EFFICIENT SPECTRUM SENSING IN COGNITIVE RADIO NETWORK-A HYBRID ERNN-RSOA APPROACH

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Abstract - *A fixed spectrum allocation policy has been adopted in recent years that allocates wireless spectrum to administrative agencies for licensing for a long period of time in high geographical areas. Mobile users will have access to a large bandwidth made available by Cognitive Radio Networks (CRN). However, due to the spectrum management problems like spectrum sensing and sharing, there are challenges in implementing the CRN networks. Therefore, in this paper, Enhanced Recurrent Neural Network (ERNN) with Rat Swarm Optimization (RSOA) is designed to enhance the energy efficiency for various spectrum sensing situations. The proposed algorithm is used to calculate the sensing time, sequence length and detection threshold. The ERNN-RSOA has the adaptive threshold detection method to efficiently able to detect the spectrum with the optimized values of transmission power and sensing bandwidth. With the support of the ERNN-RSOA algorithm, the CRN network is able to achieve spectrum sensing and spectrum sharing. The proposed method is programmed and simulated within MATLAB and performance is studied using performance metrics like Normalized Energy consumption, delay, SNR, Jitter, Blocking probability, convergence analysis, and Throughput. The proposed method is compared with the existing methods such as Artificial Neural Network (ANN) with RSOA, and RNN with Firefly Algorithm (FA) respectively.*

Keywords: *spectrum sensing, spectrum sharing, cognitive radio network, Enhanced recurrent neural network, rat swarm optimization algorithm, and energy efficiency.*
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1. INTRODUCTION

Cognitive Radio (CR) is an interesting environment that understands the surroundings and is aware of its own environment. The main merits of CR are that it minimizes the interference and thereby, enhances the spectrum utilization through dynamic reconfiguration [1].Typically, a CR network (CRN) consists of primary users (PUs) and secondary users (SUs).The licensed owners of the spectrum are the PUs. TheSUs opportunistically access the unused spectrum with the requirement of limited harmful interference to the PUs [2, 3]. The SUs achieve opportunistic spectrum access through CRcycle functions which include: spectrum sensing, spectrum decision, High spectral efficiency and energy efficiency is a challenge in CR for high performance and low energy devices as the energy consuming tasks reduces the spectral efficiency of SU. This occurs due to time and energy consumption on a different task which is not present in transmitted bits [4, 5].

In CRN, spectrum sensing is one of the important technologies for opportunistic spectrum access [6, 7]. There are two schemes for spectrum sensing, namely individual spectrum sensing and cooperative spectrum sensing, in which each SUs independently decides its spectrum sensing decision, or cooperatively exchange their sensing information with the fusion centre, which makes the final sensing decision. Nevertheless, individual spectrum sensing undergoes a widely-known hidden PU problem [8, 9]. This is why cooperative spectrum sensing has garnered more interest in the quest to increase the spectrum sensing reliability over individual spectrum sensing, which has been shown to be a better approach to the hidden PU problem [10, 11].

Spectrum sensing and spectrum prediction are two approaches to explore spectrum access opportunities in CRN. Spectrum prediction can alleviate the processing delay and energy consumption occurred in spectrum sensing, and has wide applications in future wireless networks, such as CRNs, cooperative relay networks, and 5G networks [12, 13].Spectrum sensing aims at identifying the current radio spectrum state (RSS), which is done through a number of different approaches and is energy and time consuming, while spectrum prediction infers the future possibly unknown RSS from the historically known RSS measurements by leveraging the inherent correlations and/or regularities [14, 15].Classic spectrum-sensing techniques, such as energy detection, matched-filter-based detection, cyclo-stationary feature detection, and covariance-matrix-based detection were established decades ago. Advanced detection techniques like cooperative sensing were suggested to further enhance performance using spatial, temporal and/or spectral correlation between the sensors. More recently, the machine learning approaches, such as Support Vector Machines (SVM), the K-means clustering algorithm and the Gaussian Mixture Model (GMM) have been used in spectrum sensing [16, 17] respectively. Because SS based channel status estimation is a classification problem, a number of researchers used the Machine Learning (ML) models as a channel status estimation tool [20].

The remaining part of the paper is organized as follows, section 2 given the detailed review part of the paper. A brief description of the proposed methodology is presented in section 3. The outcomes of the proposed methodology have been presented in section 4. The conclusion part of the paper is presented in section 5.

2. LITERATURE REVIEW

Many methods are available to enable efficient spectrum sensing in CRN network. Some of the methods are reviewed in this section.

Mengbo Zhang et al. [21] have analysed the distributed cooperative spectrum sensing (CSS) method based on reinforcement learning (RL) to remove data fusion between users with different reputations in CRN. Their method regards each SU as an agent, which was selected from the adjacent nodes of CRN participating in CSS. The reward is reputation value to make sure that the agent is inclined to merge with nodes with a high reputation value. The conformance fusion was adopted to promote consensus of the whole network, while it's also compared with the decision threshold to complete CSS. Their proposed method is effective in identifying malicious users, as demonstrated by the simulation results. As a result, the whole CRN based on RL was more intelligent and stable.

Geoffrey Eappenet al. [22] have formulated the multi-objective parameters of cognitive radio network (CRN) to analyse the efficiency of the spectrum sensing. Parameters listed were throughput, interference, and energy efficiency, sensing time, power allocation, and detection threshold and so on. They were proposed a Multi-Objective Modified Grey Wolf Optimization (MOMGWO) algorithm to solve the multi-objective optimization problem in the field of spectrum sensing in a CRN. Their proposed algorithm was compared with the existing algorithms such as Non-dominated Sorting Genetic Algorithm (NSGA-II), Multi-Objective Particle Swarm Optimization (MOPSO), Multi-Objective Cat Swarm Optimization (MOCSO) and the conventional Multi-Objective Grey Wolf Optimization (MOGWO) algorithm on the non-dominated solution set. The result of the simulation demonstrates that their proposed MOMGWO has performed better than the existing algorithms in terms of the quality of the Pareto front.

Osameh M. Al-Kofahi*et al.* [23] carried out a problem of selection of sensor nodes related to the request and the objective function was achieved as the minimization of consumed energy in the CRN. They considered a spatial and temporal scheduling problem, in which, the energy levels at sensors, the maximum transmissionrange of secondary user (SUs), and the required monitoring time were taken into account. The problem was formulated as an Integer Linear Program (ILP). To solve the problem is CRN, sub-optimal greedy algorithm was proposed with twovariations. Thorough evaluation shows that their proposed algorithm performs very well with respect to theoptimal solution. Finally, results illustrate that the first algorithm variation was better in terms of energy cost,and the second variation allows for serving requests with a lower number of nodes.

In [24] Woongsup Lee et al. have studied cooperative spectrum sensing (CSS) in a CRN with a scenario in which multiple secondary users (SUs) cooperate to detect a primary user (PU) that may be using multiple bands. They were developed the convolutional neural network (CNN) for the Deep cooperative sensing (DCS). Unlike CSS, no explicit mathematical modelling was performed in DCS and the strategy for combining the individual sensing results of the SUs was learned autonomously by a CNN by training SUs with the sensing samples, whether they are quantized or not. Furthermore, both spectral and spatial correlation between the sensing results of individual sensors were considered and an environment-specific CSS was enabled in DCS.

Ramsha Ahmedet al. [25] have developed the support vector machines (SVM) in cognitive radio (CR) technology with the IoT paradigm (CR-IoTNet). Their approach is to allow it to learn and adapt to the network dynamics as the network changes, while also being able to determine the PU spectrum usage using the previously developed multi-class ($J \times 6$)-D feature set. The performance of CR-IoTNet was evaluated across several key factors, where simulation results validate the efficacy of their proposed framework in achieving high reliable identification, classification and allocation of unoccupied frequency bands in PU spectrum, especially in key areas of low signal-to-noise ratio (SNR).

Seeam daudi arthur nkalango et al. [26] have proposed a double deck cluster cooperative relay assistance model in hybrid spectrum sharing in cognitive radio networks. This presented model allows to achieve the energy efficiency by optimising the cooperative secondary users in each cluster group. Based on the results of mathematical analysis, implement the power allocation scheme in this design according to the power constraint. For both network scenarios, (with and without cognitive relays in the network), normalised energy consumptions and amplifying gains were achieved and evaluated. The simulation results demonstrate that the presented scheme has a good performance in terms of saving energy as compared to a traditional scheme.

G. Dinesh *et al.* [27] have presented the Modified Spider Monkey Optimization (MSMO) technique which utilized for spectrum sensing and detecting free spectrums, thereby enhancing the energy efficiency of the available spectrum. This technique will find the optimal solution and increases the expectation of some decisions. Modified round robin algorithm was used for scheduling load. In this algorithm, every packet flow has its packet queue presented in the network interface controller. The performance analysis was finally measured using metrics such as throughput, handoff, success probability, and false alarm probability.

Spectrum sensing is the process of sensing the spectrum and detecting the presence of a primary user. The secondary user can use the spectrum if the primary user is not present. Various types of methods that can be used to enhance the performance at low SNR like matched filter method as well as eigen value method. The eigen value detection method cannot decrease the computation complexity and sensing time at the same time. The energy detection is the most efficient method due to the properties of low cost, low computational complexity, which can be efficient spectrum sensing. In the past few years, the AI based spectrum sensing techniques are captivating the attention of researchers due to their low complexity and efficient approach. From the literature part of spectrum sensing by AI techniques, its lacks global search and local search. This AI technique can be impacted in the convergence analysis. The above-mentioned disadvantages should be addressed to make the efficient spectrum sensing feasible in CRN networks. Important issues that arise with conventional spectrum sensing are outlined below,

- ❖ The author [19] has introduced the Hybrid PSO-GSA for spectrum sharing and sensing in the CRN network. This algorithm, however, is without global search, while PSO algorithm is without local search.
- ❖ The author [20] has introduced a paradigm of considering the energy consumption of the circuit as an important indicator for calculating energy efficiency of the network system. But this method only suitable for short range applications.
- ❖ The author in [26] has introduced a double deck cluster cooperative relay assistance model in hybrid spectrum sharing for cognitive radio (CR) network. However, in all these works, the basic aim is not based on cooperating cluster groups (CCG) of CRs under double decking relay assistance (DDRA) with a target to reduce EC in CRNs at the same time maintaining the detection accuracy of the spectrum status.
- ❖ The author [27] have presented MSMO technique which utilized for spectrum sensing and detecting free spectrums, thereby enhancing the energy efficiency of the available spectrum. Whenever a large number of

primary channels occurred, then it was difficult to schedule cooperative spectrum sensing in CR networks.

To overcome the abovementioned drawbacks, the proposed methodology is designed for spectrum sensing and sharing in the CRN network during data transmission.

3. Proposed System Model

There is a trade-off between 5G heterogeneous network's spectrum sensing efficiency and energy efficiency for the CRN. In designing the battery-powered CRN network, the spectrum sensing and spectrum sharing is solved by a concentrate of energy efficiency. Solving the optimization problem of energy efficiency in spectrum sensing is the main focus in the existing methods, which uses convex optimization. The real-time spectrum sensing problem, however, is a non-convex optimization problem. In this paper, ERNN-RSOA is proposed to enhance the energy efficiency of the different spectrum sensing scenarios. The proposed algorithm is applied to calculate the sensing time, the length of the sequence and the detection threshold. The ERNN-RSOA has the adaptive threshold detection method to efficiently able to detect the spectrum with the optimized values of transmission power and sensing bandwidth. The ERNN-RSOA algorithm is used to help achieve the spectrum sensing and sharing of the CRN network. The proposed Algorithm block diagram is shown in figure-1. Initially, the CRN is designed with different channels and spectrum level for analysis of the proposed methodology which presented as follows,

- The CRN is designed for Primary Users and Secondary Users. The secondary users in the CRN utilize the unused spectrum bands of the secondary users.
- The CRN is designed with base stations.

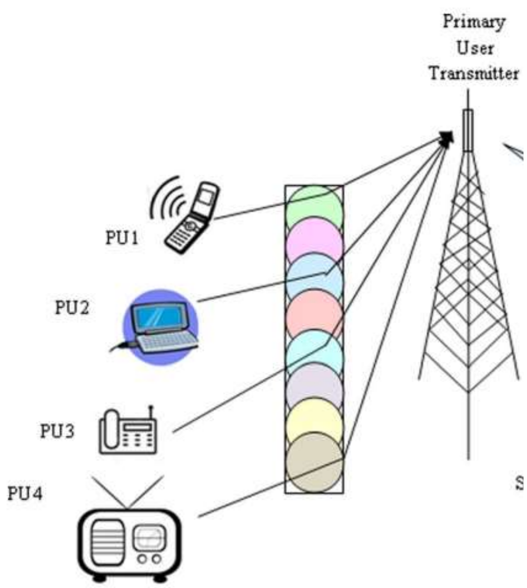


Figure 1: System Model

The mathematical model [15] of CRN network sensing is presented as follows: The computation of the local sensing time of I^{th}users in CRN is given below equation,

$$Y^I + (N) = \begin{cases} W^I(N), & h_0 \\ H_I(N)S(N) + W^I(N) & h_1 \end{cases} \quad (1)$$

Where, h_1 and h_0 can be described as primary signal status (i.e., $1 \leq I \leq n$), $H_I(N)$ can be described as

Rayleigh distribution and $S(N)$ can be described as a primary signal. The binary hypothesis of the CRN network is presented below,

$$N = 1,2, \ldots., m^I \tag{2}$$

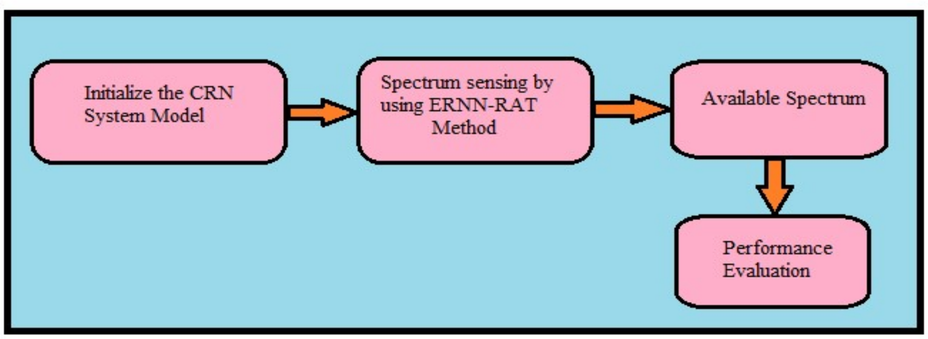
Where, m^I can be described as a number of samples with a frequency range of the primary user. The average energy of CRN is mathematically formulated as follows,

$$E^I(Y) = \frac{1}{M} \sum_{N=1}^{M^I} |Y(N)|^2 \tag{3}$$

The spectrum is being sensed and shared in the CRN network, based on the average energy. In the proposed methodology the spectrum is sensed and shared optimally with the Users. The general objective of the research as stated above, is to be achieved by the proposed method,

- ❖ To enable efficient spectrum sharing and sensing in CRN, the proposed algorithm is developed.
- ❖ In this proposed methodology, energy efficiency is considered as the main factor to select the power allocation. Using adaptive threshold detection method, the energy efficiency is calculated. This process is used to facilitate the efficient utilization of spectrum sharing and spectrum sensing in CRN network.
- ❖ Working towards energy efficiency and maintaining the sensing bandwidth with the goal of designing an energy-efficient Continuous Spectrum Sensing (CSS) method.
- ❖ Optimizing the functions that are energy efficient using the proposed algorithm by doing iterations with each variable being a subproblem.

This is a proposed methodology where the spectrum management (spectrum sharing and sensing) is supported in the CRN network by using ERNN-RSOA. The methodology is proposed based on the model of the CRN network. The users that are connected with the base station to enable the communication with a centralized and decentralized network are in the CRN network. This proposed methodology is based on the cognitive radio topology that consists of more than one SUs and PUs.



(a)

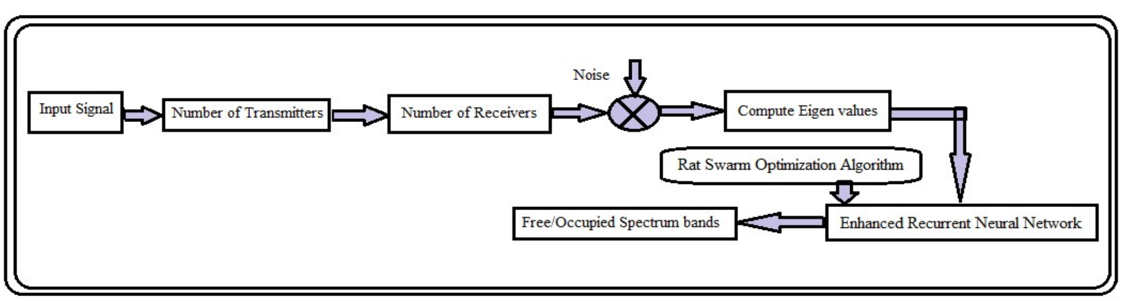


Figure 2: Block diagram of the proposed methodology

From figure 2, the SUs are located away from the Pus which enables the efficient transmission period. This type of transmission is referred to as cooperative sensing theory. The entire CRN network is involved in the participation and results are obtained. In the CRN network, the sensing time is imitating spectrum sensing and finalized at the time by detecting the user authenticated or malicious. As proposed in this methodology, the ERNN-RSOA is used in the CRN network with the entire network designed decentralized, as the PU and SU are linked in peer-to-peer technology. In order to analyse the proposed methodology, it is assumed that there are only one PU and N SU. To enable efficient spectrum sensing and sharing conditions, the ERNN-RSOA is utilized. Prior to the realization of energy detection, spectrum sensing validation is crucial. The adaptive threshold spectrum energy detection is described in detail below section.

3.1. Adaptive threshold spectrum energy detection (spectrum sensing)

The spectrum sharing and sensing processes are taken into consideration in the proposed CRN network. One of the important tasks in the spectrum sensing process is the identification of energy. In this proposed spectrum analysis, an Adaptive threshold spectrum energy detection algorithm is used. Initially, the receiver signal is collected for analysing the bandwidth and sampling rate. The power of the received signal is compared with some threshold value [16]. During the comparison analysis, the threshold value is achieved the threshold value means considered as PU is accessible. Hence, threshold value-based, the received signal is described which formulated as follows,

$$E(X) = \begin{cases} 1 & N(T) \\ 0 & S(T) + N(T) \end{cases} \tag{4}$$

Where $N(T)$ can be described as Additive White Gaussian Noise (AWGN) and $S(T) + N(T)$ can be described as AWGN with the signal. From equation (4), the received signal energy state is identified by the idle and busy state. The AWGN is named an idle channel and AWGN with a signal is named as a busy channel. From the consideration of the adaptive threshold spectrum, the energy detection algorithm is identifying the channel state. The adaptive threshold spectrum energy detection process is presented in algorithm 2.

Algorithm 2: Adaptive threshold spectrum energy detection algorithm

Input: Consider the primary user spectrum and N-1 secondary user spectrum. Here two types of channels are identified such as Idle channel and the busy channel.

Output: Sensing results are achieved with the help of an adaptive threshold spectrum energy detection algorithm.

```
Sense channel
If E(x)=N(T) then
Idle channel
Else
If E(X)=N(T)+S(T) then
Busy channel
End if
End if
```

Based on the adaptive threshold spectrum energy detection, the spectrum sensing is achieved the idle channel, and busy channel is detected in the CRN network which utilized to enhance the spectrum sharing process. During the spectrum sharing, the probability of false alarm is calculated, as follows,

Probability of false alarm:

It's a measure of probability of miss detection of the spectrum and energy. The probability is the ratio of the number of times miss detection with a number of iterations. This probability measure can be mathematically described as follows,

$$FA(P) = 1 - P^{MD} = \frac{\theta^M}{\eta} \tag{5}$$

Where, $FA(P)$ can be described as a probability function of false alarm, P^{MD} can be described as probability of spectrum detection, θ^M can be described as a number of times detect the energy detection and η can be described as a number of iterations. Based on spectrum sensing information, spectrum sharing is achieved in the CRN network. The spectrum sharing process with ERNN-RSOA is explained below section.

3.2. Recurrent Neural Network

The RNN is one of the classes of ANN, in which the connections between the units establish a directed cycle. It generates an internal state of the network which allows it to develop characteristics of dynamic temporal. Compared with the feed forward neural networks, the RNN can be utilizing their internal storage to operate Random input sequences. The main motive of RNN is to use the sequential data [27]. In the conventional neural network, complete input and outputs are connected to be independent of each other. Moreover, different applications, this connection are not sure. They repeat similar operation for each parameter of input sequence with the consideration of input to the output with previous calculations; hence, the name recurrent is given to the RNN. Likewise, there is a specific storage for the RNNs which can be used to store input data based on the computation carried out up to that point. The architecture of RNN is shown in figure 2.

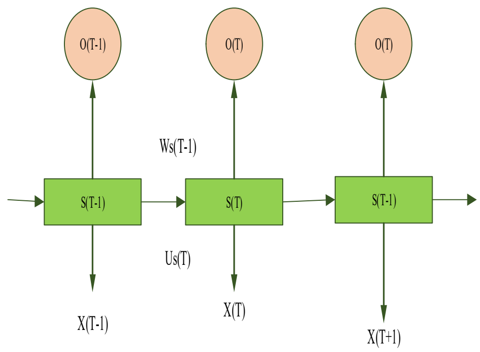


Figure 3: Structure of recurrent neural network

The RNN structure is contains the input state (x_I), hidden state (h_I), and output state (o_I) with the consideration of time step T. The RNN structure is an unfolded into a complete network. Because of unrolling RNN, the network is designed in a complete sequential format. The hidden state of the RNN structure also known as network memory. This memory is computed based on the previous input and hidden state of the present scenario which presented in equation (1). From the equation, the function (f) can be known as nonlinear. To compute first hidden state, the term $S(T-1)$ is named as initial hidden state which initialized with complete zeros.

$$S_T = F\left(U_{XT} + W_{s(T-1)}\right) \tag{1}$$

Normally, the RNN has the ability to handling sequence of data by assuming that the present timestep. The present timestep is completely depends on the previous timestep, it also affects from different drawbacks such as exploding probability and gradient vanishing. To alleviate the above drawbacks, the long short-term memory (LSTM) algorithm is utilized. It is specific class of RNN models. This LSTM is developed by Horchreiter and schmidhuber in 1997 and is utilized to collect the long-term temporal dependencies. The main objective of the LSTM model is a memory cell that state may be varied at different time. The gated nonlinear sections are utilized to decide that information should be thrown away from or stored in different advantages. In this proposed methodology, the LSTM method was utilized to achieve efficient features over an RNN.

The LSTM consists specific units' names as memory blocks in the recurrent hidden layer. The memory block consists memory cells for storing purpose and special multiplication units named as gates to control the input data. Every memory cell in the input architecture consists an output gate and input gate. The input gate maintains the flow of input activations into the memory cell. Similarly, the output gate mange the output flow of cell activations into the remaining of the RNN structure. Finally, the forget gate is added to the memory block. Additionally, the modern LSTM structure consists of peephole connections from its internal cells to the gates in the similar cell to train precise timing of the outputs. An LSTM network calculates a mapping from an input sequence $X = (X1, \ldots, XT)$ to an output sequence $Y = (Y1, \ldots, YT)$ by computing the network unit activations with the consideration of below equations with iterations $t = 1, \ldots, T$.

$$I_t = \sigma(w_{IX}X_T + w_{Im}m_{T-1} + w_{Ic}C_{T-1} + B_I) \tag{2}$$

$$F_t = \sigma\left(w_{IX}X_T + w_{fm}m_{T-1} + w_{fc}C_{T-1} + B_f\right) \tag{3}$$

$$C_t = F_t \odot \sigma C_{T-1} + i_T \odot G\left(w_{CX}X_T + w_{cm}m_{T-1} + B_f\right) \tag{4}$$

$$O_T = \sigma(w_{OX}X_T + w_{Om}m_{T-1} + w_{Oc}C_{T-1} + B_o) \tag{5}$$

$$m_T = O_T \odot \tan h(C_T) \qquad (6)$$

$$Y_t = \emptyset\left(w_{fm} m_T + B_y\right) \qquad (7)$$

Where, tanh can be described as network output activation function, G can be described as cell input, I can be described as input gate, O can be described as output gate and C can be described as cell activation vectors, F can be described as forget gate, σ can be described as logistic sigmoid function, B can be described as bias vectors, w_{IX}, w_{IX} *and* w_{OX} can be considered as diagonal weight metrices, w can be described as weight matrices and $\emptyset$ can be described as a Softmax function and $\odot$ can be described as element wise product of the vectors. To enhance the learning algorithm in the RNN model, the SOA algorithm is utilized which speed up the convergence process [28]. To achieve the fastest convergence rate by achieving efficient parameters, the SOA is suitable. In recent years, AI techniques are most appropriate to enable efficient training process, it can offer a best balance between the speed of RSOA methods and the convergence of the steepest decent. Typically, the Levenberg-Marquardt (LM) is used in feedforward networks for training process. This method may not be achieved efficient results in training process. For this reason, the use of RSOA is the solution adopted in this paper to facilitate the efficient training process in the RNN network structure..

3.3. Rat Swarm Optimization Algorithm

The algorithm rat swarm optimization is used for optimal spectrum sensing in the CRN network. The general description of the AROA is presented in this section. The RSOA and RNN regulators have gotten used to controlling the power contained in the system, which will improve the structure's strength. The RSOA algorithm recognizes rats as medium sized rodents, which have a long tail and range in size and weight. There are two main types of rats, the black and brown. In the rat family, females are called does and males are called "bucks. Rats are social and smart. They groom each other and exhibit behaviors such as jumping, chasing, tumbling and boxing [31]. Rats live in a group of both males and females and are territorial. Rats are known for their aggressive nature, which can lead to the death of certain animals. While chasing and fighting with prey, this aggressive behaviour is the key incentive for this task [32]. The chasing and fighting behaviours of rats are mathematically analysed in this study in order to construct the RSO algorithm and undertake optimization.

ERNN explores wrong boundaries of the regulator structure. The RSOA computation is used to define error estimates. The proposed technique's cycle is explained in the steps below.

Step 1:

Initialization: Initialize the rats population Pi where i = 1, 2, … , n.

$$Rats = \begin{bmatrix} X_1^1 & X_1^2 & \dots & X_d^1 \\ X_1^2 & X_1^2 & \dots & X_d^1 \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ X_1^N & X_1^N & \dots & X_d^N \end{bmatrix} \qquad (16)$$

All rats have been "warm-up"ed. In the preliminary iteration, rats don't have any initial values, and it is concluded that they have concealed their foods at starting process.

$$memory = \begin{bmatrix} M_1^1 & M_1^2 & \dots & M_d^1 \\ M_1^2 & M_1^2 & \dots & M_d^1 \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ M_1^N & M_1^N & \dots & M_d^N \end{bmatrix} \qquad (17)$$

Step 2:

Choose the initial parameters of RSO: A, C, and R.

Step 3:

Fitness Function Evaluation:

The quality of rat's locations is calculated by introducing the decision variable values in to attack detection and security. All the fitness values for all the rats are calculated in this step.

$$F = \min(T_p, C_q, E_i) \qquad (18)$$

Step 4:

Here, the optimal search agent is identified from the search space.

Step 5:

Updation

By utilizing the equation (19), the search agent positions are updated.

***Memory updating*:** The rat memory is updated based on the below equation,

$$M^{t+1} = \begin{cases} X_a^{t+1} & f(X_a^{t+1}) \text{ is better than } f(M_a^t) \\ M_a^t & Otherwise \end{cases} \quad (19)$$

Then, where f(.) is the value of the objective function of the system, if the fitness function parameter of the new position of the rat is higher than the fitness function parameter of the memory location, the fitness function parameter of the memory location is changed by the optimal location.

Step 6: Ensure that the search agent does not go past the outer boundaries of the search space before making changes. If a more effective search agent is found than the previous best, then calculate the fitness of the search agent once again and update the vector Pr.

Step 7: Stop the algorithm if the halting conditions are satisfied. Otherwise, repeat Step 5.

Step 8: The optimum solution should be returned. Administrators can be described as those who have publishing power, compulsions and problem making decisions. Check the applicability of the new position: The reliability is lost, because of the new position of the rat. Rats will change their spots when it's possible. Until an agreement can be made, the rat will remain in its current state and won't switch to the novel state of production.

Step 9:

Check the end condition: The above improvements will be re-designed until they become more relevant. The ordering of executives and/or the intensity of the problem at the final step in meeting the criteria lags the memory's optimal condition with respect to the target value. This proposed method is tested in MATLAB Simulator and the results are presented in section 4. Prior to that, the next step is examined, and a thorough explanation is given.

The pseudo-code of the RSOA is illustrated in algorithm 1.

Algorithm 1: Pseudocode of RSOA for membership function variable selection

Input: Spectrum Energy.
Output: Optimal spectrum allocation.
Begin
    Initialize the population with energy variables
    Initialize the rat parameters, brake, accelerator, gear, steering angle
    Find success rate
    Evaluate the fitness function
While t< off time
    For i=1 to R
        Update the position of rats
Rank the rats according to their fitness value
    Select the maximum leading rat
    Update the parameters
    Save the results of optimal membership function parameters.

The above process is repeated every time until the time moves the off time, within those is the above computation of the time elapsed as off time. The final result is a winner – the top rats. Considering the ERNN-RSOA proposed algorithm, spectrum sensing and sharing is enabled in the CRN network.

4. Performance Evaluation

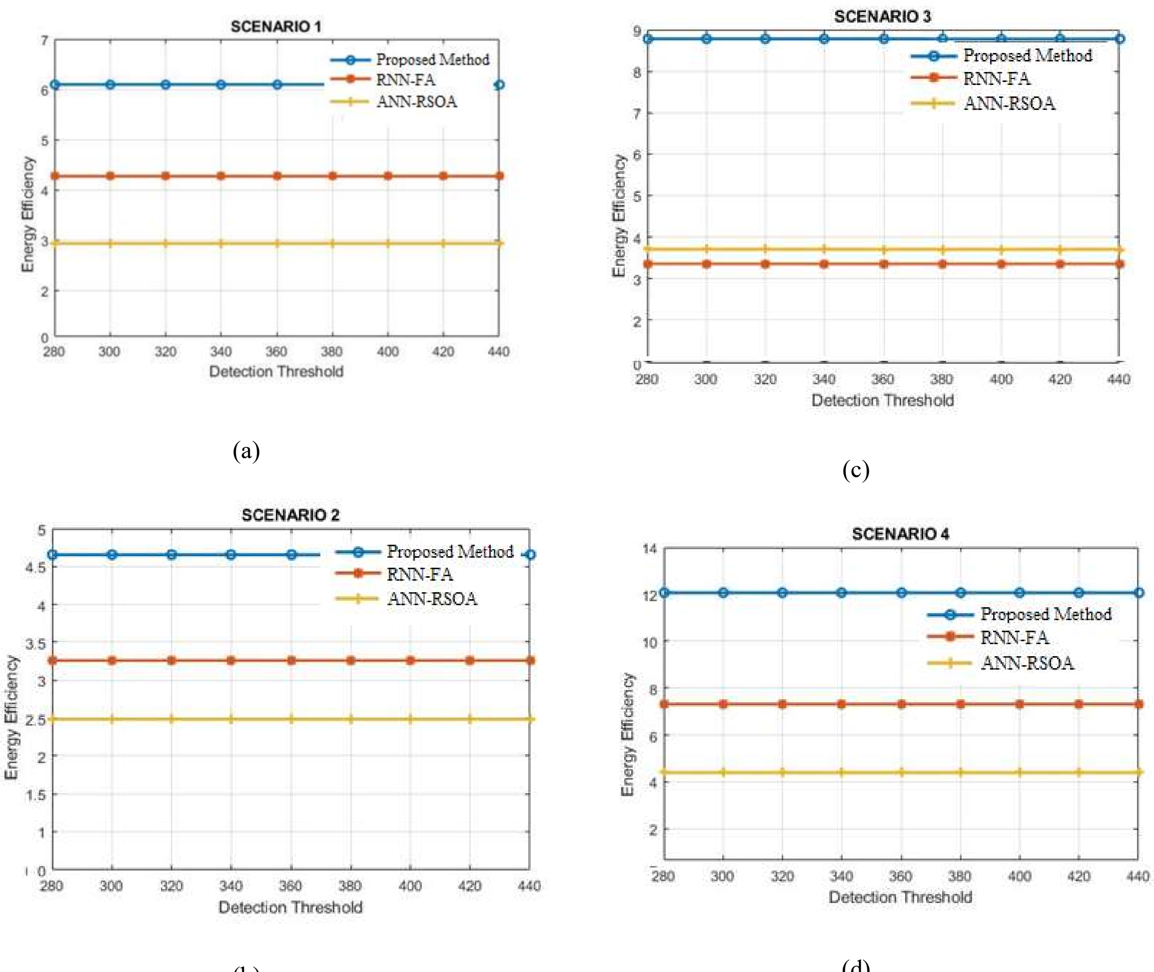
In this section the performance of the proposed methodology is analysed and validated. To validate the presence of the projected ERNN-RSOA based spectrum management of spectrum sensing and sharing in the CRN network, the proposed method is implemented in an Intel Core i5-2450M CPU 2.50GHz laptop and 6GB RAM. The MATLAB software (R2016b) implements this method. The proposed method implementation parameters are given in table 1. Implementing the proposed method and testing with the performance metrics: Normalized Energy consumption, delay, Signal Noise Ratio (SNR), Blocking probability, convergence analysis and Throughput is tested and validated. The proposed method is compared with the existing methods like Artificial Neural Network (ANN) with RSOA, and RNN with Firefly Algorithm (FA) respectively.

Table 1: Proposed method parameters

S. No	Method	Description	Value
1	Proposed Method	Channel utilization Interval	1s
2		Cognitive radio model	CRAHN
3		Queue Length	100 packets
4		Transport protocol	OHTP
5		Antenna Model	Omni
6		MAC type	Standard/Opportunistic IEEE 802.11

7		Network Interface Type	Wireless PHY
8		Channel Type	Wireless
9		Radio propagation channel	Two-way ground
10		Number of users (primary and secondary user)	100
11		Bandwidth	3MHz
12		Sensing power	100mW
13		Transmission power	3W
14		Sampling frequency	6MHz

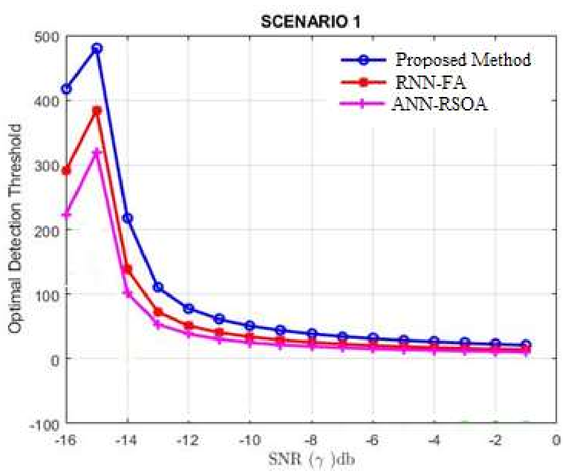
The primary user and the secondary user transmission condition with energy efficiency is analysed in the analysis. In the primary condition, Q1>Q2 and Q1<Q2 are studied. The energy efficiency of the various transmission conditions (data) is considered here as Q1 and Q2. In the same way, in the secondary user, Q1>Q2 and Q1<Q2 are examined. So, four different conditions are analysed in terms of energy efficiency, optimal detection threshold, optimal sensing time, sensing time with energy efficiency. The energy efficiency vs detection threshold for cases is illustrated in figure 4. The proposed method is compared to that of the conventional methods like ANN with RSOA, and RNN with FA.



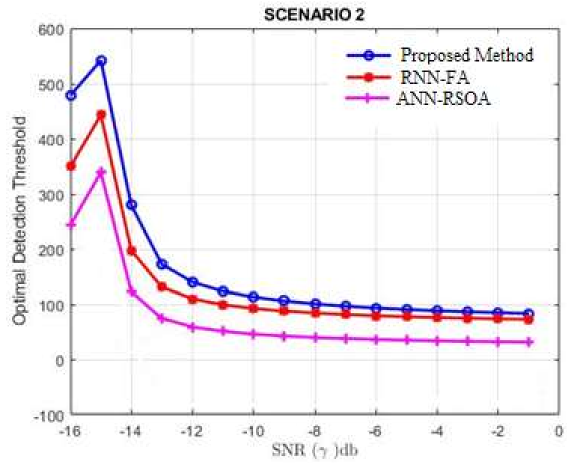
(a) (b) (c) (d)

Figure 4: Analysis of Energy efficiency vs detection threshold (a) scenario 1, (b) scenario 2, (c) scenario 3 and (d) scenario 4

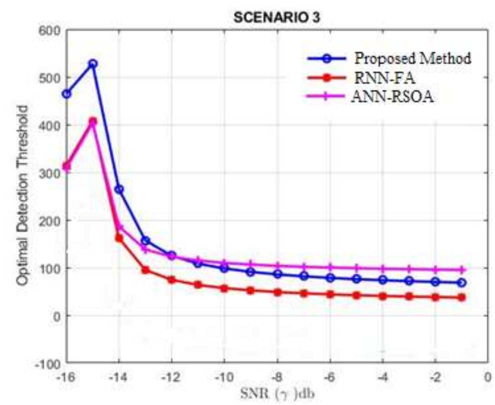
The energy efficiency vs detection threshold plot of scenario 1 is shown in figure 4(a). The proposed method is accomplished with an energy efficiency of 6.1J at a detection threshold of 280-440. Likewise, the conventional approaches, such as ANN with RSOA, and RNN with FA, have been achieved at a 280-440 detection threshold of 4.2J and 3J, respectively. From the analysis, the proposed methodology has been achieved the best energy efficiency results. The energy efficiency vs detection threshold analysis has been shown in figure 4(b) for scenario 2. The proposed methodology has resulted in 4.8J energy efficiency at 280-440 detection threshold from this figure. Similarly, the conventional approaches of ANN and RNN have been accomplished at 3.3J and 2.5J detection threshold respectively. From the analysis, the proposed methodology has been achieved the best energy efficiency results. The energy efficiency vs detection threshold analysis of scenario 3 is shown in figure 4(c). From this number, the proposed methodology has been accomplished with 9J energy efficiency at 280-440 detection threshold. Likewise, the traditional approaches of ANN and RNN with RSOA and FA respectively have been accomplished 4.2J and 3.5J at 280-440 detection threshold. From the analysis, the proposed methodology has been achieved the best energy efficiency results. The energy efficiency vs detection threshold for scenario 4 is shown in figure 4(d). From this figure, the proposed methodology has been achieved 11J energy efficiency at 280-440 detection threshold. Likewise, the conventional approach of ANN and RNN respectively with RSOA and FA has been accomplished 7J and 5.5J at 280-440 detection threshold. Based on this analysis, the proposed methodology has been obtained the best results of energy efficiency.



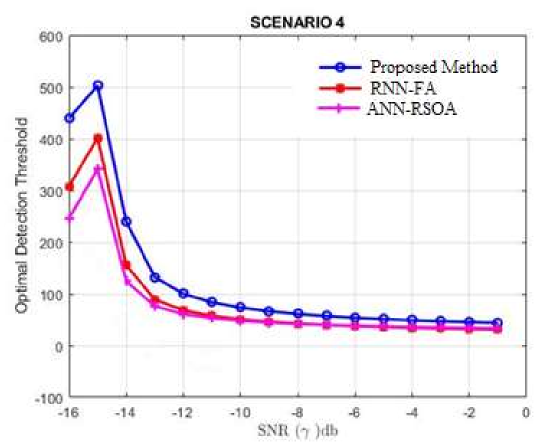
(a)



(b)



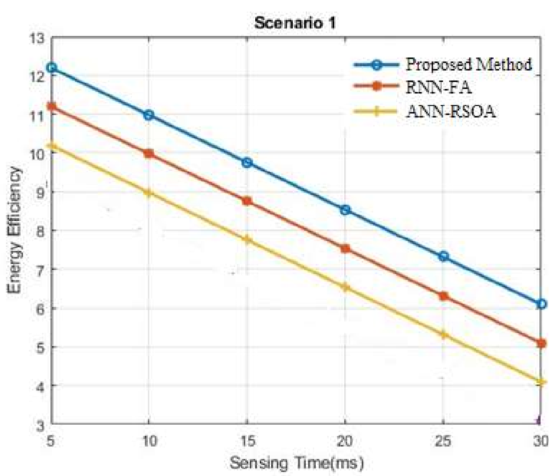
(c)



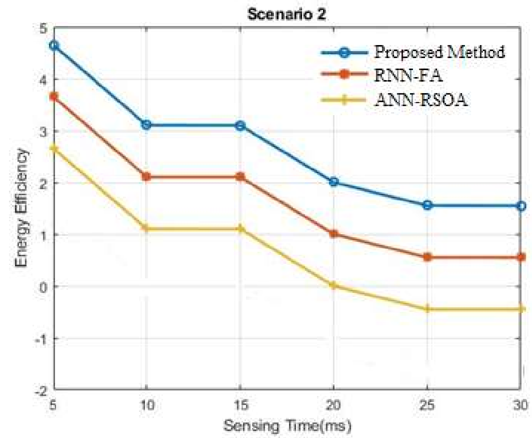
(d)

Figure 5: Analysis of optimal detection threshold vs SNR (a) scenario 1, (b) scenario 2, (c) scenario 3 and (d) scenario 4

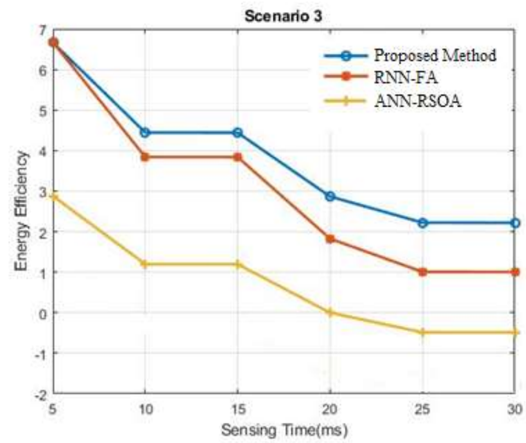
In figure 5, the optimal detection threshold (Vs SNR) is shown. The optimal energy threshold of scenario 1 is shown in figure 5(a). The methodology proposed has been accomplished at -16db for 450. Likewise, the traditional RSOA/ANN and FA/RNN solutions have been accomplished at -16db with 388 and 322, respectively. From the analysis, the proposed method has been achieved the best optimal detection threshold in the CRN network. The optimal energy threshold of scenario 2 is shown in figure 5(b). In the figure, the proposed methodology has been accomplished at -16db. Likewise, the traditional approaches of ANN and RNN with RSOA and FA have been accomplished at -16db with the performance of 392 and 312 respectively. The analysis results show that the proposed method has successfully obtained the best optimal detection threshold in the CRN network. The optimal energy threshold of scenario 3 is shown in figure 5(c). The figure indicates that the proposed methodology has been accomplished at -16db. Also, the traditional approach of ANN-RSOA and RNN-FA have been attained with 386 and 302 at -16db respectively. It is found that the proposed method has optimal detection threshold in the CRN network from the analysis. The optimal value of the energy threshold for scenario 4 is shown in figure 5(d). Based on the figure, the proposed methodology has been realised 485 at -16db. Conventionally, at -16db, the methods of ANN and RNN have been accomplished with the help of RSOA and FA respectively are 376 and 312 respectively. Based on the analysis, the proposed method is able to get the best optimal detection threshold in the CRN network.



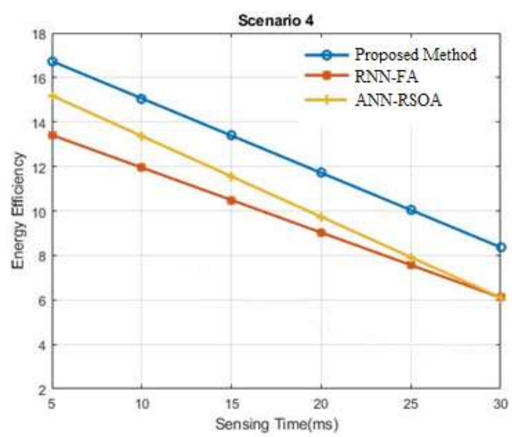
(a)



(b)



(c)



(d)

Figure 6: Analysis of optimal sensing time vs SNR (a) scenario1, (b) scenario2, (c) scenario3 and (d) scenario 4

The trade-off between the energy efficiency and sensing time of the proposed methodology is shown in figure 6. The energy efficiency of scenario 1 and the number of times the energy sensor has been used over time is shown in figure 6(a). The figure illustrates the proposed method, which can be obtained 12.05J energy efficiency by 5ms sensing time. Similarly, the conventional methods of ANN with RSOA and RNN with FA have been achieved 11.01J and 10.01J, at 5ms sensing time. The energy efficiency is shown as a function of the sensing time in figure 6(b) for the scenario 2. The results, as displayed in the figure, have attained an energy efficiency of 4.8J with a sensing time of 5ms by adopting the proposed method. Likewise, the conventional techniques of ANN (RSOA) and RNN (FA) have been attained at 3.08J and 2.06J respectively at the sensing time of 5ms. In figure 6(c), the energy efficiency vs sensing time of scenario 3 is illustrated. The figure shows that 9J energy efficiency in 5ms sensing time has been achieved with the proposed method. The same is true for the conventional approach of ANN and RNN with RSOA and FA, which have been accomplished at 5ms sensing time with 5.8J and 50.01J, respectively. The energy efficiency versus sensing time of the scenario 4 is shown in figure 6(d). It is seen from the figure that the proposed method has been realized 21J energy efficiency at 5ms sensing time. Similarly, the conventional methods of ANN with RSOA and RNN with FA have been achieved 5.8J and 50.01J, at 5ms sensing time. From the analysis, the proposed methodology energy efficiency is decreased with sensing time increased condition. Furthermore, the proposed methodology has been obtained high energy efficiency values.

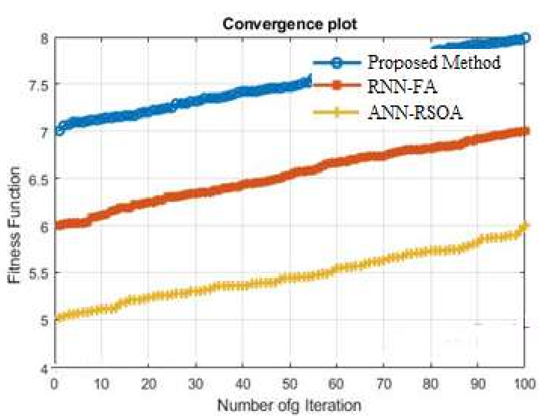


Figure 7: Comparison analysis of convergence

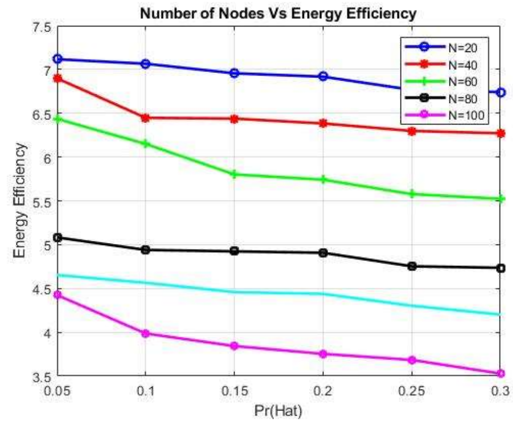


Figure 8: Comparison analysis of energy efficiency

The convergence analysis of the proposed methodology is shown in figure 7. The methodology proposed is achieved from the figure 8 times fitness function values. This is a proposed methodology where the maximization function is studied. The conventional methods of ANN with RSOA and RNN with FA has been achieved 6, and 4 fitness function value. The analysis shows that the proposed method converging easily and getting the maximum value. The comparison analysis of the energy efficiency is shown in figure 8. The analysis of the proposed methodology is carried out with varying number of nodes in figure 8. In the figure, the 20 nodes are achieved 7.1J energy efficiency, the 40 nodes are achieved 6.9J energy efficiency, the 60 nodes are achieved 6.4 energy efficiency, the 80 nodes are achieved 5.2J, the 100 nodes are achieved 4.4J respectively. The number of nodes is rising, so is the energy consumed. The energy efficiency is increased initially in proportion with the increment of energy consumption for user, which will enhance the sensing performance by reducing the losses in data transmission process and high energy consumption. Furthermore, the change in energy efficiency as a function of user did not vary significantly following a certain user by a rise in the transmission power. Therefore, the design of the proposed energy efficient model can be designed to choose a required number of users to decrease unnecessary power consumption of the users. The energy efficiency will be compared with the spectrum efficiency presented in figure 8 for the proposed method. The proposed methodology has been achieved $4.4*10^5$ bit/joule energy efficiency at 8.4 spectrum efficiency. Similarly, the conventional methodology of ANN with RSOA and RNN with FA has been achieved $3.2*10^5$ bit/joule and $2.2*10^5$ bit/joule respectively. From the analysis, the proposed methodology has been achieved the best energy efficiency in the data transmission. From the analysis, the proposed methodology has been achieved a low error rate. From the comparison analysis, we can conclude, the proposed methodology has been achieved the best results.

5. Conclusion

The focus of this paper is to develop the ERNN-RSOA for an enhanced energy efficiency for various spectrum sensing scenarios. The proposed algorithm has been used to calculate the sensing time, sequence length and detection threshold. To efficiently detect the spectrum with optimized values of transmission power and sensing bandwidth, the ERNN-RSOA has the adaptive threshold detection method. The ERNN-RSOA algorithm helps in the spectrum sensing and sharing of the CRN network. The proposed method is coded in MATLAB and the performance is analyzed using performance metrics namely, Normalized Energy consumption, delay, SNR, Jitter, Blocking probability, convergence analysis and Throughput. The proposed method is compared with the existing methods such as ANN with RSOA and RNN with FA respectively. The proposed methodology has been validated by the primary condition, Q1>Q2 and Q1<Q2 are analyzed. Here, Q1 and Q2 are considered as the energy efficiency of different transmission conditions (data). Likewise, the secondary user, Q1>Q2 and Q1<Q2 are studied. The analysis has led to the best energy efficiency and spectrum sensing behaviours for the proposed methodology.

References

[1] Mahua Bhowmik, and P. Malathi, “Spectrum Sensing in Cognitive Radio Using Actor–Critic Neural Network with Krill Herd-Whale Optimization Algorithm”, Wireless Personal Communications, 2019

[2] G. Ding, Y. Jiao, J. Wang, Y. Zou, Q. Wu, Y.-D. Yao, and L. Hanzo, “Spectrum inference in cognitive radio networks: Algorithms and applications”, IEEE Communications Surveys & Tutorials, Vol. 20, No. 1, pp. 150–182, 2017

[3] K. Cichon, A. Kliks, and H. Bogucka, “Energy-efficient cooperative spectrum sensing: A survey”, IEEE Communications Surveys & Tutorials, Vol. 18, No. 3, pp. 1861–1886, 2016

[4] Manish Kumar Giri, and Saikat Majumde, “Extreme Learning Machine Based Cooperative Spectrum Sensing in Cognitive Radio Networks”, In proceedings of IEEE 7th International Conference on Signal Processing and Integrated Networks (SPIN), 2020

[5] Saber Mohammed, Kharraz Aroussi Hatim, El Rharras Abdessamad, Abdellah Chehri and Saadane Rachid, "An Optimized Spectrum Sensing Implementation based on SVM, KNN and TREE Algorithms", In proceedings of 5th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS), 2019

[6] S. Siva Reddy and M. Siva Ganga Prasad, “Improved Whale Optimization Algorithm and Convolutional neural network based Cooperative Spectrum Sensing in Cognitive Radio Networks”, Information Security Journal: A Global Perspective, 2020

[7] Yingqi Lu, Pai Zhu, Donglin Wang and Michel Fattouche, “Machine Learning Techniques with Probability Vector for Cooperative Spectrum Sensing in Cognitive Radio Networks”, In proceedings of IEEE Wireless Conference and Networking Conference, 2016

[8] Doha Hamza, Sonia Aïssa, and Ghassane Aniba, “Equal Gain Combining for Cooperative Spectrum Sensing in Cognitive Radio Networks”, IEEE Transactions on Wireless Communications, Vol. 13, No. 8, August 2014

[9] Arash Ostovar, Yousaf Bin Zikria, Hyung Seok Kim, and Rashid Ali, “Optimization of Resource Allocation Model With Energy-Efficient Cooperative Sensing in Green Cognitive Radio Networks”, IEEE Access, Vol. 8, 2020

[10] W. Krenik, A. M. Wyglinsky, and L. Doyle, “Cognitive Radios for Dynamic Spectrum Access,” IEEE Communications Magazine, Vol. 45, No. 5, pp. 6465, May 2007

[11] Geoffrey Eappen, and T. Shankar, “Hybrid PSO-GSA for energy efficient spectrum sensing in cognitive radio network”, Physical Communication, Vol. 40, 2020

[12] Z. Feng, C. Qiu, Z. Feng, Z. Wei, W. Li, and P. Zhang, “An effective approach to 5G: Wireless network virtualization”, IEEE Communication Magazine, Vol. 53, No. 12, pp. 53–59, Dec. 2015

[13] Victor Balogun, Oluwafemi A. Sarumi, “A Cooperative Spectrum Sensing Architecture and Algorithm for Cloud- and Big Data-based Cognitive

Radio Networks”, In proceedings of IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), 2020

[14] Ling Yu, Jin Chen, Guoru Ding, Ya Tu, Jian Yang and Jiachen Sun, “Spectrum Prediction Based on Taguchi Method inDeep Learning With Long Short-Term Memory”, IEEE Access, Vol.6, 2018

[15] V. Jamali, A. Ahmadzadeh, and R. Schober, “On the design of matchedfilters for molecule counting receivers”, IEEE Communication Letters, Vol. 21, No. 8, pp. 1711–1714, Aug. 2017

[16] R Rajaguru, K.Vimala Devi, P.Marichamy, “A Hybrid Spectrum Sensing Approach to Select Suitable Spectrum Band for Cognitive Users”, Computer Networks, 2020

[17] Ziyu Ye, Kelly Levick, Andrew Gilman, Pamela Cosman, Qihang Peng and Larry Milstein, “Comparison of Neural Network Architectures for Spectrum Sensing”, 2019

[18] Abdulsahib Albehadili, Atif Ali, Farha Jahan, Ahmad Y.Javaid, Jared Oluoch, and Vijay Devabhaktuni, “Machine Learning-based Primary User Emulation Attack Detection In Cognitive Radio Networks using Pattern Described Link-Signature (PDLS)”, IEEE Wireless Telecommunications Symposium, 2019

[19] Md Abul Kalam Azad, Anup Majumder, Jugal Krishna Das, Md Imdadul Islam, “Improving signal detection accuracy at FC of a CRN using machine learning and fuzzy rules”, Indonesian Journal of Electrical Engineering and Computer Science, Vol. 21, No. 2, pp. 1140-1150, February 2021

[20] S. Cui, A.J. Goldsmith, A. Bahai, “Energy-constrained modulation optimization”, IEEE Transaction on Wireless Communications, Vol. 4, No. 5, pp. 2349–2360, 2005

[21] Mengbo Zhang, Lunwen Wang, and Yanqing Feng, “Distributed cooperative spectrum sensing based on reinforcement learning in cognitive radio networks”, International Journal on Electronics Communication, Vol. 94, pp. 359–366, 2018

[22] Geoffrey Eappen and T. Shankar, “Multi-Objective Modified Grey Wolf Optimization Algorithm for Efficient Spectrum Sensing in the Cognitive Radio Network”, Arabian Journal for Science and Engineering, 2020

[23] Osameh M. Al-Kofahi, Hisham M. Almasaeid, Haithem Al-Mefleh, “Efficient on-demand spectrum sensing in sensor-aided cognitive radio networks“,Computer Communications, Vol. 156, pp. 11–24, 2020

[24] Woongsup Lee, Minhoe Kim and Dong-Ho Cho, “Deep Cooperative Sensing: Cooperative Spectrum Sensing Based on Convolutional Neural Networks”, IEEE Transactions on Vehicular Technology, 2018

[25] Ramsha Ahmed, Yueyun Chen, Bilal Hassan, Liping Du, “CR-IoTNet: Machine learning based joint spectrum sensing and allocation forcognitive radio enabled IoT cellular networks”, Ad Hoc Networks, Vol. 112, 2021

[26] Seleman Daudi Arthur Nkalango, Hui Zhao, Yuxin Song, and Tianqi Zhang. "Energy efficiency under double deck relay assistance on cluster cooperative spectrum sensing in hybrid spectrum sharing", IEEE Access, Vol. 8, pp. 41298-41308, 2020

[27] G.Dinesh, P. Venkatakrishnan, and K. Meena Alias Jeyanthi, “Modified spider monkey optimization—An enhanced optimization of spectrum sharing in cognitive radio networks”, International Journal of Communication Systems, Vol. 34, No. 3, 2021

[28] B. Chandra and Rajesh Sharma, “On improving recurrent neural network for image classification”, In proceedings of International Joint Conference on Neural Networks (IJCNN), 2017

[29] Gaurav Dhiman, Meenakshi Garg, Atulya Nagar, Vijay Kumar, and Mohammad Dehghani, “A novel algorithm for global optimization: Rat Swarm Optimizer”, Journal of Ambient Intelligence and Humanized Computing, 2020