トラヒックの長期変動から現在のトラヒックマトリクスを推定する手法

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あらまし 現在のトラヒックマトリクスを得ることは、トラヒックエンジニアリングにとって必須である。しかしながら、トラヒックマトリクスを直接観測するのは難しく、推定する手法も提案されているものの、現実のネットワークでは、推定にもちいらたモデルが合致しない場合もあり、正確に推定することができない。本論文では、トラヒックエンジニアリングによって引き起こされた経路変更を用いて、現在のトラヒックマトリクスを正確に推定する手法を提案する。提案手法では、まず、最近 M 回の観測によって得られたリンク負荷を元に、長期変動の推定を行う。そして、現在のリンク負荷に合うように、推定された長期変動に補正を加える。さらに、推定された長期変動が、現在のトラヒックに合致しなくなった場合には、その変化を検出し、合致しなくなった原因となるトラヒックに関する過去の情報を除去した上で、長期変動の推定を行いなおす。本稿では、シミュレーションにより、提案手法の評価を行い、トラヒックが変化した場合であっても、正確にトラヒックマトリクスを推定可能であることを示す。
キーワード トラヒックエンジニアリング, GMPLS, トラヒックマトリクス推定

Estimating current traffic matrices accurately by using long-term variations information

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Abstract Obtaining current traffic matrices is essential to traffic engineering (TE) methods. However, it is difficult to monitor traffic matrices directly. The existing estimation methods also cannot estimate them accurately. In this paper, we propose a method for estimating current traffic matrices by using 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 the last M 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 cannot match the current traffic, our method detects mismatches. Then, so as to capture the current traffic variations, the method re-estimates the long-term variations after removing information about the end-to-end traffic causing the mismatches. For this paper, we evaluated 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 engineering, GMPLS, Traffic matrix estimation

1. Introduction

Obtaining current traffic matrices accurately is essential to traffic engineering (TE) methods [1, 2]. By using the current traffic matrices, TE methods configure routes on a network so as to fit the current traffic.

Because it is difficult to monitor traffic matrices directly, several methods for estimating traffic matrices from limited information have been proposed [3–5]. 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

$$X(n) = A(n)T(n), \tag{1}$$

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. However, because the number of links is much smaller than the number of elements of the traffic matrix, estimated traffic matrices include estimation errors.

Recently, several methods increasing the accuracy of estimation by using additional measurements have been proposed [4, 5]. These methods obtain the additional information by changing the routing matrices. To estimate traffic matrices by using the additional information obtained at the different times, we need to consider the time variations of traffic. Thus, Ref. [5] proposes a method for modeling traffic variations by using periodic functions and estimates these functions' parameters. However, when traffic changes unpredictably, the traffic matrices estimated by this approach cannot fit the current traffic matrices 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. [5], 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.

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 information, which can be used in estimating the traffic matrices, by monitoring link loads while some routes are changed.

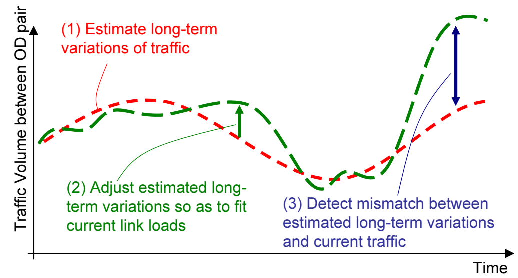


Fig. 1 Overview of proposed method

However, the current traffic can differ from the initial traffic monitored before the first route change. Therefore, we need to consider long-term variations. By using the link loads monitored the last M 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.

In addition, when the traffic variation trends change, the changes may cause significant estimation errors if we also use information obtained before the changes, since this information can be very different from the current traffic. Therefore, in our method, we check whether the estimated long-term variations match the current link loads. Then, if we detect a mismatch between the estimated long-term variations and the current link loads, we re-estimate the long-term variations after removing the traffic information causing the mismatch, so as to follow the current variations of traffic.

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 the last M 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 previous information 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 the following subsections, we describe the above steps in detail.

2.2 Estimating long-term traffic variations

2.2.1 Traffic variation model

According to [5], 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

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

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 model the long-term variations by $f_{i,j}(n)$ and estimate them by estimating the parameters of $f_{i,j}(n)$.

We model $f_{i,j}(n)$ by applying the model used in [5]. This approach models the periodic traffic variation by using *sin* and *cos* functions. With this model, the periodic variation is represented as

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

where N^{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. With N_f set to a large value, the traffic variation modeled by Eq. (3) captures more of the short-term variation, but 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.

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 the last M 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, the variables are basically estimated as

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

where

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

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):

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

where the $\alpha'_{h,i,j}$ are the variables estimated the previous time, $m_{i,j}$ is the amount of information monitored before, 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 $\alpha_{h,i,j} (0 \leqq h \leqq 2N_f)$ 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 [3], and we set the $\alpha'_{h,i,j} (1 \leqq h \leqq 2N_f)$ to 0. By using this approach, we can avoid estimating traffic variations as having significantly larger values than the actual variations.

2.3 Adjustment of estimated long-term variations

In described 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 estimated as given in subsection 2.2 so as to fit the current link loads.

The adjustment is performed through the following steps. 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:

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

where

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

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 the last M 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 very 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 estimated long-term variations are very different from the current traffic, 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 $A(n)\hat{T}^{\mathrm{est}}(n)$ is very different from the current link loads $X(n)$, 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 [5], 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 [6], 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

$$d_{i,j} = \frac{|\hat{t}^{\mathrm{est}}_{i,j}(n) - \hat{t}_{i,j}(n)| - \mu_{i,j}}{\sigma_{i,j}}, \tag{9}$$

where $\mu_{i,j}$ and $\sigma_{i,j}$ are the average and standard deviation of $|\hat{t}^{\mathrm{est}}_{i,j}(k) - \hat{t}_{i,j}(k)| (n - M + 1 \leqq k \leqq n)$, 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

$$\tau = (M-1)\sqrt{\frac{\tau^2_{\theta,M+2}}{M(M-2) + M\tau^2_{\theta,M+2}}} \tag{10}$$

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 $\theta/M\%$ 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 that are very different from the current traffic variations, we re-estimate the long-term variations by using link loads and routing matrices in which information about the end-to-end traffic causing the mismatches has been removed.

Our method removes previous information corresponding to the end-to-end traffics causing mismatches at time n through the following steps. We first remove such information from the routing matrices $A(i)(n - M + 1 \leqq i < n)$ 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 $X'(i)(n - M + 1 \leqq i < n)$ from which information 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

$$X'(i) = X(i) - \big(A(i) - A'(i)\big)\,\hat{T'}^{\mathrm{est}}(i). \tag{11}$$

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. (12), which is refined from Eq. (6) to use $X'(k)$ and $A'(k)$:

$$\begin{aligned} \mathit{minimize} \quad & \sum_{k=n-M+1}^{n-1} |X'(k) - A'(k)\hat{T}^{\mathrm{est}}(k)|^2 \\ & + |X(n) - A(n)\hat{T}^{\mathrm{est}}(n)|^2 \\ & + \Phi \sum_{i,j} \left(m_{i,j} \sum_{h=0}^{2N_f} (\alpha_{h,i,j} - \alpha'_{h,i,j})^2 \right). \end{aligned} \tag{12}$$

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

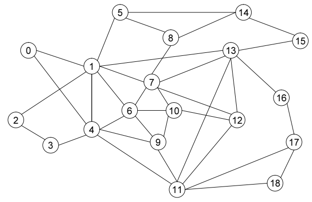


Fig. 2 EON topology

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 a specific metric – the root mean squared error (RMSE).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N^2}\sum_{1 \leqq i,j \leqq N}(\hat{t}_{i,j}(n) - t_{i,j}(n))^2} \quad (13)$$

To evaluate the performance of a TE method using the 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 [4] once an hour. The purpose of this method is to keep the maximum link utilization under the threshold T_H by adding or deleting optical layer paths with a limitation on the number of optical layer paths reconfigured at one time. 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.

In the simulation, we investigate the accuracy of the estimation when the some traffic change suddenly. Therefore, we generate end-to-end traffic by adding sudden changes to the traffic generated by adding variations to sin functions whose amplitudes and phases were randomly generated. We added sudden changes to the traffic from nodes 2 to 4, 9 to 1, and 0 to 12 at times 70, 110, and 140, respectively. The rates of the sudden traffic changes 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.

In our estimation method, we use parameters M, N_f, Φ, θ and s. In this simulation, we set M to 160, N_f to 2, Φ to 0.01, θ to 0.01, and s to 1.

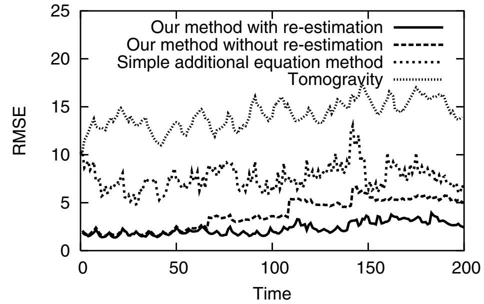


Fig. 3 Time variation of RMSE (when some traffic variations change)

3.3 Accuracy of the estimation

In our method, we obtain estimation results by adjusting the estimated long-term variations so as to fit the current link loads. In addition, when the trends of traffic variations change and the estimated long-term variations do not match the current traffic, our method detects mismatches and identifies the end-to-end traffic causing them, after which it re-estimates the long-term variations.

Therefore, we investigated the effectiveness of adjusting the estimated long-term variations and effectiveness of re-estimation, by comparing the accuracy of our estimation method with the accuracies of the following methods:

- A method using only the current link loads. For this method, we used the tomogravity method with the simple gravity model [3].
- A method using the link loads monitored at previous times but not considering the time variations of traffic [4].
- Our method without re-estimation.

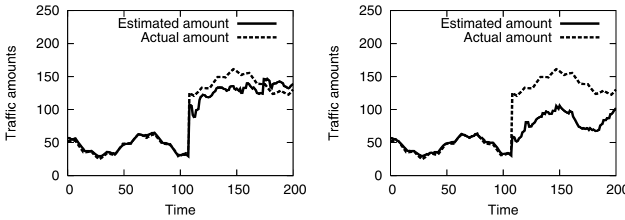
Figure 3 shows the RMSE when we added these sudden traffic changes. The results show that the errors for the tomogravity method are the largest. This is because the tomogravity method uses only the current link loads, which is an insufficient amount of information.

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 our methods are relatively small. That is, by including the link loads monitored at previous times in considering the time variations of traffic, we can estimate traffic matrices accurately. However, the RMSE for our method without re-estimation increases after time 70, whereas the RMSE for our method with re-estimation remains small after time 70.

To investigate the impact of sudden changes in detail, we compared the estimation results obtained for traffic with sudden changes added. Figure 4 shows the estimation results for our method with and without re-estimation.

This figure shows 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 with-



(a) Our method with re-estimation (b) Our method without re-estimation

Fig. 4 Estimation results of traffic between nodes 9 and 1

out re-estimation cannot capture the changes. This is because that method also uses the link loads monitored before adding the sudden changes, which are very different from the current traffic variations.

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

3.4 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. 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 5 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.

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. 4, our method without re-estimation cannot capture the added sudden changes and significantly underestimates their amounts. Because of such underestimates, when the TE method changes the routes of the underestimated traffic, it does not reserve enough bandwidth.

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.

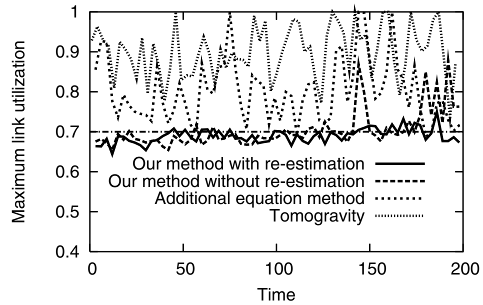


Fig. 5 Variation in maximum link utilization after TE execution

4. Concluding remarks

In this paper, we have proposed a method for estimating current traffic matrices by using 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 the last M 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 cannot match the current traffic, our method detects mismatches. Then, so as to capture the current traffic variations, the method re-estimates the long-term variations after removing information about the end-to-end traffic causing the mismatches. For this paper, we evaluated 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.

Our future work will include optimally setting parameters such as M, Φ and N_f.

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