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頑強性と効率性を備えた相互接続ネットワークの設計指針

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あらまし　Internet of Things (IoT) が実現する次世代ネットワークに向けた急速なインターネットの発達は、相互接続されたネットワーク構造の出現を加速させている。しかしながら、様々な環境変動やサービス要求に適応することのできる相互接続ネットワークの設計手法は今後取り組まれるべき重要な課題として残っている。特に通信発生時には、相互接続ネットワークでは、重要な緊急情報を即座に拡散することや、悪意のある情報の拡散を抑制、阻止することが求められる。本研究では脳のモジュール間相互接続ネットワークの性質に着想を得た Network of Networks(NoN) モデルを提案する。提案する NoN モデルは悪意のある情報の拡散をモジュールからモジュールへ伝播させることは阻止できるが、モジュール間リンクの上で発生した情報の拡散を防ぐことはできない。そこで、情報拡散の速度を変化させる方法を見出すべく提案する NoN モデルに適合するモジュール内及びモジュール間の接続構造を設計する。評価を通して、提案する NoN モデルがモジュール間通信制御を考慮しないモデルと同等に速く情報を拡散すること、モジュール間リンクを持たないネットワークと同等に遅く情報を拡散することを示す。
キーワード　Network of Networks, 脳ネットワーク, モノのインターネット

Analysis and Strategies for Improving Robustness and Efficiency in Interconnected Networks

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Abstract　The Internet is rapidly developing toward the next generation of the Internet of Things (IoT), which accelerates the emergence of interconnected network architectures even further. However, the way to design interconnected networks that can meet various changes in environment and service demands remains an important issue that has not been addressed yet. The interconnected networks should suppress or prevent diffusion of malicious information, whereas they should enhance diffuse urgent information around the whole networks. In this study, we propose an Network of Networks (NoN) model inspired by the nature of modular interconnected networks in the brain. Our proposed NoN model can prevent malicious information to diffuse one subnetwork to another, but not that takes place on interconnecting links. In order to find a strategy to change the speed of information diffusion, we further configure the connectivity within and between subnetworks of the interconnected networks that matches our proposing model. Through simulation experiments, we confirmed that our proposing model can diffuse information as fast as a purely interconnected networks, that prevent no information on the interconnecting links. The results also show that our proposed model reduce the speed of the information diffusion almost the same as that of the worst case in a independent subnetwork, that has no interconnecting links.
Key words　Network of Networks, Brain Networks, Internet of Things

1. Introduction

Modular inter-connected networks, often referred to as *Network of Networks* (NoN), have been observed in many complex systems in biology, society, science and technology, as well as the Internet [1, 6]. In contrast to more static types of complex systems, the Internet is rapidly developing toward the next generation of the Internet of Things (IoT), which permits connecting various kinds of interconnected devices in everyday life via the Internet protocol and is expected to accelerate the emergence of modular architectures even further.

An example of the modular architectures in the future Internet is the functionally interconnected networks in smart cities [7]. In the future IoT society, the number of connected devices to the Internet and the type of services provided through the Internet are expected to show an explosive and continuous increase. Smart cities automatically collect data from those IoT devices and intelligently integrate them for improving services for healthcare, surveillance, infrastructure, public utilities, etc., resulting in the realization of smart homes, smart grid, and more. To give simple examples in smart homes, air conditioning systems captures temperature, humidity, and circulation from IoT devices and provide best services responding to a variety of situations. In these situations of smart cities, a processing halt in one service module stops the functions in other interdependent modules. Adding to the situations we can predict at the moment, the number of such automated and independent service systems over the IoT infrastructure is expected to increase in future smart cities.

However, the way to design an NoN architecture that can meet various changes in environment and service demands remains an important issue that has not been addressed yet. Therefore, we first focus on interdependent models in NoN that have been among the topics in the research field of modular interconnected networks [8, 9]. Many biological systems have high robustness against network failures, and Morone *et al.* [9] proposed another NoN model from the perspective of neuroscience, i.e., brain networks. This NoN model, termed as *Brain NoN* hereafter, considers the characteristics of activation rules of neural firing in brain networks, which is well-known for its high robustness [10, 11]. The robust interdependency in Brain NoN can be applied to emerging interconnected Internet services, due to the similarity with the interconnected information networking services. Application of the activation rule of Brain NoN for services in information networking, however, has not been considered so far. Moreover, there are two important questions yet to be answered in those interconnected information networks regarding structural connectivity: (i) how is the connectivity within modules? and (ii) how is the connectivity between modules?. In this study, we attempt to answer those questions from the viewpoint of influential nodes and nodal correlations. Influential nodes in networks are defined as those nodes that have a large influence for controlling the influence over the whole networks with a tiny fraction of nodes [12–17] . Nodal correlation [18, 19] is formulated based on the correlation of nodal degrees of two nodes and termed as assortativity.

The aim of our work is to design an NoN architecture for information networking that meets environmental changes and service demands, which can be summarized as high robustness and communication efficiency, of each service module. For this aim, we first propose an NoN model inspired by the Brain NoN that matches situations in information networking with service interdependency. Second, by taking the nodal influence and nodal correlation into account, we propose a method to configure the intra-modular and inter-modular connectivities and evaluate the performance of the NoN. Evaluation results reveal that our proposed NoN model can realize both fast and slow diffusion by changing its topological connectivity, and, unlike the conventional NoN model without module interdependency, it can achieve robustness against epidemics and efficient communication. At the same time, we also show the strategies for enhancing robustness against epidemics and communication efficiency in our proposing NoN model.

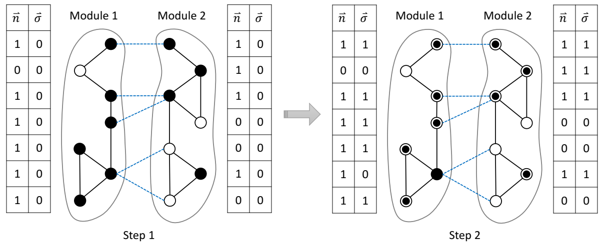


Figure 1 Activation rule in Brain NoN model [9]

2. Related Work

2.1 Models of *Network of Networks*

In the Brain NoN model, nodes can have three different states: *active, input*, and *no-input*. Each node can be active only when its own and its neighbors' input satisfy a certain condition. These three states of node i are determined by two variables, input variable n and activation variable σ, as follows:

◉ : active ($n_i = 1, \sigma_i = 1$)
● : input ($n_i = 1, \sigma_i = 0$)
○ : no-input ($n_i = 0, \sigma_i = 0$)

The patterns of each circle represent nodal states corresponding to Figure 1, which shows an example of state transition in a Network of 2 Networks (2-NoN) of the Brain NoN model. The values for the input variable n are assumed as given and they sequentially determine the values for the activation variables σ. Node i can be active only when its own input and the input of at least one node in the other modules exists, the value of σ is defined as follows:

$$\sigma_i = n_i \left[1 - \prod_{j \in \mathcal{F}(i)} (1 - n_j) \right], \qquad (1)$$

where $\mathcal{F}(i)$ denotes the set of nodes connected to node i via inter-modular links.

2.2 Identification of Influence in Networks

Our study also focuses on the vital nodes in order to control acceleration and suppression of information diffusion in interconnected networks. Identification of a set of nodes that maximizes the influence over a network is known as NP-hard problem [13], and a great number of heuristic solutions have been proposed so far [17].

We focus on one of recent works [16] which proposed the Collective Influence (CI) algorithm to identify influential nodes. CI of node i represents its influence on other nodes in the same network centered around node i, e.g. betweenness centrality, pagerank, or k-core. The CI algorithm showed superior performances for the identification of influential nodes to other methods using conventional centrality measurements by finding the smallest set of nodes that totally collapses the connectivity of the networks. CI of node i is defined as follows:

$$\mathrm{CI}_l(i) = (k_i - 1) \sum_{j \in \partial \mathrm{Ball}(i,l)} (k_j - 1) \tag{2}$$

where k_i denotes the degree of node i, $\mathrm{Ball}(i, l)$ denotes the set of nodes within l hops centered around node i, and $\partial\mathrm{Ball}(i, l)$ denotes the set of nodes on the edges of $\mathrm{Ball}(i, l)$.

2.3 Universal Assortativity

Assortativity, i.e., the correlation of nodal degrees, is firstly proposed by Newman [18]. Furthermore, universal assortativity coefficient was introduced to analyze the assortativity of any part of a network in [19].

Newman proposed measuring the assortativity of a network with the assortativity coefficient [18]. The assortativity coefficient is calculated from the remaining degree distribution $q(k)$ defined as follows:

$$q(k) = \frac{(k+1)p(k+1)}{\sum_j jp(j)}, \tag{3}$$

where $p(k)$ denotes the probability that a randomly selected node has nodal degree of k.

Then, the universal assortativity coefficient ρ_l on a link l can be introduced given $q(k)$. The definition of the universal assortativity of link l is as follows:

$$\rho_l = \frac{(j - U_q)(k - U_q)}{M\sigma_q^2}, \tag{4}$$

where j and k denote the remaining degrees of the two endpoints of link l, which have the same expected value of the remaining degree $U_q = \sum_j jq(j)$. The term M denotes the number of edges in the whole network, and the term $\sigma_q^2 = \sum_l j^2 q(j) - \left(\sum_k kq(k)\right)^2$ denotes the varince of the remaining degree distribution $q(k)$. When $\rho_l > 0$, the link is called an assortative link; otherwise when $\rho_l < 0$, a disassortative link.

3. Information Diffusion Model for Interconnected Networks

Although input to nodes and activation as the result of this input were considered in the Brain NoN model [9], effects of nodal activation on its neighbor nodes have not been considered. We expand the activation rule of the Brain NoN model to express the communication flow in interconnected networks.

First, we change the interpretation of the nodal states in the Brain NoN model to states of nodal interfaces (network devices) in information networks NoN, termed as *IN NoN*. The activation of interconnecting links is coupled with the activation of endpoint nodes of the interconnecting links in the Brain NoN model. In information networks, however, even if one endpoint node is deactivated and thus the interconnecting link is also deactivated, the other endpoint node should maintain its process within the module the node belongs.

For this reason, the meaning of the states defined by σ in the Brain NoN are re-interpreted as shown in Table. 1, where the activation of nodes is replaced with outer-interfaces. In this context, the input variable n in the Brain NoN represents the input state of information. It should be noted that inner-interfaces are always active independent of the value of σ or n. Adding to IN NoN, we note a basic model that does not consider the interdependence between modules as Pure NoN in Table. 1. Pure NoN always diffuses at the maximum speed the topological connectivity can produce.

Second, in order to express the flow of information, IN NoN adopts the notion of time-scale. In this model, the value of variables n and σ at current time step t is given by the previous states at time step $t - 1$. We then introduce a probability function p_t for nodes to decide whether to have input or depending on the states of neighbor nodes. Here, we suppose that each node can pass information at probability δ through active outer- and inner-interfaces whenever they have inputs. Therefore, the probability function $p_t(i)$ for node i to judge whether to have input is written as follows:

$$\begin{aligned} p_t(i) \;=\; 1 - &\prod_{j \in \mathcal{S}(i)} (1 - \delta n_j^{t-1}) \\ \times &\prod_{k \in \mathcal{F}(i)} (1 - \delta \sigma_i^{t-1} \sigma_k^{t-1} n_k^{t-1}), \end{aligned} \tag{5}$$

where $\mathcal{S}(i)$ denotes the set of neighbors of node i within the same module, and $\mathcal{F}(i)$ denotes the set of neighbor nodes in the other modules. It should be noted that all inner-interfaces are active, while outer-interfaces are active only when $\sigma = 1$. An important point this equation expresses is that when $\delta < 0$, node i can behave differently depending on the number of inputted neighbor nodes: the more input neighbors node i has, the more likely node i has input.

Then, activation state of node i is rewritten based on the rule in Eq. (1) of the Brain NoN model as follows:

$$\sigma_i^t = n_i^t \Big[1 - \prod_{j \in \mathcal{F}(i)} (1 - n_j^t) \Big]. \tag{6}$$

This equation shows that the inter-modular interface of node i becomes active only when node i and at least one neighbor node via inter-modular link has input.

4. Method for Configuring Connectivity of Interconnected Networks

4.1 Changing Nodal Influence in Single Networks

In order to increase/decrease the power of influential nodes in terms of information diffusion speed in a single network, we expand conventional preferential attachment method and generate topologies with controlling parameter γ. Given a seed network, we successively add nodes with m links and connect the links to existing nodes. The probability for each link of new node to be connected to a existing node i is defined as follows:

$$p(i) = \frac{k_i^\gamma}{\sum_j k_j^\gamma}, \tag{7}$$

Table 1 Re-interpretation of variables of Brain NoN for information networking

variables	Brain NoN	IN NoN
$\sigma = 0$	node is inactive	outer-interface is inactive
$\sigma = 1$	node is active	outer-interface is active

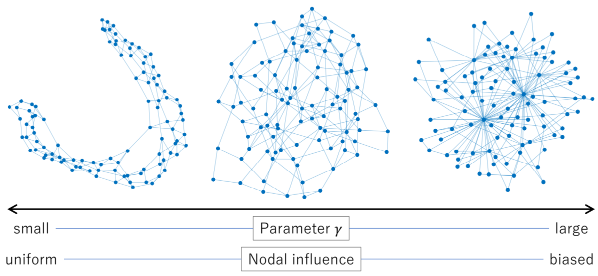


Figure 2 Single network topologies with various connectivity

where k_i denotes nodal degree of node i. The process finishes when all N nodes are added to the network. Figure 2 shows topological shape of single networks with changes in the parameter γ. When γ decreases, topology will go to have uniform degree distribution with average degree $\bar{k} \simeq 2m$ and variation of degree approaches zero, and thus nodal influence is also distributed. Whereas when γ increases, more highly influential node emerges and influencer shrinks. As a result, topologies will show nodal degree distribution following power-law $p(k) \sim k^{-\delta}$.

4.2 Configuring Connectivity between Networks

When adding an interconnecting link to an NoN, we consider two points: (i) dependency on centrality of both endpoint nodes within each module, and (ii) dependency on correlation of the centrality of the two endpoint nodes. All the possible pair of nodes with a certain centrality value can be expressed by changing these two dependency respectively, Based on this idea, we investigate which nodes should be preferentially selected as endpoint nodes of interconnecting links for achieving an NoN topology with fast/slow information diffusion. In the following part of this section, we formulate each dependency as *Dependency Coefficient (DC)*.

4.2.1 Nodal Centrality within Each Network

To begin with, we define the DC of the dependency on centrality itself as DC_{cnt}. Here, we consider the dependency on centrality of each endpoint nodes of interconnecting links independently, DC_{cnt} is simply defined as sum of centrality of each endpoint nodes as follows:

$$DC_{cnt}(h,i) = c_h + c_i, \tag{8}$$

where c_h denotes an any centrality value of node h within each module the node belongs to. The value of c_h and c_i respectively varies in the range of $[0, 0.5]$: the high value represents high centrality, and vice versa.

4.2.2 Correlation of Nodal Centrality between Networks

We measure the correlation of nodal centrality based on the ideas of universal assortativity we mentioned in Section 2.3. The universal assortativity is introduced to measure the correlation of nodal degree centrality between networks as follows.

$$\rho_l = \frac{(j-U_q)(k-U_q)}{M\sigma_q^2}, \tag{4}$$

On the calculation of the universal assortativity of an intermodular link using Eq. 4, the expected value $U_q = \sum_j jq(j)$ is based on the remaining degree. Here, we assume that interconnecting links are generated between two *different* networks independent of the connectivity within each network. Probability for nodes in each network to be selected as a endpoint node is all the same. Setting $p(c)$ as a any kind of nodal centrality distribution of a single network, the expected value of the centrality on an endpoint node of an interconnecting link is also expressed as $p(c)$. Therefore, we define another generalized universal assortativity ρ'_l of an interconnecting link l between network 1 and 2, modifying Eq. 4, as follows

$$\rho'_l = \frac{\left(c_{l_1} - U_{p_1}\right)\left(c_{l_2} - U_{p_1}\right)}{\sigma_{p_1}\sigma_{p_2}}, \tag{9}$$

where c_{l_1} and c_{l_2} denote nodal centrality of endpoint nodes in network 1 and 2 respectively. U_{p_1} and U_{p_2} denote the expected value of nodal centrality, defined as $U_p = \sum_j jp(j)$. $\sigma_{p_1}^2$ and $\sigma_{p_2}^2$ denote the variation of nodal centrality distribution $p(c)$, given as follows $\sigma_p^2 = \sum_l l^2 p(l) - \left(\sum_m mp(m)\right)^2$. Particularly, if network 1 and 2 have the same nodal centrality distribution $p(c)$, Eq. 9 can be rewritten as follows:

$$\rho'_l = \frac{\left(c_{l_1} - U_p\right)\left(c_{l_2} - U_p\right)}{\sigma_p^2}, \tag{10}$$

Finally, we define DC_{cor} of the dependency on correlation of nodal centrality of the two endpoint nodes slightly changing the generalized universal assortativity, as follows:

$$DC_{cor}(h,i) = \frac{\left(c_h - U_p\right)\left(c_i - U_p\right)}{\sigma_p^2}, \tag{11}$$

where h and i are just indexes of nodes.

4.2.3 Coefficient for varying interconnectivity

To configure the connectivity between networks, we consider two aspects as mentioned above: (i) dependency on centrality of both endpoint nodes, and (ii) dependency on correlation of the centrality of the two endpoint nodes. That is, we combine DC_{cnt} and DC_{cor} and express various interconnectivity between networks, using DC, defined as follows:

$$DC(h,i) = \left[\frac{DC_{cnt}(h,i) - DC_{cnt}^{min}}{\overline{DC}_{cnt} - DC_{cnt}^{min}} + 1\right]^{r\cos\theta} \tag{12}$$

$$+ \left[\frac{DC_{cor}(h,i) - DC_{cor}^{min}}{\overline{DC}_{cor} - DC_{cor}^{min}} + 1\right]^{r\sin\theta} \tag{13}$$

where the parameter θ varies in the range of $[-1, 1]$, and the parameter r takes {0,1}: $r = 0$ for random connectivity, and $r = 1$ for various connectivity. Each dependency coefficient is normalized by average so that the effect of the both coefficients becomes the same on average. We then added 1 to both coefficient so that the minimum dependency coefficient among all pair of nodes always stays 1 as a standard value independent of the value of θ.

Fix $r = 1$, and when $\theta \in (0, \pi)$, interconnecting links become assortative; otherwise when $\theta \in (\pi, 2\pi)$, the links become disassortative. When $\theta \in (3\pi/2, \pi/2)$, high centrality nodes tend to be selected as endpoints of interconnecting links, while when $\theta \in (\pi/2, 3\pi/2)$, low centrality nodes are preferred. These variability is shown in Figure 3.

5. Simulation Evaluation

In this section, we evaluate the performance of NoN models and topologies.

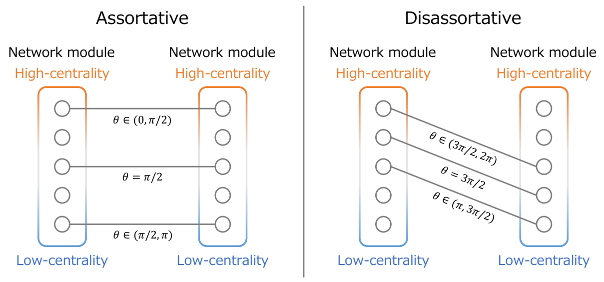


Figure 3 Various patterns of connectivity between networks

Table 2 Parameter settings

Variables	Values	Description
δ	0.5	parameter for information passing probability
γ	[-50,20]	parameter for preferential attachment
m	2	parameter for number of links in preferential attachment
r	1	parameter for connectivity between networks
θ	[0,2π]	parameter for connectivity between networks
N	100	number of nodes in a single networks
E	25	number of inter-modular links
k_{in}^{max}	25	maximum nodal degree of intra-modular links
k_{out}^{max}	1	maximum nodal degree of inter-modular links

5.1 Simulation Settings

We evaluate performances of NoN models changing their topological connectivity. We use IN NoN model as our proposal and Pure NoN as a basic comparison. Their behaviors are described in Section 3.

To conduct the evaluation, we configure the parameter settings on NoN models and topologies according to Table 2. In the evaluation, we measure the required time-steps for an information to diffuse over the entire NoN topologies to know whether the NoN diffuses information quickly or slowly. The starting points of the diffusion are (i) the highest loaded inter-modular links, and (ii) randomly selected inter-modular links. Starting the diffusion from an interconnecting link matches both our research objective the natural behavior of information networking. Although it is an original behavior in IN model that nodes become empty after passing its information, we designate the source inter-modular link, i.e., the source endpoint nodes, to continuously send the information. This is because the diffusion is following an probabilistic method and it is possible for the diffusion to disappear from the network in the first few steps.

5.2 Evaluation on Basic Properties of an Independent Subnetwork

Before we start evaluating the information diffusion efficiency, we investigate the basic properties of single networks, that will allow deeper understandings on evaluation of interconnected networks in the following section. Figure 4 shows maximum collective influence required steps for information diffusion in single networks. We can confirm that as the parameter γ increases, maximum collective influence successively grows up and the required steps decreases. This result implies the power of influential nodes can be summarized and distributed by changing the parameter γ. However, we can also find that there is a limitation on the feasible values of maximum collective influence and required steps. We can also find an straightforward tendency that the speed of information diffusion increases when γ increase.

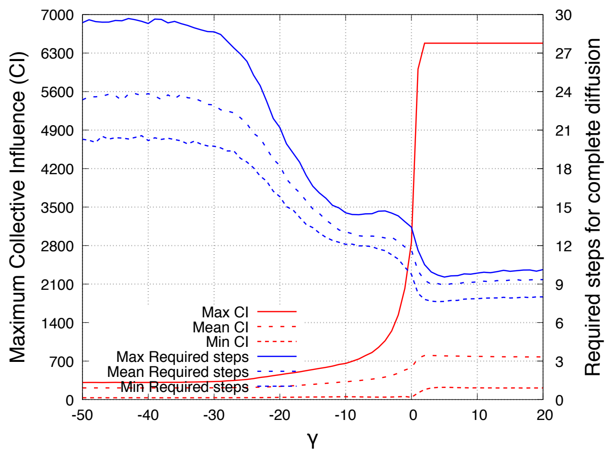


Figure 4 Collective influence and required steps for diffusion

5.3 Simulation of Information Diffusion

In this subsection, we investigate the performance of NoN models, IN NoN and Pure NoN, through the simulation of information diffusion. Information diffusion selects influential edges as a source of the diffusion. Such interconnecting links are selected based on the average collecting influence of both endpoint nodes.

In Figure 5, required time for information to completely diffuse all over the network is described. Shapes of the lines in Figure 5 is basically the same as the blue lines in Figure 4, which describes the information diffusion in a single network. As γ increases, influential nodes gradually appears and they minimizes diameter of each subnetwork in the interconnected network. However, the behavior of lines differ with each other, depending on the types of NoN models and the parameter θ.

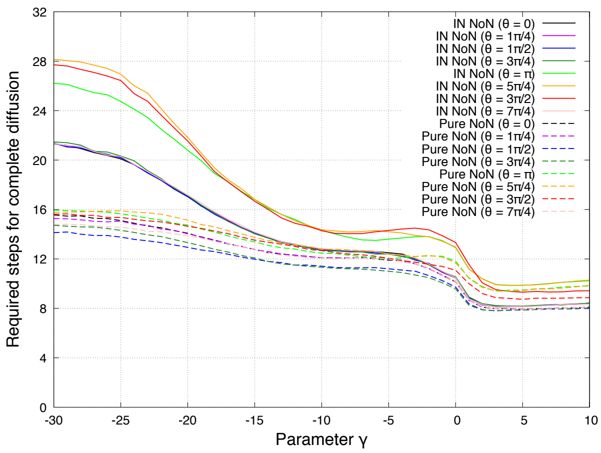
The most conspicuous point is that solid lines of IN NoN vary more extensively than the dotted lines of Pure NoN. Rather than larger parts of the horizontal axis, γ, the diffusion speed greatly slows down with smaller γ. When γ is small, each subnetwork becomes uniformly connected as we confirmed. In such stretched networks, the endpoints of interconnecting links in each network is located faraway. The activation rule for outer-interfaces of IN NoN model requires both endpoint nodes of an interconnecting link to have input when the outer-interfaces needs to be activated. Therefore, the outer-interfaces tend to be turned off in interconnected networks composed of such stretched subnetworks.

On the other hand, IN NoN achieves almost the same speed of information diffusion with Pure NoN. This nature can be seen when $\gamma \geqq 2$ and θ is around 0. In this range of parameters, the source interconnecting link is assumed to connect highest centrality nodes in each subnetwork. Therefore, the strong diffusion sources enabled quick information diffusion for IN NoN.

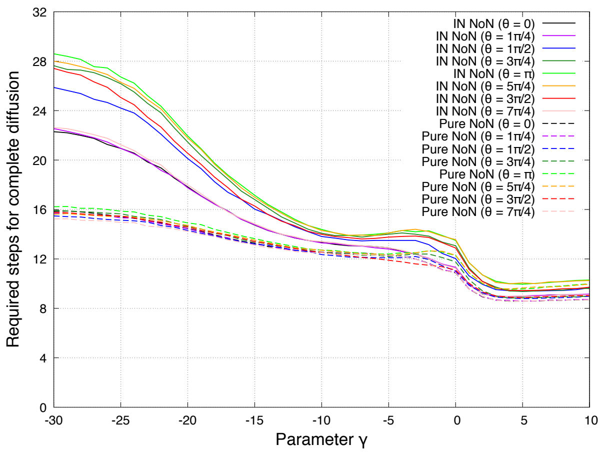
6. Conclusion and Future Work

In this study, we proposed an NoN model called IN NoN inspired by the Brain NoN model, which reproduces the activation rule of neurons of different modules that are connected via interconnecting control links. We then investigated the configuration of connectivity within and between subnetworks, so that IN NoN can change the speed of information diffusion.

As a basic characteristic, IN NoN does not allow malicious or un-



(a) Diffusion from interconnecting links with high centrality endpoint nodes



(b) Diffusion from randomly selected interconnecting links

Figure 5 Required steps for complete diffusion with changes in connectivity

accepted information to path through interconnecting links. However, it is conceivable that such bad information diffuses from interconnecting links. Otherwise, in case of emergency, we can also start the diffusion from the interconnecting links. Therefore we simulated information diffusion starting from interconnecting links, changing connectivity within and between subnetworks. The results showed that IN NoN can diffuse information as fast as Pure NoN, which does not consider the prevention of information diffusion between modules and thus proposes maximum diffusion speed with a given topology. We also found that even if malicious information spread outs from interconnecting links, we can reduce the diffusion speed as slow as the worst case of a independent subnetwork.

In the evaluation, we focused on the information diffusion starting from interconnecting links and did not investigate the diffusion starts from a node within a subnetwork, or interconnected networks composed of three or more subnetworks. The current IN NoN model never transmits information from a subnetwork to another, unless the opponent subnetwork has some traffic by other information and nodes are partially activated. Indeed, it is preferable to prevent malicious diffusion, whereas preventing urgent important information is not preferable. Therefore, our future work would be to modify IN NoN or to configure a more complicated settings.

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