

Adaptive Efficient Power Control Scheme Optimization for Digital Cognitive Radio Sensor Networks

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Abstract: Traditional distributed power control algorithms in cognitive radio networks are based on the assumption of perfect channel estimation which can lead to performance degradation in practical system. Cognitive radio sensor network (CRSN) has emerged as a promising solution to address the spectrum-related challenges of wireless sensor networks (WSN). Moreover, cognitive radio (cr) gives us a possibility to maximize the utilization efficiency of limited spectrum resources. However, because the wireless devices coexist in the same radio environment, there are harmful channel conflicts among users. First at all, this paper presents a practical model of cumulative interferences from the entire cognitive radio based industrial wireless sensor networks (CR-IWSN). Then, based on the interference model, we propose an intelligent power control scheme to address the communication requirements. The simulation results show that the proposed distributed power control scheme can efficiently increase the energy efficiencies as well as the throughput of the CR-IWSN compared with the existing protocols.

Keywords: CR-IWSN, CRSN, QoS.

I. INTRODUCTION

The traditional approach of fixed spectrum allocation leads to spectrum under-utilization. According to the studies sponsored by the Federal Communications Commission (FCC), there are vast temporal and spatial variations in the usage of allocated spectrum [1-3]. This motivates the concept of dynamic spectrum sharing through cognitive radios that allows secondary cognitive radio networks to access the spectrum licensed to primary users (PU) so long as their transmission do not cause harmful interference to PUs [4]. There are two approaches for this dynamic spectrum access, namely, overlay spectrum and underlay spectrum [5-6]. In overlay spectrum sharing, secondary users (SU) sense the spectrum and conduct transmission when the spectrum is idle. If PU starts transmission, the SU is immediately stopped. When there is interference constraint, the underlay spectrum permits simultaneous sharing of all the frequency bands available between the primary and secondary users subject to the interference constraint. On other hand, SUs implement a concurrent spectrum sharing with PUs as long

as the quality-of-service (QoS) degradation of the PU transmission due to the SU interference is [3]. This paper focuses on the underlay spectrum because of its utilization of the frequency spectrum and efficiency. Low-cost and low-power wireless sensor networks have been used in many applications, including home automation, personal healthcare, surveillance, *etc.* [2].

Motivated by the salient features of cognitive radio, cognitive radio sensor networks (CRSN) were considered a promising technique to overcome similar challenges observed in traditional wireless sensor networks [2], and have been integrated in current and future radio access networks through recent literatures [2, 3]. CRSN can be defined as a distributed wireless sensor networks of wireless cognitive radio sensor nodes equipped with cognitive radio transceivers and sensing circuitries that can observe an event, search available channels and opportunistically communicate with neighboring nodes to reliably deliver the event signal features and remotely synchronize in an energy-efficient way. The main reasons to apply cognitive radio into wireless sensor networks are:

- To help ease spectrum overcrowding in an industrial environment, since the industrial-scientific-medical (ISM) radio band is shared with other wireless technologies such as IEEE 802.11 WLANs, Bluetooth, and IEEE 802.15.4 [14].
- Cognitive radio capable sensor nodes can achieve better energy efficiency and communication range since cognitive radio sensor nodes can operate on lower frequency bands. In addition, sensor nodes do not generate data frequency; therefore, sensor nodes can exploit the unused period with cognitive function from primary users [5].

The dynamic nature of wireless channels causes energy consumption because of packet losses and retransmissions [4, 6]. CRSNs might be able to adapt to varying channel conditions, which would increase transmission efficiency, and hence reduce power used for transmission. In addition, dynamic spectrum management might significantly contribute to the efficient coexistence of spatially overlapping sensors networks in terms of resource

utilization. Power allocation plays an important role in the multiuser spectrum-sharing cognitive radio-based industrial wireless sensor networks because of the channel interference in radio transmission and interference temperature regulation. Therefore, how to allocate the transmission power to sensor nodes with a view to satisfying the interference threshold and maximizing the SUs' utilities [5] is an important task in the implementation of cognitive radio-based industrial wireless sensor networks. On the other hand, as discussed above, it has generally been assumed that the parameters defining the objective function and constraints are perfectly known or constant.

However, given the random and erratic nature of many wireless channels, the parameters are imperfectly known or time varying. In other words, when PUs are not obliged to provide any information to SUs, it is difficult for sensor nodes to obtain system information pertaining to PUs. Without considering the uncertainties of these parameters, the uncertain channel gains between sensor node and the PUs' receivers might cause the total aggregated interference of SUs on PUs' receivers to exceed the acceptable threshold. Thus, these algorithms might lead to an increase in the probability of violating the interference threshold from the CRSNs' perspective. Besides, interference levels on CRSNs' base station made by the PUs' transmitter may also reduce the actual signal-to-interference-plus-noise ratio *SINR* of each sensor node at its secondary base stations (SBS) below an acceptable threshold [18, 1]. Although increasing the throughput is an important target for CR-IWSN, spectrum efficiency and energy efficiency are also two critically crucial performance metrics to CR-IWSN and should be carefully considered in CR-IWSN. Energy efficiency plays a significant role in maximizing the network lifetime while satisfying three constraints, namely, the SUs' minimum requested *SINR*, a given interference threshold, and the upper bound on their transmit power levels.

In this paper, we consider the underlay CR-IWSN where SUs and PUs communicate with their SBSs and PBSs, respectively. Our objective is to optimizing the throughput of SUs and energy efficiency that can be supported, subject to the following constrains:

- R1: Each SUs' required normalized *SINR* must be above a predefined threshold.
- R2: The total amount of interference caused by all cognitive transmission to each PU must be maintained below a given threshold [1].

Requirement R1 is to guarantee reliable communication between the base station and each sensor node user while requirement R2 is to protect each primary user from excessive interference caused by cognitive transmission on the same channel. This paper extends the existing works on the worst case power allocation in CR-IWSN by considering two uncertainty parameters: channel gains between SUs and PBSs, and interference from PU to the SBS. In solving the problem, SUs' interference levels to PBSs are kept below a

given threshold against uncertainty channel gains between SUs and PBSs, and SUs' *SINR* are maintained above their minimum requested values against uncertainty in interference from PU to the SBS [5, 6].

II. SYSTEM MODEL

A. Cognitive radio-based industrial wireless sensor networks

We model the distributed CR-IWSN as a directed graph, where $M = \{m1; m2; \dots; mM\}$ is a set of primary users (PUs) and $N = \{n1; n2; \dots; nN\}$ is set of cognitive users (CUs). We consider a CR-IWSN where primary users communicate with the corresponding base stations through uplink transmission. The secondary users (i.e., sensor nodes), which share the spectrum band with the primary users as long as the performance degradation on the PUs transmission. In addition, consider a CR-IWSN in which the coverage area of a cognitive radio sensor cell partially overlaps with coverage area of a neighboring primary user cell. In this paper, we mainly focus on the primary networks consisting of primary base stations (PBSs) and PUs, and thus assume that the secondary networks has a priori knowledge about the locations of the PBS and the stationary PUs, which is reasonable in many existing practical cases. Besides we assume that the SBS has the dedicate channel to communicate with SUs without interfering the PUs. Thus, we do not need to consider the interference from the secondary base stations (SBSs) to the PUs. The primary user does not always occupy the channel. Given the PU's frequency vacancy and the path radio signal path loss, the sensor nodes could opportunistically utilize the licensed spectrum to access the SBS by using the underlay spectrum sharing model. Additionally, we assume that the distance between SBS and PBSs is larger than the effective transmission range of the PBS. Under this assumption, the PBS has little interference on the uplink of the cognitive radio-based industrial sensor networks. The sensor nodes communicate with their base station through code division multiple accesses (CDMA). For the CR-IWSNs, the time is partitioned into frames. Each frame includes a downlink sub frame and an uplink sub frame. During the downlink sub frame, the SBS and PBSs estimate their interference levels, and then this information is utilized to calculate the transmission power levels of SUs and PUs, respectively.

Next, during the following uplink sub frame, the sensor nodes transmit packets with the assigned transmission power. In order to protect the licensed PUs' communication, the interference to the j -th PBS caused by CUs must be kept below the predefined threshold at the primary receiver. Let g_{ij} denote the interference channel gain between the i -th SU and the j -th PBS. Also, let I_j be the maximum interference level limit tolerable at primary receiving point j . Then, the interference constraint can be written as:

$$\eta_j = \sum_{i=1}^N g_{ij} p_i \leq I_j \quad (1)$$

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Where p_i represents the transmitter power of the CR-Tx of link i . As a mentioned before, the instantaneous channel gains g_{ij} may be difficult to estimate due to the fact that PBSs are not obliged to provide any information to SUs.

B. Secondary User Communications

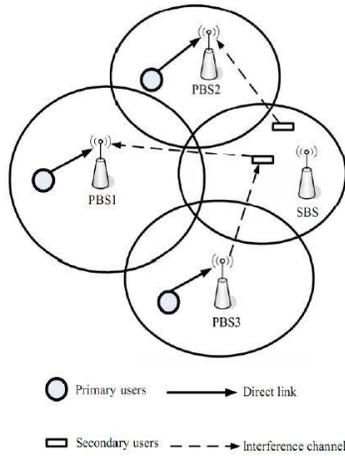


Figure 1. System model with four cells cognitive radio-based industrial wireless sensor network

We would like to adjust distributed power allocation for SUs subject to the interference and QoS constraints which is defined below. In this paper, we limit our framework to a CDMA-based wireless network, where the primary and secondary users can share the same frequency band, but the framework developed here can easily be extended to other types of wireless networks with slight modifications. When the SUs perform channel sensing, all sensor nodes should keep their radio silent for a certain amount of time to obtain an accurate sensing outcome. All the SBS and SUs can participate in channel sensing; therefore, the collaborative channel sensing can decrease false alarm probability and missed detection probability [1]. In this section, we consider how to effectively protect the communication link that corresponds to a pair of secondary users against the intranet interference from other secondary transmitters. For the subsequent analysis, we assume there exists a fixed communication link composed of a pair of secondary users who wish to communicate with each other successfully.

The signal to interference-plus-noise ratio (SINR), denoted by SU i 's signal at the SBS can be formulated as [2]

$$SINR_i^s = \frac{h_{ii}p_i}{n_i + \sum_{k \neq i} h_{ik}p_k + h_{i0}p_0} \quad (2)$$

Let h_{ii} be the channel gain between SU i and its SBS, h_{ik} be the interference caused by other SUs. In addition, h_{i0} and n_i are the aggregate interference of PUs to the SBS and the channel noise power (i.e., background noise), respectively. To satisfying the QoS requirement of cognitive users, the SINR at each CR-Rx should be larger than a threshold [1]

$$SINR_i^s \geq \gamma_i, \forall i, \quad (3)$$

Where is the SINR requirement at the CR-Rx of link i .

We can define F as normalized gain matrix of SUs whose elements are given by:

$$[F_{ik}] = \begin{cases} h_{ik} & ; i \neq k, \\ h_{ii} & \\ 0 & ; i = k. \end{cases} \quad (4)$$

III. PROBLEM FORMULATION

In this section, we consider the uncertainty of the channel gains and use the worst-case robust optimization method to deal with such uncertainties. In this scenario, we assume the worst-case primary user interference by treating all the primary users as being active. As commented in the introduction, we are interested in finding a distributed power algorithm to adjust the transmission power levels of SUs in such a way that the following two goals are simultaneously satisfied: The system throughput of SUs is maximize while each SU's required normalized SINR is maintained above a given value γ_i . Interference to the j th PBS is maintained below a given threshold I_j . In doing so, each SU's transmission power level is obtained by solving the following optimization problem (P1):

$$\text{Max} \sum u_i(\gamma_i) \quad (5)$$

subject to:

$$SINR_i^s = \frac{h_{ii}p_i}{n_i + \sum_{k \neq i} h_{ik}p_k + h_{i0}p_0} \geq \gamma_i, \quad (6)$$

$$\sum_{i=1}^N g_{ij}p_i \leq I_j, \quad (7)$$

where is the utility function of the i th SU. In our problem formulation, the two parameters related to PBS or PUs are channel gains between SUs and PBSs and interference levels caused by PUs to SBS. Estimating and tracking the exact value of the parameters indicated above is not easy because PUs are not obliged to provide any information to SUs. Both of the above parameters are contained in the linear constraint (6) and (7). From the above, the power allocation in (5) is an optimization problem with two uncertainty parameters. The uncertainty region is mathematically expressed by the distance between the exact and estimated values and can be calculated by general norm [1, 2]. In such cases, using an ellipsoid to describe the uncertainty set for the interference caused by PUs to the SBS is given by:

$$G = \left\{ \bar{G} + \Delta G : \sum_i |\Delta G_{ij}|^2 \leq \epsilon_j^2 \right\} \quad (8)$$

$$H = \left\{ \bar{H} + \Delta H : \sum_k |\Delta H_{ik}|^2 \leq \epsilon_0^2 \right\} \quad (9)$$

With $\Delta_j^{\text{tolerance}}$ being protection values against variations in channel gains, we can formulate the distributed optimal problem subject to two constraints (P2) by:

$$\text{Max} \sum u_i(\gamma_i) \quad (10)$$

subject to:

$$SINR_i^s \geq \gamma_i, \forall i, \quad (11)$$

$$\left\{ \sum_{i=1}^N g_{ij} p_i + \Delta_j^{\text{violate}} \right\} \leq I_j, \quad (12)$$

$$\sum_k |\Delta H_k|^2 \leq \varepsilon_0^2, \quad (13)$$

$$\sum_i |\Delta G_{ij}|^2 \leq \varepsilon_j^2. \quad (14)$$

Since channel uncertainties in cognitive radio-based industrial wireless sensor networks are random, the uncertainty set can be represented by an ellipsoid. We use the same method for this paper, and transform the P2 problem into an equivalent problem by considering the worst-case scenario by applying the Cauchy-Schwartz inequality [1].

IV. DISTRIBUTED POWER CONTROL ALGORITHM

Let denote Lagrange multipliers corresponding to minimum and maximum SINR constraints and local constraints, respectively. The Lagrange function of the convex equivalent of how to adjust transmit power levels is (15). From the above, the power allocation in (10) is an optimization problem with two uncertainty parameters. The uncertainty region is mathematically expressed by the distance between the exact and estimated values and can be calculated by general norm [3].

$$L(y, z, \vartheta, \lambda, \mu) = -\sum_i \mu_i \frac{h_i e^{y_i}}{e^{z_i}} + \sum_i \vartheta_i \left(\gamma_i^{\text{min}} \frac{e^{z_i}}{h_i e^{y_i}} - 1 \right) + \sum_i \lambda_i \left(\frac{1}{\gamma_i^{\text{max}}} \frac{h_i e^{y_i}}{e^{z_i}} - 1 \right) + \sum_i \mu_i \left[e^{-z_i} \left(n_i + \sum_{i \neq k} h_k e^{y_k} \right) - 1 \right] \quad (15)$$

The problem is solved via the following first-order algorithm that utilizes the gradient of L to simultaneously update dual and primary variables with constant stepsize, and $\max\{, 0\}$.

$$\mu_i(t+1) = \left[\mu_i(t) + \beta \left(e^{-z_i} \left(n_i + \sum_{i \neq k} h_k e^{y_k} \right) - 1 \right) \right]^+ \quad (20)$$

Algorithm 1: Robust distributed power control

- 1 **Initialization:** $t = 0, \beta > 0, y_i(0) > 0, z_i(0) > 0, \vartheta_i(0) > 0, \lambda_i(0) > 0, \mu_i(0) > 0$
 - 2 **At the SU:**
 - 3 At each iteration $t = 1, 2, \dots$
 - 4 The SU receives the SINR measurements and
 - 5 calculates the subgradient ϑ_i from SBS
 - 6 Locally calculate the SU's $y_i(t), z_i(t)$, and its Lagrange multipliers.
 - 7 Update $\mu_i(t+1)$
 - 8 Feed the information back to SBS of the same link
 - 9 **At the SBS:**
 - 10 At each iteration $t = 1, 2, \dots$
 - 11 Estimate h_i and every L interval and update $\lambda_i(t+1)$.
 - 12 Update transmission power: $p_i = e^{y_i}$,
- $$y_i(t+1) = \min \left\{ y_i(t) - \beta \frac{\partial L}{\partial y_i} \Big|_{y_i^{\text{min}}} \right\}$$
- 13 Broadcast h_i and $y_i(t+1)$

$$y_i(t+1) = \min \left\{ y_i(t) - \beta \frac{\partial L}{\partial y_i} \Big|_{y_i^{\text{min}}} \right\}, \quad (16)$$

$$z_i(t+1) = \left[z_i(t) - \beta \frac{\partial L}{\partial z_i} \right]^+ \quad (17)$$

$$\vartheta_i(t+1) = \left[\vartheta_i(t) + \beta \left(\gamma_i^{\text{min}} \frac{e^{z_i}}{h_i e^{y_i}} - 1 \right) \right]^+ \quad (18)$$

$$\lambda_i(t+1) = \left[\lambda_i(t) + \beta \left(\frac{1}{\gamma_i^{\text{max}}} \frac{h_i e^{y_i}}{e^{z_i}} - 1 \right) \right]^+ \quad (19)$$

The updates (16) - (20) take place at Tx i . It is assumed that SBS is able to estimate the channel gain h_{ii} and the SINR, and feed it back to its i -th SU. In order to make the aforementioned sum available at Tx i , the proposed Algorithm 1 can be adapted to the problem. Sensor nodes exchange information over a control channel to facilitate power management decisions. In detail, each sensor node transmitter broadcasts its variable. In addition, each sensor node transmitter needs to know the path gain h_{ii} of the link causing interference to the non-receiver Rx i .

Table 1. Simulation setup

Parameter	Value
Number of cells M	4
ε_0	10%
ε_i	10%
γ_{min}	8
γ_{max}	20
Minimum transmission rates of secondary users R^{min}	9.6Kbps
P_{max}	1mW
I_{max}	10×10^{-10} mW
h_{ii}	$d_i^{-\alpha}$
h_{ik}	$B^{-\alpha} d_i^{-\alpha}$
B	120

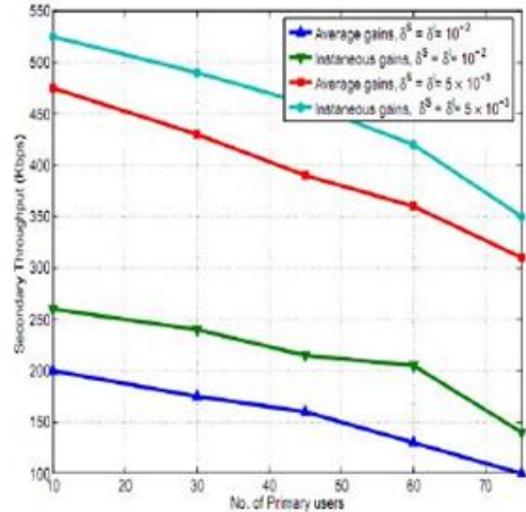


Figure 2. Throughput of secondary user versus the number of primary users

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The performance of our proposed power control in terms of its energy efficiency over the power budget is evaluated in Figure 4. From Figure 4, we can obtain the following two important observations. First, the energy efficiency initially increases with its power increasing, then the power reaches a certain point, and the energy efficiency begins to decrease. This is attributed to the fact that there is a tradeoff between the transmission capacity and the power consumption of the distributed power allocation. Second, the better the channel condition, the more energy efficiency obtained in our proposed scheme. Further, we can observe from the figure that less power is needed for our scheme with good channel condition to obtain the small energy efficiency.

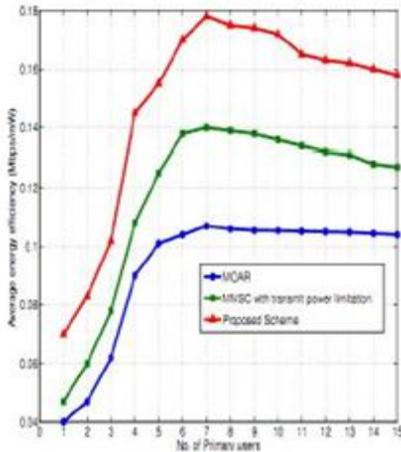


Figure 3. Average Energy Efficiency of secondary user versus the number of primary users

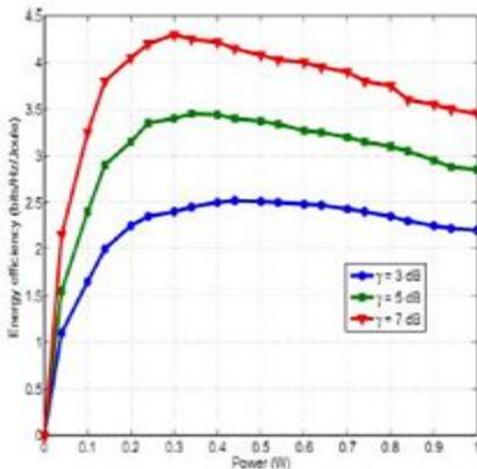


Figure 4. Tradeoff between Energy Efficiency and Power

V. CONCLUSION

This paper considered dynamic spectrum access for cognitive radio-based industrial wireless sensor network under interference temperature and QoS constraints for each secondary link. Reduced complexity optimal link subsets of links which can significantly reduce the searching space compared with naive searching. Such uncertainty may increase the probability of violating the interference

threshold of PBSs and reduce the actual normalized $SINRs$ of SUs below an acceptable level. We modeled uncertainty as a bounded distance between actual and nominal values, and showed that by using the protection value in our robust problem. By applying this new scheme, the sensors could share the spectrum without performance degradation and both of the throughput and energy consumption could be optimized. As a future direction for this research, we will investigate the analyzing access strategies for spectrum sharing systems with multiple primary and secondary users.

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