

# Predictive traffic engineering incorporating real-world information inspired by the cognitive process of the human brain

Kodai Satake, Yuichi Ohsita, Masayuki Murata  
Graduate School of Information Science and Technology, Osaka University  
1-5 Yamadaoka, Suita, Osaka, 565-0871, Japan  
Email: {k-satake, y-ohsita, murata}@ist.osaka-u.ac.jp

**Abstract**—The amount of traffic on the Internet has been increasing both in quantity and in fluctuation as the devices connected to the Internet and the services on the Internet become popular. Predictive Traffic Engineering (TE) is one approach to accommodating fluctuating traffic without causing congestion. Prediction accuracy is important for predictive TE. Real-world information is useful for the prediction of future traffic. Although the real-world information may contribute to the accurate prediction of future traffic, it is difficult to model the relation between these two types of data. Therefore, we propose a prediction method inspired by the cognitive process of the human brain, which makes decisions from uncertain information. Our method defines multiple states based on the monitored information including both traffic and real-world information and subsequently learns the future traffic corresponding to each state. Then, our method predicts future traffic by deciding the current state from the traffic and real-world information by using a process inspired by the cognitive process of the human brain. Finally, our method allocates resources based on the future traffic corresponding to the states of which the confidence levels are high. We evaluated our method by simulation. The results demonstrate that our method avoids congestion without requiring a large amount of additional resources; the amount of resources required to avoid congestion is reduced by 25 % compared with the predictive TE using only past traffic information.

**Index Terms**—Traffic Engineering, Resource Allocation, Real-World Information, Human Brain Cognition

## I. INTRODUCTION

The amount of traffic through networks has been increasing both in terms of quantity and fluctuation as the devices connected to the Internet and the services on the Internet become popular. Network operators need to accommodate such fluctuating traffic without causing congestion. Traffic Engineering (TE) is one approach to solve this problem [1]–[5]. These methods are designed to dynamically change the routes and/or resource allocations to accommodate the traffic without congestion.

Most of the methods that dynamically control network resources achieve this on the basis of observed network traffic. However, resource allocation based on observed traffic does not correspond to the actual traffic flow when the amount of traffic changes significantly, yet the configured resource allocation is not changed until the next control cycle. This

problem may be solved by setting a short control interval, which may, however, cause network stabilization.

One approach to allocating fluctuating traffic without causing network stabilization is predictive TE [6]. In this approach, a controller collects traffic information and predicts future traffic. Then, the controller allocates the resources based on the predicted traffic. Predictive TE allocates a sufficient amount of resources to avoid congestion without specifying a short control interval.

The accuracy of the prediction is important for predictive TE; inaccurate traffic prediction may lead to improper resource allocation and congestion. Many methods to predict future traffic have been proposed [7]–[10]. For example, Yu et al. proposed a traffic prediction method that combines ARIMA and FARIMA based on the multifractal spectrum for mobile networks, and Feng et al. compared prediction models such as IMA, FARIMA, ANN, and wavelet-based prediction and demonstrated that the optimal model depends on the network.

Most of the traffic prediction methods model traffic changes based on the time series of monitored traffic and predict future traffic using the model. However, it is difficult to accurately predict traffic only on the basis of previously monitored traffic, if the previously monitored traffic does not include the signs of fluctuation.

In this regard, real-world information can contribute to the accurate prediction of future traffic because this information may include the required signs of traffic fluctuation that are absent from historical traffic data. For example, information about the number of network users in each area can improve the accuracy of the prediction, because the traffic in an area would be expected to increase if the number of users in the area were to increase. In addition, an increase in the number of users in adjacent areas would enable us to easily predict that the number of users in the area is also likely to increase, which would in turn result in an increase in traffic from the area.

In this paper, we propose a predictive traffic engineering method, which predicts future traffic using the information monitored in the real world. Even though this information may contribute to accurate prediction, it is difficult to model the relation between future traffic and real-world information. That

is, we require a new method to predict future traffic using such information of which the relation to future traffic cannot be clearly modeled.

This prompted us to propose a prediction method inspired by the cognitive process of the human brain, which makes decisions on the basis of uncertain information. Bayesian decision-making theory is one of the theoretical models that explain the process the human brain uses to make decisions based on uncertain information. Bayesian decision-making theory treats observed information and the confidence of cognitive objects as stochastic variables. Then, the variables are updated by Bayesian inference every time a new observation is obtained. Finally, the human brain makes decisions based on these stochastic variables.

Bayesian Attractor Model (BAM) is one of the cognitive models of the brain based on Bayesian decision-making theory [11]. In this model, the cognitive options are embedded as attractors. Then, the brain is assigned stochastic variables related to the options, and recognizes which option is suitable by updating the variables by using Bayesian inference.

In our method, we define multiple states based on the monitored information including both traffic and real-world information. In addition, our method learns the future traffic corresponding to each state. We embed the defined states as attractors. Then, our method predicts future traffic by deciding the current state from the traffic and real-world information by a process inspired by BAM; our method contains stochastic variables to indicate the confidence level about the current traffic and real-world information belonging to each state, and updates the variables every time a new observation is obtained. Finally, our method allocates the resources based on the future traffic prediction corresponding to the states for which the confidence is high.

The remainder of this paper is organized as follows. Section II explains the Bayesian Attractor Model (BAM). Section III proposes the predictive traffic engineering method incorporating real-world information. Section IV describes the evaluation of our method. Section V concludes this paper.

## II. BAYESIAN ATTRACTOR MODEL(BAM)

The Bayesian Attractor Model (BAM) models the process by which the brain makes decisions based on uncertain sensing information [11]. The BAM encodes the predefined  $i$  options  $\phi_1, \dots, \phi_i$ , known as an attractor, and makes decisions depending on the option of the current status. The BAM has the decision state  $z_t$  as its internal state, and updates  $z_t$  based on the observation value  $x_t$  obtained from the outside by performing Bayesian inference. The remainder of this section explains the process of updating the states and the decision-making process of BAM.

### A. Update of decision state

BAM has the following generative model of the decision state  $z_t$  and observation  $x_t$ .

$$z_t - z_{t-\Delta_t} = \Delta_t f(z_{t-\Delta_t}) + \sqrt{\Delta_t} w_t \quad (1)$$

$$x_t = M\sigma(z_t) + v_t, \quad (2)$$

where  $f(z)$  is the Hopfield dynamics,  $w_t$  and  $v_t$  are Gaussian noise variables,  $M = [\mu_1, \dots, \mu_N]$  is a matrix indicating the observation values, and  $\mu_i$  is the observation value corresponding to the state  $\phi_i$ , which is the  $i$ -th predefined attractor. Further,  $\sigma(x)$  is a sigmoid function  $\frac{\tanh(ax/2)+1}{2}$ , where  $a$  is the slope of this function.

The BAM updates the decision state  $z_t$  every time the observations  $x_t$  are obtained by inverting the generative model using Bayesian inference. Because the generative model is nonlinear, Bitzer et al. use the Unscented Kalman Filter [12] to update the mean decision state of  $z_t$ . In addition to updating the mean decision state, the posterior distribution  $P(z_t|x_t)$  over the decision state is also obtained.

### B. Decision making

The above state estimation outputs the posterior probability  $P(z_t|x_t)$ . Thus, the decision is made by handling the probability. Bitzer et al. introduced the threshold  $\lambda$ . When  $P(z_t = \phi_i) > \lambda$ , it selects the option  $\phi_i$ . When  $P(z_t = \phi_i) \leq \lambda$  for all  $i$ , the decision is not made until a new observation is obtained.

## III. PREDICTIVE TRAFFIC ENGINEERING INCORPORATING REAL-WORLD INFORMATION

### A. Overview

In this paper, we propose predictive TE that incorporates real-world information for mobile networks. In mobile networks, the traffic from each area may change over the course of time because of the varying amount of traffic generated by each user and/or the change in the number of network users in the area. Network operators therefore need to ensure sufficient resources are available for each area to accommodate the variation in traffic without congestion. In this paper, we discuss a method to predict the future traffic from each area and determine the amount of resources required for each area.

A mobile network operator needs to know the number of network users in each area, because this information is useful to predict the amount of traffic from the area, which increases when the number of network users in the area increases. In addition, an increase in the number of users in nearby areas would indicate a possible increase in the number of users in the area of interest, and this would cause the traffic from the area to increase. Therefore, our method uses real-world information such as the number of users in each area in addition to the traffic volume generated by each area.

Even though the real-world information may contribute to the accurate prediction of future traffic, modeling the relation between future traffic and real-world information is difficult. That is, we need a new method to predict future traffic using information of which the relation to future traffic cannot be clearly modeled.

This led us to propose a prediction method inspired by the cognitive process of the human brain, which makes decisions on the basis of uncertain information. This model includes

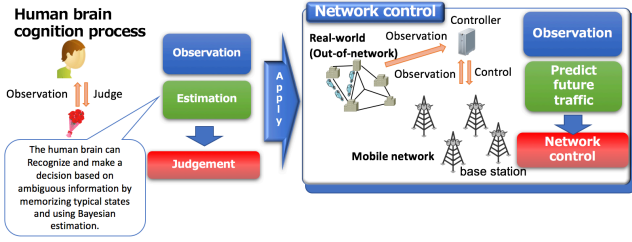


Fig. 1: Application of the cognitive process of the human brain to TE

stochastic variables that mimic the human brain and updates these variables by Bayesian inference every time a new observation is obtained. Then, a decision is made based on the stochastic variables, imitating the process followed by the human brain. Figure 1 shows an illustrative overview of our method.

The remainder of this section explains the way in which our method predicts future traffic and the process our method follows to allocate resources based on this prediction.

### B. Traffic prediction based on cognitive process of the human brain

Our method predicts the future traffic from each area and allocates the resources based on this prediction. In this section, we focus on an area and predict the traffic in the area at time slot  $t + p$  by using the information monitored at time slot  $t$ .

Our method defines the state of the network by using the monitored information. We also assign the expected amount of future traffic for each state by using the observed information. This approach enables us to predict the future traffic by determining the state of the network based on the observed information. We determine the state of the network by using the Bayesian Attractor Model (BAM) [11], which is one of the cognitive models of the human brain.

The remainder of this subsection explains the observation information used for prediction, the definition of the state of the network, and the application of BAM for decision-making regarding this state.

1) *Observed information:* In this study, we use the number of users in each area in addition to the amount of traffic from the area. As explained in Section IV-A, we also use the information pertaining to nearby areas. In addition to the absolute values of the number of users and the amount of traffic, it is useful to know whether the values are increasing; this is because an increase in the number of users in nearby areas may be a sign that the number of users and/or the amount of traffic could be expected to increase. Therefore, we also use the rates of increase in the traffic and the number of users.

Our method uses the following information in the areas of which the distance from the area of which the future traffic is to be predicted is less than  $m$  when predicting the traffic at time slot  $t + p$

- Traffic amount at time slot  $t$

- Difference between traffic amounts at time slot  $t - p$  and time slot  $t$
- Number of users at time slot  $t$
- Difference between the number of users at time slot  $t - p$  and time slot  $t$

2) *State:* If the information observed at time slot  $t$  is similar to that observed at time slot  $t'$ , the amount of traffic at time slot  $t + p$  is similar to that at time slot  $t' + p$ . Thus, we define the state by using a clustering method; we divide the observed information that is collected in advance into  $k$  clusters  $C_1, C_2, \dots, C_k$  such that each cluster includes similar information. Each cluster indicates the state to be determined by the decision-making process.

We also assign the future traffic for each cluster. The future traffic for cluster  $C_n$  is determined by

$$T_n^{\text{future}} = \max_{t \in C_n} T_{t+p}, \quad (3)$$

where  $T_{t+p}$  is the amount of traffic at time slot  $t + p$ . Definition of the future traffic by Eq. (3) enables us to avoid the case in which the amount of traffic at time slot  $t' + p$  for  $t \in C_n$  becomes larger than the traffic predicted for cluster  $C_n$ . That is, we can allocate a sufficient amount of resources to avoid congestion by using the predicted traffic.

We define the  $k$  cognitive states based on observed information using the  $k$ -means method.

3) *Application of BAM to state cognition:* We use  $k$  decision makers such that the  $i$ th decision maker decides whether the current state belongs to the  $i$ th option (i.e., the  $i$ th cluster defined in Section IV-A). Each decision maker performs decisions based on BAM.

Hereafter, we explain the use of the observed information in each decision maker and define the attractor in BAM.

a) *Using the observed information:* Each decision maker uses observations to determine whether the current state belongs to the target cluster. We calculate the input of the BAM model  $\mathbf{x}_i$  in each decision maker to enable the model to easily determine whether the current state belongs to the target cluster

$$\begin{aligned} \mathbf{x}_i &= \sigma \left( \frac{a_i}{a_i + b_i}, \frac{b_i}{a_i + b_i} \right) \\ a_i &= D(\mathbf{X}, \mathbf{M}_i) \\ b_i &= \min_{j \neq i} (D(\mathbf{X}, \mathbf{M}_j)), \end{aligned} \quad (4)$$

where  $\mathbf{x}_i$  is the input for BAM to make a decision whether the current state belongs to the cluster  $C_i$  ( $1 \leq i \leq k$ ),  $\mathbf{X}$  is the vector of the current observed value,  $D(\mathbf{y}_1, \mathbf{y}_2)$  is the Euclidean distance between vectors  $\mathbf{y}_1$  and  $\mathbf{y}_2$ , and  $\sigma$  is a sigmoid function. Further,  $\mathbf{y}_i$  is the centroid of the observed information belonging to the  $i$ th cluster.

Important is that  $\mathbf{x}_i$  approaches 0,1 when the observed value is close to the centroid of the observed information in the cluster  $C_i$ . On the other hand,  $\mathbf{x}_i$  approaches 1,0 when the observed value is close to the other clusters.

b) *Definition of attractor*: Each decision maker decides whether the current state belongs to the target cluster. That is, each decision maker has two attractors  $z_{yes}$  and  $z_{no}$ ;  $z_{yes}$  corresponds to the case in which the current state belongs to the target cluster, and  $z_{no}$  corresponds to the case in which the current state belongs to the other cluster. Then, we define the observed values for  $z_{yes}$  and  $z_{no}$  as follows.

$$\begin{aligned}\mu_{yes} &= (0, 1) \\ \mu_{no} &= (1, 0)\end{aligned}\quad (5)$$

### C. Resource allocation based on prediction

The above procedure outputs the posterior probability  $P(z_{yes}|x)$  (hereinafter referred to as the confidence) and the predicted amount of traffic for each cluster. In this study, we allocate resources based on this confidence.

If the current observed information clearly indicates that the current state belongs to a certain cluster, the value of  $P(z_{yes}|x)$  is high only for that particular cluster. However, there may be a case in which  $P(z_{yes}|x)$  is high for multiple clusters. In this case, we allocate the resources based on the maximum value of the predicted traffic of which the corresponding  $P(z_{yes}|x)$  is high to avoid the risk of congestion. That is, we allocate resources to accommodate traffic of which the volume is larger than

$$T^{\text{allocate}} = \max_{n \in \{n | P_n(z_{yes}|x) > \lambda\}} T_n^{\text{future}}$$

, where  $P_n(z_{yes}|x)$  is the confidence of the decision maker corresponding to the  $n$ th cluster, and  $\lambda$  is the threshold.

## IV. EVALUATION

This evaluation demonstrates the effect of using the real-world information, and the effect of the prediction inspired by the cognitive process of the human brain.

### A. Evaluation method

1) *Evaluation environment*: This evaluation requires data relating to the movement of users and the traffic generated by these users. However, data of the actual movement of users are unavailable.

Thus, in this study we synthetically generated data about the movement of users and the traffic generated by these users by using the pseudo-generated GPS trajectory dataset named Open PFLOW [13] (University of Tokyo CSIS-JoRAS), and Synthetic Traffic Generator [14].

Open PFLOW includes the typical movement pattern of network users in the metropolitan area for one day. This dataset contains pairs of values consisting of the time and GPS coordinates corresponding to each user. The data were recorded every 5 seconds. However, the number of people included in this dataset is 617,040 and does not include data corresponding to all users in the metropolitan area.

Therefore, assuming that multiple users move in a similar way, we generated the number of people in each area by assigning a scale factor to each user in Open PFLOW and summing the scale factors of the users in the area. We

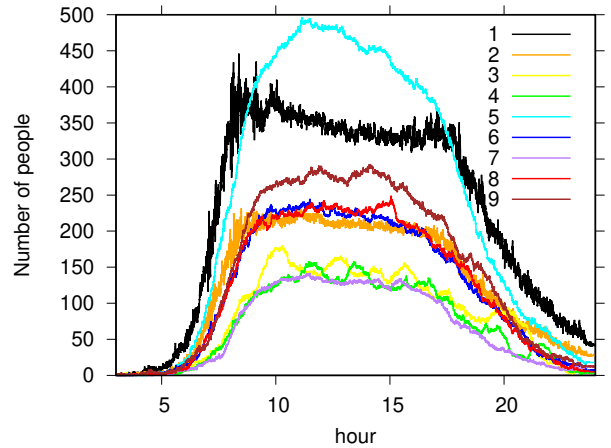


Fig. 2: Time series of the number of users in the prediction target area and its surroundings

generated multiple datasets by randomly changing the scale factors and used one of them as training data for the prediction, and the others for the evaluation.

Synthetic Traffic Generator reproduces the amounts of traffic, the number of requests, and the interval time between requests from  $x : 00 : 00$  to  $(x + 1) : 00 : 00$  ( $0 \leq x \leq 23$ ) based on the real data. This simulator generates most of the requests on  $x : 00 : 00$ , but, in the actual network, each user's request occurs in a greater variety of time zones. Therefore, in this evaluation, we regenerated the request time such that the requests were uniformly distributed between  $x : 00 : 00$  and  $(x + 1) : 00 : 00$ . The Synthetic Traffic Generator only generates requests and does not generate information on the amount of traffic in shorter time granularity. In this evaluation, the traffic produced by each user was generated assuming that the traffic rate is constant from the beginning to the end of the request.

In this evaluation, we defined the area by partitioning Chiyoda-ku, Tokyo, into areas of 0.0036 (about 350 m) in both latitude and longitude. We focused on one of the areas as the target area. Figure 2 shows the time series of the number of users in the target and nearby areas. Figure 3 shows the time series of the traffic in the areas. In these figures, sequence 1 corresponds to the target area.

In this evaluation, for simplicity, the unit of the allocated resources was set such that one unit can accommodate 16 Mbps. We set the value of  $p$  to 40 minutes. That is, we predict the amount of future traffic 40 minutes in advance and allocate resources to avoid congestion for 40 minutes.

2) *Compared method*: We evaluate the effect of using real-world information and the effect of prediction inspired by the cognitive process of the human brain. The evaluation is designed to compare the following method with the proposed method (hereinafter referred to as cognitive TE method with real-world information).

a) *Cognitive TE without real-world information*: This method predicts the future traffic in the same way as our

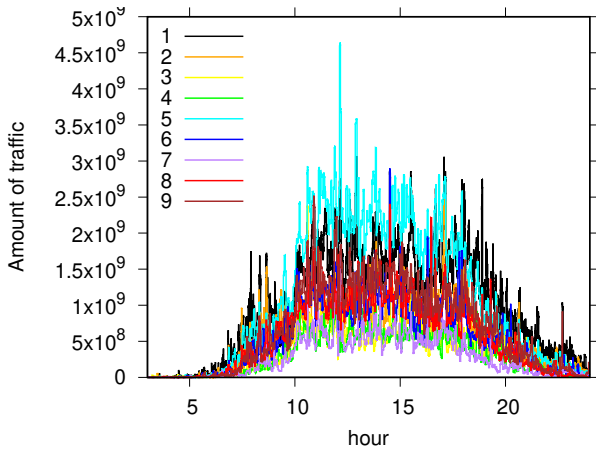


Fig. 3: Time series of the amounts of traffic in the prediction target area and its surroundings

cognitive TE with real-world information but uses only the information on traffic volumes to predict future traffic. The information used by this method at time slot  $t$  is the following information of the areas of which the distances from the target area are less than  $m$

- Traffic volume at time slot  $t$
- Difference between the amount of traffic at time slot  $t-p$  and the time slot  $t$

This method is the same as the proposed method except for the information used for prediction. The comparison of the performance of our method with that of this method is intended to demonstrate the effect of including information about the number of users.

*b) Deterministic TE With real-world information:* This method predicts the future traffic by using the same information as our method. However, this method does not use a process inspired by the cognitive model of the human brain. Instead, this method determines the cluster of the current status as being the cluster of which the centroid is the nearest to the current observation. This comparison is intended to demonstrate the effect of prediction based on the cognitive process.

*c) Deterministic TE Without real-world information:* This method predicts the future traffic in the same way as the deterministic TE with real-world information but uses only the information on the traffic volumes.

*3) Parameter settings:* In the above-mentioned comparisons, we set  $m = 2$  and  $p = 480$ . That is, all methods use the observed information of areas of which the distance from the target area is less than two areas (about 700 m). Furthermore, the difference from the observed value 40 minutes ago is used as the rate of increase in the amount of traffic and the number of people.

In the BAM, we set the sensory uncertainty to 0.42, and dynamic uncertainty to 0.3. We set the slope of the sigmoid functions  $a$  to 2.0. The other parameters in the BAM are set to the same values as those used by Bitzer et al. [11]

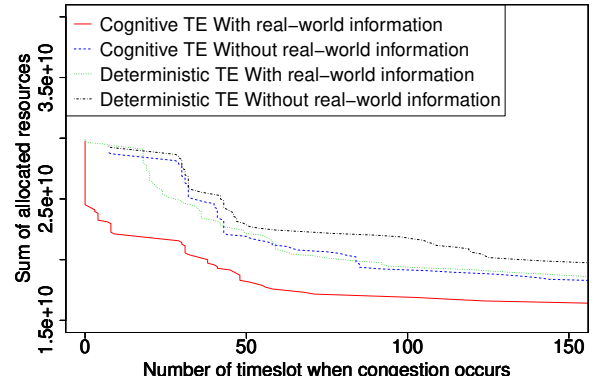


Fig. 4: Sum of allocated resources necessary to maintain the number of timeslots in which congestion occurs below a certain level

*4) Metrics:* Each of the above-mentioned methods were used to allocate resources to the target area with the aim of avoiding congestion. We allocated resources that can accommodate  $T^{\text{future}} + \alpha$  Mbps of traffic, where  $T^{\text{future}}$  is the predicted traffic and  $\alpha$  is a margin. Setting a large margin avoids congestion but requires more resources. Because it is preferable to avoid congestion with a limited amount of resources, we determined the number of time slots in which congestion occurred and the total amount of allocated resources.

## B. Evaluation results

Figure 4 shows the results. The horizontal axis indicates the number of time slots when congestion occurs due to the lack of resources and the vertical axis indicates the total amount of resources allocated when we set  $\alpha$  such that the number of time slots in which congestion occurs is less than the value on the horizontal axis. The total amount of resources indicates the total volume of traffic (KByte) that can be relayed in all time slots by the allocated resources.

Comparing the cognitive TE with real-world information and the cognitive TE without real-world information, the cognitive TE with real-world information required a smaller amount of resources to maintain the number of time slots in which congestion occurred to less than a certain value. This is because the real-world information enables us to capture the difference in the states which could not be distinguished by using only traffic volume information, thereby allowing the accurate prediction of future traffic. As shown in Figures 2 and 3, the traffic volumes are strongly correlated with the number of users. That is, the number of users is useful information for predicting the traffic. In addition, the fluctuation of the number of users does not include a large amount of noise, compared with the fluctuation of the traffic. Consequently, the large amount of noise prevents the cognitive TE without real-world information from accurately deciding the status of

the network only from the traffic information. On the other hand, the cognitive TE with real-world information accurately decides the states even in cases such as this.

We next compare the cognitive TE with real-world information and the deterministic TE with real-world information. Figure 4 shows that the cognitive TE requires a smaller amount of resources. This is because the cognitive TE with real-world information controls the traffic based on confidence. The cognitive TE requests additional resources when the confidence levels for multiple candidates become large. As a result, a small value of  $\alpha$  is sufficient to avoid congestion. On the other hand, the deterministic TE does not consider the confidence levels. As a result,  $\alpha$  needs to have a large value to avoid congestion, which requires a large amount of additional resources.

## V. CONCLUSION AND FUTURE WORK

This paper proposed a predictive traffic engineering method that predicts future traffic by using information monitored in the real world. Despite the obvious usefulness of basing the prediction on real-world information, it is difficult to model this traffic as a function of the real-world information. That is, we required a new method to predict future traffic using this information.

Therefore, we proposed a prediction method inspired by the cognitive process of the human brain, which makes decisions based on uncertain information. Our model uses stochastic variables to mimic the human brain and updates the variables by Bayesian inference every time a new observation is recorded. Then, similar to the human brain, the model makes a decision based on the stochastic variables.

Our method was designed to define multiple conditions based on the monitored information including both traffic and real-world information. Our method learns the amount of future traffic corresponding to each condition. Then, our method uses a process inspired by the cognitive process of the human brain to predict the amount of future traffic by estimating the current amount of traffic and by using real-world information; our method contains stochastic variables indicating the confidence level of the current traffic and real-world information relating to the corresponding condition, and updates the variables every time a new observation is recorded. Finally, our method allocates resources based on the future traffic corresponding to the conditions for which the confidence levels are high.

We evaluated our method by simulation. The results demonstrated that our method avoids congestion without requiring a large amount of additional resources; the amount of resources required to avoid congestion is reduced by 25 % compared with the predictive TE using only historical traffic information.

Our future work includes optimization of the parameter settings of our method. Especially, the number of clusters  $k$  may have a large impact on the accuracy of the prediction. We also plan to evaluate our method in a different environment; for example, we intend evaluating our method by specifying a different value for  $p$ .

## ACKNOWLEDGMENTS

This research was supported in part by contract research for the National Institute of Information and Communications Technology (NICT) “Research and development on new network infrastructure technology creating the future,” for which I would like to express my appreciation.

## 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] A. Elwalid, C. Jin, S. Low, and I. Widjaja, “Mate: Mpls adaptive traffic engineering,” in *INFOCOM 2001. Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, vol. 3, pp. 1300–1309, IEEE, 2001.
- [6] T. Otsoshi, Y. Ohsita, M. Murata, Y. Takahashi, N. Kamiyama, K. Ishibashi, K. Shiimoto, and T. Hashimoto, “Traffic engineering based on model predictive control,” *IEICE Transactions on Communications*, vol. 98, no. 6, pp. 996–1007, 2015.
- [7] L. Lu and C. Lianglun, “NETWORK TRAFFIC PREDICTION MODEL BASED ON OPTIMISING SVM WITH IMPROVED CUCKOO SEARCH ALGORITHM,” *Computer Applications and Software*, vol. 1, p. 033, 2015.
- [8] G. Rutka, “Neural network models for Internet traffic prediction,” *Elektronika ir Elektrotechnika*, vol. 68, no. 4, pp. 55–58, 2015.
- [9] W. Lu, “Parameters of Network Traffic Prediction Model Jointly Optimized by Genetic Algorithm,” *JNW*, vol. 9, no. 3, pp. 695–702, 2014.
- [10] G. Rutka and G. Lauks, “Study on internet traffic prediction models,” *Elektronika ir Elektrotechnika*, vol. 78, no. 6, pp. 47–50, 2015.
- [11] 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.
- [12] S. J. Julier and J. K. Uhlmann, “New extension of the kalman filter to nonlinear systems,” in *Signal processing, sensor fusion, and target recognition VI*, vol. 3068, pp. 182–194, International Society for Optics and Photonics, 1997.
- [13] T. Kashiyama, Y. Pang, and Y. Sekimoto, “Open pflow: Creation and evaluation of an open dataset for typical people mass movement in urban areas,” *Transportation Research Part C: Emerging Technologies*, vol. 85, pp. 249–267, 2017.
- [14] E. M. R. Oliveira, A. C. Viana, K. P. Naveen, and C. Sarraute, “Measurement-driven mobile data traffic modeling in a large metropolitan area,” in *Pervasive Computing and Communications (PerCom), 2015 IEEE International Conference on*, pp. 230–235, IEEE, 2015.