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AN EFFICIENT SPECTRUM ACCESSING TECHNIQUE IN COGNITIVE NETWORK USING DEEP LEARNING ALGORITHM

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Abstract: Logically, as life moves toward new developments in all fields, the number of radio spectrum users grows. As a result, even permitted band clients are asking larger radio ranges. Clients may be granted access to various groups in order to change the radio range barrier. Radio range is detected in this project for void discovery and auxiliary client tasks. Mental clients participate in the white band by either sending critical clients nearby or holding on until the opening is empty. The ways in which vital customers behave are read up during transmission in order to determine the range inhabitance status. Because of doubtful ways of functioning according to time points of view, the action of vital clients is replicated as irregular factors. Issues such as channel congestion and blurring impacts operate as range detecting interrupters, causing range openings to appear occupied as a result of such incidents. The Mental Radio organization is demonstrated using MATLAB programming so that both essential and optional customers can detect the range and successfully offer the range by utilizing the technique of delayed time assessor, which provides ways of acting and movement framework. When underlay and entwine range sharing were utilized, candidates were made to share the spectrum and afterwards to share the range, and transmission postponement and throughput were assessed in the future. Underlay, interlace, and Feed Forward Neural Network are the three ways used to share the range. The findings revealed that the feed forward brain network is outflanked in both cases.

Keywords: Primary user, Secondary user, Feed Forward Neural Network.

1. INTRODUCTION:

A Cognitive radio network (CRN) is split into two main networks, a primary network and a secondary network. The primary network owns the licensed band and consists of the primary radio base station and users. The secondary network shares the unused spectrum with the primary network. It consists of the cognitive radio base station and users [1]. The three key capabilities that differentiate cognitive radio from traditional radio are: Cognition: CR understands its geographical and operational environment. Reconfiguration: According to this cognitive knowledge, CR can decide to dynamically and autonomously adjust its parameters. Learning: CR can also learn from the experience, and experiment with new configurations in new situations. Cognitive radio facts the two main facets used in CR are spectrum sensing and spectrum database. The most frequent way of spectrum sensing is the energy detector. The energy detector is simple to use and does not require any prior knowledge of the PU signal. However, the energy detector's performance is severely limited by the uncertainty of noise power. Increasing the sensing duration below an SNR threshold will not result in a valid detection. SNR wall refers to the detector's SNR threshold. The SNR wall can be minimized with the use of PU signal information, but it cannot be eradicated [2]. Furthermore, the energy detector may be unable to discriminate the PU signal from noise and other interference signals, resulting in a significant false-alarm rate
For good communication performance, we majorly consider the two parameters. They are,

- Throughput
- Delay

Our aim is to reduce the rigorous delay and improve the throughput for the secondary user communication [3]. We are planning to use machine learning to improve the performance of sensing the availability of the spectrum and access it.

2. RELATED WORKS:

The energy detector's detection performance in cognitive radio systems is dependent on the threshold expression's high precision selection. When constructing spectrum sensing models, the goal is to fully differentiate between noise and primary user signals. The accuracy and correct positive rate of developed models are commonly used to evaluate them [5]. However, using backwardly artificially made estimations in the measurements, the actual performance can be examined. In this part, a new threshold expression model based on an online learning algorithm is introduced to help

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cognitive radio networks improve spectrum sensing and sharing performance. [4] The deep learning framework completes the spectrum sensing of the OFDM signal and the implementation framework, which is divided into a model training process and a model testing process. When compared to the previous style range sharing methods, the Convolutional Neural Network is applied to the innovations of radio range usage and shows incredible execution [6]. In any case, CNN is used in this task to improve the throughput and the time delay (to reduce the lining time). The abovementioned interaction was carried out using neural organization, which improved range consumption by learning the practices of critical and auxiliary customers and allocating the radio range to those clients who can login without (less than predicted) blockage. During the preparation step, information about the customers' actions is supplied to the Feed Forward Neural Network classifier [7], which takes this information and attempts to dissect it.

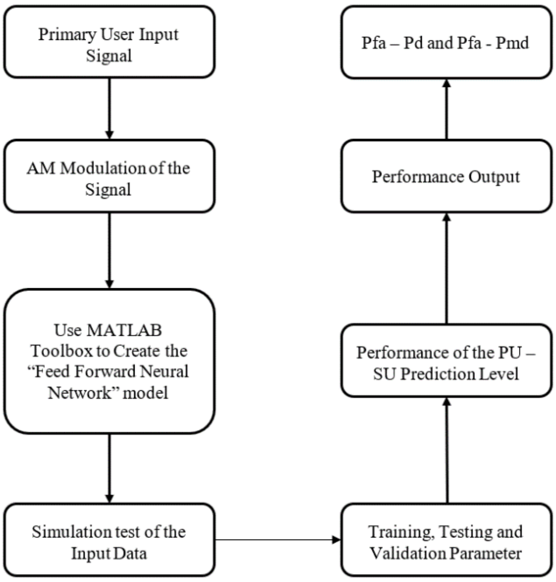

FIG.1 FLOW DIAGRAM

3. FFNN-LM ALGORITHM:

The LM algorithm is the most widely used optimization algorithm. It outperforms simple gradient descent and other conjugate gradient methods in the solution of a wide variety of problems. The LM algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real valued functions. . It is fast and has stable convergence. In the artificial neural-networks field, this algorithm is used for training networks. The LM algorithm provides a nice and optimal compromise between the speed of Newton's method and the convergence of the Steepest Descent method. When the current solution is far from the correct one, the algorithm behaves like the Steepest Descent method, slow to converge and when it is close to the correct solution, it uses the Gauss-Newton method. It has become a standard technique for solving nonlinear least-squares problems and widely adopted in a broad spectrum of disciplines. The neural network that was used for this paper is the feed-forward neural network. MLPs which are capable of finding solutions on a much wider range of problems were used in this project. Training a feed forward network is an iterative process that involves repeatedly presenting the training set (which contains exemplar patterns with known target outputs) to the network. After each iteration, the network weights are adjusted so that the total error for all patterns is gradually reduced. This type of training is known as supervised learning and the algorithm for adjusting the network weights is the training method. We choose more advanced training methods i.e. the NNLM method as it trains fast with fewer training iterations than back propagation. The MLP consists of three types of layers. The first layer is the input layer and corresponds to the problem input variables with one node for each input variable. The second layer is the hidden 18 layer used to capture non-linear relationships among variables. The third layer is the output layer used to provide predicted values. Let the function to be minimized be denoted as Fn(v) and it is minimized with respect to the parameter vector denoted as v. The technique can be given by:

$$\Delta v = -[\nabla^2 Fn(v)]^{-1} \nabla Fn(v) \quad (1)$$

Here, ∇^2 Fn (v) is the Hessian matrix and ∇F(a) is the gradient matrix. The gradient matrix is taken as the sum of squares of the error function given by

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$$Fn(v) = \sum_{i=1}^{N_c} e_i^{\ 2}(v) \quad (2)$$

Where v= [v1, v2… vN] consists of all weights of the network, 'e' is the error vector comprising the error for all the training examples. When training with the LM method, the increment of weights Δv can be obtained as follows:

$$\Delta v = [J^T(v)J(v) + \mu I]^{-1} + J^T(v)e(v) \quad (3)$$

Where J is the Jacobian matrix, μ is the learning rate which is to be updated using the β depending on the outcome. In particular, μ is multiplied by decay rate β (0<β)

4. LM ALGORITHM:

The pseudo code for LM training process can be explained in the following steps:
1. Initialize the weights and parameter μ.
2. Compute the sum of the squared errors over all inputs Fn (v)
3. Solve (2) to obtain the increment of weights Δv.
4. Re-compute the sum of squared errors Fn (v).Using v + Δv as the trial v, and judge,
IF trial Fn (v) < Fn (v) in step 2
THEN v = v+Δv
μ=μ. β (β= .1)
Go back to step 2
ELSE
μ=μ/β
Go back to step 4
END IF.

5. NEED FOR FEED FORWARD NEURAL NETWORK:

The Feed Forward Neural Network has been applied to radio spectrum usage technologies and has demonstrated superior performance when compared to traditional spectrum sharing systems. However, in this project, FFNN is utilized to optimize the time delay (to reduce queue time) and to increase throughput. The above-mentioned procedure is carried out by a neural network, which makes spectrum use considerably more efficient by learning the behaviors of primary and secondary users and therefore distributing radio spectrum to those users who are prepared to login without (less than predicted) congestion. The data of users' activities is sent to the Feed Forward Neural Network classifier in the first step of processing, which takes this data and attempts to analyze it during the training phase. The neural network is now ready for the configuration procedure, as the target will signal the band availability in distinct behaviors and possibilities of the primary user. The act of setting up the number of inputs, outputs, and hidden layer number in a neural network is known as configuration. This study's feed forward neural network has three layers: an input layer, a hidden layer, and an output layer. Data normalization entails converting the data into a normal value, which means dividing it by a factor to unify all the data as divisions of one. This process will improve the quality of training because the gradients of the data will be minimized and the neural network will learn the data more easily. The LM (LEVENBERG-MARQUARDT) algorithm, which is integrated in the MATLAB toolbox, is used to train feed forward neural networks; however, as previously stated, the LM algorithm works to update the weights and biases coefficients of neural networks until the best possible training performance is achieved (lesser error rate). FFNN is a powerful technique for binary classification that is based on the neural structure of the brain. It has a natural proclivity for storing experiential knowledge and making it available for use, implying that the network acquires knowledge through a learning process and can be used to store the knowledge.

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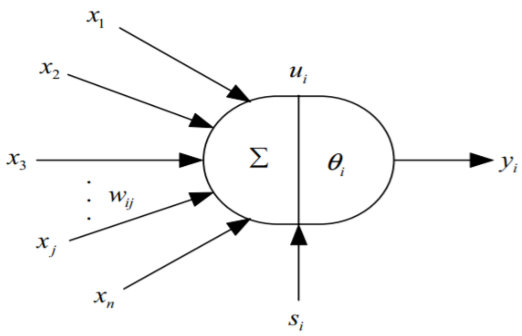

FIG.2 STRUCTURE OF NEURON

The structure of neurons is shown in Fig. 4.4. The parameter ui denotes the internal state of neural i, θi is the threshold, xi represents the input signal, wij is the value connected with neuron xj, and si indicates the external input signal. There are many different types of artificial neural networks. In this project, we focus on BPNN which is a simple and effective model of ANN. It has three layers: input layer, hidden layer and output layer. Two layers of neural network are chosen. One is the hidden layer with (2×training−sample−number+1) neurons according to the empirical value and transfer function of which is "transig", and the other is output layer with four neurons and transfer function is "logsig" (function transig and logsig are the transfer functions of BPNN). One of the training functions ``trainlm" of BPNN is selected to serve as the training function. The fundamental nature of spectrum sensing is a defined binary hypothesis testing problem that depends on the threshold expression. This relationship is illustrated in Fig. 3 This shows the expected distribution of a difference between two groups under H0 [true negative (TN)] and H1 [true positive (TP)]. It is clear that if we increase the type I error rate [false positive (FP) or false alarm], we reduce the type II error rate [false negative (FN) or missed detection], and vice versa. Changes in the accuracy of the H0 and H1 hypothesis cause changes in the total error probability.

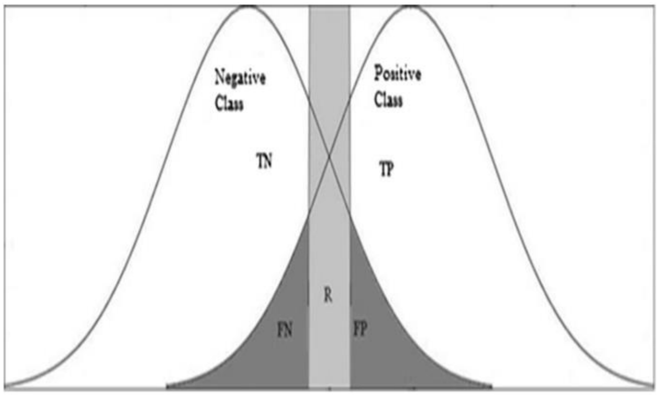

FIG.3 : STATISTICAL DISTRIBUTION CURVES RELATED TO CLASSES

As a result, the risk of miss detection and the risk of erroneous detection must be carefully balanced. Two classes are generated by classifying negative and positive data, as illustrated in to preserve and analyze the balance between these two.

6.SENSINGPERFORMANCE PARAMETERS:

The sensing process is divided into two stages and is controlled by signals from the upper layers to sense a specific bandwidth B, as shown in Fig. 4. In the first stage, the received signal x(t) is filtered to the bandwidth of interest B to reject band noise and adjacent signals. It is then amplified with a low noise amplifier and down converted to an intermediate frequency. In the second stage, the received signal is sampled and quantized using an A/D converter. Next, a square-law device and an integrator with sensing interval T measure the received signal energy.
Finally, the output of the integrator, represented by the test statistic Y, is compared to a predetermined threshold λ to determine the existence (H1) or absence (H0) of a PU. Gaussian noise (AWGN) with zero mean and variance 2. h is the channel coefficient, which is assumed to be constant during the observation period, i.e., for N samples, H0 is the hypothesis test when only noise is present and H1 is the hypothesis test when both noise and signal are present. We also

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assume that the noise samples are independent and identically distributed, and that they are independent of the signal samples.

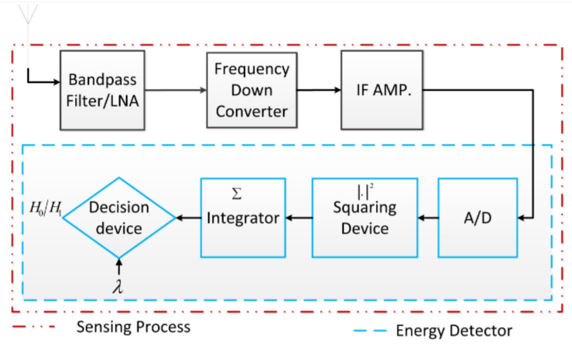

FIG.4 SCHEMATIC OF SENSING ABSTRACTION INCLUDING AN ENERGY DETECTOR

Then, the distribution of the decision variable Y will be central chi-square χ2 N under H0 and non-centrally chi-square χ˜ 2 N with N degrees of freedom under H1. Notice that to reduce the overuse of notations, we distinguish between central and noncentral chi-square by the symbol (∼). Evaluating test Y by the decision device, which is shown in Fig.5.3, may result in two types of errors. We define the notation P (Hi, Hj) to distinguish between these errors.

● When the decision device decides H1 but H0 is true, denoted as P(H1; H0), this is called the probability of a false alarm (Pfa).

● When the device decides P(H0, H1), this represents the probability of misdetection (Pmd).

● The complementary to Pmd is the probability of detection

(Pd = 1 − Pmd = P (H1; H1)) (4)

The performance of the energy detector can be characterized by the probability of detection in a low SNR regime. An alternative performance metric is the ROC curves which are generated by plotting Pmd vs Pfa.

$$P_d = P(H_1; H_1) = P(y > \lambda; H_1) = \int_{\lambda}^{\infty} f_Y(y)dy, \qquad H_1 \tag{5}$$

$$P_{fa} = P(H_1; H_0) = P(y > \lambda; H_0) = \int_{\lambda}^{\infty} f_Y(y)dy, \qquad H_0 \tag{6}$$

7. SHARING PERFORMANCE PARAMETERS:

Throughput:

It is the ratio of the total number of bits transmitted (B_{tx}) to the time required for this transmission, i.e., the difference of data transmission end time (t_{end}) and start time (t_{start}).

Throughput = (B_{tx})/ ($t_{end} – t_{start}$) bps (7)

Average Delay:

It is the average transmission delay of packets transmitted from source to destination. D is computed as the ratio of the sum of individual delay of each received data packet to the total number of data packets received.

D = no. of received packed/total time (8)

A training simulator was used to test the novel Feed Forward Neural Network Levenberg-Marquardt (FFNN-LM) algorithm, which was compared to current approaches. MATLAB was used to run simulations for analyzing channel prediction using the presented methodologies.

The input layer receives data, while the hidden layers conduct mathematical operations and the output layer provides the network's output. Each layer's circle is called a 'neuron,' which is the same as a neuron in the actual brain.

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The connection between each neuron (represented by an arrow) is a factor that determines how much signal from a particular neuron should go into the next layer. This factor is also called 'weight.' Before starting the discussion, just remember these four stages of creating a neural network -

- Data Input
- Data feeding in the forward direction (Data Feedforwarding)
- Error calculation
- Back propagation

The learning process is generated by minimizing this error after each successive iteration. The output of the hidden layer is sent to the output layer, where the final computation and visualization of the final prediction result or success in the future estimation of the PU in the wireless band takes place. The "Feed Forward" neural network is generated in Matlab using the command "newf" and the activation functions "tansig" and "purelin":

```
%Creation of the neural network
net = newff(Xecg,Yecg,[50 50 50 50],{'tansig' 'purelin' 'tansig' 'purelin'}

% For help on training function 'trainlm' type: help trainlm
% For a list of all training functions type: help nntrain
IDS.trainFcn = 'trainlm';  % Levenberg-Marquardt

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
IDS.performFcn = 'mse';  % Mean squared error
```

Then the training parameters are established, in this case 125 training times (used by the proposed algorithm), the network is trained, simulated and the trained network is displayed; finally, the data is compared and the figure of the mean square error is generated:

```
% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
IDS.performFcn = 'mse';  % Mean squared error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
IDS.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
  'plotregression', 'plotfit'};

% Train the Network
[IDS,tr] = train(IDS,inputs,targets);
```

8. SIMULATION RESULT AND ANALYSIS:

In cognitive radio networks, the receiver operating characteristic (ROC) curve can be used to characterize spectrum sensing and sharing performance. Plotting detection probability versus false alarm probability or missed detection probability versus false alarm probability yields ROC curves.

The detection and false alarm probabilities are affected by the threshold, the number of samples, the fading parameters, the number of diversity branches, and the average SNR. The proposed algorithm's sensing performance on various fading channels was evaluated using energy-based detection and matched filter detection techniques.

Spectrum sensing execution can be described by utilizing the receiver operator character (ROC) bend in psychological radio organizations. ROC bends are produced by plotting either recognition likelihood versus bogus caution likelihood or missed identification likelihood versus bogus alert likelihood.

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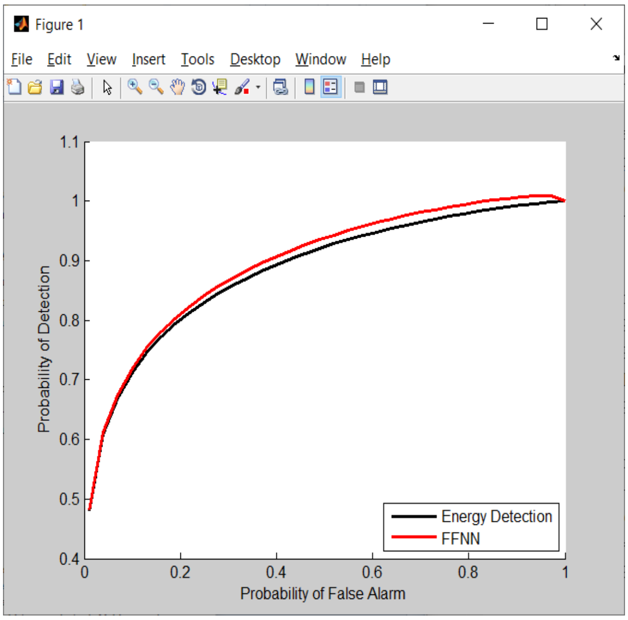

FIG.6: ROC COMPARISON Pd VS. Pfa

Detection probability and false alarm probability depend upon the limits, number of tests, blurring boundaries, number of variety branches, and normal SNR. The detecting execution of the proposed calculation has been investigated on various blurring channels utilizing energy-based identification and coordinated with channel matched filter detection discovery procedures.

Simulation results are provided to compare our existing with a conventional (FFNN) Feed Forward (calculated from Pfa=0.1). Because the performance of an energy-based technique is primarily determined by the SNR (5 dB) taken into account. The ROC curve for the AWGN channel is shown in the figure. As can be seen, the proposed algorithm outperforms the conventional algorithm FFNN (Pd=0.3383) and the proposed existing algorithm (Pd=0.5050). SNR affects the execution of spectrum sensing detection. The probability of detection increases as the SNR increases.

SPECTRUM ACCESS METHOD	Probability of Detection (Pd)	Probability of False Alarm (Pfa)
FFNN	0.5050	0.1
ENERGY DETECTOR	0.3383	0.1

The table shows the different methods of Pd value for the 5dB SNR range. The sensing detecting execution of the proposed calculation has been broken down on various blurring channels utilizing energy-based recognition and coordinated with channel identification matched filter detection methods.

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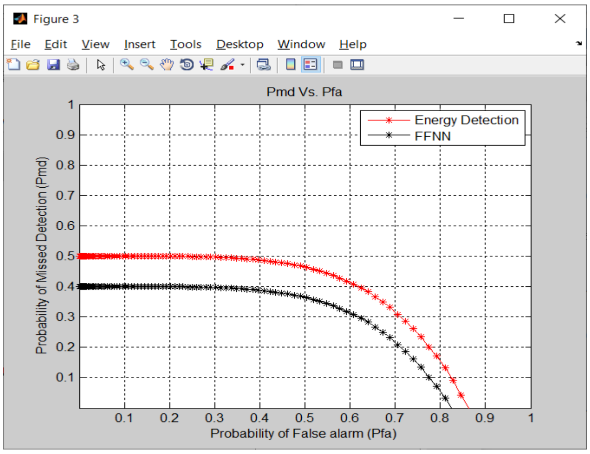

FIG.7 : ROC COMPARISON Pmd VS Pfa OF 5dB

Since the exhibition of energy-based methods essentially depends with respect to SNR. Figure shows the ROC bend for the Pmd versus Pfa. As can be seen, the presentation of the proposed calculation for various SNR situations is higher than those of existing FFNN calculation: limit (5 dB): Pmd =0.5371; and EXISTING (5 dB): Pd=0.4509; edge when the charts are analyzed, it is seen that the missing time recognition execution of intellectual radio increments with the proposed strategy. Plus, missing detection probability is less in AWGN blurring channel when contrasted with the current and other blurring channels.

SPECTRUM METHOD	Probability of Misdetection (Pmd)	Probability of False Alarm (Pfa)
FFNN	0.4	0.1
Energy Detection	0.5	0.1

The table clearly shows that the identification execution of the EXISTING learning calculation based choice threshold strategy and the location execution of the unique choice edge assurance technique are superior for different SNR esteems on different blurring channels. This is because conventional strategies provide an exacting edge model. This examination's proposed technique has made the limit articulation adaptable. Furthermore, the proposed EXISTING based learning calculation-based limit articulation model has made the spectrum detecting execution of intellectual cognitive radio organizations more sensitive to changes in correspondence channels.

Cognitive User	AVERAGE TIME DELAY IN SECONDS	
	ENERGY DETECTOR	FFNN
1	0.1443	0.0759
2	0.0037	0.0019
3	0.0062	0.0032
4	0.3326	0.1749
5	0.1559	0.0820
6	0.1351	0.0710
7	0.1954	0.1027
8	0.0187	0.0098
9	0.0020	0.0010
10	0.1995	0.1049

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Cognitive User	THROUGHPUT	
	ENERGY DETECTOR	FFNN
1	94.2455	96.2698
2	94.4936	96.5163
3	94.2455	96.2698
4	94.2456	96.2698
5	94.2456	96.2698
6	94.2456	96.2698
7	94.2456	96.2698
8	94.2455	96.2698
9	94.2455	96.2698
10	94.2456	96.2698

Both outputs display the transmission delay and maximize energy efficiency throughput for primary users. Due to secondary control, the number of interfering users has a minor effect on the throughput and energy efficiency of the primary pair; the proposed scheme is beneficial for the throughput and delay of the primary pair and can be used to compensate for secondary user interference.

9. CONCLUSION:

In this research, two spectrum sharing options were developed, with the goal of allowing secondary users to transmit across white band without interruption. A collaborative detection approach for spectrum sensing and sharing based on ANN with FFNN has been proposed in this project. When compared to FF spectrum sensing technologies, the methodology might offer improved detection performance at low SNR. Combining the benefits of existing approaches would minimize computational complexity and improve anti-inference capabilities. The results of this study suggest that neural networks outperform other methods in terms of reducing time delays and increasing throughput.

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