Traffic engineering cooperating with traffic monitoring for the case with incomplete information

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***Abstract*—Traffic Engineering (TE) accommodates traffic efficiently by dynamically configuring the routes so as to follow traffic changes. If traffic changes frequently and drastically, the interval to perform the route reconfiguration should be set to a short value, to follow traffic changes. To shorten the interval, obtaining the traffic information becomes a problem; measuring traffic information accurately of the whole network, which is required to calculate the suitable route, is difficult to be obtained in a short interval, due to the overhead to monitor and collect the traffic information. We have proposed the framework of the TE for the case that only a part of traffic information can be obtained at each time slot. This framework was inspired by the human brain mechanism. In this framework the conditional probability is considered to make decisions. In this framework, a controller is deployed. The controller (1) obtains a limited number of traffic information, (2) estimates and predicts the probability distribution of the traffic, (3) configures the routes considering the probability distribution of the predicted future traffic, and (4) selects the traffic to be monitored at the next period considering the performance of the route reconfiguration using the traffic information obtained at the next period. In this paper, we discuss the details of the each step of our framework. Then, we evaluate our framework.**

I. Introduction

Traffic engineering (TE) is a method to configure the network configuration such as routes so as to accommodate traffic efficiently, following traffic changes [1]–[4]. In TE methods, a controller periodically collects the traffic information, and changes the routes of the flows within the network based on the collected traffic information. By dynamically reconfiguring the routes, the controller avoids congestion even when traffic change occures.

Traditionally, TE methods consider the daily traffic changes and their control intervals are set to one hour or more. However, if traffic changes frequently and drastically, the control interval should be set to a shorter value; when the traffic change causes congestion, congestion cannot be mitigated until the next time slot. Benson et al. demonstrated that the routes should be reconfigured every 5 seconds in the network where traffic changes frequently and drastically, such as datacenter networks [5].

TE methods require the traffic information to calculate the suitable route at each time slot. If we set a short control interval, the traffic information should also be obtained at the short interval. However, in a large network, measuring traffic information accurately of the whole network is difficult to be obtained in a short interval, due to the overhead to monitor and collect the traffic information. Instead, we consider the case that only a part of traffic information can be monitored and collected at each time.

The methods to estimate the traffic of the whole network from a part of traffic information have also been proposed [6], [7]. In these methods, the traffic information of the flows that are not included in the collected traffic information is estimated from the collected traffic information, considering the spatial and temporal properties of the traffic. However, the estimated traffic includes the estimation errors, and the errors may affect the performance of the TE. To mitigate the impact of the estimation errors, the TE method should consider the estimation errors. On the other hand, the traffic monitoring and estimation methods can avoid estimation errors affecting the TE by improving the accuracy of the estimation of the traffic of the flows which are important for the TE. That is, the TE and traffic monitoring should cooperate with each other.

We have proposed a framework in which TE and traffic monitoring cooperate with each other to handle the situation that only a part of information is obtained at each time slot [8]. This framework was inspired by the process by which a human brain makes decisions from uncertain and incomplete information. A human brain makes many decisions well even under highly uncertain environment. One promising theoretical model to explain how a human brain makes decisions is the Bayesian decision making model [9]. In this model, a human brain has stochastic variables, and updates the variables by Bayesian estimation every time a new observation is obtained. Then, a human brain makes decision based on the stochastic variables. By doing so, a human brain can make decisions even when only uncertain and incomplete information can be obtained. We apply this process to TE. Specifically, we apply the feature that a human brain increases confidence by repeating Bayesian estimation. In our framework, the controller has stochastic variables about the traffic, and updates them every time a part of traffic information is obtained. By repeating the above steps, the controller understands the probability distributions of traffic, even when only a part of traffic is obtained at each time slot. The controller changes the routes based on the probability distributions of traffic. In addition, the controller decides the points to be monitored at the next

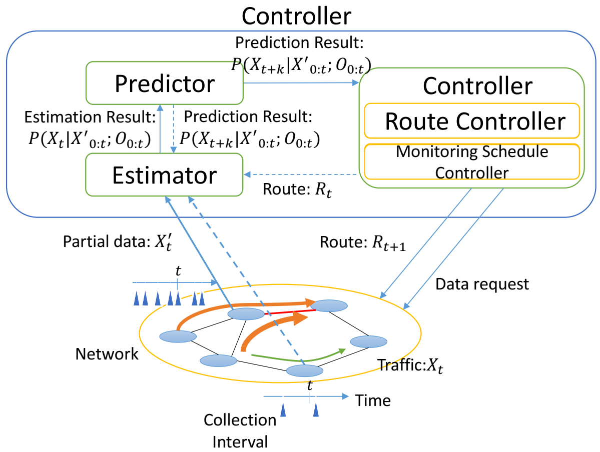

Fig. 1. Overview of our framework

time slot based on the probability distributions of traffic.

In our previous work, we have only proposed the framework, and have not discussed the details of each step. Therefore, in this paper, we specify and discuss each step of the framework. In addition, we evaluate our framework.

The rest of this paper is organized as follows. Section II explains the overview of our framework. Section III describes the details of each step of our framework. Section IV presents an evaluation of our method. Section V presents our concluding remarks.

II. Framework for Traffic Engineering under Uncertain Traffic Information

Figure 1 shows the overview of our framework. In our framework, a controller is deployed. The controller (1) obtains a limited number of traffic information, (2) estimates and predicts the probability distribution of the traffic, (3) configures the routes considering the probability distribution of the predicted future traffic, and (4) configures the traffic to be monitored at the next period considering the performance of the route reconfiguration using the traffic information obtained at the next period. To perform above operations based on the Bayes decision making theory, a controller includes the following modules; estimator, predictor, route controller and monitoring schedule controller. The rest of this subsection explains these modules.

In this paper, we denote the traffic rates of all flows at time slot t by X_t, the traffic rates of flow f at time slot t by $x_{t,f}$. In this paper, the controller observes a part of traffic. We denote the traffic observed at time slot t by X'_t, and the element of X'_t corresponding to the flow f by $x'_{t,f}$. We also denote the route at time slot t by R_t, and the set of the observed flows at time slot t by O_t. $X_{t:t+k}$ is $(X_t, X_{t+1}, \dots, X_{t+k})$. Similarly, we also define $X'_{t:t+k} = (X'_t, X'_{t+1}, \dots, X'_{t+k})$, and $O_{t:t+k} = (O_t, O_{t+1}, \dots, O_{t+k})$

A. Estimator

The estimator estimates the amount of traffic in the current network from the partially observed traffic information. In our framework, estimator estimates the posterior distribution of the traffic volume X_t after obtaining the partially monitored traffic X'_t.

The posterior distribution of the traffic volume X_t is calculated by

$$P(X_t|X'_t; O_t) = \frac{1}{P(X'_t|O(t))} P(X'_t|X_t; O_t) P(X_t) \quad (1)$$

where $P(X_t)$ is a prior distribution of X_t. The traffic volume predicted by the predictor at the time slot $t-1$ can be used as the prior distribution. That is, Posterior distribution of the traffic volume X_t is calculated by

$$P(X_t|X'_{0:t}; O_{0:t}) = \frac{1}{P(X'_t)} P(X'_t|X_t; O_t) P(X_t|X'_{0:t-1}; O_{0:t-1}) \quad (2)$$

where $P(X_t|X'_{0:t-1}; O_{0:t-1})$ is the probability distribution of X_t predicted at the time slot $t-1$. By using the traffic predicted at the previous time slots, the traffic volumes of whole network can be estimated even when only a limited part of traffic can be monitored.

B. Predictor

The predictor predicts the probability distribution of the future traffic volumes from the past traffic. That is, the predictor predicts $P(X_{t+k}|X'_{0:t}; O_{0:t})$.

The predictor uses the prediction model. By using the prediction model with parameter θ, the traffic rates after time slot $t+1$ can be predicted from the past traffic rates by $P(X_{t+1:t+n}|X_{t-m:t}; \theta)$, where m is the length of the past traffic rates used by the prediction, and n is the length of the time slot that can be predicted.

By using this prediction model, the future traffic rates are predicted from the previously monitored traffic.

$$\begin{aligned} &P(X_{t+1:t+n}|X'_{0:t}; O_{0:t}, \theta) = \\ &\sum_{X_{t-m:t}} P(X_{t+1:t+n}|X_{t-m:t}; \theta) P(X_{t-m:t}|X'_{0:t}; O_{0:t}) \end{aligned} \quad (3)$$

Then, $P(X_{t+k}|X'_{0:t}; O_{0:t}, \theta)$ can be obtained by

$$P(X_{t+k}|X'_{0:t}; O_{0:t}, \theta) = \sum_{X_{t:t+k-1}, X_{t+k+1:t+n}} P(X_{t+1:t+n}|X'_{0:t}; O_{0:t}, \theta). \quad (4)$$

C. Route controller

Route controller calculates routes so that required performance is provided, considering the predicted probability distribution of traffic rates.

We have proposed a method called stochastic MP-TE, which configures the routes, considering the predicted probability of the future traffic [10]. In the stochastic MP-TE, the routes are calculated so as to minimize the weighted sum of the cost function indicating the network performance and the cost of changing routes under the constraint that the probability that traffic passing a link exceeds the threshold should be kept less than the threshold. In this framework, the route controller is based on the stochastic MP-TE, and calculates routes by solving the following optimization problem.

$$minimize : E\left[\sum_{i=t+1}^{t+h}\{(1-w)f(X_i,R_i)+w||R_i-R_{i-1}||^2\}\right] \tag{5}$$

$$s.t. : P\left(y_i^l(X_i,R_i)>c^l\right)\leq p \tag{6}$$

where $f(X_i, R_i)$ is a cost function indicating the network performance, $||R_i - R_{i-1}||^2$ is a cost caused by changing routes from R_{i-1} to R_i, and $y_i^l(X_i, R_i)$ is the amount of traffic passing the link l when the traffic rates is X_i and the routes are set to R_i. h is the length of the predictive time series considered by the route controller, and w is the weight to the cost of changing routes. c^l is threshold to the traffic amount passing the link i, and p is the acceptable probability that the traffic exceeds a threshold.

Although the routes $R_{k+1}, \ldots, R_{k+h}$ are obtained by solving the above optimization problem, the route controller actually sets R_{k+1} to the network. After collecting the data at the following time, the later routes are recalculated with the new prediction result. By doing so, the route controller adaptively corrects the route even if the predictive distribution is temporally wrong.

D. Monitoring schedule controller

In this framework, the monitoring schedule controller decides the traffic to be monitored at the next time slot so as to minimize the expectation value of the cost after the route changes using the traffic monitored at the next time slot.

The monitoring schedule controller decides the traffic to be monitored by solving the following optimization problem.

$$minimize : E_{P(X_{t+1})P(X'_t|O_t)}\left[f\left(X_{t+1}, R_{k+1}(X'_t, O_t)\right)\right] \tag{7}$$

$$s.t. C(O_t)\leq W \tag{8}$$

where $E_{P(X)}[f(X)]$ is the expectation value of $f(X)$ under the probability distribution $P(X)$, and $R_{t+1}(X'_t, O_t)$ is the route configuration for the time slot $t+1$ calculated by the route controller when the X'_t is observed at the time slot t by monitoring the flows included in O_t. $C(O_t)$ is the overhead required to monitor the traffic in O_t, and W is the acceptable overhead. $P(X'_t|O_t) = \sum_{X_t} P(X'_t|X_t; O_t)P(X_t)$ is the probability of the observed traffic X_t when the traffic in O_t is monitored. When solving the above optimization problem, the probability distributions $P(X_t)$ and $P(X_{t+1})$ are unknown. In this framework, we use the predicted probability distributions $P(X_t|X'_{0:t-1}; O_{0:t-1})$ and $P(X_{t+1}|X'_{0:t-1}; O_{0:t-1})$ instead of them.

III. Dynamic traffic engineering and traffic monitoring based on the framework

In this section, we specify the dynamic traffic engineering and traffic monitoring based on our framework. We call this method *Stochastic Control with Considering Uncertainty (SCCU)*. Our framework is constructed of the estimator, predictor, route controller and monitoring schedule controller. Therefore, in this section, we specify these modules.

A. Estimator

The estimator estimates $P(X_t|X'_{0:t}; O_{0:t})$. To estimate $P(X_t|X'_{0:t}; O_{0:t})$, we need to define $P(X'_t|X_t; O_t)$, which indicates the probability distribution of the observed traffic.

Assuming that the monitoring O_t does not provide any information about the traffic rates of the flow $x_{t,f}$ unless the flow f is not included in O_t, and that the flow f included in O_t can be observed accurately, $P(X'_t|X_t; O_t)$ is

$$P(x'_{t,f}|X_t;O_t) = \begin{cases} \delta(x'_{t,f}-x_{t,f}) & (f\in O_t) \\ \mathcal{U}(0,\infty) & (\text{otherwise}) \end{cases} \tag{9}$$

where $\delta(x)$ is Dirac delta function, and $\mathcal{U}(a, b)$ is an uniform distribution between a and b.

By using Eq. (9), $P(x_t|X'_{0:t}; O_{0:t})$ is estimated by

$$P(x_t|X'_{0:t};O_{0:t}) = \begin{cases} \delta(x'_{t,f}-x_{t,f}) & (f\in O_t) \\ P(X_t|X'_{0:t-1};O_{0:t-1}) & (\text{otherwise}) \end{cases} \tag{10}$$

In this paper, we approximate $\delta(x'_{t,f} - x_{t,f})$ in Eq. (10) by the Gaussian distribution with a quite small variance, so that the probability distribution can be easily handled.

B. Predictor

The predictor predicts $P(X_{t+k}|X'_{0:t}; O_{0:t})$ by using the model $P(X_{t+1:t+n}|X_{t-m:t}; \theta)$. In this paper, we use the following simple model,

$$x_{t+1,f} = x_{t,f} + \epsilon_{t,f} \tag{11}$$

where $\epsilon_{t,f}$ is a Gaussian noise, though there may be more sophisticated models. By using this model, $P(X_{t+1}|X_t; \theta)$ is obtained by

$$P(x_{t+1,f}|x_{t,f};\sigma_{t,f}) = \mathcal{N}(x_{t,f},\sigma_{t,f}^2) \tag{12}$$

where $\mathcal{N}(\mu, \sigma^2)$ is a Gaussian distribution whose mean and variance are μ and σ^2, and $\sigma^2_{t,f}$ is a variance of the traffic rates of the flow f in time slot t.

By using $P(x_{t+1,f}|x_{t,f}; \sigma_{t,f})$,

$$P(x_{t+1,f}|X'_{0:t};O_{0:t},\sigma_{t,f}) = \sum_{x_{t,f}} P(x_{t+1,f}|x_{t,f};\sigma_{t,f})P(x_{t,f}|X'_{0:t};O_{0:t}) \tag{13}$$

where $P(x_{t,f}|X'_{0:t}; O_{0:t})$ is probability distribution of the current traffic rates estimated by the estimator. By continuing the following calculation, we can obtain the probability distribution of more future traffic rates.

$$P(x_{t+k,f}|X'_{0:t};O_{0:t},\sigma_{t,f}) = \sum_{x_{t+k-1,f}} P(x_{t+k,f}|x_{t+k-1,f};\sigma_{t,f})P(x_{t+k-1,f}|X'_{0:t};O_{0:t},\sigma_{t,f}) \tag{14}$$

This model has the parameter $\sigma_{t,f}$ for each flow. $\sigma_{t,f}$ can be updated by obtaining the variance of the previously observed traffic rates of the flow f.

Though this model is simple, this model captures the following features of the traffic prediction.

- The variance of the traffic of the flow with large fluctuations becomes large.
- The variance of the far future predicted traffic rates increases.

Therefore, this model can be used to identify the flows whose traffic rates are uncertain, and can be used by the route controller considering the uncertainty of the traffic rates.

C. Route controller

The route controller calculates routes so that required performance is provided, considering the predicted probability distribution of traffic rates.

In this paper, multiple routes between the source and destination node pairs are calculated in advance, and the route controller calculates the suitable ratio of traffic of the flow passing the routes calculated in advance. We define the element of R_t so that $R_t^{i,j}$ is the ratio of the traffic of flow j passing the route i. We also define a matrix G, whose element $G^{i,j}$ takes 1 if the route j goes through the link i, 0 otherwise. The traffic passing link l at the time slot t can be obtained by $\sum_{f,j} G^{l,j} R_t^{j,f} x_{t,f}$.

In this paper, we aim to avoid congestions, and define the optimization problem solved by the route controller as

$$minimize\colon \sum_{k=1}^{h} \|R_{t+k} - R_{t+k-1}\| \tag{15}$$

$$subject\ to\colon \forall 1 \le k \le h, \forall l, P\left[\sum_{f,j} G^{l,j} R_{t+k}^{f,j} x_{t+k,f} > c_l\right] \le p_k \tag{16}$$

$$\forall 1 \le k \le h, \forall i, \forall j, R_{t+k}^{i,j} \in [0,1] \tag{17}$$

$$\forall 1 \le k \sum_{i \in \wp(j)} R_{t+k}^{i,j} = 1 \tag{18}$$

where c_l is the threshold to the traffic passing the link l, and p_k is the acceptable probability that the traffic passing the link l exceeds a threshold. $P[\sum_{i,l} G^{l,j} R_{t+k}^{f,j} x_{t+k,f} > c_l]$ is the probability that the rates of the traffic passing the link l exceeds c_l. This probability is obtained from the probability distribution of the predicted traffic, $P(X_{t+k}|X'_{0:t}; O_{0:t})$. The optimal solutions are not necessary. The routes without congestion are sufficient. Thus, we obtain the routes by minimizing the below equation instead of solving the above optimization problem.

$$\begin{aligned} L(R_{t+1:t+h}) &= \sum_{k=1}^{h} \|R_{t+k} - R_{t+k-1}\| + \\ &\sum_{k=1}^{h} \sum_{l} \lambda_{l,h} \left(P\left[\sum_{j} G^{l,j} R_{t+k}^{f,j} x_{t+k,f} > c_l\right] - p_k \right)^{+} + \\ &\sum_{k=1}^{h} \sum_{l} \Lambda_{l,h} \left(E_{X_{t+k}}\left[\sum_{j} G^{l,j} R_{t+k}^{f,j} x_{t+k,f}\right] - c_l \right)^{+} \end{aligned} \tag{19}$$

Here, $(x)^+$ is x if $x \ge 0$, otherwise 0. The constraints related to the third term of Eq. (19) are not included in Eq. (15) and (16) but the third term of Eq. (19) is added to accelerate to search the solution when the predicted link utilization is larger than c_l. $\lambda_{l,h}$ and $\Lambda_{l,h}$ are the weights to the constraints.

The suitable routes $R_{t+1:t+h}$ are calculated so that $L(R_{t+1:t+h})$ is minimized. In this paper, we use the steepest decent method to minimize $L(R_{t+1:t+h})$. In the steepest decent method, the optimal $R_{t+1:t+h}$ is obtained by continuing the following update.

- Update $R_{t+1:t+h}$ so as to make $L(R_{t+1:t+h})$ small.
$$R_{t+k}^{i,j} \leftarrow \left(R_{t+k}^{i,j} - \alpha \frac{\partial L(R_{t+1:t+h})}{\partial R_{t+k}^{i,j}} \right)^{+}$$
- Scale $R_{t+k}^{i,j}$ so that Eq. (18) is satisfied.
$$R_{t+k}^{i,j} \leftarrow \frac{1}{\sum_n R_{t+k}^{n,j}} R_{t+k}^{i,j}$$

Assuming that the control interval is short enough, we do not need to obtain the optimal solution at each control interval, because the difference between the optimal solution of R_{t+k} and the current routes R_t is small unless significant traffic change occurs. In addition, even if the current solution is not optimal, the solution which is closer to the optimal solution than the current solution is obtained at the next time slot. Therefore, a small number of iterations of the above update is sufficient.

D. Monitoring schedule controller

The monitoring schedule controller decides the traffic to be monitored. In this paper, the traffic to be monitored is set by selecting the node that monitors the traffic. We denote the set of nodes by N. We also denote the set of flows whose traffic rates can be monitored by the node n by F_n. If n is selected as the node that monitors the traffic at the time slot t, all flows in F_n are added to O_t.

In this paper, the traffic to be monitored is obtained based on the following optimization problem.

$$minimize \ : \ L^{\mathrm{opt}}(O_{t+1}) \tag{20}$$

$$subject\ to \ : \ C(O_{t+1}) \le W \tag{21}$$

where $L^{\mathrm{opt}}(O_{t+1})$ is the optimal value of the Lagrange function $L(R_{t+1:t+h})$ defined in the previous section when O_{t+1} is observed, and $C(O_{t+1})$ is the overhead required to observe O_{t+1}.

In this paper, we obtain the value of $L^{\mathrm{opt}}(O_{t+1})$, assuming that $x'_{t+1,f}$ for the flow f included in O_{t+1} is $E_{P(X_{t+1}|X'_{0:t};O_{0:t})}[X_{t+1,f}]$. To obtain the value of $L^{\mathrm{opt}}(O_{t+1})$, the optimization problem defined in the previous subsection is required to be solved. It requires a large calculation time to obtain the optimal solution of O_t. Therefore, in this paper, we use a heuristic method.

In addition to selecting the traffic to be monitored based on the above optimization problem, we should consider the interval to monitor the flows. If the flow f was not monitored for a long time, $P(x_{t,f}|X'_{0:t}, O_{0;t})$ may be different from the actual traffic. Therefore, we set the maximum interval I to monitor the traffic. That is, if there are the nodes that were not selected for more than I time slots, we first select them as the nodes that monitor the traffic. Then, we select the other monitoring nodes by the following steps.

1) Set $N - N^{\mathrm{selected}}$ as the candidate nodes that monitor the traffic, where N^{selected} is the set of nodes that are already selected as the node monitoring the traffic.
2) For all $n \in N - N^{\mathrm{selected}}$, calculate the O_{t+1} when n is added to the nodes monitoring the traffic, and calculate $C(O_{t+1})$ and $L^{opt}(O_{t+1})$.
3) Select n whose corresponding $L^{opt}(O_{t+1})$ is the smallest among the nodes whose corresponding $C(O_{t+1})$ is less than W.
4) If a node is selected in Step 3, add n selected in Step 3 to N^{selected} go back to Step 1. Otherwise, end.

After completing the above steps, O_{t+1} is set by adding all flows in F_n for all $n \in N^{\mathrm{selected}}$.

IV. Evaluation

A. Simulation Environment

1) Network Topology and Network Traffic: We use the backbone network topology and traffic trace data of Internet2. The Internet2 has 9 PoP (Point of Presence) routers, but our method should be evaluated in larger network. Therefore, we connect three access routers to each PoP router. That is, the topology used in our evaluation has 27 access routers and 9 PoP routers. The flows are generated between each pair of access routers. We assign the flows included in the traffic trace data to pairs of the access routers by setting the range of IP addresses connected to each access router. In our evaluation, we consider the case that only the access routers can monitor the traffic sent from the access routers. We set the c_l to 2.5 Gbps for all links to evaluate the case that congestion may occur without dynamically reconfiguring the routes.

We use the traffic trace data monitored from November 13, 2011 07: 00 to November 13, 2011 10:00. These traffic data are collected by the Netflow protocol at each of the PoP routers. The sampling rate is one out of every 100 packets, and aggregated data are exported every 5 minutes. Though these traffic data do not include the information on the traffic rate whose granularity is less than 5 minutes, these traffic data includes the start and end times of each flow, and traffic amount of the flow. In this evaluation, we generate the traffic rate of each flow, assuming that the traffic rate of each flow is constant from the start time to the end time.

Our method needs σ_f which are calculated and updated by using the monitored traffic. Before monitoring the traffic rates of the flow f, σ_f cannot be calculated. Therefore, we use the first 1 hour as the time slots where σ_f are calculated, and evaluate the performance of our method by using the traffic trace data of the last two hours.

2) Parameter Settings: For simplicity, we set parameters as below. In this evaluation, we consider only the next time slot to focusing on the impact of considering the probability distributions. That is, we set h to 1. In addition, we ignore $|R_{t+1} - R_t|$ in Eq. (19), and set $\lambda_{l,h}$ and $\Lambda_{l,h}$ to 1 to focus on the link utilization achieved by our method. We set p_k to 0.10. We set the number of iterations to minimize $L(R_{t+1})$ to 15.We set the control interval to 10 seconds. For simplicity, we set the overhead required to observe the traffic at a monitoring node to 1.

3) Metric: In this evaluation, we evaluate the rate of links where congestion occurs, because the aim of the TE in this paper is to avoid congestion. The rate of links where congestion occurs M are defined by

$$M = \frac{\sum_{t,l} g(y_t^l)}{TL} \tag{22}$$

$$g(y_t^l) = \begin{cases} 1 & (y_t^l(X_t, R_t) > c^l) \\ 0 & (\text{otherwise}) \end{cases} \tag{23}$$

where $y_i^l(X_i, R_i)$ is the amount of traffic passing the link l when the traffic rates is X_i and the routes are set to R_i, c^l is threshold to the traffic amount passing the link i, L is the number of links, and T is the number of time slots.

4) Compared method: In this evaluation, we conpare SCCU with the following methods.

a) Control Based on Expected Rate (CBER): This method calculate routes without considering the probability distribution of the traffic. This method performs the following steps at each time slot. 1) The controller collects the traffic information from the randomly selected monitoring nodes. 2) The controller predicts the traffic rate by the same way as SCCU. 3) The controller calculates the routes by using the expected values of the traffic rate at the next time slot. The routes are calculated so as to minimize the traffic amount on each link exceeding the threshold $c_l - \Delta c$. That is, the controller solves the following problems.

$$minimize : \sum_l \left(E_{X_{t+k}} \left[\sum_j G^{l,j} R_{t+k}^{f,j} x_{t+k,f} \right] - (c_l - \Delta c) \right)^+ \tag{24}$$

where $(x)^+$ is x if $x \geq 0$, otherwise 0. In this method, setting Δc to a large value makes the amount of traffic on each link small. In this evaluation, we set Δc to several values. Compared with this method, we demonstrate the impact of considering the probability distribution of traffic amounts.

b) Stochastic Control with Random Select (SCRS): In this method, the controller randomly selects nodes monitoring the traffic at each time slot. Then, traffic are predicted, and routes are calculated by the same way as SCCU. Comparison with this method demonstrates the effect of selecting the nodes monitoring traffic at each time slot considering performance.

c) LongTermControl: This method does not change routes until traffic information of all flows are obtained. In this method, the controller simply calculates the routes so as to minimize the amount of traffic exceeding the target link capacity at each control interval based on the expected traffic rates obtained by the prediction. Comparing the LongTermControl with our proposed method, we demonstrate that shortening the control interval reduces congestions in spite of the uncertainty of observed traffic.

B. Results

1) Comparison between methods with 10-second control interval: Figure 2 shows the relationship of between the number of nodes monitoring traffic at each time slot and the rate of congestion. Δc in Figure 2 means Δc in Eq. (24). In this figure, the perfect Performance indicates the rate of congestion achieved by the method that can use measuring traffic information accurately at the next time slot. In this figure, we first compare CBER and SCRS to evaluate the impact of considering the probability distributions.

This figure indicates that M depends on Δc in CBER. If Δc is small, the prediction error causes congestion, because the expected traffic passing the link l may be close to c_l. On the other hand, if Δc is large, we do not have the enough resources allocated flows with a large traffic. As a result, congestion may occur. In this evaluation, $\Delta c = 0.6$ achieves the smallest M. However, the optimal Δc depends on the patterns of traffic changes, and is difficult to be set in advance.

Figure 2 shows that SCRS achieves smaller M than CBER with $\Delta c = 0.6$, unless the number of monitoring nodes is 1. This is because SCRS allocates the resources, considering the probability distributions; more resources are allocated to the flows whose rates are large or uncertain. As a result, the probability that congestion occur is reduced. However, when the number of monitoring nodes is 1, most of the flows that have a large impact on the performance become uncertain. This uncertainness causes the lack of resources that can be allocated. As a result, M becomes large.

Figure 3 compares M of SCRS and SCCU. similar to Fig 2. This figure indicates that SCUU achieves small M even when the number of monitoring nodes is 1, while the rate of congestion of SCRS becomes large as the number of monitoring nodes becomes small. This is because SCUU selects the monitoring nodes that can monitor the flows

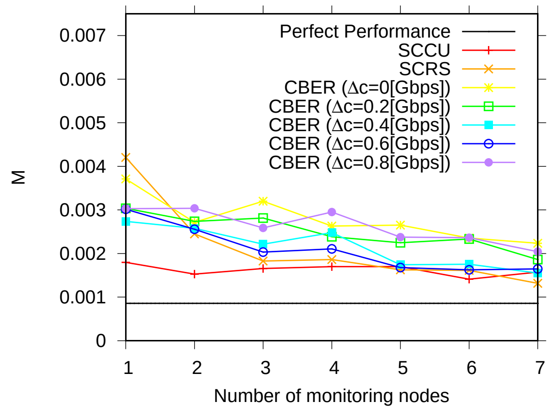

Fig. 2. The effect of stochastic control

whose uncertainties has the large impacts on the TE. As a result, SCUU accurately estimates the traffic rates of the flows.

2) Comparison with the LongTermControl: The SCRS can configure the routes even when only a part of traffic information is observed at each time slot. This enables to shorten the control interval. In this paragraph, we evaluate the impact of shortening the control interval by comparing our method with LongTermControl.

In this evaluation, we can obtain the traffic information from n of 27 monitoring nodes every 10 seconds. In this case, SCRS and SCCU can change routes every 10 seconds, while the LongTermControl can change routes every $\frac{240}{n}$ seconds.

Figure 3 shows the rate of congestion achieved by each method. This figure indicates that SCRS and SCCU achieves a smaller rate of congestion than the LongTermControl. That is, shortening the control interval reduces the rate of congestion. This is because the method with short intervals detects the risk of congestion and changes the routes so as to mitigate the risk soon after the risk becomes large. On the other hand, the method with large intervals cannot detect congestion and cannot mitigate congestion before the next control time slot.

V. Conclusion

We have proposed the framework of the TE for the case that only a part of traffic information can be obtained at each time slot. This framework was inspired by the human brain mechanism. In this framework the controller (1) obtains a limited number of traffic information, (2) estimates and predicts the probability distribution of the traffic, (3) configures the routes considering the probability distribution of the predicted future traffic, and (4) selects the traffic to be monitored at the next period considering the performance of the route reconfiguration using the traffic information obtained at the next period.

In this paper, we discussed the details of the each step of our framework. Then, we evaluated our framework. The

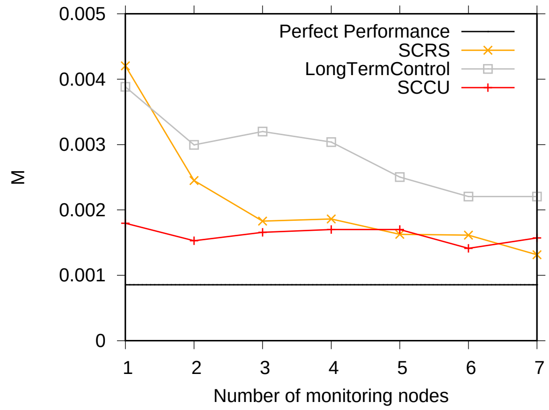

Fig. 3. performance of conventionally proposed TE and our method

results demonstrate that our framework in which the TE and the traffic monitor cooperate with each other improves the performance of the TE even when only a part of the traffic information is monitored at each time slot. It enable us to shorten the control interval. Our results also demonstrate that shortening the control interval improves the performance of the TE.

Our future work includes the evaluation of our method in an actual larger network. We will also discuss the parameter settings of our method for a larger network. Especially, the number of iterations to solve the optimization problem may have a large impact on the calculation time and the performance of the TE.

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References

[1] P. Kumar, Y. Yuan, C. Yu, N. Foster, R. Kleinberg, and R. Soulé, "Kulfi: Robust traffic engineering using semi-oblivious routing," *arXiv preprint arXiv:1603.01203*, 2016.

[2] M. Chiesa, G. Kindler, and M. Schapira, "Traffic engineering with equal-cost-multipath: An algorithmic perspective," *IEEE/ACM Transactions on Networking*, 2016.

[3] H. H. Liu, S. Kandula, R. Mahajan, M. Zhang, and D. Gelernter, "Traffic engineering with forward fault correction," *ACM SIGCOMM Computer Communication Review*, vol. 44, no. 4, pp. 527–538, 2015.

[4] I. F. Akyildiz, A. Lee, P. Wang, M. Luo, and W. Chou, "A roadmap for traffic engineering in SDN-OpenFlow networks," *Computer Networks*, vol. 71, pp. 1–30, 2014.

[5] T. Benson, A. Anand, A. Akella, and M. Zhang, "MicroTE: Fine grained traffic engineering for data centers," in *Proceedings of the Seventh COnference on emerging Networking EXperiments and Technologies*, p. 8, ACM, 2011.

[6] D. Jiang, L. Nie, Z. Lv, and H. Song, "Spatio-Temporal Kronecker Compressive Sensing for Traffic Matrix Recovery," *IEEE Access*, vol. 4, pp. 3046–3053, 2016.

[7] Y. Zhang, M. Roughan, W. Willinger, and L. Qiu, "Spatio-temporal compressive sensing and internet traffic matrices," in *ACM SIGCOMM Computer Communication Review*, vol. 39, pp. 267–278, ACM, 2009.

[8] T. Otoshi, Y. Ohsita, M. Murata, Y. Takahashi, K. Ishibashi, K. Shiomoto, and T. Hashimoto, "Framework for traffic engineering under uncertain traffic information," in *Information and Communication Technology Convergence (ICTC), 2016 International Conference on*, pp. 264–266, IEEE, 2016.

[9] S. Bitzer, J. Bruineberg, and S. J. Kiebel, "A Bayesian Attractor Model for Perceptual Decision Making," *PLoS Comput Biol*, vol. 11, no. 8, p. e1004442, 2015.

[10] T. Otoshi, Y. Ohsita, M. Murata, Y. Takahashi, K. Ishibashi, K. Shiomoto, and T. Hashimoto, "Traffic engineering based on stochastic model predictive control for uncertain traffic change," in *Integrated Network Management (IM), 2015 IFIP/IEEE International Symposium on*, pp. 1165–1170, IEEE, 2015.