Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 4 Issue 7, July - 2017

A Spectrum Decision Scheme for Cognitive Radio Ad hoc Networks

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***Abstract*— A Spectrum decision mechanism for Cognitive Radio Network (CRN) should have the ability to find the best free channels in the spectrum for Secondary Users (SUs), without causing serious interference to Primary Users (PUs). In such networks, the main objective is to reduce the interference while keeping the spectrum utilization as high as possible at the same time. In this work, we proposed an efficient scheme, named as Weight Decision Scheme (WDS), which aims to solve the above-mentioned issues. The proposed scheme is based on the primary user activity which helps to choose the best free channel for a SU, and reduces the average interference to PUs. The simulation results show that WDS improves network performance as it increases the channel utilization and decreases the interference. The achieved improvements in terms of channel utilization were 72.3%, 34.7% and 53.8% compared with RD, BFC and LITC schemes respectively. Whereas, the improvements in terms of interference were found to be 73.8%, 35.6% and 54.6% compared with the above-mentioned schemes respectively.**

Keywords—Radio network, interference ration, spectrum utilization, RD, BFC, LITC, WDS

I. INTRODUCTION

A Cognitive Radio Network (CRN) is an intelligent wireless network which uses Radio Frequency (RF) in its communications, and it is adjusted and configured dynamically. CRN has the ability to detect the free channels in the radio spectrum. In Cognitive Radio (CR) environment, there are two types of users: a licensed user called Primary User (PU) and an unlicensed user called Secondary User (SU) [1]. PUs have the right to use licensed spectrum band at any time. However, the SUs may use free channels in the same spectrum, provided that these users do not cause interference to PUs, which necessitate an efficient management of the spectrum.

In the literature, many solutions for spectrum selection have been proposed which can be classified into two main categories. The first category is nonpredictive models which work with regardless of the gathered information about PU activities, and the second is predictive models as explained in the next section.

To the best of our knowledge, and based on review of the literature, most (if not all) of the proposed schemes did not effectively handle the interference ratio. In this work, we concentrated on prediction solutions to study the PU activity which helps to choose the best available channel for the SU, and reduces the average of interference to PUs. Our approach aims to improve the network performance that suffers from the high average of interference.

The remaining of this paper is organizations as follows: In section 2, an overview of Cognitive Networks (CNs) classification and review of selection solutions for Cognitive Radio Ad hoc Networks (CRAN) are presented. In section 3 we presented our proposed Weight Decision Scheme (WDS). Section 4 shows in details the performance analysis of the proposed scheme and illustrates the comparisons between the proposed scheme and other selection schemes proposed in the literature. Finally, section 5, presents conclusions and summary of the results.

II. LITERATURE REVIEW

Cognitive radio networks can be classified into two types according to the used network typology. The first type, infrastructure Cognitive Radio Network (CRN) in which efficient solutions of the spectrum can be easily achieved. However, the second popular type, which is the focus of our research, the Ad hoc Cognitive Radio Networks (CRAN) requires more concentration on providing solutions for spectrum selection. The spectrum selections can be classified into two broad categories. The first category is the nonpredictive type, and the second category is based on prediction models or primary user's activity models which are named as predictive solutions [2, 3, 4, 5, 6].

2.1 *Nonpredictive model solutions*

Nonpredictive model solutions is based on the following three methods:

a) Random selection methods [7, 8].

b) Optimization methods [9, 10].

c) Learning methods [11, 12].

In random selection methods, the selection of channels is done randomly. Regardless of the gathered data about PU activities. The selection of channels only depends on results of sensing the spectrum, and hence the channels are classified as available or unavailable. In [7] the authors introduced a scheme which senses the channels randomly and stops when there is an idle one. By implementing this simple strategy, the authors avoided the necessity of saving information like access and sensing history. According to this strategy, a lack of the PU traffics increases the interference probability. In [8] the authors improved random selection by using the mechanism of Round-robin scheduling. For that reason, a random channel is selected as a current candidate by the CR for transmission. If the channel is not idle, adjacent frequency is adjusted to detect another idle one. However, the probability of interference between PUs and CRs remains high due to the lack of accounting on PU traffics which eventually results in weakness of the spectral opportunities and increment of the mean throughput.

On the other hand, the authors of [9, 10] convert the channel selection problems into optimization problems in order to optimize many performances. The optimized problems take the form of minimizing handoff of the spectrum without using any prediction model to estimate the channel probability at time t in the OFF-state.

For selection solutions that are based on learning techniques, the author of [11] used learning automata (LA), which is one of the learning methods that are used to train SU nodes and estimate the probability of optimal channel selection. A learning automata (LA) approach has been proposed to decide about the probabilities of channels selection in CRNs which leads to the avoidance of additional channel switching. LA is an easy method of a decision maker technique and it is done in the random environment. However, their solution did not improve the system performance as expected since they did not consider the interference rate and throughput between PUs and CRs and also they neglected the impact of sensing error.

On the other hand, authors of [12] have suggested that distributed Q-learning depends on a joint power control spectrum and a channel selection that is done through optimization of energy efficiency. The Q-learning perceives the transmitted power and the selected channel as outputs. The SUs simultaneously obtain the communication channel and the optimally transmitted power to guarantee the spectrum and energy efficiency. The same authors, suggested an efficient solution to select the best channel based on Q-learning with optimal power and succeeded to demonstrate to which extent their method improves the network performance based on energy efficiency, average throughput, successful transmission probability, and channel switching time. However, the degree of interference between PUs and CRs has been of less importance to the authors of [11, 12].

2.2 *Prediction model solutions*

The prediction model solutions, highlights the importance of PU activities. The PU determines the duration and the distribution of the spectrum opportunities. However, the critical issue that we detected in [13] is the establishment of a suitable modeling to the PU traffic in order to design schemes for the channel selection. Adjustment of the channel selection scheme and prediction of the PU traffic improve the scheme selection and the spectrum's effective search [14]. In addition to this, the dynamic range of spectrum algorithm should cover information about the PU traffic pattern occupying the channel. The traffic pattern functions according to two models: the deterministic model and the stochastic model. In the first model (deterministic), the PU takes an ON-state during the transmission, and an OFF-state in terms of time slots. On the other hand, in the second model, the traffic is described in statistical terms (e.g., broadband cellular networks) [15].

All the data collected from [13, 14] demonstrate that many solutions (e.g. PU activities modeling) apply to predictive channel selection. A study by [16] proposed an extended idle time channel selection scheme to distribute channel selection in CRNs. Since every CR node aims to achieve the highest idle time in the network, the Longest Idle Time Channel (LITC) selection becomes a target to other nodes. After the achievement of the LITC, another idle time becomes a waste resource that other channels can benefit from.

Based on the previous review of literature we could find in the field, we decided to orient our perception to focus on prediction solutions and on the interference between the PU and CR. We aim to identify the LITC and best fit channel selection, depends on predictive model. In addition, studying the PU activity helps to choose the best free channel for the SU; and reduces the average interference between CRs and PUs. Our approach aims to improve the network performance that suffers from the high average of interference rate.

III. THE PROPOSED WDS SCHEME

The proposed Weight Decision Scheme (WDS) consist of two main stages as shown in Figure 1, the channel weight computation stage, and the quality of service (QoS) parameters optimization stage.

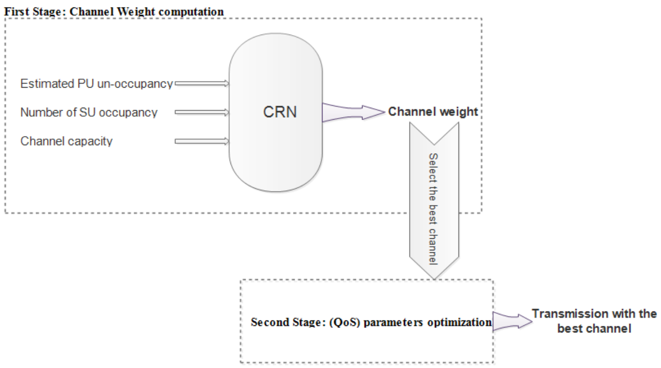

Figure 1. Basic block diagram of the proposed WDS.

3.1 *Channel weight computation*

The best weight of the channels selected in the proposed strategy needs to fulfill some goals as mentioned in stage one. The first goal is the estimation of the PU un-occupancy ($PU^{(i)}$ Un-occupancy) where each SU node senses the free channels and depends on a PU prediction model at specific time. The channel weight in this context is increased when the PUs are in OFF-state. The second goal is the calculation of the SUs' number that has been exploited by every channel ($SU^{(i)}$ occupancy). The last goal is the measurement of channel capacity that is estimated by every SU in every channel ($CC^{(i)}$). The ultimate goal at this stage is the allocation of a channel weight through estimating the PU un-occupancy, calculating the number of SUs who look for free channels, and measuring channel capacity. Determining the transmission method to achieve the previous goals depends on a channel that has a high PU un-occupancy, a low number of SU neighbors, and a high channel capacity.

The goals that were previously mentioned demonstrate the first stage of channel weight. A second stage is suggested to assess the Quality of Service (QOS) of the highest selected channel weight as shown in Figure 1. The details of all are given below.

a) Estimating the PU un-occupancy

Due to the technical nature of Cognitive Network, the SU communication period will not always be free. This nature makes it crucial to determine the probability of OFF-state durations for the PUs on a free channel. Based on Markov Renewal Process (MRP) modeling [11], the existence or absence of PU's signal on every channel is modeled by different techniques such as the PU Activity. PU modeling is based on measured data [13] and statistics [8], which function to determine the duration of time in which the channel is utilized by the SUs without disruption by the PUs. The PU activity pattern in CRAN is fundamentally determined by a continuous-time process instead of the ON/OFF MRP [16 -18].

The main feature of the ON/OFF PU activity model is to accurately determine when the PU is in OFF- or ON-state.

When the time period in which the channel (i) is in ON-state, the channel utilization U_i is estimated as shown in equation (1) [15]:

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

The previous equation can be simplified as:

$E\left[T_{ON}^i\right] = \frac{1}{\lambda_x}$ and $E\left[T_{OFF}^i\right] = \frac{1}{\lambda_y}$ and λ_x and λ_y .

b) Number of SU occupancy

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

$$SU^{(i)}occupancy=SU_t^{(i)} \qquad (2)$$

c) Channel capacity for each channel (CC_i)

It is possible to determine the capacity of a channel by estimating the channel parameters such as: error rate, channel interference level, path loss, and delay average. This estimation allows the derivation of channel capacity from channel parameters.

In Orthogonal Frequency Divisions Multiplex (OFDM), the different bandwidth Bi for each spectrum band i consists of multiple subcarriers. Additionally, the normalized CR capacity C_i^{CR} (k) model of spectrum band i for user k is proposed in [19] for spectrum characterization in CRN.

The C_i^{CR} model also defines the expected normalized capacity of the user k in a spectrum band i as:

$$C_i^{CR}(k) = \mathrm{E}[C_i(k)] = \frac{T_i^{off}}{T_i^{off}+\tau} . \gamma_i . c_i(k) \qquad (3)$$

The below are the descriptions of the equation (3) characters:

$C_i(k)$ represents the spectrum capacity

$c_i(k)$ represents the normalized channel capacity of a spectrum band i *(with small c)*

γ_i represents the spectrum sensing efficiency

τ represents the spectrum switching delay

T_i^{off} represents the expected transmission time without switching in the spectrum band *i*.

To oversimplify the previous equation (3), the channel or spectrum switching delay occurs within the CRN whenever the SUs move from one spectrum band to another according to the PU activity. Also, the spectrum sensing efficiency is conditioned by the fact that the RF front-ends cannot perform the sensing and the transmission at the same time which eventually results in the decrease of their transmission opportunities. Meanwhile, the sensing efficiency is influenced by the observation time and transmission time when the spectrum sensing is in the process of detecting the spectrum holes [20].

d) Channel weight calculation ($w_p^{(i)}$)

The proposed channel selection scheme arranges free bands through allocating weight $w_p^{(i)}$ to each channel (i) in all the Free Channels (FCH). Therefore, every CR node locally calculates the $w_p^{(i)}$ as depicted in equation 4:

$$w_p^{(i)} = \frac{PU^{(i)}_{Un-occupancy*CC_i^{CR}}}{SU^{(i)}_{occupancy}} \forall_i \in FCh \qquad (4)$$

$w_p^{(i)}$ illustrates the weight of the channel (i) when the it exponentially increases with PU un-occupancy (i.e., $PU^{(i)}$ *Un-occupancy* , CC_i^{CR}) and linearly decreases with the number of SUs (i.e. $SU^{(i)}$ occupancy) over the channel (i) . After the mentioned process, the channel with higher($w_p^{(i)}$) will be elected for transmission.

3.2 *QoS parameters optimization*

The spectrum decision process cannot promise a frequency band to the CR that is equipped with all the Quality of Service (QoS) requirements due to the probability of interference with PUs. The premise of our research is to study the ways that lead to reaching better QoS parameters for the cognitive nodes with minimum interference. The latter is considered as a multi-objective problem since the QoS optimizer is formulated in a multi-objective form that is based on a genetic algorithm (GA) which obtains the required optimal QoS parameters and achieves desired goals of CRN applications. The mentioned optimizer has a distributed nature, therefore, the spectrum decision's performance has been assumed through non-infrastructure solutions. In addition, we perceive that the CRs sense the surrounding environment characteristics. The previous assumptions have been used to determine the examination tools we used in our strategy that are: MATLAB and NS2 tool. Those tools are respectively selected for optimization and assimilation purposes where multiple objectives (fitness functions) are introduced to guide the proposed strategy to an optimal state.

We also used mathematical formulation to fitness functions in order to represent the nature of relationships among QoS parameters.

a) Prediction model solutions

In developing a QoS optimizer for CRN, several inputs must be taken into consideration because of the accuracy of decisions that should be determined through the quality and the quantity of inputs provided for the system. Another primary feature of CRs is the adaptability characteristic it has in relation to the surrounding environment. After the input provision, the system opts for making decisions about a certain output whose variables must be modeled internally in a wireless environment.

These variables are then directly used by the fitness function as primary parameters. An example of that type of parameter is the noise power of channel that is used in minimizing BER objective function. The same parameters directly impact the fitness score of a specific objective. Figure 2 gives a visual representation about the way the CRN parameters interact and function.

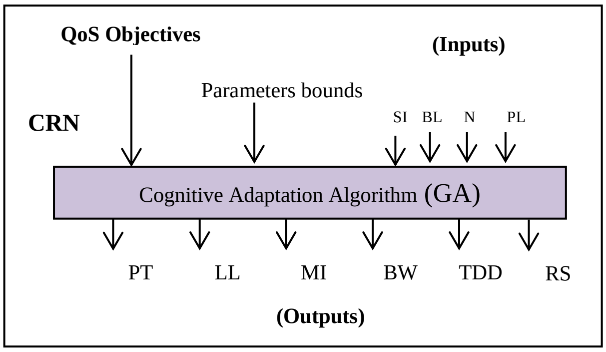

Figure 2: Visual representation of CRN Parameters

A list of environmental parameters with their labels and ranges of value are used in this work as input for fitness function as shown in Table 1. Most of the used parameter values were selected to be similar to the Kansas University Agile Radio (KUAR) hardware platform and systems [21]. In this context, the range of spectrum information and spatial knowledge cannot be specified because of the discrete nature of the values and is to be verified through the implementation of a real network using NS2.

Table 1. Environmental parameter values

Parameter	**Min value**	**Max value**
Noise Power (NP)	-114 dBm	-104 dBm
Path Loss (PL)	85 dBm	95 dBm
Battery Life (BL)	0%	100%
Spectrum Information (SI)	N/A	N/A
Spatial Knowledge (SK)	N/A	N/A

b) Formulation of fitness functins for CRN parameter

To accomplish the system goals, other five fitness functions (shown in: Table. 2) have been formulated in order to achieve an optimal state guidance of the system. The fitness functions we mention here are the ones discussed in [22]. To the best of our knowledge, there is no available research that contains all the five objectives in one system model. As a consequence, we formulate the underlying objective functions in details.

Table 2. CR Objectives

Objective name	**Description**
Minimizing power Consumption (fobj, minPT)	To Decrease power consumed by system.
Minimizing BER (fobj, minBER)	To Improve overall BER of transmission environment.
Maximizing throughput (fobj, maxTHROU)	To increase throughput transmitted by radio.
Minimizing interference (fobj, minINFR)	To reduce radio's interference contributions.
Maximizing spectral efficiency (fobj, maxSE)	To maximize efficient use of frequency spectrum.

3.3 *The WDS working-steps*

1. Start spectrum sensing technique in order to detect all the free channels in the surrounding environment.
2. Results are sent to upper layer (i.e. MAC layer) by using the spectrum sensing technique.
3. PU activity model has a MAC layer that calculates the probability of ON- and OFF-state for all idle channels.
4. The probability of ON- and OFF-state values are sent to a channel selection strategy.
5. The number of secondary users on every idle channel and channel capacity is computed through a channel selection strategy.
6. The channel selection calculates the weight function through relying on the probability of OFF-state channel capacity and the number of secondary users.
7. The algorithm arranges all channels based on weight value.
8. The algorithm selects the maximum weight value as the best one.
9. Other channels are used as a backup for the best free channel.
10. Other than channel selection, Qos optimizer runs to optimize transmission parameters.
11. The algorithm sends a packet.
12. The algorithm computes metrics, interference and spectrum utilization.

IV. PERFORMANCE EVALUATION

We adopted the cooperative routing protocol for the underlying simulation as provided in [4]. The concept is that it is used to discover an end-to-end robust path between the sender and receiver. The same protocol relies on sensing the proposed scheme as a non-routing protocol. Consequently, the end-to-end paths and the routing tables are not taken into account by the SUs.

4.1 *Simulation environment*

PUs and CRs use a Carrier Sense Multiple Access (CSMA) /Collision Avoidance (CA) based on MAC protocol in our research context. Disputations occur between CRs in CSMA protocols via carrier sensing and a back-off algorithm.

Each SU has a single radio transceiver that can be adjusted to numerous frequencies licensed to the primary network. Due to the single radio constraint, sensing and transmission are done consecutively. The average idle and busy rates (λ_i, λ_b) for PU activity are exponentially distributed. The ON-OFF values of the PU activity model are taken from [23]. The simulation input parameters used in our simulation are represented in Table 3.

In each scenario, the initial position of all nodes (including the sender and the receiver pairs), and the availability of a channel pool of each node are randomly organized inside a square area of (700 x 700). The number of CRs is fixed to 150 and the simulations' run for 600 seconds. The transmission range of CR is 250 m and packet size is 512 byte. The number of Available Channels (ACHs) for each SU is 10.

Table 3. Simulation parameters

Parameter	Value
Transmission media	WirelessChannel
Propagation model	Two-ray ground model
Network interface	WirelessPhy
Number of interfaces	Single transceiver
MAC	802.11
Antenna	OmniAntenna
Interface queue type	DropTail/Priqueue
Routing protocol	On-demand protocol [4]
Packet size	512 bytes
Transmission range	250 meters
Number of CR users	10, 25, 50, 100, 150
Simulation time	2 hours
Number of runs	10
Sensing time interval	1 sec
Simulation area	700×700 m^2

4.2 *Simulation resutls*

A performance comparison for WDS, Best-Fit Channel selection (BFC) and Longest Idle Time Channel selection (LITC) has been evaluated with a different number of SUs in the network.

a) Effect of number of SUs on channel decision

In this set of simulations, we study the ways that the proposed approach and related strategies react to the raising SU traffic demand in terms of the above-mentioned metrics. The number of free channels for each SU is set to 10 with rate parameters(λ_x, λ_y). The SUs number in the network starts from 10 to 150.

Figure 3 shows the results of different simulation experiments that are used to evaluate the average of interference ratio at diverse numbers of SUs nodes for the RD, BFC, LITC, and the proposed scheme.

The minimum improvement in average interference ratio for WDS occurred at 10 SU nodes at which the ratio is decreased by around 12% which can be compared to BFC, while the maximum average interference ratio occurred at 150 SU nodes at which the ratio is decreased by 68% compared with RD. On the average, we can realize that the WDS always outperforms RD, BFC, and LITC in relation to minimizing average interference ratio at different numbers of SU nodes by 55.2%, 23% and 31% which are compared to RD, BFC, and LITC respectively.

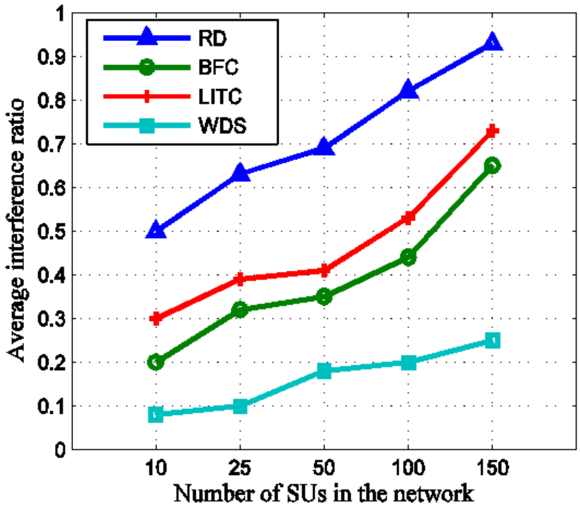

Figure 3. Average interference ratio in various SUs

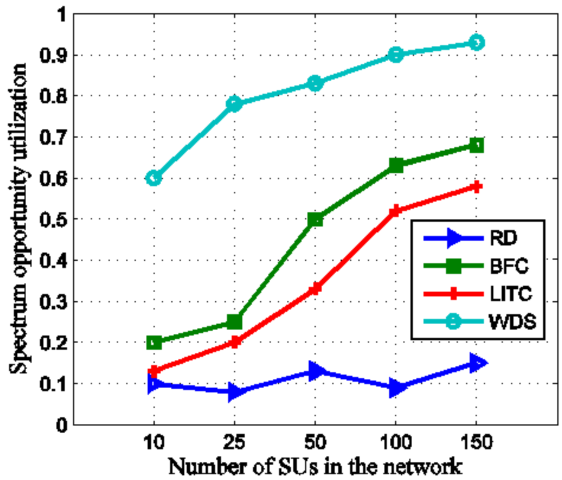

Figure 4. Spectrum opportunity utilization in various SUs

Another result demonstration is illustrated in Figure 4. Those results show the different simulation experiments that measure the spectrum opportunity utilization at different numbers of SUs nodes for the RD, BFC, LITC and the proposed scheme. The minimum improvement in spectrum opportunity utilization for WDS occurs at 10 SU nodes at which the ratio is increased by around 25% compared with BFC, while the maximum improvement in spectrum opportunity utilization happens at 150 SU nodes at which the ratio is increased by 89% compared with RD. Averagely, we realize that the WDS also outperforms RD, BFC and LITC as related to maximizing spectrum opportunity utilization at different network density by

73.8%, 35.6% and 54.6% as compared to RD, BFC and LITC respectively

b) Effect of number of free channel on channel decision

In another set of simulations, we examine the ways a number of ACHs affects the performance of each scheme in terms of the mentioned metrics in Section 4.2. The number of SUs in the network is set to 100 nodes and the number of free channels for each SU starts from 3 to 15.

Figure 5. Demonstrates the results of different simulation experiments that measure average interference ratio at different numbers of free channels for RD, BFC, LITC, and the WDS. On average, we can realize that the WDS minimizes the interference ratio by 59%, 11%, and 16.3% compared to RD, BFC and LITC respectively.

From Figure 6, we can conclude that, the WDS always outperforms RD, BFC and LITC related to maximizing spectrum utilization at different network densities by 67.6%, 18.4% and 22.3% compared to RD, BFC and LITC respectively. This is mainly because the WDS concentrates on selecting the channel in a method that guarantees the unexploited channel by the PU through weight function. For that reason, the interference ratio decreases which leads to higher spectrum utilization.

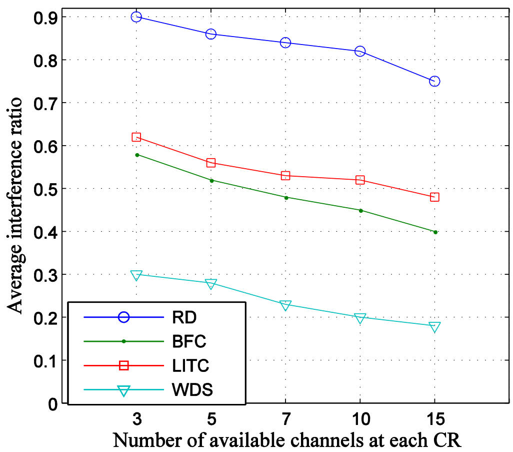

Figure 5. Average interference ratio under different numbers of free channels

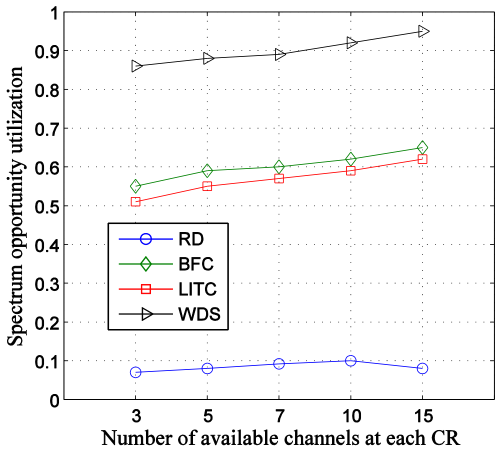

Figure 6. Spectrum opportunity utilization under different number of free channels

V. CONCLUSION

This paper presents the Weight Decision Selection (WDS) as an efficient channel selection scheme for cognitive radio ad hoc networks. The main aims of the proposed scheme is minimizing the interference between PUs and CRs through selecting the best channel by a weight formula.

There are many parameters that should be taken into account while designing any channel selection strategy. These parameters include idle duration for PU connection, channel capacity, and a number of CRs in each channel. Works like [24, 25] take the idle duration into account in connecting PUs while selecting the best channel and neglecting other parameters. Therefore, we were able to design a new channel selection strategy, known as WDS, which includes all the above-mentioned parameters in selecting the best channel that guarantees less interference for the PU and selects the best channel that provides a QoS for CRs.

The main design goals of the proposed scheme (WDS) are:

- Improving the accuracy of the channel selection in ad hoc CRNs is relative to the existing selection strategies.
- Protecting the primary radio nodes against any harmful interference.
- Maximizing the spectrum utilization and packet delivery ratio.
- Minimizing the average delay in CRNs.

Simulation results using NS2 have confirmed that WDS has better performance relative to RD, BFC, and LITC strategies under different network densities and number of free channels. The proposed WDS scheme improves (i.e., maximizes) the channel utilization by 70.7%, 27% and 38.45% compared to RD, BFC and LITC respectively and minimizes the interference ratio by 57.1%, 17% and 23.65% compared to RD, BFC and LITC respectively. In addition to that, WDS also outperforms other strategies for packet delivery ratio, average throughput, and end-to-end delay.

In time complexity analysis of WDS, the corresponding time cost of weight formula that selects the best channel and since the WDS algorithm depends on three main parts: represents the idle duration, channel capacity and the number of channels. Therefore, the simplicity of our scheme can be applied in different applications such as: cognitive radio wireless sensor networks, cognitive radio networks, and Mobile networks.

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