Framework for Traffic Engineering under Uncertain Traffic Information

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***Abstract*—Traffic engineering (TE) plays an essential role in deciding routes that effectively use network resources. The TE controller should handle the uncertainty due to the lags and lacks of collected network information. Many previous work partially tackled this uncertainty problem in various aspects e.g. data collection, estimation, prediction, routing with uncertain traffic. However there are few studies about integrating these partial processes to achieve the cooperation. In this paper, we proposed a framework to integrate partial processes in a whole TE process, and formulate it according to the Bayesian approach. In our framework, decision making process considers how the decision affects not only network but also other processes by modeling the behavior of the process as conditional probability. Thus, the cooperation of different processes is expected to be achieved.**

***Index Terms*—Traffic Engineering, Uncertain Information, Bayesian Decision**

I. INTRODUCTION

Traffic engineering (TE) is a promising solution for handling time variation of traffic [1]. In the TE, 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 the congestion even when traffic change occurs.

One imminent problem for the TE is how to handle the uncertainty of the traffic information. The control server cannot obtain the perfectly accurate information.

One factor of the uncertainty is a lack of information in the collected data. The controller hardly collects all the information at all times in a large network since the messaging overhead costumes the capacity even for the ordinal communication. Thus, the controller has to estimate the traffic information with a partially available data. In existing work, many estimation methods are proposed [2, 3], which estimate the whole traffic information with limited data such as link traffic or sampling. Moreover, a monitoring method is also proposed [4] which optimizing the deployment of the monitors to minimize the estimation error.

Another factor of the uncertainty is a lag between collecting information and setting the routes. When the controller sets the next route, the collected data is no longer correct since traffic changes during the lag between the data collection and route change. To solve the lag problem, the controller should predict how traffic changes from the collected data. The traffic prediction methods have been also proposed in many work e.g. [5].

Though a promising approach to overcome the uncertainty is integrating these technologies, there is difficulty to combine these technologies because of the interactions among them. For instance, the data collection affects whole other processes i.e. the estimation, prediction, and route setting. After the controller collects some partial data, the collected data is used for not only the estimation of the current traffic but also the traffic prediction to update the traffic model. Thus, the lack of data causes both the estimation error and prediction error, and such errors finally affect the route setting. Therefore, the data collection method should consider how the collected data affects other processes. Since such interaction can occur at any pairs of processes, the controller should orchestrate the whole processes to cooperate them. In existing work, however, only achieves the partial integration e.g. prediction and routing [6], estimation and routing [7], or observation and estimation [4].

In this paper, we proposes a framework of TE to handle the uncertainty of traffic information. Our framework is inspired by the *human brain* mechanism. In our daily life, human brain makes many decisions well even under highly uncertain environment. One promising theoretical model to explain the brain mechanism is the Bayesian decision making model [8]. Therefore, we proposes the framework to handle the uncertainty in the TE based on the Bayesian approach. Using the Bayesian model, we also introduces the cooperation mechanism among different processes, that is, the decision making process considers how the decision affects the other processes.

II. UNCERTAINTY IN TRAFFIC ENGINEERING

To clarify our target network on which the proposed framework works, this section briefly explains how the uncertainty in traffic information occurs.

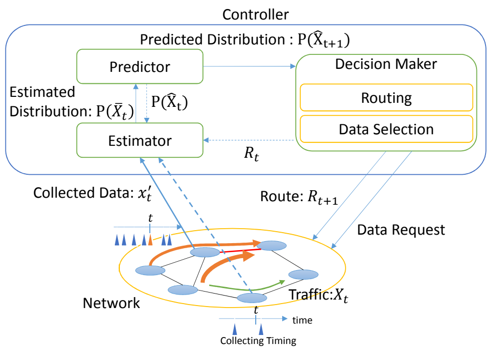

Fig. 1. Overview of Bayesian Traffic Engineering

In the TE, a controller is deployed to collect the data from the network and changes the route according to the collected data. Indeed, there is some uncertainty of the lacks and lags of the collected data. In a large network, it is hard for the controller to collect all traffic information from all nodes at all time because the messaging overhead consumes the capacity even for ordinal communication. Thus, the available information for controller is only a partial information about traffic. In addition, the collected current information is no longer accurate when the controller changes the route since the traffic amount of any flow always changes.

Although the estimation and prediction of traffic may solve the problems of the lacks and lags of the information, there are still errors. Moreover, the estimation and prediction errors are interdependent, and they also depend on the data collection method. Thus, the controller has to manage the whole process to handle the uncertainty caused in each process.

III. Bayesian Framework for Traffic Engineering

In this section, we show the Bayesian-based framework of TE, which handles the uncertainty of traffic information. In our framework, the controller sequentially collects partial information of current network and sets a route to the network. The controller is constructed by three components i.e. *estimator*, *predictor*, *decision maker*. Figure 1 shows the overview of our framework. The rest of this section explains how each components handles the uncertainty of traffic information.

A. Estimator

The estimator uses the collected partial data and the previous result of the prediction to calculate the current traffic amounts of the whole network. We denote the collected data as a vector x'_t which is a sub-vector of whole data x_t monitored on the network at time slot t. The collected data x'_t depends on the collection method O_t e.g. from which node the controller gets the data. We also denote the traffic amount of each flow as a vector X_t, its estimated probability distribution as $P(\bar{X}_t)$, and its predicted probability distribution as $P(\hat{X}_t)$. Note that the whole observed data x_t is not always same as the estimation target X_t, for instance x_t is link traffic amounts or sampling data from X_t.

According to the Bayesian estimation, the posterior probability of the traffic amounts X_t with given x'_t by the data collection method O_t is calculated as following:

$$P(X_k|x'_k;O_k)=\frac{1}{P(x'_k|O_k)}P(x'_k|X_k;O_k)P(X_k) \qquad (1)$$

where $P(X_k)$ is a *prior distribution* of X_k, $P(x'_k|X_k;O_k)$ is a *likelihood function* of X_k, and $P(x'_k|O_k) = \sum_{X_k} P(x'_k|X_k;O_k)P(X_k)$. Then, the estimator outputs the distribution of current traffic $P(\hat{X}_k) = P(X_k|x'_k;O_k)$.

The likelihood function represents the stochastic relationship between the collected data x'_k and actual data X_k, which depends on data to be used in the estimation. For instance, when estimating the traffic amounts with sampled packets, the likelihood function reflects the distribution of the sampling error. The estimator also can use the route information of current network [2]. However, the likelihood function has no information about flows which are not involved in the collected data.

To compensate the lacks in the collected data, the controller uses prior knowledge. Since the current traffic amounts are previously predicted at time slot $t-1$, the controller uses the predictive distribution $P(\hat{X}_t)$ as the prior distribution $P(X_t)$. By doing so, the estimator can calculate the traffic amounts of the flow which is not included in the collected data.

B. Predictor

After the estimation of current traffic amounts, the predictor calculates the future traffic. First, the predictor estimates a stochastic model which the current traffic follows. Then, the predictor calculates the probability distribution of the future traffic using the model. We denote the model as a conditional probability $P(X_k|X_{k-1}, X_{k-2}, \cdots, X_{k-s};\theta)$ where s is the maximum length of the model and θ is a parameter of the model. A typical model of time series is the ARIMA model [5], which is a regression model representing the next value by the linear combination of previous values and residuals.

In the estimation of model, the predictor finds the parameter θ which leads the appropriate model to the current traffic pattern. According to the Bayesian theorem, the predictor calculates the posterior distribution of θ with the previous data as following:

$$P(\theta|x'_k,\cdots,x'_1) = \frac{1}{P(x'_k,\cdots,x'_1)}P(x'_k,\cdots,x'_1|\theta)P(\theta) \qquad (2)$$

where $P(\theta)$ is a prior distribution calculated at previous time slot, $P(x'_k,\cdots,x'_1|\theta)$ is the likelihood function of θ, and $P(x'_k,\cdots,x'_1) = \sum_\theta P(x'_k,\cdots,x'_1|\theta)P(\theta)$.

According to the Bayesian prediction, the predictor calculates the predictive distribution by marginalizing over parameters and the estimated previous traffic:

$$P(X_{k+1}|\boldsymbol{x}_k) = \sum_{\theta,\boldsymbol{X}_k} P(X_{k+1}|\boldsymbol{X}_k;\theta)P(\boldsymbol{X}_k,\theta|\boldsymbol{x}_k) \qquad (3)$$

where $\boldsymbol{x}_k = (x'_k,\cdots,x'_1)$, $\boldsymbol{X}_k = (X_k,\cdots,X_{k-s+1})$, and $P(\theta,\boldsymbol{X}_k|\boldsymbol{x}_k)$ is the joint probability of the estimated values $\bar{X}_k,\cdots,\bar{X}_{k-s+1}$ and θ. The predictor outputs the predictive distribution $P(\hat{X}_{k+i}) = P(X_{k+i}|\boldsymbol{x}_k)$. Though the equation (3) shows only one-step prediction, further prediction can be conducted by repeating the calculation using the predicted distribution instead of the estimated distribution.

C. Decision Maker

Using the prediction result, the decision maker finally decides which route should be set to the network, and which data should be collected at the next time slot. Following section details these two decision processes, respectively.

1) Routing: In the routing process, the decision maker calculates an appropriate route which guarantees the communication performance with the uncertain future traffic.

In our previous work [6], we proposed a TE method called stochastic MP-TE, which handles the uncertainty of traffic. In this method, the route R_k is calculated by minimizing the cost function $f(X_k, R_k)$ and route changes while keeping the probability which the link traffic exceeds the link capacity lower than a certain level. That is, the method solves the following stochastic optimization problem:

$$minimize{:}E\left[\sum_{i=k+1}^{k+h}\{(1-w)f(X_i,R_i)+w\|\Delta R_i\|^2\}\right] \quad (4)$$
$$s.t.{:}P(y_i^l(X_i,R_i)>c^l)\le p$$

where $\Delta R_i = R_i - R_{i-1}$, $E[\cdot]$ is the expectation value about traffic $X_{k+1}, \cdots, X_{k+h}$, h is the length of predicted time series, $y_i^l(X_i, R_i)$ is the amount of traffic on the link l under traffic X_i and route R_i, c^l is the capacity of the link l, and p is the acceptable probability that the capacity constraints are broken.

Although the routes $R_{k+1}, \cdots, R_{k+h}$ are obtained by solving the above optimization problem, the decision maker 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 decision maker adaptively corrects the route even if the predictive distribution is temporally wrong.

2) Data Selection: The decision maker also decides which data to collect at the next time slot without causing unacceptable overhead of data collection. Since the collected data triggers off the correction of estimation, prediction, and routing, the decision maker should consider how the new data affects other processes. Such behavior of other processes can be calculated according to Eqs. (1)–(4). We denote the route with the new data x'_k collected by the method O_k as $R_{k+1}(x'_k, O_k)$. Also, we denote the overhead of the collection method O_k as $C(O_k)$, and the upper limit of the acceptable overhead as W.

Considering the behavior of other processes, the decision maker finds the optimal O_k by minimizing the expectation value of the cost function f in routing around the possible data x'_k to be collected by O_k and the future traffic X_{k+1}. The optimization problem is formulated as following:

$$minimize{:}E_{P(X_{k+1})P(x'_k|O_k)}\left[f(X_{k+1},R_{k+1}(x'_k,O_k))\right] \quad (5)$$
$$s.t.{:}C(O_k)\le W \quad (6)$$

where $E_{P(X_{k+1})P(x'_k|O_k)}$ means the expectation value under the joint probability distribution about future traffic X_{k+1} and the new data x'_k when the method O_k applied. $P(x'_k|O_k) = \sum_{X_k} P(x'_k|X_k; O_k)P(X_k)$ is the marginal distribution of x'_k given O_k. The controller actually calculates the above optimization by using the predictive distribution $P(\hat{X}_k), P(\hat{X}_{k+1})$ instead of $P(X_k), P(X_{k+1})$.

IV. Summary & Future Work

In this paper, we proposed a framework of the TE method with uncertainty due to lacks and lags of information. Our framework integrates different processes such as data collection, estimation, prediction, and routing; and introduces the cooperation mechanism. In our framework, each partial process is modeled in a formulation according to the Bayesian approach. Using these models, the decision maker calculates how the decision affects other processes, and achieves the cooperation.

The remaining challenge is how to implement this framework with particular methods for data collection, estimation, prediction, and routing. Especially, selecting data is has not been well established even in the previous work, since most of the previous work only focuses on the estimation accuracy. Thus, our future work includes developing a method to select data with considering the network performance and the interactions among other processes, and proof of concept of our framework with specific methods of data collection, estimation, prediction, and routing.

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