Autonomous Wireless System Optimization Method based on Cross-layer Modeling using Machine Learning

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***Abstract*—Cognitive radio technologies have been developed to utilize the limited spectrum resources and optimize the behavior of the radio system, along with the variable radio status, by intelligent learning. The optimization can be achieved through clarifying the relationship among certain variables and target performance indices. However, today's wireless systems are becoming increasingly complex due to the advances of wireless technologies; this increases the number of variables of the optimization problem, which makes the relations among the variables and system performance to be formulated with difficulty. Recent advance in the field of machine learning technologies can help us overcome such difficulties by adopting for cognitive radio systems. This paper proposes a cross-layer modeling of wireless system using machine learning and optimization method based on cognitive cycle. The experimental evaluation is shown by applying the method to the IEEE 802.11 wireless local area network.**

***Index Terms*—Cognitive Radio, Machine Learning, Cross-layer, Optimization, Wireless LAN**

I. Introduction

Wireless traffic and the number of wireless communication devices have increased rapidly in recent years. However, the frequency bands suitable for current technologies have already been exploited; thus, the resources are limited. Moreover, the radio environment becomes more unpredictable because of two reasons. First, not only the volume but also the type of traffic is increasing, making the usage of the radio resource more complex. Second, distributed wireless networks such as the IEEE 802.11 wireless local area networks (WLANs) are widely deployed, and the inner- and inter-system interactions cannot be predicted easily.

Cognitive radio technologies [1], [2] have recently been developed to improve the radio resource usage of wireless networks under such situations. The basic concept of cognitive radio technology is the adaptation of the behavior of wireless systems through the recognition and learning of the radio environment. Cognitive radio systems observe and recognize the wireless network environment, make reconfiguration decisions, and apply the corresponding action to reconfigure the network. Using this approach, various radio parameters can be optimized through appropriate actions.

However, wireless systems have recently become increasingly complex. Various physical layer techniques such as code division multiplexing, frequency hopping, orthogonal frequency division multiplexing (OFDM), and Multiple-Input-Multiple-Output (MIMO) technology have been developed. Channel access techniques in MAC layer such as time division multiple access, frequency division multiple access, carrier sense multiple access with collision avoidance (CSMA/CA) have been developed. Higher layer protocol such as IP, and TCP or UDP are also used for wireless communication. Each layer technique has a number of parameters, and modern wireless systems are equipped with various combinations of those techniques. It means that the relations among radio variables and system performance are further complicated. It makes general cross-layer modeling of wireless systems difficult. Consequently, the optimization of whole wireless systems through cross-layer modeling cannot be realized.

One of the solutions for the above-mentioned issues is the machine learning technology. Machine learning is data-driven modeling that can provide a predictable model of wireless communications. The relation between the action and performance is learned by increasing the number of samples. Thus, the complex relations among various radio parameters and network performance can be obtained, which improves the precision of decision-making for the best performance.

This paper proposes a wireless system optimization method based on the cognitive cycle using machine learning. The main contribution of this paper is the clarification of why and how machine learning is adopted in a cognitive cycle in the current context of wireless communication. In Section II, related work is discussed. In Section III, the formulation of the optimization of wireless systems is discussed, followed by a description of the concept of the proposed optimization method. Section IV shows the verification of the proposed method through computer simulation and experimental testbed.

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II. Related work

A. Cognitive radio

The concept of cognitive radio was first proposed by J. Mitola[1]. Cognitive radio is described as an intelligent radio that can learn from its past experience and autonomously decide its actions suitable for radio environments and needs for communication. The proposed cognitive cycle[1], [3] is a feedback cycle of observation, learning, decision, and action. S. Haykin proposed a more concrete process of cognitive radio in [2] from an engineering perspective. He addressed the following fundamental tasks for a cognitive radio: radio-scene analysis, channel-state estimation, transmit-power control, and dynamic spectrum management. Wireless network nodes can change the radio parameters of transmission and reception in order to avoid interference among users and improve communication quality.

B. Machine learning for wireless system

Technologies for next-generation wireless networks, such as 5G, are one of the major topics in the field of wireless communication today. In [4], discussions about the possibilities of machine learning technologies for the next-generation 5G network are given. Supervised learning techniques can be used to support channel state estimation in MIMO systems. Unsupervised learning for cell clustering, especially in heterogeneous networks, and reinforcement learning for the decision-making process of mobile users are also suggested. Authors of [5] have discussed Autonomic Communications in future software-driven networks. In particular, they suggested the potential of machine learning in network optimization and the needs to redesign more decentralized concepts.

In the next-generation wireless networks, networks become heterogeneous. There is a discussion of licensed shared access (LSA)[6]-[8]: 5G network nodes can use not only licensed spectrum but also unlicensed bands. S. Haykin discussed the comprehensive function of a cognitive dynamic system to organize the communications using both licensed and unlicensed bands[9]. The need for dynamic spectrum management by a cognitive dynamic system in 5G was discussed. In [10], the authors analyzed the performance optimization of heterogeneous cognitive wireless networks. A typical optimization problem of load balancing was analyzed in both centralized and decentralized cases. In [11], the authors introduced machine learning in mobile terminals in order to optimize the aggregation method for IEEE 1900.4[12] heterogeneous wireless networks and maximize throughput.

III. Wireless System Optimization based on Cognitive Cycle

A. Modeling of wireless system

Several studies have attempted to understand the relations among various variables and performance to optimize wireless networks[13]-[22]. These researches generally focused on a certain layer performance such as channel capacity in physical layer and throughput in MAC layer, and does not cover higher layer application throughputs. For an example of the optimization of the wireless network capacity, we refer to the resource allocation problem in [18]. In principle, assuming ideal link adaptation, the formulation of the sum capacity of a multicell wireless network is expressed as

$$C(\boldsymbol{U},\boldsymbol{P}) = \frac{1}{N}\sum_{n=1}^{N} \log(1+\Gamma([\boldsymbol{U}]_n,\boldsymbol{P})),$$

where N is the total number of cells, Γ is the signal to interference and noise ratio (SINR) at the receiver, $\boldsymbol{U}$ is the set of users simultaneously scheduled across all cells, $[\boldsymbol{U}]_n$ is the users in cell n, and $\boldsymbol{P}$ is the transmit power of the scheduled users. Then, the capacity optimization problem by resource allocation is formulated as

$$\arg\max_{\boldsymbol{U},\boldsymbol{P}} C(\boldsymbol{U},\boldsymbol{P}). \tag{1}$$

As referred in [18], this problem is nonconvex, so the solution is not straightforward; still this equation represents the fundamental relations among radio variables and system performance.

For another example, in [22], the optimization problem of cooperative sensing in cognitive radio networks was analyzed. This is a sensing-throughput tradeoff problem: a strict sensing policy minimizes the possibilities of interference to the primary user though the opportunities to gain more throughput would be missed, and *vice versa*. The achievable MAC layer throughputs of the secondary users R can be given as

$$R(\tau,k,\epsilon) = C_0 P(H_0)\left(1-\frac{\tau}{T}\right)(1-\mathbb{P}_f(\tau,k,\epsilon)),$$

where τ is the sensing time, T is the total frame time (including sensing time τ), k is the number of sensing results of sensor nodes ($1 \le k \le N$, N is the total number of sensor nodes), and ϵ is the threshold parameter of the energy detector at the sensor node. C_0 is the ideal throughput of the secondary users if the primary user is always absent, $P(H_0)$ is the probability of the primary user being absent in the channel, and $\mathbb{P}_f$ is the probability of false alarm. Focusing on the maximization of the secondary users' throughput, i.e., the minimum probability of detection of the primary user is assumed, the sensing threshold ϵ can be given by the function of τ, k, and received signal-power-to-noise ratio (SNR). Under this condition, the optimization of the throughput of secondary users is formulated as

$$\arg\max_{\tau,k} R(\tau,k). \tag{2}$$

Since the throughput depends on the probabilities of false alarm and detection, which depend on SNR, equation (2) can be expressed as a function of τ, k, and SNR. This formulation was examined by computer simulation and optimal values of τ and k for a given SNR were obtained.

The formulations of optimization problems (1) and (2) can be generalized as follows: let the radio parameters be p (such as $\boldsymbol{U},\boldsymbol{P}$, or τ,k), the observed radio environment be z (such as SINR or SNR), and the system performance be y (such as capacity or throughput). Then, they can be formulated as $y = f(p, z)$, where f represents the relations among radio parameters, environment, and performance. Then, the optimization problem is formulated as

$$\arg\max_{\boldsymbol{p}} E(\boldsymbol{y}) = \arg\max_{\boldsymbol{p}} E(f(\boldsymbol{p}, \boldsymbol{z})), \tag{3}$$

where $E(\boldsymbol{y})$ is the utility function of throughputs, for example, the summation of the expected throughput of each node. By solving the above equation, the optimal set of parameters ($\boldsymbol{p}$) required to maximize the network performance is obtained. This can be done if the relation between the inputs and output is mathematically described.

In recent wireless systems, however, the situation has become more complicated. As mentioned above, modern wireless systems are equipped with various technologies in each layer. Some systems transmit signals on a single carrier with frequency hopping, and others on a multicarrier with OFDM. The channel access of one protocol is TDMA, and others' is CSMA/CA. In general, applications of wireless communication use higher layer protocol such as IP, and TCP or UDP. Therefore, we need to consider various observables $\boldsymbol{z}$ and parameters $\boldsymbol{p}$. Moreover, the relations among these variables and network performance are hardly known. Consequently, the mathematical formulation of function f cannot be realized.

Machine learning technologies, which have the fundamental characteristics of data-driven modeling, are the aid of this difficulty. By using them, the hidden and complex relations among various wireless observables and parameters and network performance can be obtained. We propose a generalized cross-layer modeling of wireless system performance using machine learning. In the proposed modeling, $E(\boldsymbol{y})$ can denote utility of whole system performance including application. $\boldsymbol{p}$ denotes various layers' parameter, $\boldsymbol{z}$ denotes various observables. The optimization method using the proposed modeling is described in the next subsection.

B. Optimization based on cognitive cycle

Fig.1 depicts the concept of the proposed wireless system optimization method using machine learning. It is based on cognitive cycle, as described below.

1) Measurement of environment and performance: The observables of environment $\boldsymbol{z}$ are collected, which include not only the radio status but also MAC statistics, or higher layer statistics. As for $\boldsymbol{p}$, various parameters of the wireless node or network are considered. Besides these variables, network performance y is observed. They are a set of samples, S, for a machine learning algorithm:

$$S = \{(\boldsymbol{p_1}, \boldsymbol{z_1}, y_1), (\boldsymbol{p_2}, \boldsymbol{z_2}, y_2), \ldots, (\boldsymbol{p_n}, \boldsymbol{z_n}, y_n)\}.$$

2) Update learning model: Using S, the cognitive engine builds and update the model f by machine learning:

$$y = f(\boldsymbol{p}, \boldsymbol{z}). \tag{4}$$

The updating manner depends on the type of algorithm. For supervised learning, it uses S as training data, and for

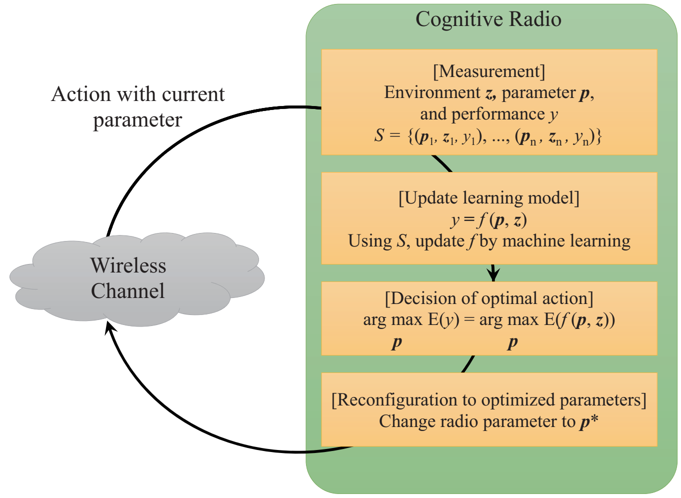

Fig. 1. The proposed method based on cognitive cycle using machine learning.

unsupervised learning, it uses S for clustering, or dimension reduction. For reinforcement learning, it updates the rewards for the actions and states.

3) Decision of optimal action: By solving the optimization problem (3), a cognitive engine decides an optimal action to adopt the current situation. The solution of (3), $\boldsymbol{p}^*$, yields the optimal parameters for communication entities.

4) Reconfiguration to optimized parameters: After deciding the optimal action, to use parameter $\boldsymbol{p}^*$, the cognitive engine starts to reconfigure the wireless network. Necessary information is sent to communication entities.

In the next section, we will describe a wireless network sample for introducing and evaluating our proposed method.

IV. Evaluation of Proposed Method

A. Application to IEEE 802.11 WLAN

In this section, we evaluate the proposed optimization method by applying it to the IEEE 802.11 WLAN. As an example of an optimization scenario, we consider the parameter optimization of the IEEE 802.11 stations (STAs) operated in the infrastructure mode. Each STA and cognitive controller connected to access points (APs) has functions of a cognitive engine described in the previous section and runs the cognitive cycle as mentioned below.

1) Measurement of environment and performance: Each STA measures wireless environment $\boldsymbol{z}$, obtains the current radio parameter $\boldsymbol{p}$, and performance y, and then adds a sample to S. $\boldsymbol{z}$ includes the radio status at the STA, such as the received signal strength indicator (RSSI) and wireless link quality. $\boldsymbol{p}$ includes wireless parameters such as transmit power, operating channel, and address of connecting AP. The uplink or downlink throughput is considered as the performance index y.

2) Update learning model: The cognitive engine in the STA updates the learning model f by using S. We consider supervised learning for the evaluation. The cognitive engine builds a model that represents the relations among z, p, and y from training samples s, and then sends the information of the model to the cognitive controller.

3) Decision of optimal action: The cognitive controller solves the optimization problem (3) by using the information of the model from STAs, and obtains the optimal parameters p^* of STAs. The information of the optimal parameters is sent to STAs to reconfigure the network.

4) Reconfiguration to optimized parameters: The STA changes its wireless parameters according to p^*, and then continues the cycle starting from the measurement of environment and performance.

B. Implementation of learning and optimization

We use support vector regression (SVR) as a learning algorithm, similar to [11]. SVR is an analog output version of support vector machines (SVMs) [23]. In SVR, the estimation function f can be expressed as[24]

$$f(\boldsymbol{x}) = \sum_{i=1}^{l} (\alpha_i' - \alpha_i) K(\boldsymbol{x}, \boldsymbol{x}_i) + b, \tag{5}$$

where l is the number of training samples, $\boldsymbol{x}_i$ is the input of the training samples ($\boldsymbol{p}$ and z), $\boldsymbol{x}$ is an unknown input set for the learning algorithm, and K is a kernel function. α_i, α_i', and b are unknown parameters obtained by the optimization technique proposed in [24], using training samples $\boldsymbol{p}$, z, and y.

We formulate the optimization problem (3) in the evaluation as below:

$$\arg\max_{\boldsymbol{p}} \sum_{n=1}^{N} \log(1 + f(\boldsymbol{p}_n, z_n)), \tag{6}$$

where N is the number of STAs, $\boldsymbol{p}_n$ is the possible parameter set for STA-n, z_n is the current measured quality of the radio environment at STA-n, and $f(\boldsymbol{p}_n, z_n)$ is the estimated throughput of STA-n obtained using the throughput model described above. Here, we use the logarithmic utility function of throughput considering fairness among STAs, where STAs with lower throughput have relatively larger gains for the objective function than those with higher throughput.

C. Experiment by IEEE 802.11 devices

We implement the method for the IEEE 802.11 WLAN devices. The experiments are coordinated in our university laboratory working space[27].

The IEEE 802.11 WLAN APs and STAs are operated in the 2.4 GHz ISM band. Laptop PCs with Ubuntu 14.04 are used as both STAs and APs. In each cognitive cycle, the STA observes the delay and packet loss ratio through pinging, RSSI from its connecting AP using the iwconfig command, the number of packets around the STA using tcpdump command as the link quality (z), and the throughput (y) using the TCP iPerf command. The STA sets the transmission power, channel number (from 1 to 13), and data rate at the physical layer (from 6 to 54 Mb/s) for the current wireless parameters ($\boldsymbol{p}$).

The STA then builds the throughput model through SVR, and sends information regarding the SVR model to its connecting AP. The AP sends it to the cognitive controller. We have setup one of the APs as the cognitive controller, which calculates the optimal set of STA parameters $\boldsymbol{p}^*$, returns the result to the AP, and then the STA obtains the result from its connecting AP. To reduce the calculation costs for solving the optimization problem, we use the particle swarm optimization (PSO) algorithm [25], [26] at the cognitive controller.

In the experiment, three APs and nine STAs are operated in channels 1, 6, and 11 in IEEE 802.11g. The operating channel is fixed for each AP. The locations of all APs and STAs are fixed during the experiment. We use uplink TCP throughputs to evaluate the performance since uplink traffic generally makes radio resource usage more competitive in CSMA/CA. We also add background UDP traffic of approximately 8 Mb/s on channel 11. To verify the performance of the proposed system, the uplink throughput performance is compared with that of other algorithms, focusing on the selection of the connecting AP at the STA as follows: (A) selection by RSSI, (B) random selection, (C) selection by radio resource utilization, and (D) selection of the number of STAs as equally as possible among channels. In algorithm (A) using RSSI, the STA selects an AP with the highest RSSI. This seems to be a popular method for devices in the market. In algorithm (C), the STA selects the AP of a channel where the minimum number of packets is observed in each cycle. In each algorithm, each cycle runs for 30 s. All STAs start iPerf traffic of 2 s at the same time in each cycle. Before starting the proposed method, the STA observes the radio environment in each channel for 1 hour and utilizes it as training data.

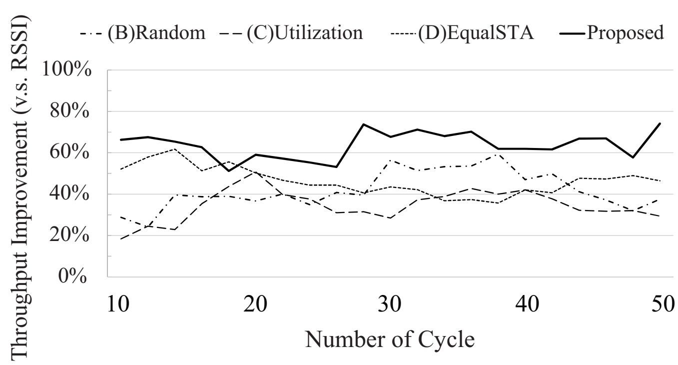

Fig. 2. Improvement in throughput relative to (A)RSSI by time in each algorithm.

Fig. 2 shows the moving average throughput by time for each algorithm. Throughputs are normalized by those in RSSI. The time is expressed as the number of cognitive cycle, and the throughput is averaged every 10 cycles (5 minutes). The proposed method shows greater throughput than other algorithms, indicating that the STAs can select APs effectively.

Fig. 3 compares the average throughput per channel among the algorithms. The utilization-based algorithm (C) shows higher throughput at channel 6, where it is detected as the most

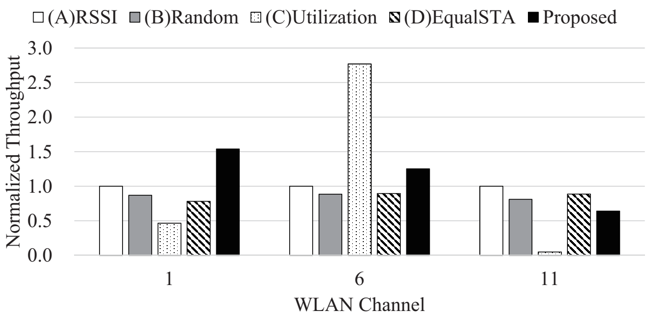

Fig. 3. Average throughput at each channel. Throughput is normalized by those in (A)RSSI.

TABLE I
SIMULATION SETTINGS

Parameter	Value
Area size	20 m x 20 m
Pathloss model	Free space decay
Channel model	Additive white gaussian noise (AWGN)
Traffic in proposed system	TCP of 1.4 Mbps in 6 STAs
	TCP of 0.7 Mbps in 15 STAs
Number of background APs	3 APs in each channel
Number of background STAs	5 STAs in channel 1
	1 STA in channel 6
	7 STAs in channel 11
Background traffic	CBR of 500 Kbps/STA in channel 1
	CBR of 100 Kbps in channel 6
	CBR of 500 Kbps/STA in channel 11

vacant channel. However, the throughputs at the other channels are much lower. This algorithm is based on the observations of a wireless environment but does neither learns, nor optimizes the whole system.

In contrast, the proposed method, which has a function of learning and optimization, shows higher throughput at channels 1 and 6 and lower throughput at channel 11, which has higher background traffic. As a whole, the proposed method can improve the network performance. These results indicate that the proposed method can build the appropriate throughput model through learning, and can select the optimized wireless parameters that improves the whole network performance.

D. Evaluation by computer simulation

We also conduct a computer simulation for an extended evaluation of the proposed method. The basic implementation is the same as that in the experiments already shown. The binary programs of learning and optimization are also the same as those in the experimental devices. Network simulator QualNet 7.4[28] is used for the platform of computer simulation. The number of STAs is 21 and that of APs is 3; the operating channels are 1,6, and 11. The variables of learning sample $(\boldsymbol{p}, z, y)$ are the same as those in the experiment conducted in the laboratory. STAs in the proposed system send uplink TCP traffic of two types of offered loads. The background traffic is generated by constant bit rate (CBR) traffic. The offered load of channel 6 is rather smaller than that of channels 1 and 11. The detailed settings of simulation are shown in Table I. The main difference in settings from those of the experiments is the offered load variation of STAs in the proposed system. Similar to the experimental results, computer simulation shows the improvement by introducing the proposed method, as shown in Fig. 4 and Fig. 5. From Fig. 5, the proposed cognitive cycle using machine learning can optimize the choice of channel in accordance with the formulation of (6).

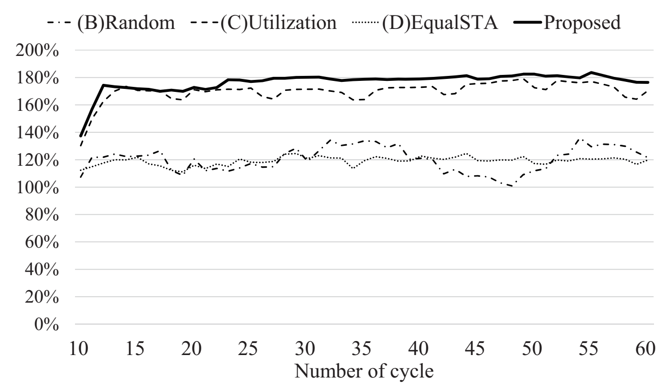

Fig. 4. Improvement in throughput relative to (A)RSSI by time in each algorithm in computer simulation.

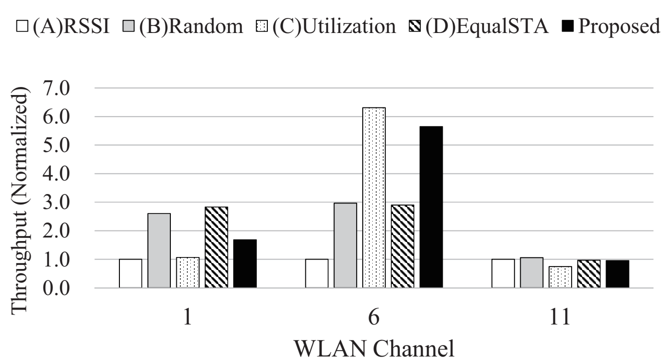

Fig. 5. Average throughput at each channel in computer simulation. Throughput is normalized by those in (A)RSSI.

V. Conclusion

This paper proposed a wireless system optimization method based on the cognitive cycle using machine learning. We reviewed several studies of traditional wireless system optimization problem, and showed that formulations of those problems can be generalized as the relations among radio variables and system performance. Modern wireless systems are becoming increasingly complex, and the optimization of them is a challenging issue. Based on the formulation of the optimization problem, we indicated that the machine learning technology, data-driven modeling that can provide a predictable model of wireless communications, can be a solution. The proposed method was evaluated by applying it to the IEEE 802.11 WLAN. Since the proposed method is based on a comprehensive, learning-based cognitive cycle, it can be applied to various wireless system optimization problems such as an adaptive MIMO parameter selection, a frequency selection and a transmit power control in heterogeneous cellular networks, and the selection of radio interfaces in a smartphone. It is important to investigate what type of machine learning algorithm is suitable for each system. From the viewpoint of practical implementation, it is also necessary to develop optimization algorithms to solve the problem of a large scale network.

Acknowledgment

This work was supported by JSPS KAKENHI Grant Number JP17K00136.

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