PAPER

Estimation of current traffic matrices from long-term traffic variations

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SUMMARY Obtaining current traffic matrices is essential to traffic engineering (TE) methods. Because it is difficult to monitor traffic matrices, several methods for estimating them from link loads have been proposed. The models used in these methods, however, are incorrect for some real networks. Thus, methods improving the accuracy of estimation by changing routes also have been proposed. However, existing methods for estimating the traffic matrix by changing routes can only capture long-term variations and cannot obtain current traffic matrices accurately. In this paper, we propose a method for estimating current traffic matrices that uses route changes introduced by a TE method. In this method, we first estimate the long-term variations of traffic by using the link loads monitored at previous times. Then, we adjust the estimated long-term variations so as to fit the current link loads. In addition, when the traffic variation trends change and the estimated long-term variations fail to match the current traffic, our method detects mismatch. Then, so as to capture the current traffic variations, the method re-estimates the long-term variations after removing monitored data corresponding to the end-to-end traffic causing the mismatches. We evaluate our method through simulation. The results show that our method can estimate current traffic matrices accurately even when some end-to-end traffic changes suddenly.

key words: *Traffic Matirx, Estimation, Traffic Engineering*

1. Introduction

Obtaining current traffic matrices accurately is essential to traffic engineering (TE) methods [1–4]. By using the current traffic matrices, TE methods configure routes on a network so as to fit the current traffic. As a result, even when traffic changes unpredictably, by reconfiguring routes, the network can efficiently accommodate all traffic without congestion.

One approach for obtaining traffic matrices is to construct fully meshed label-switched paths using Multiprotocol Label Switching (MPLS) and directly measure the traffic amounts over each path. This approach, however, does not scale because it requires N-squared label-switched paths. Another approach is to tally the numbers of packets of each end-to-end traffic flow at all edge nodes. This, however, is also difficult to apply in large-scale networks, because tallying these numbers requires a non-negligible amount of CPU resources at the edge nodes, and gathering the tallied data for all end-to-end traffic also consumes a non-negligible amount of network resources such as bandwidth.

Therefore, several methods for estimating traffic matrices from limited information have been proposed [5–14]. In such methods, an entire traffic matrix is estimated using link loads that can be collected much more easily than by directly monitoring end-to-end traffic. Because the link load is the sum of the traffic using a link, we have

$$X(n) = A(n)T(n), \quad (1)$$

where $X(n)$ is a matrix indicating the amount of traffic on each link at time n, $T(n)$ is the traffic matrix at time n, and $A(n)$ is the routing matrix (i.e., a matrix in which an element corresponding to an instance of end-to-end traffic and a link is 1 if the end-to-end traffic passes the link or 0 if it does not). However, because the number of links is much smaller than the number of elements of the traffic matrix, Eq. (1) has multiple solutions in which true traffic matrix is included.

Therefore, several methods use traffic matrix models to estimate the traffic matrix. For example, the tomogravity method [5] uses a model called the gravity model, in which the amount of traffic from a source node to a destination node is proportional to the total incoming or outgoing traffic for each edge node. According to [15], however, the gravity model does not fit the actual traffic in some real networks. Traffic matrices estimated by this method include estimation errors, such as underestimates of end-to-end traffic whose amounts are actually large. As a result, when a TE method uses traffic matrices estimated by this method, these underestimates can cause high link utilizations.

Recently, several methods estimating the traffic matrices more accurately by using additional measurements have been proposed [12–14]. These methods obtain the additional measurements by changing the routing matrices and observing the differences between the link loads before and after the route changes. For example, Ref. [12] obtains additional measurements by changing routes via a TE method. By performing TE a sufficient number of times, this approach obtains a sufficient number of measurements and then estimates the traffic matrix by assuming that the true traffic matrix does not change throughout the TE method execution. It takes a long time to change routes sufficient

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times, however, so the current traffic can differ from the initial traffic monitored before the first route change. Therefore, we need a traffic matrix estimation method that considers the time variations of traffic matrices. Ref. [14] proposes a method for modeling traffic variations by using periodic functions and estimates these functions' parameters. When traffic changes unpredictably, however, a TE method cannot configure routes suitable for the current traffic by using the traffic variations estimated by this approach, since it can only estimate the average variations of traffic for a period of a day by monitoring link loads for several days.

Therefore, in this paper, we propose a new estimation method, with which we can accurately estimate current traffic matrices by using the route changes introduced via a TE method. Unlike in Ref. [14], the purpose of our method is to estimate not the long-term variations of traffic but the current traffic matrix, which consists of both long-term variations and short-term variations. By using the accurate traffic matrix, a TE method can properly work to configure routes suitable for the current traffic.

In our method, we first estimate the long-term variations of traffic by using the link loads monitored at previous times. Then, we adjust the estimated long-term variations so as to fit the current link loads. In addition, when the traffic variation trends change and the estimated long-term variations fail to match the current traffic, our method detects mismatch between the estimated long-term variations and the current traffic. Then, our method re-estimates the long-term variations after removing monitored data corresponding to the end-to-end traffic causing the mismatches, so as to capture the current traffic variations.

The rest of this paper is organized as follows. Section 2 describes the proposed method for estimating current traffic matrices by using route changes. Then, in Section 3, we give the results of evaluating our method through simulation. Finally, Section 4 provides a conclusion.

2. Method for estimating current traffic matrix by using changes in routes

2.1 Overview of estimation method

In this paper, we propose a new method for estimating current traffic matrices accurately. We assume that a TE method sometimes changes routes in the network. Under this condition, we can obtain additional measurements, which can be used in estimating the traffic matrices, by monitoring link loads while some routes are changed.

Because it takes a long time to change routes enough times to obtain a sufficient amount of additional measurements, however, the difference between the initially monitored link loads and the current traffic might be very large. Therefore, we need to consider long-term variations. By using the link loads monitored at previous times, our method estimates the long-term variations of traffic instead of estimating the current traffic matrices directly. Then, we obtain the current traffic matrices by adjusting the estimated long-term variations so as to fit the current link loads.

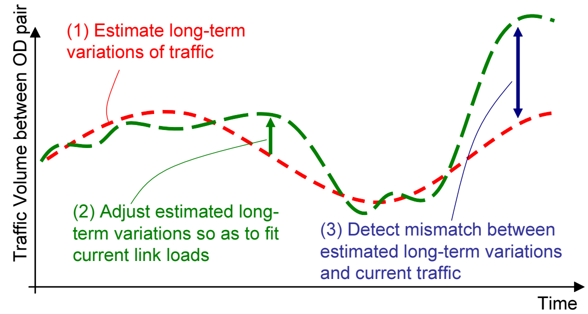


Fig. 1 Overview of proposed method

In addition, when the traffic variation trends change, the changes may cause significant estimation errors if we also use link loads monitored before the changes, since the differences between these previously monitored link loads and the current traffic can be very large. Therefore, in our method, we check whether the estimated long-term variations match the current link loads. Then, if the mismatch is detected, we re-estimate the long-term variations.

Fig. 1 shows an overview of the proposed estimation method. Our method estimates the traffic matrix through the following steps.

Step 1 Estimate the long-term variations of the traffic matrices by using the link loads monitored at previous times.
Step 2 Obtain estimation results of the current traffic matrix by adjusting the estimated long-term variations so as to fit the current link loads.
Step 3 Check whether the estimated long-term variations fit the current link loads. If they do not match the current link loads, return to Step 1 after removing the previously monitored data about the end-to-end traffic causing the mismatch. Otherwise, proceed to Step 4.
Step 4 Designate the estimation results from Step 2 as the final estimation results.

In subsection 2.2, we describe the method for estimating the long-term traffic variations. Subsection 2.3 explains how to adjust the estimated long-term variations so as to fit the current link loads. Subsection 2.4 describes how to the detect mismatches between the estimated long-term variations and the current traffic, and how to re-estimate the long-term variations and the current traffic matrix after mismatch detection.

2.2 Estimating long-term traffic variations

2.2.1 Traffic variation model

According to [14], the amount of traffic between each node pair varies periodically with a certain cycle, such as one day or one week. Therefore, in this paper, we model the traffic amount between nodes i and j as

$$t_{i,j}(n) = f_{i,j}(n) + \delta_{i,j}(n), \qquad (2)$$

where $t_{i,j}(n)$ is the traffic volume between nodes i and j at time n, $f_{i,j}(n)$ is a function modeling the periodic variation, and $\delta_{i,j}(n)$ is the variation not included in $f_{i,j}(n)$. In our method, we estimate the long-term variations by modeling $f_{i,j}(n)$ and estimating its parameters.

We model $f_{i,j}(n)$ by applying the model used in [14]. This approach models the periodic traffic variation by using Fourier series expansion. With this model, the periodic variation is represented as

$$f_{i,j}(n) = \sum_{h=0}^{N_f} \alpha_{h,i,j} cos\left(\frac{2\pi nh}{N^{\rm cycle}}\right) + \sum_{h=0}^{N_f} \alpha_{h+N_f,i,j} sin\left(\frac{2\pi nh}{N^{\rm cycle}}\right). \quad (3)$$

where $N^{\rm cycle}$ is the number of times monitoring link loads in each cycle, N_f is a parameter determining the number of terms in Eq. (3), and the $\alpha_{h,i,j}$ are the variables to be estimated by our estimation method.

This equation can model any periodic traffic variations by setting N_f to a sufficiently large value. However, setting N_f to a large value, the number of variables to be estimated also increases. In our method, we only have to roughly model the traffic variations, because we can estimate the current traffic matrix by adjusting the roughly estimated long-term variations. That is, in our method, a small N_f is sufficient.

Though our method uses the periodical function to model the traffic variation, there are other estimation methods that do not use the periodical function. For example, Ref. [16] uses Kalman filter. The method requires to monitor end-to-end traffic in advance. In our model, we can estimate the traffic from $\alpha_{h,i,j}$ that is estimated from the link loads. We discuss the method to estimate them in subsection 2.2.2.

2.2.2 Method for estimating long-term variations

In the model described by Eq. (3), the variables $\alpha_{h,i,j}$ determine the long-term variations. Therefore, our method estimates the long-term variations by estimating the $\alpha_{h,i,j}$. We estimate the $\alpha_{h,i,j}$ by using the link loads monitored at previous times. At any time n, the link loads and the traffic matrix have a relation described by Eq. (1). Therefore, we estimate all variables so as to satisfy Eq. (1) in any time. In this paper, we use a least square algorithm to estimate the variables. That is, when the number of nodes is N, by using the link loads monitored from the time $n-M+1$ to n, the variables are basically estimated as

$$minimize \sum_{k=n-M+1}^{n} |X(k) - A(k)\hat{T}^{\rm est}(k)|^2 \quad (4)$$

where

$$\hat{T}^{\rm est}(k) = \begin{bmatrix} f_{0,0}(k) \\ \vdots \\ f_{i,j}(k) \\ \vdots \\ f_{N,N}(k) \end{bmatrix}. \quad (5)$$

By using Eq. (4), when some routes are changed, we can use additional equations for estimating the variables.

With Eq. (4), however, we may not be able to estimate the long-term variations accurately because of the effects of traffic variations that cannot be modeled by Eq. (3). Because the actual traffic variations do include variations that cannot be modeled by Eq. (3) (i.e., $\delta_{i,j}(n)$ in Eq. (2)), long-term variations modeled by Eq. (3) cannot completely fit all the monitored link loads. With Eq. (4), however, we estimate the long-term variations so as to completely fit all the monitored link loads. As a result, estimation results from Eq. (4) can be affected by traffic variations that cannot be modeled by Eq. (3), making the results very different from the actual traffic.

To mitigate the impact of $\delta_{i,j}$ on the estimated long-term variations, in our method, by placing constraints on the variables themselves, we avoid estimating the long-term variations so as to completely fit all the monitored link loads. We thus use the following equation instead of Eq. (4):

$$minimize \sum_{k=n-M+1}^{n} |X(k) - A(k)\hat{T}^{\rm est}(k)|^2 + \Phi \sum_{i,j}\left(m_{i,j}\sum_{h=0}^{2N_f}(\alpha_{h,i,j} - \alpha'_{h,i,j})^2\right), \quad (6)$$

where the $\alpha'_{h,i,j}$ are the variables estimated the previous time, $m_{i,j}$ is the amount of previously monitored data, and Φ denotes a parameter by which we can set the weight to the constraints on the variables themselves. Using this equation, we estimate all the $\alpha_{h,i,j}(0 \leq h \leq 2N_f)$ of $f_{i,j}(n)$ so as to fit all the monitored link loads while keeping the values close to the values estimated the previous time.

When we estimate the long-term variations the first time, however, we have not obtained the $\alpha'_{h,i,j}$. Thus, in such cases, we set the $\alpha'_{0,i,j}$ to the elements of traffic matrices estimated by other methods [5–11], and we set the $\alpha'_{h,i,j}(1 \leq h \leq 2N_f)$ to 0. By using this approach, we can avoid estimating traffic variations as having significantly larger values than the actual variations.

In addition, even if the initial $\alpha'_{h,i,j}$ are not accurate, we can estimate the long-term variations more accurately by using link loads monitored at multiple times as additional measurements. Then, when we estimate the long-term variations the next time, we can use more accurate $\alpha'_{h,i,j}$. That is, as we estimate the long-term variations more times, the accuracies of these estimations increase.

The estimated long-term variation $\hat{T}^{\rm est}(n)$ may include negative values. However, we do not eliminate the negative values included in $\hat{T}^{\rm est}(n)$ here, because we eliminate the negative elements during the adjustment of long-term variations as described in subsection 2.3.

2.3 Adjustment of estimated long-term variations

By using the method in subsection 2.2, we estimate the long-term variations. Because these estimates do not include the $\delta_{i,j}(n)$ in Eq. (2), however, they do not fit the current link loads. Therefore, we adjust the long-term variations so as to fit the current link loads.

The adjustment is performed by the method used in Ref. [5, 7]. This method calculate the traffic matrix that is consistent with the current link loads and that is close to a (given) initial traffic matrix. In our case, the initial traffic matrix is the estimated long-term variations. The method works as follows. First, by assigning n to the functions corresponding to the estimated long-term variations, we obtain a roughly estimated traffic matrix $\hat{T}^{\mathrm{est}}(n)$. Then, we obtain a traffic matrix $\hat{T}(n)$ that is close to $\hat{T}^{\mathrm{est}}(n)$ and fits the link loads monitored at time n. That is, we obtain the estimation results by applying a least square algorithm so as to satisfy the following conditions:

$$minimize|\hat{T}(n) - \hat{T}^{\mathrm{est}}(n)|^2 \tag{7}$$

where

$$A(n)\hat{T}(n) = X(n). \tag{8}$$

A traffic matrix estimated by a least square algorithm, however, can include negative values, which are meaningless in the context of a traffic matrix. Therefore, we eliminate negative values through the following steps. We denote the estimated traffic matrix for the i-th iteration as $\hat{T}^{(i)}(n)$.

Step 1 Let $\hat{T}^{(0)}(n) \leftarrow \hat{T}(n)$.

Step 2 Obtain the matrix $\hat{T}'^{(i)}(n)$, in which we replace all the negative values of $\hat{T}^{(i)}(n)$ with zero.

Step 3 Obtain $D^{(i)}(n)$ satisfying the following condition:

$$minimize|D^{(i)}(n)|^2 \tag{9}$$

where

$$A(n)\left(\hat{T}'^{(i)}(n) + D^{(i)}(n)\right) = X(n). \tag{10}$$

Step 4 Let $\hat{T}^{(i+1)}(n) \leftarrow \hat{T}'^{(i)}(n) + D^{(i)}(n)$.

Step 5 If all elements of $\hat{T}^{(i+1)}(n)$ are non-negative, proceed to Step 6. Otherwise, return to Step 1.

Step 6 Let $\hat{T}^{(i+1)}(n)$ be the final result for the traffic matrix $\hat{T}(n)$.

2.4 Re-estimation of traffic matrix after mismatch of estimated long-term variations

When traffic variation trends change, long-term variations estimated by using all the link loads monitored at previous times can exhibit mismatches with the current traffic. This is because the long-term variations are estimated so as to fit the link loads before the change, which can be significantly different from the current traffic variations.

In such cases of mismatch, we cannot estimate the current traffic matrices accurately even after adjustment, because the adjustment uses only the current link loads, which are insufficient for estimating the traffic matrices accurately.

Therefore, in our method, when the estimated long-term variations exhibit mismatches with the current traffic, we detect the mismatches and re-estimate the long-term variations without using link loads that do not match the current traffic. In this subsection, we describe how to detect mismatches and identify the end-to-end traffic causing the mismatches, as well as how to re-estimate the long-term variations after mismatch detection.

2.4.1 Detecting mismatches and identifying end-to-end traffic causing mismatches

When the difference between the estimated long-term variation and the current traffic is large, the differences between the current link loads and the link loads calculated using the estimated long-term variations are large. In this case, because the results of adjusting $\hat{T}(n)$ must satisfy Eq. (8), while difference between $A(n)\hat{T}^{\mathrm{est}}(n)$ and the current link loads $X(n)$ is very large, the elements of $\hat{T}^{\mathrm{est}}(n) - \hat{T}(n)$, corresponding to the traffic causing the mismatches, become large. Therefore, we detect mismatches and identify the end-to-end traffic causing the mismatches by evaluating $\hat{T}^{\mathrm{est}}(n) - \hat{T}(n)$.

Because the size of traffic variation that cannot be included in Eq. (3) depends on the end-to-end traffic [14], if we set a single threshold for the elements of $\hat{T}^{\mathrm{est}}(n)-\hat{T}(n)$, traffic with large variations that cannot be modeled by Eq. (3) will be erroneously detected as traffic causing mismatches.

Therefore, we detect mismatches and identify their sources by comparing $\hat{T}^{\mathrm{est}}(n)-\hat{T}(n)$ with its previous values. Our method performs the comparison by using the Smirnov-Grubbs method [17], which can easily detect outliers in sampled data.

Here, we define the elements of $\hat{T}^{\mathrm{est}}(n)$ and $\hat{T}(n)$ corresponding to the traffic between nodes i and j as $\hat{t}^{\mathrm{est}}_{i,j}(n)$ and $\hat{t}_{i,j}(n)$ respectively. In the Smirnov-Grubbs method, we detect whether $|\hat{t}^{\mathrm{est}}_{i,j}(n) - \hat{t}_{i,j}(n)|$ is an outlier by calculating

$$d_{i,j} = \frac{|\hat{t}^{\mathrm{est}}_{i,j}(n) - \hat{t}_{i,j}(n)| - \mu_{i,j}}{\sigma_{i,j}}, \tag{11}$$

where $\mu_{i,j}$ and $\sigma_{i,j}$ are the average and standard deviation of $|\hat{t}^{\mathrm{est}}_{i,j}(k) - \hat{t}_{i,j}(k)|(n - M + 1 \leq k \leq n)$, respectively. Then, $|\hat{t}^{\mathrm{est}}_{i,j}(n) - \hat{t}_{i,j}(n)|$ is detected as an outlier if $d_{i,j}$ is larger than the theshold

$$\tau = (M-1)\sqrt{\frac{\tau^2_{\theta,M+2}}{M(M-2) + M\tau^2_{\theta,M+2}}} \tag{12}$$

where M is the number of samples, θ is a parameter specifying the detection sensitivity, and $\tau_{\theta,M}$ is a value corresponding to the top θ/M% points of the T distribution with $M-2$ degrees of freedom.

Too small $\sigma_{i,j}$ causes detection of points where $|\hat{t}^{\mathrm{est}}_{i,j}(n) - \hat{t}_{i,j}(n)|$ is small. We do not, however, need to detect such points, because the estimated long-term variations there fit the current traffic, since $|\hat{t}^{\mathrm{est}}_{i,j}(n) - \hat{t}_{i,j}(n)|$ is small. Therefore, to avoid detecting such points, we introduce a parameter s and set $\sigma_{i,j}$ to s if $\sigma_{i,j}$ is smaller than s.

2.4.2 Re-estimation of long-term variations after detection

When mismatches between the estimated long-term variations and the current traffic are detected, we need to re-estimate the long-term variations so as to fit the current traffic. Because such mismatches occur when we estimate the long-term variations by using previously monitored link loads which are significantly different from the current traffic variations, we re-estimate the long-term variations by using link loads and routing matrices in which elements corresponding to the end-to-end traffic causing the mismatches has been removed.

Our method removes elements corresponding to the end-to-end traffics causing mismatches at time n through the following steps. We first remove such elements from the routing matrices $A(i)(n-M+1 \leq i < n)$ by setting elements corresponding to the identified end-to-end traffic to 0. We denote the routing matrix after such replacement as $A'(i)$.

Then, we create a link load matrix $X'(i)(n-M+1 \leq i < n)$ from which elements about the identified end-to-end traffic has been removed. The sum of the elements of traffic matrix T corresponding to the identified end-to-end traffic traversing each link at time i is calculated as $(A(i) - A'(i))\,T$. Therefore, X'_i is given by

$$X'(i) = X(i) - (A(i) - A'(i))\,\hat{T}'^{\mathrm{est}}(i). \qquad (13)$$

where $\hat{T}'^{\mathrm{est}}(i)$ is the traffic matrix at time i calculated using the estimated long-term variations. In calculating $\hat{T}'^{\mathrm{est}}(i)$, we use the long-term variations estimated at time $n-1$, since the long-term variations estimated at time n can be affected by changing trends.

Next, our method re-estimates the long-term variations by using Eq. (14), which is refined from Eq. (6) to use $X'(k)$ and $A'(k)$:

$$\begin{aligned} minimize \sum_{k=n-M+1}^{n-1} &|X'(k) - A'(k)\hat{T}^{\mathrm{est}}(k)|^2 \qquad (14) \\ &+|X(n) - A(n)\hat{T}^{\mathrm{est}}(n)|^2 \\ &+\Phi \sum_{i,j} \left(m_{i,j} \sum_{h=0}^{2N_f} (\alpha_{h,i,j} - \alpha'_{h,i,j})^2 \right). \end{aligned}$$

We only have to re-estimate the long-term variations so as to fit the current traffic, because the purpose of our method is to estimate the current traffic matrix. Moreover, in estimating the traffic amounts of the identified end-to-end traffic by using Eq. (14), we do not need to consider the related traffic variations, because the traffic amounts corresponding to the identified traffic are included only in $X(n)$.

Therefore, in re-estimating the long-term variations, we model the amounts of the identified end-to-end traffic by

$$f_{i,j}(n) = \alpha_{0,i,j}, \qquad (15)$$

instead of using Eq. (3). By using Eq. (15), we can minimize the number of variables to be estimated.

In this re-estimation method, we remove a previously monitored data corresponding only to the end-to-end traffic causing the mismatch. Yet, the end-to-end traffic causing the mismatch can be estimated accurately from the current link loads, because the other end-to-end traffic not causing the mismatch are accurately estimated by using the previously monitored data.

2.4.3 Re-estimation of traffic matrix after re-estimation of long-term variations

After re-estimating the long-term variations, we re-estimate the current traffic matrix through the same steps described in subsection 2.3.

3. Evaluation

3.1 Metrics

In this section, we describe an evaluation of our method by simulation. In the simulation, we evaluated our method by two general metrics: (1) the accuracy of estimation, and (2) the performance of a TE method using the estimated traffic matrices.

To evaluate the accuracy, we used two specific metrics – the root mean squared error (RMSE), and the root mean squared relative error (RMSRE) – as defined below:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N^2} \sum_{1 \leq i,j \leq N} (\hat{t}_{i,j}(n) - t_{i,j}(n))^2} \qquad (16)$$

$$\mathrm{RMSRE} = \sqrt{\frac{1}{N_{\tilde{t}}^2} \sum_{1 \leq i,j \leq N, t_{i,j} > \tilde{t}} \left(\frac{\hat{t}_{i,j}(n) - t_{i,j}(n)}{t_{i,j}(n)} \right)^2} \qquad (17)$$

The RMSE gives an overall measure for the errors in estimation, while the RMSRE gives a relative measure. For small matrix elements, however, the relative errors are not really important. Thus, in computing the RMSRE, we consider only matrix elements greater than a threshold $\tilde{t}$. $N_{\tilde{t}}$ is the number of elements greater than $\tilde{t}$ in a traffic matrix. In the following simulation, $\tilde{t}$ was set so that the sum of the end-to-end traffic whose actual rate was greater than $\tilde{t}$ composed 75 % of the total traffic.

To evaluate the performance of a TE method using the

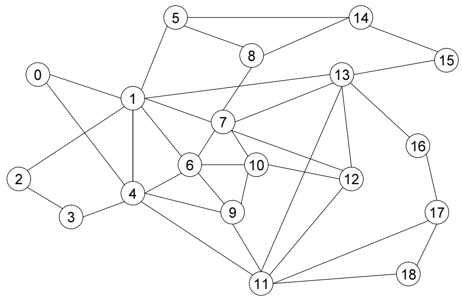


Fig. 2 EON topology

estimated traffic matrices, we investigated whether the purpose of the TE method was achieved. The next subsection describes the purpose of the TE method used in our simulation.

3.2 Environment used in evaluation

In our method, we assume that a TE method changes routes sometimes. In this evaluation, we used the optical layer TE as an example of a TE method. The optical layer TE establishes optical layer paths between two IP routers over a physical network consisting of IP routers and optical cross-connects (OXCs). A set of optical layer paths forms a virtual network topology (VNT). Traffic between two routers is carried over the VNT by using IP layer routing. Under these conditions, the optical layer TE accommodates traffic that fluctuates widely by dynamically reconfiguring the VNT.

In our simulation, we used the European Optical Network (EON) (19 nodes, 37 links) shown in Fig. 2 as the physical topology and executed the optical layer TE method proposed in [12] once an hour. The purpose of this method is to keep the maximum link utilization under the threshold T_H. In this method, optical layer paths are added or deleted with a limitation on the number of optical layer paths reconfigured at one time. Optical layer paths are added if at least one path whose utilization exceeds the threshold T_H exists. Otherwise, if there is an optical layer path whose utilization is less than a threshold T_L, the path is deleted. In this simulation, we set the maximum number of optical layer paths reconfigured at one time to 30, T_H to 0.7, and T_L to 0.4. We set the bandwidth for an optical layer path to 10 Gbps. We implement the above TE method by using C++.

In our simulation, we implement our estimation method by using MATLAB. The link loads used as the inputs of the estimation program are calculated by the actual traffic matrices and current routes. In the simulation, the actual end-to-end traffic are generated by setting the amplitudes and phases of the sin functions randomly to show that our method can estimate traffic matrices accurately even when there are no correlation between phases of end-to-end traffics. The cycles of the *sin* functions are set to 1 day. Futhermore, we add the random variations less than 0.25 times the amplitudes to the sin functions. Link loads are monitored once per 20 minutes. That is, N^{cycle} is $\frac{24\times60}{20} = 72$.

3.3 Case without sudden traffic changes

In this subsection, we investigate the accuracy of our method for estimating the long-term variations and the effectiveness of adjusting the estimated long-term variations when there are no sudden traffic changes. In the simulation, we set $M = 160$ and $N_f = 2$.

3.3.1 Accuracy of estimation of long-term variations

In our method, we estimate long-term traffic variations by using Eq. (6) instead of Eq. (4) to avoid the impact of traffic variations that cannot be modeled by Eq.(3). Therefore, to verify the effectiveness of using Eq. (6), we compared the estimation results obtained with Eqs. (4) and (6).

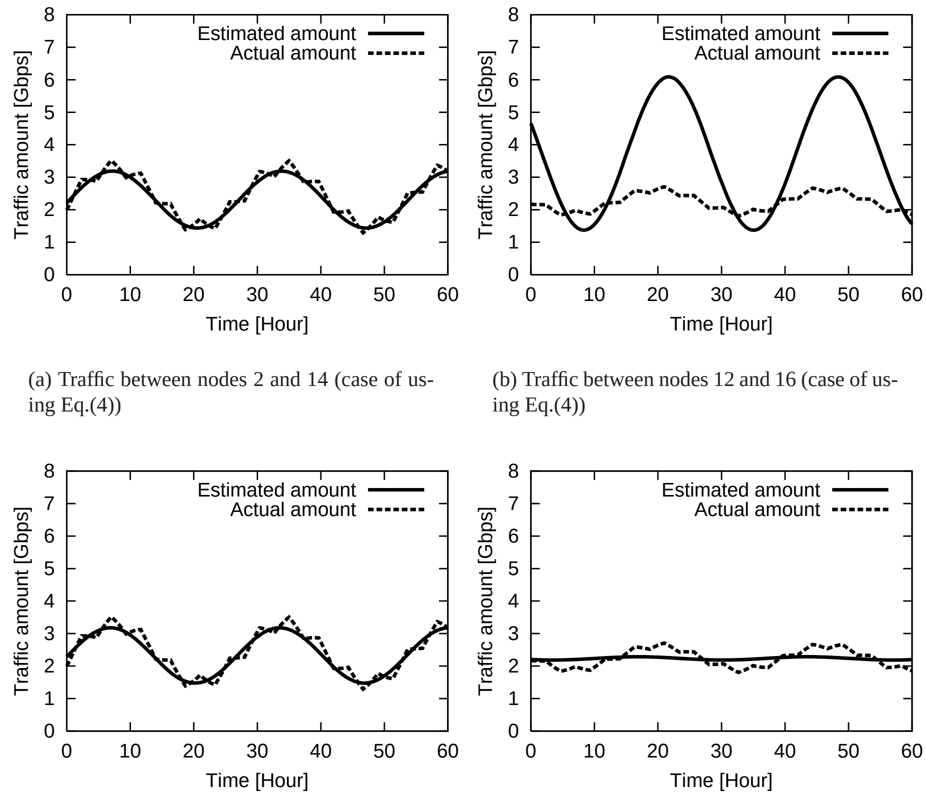
Note that estimation results obtained with Eq. (6) depend on previously estimated variables (i.e., the long-term variations are accurately estimated when the estimation results of the previous time are accurate). Here, however, because the purpose of this comparison was to verify the effectiveness of adding constraints on the variables themselves even in the case of inaccurate $\alpha'_{h,i,j}$, we set $\alpha'_{0,i,j} = \mu$ and $\alpha'_{h,i,j} = 0 (1 \leq i \leq 2N_f)$, where μ is the total volume of incoming traffic divided by the amount of end-to-end traffic.

Figure 3 shows the comparison results. As seen from this figure, both Eq. (4) and Eq. (6) can be applied to accurately estimate the traffic between nodes 2 and 14. The traffic between nodes 12 and 16, however, cannot be estimated accurately with Eq. (4), and the estimated traffic variation is significantly larger than the actual traffic variation.

This is because Eq. (4) estimates the variables so as to completely fit all the link loads monitored at previous times, even though the actual traffic variations include those that cannot be modeled by Eq. (3) (i.e., $\delta_{i,j}(n)$ in Eq. (2)). As a result, the long-term variations estimated by Eq. (4) are affected by $\delta_{i,j}(n)$, and the long-term variations of some end-to-end traffic become very different from the actual variations.

On the other hand, by using Eq. (6), we can avoid estimating variations as significantly larger than the actual variations. That is, by adding constraints on the variable themselves, we can mitigate the impact of $\delta_{i,j}(n)$ and increase the accuracy of estimating long-term variations.

Next, to evaluate the effectiveness of the constraints on the variables themselves in detail, we estimated the long-term variations with various values of Φ. Figure 4 shows the relation between Φ and the maximum RMSRE for the estimated long-term variations. According to this figure, when Φ is set to a value close to 0, the RMSRE becomes larger. This is because with small values of Φ, the estimation results become more sensitive to $\delta_{i,j}(n)$. As a result, $\delta_{i,j}(n)$ causes estimation errors like that shown in Fig. 3(b). On the other hand, with large values of Φ, the variables in the long-term variations are estimated so as to be close to the $\alpha'_{h,i,j}$. As a result, when Φ is too large, the long-term variations cannot be estimated so as to fit the monitored link loads. The opti-



(a) Traffic between nodes 2 and 14 (case of using Eq.(4))

(b) Traffic between nodes 12 and 16 (case of using Eq.(4))

(c) Traffic between nodes 2 and 14 (case of using Eq.(6) with Φ=0.01)

(d) Traffic between nodes 12 and 16 (case of using Eq.(6) with Φ=0.01)

Fig. 3 Results of estimating long-term variations

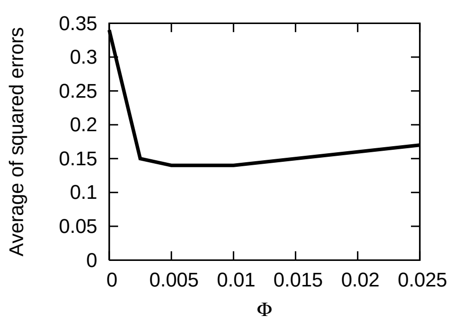


Fig. 4 RMSRE vs. Φ

mal Φ depends on the environment (e.g., the amplitudes of traffic variations), and determining optimal value of Φ is a goal for our future works. From Fig. 4, however, we can see that the estimation errors are not significant even if Φ is not optimal.

3.3.2 Effectiveness of adjustment

In our method, we obtain estimation results by adjusting the estimated long-term variations so as to fit the current link loads. Therefore, we investigated the effectiveness of adjusting the estimated long-term variations, by comparing the accuracy of the estimated traffic matrices after adjustment with the accuracies of the following methods:

- A method using only the current link loads. By comparison with this method, we investigated the effectiveness of using the link loads monitored at previous times. For this method, we used the tomogravity method with the simple gravity model [5]. Although the simple gravity model does not fit the traffic matrices used in our simulation, because we use randomly generated traffic matrices, this model also is not incorrect in some real networks [15]. The focus of this comparison is the effectiveness of using link loads monitored at previous times when the simple gravity model is not correct.
- A method using the link loads monitored at previous times but not considering the time variations of traffic. By comparison with this method, we investigated the effectiveness of modeling long-term traffic variations. For this method, we used the additional equation method proposed in [12].
- A method using the link loads monitored at previous times but only estimating the long-term variations. That is, this method uses $\hat{T}^{\mathrm{est}}(k)$ described in subsection 2.3 as the final estimation results. We call this

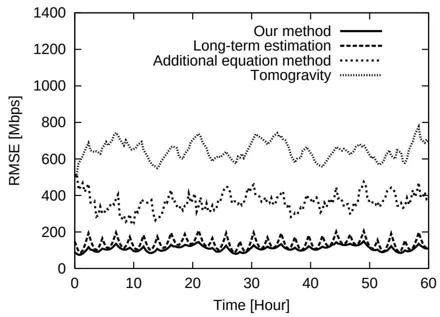


Fig. 5 Time variation of RMSE

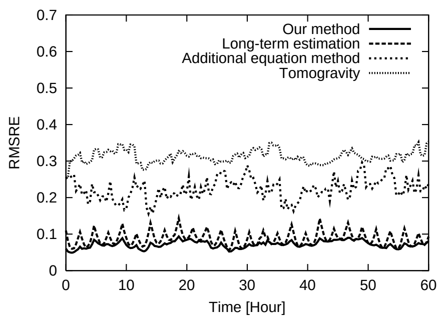


Fig. 6 Time variation of RMSRE

method *Long-term estimation*. By comparison with this method, we investigated the effectiveness of adjusting the estimated long-term variations so as to fit the current link loads. In this simulation, for estimating the long-term variations, we set Φ to 0.01.

Figures 5 and 6 show the RMSE and RMSRE, respectively, at each time. The results show that the errors for the tomogravity method are the largest. This is because the tomogravity method uses only the current link loads, which is an insufficient amount of measurements, while other methods use the additional measurements caused by route changes.

However, the errors for the additional equation method are also large. This is because that method does not consider traffic variations but assumes instead that the true traffic matrix does not change during TE execution. Therefore, this method cannot estimate traffic matrices accurately when traffic varies, even while monitoring the link loads a sufficient number of times.

On the other hand, the errors for the method estimating the long-term variations are relatively small. That is, by including the link loads monitored at previous times in considering the time variations of traffic, we can effectively use the additional measurements caused by route changes and estimate traffic matrices accurately. In addition, by adjusting the estimated long-term variations, we can estimate traffic matrices even more accurately. This is because the adjustment enables the estimation results to also follow traffic variations that cannot be modeled by Eq. (3).

The traffic variations in the real networks may be different from the traffic matrices used in this simulation. Even if the traffic variations are different from the case of this simulation, our method can estimate traffic matrices accurately as long as the amount of traffic between each node pair varies periodically because Eq. (3) can model any periodic traffic variations by setting N_f to a sufficiently large value.

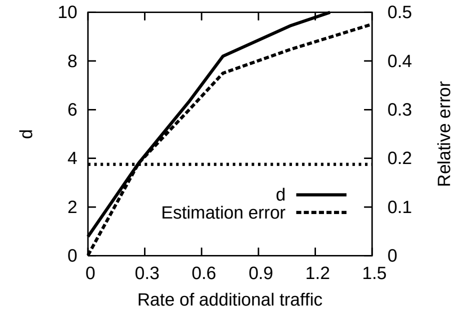


Fig. 7 $d_{2,14}$ vs. rate of added traffic

3.4 Case with sudden traffic changes

In the previous subsection, we evaluated our method in the case without sudden traffic changes. In real networks, however, traffic can change suddenly, and traffic variation trends can also change. When the trends change and the estimated long-term variations do not match the current traffic, our method detects mismatch and identifies the end-to-end traffic causing them, after which it re-estimates the long-term variations. In this subsection, we investigate the accuracy of this detection and the effectiveness of re-estimation after detection. In addition, we investigate how well a TE method works when it uses traffic matrices estimated by our method. In all the simulations described below, we set Φ to 0.01, θ to 0.01, and s to 60 Mbps.

3.4.1 Accuracy of detection of trend changes

To investigate the accuracy of mismatch detection, we calculated $d_{2,14}$ for the traffic generated by adding sudden changes to the traffic between nodes 2 and 14 in the scenario from the previous subsection. Figure 7 shows the results. In Fig. 7, the horizontal axis represents the rate of added traffic divided by the maximum rate of traffic before the addition, and the vertical axis represents $d_{2,14}$. In addition, we show the maximum relative error corresponding to the traffic between nodes 2 and 14 for the case without re-estimation.

From this figure, we can see that the larger the added traffic is, the larger $d_{2,14}$ becomes. This is because the difference between the estimated long-term variations and the current link loads becomes large when the rate of added traffic is large. As a result, the differences between the traffic matrices before and after adjustment also become large. In this simulation, because we set M to 160 and θ to 0.01, the threshold τ calculated from Eq. (12) is 3.75. Therefore, if the added traffic is more than 0.3 times the rate of the traffic before addition (i.e., when the added traffic causes a relative error of more than 0.20 in the case without re-estimation), we can detect mismatches between the estimated traffic variations and the current traffic. In this situation, our method

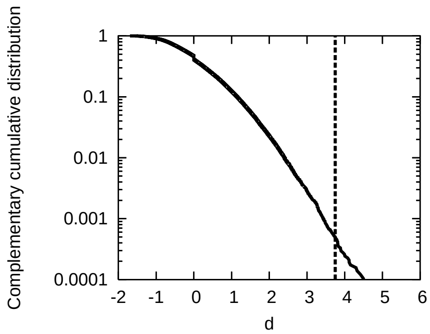


Fig. 8 Complementary cumulative distribution of $d_{i,j}$ with no changes

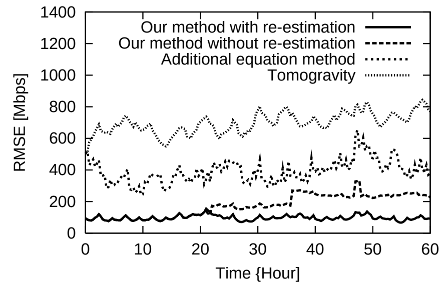


Fig. 9 Time variation of RMSE (when some traffic variations change)

re-estimates the long-term variations so as to fit the current traffic.

In detecting mismatches, false positives (i.e., the cases of mistakenly detecting end-to-end traffic with no changes) can occur. Thus, we investigated the likelihood of such false positives. Figure 8 shows the complementary cumulative distribution of $d_{i,j}$ in the case without adding sudden changes. The vertical line in Fig. 8 represents 3.75, the threshold τ calculated above. This figure shows that the probability of mistaken detection in the case with no changes is about 0.03 %. We discuss the impacts of these false positives later.

3.4.2 Effectiveness of re-estimation

When mismatches between the estimated long-term variations and the current traffic are detected, we re-estimate the long-term variations after removing monitored data about the end-to-end traffic identified as causing the mismatches. In this subsection, we investigate the effectiveness of the re-estimation through simulation. In this simulation, we used traffic generated by adding sudden changes to the traffic used for the simulation described in the previous subsection. We added sudden increases to the traffic from nodes 2 to 4, 9 to 1, and 0 to 12 at times 22, 36, and 47, respectively. The rates of the sudden increases from nodes 2 to 4, 9 to 1, and 0 to 12 were, respectively, 120 % , 150 %, and 160 % of the maximum rate of traffic before the addition. The increased rates from nodes 2 to 4 and 9 to 1 continue until the end of this simulation. The increased rate from 0 to 12 continues for 1 hour.

Figure 9 shows the RMSE when we added these sudden traffic changes, for four different methods: our method with re-estimation, our method without re-estimation, the additional equation method, and the tomogravity method. For our method without re-estimation, we estimated the long-term variations and adjusted them but did not re-estimate them even when the variation trends changed.

From this figure, similarly to the results shown in Figs. 5 and 6, we can see that the RMSEs for the tomogravity method and the additional equation method are large. The figure also shows that the RMSE for our method without re-estimation is small before time 22 but increases afterward, whereas the RMSE for our method with re-estimation remains small after time 22. This difference is caused by the sudden changes, whose impact we discuss in detail later.

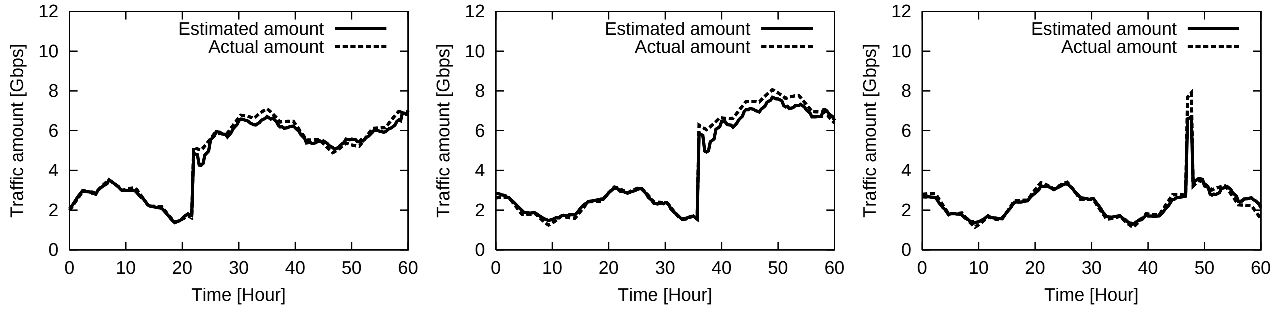
The results shown in Fig. 9 also verify that the impact of false positives is small. As described above, about 0.03 % of the end-to-end traffic without changes in the traffic variation trends will be mistakenly identified as causing mismatches between the estimated long-term variations and the current traffic. For example, at time 21 in Fig. 9, the end-to-end traffic between nodes 1 and 10 is mistakenly identified as causing a mismatch. From the figure, however, we can see that the RMSE for our method does not become significant even when such false positives occur; it always remains the smallest among the four methods. This is because we have sufficient measurements to estimate the long-term variations and traffic matrices accurately even when some false positives occur and measurements about the mistakenly identified end-to-end traffic is removed.

To investigate the impact of sudden changes in detail, we compared the estimation results obtained for traffic with sudden changes added. Figures 10 and 11 show the estimation results for our method with and without re-estimation, respectively.

These figures show that both methods can accurately estimate all the traffic amounts before adding the sudden changes. After adding the changes, however, the traffic rate estimated by our method without re-estimation cannot capture the changes. This is because that method also uses the link loads monitored before adding the sudden changes, which are significantly different from the current traffic variations. Therefore, because of this link loads that does not fit the current traffic variations, the long-term variations cannot be estimated accurately. Even though we adjust the estimated long-term variations so as to fit the current link loads, the adjusted results still do not capture the sudden changes, because the adjustment process can use only the current link loads, which is insufficient to estimate the traffic matrices accurately.

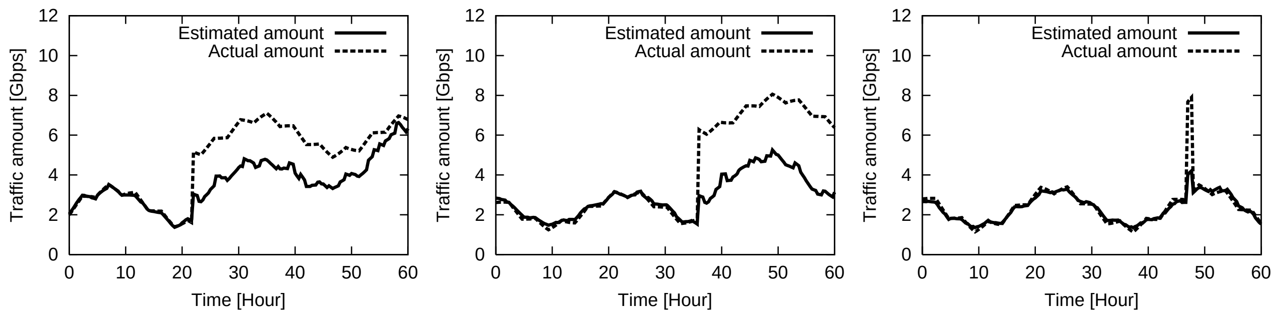
On the other hand, our method with re-estimation can estimate all the traffic amounts accurately even after adding the sudden changes. This is because by re-estimating the long-term variations after removing monitored data about the end-to-end traffic causing the mismatches between the estimated long-term variations and the current traffic, we avoid the impact of monitored link loads which are significantly different from the current traffic variations.

According to the result of traffic between nodes 0 and 12, our method can correctly detect sudden changes in the



(a) Traffic between nodes 2 and 4 (b) Traffic between nodes 9 and 1 (c) Traffic between nodes 0 and 12

Fig. 10 Estimation results for our method with re-estimation



(a) Traffic between nodes 2 and 4 (b) Traffic between nodes 9 and 1 (c) Traffic between nodes 0 and 12

Fig. 11 Estimation results for our method without re-estimation

traffic rate and can estimate traffic matrices accurately even when the increase of the traffic is temporal.

3.4.3 Impact on performance of TE methods

Finally, we evaluate the performance of TE methods using traffic matrices estimated by our method. The TE method used in our simulations configured the VNT and routes over the VNT so as to keep the maximum link utilization under the threshold T_H. When we use traffic matrices including estimation errors, however, these errors can cause the maximum link utilization to be above T_H. Therefore, in this evaluation, we investigated the maximum link utilization after TE was performed. For this simulation, we used the same traffic described in the previous subsection.

Figure 12 shows the results of this simulation. The figure shows that when using the tomogravity method or the additional equation method, the maximum link utilization becomes significantly larger than the threshold T_H. This is because the estimation errors of these methods are large, as described above. When the estimation errors are large, the link utilizations after executing the TE method, as calculated using the estimated traffic matrix, can be very different from the actual link utilizations. As a result, the link utilizations after TE are mistakenly regarded as being lower than T_H, even though the actual link utilizations are still high and the necessary optical layer paths have not been added.

This figure also shows that the maximum link utilizations in the case of using our method without re-estimation sometimes become significantly larger than the threshold, as well. This is caused by significant underestimation of the traffic including the sudden changes. As shown in Fig. 11, our method without re-estimation cannot capture the added sudden changes and significantly underestimates their amounts. Because of these underestimates, when the TE method changes the routes of the underestimated traffic, it does not reserve enough bandwidth. As a result, since the actual traffic rates are much higher than expected, the link utilizations become high.

On the other hand, in the case of using our method with re-estimation, we can reduce the maximum link utilization to around T_H at all times. This is because, with re-estimation, our method can estimate traffic matrices accurately even when the traffic changes suddenly.

Although the maximum link utilization is reduced to around T_H with traffic matrices estimated by our method with re-estimation, however, it is not always smaller than T_H. This is because estimation errors can still be included in the results of our method with re-estimation, even though this method is the most accurate of the four methods considered here.

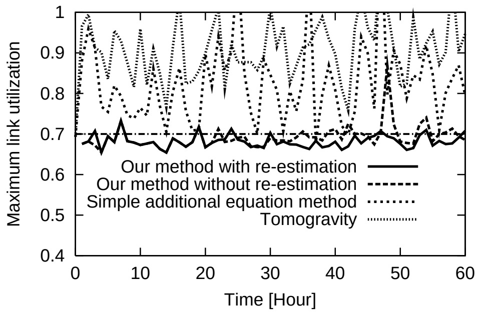


Fig. 12 Variation in maximum link utilization after TE execution

Especially when multiple instances of end-to-end traffic are identified as causing mismatches between the estimated long-term variations and the current traffic, the estimation errors increase, because removing the previously monitored data about these multiple instances decreases the amount of monitored data used for estimation. That is, if many instances of end-to-end traffic are errorneously identified as causing the mismatch at the same time, these false positives cause a increase in the estimation error. Thus, to estimate traffic matrices more accurately, we need to minimize the number of false positives by setting parameters optimally or using a more sophisticated detection method. These considerations remain for our future work.

Minimizing the number of false positives is insufficient, however, because it is possible for multiple instances of end-to-end traffic to actually change suddenly, causing mismatches between the estimated long-term variations and the current traffic. When this happens, increases in estimation errors are difficult to avoid, because we cannot obtain sufficient measurements about such traffic changing suddenly. Therefore, to avoid the impact of such errors on methods using estimated traffic matrices, TE methods also need to consider estimation errors. This is another topic for our future work.

4. Concluding remarks

In this paper, we have proposed a method for estimating current traffic matrices by using the changes in routing matrices introduced via a TE method. In this method, we first estimate the long-term variations of traffic matrices by using the link loads monitored at previous times. Then, we obtain the current traffic matrix by adjusting the estimated long-term variations of traffic so as to fit the current link loads. In addition, when the traffic variation trends change and the estimated long-term variations cannot fit the current variations, our method detects mismatch and identifies the end-to-end traffic causing them. Then, our method re-estimates the long-term traffic variations after removing monitored data about the end-to-end traffic causing the mismatches.

We evaluated our method through simulation. According to the results, our method can obtain accurate traffic matrices by adjusting the estimated long-term variations. In addition, when some end-to-end traffic changes suddenly and the estimated long-term variations do not match the current traffic, our method can detect mismatches accurately. Then, by re-estimating the long-term variations after removing monitored link loads about the end-to-end traffic causing the mismatches, the method can estimate current traffic matrices accurately even when some end-to-end traffic changes suddenly.

In addition to evaluating the proposed method, we evaluated a TE method using traffic matrices estimated by our method. According to these results, by using the traffic matrices estimated by our method, a TE method can reduce the maximum link utilization to around its target value, whereas the maximum link utilization becomes high with other methods considered here.

Our future works include optimally setting parameters such as Φ and N_f. In particular, although we used fixed values of N_f in this work, it might be possible to estimate traffic matrices more accurately by setting N_f dynamically according to the current measurement. Another future work is to evaluate our method using the traffic traces of the real networks. In addition, our future works also include constructing a TE method that considers estimation errors.

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