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Energy Efficient Spectrum Sensing and Sensor Scheduling Scheme for MIMO-OFDM Based Cognitive Radio Network

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ABSTRACT: Multiple-Input Multiple-Output -Orthogonal Frequency Division Multiplexing (MIMO-OFDM) is considered to be one of the most auspicious technology for the upcoming mobile communication system. At the same time, as an efficient spectrum sharing technology, Cognitive Radio (CR) is proposed to increase the usage of the available spectrum. The combination of this three techniques, MIMO-OFDM based Cognitive Radio technology is considered as a promised scheme for future robust spectrum access network or spectrum distribution system. Since only a finite number of sub carriers are occupied by the Primary Users (PUs) present in the CR networks, the Secondary Users (SUs) can detect the spectrum holes (the unoccupied subcarriers) and opportunistically find those vacant spectrum subcarriers. Thus, spectrum sensing or detection is an important division for the execution of CR. In MIMO-OFDM based cognitive radio network system, the signals received in all antennas are sampled by a single Analog-to-Digital Converter (ADC), which will lead to a significantly decrease of front-end cost for the whole system and minimizing the power consumed. For effective spectrum sensing compressed sensing is used here. In existing system there is no efficient scheme for schedule the sensors in the network. To overcome that disadvantage an Ant COlony-based Energy-efficient Sensor Scheduling (ACO-ESS) algorithm is introduced to optimally schedule the activities of the sensors. By introducing this algorithm it is possible to arrange activities of various sensors and increase the overall secondary system throughput.

KEYWORDS: Cognitive Radio, Spectrum Sensing, Sensor Scheduling.

I.INTRODUCTION

Both MIMO and OFDM techniques have acquired extensive consideration in last few years. For OFDM, it can adequately overcome frequency selective fading. Besides, inter channel interference (ICI) and inter symbol interference (ISI) can also be conquered by adding cyclic prefix (CP) into the data frame of OFDM symbols. For MIMO, it can raise the transmission capacity by utilizing space diversity technology. Based on these reasons, the combination of MIMO and OFDM techniques can extremely promote the transmission performance of the wireless system. Thus, MIMO-OFDM have also been introduced as the standards of many wireless systems. Cognitive Radio(CR) [1] is a rising technology to increase the ability of spectrum handling in present day. So, spectrum sensing technology is an important work for the performance of the whole CR system. By linking MIMO-OFDM technology with CR network system, the MIMO-OFDM based CR technology can have great possibilities in the utilization of prospective dynamic spectrum access network and spectrum sharing system. In most cases only a certain number of subcarriers are utilized by the PUs in a MIMO-OFDM based CR system. Thus, by receiving and decoding the signals from the multiple channels, the SUs can detect the inactive subcarriers. However, in traditional MIMO-OFDM system, the signals received in each antenna are sampled by individual ADC, which is considered to be power consuming since there are multiple antennas in system, which are corresponding to multiple ADCs.

Thus, to overcome the above mentioned problem, this paper introduce a new method for spectrum sensing in MIMO-OFDM based CR system. Compared to old MIMO-OFDM system, there are only one ADC in receiver to sample the mixed signals from all channels in this scheme[2]. Since only a part of subcarriers are used by the PUs, the whole subcarriers are sparse in frequency domain. Thus, the transmission signals can be recovered by exploiting the compressive sensing (CS) [3] technology. By estimating the transmission signals, the usage of subcarriers can also be detected at same time.

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One of the main requirements of cognitive radio (CR) is dependable for detection of vacant frequency bands[5]. Instead of embedding a sensing functionality into each individual secondary user (SU), we take advantage of a dedicated sensor networks that performs the sensing and report conclusion to the SUs through the base station (BS), which is less costly. To improve the sensing performance in fading environments, compressive spectrum sensing is proposed. Since battery-powered sensors are energy-constrained and it is impractical to replace or recharge the batteries, energy efficiency is one of the important issues to be considered in the implementation spectrum sensor networks[6]. By more efficient use of the limited amount of energy, the general secondary system performance may be increased. A number of methods that aim to efficiently schedule the sensor activities to extend the network lifetime while the area of interest is fully covered have been proposed, including heuristic methods and intelligent and evolutionary methods[7]-[8] .Particularly, sensor scheduling method[9]s, which only activate a subset of sensors is used to sense at any one time while keeping other sensors in low-energy sleep mode, have been shown to be effective.

These existing methods are able to maximize the network lifetime with the premise that sleep sensors do not consume energy. In practice, a specific amount of energy is consumed by an inactive sensor to maintain the internal clock and activate the sensor at predetermined times. Furthermore, the aim of CR is to improve the spectrum usage efficiency. This motivates our objective of maximizing the throughput of CRNs. Inspired by existing research, we propose an ant colony optimization (ACO)-based energy-efficient sensor scheduling algorithm[10] for throughput maximization in CRNs employing heterogeneous sensors (CRNHSs)

II.SYSTEM MODEL AND ASSUMPTIONS

A MIMO-OFDM based CR network by exploiting sparse signal modeling is considered in this paper. Initially consider an OFDM primary user present in a MIMO system with N_p transmitting antennas. Also consider that there are N_f subcarriers used for transmission in each MIMO antenna in the network. In each antenna, the transmitted signal is sparse for only a finite number of subcarriers are used. In this paper, we set the number of active subcarrier as $N_{f'}$. Then consider an OFDM secondary user in a MIMO system having N_s receiving antennas. In order to make use of the spectrum holes to send its signals, the SU need to sense the spectrum usage of the PU is the initial task. By reconstructing or estimating the signals transmitted from the PU in receiver, the SU can find out the frequency of active subcarriers in the network, which also represent the information of spectrum usage. Different with traditional MIMO-OFDM receiver, the signal received in each antenna of our receiving scheme is modulated by a set of random sequence at first. Then all received and modulated signals are mixed together and sampled by a single ADC. The sampled (converted) signals are sent to a DSP (digital signal process) block. Moreover, the converted signals in this scheme can be recovered by compressive sensing algorithm on the frequency domain directly, without be transformed to time domain by the FFT units, which is different with the method in conventional DSP block . Here consider a CRNHS that consists of *Ns* randomly deployed heterogeneous sensors $\Omega = \{sn|n = 1, 2, . . . , Ns\}$ and one secondary BS. In each sensing phase, every active sensor performs spectrum sensing individually and makes a binary decision. All the sensors then send their decisions to the BS successively for decision combination. The BS employs an OR fusion rule to make the final decision. That is, the BS declares the presence of the primary signal if any sensor detects the primary signal.

A. Transmission and Channel Model

Let $b_i(k)$ stands for the *k*th transmitted OFDM symbol from the *i*th antenna. We set ***bi*** as the modulated OFDM symbol which are allocated to all subcarriers. Then the modulated symbols are processed by the IFFT (inverse fast fourier transform) unit. The *n*th coefficient of the IFFT on the *i*th antenna is given by

$$\boldsymbol{x_i(n)} = \boldsymbol{1}\Big/\sqrt{\boldsymbol{N_f}}\sum_{\boldsymbol{k=1}}^{\boldsymbol{N_f}} \boldsymbol{b_i(k)}\boldsymbol{e}^{\frac{\boldsymbol{j2\pi n(k-1)}}{\boldsymbol{N_f}}} \qquad (1)$$

Here $b_i(k)$ is the modulated signals on *k*th subcarrier of the *i*th antenna and $j = \sqrt{-1}$When the PU want to access the MIMO-OFDM channel, some of the subcarriers are allocated to the PU for its usage. Since we only consider $N_{f'}$ subcarriers are used, there are only non-zero elements in ***bi***. The transmitted signal on *i*th antennas is expressed as

$$\boldsymbol{x_i} = \boldsymbol{F_{N_f}^{-1} b_i} \qquad (2)$$

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where $F_{N_f}^{-1}$ stands for the IFFT matrix. Then the signal x_i is transmitted through the wireless channels to the receiver. We set channel impulse response vector which between the ith transmit antenna and the jth receive antenna as $h_{i,j}$. We consider there are L multipath among the wireless channels between the transmitter and the receiver. $h_{i,j}$ can be expressed as

$$\boldsymbol{h}_{i,j} = \begin{pmatrix} \boldsymbol{h}_{i,j}^{(0)} \\ \cdot \\ \cdot \\ \boldsymbol{h}_{I,J}^{(L-1)} \end{pmatrix} \tag{3}$$

Thus, the signal received at the receiver can be expressed as

$$\boldsymbol{y}_{i,j} = \boldsymbol{H}_{i,j}\boldsymbol{x}_i \tag{4}$$

where $y_{i,j}$ stands for the signals which are transmitted from i th antenna and received by jth antenna. $H_{i,j}$ stands for the matrix which is the result of the cyclic convolution with $h_{i,j}$. Since there are N_p transmit antennas and N_S receive antennas in the MIMO-OFDM system, the signals which are transmitted from all $N_p$antennas and received on j th antenna is denoted by y_j . Here we express it as

$$\boldsymbol{y}_j = \sum_{i=1}^{N_p} \boldsymbol{y}_{i,j} \quad \boldsymbol{j} = \boldsymbol{1}, \ldots \boldsymbol{N_s} \tag{5}$$

Thus, the received signals from all receive antenna can be expressed, which is shown as the following

$$\boldsymbol{y} = \boldsymbol{Hx} + \boldsymbol{V} \tag{6}$$

where H stands for channel matrix. To the receiver in conventional MIMO-OFDM system, after sampled by ADC, the received signal will be sent to a FFT unit, where signals can be transformed to Fourier domain. Then the transmitted symbols are demodulated by MIMO detector based on the transmission-receiving equation in Eq. (6).

B. Sparse Signal Model

Since there are multiple antenna in the receiver, traditional MIMO-OFDM system is considered to be power consuming for multiple ADC need to be used. Thus, we introduce a sparse signal model for the MIMO-OFDM based CR scheme. Instead of sampled by ADC individual on each antenna, the received signals are mixed together and then sampled by a single ADC. The sampled signal can be expressed as

$$\boldsymbol{y}_r = \sum_{j=1}^{N_s} \boldsymbol{d}_j \boldsymbol{y}_j^r \tag{7}$$

where y_j^rstands for the signal received on jth antenna before sampled by ADC and d_j is a vector, which is used to modulate the received signal on each antenna. Usually, we will select a pseudo-random sequence to modulate the received signals at each antenna, which also should be friendly to the hardware. In this paper, we prefer to use random binary value ± 1 as $d_j(n)$ to be the random sequence. Then, mix all modulated signals together and send to the DSP block. Moreover, Eq. (7) can be re-expressed as

$$\boldsymbol{y}_r = [\boldsymbol{D}_1 \ \boldsymbol{D}_2 \ \ldots \ldots \boldsymbol{D}_{N_S}] \begin{bmatrix} \boldsymbol{y}_1^r \\ \boldsymbol{y}_2^r \\ \cdot \\ \cdot \\ \cdot \\ \boldsymbol{y}_{N_s}^r \end{bmatrix} \tag{8}$$

``````````````````````````````````````````````````````where $D_J$ stands for a diagonal matrix where its diagonal elements are picked sequentially from the vector $d_j$, as

$$\boldsymbol{D}_j = \begin{bmatrix} \boldsymbol{d}_j(\boldsymbol{1}) & \cdots & \boldsymbol{0} \\ \vdots & \ddots & \vdots \\ \boldsymbol{0} & \cdots & \boldsymbol{d}_j(\boldsymbol{N}_f) \end{bmatrix} \tag{9}$$
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Besides, we just define the set of matrix D_J in Eq. (8) as $\boldsymbol{D}$ for the convenience, which is expressed as

$$\boldsymbol{D} = [\boldsymbol{D}_1 \ \boldsymbol{D}_2 \ \dots\dots \ \boldsymbol{D}_{N_s}] \quad (10)$$

Based on the definition of $\boldsymbol{D}$, We can find the received signals can be compressed by this modulating matrix, which also means the total number of samples has been reduced too. Based on Eq. (2) and Eq. (6)

$$\begin{bmatrix} \boldsymbol{y}_1^r \\ \boldsymbol{y}_2^r \\ \cdot \\ \cdot \\ \cdot \\ \boldsymbol{y}_{N_s}^r \end{bmatrix} = \boldsymbol{H} \begin{bmatrix} \boldsymbol{F}_{N_f}^{-1} & \cdots & \boldsymbol{0} \\ \vdots & \ddots & \vdots \\ \boldsymbol{0} & \cdots & \boldsymbol{F}_{N_f}^{-1} \end{bmatrix} \begin{bmatrix} \boldsymbol{b}_1 \\ \boldsymbol{b}_2 \\ \cdot \\ \cdot \\ \boldsymbol{b}_{N_s} \end{bmatrix} + \boldsymbol{V} \quad (11)$$

Thus the receiving and sampling process can be expressed

$$\begin{aligned} \boldsymbol{y}_r &= \boldsymbol{DH} \begin{bmatrix} \boldsymbol{F}_{N_f}^{-1} & \cdots & \boldsymbol{0} \\ \vdots & \ddots & \vdots \\ \boldsymbol{0} & \cdots & \boldsymbol{F}_{N_f}^{-1} \end{bmatrix} \begin{bmatrix} \boldsymbol{b}_1 \\ \boldsymbol{b}_2 \\ \cdot \\ \cdot \\ \boldsymbol{b}_{N_s} \end{bmatrix} + \boldsymbol{v} \\ &= \boldsymbol{DHF}^{-1}\boldsymbol{b} + \boldsymbol{v} \\ &= \boldsymbol{Ab} + \boldsymbol{v} \end{aligned} \quad (12)$$

where $\boldsymbol{v}$ stands for the equivalent noise, F^{-1} is the matrix by consisting of the set of IFFT matrix $F_{N_f}^{-1}$,b_i is the OFDM symbols transmitted on ith antenna and $\boldsymbol{b}$ is a concatenation of b_i. Since only a finite subcarriers are used, b_i is sparse for only a finite number of nonzero elements on the vector. Besides, the sensing matrix is defined as

$$\boldsymbol{A} = \boldsymbol{DHF}^{-1} \quad (13)$$

Thus, our target is how to detect the subcarriers symbols $\boldsymbol{b}$ from the sampled signals y_r and sensing matrix $\boldsymbol{A}$. In the following section, we will introduce the algorithm to solve this problem.

C. Sparse Signal Reconstruction in DSP

In our scheme, the compressively sampled signals are separated and reconstructed in the DSP block by exploiting the sparsity model. Thus, the reconstruction of the sampled signals is equivalent to the compressive sensing problem, also called as sparse signal recovery problem. This problem has been widely studied and a variety of algorithms have been proposed to solve the sparse signal recovery problem. However, considering in the MIMO-OFDM based CR network, usually it's a hard work for the SU to obtain the prior spectrum usage information like the occupancies of the frequency points or their locations, which can be presented by the sparsity and elements' locations in the transmission signals. Thus, here need a sparsity adaptive algorithms to solve the spectrum sensing problem. Besides, considering the application in dynamic spectrum access system, the adopted reconstruction algorithm also need to perform with low computation complexity. Based on above reasons, we choose the regularized FOCUSS (FOCal Underdetermined System Solver) algorithm to reconstruct the sampled signals. Compared to previous algorithms, regularized FOCUSS (RFOCUSS). Thus, it makes regularized FOCUSS algorithm as a promising method for solving the sparse recovery problem in many practical applications, especially in our scheme.

III.SPECTRUM SENSING SCHEME

In our problem, the target of spectrum sensing is to find out the occupied subcarriers, which now is same to the compressive sensing problem. Considering the prior information of occupied subcarriers like sparsity are not easily obtained by the CR receiver, the sensing algorithm should run without the prior information of the activity of subcarriers. Thus, we need the algorithm which has the feature of *sparsity adaptive*. Besides, consider the application in the dynamic and complex wireless environment, the reconstruction algorithm need faster speed with lower computation complexity. Based on the above reasons, we introduce the R-FOCUSS algorithm to detect the activity of subcarriers.

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Algorithm 1 Spectrum Usage Detection Algorithm
Input: A,y_r
intialize $\gamma = \delta, j\epsilon[1, \dots \dots . . N_s], k = 1$
repeat
$W_k = diag(b_{k-1}(j))^{1-p/2})$
$q_k = W_k(A_k^T A_k + \gamma I)^{-1} A_k y_r$
where $A_k = AW_k \; with \, \gamma \geq 0$
$b_k = W_k q_k$
Until $||b_k - b_{k-1}|| < \theta$
compute: $\omega_b = arg\max(|b_k|, S), \; b^* = b_k$
where S stands for the number of non zero elements in b_k
Output: ω_b, b^*

For the Algorithm 1 given in the following, k denotes the iterative step index. From the algorithm, we can find the outputs are estimated signals b^* and the estimated support ω_b. Since the support stands for the indices of nonzero entries, which also stands for the location of the occupied frequency points, usually we can detect the activity of subcarriers by only analyzing the support of the sparse signals. Besides, from the table we also can find this algorithm is suitable for the application in spectrum detection when the prior information of subcarriers is unknown. Besides, the value of θ can be varied according to different situation.

IV.SENSOR SCHEDULING SCHEME

Here a CRNHS that consists of N_s randomly arranged heterogeneous sensors $\Omega = \{s_n \,|n = 1,2 \dots \dots . . N_S\}$ and one secondary BS is treated. At each sensing phase, every active sensor executes spectrum sensing separately and creates a binary decision. All the sensors then transmits their decisions to the BS respectively for decision sequence. The BS operate an OR fusion rule to create the ultimate choice. That is, the BS disclose the existence of the primary signal if any sensor find out the primary signal. The final choice is then reported to the SUs who want to approach the spectrum. Under the OR rule, the spectrum sensing execution, which is indicated by the global probability of false alarm Q_f and the global probability of misdetection Q_m, is calculated as

$$\boldsymbol{Q_f = 1 - \prod_{n=1}^{N_s} (1 - \theta_n P_{f,n}), \qquad Q_m = \prod_{n=1}^{N_s} P_{m,n}^{\theta_n}} \tag{14}$$

where $P_{f,n}$ and $P_{m,n}$ are the false alarm and misdetection probabilities of s_n, respectively, and $\theta_n \in \{0,1\}$ ($\theta_n = 1$ if and only if s_n is active).The sensor scheduling issue in sensing problem can be illustrated as finding a number of non disjoint feasible subsets $\varphi_1, \varphi_2 \dots \dots \dots . \varphi_k$ of sensors from Ω under the energy constraints. Each subset is stimulated separately and lasts for an individual time frame. Here, the ACO-ESS algorithm is proposed, as shown in Fig. 1, for maximizing the secondary system throughput in CRNHS due to the outstanding performance of ACO in solving combinatorial optimization and graph problems

A. Representation and Objective Function

A candidate solution is represented as ant in the colony. The solution is defined as a $K \times N_s$ matrix (where K is the scheduled subset) i.e A, that subsist of sensor assignment indicators $\theta_{kn} \forall k$, n, as indicated in the left-hand side of Fig. 2. The uniqueness of this 2-D result development is that the k_{th} row of A, i.e.,$a_{k,*}$ compare to the feasible subset φ_k. Along with it the total energy utilization of s_n does not beat its battery capacity B_n.If two ants have the equivalent average network throughput, an ant having high residual energy will be selected to increase the network throughput. By incorporating this criterion into the network throughput, the objective function of the solution can be find out using the equation given below.

$$\boldsymbol{f(A) = \omega_1 R_{total} + \omega_2 \sum_{n=1}^{N_s} \frac{\left\lfloor \frac{E_{r,n}}{E_{a,n}} \right\rfloor}{P_{f,n} + P_{m,n}}} \tag{15}$$

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where $\omega 1$ and $\omega 2$ are predetermined weights, $\lfloor * \rfloor$ is the floor function, $E_{r,n}$ is the residual energy of subset and $E_{a,n}$ is the energy consumption by the frame of sensors which are in active mode.$P_{f,n}$ and $P_{s,n}$ denote the probabilities of false alarm and misdetection.

B. Construction Behaviour of Ants

The construction criteria that the ants pursue to build their own solutions is introduced here. A multiple-layer mechanism to build the variable length 2-D solutions is proposed here. In each layer, the ants concentrate on finding one beneficial subset, as shown on the RHS of Fig. 2. Starting from an empty subset, artificial ants add a sensor to the subset one by one according to a set of criteria.

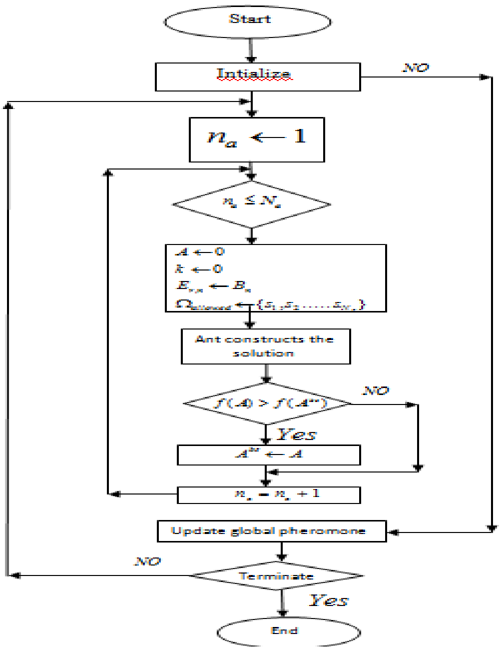

Fig.1. Flowcharts of the proposed ACO-ESS

When a feasible subset is found, the residual energy of each sensor is updated. Then, the ants carry out the above process repeatedly until the sensing requirement is no longer satisfied by any set of sensors. In selecting a sensor s_n from for the current subset (layer) ,φ_k the ants follow the following construction rules.

$$n = \begin{cases} \arg\max H_n \eta_n^{\beta}, & \text{if } q \leq q_0 \\ \text{roulette wheel selection}, & \text{otherwise} \end{cases} \quad \textbf{(15)}$$

where Ωallowed = $\{s_n | \theta_{kn} = 0 \; and \; E_{r,n} \geq E_{a,n}\}$ is the set of un allowed sensors whose residual energy is acceptable for at least single time sensing, $q_0 \in (0,1)$ is a fixed value, q is a uniform dispersed variable between 0 and 1, H_n is the historical data. In the roulette wheel selection, a possibility of selection is correlated with each individual sensor in Ωallowed and is find using the equation given below,

$$P_v = \frac{H_n \eta_n^{\beta}}{\Sigma_{s_m \Omega_{allowed}} H_m \eta_n^{\beta}} \; for \; S_n \epsilon \Omega_{allowed} \quad \textbf{(16)}$$

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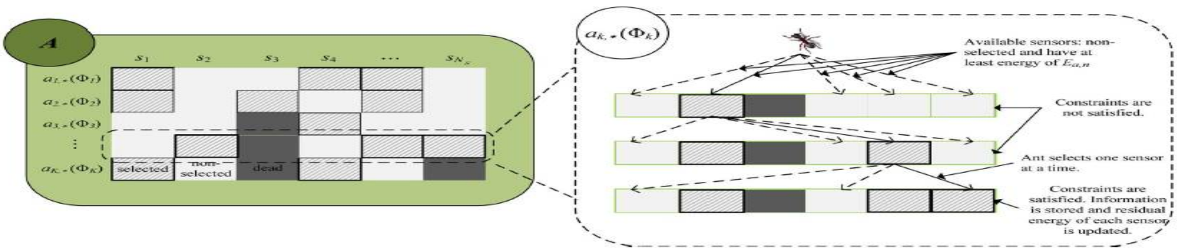

Fig. 2. Representation and construction behaviour of ants

Initially finds out the historical information $H_n$of s_n. In this proposed algorithm, the pheromone is accumulated on the edges between the sensors to trace the desirability of categorizing the sensors into the equivalent subset based on search practice. To select an unassigned sensor into a subset φ_k , the ant calculates the moderate pheromone level between a candidate sensor s_n and the sensors that are already assigned to φ_k . Suppose that the pheromone between s_n and s_m is represented by τ_{nm}. The historical data respecting the unassigned sensor s_n and the subset is given by

$$H_n = \begin{cases} \frac{1}{\sum_{m=1}^{N_s} \theta_{km}} \sum_{m|\theta_{km}=1} \tau_{nm}, & \text{if } \sum_{m=1}^{N_s} \theta_{km} \neq 0 \\ \tau_{nn}, & \text{otherwise} \end{cases} \tag{17}$$

where τ_{nn} is the self-pheromone that express the probability of s_n not cooperate with any other sensors. The heuristic information is associated with s_n in ACO-ESS to calculate the cost of s_n. Mathematically, the heuristic value for activating sensor s_n is calculated as given below,

$$\eta_n = K_1^{\left\lfloor \frac{E_{r,n}}{E_{a,n}} \right\rfloor} \cdot K_2^{\left\lfloor \frac{E_{r,n} \bmod E_{a,n}}{E_{s,n}} \right\rfloor} \tag{18}$$

where $K_1 \in (1 + \infty)$ and $K_2 \in (0,1)$ are predetermined parameters. The algorithm is encouraged to choose the sensors with more energy for sensing and less energy to maintain necessary functionality in the sleep state. After an ant finishes building its own solution, the pheromone trail amount τ_{nm} is updated locally according to the following formula.

$$\tau_{nm} = (1-\rho)^{\alpha}\tau_{nm} + (1-(1-\rho)^{\alpha})\tau_0 \tag{19}$$

where $\rho \in (0,1)$ is the local pheromone decay parameter and $\propto$ is the number of subsets containing both sensor sn and sm. (For n=m , $\propto$ is the number of subsets consisting of single sensor s_n.)

V. RESULT AND DISCUSSION

The figure below represent relative mean squared error versus different number of active subcarriers under different number of SNR. Here consider that there are 2 transmit antennas and 2 receive antennas in this system. From the figure, it is observed that when less subcarriers are occupied, less relative mean square error will be obtained. However, if more subcarriers are active in the CR network at same time, the mean square error will increase.

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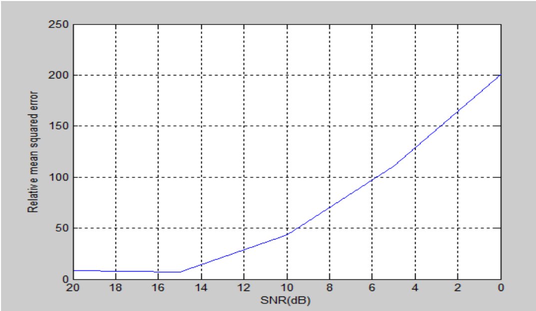

Fig. 3 Probability of bit error rate versus different SNR in 2×2 MIMO system

Fig. 4 shows the influence of the number of sensors on the secondary system throughput. The results indicate that the average throughput, which is obtained by ACO-ESSP increases almost linearly when the number of sensors increases. This is because that increase in number of sensors can lead to finding more feasible subsets. The figure also demonstrates the advantage of ACO-ESSP over its variants. By analyzing the simulation result, it is find that the use of R-FOCUSS algorithm increase the spectrum sensing ability of a CR network and ACO-ESS algorithm improves the network throughput by properly scheduling the various heterogeneous sensors in the CR network.

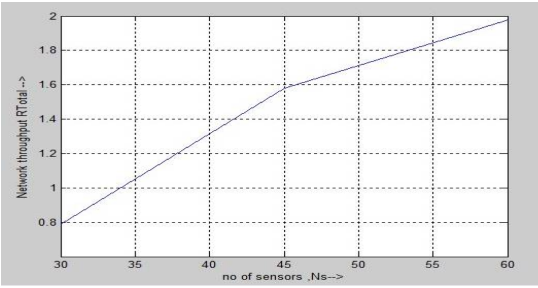

Figure 4: Network lifetime versus number of sensors

VI. CONCLUSION

A novel scheme for spectrum sensing and sensor scheduling in MIMO-OFDM based Cognitive Radio system is proposed here. An algorithm called R-FOCUSS for spectrum sensing is introduced here. This scheme can detect the spectrum usage without the preceding information of sparsity, which is also suitable for the real wireless application environment. A new algorithm called ant colony-based energy efficient sensor scheduling (ACO-ESS) is introduced for sensor scheduling. This algorithm optimally arrange the activities of the sensors to provide the required sensing performance and increase the overall secondary system throughput.

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BIOGRAPHY

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