INVITED PAPER

Optimization for Centralized and Decentralized Cognitive Radio Networks

The paper focuses on optimization algorithms for decision making on radio resources in heterogeneous cognitive wireless networks, with base stations or being self-organized.

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ABSTRACT | Cognitive radio technology improves radio resource usage by reconfiguring the wireless connection settings according to the optimum decisions, which are made on the basis of the collected context information. This paper focuses on optimization algorithms for decision making to optimize radio resource usage in heterogeneous cognitive wireless networks. For networks with centralized management, we proposed a novel optimization algorithm whose solution is guaranteed to be exactly optimal. In order to avoid an exponential increase of computational complexity in large-scale wireless networks, we model the target optimization problem as a minimum cost-flow problem and find the solution of the problem in polynomial time. For the networks with decentralized management, we propose a distributed algorithm using the distributed energy minimization dynamics of the Hopfield–Tank neural network. Our algorithm minimizes a given objective function without any centralized calculation. We derive the decision-making rule for each terminal to optimize the entire network. We demonstrate the validity of the proposed algorithms by several numerical simulations and the feasibility of the proposed schemes by designing and implementing them on experimental cognitive radio network systems.

KEYWORDS | Cognitive radio; minimum cost-flow problem; neural networks; optimization; radio resource management

I. INTRODUCTION

Cognitive radio technology [1], [2] has been developed to improve radio resource usage of the wireless network environment. Recently, various wireless services have been widely deployed, and the amount of mobile traffic is continuously and rapidly increasing. To satisfy such a high demand for mobile communications, the capacity of mobile wireless networks has to be increased, requiring additional radio-frequency bands. However, most of the frequency bands suitable for mobile communications have already been assigned to existing wireless services, and the remaining bands are limited. Therefore, optimization of the radio resource usage of the wireless network is a very important issue in the current wireless networks.

The key idea of cognitive radio is to efficiently utilize limited radio resources by dynamic spectrum access. In conventional wireless systems, the radio access networks and spectrum bands are statically assigned to mobile systems. In such a case, a network or a frequency band may be highly congested, while others have many available resources with low traffic. By dynamic use of the radio access networks or spectrum bands, usage of limited radio

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resources can be optimized, and the capacity and quality of the wireless systems can be highly improved.

The original definition of cognitive radio [1], [2] is that it is a type of cognitive dynamic system [3]. Cognitive radio systems observe and recognize a radio network environment, make reconfiguration decisions, and apply the corresponding action to reconfigure the network. By this approach, various types of radio parameters in wireless communication systems can be optimized by appropriate actions. By learning the relationship between the actions and the improvement in the performance, recognition will be improved with an increase in the number of samples. For several performance factors, the relationship between the actions and the performance improvement can be approximately predefined. The best decision can be selected by solving an optimization problem, which can be formulated on the basis of the relation between the actions and the performance improvement. In this paper, we focus on an optimization algorithm for the best decision.

There are various optimization problems that can be defined to improve radio resource usage [4]–[8]. The type of problem utilized depends on the observable factors and tunable parameters of the system. In this paper, we consider the problem in heterogeneous wireless networks in which different types of wireless services coexist. As one of the standards to realize such a cognitive radio system, IEEE Std. 1900.4 [9] includes distributed radio resource usage optimization (DRRUO) as a use case of its defined cognitive radio system. The terminals select the best radio resource from various types to optimize the efficiency of the radio resource usage. In order to make an optimal decision, necessary information can be collected using the architecture and protocol defined in IEEE1900.4.

In this paper, we focus on optimization techniques to maximize the efficiency of radio resource usage in heterogeneous wireless networks. First, we define an optimization problem for load balancing, which improves the service quality of IP-based heterogeneous wireless networks. Second, we develop an optimization algorithm to obtain a rigorous solution in a short time under the assumption that the entire network can be managed at a centralized server on the basis of IEEE1900.4. Third, because such a centralized management becomes difficult for large-scale networks, we develop a distributed optimization algorithm based on the theory of Hopfield–Tank neural networks [10]. Finally, we show how to implement such a management system using the IEEE1900.4 framework.

II. COGNITIVE SYSTEM FOR HETEROGENEOUS WIRELESS NETWORKS AND ITS OPTIMIZATION PROBLEM

A. Cognitive System for Heterogeneous Wireless Networks

Recently, several wireless communication standards based on the idea of cognitive radio have been developed. Under the IEEE802 standard, wireless local area networks (LANs), 802.11af [11], wireless broadband systems, 802.22 [12], and IEEE802.16h [13] have been developed as real services using cognitive radio technology, which utilize the white space of the TV spectrum bands. Such cognitive radio systems collect available spectrum resource information and select the most appropriate resources while avoiding interference with the primary wireless systems, which involve TV broadcasting.

On the other hand, optimal selection of the best wireless service also improves the quality of wireless services by efficient radio resource usage, defined as the DRRUO in IEEE1900.4 [9]. In such wireless networks, the selection of the most appropriate action can be defined as an optimization problem when the improvement in quality can be estimated by the collected information.

Fig. 1 shows a general cognitive radio system, which can be applied to the systems described above. The cognitive radio system observes the state of the wireless network, estimates the relation between the action and the performance improvement, and finds the best action on the basis of the estimated relation. Generally, the relation between the action and the corresponding performance $f(\mathbf{x})$ is unknown and has to be estimated by a learning algorithm. Selection of the best action can be achieved by searching for the optimal state of $f(\mathbf{x})$, which corresponds to solving the optimization problem. In this paper, we focus on the selection of the best action by optimization algorithms.

There are two approaches to optimize the network. One approach is to calculate the optimal state at a centralized server, which manages all of the wireless connections. For such a case, it is possible to rigorously optimize the entire network. The drawback of such centralized schemes is that it is necessary to collect all of the information at the central

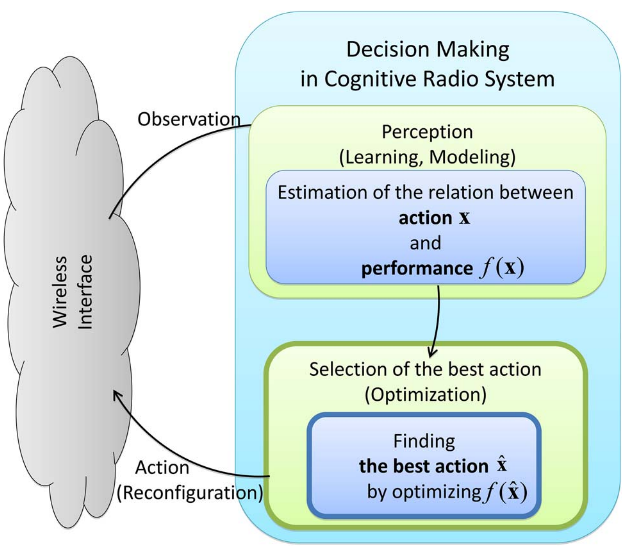

Fig. 1. *Cognitive radio system.*

server, which may generate overhead for exchanging the context information and control information of the entire network. Therefore, in the second approach, we consider the application of distributed optimization algorithms, which run in parallel, for large-scale network optimization.

As a cognitive radio system, which can be optimized by optimization algorithms, IEEE1900.4 defines the architecture to exchange the context information and the spectrum selection policy between the terminal side and the network side [9], whose management architecture is shown in Fig. 2. The network reconfiguration manager (NRM) collects context information of the radio access networks (RAN) via the RAN measurement collector (RMC). The terminal reconfiguration manager (TRM) collects the terminal context information with the terminal measurement collector (TMC). The collected information at the NRM and TRM is exchanged between the terminal side and the network side, via the radio enabler (RE). After information collection, the NRM and the TRM can make decisions for reconfiguration. The action for the selected reconfiguration will be taken using the RAN reconfiguration controller (RRC) for the network side and the terminal reconfiguration controller (TRC) for the terminal side. Using this architecture, an optimization algorithm for making the best decision can be calculated either at the NRM or at the TRM. For centralized optimization, the NRM will collect all of the information, make decisions, and notify the best action for all of the TRMs on the terminals. For distributed optimization, the TRMs on the terminals will collect the necessary context information via the NRM and make the best decisions independently.

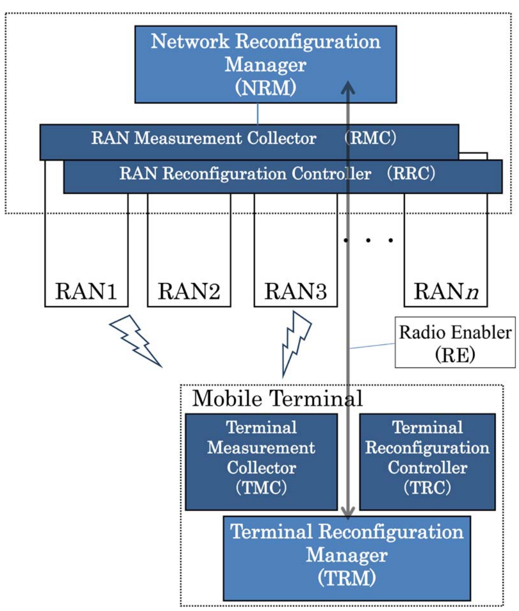

Fig. 2. ***Management architecture of IEEE1900.4 for optimizing radio resource usage in heterogeneous wireless networks [9].***

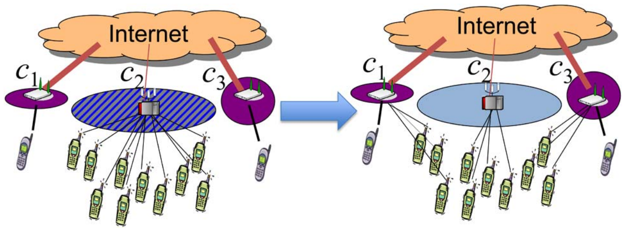

Fig. 3. ***Optimization of traffic load balancing in heterogeneous wireless networks in which the BSs have different capacities.***

B. Optimization Problems to be Addressed by Cognitive System

In this paper, we focus on optimization algorithms for best action selection in heterogeneous cognitive wireless networks. As a typical example of optimization problems for cognitive radio networks, we consider the avoidance of traffic congestion by load balancing, as shown in Fig. 3. In the IEEE1900.4 standard [9], load balancing is defined as a typical example use case to improve radio resource usage.

There may be several ways to formulate the optimization problem of load balancing. In this paper, we formulate the objective function on the basis of several assumptions that should be introduced for the optimization of heterogeneous wireless networks.

The first assumption is that the cognitive wireless network is heterogeneous. Various types of wireless networks are available, such as cellular phone systems, wireless LANs, and wireless broadband systems, to connect to the Internet. Recent mobile terminals have been equipped with several wireless modules to connect several of these heterogeneous wireless networks. The capacities of the networks are different among these systems. In such heterogeneous wireless networks, a high-capacity network can accept more terminals for the same congestion level. Therefore, the optimum state of traffic load balancing should be defined so that all of the communicating terminals will have the same throughput to the transmit packets. Because the communicating terminals will utilize all of the network resources, whose entire capacity is constant, $\sum_{j=1}^{n} c_j = \sum_{i=1}^{m} T_i = \text{const.}$ will be satisfied, where c_j is the capacity of the jth base station (BS), T_i is the available throughput for the ith terminal, n is the number of BSs, and m is the number of the communicating terminals. Therefore, the optimum state of load balancing in the heterogeneous network can be obtained by minimizing

$$F_{\mathrm{OBJ}}(\mathbf{T}) = \sum_{i=1}^{m} \frac{1}{T_i} \tag{1}$$

while satisfying $\sum_{i \in \mathbf{S}_j} T_i < c_j$ for all j, where $\mathbf{S}_j$ is the set of terminals connected to the jth BS. By minimizing $F_{\mathrm{OBJ}}(\mathbf{T})$, differences among T_i will be minimized, because

$F_{\mathrm{OBJ}}(\mathbf{T})$ will be smallest when all $T_i (i = 1, \ldots, m)$ become equal, under the condition that the total of the throughputs is kept constant, $\sum_{i=1}^{m} T_i = \mathrm{const}$.

The second assumption is that these wireless networks are IP based. Recent wireless services such as wireless LAN and long-term evolution (LTE) are packet-based networks, which share limited radio resources with many terminals. For example, in the wireless LAN systems, the transmission opportunities for the mobile terminals are almost equal with a highly fair medium access control (MAC) protocol. Therefore, the throughput of each terminal can be assumed to be $T_i = c_{L(i)}/|\mathbf{S}_{L(i)}|$ for such networks, where $|\mathbf{S}_j|$ is the number of mobile terminals connected to the BS j, and $L(i)$ is the BS to which the terminal i is connecting.

On the basis of the above assumptions, the traffic load-balancing problem in heterogeneous IP-based wireless networks can be formulated as a minimization of

$$F_{\mathrm{OBJ}}(\mathbf{L}) = \sum_{i=1}^{m} \frac{|\mathbf{S}_{L(i)}|}{c_{L(i)}} \tag{2}$$

under the condition that every communicating terminal i is located in the service area of its selected BS $L(i)$, $L(i) \in \mathbf{A}_i$, where $\mathbf{A}_i$ is the set of available BSs for terminal i.

This objective function depends on the vector $\mathbf{L}$, which is the list of connecting BSs of each communicating mobile terminal. In this combinatorial optimization problem, the number of combinations becomes n^m, and the problem becomes very difficult to solve when the number of BSs increases. For such a problem with combinatorial explosion, it is difficult to find the optimum state. Therefore, we usually stop trying to find the optimum solution and try to find a good approximate solution. In Section III, we show that this problem can be rigorously solved with a small computational load.

III. OPTIMIZATION OF COGNITIVE RADIO NETWORKS BY CENTRALIZED MANAGEMENT

In the combinatorial optimization problem in (2) for finding the optimum BS selections $\mathbf{L}$, the number of combinations increases exponentially with the increase in the number of BSs. In this section, we show that the problem can be solved rigorously by the following algorithm, even for large-scale heterogeneous wireless networks.

A. Rigorous Algorithm to Solve the Optimal State of the Cognitive Radio Network

Our proposed approach is to formulate a combinatorial optimization problem as a network flow problem by modeling the system as a graph. We transform the heterogeneous BS selection problem in (2) to a minimum cost-flow problem, which can be rigorously solved with low computational complexity.

The minimum cost-flow problem is to find the optimal flow z_e for each edge e in the graph G, $e \in E(G)$, by minimizing the entire cost in a directional graph. The following equation is minimized:

$$F_{\mathrm{MCF}}(\mathbf{z}) = \sum_{e \in E(G)} u_e z_e \tag{3}$$

with $z_e < p_e$ satisfied, where u_e is the cost, and p_e is the capacity of the edge e. Several of the vertices in G have a supply or demand of flow, which is defined as b_v. When $b_v > 0$, the vertex v supplies the output flow of $|b_v|$, whereas when $b_v < 0$, v demands the input flow of $|b_v|$. The total flow z_e should be integers in this problem. There are several optimization algorithms used to obtain the exact minimum value of (3), which have low computational complexity [14]–[17]. In this paper, we formulate the BS selection problem defined in Section II as the minimum cost-flow problem to obtain the exact optimum solution, even for large-scale networks.

Assuming that the BS of the IP-based wireless network gives fair transmission timing to each connecting terminal, the throughputs for the terminals connected to the same BS become equal. Therefore, the objective function in (2) can be transformed to the following form using the set of connecting terminals to the jth BS $\mathbf{S}_j$:

$$F_{\mathrm{OBJ}} = \sum_{i=1}^{m} \frac{1}{T_i} = \sum_{j}^{n} \frac{1}{T_{\mathbf{S}_j}} \cdot |\mathbf{S}_j| = \sum_{j}^{n} \frac{1}{c_j} |\mathbf{S}_j|^2. \tag{4}$$

This objective function is optimized by the selection of the links between the terminals and the BSs. Because $|\mathbf{S}_j|$ can be regarded as the flow between the BS j and the global network, we can formulate the minimization problem in (4) as a minimum cost-flow problem, which can be rigorously solved without an exponential increase in the computational load.

In order to formulate this problem as the minimum cost-flow problem in (3), we need to remove the square term $|\mathbf{S}_j|^2$ in (4). Using $|\mathbf{S}_j|^2 = \sum_{l=1}^{|\mathbf{S}_j|} 2l - 1$, we modify (4) to the following form:

$$F_{\mathrm{OBJ}} = \sum_{j}^{n} \frac{1}{c_j} \sum_{l=1}^{|\mathbf{S}_j|} 2l - 1 = \sum_{j}^{n} \sum_{l=1}^{|\mathbf{S}_j|} \frac{2l-1}{c_j}. \tag{5}$$

To minimize this equation, we design the graph in Fig. 4. The cost and the capacity are expressed as (w_{ij}, p_{ij}) for each edge. The vertices v_i^M correspond to the ith mobile terminals, and the vertices v_j^B correspond to the jth BSs.

The supplied flow from the source s and the demanded flow by the sink t are set at the number of mobile terminals m.

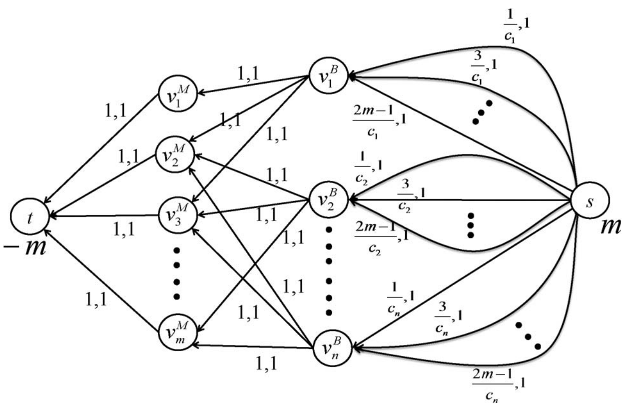

Fig. 4. ***Load-balancing problem formulated as a minimum cost-flow problem.***

The edges between the sink t and all v_i^M are set as $(1, 1)$. For the pairs for which the BS j is available for the communicating terminal i, $j \in \mathbf{A}_i$, the edges between the vertices v_i^M and v_j^B are prepared and set $(1, 1)$. For the edges between the source vertex s and the vertices v_j^B, we assigned the cost $(2l-1)/c_j$.

Because it is assumed that each terminal establishes a wireless link with one BS, the edges between the sink t and all v_i^M and those between vertices v_i^M and v_j^B are set as $(1, 1)$. Since the demanded flow by t and the number of vertices v_i^M are m, all flows $z_{v_i^M,t}$ on the edges between t and v_i^M should have a flow of 1. Therefore, exactly one edge to v_i^M from vertices $v_j^B (j = 1, \ldots, n)$ will have a flow of 1, because each v_i^M has one exit. The selected edge with this flow 1 will be the BS for the communicating terminal i, which should be established in the optimal state.

The cost calculated in (5) is added in the edges between the source vertex s and the vertices v_j^B, which have cost $(2l-1)/c_j$. When $|\mathbf{S}_j|$ terminals select BS j, $|\mathbf{S}_j|$ edges with smaller costs, $1/c_j, 3/c_j, \ldots, (2|\mathbf{S}_j|-1)/c_j$, will be selected by minimization of the total cost of the corresponding minimum cost-flow problem. Therefore, $\sum_{l=1}^{|\mathbf{S}_j|}((2l-1)/c_j)$ will be summed up for the BS j, whose total for all BSs $(j = 1, \ldots, n)$ will be calculated in the objective function of the graph, which will be the same as the objective function of the target problem shown in (5). More exactly, the minimum of the objective function will be $\sum_j^n \sum_{l=1}^{|\mathbf{S}_j|}((2l-1)/c_j) + 2m$. Because $2m$ is constant, the minimized function will be the same as (5). Therefore, the transformed objective function $\sum_j^n (1/c_j)|\mathbf{S}_j|^2$ in (4) can be minimized, and the selection of the optimal wireless links will be found by checking the edges between v_i^M and v_j^B, which have a flow of 1.

B. Computational Complexity and Results

In order to obtain the solution of this minimum cost-flow problem for RAN selection, we use the algorithm in [17], which solves the exact optimum solution with low computational complexity with an order of $O(N_v N_e \log(N_v C))$, where N_v and N_e are the numbers of vertices and edges, respectively, and C is the maximum cost on the edges. In the minimum cost-flow problem designed in Fig. 4, the computational complexity becomes $O(m(m+n+2)(m+n+1)\log(C(m+n+2)))$. In the originally defined combinatorial optimization problem of load balancing for the packet-based heterogeneous wireless networks in (2), the number of combinations is n^m, which increases exponentially. It is difficult to obtain the exact solution of such combinatorial optimization problems with a large size. Our proposed algorithm clarifies that such a problem with combinatorial explosion is not always NP-hard, and we can obtain the exact solution with a small computational load. The proposed scheme does not require a large computational load, even for very large problems.

We evaluate the increase in the computational time of the proposed scheme by computer simulations. Fig. 5 shows the central processing unit (CPU) time required to obtain rigorous solutions by our proposed scheme by changing the numbers of BSs and terminals. We ran the scheme on Solaris 10 installed on a server computer with floating-point operation at 2926 MHz.

The results in Fig. 5 clarify that the proposed scheme can obtain rigorous solutions in a short time, even for large-scale networks. In the largest case with 500 BSs and 1000 mobile terminals, only 0.036 s were required to obtain the rigorous solution. The increase in the computational time is not exponential but rather almost proportional to the number of mobile terminals or the number of BSs. In the maximum case with 1000 terminals, the required time was approximately 0.007 s for 100 BSs and approximately 0.036 s for the case with 500 BSs. This means that we do not have to use heuristic algorithms, which can only obtain approximate solutions for network load balancing, when the centralized server can manage all of the heterogeneous wireless connections of the terminals.

IV. OPTIMIZATION OF COGNITIVE RADIO NETWORKS BY DECENTRALIZED MANAGEMENT

In Section III, we showed that it is possible to solve for the exact optimum state of the heterogeneous wireless network by modeling the problem as a minimum cost-flow problem. However, it is not easy to develop a centralized management network for large-scale wireless systems in which a centralized server manages a large number of wireless links by notifying all of the communicating terminals of the optimum selection. Therefore, in this section, we consider the case in which there is no centralized server to compute the optimum state where the computation has to be performed using a distributed method.

A. Distributed Algorithm to Search the Optimal State of the Cognitive Radio Network

As a distributed optimization algorithm to minimize the objective function, we introduce the Hopfield–Tank

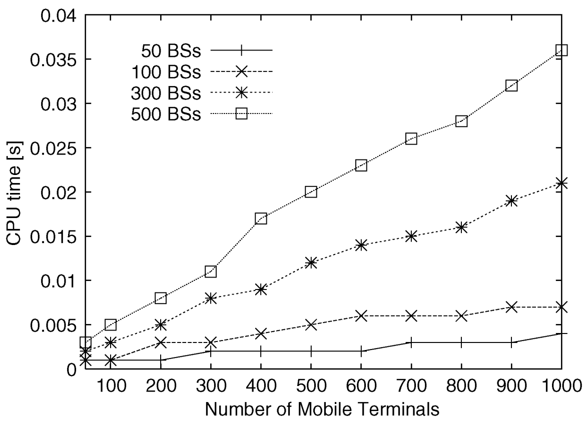

Fig. 5. *CPU time to obtain rigorous solutions of the BS selection problem for large-scale wireless networks.*

neural network [10], which is a mutually connected neural network in which each neuron updates its state by

$$x_{ij}(t+1) = \begin{cases} 1, & \text{when } \sum_{k=1}^{m}\sum_{l=1}^{n} w_{ijkl}x_{kl}(t) > \theta_{ij} \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

where $x_{ij}(t)$ is the state of the (i,j)th neuron at time t, w_{ijkl} is the connection weight between the (i,j)th and (k,l)th neurons, and θ_{ij} is the threshold of the (i,j)th neuron.

In this neural network, by setting the same weights for both directions of each connection $w_{ijkl} = w_{klij}$, zero weights for the self-connections $w_{ijij} = 0$, and updating each neuron asynchronously, the update of the neural network will converge to some local-optimum state within some number of iterations. At each update of this neural network, the energy function

$$E(\mathbf{X}) = -\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{m}\sum_{l=1}^{n} w_{ijkl}x_{ij}x_{kl} + \sum_{i=1}^{m}\sum_{j=1}^{n}\theta_{ij}x_{ij} \quad (7)$$

always decreases. The state the neural network converges to is a state corresponding to a minimum of the energy function $E(\mathbf{X})$ by updating with (6). This means that the simple neuronal update can perform a distributed search of a state $\mathbf{X}$ corresponding to the minimum of the energy function $E(\mathbf{X})$.

In the previous studies, this minimization property has been applied to combinatorial optimization problems [10]. First, the state of the optimization problem should be defined by the states of neurons x_{ij}, and the objective function must be expressed as a function of the neuronal states. By comparing the objective function with the energy function of the neuronal state in (7), the connection weight w_{ijkl} and the threshold θ_{ij} can be determined. By updating neurons using (6) with w_{ijkl} and θ_{ij}, the state of the neural network corresponding to the minimum value of the energy function can be autonomously obtained by distributed neuronal updates. This minimum corresponds to the minimum of the objective function of the original problem, and the local-optimum state will be obtained by checking the states of the neurons.

In this paper, we present a scheme for optimizing the BS selection problem by this distributed optimization algorithm. We defined the state matrix $\mathbf{X}$ of the neural network for the connection matrix between the terminals and the BSs. $\mathbf{X}$ is defined only for the available connections $x_{ij} \in \mathbf{A}_i$. When the terminal i is connected to the BS j at time t, $x_{ij}(t) = 1$. Otherwise, $x_{ij}(t) = 0$. By using x_{ij}, the number of terminals connecting to the BS j, which is $|\mathbf{B}_j|$, can be counted by

$$|\mathbf{B}_j| = \sum_{k=1}^{m} x_{kj}. \quad (8)$$

Because each communicating terminal selects only one BS, only one x_{ij} among $x_{i1}, \ldots, x_{in}$ becomes one, corresponding to the selected BS j by terminal i. Therefore, $|\mathbf{B}_{L(i)}|/c_{L(i)}$ for terminal i can be determined using x_{ij} as

$$\frac{|\mathbf{B}_{L(i)}|}{c_{L(i)}} = \sum_{j=1}^{n}\frac{|\mathbf{B}_j|}{c_j}x_{ij}. \quad (9)$$

Using (8) and (9), the problem defined in (2) can be transformed to a minimization of

$$\begin{aligned} F_{\mathrm{OBJ}}(\mathbf{X}) &= \sum_{i=1}^{m}\sum_{j=1}^{n}\frac{1}{c_j}x_{ij}\sum_{k=1}^{m}x_{kj} \\ &= \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{m}\frac{1}{c_j}x_{ij}x_{kj} \end{aligned} \quad (10)$$

under the constrain that $x_{ij} = 0$ for $j \notin \mathbf{A}_i$.

In order to minimize this objective function by the neuronal updates, the objective function defined in (10) is transformed to the following form of the energy function:

$$F_{\mathrm{OBJ}}(\mathbf{X}) = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{m}\sum_{l=1}^{n}\frac{1}{c_j}\delta_{jl}x_{ij}x_{kl} \quad (11)$$

where δ_{ij} is the Kronecker delta, which means $\delta_{ij} = 1$ when $i = j$, and $\delta_{ij} = 0$ otherwise. For minimization of the energy function by neuron updates, the self-connection weight should be zero but there are coefficients for $x_{ij}x_{kl}$ in the form in (11). In order to remove the self-connections, we transform (11) to the following form by using $x_{ij}x_{ij} = x_{ij}$ because x_{ij} takes the values of zero or one only:

$$F_{\mathrm{OBJ}}(\mathbf{X}) = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{m}\sum_{l=1}^{n}\frac{1}{c_j}(1-\delta_{ik})\delta_{jl}x_{ij}x_{kl} + \sum_{i=1}^{m}\sum_{j=1}^{n}\frac{1}{c_j}x_{ij}. \quad (12)$$

Comparing the coefficients of the neuronal states $x_{ij}(t)$ in this form of the objective function with the energy function of the neural network in (7), the connection weight w_{ijkl} and the threshold θ_{ij} that minimizes the objective function is obtained as follows:

$$w_{ijkl} = -2\frac{1}{c_j}(1-\delta_{ik})\delta_{jl} \quad (13)$$

$$\theta_{ij} = \frac{1}{c_j}. \quad (14)$$

Because we assume that each terminal can have a wireless connection with only one BS at the same time, we use the following update function to keep that only one neuron fires for each terminal

$$x_{ij}(t+1) = \begin{cases} 1, & \text{when } y_{ij}(t+1) = \max[y_{i1}(t+1), \ldots, y_{in}(t+1)] \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

$$y_{ij}(t+1) = \sum_{k=1}^{m}\sum_{l=1}^{n} w_{ijkl}x_{kl}(t) - \theta_{ij}. \quad (16)$$

This updating method takes the maximum firing neuron for each terminal i. Because terminal i can establish connection with one BS, no more than one neuron related to terminal i can fire. Although the original update equation in (6) permits firing of more than one neuron related to i, the update equation in (15) and (16) keeps only one firing neuron in $x_{ij}(t)$ with $j = 1, \ldots, n$ by taking the maximum internal state. The internal state $y_{ij}(t)$ in (16) is derived from the original update equation in (6) by transposition of θ_{ij}. Equation (15) selects the maximum of $y_{ij}(t)$ $(j = 1, \ldots, n)$ and only the neuron corresponding to the maximum will have the output of 1.

By updating the neurons by (15) and (16) with the connections and thresholds in (13) and (14), the state of the neural network converges to the local minimum of (12), which corresponds to the local-optimum state of the BS selection.

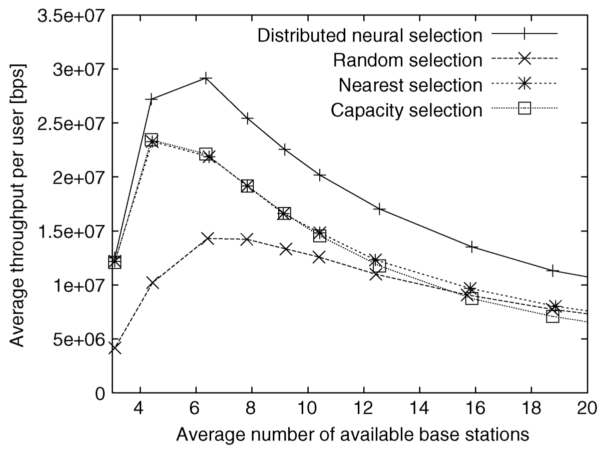

Fig. 6. ***Experimental results for the average throughput of the distributed load-balancing optimization implemented on a heterogeneous cognitive wireless network system.***

B. Results

Examples of simulation results are shown in Figs. 6 and 7. In these simulations, 1000 BSs are located in a square field of varying size. In order to check the effectiveness of the proposed scheme, the average throughput and the fairness of the throughput are evaluated. For the fairness, Jain's fairness index is used [18]. For the comparison, generally distributed BS selection schemes, random selection, nearest BS selection, and capacity-based selection are also shown.

Figs. 6 and 7 clarify that the proposed neural selection has the highest throughput and highest fairness. Because a distributed implementation of the neuronal update is possible, this neural approach can be applied to the case in

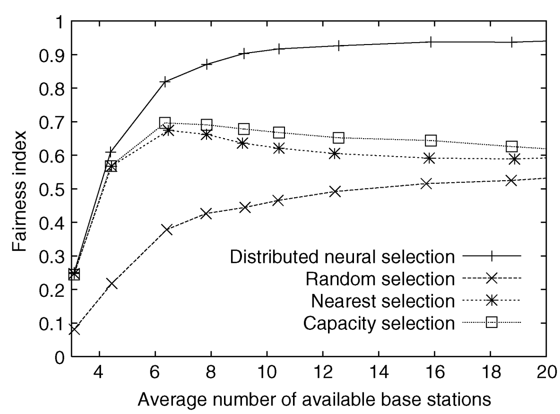

Fig. 7. ***Experimental results of the fairness index of the distributed load-balancing optimization implemented on a heterogeneous cognitive wireless network system.***

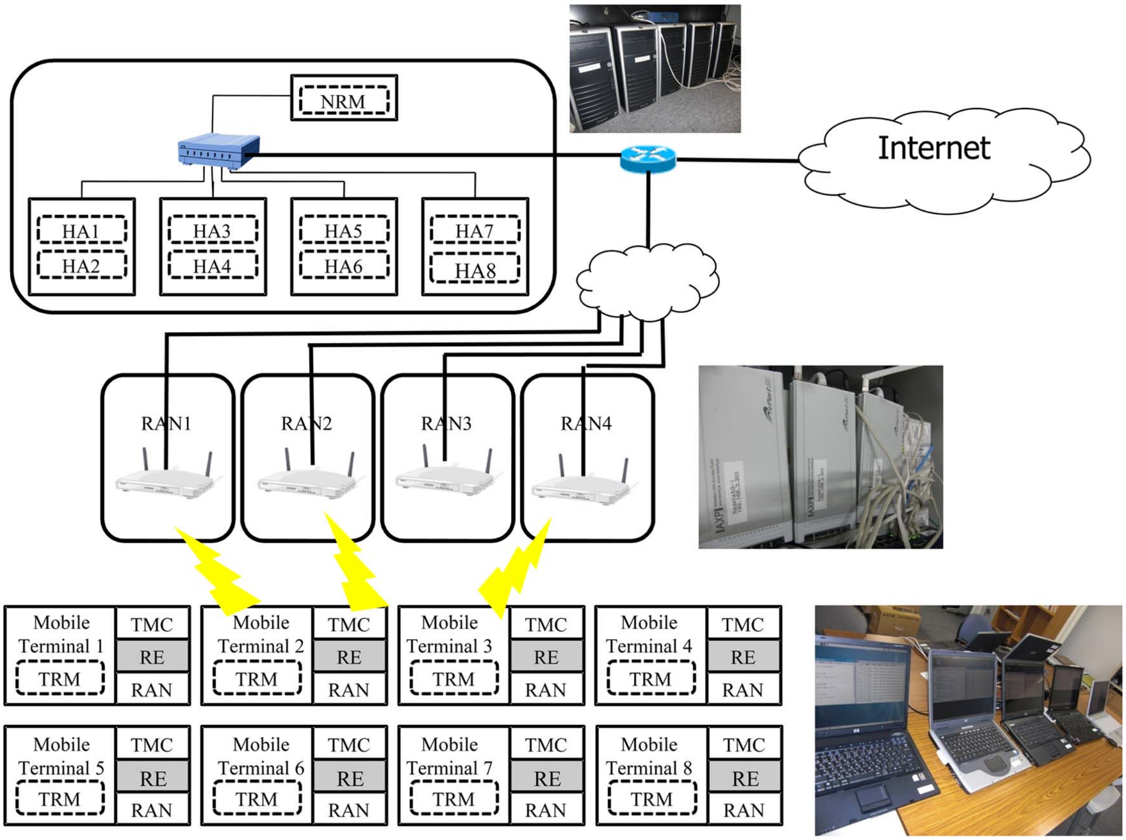

Fig. 8. *Experimental cognitive wireless network system for the optimum selection of BSs.*

which a centralized server is not available or not prepared in the networks. By the cooperative exchange of the states of neurons among the updating devices, each device can select the best resource without any centralized management.

The optimization problem, which we have dealt with in this paper, is very simple, and its objective function could be transformed to a second-order function of the neural network state x_{ij}, the same order as the original Hopfield–Tank neural networks. For a higher order objective function, we can introduce high-order neural networks [19], which autonomously decrease the higher order energy function by distributed neuronal updates. We have already applied such a higher order neural network in [20] to higher order optimization problems in distributed cognitive radio networks.

V. IMPLEMENTATION AND EXPERIMENTS OF THE COGNITIVE RADIO NETWORK

In this section, we implement the optimization algorithms on cognitive wireless networks with the functionality of IEEE1900.4. We use the cognitive wireless system of [21] and [22] as the basic wireless network architecture for our implementation. This architecture enables seamless use of the RANs for all of the mobile terminals with vertical handover functionality across different wireless networks. In our experiments, we use this system with the wireless LANs in our laboratory to evaluate our algorithms. The structure of the experimental system, which is implemented with supporting IEEE1900.4 functionality, is shown in Fig. 8. There may be several ways to implement the proposed algorithms in this cognitive wireless network.

For the centralized algorithm described in Section III, the NRM calculates the optimal connections for all of the terminals. To run the centralized optimization algorithm at the NRM, the capacities of each RAN, c_j, and the available connection lists for each terminal, $\mathbf{A}_i$, are collected by the NRM via the RMC and the RE interfaces, respectively. Using the collected information, the NRM runs the rigorous optimization algorithm and obtains the optimal selections of RANs for all of the terminals. This information is transmitted to all of the mobile terminals using their RE interfaces. According to the notification, each mobile terminal establishes the communication link to the suggested one by the NRM, and the optimal state of the wireless network can be realized. When a part of c_j or $\mathbf{A}_i$ changes, the NRM updates the optimum state and notifies each terminal of the updated information, which switches the connection to the updated best BS. During this switching, the communication session on the mobile terminals can be continued by the mobile IP, which is supported by the home agents (HAs) on the server side.

There are several ways to implement the distributed algorithm described in Section IV in the network. For example, the updates of the neurons can be executed at each RAN, at each BS, or at each mobile terminal. In the following, the neuronal updates are distributed to the mobile terminals because it may be the most suitable for IEEE1900.4 to add neuronal update functionality on the TRM. Each neuron defined in Section IV corresponds to each wireless link from a mobile terminal to a BS. Therefore, in this distribution, the neurons $x_{i1}, x_{i2}, \ldots, x_{in}$ are assigned to the corresponding terminal i. The TRM on terminal i updates the assigned neurons by (15) and (16), selects the access point corresponding to the maximum firing neuron, and the terminal hands over the connection to the selected access point.

First, the mobile terminals discover the available access points $\mathbf{A}_i$ by the TMC and establish wireless links with the BS with the highest capacity. According to $\mathbf{A}_i$, each TRM defines neurons for each terminal. To run the proposed algorithm in such a distributed scheme, the TRMs need to obtain the states of other neurons, which have nonzero connection weights with the updating target neuron. In our algorithm, the state of each neuron can be derived from the connecting access point of each terminal because the states of the neurons correspond to the wireless links between the user terminals and the access points. Therefore, in the implemented experimental system, the TRM collects that wireless link information from the NRM via the RE and updates neurons. Using the collected information, each TRM updates their assigned neurons. According to the updated states of the neurons, each terminal autonomously selects an access point, and hands over the connection to the selected one.

Fig. 9 shows an example of access-point selection by the implemented system on which the distributed algorithm based on the neural networks in Section IV is running. We used four wireless LAN access points and eight mobile terminals in this experiment. The mobile terminals MT1, MT3, MT5, MT7, and MT8 are initially connected to one of these access points and communicate by the best-effort protocol. Between 50 and 100 s after the start of the experiment, the mobile terminals MT2, MT4, and MT6 start their communications. As shown in Fig. 9, the traffic load could be balanced autonomously after joining the additional terminals. Several neuronal updates are required to converge to an optimal state in which the loads of the access points are balanced.

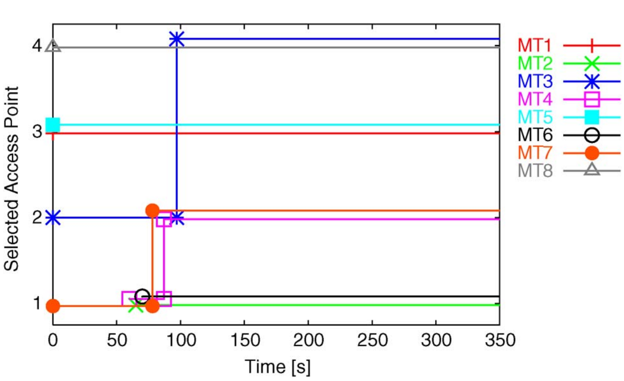

Fig. 9. ***Load balancing by the distributed algorithm based on the neural network for the experimental implemented system.***

VI. CONCLUSION

In this paper, we have defined optimization algorithms for heterogeneous cognitive wireless networks. As a typical optimization problem, we introduced load balancing to improve the service quality of the entire wireless networks. To optimize the problem, we proposed two algorithms. For a network that can be managed by a centralized server, we have realized a rigorous optimization algorithm by modeling the problem as a minimum cost-flow problem. For the network that cannot be managed by a centralized server, we applied a distributed algorithm based on the Hopfield–Tank neural network. Further, we have implemented the proposed algorithms on an experimental wireless network, which is a cognitive wireless cloud system [21], [22]. Using the implemented system, we show that the distributed algorithm works correctly using our design of a protocol based on the IEEE1900.4 architecture.

We have considered a problem in heterogeneous wireless networks, namely, traffic load balancing, which is a typical optimization problem that seeks to avoid traffic congestion. In order to improve the radio resource usage of the wireless networks, there are various other factors that should be optimized. In this paper, we presented two examples of how to optimize the network. The proposed optimization framework can also be applied to other more complicated optimization problems in wireless networks.

As an important remaining issue, we have to clarify which is the better, the centralized, or the decentralized, for some practical network. In the centralized management, we have shown that it is possible to obtain the rigorously optimal state of the network, but the entire context information should be collected into the centralized manager and the decision made by the manager should be distributed to all of the terminals in entire networks. Therefore, the signaling delay may influence the performance. On the other hand, in the decentralized management, although it is not possible to guarantee the optimality of the obtained solution by the algorithm, there is no need to distribute the decision from one point to entire networks. The better approach will be decided on the basis of various factors of the network such as the signaling delay, the network size, and so on. More detailed analysis on the comparison of these two approaches will be shown elsewhere.

Our most important future task is to realize a general optimization algorithm, which can be applied to a cognitive radio system, including the estimated function $f(\mathbf{x})$ defined in Fig. 1. Although this paper focused on a predefined static optimization problem, the relation between the action and the performance improvement $f(\mathbf{x})$ has to be learned on the basis of the experiences in more general cognitive radio systems. As an example of such cognitive radio systems optimizing the decision on the basis of the estimated $f(\mathbf{x})$, as in Fig. 1, we have applied a full search for the throughput maximization of network aggregation in [23]. We are working toward the development of more efficient optimization algorithms for the function estimated by learning algorithms in a cognitive radio system. ■

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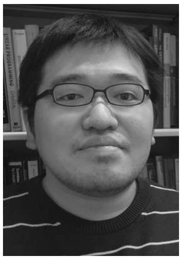

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