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전파인지 네트워크에서 신뢰성 보장 비대칭 스케줄-데이터율 결합제어

(Asymmetric Joint Scheduling and Rate Control under Reliability Constraints in Cognitive Radio Networks)

Hung Khanh Nguyen*, 송 주 빈**

(Hung Khanh Nguyen and Ju Bin Song)

요 약

스케쥴링 및 데이터율의 결합 제어와 같은 자원할당 기술은 전파인지 네트워크에서는 매우 중요한 문제이다. 그러나 전파인지 네트워크에서는 주사용자 채널의 스토케스틱 특성으로 인하여 데이터율 및 스케쥴링을 결합하여 제어하는 것은 매우 어렵다. 본 논문에서는 전파인지 네트워크에서 신뢰성 제한 조건들을 고려한 비대칭 데이터율 및 스케쥴링 결합 제어 기법을 제안한다. 데이터율 및 스케쥴링 문제를 컨벡스 최적화 기법으로 공식화하고 쌍대성 분해 기법을 사용하여 부분 문제로 변환하여 분산화 하였다. 본 논문에서는 전체 시스템의 효용함수를 최대화 하도록 분산 노드들의 데이터율을 분산적으로 제어하는 알고리즘을 제안 하였다. 반면, 스케쥴링은 기지국이 최적화하는 비대칭 기법을 제안하였다. 본 논문에서 제안한 비대칭 결합 제어 알고리즘은 전체 최적화 해로 수렴하는 것을 수치해석 기법으로 검증하였다.

Abstract

Resource allocation, such as joint rate control and scheduling, is an important issue in cognitive radio networks. However, it is difficult to jointly consider the rate control and scheduling problem due to the stochastic behavior of channel availability in cognitive radio networks. In this paper, we propose an asymmetric joint rate control and scheduling technique under reliability constraints in cognitive radio networks. The joint rate control and scheduling problem is formulated as a convex optimization problem and substantially decomposed into several sub-problems using a dual decomposition method. An algorithm for secondary users to locally update their rate that maximizes the utility of the overall system is also proposed. The results of simulations revealed that the proposed algorithm converges to a globally optimal solution.

Keywords : 전파인지, 자원할당, 비대칭결합 스케줄-데이터율, 컨벡스최적화, 쌍대성분해기법,
(Cognitive Radio (CR), resource allocation, asymmetric joint rate control and scheduling, convex optimization, dual decomposition method.)

Ⅰ. Introduction

Due to the under-utilization of available spectrum resources, dynamic spectrum access technology has been proposed as an efficient method to improve the spectrum utilization in wireless communication systems[1~3]. Two schemes for dynamic spectrum access technology have been employed: spectrum underlay and spectrum overlay[4]. In the spectrum underlay approach, secondary users (SUs) can use

* 학생회원, ** 정회원-교신저자, 경희대학교 전자전파공학과
(Department of Electronics and Radio Engineering, Kyung Hee University)
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the frequency bands that are licensed to primary users (PUs), as long as they do not cause harmful interference to the primary user's transmission. This requirement can be satisfied if the interference signal caused by secondary users' transmission at the primary received point is below the tolerable interference threshold of the primary user. This is referred to as the interference temperature constraint in underlay cognitive radio. In contrast, the spectrum overlay scheme allows secondary users to opportunistically access the unused frequency bands of primary users when the frequency bands are sensed as being idle.

The rate control problem at SUs in a spectrum overlay cognitive radio network is related to the scheduling problem, since the rate control will depend on the number of idle channels, as well as the capacity of each channel.

In this paper, we model and analyze the joint rate control and scheduling problem for an overlay spectrum sharing cognitive radio network. Due to the stochastic behavior of primary users, the number of idle channels will vary over different time slots. This makes the joint rate control and scheduling problem much more difficult to implement. As outlined in [5], we defined the time average proportion of a given channel allocated to a secondary user and formulated the joint rate control and scheduling problem under reliability constraints as a convex optimization problem. Using decomposition technique, we design a distributed algorithm that allows secondary users to update their transmission rate and maximize the total utility of the system.

The remainder of this paper is organized as follows. Related research is introduced in Section Ⅱ. In Section Ⅲ, the system model is described and the joint rate control and scheduling problem is formulated. The decomposition procedures and the proposed update-algorithm are outlined in Section Ⅳ, while numerical results are given in Section Ⅴ. Conclusions are stated in Section Ⅵ.

Ⅱ. Related Works

Recently, there have been a number of works in the literature addressing the resource allocation problem in cognitive radio networks. In [6], the power control and channel allocation problem for wireless cellular cognitive radio networks was studied. The authors proposed two-phased power control and channel allocation algorithm for secondary users that requires minimal cooperation between cognitive and primary devices. In this scheme, channels and power are first allocated to the cognitive radio base stations so as to maximize their total coverage area while maintaining both the interference constraints for primary users and the signal to interference ratio for secondary users. Each base station then allocates the channels among the cognitive radios within its cell such that the total number of cognitive radio served is maximized. However, the high computational complexity and unreasonable assumption that the aggregated interference caused by all PU transmissions to a SU on the same channel can be ignored make the proposed algorithm difficult to implement in an infrastructure-based system with many PUs and SUs.

To overcome the above limitation, M. Nguyen et al.[7] investigated the joint scheduling and power control problem in order to maximize the spectrum utilization of SUs under quality-of-service (QoS) constraints for both SUs and PUs. The formulated problem was a mixed-integer linear programming that could be solved in a centralized fashion with NP-hard complexity. To reduce the high complexity of the optimization problem, the authors proposed a heuristic greedy algorithm based on the coloring interference graph among unserved SUs affected by serviced SUs and active PUs. The results of simulations also showed that the new algorithm exhibited better performance than the existing one.

In [8], the authors proposed a stochastic channel selection algorithm based on the learning automata (LA) techniques in order to maximize the probability of successful transmissions of secondary user transmissions in cognitive radio networks. This LA algorithm observes the current network condition and dynamically adjusts the probability of choosing one channel. It was found that this LA algorithm converges to the ϵ-optimal solution.

The problem of joint scheduling, routing, and flow control in multi-hop networking with cognitive radio nodes was considered in [9]. The authors formulated the spectrum sharing problem with sub-band division characteristics as a mixed-integer non-linear program that maximizes the radio spectrum resources of the required networks. In particular, the transmission range and interference range were taken into account when considering the joint scheduling and routing problem. By applying a relaxation technique, the new (relaxed) problems, a standard linear program, and the optimal solution can be obtained in polynomial time. However, this optimal solution value is only the lower bound of the objective function of the original problem. As such, the authors proposed a near-optimal algorithm based on a novel sequential fixing procedure to solve the above problem. It was subsequently shown that the optimal solution obtained by the algorithm was very close to the lower bound.

In [5], an opportunistic scheduling policy for cognitive radio networks that maximizes the throughput utility of secondary users was proposed. This problem takes into account the collision for secondary users with primary users. The authors developed an online flow control, scheduling, and resource allocation algorithm using Lyapunov optimization technique. The algorithm was decoupled into two separate steps. First, the optimal flow control at the transport layer is conducted at each secondary user based on the current queue backlog, which requires only local information. In the second step, the network resource allocation was performed collectively at every time slot by secondary users. The authors proposed distributed implementation of the above algorithm.

In [10], the authors studied an efficient and fair dynamic carrier allocation problem in a distributed cognitive radio wireless network. Based on partial knowledge of the network parameters, the available carriers were allocated to achieve a maximum rate. The authors also proposed a fast iterative algorithm to allocate the available carriers in order to reduce the control traffic and provide fairness with only linear-computational complexity.

In [11], the cross-layer optimization problem including rate allocation, routing, and spectrum sharing for multi-hop cognitive radio networks was considers using a dynamic programming technique. The optimization problem was formulated as a sequential decision process with the goal of minimizing the average total power consumption in each scheduling cycle with the constraint that all cognitive radio users can achieve their pre-determined traffic demands. Using the dynamic programming technique, the authors defined the system state as the remaining traffic demand vector that must be finished for all cognitive radio source nodes. The authors also derived an optimal rate allocation, routing, and spectrum sharing policy that could fully exploit the dynamic system information. The formulated problem was also considered for imperfect spectrum sensing of a cognitive radio network.

In [12], the authors formulated a fair scheduling problem in an ah-hoc cognitive radio wireless network with the spectrum underlay scenario. The scheduling problem was constructed with the goal of achieving proportional fairness of the long-term average transmission rates among different links under some QoS constraints for the primary network. Due to the difficultly in collecting all required information to solve the optimization problem in a centralized fashion, the authors proposed two heuristic scheduling schemes that were performed in a distributed manner by secondary network with some limited assistance from the primary base station. In the first scheme, the scheduling decision takes into consideration the transmission priorities of the links that are determined by their potential contributions to an objective function. The scheduling procedure is conducted periodically at the beginning of each scheduling interval under an assumption that the scheduling interval is much longer than a time slot. Such a procedure was implemented so that the overhead for making the scheduling decisions has a minimum impact on the transmission throughput. In the second scheme, both the contribution to the objective function and the interference induced in the primary network were considered for deriving the transmission priorities for the links. By using exclusive regions to eliminate interference among simultaneous transmissions, the system throughput could be improved.

In [13], the weighted sum rate maximization problem for a cognitive radio network in multi-cell primary radio networks under many important system and QoS constraints was studied. In the optimization problem, the authors included system and QoS constraints, such as the available secondary user transmit power, the power spectral mask of secondary user transmitters, the minimum-rate per link, and the maximum-allowed rate per sub-channel. Furthermore, the authors analyzed the optimization problem for both continuous rate and discrete rate modulation formats and showed that the proposed distributed update-algorithm, which was designed based on the Lagrange duality optimization technique, achieved fast and stable convergence to the optimal solution.

In [14], a utility maximization problem was investigated by considering the trade-off between rate and reliability. By adapting the physical layer channel coding or transmission diversity, the authors formulated a network utility maximization problem in which the utility for each user depends on both the transmission rate and the reliability level. Distributed algorithms were proposed to determine the trade-off point between rate and reliability.

While many researchers have investigated resource allocation problems in cognitive radio networks, the number of works pertaining to joint rate control and scheduling problems in limited. In this paper, we consider an asymmetric joint rate control and scheduling problem for secondary users in spectrum overlay cognitive radio networks under a reliability constraint for each secondary transmitter. Using a decomposition technique, we design a distributed algorithm in which each user updates its transmission rate independently and locally with some information exchange with a base station. The base station collects information from secondary users and solves the scheduling problem in a centralized fashion.

Ⅲ. System Model and Problem Formulation

We consider a multi-channel spectrum sharing cognitive radio networks comprising a set of $\boldsymbol{M}=\{1,2,\dots,M\}$ of SUs. Each SU is a cognitive transmitter-receiver pair. SUs share a common set of $\boldsymbol{K}=\{1,2,\dots,K\}$ orthogonal channels with the PUs. Let c_m be the link capacity (which is fixed) of the SUs. Similar to [12], we assume that each transmitter m has a utility function, $U_m=(x_m,R_m)$, where x_m is the data rate and R_m is the reliability of transmitter m. We assume that the utility function is a continuous, increasing, and strictly concave function of x_m and R_m. Each source m has a minimum reliability requirement, $R_m^{\min}$. The reliability R_m of source m must then satisfy the constraint

$$R_m \le 1-E(r_m), \tag{1}$$

where $E(r_m)$ is a convex function defined as

$$E(r_m) = 2^{-N(R_0 - r_m)}, \tag{2}$$

In (2), r_m is the code rate of source m [14].

The system is assumed to be a time-slotted system. Let $S(t) = (S(t), \ldots, S_K(t))$ be the current primary user occupancy state of the K channels, where $S_K(t) = 0$ denotes that channel k is occupied by primary user in time-slot t and $S_K(t) = 1$ indicates primary user is idle in time-slot t. The channel state information available to the secondary users in time-slot is denoted by a probability vector $\pi(t) = (\pi_1(t), \pi_2(t), \ldots, \pi_k(t))$. $I_{mk}(t) \in \{0, 1\}$ denotes the allocation decision that allocates channel k to secondary user m in time-slot t. If $I_{mk}(t) = 1$, secondary user m transmits on channel k; otherwise $I_{mk}(t) = 0$. The optimization problem studied in this work can then be formulated as

$$\max. \sum_m U_m(x_m, R_m) \tag{3}$$

subject to

$$R_m \le 1 - E(r_m), \ \forall m, \tag{4}$$

$$\frac{x_m}{r_m} \le \sum_k c_m \pi_m \phi_{mk}, \ \forall m, \tag{5}$$

$$\sum_m \phi_{mk} = 1, \quad \sum_k \phi_{mk} = 1, \ \forall m, k, \tag{6}$$

$$R_m^{\min} \le R_m \le 1, \ \forall m, \tag{7}$$

$$0 \le r_m \le 1, \ \forall m, \tag{8}$$

$$x_m^{\min} \le x_m \le x_m^{\max}, \ \forall m, \tag{9}$$

where ϕ_{mk} is the average time of a given channel k allocated to SU and is given by

$$\phi_{mk} = \lim_{t \to \infty} \frac{1}{t} \sum_{\tau = 0}^{t-1} I_{mk}(t). \tag{10}$$

Constraint (5) means that the source rate on a SU link cannot exceed its attainable link rate. Constraint (6) ensures that a secondary user can be allocated to, at most, one channel at any given time. The objective function of the optimization problem (3) is a convex optimization problem.

Ⅳ. Algorithm

To solve the optimization problem (3) we use a dual decomposition approach introduced in [15]. Since the constraint (5) can be written as $x_m \le \sum_k c_m \pi_k \phi_{mk} r_m$. The Lagrangian function associated with the problem (3) is given as follows:

$$\begin{aligned} & L(x, R, r, \phi, \mu, \lambda) \\ & = \sum_m U_m(x_m, R_m) \\ & + \sum_m \mu_m (1 - E_m(r_m) - R_m) \\ & + \sum_m \lambda_m \Big(\sum_k c_m \pi_k \phi_{mk} r_m - x_m \Big) \\ & = \sum_m \{ U_m(x_m, R_m) - \lambda_m x_m - \mu_m R_m \} \\ & + \sum_m \lambda_m \Big\{ \sum_k c_m \pi_k \phi_{mk} r_m - \mu_m E(r_m) \Big\} \\ & + \sum_m \mu_m \end{aligned} \tag{11}$$

where μ and λ are the Lagrange multipliers on source m with interpretations of a “reliability price” and a “congestion price”, respectively. The Lagrange dual function is

$$D(\mu, \lambda) = \max_{x, R, r, \phi} L(x, R, r, \phi, \mu, \lambda), \tag{12}$$

subject to (6), (7), (8), (9).

The dual problem is formulated as

$$\min. \ D(\mu, \lambda), \tag{13}$$

$$\text{subject to } \mu \ge 0, \ \lambda \ge 0. \tag{14}$$

We first consider the problem (12). Since the Langrangian is separable, the maximization can be conducted in parallel at each SU

$$\max. \ U_m(x_m, R_m) - \lambda_m x_m - \mu_m R_m, \tag{15}$$

$$\text{subject to } x_m^{\min} \le x_m \le x_m^{\max}, \tag{16}$$

$$R_m^{\min} \le R_m \le R_m^{\max}. \tag{17}$$

At each SU m, given ϕ_{mk} chooses a code rate r_m as the solution of the following problem:

$$\max.\ \sum_k c_m \pi_k \phi_{mk} r_m - \mu_m E(r_m), \tag{18}$$

$$\text{subject to } 0 \le r_m \le 1. \tag{19}$$

The resource allocation ϕ_{mk} will be the solution of the following problem:

$$\max.\ \sum_m \sum_k \phi_{mk} \lambda_m c_m \pi_k r_m, \tag{20}$$

$$\text{subject to } \sum_m \phi_{mk} = 1,\ \sum_k \phi_{mk} = 1,\ \forall_{m,k}. \tag{21}$$

If we consider problem (18) and problem (20) at an arbitrary time t, we have the equivalent problems:

$$\max.\ \sum_k c_m \pi_k I_{mk}(t) - \mu_m E(r_m(t)), \tag{22}$$

$$\text{subject to } 0 \le r_m \le 1, \tag{23}$$

and

$$\max.\ \sum_m \sum_k I_{mk}(t) \lambda_m c_m \pi_m r_m, \tag{24}$$

$$\text{subject to } \sum_m I_{mk}(t) = 1, \sum_k I_{mk}(t) = 1, \forall_{m,k}. \tag{25}$$

respectively. The problem (24) is a Maximum Weighted Match (MWM) problem where the weight for a pair (m,k) is given by $(\lambda_m, c_m, \pi_k, r_m)$; this must be solved in a centralized fashion by the base station (BS) using Hungarian algorithm [16]. Dual problem (13) can then be solved with the gradient projection algorithm as follows

$$\mu_m(t+1) = \left[\mu_m(t) - \alpha(t)\frac{\partial D}{\partial \mu_m(t)}\right]^+,\ \forall m, \tag{26}$$

$$\lambda_m(t+1) = \left[\lambda_m(t) - \alpha(t)\frac{\partial D}{\partial \lambda_m(t)}\right]^+,\ \forall m, \tag{27}$$

where $[a]^+ = \max\{a,0\}$, $\alpha(t)$ is the step size, and

$$\frac{\partial D}{\partial \mu_m(t)} = 1 - R_m(t) - E(r_m(t)), \tag{28}$$

$$\frac{\partial D}{\partial \lambda_m(t)} = \sum_k c_m \pi_k I_{mk}(t) r_m(t) - x_m(t). \tag{29}$$

The whole problem (3) can be solved entirely by the following algorithm. By locally solving the problem (15) over (x_m, R_m) at each iteration t, each source m determines its rate and desired reliability level that maximize its utility based on the prices in the current iteration. Concurrently, by locally solving problem (22) over r_m, each source determines its code rate based on the reliability price and resource allocation decision in the current iteration. Furthermore, each secondary user updates the prices μ and λ based on (26) and (27) for the next iteration. The congestion price λ and code rate are then sent to the BS. The BS determines allocation decisions by solving maximization problem (24) based on the λ and r received from the SUs. The allocation decisions are subsequently sent to every SU. Intuitively, the problem (24) tries to schedule SUs with a larger code rate over those channels that are more likely to be idle. The above algorithm can be summarized as shown in Algorithm 1.

Algorithm 1. The proposed resource allocation algorithm.

1. Repeat
2. At each iteration t, each SU determines optimal values x_m^* and R_m^* by solving problem (15).
3. Determines optimal r_m^* by solving problem (18).
4. Update congestion price and reliability price,
   $\mu_m(t+1) = [\mu_m(t) - \alpha(t)(1 - R_m(t) - E(r_m(t)))]^+$
   $\lambda_m(t+1) = \left[\lambda_m(t) - \alpha(t)\left(\sum_k c_m \pi_k(t) I_{mk}(t) r_m(t) - x_m(t)\right)\right]^+$
5. Each SUs sends $\lambda_m(t)$ and $r_m(t)$ to the BS. BS solves problem (24) and sends new to all SUs for the next iteration.
6. Until $|x_m(t+1) - x_m(t)| \le \epsilon$, $|R_m(t+1) - R_m(t)| \le \epsilon$, $|r_m(t+1) - r_m(t)| \le \epsilon$, where ϵ is the error bound.

In Algorithm 1, all operations can be performed in polynomial time since it contains only basic arithmetic operations. In addition, the complexity for BS to solve the MWM problem is $O(n^3)$.

Ⅴ. Numerical Results

In this section, we present numerical examples for the proposed algorithm by considering a simple network consists of 5 secondary users opportunistically using 10 orthogonal channels. The utility function for secondary user m is $U_m(x_m, R_m)$, which has the same form as [14]

$$U_m(x_m,R_m) = a_m \frac{(x_m)^{1-\gamma} - (x_m^{\min})^{1-\gamma}}{(x_m^{\max})^{1-\gamma} - (x_m^{\min})^{1-\gamma}} + (1-a_m)\frac{(R_m)^{1-\gamma} - (R_m^{\min})^{1-\gamma}}{(R_m^{\max})^{1-\gamma} - (R_m^{\min})^{1-\gamma}}, \quad (30)$$

where constant parameters have the following values: $\gamma = 1.1$, $x_m^{\min} = 0.1(Mb/s)$, $x_m^{\max} = 1(Mb/s)$, $c_m = 1(Mb/s)$, $R_m^{\min} = 0.9$, and $R_m^{\max} = 1$.

First, we investigate the data rate of secondary users when the value of a is varied from 0 to 1 with a step size 0.1. As shown in Fig. 1, a high value of a leads to a high value of data rate value. On the other hand, when is a assigned to a lower value, the data rate of the secondary users will decrease. This can be easily understood since when we assigned the higher value to a, the rate utility in the objective function is given a heavier weight, consequently, a higher data rate can be achieved.

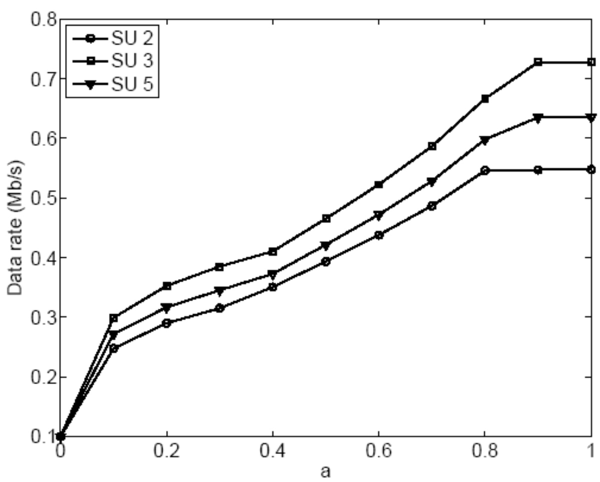

그림 1. a에 따른 각 SU의 소스 데이터율

Fig. 1. Data rate for each source when varying a.

Plots of the data rate, code rate, and reliability level of secondary users with respect to the number of iterations are shown in Figs. 2, 3, and 4, respectively. The idle probability of the channels was generated randomly in the interval [0.7, 0.9]. It can be seen that the data rate, code rate, and reliability level of each secondary user converge to a global optimal

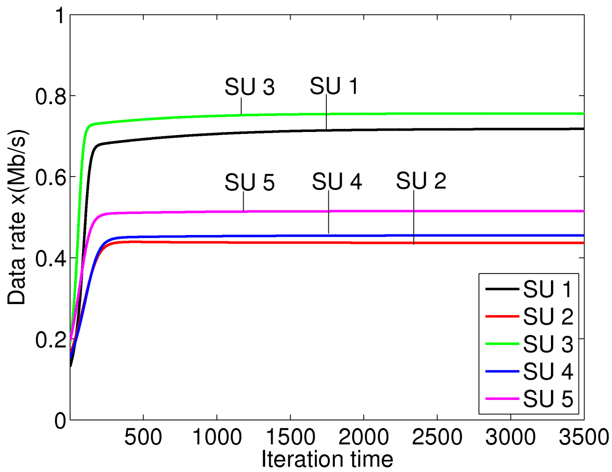

그림 2. SU에 대한 소스 데이터율.

Fig. 2. Data rate for each source.

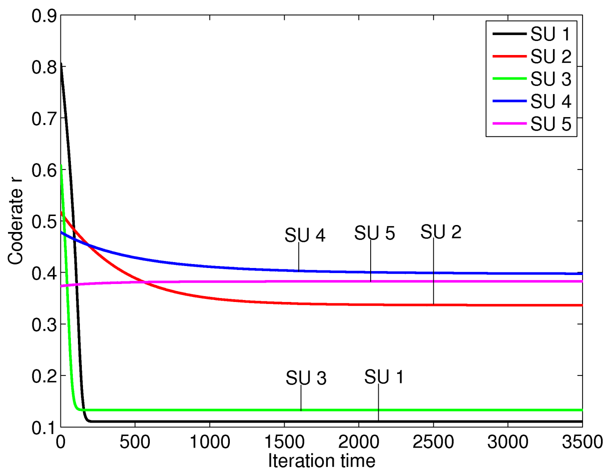

그림 3. SU 소스에 대한 코드율.

Fig. 3. Code rate for each source.

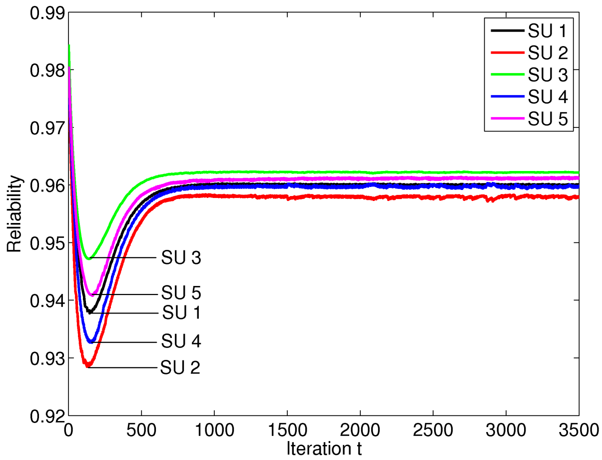

그림 4. SU 소스의 신뢰성 레벨.
Fig. 4. Reliability level for each source.

solution based on Algorithm 1. In this algorithm, the channel with higher idle probability will be assigned to the secondary user with a higher data rate. With this strategy, the total utility of the system can achieve an optimum value.

VI. Conclusions

We consider the problem of asymmetric joint rate control and scheduling for secondary users in cognitive radio networks. A symmetric and iterative resource allocation algorithm was proposed where the base station makes a schedule and users control the rate in a distributed manner. In the proposed algorithm although, secondary users can update their own data rate using only local information without the need to cooperative with primary users. However, the algorithm requires a central controller, i.e., a base station or a fusion center, which will solve the scheduling problem and send the optimal to secondary users. In the proposed algorithm, the local rate control problem can converge to a global optimal solution.

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저 자 소 개

Hung Khanh Nguyen(학생회원)

2005년～2010년 BS degree, Dept. of Electrical and Electronic Eng., Ho Chi Minh City University of Technology, Vietnam.

2010년～2012년 MS degree, Dept. of Electronics and Radion Eng., Kyung Hee University, Korea.

<Research area : optimization and resource allocation for communication systems and smart grids>

송 주 빈(정회원)-교신저자

1992년～1997년 한국전자통신연구원(ETRI) 선임연구원 통신시스템

1997년～2001년 University of London(UCL) 박사 졸업.

2002년～2003년 국립한밭대학교 정보통신컴퓨터공학부 교수

2009년～2010년 미국 휴스턴대학교 객원교수

2003년～현재 경희대학교 전자전파공학과 교수

<주관심분야 : 통신, 자원최적화, 게임이론, 협력 및 분산알고리즘, 전파인지통신, 스마트그리드>