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Ant Colony Optimization of Fuzzy Logic Based Approach for Dynamic Spectrum Access in Cognitive Radio Network

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Abstract: *One of the emerging areas in the field of next generation wireless network is the Cognitive Radio Network (CRN). The traditional spectrum access approach leads to vast underutilization of the radio spectrum assigned to primary (licensed) users. The dynamic spectrum access is the most suitable approach to achieve finest spectrum utilization. The dynamic spectrum access technique allows the secondary (unlicensed) users to sense and use the available spectrum opportunistically, hence also known as opportunistic spectrum access. In this paper, an approach using a Sugeno type Fuzzy Logic System (FLS) to control the spectrum access has been proposed. Three parameters: spectrum utilization efficiency of the secondary user, its degree of mobility, and its distance to the primary userare used to describe the system. The output of the FLS gives the spectrum band accessing possibility for secondary users and the user with the highest possibility will be assigned the existing spectrum band. The Sugeno type FIS proposed in this work has been optimized using Ant Colony Optimization (ACO) technique. The ACO optimized Sugeno FIS has also been compared favorably with Sugeno type FLS for dynamic spectrum access and with the Mamdani based FLS already reported in[1].*
Keywords: Cognitive radio network, Fuzzy logic system, Soft computing

I. Introduction

Cognitive Radio Networks (CRNs), in wireless communication, is a new paradigm that focuses on increasing the spectrum utilization efficiency, as the spectrum is a limited resource [2]. It exploits the knowledge that it gains from its neighbors and through the acquired information, helps it in using the spectrum in an efficient manner. The key point is to make the cognitive radio capable, in sensing the spectrum orders so as to efficiently increase the utilization of spectrum.In this type of network, two classes of users such as Primary Users (PU) and Secondary Users (SU) are defined. The PUs are the high prioritized licensed user whereas the SUs are the opportunistic users. These SUs (or also sometimes called as cognitive radio users) are allocated with any part of the spectrum. As a result, interference will affect both PUs and other co-located SUs. In order to get rid of this situation a proper spectrum allocation mechanism needs to be framed.

Dynamic spectrum access has been supported by cognitive radios (CRs). It can sense their surroundings and adapt their operation mode such that it maximizes the QoS (Quality of Services) for secondary users while the interference to primary users is minimized. Hence, CRs must carry out spectrum sensing to identify spectrum holes which are frequency bands assigned to primary users, but, these bands are not being utilized by those users at a specific time and specific geographic location [3]. Manymethods on spectrum sensing havebeen proposed in [4], [5]. Once spectrum holes are identified, CRs opportunistically use these holes for communication without causing interference to primary users. Consider that a spectrum band is available for secondary users. What will happen, and which secondary user will be chosen to use the available band if many secondary users try to access the spectrum? Since these SU'shave the same rights to access the spectrum, they have to compete with each other in acollective and fair manner. This paper gives a more detail answer for these questions and proposes an approach using Fuzzy Logic System (FLS), an artificial intelligence system which is capable of making real time decisions, and decide the suitable secondary user which will use the available band.

In [6], authors assumed that if two secondary users within each other's distance use the same spectrum band, they would be unsuccessful to access spectrum. With this approach, some secondary users will lose their rights to compete for using spectrum and monitoring secondary users conflicting in using spectrum band is also a challenging issue.

In the proposed approach, the rule-based FLS to assign the available spectrum to secondary users is used.To achieve these objectives, three parameters which are spectrum utilization efficiency of the secondary user, its degree of mobility, and its distance to the primary user are used. The linguistic knowledge of spectrum access based on these three descriptors is obtained from[1]. Twenty seven fuzzy rules are set up based on this linguistic knowledge. The output of the FLS gives the possibility of each secondary user which will be assigned spectrum band and the user with the highest possibility will be assigned the accessible spectrum band. The FLS is further optimized using PSO optimization technique.

The rest of this paper is organized as follows. Section II briefly introducescognitive radios. The fuzzy logic system is introduced in Section III. Design of the Fuzzy Logic Systemis proposed in Section IV. Optimization of FLS is discussed in Section V. Section VI discusses the simulation results. Conclusions and future scope are presented in Section VI.

II. Cognitive Radio

Cognitive Radios is the key technology that enables xG networks to use spectrum efficiently by allowing SU's to sense and utilize available spectrum dynamically and opportunistically.

Cognitive radios have two main characteristics [3]:

Cognitive capability: It is the ability of CRs to sense information from their surroundings in order to figure out any spectrum holes. The most suitable portion will be selected for communication withoutcausing interference to other users.

Reconfigurability: It enables CRs to be reprogrammed dynamically according to the real environment. This means that CRs can change the operating frequency, modulation scheme, transmission power, communication protocol, etc. on the fly without any modification of hardware components.

The main functions of CRs are:

•**Spectrum sensing:** It is active spectrum awareness process where CR observes its radio environment and geographical surroundings, sense usage statistics of other PUs and SUs and decides possible spectrum space holes. Spectrum sensing can be done by one CR, by multiple CR terminals or by independent sensing network exchanging information in a cooperative way which improves overall accuracy.

• **Spectrum decision:** Based on spectrum sensing information CR selects when to start its operation, operating frequency and its corresponding technical parameters. CR primary objective is to transfer as much as possible information and to satisfy required quality of service, without causing excessive interference to the PUs. Additionally, CR may use data from regulatory database and policy database in order to improve its operation and outage statistics.

• **Spectrum sharing:** Since there are a number of SUs participating in usage of available spectrum holes, cognitive radio has to achieve balance between its self-goal of transferring information in efficient way and altruistic goal to share the available resources with other cognitive and non-cognitive users. This is done with policy rules determining CR behavior in radio environment.

• **Spectrum mobility:** If PU starts to operate, CR has to stop its operation or to vacate currently used radio spectrum and change radio frequency. In order to avoid interference to primary licensed user this function has to be performed in real time, therefore CR has to constantly investigate possible alternative spectrum holes.

III. Fuzzy Logic Systems

After being mostly viewed as a controversial technology for two decades, fuzzy logic has finally been accepted as an emerging technology since the late 1980s. This is largely due to a wide array of successful applications ranging from consumer products, to industrial process control, to automotive applications [7]. Fuzzy logic is closer in spirit to human thinking and natural language than conventional logical systems [8]. Classical control theory is based on the mathematical models that describe the physical plant under consideration. The essence of fuzzy control is to build a model of human expert who is capable of controlling the plant without thinking in terms of mathematical model. Fuzzy systems are very useful in two general contexts: (1) in situations involving highly complex systems whose behaviors are not well understood, and (2) in situations where an approximate, but fast, solution is warranted [9].

Fig. 1 shows the basic structure of a fuzzy logic system (FLS). When an input is applied to a FLS, the system computes the output set corresponding to each rule. The defuzzifier then computes a crisp output from these rule output sets.

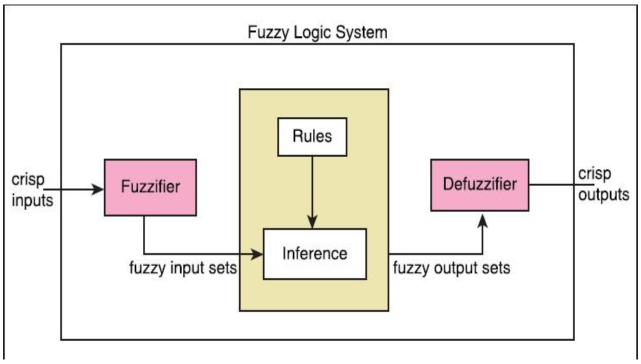

Fig. 1: The structure of a Fuzzy Logic System

IV. Designing of FLS

Here, the fuzzy inference system to solve the opportunistic spectrum access problem in CR networks is designed. Expert knowledge for selecting the best suitable SU to access the available band is collected based on three antecedents such as spectrum utilization efficiency, degree of mobility and distance to the PU, with one consequent as spectrum access decision. Based on the knowledge of linguistic variables, 27 If-Then fuzzy rules are used to take the decision for opportunistic spectrum access [1]. In this work, using rule based fuzzy logic system, the above three parametersare combined to determine optimal solution to assign spectrum opportunistically. In radio environment, many users will access available spectrum and effectively utilize spectrum band in particular time duration. Therefore, spectrum utilization efficiency η_s is introduced in the design. η_s is defined as the ratio between the spectrum band which will be used by the SU and the available band,

$$\eta_s = \frac{BW_s}{BW_a} \text{x}100 \quad (1)$$

where, BW_s and BW_a are the spectrum band which will beused by the secondary and the available band, respectively.

Mobility of the SU is the important aspects in the design. When the SU is moving at a velocity v m/s, it causes the doppler effect.

$$f_D = \frac{v\cos\theta}{c} f_c \quad (2)$$

where, f_D is the doppler shift, θ is the arrival angle of the received signal relative to the direction of motion, c is the wave velocity and $f_c$is carrier frequency. Mobility can reduce capability of detecting signal from the PUs. If the SU is not capable of detecting the primary signal, it will incorrectly determine that the spectrum is unused; therefore leading to potential interference between the users.

The third factor is the distance of the SU, because SU at a closer distance should be given priority to access spectrum, which depends upon the signal to noise ratio. Assume the primary user at the distance R from the secondary user transmits signal at powerP1 and the power gain between the primary user and secondaryuser, g(R), is a continuous, nonnegative, strictly decreasing function of R defined on the interval [0;1]. SNR at the secondary user,γ_s, is given by

$$\gamma_s = 10log\left(\frac{P_1 g(R)}{\sigma_1^2}\right) \quad (3)$$

where, P_1 is the transmit power of the PU and $\sigma_1^2$is noise power measured at the secondary user. From (3) we can derive the distance R between the PU and SU.

In the proposed FIS, three antecedent propositions are expressed in three fuzzy partitions such as Low/Near,Moderate and High/Far. The consequence i.e. the possibility that the SU is chosen to access the spectrum is divided in to five levels which are Very Low, Low, Medium, High and VeryHigh. The trapezoidal and triangular membership functions are used to represents input and constant term are used (Sugeno type) to represent output parameters of decision making structure. The membership functions for the three descriptors are shown in Fig.2,3&4. Since there are three antecedents and three fuzzy subsets, 27 rules are to be setup for this fuzzy system. The rule base obtained from [1] is shown in Table I.

TABLE I Rule Base

Rule	Antecedent 1	Antecedent 2	Antecedent 3	Consequence
1	*low*	*low*	*near*	*Very low*
2	*low*	*low*	*moderate*	*Low*
3	*low*	*low*	*far*	*Low*
4	*low*	*moderate*	*near*	*Very low*
5	*low*	*moderate*	*moderate*	*Low*
6	*low*	*moderate*	*far*	*Medium*
7	*low*	*high*	*near*	*Very low*
8	*Low*	*high*	*moderate*	*Low*
9	*Low*	*high*	*far*	*Medium*
10	*Moderate*	*low*	*near*	*Very low*
11	*Moderate*	*low*	*moderate*	*Medium*
12	*Moderate*	*low*	*far*	*High*
13	*Moderate*	*moderate*	*near*	*Very low*
14	*Moderate*	*moderate*	*Moderate*	*Medium*
15	*Moderate*	*Moderate*	*Far*	*High*
16	*Moderate*	*High*	*Near*	*Very low*
17	*Moderate*	*High*	*Moderate*	*Low*
18	*Moderate*	*High*	*Far*	*High*
19	*High*	*Low*	*Near*	*Low*
20	*High*	*Low*	*Moderate*	*High*
21	*High*	*Low*	*Far*	*Very high*
22	*High*	*Moderate*	*Near*	*Low*
23	*High*	*Moderate*	*Moderate*	*High*
24	*High*	*Moderate*	*Far*	*Very high*
25	*High*	*High*	*Near*	*Very low*
26	*High*	*High*	*Moderate*	*High*
27	*High*	*High*	*Far*	*High*

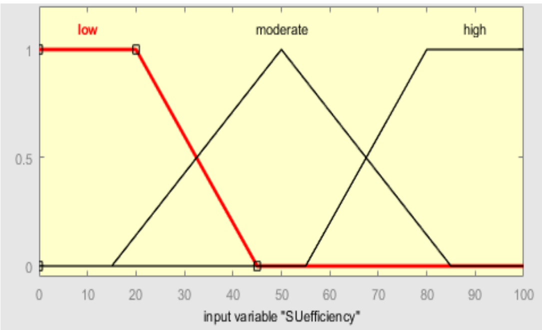

Fig. 2 Membership Function for Spectrum Utilization Efficiency

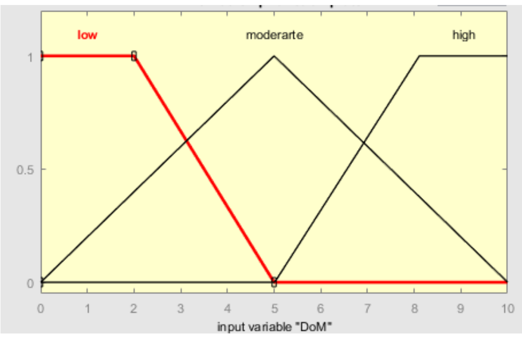

Fig. 3. Membership Function for Degree of Mobility

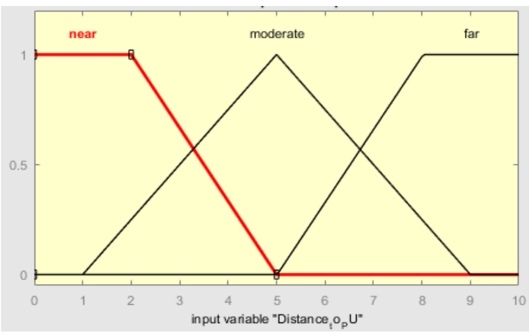

Fig. 4. Membership function for Distance to PU

V. ACO Optimization of FLS

Ant Colony Optimization (ACO) is inspired by ants and their behavior of finding shortest paths from their nest to sources of food. Without any leader that could guide the ants to optimal trajectories, the ants manage to find these optimal trajectories over time in a distributed fashion. In an ACO algorithm, the metaphorical ants are agents programmed to find an optimal combination of elements of a given set that maximizes some utility function. The key ingredient in ACO and its biological counterpart are the pheromones. With real ants, these are chemicals deposited by the ants and their concentration encodes a map of trajectories, where stronger concentrations represent better trajectories. ACO represents the class of metaheuristic optimization methods that use the concepts of distributed optimization and pheromone maps in solving combinatorial optimization problems [10].

The ACO is an algorithmic implementation that adapts the behavior of real ants to solutions of minimum cost path problems. A number of artificial ants build solutions for a certain optimization problem and exchange information about the quality of these solutions making allusion to the communication systems of the real ants.

For the functioning of ACO [11], it is necessary to find:

$$Q = \{q_a, \dots, q_f | q_1 \in C\} \tag{4}$$

Where Q is the set of nodes representing a continuous path with no obstacles; $q_a, \dots, q_f$ are former nodes of the path and C is the set of possible configurations of the free space. If $x_k(t)$ denotes a Q solution in time t, $f(x_k(t))$ expresses the quality of the solution. The general steps of ACO are the followings [25]:

• Each link (I,j) is associated with a pheromone concentration denoted as τ_{ij}

• A number of ants k = 1,2….n_k are placed in the nest.

• On each iteration all ants build a path to the food source (destiny node). For selecting the next node a probabilistic equation is used:

$$P_{ij}^k(t) = \left\{ \begin{array}{ll} \frac{\tau_{ij}^k}{\sum_{j \in N_{ij}^k} \tau_{ij}^{\alpha}(t)} & \text{if } j \in N_i^k \\ 0 & \text{if } j \notin N_i^k \end{array} \right\} \tag{5}$$

Where, N_i^k is the set of feasible nodes (in a neighborhood) connected to node I with respect to ant k, τ_{ij} is the total pheromone concentration of link ij, and α is a positive constant used as again for the pheromone influence.

• Compute each route weight $f(x_k(t))$

• Pheromone evaporation is calculated with equation (6):

$$\tau_{ij}(t) \leftarrow (1-\rho)\tau_{ij}(t) \tag{6}$$

Where ρ ∈ [0,1] is the evaporation rate value of the pheromone trail. The evaporation is added to the algorithm in order to force the exploration of the ants, and avoid premature convergence to suboptimal solutions. For ρ =1 the search becomes completely random.

• The update of the pheromone concentration is realized using equation

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \sum_{k=1}^{n_k} \Delta\tau_{ij}^k(t) \tag{7}$$

Where $\Delta\tau_{ij}^k$ is the amount of pheromone that an ant k deposits in a link ij in a time t.

• Finally, the algorithm can be ended in two different ways:

When a maximum number of epochs has been reached.

When it has been found an acceptable solution, with $f(x_k(t))$

Ant colony optimization is used in this case to determine the optimal input membership functions. The vertices for the input membership functions as shown in Fig. 5, where X1, X2, X3 corresponds to the three inputs. The parameters are selected on the basis of minimum average error obtained by varying the no. of ants, keeping α constant.

For a vertices matrix X_k with N number of ants (where i ∈ [1,N]), the vertices are arranged as,

$$X_k = [x1, x2, x3] \tag{8}$$

The goal of the system is to maximize the output, i.e to increase the probability of detection. The fitness of each ant is evaluated using (9).

$$f(x_k(t)) = \max(\text{systemoutput}) \tag{9}$$

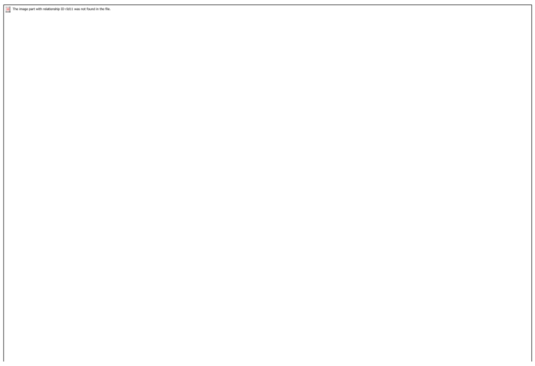

Fig. 5 Membership function distribution for inputs

The tuning of the FLC parameters can be summarized as follows:
Step 1: Encode the MF vertices for inputs as presented in Fig.5
Step 2: Initialize the ant parameters
Step 3: Update the pheromone concentration using (7)
Step 4: Decode the output into a fuzzy inference system (FIS) structure and output the results. The fitness of each FIS structure is then evaluated and used to update pheromones.
Step 5: Repeat Steps 3 and 4 for the set number of iterations.

VI. Simulation Results

Simulations were carried out in MATLAB, using the fuzzy logic tool box and Simulink.To evaluate the response of fuzzy system in CRs, normalized sequence values of three descriptors were randomly generated. Spectrum utilization efficiency of each SU was a random value in the interval [0 100] and its mobility degree in [0 10] with third parameter as the distances to the PU were normalized to [0 10]. The FLS was optimized by using the ACO algorithm defined as a function in MATLAB. The output of fuzzy decision making, i.e. the possibility that a SU was selected to access the available spectrum was computed for Sugeno-FIS and Fig. 6 represents the opportunistic spectrum access decision surface for the cognitive user. The user with the maximum possibility was selected to use the spectrum. Since there are three inputs and one output, i.e. total four variables, it is impossible to obtain a 4-D graph, hence the distance to PU was made constant and the 3-D graph was plotted to view the decision surface.

The output of fuzzy decision making, i.e. the possibility that a SU was selected to access the available spectrum was computed for Mamdani-FIS and Fig. 7 represents the opportunistic spectrum access decision surface for the cognitive user.
The ACO optimized membership functions of the inputs are shown in Fig.8, Fig.9, and Fig.10. The Fig. 11, represents the opportunistic spectrum access decision surface for the cognitive user for PSO optimized Sugeno based FIS.

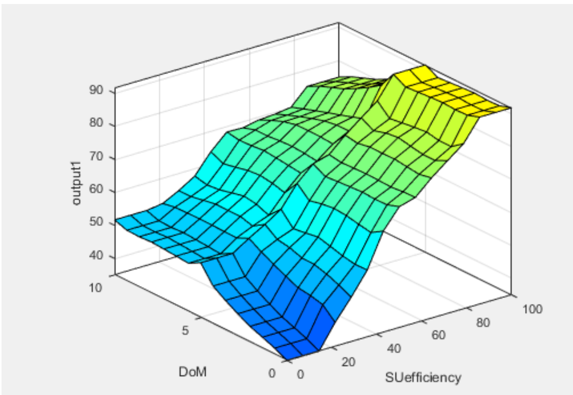

Fig. 6. Surface plot of sugeno based FLS

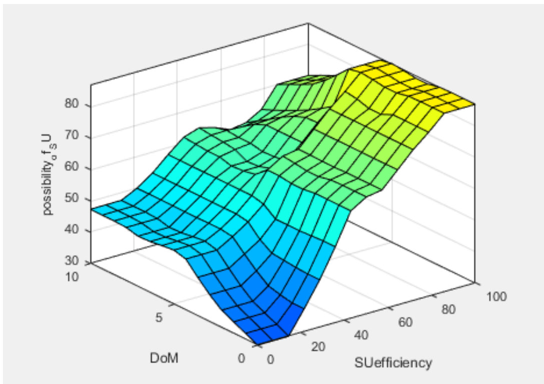

Fig. 7. Surface plot of mamdani based FLS

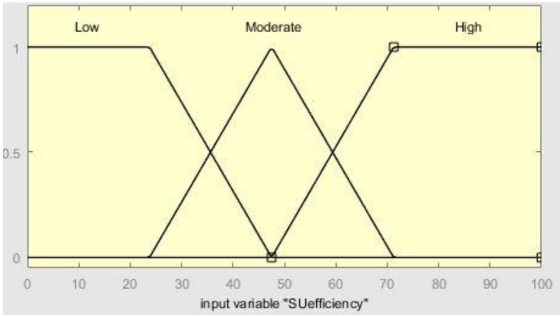

Fig. 8 ACO optimized MF for antecedent1

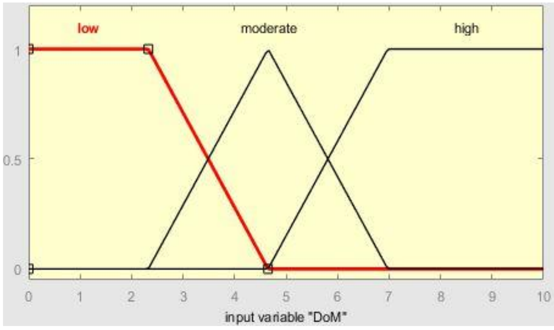

Fig.9 ACO optimized MF for antecedent2

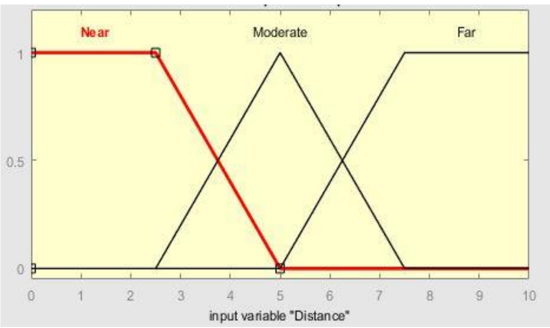

Fig.10 ACO optimized MF for antecedent3

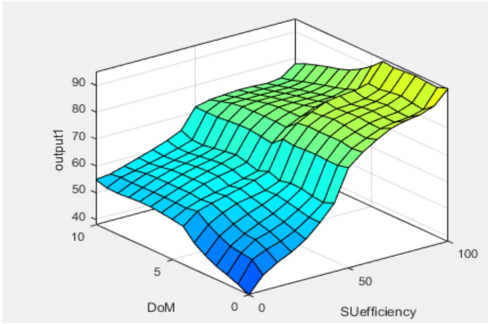

Fig. 11 Decision surface of ACO optimized Sugeno based FIS

A comparison between the Mamdani FLS, the proposed Sugeno-FLS and the ACO optimized Sugeno FLS was done. The study of the three surfaces provides an insight that sugeno model has higher probability of detection as the possibility of choosing a secondary user is high in the case of Sugeno compared to Mamdani type and also that the ACO optimization of the Sugeno type FLS increases the possibility of choosing the secondary user. Table II shows the different values of output obtained both for mamdani sugeno, and ACO optimized sugeno for same input.

Table II Comparison of Mamdani ,Sugeno and PSO optimised Sugeno for different inputs

Descriptors			**Possibility of selecting Secondary USer**		
Antecedent 1	**Antecedent 2**	**Antecedent 3**	**Mamdani FIS**	**Sugeno FIS**	**ACO Sugeno FIS**
76.18732	7.61873	7.05981	66.981	73.2765	77.916208
57.1621	5.71621	4.90735	46.927	50.7663	56.918667
37.65443	3.76544	2.70032	28.409	30.6356	34.1746121
47.43126	4.74326	3.80642	36.2774	40.4645	42.7195313
10.374316	1.03763	0.38601	11.5519	17.2662	18.9476231
94.96725	9.496769	9.18423	71.3494	76.4708	78.6218425
37.088848	3.70880	2.63691	28.4470	30.5154	33.1128665
98.536223	9.85382	9.58135	70.396	75.5148	78.2365512
44.336232	4.433623	3.45627	32.927	36.4605	38.5251933
65.818304	6.581830	5.886693	55.2894	66.628	69.9976233

VII. Conclusion And Future Scope

A rule-based Sugeno type FLS to control the dynamic spectrum access for SU in cognitive radio networks was proposed. The SU is selected based on three parameters i.e., spectrum utilization efficiency of the secondary user, its degree of mobility, and its distance to the primary user. The scenario was analyzed and simulated. Further, the FLS was optimized using ACO algorithm. The comparison between Sugeno type, ACO optimized Sugeno type and Mamdani type FLS revealed that the proposed system can have more probability of detection, as the decision surface is improved compared to the Mamdani type FLS and also optimizing the Sugeno type FLS using ACO algorithm, increases the possibility of selecting the secondary user.

In the proposed approach, the membership functions of parameters can be modified in accordance to requirements of the primary network and the spectrum using policy. Hence, this approach can be implemented practically in future cognitive radio networks. Since this model is based on Sugeno type system, further optimization techniques such as genetic algorithm, particle swarm optimization etc. can be implemented to optimize the system so as to increase the probability of detection.

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