A Bayesian-based Approach for Virtual Network Reconfiguration in Elastic Optical Path Networks

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Abstract: We investigate a Bayesian approach for VN reconfiguration in elastic optical networks. The approach identifies traffic condition from simple observations and selects VN suitable to the condition. Results show a fast converge of VN reconfiguration.
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1. Introduction

Network virtualization is one of key concepts for network operators to provide a flexible infrastructure to the customers. Against the change of the customer's demand, network operators construct or reconfigure a virtual network (VN) in a dynamical manner by slicing physical resources such as wavelengths in WDM networks or frequency slots in elastic optical networks. The dynamical nature of the network virtualization will lead to the need for the VN reconfiguration approaches.

A typical approach for constructing/reconfiguring a VN is to design an optimal topology and the amount of resources with a knowledge of the end-to-end traffic demand matrix [1, 2]. However, it is not an easy task to obtain the end-to-end traffic demand matrix since traffic inspection is necessary to count the volume for each source-destination pair. Ref. [3] therefore developed a method to estimate the end-to-end traffic demand matrix using link-level information which is easy to collect. However, when the estimation fails, we do not have a way to design the optimal VN because we have incorrect knowledge of the end-to-end traffic demand matrix.

In this paper, we develop a VN reconfiguration framework without using the traffic demand matrix. Our basic idea is to follow the human's recognition and decision-making. That is, we memorize a set of "good" VNs, each of which works well for a certain traffic situation, and then retrieve one of the VNs suitable for the current traffic situation. Here, the traffic situation is not necessarily the traffic demand matrix itself, thereby more easily available traffic information can be used. We will use the amounts of outgoing/incoming traffic at edge routers as the traffic information. Challenges are 1) how to identify the traffic situation from easily available information in a changing environment, 2) how to reconfigure a VN when the performance of the VN is not adequate even though the identification succeeds, and 3) how to reconfigure a VN if the identification fails. For the first point, we apply a concept of Bayesian inference [4]. Bayesian inference is a fundamental method to infer the probability for a hypothesis from observed information based on Bayes' theorem. In our current case, given a set of pre-specified traffic situations, the probability for taking each traffic situation is updated as more traffic information is observed. For the second and third points, we incorporate a noise-induced VN reconfiguration method proposed in [5] with our framework. The noise-induced method also does not use the traffic demand matrix but observes only the service quality on a VN and searches for good VNs induced by noise. However, our framework with the Bayesian inference is superior to the noise-induced method in terms of stability, since the noise-induced method changes a VN in nature while our framework will not change a VN unless its performance is bad. In what follows, we will explain the VN reconfiguration framework based on the Bayesian inference method, and then evaluate the advantage of our framework over the noise-induced method.

2. Virtual Network Reconfiguration Framework Based on Bayesian Inference

2.1. Bayesian Attractor Model (BAttM)

As a way for the Bayesian inference, we explain the Bayesian Attractor Model (BAttM) [6] that models a humans's behavior where the brain accumulates evidence extracted from noisy sensory information and makes perceptual decisions. The BAttM has a decision state $\mathbf{z}$ that eventually settles into a fixed point, ϕ^*, that is defined by the attractor dynamics, i.e., the winner-take-all dynamics, as the evidence is accumulated. Internally, the BAttM has several decision alternatives for the average of observation values, and each decision alternative, μ_i, is associated with its corresponding fixed point ϕ_i. Let's denote the observation values up to time t as $\mathbf{X}_{1:t} = \{\mathbf{x}_1, \cdots, \mathbf{x}_t\}$. At a time t, the model infers the posterior distribution of the decision state $\mathbf{z}_t$, denoted by $p(\mathbf{z}_t|\mathbf{X}_{1:t})$, using the unscented Kalman filter (UKF). Finally, the model makes a decision for the alternative i that satisfies $p(\mathbf{z}_t = \phi_i|\mathbf{X}_{1:t}) \geq \lambda$, where $p(\mathbf{z}_t = \phi_i|\mathbf{X}_{1:t})$ is the posterior belief or simply called the confidence in the alternative i.

2.2. VN reconfiguration framework

We apply the BAttM approach to a VN reconfiguration framework. In our framework, a VN g_i is selected when the traffic situation is identified to μ_i under the observation values $\mathbf{X}_{1:t}$. More precisely, we select the VN g_i when the confidence in the alternative i is sufficiently large. We use the amounts of outgoing/incoming traffic at edge routers as the observation values $\mathbf{X}_{1:t}$. Note that the VN g_i is prepared in advance such that the VN works well for the traffic situation μ_i.

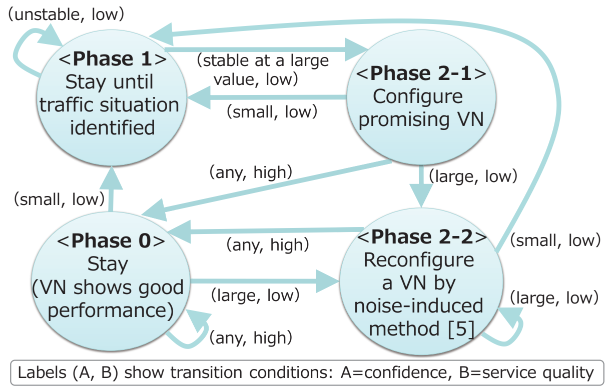

Fig. 1. State transition diagram for VN reconfiguration

Applying only the BAttM approach is insufficient for VN reconfiguration because the performance of the VN g_i may not be adequate even though the identification succeeds. Therefore, we prepare a set of control phases and change the control phase based on both the confidence from the BAttM approach and the service quality on the VN. We briefly explain our control phases in following, and their state transition diagram is shown in Fig. 1.

- Phase 1: Stay until the traffic situation is identified
  - We do not reconfigure a VN until the confidence becomes stable at a large value by considering the confidence becomes equal to or larger than λ in c_{th} consecutive times. Following Ref. [7], we use $\log_{10} \frac{p(\mathbf{z}_t=\phi_i|\mathbf{X}_{1:t})}{p(\mathbf{z}_t=\phi_j|\mathbf{X}_{1:t})}$ as the confidence, which represents the difference between the logarithm of the largest posterior belief among alternatives and the second largest, in order to identify the situation.
- Phase 2: Reconfigure a VN based on the traffic situation identified
  - We configure a promising VN g_i that works well for a traffic situation μ_i when the current traffic situation is identified to μ_i (Phase 2-1). In the case where the performance of the VN g_i is not adequate, we search for good VNs by the noise-induced method [5](Phase 2-2).
- Phase 0: Stay (The VN shows good performance)
  - We do not reconfigure a VN since the VN can accommodate the traffic successfully.

In summary, our framework first identifies traffic situations using the BAttM (Phase 1) and immediately changes a VN after the identification (Phase 2-1). Then, we observe the service quality on the VN, and reconfigures if necessary (Phase 2-2). Note that, in this paper, we do not cover the case where the identification of traffic situations fails, i.e., the confidence is stable at a small value. However, we believe that it is enough to just apply the noise-induced control as Phase 2-2 does to search for a good VN.

3. Evaluation

We evaluate the advantage of our VN reconfiguration method over an elastic optical path network by comparing the results of the noise-induced method [5]. Since our framework includes the noise-induced behavior at Phase 2-2, we call the existing noise-induced method as the reference method. Both of them do not use the traffic demand matrix information.

The parameters of the physical network that has the USNET topology are the same as Ref. [5]. Here, all the nodes are edge routers. The goal of the control is to make the maximum link utilization on a VN less than 0.5. We generate traffic demand matrices $\mathbf{T}_i$ $(1 \le i \le 5)$ which follow a log-normal distribution. We denote the amounts of outgoing/incoming traffic at edge routers by $\mathbf{E}_i$ $(= \mu_i)$ when the traffic demand matrix is $\mathbf{T}_i$, and calculate the configuration of VNs $g_1, \cdots, g_5$, each of which can accommodate $\mathbf{T}_1, \cdots, \mathbf{T}_5$. Specifically, we determine the virtual topology using MSF (Most Subcarriers First) algorithm [8], and allocate frequency slots using First-last fit algorithm [9]. We set c_{th} to 3, and set λ to 10.

For the evaluation, traffic demand matrices are generated based on the normal distribution $N(\mathbf{T}_1, \Sigma)$ at every unit time, where $\mathbf{T}_i = (\overline{T}_{i,11}, \cdots, \overline{T}_{i,NN})$ and $\Sigma = CV^2 \mathrm{diag}(\overline{T}_{i,11}^2, \cdots, \overline{T}_{i,NN}^2)$. N is the number of nodes, and CV is the coefficient of variation which represents the degree of traffic fluctuation. The reference method changes its control phase based on the service quality on a VN; the method searches for good VNs at Phase 2-2, then changes to Phase 0 when the performance of the VN is improved.

Fig. 2 shows the transition of the control phases of each method when CV is 0.75. The horizontal axis shows the time and the vertical axis shows the control phase staying at each time. The figure clearly shows the behavior of our

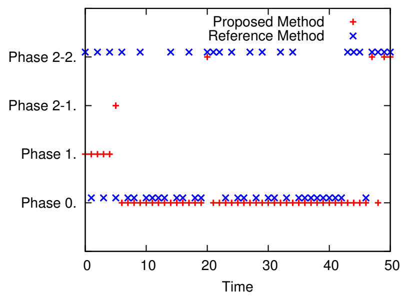

Fig. 2. Transition of the control phase

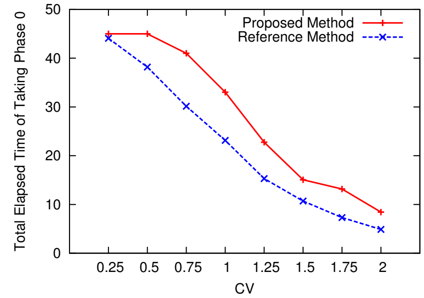

Fig. 3. Total elapsed time of taking Phase 0

framework. Our method starts with Phase 1 and continues to stay at Phase 1 until the traffic situation is identified. At time 5, the control phase shifts to Phase 2-1, and our method reconfigures a VN to the most promising VN. Note that our method can identify the traffic situation using the amounts of outgoing/incoming traffic at edge routers which are available more easily than the traffic demand matrix. After that, the control phase becomes Phase 0 since the VN can accommodate traffic. Even when the control phase shifts to Phase 2-2 due to a traffic fluctuation (time 20), the control phase is immediately back to Phase 0 by the noise-induced control. This is because a VN is configured to the most promising VN and therefore the noise-induced control requires a little effort to search for a good VN . In contrast, the reference method repeatedly changes the control phase between Phase 2-2 and Phase 0.

Next, we evaluate the stability of our VN reconfiguration framework. Fig. 3 shows the total elapsed time of taking Phase 0 for each method. The horizontal axis shows the value of CV, and the vertical axis shows the average of the total elapsed time. For each VN, the total elapsed time is averaged over 100 trials of the noise-induced control. In Fig. 3, we can see that the total elapsed time of our method is longer than that of the reference method against varying CV. Our method successfully decreases the number of VN reconfiguration to reach a VN suitable for the traffic situation.

4. Conclusion

We develop a virtual network reconfiguration framework with the Bayesian inference. Specifically, we introduce the Bayesian Attractor Model to infer the current traffic situation. Evaluation results show that our method can identify the traffic situation using the amounts of outgoing/incoming traffic at edge routers, which are available more easily than the traffic demand matrix, and decreases the number of VN reconfiguration to reach a VN suitable for the traffic situation.

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