OPTIMIZATION OF RESOURCE ALLOCATION IN COGNITIVE RADIO NETWORK USING ARTIFICIAL INTELLIGENCE

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Abstract
Cognitive radio network (CRN), which has been adopted as a promising solution for optimization of the limited available radio-frequency spectrum, has two major drawbacks: Missed Detection (MD) and False Alarm (FA). This work proposed fuzzy-based intelligent resource allocation in cognitive radio network (FIRA-CRN) as a solution to the identify drawbacks. In the methodology, the available channels are classified based on the primary users' (PUs) utilization, the number of cognitive radio neighbours using the channels and the capacity of available channels. The Fuzzy Logic technique is used to determine a channel's weight value by combining these parameters. The channels with the highest weight value are selected for transmission. The proposed strategy takes into account false alarm (FA) and miss detection (MD) metrics to classify the sensed channels into four categories (FA, MD, ON and OFF) based on K-means learner. This classification helps the strategy to avoid accessing occupied channels. Average interference ratio (AIR), end-to-end delay (EED) and packet delivery ratio (PDR) were used as key performance indicators to evaluate the proposed scheme while comparing it with other schemes visa-viz: best-fit channel selection (BFC), GA-based selection (GA), Intelligent Channel Selection Scheme a Self-Organized Map Followed by Simple Segregation (ICSSSS), and longest idle time channel selection (LITC). Results showed that FIRA-CRN reduced the AIR by 60%, 40%, 32%, and 7% when compared with LITC, GA, BFC and ICSSSS respectively. With respect to PDR, it is also observed that FIRA-CRN outperformed ILTC, BFC, GA, and ICSSSS by 45%, 28.3%, 14.8%, and 7.5% respectively. Besides, FIRA-CRN reduced EED by 88.7%, 84.4%, 77.8%, and 28.3% for LITC, BFC, GA, and ICSSSS respectively. This work can be used to improve the overall performance of cognitive radio networks.

Keywords: Cognitive radio, Radio-Frequency, Fuzzy Logic, Optimization.

1.0 INTRODUCTION

The rapid development of mobile Internet generated tremendous amount of traffic which consequently requires more bandwidth for better quality of service (QoS). To satisfy the growing demand for data traffic, wireless networks are emerging with different types of model. In the future 5G mobile communication system for example, the network consists of multiple layers of cells (macro, femto, pico, relays) and the radio resources are reused more efficiently to improve the network coverage and capacity (Yang and Zhao, 2017). A promising method is to introduce artificial intelligence (AI) into the network control and management, instead of manual optimization processes. With artificial intelligence, the networks are managed more independently and efficiently with enhanced performance.

Cognitive radio (CR) is a radio that can be programmed and configured dynamically to use the best wireless channels in its vicinity to avoid user interference and congestion or an adaptive intelligent radio and network technology that can automatically detect available channels in a wireless spectrum and change transmission parameters enabling more communication to run concurrently and also improve radio operating behavior. The concept of CR was introduced by (Mitola and Maguire , 1999). The aim was to design a fully reconfigurable radio that is able to adapt its parameters according to the current environment and users' status. This opens the path to exploit cognitive approach in radio resource management. Artificial intelligence algorithms are the tools used to develop efficient cognitive radio resource management schemes. In addition, these algorithms are extended to tackle resource allocation (RA) problems in advanced network structures such as cellular networks.

The concept of software defined radios (SDR) was introduced by Mitola, 2000, referring to a radio which can be easily reconfigured and reprogrammed. The ability to change the radio configuration gives the device the flexibility to perform variety of functions at different times. The technical definition for SDRs is that they are software implementation of the radio functionality, which allows the mobile terminal to adapt the radio environment accordingly.

A cognitive engine (CE) is the intelligent agent that performs decisions driven by certain performance objectives to adapt system parameters according to it. Observation and learning from the environment to achieve reliable communication and efficient resource utilization is its hallmark (Aiqerm and Shihada, 2014). Cognitive engines have three attributes:

- **Observation:** collect information about the operating environment, capability and characteristics of the radio.
- **Reconfiguration:** change the operation parameters of the radio.
- **Cognition:** understanding the environment and capability of the radio (awareness), make informed decision on actions (reasoning) and learning the impact of these actions on the performance of the radio, as well as the performance of the network in which the radio is embedded (learning).

There are many Artificial intelligence techniques exploited for radio resource management and transmission parameter configuration scheme such as rules based system (RBS) (Ishibuchi, 2007), (Zadeh, 1996),(Shi and Xue, 2005). The approach used in this work is Fuzzy Logic. A Fuzzy element has a degree of membership or compatibility with the set and it's negation. Fuzzy logic provides the system with the following:

1. Approximate reasoning by taking Fuzzy variables as an input and producing a decision by using sets of if – then rules.
2. Decision – making capability under uncertainty by predict tiny consequences.
3. Learning from old experience and
4. Generalization to adapt to the new situations (Dadios, 2012). The Fuzzy logic set theory was proposed by Lotfi A. Zadeh in 1965 to solve and model uncertainty, ambiguity, imprecisions, and vagueness using mathematical and empirical models (Zadeh, 1965). The variables (True or False) are as defined in classical and crisp sets (Gavrilovska et. al, 2013).

Cognitive Radio Network is a type of wireless communication in which a device known as transceiver senses which communication channels are vacant and which ones are occupied. After sensing the channels, it moves to vacant channels by avoiding occupied channels. In simple terms, a transceiver tends to use the best available wireless communication channel for communication. It uses the radio frequency spectrum with less interference with respect to the other. Mitola and Maguire, 1999 developed the idea of Cognitive Radio at the Defense Advanced Research Projects Agency (DARPA).

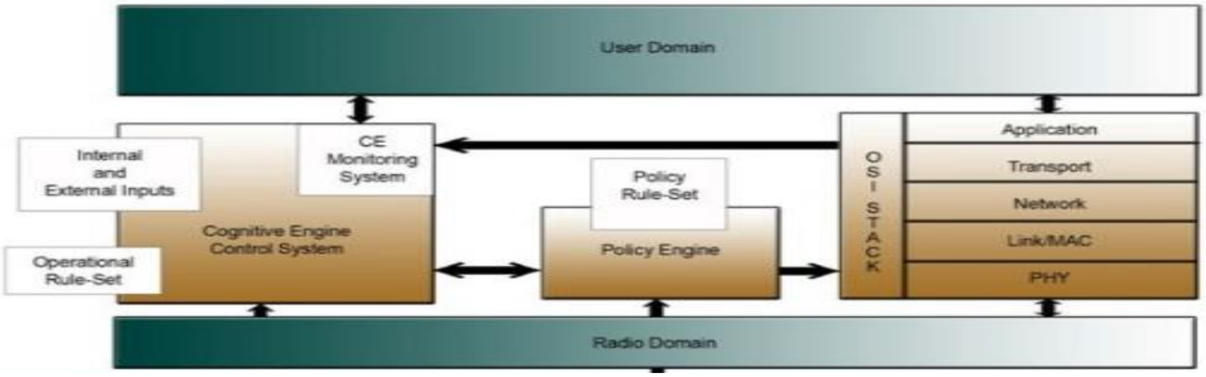

Figure 1: Architecture of Cognitive Radio Network (Chen et. al, 2008)

Cognitive radio network architecture is shown in figure 1. Cognitive radio network is a new concept in the area of wireless sensor network that can utilize the spectrum frequency efficiently. Cognitive radio systems have the capabilities handle packet loss reduction, power waste reduction, buffer management etc.

3.0 METHODOLOGY

3.1 Proposed Optimized Resource Allocation in Cognitive Radio Network (ORACRN)

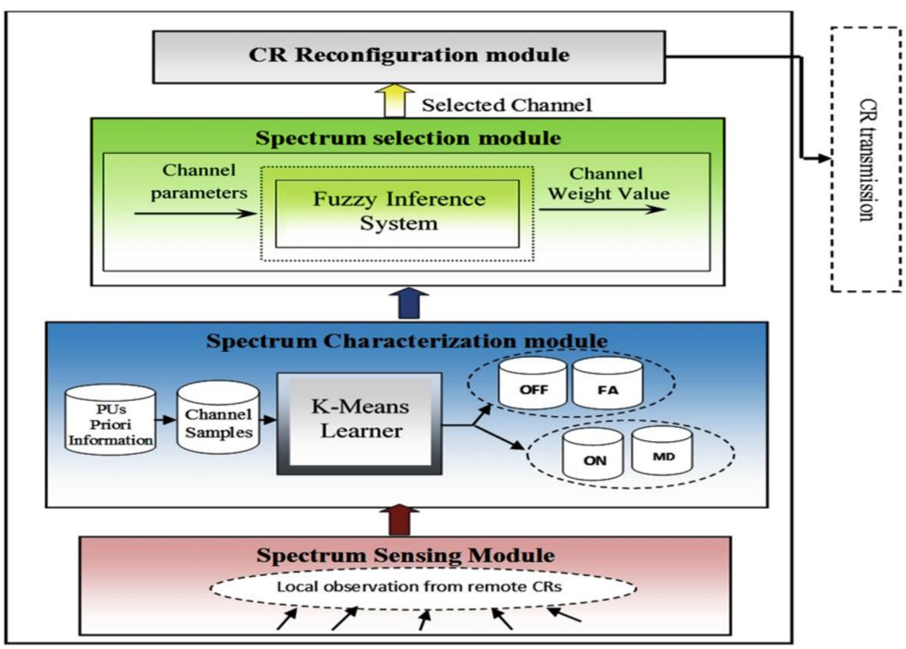

Figure 2: Proposed Frame Work for Optimized Resource Allocation in Cognitive Radio Network (ORACRN)

Figure 2 shows the proposed intelligent learning fuzzy-based channel (ILFCS) framework for the optimization of resource allocation in cognitive radio network. The selection consists of four major modules: i. Channel sensing module, ii. Spectrum characterization module, iii. Spectrum selection module and iv. Cognitive radio reconfiguration module.

3.2 Mathematical Model of Fuzzy Input Parameters

The most important challenge to maximize the performance of a CRN is to minimize interference caused to Pus and among CRs (Placeholder2). Thus, best channels with minimum PUs' activities, less congested with CR users, and high capacity should be selected. Output channels that resulted from *K*-means clustering are classified by assigning a weight value to each channel. FIS system is used to calculate each channel weight value considering three parameters: primary user's utilization, cognitive user's number, and channel capacity.

3.3.1 Modeling of Primary user's utilization

Primary user channel utilization is the fraction of time in which channel *i* is in on state, i.e., utilized by primary nodes. Channel utilization *u* is calculated by equation 3.1(M. H., A.C., Khalife, & S. Fdida, 2013) The most important requirement for CR networks is that CRs should not interfere with licensed PUs transmission. Therefore, the best channel is the one with low primary user's utilization rate, U_i.

$$U_i = \frac{E[\mathrm{T}^{i-on}]}{E[\mathrm{T}^{i-on}] + E[\mathrm{T}^{i-off}]} = \frac{\lambda_x}{\lambda_x + \lambda_y} \qquad (1)$$

Where

$E\left[\mathrm{T}^{i-on}\right] = \frac{1}{\lambda_x}$, $E\left[\mathrm{T}^{i-off}\right] = \frac{1}{\lambda_y}$. $\lambda_x, \lambda_x,$ are rate parameters for exponential distribution, and $E\left[\mathrm{T}^{i-on}\right]$, $E\left[\mathrm{T}^{i-off}\right]$ are the mean exponential distribution. The values of λx *and* λy can be easily measured by CR nodes by collecting the historical samples of channel state transitions. Values of λx *and* λy recorded in Khalife and Fdida, 2013 are used to calculate channel utilization as shown in Table 1.

Table 1: Wireless channel parameters

	Ch1	Ch2	Ch3	Ch4	Ch5	Ch6	Ch7	Ch8	Ch9	10
Λx	1.25	0.40	1	0.4	0.5	2	1	0.18	0.5	0.67
Λy	0.67	2	1	0.33	1	0.29	0.25	2	1.33	0.5
U_i	0.35	0.83	0.5	0.45	0.67	0.13	0.2	0.92	0.73	0.43

3.3.2 Cognitive user's number

Good channel selection strategy chooses the channel with lower number of CR neighbors using the channel. Lower number of CR reduces interference among CRs, which increases transmission rate, resource utilization, and throughput, and at the same time, it decreases packet loss ratio and packet delay. In order to determine the number of CR users, each CR node discovers their neighbors by using a common control channel (CCC) mechanism.

3.3.3 Model of Channel Capacity

Channel capacity indicates users' data rate per each HZ of the spectrum band used. The expected normalized capacity of a user *k* in spectrum band *i* is calculated using Equ. 2:

$$C_i(k) = E[C_i(k)] = \frac{\mathrm{T}^{i-off} \cdot y_i . C_i(k)}{\mathrm{T}^{i-off} + \tau} \qquad (2)$$

where *Ci(k)* represents spectrum capacity, *ci(k)* is the normalized channel capacity of spectrum band *i* in bits/sec/Hz, τ is the spectrum switching delay, γi is the spectrum sensing efficiency, and T^{i-off} represents the expected transmission time without switching in spectrum band.

3.4 Fuzzy Logic Inference System

The fuzzy inference system employs fuzzy logic concepts to perform tasks such as decision making. There are four basic steps in the operation of the fuzzy logic algorithms:

- Fuzzification system inputs (crisp numbers) are changed into fuzzy sets by applying a fuzzification function
- Rule evaluation stores IF-THEN rules written by a professional designer in the related field.
- Inference engine simulates the human reasoning process by making fuzzy inference on the inputs and IF-THEN rules.
- Defuzzification converts the fuzzy outputs obtained by the inference engine into a crisp value.

In the first module, each CR node senses the available channels using the spectrum sensing technique that is implemented in the physical layer. After that, the available channels pass to the second module that is implemented in media access controlled (MAC) layer. In the second module, the available spectrum channels are classified into four classes, (correct OFF, correct ON, FA, and MD) based on the *K*-means unsupervised learning technique. This classification helps the CR to select true idle channels in an intelligent way and to avoid the channels with sensing errors (MD and ON). This in turn leads to minimizing the spectrum sensing errors in the upper layer and subsequently enhances the spectrum usage level and reduces collision with PUs. The available channels (correct OFF and MD) pass to the spectrum selection module. In the third module, the channel with higher weight value is selected. This channel is associated with three parameters, PU utilization, channel capacity, and number of CRs on each channel, based on fuzzy based system.

Consequently, the proposed framework has a cross layer scheme. Each layer has distinct role. After the best channel is selected, the QoS parameters will be optimized in the fourth module. At the end, the CR makes a transmission using the selected channel and QoS parameters. The selection of the appropriate channels for transmission in the proposed ILFCS is based on the channels that have low primary radio node utilization, less congestion with CR users and higher capacity. Channel parameters are fed into the fuzzy inference system in order to compute the channel weight value. Finally, the channel with the highest weight value is selected for transmitting the packet and the remainder channels are stored in a descending order to be kept as a backup for the selected channels. In the following subsections, the operation of *K*-means learner and the fuzzy channel selector are explained in details. The contributions in this work focus on spectrum characterization and spectrum selection modules. In spectrum characterization module, K-means learning algorithm is proposed to handle the problem of sensing errors from the spectrum sensing technique. While in spectrum selection module, FIS is proposed to select the best channel.

4.0 RESULTS AND DISCUSSION

A performance comparison for ILFCS, best-fit channel selection (BFC), GA-based selection (GA), Intelligent Channel Selection Scheme a Self-Organized Map Followed by Simple Segregation (ICSSSS), and longest idle time channel selection (LITC) were evaluated with respect to different numbers of CR nodes, different number of channels, and different PU activity patterns.

The impact of the growth of CR users' traffic demand on each scheme is studied considering the mentioned performance metrics. The number of available channels at each CR users is set to 10. The behavior of PUs activities is not identical for all the available channels. It varies from channel to channel. The number of CR users in the network varies from 10 to 250. Simulation results show that the ILFCS achieves its minimum enhancement in the average interference ratio compared with ICSSSS when the numbers of CR nodes are 25 and 250. As it is shown in figure 3, the ratio is decreased by around 5% compared with ICSSSS.

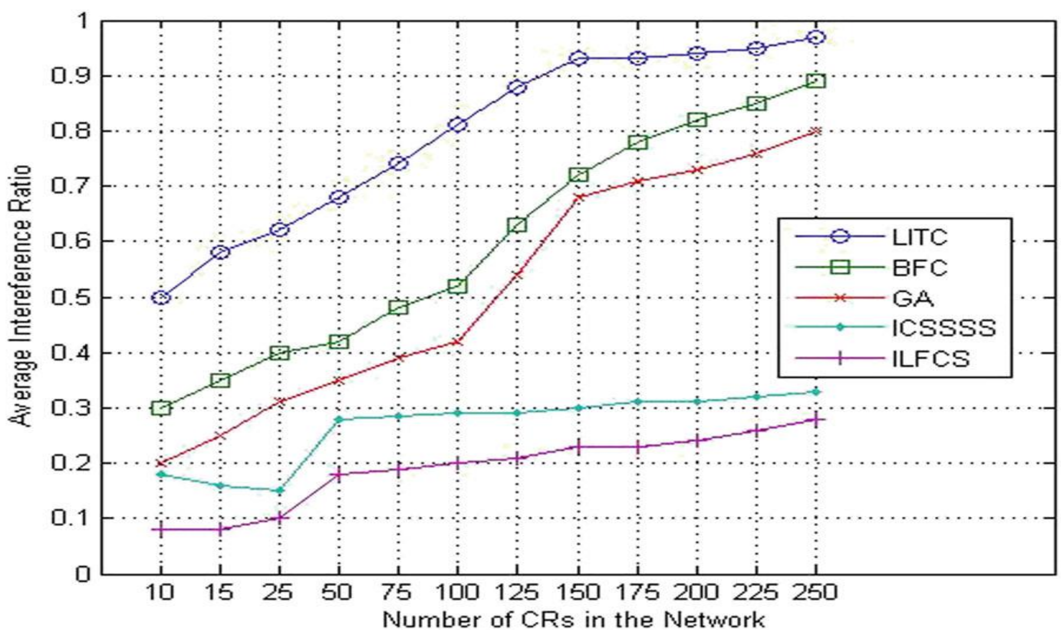

Figure 3: The Average Interference Ratio at Different Numbers of CR Nodes for the BFC, LITC, GA, ICSSSS, and the ILFCS.

ILFCS achieves the minimum average interference ratio compared with LITC when the numbers of CR nodes are 150 and 175 as the ratio is decreased by 70 %. Moreover, it is noticed that ILFCS outperforms LITC, GABFC, and ICSSSS where it reduces the average interference ratio by 60%, 40%, 32%, and 7% compared to LITC, GA, BFC, and ICSSSS respectively. The experimental results depicted in 4.1show that when the number of CRs increased, the ratio of interference is increased in all schemes. This is due to the increase of CRs' density of the network which increase the contention and interference ration between CRs. In addition, the inaccurate prediction of PUs traffic leads the CR user to select the wrong channel. Accordingly, PU disconnect the transmission of the CR. This increases the CR users channel switching rate. The ILFCS outperforms all related scheme because the prediction of PU is estimated in an intelligent way by removing the sensing errors from the list of available channel.

As shown in figure 4.2, with respect to average throughput, the ILFCS achieves its maximum enhancement compared with ICSSSS when number of CR nodes is 225.

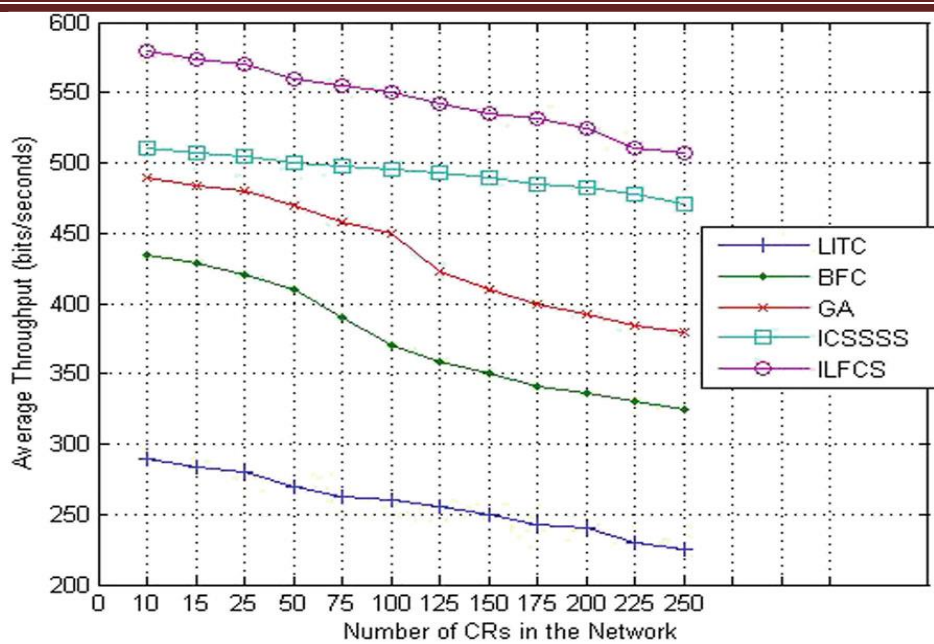

Figure 4: The Average Throughput at Different Numbers of CR Nodes for the BFC, LITC, GA, ICSSSS, and the ILFCS.

As shown in figure 4, the ratio is increased by around 5.3% compared with ICSSSS. Also ILFCS achieved its maximum average throughput compared with LITC when number of CR nodes is 75. The ratio is increased by 48.8% compared with LITC. It can be seen that ILFCS outperforms LITC, GA, BFC, and ICSSSS as the results showed that average throughput of ILFCS surpassed every other one.

The average throughput is more related to the ratio of the total packets received in the network and the ratio of interference. When the number of CRs successfully completed its transmission, this leads to the increase of the total number of successfully received packets. Consequently, the average throughput increases. As shown in figure 4.3, in all the schemes, when the number of CRs increased, the packet delivery ratio decreased.

This is because with increase in the density of CRs in the networks, contention between them are high and the ratio of interference increased though different from scheme to scheme. Again, the ILFCS out performs other scheme because the ratio of interference is small. This leads to the increase in the packet delivery ratio which in turn increases the average throughput over the network in specific time.

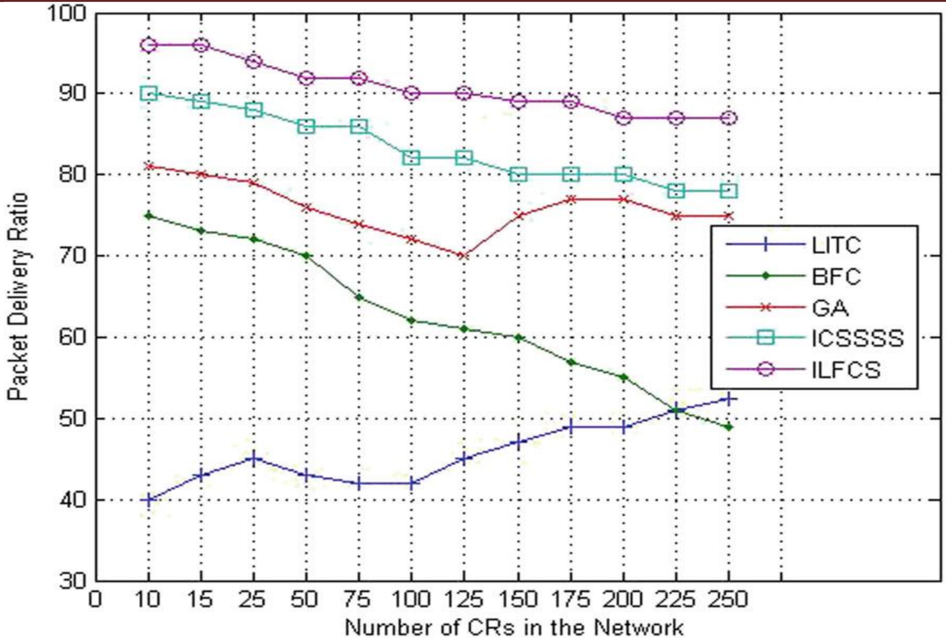

Figure 5: Packet Delivery Ratio at Different Numbers of CR Nodes for the BFC, LITC, GA, ICSSSS, and the ILFCS.

Figure 5 shows the packet delivery ratio at different numbers of CR nodes for the LITC, BFC, GA, ILFCS, and ICSSSS. It can be seen that ILFCS outperforms ILTC, BFC, GA, and ICSSSS by achieving maximum packet delivery ratio at different network densities by 45%, 28.3%,14.8%, and 7.5% respectively. For all scheme, when the number of CRs increased, the packet delivery ratio decreased. And with the increase in number of the CRs in the network the competition for the unoccupied channels becomes more compelling. Consequently, the average throughput per CR decreases in all schemes. Moreover, selecting the best channel in an intelligent process by using *K*-means and FIS techniques leads to decrease the interference between CRs-CRs and CRs-PUs. Hence, the packets sent over the ILFCS network will be transmitted successfully without any interrupt with Pus connections. Figure 10 illustrates the results of measuring the spectrum opportunity utilization at different numbers of CR nodes for the LITC, BFC, GA, ICSSSS, and ILFCS.

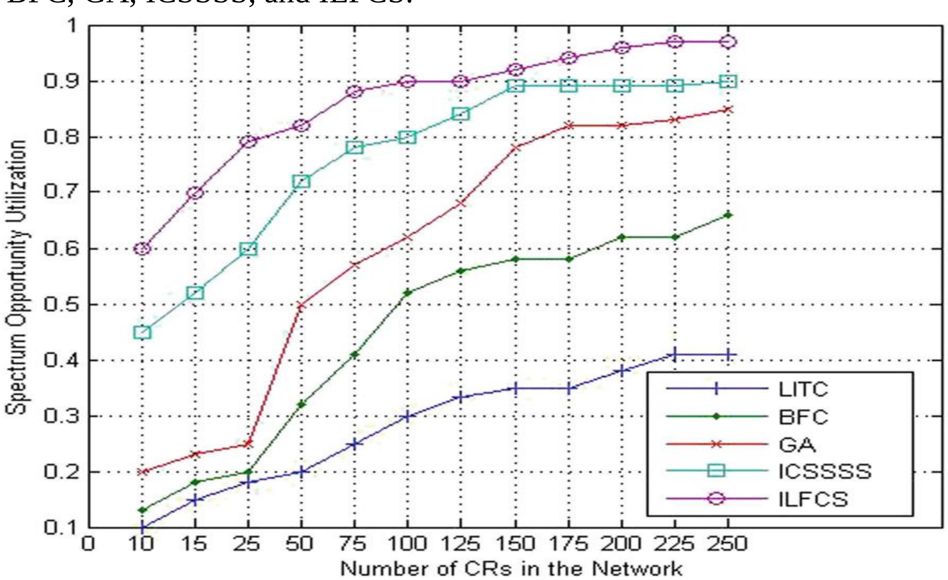

Figure 6: Spectrum Opportunity Utilization at Different Numbers of CR Nodes for the BFC, LITC, GA, ICSSSS, and the ILFCS.

In figure 6, ILFCS achieved maximum enhancement in the spectrum opportunity utilization compared with ICSSSS LITC, BFC, GA, and ICSSSS. ILFCS outperforms other schemes because of the assistance of the *K*-means and FIS in selecting the channel the channel not being utilized by PU per time. Finally, figure 7 illustrates the results of measuring the end-to-end delay at different numbers of CR nodes for the LITC, BFC, GA, ICSSSS, and ILFCS. ILFCS achieved its maximum enhancement in end-to-end delay compared with LITC, BFC, GA, and ICSSSS. It is noticed that ILFCS outperforms LITC, BFC and GA and ICSSSS. The result shows that the end-to-end delay is decreased by 88.7%, 84.4%, 77.8%, and28.3% compared to LITC, BFC, GA, and ICSSSS respectively.

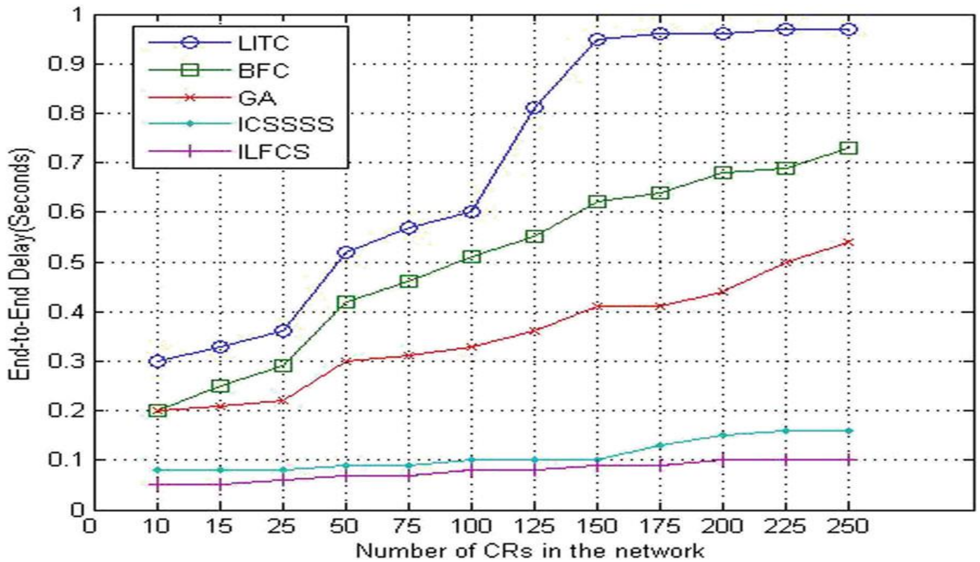

Figure 7: End-To End Delay at Different Numbers of CR Nodes for the BFC, LITC, GA, ICSSSS and the ILFCS.

Actually, ignored sensing error in selecting the best channel leads to a critical decrease in the interference ratio. Therefore, the hopping rate for CR from channel to another channel is high. So the switching time for discovering available channel takes a lot time which leads to increasing the average end-to-end delay over the network. In ILFCS, sensing errors are handled by *K*-means algorithm to remove ON state channels and MD channels. This leads to selecting the best channel in an intelligent way. Consequently, CRs are allowed to transmit their packets without any interference with PUs or switching from channel to other which in turn reduces the average delay over the entire network**.**

It is clear that the intelligent learning fuzzy-based channel selection (ILFCS) developed in this work outperforms best-fit channel selection (BFC), GA-based selection (GA), Intelligent Channel Selection Scheme a Self-Organized Map Followed by Simple Segregation (ICSSSS), and longest idle time channel selection (LITC) in terms spectrum opportunity utilization (SOU), average interference ratio (AIR), average throughput (AT), packet delivery ratio (PDR), and end-to-end delay (EED).

CONCLUSION

Cognitive Radios are allowed to transmit their packets without any interference with PUs or switching from channel to other which in turn reduces the average delay over the entire network. Furthermore, it can be concluded that ILFCS performance is enhanced even with increase of the number of channels. ILFCS achieved maximum enhancement in the spectrum opportunity utilization compared with ICSSSS LITC, BFC, GA, and ICSSSS. ILFCS outperforms other schemes because of the assistance of the *K*-means and FIS in selecting the channel the channel not being utilized by PU per time. Finally, figure 4.5illustrates the results of measuring the end-to-end delay at different numbers of CR nodes for the LITC, BFC, GA, ICSSSS, and ILFCS. ILFCS achieved its maximum enhancement in end-to-end delay compared with LITC, BFC, GA, and ICSSSS. It is noticed that ILFCS out performs LITC, BFC and GA and ICSSSS. The result shows that the end-to-end delay is decreased by 88.7%, 84.4%, 77.8%, and28.3% compared to LITC, BFC, GA, and ICSSSS respectively. In ILFCS scheme developed in this work, the sensing errors were done by K-means algorithm which was validated via simulations. It is recommended that the concept presented in this work be further validated via a physical testbed.

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