# Energy Efficient Adaptive Modulation in Wireless Cognitive Radio Sensor Networks

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*Abstract*—**In this paper, we consider the lifetime maximization problem in a wireless cognitive radio sensor network, where the joint design of cognitive radio and multi-carrier modulation is proposed to achieve high power efficiency. Sensor nodes first sense the entire spectrum and locate the available subcarriers based on a pilot tone detection scheme. After each node locates the available subcarrier set, information is transmitted over the favorite channel that has the largest channel gain. Under this setting, an adaptive modulation strategy is proposed to maximize the network lifetime by selecting the optimal constellation size. Simulation results demonstrate the effectiveness of our approach. In addition, the impact of conflicting transmissions upon the network lifetime is also investigated.**

***Keywords-adaptive modulation, cognitive radio, wireless sensor network, lifetime***

## I. INTRODUCTION

Wireless sensor network (WSN) is one of the recent rising technologies in wireless communications with a wide range of applications, such as environment surveillance, health care, intelligent buildings and battle field control [1]. A typical wireless sensor network consists of resource-constraint sensors responsible for monitoring physical phenomena and reporting to access points. One of the primary objectives of a wireless sensor network is its long time functionality. Therefore, the network lifetime becomes a critical issue when designing WSNs. In addition, 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. And one way to achieve this is by joint design of cognitive radio and multi-carrier modulation [7].

A lot of work has been done to address the multi-user resource allocation problem based on multi-carrier modulation [5-8], such as orthogonal frequency division multiplexing (OFDM), where subcarrier band, data rate and power are adaptively allocated to each user. A potential drawback of this technique is that, at any particular instant of time, the active users generally do not need the entire spectrum for their transmissions, and thus a good number of spectral bands are not utilized. This results in inefficient spectrum utilization. Furthermore, the resource allocation in [5-8] is performed by assuming 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, such as in wireless ad hoc networks.

In this study, it is assumed that cognitive radio [13, 14] is installed at each sensor node. The sensor network is a multi-carrier system and operates on time slots. A subcarrier detection mechanism is designed using a cognitive radio perspective, in order to achieve high bandwidth efficiency and power efficiency. Cognitive radio provides a technique to avoid low bandwidth efficiency in multi-carrier systems [9]. It allows users to dynamically sense the frequency spectrum, find the available spectrum bands in a target spectral range, and then transmit immediately without introducing harmful interference to the existing users in this spectral range [13, 14].

There have been extensive works focused on maximizing the lifetime of WSNs. Most of them [2, 3, 4] deals with the problem of finding routes to maximize the lifetime by balancing the power consumption of each node. In [2, 3], the authors formulate the maximum lifetime routing problem as a linear programming problem. The flow redirection algorithm is extended to the multi-commodity case to solve the problem. In addition, a heuristic called flow augmentation algorithm is proposed by the authors to find and maintain the routes of the network. In [4], the maximum lifetime routing problem is formulated as a maximum concurrent flow problem and a distributed flow algorithm is adapted to find an approximation to a feasible flow if it exists. The authors theoretically analyze the algorithm to guarantee the approximation factor and give lower bounds on its performance.

In this paper, it is assumed that routing has been done and the route between any source/destination pair is given. Adaptive modulation technique is used to control the power consumption of each node at the physical layer. By adapting the constellation size, different data rate can be achieved which will directly influence the power consumption of each node, and in turn will affect the lifetime of the whole sensor network. Assuming QAM is adopted as the modulation scheme; the optimal constellation size of QAM that maximize the network lifetime is derived analytically and is verified by simulations. The effects of subcarrier detection error and subcarrier selection error are also investigated through simulations.

The remainder of this paper is organized as follows. In section II, the system model and problem formulation are

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introduced. The detection process of available subcarrier with cognitive radio is depicted in section III. In section IV, the system model for network lifetime is formulated and the lifetime is maximized with adaptive QAM modulation techniques. Section V contains the simulation results and performance comparison. Section VI gives concluding remarks.

## II. System Model And Problem Formulation

We consider a wireless sensor network of uniformly distributed nodes; each node operates on limited battery energy consumed mostly by transmission and reception of data at its radio transceiver. The sensor network is assumed to be in a limited area. The system is a time-slotted system with fixed slot duration $T_S$, and 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 choose the optimal modulation scheme. In the network, we further assume that each node transmits with a probability $p_t$ at each time slot, and the transmission is destined 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 [9]. Given a time slot, some 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. Hence, the first problem is: **(P.1)** *Given the current spectral condition, a detection scheme needs to be designed in order to detect the entire spectrum and find an available subcarrier set Fi for node i who needs transmission at this given time slot.* The available subcarrier set Fi contains the number and positions of those free subcarriers in the spectrum. Under perfect condition, i.e., no detection error, Fi should be the same for every user; however, due to the detection error, Fi may be different for different users.

Given the available subcarrier set of each user, the best subcarrier (in terms of the largest channel gain) may be selected to transmit data [7]. In this work, perfect channel state information (CSI) is assumed to be available via some robust estimation scheme. Hence, given the maximum energy of each node $E_{max}$, the second question is: **(P.2)** *If QAM is chosen as the modulation scheme, how can we maximize the lifetime of the network via varying system parameters, specifically, constellation size?*

In what follows, we first investigate the detection on the availability of each subcarrier via a pilot tone scheme, and then, we propose an energy efficient adaptive QAM modulation approach to maximize the network lifetime.

## III. Detection on the Subcarrier Availability

In this work, we assume that 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 cognitive radio users can determine if that particular subcarrier is available or not. The pilot signal is a sinusoid signal, $A_0 \cdot \cos(\omega_c t)$, $0 \le t \le T$, where $\omega_c$ is the subcarrier frequency, $A_0$ is the amplitude of the sinusoid signal. At the detector, pilot signal can be expressed as $A\cos(\omega t+\theta)+n_0(t)$, where $n_0(t)$ is a white Gaussian noise with P.S.D. $N_0/2$, the signal is assumed to be corrupted by a Rayleigh fading process and thus the amplitude $A$ is Rayleigh distributed with average power $2\sigma_A^2$, the frequency $\omega$ is located around the subcarrier frequency $\omega_c$ and the frequency shift $\omega_d=\omega-\omega_c$ , may be caused by frequency synchronization error and Doppler spread, $\theta$ is the random phase (without loss of generality, we assume $\theta = 0$). Here, we assume perfect slot synchronization and the time instants at which the pilot signals are sent can be pre-specified. Synchronization is an important issue in wireless ad hoc network, but it is out of the scope of this work. However, for reality, the frequency $\omega$ and amplitude $A$ are not known at the detector. Then, the detection hypotheses are:

$$\begin{aligned} H_1: &\quad r(t) = A\cos(\omega t+\theta)+n_0(t),\ 0\le t\le T \\ H_0: &\quad r(t) = n_0(t),\ \ 0\le t\le T \end{aligned} \quad (1)$$

Based on the detection likelihood ratio for a sinusoid signal with random phase and Bayes' criterion [10], by treating the frequency shift as a phase modulation $\theta(t)=\omega_d t$, the likelihood ratio for (1), conditioned on the unknown frequency shift $\omega_d$ and the Rayleigh distributed amplitude $A$, can be written as [10, Eq.7-30],

$$\begin{aligned} \lambda\{r_C(t)\,|\,\omega_d, A\} &= \frac{p(r_C\,|H_1)}{p(r_C\,|H_0)} \\ &= I_0\left(2Aq/N_0\right)\exp\left(-A^2T/2N_0\right) \end{aligned}, \quad (2)$$

where $I_0$ is the modified Bessel function of the first kind of order 0, $r_c(t)$ is the corresponding complex envelop of the received signal $r(t)$ and according to [10, Eq.7-31], $q$ can be expressed as

$$q = \frac{1}{2}\left|\int_0^T r_C(t)\exp(-j\omega_d t)\,dt\right|. \quad (3)$$

We further assume that the frequency shift $\omega_d$ is distributed in the range $0 \le \omega_d \le \omega_u$ with PDF $p(\omega_d)$, where $\omega_u$ is the maximum frequency shift and is known to a detector a priori. We then divide the frequency range into J equal intervals of width $\Delta\omega$ centered at $\omega_i$, $i$=1…J. Now the conditioned likelihood ratio, conditioned on the Rayleigh distributed amplitude $A$, can be rewritten as

$$E(\lambda|A) = \Delta\omega\cdot\exp\left(\frac{-A^2T}{2N_0}\right)\sum_{i=1}^{J} p(\omega_i)I_0\left(\frac{2Aq_i}{N_0}\right), \quad (4)$$

where $q_i$ is obtained from a Fourier analysis complex envelop of the data in the $i$-th frequency interval and is expressed as

$$q_i = \frac{1}{2}\left|\int_0^T r_C(t)\exp(-j\omega_i t)\,dt\right|. \quad (5)$$

Now, given the Rayleigh distribution of $A$, the expected likelihood ratio can be computed as

$$E(\lambda) = \Delta\omega \cdot \sum_{i=1}^{J} p(\omega_i) \int_0^{\infty} \frac{A}{\sigma_A^2} \exp\left[ -\frac{A^2}{2\sigma_A^2} - \frac{A^2 T}{2N_0} \right] \cdot I_0\left( \frac{2Aq_i}{N_0} \right) dA \quad . (6)$$

If we further assume a uniform density function for the frequency shift, and put all the constants into the comparison threshold, the detector finally reaches a decision rule:

$$\sum_{i=1}^{J} \exp\left[ \frac{2q_i^2 \sigma_A^2}{N_0^2 + N_0 \sigma_A^2 T} \right] \geq \psi \quad . \quad (7)$$

Where the pilot signal is declared to be present if the sum in (7) exceeds the pre-specified threshold $\psi$. We may note that, when the signal to noise ratio of the detection is relatively high, the qi associated with the frequency interval in which the signal is located, would dominate the sum in (7). In this case, the sum may be approximated by its largest term, and (7) becomes

$$\max_i \exp\left[ \frac{2q_i^2 \sigma_A^2}{N_0^2 + N_0 \sigma_A^2 T} \right] \geq \psi \quad , \quad (8)$$

and it is equivalent to

$$\max_i q_i \geq \psi^* \quad (9)$$

Where $\psi^*$ is set by the desired false alarm probability as shown in Appendix A.

The detection of the pilot signal enables us to determine whether the current subcarrier is available or not according to (9). The block diagram of the detector is depicted in Figure 1.

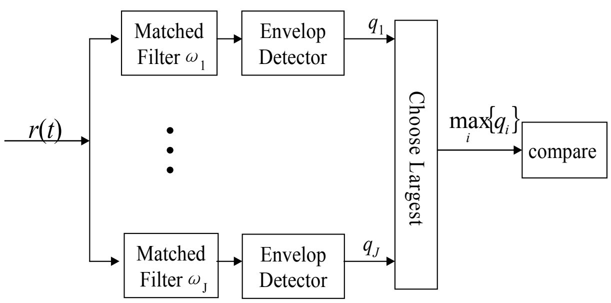


Figure1. The block diagram of the subcarrier detector

By sensing all the subcarriers, the $i$-th transmitter can determine its available subcarrier set $F_i$. Then, a simple subcarrier selection scheme is applied: the favorite subcarrier with the largest channel gain is selected by node $i$ for its transmission. Ideally, each user will employ a subcarrier without interfering with other users. However, this may not be true in reality. The conflict may happen due to 1) detection error which can induce both false alarms and miss; 2) subcarrier selection error where multiple users select a common subcarrier. The probability of a conflict is expected to be very small, since in general the number of subcarriers is relatively large compared to the number of users. Therefore, we first investigate the adaptive modulation scheme under the assumption that no conflict occurs as in the next section. When conflict does occur, one may have interference from other users who share the same subcarrier with it. In this work, we assume the interference from other users can be modeled as Gaussian noise, and the effect of interference can be incorporated together into the thermal noise power $N_0/2$. We will investigate the effect of conflicts (due to detection error and/or subcarrier selection error) upon system performance in the numerical results in Section V.

## IV. LIFETIME MAXIMIZATION USING ADAPTIVE QAM MODULATION

In this section, we first define the lifetime of a network given the maximum energy $E_{max}$ of each node; then, we show how the lifetime of a network can be expressed as a function of system parameters, such as noise power, required BER as well as the modulation scheme, and how the network lifetime can be maximized via the proposed adaptive modulation scheme.

The lifetime of node $i$ under a maximum energy constraint, $E_{max}$, is given by

$$T_i = \frac{E_{\max}}{\bar{E}_T(i) + \bar{E}_R(i) + \bar{E}_S(i)} \, . \quad (10)$$

Where $\bar{E}_T(i)$ and $\bar{E}_R(i)$ are the average energy of transmission and average energy of reception for node $i$ at each time slot, respectively. $\bar{E}_S(i)$ is the average power consumption in sleep mode for node $i$. The unit of $T_i$ is number of slots. The lifetime of a wireless sensor network is defined as the period before the first node in the network runs out of power. Thus, the lifetime of the whole network can be expressed as:

$$T_{network} = \min_{i \in N} T_i = \min_{i \in N} \left( \frac{E_{\max}}{\bar{E}_T + \bar{E}_R + \bar{E}_S} \right). \quad (11)$$

It is worth noting that, in order to maximize the network lifetime, it is equivalent to maximize the minimum node lifetime among all nodes. Hence, the network lifetime optimization problem may be written as

$$Max[T_{network}] = Max[\min(\frac{E_{\max}}{\bar{E}_T(i) + \bar{E}_R(i) + \bar{E}_S(i)})] \, . \quad (12)$$

Because the network is assumed to be composed of uniformly distributed sensor nodes and every node has the same traffic pattern, it is sufficient to consider any one of the sensor nodes, and "($i$)" in the formulation can be dropped. In other words, we need to minimize the sum of the average energy of transmission, reception and sleep. And the network lifetime maximization problem becomes

$$Max[T_{network}] = Max[\frac{E_{\max}}{\bar{E}_T + \bar{E}_R + \bar{E}_S}] \Leftrightarrow Min[\bar{E}_T + \bar{E}_R + \bar{E}_S] \, . \quad (13)$$

It is clear that the average energy of transmission, $\bar{E}_T$, is the product of the average number of bits a node transmits during a time slot and the average transmission energy per bit, $\bar{E}_{bt}$. On the other hand, the average energy of reception $\bar{E}_R$ can be approximated as a product of the average reception time $T_r$ and the average reception power, $P_r$, as follows:

$$\bar{E}_R = P_r \times T_r \, . \quad (14)$$

Where $P_r$ is assumed to be a constant due to the power consumption of the receiver circuit, and $T_r$ is related to the modulation scheme and the data amount to be transmitted as described later. First of all, we will derive the average transmission energy per bit, $\bar{E}_{bt}$.

For QAM modulation, the target BER and the constellation size $b$ can be related according to [8]

$$P_b \approx \frac{4}{b}\left(1-\frac{1}{2^{b/2}}\right)Q\left(\sqrt{\frac{3b}{2^b-1}\gamma_b}\right). \qquad (15)$$

Where the BER is calculated over the Rayleigh fading channel, $\gamma_b$ is the average SNR per bit defined as $\gamma_b = \bar{E}_b/N_0$, where $\bar{E}_b$ is the required energy per bit at the receiver for a given BER requirement, and $N_0/2$ is the thermal noise power. Based on [8], using Chernoff bound, (15) can be reduced to

$$P_b \le \frac{4}{b}\left(1-\frac{1}{2^{b/2}}\right)\left(\frac{1.5\bar{E}_b b}{N_0\left(2^b-1\right)}\right)^{-1}. \qquad (16)$$

From which we can derive an upper bound for $\bar{E}_b$ as

$$\bar{E}_b \le \frac{2}{3}\left(\frac{P_b}{4}\right)^{-1}\frac{2^b-1}{b^2}N_0. \qquad (17)$$

And we can obtain the average transmission energy per bit, $\bar{E}_{bt}$, as follows

$$\bar{E}_{bt} \le \frac{2}{3}(1+\alpha)\left(\frac{P_b}{4}\right)^{-1}\frac{2^b-1}{b^2}N_0\times G\times d^2. \qquad (18)$$

Where α is related to the drain efficiency of the RF power amplifier and can be assumed to be a constant; $d$ is the distance between the transmitter and the receiver, and we assume path loss obeys the square law; G is a parameter related to the antenna gain at both the transmitter side and the receiver side.

In what follows, we assume that

1). 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. An example is shown in Figure 2, where the node transmits data in the first slot, sleeps in the second slot, and receives data in the third slot. $T_S$ is the duration of each time slot, $T_{TX}$ is the transmission time, $T_{RX}$ is the receiving time, and $T_{SX} = T_{SX1} + T_{SX2} + T_{SX3}$ is the sleeping time.

2). Denote the transmission and the reception probabilities of a node in each time slots as $p_t$ and $p_r$, respectively. $p_t$ equals to $p_r$ here since the nodes and traffic patterns are homogeneous and a node transmits or receives with equal probability at any given time slot.

3). The amount of data that a node transmits or receives in one time slot is $L$ bits. It corresponds to a typical situation, where a node transmits or receives a fixed-length packet at a given time slot.

4). Because all nodes are uniformly distributed in a certain area, we can further assume that a node has $H$ one-hop-away neighbors on average.

According to the above assumptions, the average amount of bits a node transmits and receives ($\Delta_T$ and $\Delta_R$, respectively) during a time slot can be approximated as follows:

$$\begin{aligned}\Delta_T &= p_t \cdot L \\ \Delta_R &= H\cdot\frac{p_t}{H}\cdot L = p_r\cdot L = p_t\cdot L\end{aligned}. \qquad (19)$$

Hence, the lifetime of a node can be lower-bounded as

$$T_i = \frac{E_{\max}}{\bar{E}_T+\bar{E}_R+\bar{E}_S} \ge \frac{E_{\max}}{\Delta_T\cdot\bar{E}_{bt}+P_r\cdot\dfrac{\Delta_R}{b\cdot B}+\bar{E}_S}. \qquad (20)$$

Where B is the modulation bandwidth and it is a constant. $\bar{E}_S$ is the average energy consumption when the nodes fall asleep. It includes the time slots when the node falls asleep and the residual time in each time slot after the node transmits or receives data.

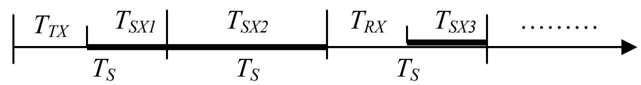


Figure2. Illustration of sleeping duration calculation in time slots

The total energy consumed by the nodes in sleeping mode can be calculated by $\bar{E}_S = P_S \bullet T_{SX}$, $P_S$ is the sleeping power of sensor nodes. $T_{SX}$ can be divided into three parts. The first one is the residual time $T_{SX1}$ after the node transmits data. The second part $T_{SX2}$ is the time slot when the node sleeps without transmitting or receiving. The third part is the remaining time $T_{SX3}$ after the node receives data. $T_{SX1}$, $T_{SX2}$, $T_{SX3}$ can be respectively expressed as:

$$\begin{aligned}&T_{SX1} = (T_S - \frac{L}{b\times B})\times p_t,\ T_{SX2} = T_S\times(1 - p_t - p_r), \\ &T_{SX3} = (T_S - \frac{L}{b\times B})\times p_r\end{aligned} \qquad (21)$$

Because $T_{SX} = T_{SX1} + T_{SX2} + T_{SX3}$, $\bar{E}_S$ can be calculated as

$$\bar{E}_S = P_S\times T_{SX} = P_S\times(T_S - \frac{2\times L\times p_t}{b\cdot B}). \qquad (22)$$

From (18), (19), (20) and (22), the network lifetime can be rewritten as

$$T_i \ge \frac{E_{\max}}{p_t L\left(\dfrac{2}{3}(1+\alpha)\left(\dfrac{P_b}{4}\right)^{-1}\dfrac{2^b-1}{b^2}N_0 G d^2+\dfrac{P_r}{b\cdot B}\right)+P_S\times(T_S-\dfrac{2\times p_t\times L}{b\cdot B})}. \qquad (23)$$

In order to maximize the lifetime of a node, the modulation consternation size $b$, should be appropriately chosen such that the denominator of (23) is minimized. Therefore, the problem becomes how to select the optimal constellation size $b^*$, given the required BER and other system parameters:

$$b^* = \arg\min_b \left(\begin{aligned}&p_t L\left(\frac{2}{3}(1+\alpha)\left(\frac{P_b}{4}\right)^{-1}\frac{2^b-1}{b^2}N_0 G d^2+\frac{P_r}{b\cdot B}\right) \\ &+P_S\times(T_S-\frac{p_t L}{b\cdot B}-\frac{p_r L}{b\cdot B})\end{aligned}\right). \qquad (24)$$

Practically, the constellation size $b$ can not be too large. In our work, we consider the value of $b$ from 2 to 10. In order to solve this problem, we first assume $b$ is continuous instead of discrete. After we get the optimal value, we will approximate it to the closest integer. In this interval, we prove that (24) is continuously differentiable and strictly convex with respect to

$b$. The proof is given in Appendix B. In order to get the optimal value on the interval, we take the first derivation of (24),

$$f'(b)=\left(\begin{array}{l} p_t L\left(\frac{2}{3}(1+\alpha)\left(\frac{P_b}{4}\right)^{-1} N_0 G d^2 \frac{2^b-1}{b^2}+\frac{P_r}{b\cdot B}\right) \\ +P_S\times(T_S-\frac{2\times p_t\times L}{b\cdot B}) \end{array}\right)' . \quad (25)$$

By replacing $2^b$ with $t$, and letting $f'(b)$=0, we can obtain (since $b\geqslant 2$)

$$p_t L\frac{2}{3}(1+\alpha)\left(\frac{P_b}{4}\right)^{-1} N_0 G d^2[1-2(t-1)/(t\cdot\ln t)]- \quad (26)$$
$$(p_t\cdot LP_r-2P_S\cdot p_t\cdot L)/B\cdot t=0$$

From (26), we can get the value of $t$ using numerical methods. Then the optimal value of constellation size $b^*=log_2 t$.

## V. NUMERICAL RESULTS AND DISCUSSIONS

In this section, we will evaluate the proposed approach using network lifetime as the criterion. In addition, we will also investigate the impact of the false alarm probability $P_f$ and the ratio between the number of users ($N$) and the number of available subcarriers ($M$).

Suppose there are 20 nodes uniformly distributed in an area of 150m x150m. In our simulation, we use the experimental data measured from mica2 Berkeley sensor motes [11]. The setup of the experiment is as follows

1). The maximum distance between one-hop neighbors is 50m, which is the transmission range of the mica2 Berkeley motes.

2). The interference only occurs among one-hop neighbors.

3). In each time slot, the probability of transmission is 0.2 which equals to the probability of reception as we discussed before.

4). The duration of each time slot $Ts$ is $1$ms.

5). The average number of one-hop neighbors for each node is about 6 (using the approach in [12], $\frac{20\pi(50)^2}{150\times 150}-1=5.98$).

6). 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* |
|---|---|---|
| $P_t$ | transmission power | $54\times 10^{-3}$ A·V |
| $P_r$ | reception power | $48\times 10^{-3}$A·V |
| $P_s$ | sleep power | $30\times 10^{-6}$A·V |
| $d$ | distance of one-hop neighbors | 50m |
| B | Bandwidth of each time slot | $10\times 10^3$Hz |
| $t_s$ | Duration of one time slot | $1\times 10^{-3}$Sec |
| G | channel gain | 5dBi |
| L | bits transmitted in one time slot | 4000 |
| $P_b$ | bit error rate | $10^{-3}$ |
| $\sigma^2$ | variance of thermal noise | -80dBm |

The network lifetime is plotted in Figure.3 according to equation (23). It is observed that the optimal constellation size $b^*$ is approximately 4. The rationale of the concavity of the network lifetime with respect to $b$ may be explained as follows: Because the reception time is $T_{rx}=(L/b\cdot B)$, the reception power of each node monotonically decreases with $b$. In other words, since constellation size $b$ is closely related to the data rate, higher $b$ means higher data rate which requires shorter time for reception. On the contrary, the transmission power monotonically increases with $b$. Therefore, the network lifetime is a concave function with respect to $b$ and there exists an optimal value for $b$ which balances the transmission power and reception power and minimizes the total energy consumption.

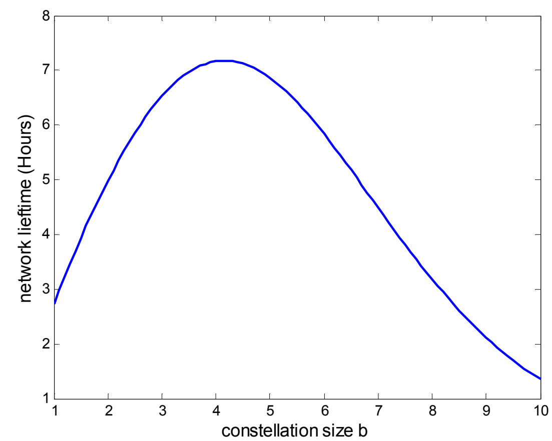


Figure3. Network lifetime VS constellation size $b$

Using the optimal value $b^*$, we further investigate the impact of the false alarm probability $P_f$ and $N/M$ (the ratio between the number of users $N$ and the number of available subcarriers $M$) to the network lifetime. When the nodes fail to detect available subcarriers that are actually available ($P_f$, increases), the total number of subcarriers that can be assigned to users reduces. This result in higher probability of conflicts in the system, and the network lifetime will decrease. It is shown in Figure.4 that when $P_f$ increases from $0.1$ to $0.3$, the network lifetime decreases as much as $50\%$. Besides the effect of false alarm probability, the ratio between the number of users $N$ and the number of available subcarriers $M$ has more significant influence on the network lifetime. Since the number of users is fixed ($N$=$20$), it's apparent that probability of conflicts will increase dramatically with the decrease of the number of subcarriers. Hence, higher *N/M* results in lower network lifetime. Specifically, the results in Figure.4 suggest that the ratio *N/M* should be kept low enough whenever possible. For example, a *50%* drop in *N/M* (from *0.4* to *0.2*) may increase the network lifetime for almost *200%* (from *2* hours to *6* hours).

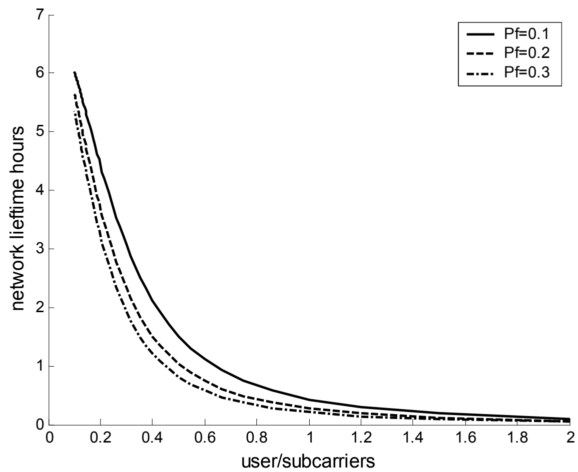


Figure4. Impact of user/subcarriers and false alarm probability $P_f$ to lifetime

## VI. CONCLUSION

In wireless sensor networks, energy efficient design is very important because nodes operate on battery. Most of the previous work deals with the routing problem to maximize the network lifetime by balancing the power consumption of sensor nodes. In this paper, we explore the energy efficient design in wireless sensor networks from a different perspective. First, a joint design of cognitive radio and multi-carrier modulation is proposed to achieve both high bandwidth efficiency and power efficiency. A subcarrier detection mechanism is proposed and analyzed in detail. Second, after each user determine its optimal subcarrier, an adaptive modulation technique is employed to minimize the power consumption at each node by adjusting the constellation size *b*, and hence maximize the network lifetime. Simulation results demonstrate the effectiveness of the proposed scheme. In addition, the impact of the false alarm probability $P_f$ and the ratio between the number of users *N* and the number of available subcarriers *M* to the network lifetime is also investigated by simulations. Note that although the proposed scheme functions at the physical layer, it may be combined with power conservation techniques at other layers. This will be one of our future efforts.


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## APPENDIX

**Appendix A. Derivation on the Decision Threshold ψ***

Based on (9), the false alarm probability $P_f$ can be computed as

$$P_f = P(H_1 | H_0) = \int_{\psi^*}^{\infty} f_{q_i}(x | H_0) dx \cdot \quad \text{(A.1)}$$

Where $f_{qi}(x|H_0)$ is the PDF of $q_i$ given $H_0$ is present and $\psi^*$ is the desired threshold. Based on (5) and $H_0$ is present, we have

$$\frac{1}{2}\int_0^T n_C(t)\exp(-j\omega_i t)\,dt \equiv z(t) = x(t) + jy(t) \quad . \quad \text{(A.2)}$$

Where nc(t) is the complex envelope of the white Gaussian noise after n0(t) passes through a band-pass filter. We can write nc(t) as nc(t) = nR(t) + jnI(t), where nR(t) and nI(t) are independent, zero-mean, white Gaussian noise with variance N0. Therefore, x(t) and y(t) are independent Gaussian noise with zero-mean. Now we only need to find the variances of x(t) and y(t). Given (A.2), x(t) can be written as

$$x(t) = \frac{1}{2}\int_0^T n_R(t)\cdot\cos\omega_i t\,dt + \frac{1}{2}\int_0^T n_I(t)\cdot\sin\omega_i t\,dt \quad . \quad \text{(A.3)}$$

So, $var[x(t)] = N_0 T/4 = \sigma_q^2$. Since $var[x(t)] = var[y(t)]$, $var[y(t)] = \sigma_q^2$. Now, since $x(t)$ and $y(t)$ are independent zero-mean Gaussian noise with variance $\sigma_q^2$, $q_i$ is Rayleigh distributed with PDF

$$f_{q_i}(x | H_0) = \frac{x}{\sigma_q^2}\exp\left(-\frac{x^2}{\sigma_q^2}\right) \cdot \quad \text{(A.4)}$$

Thus, the false alarm probability $P_f$ is

$$P_f = \int_{\psi^*}^{\infty} f_{q_i}(x | H_0) dx = \exp\left(\frac{-(\psi^*)^2}{2\sigma_q^2}\right) \quad . \quad \text{(A.5)}$$

Rewrite (A.5), we have the threshold set by a desired false alarm probability as

$$\psi^* = \sigma_q \sqrt{-2\ln P_f} \quad . \quad \text{(A.6)}$$

**Appendix B. Proof of the convexity of (24)**

Because the only variable in equation (24) is b, the equation can be simplified as

$$b^* = \arg\min_b \left( \left( C_1 \frac{2^b - 1}{b^2} + \frac{C_2 - C_4}{b} \right) + C_3 \right) \quad . \quad \text{(B.1)}$$

Here, C1, C2 and C3 are constants. In order to prove that (B.1) is convex, we need to show that f*(αx1+βx2)<αf(x1)+βf(x2)*, where *α+β=1. f(αx1+βx2)* can be written as follows

$$C_1 \times \frac{2^{\alpha x_1 + \beta x_2} - 1}{\alpha x_1 + \beta x_2} + \frac{C_2 - C_4}{\alpha x_1 + \beta x_2} + C_3 = C_1 \times \frac{2^{\alpha x_1 + \beta x_2}}{\alpha x_1 + \beta x_2} + \frac{C_2 - C_4 - C_1}{\alpha x_1 + \beta x_2} + C_3 \quad ,\text{(B.3)}$$

and αf(x1)+ βf(x2) can be expressed as

$$\alpha \times \left[ C_1 \times \frac{2^{x_1} - 1}{x_1} + \frac{C_2 - C_4}{x_1} + C_3 \right] + \beta \times \left[ C_1 \times \frac{2^{x_2} - 1}{x_2} + \frac{C_2 - C_4}{x_2} + C_3 \right] . \quad \text{(B.4)}$$

(B.4) can be further written as

$$C_1\times\left[\alpha\times\frac{2^{x_1}}{x_1}+\beta\times\frac{2^{x_2}}{x_2}\right]+(C_2-C_4-C_1)\times\left[\frac{\alpha}{x_1}+\frac{\beta}{x_2}\right]+C_3 \quad . \quad \text{(B.5)}$$

Because all of the constants are positive, and the range of the constellation size b is from 2 to 10, it is easy to verify that

$$\frac{1}{\alpha x_1+\beta x_2}<\frac{\alpha}{x_1}+\frac{\beta}{x_2}, \quad \text{(B.6)}$$

and

$$\frac{2^{\alpha x_1+\beta x_2}}{\alpha x_1+\beta x_2}<\alpha\times\frac{2^{x_1}}{x_1}+\beta\times\frac{2^{x_2}}{x_2} \quad . \quad \text{(B.7)}$$

Thus completes the proof.

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