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Self-Optimized Wireless Distributed Networks

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Abstract– Distributed optimization dynamics of the mutually connected neural networks is applied to radio resource usage optimization in heterogeneous type cognitive radio networks. For performance evaluation, the proposed algorithm is implemented on an experimental heterogeneous wireless network system called Cognitive Wireless Cloud, which supports vertical handover between different radio access networks and various information exchange defined in IEEE1900.4. The proposed cognitive radio system optimizes objective function without any centralized computation. As the objective functions, two types of problems are introduced, load balancing and QoS satisfaction rate optimization, and the performance of the proposed method is compared with other distributed RAN selection algorithms on the real wireless system. Since the proposed algorithm based on the neural network dynamics directly optimizes the objective functions defined for radio resource usage optimization of the entire wireless network by distributed computation on each terminal, its performance becomes better than other algorithm which is based on the improvement of each terminal's QoS.

1. Introduction

The cognitive radio technology is important research topic to optimize efficiency of radio resource usage, since the available radio resources for mobile wireless communications are limited but the demand for high-speed wireless communications is increasing. As mentioned in Ref. [1], there are at least two types of cognitive radio systems, the Heterogeneous Type and the Spectrum Sharing Type Cognitive Radio Systems. The Heterogeneous Type Cognitive Radio System improve efficiency of the radio resource usage by utilizing any available radio access networks (RANs) provided by existing operators, such as the cellular phone systems, WiMAX, wireless LAN, and so on. The Spectrum Sharing Type Cognitive Radio Systems enable to utilize locally or temporally unused white space spectrum bands for the secondary cognitive systems. Recently, standardization of such cognitive radio systems is active [2]. This paper deals with the former cognitive radio system, the Heterogeneous Type Cognitive Radio Systems, which improves radio resource utilization of the entire wireless networks by selecting the best access point for each terminal and switching their connections dynamically by vertical handover technologies [3]-[5].

As one of the approaches to optimize radio resource usage distributively in heterogeneous wireless networks which includes several different types of RANs, the mutually connected neural networks [6] have been applied whose energy function autonomously minimizes by distributive updates of each neuron [7]-[10]. Refs. [9] and [10] showed that it is possible to optimize load balancing and QoS satisfaction rate by such optimization algorithms based on the neural network dynamics. Those algorithms were implemented on an experimental wireless network called Cognitive Wireless Cloud (CWC) [11], and their experiments showed that the algorithms based on the neural network can optimize the radio resource usage without any centralized computation [12].

This paper evaluates the throughput performance of the RAN selection algorithm implemented on the real experimental wireless network system, and compare it with other distributed RAN selection algorithms. Those distributed algorithms are applied to two types of RAN selection problems, load balancing and QoS satisfaction rate optimization. For both problems, four kinds of distributed algorithms are introduced for comparisons and implemented on the experimental wireless network composed of two kinds wireless LANs. Real throughputs achieved by each algorithm are evaluated and compared on such an experimental system.

2. Optimization of RAN Selection by Neural Network Dynamics

There are various radio resource usage optimization problems in heterogeneous wireless networks. This paper introduces two problems, load balancing of the throughput and QoS satisfaction rate optimization. In order to optimize the objective functions of those problems, the mutually connected neural network is applied to the optimization problems. This algorithm does not require any centralized computation for optimizing objective functions, and is applicable to large-scale networks.

To apply such minimization dynamics of the neural network to solution search in a combinatorial optimization problem, first we have to define the relation between the state of the solution and the firing pattern of the neural network. Since the problem is to find the appropriate wireless links which should be connected, in this paper, each firing of the neuron (i, j) $(x_{ij}=1)$ is defined as the establishment of the wireless link between the user terminal i and the base station j, as shown in Fig. 1.

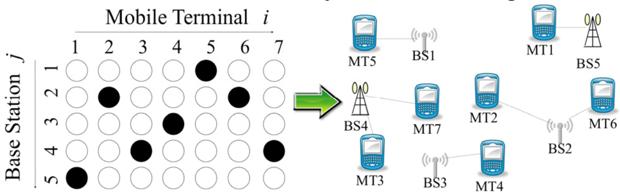

Fig. 1 Relation between firings of the neurons and establishments of the wireless links.

Based on this definition of the neurons, update equation of each neuron can be defined as follows,

$$x_{ij}(t+1)=\begin{cases} 1 \quad \text{for} \quad \sum_{k}^{N_\mathrm{m}}\sum_{l}^{N_\mathrm{BS}} w_{ijkl}x_{kl}(t)>\theta_{ij} \\ 0 \quad \text{otherwise} \end{cases}, \tag{1}$$

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, θ_{ij} is the threshold of the (i, j) th neuron, N_m is the number of the user terminals, and N_BS is the number of the access points in the network, respectively. By updating each neuron distributively, the following energy function decreases autonomously and converges to a minimum of this function,

$$E_\mathrm{NN}(t)=-\frac{1}{2}\sum_{i=1}^{N_\mathrm{m}}\sum_{j=1}^{N_\mathrm{BS}}\sum_{k=1}^{N_\mathrm{m}}\sum_{l=1}^{N_\mathrm{BS}} w_{ijkl}x_{ij}(t)x_{kl}(t)+\sum_{i=1}^{N_\mathrm{m}}\sum_{j=1}^{N_\mathrm{BS}}\theta_{ij}x_{ij}(t), \tag{2}$$

when the following three conditions are satisfied, the neural network has symmetric connections, $w_{ijkl} = w_{klij}$, zero self-feedback connection, w_{ijij}=0, and has to be updated asynchronously. This minimization dynamics of the distributed neural network has been applied to various combinatorial optimization problems. In this paper, it is applied to optimization problems in the RAN selection in the cognitive wireless cloud networks.

2.1. Neural Network for Load Balancing Problem

In the best-effort packet based wireless systems such as the wireless LAN, we can assume that the radio resource is almost equally shared among the mobile users. Based on such an assumption, available throughput T_i for the user i can be approximately defined as, $T_i = c_{L(i)} / N^\mathrm{BS}_{L(i)}$, where c_j is the total of the throughput which the base station j can provide, N^BS_j is the number of terminals which is connecting to the base station j, and $L(i)$ is the base station which the terminal i is connecting, respectively. This available throughput for the user depends on the number of the user terminals connecting to the same access point. Therefore, the optimization of the user throughput becomes a problem to find the optimal combinations of the wireless connections between the access point j and the user terminal i.

In order to optimize the load balancing with keeping the higher throughput for each user, the following objective function is defined,

$$E_1^\mathrm{OBJ}(t)=\sum_{i=1}^{N_\mathrm{m}}\frac{1}{T_i(t)}=\sum_{i=1}^{N_\mathrm{m}}\frac{N^\mathrm{BS}_{L(i)}}{c_{L(i)}}. \tag{3}$$

By minimizing this simple function, load balancing and the total of the throughput maximization can be optimized at the same time. Minimization of the reciprocal of the throughput T_i means maximization of the throughput. The value of $E_1^\mathrm{OBJ}(t)$ becomes smallest in the case that all T_i becomes equal, when the total available amount of radio resource is fixed. This access point selection problem to optimize load balancing can be formulated as a combinatorial optimization problem to minimize the value of $E_1^\mathrm{OBJ}(t)$ by finding the best combination of the wireless connections between the access points and the user terminals.

Based on the relation described in Fig. 1, Eq. (3) can be transformed to the following form, as a function of the state of neurons $x_{ij}(t)$ [9],

$$E_1^\mathrm{OBJ}(t)=\sum_{i=1}^{N_\mathrm{m}}\sum_{j=1}^{N_\mathrm{BS}}\sum_{k=1}^{N_\mathrm{m}}\sum_{l=1}^{N_\mathrm{BS}}\frac{1}{c_j}(1-\delta_{ik})\delta_{jl}x_{ij}(t)x_{kl}(t)+\sum_{i=1}^{N_\mathrm{m}}\sum_{j=1}^{N_\mathrm{BS}}\frac{1}{c_j}x_{ij}(t). \tag{4}$$

where, δ_{ij} is the Kronecker delta. In this transformation, the objective function in Eq. (3) is transformed to the form of the neural network energy function in Eq. (2), with carefully satisfying the condition for autonomous minimization described above, to keep zero the weight of self-feedback connection.

By comparing the coefficients of the neuron states, $x_{ij}(t)$, in Eqs. (2) and (4), we can obtain the connection weights and the threshold to minimize Eq. (3) as $W^A_{ijkl}=-2\frac{1}{c_j}(1-\delta_{ik})\delta_{jl}$ and $\theta^A_{ij}=\frac{1}{c_j}$, respectively.

By autonomously updating each neuron by Eq. (1) with these obtained values of the connection weights and the thresholds, the state of the entire wireless network converges to an optimal state having fair radio resource sharing. In order to run this algorithm without centralized computation, we can distribute the computational load to the entities in the wireless networks, such as the RANs, the access points and the user terminals, and the neurons can be updated at those entities distributively. According to the state of those updated neurons, each terminal can select an access point to optimize radio resource usage, and hands over to the corresponding selected access point autonomously. This decentralized process optimizes the radio resource usage of the entire wireless network without any centralized computation.

In this paper, it is assumed that each terminal can establish one wireless link with one access point at the same time. Therefore, the maximum firing neuron [13] is introduced to select exactly one access point for each user.

2.2. Neural Network for Application to QoS Satisfaction Rate Optimization

The goal of the optimization problem introduced in this subsection is to increase the number of user terminals whose QoS requirement is satisfied. Although there are various measures of the QoS, this paper focuses on the throughput. It is not difficult to extend the proposed algorithm to include other QoS metrics.

To satisfy the required throughput per user, easiest strategy is to maximize assigned throughput per terminal. However, the total amount of available radio resource is limited. To assign limited radio resources to each terminal efficiently, it is important to minimize differences between the available throughput and the required throughput for each terminal. Therefore, its objective function is defined as the following equation,

$$\begin{aligned} E_2^{\mathrm{OBJ}} &= \sum_{i=1}^{N_{\mathrm{m}}} \left\{ \left(\frac{1}{T_i} \frac{1}{c_{L(i)}} - \frac{1}{R_i} \frac{1}{c_{L(i)}} \right)^2 + \lambda \frac{1}{T_i} \right\} \\ &= \sum_{i=1}^{N_{\mathrm{m}}} \left[\sum_{j=1}^{N_{\mathrm{BS}}} \left\{ \sum_{k=1}^{N_{\mathrm{m}}} \left(\frac{1}{c_j} \right)^2 x_{ij} x_{kj} - \frac{1}{c_j} \frac{1}{R_i} x_{ij} \right\} \right]^2 + \lambda \sum_{j=1}^{N_{\mathrm{BS}}} \sum_{k=1}^{N_{\mathrm{m}}} \frac{1}{c_j} x_{ij} x_{kj} \end{aligned} , \qquad (5)$$

where, R_i is the required throughput by the terminal i, and λ is the parameter for weight on the maximization of the throughput, respectively. This equation becomes fourth order function of the neuron state, $x_{ij}(t)$. However, the conventional Hopfield-Tank neural network [6] cannot be applied to this problem, because its energy function is second order function. To minimize the fourth order objective function in Eq. (5), this paper introduces the higher order neural networks [14]. The third order neural network, whose energy function is the fourth order energy function, is applied to the optimization problem. The update equation of the third order neural network can be defined as follows,

$$x_{ij}(t+1) = \begin{cases} 1 \cdots \frac{1}{6} \sum_{k=1}^{N_{\mathrm{m}}} \sum_{l=1}^{N_{\mathrm{AP}}} \sum_{m=1}^{N_{\mathrm{m}}} \sum_{n=1}^{N_{\mathrm{AP}}} \sum_{o=1}^{N_{\mathrm{m}}} \sum_{p=1}^{N_{\mathrm{AP}}} U_{ijklmnop} x_{kl}(t) x_{mn}(t) x_{op}(t) \\ \quad + \frac{1}{2} \sum_{k=1}^{N_{\mathrm{m}}} \sum_{l=1}^{N_{\mathrm{AP}}} \sum_{m=1}^{N_{\mathrm{m}}} \sum_{n=1}^{N_{\mathrm{AP}}} V_{ijklmn} x_{kl}(t) x_{mn}(t) + \sum_{k=1}^{N_{\mathrm{m}}} \sum_{l=1}^{N_{AP}} W_{ijkl} x_{kl}(t) + \theta_{ij} > 0 \\ 0 \cdots \text{otherwise} \end{cases} , \qquad (6)$$

where, $U_{ijklmnop}$, V_{ijklmn}, W_{ijkl} and θ_{ij} are the third, the second and the first order connection weights and threshold, respectively. By updating each neuron by this equation, the following fourth order energy function can be autonomously minimized,

$$\begin{aligned} E_2^{\mathrm{OBJ}} = &-\frac{1}{24} \sum_{i=1}^{N_{\mathrm{m}}} \sum_{j=1}^{N_{\mathrm{BS}}} \sum_{k=1}^{N_{\mathrm{m}}} \sum_{l=1}^{N_{\mathrm{BS}}} \sum_{m=1}^{N_{\mathrm{m}}} \sum_{n=1}^{N_{\mathrm{BS}}} \sum_{o=1}^{N_{\mathrm{m}}} \sum_{p=1}^{N_{\mathrm{BS}}} U_{ijklmnop} x_{ij} x_{kl} x_{mn} x_{op} \\ &- \frac{1}{6} \sum_{i=1}^{N_{\mathrm{m}}} \sum_{j=1}^{N_{\mathrm{BS}}} \sum_{k=1}^{N_{\mathrm{m}}} \sum_{l=1}^{N_{\mathrm{BS}}} \sum_{m=1}^{N_{\mathrm{m}}} \sum_{n=1}^{N_{\mathrm{BS}}} V_{ijklmn} x_{ij} x_{kl} x_{mn} - \frac{1}{2} \sum_{i=1}^{N_{\mathrm{m}}} \sum_{j=1}^{N_{\mathrm{BS}}} \sum_{k=1}^{N_{\mathrm{m}}} \sum_{l=1}^{N_{\mathrm{BS}}} W_{ijkl} x_{ij} x_{kl} - \sum_{i=1}^{N_{\mathrm{m}}} \sum_{j=1}^{N_{\mathrm{BS}}} \theta_{ij} x_{ij} \end{aligned} . \qquad (7)$$

By transforming Eq. (5) to the form of Eq. (7) and comparing those coefficients, with satisfying the conditions for autonomous minimization, $U_{ijklmnop}$, V_{ijklmn}, W_{ijkl} and θ_{ij} to optimize the objective function $E_2^{\mathrm{OBJ}}(t)$ can be obtained as follows,

$$\begin{aligned} U_{ijklmnop} = &-(1-\delta_{ik}\delta_{jl})(1-\delta_{im}\delta_{jn})(1-\delta_{io}\delta_{jp})(1-\delta_{km}\delta_{\ln})(1-\delta_{ko}\delta_{lp})(1-\delta_{mo}\delta_{np}) \\ &\bullet \left[\left\{ \left(\frac{1}{c_n}\right)^2 \left(\frac{1}{c_j}\right)^2 + \left(\frac{1}{c_p}\right)^2 \left(\frac{1}{c_l}\right)^2 \right\} \right. \\ &\bullet \left(\delta_{mo}\delta_{jp}\delta_{nl} + \delta_{io}\delta_{np}\delta_{jl} + \delta_{ik}\delta_{nl}\delta_{jp} + \delta_{km}\delta_{pn}\delta_{lj} \right) \\ &+ \left\{ \left(\frac{1}{c_n}\right)^2 \left(\frac{1}{c_l}\right)^2 + \left(\frac{1}{c_p}\right)^2 \left(\frac{1}{c_j}\right)^2 \right\} \\ &\bullet \left(\delta_{mo}\delta_{lp}\delta_{nj} + \delta_{im}\delta_{np}\delta_{jl} + \delta_{ik}\delta_{pl}\delta_{jn} + \delta_{ko}\delta_{pn}\delta_{lj} \right) \\ &+ \left\{ \left(\frac{1}{c_l}\right)^2 \left(\frac{1}{c_j}\right)^2 + \left(\frac{1}{c_p}\right)^2 \left(\frac{1}{c_n}\right)^2 \right\} \\ &\left. \bullet \left(\delta_{ko}\delta_{jp}\delta_{nl} + \delta_{km}\delta_{nj}\delta_{lp} + \delta_{io}\delta_{pl}\delta_{jn} + \delta_{im}\delta_{\ln}\delta_{jp} \right) \right] \end{aligned} , \qquad (8)$$

$$\begin{aligned} V_{ijklmn} = &-(1-\delta_{ik}\delta_{jl})(1-\delta_{im}\delta_{jn})(1-\delta_{km}\delta_{\ln}) \\ &\bullet \left[\delta_{im}\delta_{nl} \left\{ \left(\frac{1}{c_j}\right)^2 \left(2\left(\frac{1}{c_l}\right)^2 + \left(\frac{1}{c_n}\right)^2 \right) - 2\left(\frac{1}{c_n}\right)^2 \frac{1}{c_j}\frac{1}{R_m} \right\} \right. \\ &+ \delta_{jl}\delta_{im} \left\{ \left(\frac{1}{c_n}\right)^2 \left(2\left(\frac{1}{c_l}\right)^2 + \left(\frac{1}{c_j}\right)^2 \right) - 2\left(\frac{1}{c_j}\right)^2 \frac{1}{c_n}\frac{1}{R_i} \right\} \\ &+ \delta_{ik}\delta_{nl} \left\{ \left(\frac{1}{c_j}\right)^2 \left(2\left(\frac{1}{c_n}\right)^2 + \left(\frac{1}{c_l}\right)^2 \right) - 2\left(\frac{1}{c_l}\right)^2 \frac{1}{c_j}\frac{1}{R_k} \right\} \\ &+ \delta_{jn}\delta_{ik} \left\{ \left(\frac{1}{c_l}\right)^2 \left(2\left(\frac{1}{c_n}\right)^2 + \left(\frac{1}{c_j}\right)^2 \right) - 2\left(\frac{1}{c_j}\right)^2 \frac{1}{c_l}\frac{1}{R_i} \right\} \\ &+ \delta_{km}\delta_{jn} \left\{ \left(\frac{1}{c_l}\right)^2 \left(2\left(\frac{1}{c_j}\right)^2 + \left(\frac{1}{c_n}\right)^2 \right) - 2\left(\frac{1}{c_n}\right)^2 \frac{1}{c_l}\frac{1}{R_m} \right\} \\ &+ \delta_{km}\delta_{lj} \left\{ \left(\frac{1}{c_n}\right)^2 \left(2\left(\frac{1}{c_j}\right)^2 + \left(\frac{1}{c_l}\right)^2 \right) - 2\left(\frac{1}{c_l}\right)^2 \frac{1}{c_n}\frac{1}{R_k} \right\} \\ &\left. + 2\delta_{jl}\delta_{jn}\left(\frac{1}{c_j}\right)^4 + 2\delta_{jl}\delta_{nl}\left(\frac{1}{c_l}\right)^4 + 2\delta_{jn}\delta_{nl}\left(\frac{1}{c_n}\right)^4 \right] \end{aligned} , \qquad (9)$$

$$\begin{aligned} W_{ijkl} = -(1-\delta_{ik}\delta_{jl}) \bullet &\left[\delta_{jl} \left\{ 3\left(\frac{1}{c_j}\right)^4 - 2\left(\frac{1}{c_j}\right)^3 \frac{1}{R_i} + 2\lambda\frac{1}{c_j} + 3\left(\frac{1}{c_l}\right)^4 - 2\left(\frac{1}{c_l}\right)^3 \frac{1}{R_k} + 2\lambda\frac{1}{c_l} \right\} \right. \\ &\left. + \delta_{ik} \left\{ -2\left(\frac{1}{c_j}\right)^2 \frac{1}{c_l}\frac{1}{R_i} - 2\left(\frac{1}{c_l}\right)^2 \frac{1}{c_j}\frac{1}{R_k} + \frac{1}{c_j}\frac{1}{c_l}\left(\left(\frac{1}{R_i}\right)^2 + \left(\frac{1}{R_k}\right)^2 \right) \right\} \right] \end{aligned} , \qquad (10)$$

$$\theta_{ij} = \left(\frac{1}{c_j}\right)^4 - 2\left(\frac{1}{c_j}\right)^3 \frac{1}{R_i} + \left(\frac{1}{c_j}\right)^2 \left(\frac{1}{R_i}\right)^2 - \lambda\frac{1}{c_j}, \qquad (11)$$

By updating the neurons' state using Eq. (6) with these obtained connection weights and thresholds in Eqs. (8)—(11), the RAN selection problem to optimize the QoS satisfaction rate can be autonomously solved. Even when the neurons are updated distributively on the base stations or on the mobile terminals, the state of the network converges to the optimal state, without any centralized computation.

3. Implementation and Experimental Environment

The proposed scheme is implemented on the CWC system [1,11], which is a cognitive radio network supporting the protocols defined in IEEE 1900.4. The CWC enables seamless use of the best RANs for all of the mobile terminals, with vertical handover across different wireless networks and network/terminal reconfigurations. In the following experiments, the CWC with the wireless LANs is implemented in our laboratory for evaluating the proposed algorithm based on the neural network dynamics.

The first experiment evaluates the performance of the RAN selection method to optimize load balancing proposed in Sec. II A. Its performance is compared with three other distributed RAN selection algorithms, (1) selection of the highest RSSI RAN (Highest RSSI), (2) selection of the RAN corresponding to the highest total throughput (Highest Total TH), and (3) selection of the RAN corresponding to the highest available throughput which can be shared to the terminal (Highest Shared TH). Average and variance of the throughputs per terminal are shown in Figs. 3 and 4. All of those algorithms, including the proposed neural network, are distributively run on the experimental network without any centralized computation. In these algorithms, each terminal updates their selections of the base stations in randomly selected intervals between 10 to 20 seconds. To avoid too many unnecessary handovers, the terminals really perform a handover only at the case that the same RAN selection is repeated three times.

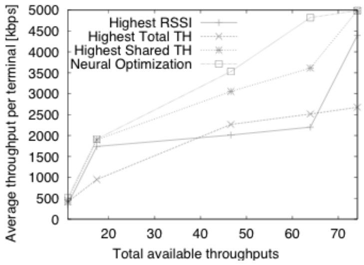

Fig. 3 Average throughputs per terminal of four distributed RAN selection algorithms.

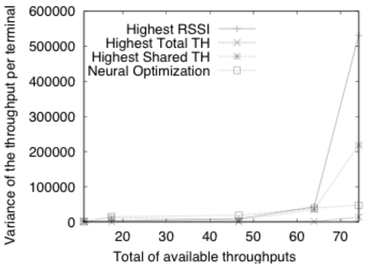

Fig. 4 Variance of the throughputs of four distributed RAN selection algorithms.

From Fig. 3, we can see that the RAN selection algorithms, selection of highest shared throughput (Highest Shared TH) and the proposed neural network based algorithms have the best throughputs. It is because these two algorithms increase available radio resources shared to each terminal. On the other hand, from Fig. 4, variance of the Highest Shared TH algorithm becomes much larger than the neural network, and fairness of the throughput becomes much worse. The proposed algorithm, whose objective function is Eq. (4), optimizes the fairness and throughput maximization at the same time only by very simple computation that is neuron update by Eq. (1). Therefore, the variance of the throughput can be also kept smaller.

The second experiment evaluates the performance of the RAN selection method to optimize the QoS satisfaction rate proposed in Sec. II B. Its performance is compared with three different distributed RAN selection algorithms, (1) selection of the RAN whose total throughput is larger than the required throughput (Total TH larger than required), (2) selection of the RAN which is able to share the throughput larger than the required throughput (Shared TH larger than required), and (3) selection of the RAN which satisfies the following both conditions, available throughput is larger than the required throughput and the differences between the available and the requested throughputs is the smallest (Min gap Shared and Required).

The QoS satisfaction rates obtained by such four types of distributed RAN selection algorithms, including the proposed neural network based distributed algorithm to optimize Eq.(10), are shown in Fig. 5. Fig. 5 shows that the proposed neural network has the best performance. It is because that only the proposed algorithm deals with the optimization problem of the entire network. On the other hand, other four algorithms make satisfaction of the required QoS only for each terminal separately. The proposed algorithm can optimize various kinds of complicated objective functions without any centralized computation.

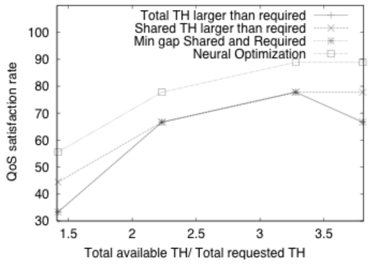

Fig. 5 QoS satisfaction rates of four distributed RAN selection algorithms.

4. Conclusion

In this paper, a distributed optimization dynamics of the mutually connected neural network is applied to optimal RAN selection in heterogeneous type cognitive radio networks, and its performance is evaluated. The results show that the proposed algorithm exhibits the best performance in such real experimental system. The proposed algorithm using mutually connected neural network directly optimizes an objective functions defined for the entire networks by distributed computation on each terminal. Therefore, its performance becomes better than other algorithm, which is based on the improvement of each terminal's QoS.

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