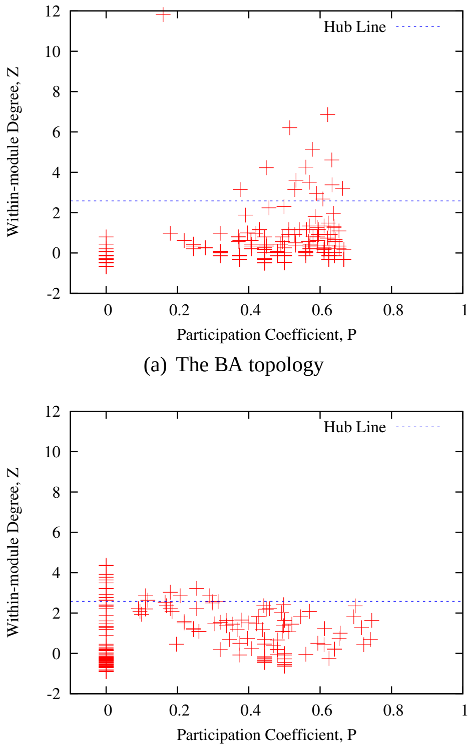
$$P_i = 1 - \sum_{s_i=1}^{N_m} \left(\frac{k_{is}}{k_i} \right)^2, \qquad (2)$$

where k_{is} represents the fraction of links connecting with nodes in module s_i and N_m represents the number of modules. That is, when all the links of node i connect with nodes belonging to the same module s_i, P_i becomes 0. Figure 1 shows that the roles of nodes are categorized by the values of Z_i and P_i. Depending on the values of P and Z, the role of the node is categorized into several classes. For example, when Z_i is large and P_i is relatively large, the node i has many links connecting to other modules. Thus, the node i is categorized as a *connector hub*. On the other hand, a *provincial hub* node has large Z_i and small P_i; that is, it has many links connecting with nodes in the same module.

Figure 2(a) and Fig. 2(b) show the results of applying Guimerà's method to the BA topology and the AT&T topology. The module is calculated using the method in [18]. In Fig. 2, the vertical axis indicates within-module degree Z, and the horizontal axis the participation coefficient P. Looking at Fig. 2(a), we observe that the BA topology has many connector hub nodes that connect between modules. However, Fig. 2(b) shows that there are few connector hubs in the AT&T topology.

2.2 Traffic Dynamics in Power-law Networks

Some studies have investigated traffic-level behavior in topologies having power-law degree distributions [13, 19]. Reference [13] demonstrates that congestion spreads easily over BA topologies because of their low diameter. Low-diameter effects also appear in the queuing delay distribution of these topologies. They show that the queuing delay distribution of BA topologies has a long tail. The effect of end-to-end flow control in the topology obtained by the BA model has also been investigated [19]. The authors examined TCP control with LRD input traffic and Poisson input traffic and revealed that the average end-to-end delay



(a) The BA topology

(b) The AT&T topology

Fig. 2 Classification of node function in each topology

sharply increases for both types of input traffic since packets concentrate more at hub nodes in the BA topology. Previous studies have used topologies generated by the BA model or its variants. However, even when the degree distributions of some topologies are the same, their more detailed characteristics are often quite different. As discussed in Section 2.1, the BA model does not adequately describe the structure of ISP topologies. This clearly indicates that the power-law degree distribution alone does not determine traffic-level behavior in ISP topologies.

Traffic dynamics has received great interest from the networking research community. It has been revealed that Internet wide-area and local-area traffic can show LRD or self-similarity [8]. That is, network traffic exhibits a large variability even at a wide range of time scales. Recently, these statistical properties have also been observed in peer-to-peer traffic [9]. In Refs. [10,11], TCP flow control is considered to be the cause of LRD in Internet traffic. Simulation results of Ref. [12] show that LRD is still observed when the stop-and-wait protocol is used instead of TCP. That is, the flow control functionality is an essential factor for the cause of LRD. However, these studies deal with small, simple topologies. Thus, we investigated how the structures of topologies impact the traffic dynamics.

3. Simulation Model

3.1 Network Topologies

For the simulation, we use several ISP topologies using the Rocketfuel tool [15] and BA topologies generated by the BA model. BA topologies are generated such that the numbers of nodes and links are the same as the corresponding ISP topologies. In Ref. [4, 7], it is shown that the BA model is insufficient to model ISP topologies. However, we use the BA topology in this paper, because one of our purposes in the current paper is to clarify the essential structure of ISP topologies that characterizes their traffic dynamics by comparing with the BA topology. The Rocketfuel is a topology measurement tool based on `traceroute`. Note that the authors of Ref. [15] pointed out that the Rocketfuel might not cover some parts of ISP topologies. Even when the Rocketfuel misses some of routers, it is sufficient to investigate traffic dynamics because the Rocketfuel provides active paths, including MPLS-based paths, between routers. The actual ISP networks may have some routers invisible from `traceroute`. We believe that the routers are used for a backup purpose because they are placed on the inactive path for Internet users.

In the following simulation, we first evaluate and compare the AT&T topology with the corresponding BA topology to identify the essential structure of ISP topologies that characterizes their traffic dynamics.

3.2 Packet Processing Model of Nodes

Each node has limited buffers at each outgoing link. When a packet arrives at a given node and when the node is the packet's destination, the node removes the packet from the network. Otherwise, the node selects the next node based on a minimum hop routing algorithm and forwards the packet to a buffer of an outgoing link connecting to the next node. Each outgoing link sends packets to the next node based on FIFO and a drop-tail queuing discipline, delivering C packets per unit time. Note that capacity of links is heterogeneous in actual ISP topologies. However, we use the same link capacity to evaluate traffic dynamics induced only by topological structure. Here, we do not use dynamic routing; i.e., each packet traverses the shortest path calculated beforehand. When multiple shortest paths to reach the destination are found, the next node is determined by a packet's source node. According to Ref. [20], traffic fluctuation caused by TCP-like flow control appears in short time scales such as the round trip time (RTT). So, we use a static routing strategy.

3.3 Flow Control between End Hosts

We examined stop-and-wait model and TCP model for flow control between end hosts. The stop-and-wait model is introduced to clarify the impact of flow control functionality of TCP. In the simulation, pre-specified numbers of sessions are created between nodes. Source and destination nodes are randomly selected and each session arrives at a node pair according to the Poisson process with mean rate λ. Each session always has data to send during the simulations, i.e., once a session is generated, it continues to send data to destination node until the simulation ends.

3.3.1 Stop-and-Wait Model

In this model, when a source node sends a DATA packet to its destination node, the source node stops sending a new packet until the source node receives the acknowledgement (ACK) packet from the destination node. If a source node does not receive the ACK packet within the retransmission time out (RTO) period, the source node thinks that packet loss has occurred and resends the packet. The time-out period is defined based on the RTT and is doubled for every time out.

3.3.2 TCP Model

In this model, source nodes control the amount of DATA packets based on the slow start and congestion avoidance algorithms. The slow start and congestion avoidance algorithms are basic flow-control functions of TCP. If the window size is lower than the slow start threshold (*ssthresh*), the source node uses the slow start algorithm. When the source node receives an ACK packet, it extends the congestion window (*cwnd*) by one packet size (= segment size, *smss*) and sends two new DATA packets to the destination node. If the window size exceeds *ssthresh*, the source node uses the congestion avoidance algorithm. When the source node receives an ACK packet, it extends the congestion window by 1/*cwnd*, and it sends an adequate number of DATA packets to the destination node. In our model, the congestion window size does not exceed a pre-decided maximum window size. If the source node does not receive any ACK packet within the RTO period, the source node recognizes that serious congestion has occurred. The source node resends the lost DATA packet and reduces the congestion window by one packet size. The time-out period is defined in the same way as in the stop-and-wait model.

In addition, we use the fast retransmit and fast recovery algorithms defined by RFC 2581 [21]. The source node uses the fast retransmit algorithm when it detects packet loss and light congestion by the arrival of three duplicate ACKs. When the source node receives the third duplicate ACK, it reduces the congestion window to half and resends the lost DATA packet. After the retransmission, the source node extends the congestion window based on the fast recovery algorithm. The source node keeps extending the congestion window by one packet size as long as it receives the same duplicate ACKs.

Table 1 The simulation parameters used in the TCP model

Buffer size	1,000 packets
Session arrival rate (λ)	1 session / unit of time
Maximum *cwnd*	10 packets
Link capacity (C)	3 packets / unit of time
Simulation time	300,000 units of time

4. Dynamics of TCP in Power-law Networks

In this section, we show the results of simulation for TCP and discuss the end-to-end delay and queue-length fluctuation in detail. In the simulation, each link can transfer three packets per unit time. The other parameters are summarized in Table 1.

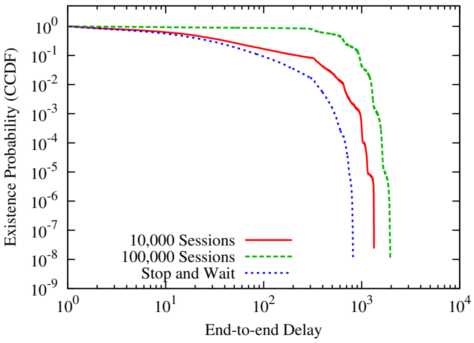
4.1 End-to-End Delay Distribution

Figure 3 shows the end-to-end delay distribution of the BA (AT&T) topology and the AT&T topology. The end-to-end delay represents one-way delay for DATA or ACK packets. In this figure, the end-to-end delay distribution in the stop-and-wait model (the number of sessions is 100,000) is also plotted. From comparison with the stop-and-wait model, end-to-end delay gets larger in the TCP model. In the AT&T topology, when the number of sessions is 10,000, packets take longer to reach their destinations compared with the BA topology. In contrast, the end-to-end delay distribution of the BA topology changes drastically when the number of sessions is 100,000. It has a long-tail distribution; i.e., many packets take a long time to reach their destinations. End-to-end delay of less than 500 time units is hardly observed in the BA topology. However, the end-to-end delay distribution of the AT&T topology does not vary widely when the number of sessions increases.

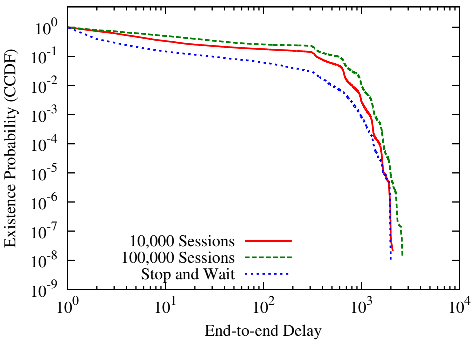
The reason for this is that the congestion tends to occur in the BA topology when TCP is applied. The term ”congestion” means that a buffer is occupied by packets and cannot receive any more packets. To explain the reason more clearly, we show the number of congested links dependent on each time step in Fig. 4. The figure shows that the frequency of congestion in the BA topology is about 4 times larger than that in the AT&T topology. As discussed in Section 2.1, the BA topology has many connector hub nodes, and the connector hub nodes transfer a large amount of packets between modules. Packets concentrate at connector hub nodes in the BA topology. Thus, the links connected to connector hub nodes tend to be congested. Since most of sessions concentrate on the connector hub nodes and the congested links, the end-to-end delay distribution of the BA topology has a long tail.

4.2 Queue Length Fluctuation

Next, we evaluate the fluctuation of queue length. If queue length of a link fluctuates drastically, a session encounters a temporal congestion on the link, which leads to a packet

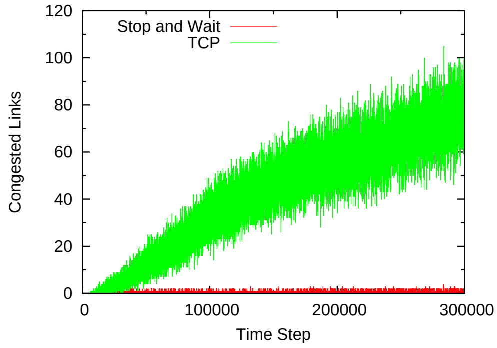


(a) The BA topology

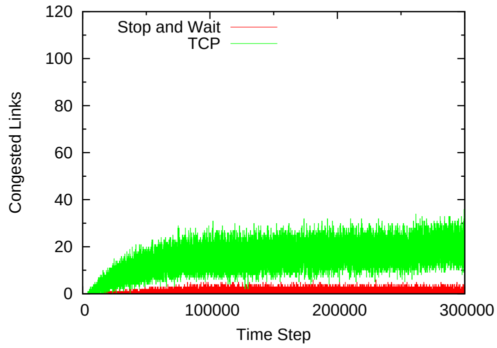


(b) The AT&T topology

Fig. 3 End-to-end delay distribution



(a) The BA topology



(b) The AT&T topology

Fig. 4 The number of congested links

drop and a longer delay. We evaluate the fluctuation using the Hurst parameter ($H, 0.5 < H < 1$) by applying the R/S plot method [22]. The Hurst parameter represents the degree of LRD. High Hurst parameter means that queue length of the link highly fluctuates.

Details of the R/S plot method are as follows. First, we define $R/S(n)$ as

$$\begin{aligned} R/S(n) &= 1/S_n[\max(0, W_1, W_2, \cdots, W_n) \\ &\quad - \min(0, W_1, W_2, \cdots, W_n)], \\ W_k &= (X_1 + X_2 + \cdots + X_k) - kX(n), \end{aligned} \tag{3}$$

where $(X_k : k = 1, 2, \cdots, n)$ is an observation data set. $X(n)$ represents the mean value, and S_n represents the standard deviation of the data set X. By estimating $R/S(n)$ for an observation scale n and plotting the correlation between n and $R/S(n)$, we can observe the statistical dependence over time. We set the observation scale of n from $10^5/2^{13}$ to 10^5 time units and use the time series of queue length extracted from the last 100,000 time units of simulation. The slope of the fitted curve of the correlation function, αn^H, represents the Hurst parameter of a set X.

Figure 5 shows Hurst parameters for each link. The y-axis represents the Hurst parameter and the x-axis represents its rank in a descending order. In this figure, the results for the stop-and-wait model are also added. Looking at this figure, we observe that the number of links that take high Hurst parameters increases in the TCP model. Besides, we observe that the AT&T topology reduces the number of fluctuating links compared with the results of the BA topology.

To see the relation between the Hurst parameter and topological structure in the AT&T topology clearly, we show the ratio of links that take high H values ($H \geq 0.8$) in Table 2. When the number of sessions is small, the queue length of the links that connect two regions fluctuates drastically. That is, inter-module links tend to have highly fluctuating queue lengths. This is because many packets concentrate at inter-module links. As the number of sessions gets higher, the queue length of the links that connect inside a region fluctuates, whereas the Hurst parameter of inter-module links decreases. That is, the fluctuation spreads to tributary links of the bottleneck.

4.3 Fluctuation Reduction Effect of High-Modularity Structure

In the previous section, we showed that the structure of the AT&T topology reduces the number of fluctuating links. In this section, we examine the relationship between the modularity of topologies and the fluctuation reduction effects of those topologies.

Newman et al. [23] defined a modularity value (Q) as

$$Q = \sum_i (e_{ii} - a_i^2), \tag{4}$$

where e_{ii} is defined as the number of links connecting nodes

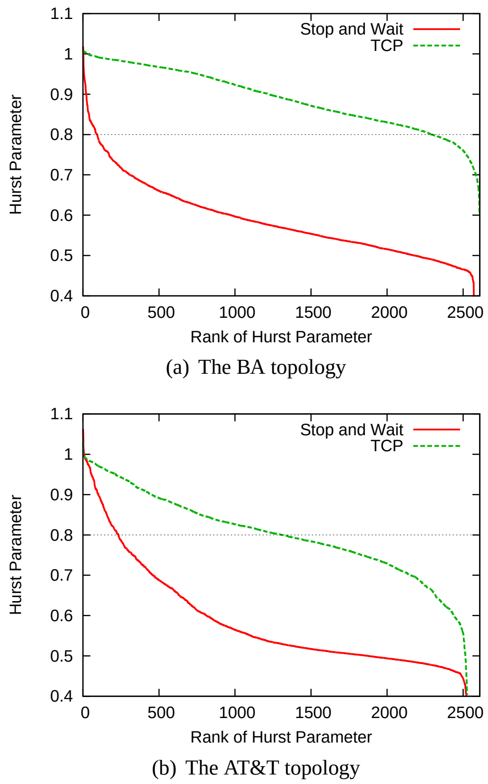


Fig. 5 Correlations between Hurst parameter and rank of Hurst parameter

Table 2 The ratio of highly fluctuating links in each topology

Topology	10,000 sessions			100,000 sessions		
	Total	Inter	Intra	Total	Inter	Intra
BA topology	0.54	0.19	0.35	0.88	0.30	0.58
AT&T topology	0.39	0.080	0.31	0.50	0.066	0.44

of module i divided by the number of all links. While, a_i is defined as the number of links that have one or both vertices inside of module i divided by the number of all links. The module is calculated using the method in [18]. According to this definition of Q, high Q value means that the topology has high modularity structure, that is, some modules are connecting with each other by a few inter-module links. The modularity value of the BA topology is nearly 0.32, and that of the AT&T topology is about 0.68. This result indicates that a high-modularity structure reduces the number of highly fluctuating links.

To confirm that ISP topologies reduce the number of fluctuating links, we conduct simulations with other ISP topologies and compare them with BA topologies. Three ISP topologies, Sprint, Verio, and Telstra, are used for the simulations because the topologies have the similar numbers of nodes and links to the AT&T topology. The topological properties of ISP topologies and its corresponding BA topologies are summarized in Table 3. The simulation parameters are the same as the evaluation of AT&T topology and are summarized in Table 1. Note that the number of

Table 3 Simulation results of ISP topologies

Topology	Nodes	Links	Modularity	Ratio of highly fluctuating links
AT&T	523	1,304	0.68	0.50
BA (AT&T)			0.32	0.88
Sprint	467	1,280	0.66	0.53
BA Sprint			0.30	0.81
Verio	817	1,874	0.70	0.46
BA Verio			0.25	0.77
Telstra	296	594	0.74	0.46
BA Telstra			0.29	0.78

sessions is 87,320 in the Telstra topology and the BA Telstra topology due to limit of the number of node pairs. In Table 3, the ratio of highly fluctuating links for each topology is also presented. We observe that each ISP topology reduces the number of fluctuating links compared with the results of the corresponding BA topologies. We also observe that each ISP topology has higher modularity value than the corresponding BA topology. These results indicate that topologies having high-modularity structure reduce the number of highly fluctuating links, as we observed in the AT&T topology.

To see the impact of modularity structure more clearly, we investigate queue fluctuation on three topologies that have the same number of nodes and links to the AT&T topology, but have different modularity values. We generated three topologies having N (=523) nodes and E (=1,304) links, m inter-modules links, and then control the modularity value by changing m. More precisely, we generated the three topologies through following steps.

1. Generates 10 sub-networks each of which consists of $\frac{N}{10}$ nodes and $\frac{E-m}{10}$ links and is connected based on the BA model.
2. Considers each sub-network as a module.
3. Adds m inter-module links by randomly selecting two nodes belonging to different modules and connecting the nodes.

As the number of inter-module links increases, the modularity value decreases. The modularity values of the generated topologies were 0.86, 0.81, and 0.76, and we confirmed that these topologies had power-law degree distributions.

Figure 6 shows the Hurst parameters of each link from the results of the simulations with the TCP model. The x-axis and y-axis represent the same parameters as those in Fig. 5. In the simulations, we again used the parameters in Table 1 and again randomly select the source and destination nodes for each session. In Fig. 6, as the modularity value increases, the number of links that take high Hurst parameters decreases. This result is confirmed by the ratio of highly fluctuating links that have a Hurst parameter larger than 0.8 shown in Table 4. Thus, topological structures that have high modularity values prevent the appearance of highly fluctuating links.

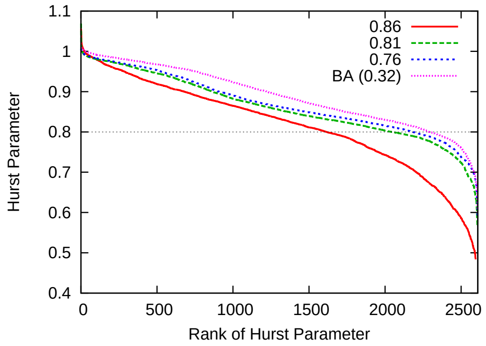


Fig. 6 Correlations between Hurst parameter and Hurst parameter rank of generated topologies

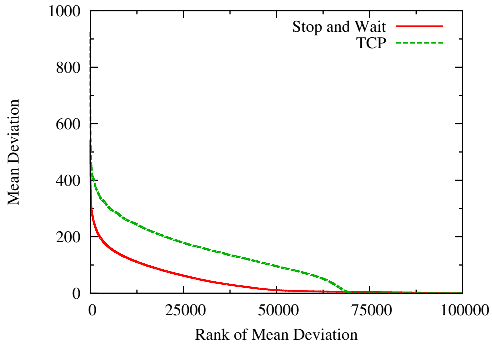


Fig. 8 Correlations between deviations of RTT for each session and deviation rank in the AT&T topology: The number of sessions is 100,000.

Table 4 Simulation results of generated topologies

Modularity	Ratio of highly fluctuating links	Number of arriving packets		
		Total	Intra	Inter
0.86	0.62	4.7×10^8	4.5×10^8	1.7×10^7
0.81	0.78	3.6×10^8	2.9×10^8	7.4×10^7
0.76	0.84	3.2×10^8	2.2×10^8	1.0×10^8

A question is why the high-modularity structure reduces the number of highly fluctuating links. To answer this, we show queue fluctuation on links having different link load in Fig. 7. Here, the link load is the number of end-to-end sessions that pass through the link. When a link load is low, the queue length does not fluctuate (Fig. 7(a)). However, if the link load exceeds a certain level, the queue length is mostly constant due to a limit of buffer size in queue (Fig. 7(c)). Although the queue length keeps nearly-constant, each of TCP sessions dynamically changes its sending rate. Thus, the queue length of the tributary links to the inter-module links is governed by the dynamics of each TCP session and thus fluctuates like Fig. 7(b). The situation in Fig. 7(b) occurs when the links are close to the inter-module links because the large number of TCP sessions is aggregated. More precisely, connector hub nodes or non-hub connector nodes in Fig. 1 perform the aggregation of TCP sessions. However, connector hub nodes rarely exist in topologies with the high-modularity structure: most of hub nodes are provincial hub nodes. Thus, the situation in Fig. 7(b) occurs around the connector non-hub nodes, and therefore the number of such links is small.

The number of arriving packets forwarded between different modules also decreases in a topology that has a high modularity value. Table 4 shows the number of arriving packets. Here, *Intra* (-module) means the number of arriving packets between two nodes in the same module, and *Inter* (-module) means the number of arriving packets between two nodes belonging to different modules. According to this table, as the modularity value gets higher, the number of arriving inter-module packets decreases, whereas the number of arriving intra-module packets increases. That is, the throughput of intra-module sessions gets high in the high modularity topology. In topologies having a high modularity value, a few inter-module links tend to become congested, and it becomes more difficult for inter-module packets to arrive at their destination.

4.4 Effects of TCP

In Section 4.1, 4.2, and 4.3, we discussed packet delay dynamics in the TCP model. In this section, we explain the merits and demerits of TCP. One of the merits of TCP is improved throughput. Comparing the results of the stop-and-wait model with those of the TCP model, we found that network throughput is improved in the AT&T topology due to the function of TCP that adjusts the packet sending rate according to the network conditions. In the AT&T topology, the ratio of links having utilization larger than 80% is 74% by the TCP model, while the ratio is 58% by the stop-and-wait model. Note that, the number of sessions is 100,000 and other parameters are the same as used in previous subsections (see Table 1 for details).

In contrast, when the number of sessions gets larger, TCP causes fluctuation of the queue length, as depicted in Fig. 5, which leads to the high fluctuation in the end-to-end delay of packets. Figure 8 shows deviations of RTT, RTT_{dev}, for each session in the AT&T topology. The y-axis represents the mean deviation of RTT for each session, defined as

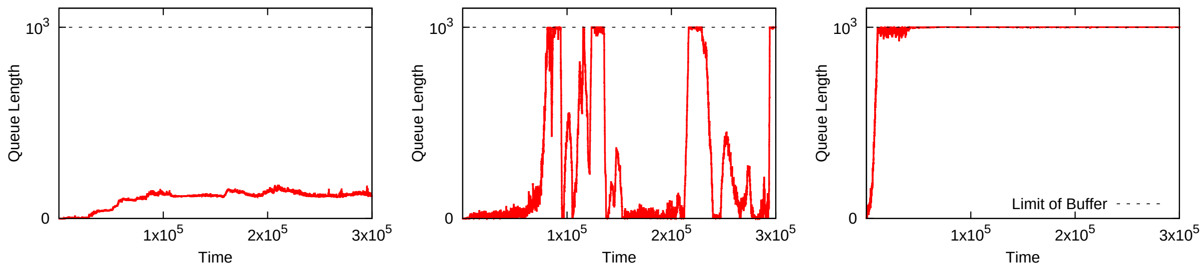
$$\mathrm{RTT}_{dev} = (1-\alpha)\times\mathrm{RTT}_{dev} + \alpha\times|e\mathrm{RTT}-\mathrm{RTT}|, \quad (5)$$

where $\alpha = 0.125$, and the x-axis represents its rank. Every time the source node receives the ACK, the source node measures an instantaneous round-trip time (RTT in Eq. 5) and estimates the average round-trip time (eRTT) by the following equation:

$$e\mathrm{RTT} = (1-\alpha)\times e\mathrm{RTT} + \alpha\times\mathrm{RTT},$$

In the figure, the results of the stop-and-wait model are also plotted for comparison. As shown in Fig. 8, in the TCP model, the number of sessions that have a large deviation increases as compared with that in the stop-and-wait model.

The complex functionality of TCP, such as flow control, congestion control, and fast retransmit functionalities,



(a) When a link load is low, queue length does not fluctuate.
(b) As a link load increases, the queue fluctuation becomes large.
(c) The queue length is mostly constant due to a buffer limit

Fig. 7 Relationships between link load and queue fluctuation

causes fluctuation of the queue length. This is one of the disadvantages of TCP. We confirmed that the fraction of links having a high H value in the stop-and-wait model is smaller than the number of links in the TCP model. As shown in Fig. 5(b), when the number of sessions is 100,000, 50% of all links are highly fluctuating in the TCP model, whereas 9% of all links are highly fluctuating in the stop-and-wait model.

5. Conclusion

In this paper, we investigated the interaction between the structures of topologies and flow control between end hosts. Comparing the simulation results of the stop-and-wait model and the TCP model, the functionality of TCP improves network throughput in the AT&T topology. On the other hand, the functionality of TCP makes the queue length fluctuate. Even in this case, the highly modular structure of the AT&T topology reduces the number of highly fluctuating links compared with the BA topology. We also evaluated the queue length on other topologies and confirmed that the modularity structure can reduce the number of highly fluctuating links.

Our results suggest that reproducing the modularity structure is important when evaluating the performance of transport protocols. Our future work is to develop a topology generation method that reproduces the modularity structure and apply it to performance evaluations.

Acknowledgements

This work was partly supported by Grant-in-Aid for Scientific Research (A) 21240004 from the Japan Society for the Promotion of Science (JSPS).

References

[1] A. Veres and M. Boda, "The chaotic nature of TCP congestion control," Proceedings of IEEE Conference on Computer Communications, pp.1715–1723, March 2000.
[2] M. Cusumaano, "Cloud computing and saas as new computing platforms," Communications of the ACM, vol.53, pp.27–29, April 2010.
[3] A.L. Barabási and R. Albert, "Emergence of scaling in random networks," Science, vol.286, pp.509–512, Oct. 1999.
[4] L. Li, D. Alderson, W. Willinger, and J. Doyle, "A first-principles approach to understanding the Internet's router-level topology," ACM SIGCOMM Computer Communication Review, vol.34, no.4, pp.3–14, Oct. 2004.
[5] D. Alderson, L. Li, W. Willinger, and J.C. Doyle, "Understanding internet topology: principles, models, and validation," IEEE/ACM Transactions on Networkingt, vol.13, no.6, pp.1205–1218, Dec. 2005.
[6] R. Fukumoto, S. Arakawa, and M. Murata, "On routing controls in ISP topologies: A structural perspective," Proceedings of Chinacom, pp.1–5, Oct. 2006.
[7] P. Mahadevan, D. Krioukov, K. Fall, and A. Vahdat, "Systematic topology analysis and generation using degree correlations," ACM SIGCOMM Computer Communication Review, pp.135–146, Aug. 2006.
[8] V. Paxson and S. Floyd, "Wide-area traffic: The failure of poisson modeling," IEEE/ACM Transactions on Networking, vol.3, no.3, pp.226–244, July 1995.
[9] N. Basher, A. Mahanti, A. Mahanti, C. Williamson, and M. Arlitt, "A comparative analysis of web and peer-to-peer traffic," Proceedings of the international conference on World Wide Web, pp.287–296, April 2008.
[10] K. Park, G. Kim, and M. Crovella, "On the relationship between file sizes, transport protocols, and self-similar network traffic," Proceedings of the International Conference on Network Protocols (ICNP), pp.171–180, Oct. 1996.
[11] A. Feldmann, A.C. Gilbert, W. Willinger, and T.G. Kurtz, "The changing nature of network traffic: scaling phenomena," ACM SIGCOMM Computer Communication Review, vol.28, no.2, pp.5–29, April 1998.
[12] K. Fukuda, M. Takayasu, and H. Takayasu, "A cause of self-similarity in TCP traffic," International Journal of Communication Systems, vol.18, no.6, pp.603–617, Aug. 2005.
[13] B. Tadić, S. Thurner, and G. Rodgers, "Traffic on complex networks: Towards understanding global statistical properties from microscopic density fluctuations," Phys. Rev. E, vol.69, 36102, March 2004.
[14] Y. Zhang, S. Zhou, Z. Zhang, J. Guan, S. Zhou, and G. Chen, "Traffic fluctuations on weighted network," arXiv:0902.3160, Nov. 2011.
[15] N. Spring, R. Mahajan, D. Wetherall, and T. Anderson, "Measuring ISP topologies with Rocketfuel," IEEE/ACM Transactions on Networking, vol.12, pp.2–16, Feb. 2004.
[16] R. Fukumoto, S. Arakawa, T. Takine, and M. Murata, "Analyzing and modeling router-level Internet topology," Proceedings of the International Conference on Information Networking, pp.171–182, Jan. 2007.
[17] R. Guimerà and L.A.N. Amaral, "Functional cartography of complex metabolic networks," Nature, vol.433, pp.895–900, Feb. 2005.
[18] M.E.J. Newman, "Modularity and community structure in networks," Proceedings of the National Academy of Sciences of the

United States of America, pp.8577–8582, April 2006.
[19] M. Woolf, D. Arrowsmith, R. Mondragon, J. Pitts, and S. Zhou, "Dynamical modelling of TCP packet traffic on scale-free networks," Institut Mittag-Leffler, p.7, Oct. 2004.
[20] A. Feldmann, A.C. Gilbert, P. Huang, and W. Willinger, "Dynamics of IP traffic: a study of the role of variability and the impact of control," ACM SIGCOMM Computer Communication Review, vol.29, no.4, pp.301–313, Oct. 1999.
[21] M. Allman, V. Paxson, and W. Stevens, "TCP congestion control," RFC 2581, April 1999.
[22] W.E. Leland, M.S. Taqqu, W. Willinger, and D.V. Wilson, "On the self-similar nature of ethernet traffic (extended version)," IEEE/ACM Transactions on networking, vol.2, no.1, pp.1–15, Feb. 1994.
[23] M.E.J. Newman and M. Girvan, "Finding and evaluating community structure in networks," Physical Review E, vol.69, 026113, Feb. 2004.

Takahiro Hirayama received a M.S. degree from Osaka University in 2010, where he is currently a doctoral student in Information Science and Technology. His research interest includes complex networks.

Shin'ichi Arakawa received M.E. and D.E. degrees in informatics and mathematical science from Osaka University in 2000 and 2003. From August 2000 to March 2006, he was an Assistant Professor with the Graduate School of Economics, Osaka University, Japan. In April 2006, he moved to the Graduate School of Information Science and Technology, Osaka University, Japan. He has been an Associate Professor from October 2011. His research interests include optical networks and complex networks. He is a member of IEEE and IEICE.

Ken-ichi Arai received the B.S, M.S. and Ph.D. degrees in science from Waseda University, Tokyo, Japan, in 1991, 1993 and 2003, respectively. In April 1993, he joined Nippon Telegraph and Telephone Corporation (NTT) and is now a research scientist of Communication Science Laboratories in NTT. His research interests are in the field of nonlinear science, complex networks, noise assisted effects and physical number generation. He is a member of JPS (Physical Society of Japan).

Masayuki Murata received M.E. and D.E. degrees in information and computer sciences from Osaka University in 1984 and 1988. In April 1984, he joined the Tokyo Research Laboratory IBM Japan as a Researcher. From September 1987 to January 1989, he was an Assistant Professor with the Computation Center, Osaka University. In February 1989, he moved to the Department of Information and Computer Sciences, Faculty of Engineering Science, Osaka University. From 1992 to 1999, he was an Associate Professor with the Graduate School of Engineering Science, Osaka University, and since April 1999, he has been a Professor. He moved to the Graduate School of Information Science and Technology, Osaka University in April 2004. He has published more than 300 papers in international and domestic journals and conferences. His research interests include computer communication networks, performance modeling, and evaluation. He is a Member of IEEE, the Association for Computing Machinery (ACM), The Internet Society, and IPSJ.