Master's Thesis

Title

Network Resource Allocation using Real-World Traffic Flow Information inspired by Human Brain Cognition Process

Supervisor

Professor Masayuki Murata

Author

Semin An

January 29th, 2021

Department of Information Networking

Graduate School of Information Science and Technology

Osaka University

Master's Thesis

Network Resource Allocation using Real-World Traffic Flow Information inspired by Human Brain Cognition Process

Semin An

Abstract

Networks are required to allocate network resources so as to satisfy the requirements of services and accommodate the generated traffic. One approach to accommodating services with different requirements is to use network slicing technologies. By constructing a network slice for each service, network operators flexibly configure their network slices as as to satisfy their requirement.

Resource allocation to each network slice is important for network operators. The amount of traffic changes in time. If a slice does not have a sufficient amount of resources to accommodate current traffic, the quality of the communication within the slice degrades and does not satisfy the requirement. Resource allocation based on prediction is one approach to handling traffic changes. In this approach, the resources are proactively allocated so as to accommodate the predicted future traffic.

Prediction accuracy is important for resource allocation based on prediction. There are many method to predict future traffic demands. Most of them predict future traffic by the time series of the monitored traffic. However, it is difficult to predict future demands accurately from only on previously monitored traffic if the signs of the traffic changes are not included in the previously monitored traffic.

Real-world information may include the signs of traffic changes that are not included in previously monitored demands, and is useful for the prediction of future traffic. However, it is difficult to accurately model the relationship between the real-world information and future traffic demands information may include the signs of traffic changes that are not included in previously monitored demands, and is useful for the prediction of future traffic. However, it is difficult to accurately model the relationship between the real-world information and future traffic demands.

Therefore, our research team has proposed a method a predictive network control method using the real-world information of which the relation to future traffic cannot be clearly modeled. This method is based on the Bayesian Attractor Model (BAM), which is one of the models of the cognition process of human brain. The method based on the BAM makes decisions even if the monitored real-world information is uncertain.

In this thesis, we apply the network control method based on the cognitive process of a human brain to the resource allocation of the network slices for connected vehicles. The traffic amount of the slice changes, following the number of connected vehicles in each area. That is, the transport traffic information includes the signs of the increase of the number of the connected vehicles. Therefore, we use the transport traffic information in addition to the traffic amount from/to each area and the number of users in each area.

In this thesis, we demonstrate that our method using road traffic information avoids resource shortage without allocating a large amount of redundant resources and frequent change of the allocated resources. The number of changes of allocated resources by our method is less than 1/9 of that by the method that predict the required resources based on the k nearest neighbor algorithm.

Keywords

Network slicing

Resource allocation

Resource shortage avoidance

Bayesian Attractor Model

Traffic flow information

Contents

List of Figures

List of Tables

1 Introduction

Networks are required to allocate network resources so as to satisfy the requirements of services and accommodate the generated traffic. One approach to accommodating services with different requirements is to use network slicing technologies [1, 2]. By using network slicing technologies, a network can be virtually divided into multiple network slices. By constructing a network slice for each service, network operators flexibly configure their network slices as as to satisfy their requirement.

Resource allocation to each network slice is important for network operators. The amount of traffic changes in time. If a slice does not have a sufficient amount of resources to accommodate current traffic, the quality of the communication within the slice degrades and does not satisfy the requirement. One approach to avoiding the lack of resources is to allocate a sufficient amount of resources considering traffic changes. However, this approach requires a large amount of resources, which causes a substantial cost.

Therefore, dynamic resource allocation is required. There are many method to dynamically allocate resources [3–8]. By allocating the resources dynamically to follow the traffic changes, the requirements can be satisfied with a limited amount of resources. However, most of them allocate resources based on the observed traffic. But the resource allocation based on the observed traffic does not provide a sufficient amount of resource when significant traffic changes occur. Even in such cases, the configured resource allocation is not changed until the next control cycle.

Resource allocation based on prediction is one approach to handling traffic changes [3–8]. In this approach, the resources are proactively allocated so as to accommodate the predicted future traffic. Prediction accuracy is important for resource allocation based on prediction. There are many method to predict future traffic demands [3–8]. Most of them predict future traffic by the time series of the monitored traffic. That is, the future traffic demands are predicted from the previously observed traffic demands. However, it is difficult to predict future demands accurately from only on previously monitored traffic if the signs of the traffic changes are not included in the previously monitored traffic.

Real-world information may include the signs of traffic changes that are not included in previously monitored demands, and is useful for the prediction of future traffic. However, it is difficult to accurately model the relationship between the real-world information and future traffic demands.

Therefore, our research team have proposed a predictive network control method using the real-world information of which the relation to future traffic cannot be clearly modeled [9]. This method is based on the Bayesian Attractor Model (BAM) [8], which is one of the models of the cognition process of human brain, which makes decisions from uncertain information. BAM has the decision-making state z_t as the internal state, and updates z_t based on the observed value x_t obtained from the outside. The situation judgment made by BAM is determined by the decision-making state z_t. When the state z_t arrives at any of the state values $\phi_1, \cdots, \phi_S$ corresponding to the S options prepared in advance, the option corresponding to the reached state is the result of the decision making. At this time, the concept of Bayesian estimation is used for updating the state, and z_t is updated as one point. Instead, it is updated as a probability distribution $P(z_t)$ that reflects the uncertainty contained in the observed values and the uncertainty of the decision-making state, and the value of z_t is expressed with probability. Therefore, the judgment as to whether or not it corresponds to the i th option is not the binary value of corresponding or not, but the certainty that the i th option is based on the obtained probability distribution, $P(z_t = \phi_i)$ and make a decision based on $P(z_t = \phi_i)$. The method use the above model to predictive network control. In this method, we first define the options in decision making by considering the future traffic and the currently monitored traffic and real-world information. Then, the method based on BAM identifies the option corresponding to the current state from the observed information. Based on the identified option, we allocate the resources.

They demonstrated the effectiveness of the proposed method only considering the daily traffic changes, and used only the information of the number of users in each area as the real-world information. On the other hand, the real-world information is useful especially in the case that some events occurs and the information related to the events is included in the real-world information. One example of such real-world information is the transport traffic information. The number of the connected vehicles has a large impact on the traffic amount from the connected vehicles. The number of the connected vehicles may drastically changes when some kinds of events such as traffic accidents causes traffic congestions. The transport traffic information may include the signs of the traffic congestions.

In this thesis, we apply the network control method based on the cognitive process of a human brain to the resource allocation of the network slices for connected vehicles. The traffic amount of the slice changes, following the number of connected vehicles in each area. As discussed above, the transport traffic information includes the signs of the increase of the number of the connected vehicles. Therefore, we use the transport traffic information in addition to the traffic amount from/to each area and the number of users in each area.

2 Related work

2.1 Network slicing

Networks are required to allocate network resources so as to satisfy the requirements of services and accommodate the generated traffic. The amount of traffic changes in time. Thus, the dynamic reconfiguration of the network is required.

Software defined networking (SDN) is one of the technologies that enable flexible network control [10,11]. In the SDN, the route within a network can be dynamically changed by a central controller. Network Function Virtualization is another key technology to enable flexible network reconfiguration. In this technology, the network functions are virtualized and can be migrated to any place in the network.

Several methods to construct multiple network slices on a single physical network has been proposed. S. Rob et al. proposed a switch-level virtulization technology [12]. By using this technology, multiple network slices are provided on a physical network.

In addition to the network resources, the computational resources of a data center are also virtually divided [13]. In recent years, edge computing resources, which are computing resources located closer to users, are divided into virtual slices to accommodate multiple services using common resources [14].

In recent years, wireless network resources can also be virtualized [2].

There are two kinds of wireless network virtulization technologies; spectrum-level slicing and network level slicing. Spectrum-level slicing divide the frequency bands into multiple slices. The network-level slicing divides the network resources including frequency bands used by base stations and bandwidth within the core network. By using these technologies, multiple virtual network can be provided over a single physical wireless network.

By using these technologies, we can dynamically configure the virtual network slices. In the virtual network slices, the resource allocation is important. The amount of traffic changes in time. If a slice does not have a sufficient amount of resources to accommodate current traffic, the quality of the communication within the slice degrades and does not satisfy the requirement.

In this thesis, we discuss a method to dynamically allocate resources based on the real-world information.

2.2 Bayesian Attractor Model

The Bayesian attractor model (BAM) is a model of the cognition process of a human brain, based on the Bayesian decision-making theory [8]. This model encodes the predefined i option $\phi_1, \cdots, \phi_i$ and makes decisions depending on the option corresponding to the current status. The decision state z_t is the internal state of this model, where z_t is updated by performing Bayesian inference every time a new observation.

Every time a new observation is obtained, the observation is first abstracted into x_t. Then, z_t is updated by inversing the following generative model using Bayesian inference.

$$
\begin{aligned}
z_t - z_{t-\Delta_t} &= \Delta_t f(z_{t-\Delta_t}) + \sqrt{\Delta_t} w_t & (1) \\
x_t &= M\sigma(z_t) + v_t & (2)
\end{aligned}
$$

where $f(z)$ is the Hopfield dynamics, w_t and v_t are Gaussian noise variables, $M = [\mu_i, \cdots, \mu_N]$ is a matrix containing the observation values, and μ_i is the observation value corresponding to the state ϕ_i, which is the ith predefined option. Further, σ(x) is a sigmoid function $\frac{tanh(ax/2)+1}{2}$, where a is the slope of this function.

The above inference outputs the posterior probability $P(Z_t|X_t)$. Thus, the decision is made by handling the probability. Bitzer˜et˜al. introduced the threshold λ. When $P(Z_t = \phi_i) > \lambda$, the option ϕ_i is selected. When $P(Z_t = \phi_i) \leq \lambda$ for all i, no decision is made until a new observation is obtained.

3 Proposed Method

3.1 Overview

Figure1 shows the overview of the resource allocation system.

In this system, we deploy a controller of the network slice for the connected vehicles. This controller periodically collects the information of current communication network and future road traffic. The information on current road traffic is used to predict future road traffic. Then, the controller predicts the required resources by using both of the predicted future road traffic and monitored information on the communication traffic.

By using the predicted future road traffic, the controller can predict the communication traffic increase on the slice. However, the prediction of future road traffic may include prediction error. Thus, we apply a method based on the Bayesian Attractor Model, that make decisions even if the information monitored at each time slot is uncertain, to the prediction of the required resources.

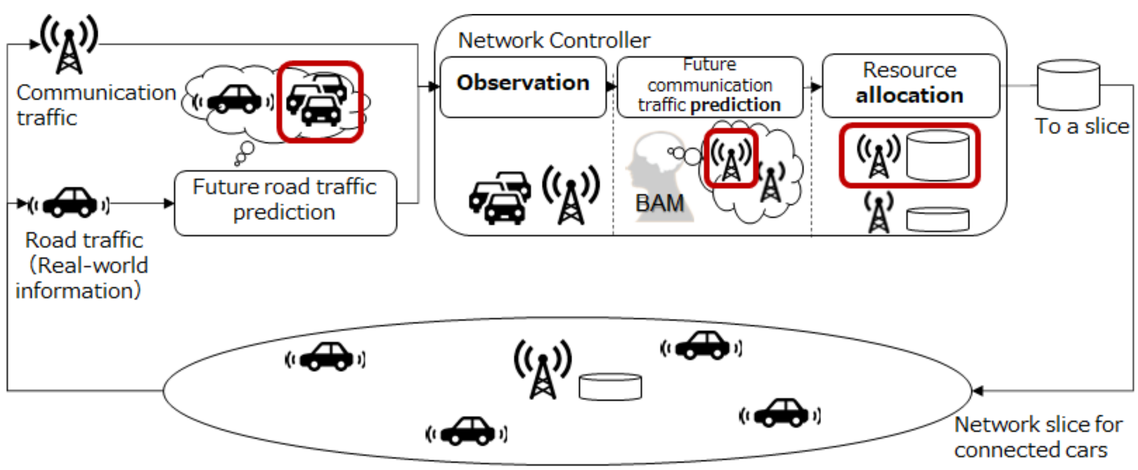

Figure 1: Overview of the resource allocation system

3.2 Prediction of road traffic

The future road traffic is predicted by using the collected current road traffic information including the number of vehicles on each lane of the monitored roads. We can apply any methods to predict future road traffic.

3.3 Prediction of required resources

The controller predicts the required resources every time slot. New observations including the future predicted road traffic and monitored communication traffic are obtained. We apply the method based on the BAM to predict the required resources. In this method, we define decision options and the amount of required resources for each option. Then, the controller identifies the current option by the cognitive process based on the BAM. By doing so, we can predict the required resources by identifying the option corresponding to the current condition.

3.3.1 Definition of the options in decision making

We define the options by using the previously obtained observations. We denote the observation at time t by O_t. O_t is a vector including the predicted road traffic and the information on the communication traffic on network. We first scale O_t by using the predefined scale factor for each element so that each element of O_t becomes less than 1. We denote scaled O_t by X_t. Then, we define the options by clustering X_t; we divide the set of the observations into multiple clusters so that each cluster includes similar observations and define one option for each cluster. Any method can be used to divide the set of X_t into clusters, such as $k - means++$ [15]. For each option, we define the required amount of resources considering the future traffic amount. We denote the traffic amount at time t by d_t. By using d_t, we define the required amount of resources as the resources that can accommodate the traffic whose amount is d'_t given by

$$d'_t = \max_{t \le k \le t+p} d_k. \tag{3}$$

In this equation, we consider the traffic amount from the time t to $t + p$. By considering the future traffic, we can allocate the resources in advance. By using d'_t, we define the amount of required resources for the ith option as the resources that can accommodate the traffic whose amout is $\hat{D}_i$ given by

$$\hat{D}_i = \max_{t \in C_i} d'_t \tag{4}$$

where C_i is the set of time slots whose observations are included in the cluster corresponding to the ith option.

By defining the required resources as the maximum value of the required resources, we avoid the lack of allocated resources.

The BAM requires the observation values for each option. In this thesis, we define the mean of X_t belonging to a cluster as the observation values of the options corresponding to the cluster.

3.3.2 Prediction of required resources based on Bayesian Attractor Model

In this thesis, we predict the required resources based on BAM. We use the same process as BAM. That is, the controller has the decision state Z_t and update it Z_t by performing the Bayesian inference every time a new observation X_t is obtained. The BAM outputs the posterior probability $P(Z_t|X)$. By using $P(Z_t|X)$, the controller predicts the required resources. In this paper, the controller selects the options whose corresponding $P(Z_t|X)$ exceeds the predefined threshold λ. If $P(Z_t|X)$ for multiple options exceeds λ and multiple options are selected, the controller selects the decision state associated with the maximum resource from multiple decision states. Then, the amount of allocated resources is predicted based on the selected state.

4 Evaluation

4.1 Settings

4.1.1 Road traffic generation

In this evaluation, we focus on an area around JR Shinjuku Station the size of which is about $2.4km^2$ as shown in Figure 2. We generate road traffic by using the Simulation of Urban MObility (SUMO) [16]. We obtain the actual road information from OpenStreetMap [17]. We generate the vehicle for the simulation-based on Open PFLOW [18], which is the open dataset for typical people mass movement. Open PFLOW includes information on only sampled people, we generate multiple vehicles for each person in a vehicle included in Open PFLOW. By randomly generating the scale factor, we generate multiple patterns. We generate the scale factor so as to follow the Gaussian distribution whose mean is 8 and variance σ^2. By setting σ to a large value, we generate various traffic patterns, and the prediction of road traffic becomes difficult. In this thesis, we set σ to 1, 4, and 9.

In addition, we also generate the case for road traffic accidents. We generate the case for road traffic accidents by reducing the lanes at the point accidents occur. In this evaluation, we generated the accidents at the starting point of Ome Kaido.

4.1.2 Communication traffic generation

This paper focuses on the network slice for the connected vehicle. Therefore, we focus on the communication traffic generated from the connected vehicles. For simplicity, we assume that each vehicle generates a similar amount of communication traffic, and generates the amount of communication traffic by adding the number of vehicles and Gaussian noise. In this evaluation, we set the mean and variance ρ^2 of the Gaussian noise to 0 and 0.2.

4.1.3 Road traffic prediction

In this paper, the controller uses the predicted road traffic. Any method to predict road traffic can be used. In this evaluation, we use the method proposed by Lun Zhang [19].

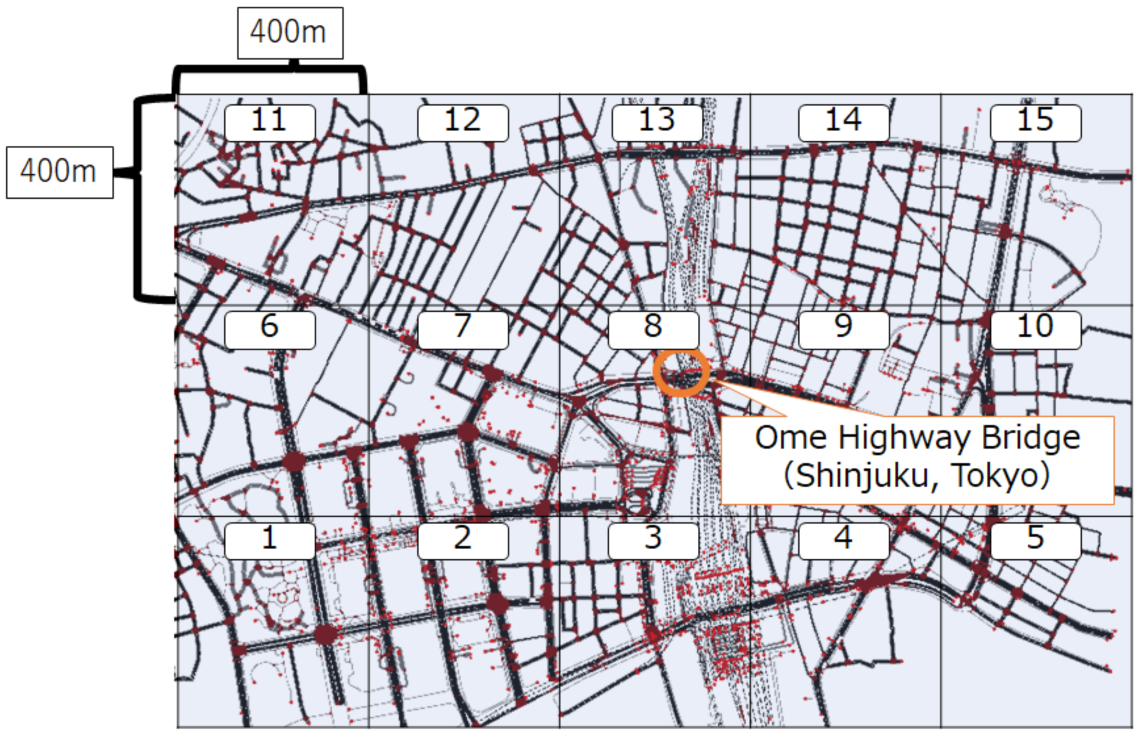

Figure 2: Divided areas around JR Shinjuku Station

This method is based on k Nearest Neighbors. This method stores the set of pairs of the observations and the number of vehicles on each road in the future. When a new observation is obtained, this method selects k nearest observation from the stored observations. Finally, the number of vehicles is predicted by the weighted sum of the number of vehicles corresponding the selected observations. In this paper, we use the numbers of vehicles on the primary roads as the observations for the road traffic prediction, and we set k to 82. After obtaining the predicted road traffic information, we merged them to calculate the predicted number of vehicles in each area, which is used as an input of the estimation of the required resources.

4.2 Compared methods

In this evaluation, we compare the following methods.

Cognitive Allocation with Road Traffic Information (CA w/)

Proposed method. This method uses both of the information on the road traffic and communication traffic and estimates the required resources by using the method based on

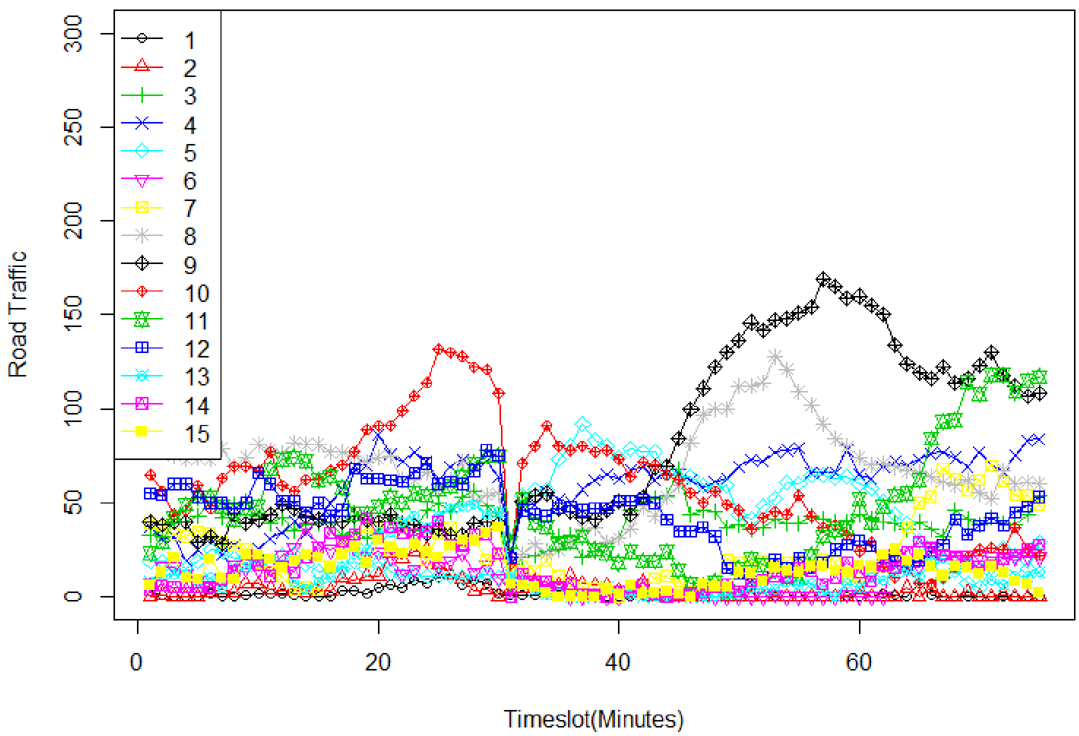

Figure 3: Road traffic in each area

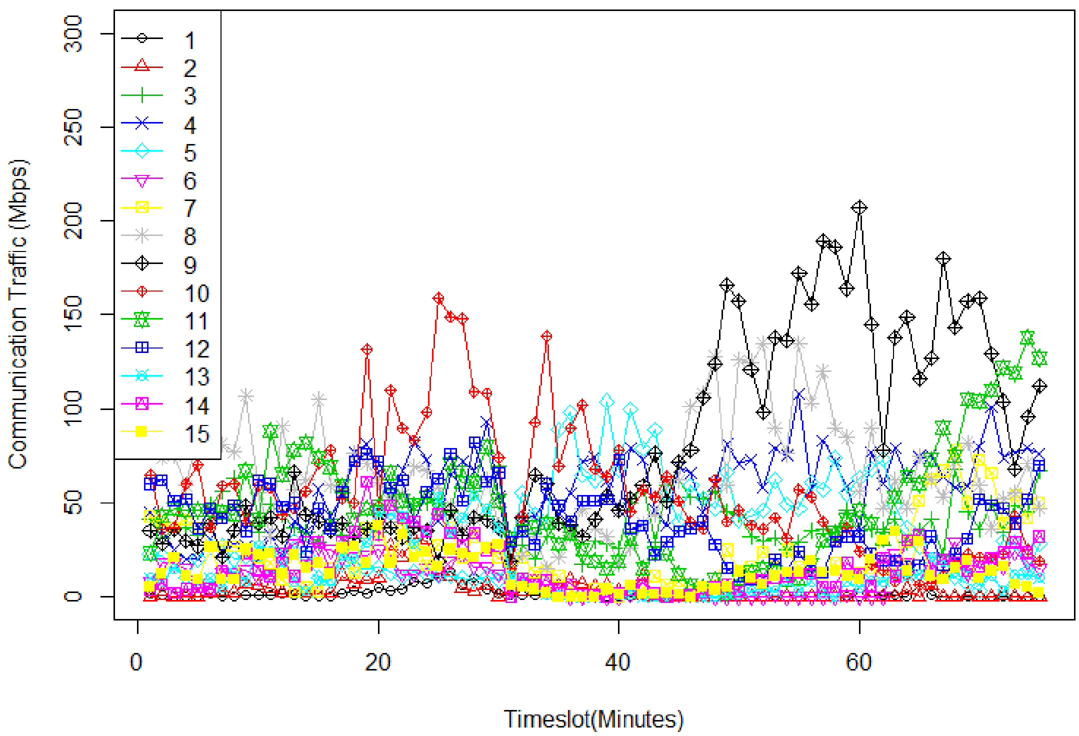

Figure 4: Communication traffic in each area

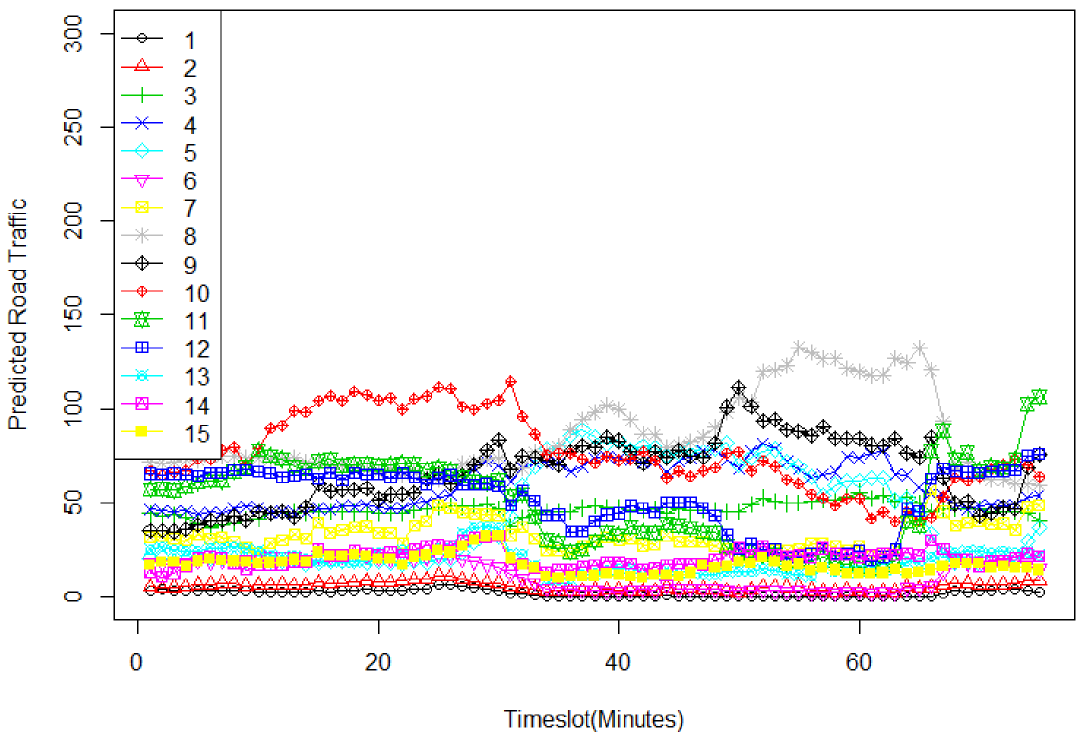

Figure 5: Predicted road traffic in each area

BAM. BAM has two parameters s and q. The suitable values of these parameters depends on the condition. In this thesis, we set them so that the resources are dynamically allocated following the traffic changes.

kNN-based Allocation with Road Traffic Information (kNN w/)

This method uses both of the information on the road traffic and communication traffic but estimates the required resources by selecting the K-Nearest-Neighbor instead of using BAM. In this method, the controller selects the nearest neighbor of the current observation from the stored past observations. Then the controller estimates the required resources by the required resources corresponding to the selected neighbor. The compared with this method demonstrates the effectiveness of the method using the BAM. In this paper, the value of K in the kNN method is set to 2.

Cognitive Allocation without Road Traffic Information (CA w/o)

This method uses the BAM but uses only the information on the communication network. The comparison with this method demonstrates that the effectiveness of the method using the information on road traffic.

4.3 Result

In evaluating the proposed method in this paper, there is the problem of how much noise contained in the observed values should be considered. Bayesian Attractor Model has sensory uncertainty (s) as an internal parameter. This parameter is a parameter that determines how much noise is included in the observed value. If the value is set large, the state is updated without being swayed by the change in the observed value, and if it is set small, it corresponds to the change in the observed value. In addition, there is dynamic uncertainty (q) as another internal parameter. This parameter is a parameter that determines the ease of change of the internal state in the internal state update phase, and if the value is set large, it tends to be easier to select a state different from the previous one, and if it is set small, it becomes more difficult to select. Therefore, the appropriate value changes depending on the noise ratio included in the observed value. In this paper, we specify multiple random numbers to be used in the generation of road traffic and communication traffic, and evaluate the proposed method under various environments. Then, set the parameters s and q of Bayesian Attractor Model to the values according to the environment.

4.3.1 Simulation example

Figures6 to 8 show the time series of the allocated resources. In these figures, the horizontal axis indicates time and vertical axis indicates the allocated resources. In addition to the allocated resources, we also plot the time series of the traffic amount. These figures

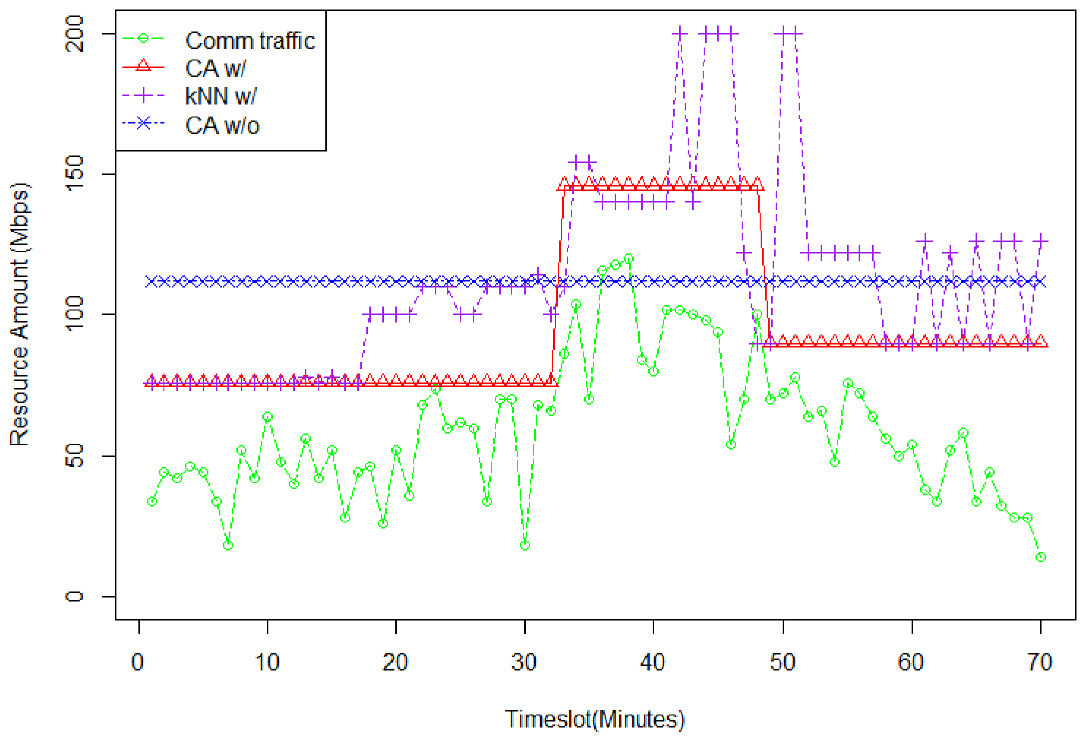

Figure 6: Simulation example (σ^2=1)

show that CA w/o does not change the resources. Even if the required resources becomes small, CA w/o allocates unnecessary resources. This is because the situation that does not require a large mount resources cannot be identified only from the network traffic information. As a result, even in such cases, unnecessary resources are allocated.

On the other hand, CA w/ and kNN w/ dynamically changes the allocated resources. That is, the information on transport traffic is useful to estimate the required resources.

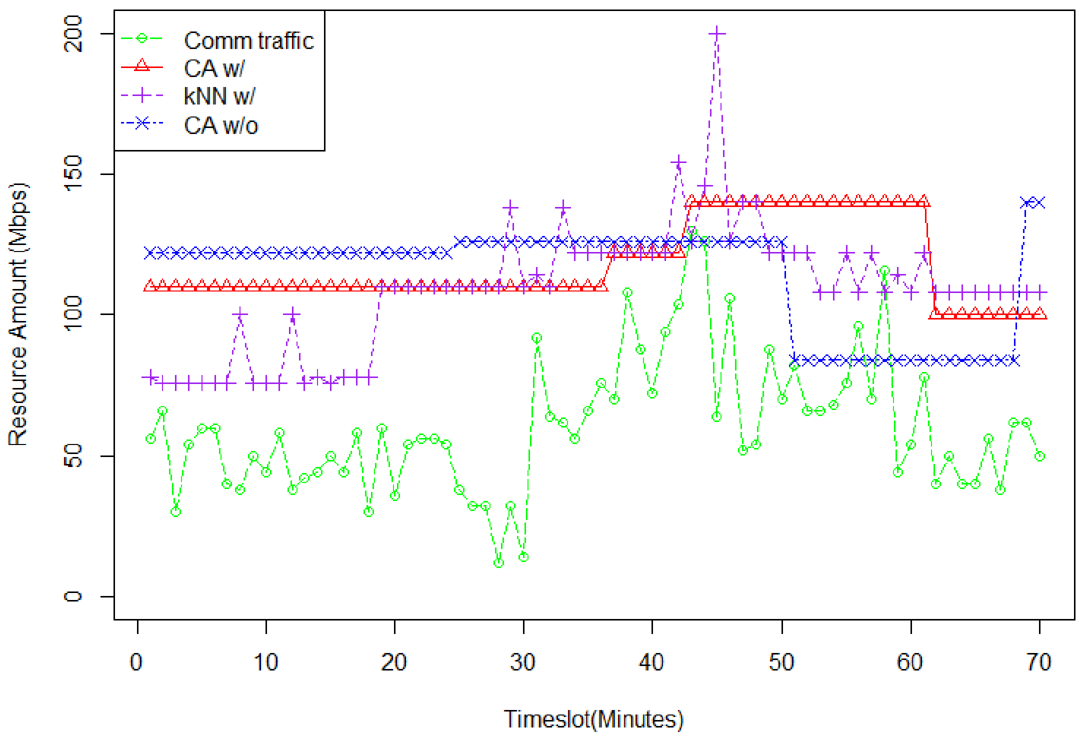

Figure 7: Simulation example (σ^2=4)

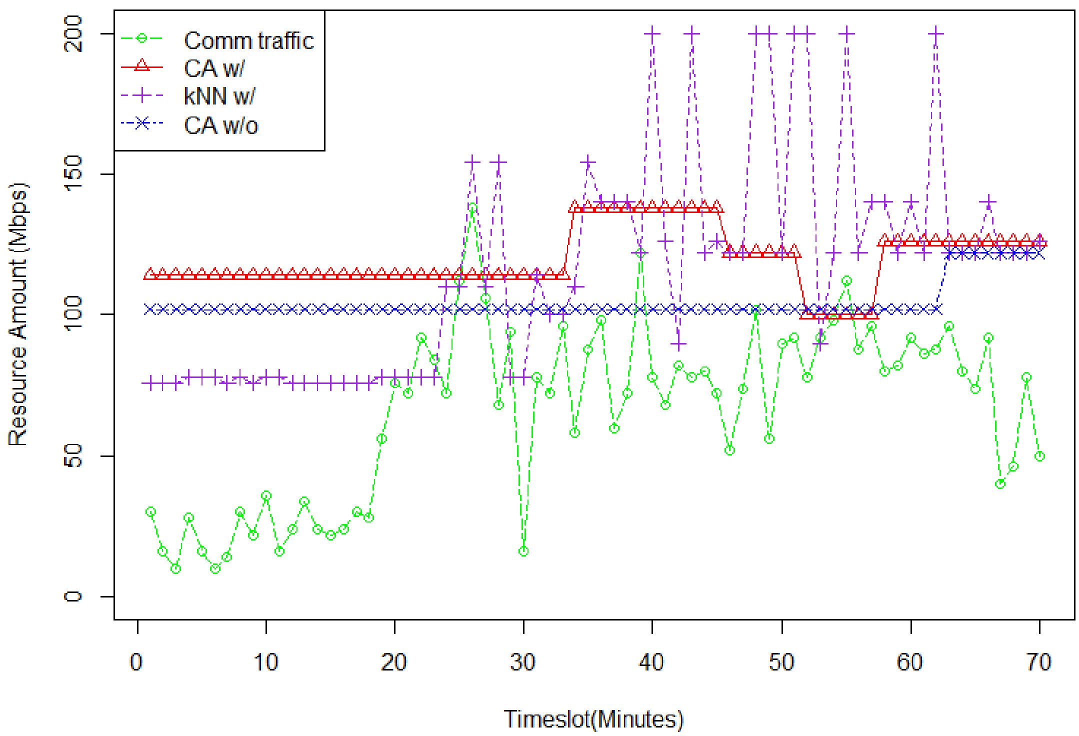

Figure 8: Simulation example （σ^2=9）

kNN w/ changes the allocated resources more frequently than CA w/. This is because kNN uses only the information monitored at each time slot. As a result, kNN w/ is too sensitive to the changes of the monitored information.

4.3.2 Resource shortage ratio

To compare these methods, we evaluate the relation between the sum of allocated resources and the number of time slots when congestion occurs due to lack of resources. Figures 9 to 11 show the results. To obtain the results, we allocate resources for accommodate $R + \alpha$ Mbps where R is the required resources estimated by each method and α is a parameter. By changing α, we plot the relation.

The horizontal axis indicates the number of time slots when congestion occurs due to lack of resources and the vertical axis indicates the total amounts of resources allocated when we set α so as to make the number of time slots when congestion occurs less than the value on the horizontal axis.

These figures indicate that CA w/ and kNN w/ avoid lack of resources without requiring a large amount of resources. This is because these methods change the allocated resources dynamically following the traffic changes.

4.3.3 Number of resource change

Tables 1 and 2 show the number of time slots that the resources are added or removed. To obtain the results, we run 100 simulations and each simulation includes 70 time slots. The tables indicates the number of time slots when the allocated resources are changed among 7000 time slots.

Table 1: Number of resource increase

σ^2	1	4	9
CA w/	151	133	129
kNN w/	1202	1244	1307
CA w/o	99	87	83

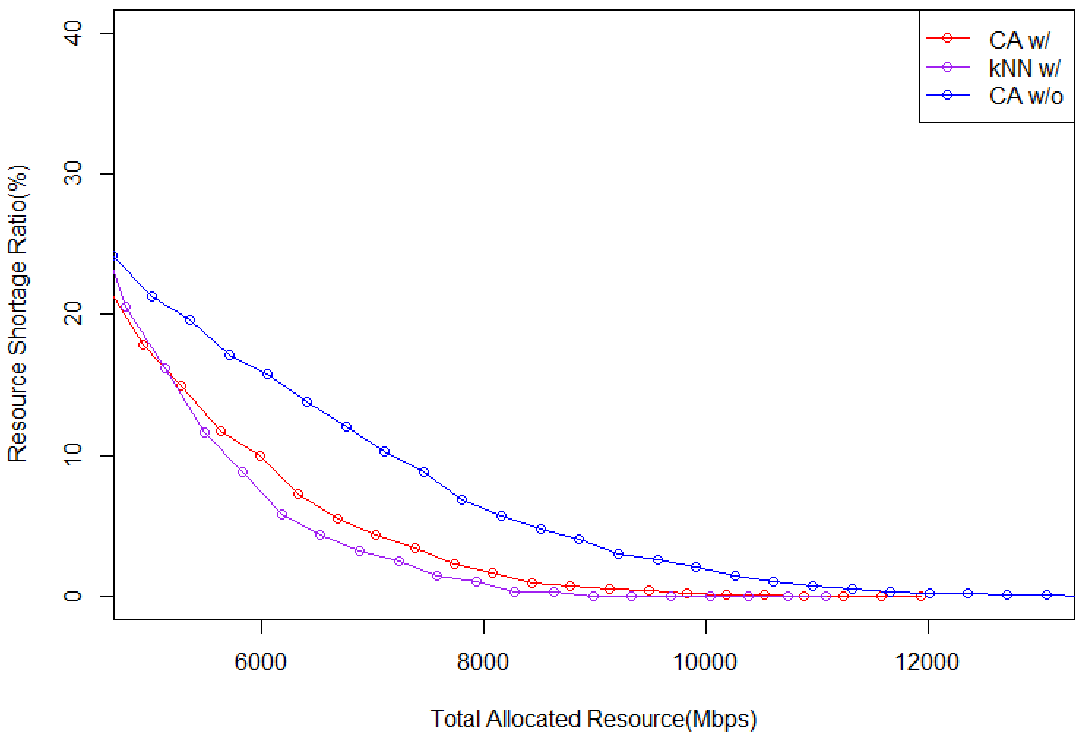

Figure 9: Resource shortage ratio $(\sigma^2{=}1)$

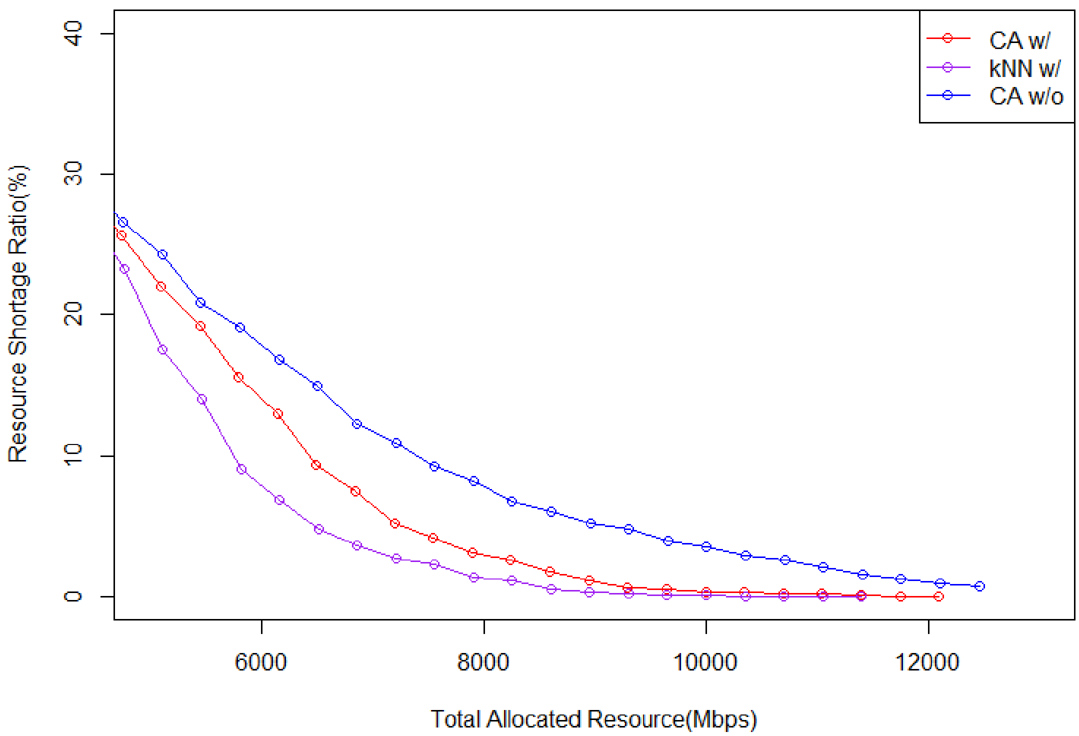

Figure 10: Resource shortage ratio $(\sigma^2{=}4)$

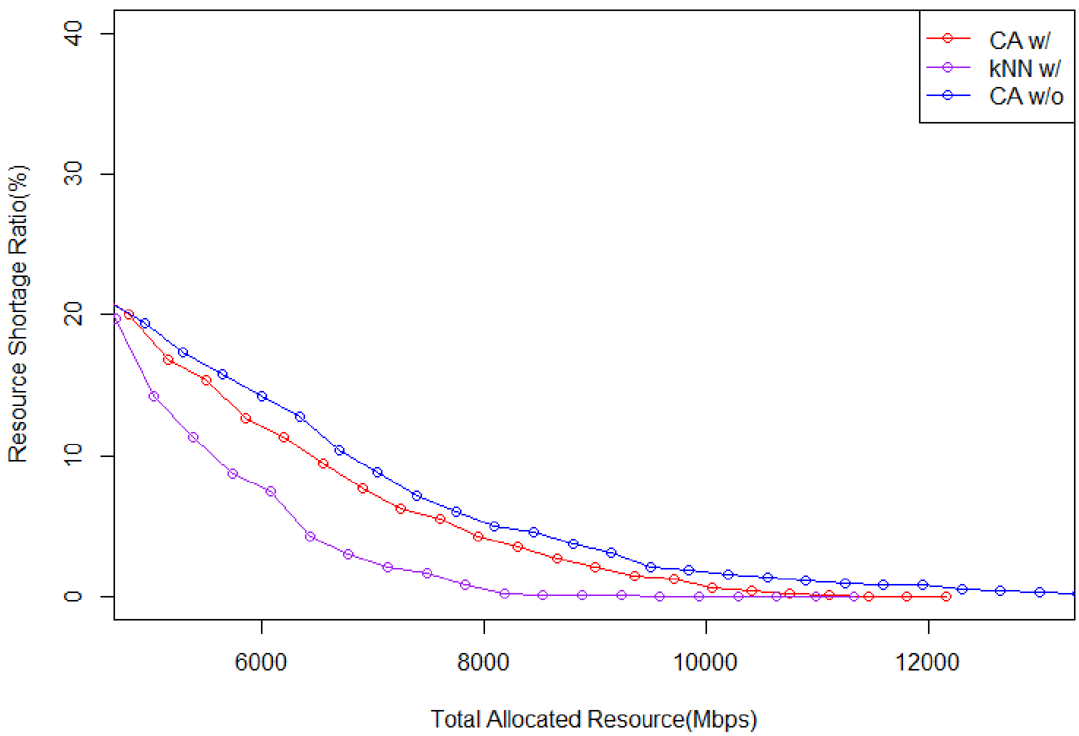

Figure 11: Resource shortage ratio $(\sigma^2{=}9)$

Table 2: Number of resource decrease

σ^2	1	4	9
CA w/	135	119	98
kNN w/	1111	1166	1196
CA w/o	69	71	74

From this table, kNN w/ change the resource allocation frequently; the number of the resource changes by the kNN w/ is about 9 times as large as the that by the CA w/. That is, CA w/ allocates resources so as to follow the changes of the required information without frequent change of the allocated resources.

5 Conclusion

In this thesis, we applied the network control method based on the cognitive process of a human brain to the resource allocation of the network slices for connected vehicles. The traffic amount of the slice changes, following the number of connected vehicles in each area. That is, the transport traffic information includes the signs of the increase of the number of the connected vehicles. Therefore, we use the transport traffic information in addition to the traffic amount from/to each area and the number of users in each area.

We demonstrated that our method using road traffic information avoids resource shortage without allocating a large amount of redundant resources and frequent change of the allocated resources. The number of changes of allocated resources by our method is less than 1/9 of that by the method that predict the required resources based on the k nearest neighbor algorithm.

Our future research topics include the evaluation of our method in the different environments such as different place and different communication traffic model. The parameter setting such as the number of predicted time slots is also one of our future research topics.

Acknowledgments

I would like to express our deep gratitude to Professor Masayuki Murata of the Graduate School of Information Science and Technology, Osaka University for his guidance and encouragement in advancing this paper. I would also like to express our sincere gratitude to Associate Professor Yuichi Ohsita of the Graduate School of Information Science and Technology, Osaka University for giving me appropriate advice and guidance by sincerely addressing various questions, including the policy of this paper. I would also like to express our sincere gratitude to Associate Professor Shin-ichi Arakawa and Assistant Professor Daichi Kominami of the Graduate School of Information Science and Technology, Osaka University for their continued guidance. I would also like to express our sincere gratitude to Assistant Professor Tatsuya Otoshi of the Graduate School of Economics, Osaka University for constructing the Bayesian Attractor Model program used in this report and answering many questions. Finally, I would like to express our gratitude to Mr. Masaaki Yamauchi and everyone in the Murata laboratory for their support.

References

[1] H. Zhang, N. Liu, X. Chu, K. Long, A.-H. Aghvami, and V. C. M. Leung, "Network Slicing Based 5G and Future Mobile Networks: Mobility, Resource Management, and Challenges," *IEEE Communications Magazine*, vol. 55, pp. 138–145, Aug. 2017.

[2] C. Liang and F. R. Yu, "Wireless Virtualization For Next Generation Mobile Cellular Networks," *IEEE Wireless Communications*, vol. 22, no. 1, pp. 61–69, Feb. 2015.

[3] L. Lu and C. Lianglun, "Network traffic prediction model based on optimizing SVM with improved cuckoo search algorithm," *Computer Applications and Software*, vol. 1, p. 33, 2015.

[4] G. Rutka, "Neural network models for Internet traffic prediction," *Elektronika ir Elektrotechnika*, vol. 68, no. 4, pp. 55—58, 2015.

[5] G. Rutka and G. Lauks, "Study on internet traffic prediction models," *Elektronika ir Elektrotechnika*, vol. 78, no. 6, pp. 47–50, 2015.

[6] C. Daly, "Novel H.265 video traffic prediction models using artificial neural networks," *Honors College Theses*, Apr. 2016.

[7] W. Lu, "Parameters of Network Traffic Prediction Model Jointly Optimized by Genetic Algorithm," *JOURNAL OF NETWORKS*, vol. 9, no. 3, pp. 695–702, Mar. 2014.

[8] S. Bitzer, J. Bruineberg, and S. J. Kiebel, "A Bayesian Attractor Model for Perceptual Decision Making," *PLOS Computational Biology*, vol. 11, no. 8, Aug. 2015.

[9] K. Satake, Y. Ohsita, and M. Murata, "Predictive traffic engineering incorporating real-world information inspired by human brain cognition process," feb 2018.

[10] B. N. Astuto and et al, "A survey of Software-Defined Networking: Past, Present, and Future of Programmable Networks," *IEEE Communications Surveys and Tutorials*, vol. 16, no. 3, pp. 1617–1634, Feb. 2014.

[11] H. Hassan and et al, "NFV: state of the art, challenges, and Implementation in next generation mobile networks (vEPC)," *IEEE Network*, vol. 28, no. 6, pp. 18–26, 2014.

[12] S. Rob and et al, "Flowvisor: A Network virtualization layer," *OpenFlow Switch Consortium*, Oct. 2009.

[13] B. Sushil, L. Jain, and S. Jain, "Cloud Computing: A Study of Infrastructure as a Service (IAAS)," *International Journal of engineering and information Technology*, vol. 2, no. 1, pp. 60–63, Jan. 2010.

[14] A. Mohammad and E.-N. Huh, "Dynamic Resource Provisioning Through Fog Micro Datacenter," *IEEE International Conference*, 2015.

[15] D. Arthur and S. Vassilvitskii, "k-means++: The advantages of careful seeding," *Proceedings of the Eighteenth Annual ACM-SIAM Symposium on Discrete Algorithms*, pp. 1027–1035, Jan. 2007.

[16] D. Krajzewicz, "Traffic Simulation with SUMO - Simulation of Urban Mobility," *Fundamentals of Traffic Simulation International Series in Operations Research and Management Science*, vol. 96, pp. 269–294, 2010.

[17] J. J. Arsanjani, A. Zipf, P. Mooney, and M. Helbich, "An Introduction to OpenStreetMap in Geographic Information Science: Experiences, Research, and Applications," *ISSN 1863-2246*, 2015.

[18] 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, Dec. 2017.

[19] L. Zhang, Q. Liu, W. Yang, N. Wei, and D. Dong, "An Improved K-nearest Neighbor Model for Short-term Traffic Flow Prediction," *Procedia - Social and Behavioral Sciences*, vol. 96, pp. 653–662, Aug. 2013.