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[招待講演] ネットワークトポロジが 情報探索・配送・拡散に与える影響

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あらまし　ネットワークトポロジとは、通信ネットワークを構成する (通常) 多数のノード (ホスト、スイッチ / ルータ) と、それらのノード間を接続する多数のリンクの論理的な構造である。さまざまな通信ネットワーク (例: イーサネット LAN/WAN、TCP/IP ネットワーク、無線ネットワーク、遅延/分断耐性ネットワーク、情報指向ネットワーク) は、ネットワークを構成するノードやリンクの特徴・機能、物理的制約、利用形態の違いなどにより、それぞれ異なったネットワークトポロジを有している。ネットワークトポロジは一種のグラフであり、古くはグラフ理論の分野において、また比較的新しくはネットワーク科学の分野において理論的・数理的な観点から研究されてきた。 ただし、通信ネットワークでは、ネットワークトポロジの特性そのもの (例: 規模、密度、次数分布、直径、連結性、クラスタ性) だけでなく、ネットワークトポロジが通信ネットワークの特性 (例: 性能、品質、効率、可用性、信頼性) に与える影響も重要である。 本稿では、通信ネットワークのネットワークトポロジが、情報ネットワーク上での情報探索・配送・拡散などの動的プロセスに与える影響を分析した 4 つの研究トピックを紹介する。

キーワード　ネットワークトポロジ、複雑ネットワーク、動的プロセス、ランダムウォーク、メッセージ配送遅延、ロバスト性、数学的解析

[Invited Talk] On the Impact of Network Topology on Information Search, Delivery, and Diffusion

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Abstract　A network topology is the logical structure of a communication network consisting of a large number of nodes (e.g., hosts and switches/routers) and links connecting among those nodes. Every communication network (e.g., Ethernet-based networks, TCP/IP networks, wireless networks, DTN (Delay/Disruption-Tolerant Networking), and ICN (Information-Centric Networking)) has a different network topology, depending on the features and capabilities of nodes (e.g., the maximum number of ports/interfaces and the tolerance to a network loop) and links (e.g., unidirectional/bidirectional, wired/wireless, and the maximum length) as well as several physical restrictions and usage patterns. Since a network topology is a sort of graphs, in the literature, it has been actively studied from theoretical and mathematical viewpoints in the field of graph theory and recently in the field of network science. In a communication network, not only the characteristics of the network topology itself (e.g., size, density, degree distribution, diameter, and connectivity), but the characteristics of communications performed on it (e.g., speed, quality, efficiency, availability, and reliability) are also important. This paper introduces four research topics recently published by our research group, each of which reveals the impact of the network topology on the characteristics of a dynamical process such as information search, delivery, and diffusion in a different context.

Key words　Network Topology, Complex Networks, Dynamic Process, Random Walk, Message Delivery Delay, Robustness, Mathematical Analysis

1 Introduction

A network topology is the logical structure of a communication network consisting of a large number of nodes (e.g., hosts and switches/routers) and links connecting among those nodes. In communication networks, nodes and links are generally heterogeneous; e.g., the processing speed and the buffer size of nodes are not identical, and the bandwidth and the transmission delay of links vary. A network topology often focuses solely on the logical connections among nodes.

Every communication network (e.g., Ethernet-based networks, TCP/IP networks, wireless networks, DTN (Delay/Disruption-Tolerant Networking), and ICN (Information-Centric Networking)) has a different network topology, depending on the features and capabilities of nodes (e.g., the maximum number of ports/interfaces and the tolerance to a network loop) and links (e.g., unidirectional/bidirectional, wired/wireless, and the maximum length) as well as several physical restrictions and usage patterns.

A network topology is generally *dynamic*; e.g., nodes and links are added/removed because of several reasons such as network expansion and device failure/replacement. By limiting the timescale of the interest in network topology, it can be regarded as being *static*, which simplifies mathematical modeling of the network topology as a graph.

Since a network topology is a sort of graphs, in the literature, it has been actively studied from theoretical and mathematical viewpoints in the field of graph theory and recently in the field of network science. Network science, which covers generally large-scale and complex networks, has developed analysis techniques for complex networks such as the scale-free property, the tail distribution of node degrees, and the clustering coefficient.

In a communication network, not only the characteristics of the network topology itself (e.g., size, density, degree distribution, diameter, and connectivity), but the characteristics of communications performed on it (e.g., speed, quality, efficiency, availability, and reliability) are also important. A communication network itself consisting of nodes and links is infrastructure, and traffic is transferred over the network according to a specific communication protocol. Many communication protocols adopt reactive (e.g., feedback-based) control mechanisms, and their operations dynamically change according to the environment. Thus, it is crucial to understand how the characteristics of a dynamical process are affected by the topology of an underlying communication network.

This paper introduces four research topics [1–4] recently published by our research group, each of which reveals the impact of the network topology on the characteristics of a dynamical process such as information search, delivery, and diffusion in a different context (Tab. 1).

Section 2 addresses the impact of the network topology on the performance of node discovery in an unknown network [1]. Node discovery in an unknown network is a problem of finding a target node as quickly as possible by utilizing a mobile agent moving around the network when the network topology is unknown to the agent. This section presents the average discovery time (the average first hitting time) when the mobility of the agent obeys either the random walk or one of its variants through simulation experiments.

Section 3 discusses the impact of the underlying network topology on message delivery in a geographic DTN routing, where messages are transferred among fixed nodes relying on the store-carry-and-forward capability of many mobile agents moving on the field [2]. This section reveals how significantly the average message delivery delay between fixed nodes is affected by the underlying network topology.

Section 4 considers the robustness of a network topology against random node removal [3]. This section discusses, when a fraction of nodes are randomly removed from the network, how the size of the largest cluster component (i.e., the size of the maximum connected component) differs depending on the network topology.

Section 5 focuses on how the performance of epidemic-based routing in DTNs is affected by the network topology — in this case, the contact relationships (i.e., the possibility of contacts between mobile node pairs). This section examines the average message delivery delay in restrained epidemic routing — an extension to the conventional epidemic routing — when the contact relationship between mobile nodes is given by a complex network.

2 First Hitting Time of Self-Avoiding/Biased Random Walk on Graph

A wide range of problems in information networking and social networking such as information search, retrieval, delivery, and dissemination can be modeled by one or more random walks of agents on a graph. In the literature, studies on mobility models of one or more agents such as discrete random walks on a graph and their characteristics have been actively performed [5].

A random walk on a graph is a discrete process of an agent starting from a source node and repeatedly performing transitions from a currently-visiting node to a randomly-chosen neighbor node. Various properties of the random walk (e.g., sojourn probability of each node in the steady state, the expected time elapsed since the agent started its movement from the source node until it arrives at the destination node at first (i.e., the first hitting time), and the expected time until the mobile agent starting from a source node revisits the source node (i.e., the recurrence time)) are clarified [6].

In the simple random walk, the agent has the quite limited capability; i.e., at any point, the agent only knows the list of neighbor nodes of the currently-visiting node. Provision of different types of agent's capability enables several variants of the simple random walk [7–12].

In this section, among different types of agent's capability, we particularly focus on memory (the capability of remembering the

Table 1 Network topologies and dynamical processes in four research topics

Section	network	node	link	scale	dynamical process	objective
2	graph	vertex	edge	small–large	agent movement	node discovery
3	field	intersection	street/road	large	store-carry-and-forward message forwarding	message delivery
4	computer network	router	communication link	medium–large	node removal	maintaining connectivity
5	contacts relationship among agents	agent	contact	medium–large	epidemic routing	message delivery

history of visited nodes in the past) and local visibility (the capability of perceiving attributes of neighbors nodes of the currently-visiting node).

An agent with memory can make the decision on the next transition based not only on the list of neighbor nodes of the currently-visiting node but also on the record whether every neighbor node has been visited in the past. An agent with local visibility can decide the decision on the next transition based on attributes of neighbor nodes of the currently-visiting node.

The agent with memory capability allows us to implement several classes of random-walk-based mobility models such as self-avoiding random walk and non-backtracking random walk [7–10].

Another approach for improving the efficiency of the simple random walk on a graph is to allow the agent to chose the next node to visit based on certain criteria. If the agent has local visibility, the agent can preferentially choose the next node from all neighbor nodes, which may improve the efficiency of the simple random walk. Examples of random-walk-based mobility models with local visibility include biased random walk [11, 12].

This section investigates how the agent's capability (i.e., memory and local visibility) may contribute to improving the efficiency of a random walk on a graph —- in particular, the first hitting time (i.e., the expected time elapsed since the agent starts its random walk from a source node until it arrives the destination node at first) — through simulation experiments.

We compare the hitting time between a randomly-chosen node pair of two random-walk-based mobility models (irreversible random walk and biased random walk) on four types of networks (ER (Erdõs-Rényi) model, generalized BA (Barabási Albert) model, Li-Chen model, and Voronoi diagram).

The simple random walk is the baseline in our experiments. The impact of the amount of agent's memory is examined through the K-irreversible random walks, which is a generalization of the non-backtracking random walk and the self-avoiding random walk, and the DFS (Depth-First Search), which achieves the near-optimal cover time. The impact of (existence of) local visibility is examined through the α-biased random walk [1] where the parameter α controls the preference to high-degree neighbor nodes.

We used four types of synthetic networks generated with different types of network generation models for random graphs, scale-free graphs, and planar graphs. For a given network, we measured the average of first hitting times between a randomly-chosen node pair.

The impact of the agent's memory on the average first hitting time

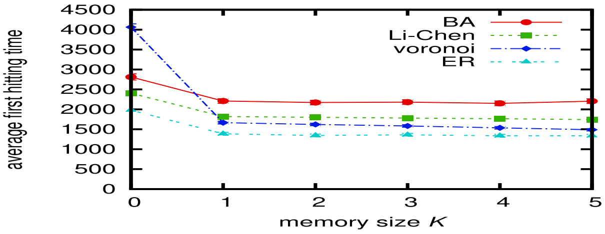


Figure 1 Relation between agent's memory size K and average first hitting time ($N = 1,000, k = 4$)

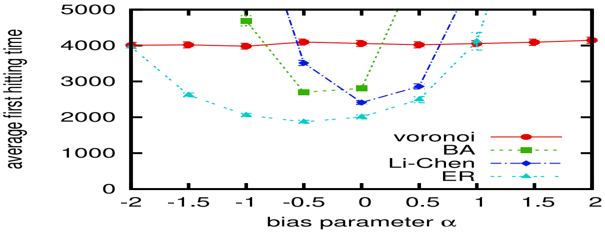


Figure 2 Relation between bias parameter α and average first hitting time ($N = 1000, k = 4$)

on different types of networks with $N = 1,000$ (1,000 nodes) and $k = 4$ (the average degree of 4) is shown in Fig. 1. This figure clearly indicates that provision of a minimal amount of memory (e.g., $K = 1$) significantly reduces the average first hitting time regardless of the type of networks. On the contrary, this figure also shows that further increasing the memory size does not contribute to improving the efficiency of random-walk-based mobility models. The benefit caused by the introduction of a agent's memory is more significant than that in *less* connected networks.

The average first hitting times on four types of networks for different settings of bias parameter α are plotted in Fig. 2. Different from the impact of agent's memory, the impact of agent's local visibility is quite dependent on the type of networks; i.e., appropriate utilization of local visibility (i.e., $\alpha \neq 0$) accelerates network exploration in some networks (ER and BA), but, in other cases, the average first hitting time is considerably increased.

3 Message Delivery Delay in Large-Scale Geographic DTN Routing

To the best of our knowledge, most of existing DTN routing algorithms are designed for message delivery between mobile nodes (i.e., message transmission from a mobile node to one or more other mobile nodes) [13, 14]. However, in practical applications of DTNs in several fields, endpoints of communication might not always be

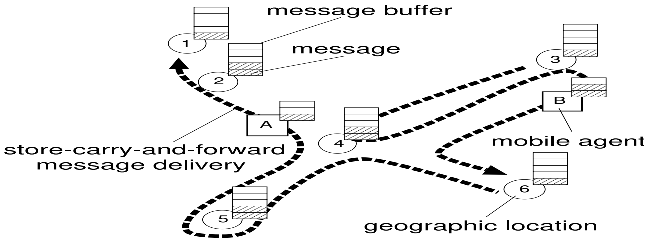


Figure 3 An overview of geographic DTN routing with mobile agents

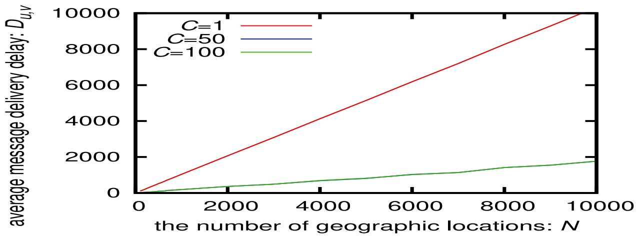


Figure 4 Relation between the number N of geographic locations and average message delivery delay $D_{u,v}$

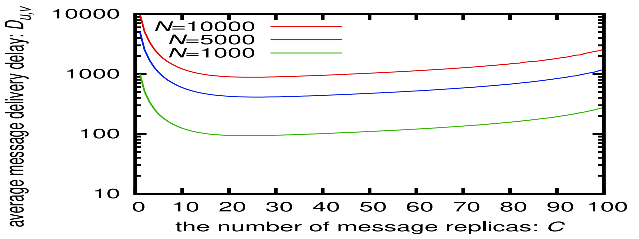


Figure 5 Relation between the number C of message replicas and average message delivery delay $D_{u,v}$

mobile nodes. In other words, endpoints might also be *fixed* nodes, so other types of communications between mobile and fixed nodes and also between fixed nodes should be required. In this paper, a class of DTN routing utilizing mobile nodes for store-carry-and-forward communication among fixed nodes is called *geographic DTN routing*.

A geographic DTN routing aims at realization of message delivery among multiple (generally, geographically-dispersed) *geographic locations* on a field without the necessity of specific communication infrastructure by utilizing the mobility of *mobile agents*. On the field, there exist multiple geographic locations (i.e., fixed nodes) and mobile agents (i.e., mobile nodes), and messages are transferred among geographic locations using store-carry-and-forward operations of mobile agents.

In this section, we address the research question: *how is the performance of geographic DTN routing affected by the topology of the network (i.e., connections of many geographic locations)?*

In what follows, a *network* means a network of geographic locations and the *topology* means the topology of the network composed of geographic locations and connections among them [2]. The performance of geographic DTN routing should be affected by several factors: a geographic DTN routing algorithm, a buffer management mechanism of mobile agents, the capability (e.g., bandwidth and BER (Bit Error Ratio)) of wireless communication among mobile agents and geographic locations, the mobility of mobile agents, and the topology of geographic locations. Among those, the first four factors are *controllable* to some extent. For instance, the capability of wireless communication among mobile agents and geographic locations can be changed by replacing communication protocols and adjusting wireless device parameters. On the other hand, the last two factors are generally *uncontrollable*. It is generally difficult or impossible, for instance, to force mobile agents a specific mobility and/or to change the topology of geographic locations, which usually requires replacement of geographic locations and/or reconstruction of paths among geographic locations. Hence, it is quite essential to understand the impact of the network topology on the performance of geographic DTN routing.

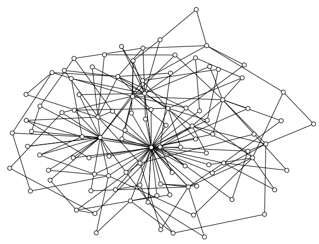
In the literature, the impact of the network topology on conventional DTN routing has been investigated [15]. These studies show that the performance of conventional DTN routing is dependent on the underlying network topology. Also, in the field of network science, the relation between the topological structure of a complex graph and its dynamical properties such as the percolation, epidemics, and information dissemination has been extensively studied [16, 17]. These studies show that the network topology considerably affects the dynamical properties such as probabilistic information dissemination on a complex network. By taking account of these findings, it is natural to assume that the performance of geographic DTN routing should be significantly affected by the network topology since geographic DTN routing has similarity with conventional DTN routing and dynamical processes on a complex network. However, the impact of the network topology on geographic DTN routing has not been well understood.

In what follows, we summarize numerical results and discussions in [18]. Refer to [18] for details.

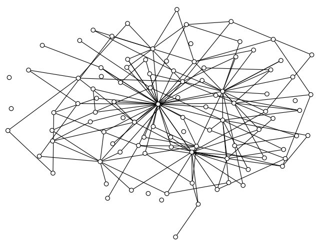
For a given network size $N\,(=|V|)$ (i.e., the number of geographic locations), a network topology is synthetically generated using ER (Erdös-Rényi) model [19]. The average degree (i.e., the average number of paths connected to a geographic location) k is fixed at $k=6$.

Figure 4 shows the average message delivery delay $D_{u,v}$ for different network sizes N. In this figure, the number C of message replicas is changed to 1, 50, or 100. Note that results with $C=50$ and $C=100$ (blue and green lines) are almost indistinguishable.

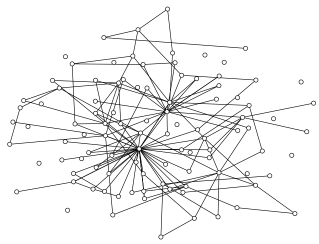
Figure 5 shows the average message delivery delay $D_{u,v}$ as a function of the number C of message replicas. In this figure, the load factor [18] is set to $\alpha=0.9$ to simulate highly loaded conditions. This figure clearly illustrates that the average message delivery delay $D_{u,v}$ is a concave function. The optimal number of message replicas is around $C=20$, but it is almost independent of the network size N in this case.



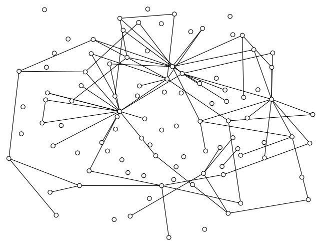
(a) original network



(b) degenerated network with 10% node removal



(c) degenerated network with 20% node removal



(d) degenerated network with 30% node removal

Figure 6 An example of random node removal

The research question presented above can be rephrased as follows: how the average message delivery delay $D_{u,v}$ in Fig. 4 is changed if *the average degree* is different (i.e., $k \neq 6$) and if *the degree distribution* of graph G is not binomial (e.g., power-law distribution as in scale-free networks). Except for highly loaded conditions, the dominant factor of the replica delivery delay is the transfer delay rather than the queueing delay [18]. As Eq. (12) in [18] implies, the transfer delay is mostly determined by the average hitting time $H_{u,v}$, which is then determined solely by the ratio of *the number* $|E|$ *of edges* to *the degree* v *of the destination node* v. Namely, in geographic DTN routing under random walk mobility, the network topology has *limited* impact on the performance of geographic DTN routing; the average message delivery delay is mostly determined by the degree of the destination node.

4 Robustness of Complex Networks against Random Node Removal

It is widely known that scale-free networks are robust against random node removal, which is one of the major interesting findings in network science [20, 21]. In a scale-free network, a small number of high-degree nodes called *hub* nodes exist. Therefore, even though a part of nodes in the network is removed, the connectivity among nodes is likely to be maintained.

Figure 6 illustrates how the network connectivity is degraded as the fraction of nodes (i.e., vertices) are randomly removed from the network. As the node removal ratio increases, nodes are likely to be disconnected from the network and also clusters of nodes are isolated from each other.

In the literature, the robustness of scale-free networks against node removals (e.g., random node failures/attacks in communication networks) has been extensively studied [20, 21]. For instance, authors of [20] showed that by removing high-degree nodes, the diameter (i.e., the average path length of shortest-paths between any node pair in a network) of scale-free networks rapidly increases as the node removal ratio increases. In contrast, the authors showed that scale-free networks have the robustness against random node removals since the connectivity of a network can be preserved because of the existence of hub nodes, even though a part of nodes are eliminated.

On the contrary, in the literature, several questions on the robustness of scale-free networks and its implication to communication networks have been raised [22, 23]. For instance, the authors of [22] have pointed out the confusion in [20] that AS-level network topologies and router-level network topologies are not distinguished. Even if an AS-level network topology has scale-free property, it does not mean the underlying router-level topology has scale-free property. Also, authors of [22] suggest that router-level network topologies might not be scale-free since routers on the Internet has a practical limitation on the number of links (i.e., the number of communication interfaces).

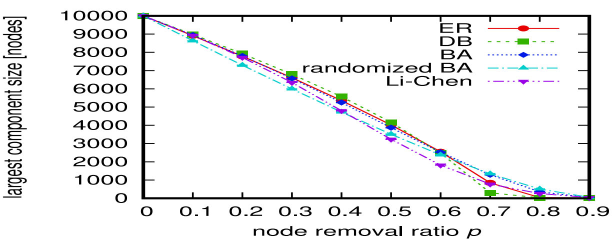
In this section, we revisit the robustness of complex networks against random node removal. As explained above, it is clarified that a scale-free network is robust when a significant portion of the nodes are removed. However, such finding — scale-free networks are robust — might not be valid under a typical node removal ratio of real computer networks.

In what follows, through simulations, we compare the robustness of scale-free and non-scale-free networks — scale-free networks generated with Barabási Albert (BA) model [24], randomized BA model and Li-Chen model [25] and non-scale-free networks generated with Erdõs-Rényi (ER) model and Degree-Bounded (DB) model [3] — against different levels of random node removal. Specifically, we compare the largest component sizes in five classes of networks (i.e., networks generated with BA, randomized BA, ER, DB, and Li-Chen models) after random node removal.

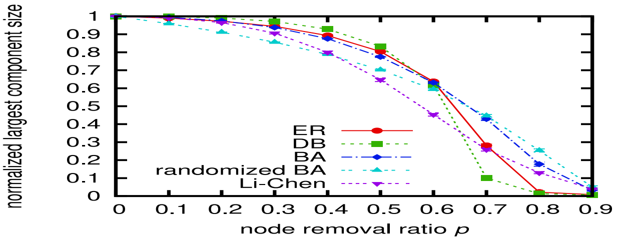
Using synthetic network generation models, we generated scale-free and non-scale-free networks, and we compared the robustness of scale-free networks and non-scale-free networks against random node removal when changing the node removal ratio (i.e., the ratio of the number of removed nodes to the initial network size).

We denote the node removal ratio by p. By randomly removing selected nodes from a generated network, we obtained a degenerated network. The original network and the degenerated network with the node removal ratio p are denoted by G and $G(p)$, respectively.

To investigate the robustness of scale-free and non-scale-free networks against random node removal, we obtained the largest component size in network $G(p)$. The largest component size is the maximum number of nodes in connected components (e.g, a subgraph in which any two vertices are connected by paths, and which is connected to no additional vertices in the supergraph) in a graph.



(a) largest component size



(b) normalized largest component size

Figure 7 Relation between node removal ratio p and the largest component size for $N = 10,000$ and $k = 4$

Refer to [3] for details of experiments.

Figure 7 shows the relation between the node removal ratio and the largest component size in five types of networks with $N = 10,000$ and $k = 4$. Figure 7(b) shows the *normalized* largest component size. The normalized largest component size is defined as the ratio of the largest component size to the network size (i.e., the number of remaining nodes excluding removed nodes).

From this figure, it is found that when the node removal ratio is small, the largest component size in non-scale-free networks is larger than that of scale-free networks. In particular, it is also found that the degree-bounded random network shows the best robustness among networks generated with other network generation models. However, the normalized largest component size in scale-free networks is larger than that of non-scale-free networks when the node removal ratio is very high (i.e., $p \geqq 0.7$), which coincides with the observation reported in [20, 21].

Our findings in [3] are summarized as follows.

- Contrary to common understanding, non-scale-free networks are more robust than scale-free networks except for under extremely high node removal ratios.
- The robustness of non-scale-free networks can be further improved by bounding the minimum node degree of those networks.

Our findings imply that under extremely severe failures (e.g., 90% of routers were destroyed or malfunctioning due to some reason), scale-free communication networks would be more robust than non-scale-free communication networks. If communication networks are scale-free, the majority of 10% nodes would likely to be connected with others. On the contrary, if communication networks are non-scale-free, that 10% of nodes would be likely to be isolated with others. However, if the failure ratio is not so exceptional (e.g., if the failure ratio is between 1–20%), non-scale-free communication networks are *more* robust than scale-free communication networks.

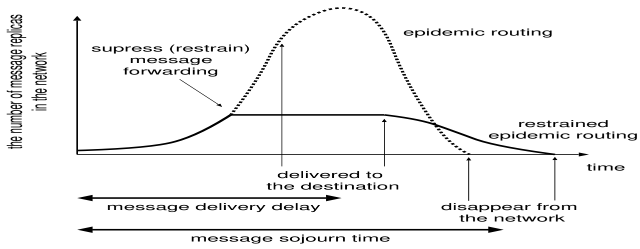


Figure 8 Comparison of epidemic routing and restrained epidemic routing

Phase transition at the critical threshold in a complex network — the giant cluster in the network will disappear as the node removal ratio exceeds the critical threshold — is an interesting phenomenon. Hence, a vast number of studies in the literature investigate the robustness of complex networks at around the critical threshold. However, we should take account of the likelihood of those failures. For instance, what are the chances that 90% of routers on the Internet were destroyed? 1% node failure is likely to happen. The occurrence probability of 5% node failure is much smaller than that of 1% node failure. Our findings indicate that communication networks should be designed by taking account of occurrence probabilities of different levels of network failures.

5 Message Dissemination with Restrained Epidemic Routing on Complex Networks

For realizing high-speed and efficient DTN routing, it is crucial to deliver a message to the destination node immediately, and to delete copies of the delivered message from the network quickly.

A promising approach for deleting redundant duplicates messages from a network is broadcasting ACKs [26]. Broadcasting ACKs is a technique to avoid waste of network resources by broadcasting information on successful delivery of the message to all other nodes, asking for eliminating unnecessary copies.

In [27], we proposed *restrained epidemic routing* to improve the performance of epidemic broadcast using broadcast ACKs. The basic idea of restrained epidemic routing is that if the message replication can be *restrained just before* the message is delivered to the destination node, the number of generated message copies will be moderately limited and we can expect message delivery delay will decrease.

In epidemic routing, the number of message replicas in the network increases exponentially. As soon as epidemic routing started, it is necessary to increase the message copy as quickly as possible. However, from the middle stage of epidemic routing to the latter half, there is a possibility that network resources are wasted due to an increase in message replication excessively. Therefore, in restrained epidemic routing, the increase in the number of message copy is restrained by restraining message relay intentionally from the middle to the latter half of epidemic routing (Fig. 8).

In this section, we analyze the characteristics of restrained epi-

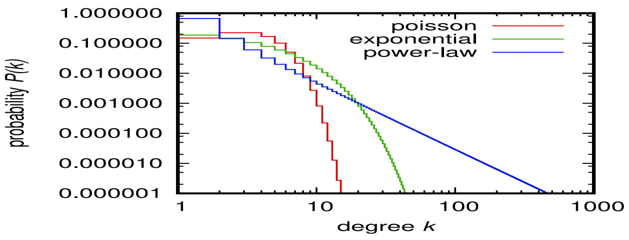


Figure 9 Degree distributions (Poisson distribution, Exponential distribution, Power-law distribution) used for numerical examples

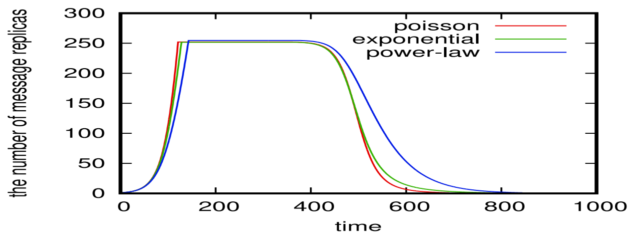


Figure 10 Effect of difference in contact relationship between nodes on message delivery ($N = 1,000$, contact rate: $1/60$, control parameter p_T: 0.25)

demic routing when the contact relationship between nodes is given by a general contact model such as a complex network. Specifically, we investigate the dynamics of restrained epidemic routing as a differential equation when the contact relation between nodes is given by the undirected graph $G = (V, E)$. We analyze restrained epidemic routing in the complex network composed of many nodes by using mean field approximation (Degree-Based Mean Field Approximation) [28] in a complex network with a given degree distribution.

In what follows, we show several numerical examples to investigate the characteristics of restrained epidemic routing in complex networks. Refer to [4] for details.

We use three probability mass functions — Poisson distribution, Exponential distribution, and Power-law distribution — as the degree distribution of the graph G representing the contact relationship of nodes (Fig. 9) [4].

- Poisson distribution

$$P(k) = e^{-k}\frac{k^k}{k!} \tag{1}$$

- Exponential distribution

$$P(k) = (1 - e^{-\mu})e^{-\mu k} \tag{2}$$

- Power-law distribution

$$P(k) = \frac{k^{-\alpha}}{\zeta(\alpha)} \tag{3}$$

The time variation of the total number of message copies in the network when changing the degree distribution of the graph G representing the contact relationship between nodes is shown in Fig. 10. In this figure, the results are shown in the case of the degree distribution are Poisson distribution, Exponential distribution, and Power-law distribution. These results indicate the followings.

- The average message delivery delay is the smallest when the degree distribution is a Poisson distribution (in three types of degree distribution). However, there is no significant difference depending on the difference in degree distribution.
- The average message sojourn time has a big difference depending on the difference in degree distribution.

6 Conclusion

In Section 2, we have investigated how agent's capabilities (i.e., memory and local visibility) can contribute to improving the efficiency of a random walk on a graph —- in particular, the first hitting time (i.e., the time elapsed since the agent starts its random walk from a source node until it arrives the destination node at first) — through simulation experiments. Specifically, we have compared the first hitting time between a randomly-chosen node pair of two random-walk-based mobility models (irreversible random walk and biased random walk) on four types of networks (ER model, generalized BA model, Li-Chen model, and Voronoi diagram) through simulation. Our findings include that the impact of agent's local visibility is quite dependent on the type of networks; i.e., appropriate utilization of local visibility accelerates network exploration in some networks, but, in other cases, the average first hitting time is considerably increased.

In Section 3, we have examined the average message delivery delay in geographic DTN routing under random walk mobility on a large-scale network. In particular, we have addressed the research question — how is the performance of geographic DTN routing affected by the topology of the network (i.e., connections of many geographic locations)? Through numerical examples, we have shown that the network topology has limited impact on the performance of geographic DTN routing except for heavily loaded conditions; the average message delivery delay is mostly determined by the degree of the destination node.

In Section 4, we have compared the robustness of scale-free and non-scale-free networks against random node removal through simulations. Specifically, we have generated multiple scale-free and non-scale-free networks using five network generation models, and compared the largest component sizes after random node removals. Our findings include that, when the node removal ratio is not extremely high, non-scale-free networks are more robust than scale-free networks. In particular, the degree-bounded random network with bounding the minimum node degree shows the best robustness against random node removal among five types of networks.

In Section 5, we have investigated the characteristics of restrained epidemic routing in a general contact model where nodes contact only some nodes. Specifically, we have examined the dynamics of restrained epidemic routing when the contact relation between nodes is given by an undirected graph. Thus, we have obtained analytically the average message delivery delay and average message sojourn time of restrained epidemic routing in a complex network composed of many nodes. We also have clarified how the average message delivery delay and the average message sojourn time of restrained epidemic routing are affected by the difference in degree distribution of complex networks.

So, what are lessons learned from these four research topics? First, the impact of the network topology on the performance and reliability of dynamical processes are multi-faceted. As we have observed, if the dynamical process is a random-walk-based node search (Section 2) or message delivery (Section 3), the network topology might not have a significant impact. If the dynamical process is a message routing (Section 4) or a flooding-like message delivery (Section 5), its performance should vary considerably depending on the topology of the underlying network.

We should note that the scale-free property of the network (or almost equivalently, the power-law distribution of node degrees) is not a *silver bullet* for communication networks. The scale-free property of the network topology is often harmful in terms of the network robustness (Section 4) and the average message delivery delay (Section 5). It seems that, in the literature, the advantages of scale-free networks have been rather overstated. Further explorations on the impact of the network topology on the characteristics of a wide range of dynamical processes on the network are necessary. Developing a theoretical framework to understand the interactions between the underlying network topology and the dynamical process running on top of it would be of great importance.

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