Adaptive Model based on Proactive Spectrum Sensing for Emergency Cognitive Ad hoc Networks

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Abstract— **Emergency Cognitive Ad hoc Networks (ECANs) require proactive, adaptive and resource efficient spectrum sensing. In general, work in the area of spectrum sensing for cognitive radio networks, has been focused on improving the performance and resource efficiency in static models based on reactive sensing. In this paper, an adaptive model based on proactive spectrum sensing is proposed for ECANs that have dynamic number of users and varying signal to noise ratios. The proposed model uses collaborative spectrum sensing scheme, where each cognitive radio senses the spectrum with certain probability. A Spectrum Coordinator (SC) plays the role of fusion center, generating a fused group decision based on the sensed information obtained from SUs in the network. SC allocates a 'reward' to each SU proportional to its sensing effort and the targeted performance. It can be seen that fairness in energy consumption across SUs is achieved in the proposed scheme.**

Keywords- Spectrum sensing; Cognitive adhoc networks; Proactive sensing; Bayesian risk; Resource efficiency

I. INTRODUCTION

Emergency Cognitive Ad hoc Networks (ECANs) are infrastructure-less networks formed within a short span of time, having time-varying number of users experiencing varying Signal to Noise Ratios (SNRs). They find applications in disaster management, military and other emergency situations. Adaptive Ad hoc Freeband communications (AAF) project [1] is such example, where the ideas of cognitive radio are applied to the field of public safety and emergency control communications. Sensing the spectrum to identify its occupancy by the licensed Primary Users (PUs) is a crucial functionality of any cognitive radio network. Cognitive radios, also referred to as Secondary Users (SUs) are involved in identifying the unused licensed spectrum. Sensing of spectrum may be performed either reactively or proactively. Reactive sensing is done 'on request' when that particular frequency is planned to be used. Though reactive sensing gives more current information on the spectral occupancy, it tends to add latencies in the operation, especially when the sensing time is longer [2]. Spectrum sensing can be performed in a standalone manner by each SU independently or can be done in a collaborative way [3]. In collaborative spectrum sensing, the local sensing information from each SU is received by the fusion center, which fuses this information and generates a group decision. Latencies of reactive sensing become more pronounced when collaborative spectrum sensing is applied because of the above mentioned processing involved.

ECANs require the sensing models to meet the targeted sensing accuracy, resource efficiency and low latency in the delivery of packets. They also need to be adaptive to varying number of SUs and SNR conditions. Since the radios are battery operated, fairness in energy consumption is also an important factor. Only few SUs sensing most of the time could lead to the depletion of their energies and decrease their life in the network. For a longer sustenance of the network, it is necessary that the sensing load should be distributed uniformly across all SUs. Data fusion technique applied to ECANs needs to be resilient to data falsification attacks (Byzantine attacks) [4]. In such attacks malicious users send false sensing data to the fusion center leading to increased probability of incorrect sensing. 'OR'ing is a technique used commonly for data fusion because of its simplicity [3]. However, the technique is prone to data falsification attacks. Likelihood Ratio Test (LRT) based techniques are more resilient and are thus more suitable for the ECANs. The performance superiority of LRT based fusion in this respect is shown in [5].

Literature survey shows that there is no existing model to cater for all the above requirements of ECANs. Most of the earlier work done on collaborative spectrum sensing has been focused on the performance and resource optimization for static situations and reactive schemes that may not be suitable for ECANs. For example, [6] discusses the sensing parameter optimization *w.r.t.* the number of cooperating users. Optimization of sensing throughput tradeoff has been presented in [7]. [8] Shows that it will suffice if an optimal subset of SUs sense the spectrum in a given time epoch resulting in resource efficiency without loss of spectral information.

This paper presents a new proactive adaptive model, where the spectral band is periodically sensed by the SUs in the synchronized quiet period. Discussion about the quiet periods can be found in [9]. The frequency as well as duration of these quiet periods is adapted according to the PU behavior as discussed in [10]. The proposed model is adaptive to the changes in the network size and SNR conditions. The analytical model and simulation results confirm that the targeted sensing performance can be met with minimal number of SUs sensing in each epoch and with fairness in energy consumption. The proposed adaptive model meets all the requirements using collaborative spectrum sensing scheme, where each SU senses with certain probability of sensing (P_s) and a spectrum coordinator receives sensing information from the different SUs in the network and generates a 'fused decision' based on LRT (Refer Figure 1).
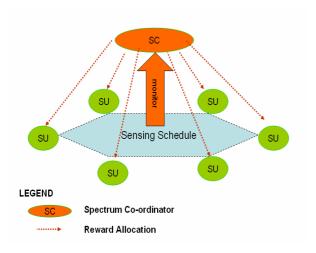
Figure 1. Cognitive Adhoc Network Scenario

The rest of the paper is organized as follows: Section II describes the system model; Section III gives the analytical model; and Section IV discusses the proposed adaptive system model and its ability to adapt to the varying network size and SNR conditions. Section V presents the simulation results. Section VI contains the discussions on the proposal. Finally the conclusions and future work are presented in section VII.

II. SYSTEM MODEL

Consider an ECAN with a collaborative spectrum sensing mechanism and a chosen SC as shown in figure 1. The network size could be varying from a small values to medium sized one (*i.e.* less than 100). The Primary Users (PUs) are the licensed users operating in a subset of these frequencies *[f₁,f₂,....fᵣ]*. It is assumed that the distance between the secondary users or sensors is much smaller compared to their distance from the PU. As a result, the measurements from the SUs are essentially correlated. The SUs however, experience independent and identically distributed fading channels [11]. Each SU makes independent measurement of the spectral information and the individual local decisions about spectral occupancy are sent to SC for data fusion.

Common Control Channel: A common error-free control channel is used to communicate the local decisions from each SU across the network to the SC [12].

Mobility Model: Mobility can be classified as a "nomadic community" model. In this model, a group of mobile nodes move from one position to another. Such models are beneficial in real life emergency applications such as disaster management and military. Restricted movement among the nodes is required when group travels from one location to another. In this model, reference point of each node is determined based on the general movement of the group. The SNRs of the SUs are assumed to be exponentially distributed with an average γ, referred to as the group SNR. This network is associated with an average probability of detect P_d and probability of false alarm P_f corresponding to the group SNR γ [13].

Spectrum Sensing details: Each Secondary User (SU) senses a set of *r* spectral bands centered at frequencies *[f₁, f2,....fᵣ]* using energy detection. The threshold is set for a desired probability of false alarm and the estimated noise power. The SUs sense a given set of frequencies proactively in the quiet period of the network. The quiet periods are synchronized across the network. Though difficult, time synchronization is indispensable is CAN due to the requirements of coordinated and simultaneous quiet periods for spectrum sensing, as well as the common understanding of time frame/slot in many CR MAC designs. CR-Sync protocol has been proposed in [14], that achieves network-wide time synchronization in a fully distributed manner. The local spectrum sensing could be based on simple energy detection, matched filter, cyclostationarity or any other proven method [3].

PU usage pattern: The usage pattern could be of any distribution which is known prior and can be modeled using a 2 stage Markov model [10].

Data Fusion: LRT based fusion rule is considered in the model. The probability of detect and probability of false alarm of each SU required for LRT may be estimated by the spectrum coordinator using the counting rule [15 & 23]. Any other fusion technique like 'AND', 'OR' or Majority Logic may also be used instead [3]. The objective of the SC is to provide communication within the network while ensuring minimal interference to the primary users. In order to achieve this objective, the spectrum coordinator performs the following functions. a) Data Fusion b) Monitoring and estimating the sensing probability, probability of detect and probability of false alarm of each SU c) Allocate reward to each SU based on the sensing probability estimated and the targeted sensing performance. This is discussed further in section IV.

III. ANALYTICAL MODEL

For the system model described in Section II, the analytical model is derived in this section.

Let R_k be the Bayesian risk factor defined in terms of probability of detection of the fused decision (Q_{dk}) and the probability of false alarm of the fused decision (Q_{fk}) as given in [17]; where *k* is the number of inputs fused using LRT obtained from *k* sensing SUs.

$$R_k = C_F Q_{fk} - C_D Q_{dk} + C \qquad (1)$$

Where

$$C_F = P_0 (C_{10} - C_{00})$$
$$C_D = (1 - P_0)(C_{01} - C_{11})$$
$$C = C_{01}(1 - P_0) + C_{00} P_0$$

P_0 is the Probability of the PU being off; C_{00}, C_{01}, C_{10} and C_{11} are the costs associated with making the right and wrong decisions [17]. P_d and P_f denote the average values of the probability of detection and probability of false alarm of the network as a whole, related to the combined or fused decision. The notation of the various terms is tabulated in Table I.

Notation	Description
k	Number of sensing SUs in a given time epoch
γ	*Group SNR*
P_d	Average probability of detect of the group
P_f	Average probability of false alarm of the group
N	Network size (integer)
Q_{dk}	Probability of detect of fused data obtained by fusing k inputs
Q_{fk}	Probability of false alarm of fused data obtained by fusing k inputs
m	Lower limit of summation of (3) and (4) as given in [17]
P_0	Probability of PU being in off state
M	Observation interval as an integer number of time epochs
R_k	Risk Factor [17]
R_{kt}	Risk Factor in each time epoch t
K	Minimal Number of SUs required to maximize the network utility J_k
P_{s_opt}	Desired probability of sense equal to K/N
P_{s_av}	Average probability of sense in M time epochs
J_k	Network utility function in terms of k
J_{Ps_av}	Network utility function in terms of average probability of sense
η_k	Resource efficiency
I_k	Certainty factor = 1- risk factor
I_{Ps_av}	Certainty factor in terms of average probability of sense
α	the weightage given to the accuracy and resource efficiency η_k.

$$Q_d(k) = \sum_{i=m}^{k} \binom{k}{i} P_d^i (1-P_d)^{k-i} \tag{2}$$

$$Q_f(k) = \sum_{i=m}^{k} \binom{k}{i} P_f^i (1-P_f)^{k-i} \tag{3}$$

Where m is the number of users that need to be in agreement to make a decision about presence or absence of PU, as described in detail in [17]. Certainty Factor (CF) defined below is used to define the Network utility function similar to one in [16]

$$I_k = 1 - R_k \tag{4}$$

$$J_k = \alpha I_k + (1-\alpha)\eta_k$$
$$0 \leq \alpha \leq 1, \eta_k = \frac{N-k}{N} \tag{5}$$

Where N is the network size and N is expected to be time-varying with new SUs joining as well as leaving the network. k is the number of sensing SUs, which again may vary from epoch to epoch. It is assumed that change in value of N is updated with a frequency lesser than that of $1/M$ time epochs, where M time epochs is the observation period. The weighting

factor α signifies the weightage given to the accuracy and resource efficiency η_k.

When averaged over M time epochs, CF can be expressed as a function of average probability of sense P_{s_av}, instead of the number of sensing SUs. With each SU sensing with average probability P_{s_av}, k can be approximated as $k = P_{s\_av} N$.

$$I_{P_{s\_av}} = 1 - \frac{1}{M}\sum_{t=1}^{M} R_{k_t} \tag{6}$$

Equation (5) can be rewritten as,

$$J_{Ps\_av} = \alpha I_{P_{s\_av}} + (1-\alpha)(1-P_{s\_av}) \tag{7}$$

As the average probability of sensing P_{s_av} increases, the CF improves, while the network efficiency decreases and vice versa. Let us say, the maximum of the utility function occurs some $P_{s\_opt}=K/N$. The average probability of sense corresponding to the maximum is what a network should adapt and converge to.

Location of this maximum depends upon values of α, γ, N. Figure 2 depicts the relationship between optimum P_{s_av} that will maximize the network utility and α, N and average P_d. As α increases, the weightage given to resource utilization decreases, as a result, the required sensing probability is higher. With increasing N the sensing probability to achieve the maximum decreases as the sensing effort for the same information gain required to be put in by each SU reduces. Increasing P_d (for constant P_f) or decreasing P_f (for constant P_d) means improved SNR. Increase in average SNR reduces the sensing effort required by each SU for a targeted sensing performance. It should be noted that Q_{dk}, Q_{fk}, R_k and I_k depict various metrics for measuring the sensing performance. They are related as expressed in (2), (3), (4) & (5).

Having derived the analytical model for the network utility function, the following section discusses how to achieve maximum utility adaptively with minimal resource consumption while maintaining the targeted information gain.

IV. ADAPTIVE SYSTEM

In order to achieve the maximum utility for a given N and SNR conditions, a feedback mechanism is required between the SC and the SUs. This feedback is provided by a 'reward' allocated to each SU by the SC, which could be in the form of bandwidth, priority in scheduling [18], billing concession [19] or just a factor used for adaptation. Light handed methods of introducing such incentives without imposing too much of overhead have been discussed in depth in [19]. How to built systems that can incentivize radios to follow the spectrum rules has been discussed in [19]. This motivates the proposed adaptive system. The reward is proportional to the sensing effort and the targeted performance measured as $Q_{d\,target}$ for a constant Q_f. This metric was chosen for its simplicity and can be replaced by any of the other mentioned sensing performance metrics. The sensing effort of the ith SU is measured as
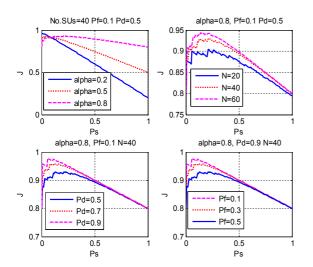
Figure 2. J_{Ps_av} versus P_{s_av} for constant N and different α s

$$\hat{P}_{si} = \frac{s_i}{M} \qquad (8)$$

where s_i is the number of times an SU senses in M epochs of the observation interval which is the estimate of probability of sense of each SU i. The sensing effort required to achieve the targeted accuracy is given by P_{s_opt} which should be learnt and adapted to by each SU based on events tabulated in Table II. These events encompass the different situations that arise in ECANs with changing number of users and SNRs.

Figure 3 shows the working of the adaptation scheme. The operations of data fusion, estimation of the parameters $[P_{di}$, P_{fi} , $P_{si}]$ for each SU and learning of K (optimum number of sensing SUs for the given situation) are performed at the SC. P_{s_opt} is computed as K/N. It is compared with the sensing probability estimate P_{si} of each SU. The normalized reward F_{si} is computed for each SU as P_{si}/P_{s_opt}. This reward factor F_{si} is sent in real time to each SU. Each SU adapts its sensing probability according to the observed reward. If reward is less than 1, it implies that the sensing probability needs to be improved. If reward is 1 then the sensing probability can be reduced.

The update equation for probability of sense when F_{si} is less than 1 is as shown below.

$$P_{s\_new} = P_{si} + \Delta P_{si} \qquad (9)$$

where

$$\Delta P_{si} = \mu_p (1 - F_{si}) / P_{si} \quad \text{where}$$

$$0 \leq \mu_p \leq (1 - P_{si}) P_{si} / (1 - F_{si}) \qquad (10)$$

This equation shows that the change in P_{si} is directly proportional to the difference $(1-F_{si})$. Correction will be higher for smaller values of F_{si} and vice versa.
The update equation for F_{si} equal to 1 is shown below. In this case, the update only depends upon the current value of P_{si}. Higher the original P_{si}, higher is the update and vice versa.
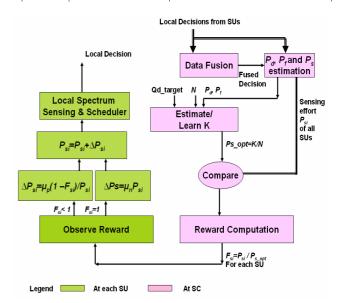
$$P_{s\_new} = P_{si} - \Delta P_{si} \qquad (11)$$

$$\Delta P_{si} = \mu_n P_{si}$$
$$0 \leq \mu_n \leq 1 - (1 / P_{si})$$

The adaptation algorithm at the SC and SU is listed below:

Adaptation Algorithm at SC
Step 1: *Init k=1, Set M*
Qd_target=0.9   // can be set to any targeted value
Ps_opt = 1

TABLE II: EVENTS FOR TRIGGERING ADAPTATION

Sl. No.	Events	Action
1.	Network Startup	Learn P_{s_opt} for given N and SNR conditions
2.	N changes	Update $P_{s\_opt} \leftarrow N_{old} * P_{s\_opt}/N$
3.	SNR changes	Learn P_{s_opt} for given N and SNR conditions

Figure 3: The block diagram of the adaptive system
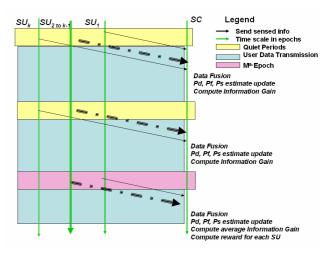

Figure 4: Event Schedule of the adaptive system

$Ps\_opt\_Learning\_flag = 0$

Step 2: *Get local decisions*
Data Fusion
Update P_{si}, P_{di}, P_{fi}
Compute Qd

Step 3: *if iter=M Compute reward for each SU*

$$F_{si} = \left(\frac{s_i / M}{P_{\_opt}} \right) \left. \begin{array}{c} P_{si} < P_{\_opt} \\ \\ \\ P_{si} \geq P_{\_opt} \end{array} \right.$$

Set iter =1
Compute Q_{d_av} (Average Q_d over M iters)
If $Q_{d\_av} > Q_{d\_target}$ & If $P_{s\_opt}\_Learning\_flag = 0$
set $P_{s\_opt} \leftarrow mean(P_{si})$ of all SUs;
set $P_{s\_opt}\_Learning\_flag = 1$

Step 4: *iter $\leftarrow$ iter+1*
go to **Step 2**

Step 5: *If event 2 set $N\_old \leftarrow N$, $P_{s\_opt} \leftarrow P_{s\_opt}*N\_old/N$*

Step 6: *If event 3 set $P_{s\_opt}\_Learning\_Flag \leftarrow 0$*

Adaptation Algorithm at the ith SU

Step 1: *Init: Set M;*
Set P_{si} =Random value {0 to 1};
$F_{si}= 0$; $\mu_p=0.02$; $\mu_n=0.2$

Step 2: *Energy Detection collecting m samples[3]*

Step 3: *Make local decisions and send to SC*

Step 4: *if iter =M, observe F_{si}*

Step 5: *If $F_{si} < 1$ and $P_{si} < 1$ set $P_{si}=P_{si}+\Delta P_{si}$*
else $P_{si}=P_{si} -\Delta P_{si}$
go to **Step 2**

Figure 4 shows the scheduling of events of the adaptive system. The SUs sense the spectrum in the quiet period and send the sensing information to the SC, which fuses the data.

V. SIMULATION MODEL AND RESULTS

The simulation model was built using Netlogo [20] to validate the performance of the adaptive system. The parameters considered for the simulation are as listed in Table III. Each of the SUs has identical code but for one SU which is allotted the role of SC. This choice of SC can be done based on the sequence of entry into the network, *i.e.* first SU that starts the ad hoc network could be the SC. Choice of SC could also be based on hierarchy of ranks or could be dynamic depending on the application. It should be noted that the choice of SC would not affect the simulation results.

Figure 5 shows the variance of the energy spent by each SU and the sensing performance Q_{d_av} versus number of iterations (time epochs). The convergence is towards a fair system where all SUs put in equal effort towards sensing, while maintaining targeted Q_d, *i.e.* Q_{d_target}. The group SNR was set to 0dB and counting rule was used to estimate P_d ($P_f =0.1$). Figure 5 alsoshows an SU initializing with a random probability of sensing converging to P_{s_opt} learnt by the SC (event 1 of Table

TABLE III: LIST OF PARAMETERS FOR SIMULATION.

Parameter/Scheme	Value/Type	Comments
Local Spectrum Sensing	Energy Detection	Can be replaced by any other local sensing mechanism
Number of Samples m	100	Can be varied and decides the accuracy of ED
SNR Distribution across SUs		Exponential distributed with different average values
Initial Number of SUs	10	Considering medium sized networks with N between 3 to 50 SUs
μ_p	0.02	Adjusted Empirically
μ_n	0.2	Adjusted Empirically

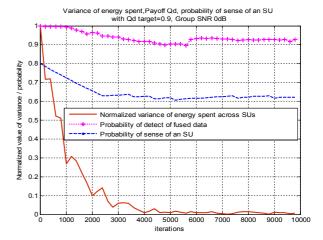
Figure 5:The convergence of the variance of energy spent across SUs while maintaining performance
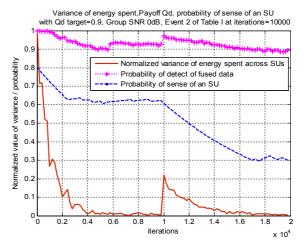

Figure 6:The convergence of the variance of energy spent across SUs,P_s at an SU to P_{s_opt} with number of users N changing at 10000th time epoch

II). Figure 6 shows the variance of the energy spent by each SU, the sensing performance Q_{d_av} and convergence of probability of sense of an SU when event 2 of Table II occurs at the 10000th time epoch, *i.e.* new SUs are added to the network. Then the sensing probability is reduced to the updated
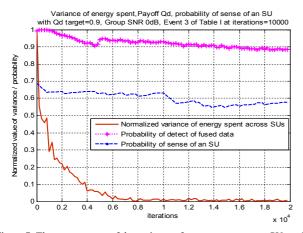
Figure 7: The convergence of the variance of energy spent across SUs and the probability of sense of an SU while maintaining performance with SNR changing at 10000th time epoch

P_{s_opt}. Similarly, occurrence of event 3, *i.e.* change in SNR values is shown in Figure 7. SNR changes do not cause any abrupt changes in the variance but the P_{si} of the SUs is adapted to the required new value. This interval time between changes in SNR depends on the channel fading conditions, which in turn depends on the speed of the nomadic group. The model proposed is independent of this parameter. The changes in SNR can occur at any time period that is greater than *M*.

VI. DISCUSSION

Having observed the convergence of the system under various conditions, an analysis of the convergence time is discussed in this section. The convergence time is directly proportional to the observation time period M which is measured in epochs of time between quiet periods. This quiet period can be determined based on the PU usage pattern [10]. The convergence time also depends on the amount of adaptation and the size of the adaptation step size.

VII. CONCLUSIONS

An adaptive model for collaborative spectrum sensing in ECAN was developed. The analytical and simulations models were presented. The model supports dynamic number of SUs as well as dynamic SNR conditions. The sensing is done by SUs in the quiet periods which are synchronized. Each SU senses with a probability of sense which is adapted based on the feedback from the SC provided in the form of reward. Results showing the convergence of the adaptation towards a resource efficient condition while maintaining the sensing performance and fairness. The SUs of the CAN are assumed to be embedded systems which are not been tampered. Attacks against cognitive radio networks have been well addressed in [21, 22]. The model presented is relatively resilient to data falsification attacks because of the LRT based data fusion.

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