Fall 2012

Cooperative power control approaches towards fair radio resource allocation for wireless network

Liuju Wu

COOPERATIVE POWER CONTROL APPROACHES TOWARDS FAIR RADIO RESOURCE ALLOCATION FOR WIRELESS NETWORK

by

LIUJU WU

A THESIS

Presented to the Faculty of the Graduate School of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE IN ELECTRICAL ENGINEERING

2012

Approved by

Dr. Maciej Zawodniok, Advisor
Dr. Kurt Kosbar
Dr. R. Joe Stanley

PUBLICATION THESIS OPTION

This thesis consists of two papers – the first paper [1] is intended to be submitted to IEEE Transaction on Wireless Communications and the second paper [2] is intended to be submitted to International Journal of Wireless & Mobile Networks. Details of the papers included in this thesis are listed below.

[1] Liuju Wu and Maciej Zawodniok, "Cooperative and Fair Power Control for Peer-to-Peer Wireless Networks,"

[2] Liuju Wu, Hao Xu and Maciej Zawodniok, "Cooperative Power Control Approaches Regarding Radio Resource Allocation for Cognitive Radio Network,"

ABSTRACT

Performance optimization in wireless networks is a complex problem due to variability and dynamics in network topology and density, traffic patterns, mutual interference, channel uncertainties, etc. Opportunistic or selfish approaches may result in unbalanced allocation of channel capacity where particular links are overshadowed. This degrades overall network fairness and hinders a multi-hop communication by creating bottlenecks. A desired approach should allocate channel capacity proportionally to traffic priority in a cooperative manner. This work consists of two chapters that address the fairness share problem in wireless ad hoc, peer-to-peer networks and resource allocation within Cognitive Radio network.

In the first paper, two fair power control schemes are proposed and mathematically analyzed. The schemes dynamically determine the viable resource allocation for a particular peer-to-peer network. In contrast, the traditional approaches often derive such viable capacity for a class of topologies. Moreover, the previous power control schemes assume that the target capacity allocation, or signal-to-interference ratio (SIR), is known and feasible. This leads to unfairness if the target SIR is not viable. The theoretical and simulation results show that the capacity is equally allocated for each link in the presence of radio channel uncertainties.

In the second paper, based on the fair power control schemes, two novel power control schemes and an integrated power control scheme are proposed regarding the resource allocation for Cognitive Radio network to increase the efficiency of the resource while satisfying the Primary Users' Quality of Service. Simulation result and tradeoff discussion are given.

ACKNOWLEDGMENTS

It is my honor and pleasure to extend my warm thanks to all the following people for their support and help that leads to the successful completion of the thesis.

I would like to extend my great thanks and appreciation to Dr. Maciej J. Zawodniok, my advisor and friend. His guidance and support along with a warm and kind heart have inspired me both academically and personally. I'm very lucky and grateful to encounter such a great person to be my advisor in my life. I would also like to extend my best wishes towards his future life. I would also like to acknowledge National Science Foundation for supporting the research.

I am grateful to have Dr. Kurt L. Kosbar and Dr. R. Joe Stanley as my committee members. I am very thankful for the kind support from them. I would also like to thank the faculty and staff of Dept. of ECE at Missouri S&T for helping me in all ways.

I would like to extend my great thanks to my all my friends world-wide. Their support gives me the strength to survive the difficult time in my life. I would like to deliver my special thanks to my Rolla friends and Mr. Nilges who loves and supports me all along. They made my time at Rolla be life-time unforgettable.

I am fortunate to have a nice group of research mates. I enjoyed the wonderful time working with them at ERL and the enjoyble discussion both technical and otherwise.

At last, I would like to give my great thanks to my entire family. Without their support, I would not accomplish such work and have such happy time of my life. The greatest thanks belongs to my parents, Mr. Xianze Wu and Mrs. Wei Liu who I know will always be there for me.

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

LIST OF TABLES

1. INTRODUCTION

Fair radio resource sharing is a desired behavior in modern wireless networks including wireless sensor networks (WSN), cognitive radio network (CRN), and data access networks [1-4]. However, that goal is challenging to achieve in wireless networks due to channel uncertainties, random topology, dynamic environment, etc. Furthermore, the increased usage of the wireless communication in many applications exacerbates the challenge since increasing number of competing users worsens the congestion. Efficiency of radio resource allocation impacts performance of a wireless network. In particular, in a large network, multiple transmissions could create more interference among adjacent links. Non-cooperative solutions often lead to unbalanced allocation of channel capacity where specific links overshadow others. In contrast, a cooperative approach has potential to control the entire network and provide global fairness. This work considers to types of fairness: equal capacity allocated to each user or link, and a weighted sharing where the capacity is proportional to a predefined priority.

One of the most important quality-of-service (QoS) metric is throughput. In the wireless networks, the achievable throughput is limited by the channel capacity. It is defined by the Shannon –Hartley theorem in terms of Signal-to-Interference Ratio (SIR). Hence, the channel capacity can be managed through selection of an appropriate target SIR. In turn, power control mechanism is often employed to dynamically achieve the target SIR on a link level. Hence, we propose a cooperative scheme that both determines a fair, achievable SIR and controls the power. The goal of both papers is to design the cooperative resource allocation and power control schemes for wireless peer-to-peer networks and CRNs.

Typically, theoretical study of the channel capacity is done as in [5]. The study in [5] shows that under assumption of a non-interference protocol, the attainable throughput is $\Theta\left(\frac{W}{\sqrt{n}\log n}\right)$ bits per second for a network with n randomly located nodes and bandwidth, W. The general results give the relationship between the number of nodes and statistically attainable throughput. However, for a particular network, for example non-grid, random topology, the achievable, fair capacity varies. Links in densely populated area could be significantly congested thus resulting in lower throughput than the general studies indicate. At the same time, other nodes in less densely areas are more likely to achieve higher throughput. Such an imbalance is often undesirable.

Some link-level power control schemes have been proposed at previous work [6]-[10]. The channel capacity efficiency improves with more accurate control of SIR which results in lower interference. Due to local, distributed control, these schemes are not cooperative. Additionally, these works often define an arbitrary utility or pricing function that maximizes only the local performance. As a result, those schemes satisfy the utility and pricing functions, while the overall network performance often suffers. In [11]-[12], the fairness in radio channel capacity allocation is addressed by selecting an appropriate target SIR for the power control. However, the schemes require the target SIR to be feasible. Otherwise, the schemes will result in unfairness when congested links maximize the transmission power without reaching the target SIR. Moreover, this results in significant interference injected into the radio channel.

In contrast, the Paper I achieves equal allocation of the channel capacity on each link by discovering the feasible SIR level. First, we reformulated the SIR and power control problem by inverting the SIR and considering a ratio-of-interference-to-signal

(RIS). Note, that the RIS formulation retains the property of equal fairness when all links converge to the same RIS value. Then, we propose a Cooperative RIS-based Power Control (CRPC) scheme where the nodes update their power such that the link-level and network average value of RIS converge. The nodes exchange information about the average RIS value. The scheme can employ one of several implementation techniques for the calculation of the average RIS including centralized and distributed methods. The analysis and simulation results in Paper I demonstrate that either approach ensures convergence to a common RIS value. However, only the centralized scheme is mathematically guaranteed to converge. Moreover, it performs the update of the target RIS based on the average from entire network thus identifying a more efficient, low power solution. Overall, two benefits of the CRPC have been shown:

- Network fairness equilibrium regarding capacity for each link is identified for each particular, randomly generated network topology. Consequently, the radio resources are fairly allocated when the power update is applied
- The distributed version of CRPC achieves the same fairness goal through iterative dissemination of the average RIS, one hop at a time. However, the updates are based on a one-hop information only thus leading to selection of a higher power

Next, in Paper II, we consider application of the RIS-based scheme in cognitive radio networks (CRNs) where pairs of primary and secondary users share common channel resources. The topology of a CRN is similar to the peer-to-peer type networks considered in Paper I. However, the CRNs differentiate users by giving priority to the primary users. Hence, the revised scheme supports a proportional fairness instead of simple equal fairness in Paper I. The work in Paper II addresses three important issues in CRNs:

- Ensure the minimum QoS for the primary users while fairly sharing the remaining radio resources among the secondary users
- Support various types of primary users including legacy, new or adoptive, and cooperating ones
- Support quick adaptation of resource sharing in the presence of primary users who periodically switch between active and idle operating modes. For example data access networks, which transmit only when there are data to send

In CRN type applications, varying levels of capacity are required for each user based on their priority. Hence, a Cooperative Proportional RIS Power Control (CPRPC) is proposed in Paper II. Each link is assigned a weight that determines the fraction of resources allocated to that link. The CPRPC scheme is analyzed theoretically and in simulations. It is shown to guarantee the proportional fairness in channel capacity allocation based on the links weight.

However, a direct application of the CPRPC scheme in CRNs is not suitable since the primary users have to achieve certain minimal level of service, or SIR. Only then the secondary users can share the remaining resources. In many locations there is a significant amount of white spectrum space that the secondary users can utilize. Thus a large amount of research has been conducted on supporting the CRNs [13]-[19]. In [15]-[18], transmit power control systems are designed to addressing the challenge of dynamically adjust the power with respect to interference level of PU in a cognitive network. An integration scheme with power control, access control, and multi-hop transmission on efficiency of spectral resource with a cognitive radio system is evaluated [19]. However, those existing works do not explicitly address fairness aspect of channel access, both between the primary and secondary users, and among the secondary users. Overall, we propose a set of three schemes that address the fairness in CRN:

- Cooperative RIS Power Control with Fixed power of PU (CRPCF)
- Cognitive Radio Power Control with Variable PUs' power (CRPCV)
- An integrated power control scheme addressing two modes of PUs

The first two perform iterative update of link weights in order to ensure the PU achieves the minimum service. The third scheme improves convergence time when the PU periodically switches between an active, transmitting mode and an idle, sleep mode. The third scheme controls SUs to improve utilization of the network resources when PU is in sleep mode while ensuring quick release of the resources when the PU activation is detected. The system memorizes the scheme's parameters and restores them when the PU' mode switch is detected. All three proposed schemes are able to reach two main CRN's goals:

1) Satisfy the QoS of Primary Users (PUs) such that channel capacity for each PU is guaranteed at a minimum, threshold capacity

2) Secondary Users (SUs) share the spare resource of the network proportionally to the assigned weight

The specific application requirements, constraints, and environment conditions would determine the most suitable scheme. The presented simulations and tradeoff analysis provide guidance for that decision process.

In summary, this work addresses the fairness in wireless networks. Cooperative resource allocation and power control schemes are proposed and applied to peer-to-peer and cognitive radio networks. Analysis of the network performance is presented in both papers including mathematical proofs and simulation results.

REFERENCES

[1] Pradnya Gajbhiye, Anjali Mahajan, “A Survey of Architecture and Node deployment in Wireless Sensor Network,” First International Conference on the Application of Digital Information and Web Technologies, Aug., 2008

[2] Khajonpong Akkarajitsakul, Ekram Hossain, Dusit Niyato, and Dong In, “Game Theoretic Approaches for Multiple Access in Wireless Networks: A Survey,” IEEE Communications Surveys & Tutorials, Vol. 13, No. 3, Third Quarter 2011

[3] Sherry Wang, Harold Zheng, “ A Resource Management Design For Cognitive Radio Ad Hoc Networks,” IEEE Military Communications Conference, Oct., 2009

[4] Atef Abdrabou and Weihua Zhuang, “Statistical QoS Evaluation for Cognitive Radio Networks,” IEEE Global Telecommunications Conference, Dec, 2011

[5] P. Gupta and P R. Kumar, “The Capacity of Wireless Networks," IEEE Transactions on Information Theory, vol. 46, No. 2, 2000, pp. 388-404

[6] Falomari, N. B. Mandayam, and D. J. Goodman, “A new framework for power control in wireless data networks: Games utility and pricing,” in Proc. Allerton Conf. Commun., Control, Comput., IL, Sep. 1998, pp. 546–555

[7] U. Saraydar, N. B.Mandayam, and D. J. Goodman, “Efficient power control via pricing in wireless data networks,” IEEE Trans. Commun., vol. 50, no. 2, pp. 291–303, Feb. 2002

[8] R. Fattahi and F. Paganini, “Neweconomic perspectives for resource allocation in wireless networks,” in Proc. Amer. Control Conf., Portland, OR, Jun. 2005, pp. 3690–3695

[9] T. Alpcan, T. Basar, and R. Srikant, “CDMA uplink power control as a noncooperative game,” Wireless Netw., vol. 8, pp. 659–670, 2002

[10] W. Sung and W. S. Wong, “A noncooperative power control game for multirate CDMA data networks,” IEEE Trans. Wireless Commun., vol. 2, no. 1, pp. 186–194, Jan. 2003

[11] N. Bambos, S. Chen, and G. J. Pottie, “Channel access algorithms with active link protection for wireless communication networks with power control,” IEEE/ACM Trans. Networking, pp. 583-597, Oct. 2000

[12] Kin K. Leung, "Power Control by Interference Prediction for Broadband Wireless Packet Networks," IEEE Transactions on Wireless Communications, Vol. 1, NO. 2, APRIL 2002

[13] F. Akyildiz, W. Y. Lee, M. C. Vuran and S. Mohanty, "Next generation/dynamic spectrum access/cognitive radio wireless network a survey," Computer Network Journal (Elsevier), Sep. 2006

[14] N. Devroye, P. Mitran, and V. Tarokh, "Achievable rates in cognitive radio channels," IEEE Trans. Inf. Theory, vol. 52, pp. 1813–1827, May,2006

[15] Hong-Sam T. Le and Qilian Liang, "An Efficient Power Control Schemefor Cognitive Radios," IEEE Communications Society subject matter experts for publication in the WCNC

[16] Yan Chen, Guanding Yu, Zhaoyang Zhang, Hsiao-Hwa Chen, and Peiliang Qiu, "On cognitive radio networks with opportunistic power control strategies in fading channels,"IEEE Transactions on Wireless Communications, Vol.7, No.7, July 2008

[17] Shunqiao Sun, Weiming Ni, and Yu Zhu, "Robust Power Control in Cognitive Radio Networks: A Distributed Way," IEEE International Conference on Communication, June, 2011

[18] You-En Lin, Kun-Hsing Liu and Hung-Yun Hsieh, "Design of Power Control Protocols for Spectrum Sharing in Cognitive Radio Networks: A Game-Theoretic Perspective," IEEE International Conference on Communication, May, 2010

[19] Naotaka Shibata, Koji Yamamoto, Hidekazu Murata, and Susumu Yoshida, "Joint effect of power control, access control, and multi-hop transmission on area spectral efficiency of cognitive radio system, " 6th International Conference on Information, Communications & Signal Processing, Dec., 2007

PAPER

I. COOPERATIVE AND FAIR POWER CONTROL FOR PEER-TO-PEER WIRELESS NETWORK

Liuju Wu, Maciej Zawodniok, Member, IEEE
Electrical and Computer Engineering Department
Missouri S&T, Rolla, USA

(lw6t9@mail.mst.edu, mjzx9c@mst.edu)

ABSTRACT

Performance optimization in wireless networks is a complex problem due to variability and dynamics in network topology and density, traffic patterns, mutual interference, channel uncertainties, etc. In particular, it is difficult to fairly allocate radio resources in large networks. Opportunistic or selfish approaches may result in unbalanced allocation of channel capacity where particular links overshadow others. A desired approach should provide every link in the network with the fair share of radio resource. Addressing this issue, analysis about the wireless network and a cooperative power control update scheme for the peer-to-peer wireless network are introduced. The discussion and proposed scheme dresses on the point that every node in the network should achieve the same share of the resource or capacity i.e. each node pair will have the same Signal-to-Interference ratio (SIR) in the same shared channel. The simulation shows that with the same initial power, the network can achieve the same SIR value for each node pairs with the power update using the proposed scheme. The proofs for the proposed scheme are also given in the paper.

1.1. INTRODUCTION

A peer-to-peer wireless communication is employed in wireless networks with neither centralized access points nor a pre-established infrastructure. There is a wide range of practical applications of a peer-to-peer based communication including cognitive communication, mobile ad hoc networks, wireless sensor networks, multimedia sharing, etc. Such distributed wireless networks share the common radio frequency spectrum. Theoretical analysis of basic topologies [31] shows that for *n* randomly located nodes the attainable throughput under a non-interference protocol is $\Theta\left(\frac{W}{\sqrt{n}\log n}\right)$ bits per second. Ideally, the entire radio spectrum is fairly shared among the links, either equally or proportionally to the link's priority and demand. However, in a random topology the links may achieve varying and unfair share of the channel capacity because of non-uniform distribution of traffic and interference. For example, nodes in densely populated area experience high interference thus reducing achievable throughput while nodes in sparsely populated regions may be able to achieve high performance. Conversely, the nodes from sparse area can dominate and overuse the channel while injecting significant interference into the adjacent densely populated areas. As a result, the imbalance in spectrum sharing increases.

Moreover, in multi-hop networks, the end-to-end performance depends on the weakest links in the path (bottlenecks). The interference among the adjacent links may cause increased interference from strong links to the bottlenecks thus further weakening their performance. As a result, the wireless network performance further degrades. In contrast, the overall network performance increases if the links along the routing paths maintain the same capacity. In such scenario there is no single bottleneck link.

Additionally, the mutual interference is reduced thus improving the average SIR and overall throughput.

Traditionally, the power update schemes achieve it by setting a target signal to interference ratio (SIR) to the same (or proportional) value and applying a power control scheme at a link level. However, those works make the assumption that the target SIR is achievable by all nodes. While, for non-congested network such an approach is sufficient, it fails in congested, dense scenarios where the maximum achievable SIR is not known. In case of traditional power control schemes, when a single link is not able to achieve its target SIR it attempts to increase transmission power to compensate for the high interference. However, the adjacent links will react by increasing their power to compensate for higher interference. Consequently, the power control may quickly reach the node's maximum transmission power without actually achieving the target SIR thus causing the link outage. At the same time, by using the maximum transmission power it injects a significant interference to the channel thus increasing probability of other links outages.

Among the existing power control schemes, a few non-cooperative game theoretic schemes have been introduced [1]-[5]. These schemes are more focused on improving the performance of each link according to the local information from the link itself. The utility and pricing function is also derived based on non-cooperative theory and try to reach the Nash equilibrium. They are non-cooperative because each user in the network tries to maximize the defined utility function of its own and increase its own transmission without looking at all the other nodes' information and demands or at least the neighborhood nodes' information. This kind of non-cooperative can guarantee the optimal performance at link level but may degrade the overall performance including losing the fair share of the radio resource. In this the section IV of this paper, a novel power scheme is proposed based on not only the information at the aim link but also the information from other links which may be impacted by the energy that the transmitter generates. As a result, the power update is not selfish but more cooperative with the other users in the network. A goal of fair share of the network resource is guaranteed which is missed among those existing power control schemes.

In the analysis section of this paper, other peers' information in the network is utilized to guarantee fairness with achieving the same SIR on the receiver end of each link. Based on this cooperative concept, the power update scheme is proposed to control the power from the transmitter end of the link in order to reach the goal of fairness in the network at each time instant.

The main contributions of this scheme are: (1) the modeling and analysis of the peer-to-peer wireless network in terms of fair sharing of the radio resources; (2) development of a power control scheme which determines the appropriate SIR for each node pair based on network-wide cognition of channel state; (3) the mathematical proof of the control scheme which guarantees its reliability.

1.2. RELATED WORK

A number of power control schemes are proposed for the wireless network to improve the performance of peer-to-peer transmission link. They aim at achieving the fair channel allocation through power control with assumption of known target capacity or SIR. In [28], a distributed adaptive power control for wireless network is proposed to optimize spectral reuse to decrease the interference within the network. It helps to increase the overall capacity of the network but the fairness share of the network resource is not considered. In [26], the power control is proposed to reduce the power dissipation with satisfying the SNR threshold and the fairness share of the network is satisfied by the joint link scheduling rather than power control. In [6] , [7], [27] and [29], the power controls are based on a known desired SIR that is desired to achieve which means a certain desired SIR is determined before the power control is implemented to the network. However, in peer-to-peer wireless network, the *desired SIR value is often unknown* due to lack of preexisting infrastructure and random topology. Therefore, in this paper, the analysis considers a realistic scenario when the desired SIR is *not known* and cannot be calculated before deployment. The proposed scheme determines the desired SIR online. It iteratively calculates the adequate power and SIR target based on the information of other nodes in the network. In contrast to the traditional approaches it dynamically calculates the achievable desired SIR without a priori knowledge. Moreover, the presented theoretical proof using Lyapunov approach guarantees that the network maintains fairness in terms of per link capacity.

There is a large literature that either studies the theoretical limits of network capacity with analysis of the network channel models [31] [33] or physics law [32]. The conclusion with respect to the capacity limits is general towards the different network topologies and channel environments. They assume that there is an implementable, online scheme that determines the best, fair SIR level for all links in the specific network topology and under dynamic, fading channel. Hence, for certain case, the capacity will be within the limits but the certain value of capacity is unknown. In contrast, the proposed scheme is more practical in a realistic, fading environment and random deployment since it determines the capacity limit online. Finally, the reliability of the scheme is guaranteed through a theoretical proof.

The rest of the paper is organized as following. First, the relevant background is discussed in Section III. In Section IV, the analysis for the wireless network addressing the SIR is discussed. Next, the proposed spectrum allocation and power control schemes is presented in Section V. The mathematical proof of the reliability of the proposed scheme is included in Section V. In section VI, the simulation results with comparison with some previous schemes are discussed. Finally, the conclusions are given in Section VII.

1.3. BACKGROUND ON MODELING

Each receiver node in the wireless network, besides receiving the signal from the corresponding transmitter, receives interference from other transmitters in the network. The links performance is impacted by such interference. Shannon's capacity formula defines the available capacity on each link based on the signal-to-interference (SIR) ratio at the receiver. Traditional approach of describing the dynamics of wireless channel in terms of per-link channel capacity and power usage considers signal-to-interference ratio [21-25]:

$$SIR_i(t) = \frac{g_{ii}(t)p_i(t)}{\sum_{j\neq i}[g_{ij}(t)p_j(t)]+\eta(t)} \quad (1)$$

where $g_{ij}(t)$ is a attenuation from transmitter of j^{th} link to receiver of i^{th} link, $p_i(t)$ is transmission power on i^{th} link, and $\eta(t)$ is thermal noise.

Ideally, the power and spectrum allocation scheme should minimize the interference for each link in order to maximize the energy efficiency and maximize throughputs.

1.3.1. Power attenuation model

In the radio channel, the signal is attenuated during propagation from the j^{th} link transmitter to the i^{th} link receiver. This paper considers the channel uncertainties including path loss, multipath fading, and shadowing effect. The power attenuation is equal to the combination of those factors, which is modeled using [10]:

$$g = f(d, n, X, \xi) = \bar{g}d^{-n} \cdot X^2 \cdot 10^{0.1\xi} \qquad (2)$$

where $\bar{g}d^{-n}$ is the path loss component, X^2 random variable represents the Rayleigh fading [9], and $10^{0.1\xi}$ denotes the shadowing [10][11]. For the shadowing, ξ is a Gaussian random variable, while Rayleigh fading follows probability density function as in [9]

$$pdf(x) = \begin{cases} \frac{x}{\delta^2} exp\left(-\frac{x}{2\delta^2}\right) & (0 \le x \le \infty) \\ 0 & (x < 0) \end{cases} \qquad (3)$$

1.3.2. Cooperative Proportional Power Control (CPPC)

Assume there are n pairs of node pair in the peer-to-peer wireless network with n transmitter nodes and n receiver nodes which means 2n nodes in total. For each time instant k, we calculate the average SIR level of the network as below:

$$SIR_{aver}(k) = \frac{\sum_{i=1}^{n} SIR_i(k)}{n} \qquad (4)$$

where SIR_{aver} stands for the average SIR of all the receiver nodes at instant k; n is the number of the link in the network; $SIR_i(k)$ is the i^{th} receiver's SIR level.

In [30], a power update scheme named as Cooperative Proportional Power Control (CPPC) is introduced. With the power update law

$$P_i(k+1) = \frac{n(K_V - 1)error_i(k)}{(n-1)\, g_{ii}(k)} I_i(k) + P_i(k) \tag{5}$$

where $error_i(k) = SIR_i(k) - SIR_{aver}(k)$, the links will achieve the same SIR level i.e. $error_i(k)$ will converge to zero eventually.

The CPPC power is updated based on both the local information – including current power, link gain, and interference – and network-wide metric of the average SIR. The latter facilitates collaboration among the nodes in the form of a game theory based control. However, the scheme has some limitations. First, it is a relatively simple proportional update that does not consider the interactions among the adjacent links. Also, it relies on strong assumptions including a static environment and channel. It leads to a slow convergence time and high power requirements. The scheme proposed in section V has overcome the weakness and analytically guarantees fairness thus resulting in scheme with quicker convergence and lower power requirements.

1.4. ANALYSIS OF SYSTEM MODEL

The Shannon-Hartley theorem defines the channel capacity as equal to:

$$C = Blog_2(1 + SIR) \tag{6}$$

where C stands for the channel capacity, B denotes the bandwidth of the channel; SIR denotes the signal-to-interference ratio. The goal of the proposed scheme is to allocate the radio resources equally, that is the capacity of each link is the same. Consequently, from (6) the goal can be restated as to achieve equal SIR value for each link. Thus the problem is converted into power control for each transmitter node such that the same SIR is maintained on each link.

The traditional SIR-based formulation (1) has been exploited in the past to study and design power and rate control schemes for cellular, wireless ad hoc, and sensor networks. However, those schemes either (a) do perform opportunistic, i.e. selfish, optimization at link level [21,29-31] that may lead to unfair allocation of channel to links, or (b) assume that the target values for SIR or target rate are known for entire network and achievable [29]. Hitherto, there was little work done that performs such a power and rate adaptation without these assumptions while ensuring fairness among the links and sources.

Guarantying fairness in a random peer-to-peer, ad hoc network is both beneficial and challenging. The challenge is due to nonlinear channel fading, interactions among adjacent links, and random topologies with mobility and often non-uniform nodes density. The fairness' guarantee benefits various wireless applications where fair spectrum resource allocation. This includes multimedia network, real-time network control, and flow control in multi-hop networks. Furthermore, the network-wide guarantee of performance in an inherently distributed system of wireless networks is essential for practical implementations.

A novel approach is proposed to the above problem by deriving a fair power control. First, the channel model (2) is redefined as a ratio-of-interference-to-signal (RIS) that is an inverse of SIR:

$$RIS_i(t) = \frac{\sum_{j\neq i} c_{ij}(t)+\eta(t)}{c_{ii}(t)} \tag{7}$$

where $RIS_i(t)$ is the i^{th} link RIS value, and $c_{ij}(t) = g_{ij}(t)p_j(t)$ is the j^{th} link component of received signal.

Remark 1: Such formulation has several advantages including simpler dynamic model of the entire network, a better scaling in low SIR rage typical for highly congested multimedia networks, and a new insight into channel capacity.

As discussed in the introduction, the ideal outcome is when the spectrum is fairly shared among the links. For simplicity, we will assume the fairness criteria to be equal throughput that is equivalent to the equal target SIR. Note, that when all links reach the same SIR level, the corresponding links' RIS values are also equal.

For the analysis in the following sections, we made the following assumptions:

1) The thermal noise is considered as another source of interferences represented as C_n besides the interference from the other N-1 nodes and is not controlled by anything else and random. Its impacts on RIS is in the form of an upper bound on achievable RIS value which means $\mathrm{RIS_i(t)} \gg \mathrm{C_n}$

2) We assume that the proposed update scheme is updated faster than the changes to the network due to mobility and the environment changes. Hence, the average attenuation changes are considered small enough to be ignored during each update period. The iterative and converging properties of the proposed work ensure that such changes are accommodated and countered by the updates.

First, we derive the dynamic equation of RIS by differentiating (7).

$$RIS_i(t)' = \frac{\sum_{i\neq j} C_{ij}(t)' C_{ii}(t) - C_{ii}(t)' \sum_{i\neq j} C_{ij}(t)}{C_{ii}(t)^2} \tag{8}$$

where $RIS(t)^{'}$ is the derivative of $RNS(t)$, and $C_{ij}(t)^{'}$ and $C_{ii}(t)^{'}$ are derivatives of $C_{ij}(t)$ and $C_{ii}(t)$ respectivelly. Note that the noise component can be considered as one of the interference term $c_{ij}(t)$ thus simplifying the analysis. We discretize the system description using the Euler's formula, $\frac{x(k+1)-x(k)}{T}$, where T is the sampling interval:

$$\frac{RIS_i(k+1)-RIS_i(k)}{T} = \frac{\sum_{i\neq j}\frac{C_{ij}(k+1)-C_{ij}(k)}{T}\cdot C_{ii}(k)-\frac{C_{ii}(k+1)-C_{ii}(k)}{T}\cdot\sum_{i\neq j}C_{ij}(k)}{C_{ii}(t)^2} \qquad (9)$$

Now, we select a multiplicative power update law:

$$p_i(k+1) = \beta_i(k)p_i(k) \qquad (10)$$

where $\beta_i(k)$ is the update coefficient for ith link which we derive below. Using the power update law (10), the discrete state equation (9) can be rewritten as

$$RIS_i(k+1) = RIS_i(k) + \frac{\sum_{i\neq j}[\beta_j(k)-\beta_i(k)]C_{ij}(k)}{C_{ii}(k)} \qquad (11)$$

The network-wide average of the RIS values at instance k is equal to:

$$RIS_a(k) = \frac{1}{n}\sum_{i=1}^{n} RIS_i(k) = \frac{1}{n}\sum_{i=1}^{n}\frac{\sum_{i\neq j}C_{ij}(k)}{C_{ii}(k)} \qquad (12)$$

For the average RIS, we made the assumption that for the consecutive iteration the average RIS doesn't change much since the interference will not change much for consequent iterations because of the update law which will be shown in the latter part of this paper.

And the average RIS for next time instance, k+1, would expressed as:

$$RIS_a(k+1) \cong RIS_a(k) \qquad (13)$$

The goal of the fair resource allocation is to reaching the same RIS on each link. Hence, the error is defined as the difference between each link's RIS and the average RIS. The error becomes zero when that goal is achieved. This error is expressed as

$$e_i(k) = RIS_i(k) - RIS_a(k) \qquad (14)$$

Then for the next time interval,

$$e_i(k+1) = RIS_i(k+1) - RIS_a(k+1) = e_i(k) + \frac{\sum_{i\neq j}[\beta_j(k)-\beta_i(k)]c_{ij}(k)}{c_{ii}(k)} = e_i(k) + \gamma_i(k) \quad (15)$$

where

$$\gamma_i = \frac{\sum_{i\neq j}[\beta_j(k)-\beta_i(k)]c_{ij}(k)}{c_{ii}(k)} \quad (16)$$

With the analysis, a power scheme named is proposed in Section V.

1.5. METHODOLOGY

A power control scheme is introduced in this section with respect to the analysis in the last section. It is named as cooperative RIS power control (CRPC). The inverse of SIR is defined and used in this control scheme. Since the RIS of the other nodes are also taken into consideration, the scheme is cooperative and reaches the goal of fairness.

With the analysis in RIS aspect in the section IV, the problem is converted into finding the appropriate power update to converge the error (15).

For the purpose of convenience, the minimum value and the maximum value of the RIS in the network are expressed as: $RIS_{min}(k) = min\{RIS_i(k)\}$, $RIS_{max}(k) = max\{RIS_i(k)\}$.

For the multiple nodes pairs the power control should asymptotically decrease the absolute value of the summation of the error (15) to zero. Hence, the following power update law is proposed.

Theorem 1: For any pair of links with dynamics (11) and channel uncertainties, the links will achieve the same SNR level when the transmission power is updated using

$$\beta_i(k) = \frac{k_v(k)e_i(k)}{RIS_a(k)} + 1 \quad (17)$$

Provided that $k_v(k)$ satisfies the flowing constraint:

$$k_v(k) < min\left\{\frac{RNS_a(k)}{RNS_i(k)}, \left|\frac{2\left(RIS_a(k) - RIS(k)\right)RIS_a(k)}{\left(RIS_{max}(k) - RIS_i(k)\right)RIS_i(k)}\right|, \left|\frac{2\left(RIS_a(k) - RIS_i(k)\right)RIS_a(k)}{\left(RIS_{min}(k) - RIS_i(k)\right)RIS_i(k)}\right|\right\} \quad (18)$$

Proof: The proof below will show that with the (17), the upper and lower bound of $e_i(k)$ for each iteration is getting closer to zero.

Define the Lyapunov function candidate as $L = e_i^2(k)$ where. Then, the first difference of Lyapunov candidate function is equal to

$$\Delta L = e_i^2(k+1) - e_i^2(k) = \left(e_i(k) + \gamma_i(k)\right)^2 - e_i^2(k) = 2e_i(k)\gamma_i(k) + \gamma_i^2(k) \quad \textit{(19)}$$

Then applying the control law (17) to (19) we get

$$\Delta L = 2e_i(k)\frac{k_v(k)}{RIS_a(k)}\frac{\sum_{i\neq j}[e_j(k) - e_i(k)]C_{ij}(k)}{C_{ii}(k)} - \left(\frac{k_v(k)}{RIS_a(k)}\frac{\sum_{i\neq j}[e_j(k) - e_i(k)]C_{ij}(k)}{C_{ii}(k)}\right)^2 \quad (20)$$

Then replace (14) into (20) we get

$$\Delta L = 2e_i(k)\frac{k_v(k)}{RIS_a(k)}\frac{\sum_{i\neq j}[RIS_j(k) - RIS_i(k)]C_{ij}(k)}{C_{ii}(k)} - \left(\frac{k_v(k)}{RIS_a(k)}\frac{\sum_{i\neq j}[RIS_j(k) - RIS_i(k)]C_{ij}(k)}{C_{ii}(k)}\right)^2 =$$

$$2e_i(k)H_i(k) + H_i^2(k) \quad (21)$$

where $H_i(k) = \frac{k_v(k)}{RNS_a(k)}\frac{\sum_{i\neq j}[RIS_j(k) - RIS_i(k)]C_{ij}(k)}{C_{ii}(k)}$

In the following proof, four cases are considered to demonstrate that for $i = 1,2,\dots,n$, the network-wide error range decreases after every iteration. That is $max\{e_i(k)\}$ and $min\{e_i(k)\}$ are converging to zero in each iteration. Also, it is shown that the error in next iteration $\{e_i(k+1)\}$ will not exceed the $max\{e_i(k)\}$ and $min\{e_i(k)\}$. The convergence condition holds with the constraint (18) on dynamic gains of the controller. The controller design and analysis is conducted using Lyapunov stability analysis thus guaranteeing network-wide convergence to the common, fair capacity allocation.

Case I: $H_i(k) > 0$ and $RIS_i(k) < RIS_a(k)$, that is $(e_i(k) < 0)$

The first difference of Lyapunov candidate function is equal to:

$$\Delta L = 2e_i(k)H_i(k) + H_i^2(k) = H_i(k)\big(2e_i(k) + H_i(k)\big) = H_i(k)\Big(2e_i(k) +$$

$$kvkRISaki\neq jRISjk{-}RISikCijkCiik<$$

$$H_i(k)\left(2e_i(k) + \frac{k_v(k)}{RIS_a(k)}\frac{\sum_{i\neq j}[RIS_{max}(k)-RIS_i(k)]C_{ij}(k)}{C_{ii}(k)}\right) =$$

$$H_i(k)\left\{2e_i(k) + \frac{k_v(k)}{RIS_a(k)}\big(RIS_{max}(k) - RIS_i(k)\big)\frac{\sum_{i\neq j}C_{ij}(k)}{C_{ii}(k)}\right\} = H_i(k)\Big\{2e_i(k) +$$

$$kvkRISakRISmaxk{-}RISikRISik \qquad (22)$$

In this case $\Delta L < 0$ as long as the following condition holds:

$$k_v(k) < \frac{2\big(RIS_a(k)-RIS_i(k)\big)RIS_a(k)}{\big(RIS_{max}(k)-RIS_i(k)\big)RIS_i(k)} = \left|\frac{2\big(RIS_a(k)-RIS_i(k)\big)RIS_a(k)}{\big(RIS_{max}(k)-RIS_i(k)\big)RIS_i(k)}\right| \qquad (23)$$

Consider the pair i such that $RIS_i(k) = RIS_{min}(k)$. Then the condition (23) holds since $RIS_{min}(k) < RIS_a(k)$ and $H_i(k)$ is positive for $RIS_i(k) = RIS_{min}(k)$. In conclusion, the lower bound of $e_i(k)$ for each iteration asymptotically converges to zero provided (23) holds in this case.

Case II: $H_i(k) < 0$ and $RIS_i(k) > RIS_a(k)$, that is $(e_i(k) > 0)$

The first difference of Lyapunov candidate function is equal to:

$$\Delta L = 2e_i(k)H_i(k) + H_i^2(k) = H_i(k)\big(2e_i(k) + H_i(k)\big) = H_i(k)\Big(2e_i(k) +$$

$$\frac{k_v(k)}{RIS_a(k)}\frac{\sum_{i\neq j}[RIS_j(k)-RIS_i(k)]C_{ij}(k)}{C_{ii}(k)}\Big) < H_i(k)\left(2e_i(k) + \frac{k_v(k)}{RIS_a(k)}\frac{\sum_{i\neq j}[RIS_{min}(k)-RIS_i(k)]C_{ij}(k)}{C_{ii}(k)}\right) =$$

$$H_i(k)\left\{2e_i(k) + \frac{k_v(k)}{RIS_a(k)}\big(RIS_{min}(k) - RIS_i(k)\big)\frac{\sum_{i\neq j}C_{ij}(k)}{C_{ii}(k)}\right\} = H_i(k)\Big\{2e_i(k) +$$

$$\frac{k_v(k)}{RIS_a(k)}\big(RIS_{min}(k) - RIS_i(k)\big)RIS_i(k)\Big\} \qquad (24)$$

In this case $\Delta L < 0$ as long as the following condition holds:

$$k_v(k) < \frac{2\left(RIS_a(k)-RIS_i(k)\right)RIS_a(k)}{\left(RIS_{min}(k)-RIS_i(k)\right)RIS_i(k)} = \left|\frac{2\left(RIS_a(k)-RIS_i(k)\right)RIS_a(k)}{\left(RIS_{min}(k)-RIS_i(k)\right)RIS_i(k)}\right| \quad (25)$$

Consider node pair i such that $RIS_i(k) = RIS_{max}(k)$. Then condition (25) holds since $RIS_{max}(k) < RIS_a(k)$ and $H_i(k)$ is negative for $RIS_i(k) = RIS_{max}(k)$. In conclusion, the upper bound of $e_i(k)$ for each iteration asymptotically converges to zero provided (25) holds.

Case III: $H_i(k) > 0$ and $and\ RIS_i(k) > RIS_a(k)$, that is $(e_i(k) > 0)$

In this case, it should be noted that the error term $e_i(k+1) = e_i(k) + \gamma_i(k) = e_i(k) + H_i(k) > e_i(k)$ and $RIS_i(k) > RIS_a(k)$. This leads to the conclusion that $RNS_i(k)$ is moves away from $RIS_a(k)$ and error increases. However, if $e_i(k+1) < e_{max}(k)$ is proven for this case, then the convergence condition holds, i.e. $e_{max}(k+1) = e_i(k+1) < e_{max}(k)$. Consequently, the upper and lower bound of all $e_i(k)$ for each iteration converges to zero. Therefore, the following proof is showing that$e_i(k+$ $1<emaxk$ in this case.

Note that with assumption (13), the condition $e_i(k+1) < e_{max}(k)$ is equivalent to proving $RIS_i(k+1) < RIS_{max}(k)$. According to (11) and (17)

$$RIS_i(k+1) - RIS_{max}(k) = RIS_i(k) - RIS_{max}(k) + H_i(k)$$

$$= RIS_i(k) - RIS_{max}(k) + \frac{k_v(k)}{RIS_a(k)} \frac{\sum_{i\neq j}\left[RIS_j(k) - RIS_i(k)\right]C_{ij}(k)}{C_{ii}(k)}$$

$$< RNS_i(k) - RNS_{max}(k)$$

$$+ \frac{k_v(k)}{RNS_a(k)} \frac{\left[RIS_{max}(k) - RIS_i(k)\right]\sum_{i\neq j} C_{ij}(k)}{C_{ii}(k)}$$

$$= RIS_i(k) - RIS_{max}(k) + \frac{k_v(k)}{RNS_a(k)}[RIS_{max}(k) - RIS_i(k)]RIS_i(k)$$

$$= [RIS_{max}(k) - RIS_i(k)]\left(-1 + \frac{k_v(k)}{RNS_a(k)}RIS_i(k)\right)$$

(26)

$RIS_{max}(k) - RIS_i(k) > 0$ is true, then $RIS_i(k+1) - RIS_{max}(k) < 0$ as long as the following condition holds:

$$k_v(k) < \frac{RIS_a(k)}{RIS_i(k)} \tag{27}$$

Then the inequality $e_i(k+1) < e_{max}(k)$ is proven provided the condition (27) holds.

Case IV: $H_i(k) < 0$ and $RIS_i(k) < RIS_a(k)$, that is $(e_i(k) < 0)$

In this case the error dynamics become $e_i(k+1) = e_i(k) + \gamma_i(k) = e_i(k) + H_i(k) < e_i(k)$ and $RIS_i(k) < RIS_a(k)$. Consequently, $RIS_i(k)$ is getting farther away from $RIS_a(k)$. However, if $e_i(k+1) > e_{min}(k)$ can be proved in this case, the conclusion that the upper and lower bound of all $e_i(k)$ for each iteration is getting closer to zero still can be held. Therefore, the following proof is showing that $e_i(k+1) > e_{min}(k)$ in this case.

Note that with assumption (13), the condition $e_i(k+1) > e_{min}(k)$ is equivalent to proving $RIS_i(k+1) > RIS_{min}(k)$. According to (11) and (17)

$$RIS_i(k+1) - RIS_{min}(k) = RIS_i(k) - RIS_{min}(k) + H_i(k)$$

$$= RIS_i(k) - RIS_{min}(k) + \frac{k_v(k)}{RIS_a(k)} \frac{\sum_{i \neq j}\left[RIS_j(k) - RIS_i(k)\right]C_{ij}(k)}{C_{ii}(k)}$$

$$> RIS_i(k) - RIS_{min}(k) + \frac{k_v(k)}{RIS_a(k)} \frac{[RIS_{min}(k) - RIS_i(k)] \sum_{i \neq j} C_{ij}(k)}{C_{ii}(k)}$$

$$= RIS_i(k) - RIS_{min}(k) + \frac{k_v(k)}{RIS_a(k)} [RIS_{min}(k) - RIS_i(k)] RIS_i(k)$$

$$= [RIS_{min}(k) - RIS_i(k)] \left(-1 + \frac{k_v(k)}{RNS_a(k)} RIS_i(k) \right) \tag{28}$$

$RIS_{min}(k) - RIS_i(k) < 0$ is true, then $RIS_i(k+1) - RIS_{max}(k) < 0$ as long as the following condition holds

$$k_v(k) < \frac{RIS_a(k)}{RIS_i(k)} \tag{29}$$

Then the inequality $e_i(k+1) > e_{max}(k)$ is proven provided the condition (29) holds.

Inference from Cases I-IV: The conditions (23), (25), (27) and (29) from the Cases I-IV have to be satisfied by the power control scheme to guarantee convergence in all scenarios. Those can be combined into (18) thus defining a comprehensive, common condition. If it is satisfied for each iteration, then the upper and lower bounds of $\{e_i(k)\}$ are asymptotically converging to zero. In other words, $\sum_{i=1}^{n} e_i(k)$ is asymptotically stable. Therefore, each link's RIS_i will converge to a common RIS_a.

It should be noted that the convergence rate is controlled through tuning of the learning rate K_v value, provided the condition (18) holds. The convergence speed increases with the K_v since the power changes proportionally to the RIS error and the K_v value.

1.6. RESULTS AND DISCUSSIONS

In this section, a MATLAB-based simulation results are shown to demonstrate the convergence of the proposed scheme. Various simulation scenarios demonstrate the performance improvement over a baseline scheme.

1.6.1. Results and discussion of CPPC and CRPC

The comparative results of the CPPC and CRPC schemes [30] demonstrate that both CRPC and CPPC converge to the common SNR level. However, CRPC scheme has the advantage of reduced control overhead and shorter conergence time. Two variants of the CPPC scheme are also evaluated: (a) centralised and (b) distributed. The distributed form has reduced overhead and thus is more practical in real deployment scenarios. However, there is no analytical guarantee that the distributed scheme converges in any scenario.

1.6.2. Statistic simulation and discussion for 2 scenarios of CRPC

The centralized and distributed variants of the CRPC are simulated in MATLAB. The results are discussed bellow.

1.6.2.1. Centralized power control

In the scenario of centralized power control, it is assumed that every node pair is in the range of transmission. So each node's power update will be based on the average RIS which is calculated with all the other nodes' information. Figure 1 is given to demonstrate the scenario of centralize power control. The 1th transmitter collects the RIS feedback information from all the receiver nodes in the network. The $RIS_a(k)$ used for the power update of the 1th transmitter is calculated with full understanding of the receivers' RIS information.

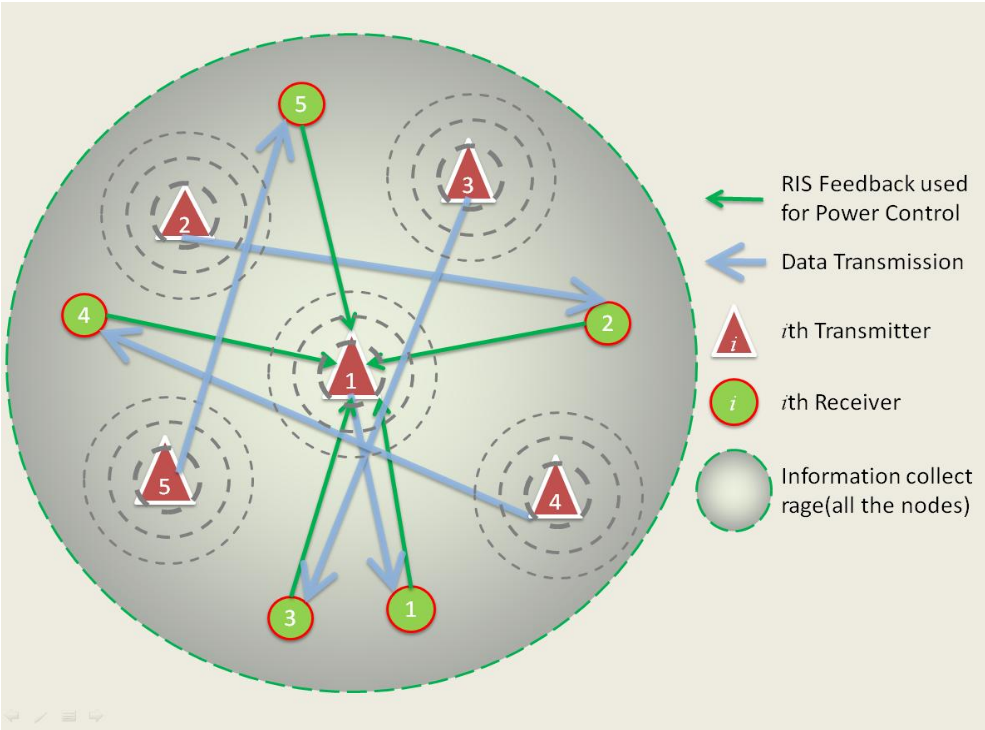


Figure 1. Centralized power control illustration

1.6.2.2. Distributed power control

The second scenario is the distributed power control. In the practical environment, some transmitters are very far away from receivers. Hence the interference brought by those far-away transmitters can be ignored. Additionally, it is also difficult for the RIS information to get delivered back from receiver to far-away transmitters. As a result, distributed power control only uses the RIS information from neighborhood receivers which are inside the transmission range when doing the power update with CRPC. This idea is illustrated as Figure 2. The CRPC is still applicable and. The overall stability of the control is kept through the propagation of the update information. However, if there are nodes that are totally isolated from the other nodes in the network, the scheme will fail since there is no media for these nodes to exchange information within the network.

As shown in Figure 2, unlike other transmitters, the 4th transmitter does not get network information through other receivers. Thus the CRPC will fail for this transmitter.

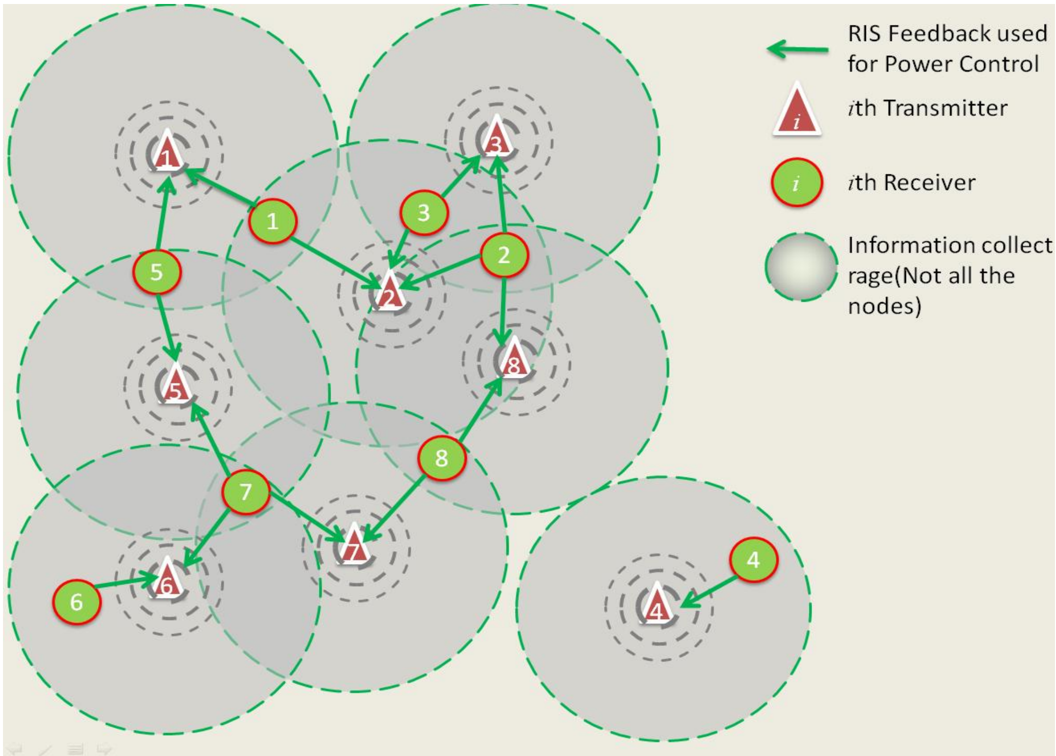


Figure 2. Distributed power control illustration

1.6.3. Comparison and discussion of two variants of CRPC

The simulation is repeated in a 200*800 feet area under 802.11 network standards which defines the bandwidth of 20MHz with different topologies. Under each topology criteria, the simulations are repeated at 384 topologies. The reason that the number of repeated simulations is chosen as 384 is it guarantee that the average result will have the confidence level of 95% with the confidence interval of 5 [23] which fairly shows that the overall performance of each case.

For the first and second topology criteria, the nodes pairs are uniformly distributed in the area with different node densities. Here the node density is defined as the total number of node divide by the area.

In the third area, the overall node density is the same with the second one but there are 2 sub-areas with different node densities which are listed in the table below too. For the 2 sub-area, the node is uniformly distributed with the accordingly densities. The initial powers for all the cases are 1mw and we have the convergence timeout set as 160s.

The detail simulation comparison is given as shown in Table 1 and Table 2.

Generally, for different densities, both centralized and distributed form of CRPC will have different convergence RIS/throughput since there is a limit of average throughput/RIS for each density of nodes within the network. Generally speaking, with larger density of nodes, the interference would be bigger which lowers the SNR level. As a result the convergence levels of throughput and RIS have the trend as shown in the Table 2.

Table 1.Simulation description of three network topologies

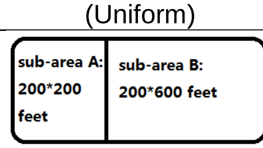
Topology Index	Overall Node Density [Nodes/feet^2]	Sub-area illustration	Sub-area Node Density [Nodes/feet^2]
1	0.001	(Uniform)	N/A
2	0.003	(Uniform)	N/A
3	0.001		A : 0.003 B: 0.00032

Table 2. Simulation comparison for three network topologies

Topology Index	Centralized			Distributed		
	Convergence throughput [kb/s]	Convergence Time [s]	Energy [w^2]	Convergence throughput [kb/s]	Convergence Time [s]	Energy [w^2]
1	18.45	1.29	2.93	22.1	0.399	6.0973
2	4.5	1.74	13.63	5.72	0.375	187.412
3	50.5	1.44	3.54	67.4	1.10	19.10

As for the comparison of 2 scenarios of CRPC, centralized CRPC can guarantee stability since all the information of the whole network is guaranteed to be got by every node and this stability is also be proven mathematically in the proof section. When updating network with distributed form, the cases that some nodes got isolated in the network since no other or not sufficient amount of nodes are around them to propagate the information exist. Theses nodes will totally break the stability of CRPC which means the RIS/throughput will never converge or not converge before timeout happens. It should be noted that the convergence rate of the third topology criteria is much lower than the previous two. The reason why it happens is that with the density distribution of criteria No.3, it is much more possible that some nodes will get isolated from the network and the stability of the scheme is broken as a result. From the energy wise, since the fully understanding of the whole network is got by each node, the final convergence state is more optimal. However, the beauty of distributed form is it is more applicable to real world and it would save much time to converge. Since each node only uses the neighborhood nodes information to update its power, then the update doesn't need to wait all the other nodes' information to pass along to finish the current update iteration. This benefit is critical if the network is more dynamic since the quick response of convergence will be necessary.

1.6.4. Simulation comparison between different channel models for CRPC

A comparison of the control scheme of simulation between different channel models is shown as below. The control scheme is simulated in a network topology in an area of 200*800 feet under 802.11 network standards which defines the bandwidth of

20MHz. The locations of the nodes within the network are uniformly randomly generated and are shown as Figure 3.

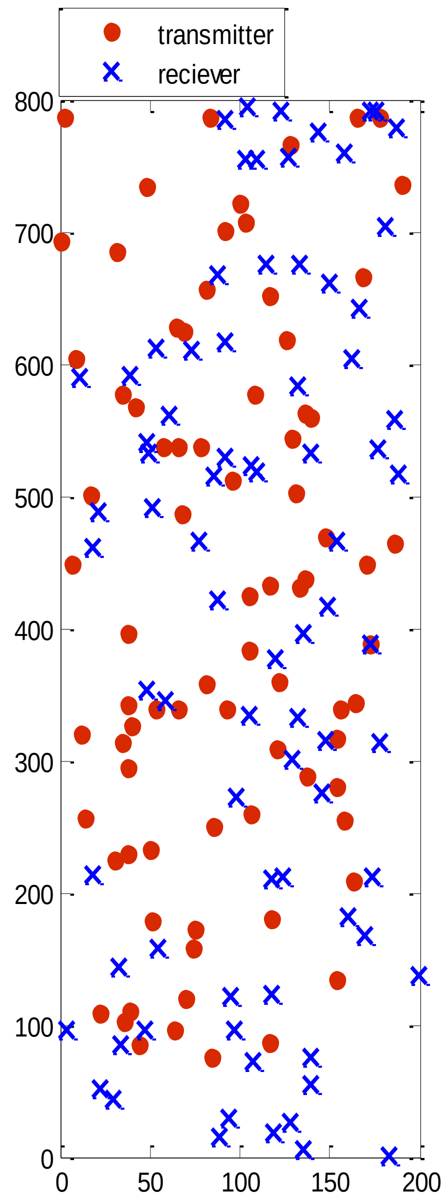


Figure 3. Location of the nodes within the network

In this comparison, two channel models are considered. The first, simplified model includes the path loss attenuation. The second, more realistic model incorporates the Rayleigh and shadowing fading. The comparisons result is shown as Table 2.

For both of the cases, the SIR error converges to 0. However, in presence of fading channel, more channel uncertainties are injecting a disturbance. Consequently, the convergence becomes bounded (or limited) by the uncertainties in the fading. In fading channel case, the control stability resembles a uniformly ultimately bounded (UUB) condition.

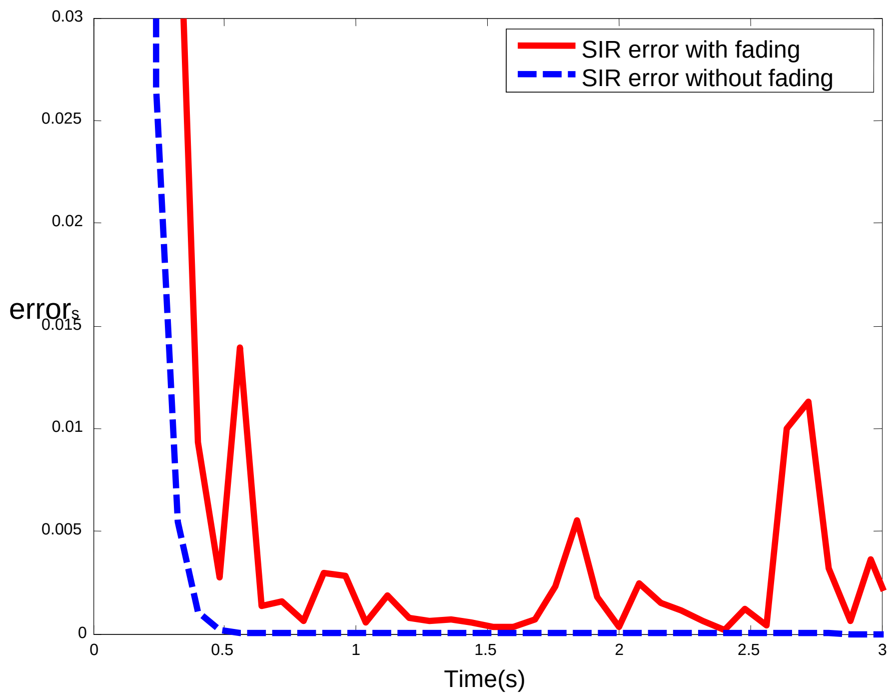


Figure 4. SIR error comparison

1.6.5. Simulation with different amount of links in the network

With the same topology shown in Figure 3 as shown earlier, the relationship between the number of links activated in the network and the average throughput using CRPC is shown as in Figure 5.

With CRPC implemented in the network with different number of node pairs activated, all the throughputs for active links converge to the same throughput. The simulation result shows the tradeoff with the number of links active in the network and the throughput which is an important aspect of the network. When more links are activated, more source of interference exists which is the reason why the trend is shown as it is in the figure. If certain throughput and ideal fairness share need to be guaranteed, the number of links needs to be limited with CRPC implemented in the wireless network and with certain number of links and topology existed in the network, then there would be a saturated throughput that needs to be aware. This result also demonstrates that with the amount of wireless nodes increased in the network, the average share of the bandwidth will be lower down. As a result, in the real world, if certain throughput or/and number of wireless users need to be ensured, a general knowledge of bandwidth can be derived with the scheme in this case.

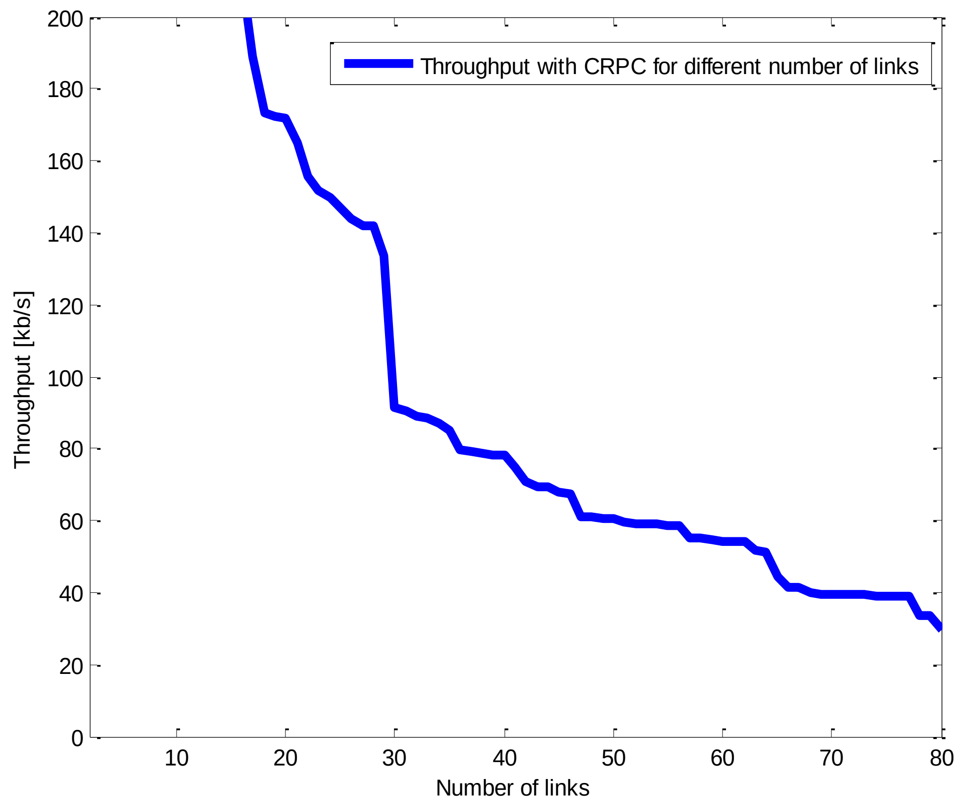


Figure 5. Throughput with different number of links active in the network

1.6.6. Simulation comparison with existing power control schemes

In this section, two existing schemes of power control for wireless network will be compared with CRPC. The two existing schemes that are used to compared are Bambos power control [6] and constrained second order power control [7].

To make the comparison more valuable, the simulation for CRPC and the other two schemes are all done at the same environment and same topology as used at section D.

The simulation is done with the target throughput set up as 31 kb/s for Bamboo power control and constrained second order power control which is a reachable target value for both of the power control and no target value is needed to set up to implement CRPC. All three cases reach the same level of throughput and the error is shown as Figure 6.

To compare the throughput distribution of different schemes, according to Kernel density estimation [24] [25], the estimated probability density functions (PDF) of throughput differences are generated as shown in Figure 7. About a half of the links in CRPC scheme have better throughput than the existing scheme. While the other links achieve worse throughput. However, the overall comparison of the positive and negative cases shows that the differences range between -0.5 and 0.8. This is at least an order of magnitude smaller than the average link throughput, which is equal to about 31 kb/s. These PDFs demonstrate that CRPC has slightly different throughput distribution but the overall performance is comparable with the existing schemes.

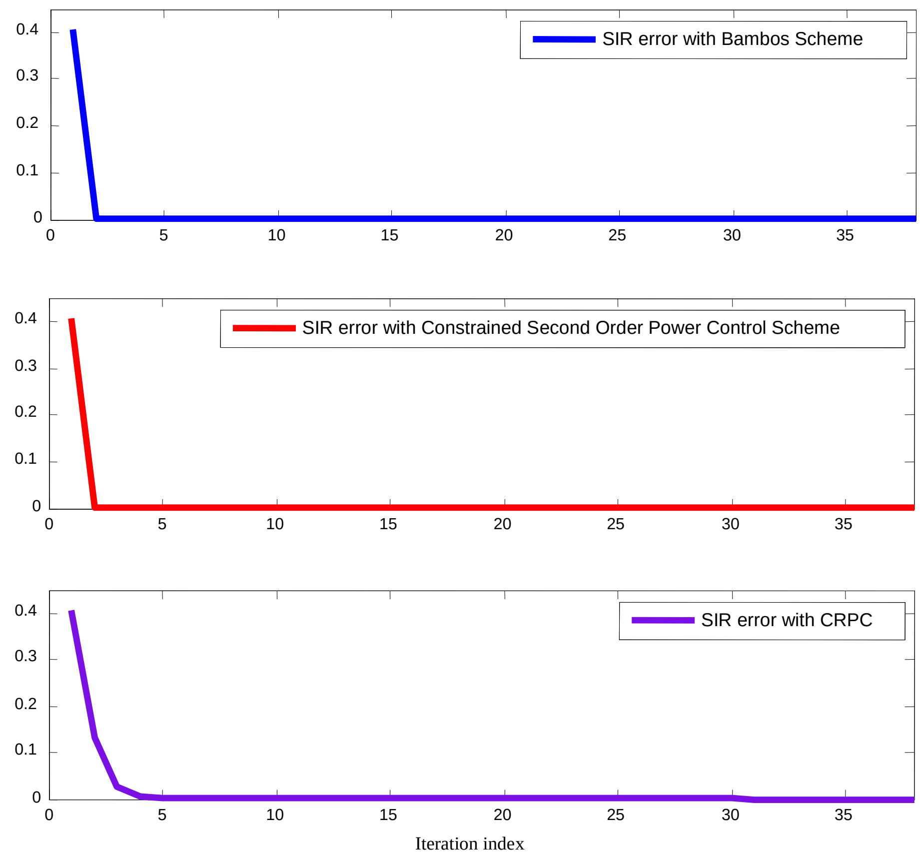


Figure 6. SNR error with different schemes

To demonstrate the benefits of CRPC, we compared it with Bambos power control with varying target SIR (target capacity). The Bambos scheme provides relatively good scheme of selecting a transmission power that satisfies the desired SIR (or capacity) threshold. However, it is expected to perform poorly when the target SNR is set too high (unachievable). The simulations are configured to follow the 802.11 network standard with the bandwidth of 20MHz. For each node, the range of allowed transmission power is 0.001mW to 500 mW. The network topology is shown in Figure 3. The results in terms of achieved throughput (SIR) and Fairness Index (FI) are shown in Figures 8 and 9.

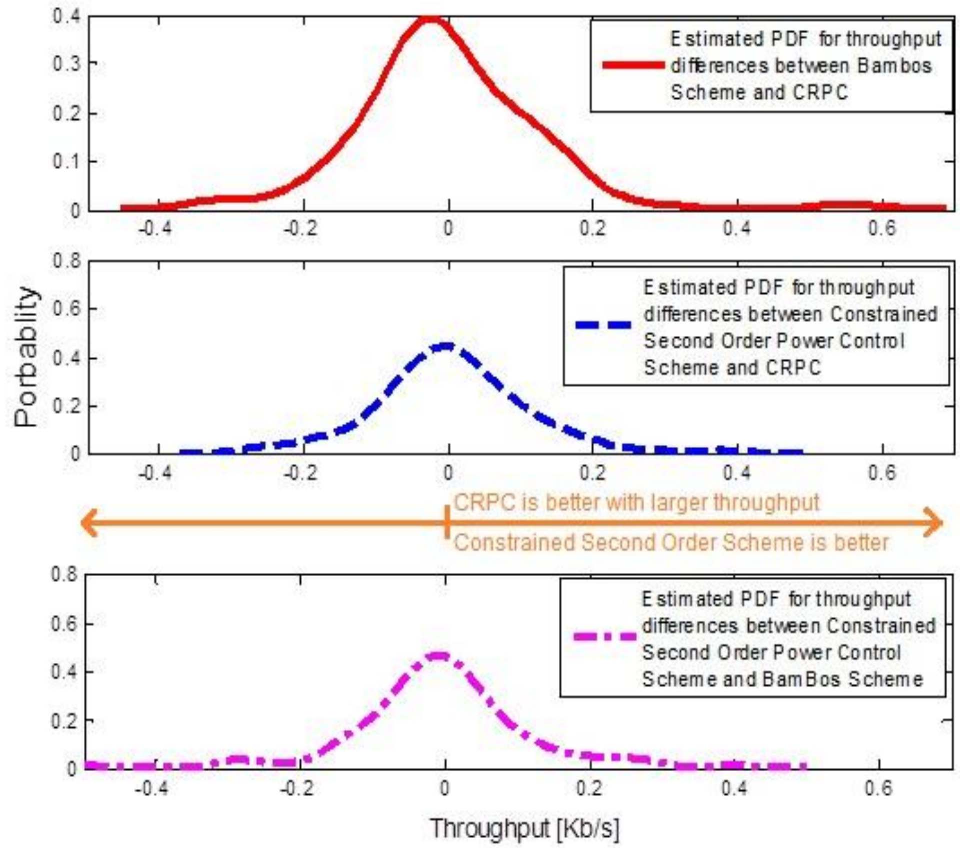


Figure 7. Estimated throughput difference PDF with different cases

For the specific target throughput or SIR, the Bambos scheme controls the power until the target SIR is satisfied. In the ideal case, the power of each node will change and the target got satisfied which is the case shown on the point where fairness index is at the peak of 1. And this is the case where appropriate target SNR/throughput is chosen. If the target is not pre-defined appropriately, the Bambos scheme fails since it increases (or decreases) the transmission power until it reaches the per-node limit, as observed in Figure 9.

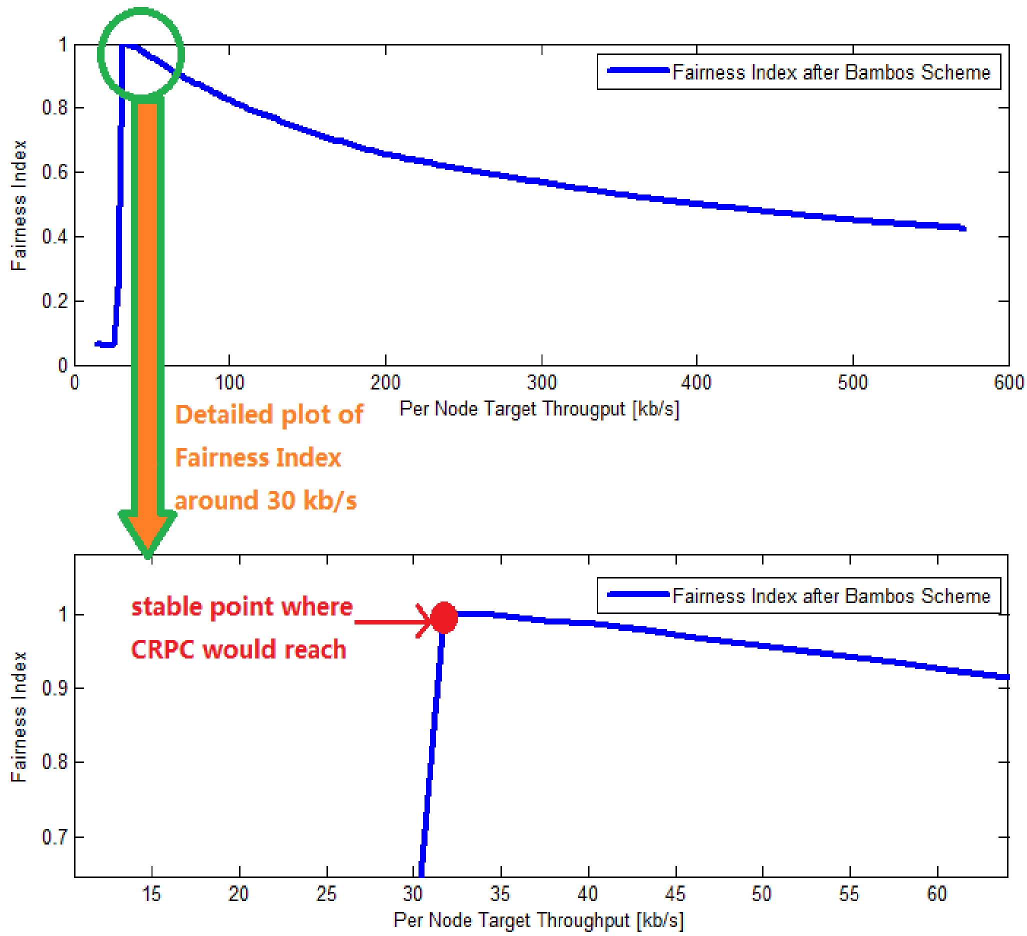


Figure 8. Fairness index with Bambos scheme at different target throughputs

The power saturates when the target SIR is set very high or when the SIR is set too low. In the former case the power on many links is set to the minimum while the Bambos scheme indicates the power should be lower than the lower bound. In the latter case, the Bambos is dictating more and more links to set power above the upper bound. The realistic power is saturated at the hardware maximum thus a slow convergence to the maximum power level is observed as more and more links use the maximum. Figure 9 also shows that the proposed CRPC scheme determines the tipping point where the required power begins increasing faster than the desired SIR (or capacity).

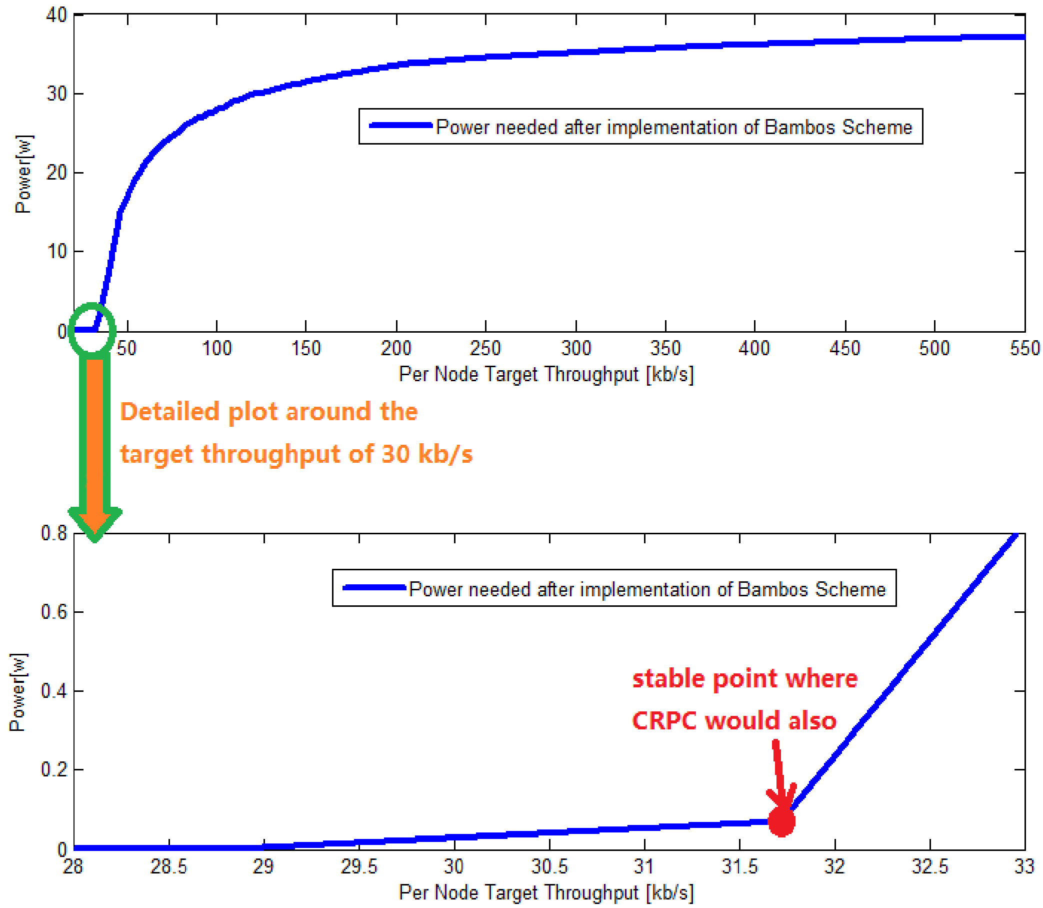


Figure 9. Power of all nodes with Bambos scheme at different target throughputs

Figure 8 shows the fairness of the capacity allocation among the links. Fairness index equals to one, “1”, thus indicating that all node achieve the same throughput (SIR). The CRPC scheme determines that maximum point dynamically thus determining the optimal SIR or capacity value for the given network topology. When the target SIR is set below that optimal point, the Bambos scheme underperforms since more and more links reach the lower power limit. At that point the SIR on those links cannot reach the desired level. Consequently, the capacity achieved on the links diverges leading to low fairness, as observed in Figure 8. Similarly, when higher then optimal SIR is set as target, the Bambos increases the transmission power. Due to increased interference from adjacent links the Bambos quickly demands the maximum transmission power to be used. The power is limited to the upper bound; hence, the desired SIR cannot be achieved for some links. The number of links that cannot achieve the desired SIR increases with the target SIR value. Consequently, larger and larger portion of the links uses the maximum allowed power as observed in Figure 9.

As a result, for an unknown network, CRPC will be a good way to control the power without setting up a preselected target SNR/throughput to make the scheme work and this is the benefit with the scheme that is proposed.

1.7. CONCLUSION

The proposed fair resource allocation and power control scheme has been presented. Both theoretical and simulation convergence to a fair resource allocation are demonstrated. The scheme is a collaborative approach to ensuring that every link achieves an equal capacity while minimizing power consumption. The CRPC scheme successfully identifies the achievable and fair SIR for a particular topology. Hence, no target SIR/throughput level is required a priori. CRPC scheme improves FI by up to 60% over the Bambos scheme. Future works includes extension of the scheme to support proportional or prioritized resource allocation, relaxation of the current assumptions, and application to cognitive networks with primary and secondary spectrum users.

REFERENCES

[1] Falomari, N. B. Mandayam, and D. J. Goodman, “A new framework for power control in wireless data networks: Games utility and pricing,” in Proc. Allerton Conf. Commun., Control, Comput., IL, Sep. 1998, pp. 546–555

[2] U. Saraydar, N. B.Mandayam, and D. J. Goodman, “Efficient power control via pricing in wireless data networks,” IEEE Trans. Commun., vol. 50, no. 2, pp. 291–303, Feb. 2002

[3] R. Fattahi and F. Paganini, “Neweconomic perspectives for resource allocation in wireless networks,” in Proc. Amer. Control Conf., Portland, OR, Jun. 2005, pp. 3690–3695

[4] T. Alpcan, T. Basar, and R. Srikant, “CDMA uplink power control as a noncooperative game,” Wireless Netw., vol. 8, pp. 659–670, 2002

[5] W. Sung and W. S. Wong, “A noncooperative power control game for multirate CDMA data networks,” IEEE Trans. Wireless Commun., vol. 2, no. 1, pp. 186–194, Jan. 2003

[6] N. Bambos, S. Chen, and G. J. Pottie, “Channel access algorithms with active link protection for wireless communication networks with power control,” IEEE/ACM Trans. Networking, pp. 583-597, Oct. 2000

[7] S. Jagannathan, Maciej Zawodniok, and Q. Shang, “Distributed Power Control for Cellular Networks in the Presence of Channel Uncertainties,” IEEE Transactions on wireless communication,VOL. 5, NO. 3,pp.540-549

[8] N. Bambos, “Towards power-sensitive network architectures in wireless communications: concepts, issues and design aspects,” IEEE Pers. Commun., pp. 50-59, June 1998

[9] T. S. Rappaport, Wireless Communications, Principles and Practice. Upper Saddle River, NJ: Prentice Hall, 1999

[10] R. Canchi and Y. Akaiwa, “Performance of adaptive transmit power control in π/4 DQPSK mobile radio systems in flat Rayleigh fading channels,” Proc. IEEE Vehicular Technology Conference, vol. 2, pp. 1261- 1265, 1999

[11] Hashem and E. Sousa, “Performance of cellular DS/CDMA systems employing power control under slow Rician/Rayleigh fading channels,” Proc. International Symposium on Spread Spectrum Techniques and Applications, vol. 2, pp. 425-429, Sep. 1998

[12] Mehdi Rasti, Ahmad R. Sharafat, and Babak Seyfe, “Pareto-Efficient and Goal-Driven Power Control in Wireless Networks: A Game-Theoretic Approach With a Novel Pricing Scheme,” IEEE/ACM Transactions on, VOL. 17, NO. 2,pp.556-569

[13] G. Owen, Game theory. Academic Press, third ed., 1995

[14] J. Nash, “Non-cooperative games,” The Annals of Mathematics, vol. 54, pp. 286–295, Sept. 1951

[15] H. Nikaido and K. Isoida, “Note on non-cooperative convex games,” Pacific Journal of Matematics, vol. 5, pp. 807–815, 1955

[16] Jianwei Huang, Zhu Han, Mung Chiang, and H.Vincent Poor, “Auction-based resource allocation for cooperative communications,” IEEE Journal on Selected Areas in Communications, 2008, 26(7): 1226- 1237

[17] Na Xia, Jianguo Jiang, Chunhua Yu, and Qiong Wu, “A coalition formation strategy based on benefit equilibrium,” Control and Decision, Dec, 2005, vol. 20, No. 12, pp:1426-1433

[18] T. Alpcan, X. Fan, T. Bas¸ar, M. Arcak, and J. T. Wen, “Power control for multicell CDMA wireless networks: A team optimization approach,” Wireless Networks, vol. 14, no. 5, pp. 647–657, October 2008

[19] M. Cesana, N. Gatti, and I. Malanchini, “A game-theoretic approach to decentralized optimal power allocation for cellular networks,” in Proc. of 2nd Intl Workshop on Game Theory in Communication Networks, Athens, Greece, October 2008

[20] Y. Pan and L. Pavel, “Games with coupled propagated constraints in optical networks: the multi-link case,” in Proc. of the 46th IEEE Conference on Decision and Control, New Orleans, USA, December 2007, pp. 3443–3449

[21] Maskin, “Nash equilibrium and welfare optimality,” Review of Economic Studies, vol. 66, no. 1, pp. 23 – 38, December 2003

[22] J. E. Suris, L. A. DaSilva, Z. Han, and A. B. MacKenzie, “Cooperative game theory for distributed spectrum sharing,” in Proc. of the IEEE International Conference on Communications (ICC), 2007

[23] Cochran, William G. (1977). Sampling Techniques (Third ed.). Wiley

[24] Rosenblatt, M. (1956). "Remarks on some nonparametric estimates of a density function," Annals of Mathematical Statistics 27: 832–837

[25] Parzen, E. (1962). "On estimation of a probability density function and mode," Annals of Mathematical Statistics 33: 1065–1076

[26] Jian Tang, Guoliang Xue, Senior Member, IEEE, Christopher Chandler, and Weiyi Zhang “Link Scheduling With Power Control for Throughput Enhancement in Multihop Wireless Networks,” IEEE Transactions on vehicular technology, VOL. 55, NO. 3, MAY 2006

[27] Kin K. Leung, “Power Control by Interference Prediction forBroadband Wireless Packet Networks,” IEEE Transactions on Wireless Communications,VOL. 1, NO. 2, APRIL 2002

[28] Wang Hei Ho and Soung Chang Liew, “Distributed Adaptive Power Control in IEEE 802.11 Wireless Networks,” International Conference on Mobile Adhoc and Sensor Systems (MASS), 2006 IEEE

[29] S. Jagannathan, A. T. Chronopoulos, S. Ponipireddy, “Distributed Power Control in Wireless Communication Systems,” Eleventh International Conference on Computer Communications and Networks, 2002. Proceedings

[30] Liuju Wu, Zawodniok, M. “Cooperative Approaches Indicating to Capacity and Power Control for Ad Hoc Wireless Network,” 2011 Proceedings of 20th International Conference on Computer Communications and Networks (ICCCN)

[31] P. Gupta and P R. Kumar, “The Capacity of Wireless Networks," IEEE Transactions on Information Theory, vol. 46, No. 2, 2000, pp. 388-404

[32] Massimo Franceschetti, Marco Donald Migliore, Paolo Minero, “The Capacity of Wireless Networks: Information-Theoretic and Physical Limits," IEEE Transactions on Information Theory, vol.55, No. 8, 2009

[33] Yoav Nebat, Rene L. Cruz, Sumit Bhardwaj, “The Capacity of Wireless Networks in Nonergodic Random Fading,” IEEE Transactions on Information Theory, vol.55, No. 6, 2009

II. COOPERATIVE POWER CONTROL AND RADIO RESOURCE ALLOCATION FOR COGNITIVE RADIO NETWORKS

Liuju Wu, Hao Xu, Maciej Zawodniok, Member, IEEE
Electrical and Computer Engineering Department
Missouri S&T, Rolla, USA

(lw6t9@mail.mst.edu, hx6h7@mail.mst.edu mjzx9c@mst.edu)

ABSTRACT

Radio resource allocation is one of the important aspects of Cognitive Radio Network (CRN) since it has potential to improve spectrum efficiency and ensure fairness among the primary and secondary users. Power control is typically employed to allocate the radio resources. A more practical power control scheme is proposed that ensures proportional fairness among the secondary users (SUs). Two algorithms are proposed based on a proportional, cooperative power control scheme. Both schemes reach the goal that Second Users (SU) reach a fair share of the accessible resource while following the primary user (PU) protection rule i.e. target QoS is guaranteed among PUs. An integrated power control scheme is proposed regarding to the active and sleep mode of PUs such that SUs have better access to the network resource. With the process of memorizing scheme configuration, the performance could be improved within the proposed integrated power control scheme. The simulation demonstrates the advantages and disadvantages of the proposed two schemes. The dynamic of the proposed integrated control is given in simulation section demonstrate the benefits.

2.1. INTRODUCTION

Cognitive radio technology is an attractive approach to utilizing white spaces in RF spectrum in a flexible and efficient way thus improving network access for both traditionally underserved and mobile users. However, this interest brought new challenges to the traditional radio resource allocation approaches including multiple users competing for common spectrum [2-3]. Two groups of users are included in such scenarios: primary users (PU) and secondary users (SU). The PUs get full and unrestricted access to the pre-assigned spectrum. They have priority in utilizing the resource including guaranteed bandwidth and signal-to-interference ratio (SIR). Moreover, the PU is typically a legacy system with limited cognitive and adaptation capabilities. In contrast, the SU employ a cognitive radio technology in order to dynamically adapt to changing spectrum availability and state including the interference and radio utilization efficiency. The SUs are required to monitor the radio resources to avoid interfering with the PUs, while maximizing resource utilization. The QoS and performance of the PUs is the primary concern and SUs have to adapt its performance with respect to PU. Consequently, both channel sensing and power control is the key functions for cognitive radios. Traditionally, the considered scenarios focused on interactions between the PU and SU. However, the increasing number of secondary users leads to extending the SU goal with ensuring fairness among the SUs. Hence, this paper considers radio resource allocation and power control problem in a multi-SU and multi-PU scenarios.

Rigorous research has been conducted in context of CRN [2-8]. In [2], a survey is done to some opportunistic approaches for spectrum access management with CRN. Two pair nodes CRN are discussed in [3] and the results give achievable rates with this CRN. In [4-7], transmit power control systems are designed to addressing the challenge of dynamically adjust the power with respect to interference level of PU in a cognitive network. These approaches consider certain type of PU with conservative targets. In contrast, this work designed the schemes with the consideration of three types of PUs and protects the QoS of PUs. An integration scheme with power control, access control, and multi-hop transmission on efficiency of spectral resource with a cognitive radio system is evaluated [8]. However, these works often insufficiently addressed the issue of fairness of radio resource sharing. Opportunistic or selfish/local approaches often result in an unbalanced allocation of channel capacity. This becomes a significant challenge in the presence of multiple SUs where particular nodes pairs overshadow others. In contrast, the proposed spectrum allocation schemes ensure fair, proportional allocation of the channel capacity through an adaptive power control schemes. The first goal that PUs is guaranteed to have enough resource will be reached. The fairness is set as the second goal among SUs performance. The goal is reach by controlling the power based on a cooperative power scheme and make SU's have the same capacity and share of the network.

The main contribution of this paper are: (1) addition of a generalized, cooperative RIS power control that guarantees proportional fairness; 2) development of two resource allocation schemes which is based on the cooperative RIS power control; 3) integration of a support for periodically active PUs which switch between active and sleep modes; and 4) simulation study of the proposed schemes in the context of cognitive radio application.

The rest of the paper is organized as following. Section II presents background information about channel attenuation and cooperative power approach. System model is discussed in Section III including a cognitive radio based peer-to-peer network and dual-mode PUs. The proposed proportional power scheme and two resource allocation schemes for cognitive radios are introduced in Section IV. Next, simulation results are discussed in the context of cognitive networks with PUs and multiple SUs, in Section V. Finally, the conclusion is given in Section VI.

2.2. BACKGROUND

Each receiver node in the wireless network, besides receiving the signal from the corresponding transmitter, receives interference from other transmitters in the network. The links performance is impacted by such interference. Shannon's capacity formula defines the available capacity on each link based on the signal-to-interference (SIR) ratio at the receiver. Traditional approach of describing the dynamics of wireless channel in terms of per-link channel capacity and power usage considers signal-to-interference ratio [21-25]:

$$SIR_i(t) = \frac{g_{ii}(t)p_i(t)}{\sum_{j\neq i}[g_{ij}(t)p_j(t)]+\eta(t)} \tag{1}$$

where $g_{ij}(t)$ is a attenuation from transmitter of j^{th} link to receiver of i^{th} link, $p_i(t)$ is transmission power on i^{th} link, and $\eta(t)$ is thermal noise.

Ideally, the power and spectrum allocation scheme should minimize the interference for each link in order to maximize the energy efficiency and maximize throughputs.

In the radio channel, the signal is attenuated during propagation from the jth link transmitter to the ith link receiver. This paper considers the channel uncertainties including path loss, multipath fading, and shadowing effect. The power attenuation is equal to the combination of those factors, which is modeled using [10]:

$$g = f(d, n, X, \xi) = \bar{g}d^{-n} \cdot X^2 \cdot 10^{0.1\xi} \qquad (2)$$

where $\bar{g}d^{-n}$ is the path loss component, X^2 random variable represents the Rayleigh fading [9], and $10^{0.1\xi}$ denotes the shadowing [10][11]. For the shadowing, ξ is a Gaussian random variable, while Rayleigh fading follows probability density function as in [9]

$$pdf(x) = \begin{cases} \frac{x}{\delta^2} exp\left(-\frac{x}{2\delta^2}\right) & (0 \leq x \leq \infty) \\ 0 & (x < 0) \end{cases} \qquad (3)$$

2.3. ANALYSIS OF SYSTEM MODEL

The cognitive radio based network is considered in the paper with a peer-to-peer topology. The total of N nodes pairs are in the network including primary and secondary users of the common spectrum. In such a scenario, the PUs are given priority in channel access such that a minimum quality of service (QoS) is maintained. In this paper, we selected the capacity as the main the metric with convergence time as the secondary one. The illustration of network model is shown in Figure 1.

The Shannon-Hartley theorem defines the channel capacity as equal to:

$$C = Blog_2(1 + SIR) \qquad (4)$$

where *C* stands for the channel capacity, B denotes the bandwidth of the channel; SIR denotes the signal-to-interference ratio. The goal of the proposed scheme is to allocate the radio resources equally, that is the capacity of each link is the same. Consequently, from (4) the goal can be restated as to achieve equal SIR value for each link. Thus the problem is converted into power control for each transmitter node such that the same SIR is maintained on each link. As given in (1), all the transmitters' power will have impact on other nodes. To reach the fairness, certain level of SIR needs to be achieved. The power scheme will need to control the power cooperatively to reach the same SIR among SUs.

There are three issues addressed in the paper according to different types of PUs':1) PUs are transmitting at a fixed power level for example PUs like TV stations and radio stations. 2) PUs are able to adapt its power level for example PUs like Wi-Fi devices. 3) dual-mode PUs which means PUs can be at active and sleep mode. Since QoS of different kinds of PUs stated above has to be protected, higher level of control will proposed beyond that as proposed in the next section.

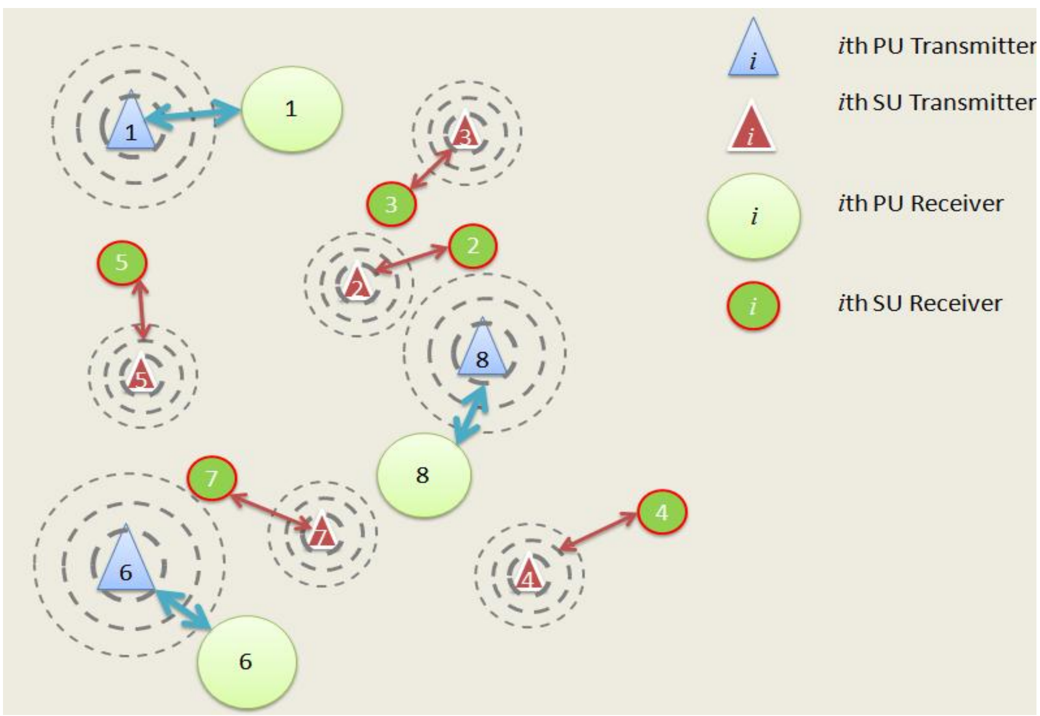


Figure 1. Network model

2.4. METHODOLOGY

This section proposes a cooperative proportional RIS-based power control (CPRPC) scheme that ensures fair, weighted radio resource allocation in wireless networks. A proportional, per-link weight is used to vary allocated channel capacity thus supporting a fair share of resource among links. In context of CRNs, the nodes are to be divided into at least two groups: PUs and SUs with corresponding weights. Note that the CPRPC supports proportional fairness that ensures relative resource allocation, while the PU's requirements in terms of SIR or capacity are absolute. Consequently, a second layer of adaptation is required when the CPRPC is employed in a CRN. Sections 2.4.2 and 2.4.3 present such two novel schemes. They are based on the CPRPC scheme and its simplified version, the Cooperative RIS Power Control (CRPC) that ensures only equal fairness. Both of the schemes are designed to reach two main goals:

1) Guarantee the minimum capacity of primary users (PUs)

2) Fairly allocate the remaining radio resource among the secondary users (SUs)

The difference between two schemes is the application constraints. The first scheme should be used when the PU use fixed transmission power, for example for TV stations. The capacity or SIR is guaranteed through the power control of SUs alone. The second scheme is intended for scenarios where the PU controls the power and can collaborate with SUs in order to achieve its desired SIR value. In general, the capacity is impacted by the changes made by both the SUs and PUs. Also, this scheme shares the resources fairly among the PUs. Finally, an integrated scheme is proposed to support PUs that periodically switch between active and sleeping modes.

2.4.1. Cooperative Proportional RIS Power Control (CPRPC)

The goal of a weighted, proportional fairness is for each link to achieve capacity, c_i, proportional to the links weight or priority, φ_i. In other words, the ratio of the capacity to weight should be constant for all links, $\frac{c_i}{\varphi_i} = const$. Applying Shannon-Hartley theorem (4) that ratio can be expressed in terms of link's SIR. In order to simplify the subsequent analysis, we recast the ratio to remove logarithm by using a scaled weight, w_i, such that the fairness constant ratio is equal to $\frac{SIR_i}{w_i} = const$. Note, that both ratios are equivalent. Also, the measure of individual link's deviation from the common constant is equal to difference between the links and weighted average ratio: $\varepsilon_i(k) = \frac{SIR_i\,(k)}{w_i} - WSIR_a(k)$, where $WSIR_a(k) = \frac{1}{n}\sum_{j=1}^{n}\frac{SIR_j(k)}{w_j}$ weighted average.

Furthermore, we observed that the analysis of the problem and derivation of updates could be simplified by studying the inverse of SIR – ratio-of-interference-to-signal, RIS. Hence, the subsequent sections consider the weighted product of $RIS_i(k)$ and the scaled weight, w_i. The weighted RIS value is defined as,

$$WRIS_i(k) = w_i * RIS_i(k) \qquad (5)$$

$$WRIS_a(k) = \frac{1}{n}\sum_{i=1}^{n} WRIS_i(k) = \frac{1}{n}\sum_{i=1}^{n} w_i * RIS_i(k) \qquad (6)$$

where $WRIS_i(k)$ and $WRIS_a(k)$ are weighted i^{th} link's RIS and weighted average RIS. w_i is the proportional weight for i^{th} link. The analysis later will show that SIR value will converge proportional to this weight parameter. Note that the weighted SIR average is defined as the inverse of $WRIS_a(k)$,

$$WSIR_a(k) = \frac{1}{WRIS_a(k)} \qquad (7)$$

The minimum value and the maximum value of the weighted RIS in the network are expressed as: $RIS_{min}(k) = min\{WRIS_i(k)\}$, $WRIS_{max}(k) = max\{WRIS_i(k)\}$.

The error term is revised to a weighted error as,

$$We_i(k) = WRIS_i(k) - WRIS_a(k) \quad (8)$$

While the ideal control scheme should force each links absolute error to asymptotically and monotonously decrease to zero, the channel dynamics makes such strict convergence impractical. Note that the convergence of individual $WRIS_i(k)$ to the average value can also be ensured be requiring that the most extreme values of WRIS converge to the average. Such formulation relaxes the need for each link's $WRIS_i(k)$ to monotonously decrease while ensuring ultimate convergence of the entire network. Hence, we defined the convergence goal as an asymptotical and monotonous decrease of the absolute, maximum and minimum errors to zero, $\lim_{k\to\infty}|WSIR_{max} - WRIS_a(k)| = 0$ and $\lim_{k\to\infty}|WSIR_{min} - WRIS_a(k)| = 0$.

Now, the following power update law is proposed in Theorem 1. The power update ensures that the summation of absolute value of weighted error will asymptotically decrease and converge to zero provided the update gain satisfies a constraint (10).

Theorem 1: For any pair of links with dynamics in paper and channel uncertainties, each link will achieve a weighted SIR level i.e, $SIR_i(k) = w_i * WSIR_a(k)$

when the transmission power is updated using

$$\beta_i(k) = \frac{k_v(k)We_i(k)}{WRIS_a(k)} + 1 \quad (9)$$

Provided that $k_v(k)$ satisfies the flowing constraint:

$$k_v(k) < \min\left\{\frac{WRIS_a(k)}{w_i WRNS_i(k)}, \left|\frac{2\big(WRIS_a(k)-WRIS(k)\big)WRIS_a(k)}{w_i\big(WRIS_{max}(k)-WRIS_i(k)\big)WRIS_i(k)}\right|, \left|\frac{2\big(WRIS_a(k)-WRIS_i(k)\big)WRIS_a(k)}{w_i\big(WRIS_{min}(k)-WRIS_i(k)\big)WRIS_i(k)}\right|\right\} \tag{10}$$

Proof: The proof below will show that with the (10), the upper and lower bound of $We_i(k)$ for each iteration is getting closer to zero.

Define the Lyapunov function candidate as $L = We_i^2(k)$. Then, the first difference of Lyapunov candidate function is equal to

$$\Delta L = We_i^2(k+1) - We_i^2(k) = \big(We_i(k) + w_i * \gamma_i(k)\big)^2 - We_i^2(k) = 2w_i We_i(k)\gamma_i(k) + {w_i}^2\gamma_i^2(k) \tag{11}$$

where $\gamma_i(k) = \frac{\sum_{i\neq j}[\beta_j(k)-\beta_i(k)]C_{ij}(k)}{C_{ii}(k)}$ is the dynamic term in the previous derivation.

Then applying the control law (9) to (10) we get

$$\Delta L = 2We_i(k)\frac{w_i k_v(k)}{WRIS_a(k)}\frac{\sum_{i\neq j}[We_j(k)-We_i(k)]C_{ij}(k)}{C_{ii}(k)} - \left(\frac{w_i k_v(k)}{WRIS_a(k)}\frac{\sum_{i\neq j}[We_j(k)-We_i(k)]C_{ij}(k)}{C_{ii}(k)}\right)^2 \tag{12}$$

Then replace (8) into (12) we get

$$\Delta L = 2We_i(k)\frac{w_i k_v(k)}{WRIS_a(k)}\frac{\sum_{i\neq j}[WRIS_j(k)-WRIS_i(k)]C_{ij}(k)}{C_{ii}(k)} - \left(\frac{w_i k_v(k)}{WRIS_a(k)}\frac{\sum_{i\neq j}[WRIS_j(k)-WRIS_i(k)]C_{ij}(k)}{C_{ii}(k)}\right)^2 = 2We_i(k)W\mathrm{H}_i(k) + WH_i^2(k) \tag{13}$$

where $WH_i(k) = \frac{w_i k_v(k)}{WRNS_a(k)}\frac{\sum_{i\neq j}[WRIS_j(k)-WRIS_i(k)]C_{ij}(k)}{C_{ii}(k)}$

The proof of stability is very similar to the proof for CRPC. All cases can be categorized into 4 cases to prove that for $i = 1,2, \dots, n$, $max\{\mathrm{W}e_i(k)\}$ and $min\{We_i(k)\}$ are getting closer to zero for each iteration while for the next iteration $\{We_i(k+1)\}$ will not exceed the $max\{We_i(k)\}$ and $min\{e_i(k)\}$ with the constraint of (10). That will lead to the conclusion that the upper and lower bound of $We_i(k)$ for each iteration is getting closer to zero. Eventually when $We_i(k) = w_i RIS_i(k) - WRIS_a(k) = 0$, the conclusion $SIR_i(k) = w_i * WSIR_a(k)$ can be drawn.

2.4.2. Cognitive Radio Power Control with Fixed PUs' power (CRPCF)

CRPC is the scheme that will search the fair share of the resource by cooperatively updating the power. With different rages of power limits and initial value, the scheme will search different sub-optimal solution with fairness guaranteed. In this case, PUs' interference will be at certain level towards SUs' node pairs and controlling SUs' power will be the only way to guarantee PUs' capacity. It is assumed that the network bandwidth is large enough to support PUs when only PUs are active in the network. Without the assumption, the network itself is not feasible to have PUs' transmissions. Addressing the two goals, two phases are included in the SUs' power control in this scheme.

Phase I. CRPC attempted fairness share

In this lower level phase, the SUs first try to implement CRPC among SUs' group with a pre-defined initial power and maximum power. It should be noted that the average RIS is calculated only among all the SUs' RIS.

$$RIS_a(k) = \frac{1}{n} \sum_{i \in SU} RIS_i(k) \tag{14}$$

After the implementation of CRPC, SU's will get to a fair share and stable state. In this phase, SUs' group attempt to reach equilibrium with the certain initial power. It addresses the second goal of the scheme that SUs will have the fair share of the rest of the radio resource and eliminate the bottleneck link in the network.

Phase II. Cognitive adjustment

In this phase, the SUs' group uses the SIR information and the target SIR to adjust the fair share status done by Phase I attempt. There are 2 cases that will be discussed.

In the first case that all the PUs' SIRs are above the target SIR threshold, the power scheme is done. At this state, SUs are at a good status that the capacity are guaranteed while SUs are fairly share the resources that SUs do not need.

In the second case, one or more PUs' SIR(s)/capacities are below the target SIR/capacity threshold. It means that SUs' power are still too high such that the PUs' Quality of Service (QoS) cannot be guaranteed. An adjustment rate $\alpha_f < 1$ is introduced. The predefined initial power and maximum power for Phase 1 will be decreased by α_f. With updated predefined configuration, another Phase I attempts will be implemented among SUs until all the PUs' capacity are guaranteed. Since with the assumption made earlier, the PUs' QoS will eventually be guaranteed since SU's power are going towards the direction of zero with $\alpha_f < 1$ holds. It is noted that with lower α_f, the convergence speed will be higher but better use of the rest of the radio source for SUs might be missed. It is obvious that with very small α_f, SUs' power will be very small accordingly and have much less impact on PUs' capacity but the utilization for the spare bandwidth will be low. Hence a trade-off between convergence time and utilization exists in this case. The summary of CPRCF scheme is given as in Table 1.

Table 1. Pseudo-code of the CRPCF scheme

Predefined a initial power $P_{initial}$, maximum power P_{max}, adjustment rate, α_f and PU target SIR SIR_{target} or target C_{target}

for $i \in SU$

  $P_i \leftarrow P_{initial}$

end

While $(\sum_{i \in SU} e_i > 0)$

  for $i \in SU$

    $P_i \leftarrow \mathrm{Min}\left(P_{max}, \left(\frac{k_v(k)e_i(k)}{RIS_a(k)} + 1\right) P_i\right)$

  end

end

for $i \in PU$

  if $(SIR_i > SIR_{target})$ or $\left(\left(C_i > C_{target}\right)\right)$

    $flag_i \leftarrow 1$

  else

    $flag_i \leftarrow 0$

  end

end

if $\prod_{i \in PU} flag_i = 0$

  $P_{initial} \leftarrow \alpha_f \times P_{initial}$

  $P_{max} \leftarrow \alpha_f \times P_{max}$

  Go back to step 2

else

  stop

end

2.4.3. Cognitive Radio Power Control with Variable PUs' power (CRPCV)

In this scheme, the CPRPC proposed in sub-section A is implemented. In this case, PUs are also cooperatively involved in the power control though with a higher weight and priority. Hence, PUs' capacity will be impacted by both PU group and SU group. The similar assumption as last sub-session is made but since PUs' power will be controlled, the assumption is revised as that the network bandwidth is large enough to support SUs' transmission when only PUs are active in the network after CRPC is implemented. Since SUs' power are variable, it is possible that after implementation of

CRPC towards SU-only network, the minimum level of capacity among PUs increases and is beyond the target capacity. Thus, higher target capacity may be achieved. This is also the benefits of CRPCV compared to CRPCF.

Similar to CRPCV two phases are included addressing two goals.

Phase I. CPRPC attempted fairness share

In this first phase, the SUs and PUs first try to implement CPRPC with pre-defined initial powers, maximum powers and initial weights.

After the implementation, PU and SU will converge to weighted capacity and stable state. Since PUs also have the power control, the minimum capacity among PUs increases not only because of the contribution from SUs but also the less interference from PUs. In most cases, the order of PUs power is higher than SU. The power restriction among PUs might have dramatically impact.

Phase II. Cognitive adjustment

In this phase, the SUs' group uses the SIR/capacity information and the target SIR/capacity to adjust the fair share status done by Phase I attempt. Similar to CRPCF, 2 cases will be discussed.

Similarly for the first case, when all the PUs' capacities are above the target SIR threshold, the power scheme is done.

In the second case, the converged PUs' SIR/capacity is below the target SIR/capacity threshold. It means that either SUs' power needs to be updated to lower level or PUs' power to higher level such that the PUs' Quality of Service (QoS) can be guaranteed. An adjustment rate $\alpha_v < 1$ is introduced. The weights for SUs' CPRPC will be decreased by α_v. With updated predefined configuration, another Phase I attempts will be implemented among SUs until all the PUs' capacity are guaranteed. With the assumption made for CRPCV, the QoS of PU will be guaranteed. The summary of CPRCF scheme is given as in Table 2.

Table 2. Pseudo-code of the CRPCV scheme

1: Predefined initial power $P_{initial}(i)$, maximum power $P_{max}(i)$ for both SUs and PUs, adjustment rate α_v ,PU target SIR SIR_{target} based on capacity, $SIR_{target}$and initial weights $w_i$for each users
2: **for** $i \in All\ users$
3: $P_i \leftarrow P_{initial}(i)$
4: **end**
5: **While** $(\sum We_i > 0)$
6: **for** $i \in All\ users$
7: $P_i \leftarrow \mathrm{Min}\left(P_{max}(i), \left(\frac{k_v(k)We_i(k)}{\mathrm{W}RIS_a(k)} + 1\right) P_i\right)$
8: **end**
9: **end**
10: **for** $i \in PU$
11: **if** $(SIR_i > SIR_{target})$ or $(C_i > C_{target})$
12: $flag_i \leftarrow 1$
13: **else**
14: $flag_i \leftarrow 0$
15: **end**
16: **end**
17: **if** $\prod_{i \in PU} flag_i = 0$
18: **for** $i \in SU$
18: $w_i \leftarrow \alpha_v \times w_i$
20: **end**
20: Go back to step 5
21: **else**
stop
23: **end**

2.4.4. Integrated scheme addressing two modes of PUs

In the CRN, PUs group can be in active mode and sleep mode. SUs try to get access to the spare resource and make the best utilization of the network. In particular, when PUs are in sleep mode, the entire network is spared. In the last two sections, both of the schemes are trying to make fair use of the spare resource while the PUs' QoS is guaranteed. The case where PUs are active is been considered. While PUs are in sleep mode, the pure CRPC could be used to share fairly with the entire network resource and eliminate bottleneck. In practical world, PUs group can be put in both modes. Some improvements can be done when integrating two cases and accordingly schemes. When PUs are initially active and either CRPCF or CRPCV is implemented, the final configuration of the schemes including initial power or proportional weights can be stored or memorized and will be helpful in future implementation of CRPCF or CRPCV. When PUs are back on from sleep mode, and either of the schemes will be implemented again for the network. Restoring those configuration will reduce the Phase II adjustment process hence reduce the overall process time for the control schemes.

Table 3 lists the steps of integrated schemes addressing two modes of PUs

Table 3. Pseudo-code of the integrated scheme

```
1:  Predefined configuration for all users and
    control schemes
2:  if (PUs are active)
3:     implement CRPCV or CRPCF
4:     store scheme configuration
5:      If(PUs mode changes)
6:           go back to step 2
7:      Else
8:           go back to step 5
9:      end
10: else
11:   Implement CRPC
12:   If (PUs mode changes)
13:        go back to step 2
14:   else
15:        go back to step 12
16    end
17: end
```

2.5. RESULTS AND DISCUSSIONS

In this section, the MATLAB simulation results are given to demonstrate the performance of each scheme and also the comparison is given and discussed. In particular, the tradeoff between CRPCF and CRPCV is demonstrated. In the last section, the integrated simulation is shown to demonstrate the SUs' behavior towards two modes of PUs.

2.5.1. Statistic results and discussion of CPRPC

The simulation runs on randomly generated topologyo over different number of nodes pairs. Similar to the concept of Cognitive Radio (CR) network, all nodes pair are evenly divided into two groups of convergence. To guaranteed the average result with the confidence level of 95% and the confidence interval of 5 [23], 384 ramdomly generated topologies are implemented with CPRPC for each amount of nodes pairs. The predefined configuration for the simulation are given in the Table 4.

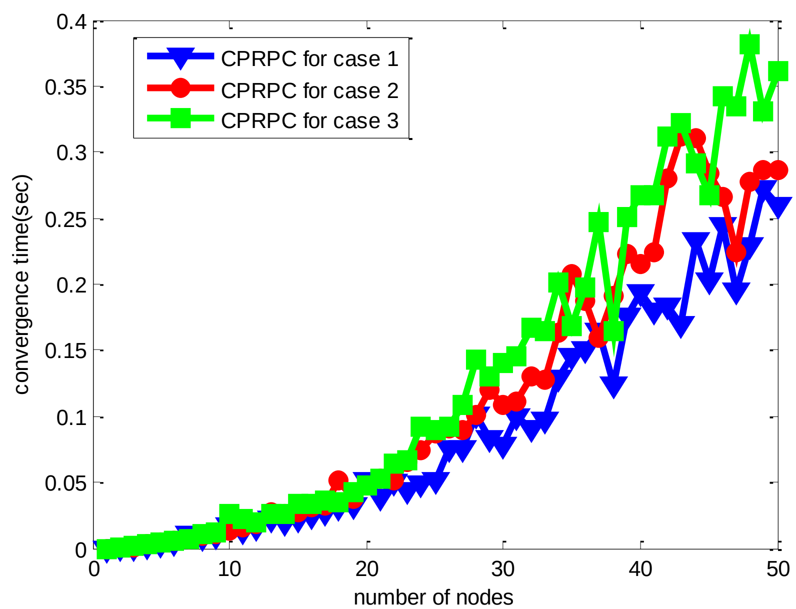


Figure 2. Network convergence time for CPRPC scheme

Table 4. Parameter configuration for CPRPC simulation

Case Index	First group's weight	second group's weight	Power Range of Transmitters [mw]	Initial Power of Transmitters [mw]
1	1	1	0-1000	1
2	1	3	0-1000	1
3	1	5	0-1000	1

As can be seen from Figure 2, the CPRPC has the quick response for convergence, for the network up to 50 nodes pairs the average convergence time is below 0.5s. Generally speaking, for all three cases, the convergence time has the trend of increase with more nodes pairs in the network. It happens because of two possible reasons. First of all, with more nodes pair in the network, the source of interference is accordingly more. The complexity of the problem is increasing. Additionally, for each update, the completion time of collecting network information is longer which built up the convergence time.

It is interesting to notice that with higher ratio of two groups' weights, the convergence time is higher for most of the time. It is explained that with higher weights, more transmitters in the second groups will potentially reach the maximum power value since higher SIR needs to be achieved. When that happens, the increase changes of power cannot make on these nodes. With the scheme, other nodes learn this fact through the cooperative information and decrease the power accordingly. The restriction on the power slows the convergence speed and hence has the trend as shown in the graph.

2.5.2. Simulation results and discussion of CRPCF and CRPCV

To better illustrate the difference and tradeoff between CRPCF and CRPCV, the simulation is conducted at a certain network topology with 7 SU nodes pair and 3 PU nodes pair. It is noted that this certain topology is a uniformly randomly generated topology in an area of 200*200 feet. However, to ensure valid comparison of equivalent topologies, the presented results are for the same, selected, and representative scenarios. The network topology is shown in Figure 4. The bandwidth of 20MHz is assumed for the numerical calculations.

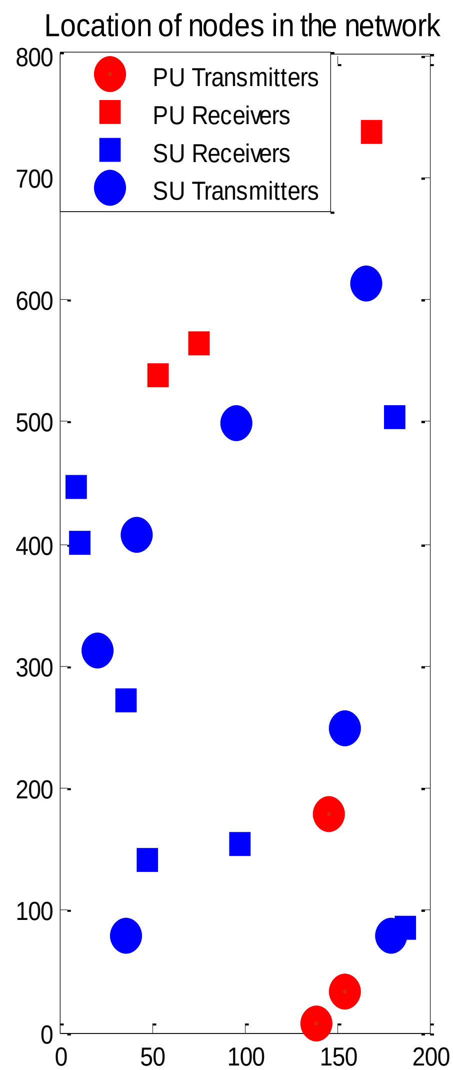


Figure 3. Network topology

Over a varied PUs Target/Threshold capacity, the simulation results regarding PUs and SUs capacities and convergence time are given in Figures 4-6.

2.5.2.1. Common performance discussion

With both schemes implemented in the network, two goals are reached. PUs are guaranteed to go beyond the target/threshold capacity while SUs share the spare resource fairly. Some general conclusion can be drawn and explained according to the results. When predefined target/threshold capacity is increasing, PUs capacity has the trend of increase while SUs has the decrease trend. It demonstrates that SUs are releasing the capacity to PUs to satisfy their needs.

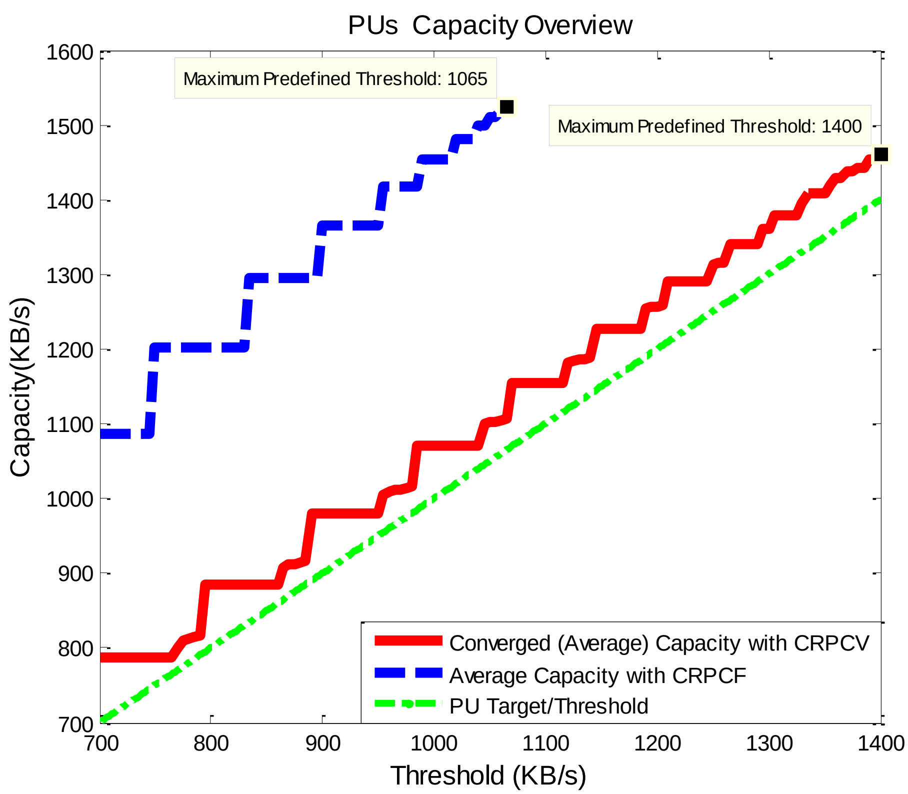


Figure 4. PU average capacity after convergence

Also, step increases are observed in each plot. That happens because of the discrete, step updates in phase 2 of both schemes. With the increased target/threshold capacity, SUs cognitively learn that under the current configuration cannot be guaranteed the QoS of PUs. Hence, the weights of the CPRPC scheme are adapted in phase II and the system converges to a new operating point with the power control schemes. Additionally, the convergence time increases with PU's threshold level, as observed in Figure 6.

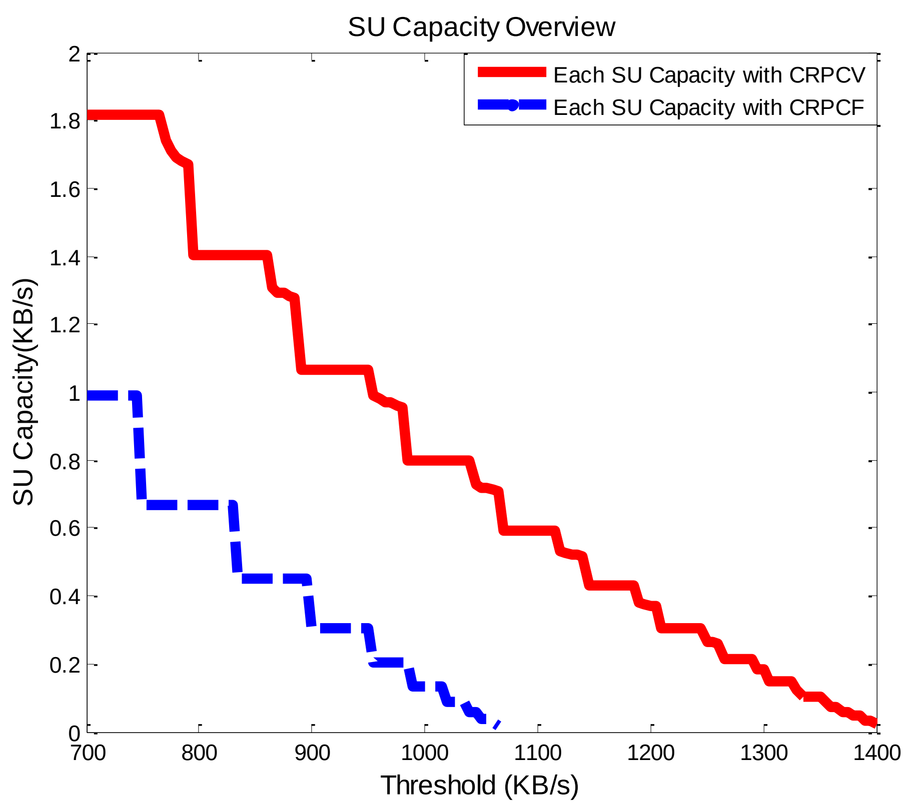


Figure 5. SU average capacity after convergence

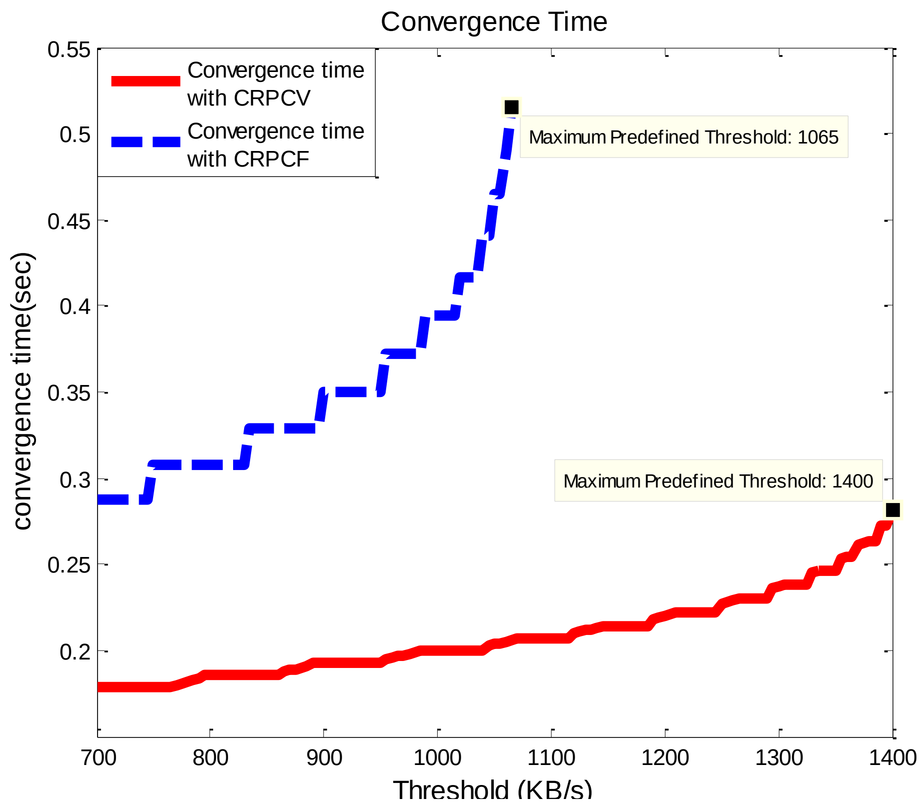


Figure 6. Network convergence time with varying PU's minimum capacity threshold

2.5.2.2. Performance comparison and discussion

At the convergence time point of view, CRPCV converges much quicker than CRPCF. CRPCV includes the power control towards PUs who usually have high order of power. Hence the control over PUs will have a big impact on the network performance and with the cooperative characteristic of the control scheme, the convergence time is shortened.

PUs average capacity after implementation of CRPCF is always higher than with CRPCV, since the PUs power is fixed at the maximum level in the CRPCF scheme. The power control in CRPCF is only employed by the SUs, and without feedback or coordination from Pus, the SUs have to conservatively release more resources to the PUs. This traditional PUs selfishness is the reason that CRPCF causes higher PUs capacity over the other case. CRPCV controls both PUs and SUs to reach a better cooperative share of the resources. By updating the PUs power, PUs release more resources to be shared among the SUs. Consequently, SUs' capacity is higher under CRPCV than CRPCF. The SUs performance in Figure 5 validates that reasoning.

The decision of which scheme is better would depend on the environment that the scheme is applied to. When uncertainties of channel and random noise exist, the CRPCF provides higher margin of error for the PUs, since they always use maximum power. It means that while fading and interference reduces the capacity for PUs, it still satisfies their minimum QoS threshold. If the environment is relatively stable, the CRPCV is a more suitable scheme with more efficient resource allocation and shorter convergence times. As shown, for this simulation, the maximum target/threshold capacity is increased by over 30%.

2.5.3. Simulation demonstration of integrated scheme

Certain PUs may periodically switch between active and sleep (idle) modes. The integrated scheme with memorization employs both CRPCF and CRPCV power control schemes. The initial configuration of each scheme is the same as in previous simulations. The target/threshold capacity is predefined as 800KB/s. The scope of the simulation is 2 seconds and table 5 gives the mode dynamic of PU group.

Table 5. Dynamic of PUs group's mode

Time Slot	PUs group's mode
0.0 - 0.5s	Active Mode
0.5 -1.0s	Sleep Mode
1.0 -1.5s	Active Mode
1.5 -2.0s	Sleep Mode

The capacity and power dynamics results are shown in Figures 7 and 8. The CRPCF scheme provides higher capacity for PUs, though exceeding the required capacity threshold by a large margin. In contrast, the CRPCV scheme increases the SUs capacity while the PUs maintains the capacity above the minimum required threshold.

When the PUs are in the sleep mode, the SUs share the entire channel capacity. Consequently, they converge to a higher capacity. The CRPCF and CRPCV achieve the same, fair capacity allocation though with different transmission power levels. It is because when PUs group switch from active to sleep mode at 0.5 or 1s, the initial status of SUs power are different which leads to CRPC search the fair share solution around different range of power. The reason that the power levels remain similar in the subsequent active modes is because the scheme parameters are memorized and restored when PUs group switch back to active mode. This re-initialization of parameters contributes to the fast convergence when PUs re-activate since the users start close to the target, fair operating point.

Control system memorizes the configuration of the stable status of last active period. When PUs group becomes active again, the configuration is restored. The restored weights, while not ideally matching the new conditions, are closer to the target level. Consequently, the scheme requires less time to converge in phase II. Table 6 summarizes the PU's convergence time for both the initial activation and the subsequent reactivations. Also, we include the network convergence time that the scheme, which corresponds to the final, fair, and stable channel allocation. The PUs convergence time corresponds to the time it takes the PU to reach the minimum required performance, i.e.

capacity threshold. The PU converges quicker since it typically exceeds its threshold before reaching its final, stable capacity share.

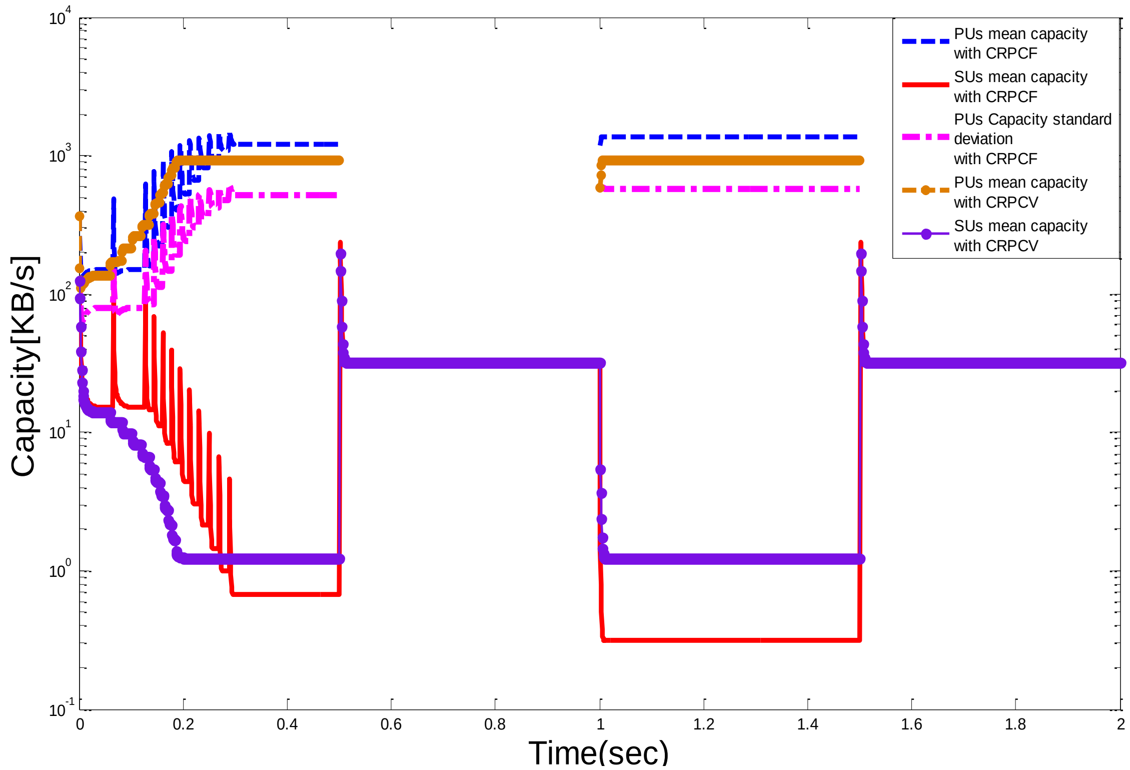


Figure 7. Capacity dynamics

The convergence time improves by over 90% when the network memorizes the weights corresponding to the PU's active mode and restores them when the PU reactivation is detected. This improvement is essential for successful implementation of cognitive networks since it ensures a quick access to the channel for the PU. Such a scenario with periodically active users has examples of on demand Internet/data access network. In this case, once the initial learning ends the PU can quickly activate and gain access to the channel. Also, the SUs will converge quicker thus improving overall efficiency of spectrum utilization.

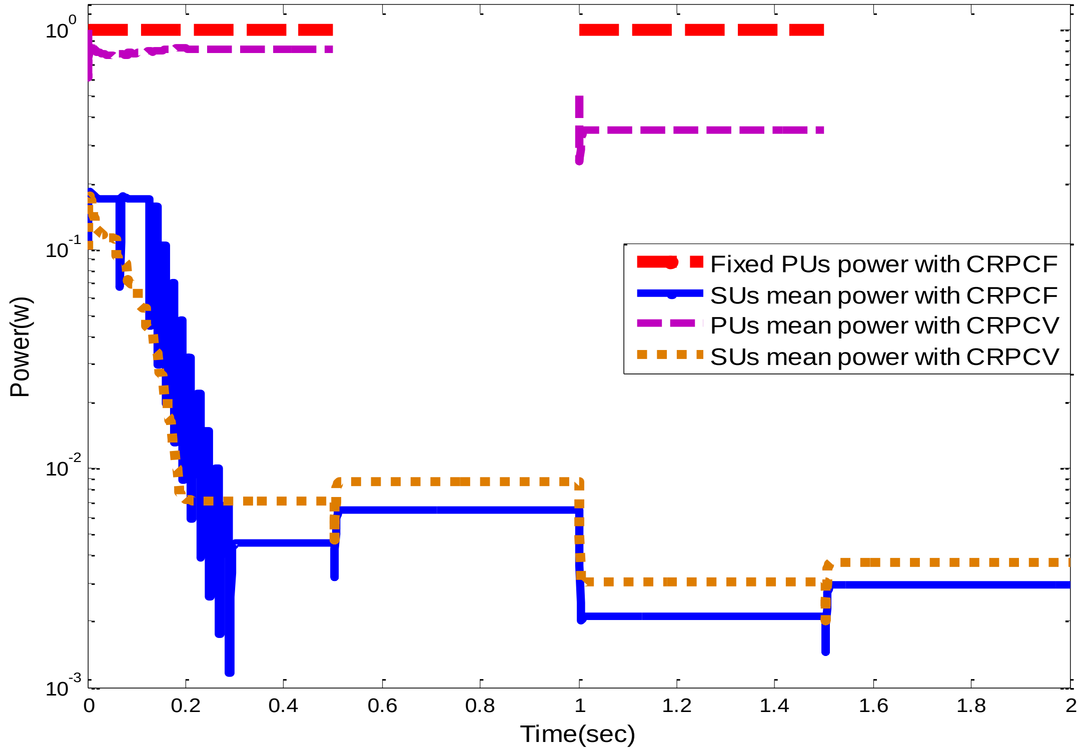


Figure 8. Power dynamics

Table 6. Convergence time comparison

	Convergence Time for CRPCF [s]		Convergence Time for CRPCV [s]	
	For entire network	For PU	For entire network	For PU
Initial Activation of PU	0.308	0.289	0.192	0.186
Subsequent Activations of PU	0.016	0.001	0.010	0.002

2.6. CONCLUSIONS

A practical, power control scheme with proportional fairness is derived. The performance is guaranteed through theoretical analysis and verified in simulations. Also, two resource allocation schemes for CRN are proposed. They ensure the primary user can access the radio channel and achieve the desired minimum QoS, while ensuring proportional fairness in channel access among the secondary users. The CRPCV scheme with collaborating PU achieves faster convergence time and increases the share of SUs' capacity than the CRPCF scheme where the PU operates independently. The CRPCV improve the convergence time by 40% over the CRPCF scheme. The SUs capacity is 80% higher for the CRPCV scheme than for the CRPCF one. Conversely, the CRPCF is more suitable for a high level of random interference and channel uncertainties since it maintains a larger margin of error in terms of its SIR and capacity. However, it results in higher transmission power. Moreover, the integrated scheme is proposed for a dual-mode PUs. SUs learn and memorize the weights corresponding to the PU's active and sleep modes. Then by restoring the memorized parameters the integrated scheme significantly improves convergence time when PUs is reactivated.

REFERENCES

[1] R. Fattahi and F. Paganini, “Neweconomic perspectives for resource allocation in wireless networks,” in Proc. Amer. Control Conf., Portland, OR, Jun. 2005, pp. 3690–3695

[2] F. Akyildiz, W. Y. Lee, M. C. Vuran and S. Mohanty, “Next generation/dynamic spectrum access/cognitive radio wireless network a survey,” Computer Network Journal (Elsevier), Sep. 2006

[3] N. Devroye, P. Mitran, and V. Tarokh, “Achievable rates in cognitive radio channels,” IEEE Trans. Inf. Theory, vol. 52, pp. 1813–1827, May,2006

[4] Hong-Sam T. Le and Qilian Liang, “An Efficient Power Control Scheme for Cognitive Radios,” IEEE Communications Society subject matter experts for publication in the WCNC

[5] Yan Chen, Guanding Yu, Zhaoyang Zhang, Hsiao-Hwa Chen, and Peiliang Qiu, “On cognitive radio networks with opportunistic power control strategies in fading channels,”IEEE Transactions on Wireless Communications, Vol.7, No.7, July 2008

[6] Shunqiao Sun, Weiming Ni, and Yu Zhu, “Robust Power Control in Cognitive Radio Networks: A Distributed Way,” IEEE International Conference on Communication, June, 2011

[7] You-En Lin, Kun-Hsing Liu and Hung-Yun Hsieh, “Design of Power Control Protocols for Spectrum Sharing in Cognitive Radio Networks: A Game-Theoretic Perspective,” IEEE International Conference on Communication, May, 2010

[8] Naotaka Shibata, Koji Yamamoto, Hidekazu Murata, and Susumu Yoshida, “Joint effect of power control, access control, and multi-hop transmission on area spectral efficiency of cognitive radio system,” 6th International Conference on Information, Communications & Signal Processing, Dec., 2007

[9] T. Alpcan, T. Basar, and R. Srikant, “CDMA uplink power control as a noncooperative game,” Wireless Netw., vol. 8, pp. 659–670, 2002

[10] W. Sung and W. S. Wong, “A noncooperative power control game for multirate CDMA data networks,” IEEE Trans. Wireless Commun., vol. 2, no. 1, pp. 186–194, Jan. 2003

[11] N. Bambos, S. Chen, and G. J. Pottie, “Channel access algorithms with active link protection for wireless communication networks with power control,” IEEE/ACM Trans. Networking, pp. 583-597, Oct. 2000

[12] S. Jagannathan, Maciej Zawodniok, and Q. Shang, “Distributed Power Control for Cellular Networks in the Presence of Channel Uncertainties,” IEEE Transactions on wireless communication,VOL. 5, NO. 3,pp.540-549

[13] N. Bambos, “Towards power-sensitive network architectures in wireless communications: concepts, issues and design aspects,” IEEE Pers. Commun., pp. 50-59, June 1998

[14] T. S. Rappaport, Wireless Communications, Principles and Practice. Upper Saddle River, NJ: Prentice Hall, 1999

[15] R. Canchi and Y. Akaiwa, “Performance of adaptive transmit power control in π/4 DQPSK mobile radio systems in flat Rayleigh fading channels,” Proc. IEEE Vehicular Technology Conference, vol. 2, pp. 1261- 1265, 1999

[16] Hashem and E. Sousa, “Performance of cellular DS/CDMA systems employing power control under slow Rician/Rayleigh fading channels,” Proc. International Symposium on Spread Spectrum Techniques and Applications, vol. 2, pp. 425-429, Sep. 1998

[17] Mehdi Rasti, Ahmad R. Sharafat, and Babak Seyfe, “Pareto-Efficient and Goal-Driven Power Control in Wireless Networks: A Game-Theoretic Approach With a Novel Pricing Scheme,” IEEE/ACM Transactions on, VOL. 17, NO. 2,pp.556-569

[18] G. Owen, Game theory. Academic Press, third ed., 1995

[19] J. Nash, “Non-cooperative games,” The Annals of Mathematics, vol. 54, pp. 286–295, Sept. 1951

[20] H. Nikaido and K. Isoida, “Note on non-cooperative convex games,” Pacific Journal of Matematics, vol. 5, pp. 807–815, 1955

[21] Jianwei Huang, Zhu Han, Mung Chiang, and H.Vincent Poor, “Auction-based resource allocation for cooperative communications,” IEEE Journal on Selected Areas in Communications, 2008, 26(7): 1226- 1237

[22] Na Xia, Jianguo Jiang, Chunhua Yu, and Qiong Wu,“A coalition formation strategy based on benefit equilibrium,” Control and Decision, Dec, 2005, vol. 20, No. 12, pp:1426-1433

[23] T. Alpcan, X. Fan, T. Basar, M. Arcak, and J. T. Wen, “Power control for multicell CDMA wireless networks: A team optimization approach,” Wireless Networks, vol. 14, no. 5, pp. 647–657, October 2008

[24] M. Cesana, N. Gatti, and I. Malanchini, “A game-theoretic approach to decentralized optimal power allocation for cellular networks,” in Proc. of 2nd Intl Workshop on Game Theory in Communication Networks, Athens, Greece, October 2008

[25] Y. Pan and L. Pavel, “Games with coupled propagated constraints in optical networks: the multi-link case,” in Proc. of the 46th IEEE Conference on Decision and Control, New Orleans, USA, December 2007, pp. 3443–3449

[26] Maskin, “Nash equilibrium and welfare optimality,” Review of Economic Studies, vol. 66, no. 1, pp. 23 – 38, December 2003

[27] J. E. Suris, L. A. DaSilva, Z. Han, and A. B. MacKenzie, “Cooperative game theory for distributed spectrum sharing,” in Proc. of the IEEE International Conference on Communications (ICC), 2007

[28] Cochran, William G. (1977). Sampling Techniques (Third ed.). Wiley

[29] Rosenblatt, M. (1956). "Remarks on some nonparametric estimates of a density function," Annals of Mathematical Statistics 27: 832–837

[30] Parzen, E. (1962). "On estimation of a probability density function and mode," Annals of Mathematical Statistics 33: 1065–1076

[31] Jian Tang, Guoliang Xue, Senior Member, IEEE, Christopher Chandler, and Weiyi Zhang “Link Scheduling With Power Control for Throughput Enhancement in Multihop Wireless Networks,” IEEE Transactions on vehicular technology, VOL. 55, NO. 3, May 2006

[32] Kin K. Leung, “Power Control by Interference Prediction forBroadband Wireless Packet Networks,” IEEE Transactions on Wireless Communications,VOL. 1, NO. 2, April 2002

[33] Wang Hei Ho and Soung Chang Liew, “Distributed Adaptive Power Control in IEEE 802.11 Wireless Networks,” International Conference on Mobile Adhoc and Sensor Systems (MASS), 2006 IEEE

[34] S. Jagannathan, A. T. Chronopoulos, S. Ponipireddy, "Distributed Power Control in Wireless Communication Systems," Eleventh International Conference on Computer Communications and Networks, 2002. Proceedings

[35] Liuju Wu, Zawodniok, M. "Cooperative Approaches Indicating to Capacity and Power Control for Ad Hoc Wireless Network," 2011 Proceedings of 20th International Conference on Computer Communications and Networks (ICCCN)

[36] P. Gupta and P R. Kumar, "The Capacity of Wireless Networks," IEEE Transactions on Information Theory, vol. 46, No. 2, 2000, pp. 388-404

[37] Massimo Franceschetti, Marco Donald Migliore, Paolo Minero, "The Capacity of Wireless Networks: Information-Theoretic and Physical Limits," IEEE Transactions on Information Theory, vol.55, No. 8, 2009

[38] Yoav Nebat, Rene L. Cruz, Sumit Bhardwaj, "The Capacity of Wireless Networks in Nonergodic Random Fading," IEEE Transactions on Information Theory, vol.55, No. 6, 2009

SECTION

2. CONCLUSIONS

The theoretical and simulation analysis of wireless network is shown to update the per-link power while ensuring a fair share of the radio resources. The proposed Cooperative RIS Power Control (CRPC) scheme dynamically, online, determines the appropriate capacity allocation. It performs a network-wide cognition of the channel state and determines the viable target SIR level. In contrast to existing works, no a priori target SIR level is required. Moreover, the mathematical proofs a theoretical guarantee of convergence to fair target SIR and resource allocation. The simulations validate the scheme's performance. In summary, the proposed scheme improves Fairness Index by up to 60% when compared with previous power control schemes.

Next, three cooperative control schemes for Cognitive Radio Network (CRN) are proposed. They ensure that the Primary Users (PUs) can access the radio channel and achieve the desired minimum QoS while supporting a proportionally fair channel capacity sharing among the secondary users (SUs). The integrated scheme is proposed for dual-mode PU, which periodically switches between active and idle modes. The scheme memorizes the scheme's parameters and restores once a PU's mode switch is detected. Consequently, it significantly improves convergence time when PUs is reactivated.

Finally, it is expected that the results and analysis will further the efficiency and employment of CRN and adaptive wireless networks. Future work includes theoretical analysis of the distributed version of the CRPC scheme, study convergence guarantee under significantly fading channel conditions, and experimental verification.

LIST OF PUBLICATIONS

Journal Submissions:

[1] Liuju Wu and Maciej Zawodniok, "Cooperative and Fair Power Control for Peer-to-Peer Wireless Networks," to be submitted to Transaction on Wireless Communications.

[2] Liuju Wu, Hao Xu and Maciej Zawodniok, "Cooperative Power Control Approaches Regarding Radio Resource Allocation for Cognitive Radio Network," to be submitted to International Journal of Wireless & Mobile Networks

Conference Submission:

[1] Roy, S., Liuju Wu, Zawodniok, M., "Spectrum Management for Wireless Networks Using Adaptive Control and Game Theory," 2011 IEEE Wireless Communications and Networking Conference (WCNC 2011), Mexico, March 2011, pp. 1062 – 1067

[2] Liuju Wu, Maciej Zawodniok, "Cooperative Approaches Indicating to Capacity and Power Control for Ad Hoc Wireless Network," 2011 Proc. of 20th International Conference on Computer Communications and Networks (ICCCN), Hawaii, Aug 2011

VITA

Liuju Wu obtained his undergraduate degree in Automation from North China Electric Power University, Beijing, China in May 2010. After completion of undergraduate degree program he started his graduate studies at Missouri University of Science and Technology (former University of Missouri – Rolla), Rolla, MO, USA with a concentration on wireless network communications. During graduate studies, he worked as a Graduate Research Assistant with the Embedded Control System and Networking Lab at the Dept. of Electrical and Computer Engineering. He received his Master's degree in Electrical Engineering from Missouri University of Science and Technology in December 2012.