

Packet traffic analysis of scale-free networks for large-scale network-on-chip design

Nobuhiko Oshida and Sigeo Ihara

Department of Advanced Interdisciplinary Studies, and Research Center for Advanced Science and Technology, The University of Tokyo, Tokyo 153-8904, Japan

(Received 25 April 2006; published 18 August 2006)

Recent progress in integrated circuit technologies requires precise evaluation between dynamic characteristics and topological architecture design. In this paper, we have investigated the performance evaluation of network-on-chip (NoC) architectures constructed with diverse scale-free network topologies by dynamic packet traffic simulation and theoretical network analysis. Topological differences of scale-free networks are evaluated by the degree-degree correlations that indicate topological tendency between the degree of a node and that of the nearest neighbors. Our simulation results quantitatively show that the NoC architecture constructed with the topology where hubs mostly connect to lower-degree nodes is found to achieve short latency and low packet loss ratio since it can disperse traffic load and avoid the extreme concentration of load on hubs.

DOI: [10.1103/PhysRevE.74.026115](https://doi.org/10.1103/PhysRevE.74.026115)

PACS number(s): 89.75.Fb, 02.70.-c, 89.20.Ff, 85.40.Qx

I. INTRODUCTION

A number of complex networks, such as protein interaction networks in a biological cell [1,2], the Internet [3], collaboration networks of scientists [4], and air transportation networks [5] are the focus of recent research targets. These networks are called scale-free [6], and their degree distributions $P(k)$, defined as the probability that a node has k edges or links, is well approximated by a power law

$$P(k) \propto k^{-\gamma}, \quad (1)$$

where the exponent γ depends on each network structure, and most of the reported exponents in real-world scale-free networks range between 2 and 3 [7]. In a scale-free network, there exist a few nodes called hubs having many more edges than others, and they have dominant roles in the network. Owing to this heterogeneous topology, the scale-free network is robust against structural breakdown since most of the connections between nodes are conserved if failures of nodes occur randomly, but at the same time it is quite vulnerable to intentionally targeted attacks on hubs [8,9]. In addition, the scale-free network is also highly scalable, since the diameter of the network does not much increase even if the number of the nodes increases. Then the scale-free network is one of the reliable networks to achieve high-speed and scalable communication. In this study, we explore the efficient packet-switching network architecture design with the topology of the scale-free network.

The progress in integrated circuit technologies such as system-on-chip (SoC), where processors, memory arrays, controllers, and the other numerous functional modules are implemented on a single chip to realize speedup as a whole system, needs more advanced design methodologies. As the size of electronic components becomes smaller, the number of modules that can be implemented on a chip increases. To integrate many functional modules as on-chip blocks that have been conventionally implemented on a board, the interconnection performance between modules becomes critical. Recently, network-on-chip (NoC) that is a new design paradigm of SoC is proposed to achieve high-performance and large-scale communication [10]. Several interconnect archi-

ture topologies of NoC have been explored so far, and there are previous evaluations on their performance [11–14], but the current proposed architectures are estimated to implement only a few dozens of module or switch nodes on a chip and their topologies are simple geometrical patterns. Since the scale-free network is highly scalable and robust topology, it is one of the promising candidates for constructing the topology of NoC architectures with hundreds of modules.

Communication between nodes on a NoC is performed through packets. To evaluate the efficiency of the communication between nodes, we must consider the trade-offs between architecture topology and dynamic characteristics of packet traffic of on-chip networks. Compared to the static characteristics of complex networks, the dynamic ones are difficult to evaluate. Especially, little work has been done to investigate the relation between topology and dynamics of complex networks. For example, Goh *et al.* [15] and Ghim *et al.* [16] studied load distribution due to packet transport, and Moreno *et al.* [17] studied failure cascades by traffic congestion instabilities in scale-free networks, but a realistic packet traffic model was not used in their studies. Woolf *et al.* [18] evaluated the models of traffic generation on packet-switching networks with quite simple network geometry. Tadić *et al.* [19] studied traffic analysis in comparing different transmission rates on a Web graph without going into the details of network topology.

There are some scale-free networks whose topologies are quite different from each other although they have the identical degree distribution [20]. To evaluate traffic performance on those diverse scale-free networks precisely, we classified the difference of topological characteristics according to their degree-degree correlations. The degree-degree correlations refer to the topological tendency between the degree of a node and that of the nearest neighbors, and their characteristics greatly change depending on the degree of the nearest neighbors of hubs. To foresee the future topological design principles for large-scale NoC architectures, we will study the dynamics on diverse scale-free networks whose degree-degree correlations are different, compare the difference of performance in different network size, and specify where congestion occurs using realistic packet traffic simulation and theoretical network analysis.

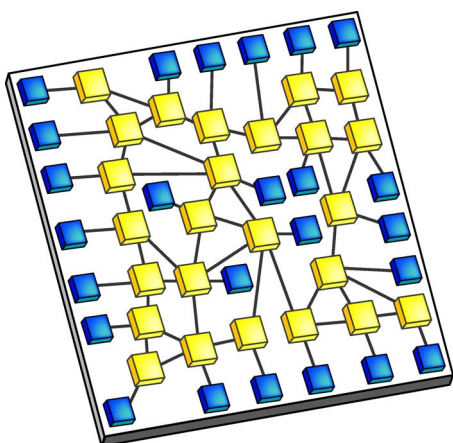


FIG. 1. (Color online) NoC interconnect architecture: The module nodes are denoted by smaller blue squares, while the switch nodes are denoted by larger yellow squares. In our simulation models, a switch node has a module node one by one, and every switch node is certain to be included in at least one closed loop.

II. METHODS

A. Network models

NoC interconnect architectures usually consist of two types of nodes as shown in Fig. 1; switch nodes that store and forward packets; module nodes that are sources and destinations of packet traffic. Our study focuses on switch-level network topologies, so from now on by “node” we mean a switch node.

When we assume the degree distribution of a network follows $P(k) \propto k^{-\gamma}$, N_k , the number of nodes that have k links, is given by

$$N_k = \frac{Nk^{-\gamma}}{\sum_{i=k_{\min}} i^{-\gamma}}, \quad (2)$$

where N is the network size that refers to the total number of nodes in the network. In this study, the exponent is $\gamma=2.5$, and seven different network sizes $N=100, 225, 400, 625, 900, 1225,$ and 1600 with $E=149, 353, 666, 1064, 1564, 2180,$ and 2882 , respectively, where E is the total number of links, are investigated to evaluate NoC performance in various network sizes. Furthermore, the minimal degree $k_{\min}=2$ is set because if we set $k_{\min}=1$, the network is almost occupied by nodes that have one link; thus each node is certain to be included in at least one closed loop.

After determining the number of links each node connects, the interconnections of on-chip networks are constructed. To investigate the effect of different degree-degree correlations on NoC performance, three network models with different degree-degree correlations are constructed, as shown in Fig. 2. One of the models has the topology where hubs mostly connect to lower-degree nodes and there are fewer direct links between hubs. This network has the correlations that higher-degree nodes connect to lower-degree nodes, and we call this architecture HL (high degree–low degree) model [Fig. 3(a)]. In HL model, as the degree of a

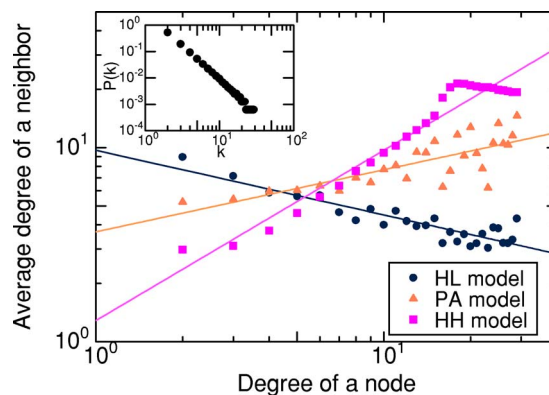


FIG. 2. (Color online) Correlations of the degree of a node vs the average degree of a neighbor in HL, PA, and HH models. Each solid line is fitted by a power law. These three models have the identical degree distribution (inset). This is the case where the number of nodes is 1600 in each model. These correlations are also seen in other network sizes.

node increases, the average degree of a neighbor decreases. The second is PA (preferential attachment) model [Fig. 3(b)] that is constructed based on preferential attachment rule [6,7]; thus, new nodes are added one by one and connected to an already existing node with a probability proportional to the number of links of the selected node, and then links are added randomly so as to correspond to the degree distribution determined beforehand. In the PA model, the average neighbor degree increases slowly as the degree of a node increases. The other is the HH (high degree–high degree) model [Fig. 3(c)] where hubs, contrary to the HL model, connect to other hubs directly as often as possible. In the HH model, as the degree of a node increases, the average degree of a neighbor also increases steeply. Additionally, to compare the difference of dynamics on different topology, we also evaluated the performance of NoCs constructed with two-dimensional (2D) mesh [11–14,21] defined as simple $n \times n$ square lattice and torus [12,14] defined as square lattice with periodic boundary conditions: $\text{node}(i+n, j) = \text{node}(i, j)$ and $\text{node}(i, j+n) = \text{node}(i, j)$. Both 2D mesh and torus are used basically in numerous packet traffic analyses of NoCs. After constructing those network models at switch level, a module is connected to each switch node one by one as shown in Fig. 1.

B. Link property and traffic model

Since the methods to evaluate NoC performance are quite similar to those of computer networks, we have adopted the network simulator ns-2 [22] that is used for dynamic traffic analyses of packet-switching communication. Each node has the same number of output queues as that of links, and the buffer size of a queue is four packets. Packet loss occurs when a packet is transferred to the nodes whose output queue is already full of former-transferred packets. All of the links are duplex, so packets are transferred in both ways on them. We assumed that a capacity of links is 200 Mbps (megabits per second) for each direction, and a wire delay of every link is 0.1 ms. To avoid the influences of interconnections be-

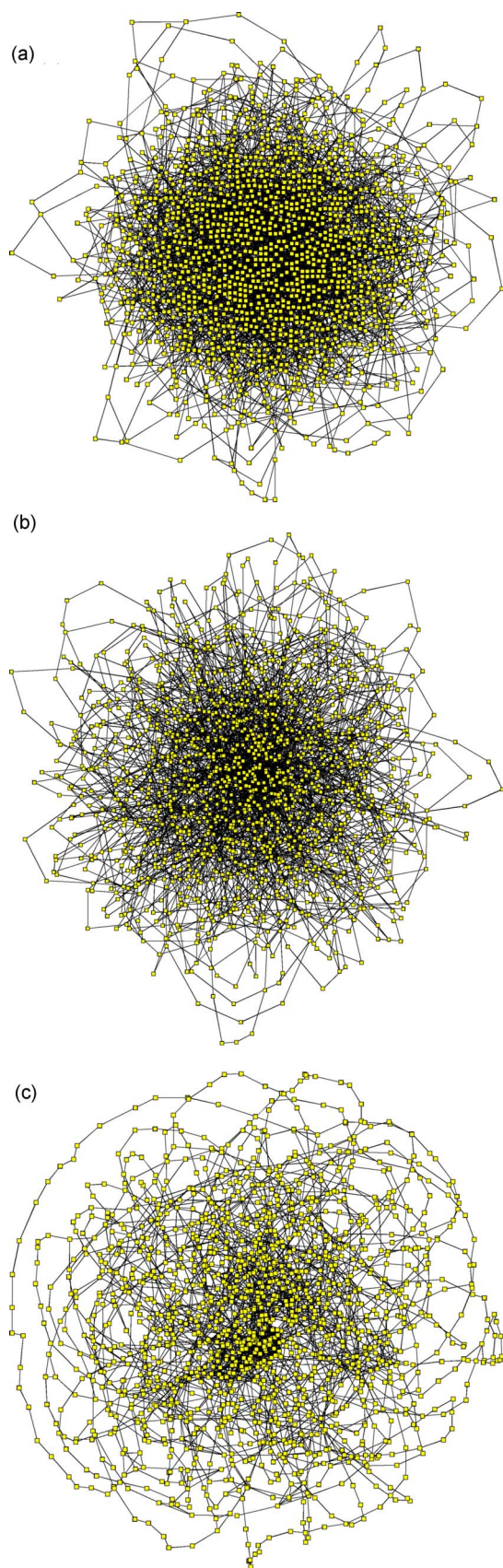


FIG. 3. (Color online) Switch-level network models used in this study: (a) HL model, (b) PA model, and (c) HH model in $N=1600$, respectively.

tween a switch and a module on NoC performance, the buffer size in every module node is infinite, and the wire delay of every link between a switch and a module is zero.

In a simulation, all modules are traffic sources that transmit packets, and the destination of each traffic is selected randomly in all of the module nodes. The size of all packets generated in all simulations is 8 bytes and every packet has the same data. The average lengths of ON state when a packet train is injected and OFF state when it is not injected are selected according to Pareto distribution [12]. Packets are injected at 50 Mbps from a source node only if the state is ON. One of the shortest paths is determined for routing packets from a source to a destination, and the routing paths do not change during simulation.

C. Performance metrics

In our study, performance metrics of NoC are transport latency of packet communication and packet loss ratio that are used for evaluating computer networks. Packet transport latency D_i is the time taken by a packet i , a unique identification given to every packet, to go through a path from the source to the destination and determined by $D_i = D_l + D_q$, where D_l is the total wire delay of links and D_q is the total queue delay according to buffering at switch nodes. Since the transport latency depends on each pair of a source and a destination, we measured transport latency of overall P packets reaching their destinations in every simulation. Then, we adopted the average transport latency $\bar{D} = \sum_i^P D_i / P$ as a performance metric.

We also used another performance metric, packet loss ratio, which is defined as probability of packets dropping from queues before reaching their destinations due to congestion in overall packets generated by every traffic source. In real-world packet communication, lost packets are usually retransmitted by source nodes so that destination nodes can completely receive all of the data transmitted. The lower packet loss ratio brings not only advancement of throughput but also higher processing performance because of the decrease of data retransmission frequency.

III. RESULTS AND DISCUSSION

We evaluated the performance of the different network models of NoC as mentioned above, and we simulated every case for 20 ms in the simulation time. Every simulation is run on a single processor AMD Opteron(tm) Processor 848 2.2 GHz with 4 GB of DRAM running Linux CentOS 4.2. In these simulations, the total runtime in the maximal case of $N=1600$ were between 60 and 150 hours, depending on network models and pairs of source and destination nodes. Simulation results make a difference depending on the combinations of source and destination nodes. Each simulation was run three times with different combinations to improve the reliability of our results, and then we averaged these results for computing performance metrics. In this paper, some of the results are shown only in the case of $N=1600$, but our main conclusions hold for all network sizes examined.

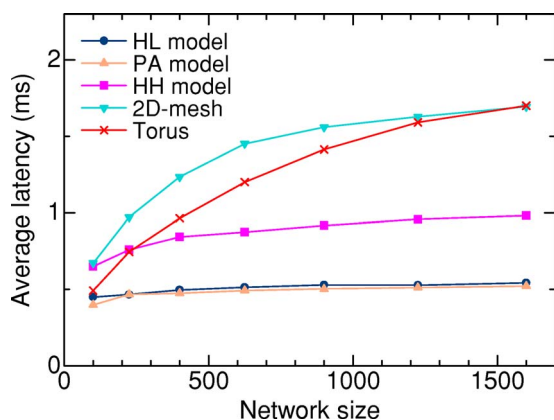


FIG. 4. (Color online) Variation of average transport latency of a packet between a source and a destination with network size.

A. Average transport latency

Figure 4 shows the variation of average transport latency of a packet between a source and a destination with network size for all the network models. Although the average latency does not so much increase in the models of scale-free network topologies, it is smaller in HL and PA models than in HH model. These results indicate that it is required not to connect hubs to other hubs directly with each other to reduce the latency as much as possible. In 2D mesh and torus, as the network size becomes larger, the average latency increases steeply.

The factor to determine the average latency is well explained by the average length of the shortest path between pairs of nodes (data not shown). In the models of scale-free network topologies, the average length of the shortest path does not almost change, but it is shorter in the HL and PA models than in the HH model, which corresponds with the results of the average latency. In this way, we can compress the average length of the shortest path and realize high-speed communication by avoiding direct interconnections between hubs in scale-free networks. On the other hand, the average length of the shortest path in 2D mesh and torus is longer as the network size becomes larger as is also seen in the case of average transport latency. Increase of average latency of 2D mesh slows down compared to the average length of the

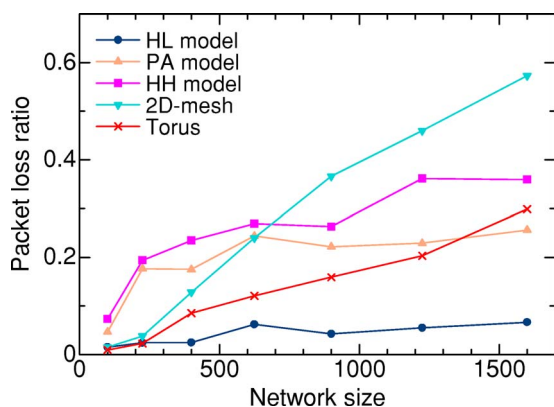


FIG. 5. (Color online) Variation of packet loss ratio with network size.

shortest path when the network size is larger than about 1000. However, these differences are attributed that many packets whose latency is much larger than the average could not reach their destinations during the simulation time, and they are not reflected in the calculation. In many cases of 2D-mesh and torus architectures, high-speed communication is realized by localization of functionally associated modules [12]. Nevertheless, the optimal localization would be difficult in 2D mesh and torus if the number of modules on a chip increases enormously. The results of simulations imply the architecture constructed with scale-free networks except a lot of interconnections of hubs can perform high-speed communication without considering the localization of modules.

B. Packet loss ratio

Figure 5 shows the variation of packet loss ratio with network size for all the models. The packet loss ratio rarely increases in the case of the HL model and the value of the ratio is the smallest even if the network size becomes larger. On the contrary, as the network size becomes larger, the packet loss ratio increases in the cases of PA and HH models, and there are even the cases when the ratio is higher than that of 2D mesh or torus in the same network size. In 2D mesh and torus, the packet loss ratio increases in proportion to network size.

Arena *et al.* [23] studied the optimal network topologies in different packet density with the same number of nodes and links, and indicated that reducing the degree of hubs makes networks decentralize load and robust against congestion. However, the network topologies compared in their studies have different degree distributions. Our simulation results with scale-free networks indicate it is possible to avoid congestion without changing the degree distribution of the networks; namely, to improve the traffic efficiency of networks, it is effective to employ the topology that hubs connect to lower-degree nodes.

Tadić *et al.* [24] also indicated the networks with closed loops can handle more traffic load than ones with no closed loops. They compared the efficiencies of directed scale-free networks with different degree distributions by complex traffic routing models named the random diffusion rule, but it seems difficult to clearly quantify the influence of the network topology on the traffic efficiency with their models. In addition, the applicability of their findings is for immature networks in the early stage of development. They constructed the networks with $N=E=1000$; therefore, the average degree of the network $\bar{k}=2E/N$ is 2. In the real world, the average degree of mature scale-free networks is usually $\bar{k} > 2$ [7]; for example, $\bar{k}=2.6$ in router level of the Internet in 2000 [25]; 2.40, in protein interaction networks of *Saccharomyces cerevisiae* [2]; and 18.1, in collaboration network of MEDLINE [4]. The simplicity of our traffic model and the range of the average degree of our network models, $\bar{k} = 2.98, 3.14, 3.33, 3.40, 3.48, 3.56$, and 3.60 where $N=100, 225, 400, 625, 900, 1225$, and 1600, respectively, are both suitable to study the topological dependency of dynamics on mature scale-free networks.

For further recognition of load distributions on scale-free networks, we explored the correlations between the local topology and the traffic load in detail. Packet losses often occur where network traffic is congested. To design on-chip networks that have few bottlenecks, we have specified the sites where the traffic load is concentrated. First, we estimated the correlations between normalized traffic and betweenness centrality of all the individual links as shown in Fig. 6, the correlations between normalized packet loss and betweenness centrality of all the individual links as shown in Fig. 7 in each network model. Betweenness centrality [26,27] is the index that counts the fraction of shortest paths between all possible pairs of nodes passing through a given node or edge. Betweenness centrality of node v and edge e is given by

$$g(v) = \sum_{\substack{s,t \\ s \neq t \neq v}} \frac{\sigma_{st}(v)}{\sigma_{st}}, \quad (3)$$

$$g(e) = \sum_{\substack{s,t \\ s \neq t}} \frac{\sigma_{st}(e)}{\sigma_{st}}, \quad (4)$$

where σ_{st} is the total number of shortest paths from node s to node t , $\sigma_{st}(v)$ and $\sigma_{st}(e)$ are the numbers of shortest paths from s to t passing through node v and edge e , respectively. Usually, node and edge betweenness centralities are rescaled by $(N-1)(N-2)/2$ and $N(N-1)/2$, respectively, so that $g \in [0,1]$. Normalized traffic refers to the fraction of communication on the link and is given by the number of packets passing through the link divided by the number of all accepted packets generated in the simulation. On the other hand, normalized packet loss refers to the fraction of packet losses at the link and is given by the number of packets lost at the link divided by the number of all lost packets in the overall networks during the simulation. The larger edge betweenness centrality, the more the traffic is concentrated and the more the fraction of packet loss increases in HL, PA, and HH models. However, in 2D mesh, there are several links where normalized traffic and packet loss are also high although their betweenness centralities are much lower. Betweenness centrality does not correlate with traffic load in 2D mesh. In NoCs with scale-free network topology, we can estimate concentration of traffic in the early stage of design, although it is difficult to specify the sites of bottlenecks in 2D mesh.

In addition, to see the difference of the distribution of edge betweenness centrality (BC) in each network model, we calculated the cumulative distribution functions $F(g) = \text{Prob}(BC \geq g)$ for HL, PA, HH models, and 2D mesh, as shown in Fig. 8. We also calculated their averages and variances as shown in Table I. In the HL model, there are no links with excessively high betweenness centrality and the range of the distribution is narrow. This means that the traffic load on the network is efficiently dispersed. In PA and HH models, some links have extremely high betweenness centrality; this means these sites tend to have heavy traffic load. Especially in the HH model, the range of the distribution is

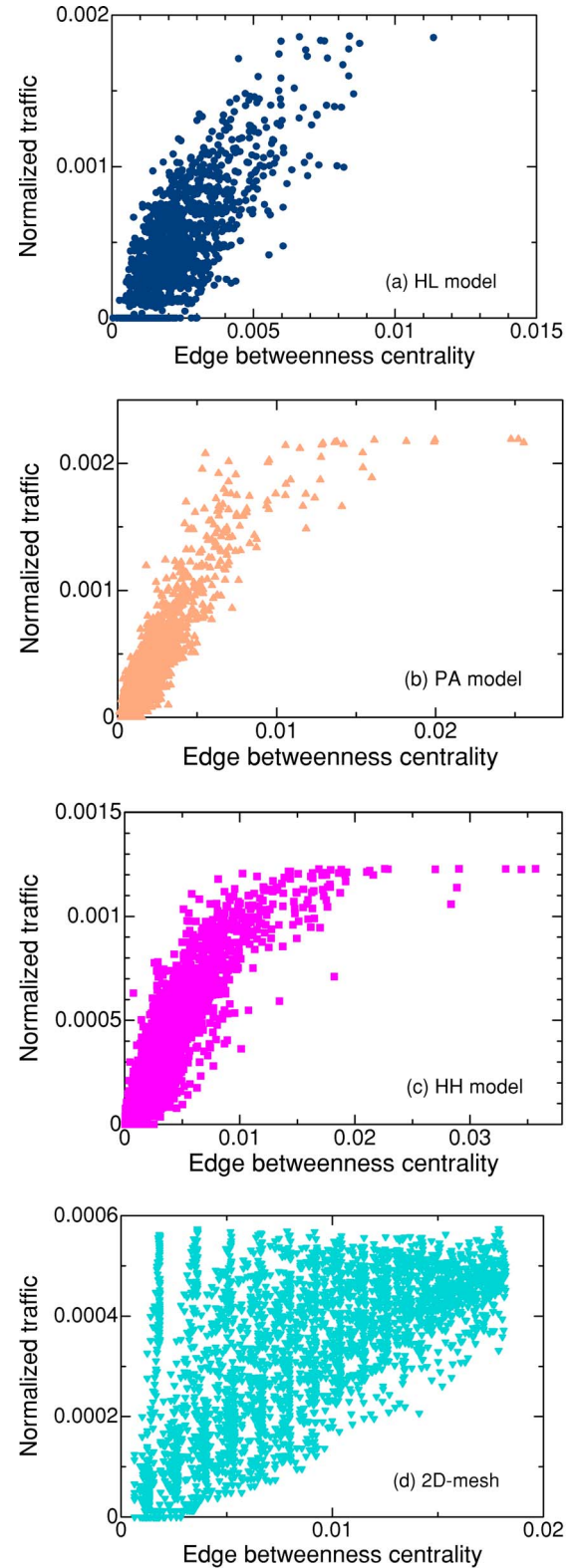


FIG. 6. (Color online) Plots of the normalized traffic of all individual links vs their betweenness centralities in each network model. In all cases the network size is $N=1600$.

the widest in the scale-free networks and there are many links with extremely low betweenness centrality. This indicates these links are not used as packet traffic routes although

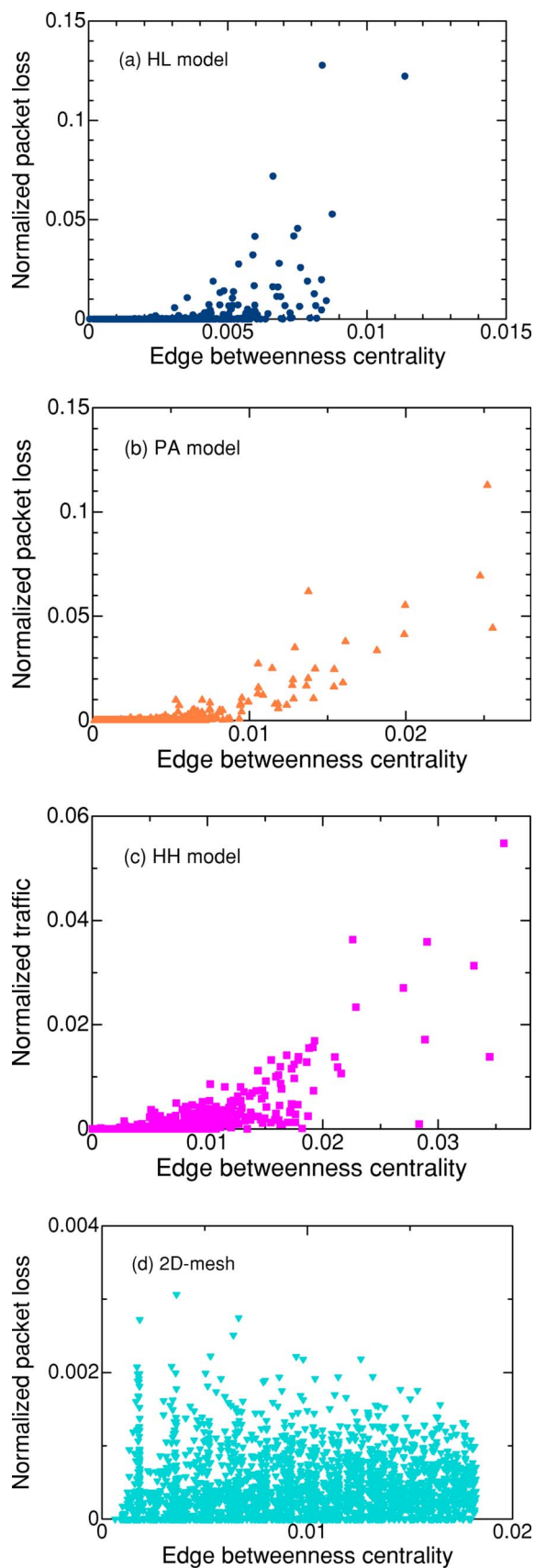


FIG. 7. (Color online) Plots of the normalized packet loss of all individual links vs their betweenness centralities in each network model. In all cases the network size is $N=1600$.

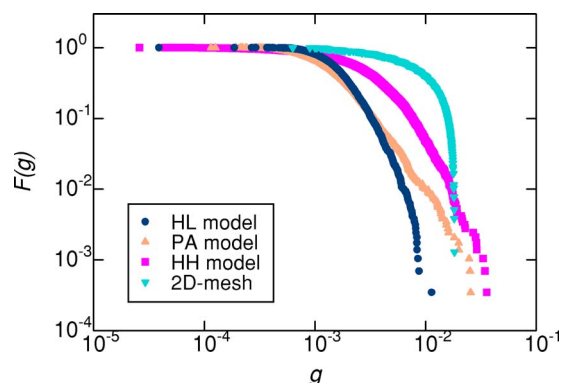


FIG. 8. (Color online) Cumulative distribution functions $F(g) = \text{Prob}(BC \geq g)$ of edge betweenness centrality (BC) for HL, PA, HH models, and 2D mesh, respectively. In all cases the network size is $N=1600$.

the heavy traffic load is concentrated on a part of the links in the same network. PA and HH models are inefficient topologies for NoC architecture. In 2D mesh, there are more links whose betweenness centrality is higher than in any other network models, which indicates a lot of bottlenecks occur in many links. Therefore, it would be difficult to construct large-scale NoC architecture with 2D-mesh topology.

To examine what kind of part the traffic load is likely to be concentrated in the scale-free network models, we compare the distributions of the relation between degree and betweenness centrality of all nodes for HL, PA, and HH models, as shown in Fig. 9. In the HL model where hubs are dispersed moderately, the betweenness centrality increases slowly as the degree of a node increases, and there are no nodes whose betweenness centrality is extremely high. Consequently, HL model can disperse traffic load efficiently and reduce the concentration of load on hubs. In the PA model, the betweenness centrality of hubs is much higher than that of lower-degree nodes. This topology results in extreme concentration of traffic load on hubs, and many packet losses occur near hubs. However, the topologies that decrease the traffic load on hubs excessively are not necessarily appropriate for network architectures. In the HH model, there are a lot of lower-degree nodes whose betweenness centrality is higher than that of hubs, and these parts result in the traffic bottlenecks where congestion occurs. Extremely localized and dense interconnections of hubs cause a lot of bottlenecks around lower-degree nodes. Besides, average length of the shortest path between pairs of nodes in the HH model is longer than that of the HL and PA models as we mentioned

TABLE I. Average and variance of the distributions of edge betweenness centrality for HL, PA, HH models, and 2D mesh, respectively. In all cases the network size is $N=1600$.

	Average	Variance
HL	1.889×10^{-3}	1.343×10^{-6}
PA	1.854×10^{-3}	3.695×10^{-6}
HH	3.603×10^{-3}	1.216×10^{-5}
2D mesh	8.547×10^{-3}	2.447×10^{-5}

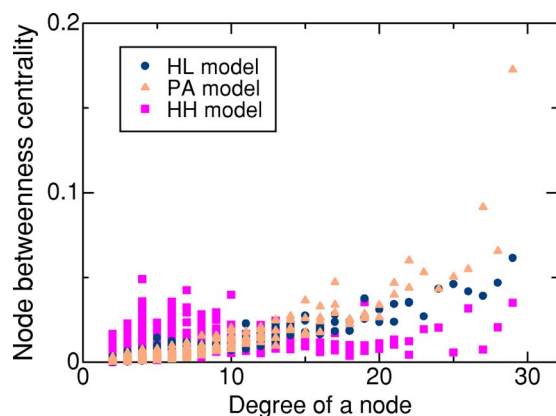


FIG. 9. (Color online) Plots of the betweenness centrality vs degree of every node for HL, PA, and HH models. In all cases the network size is $N=1600$.

above. This indicates most of the nodes are located far from hubs. The HH model can hardly provide the benefit of the general scale-free network property that one node can access many other nodes in a few hops via hubs.

The degree-degree correlations as seen in the HL model are also found in protein interaction networks in a biological cell [28] and the real-world Internet [3]. Protein interaction networks consisted of direct as well as physical interactions of proteins with each other that exists in the short range [29], and the Internet consisted of physical connections between routers or computers. Although these networks are constructed spontaneously and their degree-degree correlations are not defined in advance, they show the topological specificity of each subnetwork. This topological characteristic reduces the load on hubs and would conserve a lot of nodes or links available against noise in the network. Even if lethal damages occur in partial subnetworks, these topological structures can suppress propagation of errors and minimize deleterious perturbations over the whole network. In this way, static robustness is achieved in this topology, and the HL model we proposed in this paper is efficient architecture from aspects of spontaneous generations.

IV. CONCLUSION

We have studied dynamic analyses of NoC architectures constructed with scale-free network topologies and evaluated their performance quantitatively by packet traffic simulations. Because the limitations of computing time and

memory size prevent us from investigating all the applicable parameter range of the simulations, this study is the realistic case with finite buffer size and simple traffic model. However, from the clear difference of the simulation results in large-scale network size, we can say that the traffic efficiency of network architecture is greatly influenced by topological differences represented as degree-degree correlations.

NoC model constructed with the topology where hubs connect to lower-degree nodes can achieve short latency and low packet loss ratio, since it can disperse traffic load and avoid the extreme concentration of load on hubs. Extremely localized and dense interconnections of hubs cause a lot of bottlenecks and increase of latency, and the networks constructed by preferential attachment cause heavy load on hubs, so both the topological types are not appropriate for NoC architectures. In conventional 2D-mesh and torus architectures, the transport latency and packet loss ratio go up in proportion to their network size, which means that it is difficult to realize high-speed and high-quality NoC architecture in large-scale network size.

In future works, the following items that are out of scope in this study will be taken into account. For actual VLSI design, introduction of “technology mapping,” the layout of physical length of network links and the size of modules and switches, is required to improve accuracy of our results. Evaluation of the fault tolerance of NoCs with scale-free network topology is another important issue to investigate whether scale-free network topology still preserves high performance against dynamic traffic routing changes by structural node breakdowns.

We focused on the effect of network topology on traffic efficiency from the viewpoint of packet communication. We believe that our approach in this study is applicable to the dynamics on scale-free networks in other fields such as transportation systems and signaling pathways in a biological cell.

ACKNOWLEDGMENTS

The authors would like to thank Professor Hiroshi Nakamura for stimulating discussions. This work is supported by Special Coordination Funds for Science and Technology of Japan Science and Technology Agency and also supported partially by a Grant-in-Aid for Scientific Research on Priority Areas from the Ministry of Education, Culture, Sports, Science and Technology of Japan. The Ministry of Internal Affairs and Communications also supported this work. One of the authors (S.I) would like to thank The Mitsubishi Foundation for the financial support.

[1] A.-L. Barabási and Z. N. Oltvai, *Nat. Rev. Genet.* **5**, 101 (2004).
 [2] H. Jeong, S. P. Mason, A.-L. Barabási, and Z. N. Oltvai, *Nature (London)* **411**, 41 (2001).
 [3] A. Vázquez, R. Pastor-Satorras, and A. Vespignani, *Phys. Rev. E* **65**, 066130 (2002).
 [4] M. E. J. Newman, *Phys. Rev. E* **64**, 016131 (2001).

[5] R. Guimerà, S. Mossa, A. Turttschi, and L. A. N. Amaral, *Proc. Natl. Acad. Sci. U.S.A.* **102**, 7794 (2005).
 [6] R. Albert and A.-L. Barabási, *Rev. Mod. Phys.* **74**, 47 (2002).
 [7] S. N. Dorogovtsev and J. F. F. Mendes, *Evolution of Networks: From Biology to the Internet and the WWW* (Oxford University Press, Oxford, 2003).
 [8] R. Albert, H. Jeong, and A.-L. Barabási, *Nature (London)* **406**,

- 378 (2000).
- [9] A. E. Motter and Y. C. Lai, *Phys. Rev. E* **66**, 065102(R) (2002).
- [10] L. Benini and G. D. Micheli, *IEEE Comput.* **35**, 70 (2002).
- [11] S. Kumar, A. Jantsch, J.-P. Soininen, M. Forsell, M. Millberg, J. Öberg, K. Tiensyrjä, and A. Hemani, *Proceedings of the IEEE Computer Society Annual Symposium on VLSI, 2002*, p. 105.
- [12] P. P. Pande, C. Grecu, M. Jones, A. Ivanov, and R. Saleh, *IEEE Trans. Comput.* **54**, 1025 (2005).
- [13] A. Hegedűs, G. M. Maggio, and L. Kocarev, *Proceedings of the IEEE International Symposium on Circuits and Systems, 2005*, Vol. 4, p. 3375.
- [14] S. Santi, B. Lin, G. M. M. L. Kocarev, R. Rovatti, and G. Setti, *Proceedings of the IEEE International Symposium on Circuits and Systems, 2005*, Vol. 3, p. 2349.
- [15] K. I. Goh, B. Kahng, and D. Kim, *Phys. Rev. Lett.* **87**, 278701 (2001).
- [16] C.-M. Ghim, E. Oh, K.-I. Goh, B. Kahng, and D. Kim, *Eur. Phys. J. B* **38**, 193 (2004).
- [17] Y. Moreno, R. Pastor-Satorras, A. Vázquez, and A. Vespignani, *Europhys. Lett.* **62**, 292 (2003).
- [18] M. Woolf, D. K. Arrowsmith, R. J. Mondragón-C, and J. M. Pitts, *Phys. Rev. E* **66**, 046106 (2002).
- [19] B. Tadić, S. Thurner, and G. J. Rodgers, *Phys. Rev. E* **69**, 036102 (2004).
- [20] J. C. Doyle, D. L. Alderson, L. Li, S. Low, M. Roughan, S. Shalunov, R. Tanaka, and W. Willinger, *Proc. Natl. Acad. Sci. U.S.A.* **102**, 14497 (2005).
- [21] P. P. Pande, G. D. Micheli, C. Grecu, A. Ivanov, and R. Saleh, *IEEE Des. Test Comput.* **22**, 404 (2005).
- [22] The network simulator—ns-2, URL <http://www.isi.edu/nsnam/ns/>.
- [23] A. Arenas, A. Cabrales, A. Díaz-Guilera, R. Guimerà, and F. Vega-Redondo, e-print cond-mat/0301124.
- [24] B. Tadić and S. Thurner, *Physica A* **332**, 566 (2004).
- [25] R. Govindan and H. Tangmunarunkit, *Proceedings of the IEEE INFOCOM Conference, 2000*, Vol. 3, p. 1371.
- [26] M. Barthélemy, *Eur. Phys. J. B* **38**, 163 (2004).
- [27] U. Brandes, *J. Math. Sociol.* **25**, 163 (2001).
- [28] S. Maslov and K. Sneppen, *Science* **296**, 910 (2002).
- [29] S. Ihara, *Bull. Am. Phys. Soc.* **50**, 592 (2005).