Designing an Evolvable Network with Topological Diversity

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***Abstract*—As environments surrounding the Internet become more changeable, a design approach is needed that requires less equipment to scale up networks against traffic growth resulting from various environmental changes. Here, we propose an evolvable network design approach in which network equipment is deployed without predetermined purpose rather than for a preplanned purpose. We use mutual information on node degree to measure the topological diversity of networks, and maximize topological diversity in the network design by minimizing the mutual information. Evaluations show that, compared to networks based on an ad hoc design method, networks constructed by our design approach can re-use already installed equipment in different environments.**

I. Introduction

The Internet now plays a critical role as a part of social infrastructure. As Web services become more popular and traffic grows, the environment surrounding the Internet is becoming more changeable. Currently, operators of ISP networks usually add link capacity and routers in an ad hoc way. For example, they add link capacity when link utilization exceeds a certain threshold, or they introduce new routers when already-existing routers become unable to accommodate traffic from those enhanced links. Such ad hoc design leads to an increasing amount of equipment. This, in turn, soon leads to problems arising from technical limitations of routers and links, such as processing speed or transmission capacity. Although some researches study traffic prediction, it is hard to predict changes accurately. The network would be unmanageable and need a lot equipment to follow changes when environment changes beyond expectations, so that trying to solve an optimization problem that includes environmental uncertainty is infeasible. Hence, a design approach that uses less equipment to improve a network in response to various environmental changes is urgently required. In this paper, we discuss whether this could be achieved by constructing a network that can easily adapt to deal with new environments; we call this property evolvability.

Evolution and evolvability have long been studied in biology [1]. The heart of evolution in living species is the presence of genetic diversity at the DNA-level and the adaptability of this genetic diversity through natural selection in particular environments. Species that better adapt to their environment survive and pass on their genetic characteristics to the next generation. The variety of species that exists today is the result of evolution over billions of years, under many kinds of environments.

Information-theoretic interpretations of an evolutionary process can be used to understand adaptation and evolution in complex systems, including biological systems, as described in Prokopenko et al. [2]. In general, mutual information is defined as the differences between the heterogeneity and correlation of some variables. The mutual information of a system can be used to characterize the degree of evolution. The mutual information of system components increases as evolution progresses, since the correlation, which represents constraints between components from the system perspective, becomes stronger as the system is specialized to the environment. Thus, an unspecialized system, which has low mutual information, has the potential to evolve in various ways, while a specialized system, which has high mutual information, is more constrained and less able to evolve. For example, Solé [3] used mutual information to analyze topological characteristics of complex networks. The mutual information used in [3] is the difference between the heterogeneity in degree distribution and the degree-degree correlation, which is also known as assortativeness [4], appearing in the network structure. They showed that a software network resulted from an engineering process has high mutual information. So we expect from [2] and [3] that, by using mutual information, we can construct evolvable networks robust against short-term environmental changes including equipment failures and even long-term changes, such as unpredictable traffic growth.

In information networks, nodes or links are often added for a particular purpose: for example, aggregating or relaying traffic. However, because they are specific for that purpose, nodes and links added in such a way can be effective in only the environment in which they were introduced; when the environment changes, that equipment may become underutilized or useless. In the current network management regime, equipment is frequently added but less often removed, so useless links will accumulate, and the total amount of equipment will increase. Following the insights obtained from work in biology and complex systems, an information network topology that has a reduced degree of specialization can be expected to leave less equipment unused, even in a new environment. Hence, a design approach that reduces the degree of specialization can be expected to enhance the evolvability of a network. Hereafter, we will describe a network having a topology with low degree of specialization as having "topological diversity".

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It was shown in [5] that router-level topologies characterized by a high degree-degree correlation [6] lead to high mutual information. Following [5], we will use the mutual information proposed in [3] to strengthen topological diversity, and show the advantages of our design approach in terms of its response to environmental changes, by which we mean unpredictable traffic changes as well as equipment failures.

The rest of this paper is organized as follows. Section II explains our proposed design approach that minimizes the mutual information. In Section III, we evaluate the evolvability of networks designed by our approach in terms of the quantity of accumulated equipment to show how the designed network can easily adapt to dealing with new environments. Finally, we conclude our paper in Sec. IV.

II. Network Design by Minimization of Mutual Information

We describe our proposed design approach, which we call the EVN (EVolvable Network) design approach. Fundamentally, the purpose of our EVN design approach is to reduce the mutual information on remaining degree so that the designed network has topological diversity.

Mutual information of remaining degree was studied by Solé et al. [3]. The measurement indicates the correlation of degrees between pairs of linked nodes. Remaining degree is the number of edges leaving a node, other than the one that connects the pair. Using the distribution of remaining degree q, the mutual information on remaining degree, $I(\mathrm{q})$, is defined as

$$I(\mathrm{q}) = H(\mathrm{q}) - H_c(\mathrm{q}|\mathrm{q}'), \tag{1}$$

where $H(\mathrm{q})$ is the entropy of the remaining degree distribution and $H_c(\mathrm{q}|\mathrm{q}')$ is the conditional entropy of the remaining degree distribution.

Note that EVNs are not designed to satisfy particular design constraints, such as performance or budget constraints. Therefore, networks designed by our EVN design approach may not be comparable in terms of their optimality with highly "engineered" networks which are specialized to meet particular design constraints. Instead, as we will see later in this paper, a network with topological diversity designed by our approach is evolvable: that is, it can easily adapt to deal with new environments without requiring a lot of additional equipment.

When designing a network, we should consider various design constraints such as network performance or budget constraints. In this paper, we do not explicitly consider the validity or effectiveness of a particular design constraint; instead, we consider whether our design approach is evolvable or not. For this reason, the following assumptions are introduced. The initial topology is given and nodes are added incrementally. The number of links m added with a new node is fixed. Note that these assumptions should be relaxed for real network maintenance, but we expect that the characteristics obtained by our approach are not very different. Furthermore, for simplicity, we assume in this paper that topology is the only information we use to decide where to attach a new node, and physical distance is not considered. We believe that there is a trade-off relationship between mutual information and physical distance when connecting nodes, which is left for future investigation.

Let an initial topology be $G_0(V_0, E_0)$, where V_0 and E_0 are initial sets of nodes and links. Then, we add a node and links to the topology at each step by the following algorithm. At each step, we add a single node and the number of links introduced for each node addition is denoted by m. Also, let $G_k(V_k, E_k)$ be the topology obtained by the kth step of the algorithm. At this point there are k additional nodes and km additional links, that is, $|V_k| = |V_0| + k$ and $|E_k| = |E_0| + km$. Note that, because our aim is to show the potential of design method based on mutual information, we use exhaustive search for deciding appropriate node to connect.

(i) Calculate the entropy $H_{k-1}(\mathrm{q})$ of $G_{k-1}(V_{k-1}, E_{k-1})$.

(ii) Add a node (denoted by w) to $G_{k-1}(V_{k-1}, E_{k-1})$.

(ii-1) Pick m different nodes for creating m links connected to the new node w.

- For this purpose, first enumerate all of the topologies for all the possible additions of m links , and calculate the entropy $H(\mathrm{q})$ and the mutual information $I(\mathrm{q})$ for each topology. Note that we simply use notation q here, but formally, it should depend on the topology including the new node and links.
- Choose m nodes that minimize mutual information while making the entropy greater than or equal to the entropy $H_0(\mathrm{q})$.

(ii-2) Connect the node w and m links, and obtain $G_k(V_k, E_k)$.

With each additional node, we add m links such that the entropy $H_k(\mathrm{q})$ of the new topology is greater or equal to the initial $H_0(\mathrm{q})$. The reason why this entropy–restriction is included is that the reliability of a network is improved by increasing the entropy of the degree distribution [7], as Wang et al. showed that increasing the entropy of the degree distribution of a scale-free network will lead to higher reliability against random node failures. Note that, although $H(\mathrm{q})$ measures the heterogeneity of the remaining degree distribution, the distribution is derived from the degree distribution, so the entropy of the remaining degree distribution should not be decreased after the node addition.

Figure 1 shows the values of entropy, conditional entropy and mutual information obtained by the EVN design approach. We use the AT&T topology as an initial topology $G_0(V_0, E_0)$. We also obtained results by using Sprint topology as an initial topology. Because of the page limitation, here we only show the results using AT&T topology. The AT&T topology we used is a measurement result obtained by the Rocketfuel tool [8]. It has 523 nodes and 1304 links. Then, we apply our design approach with the number added nodes n to be 300, that is, we iterate over 300 steps of our design approach. Also, we set $m = 2$; that is, we add two links per node. The reason

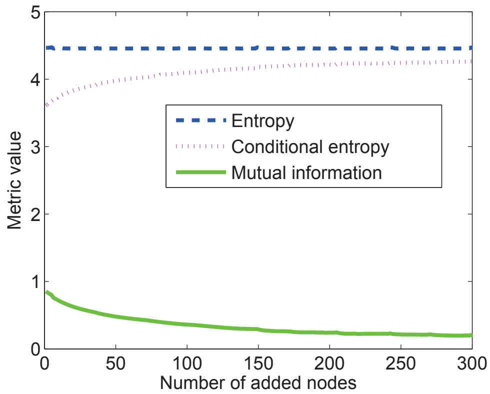


Fig. 1. Values of entropy, conditional entropy and mutual information obtained by the EVN design approach

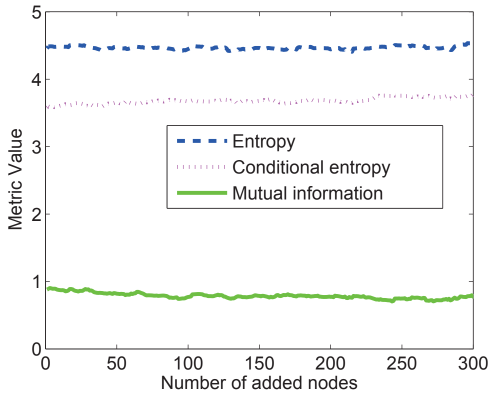


Fig. 2. Values of entropy, conditional entropy and mutual information obtained by a modified FKP-based network design method

why two links are added with each new node is to keep the average degree of the designed networks similar to the average degree (2.49) of the original AT&T topology. Because it is not possible to know the number of links added for each new node in reality, we just assume here that the average degree will not change greatly in the near future. In Fig. 1, the horizontal axis represents the number of added nodes and the vertical axis represents the value of entropy, conditional entropy and mutual information for the topology. We can see from the figure that the mutual information of the initial topology is around 1.0, and the entropy is around 4.5. As the number of added nodes increases, the mutual information decreases and the entropy of the remaining degree distribution is kept high by our algorithm, as expected.

III. Evaluation of Our Design Approach for Evolvability

In this section, we show the evolvability of designed networks, that is, how networks with topological diversity can easily be designed and adapted to meet environmental changes. To show that our designed network can be evolvable, we consider continuing traffic growth as the environmental change, and we examine how much additional equipment introduced by the network design approach is effectively used or unused.

For comparison, we could use a “purely ad hoc method,” in which we add nodes and or links at the place where capacity is in short supply. However, instead of using such a method, we consider a more intelligent approach that takes into account some optimization, for a fairer comparison. Though many complicated network design method can be considered, we consider the FKP model [9] here, in which nodes and links are incrementally added such that a new link connected to a new node is added to keep minimizing the weighted sum of physical distances and hop distances. The reason why we consider FKP model is that it includes primitive principles for designing information network. This section starts from the explanation of the ad hoc design method described above in Subsection III-A, and then we evaluate and compare the amount of equipment accumulated during the network growth in Subsections III-B and III-C.

A. Network Design Method based on the FKP Model

We briefly introduce the FKP model proposed by Fabrikant et al. [9], which incrementally adds nodes and connects existing nodes so that physical distance and hop distance metrics are minimized.

The first node n_0 is set as the root of the topology. Then, a new node incrementally arrives at a random point in the Euclidean space $[0, 1]^2$. After a new node n_{new} arrives, the FKP model calculates the following quantity for each node n_i already existing in the network:

$$\alpha \cdot d(n_{\text{new}}, n_i) + h(n_i, n_0), \tag{2}$$

where $d(n_{\text{new}}, n_i)$ denotes the physical distance in the Euclidean space $[0, 1]^2$ between n_{new} and n_i, and $h(n_i, n_0)$ denotes the hop distance between n_i and the root node n_0. The root node is prespecified for calculating the hop distance. In this paper, we set the maximum degree node in $G(V, E)$ as n_0. The parameter α determines the importance of physical distance. If α takes a low value, each node tries to connect to higher degree nodes; $\alpha = 0$ is an extreme scenario that creates a star-topology. If α takes a high value, each node tries to connect to their nearest nodes. A topology with high α has been shown to behave like a random topology. A power-law degree distribution appears at moderate values of α. The power-law attribute here is used for determine moderate α. Though power-laws degree distribution found in [9] is said to be different from those given by other Internet models, we think this point is not important here.

For comparing with our method, we modified the FKP model as follows. Given a topology $G_0(V_0, E_0)$ and physical locations of nodes, our modified version of the FKP model adds a node and m links in k-th step by the following algorithm in order to obtain $G_k(V_k, E_k)$.

(i) Map the physical location of nodes V to the Euclidean space $[0, 1]^2$

(ii) Divide $[0, 1]^2$ into 20×20 areas, and calculate the node existing ratio in each area. The node existing ratio of an area is defined as the number of nodes exist in the area over the total number of nodes.

(iii) When a new node n_{new} arrives, determine the area of the node with a probability proportional to the node existing ratio.
(iv) Calculate the distance metric defined by Eq. (2) for each existing node n_i.
(v) Select m nodes in ascending order of the value of distance metric. Then, add node n_{new} and links between n_{new} and the selected nodes to the topology.

The modifications to the original model we made in the above algorithm are as follows. First, the physical location of the added node is determined with a probability proportional to the node existing ratio (Step (ii) above). The reason for this is that, because routers are often added to areas where traffic demand is large, an area attracts more traffic as more routers are found in the area. Second, we add multiple links at each node addition so that the average degree of the designed networks can be controlled (Step (v)).

In the evaluation in Subsections III-B and III-C, the parameter α will be set to 10.0, when the average hop distance is lowest under the condition that the entropy $H(\text{q})$ is moderate so as not to obtain a star-like topology.

Figure 2 shows the entropy, conditional entropy and mutual information during network growth by the modified FKP-based design method. We use the AT&T topology as the initial topology, and set the number of added nodes n = 300 (i.e., the final topology is attained after 300 steps) and the number of links for each step is set to $m = 2$. The locations of nodes at the city-level are obtained from [8], and the latitude and longitude of each city are rescaled down to $[0, 1]^2$, by letting the southernmost node and the northernmost node be 0 and 1 for latitude, and the easternmost node and the westernmost node be 0 and 1 for longitude. We can see from Fig. 2 that entropy, conditional entropy and mutual information are unchanged during the network growth. See Fig. 1 for comparison with our EVN design approach. This is because a principle of growth in the FKP model is to minimize the distance metric (Eq. (2)) which is unchanged during the network growth. Mutual information is around 1.0 and is kept high, which means the topological diversity is kept low by the FKP-based network growth model. On the contrary, that of a network grown by the EVN design approach becomes low, which means topological diversity is kept high.

B. Evaluation of Accumulated Capacity

In this subsection, we consider the amount of equipment accumulated during network growth. That is, we measure evolvability by the amount of equipment (more specifically, link capacity) because if a network has the ability to evolve, less equipment is required to adapt to environmental changes. In the current network management practice, ISPs make incremental changes to their networks: once new equipment has been deployed to adapt to environmental changes, it is unlikely to be removed. Therefore, the amount of equipment accumulated during network growth indicates how easily the network can adapt to dealing with new environments.

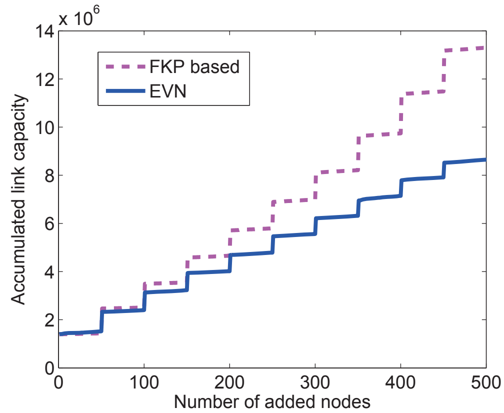


Fig. 3. Accumulated link capacity

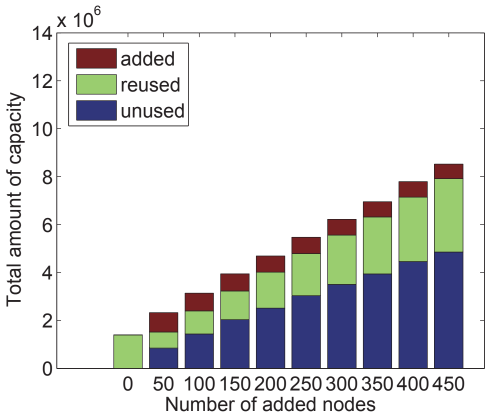
The environmental change that we consider here is traffic growth due to node addition, and we consider the enhancement of equipment needed to cope with single node failure. The reason for considering this enhancement is to see how designed networks absorb surges in traffic arising from node failure. The equipment we consider here is the total capacity of links for the same number of node and link additions in the EVN design approach and in the FKP-based design method. In principle, we should write $G_k^{EVN}(V_k, E_k)$ for the topology of the network obtained after k steps (with k nodes added) and $m = 2$ for the EVN design approach. However, in what follows, we will simply use G_k^{EVN} instead of $G_k^{EVN}(V_k, E_k)$. Similarly, we will use G_k^{FKP} for the network obtained by the modified FKP-based design method with $m = 2$. We also introduce C_k^{EVN}, which is the total capacity of G_k^{EVN} obtained by

$$C_k^{EVN} = \sum_{e \in E} C_k^{EVN}(e), \tag{3}$$

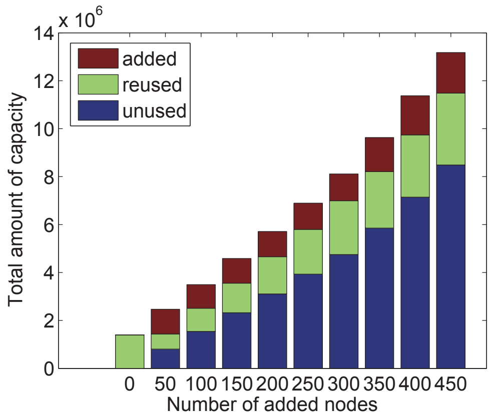
where $C_k^{EVN}(e)$ represents the capacity of link e. In the evaluation, the capacity of each link is chosen such that the link can accommodate the traffic for every pattern of single node failure in the topology G_k^{EVN}. Shortest path with equal hop path splitting [10] is applied for calculating the capacity. The traffic demand is set to 1 unit between all of node pairs in G_k^{EVN} to see whether our EVN design approach constructs an evolvable network or not.

The link capacity is re-designed to cope with the increase of traffic after every node addition and to cope with single node failures after every 50 node additions. The link capacity is incremental; that is, if link capacity $C_{(k-1)}^{EVN}(e)$ is enough to accommodate the traffic in G_k^{EVN}, we do not reduce the link capacity but set $C_k^{EVN}(e) \leftarrow C_{(k-1)}^{EVN}(e)$. The initial link capacity, $C_0^{EVN}(e)$, is also calculated to cope with every pattern of single node failure. Similarly, C_k^{FKP}, the total capacity of G_k^{FKP}.

Figure 3 shows the total link capacities of G_k^{EVN} and G_k^{FKP} dependent on the number of added nodes k. The initial topology is set to the AT&T topology (523 nodes and 1304 links). The figure indicates that our EVN design approach requires less link capacity than the FKP-based design method,



(a) EVN design approach



(b) FKP-based design method

Fig. 4. Three kinds of link capacity: newly added, reused, and unused

which means that the network with topological diversity obtained by the EVN design approach can easily adapt to dealing with new environments with less capacity. More importantly, a network with topological diversity can be effectively evolved, as we can see from the figure that the difference of total link capacity increases as k increases. Similar results were also obtained when setting the Sprint topology as the initial topology.

To see how the network with topological diversity can easily adapt to environmental changes in more detail, we show the capacity reused during the network growth. In Fig. 4(a), three kinds of link capacity, newly added, reused, and unused, are shown based on differences of link capacity before and after the addition of 50 nodes. Figure 4(a) shows the result of the EVN design approach, and Fig. 4(b) shows the result of FKP-based design method. Comparing these figures, we can clearly see that the FKP-based design method acquires more newly added and unused capacity as the network grows. The ratio of reused capacity to total capacity is kept low during network growth, which leads to the increase of the added and unused capacity. In the network obtained by the EVN design approach, the ratio of reused capacity to total capacity increases. That is, the amount of capacity added is kept low and the amount of capacity unused increases slowly. This is likely to be due to the small difference between the required capacities before and after the node additions.

C. Reused Facilities for Unexpected Environmental Changes

In the previous subsection, we showed that a network with topological diversity requires less capacity to deal with new environments. Thanks to the unspecialized design of the topology, most link capacity is reused for the new environment. The evaluation in the last section, however, assumed that link capacity is designed to cope with single node failure only.

In this subsection, we evaluate another aspect of evolvability: the ability to reuse capacity in response to unexpected environmental changes other than single node failures. However, since unpredicted environmental change is hard to define, we use a scenario of unpredicted environmental changes from [11]. We regard a single node failure between nodes as the environment assumed in designing a network. Then, we consider a scenario in which the same kind of environmental change occurs but the scale of environmental change is larger. Here, we choose two simultaneous node failures for the evaluation scenario. Note that, the amount of traffic demand we assume is the same as that assumed in Sec. III-B. Although actual traffic demand is different, our intention here is to show how the designed network reuses existing capacity in response to unexpected environmental change. Thus, we use unit traffic demand for simplicity.

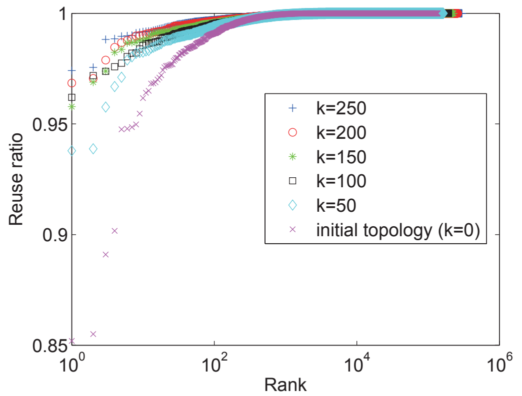
For evaluation, we define a *reuse ratio*, r_k, for a topology after k node additions:

$$r_k = \frac{F_k^{reused}}{F_k^{new}}, \quad (4)$$

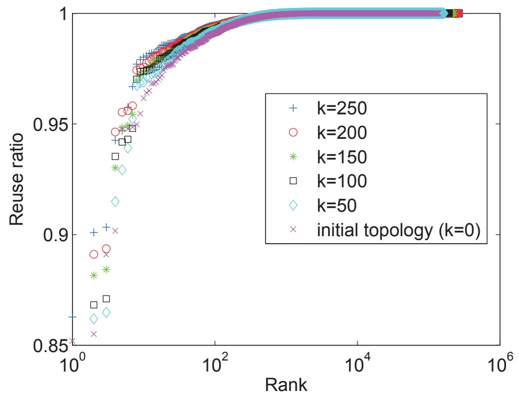
where F_k^{reused} represents the amount of capacity that can be reused from the capacity already been deployed, and F_k^{new} represents the amount of capacity that *was* required to deal with unpredicted environmental changes for the k-th network, that is, the network with k nodes added. r_k ranges from 0 to 1.0. If r_k is close to 1.0, capacity that is already in place can be reused for unpredicted environmental change. On the contrary, more capacity is required to deal with unpredicted environmental change as r_k decreases.

We evaluate the reuse ratio for two node failures in both G_k^{EVN} and G_k^{FKP}. The reuse ratio depends on the topology and failed nodes (denoted as n_1 and n_2). Thus, we refine the reuse ratios to $r_k^{EVN}(n_1, n_2)$ and $r_k^{FKP}(n_1, n_2)$.

Figure 5(a) shows the results for $r_k^{EVN}(n_1, n_2)$ for all cases of two-node (n_1, n_2) failures and Fig. 5(b) shows results for $r_k^{FKP}(n_1, n_2)$. Note that we again use the AT&T topology as the initial topology. In these figures, the horizontal axis represents the rank of reuse ratio in ascending order, and we show the results of reuse ratio by changing k. Looking at reuse ratios from rank 1 to 200, the ones obtained by the EVN design approach are higher than those of the FKP-based design method, and this tendency becomes clearer as k increases. This is a result of the increase of topological diversity. Because alternative paths for a single node failure would be less likely to be biased toward some links, the



(a) Reuse ratio for G_k^{EVN}



(b) Reuse ratio for G_k^{FKP}

Fig. 5. Evaluation result for failures of two nodes

capacity used for coping with single node failures is spread around the network. Therefore, even when a severe two node failure occurs, the required alternative paths could be provided mostly by reusing the capacity already in place. On the other hand, when the topology is less diverse, paths would be likely to be biased toward some links, so the capacity for coping with single node failures is also biased. Therefore, when a severe two-node failure occurs, alternative paths would use links that have less capacity in place other than the biased links, which leads to a lower reuse ratio.

We can also see the optimality of the EVN design approach from the figure. The number of two-node (n_1, n_2) failure patterns for which $r_{250}^{EVN}(n_1, n_2)$ is less than 1 is 26,417, and the number of patterns for which $r_{250}^{FKP}(n_1, n_2)$ is less than 1 is 6,239. This means that networks grown by the EVN design approach are less able to accommodate traffic completely. However, in the EVN design approach, because most values of $r_{250}^{EVN}(n_1, n_2)$ are almost 1, the shortfall can be covered by a slight over-provisioning of links.

IV. Conclusion and Future Work

In this paper, we have proposed a design approach based on minimizing mutual information to strengthen topological diversity and make the network evolvable. We have shown that a network grown using our design approach can grow with less capacity compared to a network grown using a method based on the FKP model. Furthermore, we have shown that capacity introduced for one environment can be used in another environment, thereby a network grown using our design approach experiences fewer changes in places where capacity is needed, and allows for more capacity reuse.

Several problems are left for future research. First, further evaluation is needed. In the simulation in this paper, we only add two links for a node to keep the average degree similar to the initial topology. However, there are also other cases in practical. Although we believe that the topology will also be diverse and evolvable when adding three links or more for a node, it should be investigated by simulation. Second, analytical investigation may be done to provide more clear discussion of evolvability of our approach to several other unexpected environmental changes. Third, the design approach of this paper considers mutual information which is characterized by degree-degree correlation only and does not consider the physical lengths of connecting links. In designing a network, the physical lengths of links is an important factor. The trade-off relationship between mutual information and physical distance when connecting nodes should be considered in the future.

Acknowledgment

This work was partly supported by Grant-in-Aid for Scientific Research (A) 24240010 from the Japan Society for the Promotion of Science (JSPS).

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