A Channel Decision strategy for Cognitive Radio Ad hoc Networks

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Abstract

In this paper, a distributed channel decision strategy (DCDS) has been proposed for cognitive radio ad hoc network (CRAN). In this strategy, DCDS classifies the available channels and uses them efficiently to increase reliability in cognitive radio networks. The classification is done on the basis of Primary User (PU) un-utilize, the number of Secondary User (SU) neighbors using the channels, and the capacity of available channels. NS2 simulator is used for comparing the performance of DCDS compared to two related strategies. Simulation results approved that our strategy is effective compared to others strategies with regard to selecting best channel, less interference with PU, and maximizing spectral efficiency.

Keywords: Cognitive Radio Networks, Distributed Solutions, Channel Selection Strategy, dynamic channel selection.

Introductions

Recent advances in communication technologies and the increase of wireless computing and communication devices make the radio spectrum congested. However, experiments from the Federal Communication Commission (FCC) show that the spectrum utilization varies from 15% − 85%. Consequently, Cognitive Radio Networks (CRNs) are proposed to utilize the radio spectrum opportunistically.

Cognitive technology is the process of knowing through perception, planning, reasoning, acting, and always updating and upgrading with a history of learning. SU has the capability to recognize unexploited available band from heterogeneous spectrum bands such as ISM, GSM, 3G, and TV bands, and utilize unused spectrum opportunistically [1]. PUs are the owner of the spectrum and can use the spectrum at any time, whereas SUs can use the spectrum only just while PU in OFF state.

One of the most tasks of a SU in CRAN is to discover vacant channels to utilize them without causing any disturb to the PU. In the lack of interaction between PUs and SUs, vacant channels should be recognized by intelligent prediction model. By using prediction model of traffic pattern for PU, each SU knows how to predict the probability that specific channels are available in the expected time period and can selects one of them which suit his requirements. With no prediction model, SU can transmit on any channel as long as no PU is using the channel.

In CRAN, chosen reliability channel is difficult to achieve due to several factors:

- The variety in the number of free channels that each SU be able to exploit adds an issue by restrictive node's connectivity to its neighbors. In CRAN, the set of vacant channels for each SU is not identical. Therefore, a SU node receives a message only if it has similar channel between it and sender's node. Therefore, the less number of neighbors for each SU leads to restrictive node's connectivity.
- SUs participate with PUs on the remaining sources of channels and exploit them without disturb with the PU. This participating must be in a method (e.g., channel decision procedure) without making interference with PUs connections.
- The existence or absence of PU's signal on each channel depends on the prediction model of traffic pattern for PU (see Section 3). This model must be more accurate and intelligent by CRAN to reduce the hopping rate for SU from channel to another frequency and interference to PU.

In DCDS, the objective of every cognitive radio node is to select the best channel ensuring a minimum interference to PU and consequently, allowing the largest data dissemination reachability in the network. This corresponds to the use of channels having low primary radio nodes (PRs) activities, as well as having lower number of CR neighbors and having high capacity. In DCDS, the classification of channels is done on the basis of PU un-exploit (OFF durations), the number of SU neighbors exploiting the channels, and estimate channel capacity for all available channels.

The performance of DCDS through NS2 simulation has been analyzed. We use the Cognitive Radio Cognitive Network (CRCN) patch [2] of Network Simulator NS2. We compare DCDS with best-fit channel selection (BFC) and longest idle time channel selection (LITC). We comprehensively analyze DCDS by varying node density, number of channels, etc. Simulation results based on NS2 approved that DCDS is effective in terms of selecting best channel, less interference with PU, and higher spectral efficiency compared to related strategies.

The rest of the paper is organized as follows: In Section 2, related work for this work is explained, system model for the proposed strategy is given in Section 3. Proposed channel decision strategy DCDS is introduced in Section 4. In Section 5, simulation setup and performance analysis between the proposed framework and other strategies are introduced. This work is concluded in Section 6.

2. Related Work

According to the network topology, cognitive radio networks (CRNs) can be classified to infrastructure networks and non-infrastructure (ad hoc) networks. Many selection solutions have been introduced for infrastructure CRNs [3]. On the other hand, many spectrum selection solutions have been proposed for cognitive radio ad hoc networks (CRANs). Such solutions are classified into two categories: predictive solutions based on prediction model [4, 5], or statistics model [6, 7], and non-predictive solutions based on random selection [8, 9], or optimization techniques [10, 11] .The classification of spectrum selection solutions for CRANs is shown in Fig. 1.

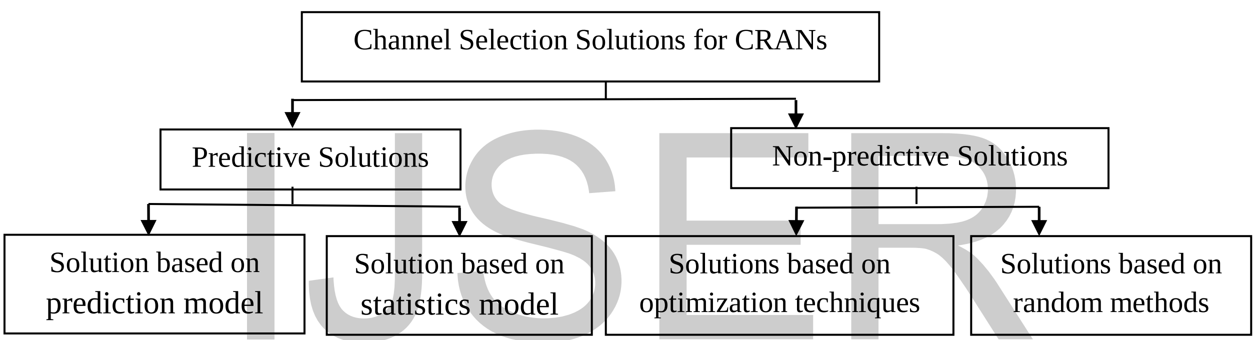

Fig. 1: The classification of channel selection solutions for CRANs

Random selection solutions are non-predictive which the channel is selected randomly without collecting information about PU activities. In [9], the CR senses channels randomly until it discovers an idle channel. This simple strategy has low complexity because it avoids keeping information such as sensing and access history. The authors in [8] improved the random channel selection by the round robin scheduling mechanism. Initially, CR selects a random channel as a candidate transmission channel, if the sensed channel is not idle; the next (adjacent frequency) channel is sensed until find idle channel.

On the other hand, for selection solutions related to optimization methods, the authors convert the problem of channel selection into an optimization problem to optimize diverse performance goals such as minimizes spectrum handoff [10] and interference rate [11] without using prediction model to estimate the probability of channel in OFF state at time t. The authors in [11] have been proposed selection solution based on partially observable markov decision process (POMDP) to determine the optimal target channel for spectrum handoff according to the partially observable channel state information. On the other hand, the authors in [12] have been proposed channel selection model based on genetic algorithm. The fitness function is used eliminate the chromosomes that dissatisfied interference constraints and the population of genetic algorithm is composed of feasible and infeasible spectrum assignments. Due to reserved ratio of feasible solutions, the spectrum assignment strategy with high fitness value can be achieved to minimize interference ratio.

On the other hand, for selection solutions based on predicative solution can be classified into two categories, solutions based on prediction model [4, 5], and solutions based on statistics model [6, 7]. For solutions based on statistics methods, the authors in [6] were used one of the methods of learning techniques such as learning automata (LA) to train SU nodes to estimate the optimal channel selection probability avoiding the costly channel switching. After a vast number of examinations, the SUs can estimate the optimal channel selection probability. On the other hand, the authors in [7] have been proposed a distributed Q learning based energy efficiency optimization with joint channel selection and power control spectrum decision which takes channel state as the input and takes the selected channel and transmit power as the output by analyzing the network channel characterization and energy efficiency. The SUs got the optimal transmitted power and communication channel to guarantee the energy efficiency and spectrum efficiency simultaneously.

For solutions based on prediction methods, the authors in [4] have been proposed best fit channel selection for distributed channel selection. Each SU calculates the primary channel accessibility times and adopt the channel for transmission depending on this calculation. Every SU, knowing its transmission time requirement and the primary channel availability times, selects the channel that has sufficiently long channel idle time to meet the CR transmission time. On the other hand longest idle time channel selection [5] scheme has been proposed for distributed channel selection in CRN to select the best channel which has longest idle time.

A more related to our approach is BFC and LITC. in our paper, we considers other parameters in selecting best channel, such as, number of secondary users in each channel and channel capacity for all available band. This consideration helps DCDS to select best channel accurately. Lowest number of SU leads to little contention among CRs; in addition, highest channel capacity helps SU to send data in faster way.

3. System Model

Here, we point out our basic assumptions for the system model in the following:

3.1. Network model

We consider a CRN [13]. Where the base station is not available, instead, each SU node will be responsible for CRN functions such as spectrum sensing, spectrum decision, spectrum sharing and mobility. The CRN is composed of a set of PU and SU nodes. Here, we assume orthogonal frequency divisions multiplex (OFDM) system as a physical technology, consisting of multiple subcarriers.

In CRN, PUs are the owner of the spectrum and can use the spectrum at any time, whereas SUs can use the spectrum only just while PU in OFF state. In additions we suppose that the cognitive radio unit is provided with a single transceiver where the SU either sense or communicate on one channel at a time. The yield from that, the computational cost of the SUs are decreased [14], in addition to avoid the probable interference when use multi-transceiver because of close proximity between them [15]. We suppose the total number of available channels is FC. The availability of a out-of-band Common Control Channel (CCC) [16] is assumed for neighbor discovery.

3.2. Spectrum sensing model

In distributed solutions, SUs are supposed to sense in autonomous way and depend on the local traffic information will make the decision. Accordingly, each SU must sense the presence of the PU signal. At each specific period of time called sensing period, the spectrum sensing is recurrently done by every SU. The spectrum sensing block in [17] is responsible for the presence of PU signal. Hence, DCDS will depend on the available channels which sensed from the spectrum sensing block.

3.3. PU activity model

According to the nature of the cognitive network, the available channel will not be available in the entire SU communication period forever. Therefore, it is essential to determine the probability of OFF durations for PUs on the available channel. The existence or absence of PU's signal on each channel is modeled by different techniques such as, PU Activity based on markov renewal process modeling [18], PU modeling based on statistics [19], and PU modeling based on measured data [20]. Each of them, determine the time duration in which the channel utilized by SUs without make disturb to PUs. One of the most important modeling used for determining PU activity pattern in CRAN is a continuous-time, alternating ON/OFF Markov Renewal Process (MRP).

A significant feature of this ON/OFF PU activity model is that to accurately determine when PU is in OFF and ON state [21]. Fig. 2 describes the wireless channel model and the state transition from ON to OFF state with probability equals 1. The ON state illustrates that the channel is busy by the PU and hence SU cannot utilize it, whereas the OFF state illustrates that the channel is not busy by PU node and SU can utilize it. The binary sequence 1/0 matches to the ON and OFF state of the channel. Channel sensing is the sampling process of a given channel to realize its state through the number of transitions a channel follows (ON to OFF, OFF to ON, ON to ON, and OFF to OFF), as mentioned in [22]. The time period of ON and OFF states of channel i are denoted as $T^{\,i}_{ON}$ and $T^{\,i}_{OFF}$, respectively. Let's $z_i(t)$ denotes the renewal periods of channel i at time t, the renewal period of a channel occur when one sequential ON and OFF period is accomplished.

Both ON and OFF periods are assumed to be independent and identically distributed. Where each PU user arrival is independent, each transition follows the Poisson arrival process. In this work, the mathematical equations of (1, 2, 3, 4) has been used that the channels ON and OFF periods are both exponentially distributed with probability density function $f_x(t) = \lambda_x \times e^{-\lambda_x t}$ for ON state and $f_y(t) = \lambda_y \times e^{-\lambda_y t}$ for OFF state.

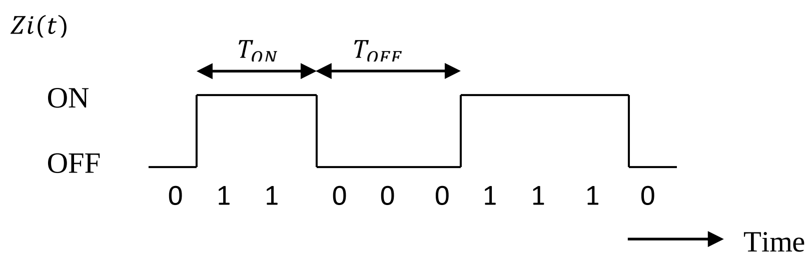

Fig. 2: MRP for PU activity model

The time period in which channel i is in ON state i.e. channel utilization U_i is estimated as (1):

$$U_i = \frac{E[T_{ON}^i]}{E[T_{ON}^i]+E[T_{OFF}^i]} = \frac{\lambda_y}{\lambda_x+\lambda_y} \tag{1}$$

Where $E\left[T_{ON}^i\right] = \frac{1}{\lambda_x}$ and $E\left[T_{OFF}^i\right] = \frac{1}{\lambda_y}$ where λ_x and λ_y are rate parameters for exponential distribution. $E\left[T_{ON}^i\right]$ and $E\left[T_{OFF}^i\right]$ is the mean of exponential distribution.

Assume $P_{ON}\ (t)$ be the probability of channel i in ON state at time t and $P_{OFF}\ (t)$ be the probability of channel i in OFF state at time t. The probabilities $P_{ON}\ (t)$ and $P_{OFF}\ (t)$ can be estimated as (2, 3, 4):

$$P_{ON}\ (t)\ = \frac{\lambda_y}{\lambda_x+\lambda_y} - \frac{\lambda_y}{\lambda_x+\lambda_y}\ e^{-(\lambda_x+\lambda_y)t} \tag{2}$$

$$P_{OFF}\ (t)\ = \frac{\lambda_x}{\lambda_x+\lambda_y} + \frac{\lambda_x}{\lambda_x+\lambda_y}\ e^{-(\lambda_x+\lambda_y)t} \tag{3}$$

Where,

$$P_{OFF}\ (t) + P_{ON}\ (t) = 1 \tag{4}$$

4. Proposed Channel decision Framework DCDS

The DCDS channel decision strategy is specially considered for CRAN. The general objective of DCDS is to improve the accuracy in select best channel over a CRAN, avoids SUs to enter in bad channel decision procedure (e.g., bad decision means, select a channel in wrong way which making disturb to PU). It must be notify that, DCDS is not a routing protocol. As a result, the routing tables and the end-to-end paths are not taking into account by the SUs. As illustrated in Fig. 1, in DCDS, the best weight of channel selected with regard to some goals needs to fulfill. **first**, each SU node sense the available channels, then, based on PU prediction model (Eq. 3), each SU calculates the probability of PU un-occupancy at specific time ($PU^{(i)}_{Un-occupancy}$) (see section 3.3). The higher the probability of PUs being in OFF state, the higher the weight is. **Second**, each SU estimates the number of SU exploited by every channel ($SU^{(i)}_{occupancy}$) by Eq. 5 (see section 4.1). **Three**, each SU independently arranges free channels based on the estimated PU un-occupancy, the number of SUs over available channels, and channel capacity ($CC^{(i)}$) (see section 4.2). The channel that has the higher PU un-occupancy and capacity, and lower number of SU neighbors, (e.g., higher weight value $w_p^{(i)}$) will be selected for transmission. The weight value for each channel is estimated by Eq. 7 (see section 4.3). **Finally**, the best channel is the one that high weight value. Note that, in both two cases, in case of the channel that has maximum weight value is busy, DCDS responds with (i) the packet is not transmitting using the elected channel, and (ii) select the next channel which exists in successfully matched. In case of all the channels are busy, no message is sent. In the following, we discuss in detail how channel capacity estimation and SU occupancy could be calculated.

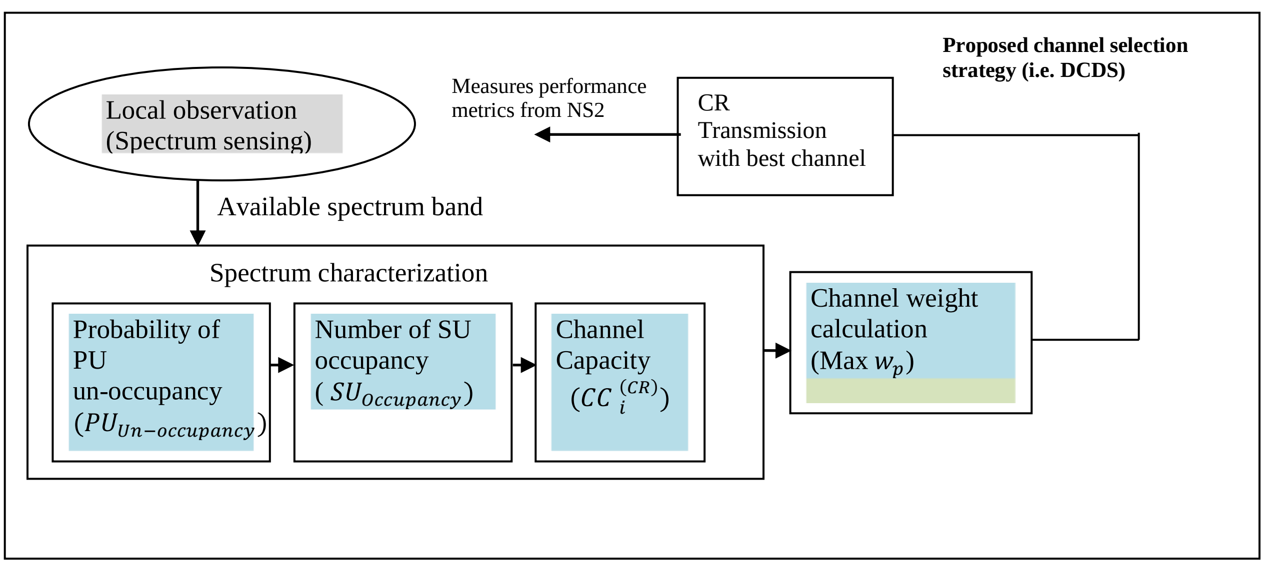

Fig. 1: DCDS Spectrum decision framework

4.1. Number of SU occupancy ($SU_{Occupancy}$)

The SU occupancy $SU^{(i)}_{occupancy}$ of channel (i) is estimated by:

$$SU^{(i)}_{occupancy} = SU^{(i)}_{t} \tag{5}$$

Where, $SU^{(i)}_{t}$ is the number of SU neighbors exploited by the channel(i).

4.2. Channel capacity estimation ($CC^{(CR)}_{i}$)

In an orthogonal frequency division multiplex (OFDM) system, each spectrum band *i* has a different bandwidth, consisting of multiple subcarriers. A normalized CR capacity $CC^{(CR)}_{i}$ model of spectrum band *i* for user *k* is proposed in [23] for spectrum characterization in CRNs. This $CC^{(CR)}_{i}$ model defines the expected normalized capacity of user *k* in spectrum band *i* as:

$$CC^{(CR)}_{i}(k) = E\left[CC_{i}\ (k)\right] = \frac{T^{off}_{i}}{T^{off}_{i}+\tau}.\gamma_i.c_i(k) \tag{6}$$

where $c_i(k)$ is the normalized channel capacity of spectrum band i in bits/sec/Hz, τ represents the spectrum switching delay, γ_i represents the spectrum sensing efficiency and T^{off}_{i} is the expected transmission time without switching in spectrum band *i*. Spectrum or channel switching delay is introduced within CRNs when SUs move from one spectrum band to another according to PU activity. The spectrum sensing efficiency can be determined by [24], whereas the spectrum switching delay can be estimated by [25].

4.3. Channel weight calculation ($w^{(i)}_{p}$)

DCDS framework arranges free bands through allocating a weight $w^{(i)}_{p}$ for each channel (i) in all available channels (ACH). Therefore, each CR node running DCDS, locally calculates the $w^{(i)}_{p}$ as depicted in Eq. 7:

$$\forall_i \in ACH: w^{(i)}_{p} = \frac{PU^{(i)}_{Un-occupancy} * CC^{(CR)}_{i}}{SU^{(i)}_{occupancy}} \tag{7}$$

$w^{(i)}_{p}$ Illustrates the weight of a channel (i) where channel weight exponentially increase with PU un-occupancy (i.e., $PU^{(i)}_{Un-occupancy}$) and channel capacity (i.e., $CC^{(CR)}_{i}$), and linearly decreases with the number of SUs (i.e. $SU^{(i)}_{occupancy}$) over channel (i). Next, the channel that have higher ($w^{(i)}_{p}$) will be elected.

The following example shows how the DCDS mechanism enables a SU to choose the best channel for transmission or overhearing As shown in Table 1, the node 5 has four available channels (1, 2, 3 and 5) at certain time. The probabilities of PU un-occupancy, number of SU exploited by every available channel, and channel capacity are determined. Then, the weight value is calculated by Eq. 7. The weight values will be 0.2, 0.66, 1.06 and 0.85 for channel numbers 1, 2, 3 and 5, respectively. It is clear that, node 5 chooses channel 3 for transmission because it has the maximum weight value. Note that, channel 5 will be backup channel for channel 3.

Table 1: The available channels' list at node 5

SU node	Available channel	PU_{OFF}	$SU_{Occupancy}$	$CC_i^{(CR)}$	**Weight value**
Node 5	1	0.2	2	2 MHz	0.2
	2	0.5	3	4 MHZ	0.66
	3	0.8	3	4 MHz	1.06
	5	0.85	2	2 MHz	0.85

Table 2: The channels' classification at node 5

As illustrated in Table. 1, although channel 5 has maximum PU_{OFF} but node 5 select channel 3 for transmission. The main reason for that, there is tradeoff between channel capacity and PU_{OFF}, the weight value handle this tradeoff by selecting the best channel which balance between channel capacity and PU_{OFF}.

5. Performance analysis

The proposed spectrum decision is mainly evaluated by the network simulator (NS2). On NS2 simulator, we developed the CR node and the required layers for network functionality. In what follows, a bottom up CRAN node architecture is described. Initially, the CR physical layer is responsible for sensing some information similar to all available spectrum bands, SINR/SNR, and propagation model. On the other hand, the CR MAC layer supports multiple channels and keeps track of PU traffic (e.g., PU activity model), collision, interference information. The CR network layer is responsible for maintaining the neighbor list. It also makes the channel selection decision on the basis of the information provided by the CR MAC layer to select best channels using DCDS strategy. Finally, the transmission is simulated and the following metrics are measured from NS2 to verify the efficiency of the proposed strategy compared to other strategies.

1) *Spectrum opportunity utilization*: It represents how much of the actual spectrum opportunities are utilized by the CRs. It is simply the ratio of CR total successful transmission time to the total PU idle time.

2) *Average interference ratio*: it is defined as the ratio of the total number of times the channel is occupied by PU node over total number of times the channel selection decision occurs.
3) *Average throughput*: it is the ratio of successfully received bits by each CR node over time needed to transport the bits.
4) *Packet delivery ratio:* It is the ratio of packets received by a particular CR node over total packets sent in the network.
5) *End-to-end delay*: it is the time for packet to reach the destination after leaving the source.

In the following, Section (5.1) explains the simulation assumption used in our simulation. Section (5.2) shows the performance comparison between DCDS with two related strategies.

5.1. Simulation assumptions

Before presenting the NS2 simulation results, we point out our basic assumptions in the following:

Cognitive Radio Cognitive Network (CRCN) patch [41] of NS2 is used. The CRCN patch has three building blocks that support cognitive radio functionalities in NS2.The rate parameters of exponential distribution (λ_x, λ_y) for PU activity model can be easily measured by CR nodes by collecting the historical samples of channel state transitions. These rate values can be measured from the sample of the number of transitions. The ON-OFF values of PU activity model are taken from [26, 27] as shown in Table 6. Note that, CRs use a CSMA/CA based medium access protocol. Contentions among CRs are resolved as done in CSMA protocols via carrier sensing and back-off mechanism. The CR MAC layer includes both medium access control and PU activity models

Table 6: Wireless channel parameters used in the simulation [26, 27]

	Ch 1	Ch 2	Ch 3	Ch 4	Ch 5	Ch 6	Ch 7	Ch 8	Ch 9	Ch 10
λ_x	1.25	0.4	1	0.4	0.5	2	1	0.18	0.5	0.67
λ_y	0.67	2	1	0.33	1	0.29	0.25	2	1.33	0.5
u^i	0.35	0.83	0.5	0.45	0.67	0.13	0.2	0.92	0.73	0.43

In each scenario, the location of nodes, source and destination pairs, and the availability channel pool of each node are randomly deployed within a square area of (700 x 700). The number of SUs is fixed to 150 and simulations run for 600 seconds. The transmission range of SU is 250 m and packet size is 512 byte. the number of available channels (ACHs) at each SU is 5 to 10. In simulation experiments, 600 packets were sent, where each packet is sent by a randomly selected node. With each packet a channel decision occurs, therefore, the number of times the channel decision occurs is 600. The total number of times the channel is occupied by PU node happens when channel selection strategy select best channel for transmission, however, the PU is existing on that selected channel.

5.3. DCDS comparison

A performance comparison for DCDS, best-fit channel selection (BFC) and longest idle time channel selection (LITC) has been evaluated with different parameters (x-axis) such as, number of SUs in the network, number of available channels at each SU node, and different PU nodes activity (e.g., Long term, high, low, and intermittent).

6. Conclusion

In this paper, we have proposed WDS, an intelligent and distributed channel selection strategy for reliable communication in multi-hop cognitive radio ad-hoc networks. The main two design objectives of WDS are firstly the protection of primary radio nodes against harmful interferences by CR transmissions, and secondly increase the reliability in cognitive radio ad-hoc network. These two goals were achieved by classifying the channels. The classification is done depending on the Primary User (PU) un-utilized time of the channel, on the number of neighbors Secondary User (SU) which can use the channels, and on the capacity of available channels. A Weight Based Decision Strategy for Dynamic Channel Selection in Cognitive Radio Ad hoc Networks is simulated using network simulator (NS2). We have compared our simulation result with the results of previous works in BFC & LITC. Moreover we have re-simulated the dynamic channel selection strategies using the three strategies considering the channel capacity performance parameter. Simulation results approved that our strategy is effective compared to others strategies on the basis of primary radio un-occupancy and the number of cognitive radio neighbors using each channel. Simulation results in NS-2 confirmed that WDS, when compared to random-based, BFC, and LITC, is effective in selecting the best channels.

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