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Fuzzy genetic based dynamic spectrum allocation approach for cognitive radio sensor networks

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Abstract: Cognitive radio sensor network (CRSN) is known as a distributed network of wireless cognitive radio sensor nodes. Such a system senses an event signal and ensures collaborative dynamic communication processes over the spectrum bands. Here the concept of dynamic spectrum access defines the method of reaching progressively to the unused range of spectrum band. As among the essential CRSN user types, the primary user (PU) has the license to access the spectrum band. On the other hand, the secondary user (SU) tries to access the unused spectrum efficiently, by not disturbing the PU. Considering that issue, this study introduces a fuzzy genetic based dynamic spectrum allocation (FGDSA) system for deciding spectrum allocation in cognitive radio sensor networks. In detail, the primary objective of the FGDSA system is to increase channel use without causing too much interference to the PU. In order to achieve that, some parameters such as signal interference noise ratio (SINR), bit error rate (BER), available channel bandwidth, SU transmission power, and the SU data rate are used as input variables for the fuzzy based inference mechanism taking place in the FGDSA. After development of the system, a performance analysis was done by comparing some metrics such as channel utilization, signal noise interference ratio, and the channel access delay for fuzzy based inference and the fuzzy genetic based inference that are both performing spectrum allocation. It was observed that the hybrid system of FGDSA outperforms fuzzy system by 2% in channel utilization, by also ensuring 16% less SINR, and 41% less channel access delay. The FGDSA was compared with also some existing spectrum allocation techniques such as edge coloring heuristic (ECH) and clique heuristic algorithm (CHA). It was seen that the FGDSA outperforms both ECH and CHA in average channel utilization, with the rates of 6% and 8%, respectively.

Key words: Wireless sensor network, fuzzy logic, genetic algorithm, dynamic spectrum access, cognitive radio sensor

1. Introduction

Thanks to innovative developments causing removal of wires from communication environments, wireless communication technologies and wireless devices have become popular in ensuring practical applications. At this

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point, wireless sensor networks have been widely used for designing and developing advanced communication applications [1–3]. It can be seen that many different wireless sensor networks operate in the context of freely available industrial, scientific, or medical wavebands such as 2.4 GHz band. Such bands are generally used in alternative wireless communication technologies like WiFi, Bluetooth, cordless phones, RFID, or microwave ovens. Considering the event-driven nature, several WSN nodes should transmit the event signal information simultaneously, when an incident occurs. In this case, the interference or collision probability will increase, by considering the event occurrence probability. For solving that problem, a cognitive radio (CR) enabling higher spectrum efficiency via dynamic spectrum access (DSA) can be exploited by wireless sensor networks (WSN) [4]. WSN structures comprised of sensor nodes with CR are briefly called as cognitive radio sensor networks [5, 6]. Sensor nodes with cognitive capability can sense event signals and dynamically perform communication tasks through available spectrum bands [7]. Here requirements of the associated communication application are satisfied in a multihop manner [8].

In the related communication systems, it is also possible to encounter with different issues. It is remarkable that majority of the time left for the radio spectrum remains unused and it is also difficult to sense that spectrum [9, 10]. Furthermore, the allocated spectrum may be used improperly, as it differs according to frequency, time, and geographical locations. At this point, alternative communication techniques that are based on CR have been introduced in order to provide an opportunistic spectrum access approach, which can overcome the spectrum scarcity and some other issues. A CR sensor network (CRSN) allows efficient usage for the radio spectrum and ensures highly reliable communication for users. That is done accordingly by sensing event signals and achieving collaborative communication processes over the spectrum bands. In this sense, the concept of DSA defines the method of reaching progressively to the unused range of spectrum band. As one of the CRSN user types, the primary user (PU) has the license to access the spectrum band. However, the secondary user (SU) should try to access the unused spectrum efficiently, by not disturbing the PU. That issue of spectrum allocation may be adjusted effectively by using additional algorithms derived from especially artificial intelligence.

Moving from the explanations so far, this study introduces a fuzzy genetic based dynamic spectrum allocation (FGDSA) system for deciding spectrum allocation within cognitive radio sensor networks, thanks to inference abilities of fuzzy logic, and fuzzy genetic algorithm. The system briefly aims to increase channel use without causing too much interference to the PU. That is done by feeding the fuzzy based inference mechanism with some parameters such as signal interference noise ratio (SINR), bit error rate (BER), available channel bandwidth, SU transmission power, and the SU data rate. It is important that many dynamic solution approaches provide maximum spectrum allocation with reduced hand-off. In this study, the introduced FGDSA system allows using the Mamdani fuzzy inference method for spectrum allocation and also hand-off to another primary spectrum. As the key component in the system, genetic algorithm is used accordingly for rule optimization. Considering the developed FGDSA system, this study gives information about technical design of the hybrid solution approach and focuses on some evaluation works, which were done for understanding better about success of the provided solution mechanism.

1.1. Main contributions

Main contributions of the study can be expressed as follows:

i) To provide an in-depth analysis of the literature including various methods, techniques, and protocols as proposed by researchers working on spectrum allocation in cognitive radio sensor networks.

ii) To design and develop a hybrid fuzzy genetic based approach as an alternative solution for spectrum allocation in cognitive radio sensor networks.
iii) To prove the proposed approach via simulation based extensive testing, by measuring the channel utilization, SINR, and channel access delay, and finally comparing the findings with existing techniques.
iv) As the fitness function used in this study, weighted sum model (WSM) and multicriteria decision making (MCDM) is a method employing an alternative decision with qualitative and quantitative results in the context of compact solutions. That can be used for numerous problems encountered in industries and our life, in order to get some alternative sets of decision. WSM MCDM is known as a generic method but the FGDSA system introduced in this study has been more specific for spectrum allocation in cognitive radio networks. The parameters used here are selected for enhancing the channel utilization, which is a novelty provided by the solution approach in this study.

The rest of the present study is organized as follows: Section 2 briefly discusses the related work, in order to better understand what was previously done regarding our research topic. Next, Section 3 explains details of the FGDSA system. Here it was aimed to inform the readers about the technical background of the introduced system. Section 4 is devoted to evaluation of some studies to better understand the success of the introduced solution approach. Finally, the last section presents conclusions and future work plans.

2. Related work

In this section, a general literature review regarding the research studies for spectrum management of cognitive radio sensor networks was conducted. The authors think that it is important for the readers to better understand the past state of the scientific literature focusing on the same/similar topic(s).

In [10], Hernandez et al. introduced a method for channel switching decision. The solution in this study included a combination of energy consumption in a channel sensing, and also switching channel detection probability with primary user emulation (PUE) protection. On the other hand, the research work in [11] followed a similar decision making approach, which is briefly based on AND/OR rule formations. The research conducted in [12] focused on maximum spectrum utilization and also energy efficiency, by considering some aspects of the CRSN. In [13], the authors provided a user satisfaction-aware approach for spectrum management, in order to achieve dynamic LSA management in 5G networks. The solution provided in this study aimed to balance both satisfaction of the connected user and the resource utilization in the context of the mobile network operator. In [14], a pure proactive hand-off strategy, which uses a control channel list, was introduced. In the proactive spectrum sensing, the SU uses proactive hand-off action. Thanks to this approach, it has been possible to predict the PU arrival so that the SU can leave the channel in a timely manner. In [15], Zhu et al. introduced a game-theoretic power control mechanism with hidden Markov model. That solution can be used for cognitive wireless sensor networks with imperfect information. In [16], a distributed spectrum-aware clustering (DSAC) approach was introduced to be used in CRSN structures. The approach in this study provides a self-organized clustering in an energy-efficient way. Considering CR, Kaniezhil et al. provided a fuzzy logic oriented solution for ensuring less interference to the PU within heterogeneous wireless networks [17]. In [18], Qiao et al. proposed a sleep scheduling approach associated with constantly changing spectrum states, in order to make some adjustments within CSRN structures. Cavdar et al. developed an instant overbooking framework, which is based on maximizing spectrum utilization and total net revenue. That solution aimed to increase spectrum utilization and decrease the total net revenue, thanks to increases in activities by users [7]. In another study, Felice et al. developed a spectrum management method by using a reinforcement learning based solution mechanism [19].

In [20], uncertain traffic information was employed accordingly for spectrum monitoring-management. Tekanyi et al. tried to optimize spectrum sensing time in the context of cooperative CR environment [21]. Khodadadi et al. focused on performance analysis of secondary users in CR network, thanks to a dynamic spectrum allocation [22]. As another perspective over the performance, Cicioglu came with an alternative MAC protocol and evaluated its overall performance [23]. In their study, Si et al. worked on the spectrum management issue regarding proactive video caching in information-centric CR networks [24]. In [25], Thakur et al. worked on spectrum sharing in CR systems, by considering power constraints. For effective spectrum management in CR networks regarding proximity service, Nandakumar et al. proposed an improved adaptive energy detection technique [26]. In their recent study, Sadreddini and Cavdar performed a performance analysis of dynamic spectrum management in CR network environments [27]. In addition to the expressed studies, readers are also referred to [28] for some more alternative studies and a remarkable view on the topic of spectrum management in CR networks.

The existing solution approaches have some disadvantages due to the following reasons: The network lifetime decreases with the increase of the number of SUs. Additionally, spectrum utilization is not done properly. Furthermore, clustering results seem weak in terms of energy consumption because of more active PU nodes and more spectrum constraints. For trying to eliminate such issues, a new hybrid system called as fuzzy genetic based dynamic spectrum allocation in cognitive radio sensor networks (FGDSA) was designed and developed in this study. The following sections provide more information regarding the developed FGDSA system.

3. Proposed FGDSA approach

This section explains details of the introduced hybrid FGDSA system along with providing technical information about the formed solution approach. In the next paragraphs, architecture of the FGDSA system and the mathematical model of the inference mechanism were explained respectively.

3.1. Architecture of the FGDSA

As it was indicated before, the FGDSA system is based on a hybrid formation. In this context, general architecture of the FGDSA is represented in Figure 1.

As it can be seen from the figure, the FGDSA includes some modules such as node deployment, cluster formation, fuzzy based spectrum decision, genetic algorithm based rule optimization, and fuzzy genetic based spectrum decision. It is important that the radio frequency environment should be sensed by the SU, in order to find the spectrum holes. In this context, the decision process for good spectrum allocation is conducted via fuzzy logic model with the Mamdani inference method [29, 30]. Additionally, a rule optimization is done by the genetic algorithm [31, 32]. Rather than using more complicated solutions from the literature, the proposed approach in this study employs an easy but effective enough algorithmic combination, thanks to two long-time successful techniques.

More details regarding the related modules in the FGDSA system can be explained briefly as follows:

3.1.1. Node deployment

Sensor nodes with cognitive capability are deployed in the radio frequency environment, in order to operate as a SU in the radio frequency environment. Here the related sensor nodes are assumed to be static sensors.

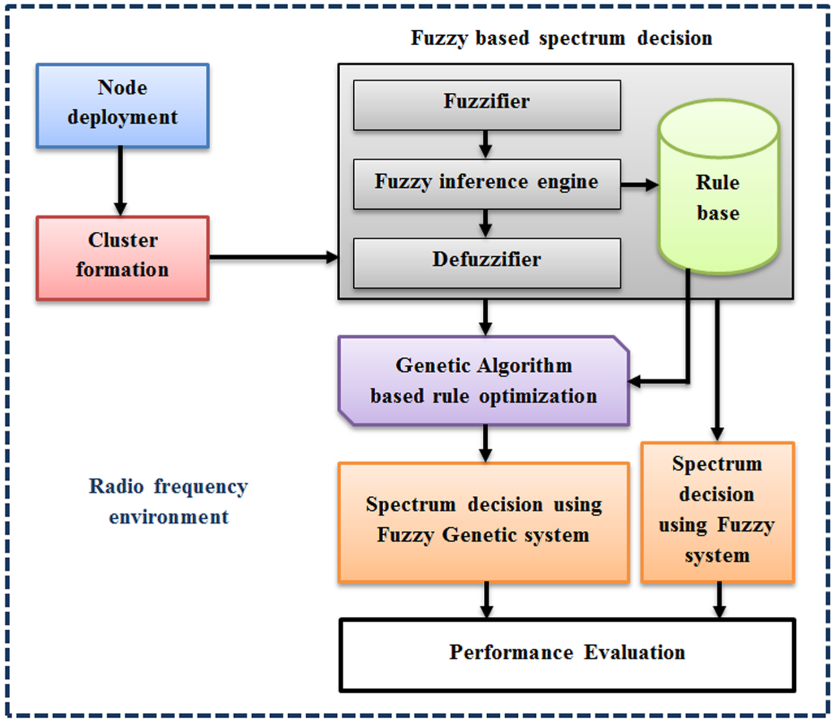

Figure 1. Proposed architecture of the FGDSA.

3.1.2. Cluster topology formation

A dynamic spectrum oriented clustering approach is used for achieving a rapid formation of spectrum in a dynamic environment with constraints. At this point, the node having the highest residual energy will be elected as the cluster head. After that, the cluster head will acquire the sensing parameters of all other cluster members in the group. Finally, it will obtain the aggregated information for supporting the inference process in the FGDSA system. The cluster topology formation here allows sharing the spectrum efficiently and ensuring better use of the available spectrum.

3.1.3. Fuzzy based spectrum inferencing

Fuzzy based spectrum inference is actually a decision making process done for the spectrum. That mechanism employs a Mamdani inference based fuzzy logic model for making channel switch and spectrum allocation. In a typical Mamdani method, each input for the fuzzy logic model is fuzzified (which is done with some mathematical phases) first. Then in the end, the obtained output(s) are defuzzified with alternative conversion approaches. In this study, the input parameters have been SINR, BER, available channel bandwidth (belonging to the PU), transmission power, and data rate (both belonging to the SU). The fuzzy inference mechanism also uses a rule base in order to make decision regarding the dynamic spectrum access. The fuzzy rule base (table) of the FGDSA system is represented in Table 1.

3.1.4. Fuzzy rules in the FGDSA system

Fuzzy rules in the FGDSA system were designed according to the widely-known fuzzy rule formation: 'If Antecedent1 AND Antecedent2 AND Antecedent3 AND... then Consequence.' Considering the chosen parameters, the rules and their linguistic variables have been as follows:

(i) Antecedent1 refers to the signal interference noise ratio, as represented by three linguistic variables: low, medium, and high.

(ii) Antecedent2 refers to the BER, as represented by three linguistic variables: low, medium, and high.

(iii) Antecedent3 refers to the available bandwidth, as represented by three linguistic variables: low, medium, and high.

(iv) Antecedent4 refers to the SU power, as represented by three linguistic variables: low, medium, and high.

(v) Antecedent5 refers to the SU data rate, as represented by three linguistic variables: low, medium, and high.

A total of five antecedents (including three linguistic variables separately) correspond to $3 \times 3 \times 3 \times 3 \times 3$ results (which means a total of 243 rules), and the system is able to produce one consequence inference-decision (for switching) such as YES, Probably Yes(PYES), Probably No(PNO), NO, UNCERTAIN

3.1.5. Genetic algorithm based rule optimization

The fuzzy rules in the FGDSA system are optimized by using a genetic algorithm. In this way, it was aimed to ensure a group of optimized rules for better results at the end. In this sense, the whole fuzzy rules are considered as input(s) to the genetic algorithm. In order to get the optimized rule(s) as output, the employed genetic algorithm follows the algorithmic steps such as selection, fitness evaluation, mutation, and crossover. Based on the general solution provided in this study, the genetic algorithm steps regarding the rule optimization are as follows:

Genetic algorithm for rule optimization of the FGDSA

Input(s): Set of rules

Output(s): Optimized rule

Step 1: Generate initial population of the rules, by considering channel parameters such as SINR, BER and available bandwidth, SU power, SU data rate.

Step 2: Evaluate the fitness of fuzzy rules by using the fitness function of the FGDSA.

Step 3: By evaluating the obtained fitness values, discard weak rules.

Step 4: Choose stronger rules for crossover and mutation processes.

Step 5: In order to get new rules, apply crossover and mutation processes over the chosen rules in Step 4.

Step 6: Go to Step 2, and repeat the above steps until optimized rule(s) are obtained.

3.1.6. Fuzzy genetic spectrum decision

The decision support provided by the FGDSA system uses a hybrid fuzzy genetic algorithm for making decision about dynamic channel allocation. The rule base used in this module employs the optimized rules so that the decision made at the final will be optimal decision for spectrum allocation.

3.2. Mathematical modeling

Mathematical modeling of the FGDSA includes some equations and fuzzy membership functions for calculating the input parameters such as signal interference and noise ratio, bit error rate, available channel bandwidth

Table 1. Fuzzy rule base (table) of the FGDSA system.

Rule No	Antecedent 1 (SINR)	Antecedent 2 (BER)	Antecedent 3 (Available bandwidth)	Antecedent 4 (SU power)	Antecedent 5 (SU data rate)	Consequence
1	Low	Low	Low	High	Medium	Uncertain
2	Low	Medium	Medium	High	Medium	No
3	Low	High	High	Medium	High	Pno
4	Low	Low	Medium	High	High	No
5	Low	Medium	High	High	High	No
6	Low	High	Low	Medium	Medium	Uncertain
7	Low	Medium	Low	Medium	Low	Pyes
8	Low	High	Medium	High	Low	Yes
9	Low	Low	High	High	High	No
10	Medium	Low	Low	High	Low	Pno
11	Medium	Medium	Medium	High	High	Uncertain
12	Medium	High	High	Low	High	Yes
13	Medium	Low	Medium	Medium	Medium	Pyes
14	Medium	Medium	High	Medium	Medium	Pyes
15	Medium	High	Low	High	Low	Yes
16	Medium	Medium	Low	High	Medium	Yes
17	Medium	High	Medium	High	High	Yes
18	Medium	Low	High	Medium	High	Pno
19	High	Low	Low	Low	Low	Yes
20	High	Medium	Medium	Low	Low	Yes
21	High	High	High	Low	Low	Yes
22	High	Low	Medium	Low	Low	Yes
23	High	Medium	High	Low	Low	Yes
24	High	High	Low	Low	Low	Yes
25	High	Medium	Low	Low	Low	Yes
26	High	High	Medium	Low	Medium	Yes
27	High	Low	High	Low	Low	Yes

(belonging to the PU), transmission power, and data rate (both belonging to the SU). The following paragraphs further explain the model:

3.2.1. Signal interference noise ratio of the PU

Signal interference noise ratio of the PU (S_{PU}) is given as:

$$S_{PU} = \frac{P}{N + \sum I_d}, \tag{1}$$

where P represents the transmit power, I represents the interference, k represents the Boltzmann constant, T represents the temperature, and B represents the bandwidth. In the FGDSA system, spectrum decision is made by sensing of n number sensor nodes (interacting with the channel). Because of that, it is necessary to calculate the average SINR of the PU, by using the following equation:

$$S_{PU(avg)} = \frac{\sum_{i=1}^{n} S_{PU}}{n}, \tag{2}$$

where $S_{PU(AVG)}$ represents the average SINR of the PU sensed by all SUs, and n represents the number of the secondary sensors (sensing the channel). The SINR of the PU uses a triangular membership function. That membership function is defined as follows:

$$\mu(S_{PU(avg)} = \begin{cases} 0 & S_{PU(avg)} \leq 1 \\ \frac{S_{PU(avg)}-b}{b-a} & a < S_{PU(avg)} \leq b \\ \frac{S_{PU(avg)}-b}{c-b} & b < S_{PU(avg)} < c \\ \\ 0 & S_{PU(avg)} \geq c \end{cases} \tag{3}$$

where $\mu(S_{PU(avg)})$ represents the membership value for the bit error rate of the PU. Further, a and c represents the lower bound of membership value, and b represents the upper bound membership value.

Figure 2 shows the membership function regarding the SINR of the PU (S_{PU}) in the context of the FGDSA system. Here the value ranges between 0 and 12. The low-range value is between 0 and 4, the medium-range value is between 3 and 9, and the high-range value is between 8 and 12, respectively. The channel with a low SINR range will be given more priority, in order to avoid interference with the PU.

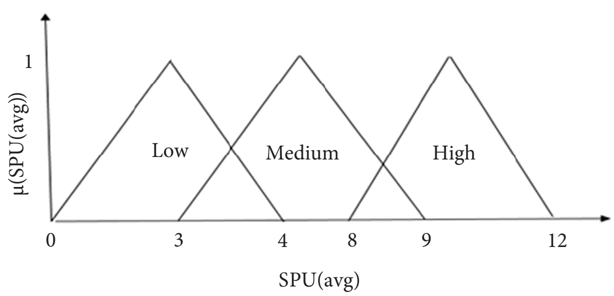

Figure 2. Membership function for the SINR of the PU.

3.2.2. Bit error rate of the PU

Bit error rate of the PU (B_{PU}) is as follows:

$$B_{PU} = \frac{1}{2} erfc\left(\sqrt{\frac{E_b}{N_0}}\right), \tag{4}$$

where $\frac{E_b}{N_0}$ represents the energy per bit to noise power, and erfc( ) represents the Gaussian error function.

In the FGDSA, spectrum decision will be made by sensing of n number sensor nodes (interacting with the channel). Therefore, it is necessary to calculate the average BER of the PU, by using the following equation:

$$B_{PU(avg)} = \frac{\sum_{i=1}^{n} B_{PU}}{n}, \tag{5}$$

where $B_{PU(avg)}$ represents the average BER of the PU sensed by all SUs, n represents the number of secondary sensors that senses the channel. BER of the PU uses a triangular membership function. The membership function is as follows:

$$\mu(B_{PU(avg)}) = \begin{cases} 0 & B_{PU(avg)} \leq a \\ \frac{B_{PU(avg)}-b}{b-a} & a < B_{PU(avg)} \leq b \\ \frac{B_{PU(avg)}-b}{c-b} & b < B_{PU(avg)} \ < c \ , \\ \\ 0 & B_{PU(avg)} \geq c \end{cases} \tag{6}$$

where $\mu(B_{PU(avg)})$ represents the membership value of bit error rate of the PU, a and c represent the lower bound of the membership value, and b represents the upper bound membership value.

In Figure 3, membership function for the BER of the PU (B_{PU}) in the context of the FGDSA system is shown. In the membership function, the value ranges between 10^{-6} and 10^{-1}. The low-range value is between 10^{-6} and 10^{-4}, the medium-range value is between 10^{-5} and 10^{-2}, and the high-range value is between 10^{-3} and 10^{-1}. The channel with low (B_{PU}) range will be given more priority, in order to avoid interference with the PU.

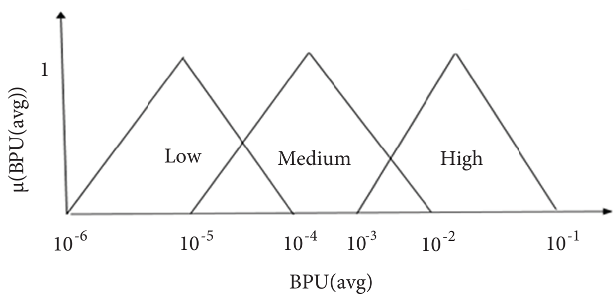

Figure 3. Membership function for the BER of the PU.

3.2.3. Available channel bandwidth of the PU

The available channel bandwidth of the PU (C_{PU}) is given as:

$$C_{PU} = B\log_2(1 + \frac{S}{N}), \tag{7}$$

where B represents the bandwidth of the channel in hertz, S represents received average signal power over the bandwidth.

In the FGDSA system, spectrum decision will be made by sensing of n number sensor nodes (interacting with the channel) so that the following equation should be used for calculating the average available channel bandwidth of the PU:

$$C_{PU(avg)} = \frac{\sum_{i=1}^{n} C_{PU}}{n}, \tag{8}$$

where $C_{PU(avg)}$ represents the available average channel bandwidth of the PU sensed by all SUs, n represents the number of secondary sensors that senses the channel.

The available channel bandwidth of the PU uses the L membership function. The membership function is as follows:

$$\mu(C_{PU(avg)}) = \begin{cases} 0 & C_{PU(avg)} < a \\ \frac{C_{PU(avg)}-b}{b-a} & a \leq C_{PU(avg)} \leq b \\ 1 & C_{PU(avg)} > b \end{cases}, \tag{9}$$

where $\mu(C_{PU(avg)})$ represents the membership value for the available channel bandwidth of the PU, a represents the lower bound of the membership value, and b represents the upper bound membership value. Figure 4 shows the membership function for the available channel bandwidth of the PU. As it can be seen, the value ranges between 0 and 15. The low-range value is between 0 and 5, the medium-range value is between 4 and 10, and the high-range value is between 9 and 15.

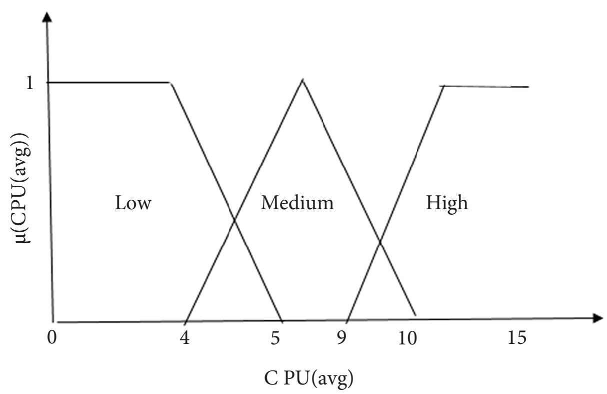

Figure 4. Membership function for the available channel bandwidth of the PU.

3.2.4. SU transmission power

The SU transmission power (P_{SU}) is calculated as:

$$\mathbb{P}_{SU} = G_t \times \; G_r(\frac{\lambda}{R})^2, \tag{10}$$

where $(G_t \times \; G_r)$ represents the gain of antenna, R represents the radius, λ represents the wavelength. The SU transmission power uses the L membership function. That membership function is defined as:

$$\mu(P_{SU}) = \begin{cases} 0 & P_{SU} < a \\ \frac{P_{SU}-b}{b-a} & a \leq P_{SU} \leq b \\ 1 & P_{SU} > b \end{cases}, \tag{11}$$

where $\mu(P_{SU})$ represents the membership value for the SU transmission power, a represents the lower bound of the membership value, and b represents the upper bound membership value.

The membership function for the SU transmission power is shown in Figure 5. As it can be seen from the figure, the value ranges between 0 and 100. The low-range value is between 0 and 40, the medium-range value is between 30 and 80, and the high-range value is between 70 and 100.

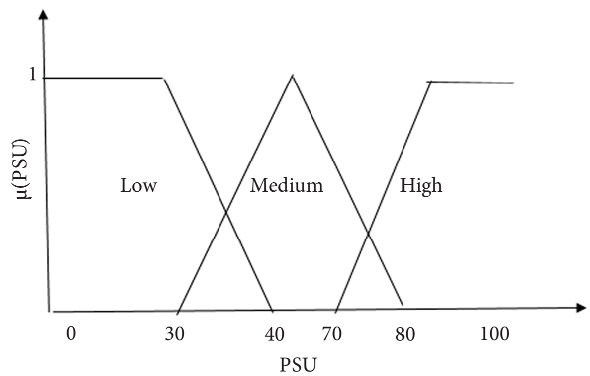

Figure 5. Membership function for the SU transmission power.

3.2.5. SU data rate

The SU data rate is given as:

$$D_{SU} = \frac{d_r - d_a}{d_r}, \tag{12}$$

where d_r represents the desired data rate, d_a represents the available data rate.

The date rate of the SU (D_{SU}) uses a triangular membership function. The membership function is as follows:

$$\mu(D_{SU}) = \begin{cases} 0 & D_{SU} \leq a \\ \frac{D_{SU}-b}{b-a} & a < D_{SU} \leq b \\ \frac{D_{SU}-b}{c-b} & b < D_{SU} \ < c \\ 0 & D_{SU} \geq c \end{cases}, \tag{13}$$

where $\mu(D_{SU})$ represents the membership value for the SU transmission power, a and c represent the lower bound of the membership value, and b represents the upper bound membership value.

Figure 6 shows the membership function for the SU data rate. In the membership function, the value ranges between 0 and 40. The low-range value is between 0 and 15, the medium-range value is between 13 and 28, and the high-range value is between 27 and 40.

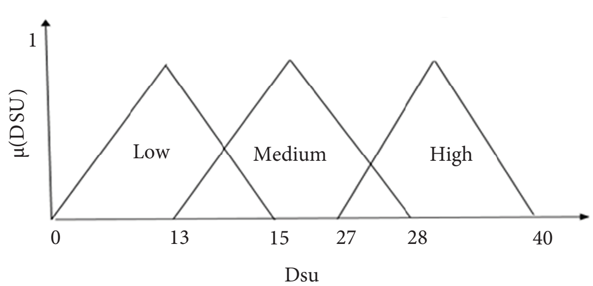

Figure 6. Membership function for the SU data rate.

3.2.6. Defuzzification in the FGDSA

Defuzzification is the process of converting fuzzy value(s) into crisp value(s). That is done by using several methods. In this study, the weighted average method was used for the defuzzification phase. The weighted average value is calculated as:

$$\mathbb{Z}^* = \frac{\sum_{i=1}^{n} \mu_{Z_i} \times Z_i}{\sum_{i=1}^{n} \times \mu_{Z_i}}, \tag{14}$$

where $\mu(Z_i)$ represents the membership value of the input parameters. Here $i=5$ because FGDSA employs a total of 5 input parameters.

3.2.7. Fitness function of the FGDSA

The fitness function employed in the FGDSA system is as follows (considering weighted input parameters of SINR, bit error rate of the PU, available bandwidth, P_{SU}, and D_{SU} respectively):

$$F(x) = W_1.S_{PU} + W_2.B_{PU} + W_3.C_{PU} + W_4.P_{SU} + W_5.D_{SU}. \tag{15}$$

As WSM has been a widely-used approach for MCDM, the decision making of the FGDSA was modeled with fitness function based on WSM. In detail, each of W coefficient is an importance weight for the corresponding parameter and all these weights are normalized since the sum of them should be equal to 1 [33, 34]. The approach here is a novelty of this study, as it was mentioned in also early paragraphs of the content.

4. Evaluation of the FGDSA system

After developing the FGDSA system, a general performance evaluation was made by comparing various parameters of both fuzzy based dynamic spectrum allocation and fuzzy genetic based dynamic spectrum allocation.

For the evaluation, a network with the size of 100×100 m^2 with randomly deployed CR sensor nodes was considered. In the network, the nodes were considered to be static. Additionally, the following conditions were assumed for the simulation of the FGDSA system:

(i) The cognitive radio sensor nodes are deployed randomly in a remote unattended environment.

(ii) The deployment area assumed to contain two primary licensed users (PUs).

The chosen network parameters for the performed simulations are shown in Table 2. The simulations are implemented in the OMNET ++ simulator.

4.1. Average channel utilization efficiency of the FGDSA

Spectrum utilization efficiency can be defined as the ratio of the spectrum band to be used by the cognitive radio and the available band. It is calculated as follows:

$$Channel\ utilization = \left(\frac{BW_{SU}}{BW_c} \times 100 \right), \tag{16}$$

where BW_{su} represents the spectrum band to be used by the unlicensed user, and BW_c represents the available band.

Average channel utilization graph is shown in Figure 7. It can be observed from the graph that the average channel utilization of the FGDSA system was obtained as 2%. That is because of the optimized rule determined by the genetic algorithm. It was also found that the proposed FGDSA technique outperforms the

Table 2. Simulation parameters of the FGDSA.

Network parameters	Values set
Number of sensor nodes	10, 20, 30, 40, 50
Channel Type	Noisy (Thermal noise)
Number of channel	3
Node type	Cognitive
Node mobility	Static
Sensor field	$100 \times 100\ m^2$
Data rate	1 Mbps
Bandwidth	2 MHz
Initial energy	0.5J
Receiver frequency	2.4 GHz
Transmitter frequency	1.8 GHz
Transmission energy per bit	50 nJ/bit
Reception energy per bit	50 nJ/bit
Packet length of the SU	10 Kb

existing edge coloring heuristic (ECH) technique by 6%, and the clique heuristic algorithm (CHA) technique by 8%. That is because the FGDSA system takes input parameters based on the dynamic spectrum and makes the decision according to inference by both fuzzy logic and the genetic algorithm.

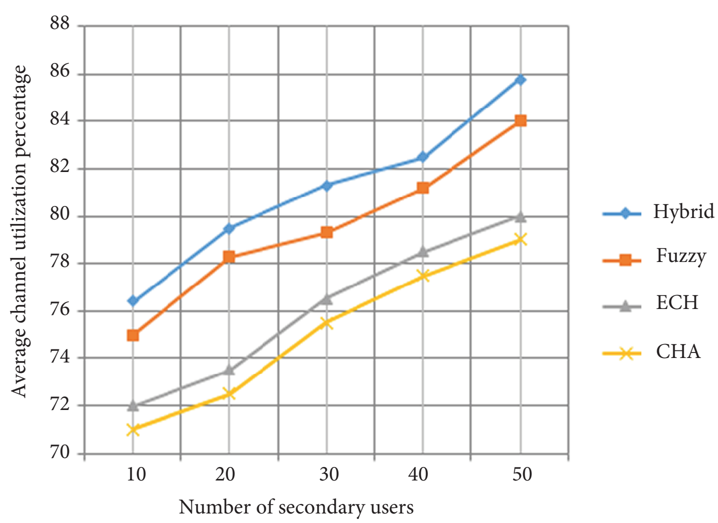

Figure 7. Average channel utilization efficiency of the FGDA.

4.2. Average SINR analysis of the FGDSA

The SINR is obtained by using the power of a certain signal of interest, which is sum of the interference power (from all other interfering signals) and the power of some background noise. It is calculated as follows:

$$SINR = SNR - 20 \times log(y + 1), \quad (17)$$

where SINR represents the signal to noise ratio caused by the primary node, and Y represents the interference to noise ratio caused by the cognitive radio.

Figure 8 represents the average SINR of the FGDSA system. It can be seen from the figure that the average SINR value of the fuzzy based system is 16%, which is higher than the value by fuzzy genetic based decision system. The decision made by the fuzzy genetic system is more optimized than the fuzzy system because the hybrid system formation evaluates only optimized rule(s).

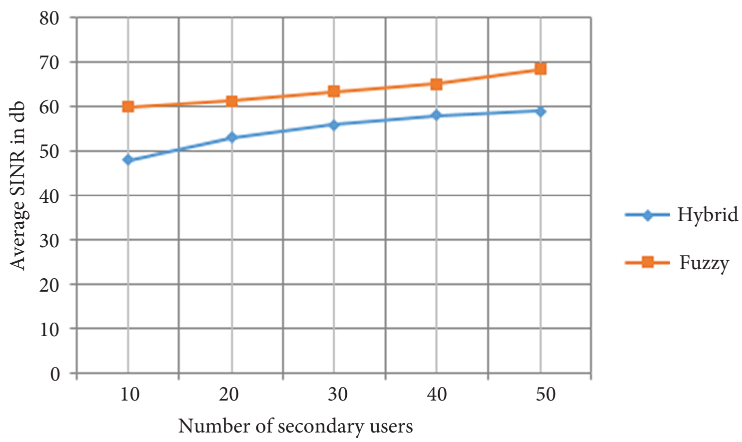

Figure 8. Average SINR analysis of the FGDSA.

4.3. Average channel access delay analysis of the FGDSA

The channel access delay is calculated by considering the estimation of an average time interval appeared between consecutive, successful channel access attempts, as done by a given node (which sends packet). The channel access delay is calculated as:

$$Channel\ access\ delay = E(X) \times \tau, \tag{18}$$

where E(X) defines the expected number of attempts in accessing the channel, as made by a selected node in order to transmit a packet successfully, and τ represents the mean length of a packet cycle in the channel access.

Figure 9 represents the average channel access delay of the FGDSA system. As it can be seen from the figure that the average channel access delay of the fuzzy based decision system is 41%, which is higher than the value by the fuzzy genetic based decision system. As similar to the findings for the SINR, the decision made by the fuzzy genetic system is more optimized than the fuzzy system. That is again because the hybrid system formation allows evaluation of only optimized rule(s).

5. Conclusions and future work

In this study, an FGDSA system for deciding spectrum allocation in cognitive radio sensor networks was introduced. The hybrid approach of the FGDSA employs inference abilities by both fuzzy logic and the fuzzy genetic algorithm. At this point, the study explained the problem definition, background, architecture of the developed FGDSA system (with detailed module descriptions), and also mathematical model on the background of the designed solution approach. The study also reported some general performance evaluations performed over the FGDSA system.

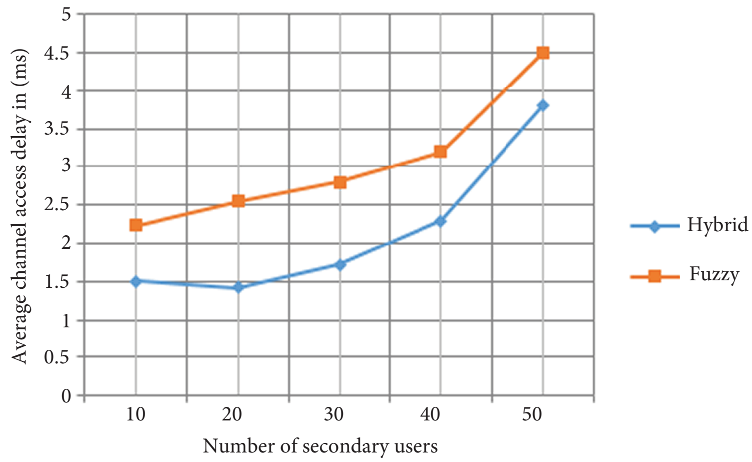

Figure 9. Average channel access delay of the FGDSA.

The developed FGDSA system performs fuzzy based dynamic spectrum allocation by using PU and SU parameters. PU parameters were chosen as SINR, BER, available channel bandwidth while SU were transmission power, and the data rate. The system allows optimizing fuzzy rules by using genetic algorithm so that the optimized rules can be used for better dynamic spectrum allocation decision. The performance evaluation of the FGDSA system/approach was done by considering some metrics such as channel utilization efficiency, SINR, and the channel access delay by both fuzzy based dynamic spectrum allocation and the genetic fuzzy based dynamic spectrum allocation. It was found that the genetic fuzzy decision-based spectrum allocation provides efficient spectrum allocation with fewer disturbances to the PU, when it is compared with the fuzzy based system. The fuzzy genetic system outperforms the fuzzy based dynamic spectrum allocation because it evaluates only optimized rules instead of evaluating all available rules. It was also found that the fuzzy genetic system outperforms existing approaches such as edge coloring heuristic (ECH) and the clique heuristic algorithm (CHA). It is remarkable that the introduced solution approach provides an optimal spectrum utilization of 12% with reduced hand-off.

Obtained positive findings-results have encouraged the author(s) to plan some additional, future studies. In this context, the current FGDSA system will be evaluated with additional evaluation scenarios, by considering also more alternative approaches from the literature. Also, future studies will include developing new hybrid systems, by using the current fuzzy logic infrastructure with alternative optimization algorithms (such as clonal selection algorithm, differential evolution algorithm) for rule optimization. In that study, current findings will be tried to be improved via alternative systems.

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