Distributed Energy Efficient Spectrum Access in Wireless Cognitive Radio Sensor Networks[‡]

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***Abstract*—In this paper, a wireless cognitive radio sensor network is considered, where each sensor node is equipped with cognitive radio and the network is a multi-carrier system operating on time slots. In each slot, the users with *new* traffic demand will sense the entire spectrum and locate the available subcarrier set. Given the required data rate and power bound, a fully distributed subcarrier selection and power allocation algorithm is proposed for each individual user to minimize the energy consumption per bit over all subcarriers, while avoid introducing harmful interference to the existing users. The multi-dimensional and non-quasi-convex/concave nature of the energy efficiency optimization problem in multi-carrier systems makes it more challenging than throughput/power optimization problems or the energy efficiency problem in the single carrier system. The optimal solution is derived by using a two-stage algorithm where the original problem is decoupled into an unconstrained problem and branch and bound method is applied thereafter to reduce the search space. In addition, a distributed power control is performed to manage the co-channel interference among new users when needed. Simulation results demonstrate that the proposed approach performs close to the centralized optimal solution, and it provides prolonged network lifetime.**

Keywords-resource allocation, cognitive radio, wireless sensor network

I. INTRODUCTION

Wireless sensor networks (WSNs) are now used in many applications, including battlefield surveillance, environment monitoring, etc [1]. It is expected that many WSNs of large number of sensor nodes will be deployed in the near future. Long network lifetime is one of the fundamental requirements for WSNs that consist of resource-constraint sensor nodes. Moreover, when a large amount of data needs to be collected in a timely fashion by the WSN, many users may need to transmit data simultaneously. In this case, it is necessary to avoid or reduce the interference from concurrent transmissions in order to achieve high power efficiency. All the above requirements call for joint design of cognitive radio and multi-carrier modulation [7].

Cognitive Radio (CR) [3, 4, 6] is a promising technology for improving spectrum utilization, and it also provides a technique to avoid low power efficiency in multi-carrier systems [5]. In this study, it is assumed that CR is installed at each sensor node. The sensor network is a multi-carrier system and operates on time slots. An existing user transmits a pilot signal periodically on a subcarrier if that subcarrier is occupied by itself. By detecting the presence of such a pilot signal, other emerging new CR users can determine if that particular subcarrier is available or not. It allows users to dynamically sense the spectrum, find the available subcarrier[1] set in a target spectral range, and then selects subcarriers and transmits without introducing harmful interference to the existing users [3, 6].

In this paper, we extend our previous work [7] by allowing each user to choose *multiple* subcarriers for data transmission. This is motivated by the fact that a single subcarrier may not be enough to accommodate the data rate requirement. Hence, a new design problem, namely, the distributed channel selection and power allocation problem, needs to be studied to maximize the energy efficiency and fulfill the QoS requirements. This is the focus of this paper.

Although the new users will not cause harmful interference to the existing users, they may choose the same subcarriers in the same time slot independently, and thus co-channel interference may be introduced. In this work, we allow multiple new users to share the same subcarriers as long as their respective Signal-to-Interference and Noise Ratio (*SINR*) is acceptable. This may be achieved by distributed power control [14], which converges very fast.

A lot of work has been done to address the multi-user resource allocation problem based on multi-carrier modulation in cellular systems [2, 8, 9, 10], such as Orthogonal Frequency Division Multiplexing (OFDM), where subcarrier band, data rate and power are adaptively allocated to each user. It is assumed in [2, 8, 9,10] that the spectral utilization information is known a priori with the aid of a base station, which is not realistic in scenarios where an infrastructure is not available. The subcarrier and bit allocation problem is explored for OFDMA-based wireless network in a distributed manner in [11]. The authors directly adopt distributed power control scheme for the power and bits allocation on all subcarriers, which may not be efficient in a resource constraint environment. An Asynchronous Distributed Pricing (ADP) scheme is proposed in [18], where the users need to exchange information indicating the interference caused by each user to others. In the context of wireless CR network, the channel allocation problem is resolved through two steps in [12]: channel assignment with objective of minimizing transmission power and channel contention, where the interference spectrum mask is assumed to be known a priori. The authors of [13] address the opportunistic spectrum access (OSA) problem in

[1] In this paper, subcarrier and channel are used interchangeably.

[‡] This work is supported by the US ARO No. W911NF-04-2-0054.

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WSN. The distributed channel allocation problem is modeled by a partially observable Markov decision process framework while assuming the transition probability of each channel is known.

In this paper, the resource allocation problem in CR-WSNs is investigated from the aspect of energy efficiency. A fully distributed subcarrier selection and power allocation scheme is proposed to minimize energy per bit over all subcarriers, subject to required data rate and power constraints. This in turn results in a prolonged network lifetime while maintaining QoS. The multi-dimensional and non-quasi-convex/concave nature of the optimization problem in multi-carrier systems makes it more challenging than the throughput maximization/power minimization problems or the energy efficiency problem in a single carrier system [19]. The optimal solution is derived by using a two-stage algorithm where the original problem is decoupled into an unconstrained problem and a branch and bound method is applied thereafter to reduce the search space. In addition, a distributed power control is performed to manage the co-channel interference among new users when needed. It is demonstrated by simulation that the proposed distributed scheme plus distributed power control performs close to the centralized optimal solution, where all the channel gains among new users are assumed to be known to a central controller and all the new users collaborate.

The remainder of this paper is organized as follows. In section II, the system model and the problem formulation are given. A fully distributed channel selection and power allocation scheme is proposed in section III. In Section IV, a distributed power control algorithm is suggested for co-channel users. Section V contains the simulation results and discussions. Section VI gives concluding remarks.

II. System Model And Problem Formulation

We consider a CR-WSN where each node operates on limited battery energy consumed mostly by transmission and reception of data at its radio transceiver. The system is a time-slotted system with fixed time slot duration T_S. A node either transmits data, receives data or sleep in each time slot. And after transmitting or receiving data, a node switches off and goes to sleep to save power. We assume slot synchronism can be achieved through some kind of beaconing (as in IEEE 802.11). Before each time slot, a guard interval is inserted which is used to achieve time synchronization, perform spectrum detection as well as channel selection and power allocation (based on the proposed scheme). In the network, we further assume that each node transmits to one of its one-hop-away neighbors. The routing in the network is assumed to be given and the routing problem is not considered in this work.

At the physical layer, the channel is assumed to be a frequency selective Rayleigh fading channel, and the entire spectrum is appropriately divided into M subcarriers with each subcarrier experiencing flat Rayleigh fading [5]. Given a time slot, primary users may already have occupied some subcarriers of the system. If there is a node wants to start a new transmission in this time slot, it first needs to detect the available subcarriers and only employs the available subcarriers that will not interfere with the existing primary users. A subcarrier detection method is given in our previous work [7], and it is assumed that perfect detection is achieved in this paper.

After each new user obtains the available subcarrier set, it will allocate power to the selected subcarriers such that the energy efficiency is maximized while satisfying data rate and power constraints. Specifically, we will minimize energy per bit over all subcarriers in each time slot. For each new user, the distributed subcarrier selection and power allocation problem can be defined as

(P.1)

$$\underset{P_t^{(i)}}{Min} \frac{\sum_{i=1}^{M} P_t^{(i)} + P_r}{B \cdot \sum_{i=1}^{M} \log_2(1+\alpha_i P_t^{(i)})}$$

$$\textit{subject to}$$

$$\sum_{i=1}^{M} R^{(i)} = B \cdot \sum_{i=1}^{M} \log_2(1+\alpha_i \cdot P_t^{(i)}) \geq R_{tar} \quad \forall\ i=1,2,\cdots M$$

$$\sum_{i=1}^{M} P_t^{(i)} \leq P_{\max}, \quad P_t^{(i)} \geq 0 \quad \forall\ i=1,2,\cdots M$$

Where $P_t^{(i)}$ is the transmission power allocated on subcarrier i, P_r is the total circuit power consumption. The power leakage during sleep mode is negligible, thus it is omitted here. B is the bandwidth of one subcarrier. α_i is the channel state information (CSI) of subcarrier i. The power allocation implies the channel selection as well. $P_t^{(i)}=0$ means subcarrier i is not selected.

III. Optimal Channel and Power Allocation Algorithm

The problem **(P.1)** is a combinatorial optimization problem and the objective function is not quasi-convex/concave. Hence, the Lagrange multipliers method cannot be applied here. Instead, we propose a two-stage algorithm to decouple the original problem into an unconstrained problem in order to reduce the search space. After the optimal solution for the unconstrained problem is obtained in stage 1, the power and data rate constraints will be examined in search of the final optimal solution.

Stage 1. Unconstrained optimization

If we remove the constraints, the original problem **(P.1)** is reduced to an unconstrained optimization problem

(P.2)

$$\underset{P_t^{(i)}}{Min} \left(\sum_{i=1}^{M} P_t^{(i)} + P_r \right) \Big/ \left(B \cdot \sum_{i=1}^{M} \log_2\left(1+\alpha_i \cdot P_t^{(i)}\right) \right)$$

$$\textit{subject to} \quad P_t^{(i)} > 0 \quad \forall i=1,2 ... M$$

The optimal transmission power $\boldsymbol{P}^* = [P_t^{(i)*}]$, $\forall\ i=1, 2....M$ of **(P.2)** is in the form of

$$\begin{aligned} & P_t^{(i)*} = Max\{B \cdot \log_2^e \cdot \zeta^* - \left(\frac{1}{\alpha_i}\right), 0\} \\ & \left(\sum_{i=1}^{M} P_t^{(i)*} + P_r \right) / \left(B \cdot \sum_{i=1}^{M} \log_2(1+\alpha_i P_t^{(i)*}) \right) = \zeta^* \end{aligned} \quad (1)$$

Where ζ^* is the optimal energy per bit. The details of the derivation are given in **Appendix A**. The value of ζ^* can be obtained from (1) by using a numerical method given M, B, α_i, and P_r. Then $\boldsymbol{P}^*$ can be determined. It is observed that $\boldsymbol{P}^*$ has similar type of "rate-adaptive"/"margin-adaptive" waterfilling results, and we name it "energy-efficient" waterfilling. However, the fundamental difference among them lies in the locations of their respective optimal points. The usual "rate-adaptive" waterfilling maximizes the achievable data rate under a fixed power constraint, and "margin-adaptive" waterfilling minimizes the total transmission power subject to a fixed rate constraint [17]. The proposed "energy-efficient" waterfilling maximizes the energy efficiency by choosing the most energy efficient operating point (in other words, choose the optimal data rate that minimizes energy per bit) and satisfies the required data rate and power constraints. Actually, the "rate-adaptive" or "margin-adaptive" waterfilling can be considered as a special case of the "energy-efficient" waterfilling solved in this paper. If we set $\sum P_t^{(i)}=P_{constant}\leq P_{Max}$ or $\sum R^{(i)}=R_{tar}$, then our problem is reduced to the well explored "rate-adaptive"/"margin-adaptive" waterfilling problem.

Multiple solutions may be obtained for ζ^* under certain conditions (determined by the settings of M, B, P_r and α_i). The unique optimal value of ζ^* can be determined by checking the corresponding $\boldsymbol{P}^*$. All the elements of $\boldsymbol{P}^*$ should be non-negative for the optimal solution.

Stage2. Constrained optimization

Given the optimal solution $\boldsymbol{P}^*=[P_t^{(i)*}]$, $\forall\, i=1, 2\ldots M$ of **(P.2)**, we can partition the solution space of the constrained problem **(P.1)** into four sub-spaces based on the power and data rate constraints, as highlighted in Fig. 1.

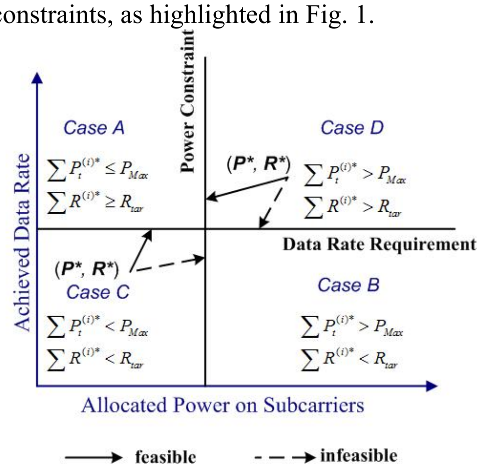

Fig. 1. Partitions of the constraint space

Case A. $\sum P_t^{(i)*}\leq P_{Max}$ and $\sum R^{(i)}\geq R_{tar}$

In this case, the optimal solution $\boldsymbol{P}^*$ of **(P.2)** satisfies the data rate and power requirements. Apparently $\boldsymbol{P}^*$ is the optimal solution of the original problem **(P.1)**.

Case B. $\sum P_t^{(i)*}\geq P_{Max}$ and $\sum R^{(i)}\leq R_{tar}$

In case B, the total power allocated on all subcarriers has already exceeded the maximal power bound, but the data rate requirement is still not met, even under the optimal channel and power allocation. Therefore, there is no feasible solution exists for the original problem **(P.1)**.

Case C. $\sum P_t^{(i)*}\leq P_{Max}$ and $\sum R^{(i)}\leq R_{tar}$

If both the power allocated on all subcarriers does not reach the maximal power bound and the data rate requirement is not met, the power should be increased to achieve the data rate requirement under the maximal power bound. Based on **(P.2)** and (1), we can modify the original problem as

(P.3)

$$\underset{\Delta P^{(i)}}{Min}\frac{\sum_{i=1}^{M}(P_t^{(i)*}+\Delta P^{(i)})+P_r}{B\cdot\sum_{i=1}^{M}\log_2(1+\alpha_i\cdot(P_t^{(i)*}+\Delta P^{(i)}))}$$

subject to

$$\sum_{i=1}^{M}(R^{(i)*}+\Delta R^{(i)})\geq R_{tar}\ \ \forall i=1,2\ldots M$$

$$\sum_{i=1}^{M}\left(P_t^{(i)*}+\Delta P^{(i)}\right)\leq P_{Max},\ \Delta P^{(i)}>0\ \ \forall i=1,2\ldots M$$

If we increase power on any single subcarrier, the energy consumption per bit can be expressed as

$$\zeta'=\left(\frac{1}{B}\right)\cdot\frac{\Delta P^{(i)}+\sum_{i=1}^{M}P_t^{(i)*}+P_r}{\sum_{j=1}^{M}\log_2(1+\alpha_j\cdot P_t^{(j)*})+\log_2\left[\frac{1+\alpha_i(P_t^{(i)*}+\Delta P^{(i)})}{1+\alpha_i\cdot P_t^{(i)*}}\right]} \tag{2}$$

If we let $\beta=B\cdot log_2^{e}\cdot\zeta^*$, the optimal power allocation $P_t^{(i)*}$ can be simplified to

$$P_t^{(i)*}=\beta-\left(1/\alpha_i\right) \tag{3}$$

Combine (2) and (3),

$$\zeta'=\left(\frac{1}{B}\right)\cdot\frac{\Delta P^{(i)}+\sum_{i=1}^{M}P_t^{(i)*}+P_r}{\log_2\left(1+\frac{\Delta P^{(i)}}{\beta}\right)+\sum_{j=1}^{M}\log_2(1+\alpha_j\cdot P_t^{(j)*})} \tag{4}$$

It is observed that given the increased power $\Delta P^{(i)}$ on subcarrier i, the increased data rate on subcarrier i does not depend on its channel condition, since β is a constant for all subcarriers. In other words, if $\Delta P^{(i)}=\Delta P^{(j)}$, then $\Delta R^{(i)}=\Delta R^{(j)}$. And the new energy consumption per bit ζ' will not vary due to different subcarrier. If we presume, in order to reach the data rate requirement, the additional required power allocated on all subcarriers (ΔP) is known, $\Delta P=\sum\Delta P^{(i)}$, then the increased power on each subcarrier ($\Delta P^{(i)}$) should be the same. The minimal required additional power ($\Delta P_{Min}=Min(\Delta P)$) to fulfill the data rate requirement R_{tar} is the optimal solution.

The minimal required additional power ΔP_{Min} can be derived by

$$B\cdot M\cdot\log_2\left(1+\frac{\Delta P_{Min}}{M\cdot\beta}\right)=R_{tar}-\sum_{i=1}^{M}R^{(i)*}$$

$$\Delta P_{Min}=M\cdot\beta\cdot\left[\exp\left(\left(R_{tar}-\sum_{i=1}^{M}R^{(i)*}\right)/\left(B\cdot\log_2^{e}\cdot M\right)\right)-1\right] \tag{5}$$

If ΔP_{min} is larger than the remaining power, i.e., $\sum P_t^{(i)*} + \Delta P_{min} \geq P_{Max}$, there is no feasible solution for **(P.3)**. Hence, the original problem **(P.1)** does not have a feasible solution. If $\sum P_t^{(i)*} + \Delta P_{min} \leq P_{Max}$, the optimal solution for the original problem **(P.1)** is

$$P_t^{(i)opt} = P_t^{(i)*} + \frac{\Delta P_{Min}}{M} \qquad (6)$$

Case D. $\sum P_t^{(i)*} \geq P_{Max}$ and $\sum R_i \geq R_{tar}$

In case D, the data rate and power allocation both exceed the upper bounds. In order to obtain feasible solution and minimize energy consumption as well, the allocated power on all subcarriers need to be decreased. The solution follows similar procedures as in case C, and it is omitted here. The details of the solution can be found in [15].

IV. DISTRIBUTED POWER CONTROL

In the previous section, an optimal subcarrier selection and power allocation is obtained individually for each of the new users without considering other new users. However, it may happen that multiple new users decide to use the same subcarrier and co-channel interference is introduced. In this section, a distributed power control scheme is adopted to manage the co-channel interference. Assume that there are $N^{(i)}$ new users decide to use the same subcarrier i in the current time slot, it can be shown that the following distributed power control algorithm converges if it is feasible

$$P_n^{(i)}(k+1) = \frac{\gamma_n^{tar,(i)}}{\gamma_n^{(i)}(k)} P_n^{(i)}(k) \qquad (7)$$

where $\gamma^{tar,(i)}$ is the target *SINR* and it can be calculated from the optimal allocated data rate $R_n^{(i)*}$. $\gamma_n^{(i)}(k)$ and $P_n^{(i)}(k)$ are the measured *SINR* and the transmission power of new user n on subcarrier i in step k, respectively.

In the power control stage of our scheme, each node only needs to know its own received *SINR* at its designated receiver to update its transmission power. This is available by feedback from the receiving node through a control channel. As a result, the proposed scheme is fully distributed. Convergence properties of this type of algorithms were studied by Yates [14]. An interference function *I(P)* is standard if it satisfies three conditions: positivity, monotonicity and scalability. It is proved by Yates [14] that the standard iterative algorithm *P(k+1)= I(P(k))* will converge to a unique equilibrium that corresponds to the minimum use of power. The distributed power control scheme (7) is a special case of the standard iterative algorithm.

When the power control problem is not feasible, a distributed Medium Access Control (MAC) scheme is needed to resolve the conflict. This will be one of our future efforts.

V. SIMULATION RESULT

In this section, we evaluate the performance and convergence of the proposed distributed channel selection and power allocation scheme. The proposed algorithm is firstly applied to a single new user case to validate the theoretical results in Section III. The impact of parameter settings (such as bits per slot, number of available subcarriers and target data rate) on energy efficiency is also analyzed. Then, the convergence of the power control scheme for multiple new users sharing the same subcarriers is demonstrated. In addition, we compare the proposed distributed scheme with the centralized global optimal solution for benchmarking. Finally, it is demonstrated that the proposed "energy-efficient" waterfilling always performs better than the "rate-adaptive" and "margin-adaptive" waterfilling in terms of network lifetime.

We use the experimental data measured from mica2/micaz Berkeley sensor motes [16]. The setup of the experiment is as follows.

1). The distance between transmitter and designated receiver is 50m, which is the transmission range of the mica2 Berkeley motes.

2). The target data rate is ($2 \times L/T_s$), where L is the number of bits per slot, assuming the probabilities of transmitting or receiving data are the same.

3). The duration of each time slot T_s is *10*ms.

4). In addition, the mica2 motes operate on 2 AA batteries and the output of each battery is about 1.5 volts, 25000mA·h.

The other system parameters are listed in Table I.

TABLE I. UNITS FOR SYSTEM PARAMETERS

Symbols	*Quantity*	*Value*
P_{Max}	Maximal allowable power	0.5 A·V
P_r	Total circuit power	48×10^{-3}A·V
B	Bandwidth of each time slot	100×10^{3}Hz
t_s	Duration of one time slot	1×10^{-2}Sec
σ^2	Variance of thermal noise	-80dBm

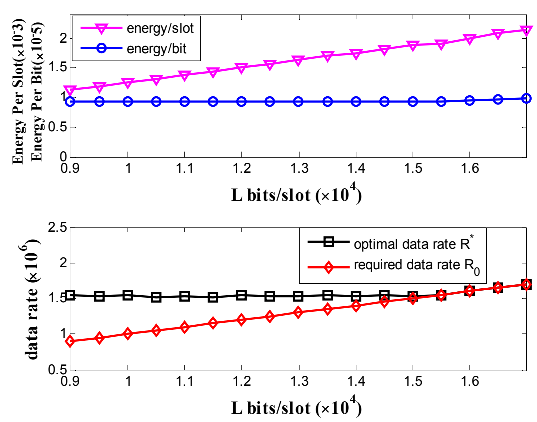

Fig. 2 Energy efficiency vs. bits per slot for a single new user

It is observed from Fig.2 that an optimal rate (and thus power) allocation exists given the channel conditions of all the available subcarriers and the required data rate (L bits per slot). This corresponds to the Case A in Section III. The energy per bit is flat until L=*15500* bits and then it goes higher when the required data rate exceeds the optimal rate (Case C in Section III). Then the required rate can only be obtained at the cost of lower energy efficiency. It is noticeable that L is a very important design parameter, and its optimal value can be pre-calculated given the channel conditions. As long as the required rate is below the optimal value, the pre-calculated allocation can be applied for maximum energy efficiency.

The energy efficiency vs. number of available subcarriers is plotted in Fig. 3. It is shown that the energy efficiency is improving as the number of available subcarriers increases. In other words, the solution of the optimization problem moves from Case C to Case A as the number of available subcarriers increase because more available subcarriers can accomodate more achievable data rate.

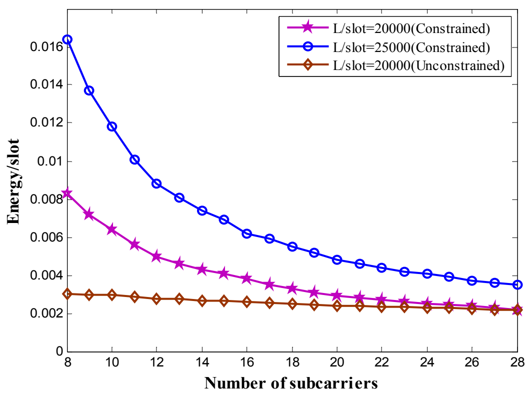

Fig. 3. Energy efficiency vs. number of available subcarriers

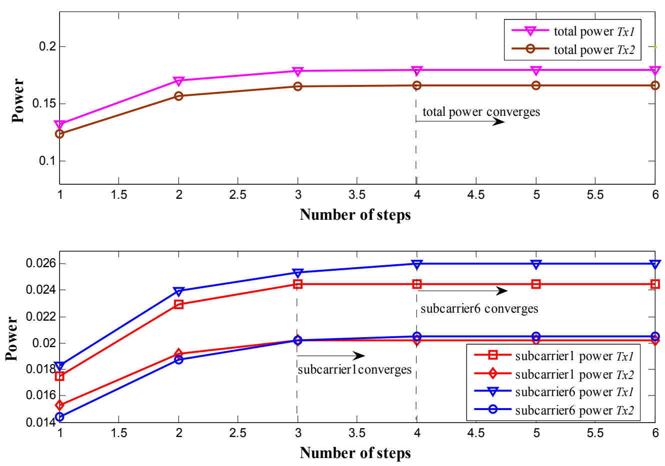

Fig. 4. The convergence of the distributed power control

Both the total power and power of two randomly chosen subcarriers are shown in Fig.4 to demonstrate the convergence of the distributed power control. It is observed that the power control algorithm converges very fast (in four steps).

In this part of the simulation (Fig. 5), the performance of the proposed distributed scheme is compared with the centralized optimal solution [15], where it is assumed that a central controller collects all the MxN^2 channel gain information from all the N new users, and calculates the global optimal solution by considering all the co-channel interference. Because the centralized optimal solution requires solving MxN nonlinear equations simultaneously, only the 2x2 case is attempted here. It is observed that the proposed distributed scheme (the upper two lines) performs closely to the centralized optimal solution (the middle line). In addition, the competitive optimal solution is also shown in Fig.5, where each user calculates its own solution *without* considering co-channel interference (thus optimistic).

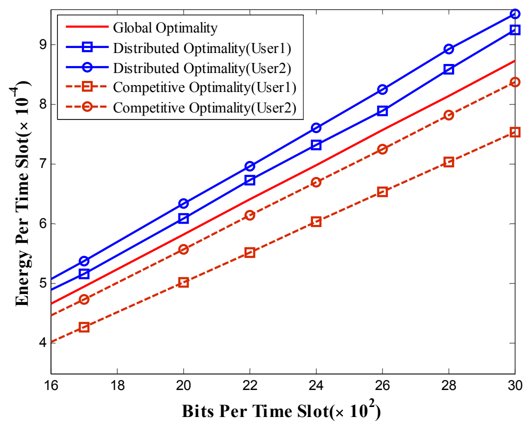

Fig. 5. Evaluation between distributed scheme and global optimality

The impact of the proposed "energy-efficient" waterfilling on network lifetime is demonstrated in Fig.6, compared with "rate-adaptive" and "margin-adaptive" waterfilling (for transmitting the same amount of data in the network). It is clear that the proposed scheme outperforms the others. As the required data rate gets closer to the optimal rate, the proposed scheme will coincide with the power minimization scheme as expected. However, since the required data rate in a typical sensor network is usually low, it is expected that the proposed scheme will improve the network lifetime in many applications.

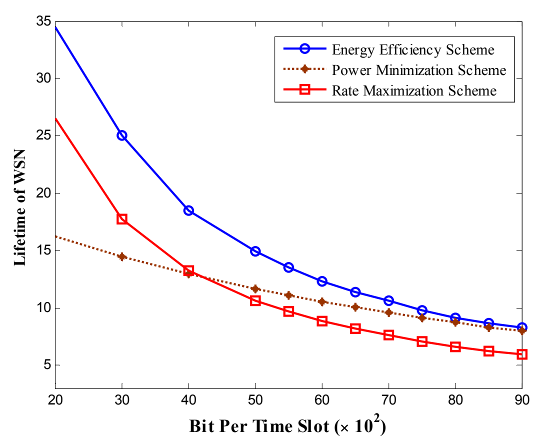

Fig. 6. Lifetime comparison between energy efficient scheme and power/rate optimization scheme

VI. Conclusions

In this study, a distributed channel and power allocation scheme is proposed for each individual user to maximize energy efficiency in a wireless cognitive radio sensor network. A distributed power control algorithm is also suggested for multiple new users to share the same subcarriers efficiently while maintaining the required data rate by managing the co-channel interference.

The proposed channel allocation plus power control provide a fully distributed solution to the optimization problem (**P.1**). Motivated by iterative waterfilling algorithm in [17], another distributed solution may be obtained by solving the multi-user distributed channel and power allocation problem iteratively. However, each user can only detect interference from other users after everyone start transmitting data. It may take many steps for the iterative algorithm to converge if it converges at all, and the delay may be too large. In addition, the cost of the additional computational complexity may be high. Hence, we believe that the proposed distributed channel allocation plus power control scheme provides an efficient and practical solution for dynamic spectrum access in wireless cognitive radio sensor networks employing multi-carrier modulation.

In this work, it is assumed that the subcarrier detection is perfect. The effects of detection errors will be investigated in our future work.

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APPENDIX A

Solution of the Unconstrained Optimization Problem

The unconstrained optimization problem **(P.2)** is

$$\underset{P_t^{(i)}}{Min}\left(\sum_{i=1}^{M} P_t^{(i)} + P_r\right)\Big/\left(B\cdot\sum_{i=1}^{M}\log_2\left(1+\alpha_i\cdot P_t^{(i)}\right)\right) \tag{A1}$$

$$subject\ to\quad P_t^{(i)} > 0 \quad \forall i = 1,2...M$$

If we define the objective function $J(P^{(i)}_t)$ as

$$J(P_t^{(i)}) = \frac{1}{B}\cdot\left(\left(\sum_{i=1}^{M} P_t^{(i)} + P_r\right)\Big/\left(\sum_{i=1}^{M}\log_2\left(1+\alpha i\cdot P_t^{(i)}\right)\right)\right) \tag{A2}$$

The first derivative of (A2) is

$$\frac{d(J)}{d\left(P_t^{(i)}\right)} = \frac{1}{B\cdot\log_2^e}\cdot\frac{\left[\ln\left(1+\alpha_i\cdot P_t^{(i)}\right)+\sum_{j=1,j\neq i}^{M}\ln\left(1+\alpha_j\cdot P_t^{(j)}\right)\right]}{\left[\ln\left(1+\alpha_i\cdot P_t^{(i)}\right)+\sum_{j=1,j\neq i}^{M}\ln\left(1+\alpha_j\cdot P_t^{(j)}\right)\right]^2} - \frac{1}{B\cdot\log_2^e}\cdot\frac{\left(P_t^{(i)}+\sum_{j=1,j\neq i}^{M}P_t^{(j)}+P_r\right)\cdot\left(\frac{\alpha_i}{1+\alpha_i\cdot P_t^{(i)}}\right)}{\left[\ln\left(1+\alpha_i\cdot P_t^{(i)}\right)+\sum_{j=1,j\neq i}^{M}\ln\left(1+\alpha_j\cdot P_t^{(j)}\right)\right]^2} \tag{A3}$$

The denominator of (A3) is actually the achieved data rate on all subcarriers which is always larger than zero, as long as there is non-zero allocated power. Thus, if we let $d(J)/d(P_t^{(i)})=0$, (A3) can be reduced to

$$\left[\ln(1+\alpha_i\cdot P_t^{(i)})+\sum_{j=1,j\neq i}^{M}\ln\left(1+\alpha_j\cdot P_t^{(j)}\right)\right]-\alpha_i\cdot\left(\frac{P_t^{(i)}+\sum_{j=1,j\neq i}^{M}P_t^{(j)}+P_r}{1+\alpha_i\cdot P_t^{(i)}}\right)=0 \tag{A4}$$

It can be re-arranged as

$$\sum_{j=1}^{M}\ln(1+\alpha_j\cdot P_t^{(i)}) = \left(\frac{\alpha_i}{1+\alpha_i\cdot P_t^{(i)}}\right)\cdot\left(\sum_{j=1}^{M}P_t^{(j)}+P_r\right) \tag{A5}$$

From (A5), the power allocated on subcarrier i is

$$P_t^{(i)} = \left(\sum_{j=1}^{M}P_t^{(j)}+P_{\mathrm{r}}\right)\Big/\sum_{j=1}^{M}\ln\left(1+\alpha_j\cdot P_t^{(j)}\right)-\frac{1}{\alpha_i} \tag{A6}$$

Apparently the first term of the right hand side of (A6) is a linear function of energy consumption per bit. If the optimal solution of **(P.2)** exists, there must be a corresponding optimal value of the energy consumption per bit ζ^*. Then (A6) can be expressed in terms of ζ^* as

$$P_t^{(i)*} = B\cdot\log_2^e\cdot\zeta^* - \left(\frac{1}{\alpha_i}\right) \tag{A7}$$