

A Biological Approach to Physical Topology Design for Plasticity in Optical Networks

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Abstract

We previously proposed a virtual network topology (VNT) control method that is adaptive to traffic changes. However, the performance of VNTs is fundamentally determined by the physical infrastructure, and the physical network therefore needs to be designed so that it is capable of utilizing the adaptiveness of the VNT control method. In this paper, we propose a design method for optical networks, e.g., wavelength division multiplexing (WDM) networks. This method is based on a biological evolution model and provides adaptability under various patterns of traffic fluctuation and traffic growth. Our method determines the set of nodes to which transceivers should be added in order to give *plasticity* to the designed network, where plasticity represents changeability of VNT against environmental variation. Evaluation results show that our method accommodates more patterns of traffic fluctuation with lower link utilization than ad-hoc design methods do.

Keywords: Wavelength Division Multiplexing (WDM), Optical network design, VNT control based on attractor selection, Physical topology design, Plasticity

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1. Introduction

In wavelength division multiplexing (WDM) networks, optical cross connects (OXCs) switch optical signals without optical-electrical-optical (OEO) conversion by using wavelength routing. A wavelength channel, called a lightpath, is established between nodes. Since the upper-layer's traffic, such as IP traffic, can change its nature, much research has examined the construction of a virtual network topology (VNT) on top of a WDM network [1, 2]. A VNT is a logical network composed of lightpaths, and the connectivity among routers can be easily reconfigured by establishing or tearing down lightpaths. When the traffic demand changes and certain performance metrics degrade to the point where they are no longer acceptable, the VNT is changed to a new VNT that exhibits optimal or near-optimal performance under the network environment as it exists at that time.

The environment of the Internet is rapidly changing. With the appearance of new web services such as video streaming and cloud computing, traffic volumes have increased rapidly and fluctuate drastically. Some VNT control methods have been studied for countering traffic fluctuations, showing good performance on metrics such as keeping link utilization lower by adaptively reconfiguring the VNT in accordance with traffic changes [3, 4]. However, when the traffic volume increases, VNT control methods may fail to find a suitable VNT. That is, there may be no solution that can provide good performance because of a lack of network resources or because of other problems. In such situations, network operators must reinforce the physical network resources. Much consideration has gone into physical network design [5, 6, 7, 8]. In Ref. [5], the authors consider designing a physical topology in which logical rings can be established for survivability while minimizing the number of physical links. In Ref. [6], the authors address both physical and logical topology design, and formulate the problem as an integer linear programming problem of minimizing the number of wavelengths used. In Ref. [7], the authors consider a routing and wavelength assignment problem in optical networks with the aim of minimizing the cost

over the long term under a restricted budget. In Ref. [8], the authors consider designing a mixed-line-rates network with minimum cost. Most of these works solve optimization problems against predicted traffic demand. However, when the environment changes drastically, it is natural that future traffic demand cannot be estimated accurately. Even if we are able to ‘specify’ future traffic demand by incorporating environmental uncertainty and use it in the design method, the designed network is specialized to the pre-specified situation, which may lose adaptability against unexpected traffic changes. Therefore, a new design approach that can accommodate various patterns of future traffic in conjunction with the VNT control method is needed.

In order to develop a new design approach, we consider biological evolution, which allows species to survive environmental changes over the long term. One important characteristic of biological evolution is *plasticity*, which describes the changeability against environmental changes [9]. In Ref. [9], the authors develop a gene expression dynamics model to explain how organisms can obtain both short-term (on the order of hours) robustness and long-term (on the order of days to years) plasticity. Following the gene expression dynamics model, we propose a method for designing physical networks and develop a design method for adding transceivers to IP routers in optical networks, e.g., IP-over-WDM networks. The number of transceivers is equal to the degree of virtual links, i.e., lightpaths, connected to the node. Our method determines a set of nodes to which transceivers should be added in order to give plasticity to the optical network. In an optical network capable of plasticity, it is expected that adaptive VNT control can enjoy plasticity of the physical infrastructure, and so network performance can avoid being degraded under various patterns of future traffic fluctuation, even unknown patterns. Through computational simulation, we confirm that our design method offers plasticity.

A preliminary version of this work has been presented in [10]. In our previous paper, we have introduced a concept of plasticity in designing optical networks and have compared with a heuristic method on the European optical network (EON) [11]. In the current paper, we introduce a mixed integer linear pro-

gramming (MILP) solution for comparison and show the effects of the plasticity on the EON, the US nationwide network (USNET) and the Japan backbone network (JBN).

65 The rest of this paper is organized as follows. In Sec. 2, we describe the purpose of our research. We then propose a method of optical network design capable of plasticity in Sec. 3 and show evaluation results in Sec. 4. We finally conclude this paper and mention future work in Sec. 5.

2. Adaptive VNT control and physical network design method

When traffic changes drastically, a dynamic VNT control method that can adapt to various changes in traffic is needed. We previously proposed a VNT control method based on attractor selection that exhibits high adaptability to unexpected changes in traffic demand [4]. In this VNT control method, lightpath reconfiguration is driven by the following expression:

$$\frac{dx_i}{dt} = \alpha \cdot f(\mathbf{x}) + \eta, \quad (1)$$

70 where x_i is a variable indicating that a lightpath between the node-pair i is configured when it exceeds a certain threshold. The function $f(\mathbf{x})$ represents deterministic behavior that causes the VNT to converge to one of the equilibrium point, that is, to an attractor. The activity α represents feedback of the network condition. When α is high, the system stays at an attractor that offers good
75 conditions. When the network condition worsens due to traffic fluctuations, α decreases towards zero until stochastic behavior dominates the system. That is, lightpaths are reconfigured at random in the search for another attractor. After a while, the VNT again converges on a new attractor thereby adapting to the traffic fluctuation.

80 Although our VNT control method is more successful in terms of obtaining robustness against traffic changes than other existing methods are, it fails to obtain a good VNT when the network resources are insufficient for the increased traffic. This is a fundamental limit that also applies to other methods. The

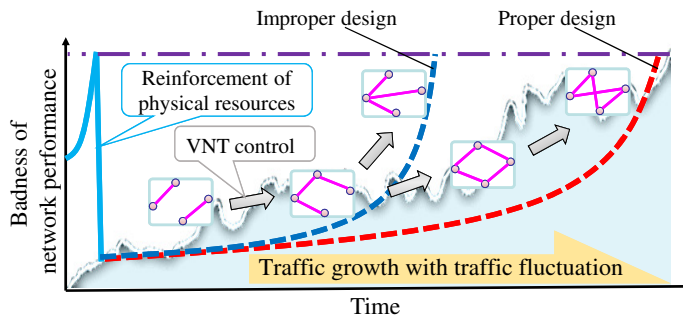


Figure 1: VNT control and network design to prepare for traffic growth

aim of this paper is therefore to consider a physical network design method
 85 for accommodating future unknown traffic demand as much as possible while
 keeping the adaptability of the attractor-based VNT control method. Figure 1
 illustrates the relation between VNT reconfiguration and our physical network
 design method. VNT control reconfigures the VNT over the physical network
 and adapts to traffic fluctuations. When traffic volume increases, we might
 90 not able to find a good VNT because of a shortage of network resources. We
 then need to add network resources such as physical links, IP routers, optical
 switches, and transceivers. Since the adaptability of VNT control depends on
 the underlying physical network, an improperly designed physical network may
 reduce the ability of VNT control to adapt to traffic fluctuations. We also note
 95 that our proposed design method is easily extended to incorporate other network
 resources. This proposal is applicable to not only our VNT control methods but
 also other existing dynamic VNT control methods.

3. Method for designing optical networks to have plasticity

In this paper, we apply a biological evolution model that mimics the ro-
 bustness and plasticity of biological systems. This is introduced in the next
 100 subsection. Note that while we understand it is a rather lengthy explanation, it
 is necessary for readers to understand how biological plasticity can be applied
 to our case.

3.1. Biological model

105 Organisms adapt to the environment through the evolution of a genetic network. Robustness and plasticity are thought to be basic characteristics in evolutionary biology. Robustness is the capacity of an organism to maintain its own state and function against disturbances. In contrast, plasticity is changeability or flexibility in response to environmental fluctuations [9]. Organisms are able
110 to adapt to new and/or unexperienced environments by greatly changing state as the external environment changes. Plasticity expresses sensitivity to external perturbations, and is an important characteristic for adaptive evolution.

In Ref. [9], the author formulates a model of the evolution process by taking account both biological robustness and plasticity. In the model, an organism
115 optimizes the value of fitness against various kinds of environmental changes by changing gene expression (phenotype), in which the dynamics are governed by activation/inhibition between genes (genotype). The model consists of several elements (Figure 2), each of which is explained below.

gene: There are M genes. Each gene i has its own expression level x_i ($-1 \leq$
120 $x_i \leq 1$). When x_i exceeds some threshold θ_i , gene i is expressed. Otherwise, gene i is not expressed.

input gene: k_{inp} genes among the M genes are input genes, and their gene expression levels are given initially and do not change regardless of the gene expression dynamics. Without loss of generality, we regard genes
125 x_i ($1 \leq i \leq k_{inp}$) as the input genes. Changes in the expression levels of these input genes represents a change in the environment.

phenotype: As a result of the gene expression dynamics, the gene expression levels x_i ($k_{inp} < i \leq M$) converge to some set of values. Note that the input gene expression levels are independent of the gene expression dynamics.
130 Some genes are expressed and others are not expressed, thus forming a pattern of expressed genes. This pattern is called a phenotype. In Figure 2, expressed genes are represented by filled circles and have a phenotypic

value of 1, while non-expressed genes are represented by open circles and have a phenotypic value of 0.

135 **genotype:** Genes are related to each other. These mutual relations are defined by a gene regulatory network. In Figure 2 each solid arrow represents an activating relation from one gene to another, and each dashed arrow represents an inhibiting relation. $J_{ij} (= \{-1, 0, 1\})$ represents the activation/inhibition relation between gene i and gene j . When $J_{ij} = 1$, gene i receives an activation effect from gene j . When $J_{ij} = -1$, gene i receives an inhibition effect from gene j . When $J_{ij} = 0$, there is no relation between genes i and j . A matrix J with elements J_{ij} is a gene regulatory network and is called a genotype. J determines the gene expression dynamics.

145 **fitness:** Fitness represents the adaptability to the present environment or condition of the system, and is calculated by a function $F(\textit{phenotype})$. That is, the fitness value is determined by the pattern of gene expression, which is governed by the genotype. From a biological perspective, a typical example of the function F is the number of expressed target genes. We select the target genes for this example from the perspective of a biological context. $F(\textit{phenotype})$ becomes the highest when the expression pattern of target genes consists of all 1s. From a network design perspective, introducing target genes is not necessary. We simply use traditional performance metrics to calculate the fitness value. In this paper, we will use the average link utilization of the VNT for calculating the fitness.

The dynamics of gene expression levels is then described by the following equation,

$$dx_i/dt = \gamma \left\{ f \left(\sum_j^M J_{ij} x_j \right) - x_i \right\} + \sigma \eta_i, \quad (2)$$

where the first term represents the deterministic behavior driven by the gene regulatory network J_{ij} , γ is a constant. Here, $f(z)$ is a sigmoid function defined

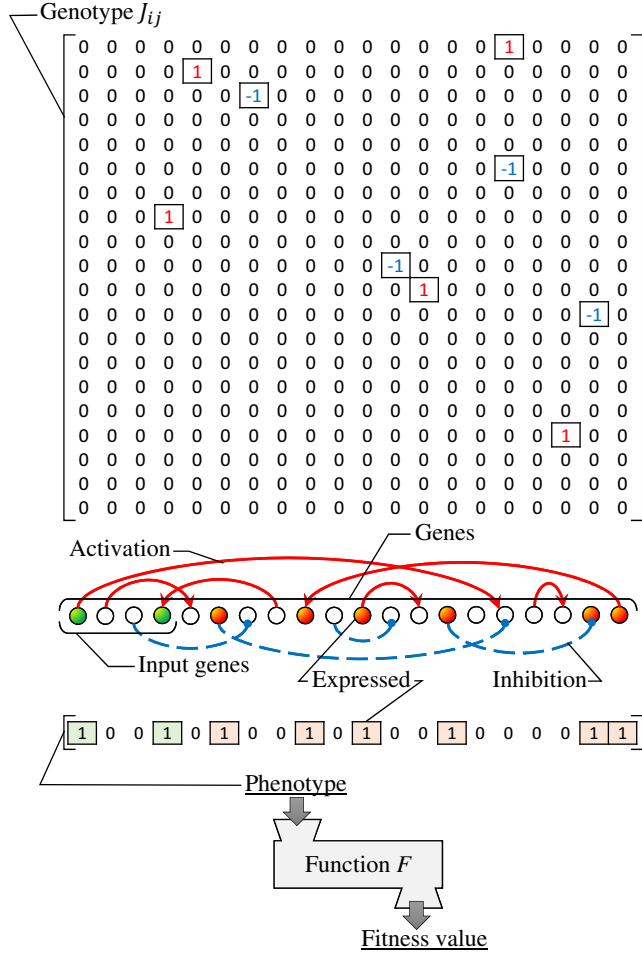


Figure 2: Genetic model for $M = 20, k_{inp} = 4$

by

$$f(z) = \frac{1}{1 + \exp^{-\beta(z-\theta_i)}} + \delta, \quad (3)$$

where β is a parameter that determines the gradient in the neighborhood of the threshold θ_i and δ is a small positive number that represents a spontaneous expression level. The second term of Eq. (2) represents stochastic behavior caused by noise from the environment. In this, η_i is a random value that follows a normal distribution with a mean of zero and variance of σ^2 .

The evolution model repeats a selection-mutation process for each genera-

tion. We start with N individuals, each of which has slightly different gene regulatory networks $\{J_{ij}^1, \dots, J_{ij}^N\}$. In each generation, each individual updates its gene expression levels, x_i , by calculating the differential equation (2) for its own J_{ij} . The pattern of gene expression levels (i.e., the phenotype) determines the value of the fitness, $F(\text{phenotype})$. That is, we obtain N fitness values that depend on the gene regulatory networks. The selection-mutation process is then applied to the N gene regulatory networks. Among the N gene regulatory networks, the N_s gene regulatory networks that show the highest fitness values are selected and kept for the next generation. The unselected gene regulatory networks are excluded from further calculations. N_s is a tunable parameter which we set to $N/4$ in the following. Each of the selected N_s gene regulatory networks is then mutated into 4 individuals by randomly choosing a few components in the matrices and changing the values to a random value from $\{-1, 0, 1\}$. This calculation of gene expression dynamics and selection-mutation process are repeated over many generations.

We can now explain how biological systems exhibit both robustness and plasticity. When the environment changes, that is, when the expression levels of the input genes change, the biological system first reacts through an increase in phenotypic variance. This reaction gives the biological system plasticity, which represents changeability in response to environmental changes. Robustness is obtained through the selection-mutation process. Once a genotype that produces a phenotype with higher fitness is found, its progeny will account for a large majority of individuals. The phenotypic variance thus decreases again.

3.2. Applying our method to add transceivers

In this paper, we consider optical transceivers as a target device for increasing the resources in a WDM network. Figure 3 shows a simple example of our application. A lightpath can be established only when transceivers are present at both end-nodes. Adding a transceiver may then result in making a new lightpath available. In this situation, the key is the selection of nodes to which we should add transceivers. Our proposed method determines the set of nodes

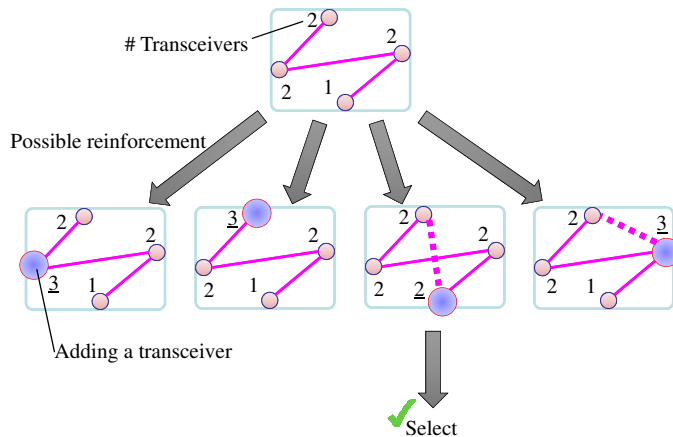


Figure 3: Example of applying our model to a WDM network

(IP routers) to which transceivers should be added in order to give plasticity to the network by applying the biological evolution model.

3.2.1. Applying the biological evolution model to WDM network design

195 Table 1 shows the correspondence between the genetic evolution model and the design method for WDM networks. When the number of nodes in the WDM network topology is n , the number of candidates for lightpaths is equal to the number of node-pairs, n^2 . Each gene i corresponds with a lightpath l_i , where $i = 1, 2, \dots, n^2$, and this correspondence is one-to-one. In each generation, the gene expression levels x_i are determined from the results of the expression dynamics (2). In the phenotype, that is, the pattern of gene expression levels that determines the VNT, the lightpath l_i is switched on (established) if x_i exceeds the threshold θ_i , and otherwise the lightpath l_i is switched off. Some constraints, such as wavelength-continuity constraints, that restrict the lightpath

200

205 establishment can be easily incorporated by restricting this phenotype-to-VNT conversion. In this paper, we will establish a lightpath only when there are available transceivers at the both source and destination IP routers. Note that, x_i where i equals to k^2 ($k = 1, \dots, n$), which represents a lightpath from one node to itself, is fixed to 0 to avoid a self-loop.

Table 1: Correspondence between evolution model and WDM network

Biological evolution	WDM network
Dynamics of gene expression level	VNT control
Phenotype	VNT
Genotype	Regulatory matrix
Fitness	Average link utilization
Environmental change	Change in traffic demand

210 We use the average link utilization of the VNT to characterize the fitness. In the biological model, fitness is calculated on basis of the expression pattern of some of the genes. In our model, we instead substitute the average link utilization for the value of fitness. Note that lower values of average link utilization are more desirable. We therefore define fitness as the multiplicative inverse of
215 average link utilization.

We treat changes to the physical network as an environmental change. In the biological model, the environment is represented by the expression of input genes with environmental changes given by modifying the values of input-gene expression levels. In our WDM design method, we assign the progress of adding
220 transceivers as the values of the input genes. The number of input genes is equal to the number of WDM nodes, n . Therefore, there are n^2 ordinary genes ($i = 1, 2, \dots, n^2$) and n input genes ($i = n^2 + 1, n^2 + 2, \dots, n^2 + n$), giving $n^2 + n$ genes in total. The gene $n^2 + i$ represents the node N_i . Initially, the expression levels of all input genes are zero. Each time a transceiver is added to node N_i ,
225 the expression level of gene $n^2 + i$ is incremented by 1 to express the effect of the physical network change, even though this may violate the allowable range of expression levels. This is one way to take changes to the WDM network into account in terms of the effect on expression dynamics and the way the VNT is constructed.

230 *3.2.2. Evaluation of the plasticity of the WDM network*

Our proposed method aims to determine the set of nodes (IP routers) to which transceivers should be added in order to give plasticity to the network. For this purpose, the degree of plasticity of a physical network needs to be evaluated. We thus examine the evolution process via the following steps.

235 **Step 1** Observe the traffic demand.

Step 2 Repeat the selection-mutation process over $T(= 15)$ generations. In each generation, determine a VNT by using Eq. (2). The fitness value is then calculated given the observed traffic demand.

Step 3 Execute the following sub-steps S times.

240 **Step 3.1** Change the traffic demand.

Step 3.2 Repeat the selection-mutation process over T generations. Calculate the fitness with the changed traffic demand.

Step 4 Calculate the degree of plasticity by using the S fitness values obtained in Step 3.

245 At the beginning of reinforcement, we first obtain the traffic demand (Step 1). In Step 2, we examine the selection-mutation process for the observed traffic demand and obtain a set of gene regulatory networks J_{ij} that are suitable for the observed traffic demand. In Step 3, we examine various patterns of traffic fluctuations in a random manner. Note that a single pattern of traffic fluctuation is not sufficient for estimating the plasticity. We obtain $S(= 16)$ fitness values
250 as a result of Step 3. In this paper, the degree of plasticity is chosen as the median fitness value.

3.2.3. Proposed design method

Our aim is to give plasticity to a WDM network as a result of adding
255 transceivers. We evaluate the plasticity by computational simulation in which some transceivers are added to a certain set of nodes. However, it is difficult to

estimate the plasticity in order to select the locations for the transceivers since the number of possible combinations of locations increases exponentially as the number of transceivers increases. We therefore apply a simple heuristic, called the ADD algorithm [12], to determine the locations for the transceivers. Given
260 the number of transceivers to add, the ADD algorithm works as follows.

Step 1 Select a node at which to add a transceiver by calculating the plasticity when a transceiver is added to the node.

Step 1.1 Temporarily add a transceiver to each node.

265 **Step 1.2** Evaluate the plasticity of the WDM network as explained in Sec. 3.2.2.

Step 1.3 Select the node that gives the highest value of plasticity in Step 1.2.

Step 2 Add a transceiver to the selected node. If there are more transceivers to add, go back to Step 1.

270 In this paper, we consider a situation in which traffic demands keep on increasing, and apply the ADD algorithm to decide where to add transceivers. In practice, the traffic demands may possibly be decreased, but we can again apply our method to decide which transceivers should be removed by replacing “add” with “remove” in the algorithm.

275 3.3. Time scale of VNT control and network reinforcement

The biological evolution model explains how organisms obtain plasticity. When we apply the biological evolution model to network design methods, the question arises of when transceivers should be added. Organisms may have their own cycle for applying the evolutionary processes discussed above. In the case of
280 our network design problem, we assume that network reinforcement is performed when the VNT control method cannot find a good VNT. Note that we define the goodness of a VNT according to link utilization under the current traffic demand. Thus, network reinforcement is performed when the VNT control cannot achieve a link utilization that is lower than a certain threshold.

285 Figure 4 illustrates the time scale of VNT control, network reinforcement,
and traffic changes. In the figure, the horizontal axis represents the time step
of traffic changes, and the volume of traffic demand increases at each time step.
At each step, if necessary, the VNT control method tries to find a good VNT
for the traffic demand. If the VNT control method finds a good VNT, then it
290 keeps the existing VNT until the next time step (see time steps 0, 1, and 2 in
the figure). If the VNT control method cannot find a good VNT at time-step
 t , then we treat the VNT control as having failed at t . Network reinforcement
is then performed as soon as we know that the VNT control has failed, and the
VNT control method is again applied at time-step $t + 1$. In this illustration, we
295 assume that the solution of the reinforcement is calculated within a time-step for
simplicity. When the algorithm takes several time-steps to find the solution, the
network operator should execute the reinforcement method more conservatively
so as not to take a high link utilization during the calculation. Note that VNT
control method works every time-step even when our design algorithm is under
300 calculation. Thus, it is necessary for our design approach to prevent lack of
resources during the calculation.

3.4. Possible extension

In this paper, we treat the transceivers in IP routers as physical network
resources. Our basic idea can easily be extended to the deployment of other
305 network resources such as physical links and/or nodes. For example, when
considering the deployment of physical links, we could assign input genes to the
node-pairs between which links can be connected instead of the nodes to which
transceivers can be added.

4. Evaluation

310 We evaluated the performance of the proposed method by computer simula-
tion. The performance is measured in terms of the adaptability of the attractor-
based VNT control method [4] on a WDM network that has been reinforced by
the design method.

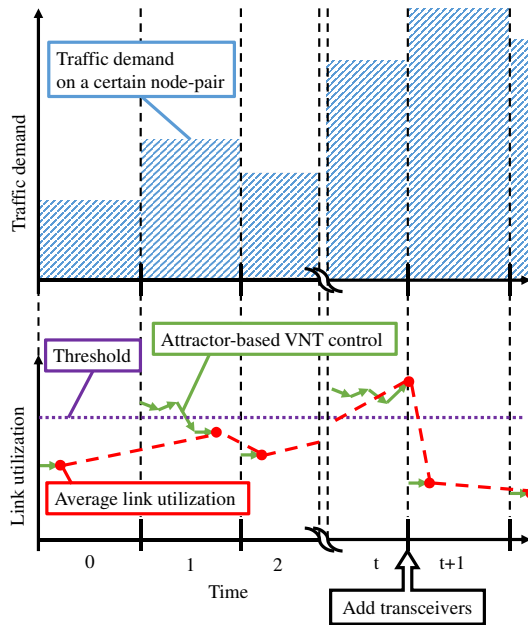


Figure 4: Relation between VNT control and network reinforcement

4.1. Methods for comparison

315 We consider an ad-hoc design approach for comparison purposes. Constructing a general design method as a method for comparison is unreasonable. This is because the design principle depends on the situation, such as the business scenario, available traffic information, or user demand.

The ad-hoc design approach here is intended to decide an effective placement
 320 of resources to achieve the best VNT performance. To do this, a VNT configuration method which intends to minimize the link utilization is applied, supposing resource reinforcement was done at a certain place. The above process is then repeated until reinforcement at all possible places is examined. For the VNT configuration method, mixed integer linear programming (MILP) methods of
 325 lightpath assignment [13] have been used, and heuristic methods have also been used. These methods collect the present traffic demand information, or predict future traffic demand in some cases, and then attempt to minimize the network load as characterized here by link utilization.

We construct the ad-hoc design by both MILP and heuristic methods. The
330 formulation of the MILP is introduced in Sec. 4.1.1. The heuristic method,
I-MLTDA, is introduced in Sec. 4.1.2. The flow of the ad-hoc design process is
as follows.

Step 1 For each candidate, do the following sub-steps.

Step 1.1 Temporarily add transceivers to the node.

335 **Step 1.2** Execute {MILP|Heuristic} against the traffic demands at the time of
reinforcement.

Step 1.3 Evaluate the average link utilization for the VNT obtained in Step
1.2.

Step 2 Determine a node at which to add transceivers. We select the node that
340 shows the lowest value of average link utilization and then add transceivers
to that node. Go back to Step 1 if there are more transceivers to add.

These design approaches are expected to show good performance in cases
where the environment changes slowly and moderately. Traffic prediction may
also help the designs. However, they are expected to show a severe degradation
345 on performance in cases where traffic demand changes drastically and traffic
prediction is not feasible. Our proposed design aims to accommodate various
types of traffic change rather than to minimize the present link utilization.

4.1.1. MILP

We use the following formulation of MILP to obtain lightpath assignment
350 that minimizes the link utilization.

Notation:

\mathbf{V} : Set of physical nodes.

N : Number of physical nodes. $N = |\mathbf{V}|$.

u, v, s, d : Node ID.

355 **Given:**

d_u : Number of transmitters and receivers at node u .

T_{uv} : Traffic demand from node u to node v , collected in some way and assumed to be known.

Variables:

360 x_{uv} : Binary variable that takes the value 1 if a lightpath is established from node u to node v , and 0 otherwise.

f_d^{uv} : Amount of traffic demand toward node d via the lightpath from node u to node v .

Constraint 1: The number of transceivers on each node limits the number of lightpaths that can be established.

$$\sum_v x_{uv} \leq d_u \quad \forall u \in \mathbf{V} \quad (4)$$

$$\sum_u x_{uv} \leq d_v \quad \forall v \in \mathbf{V} \quad (5)$$

Constraint 2: A lightpath from node u to node v must be established if there is some traffic demand to go through it. Note that traffic demand values are scaled so that the sum does not exceed 1.0.

$$x_{uv} \geq \sum_d f_d^{uv} \quad \forall u, v \in \mathbf{V} \quad (6)$$

Constraint 3: Consistency of traffic accommodation and injection.

$$\sum_u f_d^{ud} = \sum_s T_{sd} \quad \forall d \in \mathbf{V} \quad (7)$$

$$\sum_v f_d^{kv} = \sum_u f_d^{uk} + T_{kd} \quad \forall k, d \in \mathbf{V} (k \neq d) \quad (8)$$

Constraint 4: Connectivity of physical topology.

$$x_{uv} = 1 \quad \forall (u, v) \quad s.t. \quad u \text{ and } v \text{ are physically connected.} \quad (9)$$

Objective: Minimizing traffic load on links of VNT.

$$\text{minimize } \sum_d \sum_u \sum_v f_d^{uv} \quad (10)$$

4.1.2. Heuristic method (I-MLTDA)

365 The increasing multi-hop logical topology design algorithm (I-MLTDA) [3] is a heuristic method of designing a quasi-optimal VNT by using traffic demand and hop lengths. I-MLTDA establishes lightpaths between node-pairs (s, d) in order from those that show the largest values of $\Delta^{sd} \times (H^{sd} - 1)$, where Δ^{sd} is the traffic demand from node s to node d and H^{sd} is the hop length along the
370 shortest path from s to d . The details of I-MLTDA are as follows.

Step 1 Establish a lightpath between every node-pair that has a physical connection. Go to Step 2.

Step 2 Calculate the shortest path and determine the value of H^{sd} for each s and d . Go to Step 3.

375 **Step 3** Determine the node-pair (s, d) that exhibits the maximum value of $\Delta^{sd} \times (H^{sd} - 1)$. If $\Delta^{sd} \times (H^{sd} - 1)$ is 0, stop. Otherwise, go to Step 4.

Step 4 If available transceivers remain on node s and node d , then establish a lightpath from node s to node d . Otherwise, set the value of Δ^{sd} to 0. Go to Step 2.

380 In this paper, we use I-MLTDA for the heuristic algorithm. Although various design methods have been proposed, our purpose for introducing the ad-hoc design method is to examine the failure of design methods that are optimized and specialized to an environment as it exists at one point in time. We believe that our results in Sec. 4.3 are also valid for other heuristic algorithms.

385 4.2. Simulation environments

This section explains the environments used in our simulation.

Table 2: Numbers of nodes and links

Topology	# of nodes	# of links
EON	19	39
USNET	24	42
JBN	49	91

4.2.1. Topology

We evaluated our proposed method on three physical topologies: the European Optical Network (EON) model [11], the USNET model [14], and the Japan telecommunication network model (which we call the JBN model) [15]. Figure 5 shows these topologies, and Table 2 shows the number of nodes and links in each topology. Each node is composed of an IP router and an OXC. Each OXC is connected to other OXCs by links, as shown in Figure 5. Each link is a single optical fiber. Establishing lightpath between an IP router and another IP router uses one transceiver of the source node and one transceiver of the destination node. A lightpath can be established when there are available transceivers at both source and destination routers. The initial number of transceivers at each node is set to 2 plus the degree of the node in the physical topology.

We execute computer simulations on the three physical topologies. For the EON topology, we compare our proposed method with the MILP-based method and the heuristic-based method. For the USNET topology and the JBN topology, we perform comparisons with only the heuristic-based method because the computation time needed for MILP becomes enormous for large topologies. However, from the results obtained for the EON topology, the distribution of the average link utilization in the MILP-based design is much the same as that in the heuristic-based design. Similar trends are also expected to be obtained for the USNET and JBN topologies.

4.2.2. Traffic demand model

Each node-pair has its own traffic demand. The initial values follow a log-normal distribution according to [16]; specifically, each traffic demand is set to a random number following $LN(\mu = 1, \sigma^2 = 0.5^2)$. The traffic demand is then increased or decreased at each time-step. Taking $T_{act}^{i,j}(t)$ to represent the traffic demand from node i to node j at time-step t , the traffic demand model [17] is defined by the following expression

$$T_{act}^{i,j}(t) = T_{exp}^{i,j}(t) + N(0, (\sigma_{noise} \times T_{exp}^{i,j}(t))^2), \quad (11)$$

where $T_{exp}^{i,j}(t)$ is the expected value of traffic demand from node i to node j at time-step t . The second term represents unexpected traffic fluctuations and is set to a random value, following a normal distribution $N(0, (\sigma_{noise} \times T_{exp}^{i,j}(t))^2)$. Higher values of σ_{noise} represent sharper changes in traffic demand. In contrast, when σ_{noise} takes a lower value, the noise term has less effect and $T_{act}^{i,j}(t)$ is close to $T_{exp}^{i,j}(t)$. The values $T_{exp}^{i,j}(t)$ are calculated from the following recurrence formula:

$$T_{exp}^{i,j}(t) = m + T_{act}^{i,j}(t - 1). \quad (12)$$

The expected value increases by m at each time step. Therefore, traffic demands
 410 continue to increase on average, but the trends in traffic fluctuation are different for each node-pair. The traffic in the VNT is assumed to be forwarded along the path with the minimum-hop path.

4.2.3. Attractor-based VNT control method

We use the attractor-based VNT control method in the evaluation. We
 415 again apply I-MLTDA as the VNT control method as well. However, our primary purpose is to design a WDM network that maximizes the adaptability of VNT control, and so we also use our attractor-based VNT control method for evaluation.

Our VNT control method is driven by activity, which is a feedback of network status. When activity is low, the random behavior tries to seek a better VNT.

In this paper, the activity is given by the following equation

$$activity = \frac{\gamma}{1 + e^{\delta(L_{average} - \theta)}}, \quad (13)$$

where $L_{average}$ is the average link utilization and other literals are parameters. With this definition, the activity rapidly approaches zero when the average link utilization exceeds θ . That is, the VNT control method attempts to reduce the average link utilization to less than the threshold. The activity value is always in the range $(0, 1)$ since we set $\gamma = 1$. The condition of the IP network is assumed to be poor whenever the average link utilization is greater than θ . In this work, we set the threshold θ to 0.25 for the EON topology and to 0.50 for the USNET and JBN topologies. The gradient δ of the activity function is set to 50, following Ref. [4].

4.3. Simulation results

4.3.1. Evaluation against future traffic changes

We set σ_{noise} in Eq. (11) to 0 at the beginning of the simulation and apply attractor-based VNT control. Following Eqs. (11) and (12), the traffic demand eventually increases over time. At this point, we set m to 0.01. At time-step $t_{reinforce}$, the VNT control method fails to find a good VNT among 400 recon-
 435 the node at which to add transceivers. The methods select three nodes to re-
 440 reinforce transceivers, and 4 transceivers are added to each selected node. Table 3 shows the results of the calculations for each topology. For example, in the EON topology, the VNT control method fails at time-step 140, and our proposed method then adds transceivers to nodes $\{6, 6, 11\}$, where the repetition of node 6 indicates it is chosen multiple times.

Since the proposed method has higher computational complexity than the heuristic-based method does, it takes much longer to execute the simulation with this method. However, the computational time is not a significant problem here because physical network designs are not expected to be executed over short intervals but, instead, over the long term. Note that we stop the MILP execution

Table 3: Calculation results (transceivers are added to the following nodes)

Topology	$t_{\text{reinforce}}$	Proposed	MILP-based	Heuristic-based
EON	140	{6, 6, 11}	{13, 6, 18}	{11, 12, 18}
USNET	214	{6, 6, 6}	-	{18, 23, 3}
JBN	118	{24, 24, 24}	-	{37, 46, 19}

of Step 1.2 in Sec. 4.1 after 10 minutes and then use the results obtained by then as an approximate solution.

We evaluate the adaptability of the reinforced WDM network against unexpected traffic increases. After the reinforcement, we set the parameter σ_{noise} to 0.10 and examine the various patterns of traffic fluctuation to check whether the attractor-based VNT control method can find a good VNT.

Figure 6 shows the distribution of average link utilization at time-step t_{evaluate} for 1000 patterns of traffic fluctuation on the EON topology. We define $t_{\text{evaluate}} = t_{\text{reinforce}} + 70$. Note that the traffic increases and fluctuates in different ways from time-step $t_{\text{reinforce}}$ to t_{evaluate} . Therefore, Figure 6 shows the performance of the VNT control method against various patterns of traffic fluctuation. The threshold of the activity is set to 0.25, that is, the VNT control method is assumed to be successful if the average link utilization is less than 0.25. First, Figure 6(a) shows the comparison between the proposed design and the MILP-based design. Both the proposed design and the MILP-based design succeed in accommodating most traffic patterns with admissible values. However, more traffic patterns are accommodated with lower link utilization by the proposed method than are accommodated by the MILP-based design method. In addition, the proposed design fails for fewer traffic patterns than the MILP-based design does. Second, Figure 6(b) shows the comparison between the MILP-based design and the heuristic-based design. The heuristic-based design for the EON topology adds transceivers to nodes {11, 12, 18}, different from the decision of the MILP-based design. However, looking at Fig. 6(b), the distributions

of link utilization by both of the ad-hoc designs are almost the same. Thus, we
470 use the heuristic-based design as an ad-hoc design for the examination on the
USNET and JBN topologies, since they are large topologies and are difficult for
the MILP calculation.

Figure 7 shows the results on the USNET and JBN topologies. In Figs. 7(a)
and 7(b), the threshold of the activity is set to 0.5. In these situations, the
475 VNT control succeeds for almost all traffic patterns, and more traffic patterns
are accommodated with lower link utilization by the proposed design as with the
EON topology. We can conclude that the proposed method makes the optical
network more flexible, that is, our method improves the ability to accommodate
various traffic fluctuations with lower link utilization.

480 Figure 8 shows the complementary cumulative distribution function (CCDF)
for each network, using the same data as before. In Figure 8(a), the CCDF of
the intersection points with the vertical line at 0.25 are 0.143 and 0.339 respec-
tively. This indicates that the proposed method accommodates 857 patterns
of traffic fluctuation, the MILP based design method accommodates 661 on
485 the EON topology. Consequently, the proposed method raises the success rate,
which is a rate of the traffic patterns where the attracted-based VNT control
method makes the average link utilization lower than the threshold, by about
29% ($0.857/0.661 \approx 1.297$) compared with the ad-hoc design methods.

4.3.2. Evaluation with respect to noise strength

490 We evaluated additional simulations on the EON topology by changing the
noise strength σ_{noise} of traffic fluctuations to see whether the network suggested
by our design method can accommodate various patterns of traffic fluctuation.
Figure 9 shows the success rate of the VNT against σ_{noise} . We examine 100
patterns of traffic fluctuation and calculate the success rate for each σ_{noise} ,
495 and the average/minimum/maximum of success rates over 10 examinations are
plotted. We observe that the proposed design improves the success rate when
traffic fluctuates strongly. When the noise level is low, both the proposed design
achieve an almost 100% success rate, and the MILP-based design also achieves

a success rate of over 95%. This is because the networks from the ad-hoc
 500 design are optimized and specialized to the traffic-demand matrix at the time of
 reinforcement, and the traffic demand matrix does not change drastically with
 lower levels of σ_{noise} . However, as the noise level increases, the traffic changes
 more drastically and the VNT control using the ad-hoc design cannot handle
 the traffic fluctuations. In comparison, the proposed design with VNT control
 505 can accommodate more traffic patterns, even when σ_{noise} is high.

Figure 10 shows the distribution of average link utilization against different
 σ_{noise} . The upper bar indicates the maximum value of average link utilization
 against 1000 patterns of traffic fluctuation. In the same way, the lower bar
 indicates the minimum value and the center bar indicates the median value.
 510 The box region indicates the range of the average link utilizations for 80% traffic
 patterns, which excludes the worst 10% and the best 10%. Focusing on the upper
 bound of the box for each value of σ_{noise} , it can be seen that the proposed
 design keeps the values smaller than the ad-hoc design does. Therefore, the
 proposed design is able to maintain the adaptability of the VNT control against
 515 most traffic fluctuations. However, the box ranges of the proposed design are
 larger, and the maximum value sometimes exceeds that obtained with the ad-
 hoc design. This is caused by the stochastic behavior of the attractor-based
 VNT control. When the average link utilization exceeds the threshold 0.25 (or
 0.5) and the activity is reduced to 0, the system continues to search for a new
 520 VNT due to the stochastic term η . Hence, the final VNT after 400 iterations
 may be worse. However, this problem is not particularly critical and can also
 be mitigated by dynamically reconfiguring the activity [18].

5. Conclusions

We proposed a design method for optical networks with a concept of plas-
 525 ticity. The method determines the set of nodes where transceivers should be
 added and is inspired by biological evolution with the aim of network plastic-
 ity. Computer simulation for some WDM networks showed that our method

makes attractor-based VNT control methods more adaptive to unexpected traffic fluctuations and reduces degradation of the adaptability under strong traffic
530 fluctuations.

In the future, we intend to extend our method so that it can not only add transceivers to nodes but also add links between nodes.

Acknowledgment

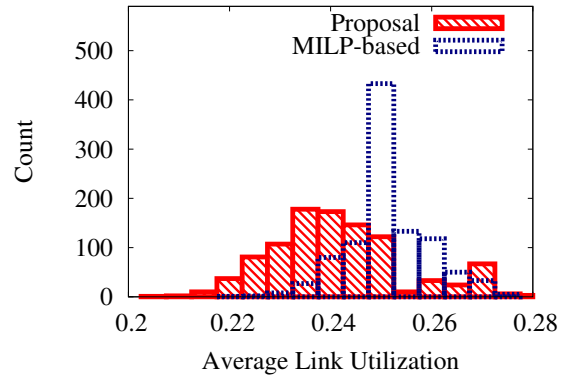
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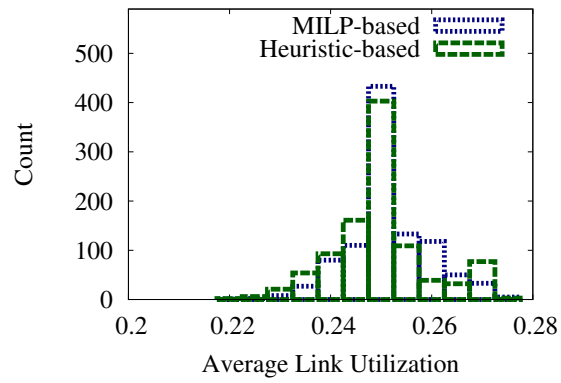
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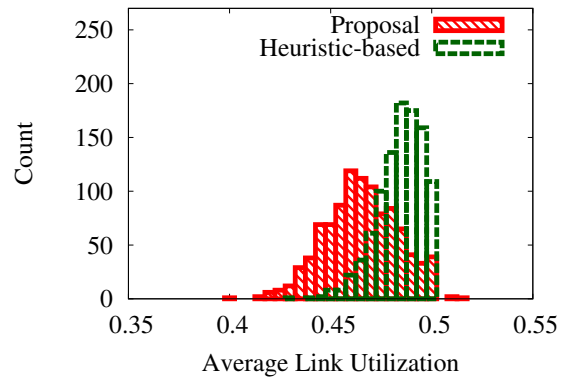


(a) Proposal - MILP

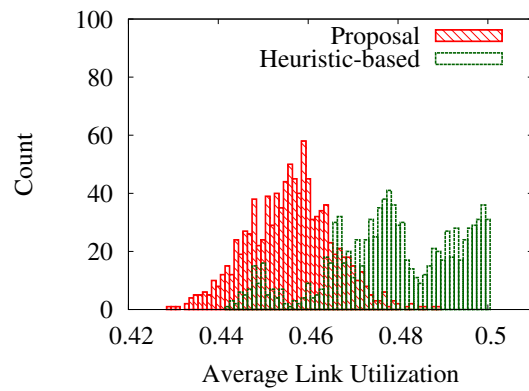


(b) MILP - Heuristic

Figure 6: Distribution of average link utilization: Histogram on EON

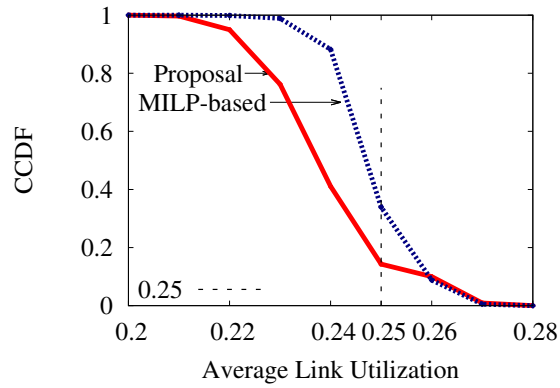


(a) USNET

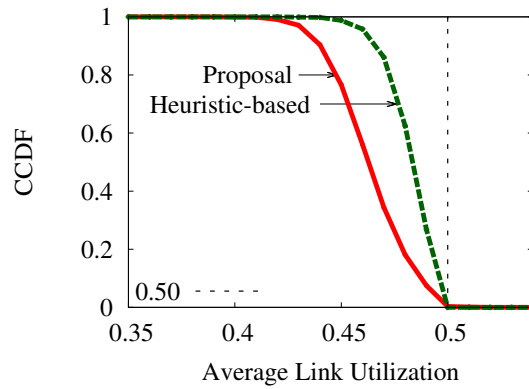


(b) JBN

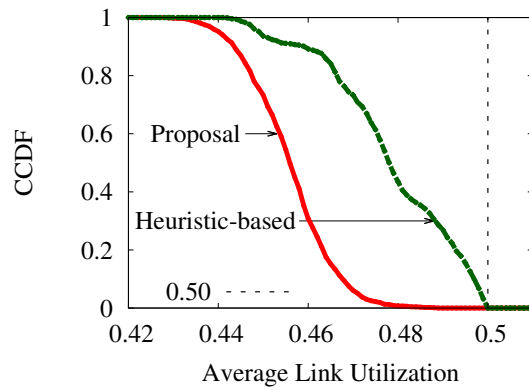
Figure 7: Distribution of average link utilization: Histogram



(a) EON



(b) USNET



(c) JBN

Figure 8: Distribution of average link utilization: complementary cumulative distribution function (CCDF)

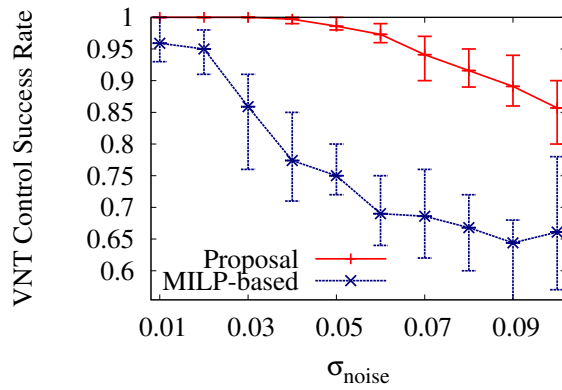


Figure 9: VNT control success rate

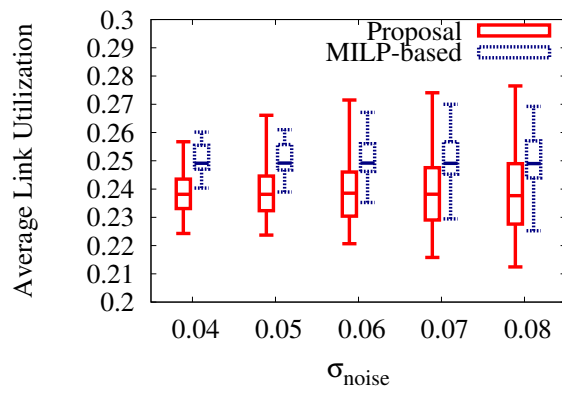


Figure 10: Distribution of average link utilization against different σ_{noise}