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ORIGINAL PAPER

Spectrum selection and decision using neural and fuzzy optimization approaches

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Abstract
In Cognitive Radio Network, after sensing process, the selection and decision for a reliable channel from the list of free channels is important for assignment to Cognitive Users (CUs) for communication with Quality of Service (QoS). In this paper a consistent spectrum selection and decision scheme with two-fold neural network has been proposed for selection and decision process and its performance is compared with the schemes of Genetic algorithm and Back Propagation Neural Network (BPNN). BPNN- Adaptive Neuro Fuzzy Inference System (ANFIS) is a two-fold spectrum selection and decision approach which combines both BPNN and ANFIS techniques. A channel with the required QoS is selected based on the parameters such as Primary User (PU) states, signal strength, spectrum demand, velocity and distance. The simulation analysis shows that the BPNN–ANFIS technique reduces probability of blocking and dropping and therefore the accuracy of reliable channel selection obtained for the CUs use is more than 92%. The blocking probability of the proposed technique ranges from 1 to 3% which is much lower than the Genetic Algorithm (9–50%) and BPNN (8–40%). The maximum dropping probability of the proposed technique is only 4% and this is lower compared to 20% dropping in the other two techniques.

Keywords Cognitive radio · Spectrum selection · Spectrum decision · Back propagation neural network · Adaptive neuro fuzzy inference system

1 Introduction

The existing cellular communication networks are not able to satisfy the needs of the customers, due to increasing demand of mobile internet. Every day, new devices have been included with some means of wireless transmissions and they exist everywhere with the Internet of Things (IoT). The diverse wireless networking technologies as well as the devices are famous infrastructures for accessing the internet and transmitting the information between the technologies and the devices. The existing radio access technique and the mobile infrastructure do not have the capability to support the users with the existing spectrum allocation methods and they also lead to congestion in the network and scarcity in spectrum resources. To satisfy the customers' needs and for fast transmission of mobile data, new generations of mobile networks have been evolved but still there exist some unused frequency bands in all the existing generations of mobile networks. To avoid the spectrum scarcity and to utilize the unused frequency bands, an emerging network such as CRN cans be used.

The traditional static spectrum allocation methods have led to inefficient use of valuable wireless telephone technology spectrum. Also, the growing demand of spectrum usage, due to massive number of wireless applications, renders these policies inapplicable. CRN is a kind of intelligent wireless communication approach that has been used to receive and identify the channels of communication abruptly which channel can be engaged or which cannot be engaged by the users.

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The new emerging CRN [1] has been an intelligent radio paradigm for efficient sharing of spectrum in a more flexible fashion by a number of operators/users/systems and it can be configured dynamically. The CRN with intelligent searching and by efficiently using the idle spectrum resources helps to use the free spectrum resources. CRN [2] can exploit vacancies in licensed frequency bands to self-organize the dynamic spectrum access (DSA) in the networks as well as it can operate over a dynamic bandwidth in both time and space domains. The CRN as an enabling technology will offer benefits to several types of users through intelligent communication and networking models in the whole wireless world and it will also provide better business opportunities for incumbent operators as well as new technical dimensions for smaller operators. CRN is also an efficient approach for spectrum requirements and to be used in Next Generation Network (NGN).

Mitola has introduced the concept of cognitive radio which can learn the current radio frequency environment and its surroundings. Then, autonomously changes the operational parameters based on the observation to access the radios which are idle. In general, the CR consists of different components such as radio, sensors, knowledge database and two different engines for learning and reasoning. The main feature of cognitive radio is that it is able to reconfigure the transmission parameters such as modulation techniques, transmission power and RF. There are three different stages such as observe, learn and reason, and act in cognitive cycle.

In RF environment, during the observing phase, through spectrum sensing techniques [3], the CR identifies the channels that are not used by the primary user and with help of knowledge database, in learning and reasoning phases; CR optimizes cognitive user objectives for selecting the suitable channel for their usage. In case of arrival of primary user, it leaves the channel immediately and again senses the next idle channel for cognitive user. Cognitive user can select the best channel through handoff and spectrum management techniques. To achieve high spectrum utilization in DSA, spectrum allocation and accessing techniques are very important.

Based on the above-mentioned activities, the CRN will identify and access the unoccupied channel which is known as spectrum hole and this process is named as DSA [4]. To improve the performance and to efficiently utilize the spectrum, the DSA process has to be strengthened. Many researchers have been focusing on sensing and sharing the spectrum for the static environmental condition. Even in dynamic environment, the time taken for the channel selection is too high and the channel switching process is also more complex. Hence, it leads to poor probability of detection as well as affects the system performance.

During the observe phase, through wrong input statistics, the throughput of the network may be reduced and it may cause interference to primary users. Knowledge of the radio can be collected in learning stage by using different algorithms such as AI, machine learning, etc,. With the help of knowledge database, CR tries to accumulate all the objective functions. By varying the input parameters, significant changes can be observed in objective functions and the optimized results can again be stored in knowledge database.

Still, some issues such as accuracy of spectrum sensing, uncertainty of primary user interference and primary user equipment attacks are unresolved in DSA [5, 6]. To address these issues in DSA, a competent as well as consistent spectrum selection scheme, using energy detector approach, which includes EM algorithm with learning approach and two fold spectrum decision approach by adopting Artificial Intelligence Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) has been proposed to improve DSA with Quality of Service (QoS) in dynamic network environment.

Earlier, many spectrum sensing algorithms have been proposed whereas at the time of accessing the spectrum, they may be occupied by the primary users and hence, it leads to poor detection. The proposed technique identifies the spectrum hole from different spectrum bands by using the cluster-based approach [7–9] with Expectation Maximization (EM) algorithm and learning approach. This EM algorithm provides a list of maximum likelihood channels based on ranking and as a result, the optimization techniques are adopted to improve the spectrum selection and decision processes.

The objective of this paper is to list the possible available channels by adopting EM algorithm with learning environment. The second objective is to enhance the accuracy of spectrum selection and decision and to reduce the error probability ratio by minimizing the occurrence of misdetection by considering various input parameters which affect the spectrum sensing decision through optimization techniques as well as to improve the overall system performance.

The rest of the paper has been outlined as follows: the background and the related works of dynamic spectrum access with sensing, sharing and optimization are reviewed in Sect. 2. In Sect. 3, the system framework for spectrum selection and decision is described. Section 4 depicts the proposed optimization techniques, BPNN and ANFIS. The result of sensing selection and the decision results are analyzed in Sect. 5 with help of simulated results and conclusion is given in Sect. 6.

2 Related work

In CRN, the primary activity is to identify the unoccupied channels through spectrum sensing. Using the spectrum sensing task, the CU monitors the spectrum and detects the spectrum hole. Several spectrum sensing techniques have been proposed in the past and among them, cooperative spectrum sensing [10–12] with energy detector approach has produced optimal result.

The energy-based technique utilized for spectrum sensing does not demand fundamental data of the signal that faces under the sub classification of semi blind detection or transmitter detection technique, and it calculates the energy of the received signal in a particular band of frequency. It is called as radiometry which is one of the most popular and simple methods for detecting the spectrum in cognitive radio networks. It is also referred as blind signal detector since the signal information is not needed. Energy Detecting (ED) module computes the energy received from the signal and matches with a known threshold value that has been attained from the statistics of noise in order to sense the presence of signal. ED technique is the most used one because of its simplicity and low computation as well as implementation complexity [13].

Anand and Chandramouli (2009) [14] have presented a dynamic spectrum access for the secondary user in dynamic network environment to select the channel and it is done based on the flow of the network. In this approach, L-commodity network flow- based framework has been considered for network selection. To improve the channel and network selection of the secondary user in dynamic network environment, the network re-assignment and channel re-assignment can be enabled for the secondary user. Even then the assignment and re-assignment cause interference to the primary user in the same network and to improve the quality of service, the secondary user has to pay for that.

In order to improve the cognitive wireless network system throughput through reducing the sensing time and transmission power, Neda Moghimet al. (2018) [15] have proposed an efficient hybrid spectrum access approach for wideband OFDM-based uplink model. In the predefined primary user interference level, the authors have formulated a convex problem by combining the sensing duration and the controlled power transmission [16]. In order to reduce the sensing time and to improve the performance of the system, rate-aware and QoS-aware algorithms have been used with low computational complexity. The rate-aware algorithm selects some promising channels for SU sensing and sensing duration whereas the transmission power is analyzed in QoS-aware algorithm and optimized solution is produced to SU. The simulation results prove that the performance of SU system has been maximized without causing interference to the PU.

To achieve reliable communication and to enhance the spectrum utilization of multi-hop cognitive radio network, Dingde Jiang et al. (2015) [11] have proposed an effective dynamic spectrum access algorithm. In this approach, to model the primary user and to learn the traffic of the network, the Pareto distribution model has been built. In multi-hop cognitive radio network, acknowledgement-based data packet transmission has been followed to achieve reliable communication. The authors have used graph theory techniques for reasonable channel allocation in both time and frequency divisions to improve the spectrum utilization. The binary matrix has been framed for channel availability and primary user interference. Efficient dynamic spectrum access can be done with the help of binary matrix to improve the channel allocation and channel switching conditions. Simulation results prove that the sensing time is reduced, and the spectrum utilization percentage is also improved. The performance of SU system has also been analyzed with help of discrete-time model and the occupancy of primary user and the possibility to access a channel can be analyzed by multi-server access model. Number of connections in a system has been derived from probability generating function.

Abdul et al. (2016) [17] have quoted that SU traffic is directly correlated with SU response time with different scenarios by varying the PU traffic or varying the channel count. From that, the authors have derived if the mean response time is closely stable, SU traffic will be moderate and the mean response time will increase, if the SU traffic is increased. It shows that the number of channels is reduced in the system and the PU traffic is increased in the system.

An investigation has been carried out on cognitive radio network for performing sensing techniques to achieve optimal throughput with low complexity whereas the minimum error rate is achieved through an iterative algorithm. Wenjie Zhang [18] has achieved optimized solution for multi-variable non convex problems by adopting sequence of actions such as:

- By using the energy detection threshold approaches, the spectrum sensing has been carried out in an optimized manner with optimization variables such as number of cognitive users, fusion parameter, and sensing time to get optimum sensing results, less error rate and high throughput
- Optimum detection threshold has been obtained only in closed form. The evidence show that the error rate which occurs in local is convex function in threshold.

- For cooperative cognitive user, to achieve the maximum target for the desired optimal throughput with less error rate, AND rule is optimal fusion rule.

To maximize the desired throughput of the cognitive user in spectrum sensing and to keep the lower total error rate, an iterative algorithm has been used to exploit the hidden convex parameters. The iterative algorithm processes high coverage with less complexity. To increase the throughput of the system with less probability of error rate and optimized spectrum sensing time, optimized energy threshold has been computed by this iterative algorithm.

To enhance the sensing results, Context- Aware Network Selection (CANS) has been proposed by Alex Monteiro [19] who has provided the mechanism to the user to select the optimal available channel in heterogeneous wireless network by providing interference intelligence based on the contextual information. CANS have also adopted the mechanism to collect all the information related to network, device and user such as bandwidth, user device information, speed, display status and power level and it has organized the information as software agent. Based on the information, the most optimum network channel has been selected for the users. The mobile devices adopt these strategies of CANS for selecting and managing the networks.

Due to continuous information collection process, the processing cost may be increased. By using CANS mechanism, the cost can be decreased and the best channel can be chosen in dynamic network environment. Saud Althunibat [20] has proposed a system based on the energy required to get the desired spectrum sensing results. In this approach, the available limited resources related to time management have been considered to identify the free spectrum holes and reporting time. Experimental analysis shows that energy consumption is high because of a greater number of cooperative users and hence, the performance of the system is degraded. The author has also proposed bisection algorithm to get optimized solution with high desired throughput from the optimal number of sensing channel with low error rate by using the predefined energy detection probability.

Rasheed et al. in (2018) [21] have improved the sensing results by collecting the results of local spectrum sensing through the centralized sensing parameters and the reliability factors based fuzzy logic approach has been used to maximize the accuracy of local spectrum sensing information. The cluster-based cooperative compressed spectrum sensing has been proposed and in which, the range discovery calculation has been executed in malicious user environment. The author has also used machine learning techniques for enlisting the distance from the cluster to PU.

Li Taifu, [22] and Xue X [23] have suggested back propagation neural network optimization technique to achieve the desired output and depicted that the performance of BPNN optimization technique is more robust and better than the genetic algorithms. In general, among all these optimization techniques, the ANN models are more proficient.

Many spectrum sensing techniques have been used to identify the unoccupied spectrum holes and at the time of accessing the spectrum hole by the CU, it may be occupied by the PU. It leads to the possibility of misdetection. Due to this reason, the performance of the system will decrease. To improve the overall performance of the system, the decision taken by the CU must be more optimal. To optimize the decision process, many optimization techniques such as Fuzzy, Artificial Neural Network, Genetic algorithms and Adaptive Neuro Fuzzy Inference System have been used.

2.1 Problem identification

To improve the performance of DSA in CRN, the selection and decision of spectrum hole for the CU are very important. Due to inappropriate selection and sudden arrival of PU, it may sometime lead to maximum misdetection. To best of the researcher's knowledge, once the identified idle channel becomes active channel, the cognitive radio starts again from sensing process and it will reduce the overall performance in DSA.

To overcome these issues, in the present work, a competent as well as consistent spectrum sensing and selection approach, using energy detector approach, which includes EM algorithm with learning approach has been proposed. As a result of this hybrid spectrum sensing technique, the list of all idle channels for that time interval has been obtained using maximum likelihood functions. Further by using spectrum characteristics such as signal strength, spectrum demand, interference and so on, a two -fold optimization technique involving BPNN and ANFIS has been adopted to optimize the spectrum selection and decision processes. By this approach, the possibility of misdetection can be reduced, and the input given to CU will be more accurate and optimized.

3 Hybrid spectrum sensing approach

Figure 1 depicts the proposed hybrid spectrum sensing approach to optimize the spectrum efficiency in CRN. For the CU, the cycle of operation has been carried out such as free spectrum identification, configuring the CU as per the identified spectrum and then, accessing the spectrum. On

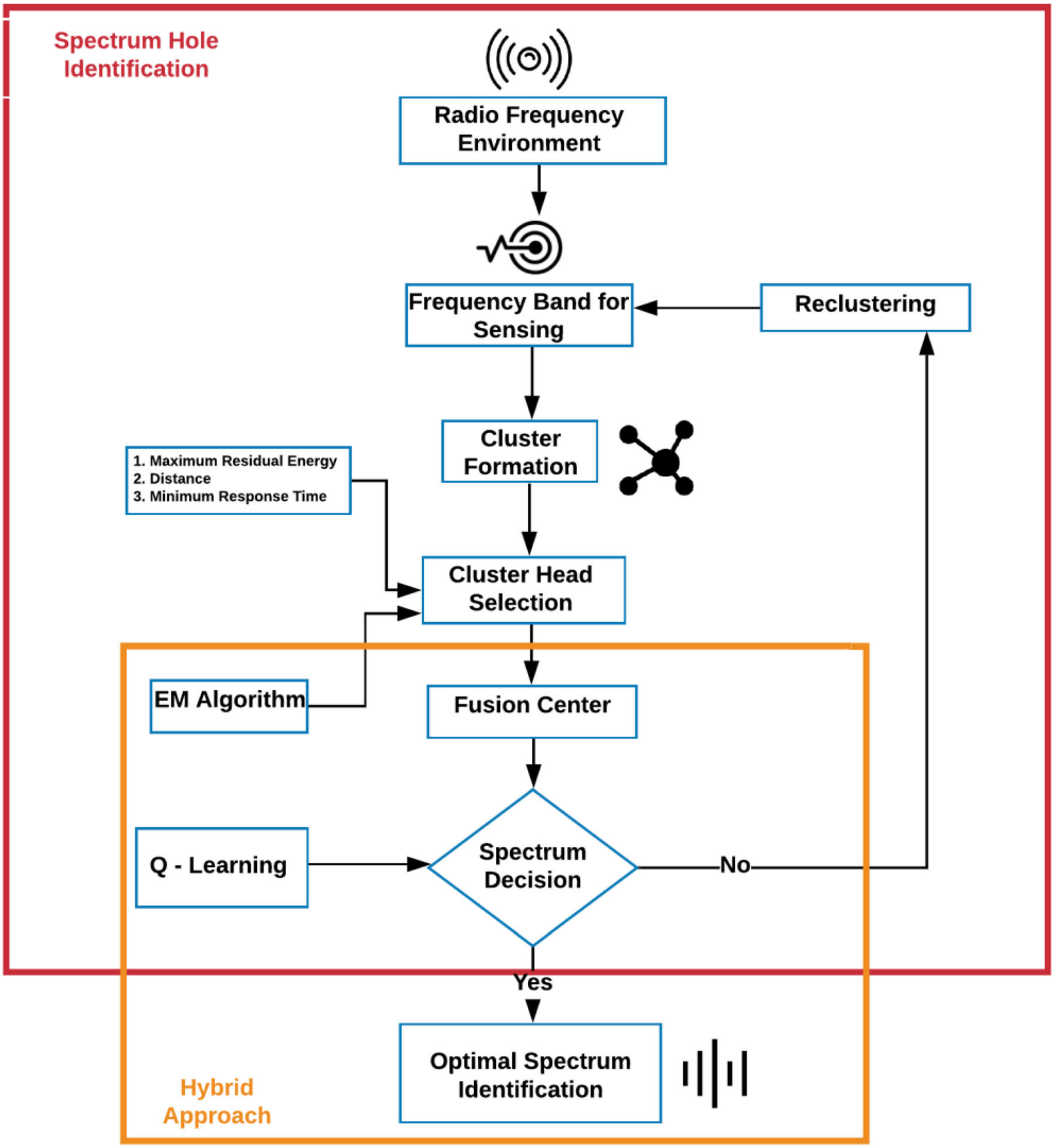


Fig. 1 Hybrid spectrum sensing approach

the arrival of spectrum owners, the next optimal spectrum has been chosen in that RF environment.

In the Fig. 1 Hybrid spectrum sensing technique proposed by Raja Guru et al. (2020) [24, 25] the cluster approaches identify the available spectrum holes through spectrum sensing results. However, at the time of accessing the spectrum holes identified by the sensing results, mis-detection may happen, if the bands are occupied by the PUs. To overcome this issue, the changes in the RF environment are also considered in spectrum decision techniques. To learn the RF environment, a Q-learning technique has been proposed in this work.

The proposed spectrum selection and decision framework BPNN–ANFIS identifies the list of solutions for the CUs to improve overall performance of the system. While performing the selection and decision, some of the characteristics of the spectrum such as signal strength, spectrum demand, signal to noise ratio, traffic priority, access latency, sensing power, and spectrum efficiency have been considered and these parameters influence the following output parameters such as channel selection probability, bandwidth allocation, collision probability, number of available channel, spectrum sensing time, percentage of time slot utilization and channel decision of the CUs.

For the desired output, the 'n' combinations based on the input parameters have been derived and from these combinations by using the two-fold neural network technique BPNN–ANFIS, the output parameters are derived for the CUs. The Tables from 1 to 5 show how the input parameters influence the desired output of the CUs.

Table 1 represents the possibility of bandwidth allocation-based changes such as traffic priority and access latency that happen in the input parameters. Similarly, the possibility of collision occurrence based on the state of PU and CU detection are shown in Table 2.

Based on collision rate and number of CUs, the possible sensing time of the CUs is shown in Table 3 and Table 4 presents the possibility of identifying the available channel based on the combinations of number of CUs, Interference level and the distance between the PUs and CUs.

The input parameters such as sensing power, velocity, efficiency of the spectrum and distance between the users will give the maximum accurate chance to the CUs to avail the unoccupied channels without harming the PUs as discussed in Table 5.

4 Optimization techniques

The list of freely available channel selection can be done by the above proposed spectrum sensing technique and the various network parameters influencing the spectrum selection and decision processes discussed in Tables 1, 2, 3, 4 and 5, are considered as input for the two-fold neural network techniques. To get the accurate results, BPNN techniques have been adopted in the proposed approach and the results are derived with some error percentage. Further to improve accuracy and to reduce the error rate, the resultant data have been fed to ANFIS technique. In the proposed approach, the two-fold neural network techniques have been utilized to maximize the accuracy and to reduce the error rate.

Table 1 Bandwidth allocation

S. No	Input 1 Access latency	Input 2 Traffic priority	Output Bandwidth allocation
1	High	Absent	Low
2	High	Present	Low
3	Moderate	Absent	Low
4	Moderate	Present	Moderate
5	Low	Absent	Moderate
6	Low	Present	High

This table represents the position of a particular bandwidth based on the input parameters such as traffic priority and access latency

Table 2 Collision probability

S. No	Input 1 State of PU	Input 2 CU detection	Output Collision probability
1	ON	ON	Moderate
2	ON	OFF	High
3	OFF	ON	Moderate
4	OFF	OFF	Low

Collision probability varies based on the state of PU and the decision of the CU and it is shown in the table

Table 3 Spectrum sensing time

S. No	Input 1 No. of CU users	Input 2 Collision probability	Output Sensing time
1	High	High	High
2	High	moderate	Moderate
3	High	Low	High
4	Moderate	High	Moderate
5	Moderate	moderate	Moderate
6	Moderate	Low	Moderate
7	Low	High	High
8	Low	Moderate	Low
9	Low	Low	Low

Spectrum sensing time varies based on the input parameters such as number of CUs and the collision probability is represented in this table

4.1 Back propagation neural network

In 1986, Lou et al. [26, 27] framed a new supervised learning procedure known as Back Propagation Neural Network (BPNN) and it can be used for linear and nonlinear classifications. From the desired output, the network identifies many inputs. In BPNN the errors are back propagated to the input layer. Since BPNN is a supervised algorithm, the error difference between the desired output and the calculated output has been back propagated. This back-propagation procedure has been repeated during learning in order to minimize the error by adjusting the weights as shown as Fig. 2.

BPNN comprises three layers and they are (1) Input Layer (2) Hidden Layer and (3) Output Layer. Numbers of hidden layers, and the hidden units. in each hidden layer depend on the sorority of the problem as shown in the Figure 3.

During this process, error has been calculated by the difference between the targeted output and the actual output of each output unit. This error is back propagated to the previous layer which is known as hidden layer. In each unit

Table 4 Number of available channel

S. No.	Input 1		Input 2		Input 3		Output	
	No. of CUs		Distance between PU and CU		Interference		Number of available channel	
1	high	3	High	3	low	1	High	1
2	high	3	High	3	moderate	2	Low	− 1
3	high	3	High	3	high	3	Low	− 1
4	moderate	2	High	3	low	1	High	1
5	moderate	2	High	3	moderate	2	Moderate	0
6	moderate	2	High	3	high	3	Low	− 1
7	low	1	High	3	low	1	High	1
8	low	1	High	3	moderate	2	Moderate	0
9	low	1	High	3	high	3	Low	− 1
10	high	3	Low	1	low	1	Moderate	0
11	high	3	Low	1	moderate	2	Moderate	0
12	high	3	Low	1	high	3	Low	− 1
13	moderate	2	Low	1	low	1	High	1
14	moderate	2	Low	1	moderate	2	Moderate	0
15	moderate	2	Low	1	high	3	Low	− 1
16	low	1	Low	1	low	1	High	1
17	low	1	Low	1	moderate	2	Moderate	0
18	low	1	Low	1	high	3	Low	− 1
19	high	3	Moderate	2	low	1	Moderate	0
20	high	3	Moderate	2	moderate	2	Moderate	0
21	high	3	Moderate	2	high	3	Low	− 1
22	moderate	2	Moderate	2	low	1	High	1
23	moderate	2	Moderate	2	moderate	2	moderate	0
24	moderate	2	Moderate	2	high	3	Low	− 1
25	low	1	Moderate	2	low	1	moderate	0
26	low	1	Moderate	2	moderate	2	moderate	0
27	low	1	Moderate	2	high	3	moderate	0

Number of available channels depending on interference, distance and the number of CUs is represented in this table

of the hidden layer N, error at that node is computed. Likewise, error at each node of the previous hidden layer, that is N-1, is also calculated. These calculated errors are utilized to adjust the weights. Hence, the error in each output unit has been minimized. Forward and backward steps are repeated until the error is minimized as per the expected level. The training algorithm of back propagation includes four processes.

1. Initialization of weights
2. Feed forward
3. Back propagation of errors
4. Updating the weights and biases

The bias acts as weights on the connection from the units whose output is always 1. During the initialization of weights, some arbitrary values are given initially to get some outputs by feed forwarding through the layers. Consequently, the difference between the obtained and the actual values has been calculated as error and back propagated. High initial weight will result in faster learning rate. But, the weights may oscillate. If the initial weights are too small, then the learning rate will be slow. For the best results, initial weights may be considered between − 0.5 and 0.5 or − 1 and 1.

In Back Propagation method, initially the output of the hidden layer is calculated by the formula

$$H_j = f\left(\sum_{i=1}^{n} \omega_{ij} x_i - a_j\right) j = 1, 2, \ldots, 1 \quad (1)$$

where $\mathbf{H_j}$ and $\mathbf{f}$ denote the output of hidden layer and the incentive function of neurons, respectively. i represents the neuron number of hidden layer, n is the neuron number of input layer, ω_{ij} is the weight factor between the input-layer and the hidden layer, and a_j is the threshold value. The next step is to predict the output values by using the formula,

Table 5 Spectrum decision

S. No.	Input 1		Input 2		Input 3		Input 4		Output
	Sensing power		Velocity		Spectrum efficiency		Distance between PU and CU		Spectrum decision
1	3	High	3	High	3	High	3	High	1
2	3	High	3	High	3	High	2	Moderate	1
3	3	High	3	High	3	High	1	Low	0
4	3	High	3	High	2	Moderate	3	High	1
5	3	High	3	High	2	Moderate	2	Moderate	0
6	3	High	3	High	2	Moderate	1	Low	0
7	3	High	3	High	1	Low	3	High	1
8	3	High	3	High	1	Low	2	Moderate	− 1
9	3	High	3	High	1	Low	1	Low	− 1
10	3	High	2	Moderate	3	High	3	High	1
11	3	High	2	Moderate	3	High	2	Moderate	1
12	3	High	2	Moderate	3	High	1	Low	1
13	3	High	2	Moderate	2	Moderate	3	High	1
14	3	High	2	Moderate	2	Moderate	2	Moderate	0
15	3	High	2	Moderate	2	Moderate	1	Low	0
16	3	High	2	Moderate	1	Low	3	High	1
17	3	High	2	Moderate	1	Low	2	Moderate	0
18	3	High	2	Moderate	1	Low	1	Low	− 1
19	3	High	1	Low	3	High	3	High	1
20	3	High	1	Low	3	High	2	Moderate	1
21	3	High	1	Low	3	High	1	Low	1
22	3	High	1	Low	2	Moderate	3	High	1
23	3	High	1	Low	2	Moderate	2	Moderate	0
24	3	High	1	Low	2	Moderate	1	Low	− 1
25	3	High	1	Low	1	Low	3	High	1
26	3	High	1	Low	1	Low	2	Moderate	− 1
27	2	High	1	Low	1	Low	1	Low	− 1
28	2	Moderate	3	High	3	High	3	High	1
29	2	Moderate	3	High	3	High	2	Moderate	0
30	2	Moderate	3	High	3	High	1	Low	0
31	2	Moderate	3	High	2	Moderate	3	High	0
32	2	Moderate	3	High	2	Moderate	2	Moderate	0
33	2	Moderate	3	High	2	Moderate	1	Low	0
34	2	Moderate	3	High	1	Low	3	High	0
35	2	Moderate	3	High	1	Low	2	Moderate	0
36	2	Moderate	3	High	1	Low	1	Low	− 1
37	2	Moderate	2	Moderate	3	High	3	High	1
38	2	Moderate	2	Moderate	3	High	2	Moderate	0
39	2	Moderate	2	Moderate	3	High	1	Low	0
40	2	Moderate	2	Moderate	2	Moderate	3	High	0
41	2	Moderate	2	Moderate	2	Moderate	2	Moderate	0
42	2	Moderate	2	Moderate	2	Moderate	1	Low	0
43	2	Moderate	2	Moderate	1	Low	3	High	0
44	2	Moderate	2	Moderate	1	Low	2	Moderate	0
45	2	Moderate	2	Moderate	1	Low	1	Low	− 1
46	2	Moderate	1	Low	3	High	3	High	1
47	2	Moderate	1	Low	3	High	2	Moderate	0

Table 5 (continued)

S. No.	Input 1		Input 2		Input 3		Input 4		Output
	Sensing power		Velocity		Spectrum efficiency		Distance between PU and CU		Spectrum decision
48	2	Moderate	1	Low	3	High	1	Low	− 1
49	2	Moderate	1	Low	2	Moderate	3	High	0
50	2	Moderate	1	Low	2	Moderate	2	Moderate	0
51	2	Moderate	1	Low	2	Moderate	1	Low	− 1
52	2	Moderate	1	Low	1	Low	3	High	1
53	2	Moderate	1	Low	1	Low	2	Moderate	− 1
54	1	Moderate	1	Low	1	Low	1	Low	− 1
55	1	Low	3	High	3	High	3	High	1
56	1	Low	3	High	3	High	2	Moderate	1
57	1	Low	3	High	3	High	1	Low	− 1
58	1	Low	3	High	2	Moderate	3	High	1
59	1	Low	3	High	2	Moderate	2	Moderate	0
60	1	Low	3	High	2	Moderate	1	Low	− 1
61	1	Low	3	High	1	Low	3	High	1
62	1	Low	3	High	1	Low	2	Moderate	− 1
63	1	Low	3	High	1	Low	1	Low	− 1
64	1	Low	2	Moderate	3	High	3	High	1
65	1	Low	2	Moderate	3	High	2	Moderate	1
66	1	Low	2	Moderate	3	High	1	Low	− 1
67	1	Low	2	Moderate	2	Moderate	3	High	1
68	1	Low	2	Moderate	2	Moderate	2	Moderate	0
69	1	Low	2	Moderate	2	Moderate	1	Low	− 1
70	1	Low	2	Moderate	1	Low	3	High	1
71	1	Low	2	Moderate	1	Low	2	Moderate	0
72	1	Low	2	Moderate	1	Low	1	Low	0
73	1	Low	1	Low	3	High	3	High	1
74	1	Low	1	Low	3	High	2	Moderate	1
75	1	Low	1	Low	3	High	1	Low	1
76	1	Low	1	Low	2	Moderate	3	High	1
77	1	Low	1	Low	2	Moderate	2	Moderate	0
78	1	Low	1	Low	2	Moderate	1	Low	0
79	1	Low	1	Low	1	Low	3	High	1
80	1	Low	1	Low	1	Low	2	Moderate	− 1
81	1	Low	1	Low	1	Low	1	Low	− 1

Representing the dependence of spectrum decision based on sensing power, velocity, spectrum efficiency and distance between the PU and CU

$$O_{k=}\sum_{j=1}^{l} H_j \omega_{jk} - b_k k = 1, 2, \ldots, m \tag{2}$$

where b_k denotes the threshold value and m represents the neuron number of the output layer. Then, as per the prediction error e_k computed by the difference between the predicted output and the expected output, the value of weight factor and the threshold can be updated as given below

$$\begin{aligned} \omega_{ij} &= \omega_{ij} + \eta H_j \left(1 - H_j\right) x(i) \sum_{k=1}^{m} \omega_{jk} \varrho_k i = 1, 2, \ldots, n;\ j \\ &= 1, 2, \ldots, l \\ \omega_{jk} &= \omega_{jk} + \eta H_j \varrho_k \ \ j = 1, 2, \ldots, l;\ \ k = 1, 2, \ldots, m \end{aligned} \tag{3}$$

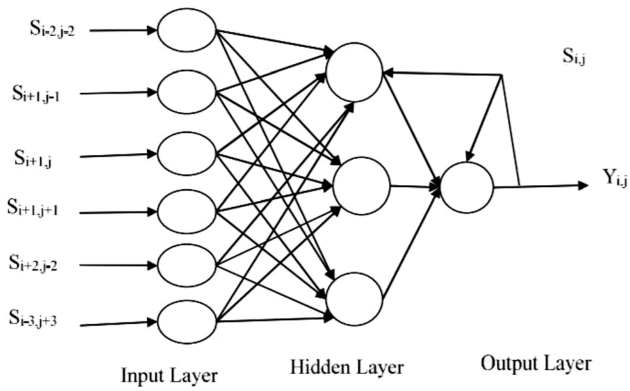


Fig. 2 Layer approaches of BPNN

$$a_j = \eta H_j(1 - H_j)x(i)\sum_{k=1}^{m} \omega_{jk}\, \varrho_k \quad j = 1, 2, \ldots, 1$$
$$b_k = b_k + \varrho_k k \ = 1, 2, \ldots, m \tag{4}$$

A popular activation function of back propagation networks is the sigmoid, a real function sc: IR → (0, 1) as defined by the expression

$$s_c(x) = \frac{1}{1 + e^{-cx}} \tag{5}$$

The constant c may be selected arbitrarily and its reciprocal 1/c is known as the temperature parameter in stochastic neural networks. An alternative to the sigmoid is symmetrical sigmoid S(x) and it can be defined as

$$S_{(x)} = 2s(x) - 1 = \frac{1 - e^{-x}}{1 + e^{-x}} \tag{6}$$

In general, two types of learning methods are available.

1. Sequential learning
2. Batch learning

In the process of sequential learning, the given input pattern is broadcasted and then, the error is calculated and back propagated. Further, the weights are reorganized until the targeted output is obtained. Whereas in the process of batch learning, the weights are reorganized only after the entire set of training network has been offered to the network. Thus, the weights are updated after every epoch.

4.2 Adaptive neuro-fuzzy inference system

Due to the changes in network environment, there is a need for algorithms which learn from the experimental results and provide optimum solution to the end user. Hence, several soft computing techniques such as Artificial Neural Network, Fuzzy Logic System, and Genetic Algorithms and so on have been evolved [28].

To minimize the output errors in fuzzy modeling system, trial steps and auxiliary calculation are needed for adjusting the fuzzy membership functions. Since there are no proper methods to convert the human idea into knowledge part of fuzzy system, they lead the system output to inadaptable nature. In the case of Artificial Neural Network, it has good adaptability of output based on the input parameters and it also supports the non-linear correlation between the input and the output parameters as represented in Fig. 4 In order to improve the performance, the advantages of both FIS and ANN have been combined and it is called as Adaptive Neuro-Fuzzy Inference System (ANFIS). This ANFIS supports the knowledge and adaptation features.

ANFIS consists of Fuzzification, Rule, Normalization, Defuzzification and output values as shown in Fig. 5.

Two different types of methods such as Mamdani and Takagi-Sugeon-Kang (TSK) have been used in FIS. In the proposed system, TSK approach has been used to derive optimized results. Here, the rules mainly focus on the input–output relationship. Simply, if–then rules are used for correlating the input and the output values.

$$\text{IF a is } X_1 \text{and b is } Y_1, \text{ THEN } f_1 = p_1 a + q_1 b + r_1$$
$$\text{IF a is } X_2 \text{and b is } Y_2, \text{ THEN } f_2 = p_2 a + q_2 b + r_2$$
$$\ldots$$
$$\text{IF a is } X_n \text{and b is } Y_n, \text{ THEN } f_1 = p_n a + q_n b + r_n$$

The values of p, q and r are constant and they can be evaluated during the training process based on the training

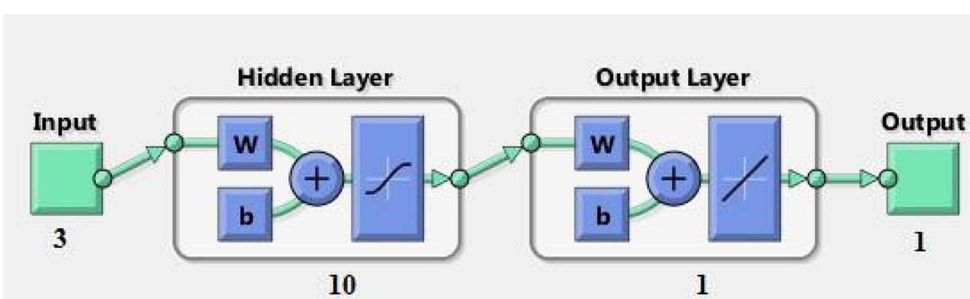


Fig. 3 Simulated layers in BPNN for channel selection

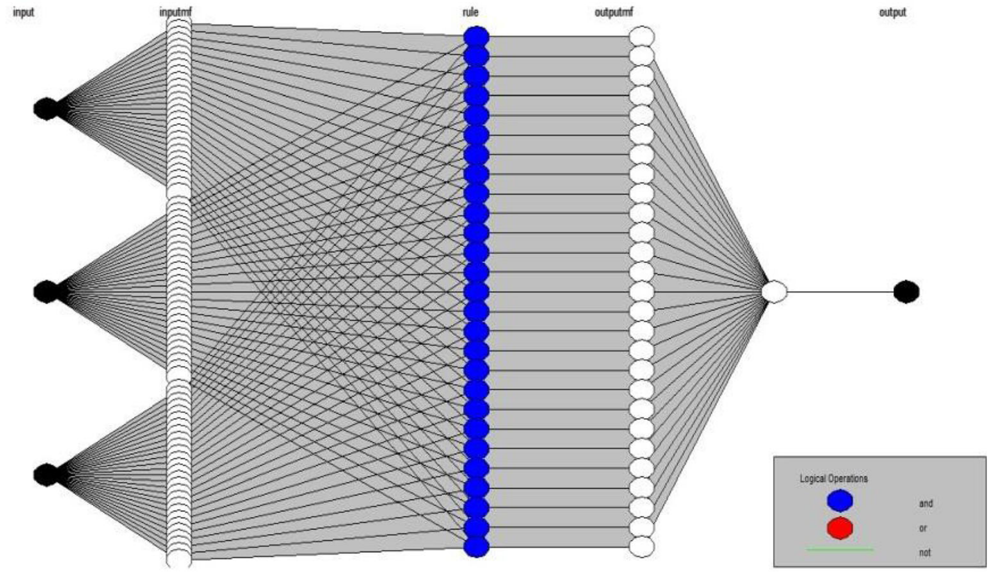


Fig. 4 Adaptive neuro-fuzzy inference system (ANFIS)

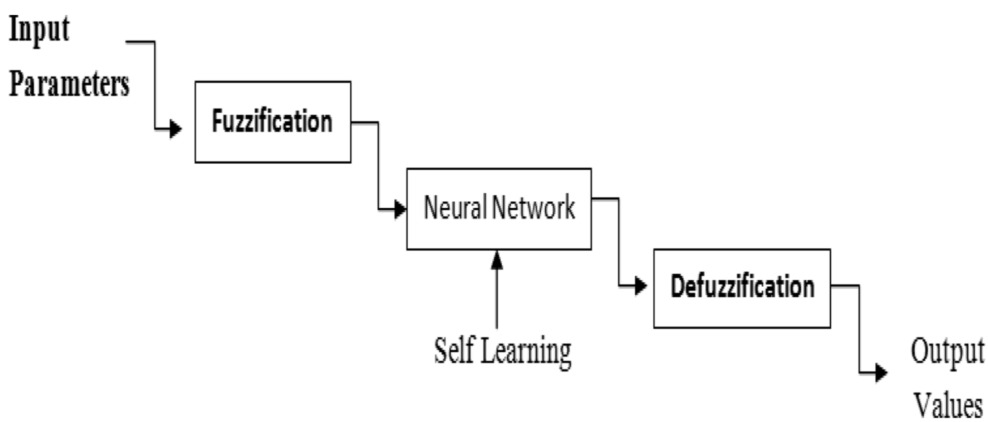


Fig. 5 ANFIS layers

data. Then, the next step is to form fuzzy rules by combining these functions with ANFIS. Simply the fuzzy inference system has been considered with two inputs v and d and one output f. In Layer 1 (Fuzzification layer), each input node is an adaptive node. It produces membership grade of linguistic label and it is a fuzzy layer. Here, v and d are the inputs of the system. $O_{1,j}$ is the output of the ith node of layer l. Each adaptive node is a square node with square function and it is represented by the following equations

$$O_{1,i} = \mu_{v,i}(v) \text{ for } i = 1, 2 \tag{7}$$

$$O_{1,j} = \mu_{d,j}(v) \text{ for } j = 1, 2 \tag{8}$$

where $O_{1,i}$ and $O_{1,j}$ represent output functions and $\mu_{v,i}$ and $\mu_{d,j}$ represent membership functions. For example, the triangular membership function, $\mu_{v,i}$ (v) is offered by

$$\mu_{v,i}(v) = \max\left[\min\left(\frac{v - a_i}{b_i - a_i}, \frac{c_i - v}{(c_i - b_i)}\right), 0\right] \tag{9}$$

where $\{a_i, b_i, c_i,\}$ are the parameters of triangular membership function and they are the parameter set which changes accordingly the shapes of member function. Parameters in this layer are known as "premise parameters". After fuzzification, the weight of member function must be checked for this purpose. Then, layer 2 has been implemented. It receives input value vi from the first layer and acts as a membership function to represent fuzzy sets of respective input variables. Every node in this layer is fixed and the node is labelled with M. Then, the output is calculated via the product of all incoming signals. The output of this layer can be calculated using the following equation

$$O_{2,i} = w_i = \mu_{v,i}(v).\mu_{d,i}(d), \ i = 1, 2 \tag{10}$$

Generally, in this layer, any T norm operator, which performs fuzzy AND, can be used as a node function. Layer 3 is the normalization layer which is implemented for normalizing the weight function. Every node in this layer is fixed and it is denoted with circle and labelled with N. It indicates normalization of firing strength from the previous layer. This layer performs pre-condition matching of fuzzy rules, i.e. activation level of each rule is computed and the number of layers is equal to the number of fuzzy rules. Further, the ith node calculates the ratio of ith rule's strength to the sum of firing strength of all rules. The output of this layer can be expressed as $\overline{w_i}$ by using the following equation

$$O_{3,i} = \overline{w_i} = \frac{w_i}{(w1 + w2)},\ i = 1,\ 2 \tag{11}$$

After obtaining the normalized firing strengths, the relationship between the input and the output of the layer is carried out in layer4 and it is called as defuzzification layer. This layer offers output value y, which has resulted from the inference of rules. The resultant output is simply the product of normalized firing rule strength and first order polynomial. Weighted output rule is represented by node function as:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i v\ + q_i d\ + r_i),\ i\ = 1, 2 \tag{12}$$

where $O_{4,i}$ represents the output of layer 4 and in this layer, p_i, q_i and r_i are the linear parameters or consequent parameters. The result obtained from the defuzzification layer has been taken as input by Layer 5 (Output layer). It also sums up all the inputs from the layer 4 and converts fuzzy classification results into crisp values. This layer comprises single fixed node label as $\sum$. This node calculates the summation of all incoming signals and it is calculated by using the Equation,

$$O_{5,i} = \Sigma_i \overline{w_i} f_i = \frac{\Sigma_i w_i f_i}{w1 + w2},\ i\ = 1,\ 2 \tag{13}$$

Thus, it is clear when the values of premise parameter are fixed, the overall output of the adaptive network can be expressed as linear combination of a consequent parameter. It can also be observed that ANFIS architecture comprises two adaptive layers: the first layer and the fourth layer. There are three modifiable parameters {ai, bi & ci} so-called premise parameters in the first layer and in the fourth layer and there are also three modifiable parameters {pi, qi & ri} which are pertaining to the first order polynomial. These parameters are known as consequent parameters.

4.3 Optimized channel selection and decision system

To get accurate results, many neural network techniques have been widely used and among them, Artificial Intelligence (AI), Adaptive Fuzzy Inference System (AFIS) and Genetic Algorithms (GA) have been mostly used [29–31]. Computers can understand the abilities of human beings with some extent such as observe, learn and think, and decide. To perform such types of tasks, the neural network will support the behavior of humans to perform matching algorithms. The neural networks consist of elements as neurons with some weighted manner and they will process independently. Back propagation is a special type of neural network and it is also known as back propagation error method. It is mostly used in multi layered neural networks.

In the proposed system, BPNN & ANFIS have been followed to obtain accurate results and to reduce the error ratio as shown in Fig. 6 for spectrum sensing and decision of unoccupied channel information. Possible list of unoccupied channel information from the selection and decision framework is built in the back propagation neural network based on the input parameters such as signal strength, spectrum demand, signal to noise ratio, distance between the users and etc. The results obtained by BPNN predict error analysis as per the desired output parameters. Here, the accuracy is up to 92%, which possesses the maximum possibility of error ratio probability and it leads to misdetection and poor performance. To increase the accuracy result and to minimize the error, the resultant data are trained in ANFIS system. ANFIS yields up to 98–99% of accuracy and it shows reduced error rate with tolerable limit. By adopting this two-fold neural network technique, the error rate has been reduced and the throughput as well as the overall performance of the system has been improved. The simulation results are discussed in detail in the subsequent section.

5 Result and discussion

5.1 Simulation environment

In this section, simulation results have been depicted to evaluate the sensing vs throughput to obtain some insights for the effectiveness of the proposed algorithm. In case, the fusion centre is at the centre of the region with the radius of 1 km. For example, the fusion centre is situated at 6 km from the PU.

In the simulations, the transmission time T = 1 s, the sampling frequency becomes fs = 100 Hz, the presence probability of the PU is P (H1) = 0.5, the sensing power of

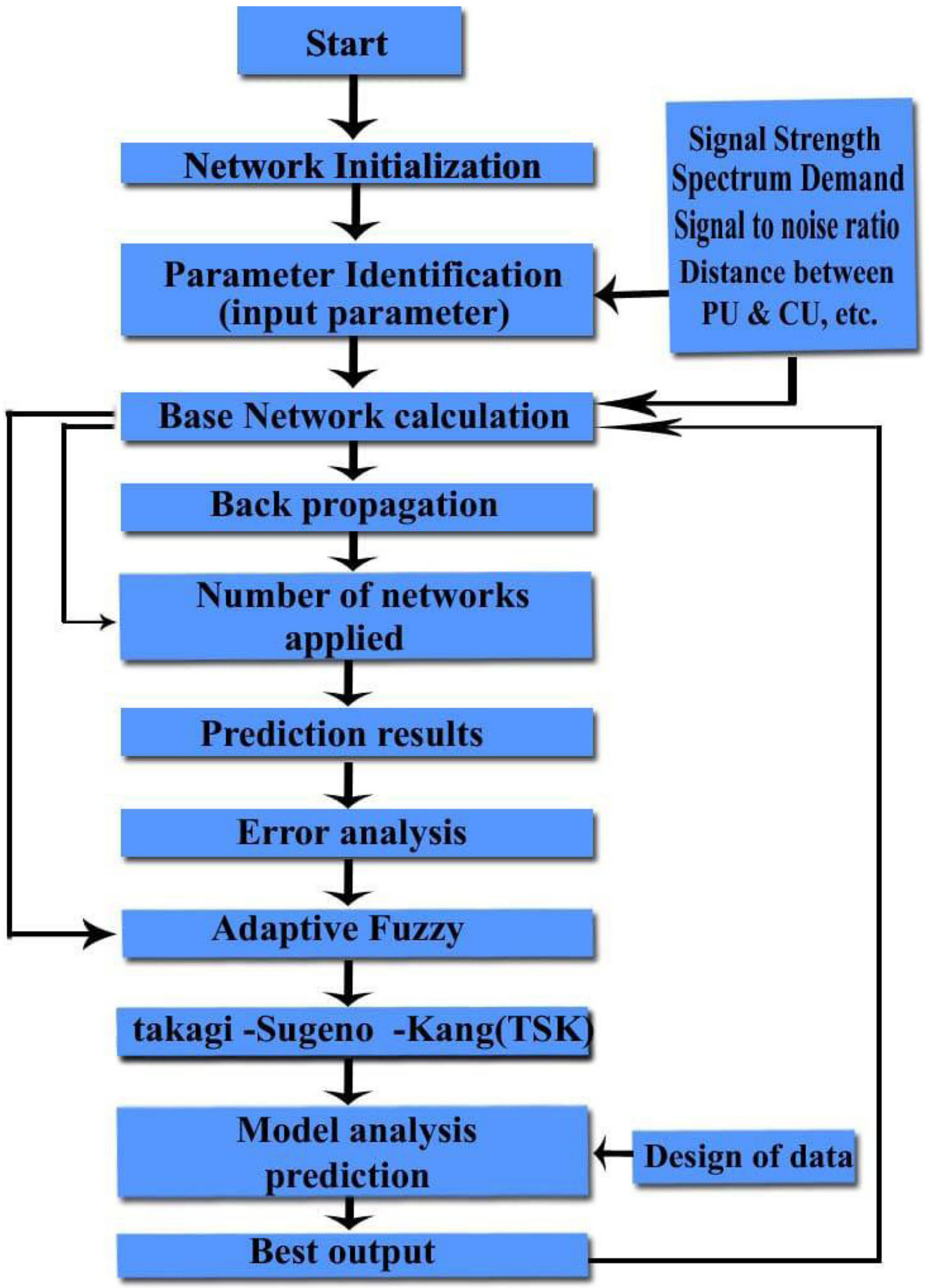


Fig. 6 Two-fold neural network techniques for spectrum management

each sampling node is $p_s = 0.01$ mW, and the noise power is $\sigma^2_n = 1$ mW.

The number of CUs is $M = 5$; the number of samples is $N = 300$; the PU signal is a zero-mean signal with 6 MHz bandwidth; the noises at CUs have identical unit variances, and the mean SNRs at CUs are 16, 14, 12, 10 and 8 dB, respectively.

All the parameters of BPNN have been selected to include the number of input parameters, the number of hidden layers, accuracy, learning rate, number of epochs and the number of output parameters. In this study, each output has been simulated individually.

5.2 Channel selection techniques

In the dynamic network environment, the channel selection for the CU is an important task. After identifying the available spectrum in dynamic environment, it is an important task for the CU to select the best available channels from the identified results. It is found that many techniques such as first identified, maximum residual time, near to the CUs etc. have been followed by different researchers to choose the channel. CUs are not satisfied with these approaches because of less accuracy and minimum system throughput. In the proposed approach, advanced technique of ANN with BPNN has been used. In this approach, input parameters such as signal strength, spectrum demand and signal to noise ratio have been considered and the results are shown in Fig. 7. From the Fig. 7, it is found that quality of channel selection probability has been improved. For 10 different epochs, the results are discussed in Fig. 8 In training, it is clear that different combinations of input parameters have achieved 99% error free results where as in validating the input parameters, 95% results has been achieved. Then in testing the samples, it is found that 97% result is error free. The overall result of BPNN is 98%.Based on the simulations results, it is observed that the channel selection probability is more accurate and maximum.

Even though the accuracy and performance of the channel selection by using BPNN are good, it has been decided to achieve maximum accuracy in channel selection probability and improve the overall system performance. Hence, the input parameters are simulated in ANFIS by applying IF–THEN rules as shown in Fig. 9 The parameters, which are directly associated with channel selection along with their different values, are listed and IF–THEN rules are applied to all the values. The list of all possible combinations of output has been obtained by varying the values of input parameters. Then, the results have been derived using ANFIS rules and the results show the surface view of possible channel selection condition based on the variations in the input parameters (Table 6).

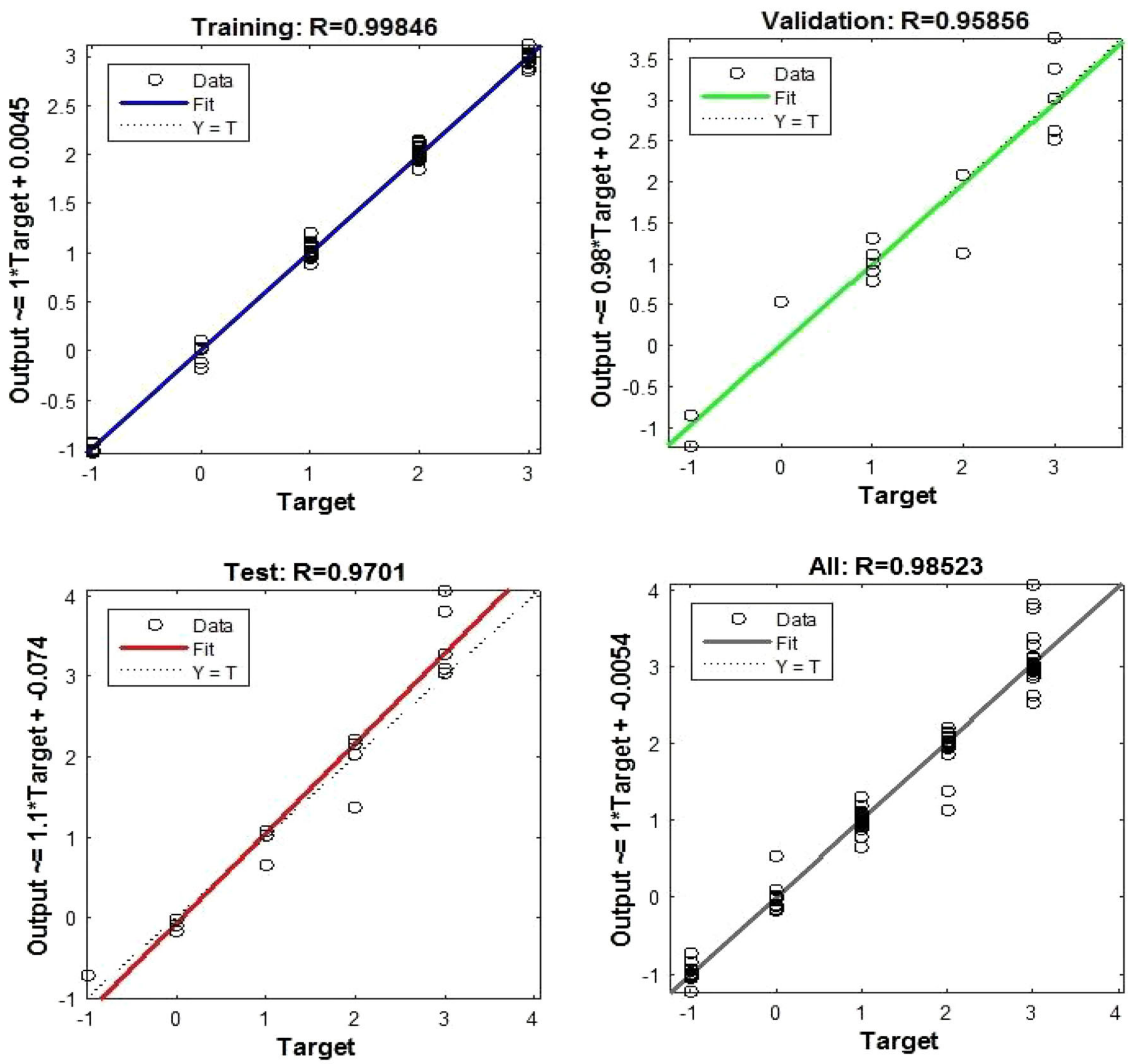


Fig. 7 Channel selection using BPNN

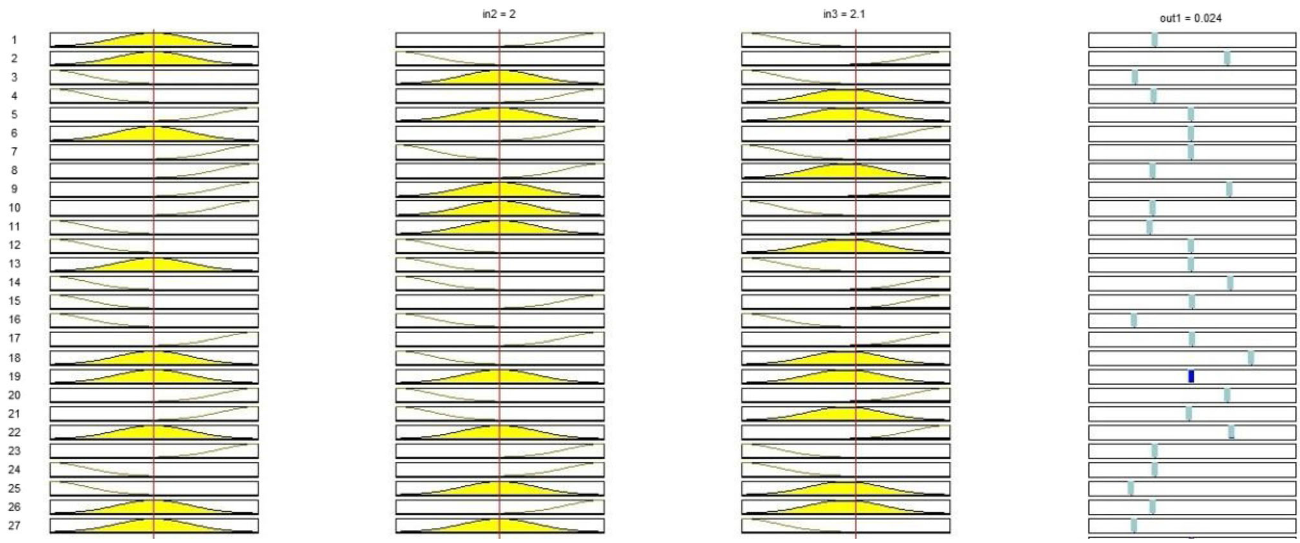


Fig. 8 ANFIS framework for channel selection

If (Signal Strength is low) and (Spectrum Demand is low) and (Signal to Noise ratio is high), then (Channel Selection Probability is high)

If (Signal Strength is Moderate) and (Spectrum Demand is Moderate) and (Signal to Noise ratio is high), then (Channel Selection Probability is high)

If (Signal Strength is Moderate) and (Spectrum Demand is low) and (Signal to Noise ratio is high), then (Channel Selection Probability is high)

If (Signal Strength is Moderate) and (Spectrum Demand is low) and (Signal to Noise ratio is Moderate), then (Channel Selection Probability is high)

If (Signal Strength is High) and (Spectrum Demand is Moderate) and (Signal to Noise ratio is high), then (Channel Selection Probability ishigh)

If (Signal Strength is High) and (Spectrum Demand is low) and (Signal to Noise ratio is high), then (Channel Selection Probability is high)

Fig. 9 ANFIS IF–THEN rule

The graphs show that the channel selection probability has been obtained by keeping the spectrum demand as constant whereas the parameters such as signal strength and signal to noise ratio are varied. From that, it has been observed that the channel selection probability is high by keeping the signal to noise ratio values more than the signal strength values. The graphs also show that the channel selection probability is against the input parameters such as signal strength and spectrum demand and the signal to noise ratio value is kept as constant. It is also clear that the spectrum demand is minimum against the signal strength for getting high channel selection probability as shown in Fig. 10a & b.

By training the input parameters, it is found that different combinations of input parameters have achieved 99% error free results. While validating the input parameters, 97% result has been achieved. Then in testing the samples; it is found that 99% result is error free. The overall result of BPNN is 99%. Based on the simulation results, it is observed that the available channel probability is more accurate and maximum as shown in Fig. 11.

Table 6 Availability of reliable channel

Number of CU	Distance between PU & CU	Interference	Number of available channel
High	High	Low	High
Moderate	High	Low	High
Low	High	Low	High
Moderate	Low	Low	High
Low	Low	Low	High
Moderate	Moderate	Low	High

Figure 12 shows the surface view of number of available channels against the input parameters such interference, number of CUs and the distance between the PU and CU. In order to get good number of available channels, the interference value has been kept minimum against the number of CUs. It is also noted that to achieve the maximum number of available channels, the distance between the PU and CU must be high and the value ofinterference will be minimum as well as the number of CU is kept as constant. Figure 13 represents that the output number of available channel varies based on the changes made in the input paremeters such as interference, distance and the number of users. Then, the number of available channels is displayed in Fig. 14.

The Fig. 15 shows that different combinations of input affect the output spectrum decision. The surface view diagram shown in Fig. 16 explains that the spectrum decision is high, when the values of input parameters such as velocity and spectrum efficiency are high and the sensing power and the distance between the PU and CU are kept constant. It is observed that to improve the spectrum decision accuracy, the distance between the PU and CU must be maximum against the sensing power. The reason behind this scenario is that the distance would cause interference problem because of maximum distance and it minimizes the interference values. Hence, the spectrum decisions are improved as shown in Table 7. The spectrum decision will also be improved with minimum velocity values against the efficiency of spectrum utilization as shown in Fig. 16.

5.3 Performances analysis

5.3.1 Blocking probability

Blocking Probability of the system is an event that arises when primary user or cognitive users cannot be allotted a channel and consequently blocked the system. The Fig. 17 shows that the blocking probability is reduced in the proposed system when compared to other two approaches. On the arrival of 0.2% of the CUs, it shows that the blocking probability is 9% in genetic algorithm, 6% in BPNN approach whereas only 4% in the proposed work it shows the blocking probability will be reduced for the proposed two-fold neural network technique. That is, the proposed approach is one time minimum than the genetic algorithm and half the time than the BPNN approach.

Similarly, for the 0.4% of CUs arrival the proposed work shows only 5% of blocking probability whereas 22% and 15% for the other approaches. That is, the proposed approach is three times minimum than the genetic algorithm and two times than the BPNN approach. Likewise, the blocking probability percentage is increased on the more percentage of CUs arrival rate.

5.3.2 Dropping probability

Dropping probability of the system is an event that arises when the primary user arrives and the cognitive users need to be dropped due to channel unavailability.

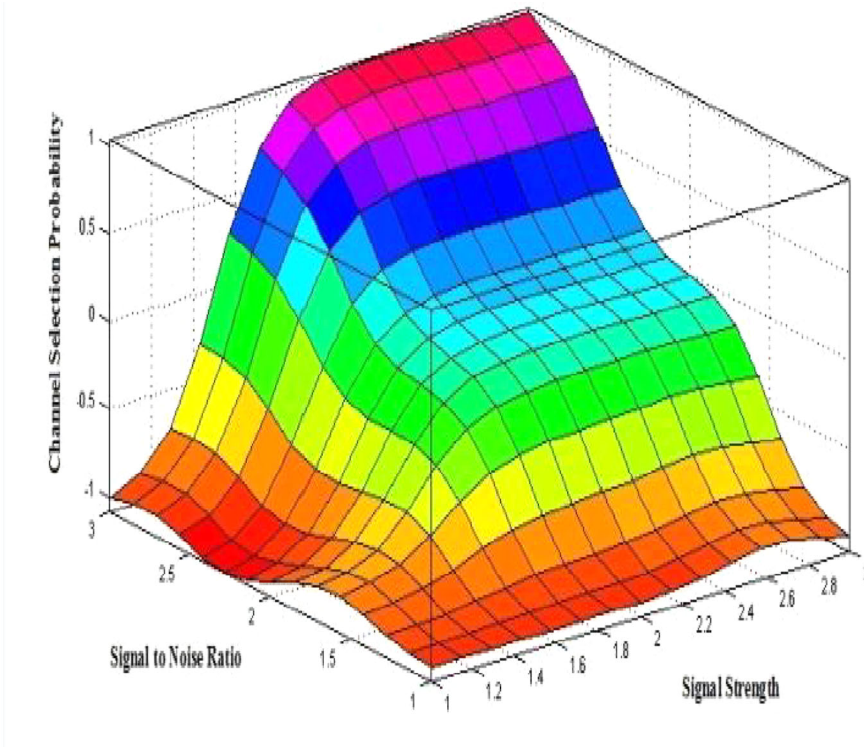
The Fig. 18 shows that the dropping probability is reduced in the proposed system when compared to other two approaches. On the arrival of 0.2% of the PUs, it shows that the dropping probability is 20% in genetic algorithm, 20% in BPNN approach whereas only 4% in the proposed work it shows the dropping probability will be reduced for the proposed two-fold neural network techniques. That is, the proposed approach is 400% minimum than the genetic algorithm and BPNN approach.

Similarly, for the 0.4% of PUs arrival the proposed work shows only 5% of dropping probability whereas 30% and 45% for the other approaches. Likewise, the dropping probability percentage is increased on the more percentage of PUs arrival rate.

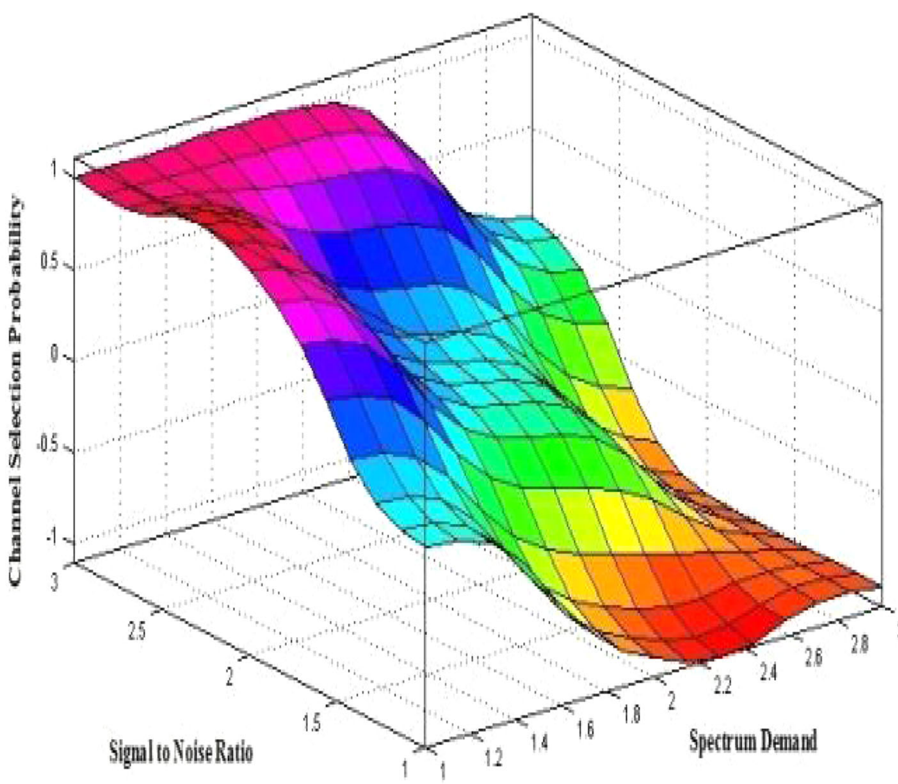
But in the proposed system the process of dropping the hold channel will have minimized when compare to other two approaches.

5.3.3 Acceptance probability

The Acceptance Probability of the CUs is defined as neither the channels in the RF Environment may be in the Blocking State nor Saturation State. The Saturation State means the channel will be maximum accommodated by the users. The Fig. 19 displays that the acceptance probability for the CUs can be increased in the proposed system. This


Channel Selection Probability
1
0.5
0
-0.5
-1
3
2.5
2
1.5
1
Signal to Noise Ratio
1
1.2
1.4
1.6
1.8
2
2.2
2.4
2.6
2.8
3
Signal Strength

(a)


Channel Selection Probability
1
0.5
0
-0.5
-1
3
2.5
2
1.5
1
Signal to Noise Ratio
1
1.2
1.4
1.6
1.8
2
2.2
2.4
2.6
2.8
3
Spectrum Demand

(b)

◀ **Fig. 10** **a** Graphical analysis of channel selection probability (z-axis) based on the inputs snr (x-axis) and signal strength (y-axis) and **b** Graphical analysis of channel selection probability (z-axis) based on the inputs snr (x-axis) and spectrum demand (y-axis)

approach will lead to the maximum utilization of channel by the users. The acceptance probability shows that it is increased in the proposed system when compare to other two approaches. On the arrival of 0.2% of the CUs, it shows that the acceptance probability is 25% in genetic algorithm, 40% in BPNN approach whereas 60% for the proposed work it shows the acceptance probability will be better in proposed two-fold neural network techniques. That is, the proposed approach is 58% higher than the genetic algorithm and 58% than the BPNN approach.

Similarly, for the 0.4% of CUs arrival the proposed work shows 65% of acceptance probability whereas 45% in other approaches. Likewise, when increase in CUs arrival rate gradually the acceptance probability also increased for the proposed approach when compare to other approaches.

5.3.4 Probability of successful transmission

In the CRN, the probability of successful transmission will play a vital role in maximizing the utilization of scared spectrum resources. The successful transmission means the user can successfully have completed their task with the

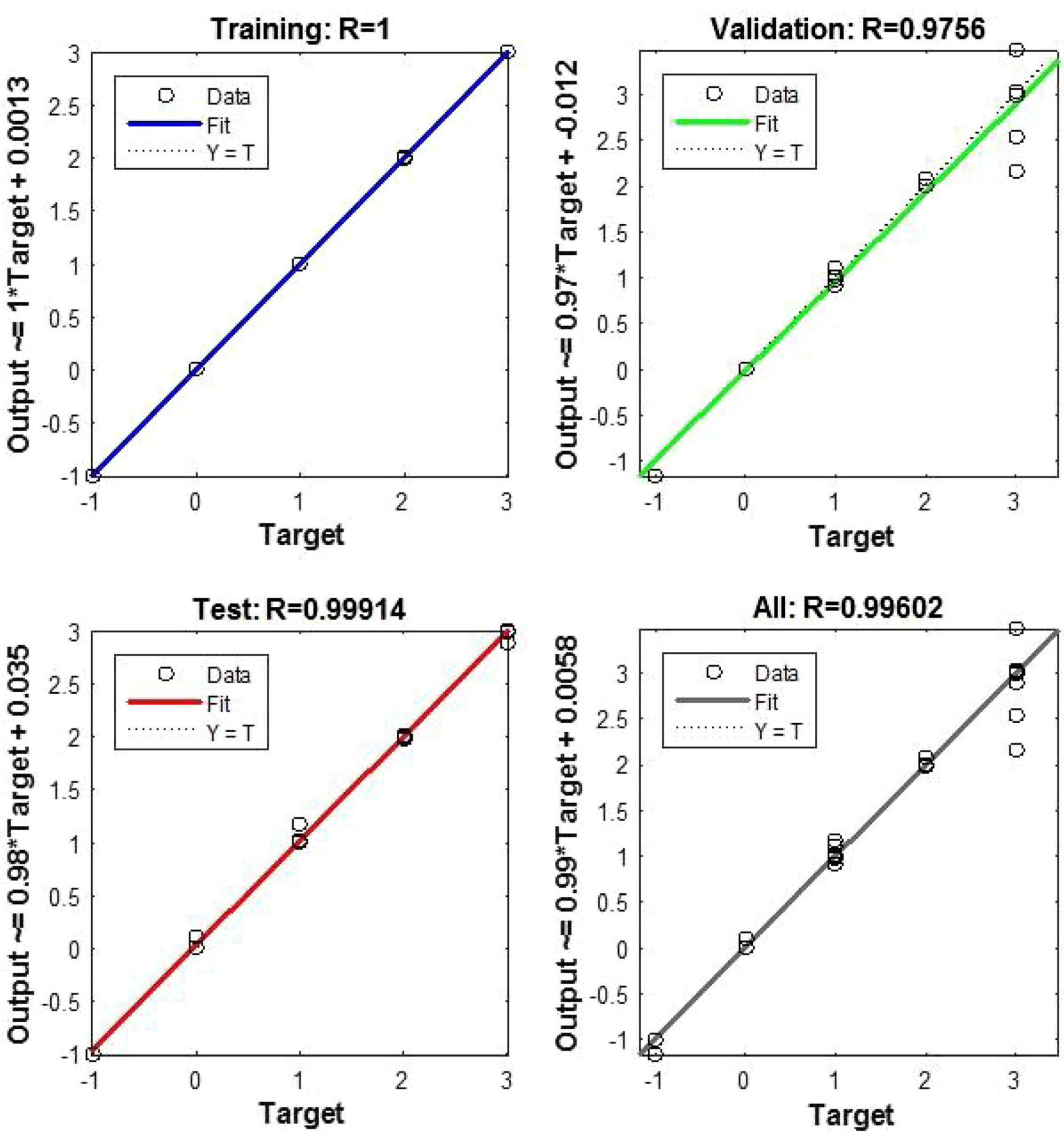


Fig. 11 BPNN techniques for available channel

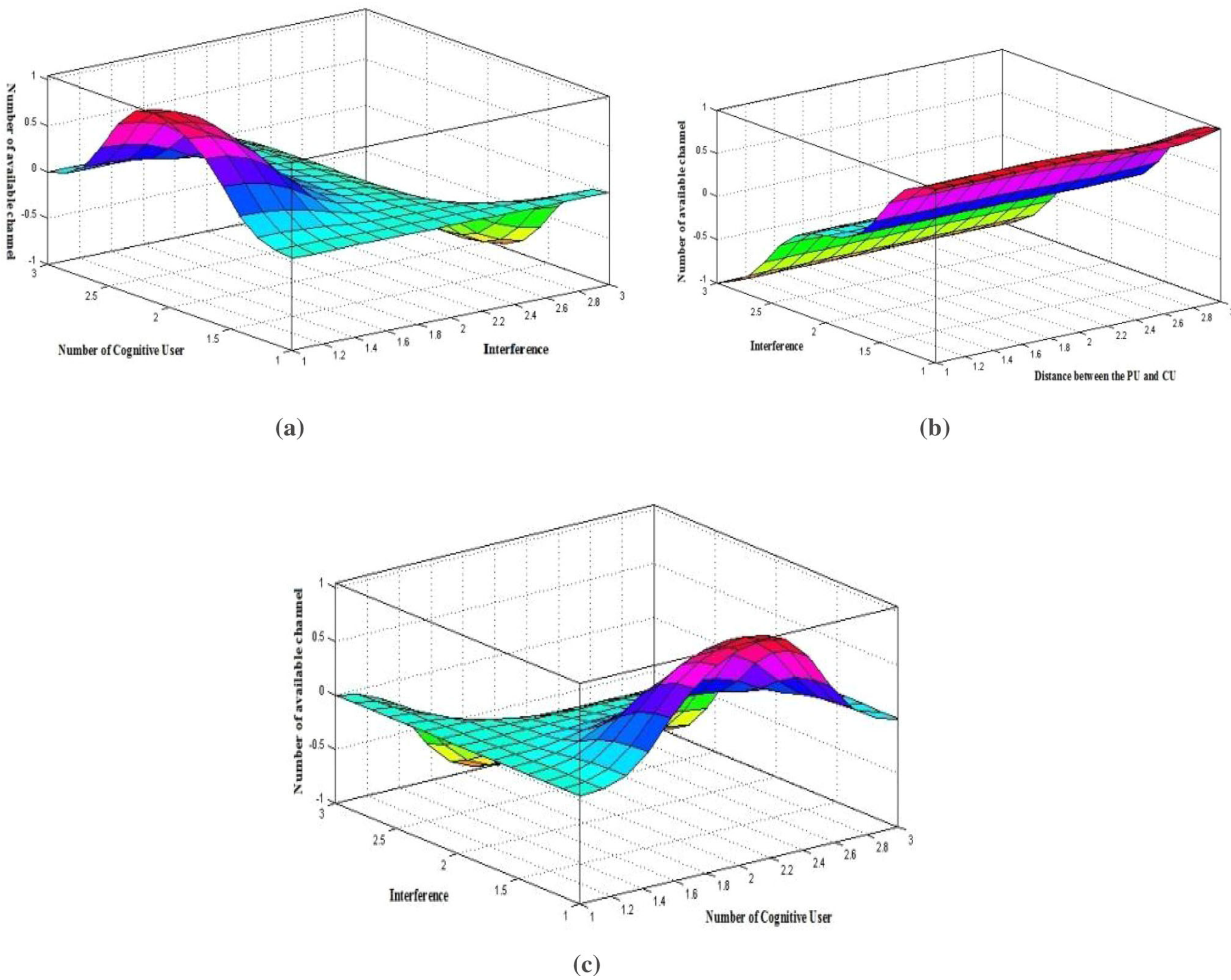


Fig. 12 **a** Surface view of available channel based on no. of cu & interference, **b** Surface view of available channel based on interference & distance and **c** Surface view of available channel based on interference and no. of Cu

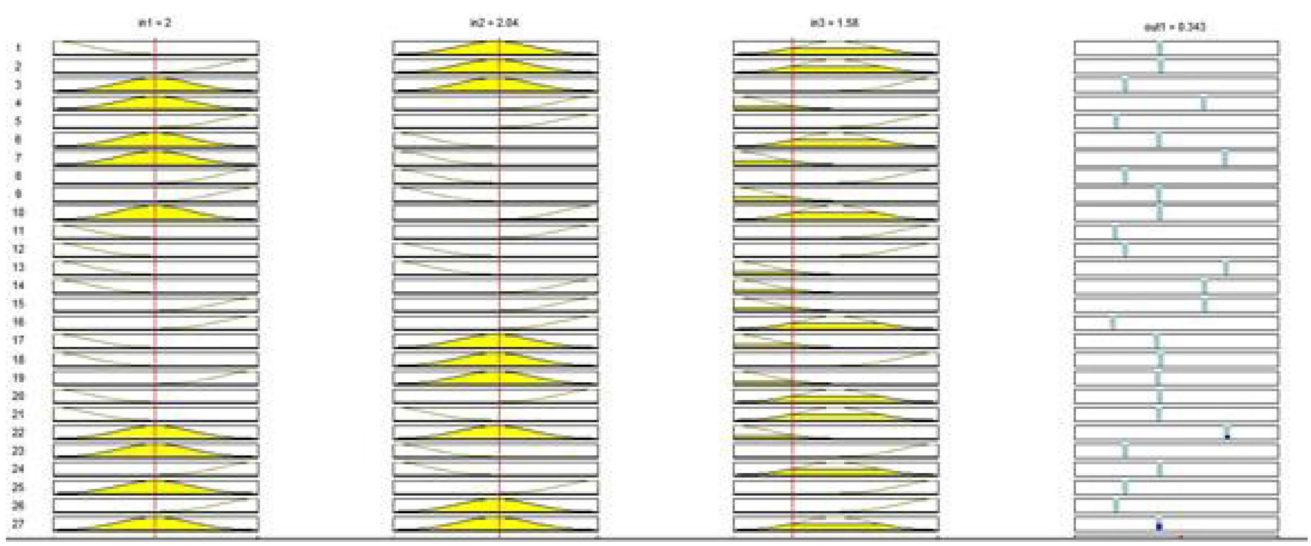


Fig. 13 Combination of I/P & O/P parameters for available channels

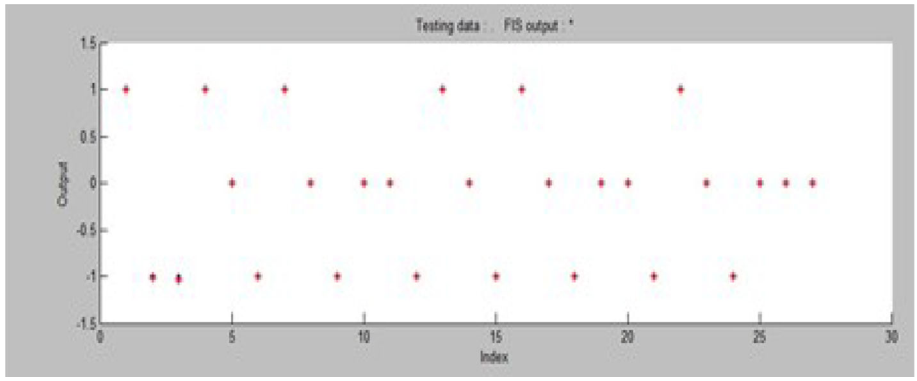


Fig. 14 ANFIS testing output parameters

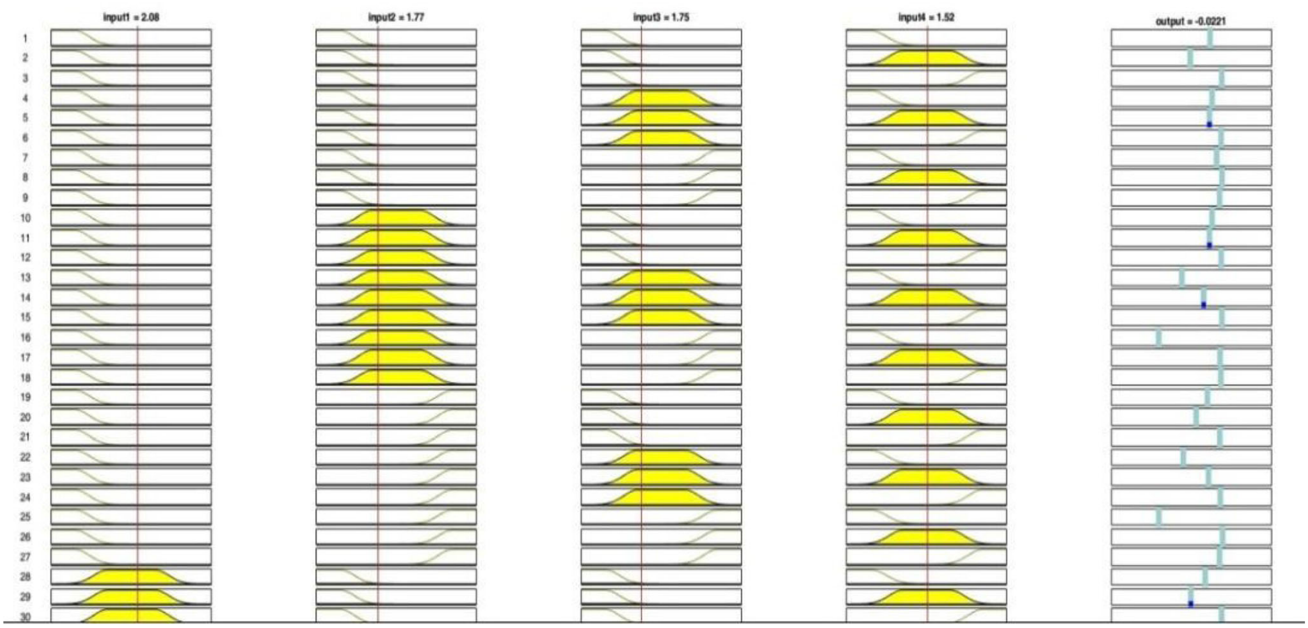


Fig. 15 Combination of I/P & O/P parameters for spectrum decision

allocated channels. The Fig. 20 shows that the probability of successful transmission is increased for the proposed system when compare to other two approaches. On the arrival of 0.2% of the CUs, it shows that the successful transmission probability is 30% for genetic algorithm, 40% for BPNN approach whereas only 60% for the proposed work it shows the successful transmission probability will be increased for the proposed two-fold neural network techniques. That is, the proposed approach is 50% higher than the genetic algorithm and 33% than the BPNN approach.

Similarly, for the 0.4% of CUs arrival the proposed work shows 70% of successful transmission probability whereas 40% and 50% for the other approaches. Likewise, the successful transmission probability percentage is increased on the more percentage of CUs arrival rate. It explains that the proposed work has maximum probability of successful transmission when compare to other approaches.

6 Conclusion

The accuracy in channel selection and decision process improves the performance of dynamic spectrum access. A twofold spectrum decision approach by combining both BPNN and ANFIS techniques is proposed and analysed in this chapter. The BPNN is trained with the parameters such as PU states, signal strength, spectrum demand, velocity and distance. On learning, the BPNN provides about 92–98% accurate channel selection for the use of CUs. The error of 2–8% occurs due to misdetections or false alarms. The use of ANFIS has resulted in the reduction of error and improved the accuracy of the selection and decision of the free spectrum assignment. The results showed that the error

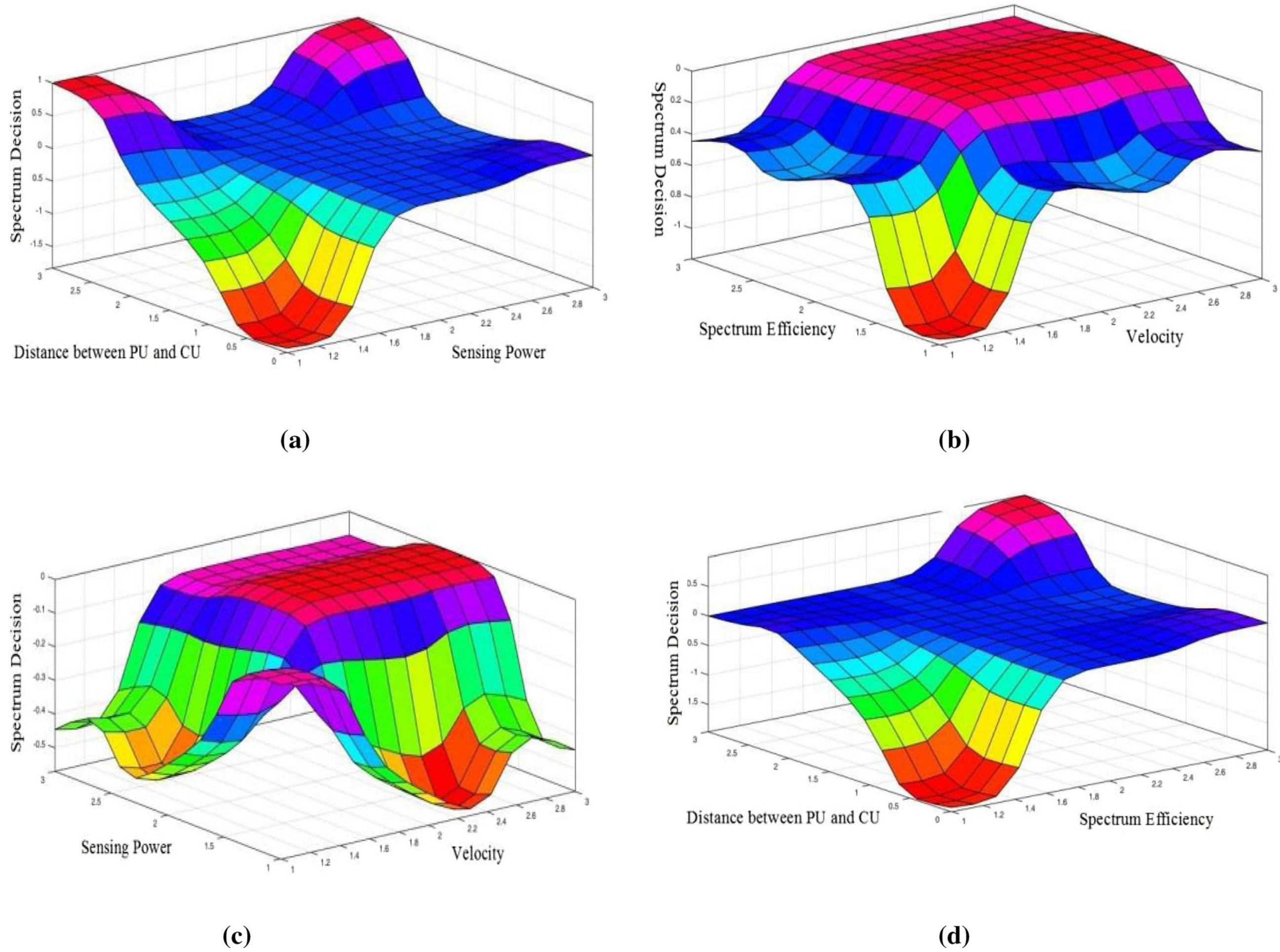


Fig. 16 **a** Pictorial representation of spectrum decision based on inputs sensing power & distance, **b** based on inputs spectrum efficiency & velocity, **c** based on inputs sensing power & velocity and **d** based on inputs distance and efficiency

Table 7 Reliable spectrum decision

Sensing power	Velocity	Spectrum efficiency	Distance between PU and CU	Spectrum decision
High	High	High	High	High
High	High	Moderate	High	High
High	Moderate	Low	High	High
High	Low	High	High	High
Moderate	High	High	High	High
Moderate	Moderate	High	High	High
Moderate	Low	High	High	High
Low	High	Moderate	High	High
Low	High	Low	High	High
Low	Low	High	High	High

of selection reduces to 1–3% and improves accuracy of selection up to 99%.

Performance of the proposed technique is also compared with the techniques of Genetic algorithm and BPNN in terms of blocking probability, dropping probability, acceptance probability and probability of successful transmission. The blocking probability of the proposed technique ranges from 3 to 8% for the increasing rate of CUs, whereas it ranges from 9 to 50% and 8 to 40% in the case of Genetic algorithm and BPNN respectively. The maximum dropping probability of the proposed technique is only 4% and this is lower compared to 20% dropping in

Fig. 17 Blocking probability

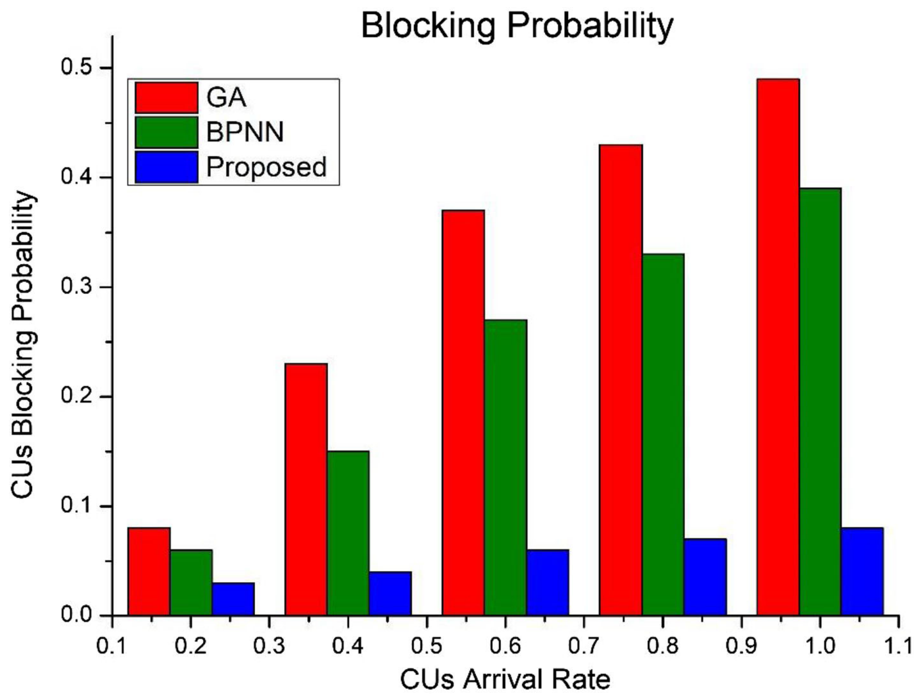
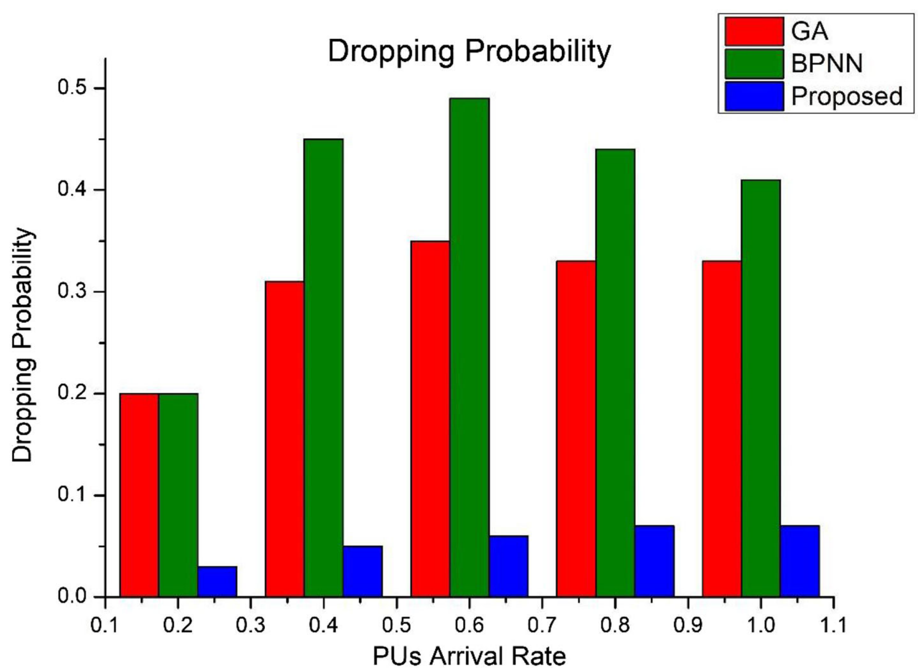


Fig. 18 Dropping probability



the other two techniques. The proposed technique shows 58% improvement in terms of acceptance probability and more than 33% improvement in terms of probability of successful transmission.

Use of cloud infrastructure may be investigated in future for reducing the delay in spectrum selection and decision. The cloud infrastructure may be utilized to store the transmission and reception parameters, availability of free channels of the locations; etc. dynamically to reduce the accessing time of the channels for the cognitive users. Activities of the cognitive users also can be modelled and included for more accurate analysis of the cognitive networks.

Fig. 19 Acceptance probability

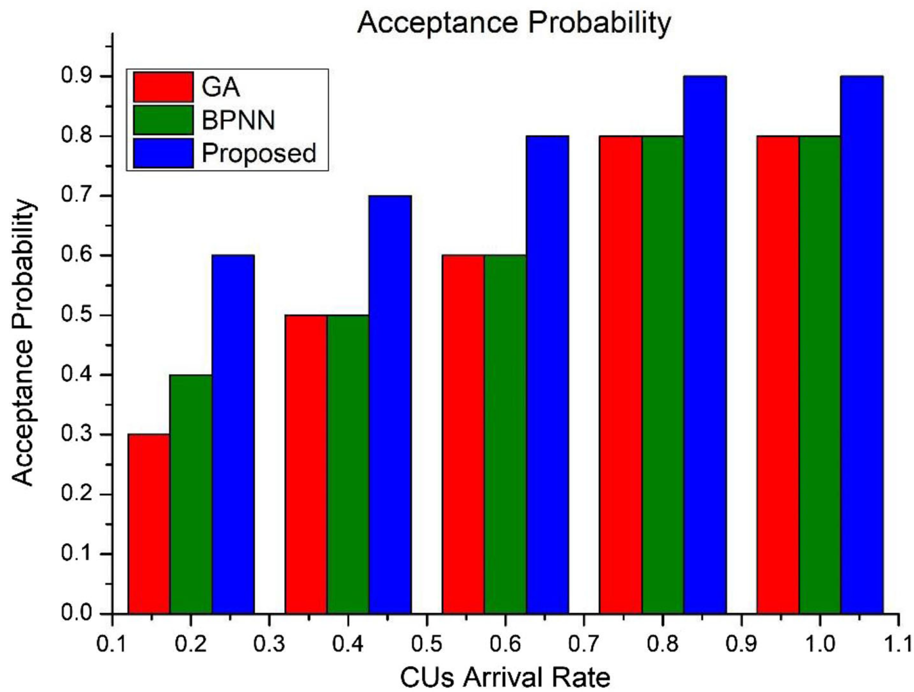
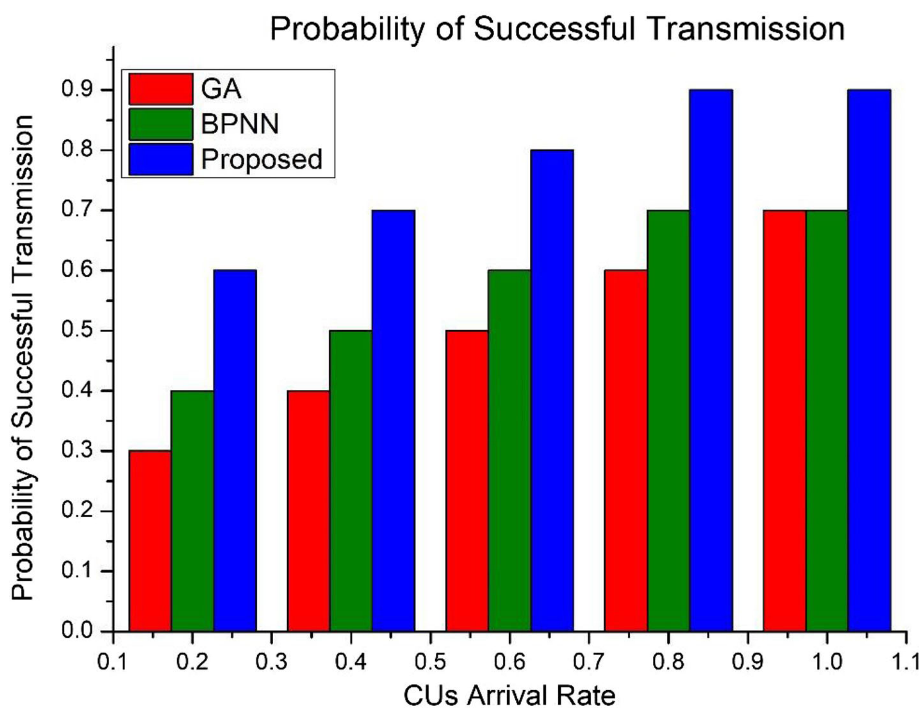


Fig. 20 Probability of successful transmission



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