

Energy Efficient Spectrum Aware Channel Sensing Routing Protocol for Cognitive Radio Mobile Ad-Hoc Networks

S. Chinnasamy
M.Phil Research Scholar
Department of IT, School of CSE
Bharathiar University, Coimbatore.

R. Vadivel, PhD
Assistant Professor
Department of IT, School of CSE Bharathiar
University, Coimbatore.

ABSTRACT

A cognitive radio ad hoc network is the thrust research area in the field of wireless communications. This paper presents the network clustering scheme, the model and algorithm for the clustered cooperative channel sensing based on reinforcement learning. It is imperative to minimize energy cost for channel sensing so as to prolong lifetime of the network. Hence an algorithm for the cooperative channel sensing based on reinforcement learning is proposed. Performance metrics such as success rate, average broadcast delay are taken into account for comparison. Simulation results portrays that the proposed EESACSRP outperforms in terms of the chosen performance metrics.

Keywords

Cognitive Radio Ad Hoc Network, Cluster Head, Quality of-Services, cognitive radio, multi-hop architectures

1. INTRODUCTION

Cognitive radio is a variety of wireless communication in which a transceiver can cleverly detect which communication channels are in use and which are not and right away move into vacant channels while avoid occupied ones. This optimizes the use of available Radio-Frequency range while minimize interference to other users. In its basic form, CR is a hybrid technology concerning Software Defined Radio as applied to spread spectrum communications probable functions of cognitive radio include the capability of a transceiver to resolve its geographic location, identify and authorize its user encrypt or decrypt signals, sense nearby wireless devices in operation and change output power and modulation characteristics. Cognitive radio is the enabling technology for supporting DSA: the policy that addresses the spectrum scarcity problem that is encounter in many countries. Thus CR is regarded as one of the most hopeful technologies for future wireless communications. To make radios and wireless network truly cognitive, however, is by no way a simple task, and it requires collaborative effort from different research communities, with communications theory, networking engineering, signal processing, game theory, software-hardware design, and reconfigurable transmitter and radio-frequency design. In this paper, we provide a logical overview on Cognitive Radio networking and communications by looking at the key functions of the

Physical, Medium Access Control, and networking layers involved in a Cognitive Radio design and how these layers are crossly related. In exacting, for the PHY layer, that will address signal processing technique for spectrum sensing, supportive spectrum sensing, and transceiver design for cognitive spectrum access: for the medium access control layer is analysis sensing scheduling scheme, sensing-access

exchange design, spectrum-aware access MAC, and Cognitive Radio MAC protocols. In the network layer, Cognitive Radio Network tomography, spectrum-aware routing, and Quality of-Services (QoS) control will be addressed. Emerging CRNs that are actively developed by various consistency committee and spectrum-sharing economics will also be review. Finally, point out some open questions and challenges that are related to the Cognitive Radio design.

2. LITERATURE REVIEW

The frequency spectrum is, indisputably, the most valuable resource in wireless communications because of its limited availability. Moreover, the use of available frequency spectrum resources is very inconsistent. There are unlicensed bands which have been overcrowded with growing technology uses, such as Bluetooth, Wi-Fi, etc. In contrast, there are licensed bands which are absolutely under-utilized. A novel solution is required in order to address both the problem where the spectrum available for certain uses is congested, and the problem where the spectrum available for other uses is allocated inefficiently. As a promising solution for this unbalanced situation, cognitive radio (CR) technology has been developed in order to enable the efficient exploitation of radio spectrum resources. CR technology has the potential to solve the wireless communications problems that result from the limited available spectrum and the inefficient use of that spectrum [1]. It is the cognitive capability that enables CR to sense and capture vital information regarding the temporal and spatial variations in the existing radio environment. CR has the ability to change its transmission parameters (e.g., transmit power, modulation scheme, and operating frequency) based upon observations of, and interactions with, the surrounding environment. The CR parameters are reconfigured depending upon the characteristics of the spectrum in order to cope with the changing radio environment [2]. This CR capability opens the door for dynamic spectrum access mechanisms that allow the opportunistic use of an underutilized frequency spectrum, thereby ensuring that both the optimum spectrum and the most convenient transmission parameters are selected.

A Cognitive Radio Network (CRN) consists of wireless nodes equipped with CR capability that gives them a unique proficiency in sensing the frequency spectrum, reconfiguring the radios and exploiting spectrum holes based on the spectral environment [3]. Such nodes represent Secondary Users (SUs), or cognitive users. In a CRN, the licensed users are called Primary Users (PUs) and have an inherent priority to operate in certain licensed frequency bands. Whenever an SU has data to transmit, it is supposed to opportunistically use the licensed spectrum that is currently unused by a PU. Therefore, the major responsibility for any SU is to ensure the opportunistic use of the available spectrum without imposing

any kind of interference for the PU. A Cognitive Radio Ad Hoc Network (CRAHN) [5] is a special type of CRN with no centralized network entity. As a result, SUs need cooperation schemes in order to exchange network related information, such as the presence of a PU, the node configuration, and spectrum holes. This information is obtained through local observation and spectrum sensing, and can be used for reconfiguration and routing purposes. CRAHNs are also distinguished by their inherent features, including dynamic topologies, spectrum heterogeneity, multi-hop architectures, self-configuration, and energy constrained power supplies [4]. In fact, these challenges make CRAHNs a very interesting field for researchers to work in. Consequently, a considerable amount of research and development effort has been put into ensuring CRAHNs are able to support a wide range of applications with the utmost efficiency.

3. PROPOSED WORK

This paper presents the network clustering scheme, the model and algorithm for the clustered cooperative channel sensing based on reinforcement learning. The clustering scheme organizes the network into structure that enhances coordination of CR nodes, data communication and vacant channels access in cognitive radio network. Each cluster consists of a Cluster Head (CH) [6] and non-cluster head nodes referred to as cluster Member Nodes (MNs). The MNs are ordinary nodes within the cluster that sense spectrum to detect vacant channels, detect event and communicate data to their respective CH via intra-cluster communications. The channel sensing problem is formulated as a Markov Decision Process (MDP) for selecting optimal set of channels to be sensed and optimal channel sensing sequence. The spectrum aware clustering scheme involves three main phases namely, initialization, set-up and maintenance phases. The initialization phase deals with neighbor discovery and determination of node eligibility El_i to contest for clusterhead role. The node degree denotes concentration of neighboring nodes within the node's radio range that can interact and communicate their data in a single-hop manner. High node degree indicates better opportunity to form a stable cluster that allows clusterhead to communicate with many member nodes. The number of vacant channels detected CV_i is a key component for robust cluster structure and efficient data communications in spectrum aware clustering. Large numbers of vacant channels improve stability of the cluster and enhance both inter-cluster and intra-cluster communications since data are communicated through the vacant channels detected. The residual energy er_i denotes node's remaining energy which is a key factor for selecting a cluster head. High residual energy suggests longer period for the clusterhead to remain active while performing additional tasks that drain more energy from the battery of the node. The distance to sink dc_i is an important parameter that suggests energy cost forwarding the aggregated data to the sink. Long distance attracts high energy cost for inter-cluster communications while short distance consumes less energy for inter-cluster communications.

The percentage of cluster heads ϕ indicates clusters configuration for the network which determines member nodes distribution in the network. If the percentage of clusterheads is too small, significant energy will be consumed for inter-cluster communications due to large number of

member nodes per cluster that may transmit over long distances. Similarly, too large percentage of clusterheads leads to high energy cost for inter-cluster communications because clusterheads may transmit at maximum power. Therefore, the percentage of clusterheads needs to be carefully chosen.

The set-up phase involves election of clusterheads based on eligibility probability P_i^s and establishment of clusters where MNs identify their respective cluster and associate with the CH in the cluster. During the clusterhead election, SUs with highest eligibility probability P_i^s among the neighboring eligible SUs would be emerged as clusterheads while the others are likely to be member nodes.

The maintenance phase allows re-election of clusterhead whenever the residual energy of the incumbent CH depletes to a level below a threshold ϕ or when the CH disconnected from network. The eligibility probability P_i^s can be expressed as

$$P_i^s = \frac{nd_i cv_i er_i \phi}{em_i n_z hc_i}, \quad (1)$$

Where em_i denotes node's energy at full charge and n_z denotes number of licensed channels. The clustering scheme begins at time τ_{st} with exchange of control packets for neighbors discovery and then follows by sensing predefined set of licensed channels to detect availability or otherwise of PU on the licensed channels. Each SU_i computes its eligibility probability P_i^s and then compares it with a given threshold Ω_e to determine its eligibility El_i to contest for the clusterhead position.

A SU is said to be eligible El_i to contest for cluster head if its eligibility probability ($P_i^s \geq \Omega_e$) is greater than or equal to a given threshold Ω_e . This means that SUs with eligibility probability ($P_i^s \geq \Omega_e$) less than a given threshold Ω_e are likely to remain as member node.

The cluster heads are model as teach agents which sequentially sense finite number of channels, and learn optimal set of channels by adopting a RL technique.

3.1. Energy cost

Energy cost for channel sensing in CR-WSN constitutes significant portion of the network energy consumption. Therefore, it is imperative to minimize energy cost for channel sensing so as to prolong lifetime of the network. Energy dissipated by SU_i for listening to the channel ch_z , receiving N_0 signal samples for a minimum duration of T_{cs} and processing the received signals for local decision can be expressed as:

$$E_{cs} = T_{cs} P_{ed} + E_{sp}, \quad (2)$$

Where P_{ed} denotes energy detector's circuit power consumption and E_{sp} denotes energy consumption for processing the received N_0 signals samples. Therefore, energy cost for channel sensing is heavily influenced by the sensing duration, minimum sensing time always minimizes energy cost for channel sensing but this may not guarantee accurate sensing results.

The narrow band cooperative channel sensing algorithm begins with initializing the array of all the state-action values $Q(|S|, |A|)$ to zero (line 2) and then performing iterations (line 3 to line 14) up to the number of episodes E_{psd} specified in the inputs (line 1). State transition is sequential (line 4) and restarted whenever the next state reaches the number of channels (line 12). In each state of the episodes (line 5), a softmax action selection strategy chooses an action with highest state-action value through exploration of random actions.

The corresponding channel parameters i.e. channel bandwidth, required bandwidth, PU birth rate, PU death rate as specified in the inputs are used to compute the rewards based on three metric functions namely channel sensing energy cost, channel availability and local decision accuracy (line8).The cumulative reward (line9) which is the weighted average of the three computed rewards is used to update the Q-values (line 10) as described. At the end of the episodes, a final Q-matrix consist all the state-action values would be obtained and the highest value (line15) of each row in the Q-table is determined.

An optimal policy, which is column index of each row in the Q-table that returns the maximum value, denotes the selected channel in that state and the sequence of the channels in the optimal Q-table denotes the optimal sequence of channel sensing S_{eq}^* (line 17).The selected channels in the optimal Q-

table form the optimal set of channels A_{ex}^* (line 18 to line 21).

Algorithm for the cooperative channel sensing based on reinforcement learning

Algorithm 1: RL based Cooperative channel Sensing

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1: input
    $|S|, |A|, |H|, |B_w|, |r_0|, |r_1|, E_{psd}, w_{\alpha_1}, w_{\alpha_2}, w_{\alpha_3}, rqB_w$ 
2: Initialize:  $Q(|S|, |A|) \leftarrow 0, k \leftarrow 0, a_k^e \leftarrow 0$ 
3: for  $e \leftarrow 1$  to  $E_{psd}$  do
4:    $k \leftarrow k + 1$ 
5:    $a_k^e \leftarrow \text{action Strategy}(s_k^e, Q)$ 
6:   if  $a_k^e \neq 0$  and  $k \leq n_z$  then
7:     Sense Channel  $(Ch_z, a_k^e = z)$ 

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8: Compute

$$rw_{ak+1}^e \leftarrow \frac{1}{2} \text{sum} \left(\frac{t_{id}}{t_b}, \frac{rqB_w}{B_w} \right), rw_{lk+1}^e \leftarrow \frac{1}{2} \text{sum}(LD_i^z, CD_j^z),$$

$$rw_{ek+1}^e \leftarrow \tau_{av} / T_{cs},$$

9: Compute

$$r_{k+1}^e \leftarrow \text{Weighted Average}(rw_{ak+1}^e, rw_{lk+1}^e, rw_{ek+1}^e)$$

$$10: \text{update } Q_k^e \leftarrow Q_k^e + \alpha [r_{k+1}^e + \gamma \max_a (Q_{k+1}^e) - Q_k^e]$$

11: else

12: $k = 0$

13: end if

14: end for

$$15: [H_{seq}, I] \leftarrow \max Q$$

$$16: j = 1, i = j + 1$$

$$17: S_{eq}^* = |H_{seq}|$$

18: while $i \leq n_z + 1$ do

19: if $I(j) \neq 0$ and $I(j) \neq I(i)$ then

$$20: A_{ex}^* \leftarrow |I|$$

21: end if

22: end while

4. SIMULATION SETTINGS

Table - 1

Number of SUs N	16
Number of PUs K	40
Number of Channels M	20
Side length of the simulation area L	10(unit length)
Radius of the sensing range r_s	2(unit length)
Radius of the transmission range r_c	2(unit length)
Number of selected channels n	1
The normalized PU arrival rate λ_p	0.5
The PU Packet length L_p	10 (times slots)
The probability of a successful transmission σ	1

5. RESULTS AND DISCUSSIONS

5.1. Number of Secondary Users Vs Success Rate

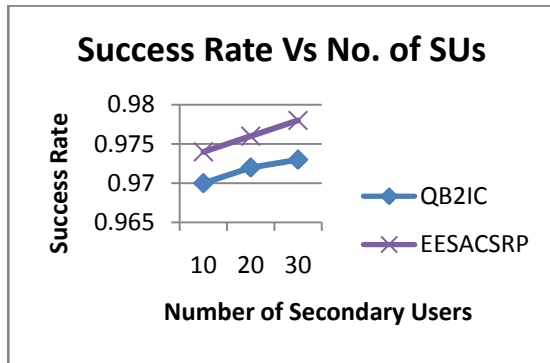


Figure.5.1. Number of Secondary Users Vs Success Rate

Table.5.1. Number of Secondary Users Vs Success Rate

No. of SUs	Protocols	
	QB2IC	EESACSRP
4	0.89	0.95
9	0.83	0.88
16	0.82	0.83

Fig.5.1. portrays the success rate performance subject to increasing the number of secondary users of the EESACSRP compared with QB2IC. It is evident that EESACSRP attains better success rate than that of QB2IC protocols. The simulation result values are shown in Table 5.1.

5.2. Number of Secondary Users Vs Average Broadcast Delay

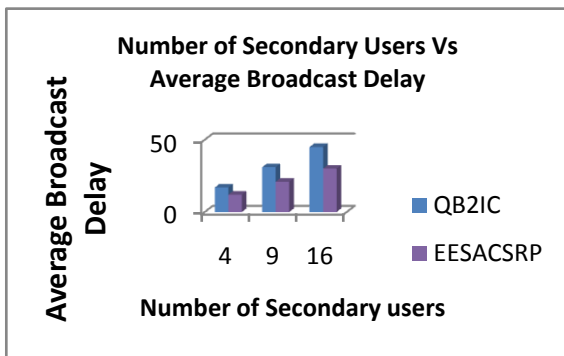


Figure.5.2. Number of Secondary Users Vs Average Broadcast Delay

Fig.5.2. Projects the average broadcast delay performance subject to increasing the number of secondary users of the EESACSRP compared with QB2IC. It is obvious that EESACSRP attains less broadcast delay than that of QB2IC protocols. The simulation result values are shown in Table 5.2.

Table.5.2. Number of Secondary Users Vs Average Broadcast Delay

No. of SUs	Protocols	
	QB2IC	EESACSRP
4	17	12
9	31	21
16	45	30

5.3. Number of Primary Users Vs Success Rate

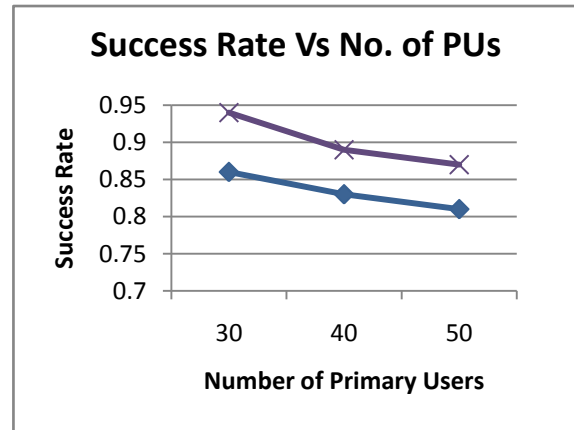


Figure.5.3. Number of Primary Users Vs Success Rate

Fig.5.3. Projects the success rate performance subject to increasing the number of primary users of the EESACSRP compared with QB2IC. It is certain that EESACSRP attains increased success rate than that of QB2IC protocols. The simulation result values are shown in Table 5.3.

Table.5.3. Number of Primary Users Vs Success Rate

No. of SUs	Protocols	
	QB2IC	EESACSRP
30	0.86	0.94
40	0.83	0.89
50	0.81	0.87

5.4. Number of Primary Users Vs Average Broadcast Delay

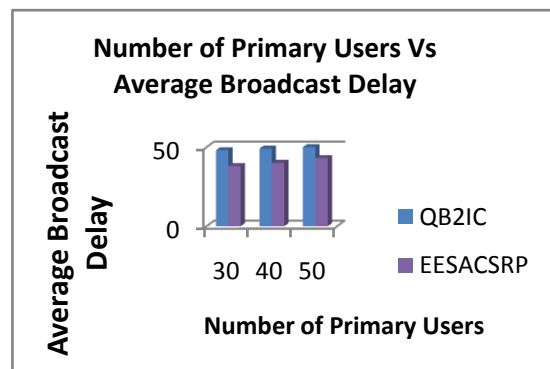


Figure 5.4 Number of Primary Users Vs Average Broadcast Delay

Fig.5.4. showcases the average broadcast delay performance subject to increasing the number of primary users of the EESACSRP compared with QB2IC. It is evident that EESACSRP attains less broadcast delay than that of QB2IC protocols. The simulation result values are shown in Table.5.4.

Table 5.4 Number of Primary Users Vs Average Broadcast Delay

No. of SUs	Protocols	
	QB2IC	EESACSRP
30	48	38
40	49	40
50	50	43

5.5.Number of Channels Vs Success Rate

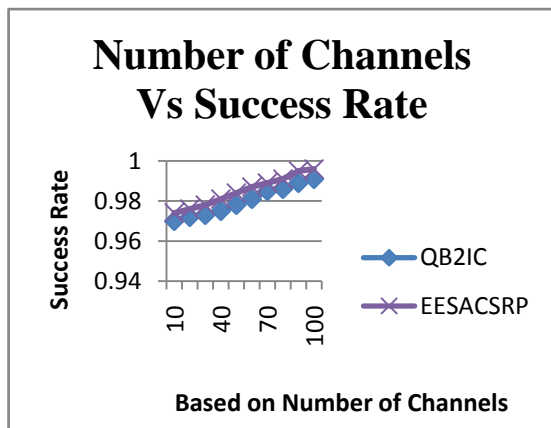


Figure 5.5 Number of Channels Vs Success Rate

Fig.5.5. envisage the success rate performance subject to increasing the number of channels of the EESACSRP compared with QB2IC. It is certain that EESACSRP attains increased success rate than that of QB2IC protocols. The simulation result values are shown in Table 5.5.

Table 5.5 Number of Channels Vs Success Rate

No. of SUs	Protocols	
	QB2IC	EESACSRP
10	0.97	0.974
20	0.972	0.976
30	0.973	0.978
40	0.975	0.981
50	0.978	0.984
60	0.981	0.987
70	0.985	0.989
80	0.986	0.991
90	0.989	0.995
100	0.991	0.996

5.6.Number of Channels Vs Average Broadcast Delay

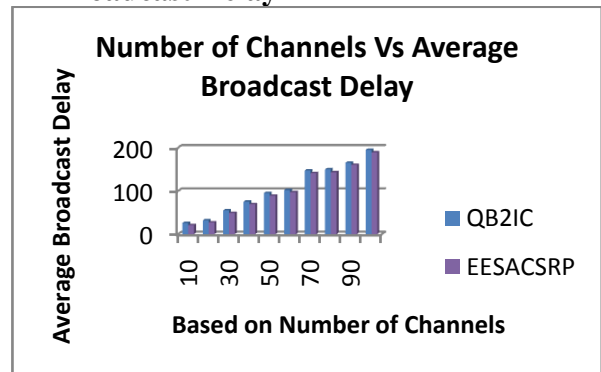


Figure 5.6 Number of Channels Vs Average Broadcast Delay

Fig.5.6. projects the average broadcast delay performance subject to increasing the number of channels to the EESACSRP compared with QB2IC. It is obvious that EESACSRP attains less broadcast delay than that of QB2IC protocols. The simulation result values are shown in Table.5.6.

Table 5.6 Number of Channels Vs Average Broadcast Delay

No. of SUs	Protocols	
	QB2IC	EESACSRP
10	26	21
20	32	27
30	55	49
40	75	69
50	95	89
60	102	97
70	147	141
80	150	143
90	165	160
100	195	189

5.7.Number of Unsynchronized Time Slots Vs Success Rate

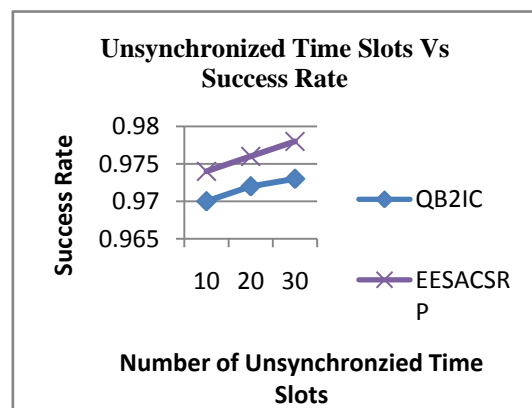


Figure 5.7 Number of Unsynchronized Time Slots Vs Success Rate

Fig.5.7. envisages the success rate performance subject to increasing the unsynchronized time slots to the EESACSRP compared with QB2IC. It is certain that EESACSRP attains increased success rate than that of QB2IC protocols. The simulation result values are shown in Table 5.7.

Table 5.7 Number of Unsynchronized Time Slots Vs Success Rate

No. of SUs	Protocols	
	QB2IC	EESACSRP
4	0.93	0.99
9	0.89	0.97
16	0.89	0.95

5.8. Number of Unsynchronized Time Slots Vs Average Broadcast Delay

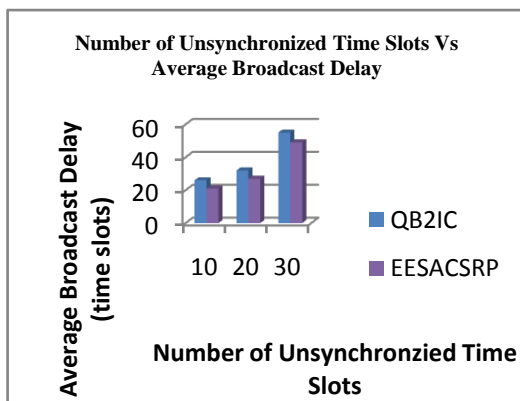


Figure 5.8 Number of Unsynchronized Time Slots Vs Average Broadcast Delay

Fig.5.8.projects the average broadcast delay performance subject to increasing the number of unsynchronized time slots to the EESACSRP compared with QB2IC. It is obvious that EESACSRP attains less broadcast delay than that of QB2IC protocols. The simulation result values are shown in Table 5.8.

Table 5.8 Number of Unsynchronized Time Slots Vs Average Broadcast Delay

No. of SUs	Protocols	
	QB2IC	EESACSRP
4	20	15

9	38	30
16	51	43

6. CONCLUSION AND FUTURE WORK

This paper presents the network clustering scheme, the model and algorithm for the clustered cooperative channel sensing based on reinforcement learning. It is imperative to minimize energy cost for channel sensing so as to prolong lifetime of the network. Performance metrics such as success rate, average broadcast delay are taken into account for comparison. Simulation results portrays that the proposed EESACSRP outperforms in terms of the chosen performance metrics.

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