Adaptive Weighted Scheduling in Cognitive Radio Networks

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***Abstract*—In this paper we present an adaptive weighted packet scheduling algorithm for cognitive radio networks. The adaptive weight factor is introduced to adjust the priority of different cognitive radio users to be selected for different services. This proposed scheme resolves the problem with unfairness which occurs when using traditional proportional scheduling schemes in cognitive radio. We use simulation to verify the performance in terms of throughput and fairness. The obtained results show the effectiveness and efficiency of the proposed scheduling scheme.**

I. Introduction

Cognitive radio has been proposed as a means to implement efficient reuse of the licensed spectrum [1]. The key feature of a cognitive radio is its ability to recognize the primary (licensed) user and adapt its communication strategy to minimize the interference that it generates. One important research topic in *cognitive radio networks* (CRNs) is about packet scheduling. Packet scheduling in wireless network have been extensively studied in previous work and there are many scheduling algorithms that have been proposed to deal with different service types based on their intrinsic characteristics in the different wireless networks. However, the unique characteristics of cognitive radio systems pose new challengers in terms of meeting fairness and other system performance requirements in CRN.

In cellular network scheduling, many schemes have been developed for achieving a high throughput and good fairness by considering wireless channel conditions. Fair sharing lowers the total throughput from the maximum, but can provide a more acceptable service to users with poorer SNRs. In [2], scheduling algorithms are developed for multi-user diversity benefits while maintaining fairness in the downlink of high data rate system, where the downlink SNR of each user is measured based on a common pilot and fed the information back to the base station. *Proportional fairness* (PF) scheduling is an effective approach to providing a good balance between the system throughput and fairness [3], [7], [8]. Generally speaking, PF scheduling schemes aim at equivalently allocating the available resources among all the users. It selects a user for service according to the ratio of the instantaneous SNR and average SNR of users at a certain frame or timeslot. The user who has the maximum ratio will be assigned the channel to transmit its data traffic. However, traditional PF scheduling strategy can cause unfairness when used in a CRN. If the transmissions are scheduled based on the channel condition, it can lead to some users deprived of spectrum resources for a long time if it experiences a poor channel condition when the channel is available and experiences a good channel condition when the channel is not available.

In cognitive radio networks, it is possible that the resources are not available when a node has a good channel condition, and when the resources are available, the node may experiencing deep channel fading. If a scheduling scheme designed for a traditional network is directly applied in CRNs, it may lead to unfair resource allocation and cannot achieve a high throughput. Therefore, new algorithms are needed to deal with these challenges and to achieve efficient and fair resource allocation [9]. In [10], a two-phase resource allocation scheme is proposed to improve the system throughput. In [11], a resource allocation algorithm is proposed to maximize CRN spectrum utilization based on dynamic interference graph, and a realistic control framework is formulated to guarantee protection to primary users and reliable communication for cognitive nodes. In [12], and adaptive packet scheduling algorithm for real-time and non-real-time multi-service applications is presented, which makes the resource allocation adapt to the varying available spectrum in a CRN. A combined channel and power allocation strategy is proposed in [13]. Scheduling the secondary users under partial channel state information is considered in [14], which uses a probabilistic maximum collision constraint with the primary users. In [15], opportunistic scheduling policies for CRNs are developed, which maximize the throughput utility of the cognitive radio units (CRUs) subject to maximum collision constraints with the *primary users* (PUs) is developed but unfortunately, this approach has high complexity.

In this paper, we propose a packet scheduling algorithm based on adaptive weight factor in a cognitive radio network. The adaptive weight factor is used to adjust the priority of different cognitive radio users to be selected for service. The adaptive weighted scheduling scheme achieves high system throughput as well as good fairness performance in a CRN by jointly considering the variable channel availability and channel condition and taking advantage of the channel diversity among multiple users.

The reminder of the article is organized as follows. In Section II, we describe the used link-layer frame structure, channel model and traffic model. In Section III, we describe our proposed adaptive scheduling algorithm in detail. Section

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IV describes the simulation set up and discusses the obtained results. Finally, in Section V we conclude our work.

II. PRELIMINARIES

For simplicity, we consider the resource allocation in a single-cell system with one channel. The cognitive radio network consists of a *cognitive radio base station* (CRBS) and M CRUs. The CRBS detects the transmission of primary networks, determines the channel availability, and allocates the channel to CRUs based on these local measurements when the channel is inactive. At a specific timeslot, we assume that only one user transmits data on this inactive channel and the CRU does not share this inactive channel with the other CRUs. In this paper we focus on downlink scheduling for transmission from the CRBS to CRUs.

A. Link-Layer Frame Structure

At the link layer, time is partitioned into three parts: i) sensing time (denoted by t_s), ii) waiting time (denoted by WT), iii) transmission time (denoted by t_{tr}), as shown in Fig 1. During a sensing time t_s, the CRBS senses the channel to determine whether the cannel can be used by CRUs. If the channel busy (used by primary users), the CRBS waits for WT before sensing the channel again. Whenever the channel is available for a CRU, it can use the channel for t_r and then the CRBS needs to sense the channel again. N_i is the number of consecutive timeslots that the channel is inactive, and T_i denotes the time length that the channel is inactive.

When primary users have synchronized transmission with an equal transmission unit of duration $t_s + t_{tr}$, the CRBS needs to sense the channel once every unit and we can choose $WT = t_{tr}$. As the sensing time t_s is generally a short period, it can be assumed to be negligible, i.e., $t_s << t_{tr}$.

The channel that the CRN can assess is assumed to be licensed to primary networks. The channel in the active state represents the unused period by primary users. Here, we use an ON-OFF model to characterize the activity of the channel, where the duration of the two states ON and OFF are independent and exponentially distributed. The ON and OFF state transitions are characterized by probability P_1 and P_2.

There are two cases that can occur after the sensing process:

1: Given the channel is inactive, it will remain inactive with probability P_1. Let ψ_1 denote the number of units that the channel remains inactive before changing to active, which follows a geometric distribution with parameter P_1,

$$P(\psi_1 = i) = P_1^{i-1}(1 - P_1). \tag{1}$$

2: Given that the channel is active, it will remain active with a probability P_2.Let ψ_2 denote the number of units that the channel remains active before changing to active, which follows a geometric distribution with parameter P_2,

$$P(\psi_2 = i) = P_2^{i-1}(1 - P_2). \tag{2}$$

On the other hand, the exponential distribution may be viewed as a continuous counterpart of the geometric distribution. If a random variable with an exponential distribution is rounded up to the nearest integer, then the result is a discrete random variable with a geometric distribution. That is:

$$N_i = Integer\left[\frac{T_i}{Length(t_{tr})}\right], \tag{3}$$

where $Length(t_{tr})$ is the length of the t_{tr}, T_i is an exponential random variable, and N_i is a geometric random variable.

B. Models

1) Traffic Model: In this paper we consider non-real time traffic for data applications. For data traffic, we consider the call arrival is a Poisson process for each user with rate λ, and each call has file size T following the Weibull distribution, i.e., $T \approx Weibull(a, b)$. The probability density function (pdf) of the Weibull distribution is given by

$$f(x; a, b) = \begin{cases} \frac{b}{a}\left(\frac{x}{a}\right)^{b-1} e^{-\left(\frac{x}{a}\right)^b}, & x \geq 0 \\ 0, & x < 0. \end{cases} \tag{4}$$

where b is the shape factor and a is the scale factor.

Meanwhile, let L denote the payload size of a packet size, which is treated as constant. Therefore, from file size and the packet payload, the number of packets in a call can be determined by

$$\tau = \left(\frac{T}{L}\right). \tag{5}$$

2) Mobility Model: We consider the two-dimensional random waypoint mobility model to describe the movement pattern of CRUs and how their speeds and directions vary over time. Each CRU moves towards a randomly chosen destination in a given area at a constant speed, which is uniformly distributed in $[v_{\min}, v_{\max}]$ and independent of the CRU's initial and destination locations. After reaching the destination, the CRU may pause for a random amount of time. A new destination and speed is then selected, independent of all previous values. To simplify the problem, we assume that the velocities of all CRUs are the same as with $v_{\min} = v_{\max} = v_i$.

3) Channel Model: In this paper we consider both short-term fading and long-term fading which includes path-loss attenuation and shadowing. With the transmission power P_w from the CRBS, the received power of CRU i is given by $P_i = |h_i|^2 \cdot P_w$, where h_i is the channel gain which reflects the effects of various physical phenomena such as scattering and absorption of radio waves, shadowing by terrestrial obstacles, and multipath propagation. The channel gain from the CRBS to CRU i can be expressed as

$$h_i = \sqrt{s_i} m_i, \tag{6}$$

where s_i is the slow fading, including the path-loss component and the shadow-fading effect, and m_i represents the multipath component. The slow fading is mainly determined by the

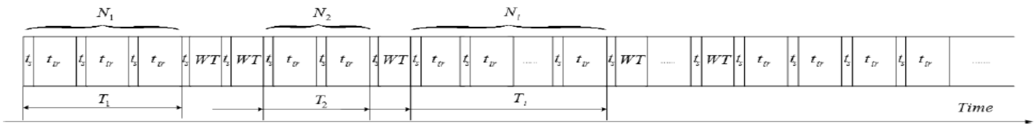

Fig. 1. Link-layer frame structure.

geographical environment and distance between the CRBS and the CRU. It concludes shadowing effect which is generally modeled by a lognormal distribution. Therefore, the slow fading s_i is given by [16], [18]

$$s_i = c \cdot d_i^{-k} \cdot 10^{\chi_i/10}, \tag{7}$$

where c is a constant, d_i is the distance between the CRBS to CRU i, which varies with the CRU's movement, k is the path loss distance exponent, and χ_i (the attenuation due to shadowing in dB) is a zero mean Gaussian random variable with variance $\sigma^2_{\chi_i}$. The distance d_i changes as CRU i moves. Let (x_0, y_0) denote the position of the CRBS, (x_i, y_i) is the current position of user i, v_i is the velocity of user i, and θ_i is the movement direction. After Δt, user i moves to a new location (x_i', y_i') that can be calculated by

$$\begin{cases} x_i' = v_i \cdot \Delta t \cdot \cos\theta_i + x_i \\ y_i' = v_i \cdot \Delta t \cdot \sin\theta_i + y_i \end{cases} \tag{8}$$

The distance d_i is a function of the position of user i, (x_i', y_i') given by

$$d_i = \sqrt{(x_i' - x_0^2) + (y_i' - y_0)^2}. \tag{9}$$

Since both slow fading and fast fading have time correlation, the fading at two instances may be correlated to each other. Thereby, the shadowing process $\chi_i(n+1)$ at time $t + \Delta t$ is modeled by [17]

$$\chi_i(n+1) = \zeta^{v_i \cdot \Delta t} \cdot \chi_i(n) + (1 - \zeta^{v_i \Delta t}) \cdot N_G(n+1), \tag{10}$$

where ζ is the correlation between two points separated by one meter, $\chi_i(n)$ is the shadowing process at time t, and $N_G(n+1)$ is the sample of a white Gaussian random process at time $t+\Delta t$, which is a Gaussian random variable with zero mean and standard deviation $\sigma_{\chi_i}\sqrt{\frac{1+\zeta^{v_i \cdot \Delta t}}{1-\zeta^{v_i \cdot \Delta t}}}$. For the multipath fading, the Jakes fading model [16] can be used, which is a deterministic method for simulating time-correlated Rayleigh fading waveforms and is good for time-varying fast fading.

III. Proposed Algorithm

In order to solve the unfairness problem when using the traditional PF scheduling schemes in the spectrum resource deprivation scenario described earlier, and taking into account the characteristics of the CRN, we propose an *adaptive weighted scheduling scheme* (AWSS) for data service in the CRN for achieving flexible resource allocation according to resource availability and channel conditions. An *adaptive weight factor* (AWF) is introduced to the proportional fairness scheduling strategy to adjust the priority of different CRUs to be selected for service. At a certain time slot, the selection probability of a CRU changes with the adjustment of the AWF. If the AWF has an appropriate value, even the CRU with bad channel condition has the reasonable chance to be selected for transmission.

In our proposed scheme, the adaptive weighted scheduling scheme considers the adaptive weighted factor, the ratio of instantaneous SNR and average SNR, and the channel availability are jointly taken into consideration when we select a CRU to assign spectrum resources to. The criterion by which the adaptive weighted scheduling scheme selects a CRU and provides the available resources for data service to this user is formulated as

$$j^*(n) = arg\max_j X_j(n) \;\; j \in S_{ne}(n), \;\; S_{ne}(n) \in \{1, 2, \ldots, M\} \tag{11}$$

$$X_j(n) = \xi_j(n)\frac{\gamma_j(n)}{\overline{\gamma}_n}(n) \;\;\; j \in S_{ne}(n) \tag{12}$$

$$Y_i(n) = \frac{\gamma_i(n)}{\overline{\gamma_n}}(n) \;\;\; i = 1, 2, \ldots, M \tag{13}$$

$$\xi_i(n+1) = \begin{cases} \xi_i(n) + \Delta\xi, & \text{if } \theta(n+1) = 1 \\ 1, & \text{if } \theta(n+1) = 0. \end{cases} \tag{14}$$

where $\gamma_i(n)$ and $\overline{\gamma_i}(n) = \frac{\sum_{n=n-n_t}^{n} \gamma_i(n)}{n_t}$ are the average and instantaneous channel gain for user i at the nth timeslot, respectively, n_t is the time period used to calculate the average SNR, S_{ne} is defined as the set of CRUs whose traffic queues are not empty with the packet to transmit at the time slot n, $X_i(n)$ represents the user i's weighted relative channel condition, $Y_i(n)$ represents the user i's relative channel condition, $\xi_i(n)$ expresses the value of adaptive weight factor (AWF) for CRU i at the nth time slot, and $\Delta\xi$ denotes the step increment of the weight. Furthermore, $\theta(n)$ indicates channel availability for the CRU at the nth time slot: if the channel is idle, $\theta(n) = 0$; otherwise, $\theta(n) = 1$.

We define (12) as the preference metric of AWSS. By averaging out the long-term channel condition in the preference metric, AWSS improves the short-term fairness. To implement the AWSS scheduling scheme, we assume that the base station has knowledge of the channel information of each CRU.

Our proposed algorithm is described as follows:

1) Initialize parameters. Assume $\xi_i(n)$ at the timeslot $n = 1$ and set the ending timeslot n_{end}.
2) Check the availability of the channel. If the channel is active, go to 3. If the channel is inactive, go to 5.
3) According to Eq. (13), a CRU i^* which has the largest Y_i is chosen, and the AWF of the CRU i^* is updated to $\xi_i(n+1)$ in the next timeslot $n+1$ according to Eq. (14), $i = 1, 2, \ldots, M$.
4) Update $n = n+1$; check whether the timeslot $n = n_{end}$ or not. If Yes, go to 9. If No, go to 2.
5) Check all users' traffic queues and get a set $S_{ne}(n)$ in which the user's traffic queue is not empty at the timeslot n.
6) If $S_{ne}(n) = \rho$, go to 8; otherwise, according to Eq. (12), a CRU j^* which has the largest X_j is selected, $j \in S_{ne}(n)$ and $S_{ne}(n) \subset \{1, 2, \ldots, M\}$.
7) Allocate the channel to user j^* for data transmission. The user j^*'s AWF in the next timeslot $n+1, \xi_{j^*}(n+1)$, is reset back to 1.
8) Update $n = n+1$; check whether the timeslot $n = n_{end}$ or not. If Yes, go to 9. If No, go to 2.
9) End

Based on the channel availability and the parameters AWF, the BS selects a CRU with the largest value of weighted preference matric (X_i) and allocates the channel timeslot for data service to it. On the other hand, when the channel is not available, the weight of the user which has the largest preference metric (Y_i) is increased. Then, in the next channel available timeslot, if the ξ_i is large enough, the user will be selected as a result of the weight ξ_i, even it it has a lower channel condition.

By manipulating the AWF in the preference metric Y_i, the proposed scheme is expected not only to be flexible resource allocation among all CRUs, but also to achieve a satisfying fairness performance due to the consideration of the channel availability after each sensing circle.

IV. Simulation and Performance Evaluation

The proposed adaptive weighted scheduling scheme is evaluated through simulation using MATLAB. To demonstrate the performance of the proposed scheme in terms of balancing the throughput and fairness, we compare our proposed scheme with the random scheduling scheme (denoted as RAN) and opportunistic scheduling scheme (denoted as OPT). The RAN scheme can achieve a good fairness performance by allocating resources to different users with equal probability while the OPT scheme can achieve maximum system throughput by allocating resources to the user with the best channel quality.

In our simulations there are two traffic cases that are studied, i) Each node has saturated traffic (buffer is never empty). In this case, we do not need to consider the traffic model; ii) Non-saturated traffic at each node using Poisson call arrivals and a Weibull file size. The buffer will become empty and non-empty from time to time.

The CRN is composed of one CRBS and M CRUs which are uniformly distributed in the circle with radius R. A 5 MHz licensed spectrum band is taken into account. The transmission power at the CRBS is P_w, and the channel model described earlier in Section II is adopted. In addition, we define $P_{r2} = 1 - P_2$, which is the transfer probability of channel of active state to inactive state. Here, P_2 is the probability of a channel staying in active state. Meanwhile, $P_{r1} = 1 - P_1$ is the transfer probability of a channel moving from inactive state to active state. Here, P_1 is the probability of a channel staying in inactive state. The main simulation parameters are listed in Table.

TABLE I
Simulation Parameters

Symbol	Value	Symbol	Value
R	200m	Δt	20ms
P_w	10w	t_{tr}	20ms
M	40	WT	20ms
N_0	$10^{-9}w$	P_{r1}	0.2
k	4	P_{r1}	0.2
c	1/1259	$\Delta\xi$	10
v_i	0.2 m/s	λ	10 call/s
σ_χ	4 dB	B	5 MHz
φ_i	$[0, \pi)$	T	$T\ Weibull(2,2)$

A. Saturated Traffic

The channel capacity provided by the physical layer is defined as the amount of information that can be reliably transmitted over a communication channel, which is given by

$$C_{sys} = \sum_{i=1}^{M} B \cdot \log_2(1 + \gamma_i), \tag{15}$$

where C_{sys} is the system capacity, γ_i is the instantaneous SNR of CRU i, B is the bandwidth and M is the number of CRUs. Assuming the overhead of the MAC layer is negligible, we can count the system throughput by the channel capacity, which is the average number of information bits transmitted over the bandwidth over a period of one second. Figure 2 demonstrates the system throughput versus the number of CRUs. It is observed that system throughput increases with the increase number of CRUs. With a larger number of CRUs, a larger channel-diversity gain can be exploited, which leads to a higher system throughput.

To evaluate the fairness we are using the Jain's fairness index [2], [7], [8]. Figure 3 shows the fairness of the proposed scheme with comparison of the other two schemes. It can be observed that the fairness indices of the proposed AWSS scheme are very close to one, which represents the ideal fairness performance. By adaptively adjusting the weight of the users, the proposed scheme can fairly allocate the available resources among different users. However, the fairness performance of the OPT scheme is noticeably worse than the other two schemes since it only takes the channel condition into account, making some users with the bad channel conditions always deprived of spectrum resources. From the obtained results it can be seen that the proposed AWSS scheme can achieve a good tradeoff between the system throughput and

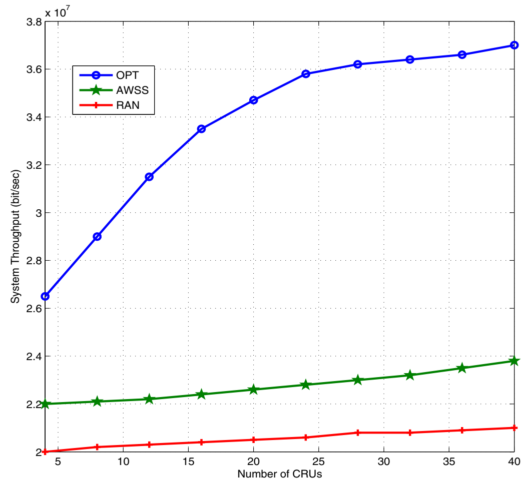

Fig. 2. System throughput versus number of CRUs ($P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

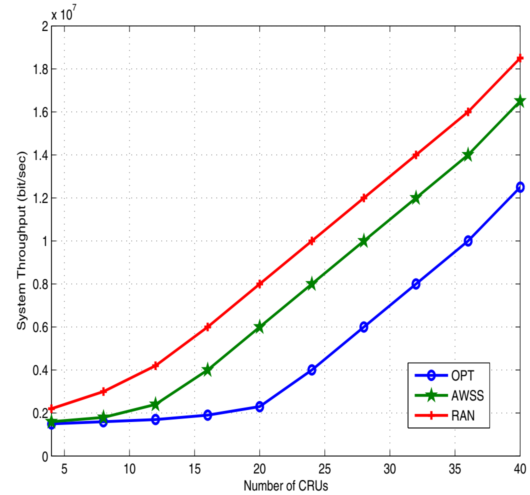

Fig. 4. System throughput versus number of CRUs in non-saturated traffic ($\lambda = 10$, $P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$)

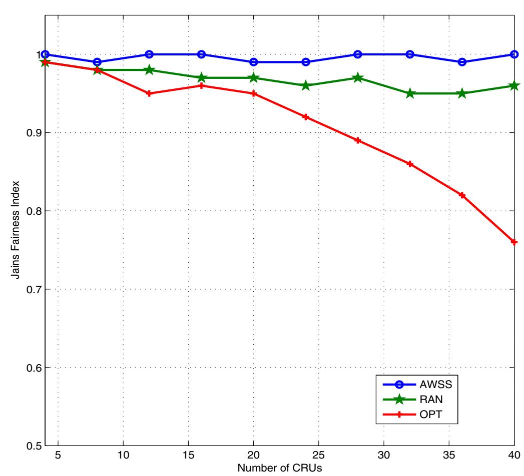

Fig. 3. The fairness performance versus the number of CRUs ($P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

the fairness. Compared to the RAN scheme, it achieves a higher throughput with a slight cost in fairness performance. Meanwhile, compared with the OPT scheme; it achieves a much better fairness performance with some sacrifice of throughput.

B. Non-Saturated Traffic

We assume that non-saturated traffic at each node uses Poisson call arrivals and a Weibull file size whose parameters are given in Table 1. Figure 4 shows the system throughput versus the number of CRUs for the three scheduling schemes. It can be observed that, with an increased number of CRUs, the system throughput increases sharply. The effect of the channel-diversity gain is very distinct in the non-saturated traffic case. In Fig. 5 we observe that the fairness in non-saturated traffic leads to the same conclusions as that found in the saturated traffic case with regards the proposed scheme when compared to the other two schemes. According to the adjustment of the weight of the CRUs, the proposed AWSS scheme could obtain almost ideal fairness performance. However, the OPT scheme, which solely considers the channel condition, has the worst fairness performance. We also observe that the AWSS scheme can achieve a good tradeoff between the throughput and fairness. Compared with the RAN scheme, it achieves a higher throughput at the cost of slightly degraded fairness performance. Meanwhile, compared with the scheme OPT; it achieves a much better fairness performance with some sacrifice of throughput. This is the same conclusions as in the saturated traffic case.

The call arrival rate λ is an important parameter to indicate the traffic load, which affects the system performance. We study the impact of this parameter on system throughput and fairness in the CRN as shown in Figures 6 and 7 , where the λ value is set from 0.1 to 100. It is obvious that the larger value of λ, more traffic of each user has in the queue, the higher system throughput. When λ is large enough, the throughput is almost equal to the throughput with saturated traffic. Since the queue is unlikely to be empty when the λ is big enough, the non-saturated traffic approaches to the saturated traffic.

V. Concluding Remarks

In this article, we have proposed an adaptive weighted scheduling scheme with the aim to achieve a better performance tradeoff in terms of throughput and fairness. The proposed scheme is simple but efficient and offers a flexible and fair scheduling of data traffic in a cognitive radio network. By jointly considering the instantaneous channel conditions, adaptive weighted factor, and the channel availability which is a unique feature of the CRN, this scheduling scheme address

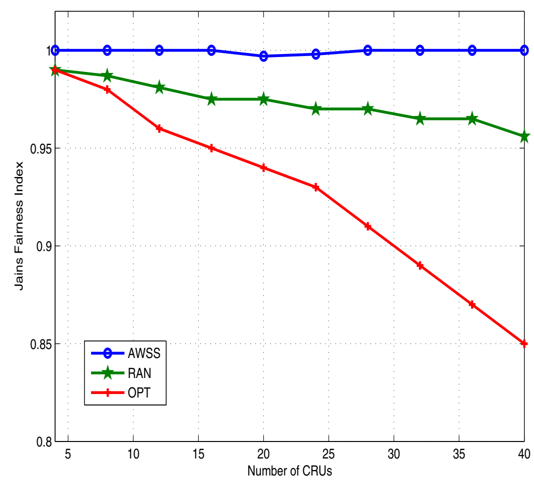

Fig. 5. The fairness performance versus the number of CRUs in non-saturated traffic ($\lambda = 10, P_{r1} = 0.2, P_{r2} = 0.2$, and $\Delta\xi = 10$)..

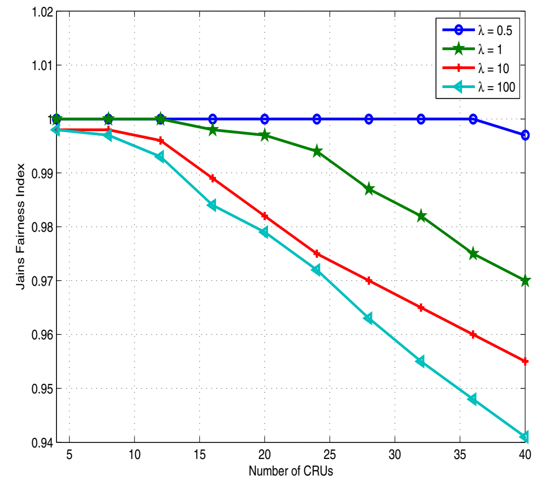

Fig. 7. The fairness performance versus number of CRUs with the different λ in non-saturated traffic ($\lambda = [0.5, 1, 10, 100], P_{r1} = 0.2, P_{r2} = 0.2$, and $\Delta\xi = 10$).

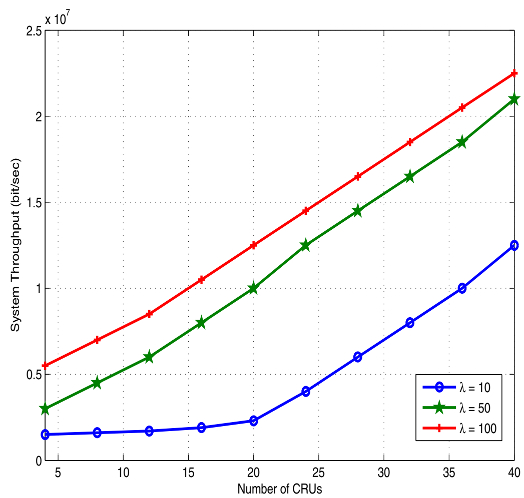

Fig. 6. System throughput versus number of CRUs with the different λ in non-saturated traffic ($\lambda = [10, 50, 100], P_{r1} = 0.2, P_{r2} = 0.2$, and $\Delta\xi = 10$).

the unfairness problem faced by traditional proportional fair scheduling schemes.

The obtained simulation results demonstrate the effectiveness and efficiency of the proposed scheme in fair resource allocation and high resource utilization.

References

[1] J. Mitola, and G. Q. Maguire, "Cognitive radios: making software radios more personal," *IEEE Personal Commun.,* vol. 6, no. 4, pp. 13-18, Aug. 1999.

[2] S. Lu, V. Bharghavan, and R. Srikant, "Fair scheduling in wireless packet networks," *IEEE/ACM Trans. Networking,* vol 7, no. 4, pp. 473-489, Aug. 1999.

[3] S. Borst, and P. Whiting, "Dynamic rate control algorithms for HDR throughput optimization," in *Proc. IEEE INFOCOM,* Anchorage, USA, April 2001.

[4] Y. Liu, E. K. P. Chong, and N. B. Shroff, "Opportunistic transmission scheduling with resource-sharing constraints in wireless networks," *IEEE J. Select. Areas Commun.,* vol. 19, no. 10, pp. 2053-2064, Oct. 2001.

[5] J. M. Holzman, "Asymptotic analysis of proportional fair algorithm," in *Proc. IEEE Symposium on Personal, Indoor, Mobile and Radio Communications,* (PIMRC 2001), San Diego, USA, Sept. 2001.

[6] J-G. Choi and S. Bahk, "Cell-throughput analysis of the proportional fair scheduler in the single-cell environment," *IEEE Trans. Veh. Technol.,* vol. 56, no. 2, pp. 766-778, March 2008.

[7] M. Gidlund and J. Laneri, "Scheduling algorithms for 3GPP long-term evolution systems: From a quality of service perspective," in *Proc. IEEE 10th International Symposium on Spread Spectrum Techniques and Applications* (ISSSTA 2008), Bologna, Italy, Aug. 2008.

[8] M. Gidlund, and N. Debernardi, "Scheduling performance of heavy-tailed data traffic in high-speed shared channels," in *Proc. IEEE Wireless Communication and Networking Conference,* (WCNC'09), May 2009.

[9] B. Wang and D. Zhao, "Scheduling for long term proportional fairness in a cognitive wireless network with spectrum underlay," *IEEE Trans. on Wireless Commun.,* vol 9. no. 3, March 2010.

[10] A. T. Hoang and Y. C. Liang, "A two-phased channel and power allocation scheme for cognitive radio networks," in *Proc. 18nd IEEE Symposium on Personal, Indoor, Mobile and Radio Communications* (PIMRC 2006), Helsinki, Finland, Sept. 2006.

[11] A. T. Hoang, Y. C. Liang and Y. Zeng, "Adaptive joint scheduling of spectrum sensing and data transmission in cognitive radio networks," *IEEE Trans. on Commun.,* vol. 58, no. 1, Jan 2010.

[12] J. Li, B. Xu, Z. Xu, S. Li, and Y. Liu, "Adaptive packet scheduling algorithm for cognitive radio system," in *Proc. IEEE ICCT*, Nov. 2006.

[13] J. Farah and F. Marx, "Combining strategies for the optimization of resource allocation in a wireless mulituser OFDM system," *International Journal of Electronics and Communications*, vol. 61, no. 10, pp. 665-677, Nov. 2007.

[14] S. Huang, X. Liu, and Z. Ding, "Opportunistic spectrum access in cognitive radio networks," in *Proc. IEEE INFOCOM,* Phoenix, USA, April 2008.

[15] R. Urgaonkar and M. J. Neely, "Opportunistic scheduling with reliability guarantees in cognitive radio networks," *IEEE Trans. on Mobile Computing,* vol. 8, no. 6, pp. 766-777, June 2009.

[16] W. Jakes, *Microwave mobile communications,* Wiley, New York, 1974.

[17] G. L. Stuber, *Principles of mobile communications,* Kluwer academic Publisher, 1996.

[18] H. Jiang and W. Zhuang, "Effective packet scheduling with fairness adaptation in ultra-wideband wireless networks," *IEEE Trans. Wireless Commun.,* vol. 6, no. 2, pp. 680-690, Feb. 2007.