A Spectrum Decision Scheme for Cognitive Radio Ad Hoc Networks

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ABSTRACT

A Spectrum decision for Cognitive Radio Network (CRN) is able to detect the best of the free channels in the spectrum for Secondary Users (SUs), without causing interference to Primary Users (PUs). The most important issues to be efficiently handled in such networks are the high level of harmful interference to primary users, and the need to find a way to achieve an efficient utilization of available spectrum at the same time. In this work, we propose 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. It helps to choose the best free channel for a SU, and reduces the average interference to PUs. 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 Random selection (RD), Best-Fit Channel selection (BFC) and Longest Idle Time Channel selection (LITC) schemes respectively. 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: Cognitive radio network, interference ration, spectrum utilization, RD, BFC, LITC, WDS

ÖZ

Birleşim birincil kullanıcılara (PUs) etki etmeden, ikincil kullanıcılar (SUs) için spektrum içindeki en iyi serbest kanalları tespit edebilmek için alınan spektrum karar Kavramsal Radyo Ağı (CRN) içindir. Bu gibi ağlarda verimli bir şekilde elde tutulması gereken en önemli konular şunlardır; birincil kullanıcılara olan zararlı birleşimlerin yüksek seviyesi ve aynı anda mevcut olan spektrumların oranının verimliliğini başarabilmenin yolunu bulma ihtiyacı olmasıdır. Bu çalışmada, yukarıda bahsedilen konuları çözmeyi hedefleyen verimli bir tasarım önerilmiş, Ağırlık Karar Tasarımı (WDS) olarak adlandırılmıştır. Önerilen tasarım birincil kullanıcı aktivitesine dayalıdır. Bu tasarım, SU için en iyi serbest kanalı seçmeye yardım eder ve PU'lara olan girişim ortalamasını azaltır. WDS, kanal oranını arttırdıkça ve birleşimi azalttıkça ağ performansını geliştirmektedir. Kanal oranı açısından başarılan gelişmeler (%72.3, %34.7 ve %53.8) sırasıyla rastgele seçim (RD), en uygun kanal seçimi (BFC) ve en uzun boşta kalan kanal seçimi (LITC) tasarımları ile karşılaştırılmıştır. Birleşim açısından başarılan gelişmeler %73.8, %35.6 ve %54.6 olarak bulundu ve sırasıyla yukarıda belirtilen tasarımlar ile karşılaştırılmıştır.

Anahtar Kelimeler: Kavramsal radyo ağı, birleşim oranı, spektrum oranı, RD, BFC, LITC, WDS.

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LIST OF SYMBOLS/ABBREVIATIONS

BFC	Best-Fit Channel Selection
CCC	Common Control Channel
CR	Cognitive Radio
CRAN	Cognitive Radio Ad hoc Network
CRN	Cognitive Radio Network
CRSN	Cognitive Radio Sensor Networks
CRU	Cognitive Radio Unit
CSS-MCRA	Channel Selection Scheme-Minimal Collision Rate Algorithm
CSS-MHRA	Channel Selection Scheme-Minimal Handoff Rate Algorithm
DSA	Dynamic Spectrum Access
FC	Frequency Channel
FCHs	Free Channels
KUAR	Kansas University Agile Radio
LA	Learning Automata
LITC	Longest Idle Time Channel Selection
LTI	Local Traffic Information
MRP	Markov Renewal Process
NLP	Non-Linear Programming
POHS	POMDP-based Handoff (Spectrum)
PU	Primary User
QoS	Quality of service
RD	Random scheme
SU	Secondary User

WDS	Weight Decision Scheme

Chapter 1

INTRODUCTION

1.1 Overview

A Cognitive Radio Network (CRN) is described as a smart network which uses Radio Frequency (RF) in its communications and is adjusted and configured dynamically. And it has the ability to detect the available channels in the radio spectrum. Correspondingly the transceiver parameters change to have more synchronous communications in a spectrum band simultaneously. Cognitive Radio (CR) technology plays an important role for achieving spectrum utilization efficiency. In CR environment, there is a Primary User (PU) (licensed) and Secondary User (SU) (unlicensed) [1]. PUs have the right to use licensed spectrum band at any time. However, the SUs may use available channels in the same spectrum, provided that they would not cause interference to PUs, which necessitate an efficient management of the spectrum.

In the literature, more concentration is done on providing solutions for spectrum selection, which can distributed into two main categories. The first one is predictive model and the second is a nonpredictive model that works with regardless of the gathered information about PU activities. The predictive model solutions, highlights the importance of PU activities and predicts the PU traffic by using varied prediction models for different traffic patterns. With regard to nonpredictive model solutions, some of the suggested schemes can be categorized as follows:

1. Random selection methods: the selection of available channels is done randomly.

2. Optimization methods: these methods change the available channel selection problemto optimization problems

3. Learning methods: the selection solutions are based on learning techniques.

But up to our knowledge, and based on review of the literature, none of them effectively handled the interference between the PUs and CRs.

1.2 Thesis Contribution

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.

1.3 Thesis Outline

The remaining of thesis is organizations as follow: In Chapter 2, an overview of Cognitive Networks (CNs) classification and review of selection solutions for Cognitive Radio Ad hoc Networks (CRANs) are presented. In Chapter 3 we presented our proposed Weight Decision Scheme (WDS). Chapter 4 shows in details the performance of the proposed scheme and illustrates the comparisons between the proposed scheme and other selection schemes proposed in the literature. Finally, Chapter 5, presents the conclusions, recommendations and suggestions for future work.

Chapter 2

THEORETICAL REVIEW

2.1 Literature Review

The network typology is classified as non-infrastructure (ad hoc) and infrastructure networks [1]. The network topology, accordingly, classifies cognitive networks into two types which are: infrastructure and non-infrastructure. The first type, infrastructure Cognitive Radio Networks (CRNs), proved efficient solutions as outcomes. However, the second type which is the focus of our research, the Cognitive Radio Ad hoc (non-infrastructure) Networks (CRANs) demonstrates more concentration on providing solutions for spectrum selection. The spectrum selections may be classified into two broad categories. The first one is based on prediction models or primary users activity models which are named as predictive solutions . The second category is the nonpredictive type.

2.2 Nonpredictive Model Solutions

Nonpredictive model solutions is based on the following three methods:

1) Random selection methods [2,3].

2) Optimization methods [4, 5].

3) Learning methods [6, 7].

The classifications of spectrum selection solutions are obvious in Figure 2.1

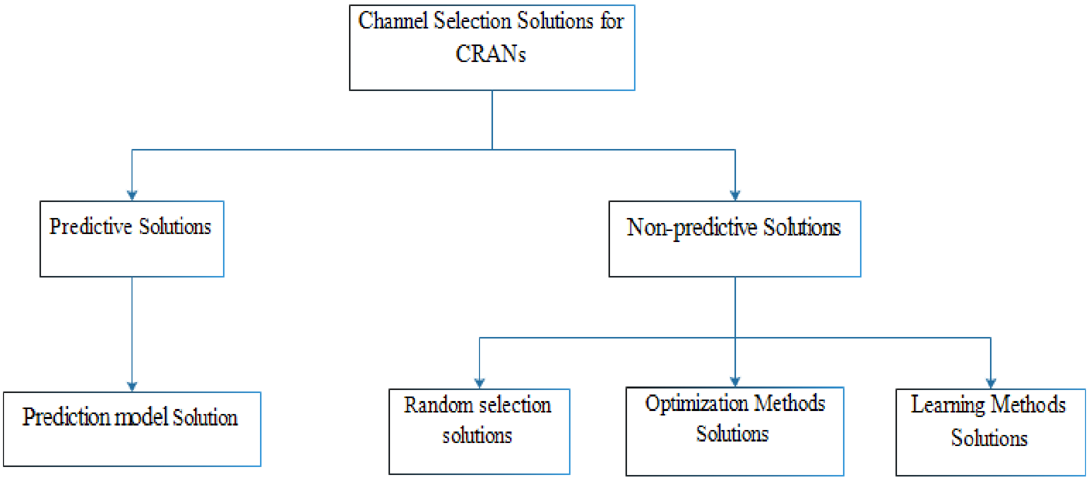


Figure 2.1: The Classification of selection solutions for CRANs

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 they are classified as available or unavailable. In [2] 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 [3] 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 Cognitive Radio CR for transmission. If the channel is active, 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 [4,5] convert the channel selection problems into optimization problems in order to optimize many performances. The optimized problems take the form of, for instance, minimizing handoff of the spectrum without using any prediction model to estimate the channel probability at time *t* in OFF-state.

In [4] the authors in their research adopted a Partially Observable Markov Decision Process (POMDP) to locate the optimal target channel for the handoff in the spectrum by obtaining the only necessary explicit state information for the channel. The POMDP is used to partially sense the frequency in available channels to discover the network information. A POMDP-based Handoff of the Spectrum (POHS) is a technique that functions as a strategy for post-sensing. The guidelines to be followed in order to reach an optimal channel may include an ability to achieve lower waiting time for each spectrum handoff occurrence and a transition probability derived from applying M/G/1 model on a channel state that offer service rate and packet arrival rate. The POSH algorithm becomes achievable at minimal waiting time if the mentioned guidelines are properly applied on the target channel selection at every spectrum handoff occurrence.

The authors of [5] proposed a selection scheme and optimized this scheme to discover the channels and minimize the delay; in other words, when the PU takes an OFF-state, less waiting time is used to find a new available spectrum that has been occupied during the OFF-state. The history of the PU which helps in determining the availability of spectrum relies on two steps: a signal detection step and a database step. The latter, database step, gathers information channels in the database when the SU node requires channel for transmission. This requirement to check in the database goes through sending inquiry and selecting the probable unoccupied channels and submitting the best channel as candidate. Then the CR selects the appropriate channel according to the priority it has due to the history of signal detection. The authors in [5] used optimization solutions and proposed a centralized solution to solve DSA. The focus of their research highlights the reexamination of discussions done in the field about the Dynamic Spectrum Access (DSA) problem which they viewed as Non-Linear Programming problem (NLP) and which they preserved its objective values of optimal functions.

The previous studies [4, 5] discussed an optimized solution to reduce the handoff of the spectrum. Similarly, authors of [5] introduced optimization solutions; however, they focused on solving DSA by considering the problem as NLP problem. The shared ground between all the authors [4, 5] lies in the neglect they demonstrated to the ways interference between CRs and PUs occurs and the opportunities it has to maximize throughput by achieving high spectral.

However, for selection solutions that are based on learning techniques, the author of [6] 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 a channel selection has in finding the traffic pattern’s uncertainty in CRAN which leads to avoidance of additional channel switching. In all automata methods, as shown in Figure 2.2, the automata connects with the environment in a series of time steps. At every moment (t), the automaton deals with the action $\alpha(t)$ as an input based on action probability for the environment. The environment from its side responses to the information that comes in the form of input and produces a reinforcement $\beta(t)$ which functions as an Automaton input that updates action probability for the next step.

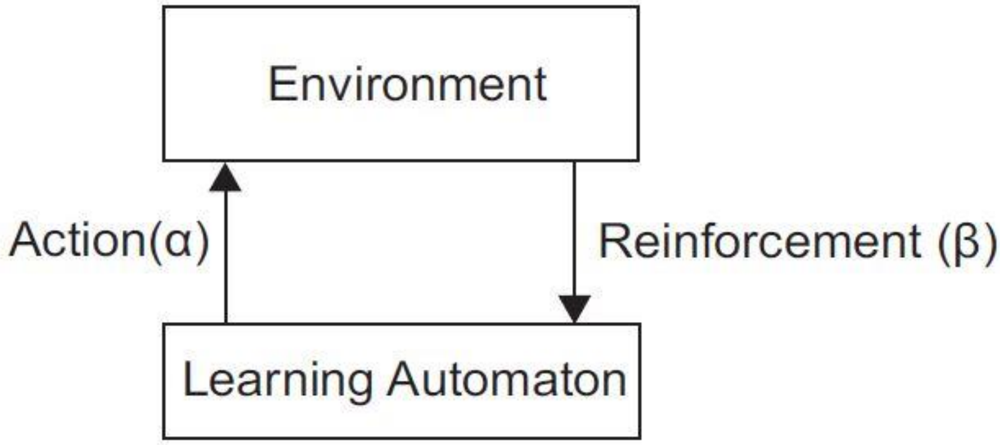


Figure 2.2: Learning automaton diagram

The SUs estimate the probability of optimal channel selection by a large number of examinations. The authors of [6] suggested a solution to select optimal channels and avoid the cost of channel switching; however, this solution does not offer to what extent it improves the system performance since they did not consider the interference rate and throughput between PUs and CRs and neglected the impact of sensing error.

On the other hand, authors of [7] 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 analysis of energy efficiency and the network channel characterization as the input provides the channel state. The SUs simultaneously obtain the communication channel and the optimally transmitted power to guarantee the spectrum and energy efficiency. The same authors, hence, 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 [6, 7].

2.3 Prediction Model Solutions

The last sub-classification in our diagram (Figure 2.1), 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 [8] 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 [9]. In addition to this, the dynamic range of spectrum algorithm necessitates covering the data around 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 time slot (e.g., the TV broadcasting model). On the other hand, in the second model, the illustration of traffic is done through statistical terms (e.g., broadband cellular networks) [10].

All that data collected from [8, 9] demonstrate that many solutions (e.g. PU activities modeling) apply to predictive channel selection.

In the same sub-classification (predictive solutions), the prediction model is used to study and predict the PU traffic (e.g., the probability of an OFF-state channel at time t), and to determine the ON-state and OFF-state probability for all channels using statistics equations.

The authors in [11] suggested an exponential mobile average method to broadcast TV channels using idle time. The method helps CRs to choose the channel with maximum idle time and therefore, it leads to have the highest spectrum utilization and the lowest minimized interference. The same study [11] considered a single-hop network to determine which CR node uses the PU activity to gather the data that is sent to the TV receiver. However, this approach, in this sense, restricts the problem to predicting a traffic model without determining a pattern.

The authors in [12], on the other hand, suggested a more general model that deals with traffic classes' variety. They ignored the role of dependent traffic patterns and only considered the primary network that consists of multiple channels. Their approach depends on collected information about the spectrum usage (determining spectrum through sensing) and the stored data in the database. Once the information of spectrum is stored, every channel traffic pattern positions itself as either deterministic or stochastic; the positioning occurs when specific prediction methods are used to estimate the predict idle times in the channels. However, the interference rate, spectrum utilization, and throughput in this method does not take into account. The same authors in [12], however, tried to further extend the predictive method classification through several traffic models and analyzed the changes in the throughput by measuring the impact of spectrum sensing and time switching [13]. However, using varied prediction models for different traffic patterns leads to more overhead and delay probability, especially in cognitive Ad-hoc networks.

Additionally, the authors of [14, 15, 16] proposed an alternative OFF/ON Markov Renewal Process (MRP) and a PU activity model to deal with different PU traffic patterns. In [17] the authors suggested two algorithms of opportunistic channel selections that are Channel Selection Scheme-Minimal Handoff Rate Algorithm (CSS-MHRA) and Channel Selection Scheme-Minimal Collision Rate Algorithm (CSS-MCRA).

In [16] the authors suggested a distributed channel selection that Best Fits the Channel selection. Every SU calculates the accessibility time of a primary channel; these calculations help to identify a channel for transmission. Knowledge about the availability times of a primary channel and the transmission time empowers the SU to choose the channel that has enough long idle time to be suitable with CR transmission.

A study by [15] proposed an extended idle time channel selection scheme to distribute channel selection in CRAN. 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 Longest Idle Time Channel Selection (LITC) according to the way it better fits in the channel selection; to propose a strategy that depends on predictive model; to study the PU activity which helps to choose the best available channel for the SU; and reduce the average of interference between CRs and PUs. Our approach aims to improve the network performance that suffers from the high average of interference rate.

Chapter 3

METHODOLOGY

3.1 System Model

The below (Network Model and Spectrum Sensing Model) are our basic assumptions about the system model:

3.1.1 Network Model

The Cognitive Radio Ad hoc Network (CRAN) fundamentally comprises of a sensing unit, a power unit, a memory, processor and a Cognitive Radio Unit (CRU) (a transceiver) as represent in Figure 3.1.

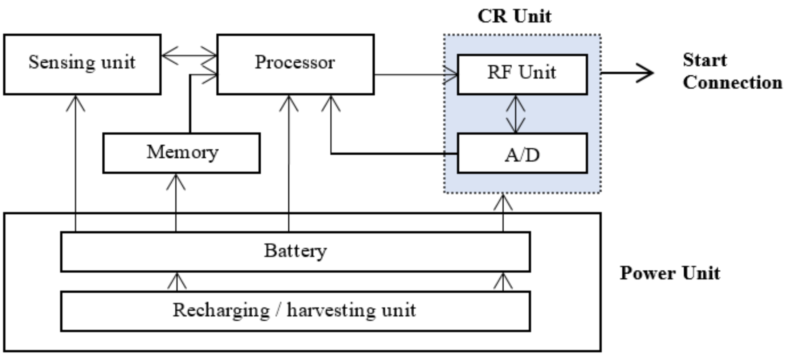


Figure 3.1: Structure of CRAN

In our assumption, we consider the information about CRAN as explained in [1]. The CRAN is composed of a set of SU and PU nodes. However, in the case of an unavailable base station, the functions of the base station (such as: mobility, spectrum sensing, spectrum decision and spectrum sharing) become the responsibility of the SU node.

Additionally, we assume that physical technology is considered as Orthogonal Frequency Divisions Multiplex (OFDM) system that consists of multiple subcarriers.

In CRAN, SUs are only able to use the spectrum when the PU is in OFF-state; however, the PUs are the owners of the spectrum and have the advantage to use the spectrum anytime.

The SU has the ability to communicate with one channel at a time while the Cognitive Radio Unit (CRU) is supposed to provide a single transceiver to the SU. The outcome of the previous operation is a decrease in the SUs' computational cost [18] that also leads to the prevention of probable inference while using the multi-transceiver due to the close proximity between them [1].

The Frequency channel (FC) is considered to be the total number of available channels. Also, the Common Control Channel (CCC) [19] has an assumed availability to be discovered by neighboring channels or nodes.

3.1.2 Spectrum Sensing Model

Depending on Local Traffic Information (LTI) in decision-making for distributed solutions leads the SUs to sense in an autonomous way. Accordingly, the presence of the PU signal is sensed by the SU. The SU determines the sensing period when the spectrum repeatedly senses at each period of time. The Spectrum Sensing Block keeps the PU signal functional and is consequently dependent on the availability of the channels sensed.

3.2 The Proposed WDS

The proposed WDS consists of two main stages, the Channel Weight and Optimizing QoS parameters.

3.2.1 Channel Weight (First Stage)

The best weight of the channels selected in the proposed strategy needs to fulfill some goals as shown in stage one of Figure 3.2. The first goal is represented in the estimation of the PU un-occupancy **($\boldsymbol{PU}^{(\boldsymbol{i})}_{\boldsymbol{Un-occupancy}}$)** where each SU node senses the available 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 **($\boldsymbol{SU}^{(\boldsymbol{i})}_{\boldsymbol{occupancy}}$).** The last goal is the measurement of channel capacity that is estimated by every SU in every channel **($\boldsymbol{CC}^{(\boldsymbol{i})}$)**. The ultimate goal at this stage is the allocation of a channel weight through estimating the PU un-occupancy, calculating the number of SUs in available channels, and measuring channel capacity. Determining the transmission method to achieve the previous goals depends on a channel that has a lower number of SU neighbors, a high channel capacity, and PU un-occupancy. The channel weight is calculated using Equation (3.8) to determine the estimated weight value for each channel.

The goals that were previously proposed 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 stage two on Figure 3.2.

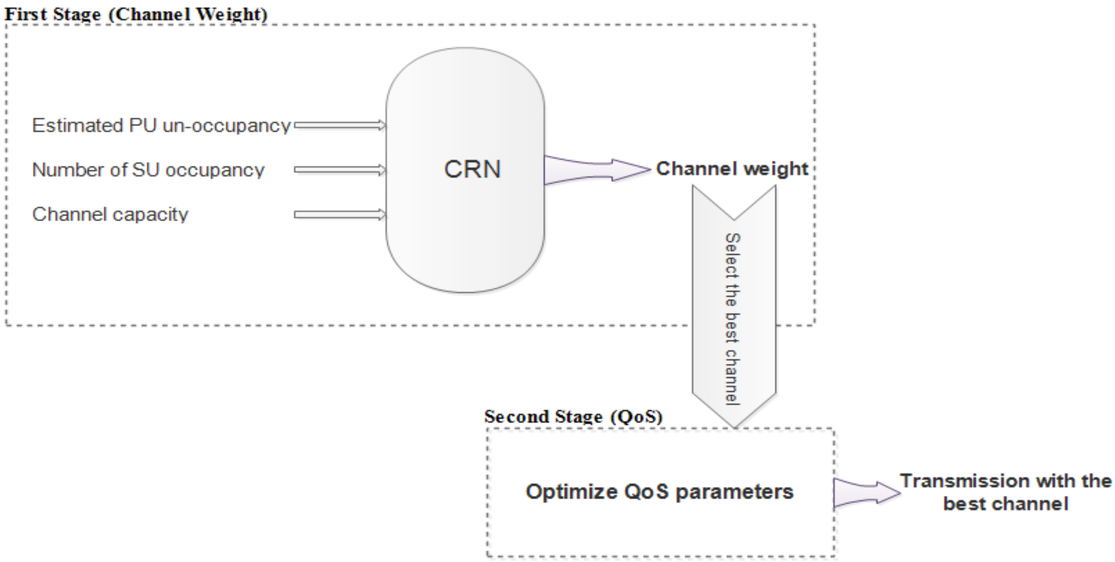


Figure 3.2: Diagram of the proposed WDS.

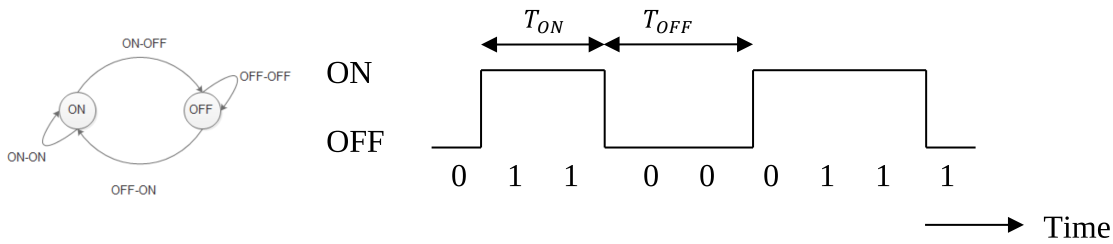
1. Estimating the PU Un-occupancy

Due to the technical nature of Cognitive Network, the SU communication period will not always be available. This nature makes it crucial to assess the possibility of OFF-state durations for the PUs on a free channel. Based on Markov Renewal Process (MRP) modeling [6], the existence or absence of PU on every channel is modeled by different techniques such as the PU Activity. PU modeling is based on measured data [8] and statistics [3], which function to determine the period 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 [14 -16].

The main characteristic of the MRP is decide the PU when is in OFF- or ON-states. Figure 3.3 presents the wireless channel model and the state transition from ON- to OFF-state through equation (3.4). The ON-state demonstrates that the SU cannot utilize the channel when it is being used by the PU. On the other hand, the OFF-state illustrates that the channel is not in use by the PU, the SU will be able to utilize it. Both

ON- and OFF-states of the channel matched by the binary sequence 1/0.

As mentioned in [10], the functions of the channel sensing operate as a simple process that provides a given channel state through a number of transitions that follow ON to ON, ON to OFF, OFF to ON, and OFF to OFF.



(a) (b)

Figure 3.3: MRP for PU activity model

When the channel i in active (On), the channel utilization U_i becomes as shown in equation (3.1) [10]:

$$U_i = \frac{E[T_{ON}^i]}{E[T_{ON}^i]+E[T_{OFF}^i]} = \frac{\lambda_y}{\lambda_x+\lambda_y} \tag{3.1}$$

The previous equation is 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. The previous are rate parameters for exponential distribution. Also, $E\left[T_{ON}^i\right]$ and $E\left[T_{OFF}^i\right]$ are the expected times that channel i ON- and OFF-states respectively.

We assume that $P_{ON}(t)$ is the probability of the channel i in ON-state at time t, and the $\mathrm{P_{OFF}(t)}$ as the probability of channel i in OFF-state at time t. Both probabilities $\mathrm{P_{ON}(t)}$ and $\mathrm{P_{OFF}(t)}$ are estimated as shown in (3) and (4) from [14]:

$$P_{ON}\ (t)\ = \frac{\lambda_y}{\lambda_x+\lambda_y} - \frac{\lambda_y}{\lambda_x+\lambda_y}\ e^{-(\lambda_x+\lambda_y)t} \tag{3.2}$$

$$P_{ON}\ (t)\ = \frac{\lambda_y}{\lambda_x+\lambda_y} - \frac{\lambda_y}{\lambda_x+\lambda_y}\ e^{-(\lambda_x+\lambda_y)t} \tag{3.3}$$

where,

$$P_{ON}\ (t)\ = \frac{\lambda_y}{\lambda_x + \lambda_y} - \frac{\lambda_y}{\lambda_x + \lambda_y}\ e^{-(\lambda_x+\lambda_y)t} \tag{3.4}$$

Therefore, when the PU be in OFF-State (un-occupancy) equal to 1- channel utilization

$$PU\ _{Un-occupancy}^{(i)} = 1 - U_i \tag{3.5}$$

2. Number of SU Occupancy ($\mathbf{SU_{Occupancy}}$)

The Occupancy $SU\ _{occupancy}^{(i)}$ of channel (i) is:

$$SU\ _{occupancy}^{(i)} = SU\ _{t}^{(i)} \tag{3.6}$$

In equation (3.6), $SU\ _{t}^{(i)}$is the SU neighbors' which placed in channel(i) at time *t*.

About requests of SUs fro available channel, SUs must have at least one cognitive radio transceiver. With the cognitive radio transceivers, SUs search for available spectrum, called spectrum opportunity, by conducting spectrum sensing. Our scheme offer way to select the best vacant channel for every request, however the requests handling done by cognitive radio protocols.

3. Channel Capacity for Each Channel ($\mathbf{CC_i}$)

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

In OFDM, the different Bandwidth (B*i*) for each spectrum band *i* consists of multiple subcarriers. Additionally, the normalized cognitive radio capacity $C_i^{CR}(K)$ model of spectrum band *i* for user *K* is proposed in [20] for spectrum characterization in CRAN. The C_i^{CR} model also defines the expected normalized capacity of the user K in a spectrum band *i* as:

$$C_i^{CR}(k) = \mathrm{E}[\mathrm{C}_i(k)] = \frac{T_i^{off}}{T_i^{off} + \tau} \cdot \gamma_i \cdot c_i(k) \qquad (3.7)$$

The below are the descriptions of the equation (3.7) terms:

$C_i(k)$ 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 (3.7), the channel or spectrum switching delay occurs within the CRAN whenever the SUs move from one spectrum band to another due to the PU activity. Also, the sensing efficiency is conditioned by the fact that the Radio Frequency (RF) front-ends cannot perform the spectrum 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 [21].

4. Channel Weight Calculation ($\mathbf{w_p^{(i)}}$)

The proposed channel selection scheme (Figure 3.2) arranges free bands through allocating weight $w_p^{(i)}$ to each channel (i) in all the Available Channels (ACh).

Therefore, every CR node calculates the $w_p^{(i)}$ locally as depicted in Equation 3.8:

$$P_{ON}\ (t)\ = \frac{\lambda_y}{\lambda_x + \lambda_y} - \frac{\lambda_y}{\lambda_x + \lambda_y}\ e^{-(\lambda_x + \lambda_y)t} \tag{3.8}$$

$\mathrm{w}_\mathrm{p}^{(\mathrm{i})}$ is the weight of the channel (i) when it exponentially increases with PU un occupancy (i.e., PU $_{\mathrm{Un-occupancy}}^{(\mathrm{i})}$, $CC\ _{i}^{CR}$) and linearly decreases with the SUs number (i.e. SU $_{\mathrm{occupancy}}^{(\mathrm{i})}$) over the channel (i). After the mentioned process, the channel with higher ($\mathrm{w}_\mathrm{p}^{(\mathrm{i})}$) channel will be selected for transmission.

3.2.2 Optimizing QoS Parameters (The Second Stage of WDS)

The spectrum decision process does not guarantee a frequency band to the CR that is equipped with all the (QoS) requirements due to the interference probability with PUs. The premise of our research is to study the ways that lead to minimum interference with reaching better QoS parameters for the cognitive nodes. 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 necessary optimal QoS parameters and achieves desired goals of CRAN applications.

The GA algorithm has an important aspect that is the fitness function which guides to the evolution of an optimal set of GA parameters. The importance that fitness function has led to our focus on the available functions of fitness which are used to locate how well a parameter set scores match a given objective. These fitness functions give a relational numerical analysis between QoS parameters and environmental parameters. Our suggested strategy represents a core controller for the CRAN parameter adaptation which intentionally neglects the parameters that change such as: OFDM or CDMA for transmission formats, WEP or PGP for encryption, or Turbo or convolution coding for error control types.

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 suggested strategy is lead to an optimal case by fitness functions (Multiple Objectives) 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.

3.3 CRAN Parameters

In developing a QoS optimizer for CRAN, several inputs must be taken into consideration because of the accuracy of decisions that should be determined through the inputs quantity and quality of the inputs quality provided for the system. Another main features of cognitive radio is the adaptability characteristic it has in relation to the surrounding environment. After the input provision, the system opts for making decisions around a specific output whose variables must be modeled internally in a wireless environment. These variables are then directly used as primary parameters by the fitness function to this function. An example of that type of parameter is the channel’s noise power that minimizes objective function of the BER. The same parameters immediately impact the fitness score of a specific objectives. Table 3.1 gives a visual representation about the way the CRAN parameters interact and function.

Table 3.1: CRAN Parameters

Parameter Type	**Parameter name**	**Abbreviation**
Input parameters	Spectrum Information Path Loss Noise Power Power Consumption Spatial Knowledge Battery Life Selected Channels due to primary users activities	SI PL NP PC SK BL SCHs
QoS Parameters	Transmission Power Modulation type Modulation index Symbol rate Bandwidth Frame Length	PT MT MI RS BW LL
Multi-objective function information	Objective function for minimizing Transmission Power Objective function for minimizing Bit Error Rate Objective function for minimizing Interference Objective function for maximizing Spectral Efficiency Objective function for maximizing Throughput	fobj, minPT fobj, minBER fobj, minINFR fobj, maxSE fobj, maxTHROU
Lower and upper bounds of output parameters	Lower Bounds List of QoS Parameters LBO Upper Bounds List QoS Parameters UBO	LBO UBO

A list of value range of parameters and their labels are applied in this thesis as input for fitness function as be in shown in Table 3.2. Most of the used parameter values were selected to be comparable to the Kansas University Agile Radio (KUAR) hardware platform and [22] systems. In this context, the range of spectrum information and the spatial knowledge unable to be specified because of the discrete nature of the values and is to be verified through implementing a real network using NS2.

Table 3.2: 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

The decision variables which demonstrates the controlled transmission by the CR system, that set is important set in optimization parameters. In addition, the environmental information that is model wireless channels. Many objectives must be determined to define the way the system should operate. Those system objectives are the map that determines the fate of a system and they permit a QoS state through steering the system by the controller. The previous are the many estimated objectives that desires to achieve in wireless communication surrounding.

3.3.1 Formulation the Fitness Functions for CRSN Parameter

Reaching the strategy goals, other five fitness functions (shown in: Table. 3.3) 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 [23-2]. After reviewing the necessary research in the field about **CRSN,** we noticed that there is no available research that deals with all the five objectives in one system model. As a consequence, we provide the underlying objective functions in details.

Table 3.3: Cognitive Radio Objectives

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

Minimizing the BER:

Two of the most common goals in wireless communications are obtain a free error signal or to minimizing BER transmission. Fitness function that minimizes BER is considered as found in [23]

$$f_{\text{obj,minBER}} = 1 - \frac{\log_{10}(0.5)}{\log_{10}(P_{ber})} \tag{3.9}$$

To oversimplify, P_{ber} represents the average BER probability which depends on the Modulation Type (MT) with Modulation index (MI) and it is computed as in case of BPSK modulation [26]

$$P_{ber} \;=\; Q(\sqrt{\gamma}\,) \tag{3.10}$$

For *m*-ary PSK modulation [26]

$$P_{ber} \;=\; \frac{2}{\log_2(MI)}\, Q(\sqrt{2 * \log_2(MI) * \gamma * \sin\frac{\pi}{MI}}) \tag{3.11}$$

For *m*-ary QAM [26]

$$P_{ber} \;=\; \frac{4}{\log_2(MI)}\, (1 - \frac{1}{\sqrt{MI}}) Q(\sqrt{\frac{3*\log_2(MI)*\gamma}{MI-1}}) \tag{3.12}$$

Also, $Q(x)$ represents Q-function by error function, γ is expressed as [26]:

$$\gamma = \frac{E_b}{N_b} = 10\log_{10}\left[\frac{PT}{NP}\right] + 10\log_{10}\left[\frac{BW}{RS*MI}\right] \quad (dB) \tag{3.13}$$

Minimizing Power Consumption (RPC)

CRSN environments place a high weighting on the RPC objective. The fitness function of minimizing RPC is given as [2]:

$$f_{\text{obj,minPT}} = 1 - \frac{PT}{P_{max}} \tag{3.14}$$

P_{max} in the previous formula represents the maximum power of available transmission.

Maximizing Throughput

The description of throughput that we consider is 'the total of the right bits which is sent through a channel in given time'. The Maximization of throughput is useful in a variety of scenarios; specifically, the multimedia environments scenario that places a large weighting on increasing throughput on stream audio and video. The fitness function of throughput increasing is defined as [25]:

$$f_{\text{obj,maxTHROU}} = \frac{LL}{LL+O+H} * (1 - P_{ber})^{(LL+O)} * RC * TDD \tag{3.15}$$

Where, LL explains "the frame length size in bytes;

H is the MAC , IP layer overhead at a value of 40 bytes;

O represents PHY layers overhead at 52.5 bytes;

and P_{ber} represents a probability of a bit error ratio.

Minimizing Interference

An important goal in shared frequency is to minimizing the interference. For example, this goal takes a high weighting by a SU that operates in a PUs band. In this case, the PU has the priority in a specific band of frequency; however, the SUs are permitted to transmit in the spectrum knowing that they do not cause any PUs interference.

The PT,BW, and TDD are transmission parameters which used to specify the spectral interference's probably total which is caused by transmission. The fitness function of minimizing interference is described as was seen in [26]:

$$f_{\text{obj,minINFR}} = 1 - \frac{(PT*BW*TDD) - (PT_{min}*BW_{min}*1)}{(PT_{max}*BW_{max}*R_{smax})} \quad (3.16)$$

BW_{min} and BW_{max} are, respectively, the minimum and maximum bandwidth available, whereas Rs_{max} is a the max-symbol rate.

Maximize the Spectrum Efficiency

Maximizing spectrum efficiency fegers to maximize the amount of transmitted data over a given bandwidth. The terminology refers to a measure of how efficient a given band of frequency is utilized by the physical layer. This objective relates directly to BW and the amount of data being transmitted. Both "RS" and MI are used to determine the total amount of transmitted information. Fitness function of maximizing spectrum efficiency is defined as was shown in [27]:

$$f_{\text{obj,minSE}} = \frac{MI * RS * BW_{min}}{BW * MI_{max} * R_{smax}} \quad (3.17)$$

3.3.2 Formulating Multi-objective Function for CRSN

Many methods had been introduced to determine the advantage of a set of objectives information**.** In our research, a weighted aggregate sum approach for multi-objective optimization problem has been implemented inside the suggested optimizer to evolve the strategy to an optimal set of QoS parameters. In what follows, we illustrate this approach in details:

3.3.3 Approach of Weighted Sum

Generally, a multi-objective fitness function problem is presented as an attempt that determines the set of *m* parameters correct mapping to a set of *n* objectives. This may be seen arithmetically as:

$\vec{y} = \langle f_{1(\vec{x}),} f_{2(\vec{x}),} f_{3(\vec{x}),} \dots \dots \dots ., f_{n(\vec{x})} \rangle$

Subject to

$\overrightarrow{x} = \langle x_1, x_2, x_3, \dots \dots, x_m \rangle \in X$

$\overrightarrow{y} = \langle y_1, y_2, y_3, \dots \dots, y_n \rangle \in Y$

In the above formulas, *x* is a set of decision variables; X is a parameter space, and *y* is a set of objectives with Y as objective space. In case of evolutionary algorithm m-objective, each $f_i\ (x)$ represents fitness function for a single objective.

In practical problems, such as the investigated problem of this thesis, the objectives under consideration might inter-conflict. For example, minimizing power and BER simultaneously create a conflict due to a single parameter (i.e., transmit power) that affects each objective in a different way. The Determination of an optimal set of decision variables for a single objective (e.g. minimize power) often results in a non-optimal set that respects other objectives (e.g. minimize BER and maximize throughput) [43].

The weighted sum approach permits the combination of single objective within one aggregated multiple objective function. Many available studies in the field, namely: [2, 23, 24, 26,] have specified three fitness function like: maximiaing throughput, power consumption and minimizing BER in one multiple objective.

Table 3.4: Example weighting scenarios for five objectives

Scenario	**Weight vector** **[w1 w2 w3 w4 w5]**
Healthcare application	[0.45 - 0.1 - 0.2 - 0.15 - 0.1]
Multimedia application	[0.1 - 0.1 - 0.35 - 0.1 - 0.35]
Emergency application	[0.3 - 0.3 - 0.05 - 0.05 - 0.3]
Dynamic Spectrum Access Mode	[0.23 - 0.08 - 0.23 - 0.23 - 0 .23]
Military Application	[0.2 - 0.2 - 0.2 - 0.2 - 0.2]

For simulation purposes, as shown in Table 3.4, our suggestion relies on different applications that demonstrate the way the weights are selected in order to attain certain goals. The functions are depicted with some goals in order to evaluate the performance of SA and GA in that states. The study in [28] has explain the way those range values are homogeneous to their function. In next, we focus on the importance of goals in every function and the conformable results to the achieved function objectives. The criterion that has been adopted in the selection of these weights is; for instance, a decision maker that first ranks all the goals whereby the aim of the function. Therefore, decision maker helps to rank the important objectives of that application. The objectives are: (1) minimizing power consumption ($f_{\text{obj, minPT}}$), (2) maximizing throughput ($f_{\text{obj, maxTHROU}}$), (3) minimizing interference ratio ($f_{\text{obj, minINFR}}$), and (4) minimizing BER ($f_{\text{obj, minBER}}$) and maximizing spectral efficiency ($f_{\text{obj, maxSE}}$). After the decision maker sorts all the objectives according to their relevance to specific applications, the next step includes providing weight value to every fitness function based on ranking.

3.4 Our Proposed WDS Scheme (See Figure 3.5)

1. Start spectrum sensing process in order to select all the available 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 channel available.

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.

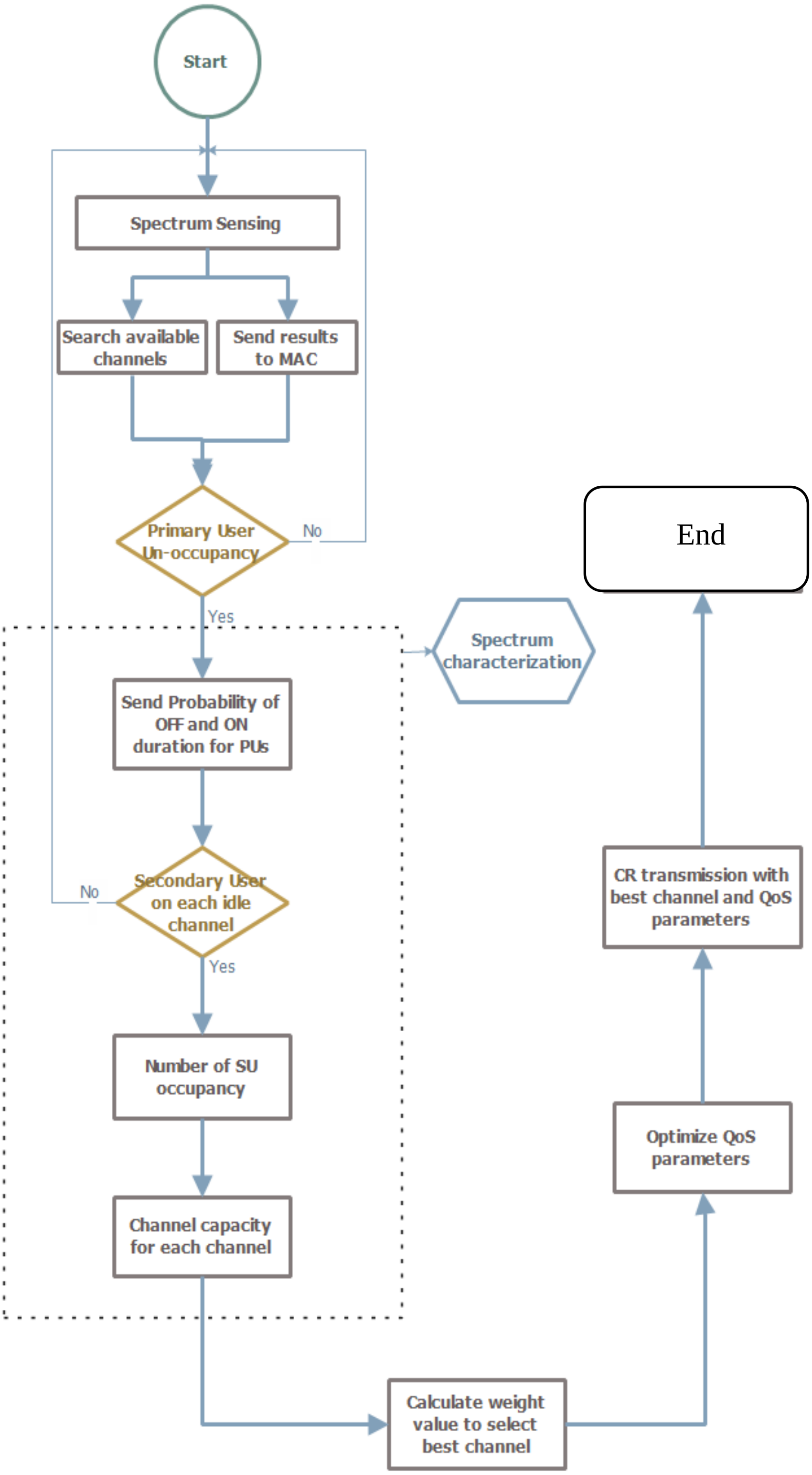


Figure 3.4: Flowchart of proposed WDS scheme

Chapter 4

SIMULATION RESULTS AND COMPARATIVE STUDY

Chapter four deals with the performance of the proposed scheme and the way it is examined through simulations. This chapter also captures the differences between the simulation results for the proposed scheme and other selection schemes through comparative techniques.

4.1 Simulation Results for the Proposed Decision Scheme

In this section, the performance of the proposed Weight Decision Scheme (WDS) is analyzed and compared with other selection strategies. Section (4.1.1) describes the process of the system model that is used in our simulation. A detailed explanation about performance metrics is provided in Section (4.2). Section (4.3) explains the simulation environment used in our simulation. Section (4.4) displays the results of the proposed scheme on the basis of NS2 simulator. Also, the performance for BFC, LITC, RD, and WDS has been evaluated.

4.1.1 System Model

At this point, it is necessary to highlight our basic assumptions for the system model. Our assumptions describe the ways the system model is built. Two categories are analyzed to explain the process: Spectrum sensing model, and PU activity model.

In this context, the CRAN is reviewed as found in [1]. Due to the non-availability of infrastructure base, each SU node would be instead responsible for CRAN tasks (such as spectrum decision and mobility). The compositions of a CRAN are a set of nodes of the PU and SU. Here, we assume Orthogonal Frequency-Division Multiplexing (OFDM) system as a physical technology and that consists of multiple subcarriers. By using OFDM as simple way of dealing with multipath, a large separation between sub-carriers to prevent interference which lowers the overall bandwidth utilization and Orthogonal packing of the subcarriers greatly increasing bandwidth utilization. OFDM is a multicarrier modulation technique that can overcome many problems that arise with high bit rate communications, the biggest of which is time dispersion. The data bearing symbol stream is split into several lower rate streams and these streams are transmitted on different carriers. Since this splitting increases the symbol duration by the number of orthogonally subcarriers, multipath echoes affect only a small portion of the neighboring symbols. Other advantages of OFDM include high spectral efficiency, robustness against narrow band interference, scalability, easy implementation using Fast Fourier Transform (FFT), and OFDM supports well-known multiple accessing techniques such as time division multiple access (TDMA). Therefore, OFDMA offers very flexible multiple accessing and spectral allocation capability for CR without any extra hardware complexity.

In CRAN, PUs are the owners of the spectrum and they have access-use to the spectrum at any time. However, the spectrum is used by the SUs only for a limited period of time when the PU is in an OFF-state. In addition to that, we suggest that the CR unit is provided with only one transceiver. In the transceiver, the SU senses or communicates with only one channel every time. As a result for the previous operation, the computational cost of the SUs is decreased as been explained by [29]. Probably interference should be avoided when multi-transceivers are used because of the close proximity between them [30]. For that, we suppose that the comprising number of free channels at each CR is Frequency Channel (FC) and the availability of an out-of-band

[31] is assumed for neighbor detection.

4.1.2 Spectrum Sensing Model

The SUs are supposed to sense autonomously and their decision-making process depends on the local traffic information in distributed solutions. Accordingly, each SU needs to detect the occurrence of the PU communication. On each specific period of time that is referred to as ‘a sensing period’, the spectrum sensing becomes a repeated process. The latter process, spectrum sensing block that is mentioned in [32], determines the presence of PU signal. That leads to the determination of the WDS by the available channels that are sensed from the spectrum sensing block channels.

4.1.3 Primary User Activity Modeling

Conferring to the environment of the CN in relation to the nature of the SUs. The free channel is not always unoccupied in the whole SU time of communication. Consequently, it is crucial to detect the possibility of OFF-state periods on the free channel for the PUs. The PU signal’s existence or non-existence on every channel should be demonstrated through different techniques that determine the PU activity such as: Markov renewal process modeling [33], statistics modeling [34], and measured data modeling [35]. Also, one of the most important types of modeling that is used to define the PU activity pattern in CRAN is a continuous-time and alternating ON/OFF Markov Renewal Process (MRP).

A major criterion of the ON/OFF PU activity model is the fact which it accurately determines when the Primary User is in ON- and OFF-states [36]. Figure 4.1 demonstrates the state transition from ON- and OFF-states and the wireless channel model through equation (4.4). When the channel is occupied (ON-state), the SU cannot use it consequently. However, when the channel is unoccupied (OFF-state) by the Primary Use, in that case, the SU can utilize it. The operation timing of ON- and OFF-states is measured through the binary sequence 1/0. The channel will be able to realize its state (from ON to OFF or vise-versa) through a number of transitions using channel sensing. The sampling process of transitions follows an ON to OFF, OFF to ON, ON to ON, and OFF to OFF process as clarified in [37]. The durations of ON- and OFF-states of a channel i are respectively signified as λ_{ON}^{i} and λ_{OFF}^{i} .

Both OFF and ON durations are supposed to be autonomous and distributed identically. Because every CR user appearance is self-determining, every occurring change has to follow the Poisson appearance procedure. In this framework, the mathematical equations of [37-38] for the channels in ON- and OFF-state time describe how jointly states are exponentially with a probability of density function as $f_x(t) = \lambda_x \times e^{-\lambda_x t}$ for ON state and as $f_y(t) = \lambda_y \times e^{-\lambda_y t}$ for OFF state.

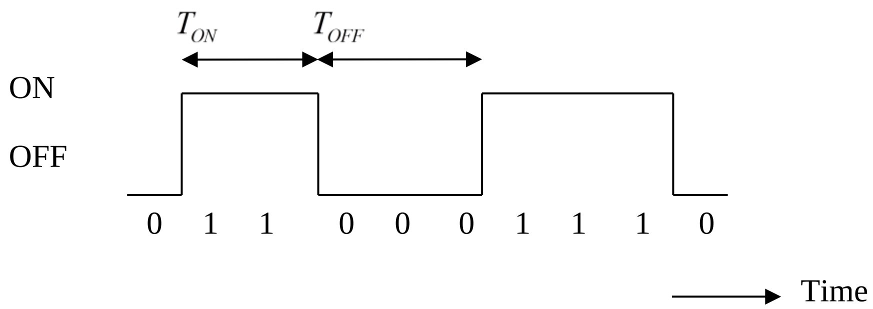


Figure 4.1: MRP for PU activity model

Channel utilization in the channel *i* be an ON-state. U_i is estimated as [37]:

$$U_i = \frac{E[T_{ON}^{i}]}{E[T_{ON}^{i}]+E[T_{OFF}^{i}]} = \frac{\lambda_y}{\lambda_x+\lambda_y} \tag{4.1}$$

In $E\left[T_{ON}^{i}\right] = \frac{1}{\lambda_x}$ and $E\left[T_{OFF}^{i}\right] = \frac{1}{\lambda_y}$, $\lambda_x = \lambda_{OFF}^{i}$ and $\lambda_y = \lambda_{ON}^{i}$ represent ratio parameters for exponential distribution, and both $E\left[T_{ON}^{i}\right]$ and $E\left[T_{OFF}^{i}\right]$ are the means used for exponential distribution.

We assume that P_{ON} (t) is the probable state of channel i in an ON-state at time t. Also, P_{OFF} (t) is the probable position of a channel i in an OFF-state at time t. Both probabilities P_{ON} (t) and P_{OFF} (t) can be estimated as [14]:

$$P_{ON}(t) = \frac{\lambda_y}{\lambda_x+\lambda_y} - \frac{\lambda_y}{\lambda_x+\lambda_y} e^{-(\lambda_x+\lambda_y)t} \tag{4.2}$$

$$P_{OFF}(t) = \frac{\lambda_x}{\lambda_x+\lambda_y} + \frac{\lambda_x}{\lambda_x+\lambda_y} e^{-(\lambda_x+\lambda_y)t} \tag{4.3}$$

Where,

$$P_{OFF}(t) + P_{ON}(t) = 1 \tag{4.4}$$

4.2 Performance Measures

In order to verify the efficiency of the suggested selection scheme for CRAHNs, the performances of our algorithms is compared to BFC [42], LITC [41], and Random (RD) [40] schemes using NS2 simulator for analysis. On this simulator, the SU node and the prerequisite layers for network operations have been developed by determining the building of CRAN layers. Among those layers is the physical layer that is used to detect some useful information to all the free bands, checks the propagation, and determine the signal strength. On other hand, the Medium Access Control (MAC) layer provides the different free channels and specifies the activities of PU activity model through the interfering information.

Within the MAC layer framework, the main operation of the network layer of the SU becomes determining for preserving the neighbors list of the CR. After that, we implement the scheme of channel selection based on the data received from CR MAC layer. The implementation is operated to select the best free channels using the WDS strategy. Following the detection of the best free channel, the traffic of the PUs and CRs is simulated using NS-2 simulator and the subsequent metrics are measured from the same simulator in order to assess the effectiveness of the WDS strategy in comparison to other strategies as shown in Section (4.4).

Considering that all the terminology should be defined in our scenario, the following are some keys to our framework:

- Packet delivery ratio is the ratios of a number of data packets that are successfully received by the CR device to the total number of data packets sent as defined in.
- Spectrum utilization is a function of the ratio of SU successful transmission period to the total PU idle period.
- Average throughput is the ratio of number of data packets that are successfully received by the CR device to the total number of data packets sent.
- Average interference ratio is defined as the number of occupied channels by the PU to the number of times the channel selection scheme happens.
- Average end-to-end delay is the average delay between the sending of the data packet by the application source and its reception at the corresponding application. This delay is a result of the route acquisition, the buffering and processing at intermediate nodes, and the retransmission delays at a MAC layer. The possibility of an end-to-end delay high value means that the protocol performance is not good due to the network congestion.

4.3 Simulation Environment

Our basic assumptions are to be presented as follows:

- We adopted the cooperative routing protocol for the underlying simulation as provided in [13]. The concept is that it is utilized 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.
- PUs and CRs have used a Carrier Sense Multiple Access (CSMA) /Collision Avoidance (CA) based on MAC protocol in our research context. Disputations occur through carrier sensing and a back-off algorithm between CRs in CSMA protocols.
- Every single radio transceiver is a component of every SU and it can be adjusted for the primary network as numerous licensed frequencies. This is seen as a constraint and for that both sensing and transmission are done consecutively.
- The average idle and busy time periods ($\lambda^i_{OFF}, \lambda^i_{ON}$) for PU activity are exponentially distributed. The Values $\lambda^i_{OFF}, \lambda^i_{ON}$ in Table 4.1 are extracted from [37] by using the following equations:

Channel utilization $$u^i = \frac{E[T^i_{ON}]}{E[T^i_{ON}] + \mathrm{E}[\mathrm{T}^i_{OFF}]} = \frac{\lambda_{T^i_{OFF}}}{\lambda_{T^i_{ON}} + \lambda_{T^i_{OFF}}} \tag{4.5}$$

The authors make estimation for $\lambda_{T^i_{OFF}}$ and u^i instead of $\lambda_{T^i_{OFF}}$ and $\lambda_{T^i_{ON}}$, the estimation of u^i is given as :

$$\hat{u}^i = \frac{1}{r^i} \sum_{i=1}^{r^i} Z^i_{t_k} \tag{4.6}$$

On the other hand, the estimation of $\lambda_{T^i_{OFF}}$ can be derived by solving the equation $\partial \ln \mathrm{L}(\theta) / \partial \lambda_{T^i_{OFF}} = 0$, yielding

$$\hat{\lambda}_{T^i_{OFF}} = \frac{u^i}{T^i_p} \ln[\tfrac{-B+\sqrt{B^2+4AC}}{2A}] \tag{4.7}$$

$$\begin{Bmatrix} A = (u^i - (u^i)^2)(r^i), \\ B = 2A + (r^i - 1) - (1-u^i)n_0 - u^i.n_3, \\ C = A - u^i.n_0 - (1-u^i)n_3. \end{Bmatrix} \tag{4.8}$$

Note that $n_0 / n_1 / n_2 / n_3$ indicates the number of $(0 \to 0) / (0 \to 1) / (1 \to 0) / (1 \to 1)$ transitions from the total of $(r^i - 1)$ transitions among r^i samples. For instance in case a sequence of samples is given as (1,1,1,1,0,1,1,0), r^i =8, we have n_0 =0, n_1 =2, n_2 =2, and n_3 =3.

Table 4.1: Channel's simulation parameters for estimation [37]

	Ch 1	**Ch 2**	**Ch3**	**Ch 4**	**Ch 5**	**Ch 6**	**Ch 7**	**Ch 8**	**Ch 9**	**Ch10**
λ^i_{OFF}	1.5	0.5	1	3	1	3.5	4	0.50	0.75	0.67
λ^i_{ON}	0.8	2.5	1	2.50	2	0.50	1	5.50	2	0.5

The simulation input parameters used in our simulation are represented in Table 4.2. In Table 4.3 demonstrates the difference between the network parameters of WDS and others schemes.

Table 4.2: Simulation parameters for NS2

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 [13] (AODV)
Packet size	512 bytes
Transmission range	250 meters
Number of CR users	10, 25, 50, 100, 150
Simulation time	600 Seconds
Number of runs	10
Sensing time interval	1 sec
Simulation area	$700 \times 700\ m^2$

Especially in battery-powered mobile nodes, the power efficiency issue is particularly important. One effort to reduce the nodes power consumption is to use On-demand routing mechanisms. On-demand routing protocols only establish a path when there is active communication taking place , thus reducing energy consumption. On-demand routing requires less network resources and is more suitable for dynamic ad hoc networks rather than the proactive routing.

Additionally, Ad hoc On-Demand Distance Vector (AODV) is routing protocol with QoS support, it is advantageous for SUs, especially when there are various kings of application traffic with different service requests. The routing protocol with QoS support could recognize the application service demands and would choose the path with the lowest loss for data transfer, and lowest end-to-end delay.

In each scenario, the initial position of nodes, of the sender and the receiver, and the accessibility to a channels by each node are unsystematically organized inside an area of (700 x 700) and the number of CRs is fixed to 150 and simulations run for 600 seconds. The transmission range of CR is 250 m and packet size is 512 byte. The number of vacant channels (ACHs) at each SU is 10. In Table 4.3 illustrates all schemes and network parameters.

Table 4.3: General parameters of all schemes

	RD	**LITC**	**BFC**	**WDS**
Channel selection	Randomly	Longest idle duration	Longest accessibility	Highest channel weight
QoS	No	No	No	Yes
Sensing duration	$12x\ 10^{-3}$	20ms	-	100ms
Number of channel	*By Matlab	10	16	10 in NS2 3-15 in Matlab
Routing protocol	-	-	-	AODV
Time process	1.9ms	210ms	240ms	-
Simulation	Matlab	Matlab	-	NS2 & Matlab

* Generate discrete channels in Matlab by special parameters

4.4 WDS Comparison

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

4.4.1 Effect of SUs Number on Channel Decision Strategies

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 available channels for the SUs is set to 10 with rate parameters (λ_x, λ_y) as shown in Table 4.1. The number of SUs in the network ranges from 10 to 150. Figure 4.2 shows the outcomes of the simulation experiments that are used to evaluate the average of interference ratio at diverse of SUs for the BFC, RD, LITC, and the WDS.

The minimum improvement in interference ratio for WDS occur at 10 SU nodes at which the ratio is decrease by around 12% which can be compared to BFC, however the maximum average interference rate happened at 150 SU nodes at that the rate is decreased by 68% is compared with Random method. On the average, it is realized that the WDS frequently outperforms RD, BFC, and LITC in relation to minimizing interference rate at different numbers of SUs by 55.2%, 23% and 31% which are compared to RD, BFC, and LITC respectively.

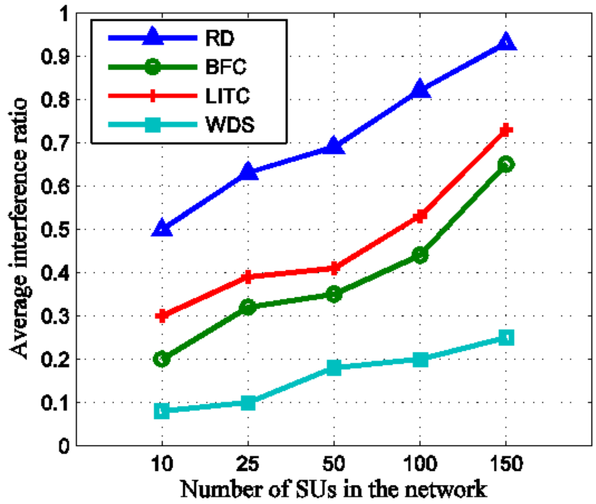


Figure 4.2: Average interference in different number of SUs

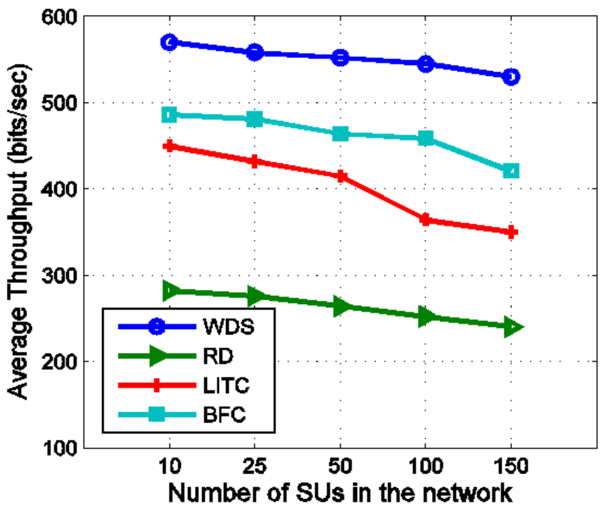


Figure 4.3: Average throughput in different number of SUs

Similarly, Figure 4.3 demonstrates that the outcomes of the different simulation experiments are meant to quantify the rate throughput at number of SUs for the BFC, RD, LITC and the proposed schemes. After 10 SU nodes occurrence, the minimum improvement of average throughput for WDS increase by around 13.7% compared with BFC. This improvement is compared with BFC, however, at 150 SU nodes, the maximum improvement in average throughput occurs and the ratio is increased by 63.8% and it is compared with RD. On an average scale, it is approved that WDS outperforms RD, BFC and LITC and is related to maximizing rate throughput at of SUs by 52.7%, 24.3% and 32.2% and compared to RD, BFC and LITC respectively.

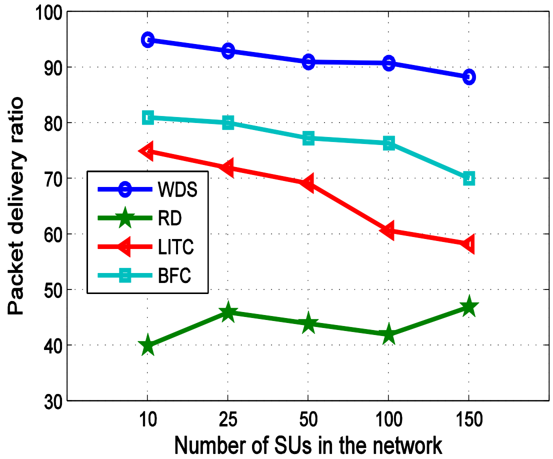


Figure 4.4: Packet delivery ratio in different number of SUs

The outcomes of different experiments of simulation that measure the packet delivery rate at of SUs for the RD, BFC, LITC and the proposed scheme are shown in Figure 4.4. We depict that the WDS outperforms RD, BFC and LITC in relation to maximizing packet delivery ratio at different network density by the averages 47.8%, 24.8% and 14.6% that is compared to RD, LITC and BFC respectively.

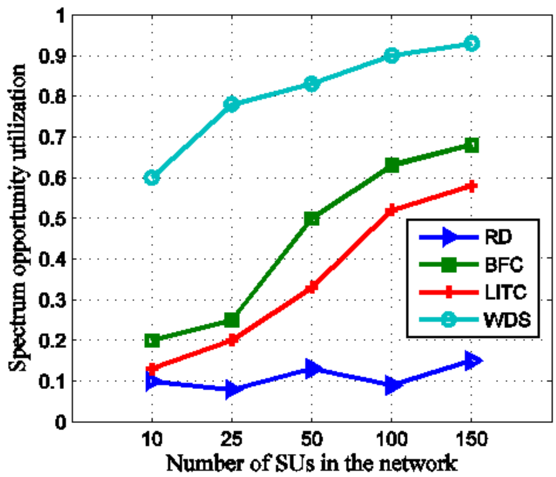


Figure 4.5: spectrum utilization in different number of SUs

Another result demonstration is illustrated in Figure 4.5 which shows measurement of the utilization of spectrum opportunity at different SUs nodes for the RD, BFC, LITC and the proposed scheme. The spectrum opportunity utilization for WDS minimum improvement occurs at 10 SU nodes where the ratio increases by 25%. At 150 SU nodes, the maximum improvement in spectrum opportunity utilization happens and the ratio increases by 89% in comparison to RD. Averagely, we realize that the WDS also outperforms RD, BFC and LITC as related to maximizing the utilization of spectrum opportunity at different network density by 73.8%, 35.6% and 54.6% as compared to RD, BFC and LITC respectively.

The last comparison in Figure 4.6 shows the outcomes of simulations that evaluate the end-to-end delay at SUs for the BFC, RD, LITC and the proposed scheme. The minimum improvement in this case of an end-to-end occurs at 10 SU nodes where the ratio decreases to 24.9%. However, the maximum improvement appears at 150 SU nodes and the ratio decreases by 86% in comparison with RD. In average, the realization that WDS always outperforms RD, BFC and LITC in relation to minimizing end-to-end delay at network by 48%, 41% and 29% as compared to RD, LITC and BFC respectively is attained.

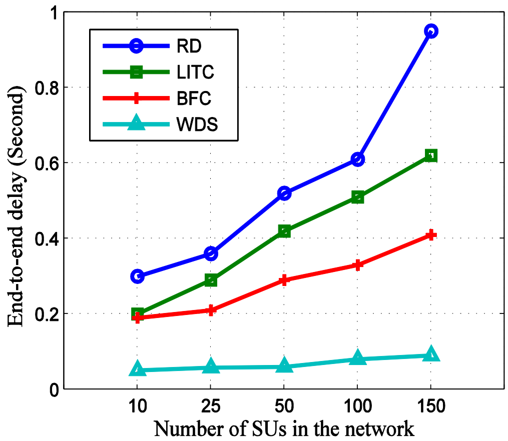


Figure 4.6: End-to-end delay in different number of SUs

4.4.2 Effect of Number of Available Channels on Channel Decision Strategies

In a set of simulations, we examine the ways a number of FCHs impact the performance of each scheme in terms of the above-mentioned metrics in Section 4.2. The number of SUs in the CRAN is set to 100 nodes and the number of available channels for SUs starts from 3 to 15.

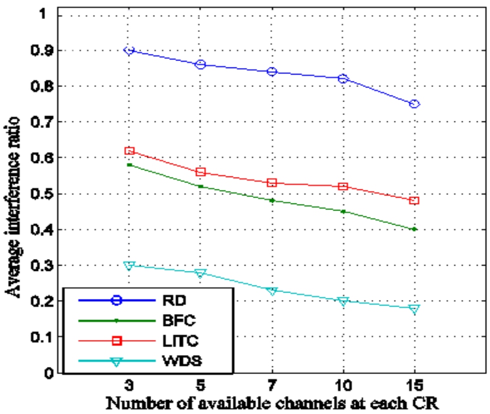


Figure 4.7: Probability of the average interference ratio under different numbers of FCHs

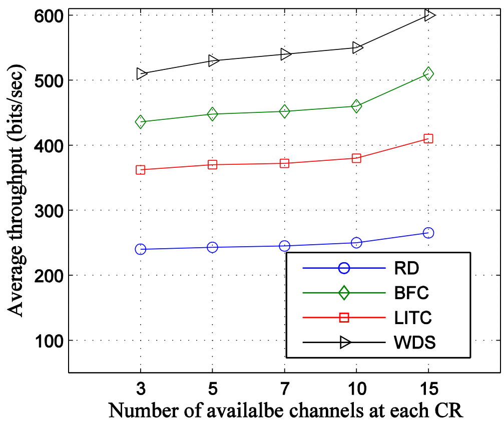


Figure 4.8: Probability of the Average throughput under different numbers of FCHs

In Figure 4.7, demonstrates the outcomes of different simulation experiments that assess average interference ratio at several of available 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. On the same figure, Figure 4.8 demonstrates the results of others simulation experiments that were intended to count the rate throughput at several of available channels for RD, BFC, LITC, and the WDS. We can realize that, the WDS could improve the average throughput by 51%, 19.8% and 28.8% compared to RD, BFC and LITC respectively.

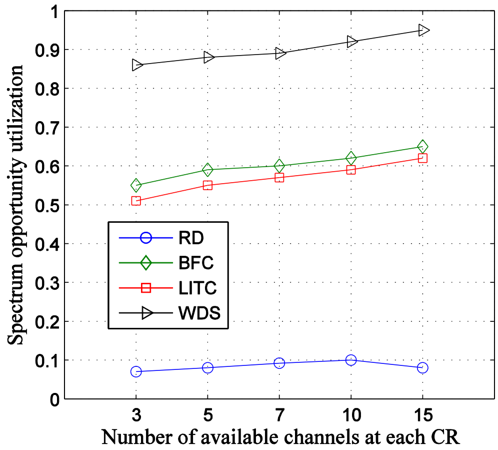


Figure 4.9: Packet delivery rate under different number of FCHs

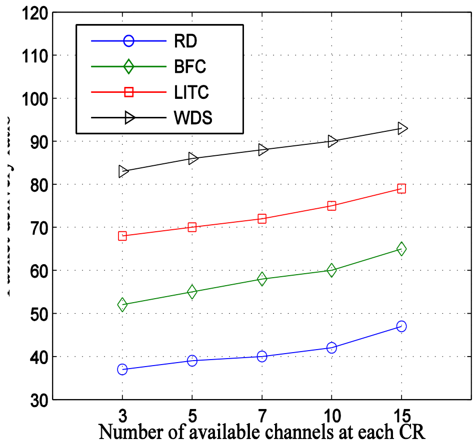


Figure 4.10: Spectrum utilization under different of FCHs

The packet delivery rate of available channels for the RD, BFC, LITC, and the WDS at different numbers is shown in Figure 4.9 where the WDS could improve packet delivery ratio by 42.8%, 20.6% and 12.7% compared to RD, LITC and BFC respectively. From Figure 4.10, 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 of the WDS highlighted 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.

The last demonstration on Figure 4.11 illustrates that the results of different simulation experiments assess at different numbers of channels for the RD the end-to-end delay, BFC, LITC and the WDS. On the average, the WDS has always outperformed RD, BFC and LITC related to minimizing delay of end-to-end at channels by 43%, 28% and 23% compared to RD, LITC and BFC respectively. As has been illustrated in Figure 4.7, in case of low channel number, i.e., FCHs=5, reducing in network performance in contrast to the case when FCHs =15. This is as result that, a few channels minimized the opportunity of Secondary Users being able to detected when the PU-un-occupancy transmission channel.

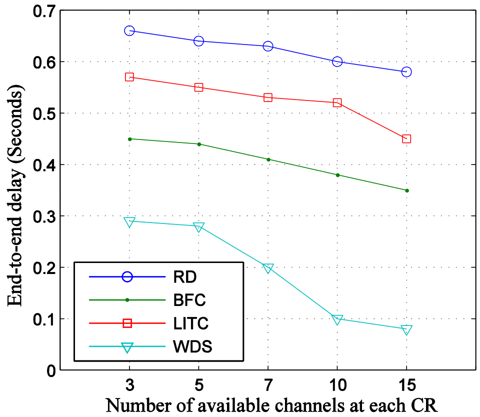


Figure 4.11: End-to-end delay under different number of FCHs

According to previous results we can see that WDS improves the network performance through an efficient selection of available channels. WDS uses two steps model, which may need more processing time comparing to other systems. This may lead to a degradation in a dynamic environment especially when we have several concurrent requests as WDS doesn’t have queue to handle such requests.

Chapter 5

CONCLUSION

5.1 Conclusion

The current thesis presents Weight Decision Selection (WDS) as an efficient channel selection scheme for CR ad hoc networks. The core aims of the suggested scheme are to minimize the interference between PUs and CRs through selecting the best channel by a proposed weight formula.

We were able to design a new channel selection strategy, known as WDS, which includes all the parameters: Idle duration for PU, channel capacity, and a number of CRs in each channel to select 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 CRAN 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 CRAHNs.

Simulation results using the simulation system NS2 have confirmed that WDS has better performance relative to RD, BFC, and LITC strategies under different network densities and number of available channels. The proposed WDS scheme improves (i.e., maximizes) the channel utilization by 72.3%, 34.7% and 53.8% compared to RD, BFC and LITC respectively and minimizes the interference ratio by 73.8%, 35.6% and 54.6% compared to RD, BFC and LITC respectively. In addition to that, WDS also outperforms other strategies for average throughput, packet delivery rate, and end-to-end delay.

In the time of 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: CRWSN, CRAN, and Mobile networks.

5.2 Future Research Suggestion

The following are the points that can be considered for future research:

- 5G systems are the next major wireless communication standards and the cognitive radio is heralded as a valid implementation method in the fifth generation standard of wireless communication industry. One interesting direction is to implement a Beyond-Next-Generation (5G) communication network that is based on Cognitive Radio.
- The proposed decision scheme can be used for other wireless networks such as: a Vehicle Ad Hoc Network (VANET) based on cognitive technique.
- We need more investigation for processing time and consider reducing it to be feasible in dynamic environments.

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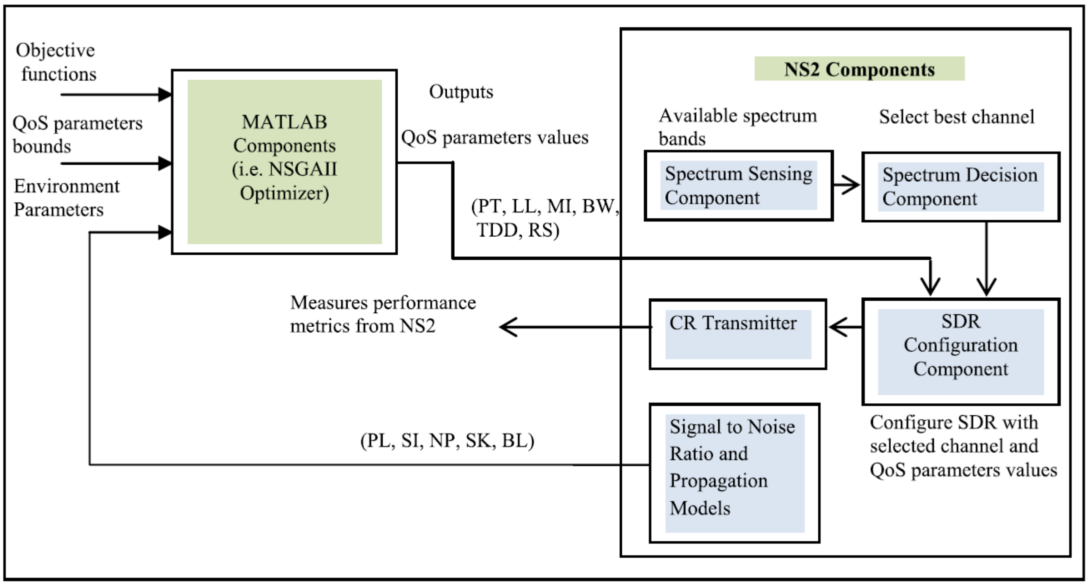
APPENDICES

Appendix A: The workflow between MATLAB and NS2



Appendix B: Optimal QoS Optimizer Algorithm

- Set LBO := {LB1, LB2, . . . , LBn} and UBO := {UL1, UL2, . . . , ULn} where n represents the number of QoS transmission parameters.

- Set GA-PARs for GA module.

- IF GA THEN

- Set Wi := {W1,W2, . . . ,Wm} where m represents the number of objective functions, GA-PARs for GA module.

- EPARs := Read_EPARs_from_CR() where EPARs is a list of environmental parameters SI, PL, NP, PC, SK, BL and SCHs.

- Case ''GA'' Module: RUN-GA -MODULE (PARs, EPARs, LBO, UBO, Wi)

- Write_Optimized_PARs_to_CR(PT, MT, MI, RS, BW, LL, TDD)

- Repeat until time expires from step 5 to step 8.