Artificial Neural Network with Firefly Algorithm-Based Collaborative Spectrum Sensing in Cognitive Radio Networks

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Abstract

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Recent advances in Cognitive Radio Networks (CRN) have elevated them to the status of a critical instrument for overcoming spectrum limits and achieving severe future wireless communication requirements. Collaborative spectrum sensing is presented for efficient channel selection because spectrum sensing is an essential part of CRNs. This study presents an innovative cooperative spectrum sensing (CSS) model that is built on the Firefly Algorithm (FA), as well as machine learning artificial neural networks (ANN). This system makes use of user grouping strategies to improve detection performance dramatically while lowering collaboration costs. Cooperative sensing wasn't used until after cognitive radio users had been correctly identified using energy data samples and an ANN model. Cooperative sensing strategies produce a user base that is either secure, requires less effort, or is faultless. The suggested method's purpose is to choose the best transmission channel. Clustering is utilized by the suggested ANN-FA model to reduce spectrum sensing inaccuracy. The transmission channel that has the highest weight is chosen by employing the method that has been provided for computing channel weight. The proposed ANN-FA model computes channel weight based on three sets of input parameters: PU utilization, CR count, and channel capacity. Using an improved evolutionary algorithm, the key principles of the ANN-FA scheme are optimized to boost the overall efficiency of the CRN channel selection technique. This study proposes the Artificial Neural Network with Firefly Algorithm (ANN-FA) for cognitive radio networks to overcome the obstacles. This proposed work focuses primarily on sensing the optimal secondary user channel and reducing the spectrum handoff delay in wireless networks. Several benchmark functions are utilized We analyze the efficacy of this innovative strategy by evaluating its performance. The performance of ANN-FA is 22.72 percent more robust and effective than that of the other metaheuristic algorithm, according to experimental findings.

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The proposed ANN-FA model is simulated using the NS2 simulator, The results are evaluated in terms of average interference ratio, spectrum opportunity utilization, three metrics are measured: packet delivery ratio (PDR), end-to-end delay, and end-to-average throughput for a variety of different CRs found in the network.

Keywords: Channel Selection, Cognitive radio, Improved genetic algorithm, Spectrum Sensing, Spectrum assignment.

1. Introduction

Current spectrum resources are becoming increasingly scarce as wireless communication technology advances. In 1999, Joseph Mitola proposed cognitive radio (CR) technology. Users of CR are permitted opportunistic access to the frequencies available to other authorized users, so long as the service quality is maintained [1]. An Effective spectrum detection technology is necessary to make sure that CR users can utilize all available resources without interfering with other users. Multipath fading, shadowing, and the problem of hidden main users (PUs) all affect detection performance in practice, though. By combining CR sensing data from different geographical areas, CSS makes use of spatial variation. This significantly improves detection ability [2].

Spectrum sensing is becoming more popular. CR accuracy is a major issue in modern communications. There are numerous methods for selecting the best spectrum nodes. Cooperative sensing, which requires the cooperation of all secondary users, provides precise, reliable sensing data while shortening sensing time [3]. Cooperative sensing requires the participation of all secondary users. Sensing time is cut in half with cooperative sensing. Because secondary users oversee monitoring and controlling data transfer, a central control unit is not required. Distributed cooperative sensing reduces latency and transmission load by allowing each user to recognize and use the primary channel [4]. The presence or absence of a critical signal may influence these decisions. Because of distributed cooperative sensing, each user has access to the main channel.

When used with CR networks, artificial intelligence and machine learning have attracted a lot of interest recently. Fuzzy logic, neural networks, and other technologies are used to allocate resources, regulate interference and power, estimate spectrum availability, allocate bandwidth, and construct cognitive engines. CSS has been studied for machine learning techniques. In [5] suggests CSS use machine learning and pattern recognition. Each CR device's energy level is part of the energy vector, a feature vector model. The energy vector is then classified as either "channel available" or "channel unavailable" by the classifier. This classifier goes through a training phase where it picks up knowledge from training feature vectors before going on to online classification. Contrary to conventional CSS technology, machine learning-based CSS technology may identify the best decision areas in the feature space, improving detection performance [6].

On the other side, CSS technology might lead to cooperative overhead. There are consequently additional time, energy, and security issues. Therefore, to be effective, a CSS approach must maximize cooperative gain while minimizing cooperative overhead. A novel machine learning-based CSS model is presented in this paper with the aim of reducing cooperative overhead while maintaining cooperative gain. Initially, CSS consisted just of training and classification modules; subsequent additions included user grouping and group scheduling [7]. In contrast to CSS, we organize original users by means of energy vector data samples and the SVM algorithm. Everyone was assigned to one of two groups. A module for group scheduling would optimize user groups for pattern recognition. In terms of cooperative sensing performance, the ANN method outperformed other cooperative sensing algorithms such as Gaussian mixture models and K-nearest neighbors. In addition, we recommend the following three grouping methods: Combining CR users can decrease collaboration costs while preserving CSS validity. Fewer CR users who collaborate can improve ANN categorization, hence decreasing CSS sensing time [8].

The indiscriminate unauthorized use of the limited frequency band the necessary licenses necessitates adaptive spectrum access. These strategies help to accommodate these clients. CR users can access unlicensed spectrum. Temporary. SUs can use CR's spectrum management tools to select the best frequency for their specific skills and needs. QoS varies over time because of dynamic channel characteristics [9]. Four factors are impeding effective spectrum management. Spectrum use, monitoring, and portability are critical. This study [10] covers mobility, common control channels, power management, spectrum sensing and scheduling, and hidden and exposed terminals.

Spectrum sensing, spectrum decision-making, spectrum sharing, and spectrum mobility are required for optimal spectrum utilization in CRNs. All four of these mechanisms must be in place for the spectrum to be used optimally. First, CRs must continuously scan the radio spectrum utilizing spectrum sensing activities to identify spectrum gaps. Spectrum sensing is expected to be extremely important in CR networks. The likelihood of missed detection and the potential for a false alarm are used to calculate the accuracy of spectrum sensing. When a CR user asserts that a channel is active when it is not, this is a false alarm [11]. When a CR user neglects to recognize the presence of PUs, a miss detection incident takes place. Numerous sensing techniques were used, such as matching filters, energy, and feature identification. Erroneous PU activity identification and miss detection concerns are a result of a variety of circumstances, such as receiver ambiguity, shadowing effects, and channel fading. Utilizing spectrum sensing information from other CRs, cooperative spectrum sensing enhances PU detection. Users of CR work together to analyze their sensing data to reach more accurate conclusions. The channel is dormant if all CRs agree. The possibility of an unnoticed detection is reduced, but the likelihood of a false alarm is increased, limiting the spectrum's utility [12].

This paper (CRAHN) presents the framework of Artificial Neural Networks (ANN) employing the Firefly Algorithm (FA) for cognitive radio wireless ad hoc networks. With the proposed ANN-FA, the performance of CRNs will be improved by addressing the problem of sensing errors, and a novel channel selection method will be presented to help CR users make wise channel selections. The ANN-FA architecture improves network performance by lessening the effects of false alarms and miss detections and giving CRs the ability to choose the best channel for transmission performance, throughput, and spectrum utilization. Fuzzy inference system (FIS) channel selection in an intelligent process and K-means unsupervised learning to reduce sensing mistakes enabled this improvement. Analyzing ANN-FA models is done using the NS2 simulator. According to the simulation findings, our technique chooses the channel with the least level of PU interference when compared to other options. Here are some key points that highlight the significant scientific contributions of the paper: (i) The research focuses on CRNs, which are intelligent wireless networks that can dynamically access underutilized spectrum bands. CRNs aim to improve spectrum utilization by allowing secondary users (SUs) to opportunistically access the spectrum allocated to primary users (PUs) without causing interference. (ii) Spectrum sensing is a crucial component of CRNs, as it enables SUs to detect the presence of PUs and identify available spectrum opportunities. Accurate spectrum sensing is essential for avoiding interference and efficiently utilizing the spectrum. (iii) This study introduces the use of the Firefly Algorithm (FA) for optimizing the weights and biases of an Artificial Neural Network (ANN) used in the spectrum sensing process. The FA is a bio-inspired optimization algorithm based on the flashing behavior of fireflies. By applying FA to ANN training, the paper aims to enhance the performance and convergence of the neural network in making accurate spectrum sensing decisions.

The author of this article suggests adopting an ANN-FA as a beginning point for instruction because it contains both historical and present information.

- Because of the ANN-high-speed FA's training and behaviour, the proposed technique has witnessed a significant improvement in We are not aware of any competing interests that the authors should disclose.
- The second goal is to provide unbiased training datasets with varying amounts of data, as well as to evaluate multiple learning models by providing a testbed for empirical hardware that is both adaptable and robust in its design.
- Finally, various statistical characteristics of PU activity, such as duty cycle, distance, timestamps, and power, are used as input data to improve the proposed model's ability to perform its intended functions.

The remainder of the article is divided into the following sections or categories: A review of prior studies is presented in Section 2 of this document. The approach underlying the proposed plan is explained in the third section. The performance evaluation is described in Section 4, which begins with the simulation settings, moves on to the performance measures, and concludes with the results and commentary. Section 5 provides a summary of the study's findings along with suggestions for future research.

2. Literature Review

Zhang et al. [13] completed spectrum sensing. This technique also comprises coordination, channel detection, and beaconing. Each unoccupied channel detected was compared to the channel sensing data. To deliver its beaconing data, the node exploited channels that were not in use. At this point, the pairwise distances were calculated, as well as the strength of the neighboring beacon signals. To coordinate between clusters, the most recent information was provided to clusters and CHs. If either the SUs or the PUs moved, the clustering procedure was resumed. The network's transfer necessitated increased levels of supervision.

According to Gallego, J.R. et al. [14], game theory is used to allocate channels in CRNs, with each agent acting on their own. This website discusses game theory. CRs choose the transmission channel options. He created game-theoretic methodologies for channel allocation and power control in CRNs to maximize network utility. The physical interference model was used to investigate the problem. In this model, a relationship exists only if the SINR is greater than a predetermined threshold. He proposed using game theory to assist CR networks in choosing spectrum in a way that conserves energy. The goal of this strategy, also known as Graph Coloring-based Dynamic Channel Allocation (GC-DCA), is to maximize channel utilization while minimizing PU interference for maximum performance.

He et al. [15] suggested a method known as distributed Q learning-based integrated channel selection and power control spectrum selection to attain the highest potential levels of energy and spectrum efficiency. In this strategy, CRs are responsible for choosing the channels that deliver the most value. The recommendations offered by L. Ding et al. regarding channel selection were implemented.

A cluster-based assignment method for channels to CRNs was provided by Pareek et al. [16]. A trustworthy resource allocation (RA) technique was presented for cognitive relay networks that contain a significant number of processing units (PUs). The suggested approach addresses the resource allocation issue by making use of reliable relay selection and power distribution while taking channel and interference uncertainty into account. The outcomes supported the suggested robust relay selection technique's robustness.

For cognitive radio ad hoc networks, T.M. Salem and associates [17] developed a basic segmentation followed by a self-organized map as a smart channel selection technique (ICSSSS). The SOM learner divides the channels into four clusters, allowing CR to choose the channels with the lowest sensing error while still being the most accessible. As a result, a simple segregated channel selector selects the best channel for secondary users in a respectable period. Using a dynamic evolutionary algorithm.

A.H. Mutlag et al. [18] The importance of using optimization approaches to improve AI, ML, and DL has grown in recent years. Numerous studies are being done right now that make use of optimization to increase or improve performance by figuring out the best parameter values to support architecture design. The best membership function patterns are chosen via differential search optimization, increasing the fuzzy controller's precision. For PV inverters, this fuzzy logic controller design innovation is offered.

Ardabili et al. [19] devised distributed channel selection (BFC). When selecting a channel, BFC takes both primary and CR traffic into account. CR nodes can predict a channel's inactivity by analyzing PU traffic patterns and the channel's present condition. It selects channels with longer stretches of inactivity than its own transmissions. A CR user who employs LITC will choose the channel that is anticipated to have the longest period of idle time, regardless of any transmission restrictions. It demonstrates a lack of altruism and is detrimental to the network.

Sundous Khamayseh et al. [20] Conducted a survey to examine specific CSS Schemes built with machine learning approaches and ideas. It was concluded that the unsupervised-based CSS strategy was not only less complicated but also marginally less reliable than the other approaches. The supervised-based CSS delivered outstanding precision despite a little training overhead. However, it may be challenging to employ in near-real-time and may necessitate a large amount of computation. On the other side, reinforcement learning provided high precision and throughput.

K-nearest neighbor is one type of machine learning algorithm. Hurmat Ali Shah et al. [21] proposed a trustworthy spectrum sensing strategy based on this method. The most recent sensing data is then classified based on the PU's current state. Sensing reports are compiled and organized by sensing class. The findings of this study can then be used to determine whether the PU exists. Spectrum sensing is ensured through the collaboration of mechanisms present at the CR and FC levels. The reproduction results show that the newly devised method outperforms the classic OR rule in standings of detection, even when subjected to fading conditions and utilising spectral gaps.

Sana Ullah Jan et al. [22] explored how well an SVM-based classifier performed in CR networks for spectrum sensing. If the main user cannot be located, the amount of classes will be improved. Even if a false detection is made, the principal user's operations are safe. The

SU can maintain a consistent amount of energy by using a variable transmission power that responds to the strength of the detecting signal. To compare and assess the effectiveness of various classifiers, two metrics are used: accuracy and area under the receiver operating characteristic curve.

Oliver et al. [23] proposed a unique energy management strategy with enhanced security based on a heuristic green computing technique and an optimized routing protocol. Energy management in green computing is used to improve the energy efficiency of the network by employing a heuristic green computing technique. The security analysis was then performed for the network's safe data transfer utilizing the Hybrid Greedy safe Optimal Routing Protocol (Hy_GSOpRP). According to simulation results, the proposed routing approach outperforms the existing ones in terms of MAPE of 62%, MLR of 55%, RMSE of 45%, energy consumption of 59%, network lifetime of 95%, latency of 40%, and throughput of 98%.

Table 1. Literature survey of Cognitive radio networks (CRN)

References	Objective	Techniques	Algorithm	Key Consideration
X. Zhou et al [24]	Minimizing transmit power	Channel and traffic statistics	Power and rate allocation	Transmission costs, Energy efficiency
E. Nachmani et al. [25]	Modulation classification	Maximum likelihood estimation	Support vector machines (SVM)	Bandwidth and time coherence
H. Sun et al. [26]	Power allocation optimization	Supervised deep neural networks	Weighted MSE	DNN size and computational complexity
A. Balatsoukas [27]	Interference cancellation	Supervised neural networks	Feed forward NN canceller	NN size and computational complexity
N. Strodthoff et al. [28]	Prediction channel decoder	Supervised auto encoder	Binary predictor	Effective block error rate
M. Saber et al [29]	Primary user signal detection	K-nearest neighbour (KNN)	Sub linear algorithm	Transmission costs, Energy efficiency

3. Proposed methods

As shown in **Fig. 1**, the four modules comprising the proposed channel selection architecture are 1) channel sensing, 2) spectrum characterization, 3) spectrum selection, and 4) CR reconfiguration. All CR nodes in the initial module makes advantage of the spectrum sensing system of the physical layer to determine which channels are open. The second module, which is a component of the MAC layer, is then supplied the list of accessible channels.

The second module employs unsupervised K-means learning to categories spectrum channels into four distinct sections. This organization enables the CR to recognize true idle channels and prevent sensing errors (MD and ON). This prevents PU clashes, improves spectrum use, and lowers spectrum sensing errors at higher levels. Channels are obtained by means of spectrum selection (correct OFF and MD). The third module employs the heaviest weight channel. This channel is characterized by its PU utilization, channel capacity, and CR count. As a result, the suggested framework employs a tiered approach. Every layer has a certain purpose. The fourth module will optimize QoS parameters when the best channel has been chosen. The CR then uses the chosen channel and QoS parameters to transmit a signal.

The proposed ANN makes use of channels with low primary radio node use, low CR user congestion, and high capacity. Channel weight is calculated through fuzzy inference using channel parameters. After storing the remaining channels in descending order as backups, the channel with the maximum weight value will be used for packet delivery. When the remaining channels have been saved, this occurs. The fuzzy channel selector and K-means learner are explained in the next sections. This work encompasses spectrum selection and characterization. The spectrum characterization module utilizes K-means learning to minimize spectrum sensing mistakes. For channel selection, the spectrum selection tool proposes FIS.

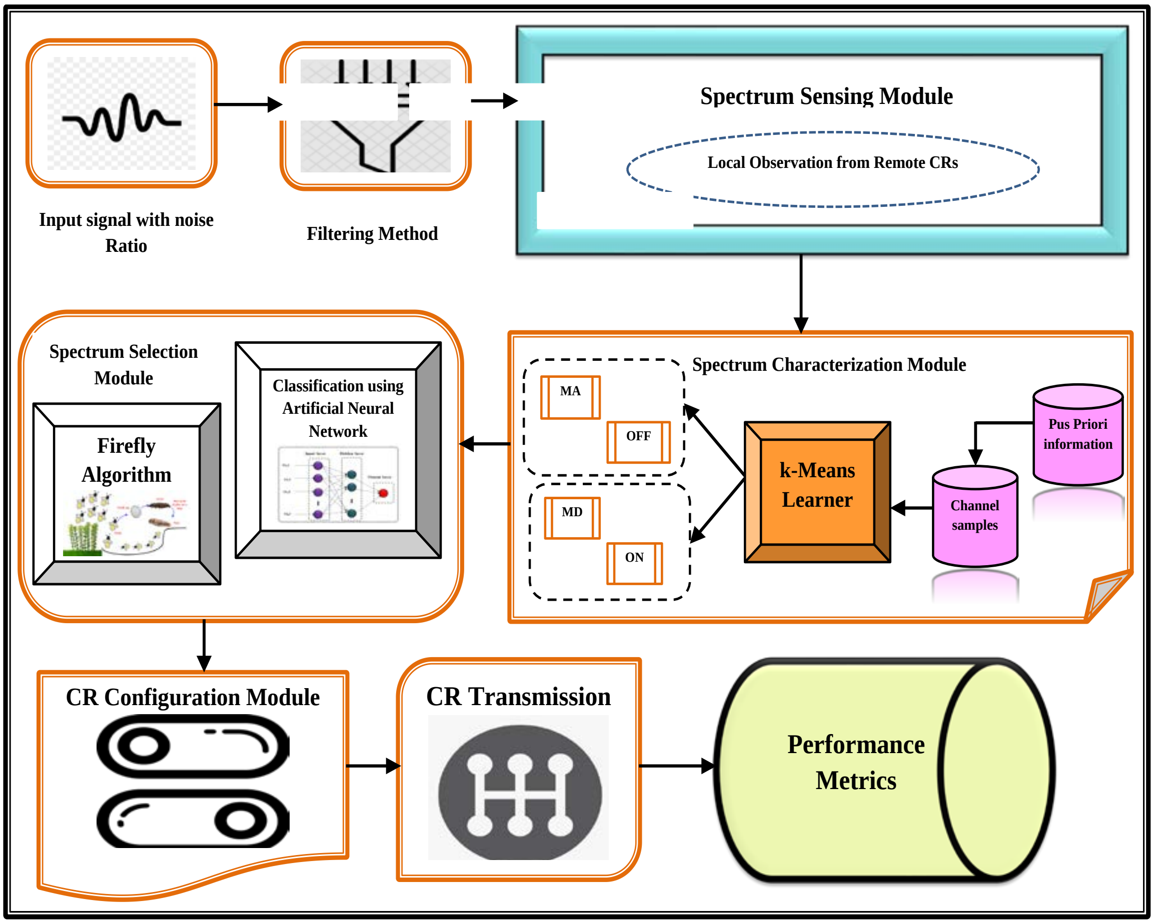

Fig. 1. Proposed model of ANN-FA

3.1 Artificial Neural Network (ANN) Model

The workings of the human brain inspired the development of the Artificial Neural Network (ANN). ANN is a model of information processing that consists of many single processing units, often known as neurons, that work in parallel to accomplish complex computations. The basic goal of ANN is to allow a computer to learn from examples and adapt to different datasets. ANN is very useful for tasks requiring pattern recognition, speech recognition, and data classification [30].

The most popular network design in use today, the neural network, is made up of three layers, each having distinct feed-forward architecture. A group of input units that accept feature vector inputs make up the input layer. The input units are totally connected to the hidden layer together with the hidden units. The hidden units are also fully connected to the output layer. The neural network's response to the activation pattern applied to the input layer is provided by the output layer. One or more hidden layers are used to transmit data one layer at a time from the input layer to the output layer. Here, the most basic NN model is displayed [31].

The weights $WT_1, WT_2, WT_3, \ldots., WT_n$ are used to estimate the strength of the input vectors $In = [In_1, In_2, In_3, \ldots In_n]$. Each input is multiplied by the accompanying neuron connection $In^T WT$, which may be expressed as the following equation. Positive weights stimulate and negative weights inhibit node output.

$$In = In^T.WT = In_1 WT_1 + In_1 WT_2, \ldots., + In_n WT_n \tag{1}$$

The magnitude offset is determined by the node interval threshold. It influences the activation of node output OT as surveys:

$$OT = f(In) = f\{\sum_{i=1}^{n} In_i WT_i - \Phi_k\} \tag{2}$$

For the Classification challenge, ANN must be trained in order for the networks to create the desired the human brain inspired the development of the Artificial Neural Network (ANN). ANN is an information processing model that consists of many single processing units, often known as neurons, that work in parallel to accomplish complex computations. The basic goal of ANN is to enable a computer to learn from examples and adapt to specific datasets. ANN is highly effective in jobs requiring pattern recognition, speech recognition, and data classification.

The neural network is composed of three layers, each with its own feed-forward architecture, and is the most often used network design today. The input layer is made up of a collection of input units that take the constituents of input feature vectors. The input units, like the hidden units, are entirely connected to the hidden layer. The output layer is also completely connected to the hidden units. The response of the neural network to the activation pattern applied to the input layer is providing by the output layer. The data is transferred layer by layer from the input layer to the output layer via one or more hidden layers. The most basic NN model is shown in **Fig. 2**.

$$H = \sum_{i=1}^{m} (tg_i - ot_i) \tag{3}$$

Where tg represents the target output and ot represents the computed output from training data.

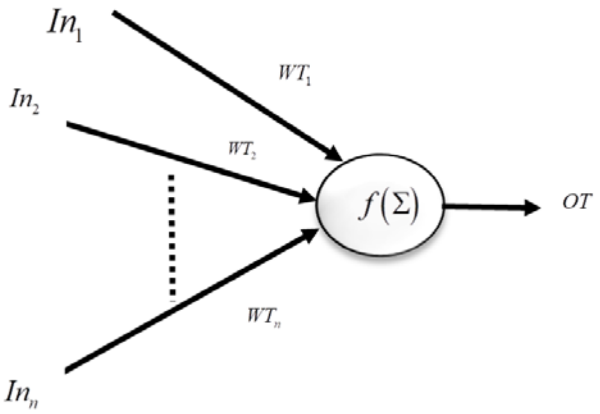

Fig. 2. A simple structure of ANN

3.1.1 Neural Network Training

After a network has been constructed for a particular purpose, it can be trained. Most ANN training falls into two classes: During supervised learning, the network compares actual outputs to predicted outcomes. Unsupervised training is utilized when both input and output are known. In NN-based systems, the loss function and the training methods are commonly believed to be the two most essential qualities. It is sometimes referred to as the objective function or criterion due to the effort put on minimization or optimization of this function or criterion. It will also be referred to as the cost, loss, or error function when we are aiming to lower it.

• When training neural networks, an optimization strategy that uses a loss function to calculate model error is used as part of the training process.

• When developing neural networks and other kinds of machine learning models, maximum likelihood offers a way to choose a loss function.

• When creating neural network models, the mean squared error and cross-entropy are the two most frequently used loss functions.

Backpropagation is one of the few ANN training techniques known to exist, and it is currently employed. An artificial neural network (ANN) that processes inputs and might provide results needs the data to be trained. The following techniques are used in instruction:

1. Begin by considering the inputs and potential results.

2 Once you've identified and added the weights for each input, you can use transfer functions.

3 Consider the actual outcome while evaluating the expected output.

4. The fitness value can be established and updated based on the comparison.

5. Return to steps 2 and 3 until your training is at the appropriate level.

6. Adjust the weights in the right way to improve fitness.

7. Repeat Steps 1-6 until your fitness value is high enough.

The back-propagation approach is intended to change a network's weights, although training can take a while. The author of this study supports FA as a training technique.

Each neuron has a transfer function connected to its input that can activate the neuron. It determines the inputs of a neuron's weighted sum. It is wise to use the sigmoid function, which was used in this study. A sigmoid function with a range of [0, 1] can be used to represent the following equation (4):

$$Sigmoid(x) = 1 / 1 + e^{-ax} \tag{4}$$

In this article, the sigmoid function is used since it exists between two locations (0 and 1). Because of this, it excels in models that need the estimation of the likelihood as an output. The sigmoid is the most obvious option because the possible outcomes only range from 0 to 1. Differentiating the function is possible.

In neural networks, it has the following applications:

1. A technique in mathematics that takes linear inputs and transforms them into nonlinear inputs.
2. Make it possible for the output to be interpreted as a probability by limiting the range of the output to the numbers 0 and 1.
3. Utilizing specified activation functions can simplify calculations.

3.2 Firefly Algorithm (FA)

Yang proposed the name "Firefly" in 2008. It was influenced by how fireflies react to a strong amount of light. The firefly's brilliance and appeal are assessed. Consider two flies, one of which is lighter than the other. Therefore, in Algorithm 1, the brighter fly is drawn to the fly that is less lighted. Flowchart of firefly algorithm shown in **Fig. 3**. The Euclidean form, Eq, is utilized to determine the separation between any two fireflies, dp_i and dp_j (5).

$$S_{ij} = \left(\sum_{k=1}^{d} (dp_{ik} - dp_{jk})^2 \right)^{\frac{1}{2}} \tag{5}$$

Eq. calculates and measures attraction (6).

$$\alpha_{ij} = \alpha_{lig} e^{-\beta s^2_{ij}} \tag{6}$$

where set αlig ¼ 1 is the light attractiveness at S = 0 and β = 1 is the light coefficient

Eq. calculates the effort needed to relocate one firefly fsi to the most desirable fireflies fsj and the updated current position (7).

$$dp_i = \alpha_{ij} + (dp_j - dp_i) + \varnothing (rand\,(0,1) - 0.5) \tag{7}$$

Rand (0,1) and Φ are the random numbers from 0 to 1

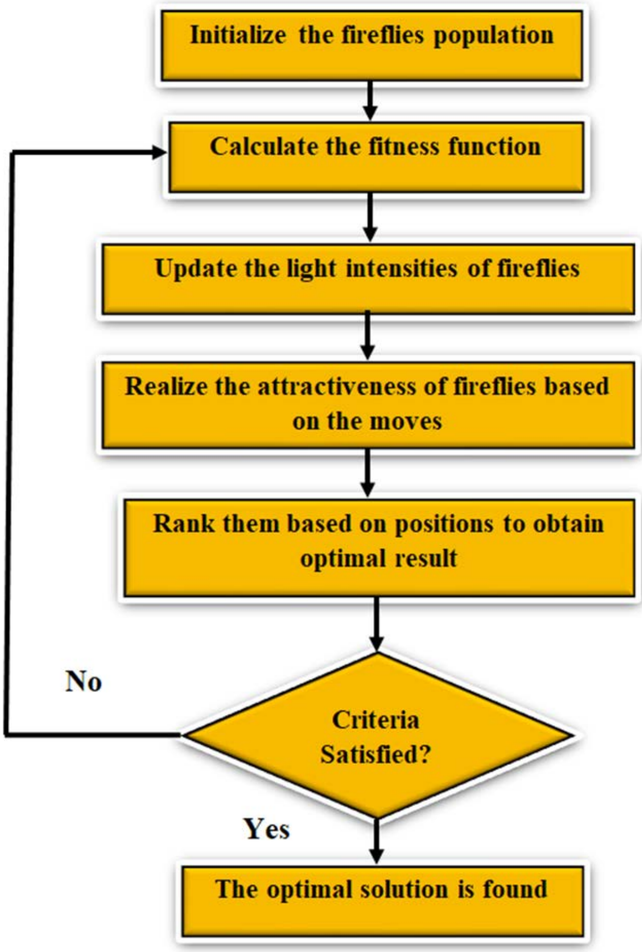

Fig. 3. Flowchart of firefly algorithm

Algorithm1 Firefly Algorithm (FA)

Step:1 Set α,β parameter and randomly initialize the population Step :2 Find the distance between the less illumination and brighter fly Step :3 set t=0 Step :4 While t < Maxiter Step : 5 Find the either new position or the previous position Step : 6 Calculate the either fitness function value and probability values prob(i) Step :7 Now determine the brighter attractiveness of the flies and the new position using Eq (6) and Eq (7) Step :8 t=t+1 Step :9 Untill t=Maxiter

3.3 The proposed ANN-FA based spectrum handoff process

The proposed ANN-FA examines a spectrum handoff procedure based on ANN-FA. A new approach is developed for the analysis and formulation of spectrum handoff [32]. The capacity of secondary user C_s is used to calculate the throughput and spectrum handoff delay in Eq. (8).

$$C_s = \partial_s N_s \tag{8}$$

where ∂_s is the secondary user arrival rate and N_s is the total amount of secondary users. Throughput TR_s Eq. (9) uses the Poisson distribution to compute the probability of a secondary user for efficient and smooth packet transfer. The ratio of the effective amount of packets received by the receiver to the entire amount of slots in a given time is used to indicate the secondary user's throughput.

$$TR_s = \frac{C_s^n e^{-C_s}}{n!} P_t (1-P_t)^{N_{s-1}} \tag{9}$$

P_t is the likelihood that a secondary user will successfully transmit a packet, and n is the total number of packets that are transmitted within each estimated time slot. The switching delay and the sensing time are the foundations of the spectrum handoff delay. The switching delay is the amount of time until the SU determines the free channel to switch to, whereas the sensing period is the amount of time required to detect the channel from the spectrum. In Eq. (10) HF_d is expressed.

$$HF_d = Sw_t + Sen_t \tag{10}$$

When proactive spectrum handoff systems are utilized, both are regarded as zero because the prescheduled channels are being used. In this scenario, Sw_t is the switching time at which the secondary user is compelled to switch to a different channel, and Sn_t is the sensing time used to detect the idle channel for the SU.

Eq. (11) derives the mean spectrum handoff delay $\mu(HF_d)$.

$$\mu(HF_d) \frac{\partial_p [Sw_t Iat_s + (\mu[St_p])^2 \partial_p Iat_s + \mu[St_p](\partial_s - Sw_t Iat_s \partial_p)]}{(1-\partial_p \mu[St_p])(Iat_s)^2} \tag{11}$$

The primary and secondary users' respective arrival rates are represented by ∂_p and ∂_s, while their respective mean service times and interarrival times are represented by St_p and Iat_s. For each channel, the overall service interval time, or " O_{pro}," is taken into account and designed to get the values that are stated in Eq. (12).

$$\mu = (O_{pro}) = Ser_t + C_p Ser_t \frac{H_{hf}}{1-C_p T_{hf}} \tag{12}$$

SS_t stands for service time, C_p for primary user capacity, and H_{hf} for secondary user's first handoff process. In Eq. (13), the service time is calculated, and stands for the use of spectral density.

$$SS_t = \frac{1}{\phi} \tag{13}$$

All of the ABC algorithm's phases are used to explain the ANN-FA, and Algorithm 3's description of FA is included [33-34]. The worker bee phase employs the search equation by offering the optimum informational remedy for advancement. In order to produce the optimum answer as B, the observer bee substitutes 5% of the worst position for the new location while using 25% of the employee bee for future search steps. The firefly algorithm is used in the scout bee phase to explore a new location by trading obsolete locations in order to find the optimal response.

Initialization: Using the search space created by Eq. (14) and the food source $dp_{i,j}$, the initial solution is created.

$$dp_{i,j} = L_j + \frac{(rand_{ij} + 2i - 1)}{2NB}(U_j - L_j) \tag{14}$$

Here $i = 1, 2, ..., NB$, $j = 1, 2, ..., D$ and $rand_{ij} = random\ number\ in\, range[-1, 1]$

1. Employee bee phase: the subsequent expression in Eq. (15) dp_{best} is the optimal location to recognise the new location.

$$Curr_{i,j} = \begin{cases} dp_{best,j} + rand(dp_{i,j} - dp_{k,j}); & j = j^{\circ} \\ dp_{i,j}; & j \neq j^{\circ} \end{cases} \tag{15}$$

where k is selected at random from $1, 2, ..., NB$ and if $k \neq i, j^{\circ}$ is selected from $j = 1, 2, ..., D$. and $rand_{ij}$ is in range [-1, 1]. Comparison between the present position $Curr_{i,j}$ and the preceding position dp_i. If current position $d(Curr_{i,j}) < d(dp_i)$, update current position $Curr_{i,j}$ by dp_i; else, place dp_i. Set the counter for the next unmodified iteration, $count(i) = count(i) + 1$.

2.Onlooker bee phase: The probability value in the onlooker bee is configured to be constant at $\Pr ob_i = 0.25$; if $rand_{ij} < \Pr ob$, the new position $Curr_{i,j}$ is updated. If $d(Curr_{i,j}) < d(dp_i)$, then dp_i should be swapped out for $Curr_{i,j}$; else, keep dp_i. Using Eq. (16), the new position is replaced for the worst position.

$$dp_{Z_t} = B[dp_{best} + rand_t(dp_{Z_t} - dp_{R_1}) + \omega_t(dp_{best} - dp_{R_2})] \tag{16}$$

For all t between 1 and NB, R1 and R2 are randomly chosen keys such that are the arbitrary integers in the variety [-1, 1], and B is the total amount of observed best locations. For $Z_t = 1, 2, ...[0.05]NB$ are the 5% of worst position.

3. Scout bee phase: From the positions that aren't changed in Eq. (17), the new position is obtained using the firefly algorithm.

$$dp_i = dp_i + e^{-S_{ip}^2}(dp_q - dp_i) + (rand(0,1) - 0.5) \tag{17}$$

Hence, if $f(dp_q) < f(dp_i)$, p is the first index.

Fig. 4, depicts the suggested ANN-FA algorithm's architecture diagram, highlighting the primary user's arrival and the spectrum sensing process employing metaheuristics during the secondary user's handoff. Based on artificial neural networks and firefly optimization, the proposed approach is intended to determine the ideal channel from available spectrum in cognitive radio networks.

1. The worker bee is in charge of detecting open frequency channels for the active secondary user. It checks the channels and takes into account any fresh bandwidth it discovers.

2. The worker ANN-FA communicates with the observation FA, which is stationed within the hive. The secondary user selects the best channel based on this data by evaluating its fitness value. This is then applied to the spectrum handoff.

3. The scout bee checks the entire channel, noting which channels are in use and which are open. Any prior information about busy channels is wiped from memory if an idle frequency channel is identified.

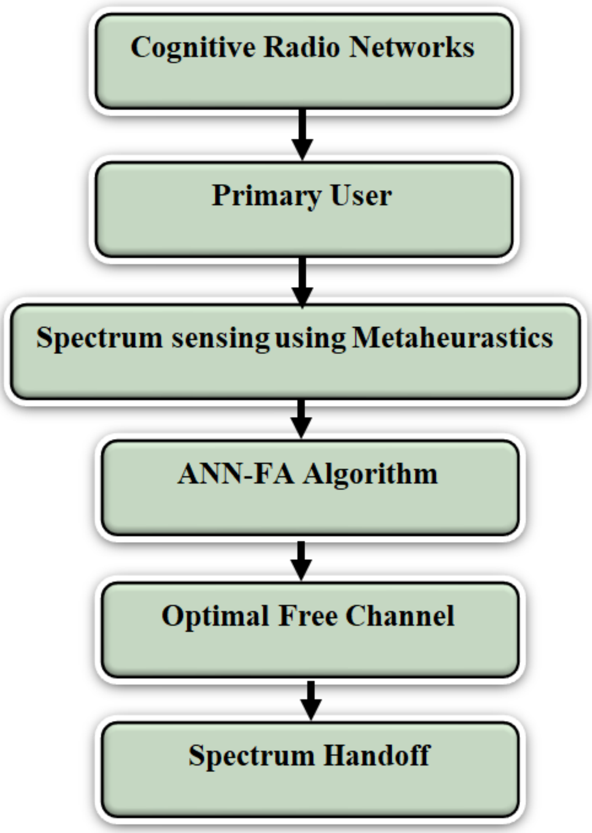

Fig. 4. Proposed ANN-FA architecture

Algorithm 2: Proposed ANN-FA Algorithm.

1. Fix parameter: NB , Maxitier, count, N_S
2. Apply Eq.(14) to set the food source and estimate it. Set t=0.
3. While t<Maxiter
4.//Employee bee phase
5. For entire employee bee, Eq.(15) is submitted and compared to find the entire new channel or the previous channel.
6. Calculate the fitness function value and probability values.
Prob(i)
7.//Onlooker bee phase
8. For onlooker bee, set probability value =0.25 & Z_t =0.05 is collected from employee bee and consider B as best value
9. Using Eq.(16) is compared with rand(0,1) then the some new channels are observed
10. Stores the best value that are found in memory
12.//Scout bee phase
13. Decide the solution until Maxitier using Eq.(17) and store the best optimal value by replacing the previsous value in memory
14. t=t+1
15.Till t= Maxi

4. Result and Discussion

In the following part, the effectiveness of the proposed framework for the selection process will be evaluated by in-depth simulations. The results of the network simulator's simulation utilizing the provided framework will be shown in the section that follows this one. When analyzing the NS2 simulation, it is critical to consider the FIS result, which shows the channel weight. It concisely and simply demonstrates how MATLAB and NS2 are related.

The Network Simulator - 2 (NS2) was used to test the performance of the proposed ANN-FA on the CR network, as shown in this section. how many processing and server units are needed for access channels in total according to the optimal K number (the number of connections between clustered structures). In terms of dynamic spectrum access, ten major user nodes and 90 subsidiary user nodes are employed to test the performance of the proposed method. The user nodes are scattered at random across the 1000 m × 1000 m fields, with each of the ten available channels designated by a distinct colour from the others. While the NS2 simulation (Version 2.34) is running, the SU-occupied channels are identified as 0, 1, and 9, while the PU-occupied channels are identified as C0, C1, and so on in ascending order [35-36]. Both single-user and single-channel are abbreviated as SU and 1. The fortification range is approximately 200 meters; beyond this range, reaching the channels chosen by the CRN neighbor who has stayed is impossible. The same ten channels are chosen by each PU. The experiment is conducted for 131 seconds with packet sizes set to around 512 bytes apiece [37-38].

4.1 Energy Efficiency Calculation

Table 2. Energy Efficiency Analysis ANN-FA with Existing methods

No of Nodes	BFC	GA	ICSSSS	ANFIGA-CS	ANN-FA
0	68.67	70.12	71.12	73.76	85.87
20	68.23	67.21	70.75	73.56	85.22
40	69.22	65.79	71.22	74.77	86.55
60	68.33	69.78	72.55	78.33	84.43
80	67.88	69.25	70.22	79.21	84.78
100	68.33	70.21	70.89	78.67	85.76

In **Fig. 5** and **Table 2** depicts the amount of energy still available after network data transmission is complete is the energy efficiency. The nodes' energy efficiency performance for the BFC, GA, ICSSSS, and ANFIGA-CS protocols is shown in above. There are 100 nodes in the simulation experiment for this circumstance. The energy effectiveness of the ANN-FA procedure is 85.87%. Older protocols including BFC, GA, ICSSSS, and ANFIGA-CS had energy efficiency of 68.67%, 70.12%, 71.12%, and 73.76 percent, respectively. Analysis shows that the ANN-FA protocol outperforms the competition in terms of performance.

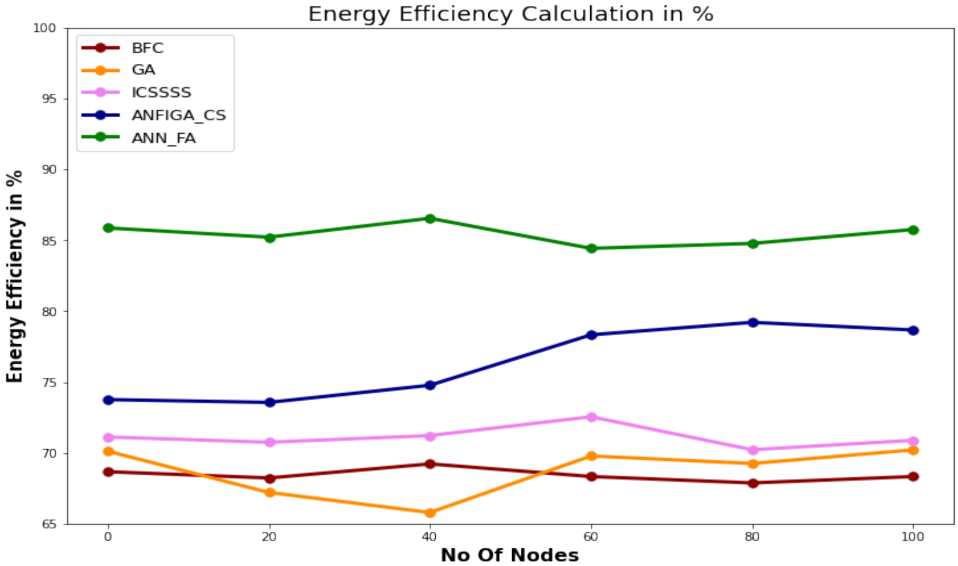

Fig. 5. Energy Efficiency Analysis ANN-FA with Existing methods

4.2 End to End Delay Calculation

Table 3. End to End Delay Analysis ANN-FA with Existing methods

No of Nodes	BFC	GA	ICSSSS	ANFIGA-CS	ANN-FA
0	190.11	170.45	150.54	123.32	98.33
50	187.23	171.67	161.33	125.52	99.23
100	183.33	173.89	154.67	126.53	98.11
150	189.23	179.97	155.54	127.74	99.65
200	188.56	180.33	160.42	126.32	98.34

In Fig. 6 and Table 3 depicts determining the network delay is the Network latency, or the more often used phrase, is a delay from start to completion. In several node capabilities, including the BFC, GA, ICSSSS, and ANFIGA-CS, among others the length of the performance, from start to finish, indicates its caliber. This simulation experiment makes use of 200 nodes. The end-to-end latency of ANN-FA is 98.33 milliseconds. The energy efficiency ratings of more traditional protocols like BFC, GA, ICSSSS, and ANFIGA-CS are 190.11 ms, 170.45 ms, 150.54 ms, and 123.32 ms, respectively. Analyses show that the ANN-FA approach outperforms the competition in terms of delay.

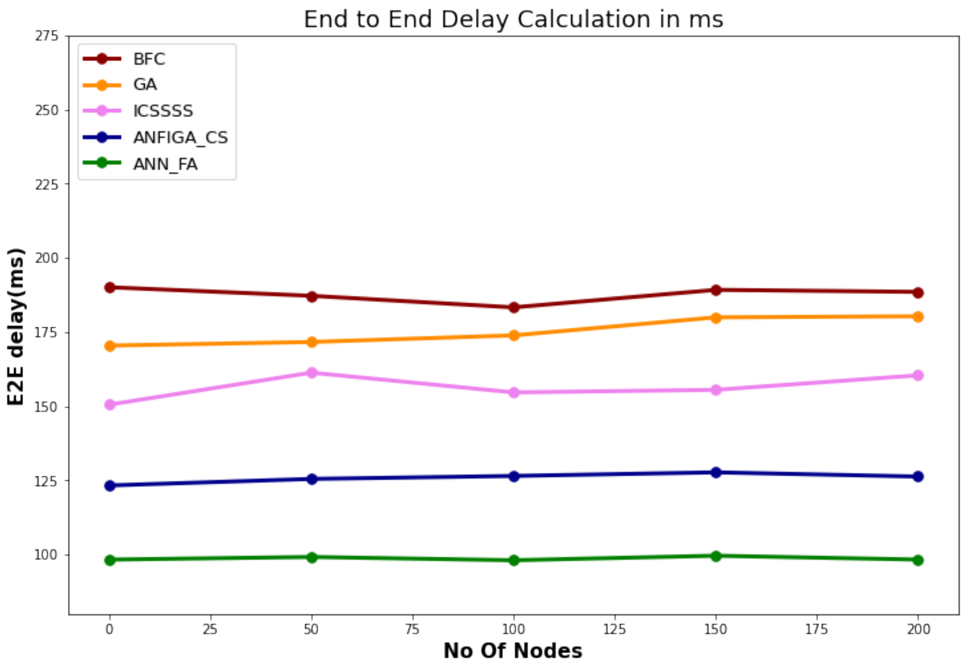

Fig. 6. End to End Delay Analysis ANN-FA with Existing methods

4.3 Packet drop calculation

Table 4. Packet drop Analysis ANN-FA with Existing methods

No of Nodes	BFC	GA	ICSSSS	ANFIGA-CS	ANN-FA
0	390.11	350.45	320.44	233.32	152.54
50	387.34	351.57	361.33	225.32	151.33
100	387.38	357.89	354.67	276.53	153.67
150	389.23	359.77	355.74	257.74	155.44
200	385.36	359.33	345.42	276.32	157.42

In Fig. 7 and Table 4 depicts to determine the amount of packet loss, the formula is utilized (number packet number of packets transmitted, received, and so on). The BFC performance of the nodes, GA, ICSSSS, and ANFIGA-CS protocols based on the quantity of missed packets. This simulation experiment makes use of 200 nodes. Packet loss performance for the ANN-FA protocol is 152.54. The energy efficiency ratings of earlier protocols like BFC, GA, ICSSSS, and ANFIGA-CS are 390.11, 350.45, 320.44, and 233.32 packets, respectively. The analysis shows that the ANN-FA protocol operates more effectively than other protocols and experiences fewer packet drops.

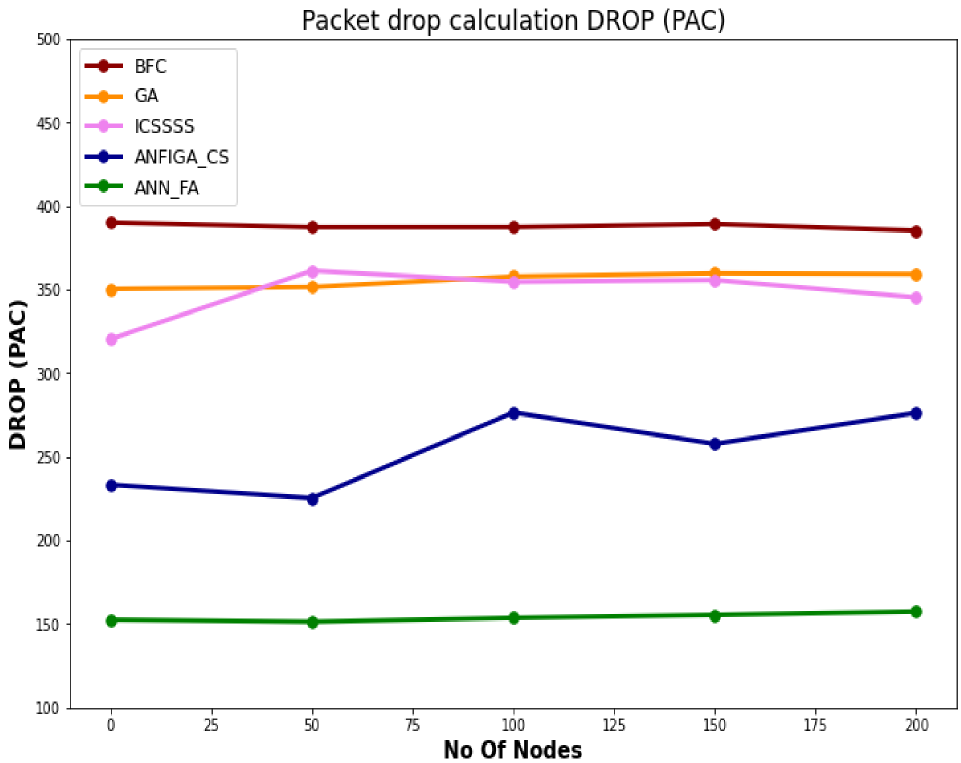

Fig. 7. Packet drop Analysis ANN-FA with Existing methods

4.4 Network throughput calculation

Table 5. Network throughput Analysis ANN-FA with Existing methods

No of Nodes	BFC	GA	ICSSSS	ANFIGA-CS	ANN-FA
0	350.61	379.96	365.98	454.24	601.33
50	357.78	385.27	373.54	455.76	602.21
100	359.65	391.67	385.23	444.32	603.45
150	355.57	378.18	395.39	453.37	604.54
200	356.88	385.67	385.29	454.57	604.89

In **Fig. 8** and **Table 5** depicts the maximum allowable number of packets on a network in each period is referred to as " network throughput depicts how well nodes using various protocols perform in terms of throughput, involves BFC, GA, ICSSSS, and ANFIGA-CS. In this simulation experiment, 200 nodes are utilized. The ANN-FA protocol has a throughput of 601,33 Kbps. The network throughputs of older protocols such as BFC, GA, ICSSSS, and ANFIGA-CS are 350.61 Kbps, 379.96 Kbps, 365.98 Kbps, and 454.33 Kbps, respectively. Analyses reveal that, in terms of performance, the ANN-FA protocol beats the others.

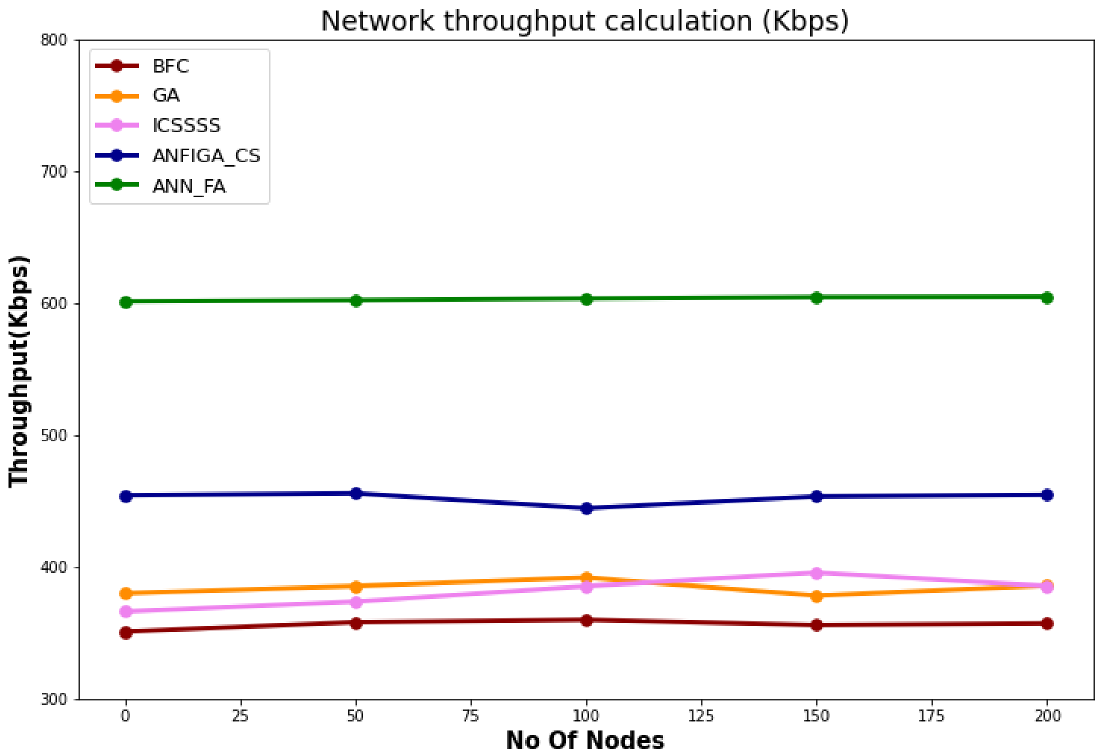

Fig. 8. Network throughput Analysis ANN-FA with Existing method

4.5 Packet delivery ratio calculation

Table 6. Packet delivery ratio Analysis ANN-FA with Existing methods

No of Nodes	BFC	GA	ICSSSS	ANFIGA-CS	ANN-FA
0	80.78	82.90	87.45	91.11	95.64
50	79.34	82.32	88.23	91.25	94.23
100	79.45	81.34	86.56	92.13	95.43
150	78.65	81.78	85.45	92.10	95.67
200	79.65	82.43	85.09	90.89	95.89

In **Fig. 9** and **Table 6** depicts the packet delivery ratio computes the percentage of data packets that successfully make it from the origin node to the node designated as the packet recipient. An illustrates how well certain nodes fared in terms of the percentage of correctly delivered packets when applying the various protocols BFC, GA, ICSSSS, and ANFIGA-CS. This simulation experiment utilizes 200 nodes. The ANN-FA protocol achieves a 95.64 percent delivery rate. ANN-FA beats older protocols such as BFC, GA, ICSSSS, and ANFIGA-CS, which have respective energy efficiencies of 80.78 percent, 82.9 percent, 87.45 percent, and 91.15 percent.

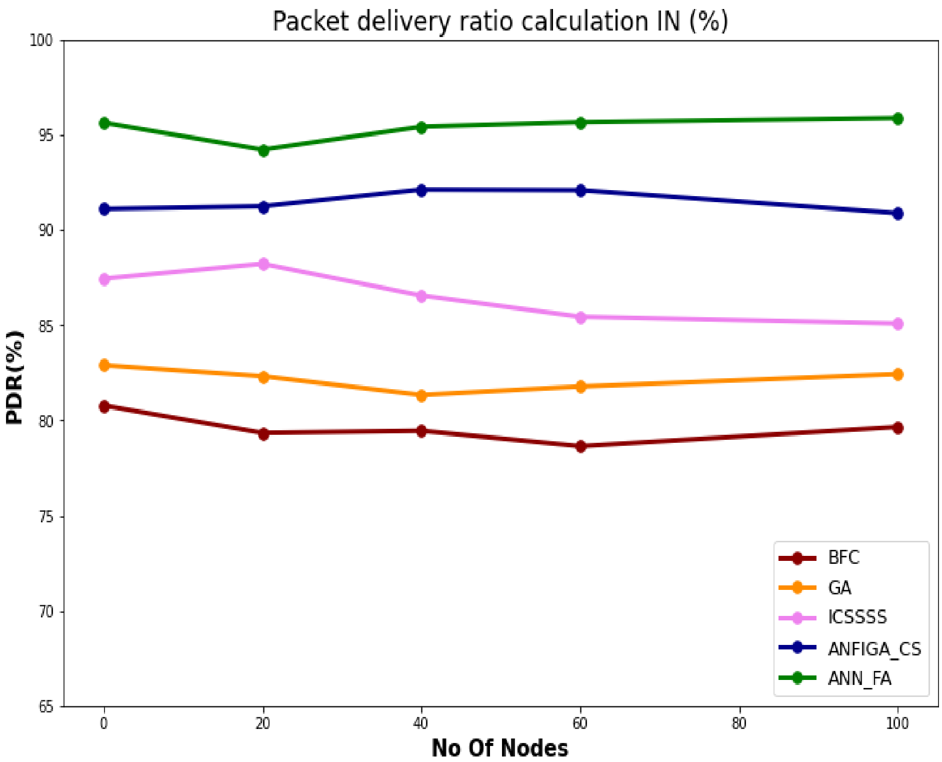

Fig. 9. Packet delivery ratio Analysis ANN-FA with Existing methods

4.5 Pd, Pmd and Pfa calculation

In **Fig. 10** and **Table 7** depicts to the conventional method of individually detecting each user with the proposed artificial neural network (ANN)-based Firefly The proposed ANN-FA algorithm outperforms the state-of-the-art ANN-FA method in terms of accuracy, with a higher probability of detection (Pd) and fewer false positive rates. When comparing the two, this is true and lower Errors in detection and notification are also conceivable. The suggested ANN-FA has a lower chance of false detection, which explains why.

Table 7. Pd, Pmd and Pfa Analysis ANN-FA with Existing method

Techniques	AND	OR	ANN-FA
Probability of Detection	0.6	1	1
probability of False Alarm	0	0.2	0
Probability of Missed Detection	0	0	0
Total Average	0.2	0.8	1.1

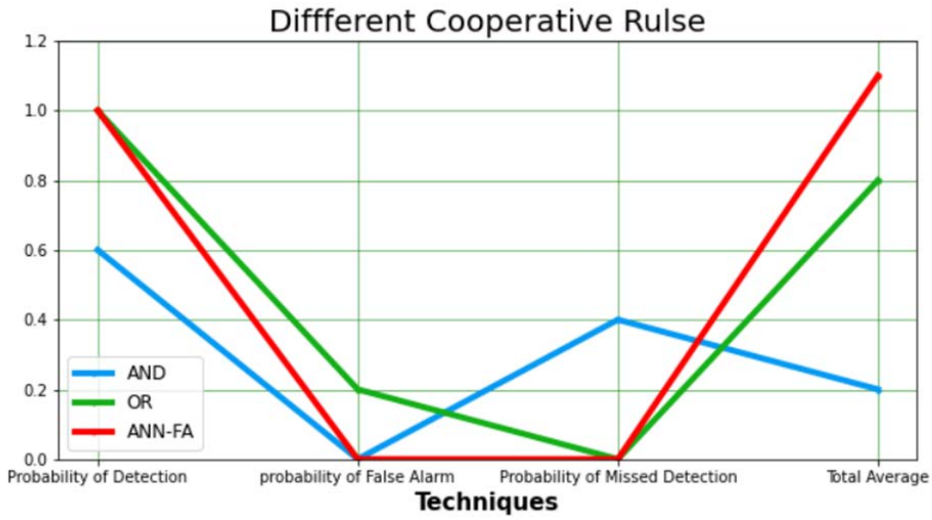

Fig. 10. Pd, Pmd and Pfa Analysis ANN-FA with Existing methods

An ANN-FA-based cooperative detection outperforms Pd, Pfa, and Pmd are abbreviations. Pfa is only 20%, and the probability is 80%, even though Pd is close to 100% when the OR algorithm is used. AND yields a 40% high Pmd and a 60% low Pd. Using the established ANN-FA, the ideal Pd increases to 100% while the Pmd, Pfa probability decreases to 0%, resulting in an average probability of 100%. As shown in the graph, ANN-FA performed better than other cooperative rules.

5. Conclusion

Artificial neural networks techniques and applications are growing and becoming more common in many areas of information and communication systems. This is because artificial neural networks can handle several problems and Spectrum sensing and spectrum management are two issues that must be addressed in the cognitive radio era. It is possible to fully realize a cognitive engine design that includes spectrum sensing, monitoring, and management by selecting the appropriate ANN-FA-based strategy. The purpose of this study is to investigate the requirements for CRAHN performance improvement utilizing an intelligent distributed channel selection method. The authors provide a framework for Channel selection in cognitive radio networks using fuzzy logic and intelligent learning (ANN-FA). ANN-FA aims to find the optimal channel for CRs' transmission needs while also addressing channel sharing difficulties. The key advantage of ANN-FA is that it reduces metrics for false alarm and miss detection, assisting in avoiding the use of subpar sensing channels. By using the K-means algorithm to control sensing failures, ANN-FA eliminates the ON state channels and MD channels. As a result, you may wisely select the best channel. As a result, the average network delay is decreased since CRs can broadcast their packets without interfering with PUs or switching channels. Additionally, it can be established that ANN-FA performs better when there are more current channels available. Users of CR could struggle to find open transmission channels because of the limited number of channels that are available. The proposed ANN-FA is evaluated in light of the impacts of modifying the density of CRs, the number of channels, and the activity patterns of PUs. ANN-FA outperforms ANFIGA-CS, BFC, GA, and ICSSSS according to the results of the NS2 simulation in terms of the proportion of delivered packets, end-to-end delay, average interference ratio, average throughput, usage of available spectrum, and average interference ratio ANN-FA has a lower end-to-end delay than other protocols. Despite the theoretical ratio of 10%, the actual ratio was just 1% of packets successfully delivered after 500 training repetitions. The simulation results show that the proposed cooperative model, which is based on ANN-FA detection, is a better detection system than other typical conventional detection rules. In the Future research may optimize spectrum sensing and handoff using a few more heuristic algorithms and machine learning principles.

Data Availability

All data are available within the manuscript.

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Conflict of Interest

The authors declare that they have no conflicts of interest.

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