

Optical-Layer Traffic Engineering with Link Load Estimation for Large-Scale Optical Networks

Yuya Tarutani, Yuichi Ohsita, Shin'ichi Arakawa, and Masayuki Murata

Abstract—Traffic information is required to perform optical-layer traffic engineering (TE). However, as the number of nodes in optical networks increases, the overhead for collecting the traffic volume information becomes large. In this paper, we develop a method that reduces the overhead for collecting traffic volume information by selecting a subset of nodes and by only collecting the traffic volume information from the selected nodes. Then, we estimate the traffic volume using the information gathered from the selected nodes. According to the simulation results, we clarify that our method can accurately identify the congested links in real ISP topologies, where the number of traffic demands passing through some links is large; however, the estimation errors of our method become large when the number of traffic demands passing each link is small. Furthermore, optical-layer TE can sufficiently mitigate congestion by using the traffic volume estimated by our method from the information of 50% of all nodes in the case of Japan topology and 30% of all nodes in the case of AT&T topology.

Index Terms—Estimation; Selection of Source Nodes; Traffic Engineering; Optical Network;

I. INTRODUCTION

In recent years, various new applications, such as peer-to-peer and video on demand have been deployed over the Internet, leading to sudden and significant changes in traffic volume. Network providers must cost-effectively handle such significant traffic changes. Optical-layer traffic engineering (TE) [1-7] is one approach for handling traffic changes in a cost-effective manner. In optical-layer TE, in response to the changes of traffic volume in a network, a virtual network topology (VNT) is dynamically configured by setting up optical paths through optical cross-connects. The optical path is considered a directly connected high-capacity link for edge nodes. The traffic between two edge nodes is conveyed over the VNT by IP-layer routing. By reconfiguring the VNT to suit the current traffic, optical-layer TE handles significant traffic changes and mitigates the congestion caused by traffic changes. In optical-layer TE, the VNT and the traffic route are calculated and controlled with a centralized server.

To perform optical-layer TE, the centralized server needs to collect traffic information from the network. However, the granularity of the traffic information may differ depending on the required optimality and the overhead introduced by TE. For example, when we apply optimization techniques to determine the VNT and the traffic route, we need a traffic matrix that expresses the traffic demands between edge-to-edge nodes. However, collecting all traffic demands

requires monitoring overheads at each node; i.e., a packet-header inspection is necessary to identify the destination node. In addition, because the centralized server needs to collect information about the traffic demand from every node, a collecting overhead is required. The CPU loads and the bandwidth required for collecting the traffic demands increase with the number of nodes in the network [8]. One reason for this is that the centralized server must query all nodes to retrieve the traffic information.

One of the approaches for reducing the monitoring overhead is to perform TE by using the traffic volume information on each link. The traffic volume information can be easily counted at the node. Juva [9] calculated the range of each traffic demand by using the traffic volume information on each link and optimized the traffic routes to minimize the worst case of link utilization. Roughan et al. [1] and Ohsita et al. [2, 3] calculated the VNT and/or the traffic routes by estimating the traffic demand matrices from the traffic volume information on each link. However, these studies are not concerned with the collecting overhead at the centralized server. Even when we only use the traffic volume information on each link, the centralized server has to collect the traffic information from all nodes. Thus, in this case, the collecting overhead remains large. To avoid the large CPU loads of the centralized server or bandwidths required to collect the traffic demands, the collecting interval needs to be set to a large value. However, the large collecting interval prevents optical-layer TE from handling unpredictable traffic changes that occur in a short period of time (e.g., less than a minute [10]).

In this paper, we develop a method to reduce the overhead for collecting the necessary traffic information for optical-layer TE by estimating the traffic matrix from the traffic information collected from a subset of nodes. First, we select the nodes and collect the traffic volume information on each link from the selected nodes. Then, we estimate the traffic matrix by using the information collected from the selected nodes. In this paper, the selected nodes are referred to as *source nodes*.

The rest of this paper is organized as follows. Section II provides an overview of the traffic matrix estimation. In Section III, we introduce a method to estimate the traffic matrix by using the information collected from the source nodes and evaluate the accuracy of the estimation. In Section IV, to improve the accuracy of the estimation, we develop a method for selecting source nodes in order to obtain the traffic information required to accurately estimate the traffic matrix. In Section V, we evaluate our method by using multiple traffic patterns, topologies, and optical-layer TE methods and clarify the environments in which our method can estimate the traffic matrix accurately enough to perform optical-layer TE. Then, in Section VI, we evaluate our method by using a large-scale topology to clarify that it can efficiently estimate the traffic matrix even in a large-scale network. Finally,

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Yuya Tarutani, Shin'ichi Arakawa, and Masayuki Murata are with the Graduate School of Information Science and Technology, Osaka University, Suita-shi, 565-0871, Japan (e-mail: y-tarutn, arakawa, murata@ist.osaka-u.ac.jp).

Yuichi Ohsita is with the Graduate School of Economics, Osaka University, Toyonaka-shi, 560-0043, Japan (e-mail: y-ohsita@econ.osaka-u.ac.jp).

Section VII provides a conclusion.

II. TRAFFIC MATRIX ESTIMATION

A. Overview

Traffic matrix is the matrix of $T_{s,d}$ that represents the traffic volume from nodes s to d . Let N be the number of nodes in the network. Then the traffic matrix is represented as follows:

$$T = \begin{bmatrix} T_{1,1} \\ T_{1,2} \\ \vdots \\ T_{N,N} \end{bmatrix}. \quad (1)$$

As this equation indicates, for obtaining the traffic matrix, the traffic information between all nodes is required. The overhead to collect the traffic information increases it as the number of nodes. Therefore methods have been investigated to estimate a traffic matrix from the traffic volume on each link, which is determined from routing information A , and traffic matrix T . Routing information A is known to the network administrator and traffic matrix T is unknown. The following equation holds:

$$AT = X, \quad (2)$$

where X is a matrix of X_i that represents the traffic volume passing through link i :

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_L \end{bmatrix}. \quad (3)$$

In the above equation, L is the number of links in the networks. A is a routing matrix with element $A_{s,d,l}$ representing the route of traffic between nodes s and d ; when the traffic passes through link l , $A_{s,d,l}$ is one, otherwise it is zero. A is represented as follows:

$$A = \begin{bmatrix} A_{1,1,1} & A_{1,2,1} & \cdots & A_{N,N,1} \\ A_{1,1,2} & A_{1,2,2} & \cdots & A_{N,N,2} \\ \vdots & \vdots & \ddots & \vdots \\ A_{1,1,L} & A_{1,2,L} & \cdots & A_{N,N,L} \end{bmatrix}. \quad (4)$$

Note that when we consider the splittable flow, $A_{s,d,l}$ is the rate of traffic demand $T_{s,d}$ conveyed through link l .

Traffic matrix estimation is an approach to estimate T satisfying Eq. 2 on the basis of matrix X and routing matrix A . Therefore, we collect the traffic volume on each link to create matrix X . We cannot estimate the unique traffic matrix satisfying Eq. 2 because the number of equations in Eq. 2 is usually lesser than the number of elements in T that is, several traffic matrix candidates satisfy Eq. 2. Therefore, the traffic matrix estimation methods [11-16] obtain the estimated traffic matrix that is close to the true traffic matrix from the candidates by using a model of the traffic matrix.

One of the challenges of traffic matrix estimation is to accurately estimate the traffic matrix from as little traffic information volume as possible. We can reduce the collecting overhead by reducing the traffic information volume as much as possible without degrading the performance of optical-layer TE using the estimated traffic matrix. However, the traffic information volume used by traffic matrix estimation has rarely been discussed. In this paper, we develop a method for estimating the traffic matrix from the information of a

subset of nodes and discuss the traffic information volume required to estimate the traffic matrix accurately enough to perform optical-layer TE.

B. Related Work

Many approaches have estimated the traffic matrix using a traffic matrix model [11-16]. For example, Zhang et al. [15] developed an estimation scheme called the *tomogravity method* that estimates traffic matrices by following a gravity model in which the traffic volume between two nodes is proportional to the product of their traffic. The tomogravity method works as follows. First, it estimates traffic demand $T_{s,d}^{grav}$ on the basis of the monitored traffic in the ingress and egress links in order to follow the gravity model by the following equations:

$$T_{s,d}^{grav} = X_{l_s^{in}} \frac{X_{l_d^{out}}}{\sum_k X_k^{out}}, \quad (5)$$

where l_s^{in} is the ingress link at node s and l_d^{out} is the egress link at node d . We denote T^{grav} as the matrix in which each entry is $T_{s,d}^{grav}$. Then the tomogravity method estimates traffic matrix \hat{T} by the following equations:

$$\begin{aligned} \min \|\hat{T} - T^{grav}\|, \\ \text{s.t. } A\hat{T} = X. \end{aligned} \quad (6)$$

That is, this method calculates \hat{T} satisfying Eq. 2 and minimizes the difference between \hat{T} and T^{grav} . Although the traffic information required for the tomogravity method is much smaller than that needed for directly collecting traffic matrix information, L numbers of traffic information must still be collected to estimate traffic matrices.

One approach to reducing the collecting overhead is to divide the collection of traffic information into multiple steps. In this approach, the centralized server collects the traffic information from a subset of nodes in each step and constructs the traffic information of all links from the traffic information collected at all steps. However, this approach cannot follow the traffic changes that occur during the traffic information collection steps.

Zhang et al. [16] developed a more sophisticated method in which they calculated the correlation between each bit of traffic volume information collected at different times or different points. Then they estimated the uncollected traffic volume information using the correlation. However, this method cannot accurately estimate the uncollected traffic volume information when a traffic change that is different from past tendencies occurs.

C. Our Approach

In this paper, we develop a method that estimates the traffic matrix from the information collected from a subset of nodes without using the past traffic volume information. Before estimating the traffic matrix, we estimate the uncollected traffic volume on each link and create matrix X' indicating the roughly estimated traffic volume on each link as follows

$$X' = \begin{bmatrix} X'_1 \\ \vdots \\ X'_L \end{bmatrix}, \quad (7)$$

where

$$X'_l = \begin{cases} X_l & \text{if } l \text{ is the link connected} \\ & \text{to the source nodes,} \\ U_l & \text{otherwise.} \end{cases} \quad (8)$$

In the above equation, X_l is the monitored traffic volume on link l and U_l is the traffic volume on link l estimated from the collected traffic volume information of other links.

Then we estimate the traffic matrix to match X' and A by minimizing the following equation:

$$\min \|A\hat{T} - X'\|. \quad (9)$$

There are two challenges in our approach. The first is estimating U_l from the monitored traffic volume on other links without the past traffic volume information. We estimate U_l using the relationship between the number of traffic demands that pass a link and the traffic volume on it. The details of our estimation method are described in Section III. Another challenge is selecting the source node. The accuracy of the estimated traffic matrix depends on the selection of the source node. Thus, in our method, we select the source node to avoid large estimation errors of the traffic matrix. The details of the method to select the source nodes are described in Section IV.

III. TRAFFIC MATRIX ESTIMATION FROM SUBSET INFORMATION OF NODES

In this section, we introduce a method that estimates the traffic matrix using the traffic volume monitored at a subset of the nodes. Figure 1 shows the steps of our method. In Step. 1, we select source nodes and collect the traffic information from them. In this step, the source nodes are randomly selected. The details of Step 2 and 3 are described below.

A. Estimation of traffic volume using the number of traffic demand

In this approach, we only use the traffic volume information monitored at the selected source nodes. However, because the lack of traffic volume information complicates the estimation of traffic matrices, we estimate the uncollected traffic volume information before estimating the traffic matrix.

1) *Method to estimate traffic volumes:* The traffic volume on each link is proportional to the number of traffic demands passing the link unless the variance of the traffic demands is large. Thus, we model the relationship between the number of traffic demands passing a link and its traffic volume as follows

$$W_i = \alpha Z_i + \beta, \quad (10)$$

where W_i is the traffic volume on link i , Z_i is the number of traffic demands passing link i , and α and β are constant parameters. Z_i for any node i can be calculated from the routing matrix.

With this relation, we can estimate the traffic volume on each link in the following steps. First, we calculate the constant parameters α and β using the traffic volume on each link collected from the selected source nodes with the least-square method:

$$\alpha = \frac{|S| \sum_{i \in S} Z_i W_i - \sum_{i \in S} Z_i \sum_{i \in S} W_i}{|S| \sum_{i \in S} Z_i^2 - (\sum_{i \in S} Z_i)^2}, \quad (11)$$

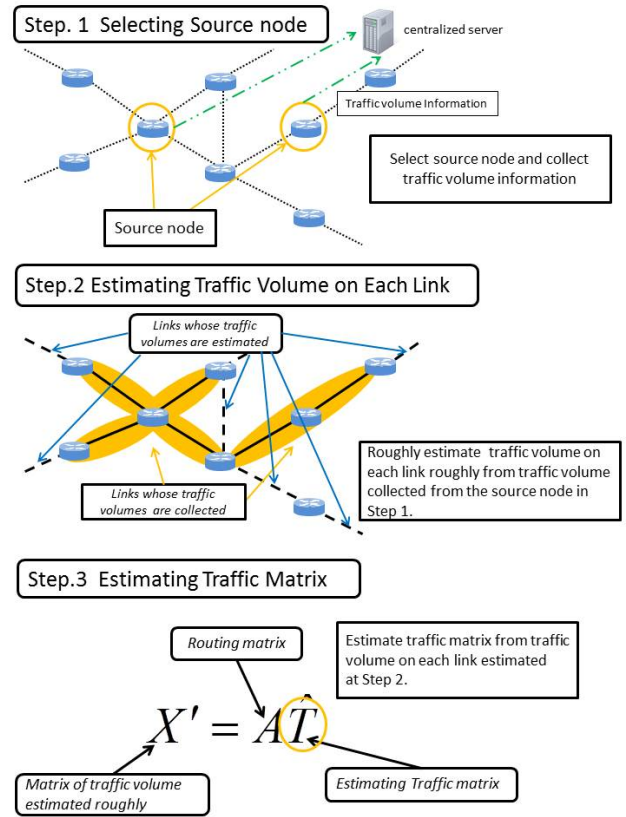


Fig. 1. Flowchart for traffic matrix estimation

$$\beta = \frac{\sum_{i \in S} Z_i \sum_{i \in S} W_i - \sum_{i \in S} Z_i W_i \sum_{i \in S} Z_i}{|S| \sum_{i \in S} Z_i^2 - (\sum_{i \in S} Z_i)^2}, \quad (12)$$

where S is the set of links connected to the source nodes. Then we estimate traffic volume U_j on link j that is not collected from the source nodes as follows:

$$U_j = \alpha Z_j + \beta. \quad (13)$$

Finally, we create matrix X' defined by Eq. 7 by using the estimated volume of traffic U_j .

2) *Validation of the model used to estimate the traffic volume:* We validate the relationship modeled by Eq. 10 using a simulation. In this simulation, we use AT&T's router-level topology (523 nodes and 1304 links) measured in Ref. [17]. We add one ingress link and one egress link for all nodes in the AT&T topology and generate traffic between each pair of ingress and egress links.

According to Ref. [18], each element of the actual traffic matrices obeys a lognormal distribution. Thus, in this simulation, we generate traffic matrix T to follow a lognormal distribution as follows:

$$T = \Theta (T^{init} + \Delta), \quad (14)$$

where T^{init} is a traffic matrix generated to follow a lognormal distribution, Δ is a matrix indicating the white Gaussian noise with a mean of 0 and a variance of 1, and Θ is a scale parameter. We generate $T^{init}_{i,j}$ on the basis of the lognormal distribution with $\mu = 16.6$, $\sigma = 1.04$ to match the results described in Ref. [18]. The unit of the traffic volume of the traffic demand generated by the above steps is Mbps and Θ is set to 0.1 so that the generated traffic can be accommodated in the topology used in this simulation.

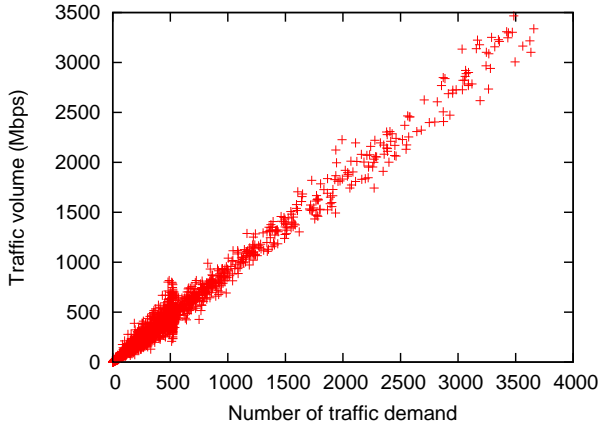


Fig. 2. Relationship between traffic demand and traffic volume on each link in the case of AT&T topology ($\mu = 16.6$, $\sigma = 1.04$)

Figure 2 shows the relationship between the number of traffic demands passing a link and the traffic volume on the link obtained by our simulation. According to Fig 2, the model described by Eq. 10 fits the traffic volume on each link when the traffic demands are generated using the same parameters as the actual traffic demand monitored at the real network in Ref. [17]. Therefore, Eq. 13 is considered to estimate the traffic volume on each link without the large estimation errors found in real networks.

The difference between the actual traffic volume and the traffic volume modeled by Eq. 10 becomes large as the variance of the traffic demands increases. This difference leads to the estimation errors of the traffic volumes on some links. However, if we obtain sufficient traffic volume information from the source nodes, the estimation errors of the traffic volumes on some links do not have large impacts on the accuracy of the traffic matrix estimated by the steps described in subsection III-B. The accuracy of the estimated traffic matrix when the variance of the traffic demands is large is discussed in Section V-B2.

B. Estimation of the traffic matrix

We estimate the traffic matrix from the roughly estimated traffic volume on each link. If we apply the tomography method to estimate the traffic matrix from the estimated traffic volume on each link, estimation errors may become large. The errors included in the traffic volume on the ingress and egress links cause the inaccurate estimation of T^{grav} and the large estimation errors of the tomography method, even when the traffic volumes on other links are estimated accurately. Therefore, we need a traffic matrix estimation method in which the estimation errors included in the traffic volumes on particular links do not significantly affect the estimation results.

Although a more sophisticated estimation method may exist, in our evaluation described in Section V, we use a simple approach to estimate the traffic matrix by minimizing the following equation:

$$\min \|X' - A\hat{T}\|. \quad (15)$$

The results shown in Section V clarify that we can accurately identify the congested links and perform optical-layer TE to mitigate the congestion by using the estimated traffic matrix, even with the simple approach to estimate the traffic matrix.

C. Accuracy of the estimation

We evaluate the accuracy of the estimation by simulation. The source nodes are randomly selected. We use Japan topology (49 nodes and 91 links) and set the routes of packets by the shortest path first (SPF) algorithm.

1) *Metric*: We use two metrics to evaluate the accuracy of the estimation.

a) *Accuracy of the estimated traffic matrix*: We use the Root Mean Squared Error (RMSE) to evaluate the accuracy of the estimated traffic matrix. RMSE (T_{RMSE}) of the traffic matrix is defined as follows:

$$T_{RMSE} = \sqrt{\frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N (\hat{T}_{i,j} - T_{i,j})^2}, \quad (16)$$

where N is the number of nodes in the network, $\hat{T}_{i,j}$ is the estimated traffic demand between nodes i and j , and $T_{i,j}$ is the actual traffic demand between nodes i and j . In our evaluation, we show RMSE normalized by the average amount of traffic demand instead of the absolute value of RMSE in order to compare the accuracy of the estimated traffic matrix in the different environments.

b) *Accuracy of the estimated traffic volume on each link*: The traffic volume on each link is important information for optical-layer TE because inaccurate traffic volume on each link may cause misidentification of the congested links. Thus, we also investigated the accuracy of the traffic volume on each link estimated from the estimated traffic matrix \hat{T} and the routing matrix A . The volume on each link \hat{X} is estimated as follows:

$$\hat{X} = A\hat{T}. \quad (17)$$

Similar to the accuracy of the estimated traffic matrix, we use the RMSE to evaluate the estimated volume of traffic on each link. RMSE (X_{RMSE}) of the estimated volume of traffic on each link is defined as follows:

$$X_{RMSE} = \sqrt{\frac{1}{L} \sum_{k=1}^L (\hat{X}_k - X_k)^2}, \quad (18)$$

where L is the number of links in the network, \hat{X}_k is the estimated traffic volume on link k , and X_k is the actual traffic volume on link k . In our evaluation, we show RMSE normalized by the average amount of traffic volume on each link instead of the absolute value of RMSE for comparing the accuracy of the estimated volume of traffic on each link in different environments.

2) *Simulation result*: Figures 3 and 4 show T_{RMSE} normalized by the average amount of traffic demand and X_{RMSE} normalized by the average volume of traffic on each link when we change the number of source nodes, respectively. In these figures, the vertical axes are normalized T_{RMSE} and normalized X_{RMSE} , and the horizontal axis is the number of source nodes. We plot the results for the average of 20 cases randomly selected from the source nodes with the error bar representing the 95% confidence interval. According to Figs. 3 and 4, the estimation errors become large as the number of source nodes reduces. This is because a large number of traffic demands do not pass any randomly selected source nodes. Furthermore, the traffic demand that does not pass any source nodes is difficult to estimate because we cannot obtain any information of the traffic passing no source nodes. Therefore, we should select the source nodes

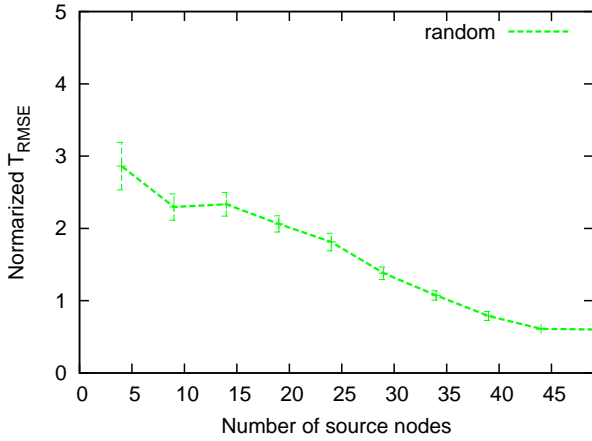


Fig. 3. RMSE of the amount of traffic demand in the case of Japan topology ($\mu = 16.6, \sigma = 1.04$)

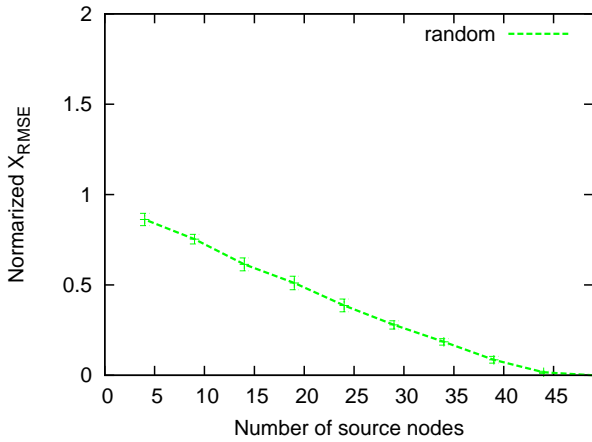


Fig. 4. RMSE of the traffic volume on each link in the case of Japan topology ($\mu = 16.6, \sigma = 1.04$)

so that maximum possible traffic demands pass at least one of the source nodes in order to accurately estimate the traffic matrix from the small subset of nodes.

IV. SELECTING SOURCE NODES

In this section, we propose a method for selecting the source nodes to avoid large estimation errors of the traffic matrix. In our method, we select source nodes so that maximum possible traffic demands pass at least one of the source nodes.

A. Method to select source nodes

Our method selects the source nodes by the following steps. First, we set all nodes as candidates for the source nodes. Then we eliminate the nodes passed only by the traffic passing the other candidates from the candidates in the *elimination phase*. Finally, we select the source nodes from the candidates in the *selection phase*.

The details of the elimination phase and the selection phase to select N source nodes are described below.

1) *Elimination phase*: We eliminate the nodes only passed by the traffic demands passing the other candidates. By eliminating such nodes from the candidates, we can reduce

the number of candidates without reducing the number of traffic demands passing at least one of the candidates of the source nodes.

We use the following variables: Q_i is the number of traffic demands that does not pass any other candidates except node i and $L_{n,m}$ is the number of candidates that passed by the traffic demand from node n to node m . We select the nodes to be eliminated on the basis of the number of traffic demands passing node i , P_i . In the elimination phase, our method eliminates the candidates by the following steps:

- Step. 1.1 Initialize Q_i to 0, and $L_{n,m}$ to the number of nodes that passed by the traffic demand from nodes n to m .
- Step. 1.2 Eliminate node x whose P_i is the smallest among the candidates whose Q_i is 0 from the candidates.
- Step. 1.3 Update $L_{n,m}$ by decrementing $L_{n,m}$ whose corresponding traffic demand passes node x .
- Step. 1.4 Update Q_i for all candidates by counting the elements of $L_{n,m}$ whose value is 1 and whose corresponding traffic passes node i . If a node whose Q_i is 0 exists, go to Step. 1.5, otherwise go to Step. 1.6.
- Step. 1.5 If the number of candidates is larger than N , go back to Step. 1.2. Otherwise, go to Step. 1.6.
- Step. 1.6 End.

2) *Selection phase*: In the selection phase, we select the source nodes so that maximum possible traffic demands pass at least one of the source nodes. In our method, we use a greedy approach that iteratively selects the source nodes so as to maximize the number of traffic demands passing the selected source nodes.

In each iteration of the selection phase, we select the source nodes by using the number of traffic demands that passes node i and does not pass the currently selected source nodes, R_i .

In the selection phase, we select the source nodes by the following steps.

- Step. 2.1 If the number of candidates is less than N , select all nodes in the candidates and go to Step. 2.6. Otherwise go to Step. 2.2.
- Step. 2.2 Initialize R_i to P_i .
- Step. 2.3 Select node x whose R_x is the largest among the candidates. If there are multiple candidates whose R_x are the largest, select node x with the largest P_i .
- Step. 2.4 Check the route of each traffic demand passing selected node x . Then update R_i by decrementing its value if a traffic demand passing selected node x also passes node i .
- Step. 2.5 If the number of the selected source nodes is less than N , go back to Step. 2.3. Otherwise go to Step. 2.6.
- Step. 2.6 End.

B. Accuracy of the estimation using the information from the selected source nodes

We evaluate the accuracy of the estimation using the traffic information from the source nodes selected by our method. In this evaluation, we use the same metrics, topology and traffic demands as in Subsection III-C.

Figure 5 shows T_{RMSE} normalized by the average amount of traffic demand when we change the number of source nodes.

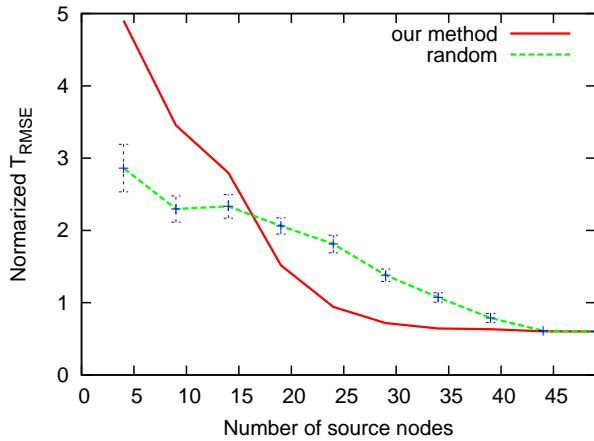


Fig. 5. RMSE of the traffic matrix in the case of Japan topology ($\mu = 16.6$, $\sigma = 1.04$)

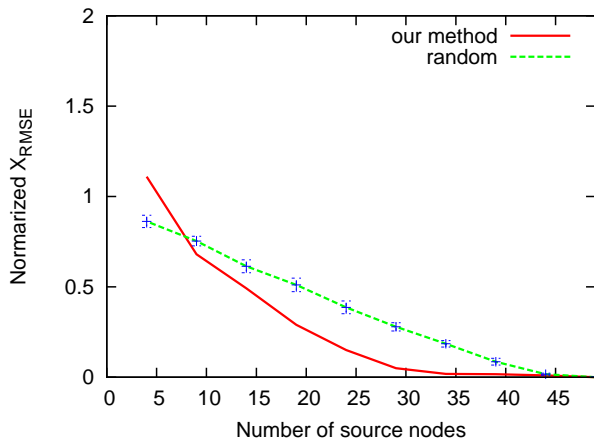


Fig. 6. RMSE of the traffic volume on each link in the case of Japan topology ($\mu = 16.6$, $\sigma = 1.04$)

The vertical axis is normalized T_{RMSE} , and the horizontal axis is the number of source nodes. “our method” indicates the results for the case that we select the source nodes by our method. We also plot the results for the average of 20 cases of the randomly selected source nodes indicated as “random” with the error bar representing the 95% confidence interval.

According to Fig. 5, by selecting more than 24 source nodes, our method can estimate the traffic matrix with an estimation error of less than 0.6 times the average of the actual traffic matrix, while the method that randomly selects source nodes cannot. This is because our method selects source nodes to cover maximum possible traffic demands. Therefore, most traffic demands pass at least one source node selected in our method and can be estimated from the traffic volume information collected from the source nodes.

Even when we select the source nodes by our method, the estimation error shown in Fig. 5 is larger than the results shown in Refs. [11-16]; this is because since our method uses only the information of the selected source nodes. However we do not have to accurately estimate traffic matrices if we can accurately identify the congested links and perform optical-layer TE to mitigate the congestion with the estimated traffic matrix. Figure 6 shows X_{RMSE} normalized by the average volume of traffic on each link as a function of

the number of source nodes similar to Fig. 5. According to Fig. 6, our method accurately estimates the traffic volume on each link by selecting more than 24 source nodes, whereas the method that randomly selects source nodes cannot. That is, we can accurately identify the congested links from the traffic volume on each link estimated by our method.

V. EVALUATION OF OPTICAL-LAYER TRAFFIC ENGINEERING USING THE ESTIMATED TRAFFIC DEMANDS

In this section, we evaluate optical-layer TE using the traffic demands estimated by our method through simulations with multiple traffic patterns, topologies and the optical layer TE methods. Then, we clarify the environment in which our method estimates the traffic matrix and the traffic volume on each link accurately enough to perform optical-layer TE.

A. Simulation settings

1) *Topology*: In our evaluation, we use Japan topology (49 nodes and 91 links) and a random graph (100 nodes and 200 links). Japan topology is a real ISP topology constructed by considering the geographical distance between each node. Thus, there are no links between the node pairs at a large distance. This causes the concentration of traffic demands on certain links. On the other hand, the random graph is constructed without the geographical distance. Therefore, there are no links where the traffic demands are concentrated.

We set the bandwidth for an optical path to 10 Gbps and the number of transmitters/receivers of node i to $D_i + 8$ where D_i is the degree of node i . In this simulation, we assume that the number of wavelengths on optical fibers will be sufficient. The initial VNT is configured to suit the traffic matrix generated by Eq. 14 with $\mu = 16.6$ and $\sigma = 1.04$.

2) *Traffic*: Optical-layer TE reconfigures the VNT when the traffic demand changes and the VNT becomes unsuitable for the current traffic. In this simulation, we assume that the traffic changes significantly and that the actual traffic matrix after the traffic change is again generated randomly by Eq. 14. We generate two types of actual traffic matrices: *realistic traffic* and *skewed traffic*. Realistic traffic is generated using $\mu = 16.6$ and $\sigma = 1.04$ so that the generated traffic follows the traffic distribution monitored at the real ISP [18]. Skewed traffic is generated using $\mu = 16.6$ and $\sigma = 2.08$ so that the variance of the generated traffic demand is large. For skewed traffic, the traffic volume on each link may be different from the traffic volume modeled by Eq. 10 owing to the traffic demand whose volume is significantly larger than the other traffic. We set Θ to 1 in the cases of Japan topology and random graph so that the generated traffic can be accommodated in the topologies used in this simulation

3) *Optical-layer TE method*: In this evaluation, we use two optical layer TE methods; One is the method proposed in Ref. [4] that we call the Adaptive Reconfiguration based on Link Utilization (ARLU) in this paper. The other is the Minimum Delay Logical Topology Design Algorithm (MLDA) proposed in Ref. [5].

a) *ARLU[4]*: The ARLU adds a new optical path to mitigate congestion and, if possible, deletes currently under-utilized optical paths for reclamation. Although the original version of this method adds or deletes only one optical path at a time, such addition or deletion cannot sufficiently

mitigate the congestion in a large-scale network. Thus, we use the extended method to add or delete multiple optical paths.

This method uses two thresholds for the utilization of each optical path to define the congested and underutilized states T_H and T_L , respectively. In our evaluation, we set T_H to 0.3 and T_L to 0.2. The general sequence of the algorithm to calculate the VNT is as follows:

- Step. 1 Calculate the utilization of all links of the VNT from the estimated traffic matrix. If at least one congested link (i.e., a link whose utilization exceeds threshold T_H) is found, go to the optical path addition phase (Step 2). If there is a link whose utilization is less than threshold T_L , go to Step. 3.
- Step. 2 Execute the optical path addition phase described below and go to Step. 4.
- Step. 3 Execute the optical path deletion phase described below and go to Step. 4.
- Step. 4 Calculate the packet routes over the new VNT and re-calculate the utilization of all links of the new VNT from the estimated traffic matrix.
- Step. 5 If the optical path is not added/deleted, go to Step. 6. Otherwise, return to Step. 1.
- Step. 6 End.

In the above steps, the routes of the packets over the VNT are calculated using the SPF algorithm. The following are the details of the optical path addition/deletion phases.

In the optical-path addition phase, if the link utilization of the current VNT exceeds T_H , a new optical-path is set up to reroute traffic away from the congested link. First, we collect a set of traffic demands that passes the most congested link. Then, we select the busiest set of collected traffic demands. Finally, we add the direct optical path (i.e., a single directly connected link) from the ingress to the egress nodes of the selected traffic demands.

In the optical path deletion phase, if the utilization of an optical path is less than T_L and its deletion doesn't cause congestion, the path is torn down so that the IP router ports and wavelengths can be reclaimed for future use. The optical path is checked for the potential of its deletion to cause congestion by calculating the utilization of the optical paths after deletion using the traffic matrix. If there is more than one deletion candidate, each candidate path is tested in the ascending order of utilization.

b) *MLDA*[5]: The MLDA is a method that aims to minimize the maximum link utilization. It uses the following parameters; $T_{i,j}$ is the element of the traffic matrix corresponding to the traffic from node i to node j , d_i^{out} is the number of transmitters in node i , and d_i^{in} is the number of receivers in node i . The MLDA reconfigures the VNT by the following steps:

- Step. 1 Select the node pair $i-j$ whose traffic volume is the largest. If the traffic volume $T_{i,j}$ corresponding to the selected node pair is 0, go to Step. 6. Otherwise, go to Step. 2.
- Step. 2 If $d_i^{out} > 0$ and $d_j^{in} > 0$, configure the optical path from node i to node j and go to Step. 3. Otherwise, go to Step. 4.
- Step. 3 Decrement d_i^{out} and d_j^{in} .
- Step. 4 Select the node pair $k-l$ whose traffic volume is the second largest.
- Step. 5 Update $T_{i,j} \leftarrow T_{i,j} - T_{k,l}$, and go to Step. 1.

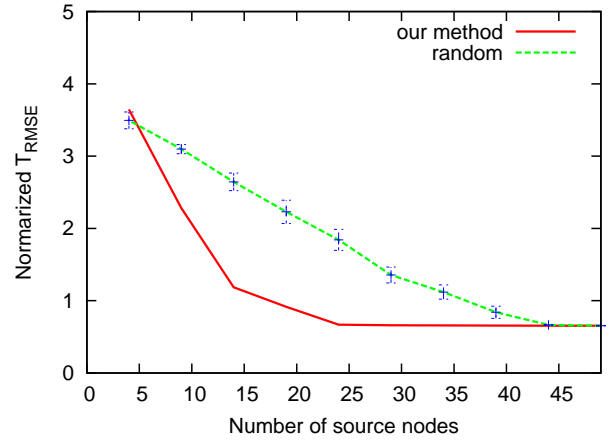


Fig. 7. RMSE of the traffic matrix using the ARLU in the case of Japan topology ($\mu = 16.6$, $\sigma = 1.04$)

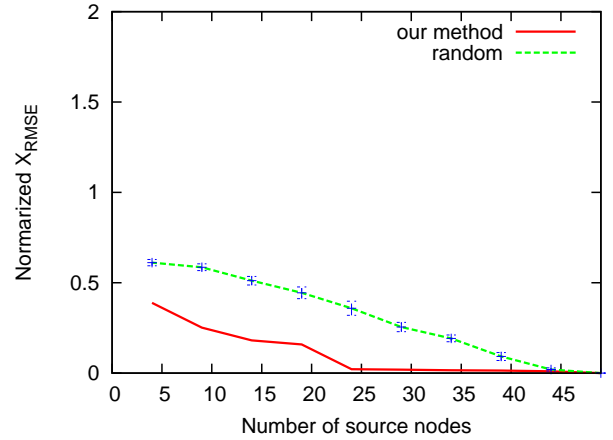


Fig. 8. RMSE of the traffic volume on each link using the ARLU in the case of Japan topology ($\mu = 16.6$, $\sigma = 1.04$)

Step. 6 End.

4) Metrics:

a) *Accuracy of the estimation:* We evaluate the accuracy of our estimation method by using the same metric described in subsection III-C1.

b) *Performance of TE using the estimated traffic matrix:* The goal of the optical-layer TE used in this simulation is to mitigate the congestion. Thus, we evaluate the performance of the TE using the estimated traffic matrix by the maximum link utilization achieved by it.

B. Performance of the ARLU in the case of Japan topology

In this subsection, we evaluate the ARLU using the traffic demands estimated by our method using Japan topology (49 nodes and 91 links) as a physical topology. In the evaluation in this subsection, the initial VNT is also constructed by the ARLU so as to suit the initial traffic demands.

1) *Realistic Traffic:* In this subsection, we generate the realistic traffic for the traffic demands.

Before evaluating the performance of the ARLU, we investigate the accuracy of our estimation method when the VNT is constructed using the ARLU. Figures. 7 and 8 show T_{RMSE} normalized by the average amount of traffic demand and X_{RMSE} normalized by the average volume of traffic on each

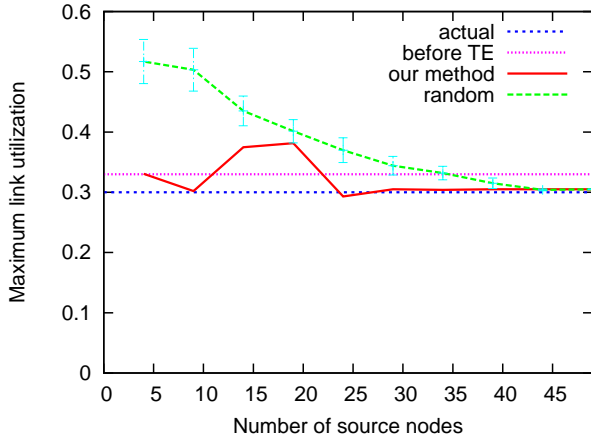


Fig. 9. Maximum link utilization after TE using the estimated traffic matrix using the ARLU in the case of Japan topology ($\mu = 16.6$, $\sigma = 1.04$)

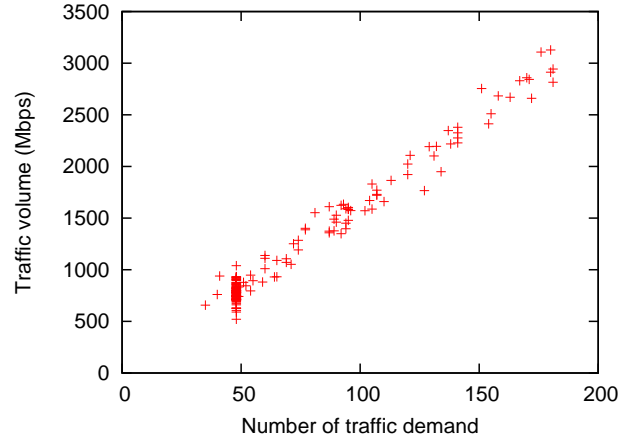
link, respectively. In these figures, the vertical axes are the normalized T_{RMSE} and normalized X_{RMSE} , and the horizontal axis is the number of source nodes. “our method” indicates the results for the case that we select the source nodes by our method. We also plot the results for the average of 20 cases randomly selected from the source nodes indicated as “random” with the error bar representing the 95% confidence interval.

According to Figs. 7 and 8, similar to the results described in Subsection IV-B, by selecting more than 29 source nodes, our method can estimate the traffic matrix with an estimation error of less than 0.7 times the average of the actual traffic matrix, whereas the method that randomly selects source nodes cannot. Our method can also estimate the traffic volume on each link accurately by selecting more than 29 source nodes. That is, we can accurately identify the congested links from the traffic volume on each link estimated by our method.

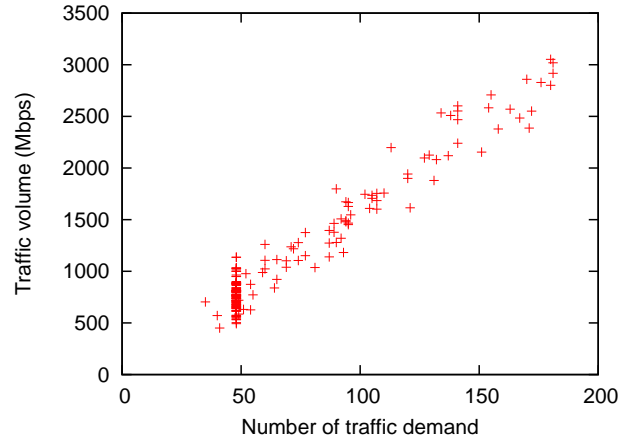
Figure 9 shows the maximum link utilization achieved by the ARLU using the estimated traffic matrix as a function of the number of source nodes. The vertical axis is the maximum link utilization, and the horizontal axis is the number of source nodes. “Our method” indicates the results for the case that we perform the ARLU using the traffic matrix estimated by our method, “actual traffic” indicates the case that we perform the ARLU using the actual traffic matrix, and “before TE” indicates the maximum link utilization before we reconfigure the VNT. In addition, we plot the results for the average of 20 cases randomly selected from the source nodes indicated as “random” with the error bar representing the 95% confidence interval.

According to Fig. 9, when we select more than 24 source nodes, the ARLU using the traffic matrix estimated by our method achieves maximum link utilization similar to the ARLU using the actual traffic matrix; on the other hand the maximum link utilization after performing the ARLU using the traffic matrix estimated from the information of randomly selected nodes remains large. This is because we can accurately identify the congested links from the traffic matrix estimated by our method, as shown in Fig. 8.

2) *Skewed traffic*: In this subsection, we evaluate our method when the variance of the traffic demand is large.



(a) Case of realistic traffic ($\mu = 16.6$, $\sigma = 1.04$)



(b) Case of skewed traffic ($\mu = 16.6$, $\sigma = 2.08$)

Fig. 10. Relationship between the number of traffic demands and the traffic volume on each link in the case of Japan topology

In this case, the traffic volume on each link may be different from the traffic volume modeled by Eq. 10.

Figure 10(b) shows the relationship between the number of traffic demands passing a link and the traffic volume on each link in the initial VNT constructed by the ARLU in the case of the skewed traffic. Compared with Fig. 10(a), the difference between the actual traffic volume on each link and the traffic volume modeled by Eq. 13 is large because of the large variance of traffic demands.

Figure 11 shows X_{RMSE} normalized by the average volume of traffic on each link. According to Fig. 11, even when the variance of traffic demand is large, our method can accurately estimate the traffic volume on each link by selecting more than 24 source nodes. This is because our method selects source nodes to cover maximum possible traffic demands similar to the case in Fig. 8. Most traffic demands pass at least one of the source nodes selected in our method and can be estimated from the traffic volume information collected from the source nodes. Therefore, even if the traffic volume estimated by Eq. 13 includes a large estimation error, we can accurately identify the congested links.

Figure 12 shows the maximum link utilization achieved by the ARLU using the estimated traffic matrix as a function of the number of source nodes. According to Fig. 12, when the number of source nodes is more than 19, the ARLU using the

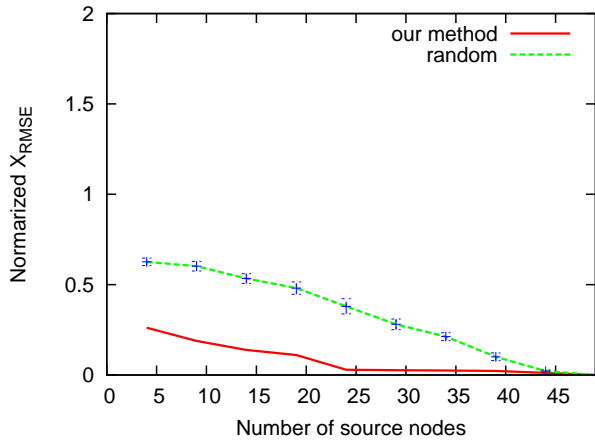


Fig. 11. RMSE of the traffic volume on each link using the ARLU in case of Japan topology ($\mu = 16.6, \sigma = 2.08$)

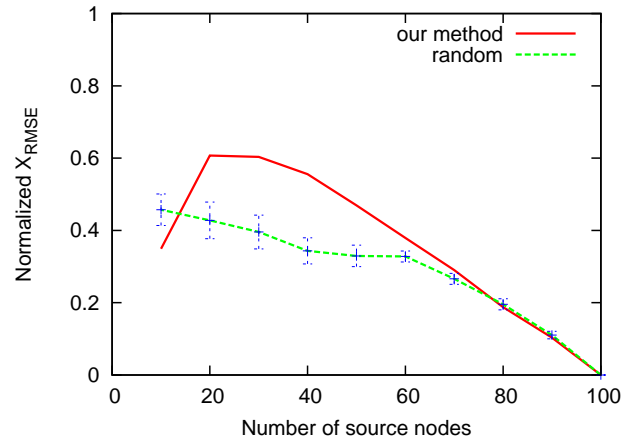


Fig. 13. RMSE of the traffic volume on each link in the case of the random graph ($\mu = 16.6, \sigma = 1.04$)

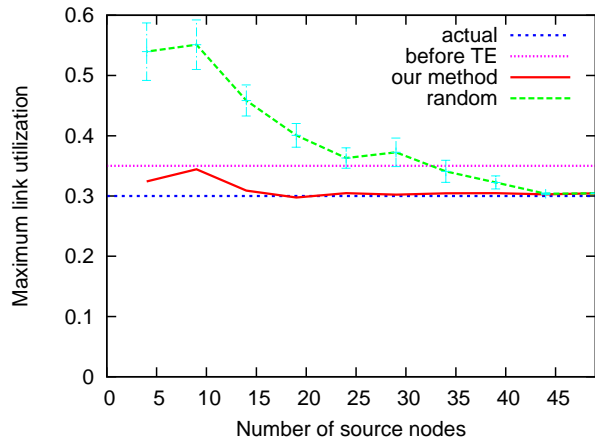


Fig. 12. Maximum link utilization after TE using the estimated traffic matrix using the ARLU in the case of Japan topology ($\mu = 16.6, \sigma = 2.08$)

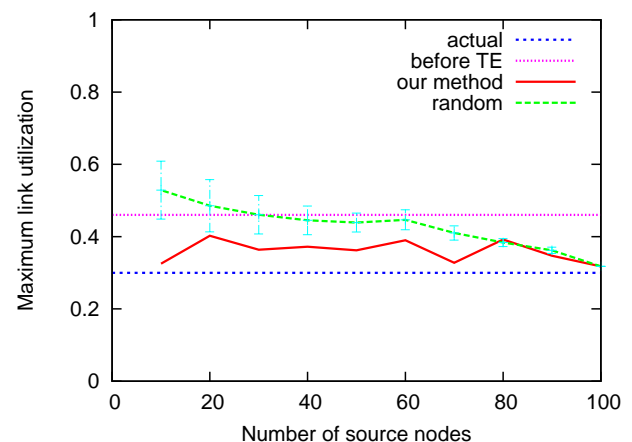


Fig. 14. Maximum link utilization after TE using the estimated traffic matrix in the case of random graph ($\mu = 16.6, \sigma = 1.04$)

estimated traffic matrix can achieve link utilization similar to the ARLU using the actual traffic matrix. This is because our method can accurately estimate the traffic volume on each link by selecting more than 19 source nodes.

C. Performance of the ARLU in the case of the random graph

In this subsection, we evaluate our method using the random graph (100 nodes and 200 links) as a physical topology. The initial VNT is configured by the ARLU. Now, we generate the realistic traffic.

Figures 13 and 14 show normalized X_{RMSE} and the maximum link utilization achieved by the ARLU using the estimated traffic matrix, respectively. According to Fig. 13, our method cannot accurately estimate the traffic volume on each link. The estimation errors of our method are larger than the method that randomly selects source nodes. As a result, the ARLU using the estimated traffic matrix cannot reduce the maximum link utilization as much as the ARLU using the actual traffic matrix unlike the case of Japan topology.

This large estimation error is caused by the small number of traffic demands passing each link. Because the number of traffic demands passing each link is small in the VNT

constructed over the random graph, a large number of traffic demands do not pass any of the selected source nodes and are estimated from the traffic volume estimated by Eq. 13.

In addition, the small number of traffic demands passing each link causes the large estimation errors in the traffic volume estimated by Eq. 13. As shown in Fig. 15, a large number of links are passed by only a smaller number of traffic demands than the number of traffic demands passing the ingress/egress link. However, our method does not obtain the traffic information on such links because it selects the nodes passed by a large number of traffic demands. This causes large estimation errors on the parameters, α and β in Eq. 13. Because the traffic volume estimated by Eq. 13 includes large estimation errors, we cannot accurately estimate the traffic volume.

On the other hand, the number of traffic demands passing each link in the real ISP topology is much larger than the random graph because the real ISP topology is constructed by considering the geographical distance. According to Fig. 10(a), many links are passed by much larger number of traffic demands than the ingress/egress links in the Japan topology. In this case, the traffic information on the links passed by a small number of traffic demands is also obtained from the selected source nodes; this is because the number

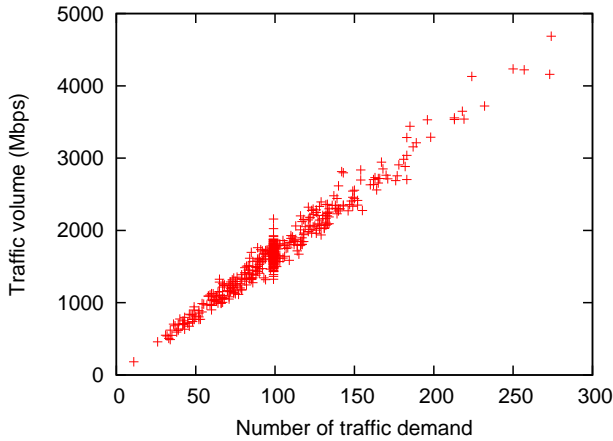


Fig. 15. Relationship between the number of traffic demands and the traffic volume on each link in the case of the random graph ($\mu = 16.6, \sigma = 1.04$)

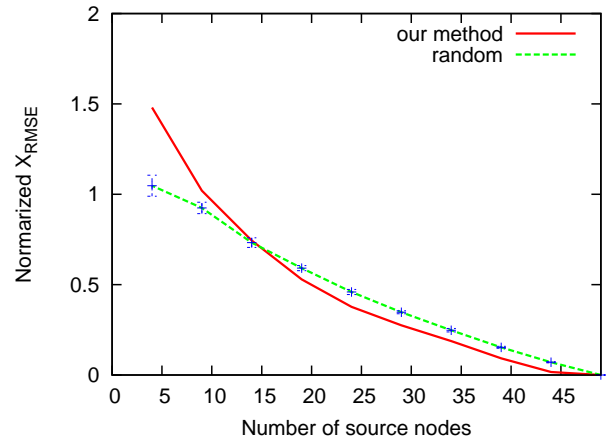


Fig. 17. RMSE of the traffic volume on each link using the MLDA in the case of Japan topology ($\mu = 16.6, \sigma = 1.04$)

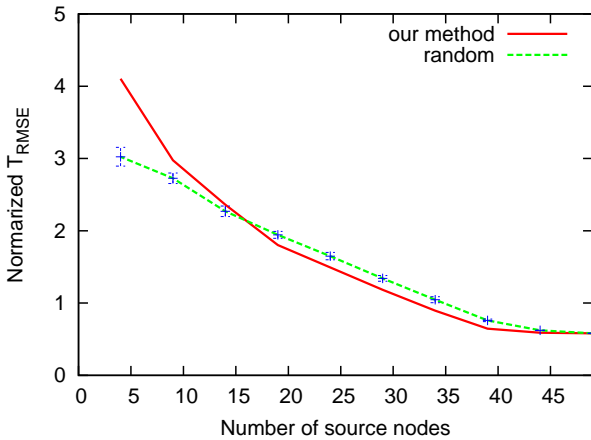


Fig. 16. RMSE of the traffic matrix using the MLDA in the case of Japan topology ($\mu = 16.6, \sigma = 1.04$)

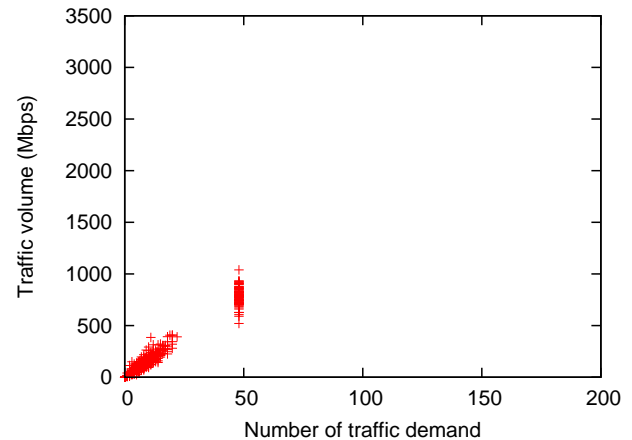


Fig. 18. Relationship between the number of traffic demands and the traffic volume on each link in the case of Japan topology using the MLDA ($\mu = 16.6, \sigma = 1.04$)

of traffic demands passing the ingress/egress link connected to the selected source node is smaller than that passing the other links. Thus, we can accurately estimate parameters, α and β in Eq. 13. Therefore, the large estimation errors caused by the small the number of traffic demands passing each link do not occur in the real ISP topology.

D. Performance of the MLDA

We evaluate our method for the case when the MLDA is used for reconfiguration. In this evaluation, we configure the initial VNT by the MLDA using the initial traffic matrix. In this subsection, we generate the realistic traffic.

1) *In the case that the number of transmitters/receivers are large:* In this section, we evaluate the MLDA when each node has $D_i + 8$ transmitters/receivers where D_i is the node degree of node i .

Before evaluating the performance of the MLDA, we evaluate the accuracy of the estimation when the initial VNT is configured by the MLDA. Figures 16 and 17 show T_{RMSE} normalized by the average amount of traffic demand and X_{RMSE} normalized by the average volume of traffic on each link, respectively. According to Figs. 16 and 17, the estimation errors of our method are significantly larger than the results

of the case of the ARLU and similar to the estimation errors of the case when the source nodes are randomly selected. This is because of the difference between the initial VNT constructed by the ARLU and that constructed by the MLDA. Thus, we compare the VNT constructed by the ARLU and the MLDA.

Figure 18 shows the relationship between the number of traffic demands passing a link and the traffic volume on the link obtained by our simulation when the initial VNT configured by the MLDA is used. Comparing Figs. 18 and 10(a), the number of traffic demands passing each link is much smaller in the VNT configured by the MLDA than that configured by the ARLU. This is because the MLDA constructs maximum possible optical paths, whereas the ARLU constructs only the optical-paths required to mitigate the congestion. This small number of traffic demands passing each link causes the large estimation errors as discussed in subsection V-C,

Figure 19 shows the maximum link utilization achieved by the MLDA using the estimated traffic matrix as a function of the number of source nodes. According to Fig. 19, the maximum link utilization achieved by the MLDA using the estimated traffic matrix is greater than that achieved by the

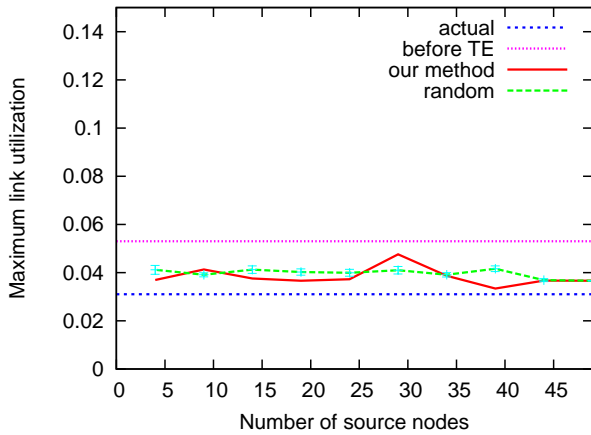


Fig. 19. Maximum link utilization after TE using the estimated traffic matrix using the MLDA in case of Japan topology ($\mu = 16.6$, $\sigma = 1.04$)

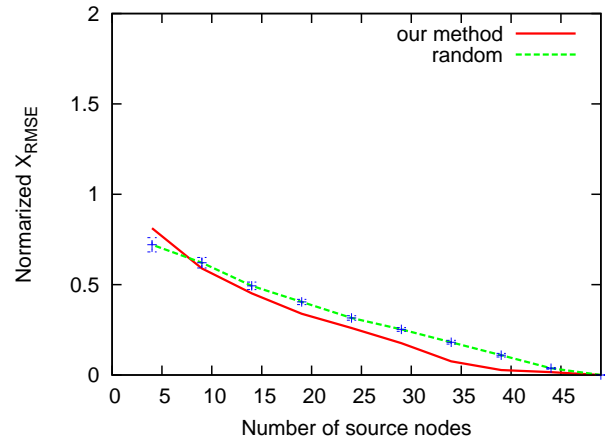


Fig. 21. RMSE of the traffic volume on each link using the MLDA when the number of the transmitters/receivers is small in the case of Japan topology ($\mu = 16.6$, $\sigma = 1.04$)

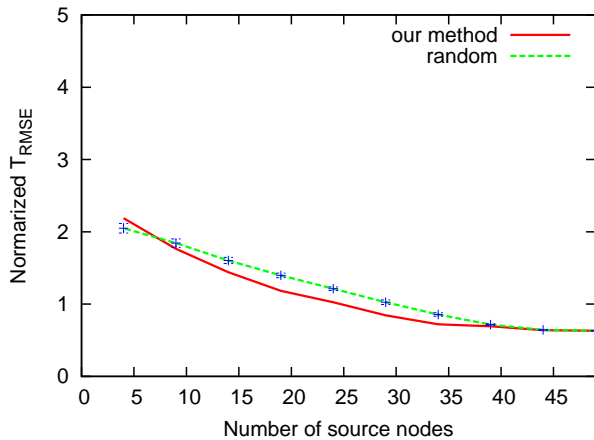


Fig. 20. RMSE of the traffic matrix using the MLDA when the number of the transmitters/receivers is small in the case of Japan topology ($\mu = 16.6$, $\sigma = 1.04$)

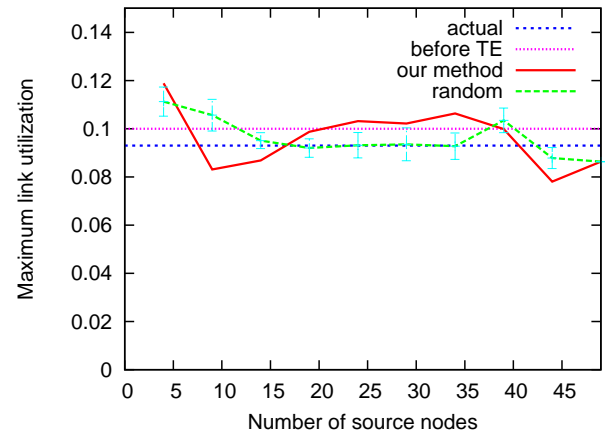


Fig. 22. Maximum link utilization after TE using the estimated traffic matrix using the MLDA when the resource is reduced in the case of Japan topology ($\mu = 16.6$, $\sigma = 1.04$)

MLDA using the actual traffic demand. This is because of the large estimation errors shown in Figs. 16 and 17. However, we can reduce the maximum link utilization compared with that before TE. This is because we can add many optical paths in the environment used in this evaluation. We add optical paths to the node pairs whose traffic amounts are large despite the large estimation errors.

2) *In the case that the numbers of the transmitters/receivers are small:* Now, we evaluate our method when the numbers of the transmitters/receivers is small. Each node has $D_i + 2$ transmitters/receivers where D_i is the node degree of the node i . As mentioned earlier, we configure the initial VNT by the MLDA.

Figures 20 and 21 show normalized T_{RMSE} and X_{RMSE} , respectively. According to the figures, our method can estimate the traffic matrix and the traffic volume on each link more accurately than the case of $D_i + 8$ transmitters/receivers. This is because the number of constructed optical paths in the case of $D_i + 2$ transmitters/receivers is smaller than that in the case of $D_i + 8$ transmitters/receivers. Because the number of constructed optical paths is small, the number of traffic demands passing a node is larger than for the case of $D_i + 8$ transmitters/receivers. Thus, the number of traffic demands

that do not pass any selected source nodes in the case of $D_i + 2$ is smaller than that for the case of $D_i + 8$.

Figure 22 shows the maximum link utilization achieved by the MLDA using the estimated traffic matrix as a function of the number of source nodes. The MLDA using the traffic matrix estimated by our method cannot reduce the maximum link utilization even when we select 39 source nodes, although the estimation error of the traffic matrix (Fig. 22) is as small as that for the case of the ARLU shown in subsection V-B1. That is, when the numbers of transmitters/receivers is small, the MLDA is less robust to the estimation errors of the traffic matrix than the ARLU. This is because the MLDA uses only the traffic matrix to decide where to add the optical paths, while the ARLU uses both the traffic matrix and the traffic volume on each link. As shown in Figs. 7 and 8, the traffic volume on each link can be estimated more accurately than the traffic matrix. Thus, the ARLU can configure the adequate VNT even when using the estimated traffic matrix.

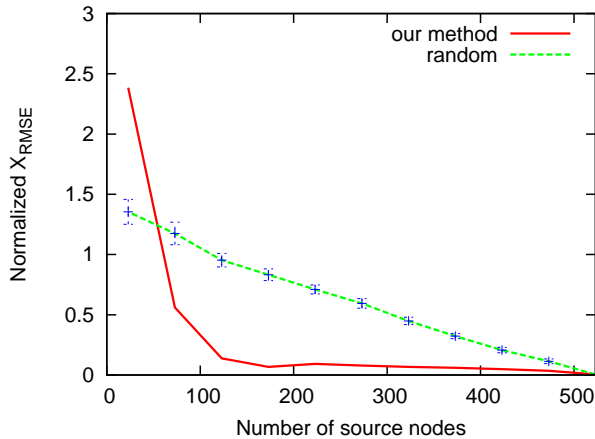


Fig. 23. RMSE of traffic volume on each link in the case of AT&T topology ($\mu = 16.6, \sigma = 2.08$)

E. Summary of the results

According to the results in this section, our method can estimate the traffic matrix accurately enough to perform the ARLU. Although the estimation errors become large when the number of traffic demands passing each link is small, such large estimation errors do not occur in the real ISP topology. This is because the number of traffic demands passing some links in the real ISP is large since the real ISP topology is constructed by considering the geographical distance between each node.

The evaluation also shows that the MLDA is less robust to estimation errors than the ARLU. This is because the MLDA uses only the traffic matrix to decide where to add the optical paths, while the ARLU uses both the traffic matrix and the traffic volume on each link. That is, the TE method using both the traffic matrix and the traffic volume on each link is suitable for the case when the estimated traffic information is used.

VI. EVALUATION IN A LARGE SCALE NETWORK

Here, we evaluate our method using AT&T topology (523 nodes and 1304 links) measured in Ref. [17] as a physical topology. The initial VNT is configured by the ARLU. In addition, we show the results for the case of the skewed traffic that is generated by Eq. 14 using $\mu = 16.6, \sigma = 2.08$ and $\Theta = 0.1$. We omit the results for the case of the realistic traffic because the realistic traffic is easier to estimate than the skewed traffic.

A. Accuracy of estimated traffic volume

Figure 23 shows the normalized X_{RMSE} when we change the number of source nodes. According to Fig. 23, our method accurately estimates the traffic volume on each link by selecting more than 123 source nodes, while the method that randomly selects source nodes cannot. That is, our method can identify the congested links more accurately than the case of the estimation from the randomly selected nodes in the large scale ISP topology.

B. Performance of the ARLU

Figure 24 shows the maximum link utilization achieved by the ARLU using the estimated traffic matrix. According

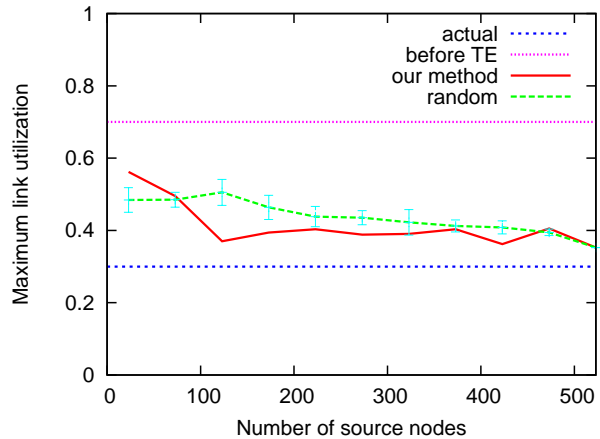


Fig. 24. Maximum link utilization after TE using the estimated traffic matrix in the case of AT&T topology ($\mu = 16.6, \sigma = 2.08$)

to Fig. 24, the ARLU using the traffic matrix estimated by our method can significantly reduce the maximum link utilization. In addition, it can achieve 1.3 times the maximum link utilization achieved by the ARLU using the actual traffic matrix by selecting 123 source nodes in the case of skewed traffic. That is, our method can estimate the traffic volume on each link accurately enough to be used by the ARLU by collecting traffic information from 30% of all nodes in AT&T topology.

C. Calculation time

The calculation time to estimate the traffic volume is important for handling traffic changes that occur in a short period of time. The complexity of our method to select source nodes is $O(N^3)$ and the complexity of our method to estimate the traffic matrix is $O(N^2L)$ where N is the number of nodes and L is the number of links in the topology.

We measure the time to estimate the traffic volume by our method. In this simulation, we use a server with a 3.16GHz Intel Xeon 5460 Processor to measure the time to estimate the traffic volume. We implement the method to select source nodes in C++ and the method to estimate the traffic matrix in MATLAB.

In our method, selecting source nodes requires 40 seconds and estimating traffic volume requires only 1.5 seconds for the VNT constructed over the AT&T topology. We do not have to select the source nodes within a small interval because our method continues to collect the traffic information from the same source nodes unless the VNT is changed. Therefore, even in a large scale network such as AT&T topology, our method can estimate the traffic volume in a sufficiently short time to handle the traffic changes that occur in a short period of time.

VII. CONCLUSION

In this paper, we developed a method to select the source nodes and estimate the traffic matrix on the basis of the traffic information collected from the selected source nodes. We evaluated our method through simulations. According to the simulation results, our method estimates the traffic matrix and the traffic volume on each link accurately enough to perform TE in real ISP topologies; however our method

cannot accurately estimate the traffic matrix when the number of traffic demands passing each link is small. The simulation results show that we can mitigate the congestion by using the traffic matrix estimated from 50% of all nodes in the case of Japan topology and 30 % of all nodes in the case of AT&T topology.

Future researches include improving the accuracy of the estimation by developing more sophisticated method to estimate the uncollected traffic volume on each link and the traffic matrix by using the information from the source nodes.

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Yuya Tarutani received a B.E. degree from Osaka University in 2010, where he is currently a graduate student in Information Science and Technology. His research interest includes traffic matrix estimation.



Yuichi Ohsita received M.E. and Ph.D. degrees in information science and technology from Osaka University in 2005 and 2008. He is currently an Assistant Professor in the Graduate School of Economics, Osaka University. His research interests include traffic matrix estimation and countermeasures against DDoS attacks. He is a Member of IEICE, IEEE and the Association for Computing Machinery (ACM).



Shin'ichi Arakawa received M.E. and D.E. degrees in informatics and mathematical science from Osaka University in 2000 and 2003. He is currently an Assistant Professor at the Graduate School of Information Science and Technology, Osaka University. His research interests include optical networks and complex networks. He is a Member of IEICE and IEEE.



Masayuki Murata received M.E. and D.E. degrees in information and computer sciences from Osaka University in 1984 and 1988.

In April 1984, he joined the Tokyo Research Laboratory IBM Japan as a Researcher. From September 1987 to January 1989, he was an Assistant Professor with the Computation Center, Osaka University. In February 1989, he moved to the Department of Information and Computer Sciences, Faculty of Engineering Science, Osaka University. From 1992 to

1999, he was an Associate Professor with the Graduate School of Engineering Science, Osaka University, and since April 1999, he has been a Professor. He moved to the Graduate School of Information Science and Technology, Osaka University in April 2004. He has published more than 300 papers in international and domestic journals and conferences. His research interests include computer communication networks, performance modeling, and evaluation.

He is a Fellow of IEICE and a Member of IEEE, the Association for Computing Machinery (ACM), The Internet Society, and IPSJ.