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Spectrum Sensing using Enhanced Restricted Boltzmann Machine for Cognitive Radio Network

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Abstract: Cognitive radio network (CRN) came in to existence as a promising solution to tackle issues due to scarcity of spectrum. Spectrum sensing plays an important role for maximizing the spectrum utilization where spectrum of the primary users (PU) is sensed by the secondary user (SU) at particular time and space. Researchers have presented machine learning techniques for spectrum sensing, though, challenges exists for the improvement in the throughput, energy efficiency, detection probability and delivery ratio. In this paper, an enhanced restricted Boltzmann machine (ERBM) is presented for spectrum sensing based on RBM. Particle Swarm Optimization (PSO) is incorporated for enhancing the performance of spectrum sensing and computation of optimal momentum coefficient of RBM. Simulation results shows that the performance of the proposed spectrum sensing technique is comparable to the existing techniques in terms of throughput, energy efficiency and detection probability and delivery ratio.

Keywords: Cognitive radio network (CRN), spectrum sensing, restricted Boltzmann machine (RBM), particle swarm optimization (PSO).

I. INTRODUCTION

Adaptations of dynamic spectrum allocation techniques are inevitable as the demand for spectrum in the unlicensed user systems keeps increasing. In the recent times the opportunistic use of TV spectrum by unlicensed users has been approved by the U.S. Federal communications commission [1]. Through the technology of cognitive radio, this concept can be branched to other licensed user systems. In many of the cases, the channels assigned to the primary user spectrum are logically separated into slots by the secondary users in a cognitive radio network [2].

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The unused slots which were left by the primary user are known as white spaces or spectrum holes. The secondary user (SU) has to sense the activity of the primary user for a short period of time within every slot and accesses based on this [3]. Cognitive Radio is considered as a reliable technology for enhancing the effectiveness of wireless communication systems. For the functioning of CR devices, the best available channel is chosen by the DSA techniques from the spectrum pool. To be precise, CR allows secondary users to perform a series of functions of spectrum management, spectrum sensing, spectrum mobility and spectrum sharing [4]. For identifying the radio environment such as recognizing both SUs and PUs' spectrum occupancy state, the spectrum sensing module assists the SUs [5]. The spectrum analysis module uses the spectral information for analyzing the available channel quality and the spectrum decision module uses the spectral information for making decision on channel assignment [6]. By implementing collaboration and cooperation between the secondary users that are spatially dispersed, the uncertainty issues are minimized. Unless there is some need for sensing performance to be met, it is not necessary for the secondary user to go through spectrum sensing for individual time slot. In some cases, the SUs function selfishly without contributing in spectrum sensing because of high energy consumption. The SUs' throughput is further minimized as the sensing performance can never be guaranteed whenever there is scarcity in the SUs having role in spectrum sensing [7]. In recent times, many of the researches have concentrated on the techniques of machine learning that is implemented in the cognitive radios and they focused on many of the case studies that propose learning problem. Artificial Intelligence (AI) is a likeable sector for the experiential based future learning. In AI, Artificial Neural Network (ANN) is the prominent domain in which the individual features' training samples based future predictions are made. Thus the worthiness of the technology is enjoyed by the CR and wireless communication systems. The neural network attains lot of interest in spectrum sensing [8]. Contribution of this paper is described as follows:

For spectrum sensing in CRN, Enhanced Restricted Boltzmann Machine (ERBM) is presented in this paper. The performance of the RBM is improved by presenting particle swarm optimization (PSO) algorithm.

Using this algorithm, momentum coefficient, which is used to update the weight and bias values in RBM, is optimally selected.

This proposed approach is implemented in the Network Simulator platform.

The performance of this proposed approach is evaluated in terms of throughput, energy efficiency, delivery ratio and delay. Rest of this paper is organized as follows. Section 2 surveys some recent literatures which focused research on spectrum sensing in CRN. Section 3 describes the basic of restricted Boltzmann machine algorithm. Section 4 propose enhanced restricted Boltzmann machine algorithm for spectrum sensing. Results of this proposed approach are discussed in section 5. Finally, conclusion section concludes this research work.

II. RELATED WORKS

In this section, some recent literatures which focused research on spectrum sensing in cognitive radio network. Reena Rathee Jaglan, Rashid Mustafa and Sunil Agrawal [9] have proposed an efficient cooperative spectrum sensing based on artificial neural network (ANN) for Cognitive Radio Networks. The authors aimed to enhance the spectrum detection performance in CRN. To achieve this aim, they have presented ANN at fusion center where sensing information of secondary users are received for making decision on the presence of primary users. This proposed ANN enhanced the CRN scalability. By presenting this proposed approach, they have achieved better SNR and accuracy.

Zan Li et al [10] have presented Optimal Spectrum Sensing Interval in Energy-Harvesting CRN. In CRN, a secondary user executes spectrum sensing toward the beginning of each time space, which may squander energy and the transmission openings for the secondary user. So, the authors aimed to enhance spectral efficiency and energy efficiency. To achieve these aims, they have considered energy harvesting schemes. They have utilized Markov decision process and partially observable Markov decision process for estimating the transmission energy, optimal spectrum sensing energy and spectrum sensing interval. Because of this proposed approach, the authors have achieved better throughput of secondary user and energy efficiency.

C. S. Karthikeyan and M. Suganthi [11] have proposed an Optimized Spectrum Sensing Algorithm for CRN. The authors aimed to present efficient spectrum-sensing scheme in field programmable gate array with less complexity in CRN. To achieve this aim, they have proposed adaptive absolute-self-coherent-restoral algorithm for spectrum sensing. This proposed approach was implemented in Xilinx and Spartan 6 FPGA. Simulation results showed that this proposed approach reduced complexity in spectrum sensing for CRN than the existing algorithms self-coherent-restoral algorithm which was abbreviated as SCORE, adaptive cross-SCORE and adaptive least-SCORE.

Mengbo Zhang, Lunwen Wang and Yanqing Feng [12] have presented reinforcement learning based distributed cooperative spectrum sensing in CRN. Final sensing outcome is degraded because of the false sensing data of the malicious secondary user. So, the authors aimed to present efficient spectrum sensing technique against the malicious secondary user. To achieve this aim, they have utilized reinforcement learning for distributed cooperative spectrum sensing. By using this proposed approach, data fusion among users in CRN was removed. Also, each secondary user was chosen from the neighbor nodes of CRN using the proposed method. This proposed approach is simulated in the platform of MATLAB. By presenting this approach, they have achieved better detection probability and detection time.

Bhawna Ahuja and Gurjit Kaur [13] have designed an enhanced spectrum sensing scheme with dynamic double thresholds for CRN. The authors aimed to enhance the spectrum detection performance. To achieve this aim, they have proposed two phases for spectrum sensing and utilized dynamic threshold. In the first phase, energy detection was considered and a detector based on fuzzy logic with dynamic thresholds was utilized in the second phase for final decision making. This proposed approach never utilized the primary user signal format. By presenting this proposed approach, they have improved the performance of local sensing. They have decreased the number of optimal users at low SNR.

Tony Cladia A and Esakki Rajavel S [14] have proposed Optimizing Spectrum Sensing for energy efficient CRN. Main objective of this literature was to improve the throughput of the primary user. To attain this objective, the authors have utilized dijkstra algorithm. Using this algorithm, shortest path to the destination is estimated and data is sent with more energy efficiency. Also, this proposed approach avoided interference and offered protection to primary user. This proposed approach was implemented in the platform of Network Simulator. By presenting this proposed approach, they have achieved better energy efficiency and delivery ratio.

Shanigarapu Nareshkumar and Kalagadda Bikshalu [15] have presented Adaptive absolute SCORE algorithm based spectrum sensing in CRN. The performance of energy detection of spectrum sensing technique reduced at low SNR environment. Also, sensing technique based on cyclostationary degraded the performance of Primary Users detection with high utilization of hardware and implementation complexity. Besides, conventional median and Finite Impulse Response filters consumed large memory space for storing the filter coefficients. By considering these issues, the authors have designed optimal FIR filter based Adaptive Absolute SCORE which was abbreviated as AA-SCORE. They have designed the FIR filter with Radix-8 and Carry Select Adder which reduced the complexity of the filter. This proposed approach was implemented in FPGA platform. By presenting this proposed model, spectrum utilization efficiency of CRN was improved.

Bao Peng et al [16] have proposed Bayesian learning based intelligent clustering cooperative spectrum sensing for CRN. The authors aimed to enhance the sensing performance of cooperative spectrum sensing under the situation of shadowing effect and severe fading of sensing channel. To achieve this aim, they have proposed Bayesian learning for intelligent clustering cooperative spectrum sensing.

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In this approach, clustering cooperative spectrum sensing was executed by inter-cluster and intra-cluster cooperative spectrum sensing. Total Bayesian cost was minimized by setting the optimal sensing threshold for the intra-cluster cooperative spectrum sensing.
The Bayesian fusion achieved the total probability of detection and false alarm for inter-cluster cooperative spectrum sensing. For clustering the sensing nodes, K-means learning algorithm was proposed. Because of this proposed approach, they have achieved better cooperative overhead.

III. BASIC OF RESTRICTED BOLTZMANN MACHINE

Restricted Boltzmann Machine is a type of stochastic artificial neural network. Figure 1 shows the basic architecture of RBM. There are two primary layers such as hidden unit layers and visible units layer in RBM which is shown in the figure. In this architecture, there are no connections within a layer but the hidden units and visible units are connected to one another in the form of bipartite graph. Only when the state of visible unit is given, every hidden unit activation function is independent.

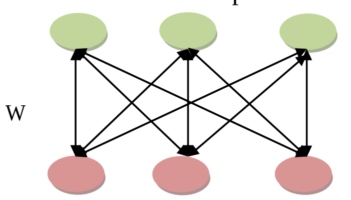

Fig.1 .RBM architecture

At first, the visible layer's (v) and hidden layer's (h) energy function is estimated in training phase. The following details the hidden and visible units of an RBM's joint configuration energy.

$$E(v,h;\theta)=-\sum_{i=1}^{I}\sum_{j=1}^{J}w_{ij}v_ih_j-\sum_{i=1}^{I}b_iv_i-\sum_{j=1}^{J}a_jh_j \quad (1)$$

Here, the weight value between i^th visible unit and j^th hidden unit is represented as wij. The bias terms are represented as aj and bi. Total number of visible units is denoted as I and total number of hidden units is denoted as J. For the given model parameters θ, probability distribution $p(v,h;\theta)$ over the visible units and hidden units based on the energy function $E(v,h;\theta)$ is given below

$$p(v,h;\theta)=\frac{exp(-E(v,h;\theta))}{Z} \quad (2)$$

Here, the normalization factor which is also known as partition function is denoted as Z. It is represented as follows,

$$Z=\sum_{v}\sum_{h}exp(-E(v,h;\theta)) \quad (3)$$

Visible vector v is assigned with the marginal probability by the model and it is defined as

$$p(v;\theta)=\frac{\sum_{n}exp(-E(v,h;\theta))}{Z} \quad (4)$$

The following equation defines the activation function's probability if the RBM is considered with the binary unit i.e. $v_i\, and\, h_j\in[0,1]$.

$$p(h_j=1|v;\theta)=\sigma\left(\sum_{i=1}^{I}w_{ij}v_i+a_j\right) \quad (5)$$

$$p(v_i=1|h;\theta)=\sigma\left(\sum_{j=1}^{J}w_{ij}h_j+b_i\right) \quad (6)$$

Here, the Logistic sigmoid function is denoted as $\sigma(x)$.
The convergence rate may degrade because of the number of parameters in the RBM model. Therefore for training the RBM, particle learning algorithm based on Contrastive Divergence (CD) is presented. As given below, the parameters vi, hj and wij are updated utilizing the CD algorithm.

$$\Delta w_{ij}=\eta\left(\langle v_ih_j\rangle_{data}-\langle v_ih_j\rangle_{recon}\right) \quad (7)$$

Also,

$$\Delta a_j=\eta\left(\langle h_j\rangle_{data}-\langle h_j\rangle_{reccon}\right) \quad (8)$$

$$\Delta b_i=\eta\left(\langle v_i\rangle_{data}-\langle v_i\rangle_{reccon}\right) \quad (9)$$

Here, the learning rate is represented as η and the reconstruction distribution from the input is represented as $\langle\,\rangle$.

IV. ENHANCED RESTRICTED BOLTZMANN MACHINE BASED SPECTRUM SENSING

A. If you Overview

In this paper, enhanced restricted Boltzmann machine (ERBM) algorithm is presented for spectrum sensing in CRN. Initially, states of each channel in the network such as idle state and busy state are derived. Then the symbols with derived states are given as input to the proposed ERBM mechanism. The performance of the RBM is improved by presenting PSO Algorithm. Momentum coefficient which defined in the weight and bias updating rules is optimally selected with the PSO algorithm. Then based on the input symbols, the proposed ERBM is trained and is tested.

B. Pre-processing

An essential process in communication system is to forms an idle selection of channel.

Let's assume the architecture is having β number of channels where channels are shown by $\vartheta=\{\vartheta_1,\vartheta_2,...,\vartheta_\eta\}$. Each channel is represented by channel state which is given by η, where $\eta\in\{\rho,\varphi\}$. Here, ρ indicates busy state whereas φ indicates idle state. The discrete- time Markov process are assumed to be satisfied by network's traffic statistics.

The state $\eta_i(\alpha)$ denotes for i^{th} channel for time slot α. The binary values 0 or1 can be used to denote the channel state like busy and idle states.

Following are the equation:

$$\eta_i(\alpha)=\begin{cases}0, \eta_i(\alpha)\in\rho\\ 1, \eta_i(\alpha)\in\varphi\end{cases} \quad (10)$$

The data is transmitted from transmitter to receiver through an ideal channel, which is unknown to the secondary user. Therefore, an algorithm is being used for finding the channel state prediction results. The algorithms are neural network based on probability along with the gravitational search.

At time instant t the system goes to η_t State based on probabilities of state transitions. Each state is associated with symbols given by $\omega=\{\omega_1,\omega_2,...,\omega_{\alpha s_s}\}$, where αs is the number of symbols associated with states. A symbol denoted by τ (where $\tau\in\omega$) is produced by state $\omega\in\eta$ for probability distribution of each state transition.

The idle or busy states of channel are represented by ones or zeros values respectively.

The τ_{t+1} is to be predicted by the previous sets of observations.

In each cycle of a multi-cycle process, a fixed number of states (n) are taken as training set (tr) and one is fixed as target set (ts) represented as:

$$\begin{cases}\alpha_1,\alpha_2,...,\alpha_{n-1}\in tr\\ \alpha_n\in ts\end{cases} \quad (11)$$

C. PSO based RBM for spectrum sensing

The presented RBMs model in this section may fall into a local minimum and can never jump out. Therefore, in this paper, an additional method is to be added a momentum on updating weights and other parameters of the model so as to improve the time efficiency and accuracy of the model. The following provides the new updating formula.

$$\Delta w_{ij}=\eta\left(\left\langle v_i h_j\right\rangle_{data}^{n}-\left\langle v_i h_j\right\rangle_{recon}^{n}\right)+\beta\Delta w_{ij}(n-1) \quad (12)$$

$$\Delta a_j=\eta\left(\left\langle h_j\right\rangle_{data}^{n}-\left\langle h_j\right\rangle_{recon}^{n}\right)+\beta\Delta a_j(n-1) \quad (13)$$

$$\Delta b_i=\eta\left(\left\langle v_i\right\rangle_{data}^{n}-\left\langle v_i\right\rangle_{recon}^{n}\right)+\beta\Delta b_i(n-1) \quad (14)$$

The second term in the equations is represented as momentums and β denotes the momentums coefficient within the interval [0, 1]. To attain the optimum results, the model is to be jumping out of the local optimum in the training process. The updating weights and bias rules can speed up the convergence of the model in the same direction. However, to obtain better results, the momentums coefficient is to be selected optimally with the particle swarm optimization (PSO) algorithm. The following section describes the optimal selection momentums coefficient using PSO.

In 1995, Eberhart and Kennedy developed the PSO algorithm. The behavior of bird flocking is taken as an inspiration for this algorithm. This algorithm is an evolutionary algorithm depending on population and started with a population of arbitrary solutions. These initialized solutions are known as particles.

Their very own velocity and position are provided to every particle when they are initialized. Utilizing this algorithm, optimal value of momentum coefficient is chosen and it is detailed below:

Initialization: With a d dimensional vector, initializations of the candidate solutions or particles are done. In this algorithm, the candidate solution is momentum coefficient i.e., optimal value of momentum coefficient is represented by every solution.

$$X_r(s)=\{X_{r1}(s), X_{r2}(s),.....X_{rd}(s)\} \quad (15)$$

Here, in the d[th] vector dimension, the position of the r[th] particle is denoted as $X_{rd}(s)$. At iteration‘s’, the algorithm population is measured as follows,

$$X(s)=\{X_1(s), X_2(s),.....X_m(s)\} \quad (16)$$

Fitness: each solution fitness value is evaluated after initializing the candidate solutions. Fitness function is calculated based on the error output of the RBM. This error function (E_r) is calculated as follows:

$$E_r=[A(r)-D(r)]^2 \quad (17)$$

Where, A (r) denotes the actual output and D (r) denotes the desired output or target output. Using (17), fitness function is calculated as follows,

$$Fit_r=Min(E_r) \quad (18)$$

From equation (17), the solution with minimum error is selected as an optimal solution.

Updation: The position and velocity vector is updated for a solution after calculating the fitness of the solution. Using equations (19) and (20) each solution is updated until an optimal solution is achieved. Pbest and Gbest i.e. personal best value and global best value respectively are estimated for each iteration.

$$V_{rd}(s+1)=w*V_{rd}(s)+\left(P_{best_{rd}}(s)-X_{rd}(s)\right)c_1r_1+\left(G_{best_d}(s)-X_{rd}(s)\right)c_2r_2 \quad (19)$$

$$X_{rd}(s+1)=X_{rd}(s)+V_{rd}(s+1) \quad (20)$$

Where, $X_{rd}(s)$ and $V_{rd}(s)$ indicate the position and velocity of the r[th] particle in d[th] space at iteration s. $c1$ and $c2$ indicate the acceleration which is equal to 2. $r1$ and $r2$ represent the random variables in the range [0, 1]. w is weight used to manage the searching process. The value of the weight is decreasing with increasing the iteration. Can be computed as,

$$w=w_{\max imum}-\frac{w_{\max imum}-w_{\min imum}}{t_{\max imum}}\times t \quad (21)$$

Where, $w_{\max imum}$ and $w_{\min imum}$ signifies the maximum and minimum weights respectively. $s_{\max imum}$ shown the maximum number of iterations.

$P_{bestr\,d}(s)$ and $G_{best\,d}(s)$ represent the best position of the particle r and best position of the group at iteration s.

If the fitness of the r^th^ particle ($X_{r\,d}(s+1)$) is smaller than that of previous $P_{bestr\,d}(s)$, then the particle is considered as new $P_{bestr\,d}(s+1)$. Otherwise, the particle $X_{r\,d}(s)$ is considered as new $P_{bestr\,d}(s+1)$. Besides, if the fitness of the r^th^ particle ($X_{r\,d}(s+1)$) is greater than that of previous $G_{best\,d}(s)$, then the particle is considered as new $G_{best\,d}(s+1)$. Otherwise, the particle $X_{r\,d}(s)$ is considered as new $G_{best\,d}(s+1)$.

$$P_{bestr\,d}(s+1)=\begin{cases} X_{rd}(s) & \text{if } F(X_{r\,d}(s+1))\geq F(P_{bestr\,d}(s)) \\ X_{r\,d}(s+1) & \text{otherwise}\end{cases} \quad (22)$$

$$G_{best\,d}(s+1)=\begin{cases} X_{r\,d}(s) & \text{if } F(X_{r\,d}(s+1))\geq F(G_{best\,d}(s)) \\ X_{rd}(s+1) & \text{otherwise}\end{cases} \quad (23)$$

Termination: Until the optimal value of the momentum coefficient is found the above phases are continued. Once the optimal solution is attained, the algorithm will be terminated.

Algorithm: Selection of optimal value of momentum coefficient using PSO

Input: Random values of momentum coefficient (β), *w, c1, c2, r1* and *r2.*

Output: Optimal momentum coefficient ($\beta_{Optimal}$).

1. Initialize the candidate solutions or values of momentum coefficient.
2. Find the fitness for each solution using (18).
3. Update velocity and position of the solution using (19) and (20).
4. IF

$$F(X_{r\,d}(s+1))\geq F(P_{bestr\,d}(s))$$

$$F(X_{r\,d}(s+1))\geq F(G_{best\,d}(s))$$

5. Then

$$P_{bestr\,d}(s+1)=X_{r\,d}(s+1)$$

$$G_{best\,d}(s+1)=X_{r\,d}(s+1)$$

6. Else

$$P_{bestr\,d}(s+1)=X_{r\,d}(s)$$

$$G_{best\,d}(s+1)=X_{rd}(s)$$

7. End
8. Phases 2-7 are continued until finding the optimal $G_{best\,d}$ or optimal value of momentum coefficient.

V. RESULTS AND DISCUSSION

Network Simulator (NS2) is used to implement the proposed scenario. In this simulation 250 nodes are deployed in the simulation area 1000m×1000m. Among the nodes, 250 nodes are considered as secondary users rest of them is considered as primary nodes. Transmission range of each node is 250m. 20 channels are considered in this simulation. Bandwidth of each channel is 1MHz. Initial energy of each node is 100J. Packet size is 512bytes. This proposed approach is simulated within the simulation time 100 seconds. Table 1 shows the simulation setting.

Table 1: Simulation settings

Parameter Name	Value
No of nodes	250
Area	1000m×1000m
Mac	802.11
Simulation time	100s
Routing protocol	DSDV
Antenna	Omni Antenna
Transmission range	250m
Packet size	512
Transmit power	0.660W
Receiving power	0.395W
Initial energy	100J

A. Performance analysis

The performance of this proposed Enhanced Restricted Boltzmann Machine based spectrum sensing (ERBM-SS) is evaluated in terms of throughput, detection probability, delivery ratio and energy efficiency by varying number of secondary users and simulation time. The performance of this proposed approach is compared with that of RBM-SS and ANN-SS.

B. Performance analysis based on varying number of secondary users (SUs)

The comparison of performance metrics of different spectrum sensing techniques for varying number of secondary users as showed from figure2-5. Figure 2 shows the comparison of throughput of different spectrum sensing techniques for varying number of SUs. As shown in the figure, throughput of the network is decreased when the number of SUs increases. As the PSO algorithm enhances the performance of RBM algorithm, secondary users can sense the spectrum which is in idle state preciously. So, compared to RBM-SS and ANN-SS, throughput of the ERBM-SS is increased to 83% and 96% respectively.

Comparison of detection probability of different spectrum sensing techniques for varying number of SUs is shown in Figure 3. As shown in the figure, detection probability of the proposed ERBM-SS reaches to 0.9 when the number of SUs is 20. But, when the number of SUs increases detection probability of ERBM-SS decreases. But compared to RBM-SS and ANN-SS, detection probability of the proposed spectrum sensing techniques is improved to 88% and 97% respectively. Although the proposed ERBM algorithm has better accuracy, the performance can be further improved by optimizing the momentum coefficient. Figure 4 shows the tradeoff between energy efficiency and number of SUs for different spectrum sensing techniques. Energy efficiency of the network is decreased when the number of SUs increases nevertheless energy efficiency of the ERBM-SS is increased to 12% and 30% as compared to RBM-SS and ANN-SS respectively. Delivery ratio is improved to 27% and 37% in comparison to RBM-SS and ANN-SS by ERBM based spectrum sensing as shown in Figure 5.

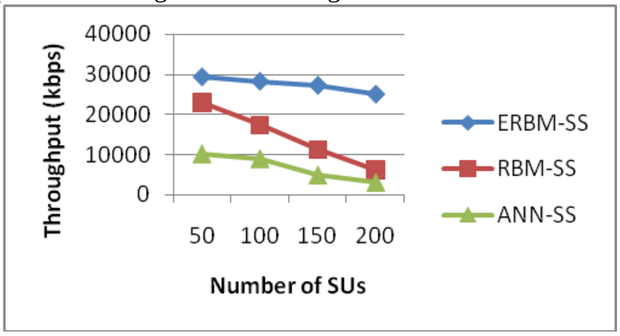

Fig.2 . Comparison of throughput of different spectrum sensing techniques for varying number of SUs

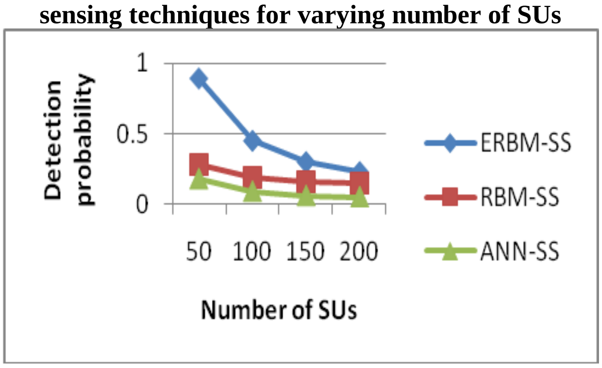

Fig.3 . Comparison of detection probability of different spectrum sensing techniques for varying number of SUs

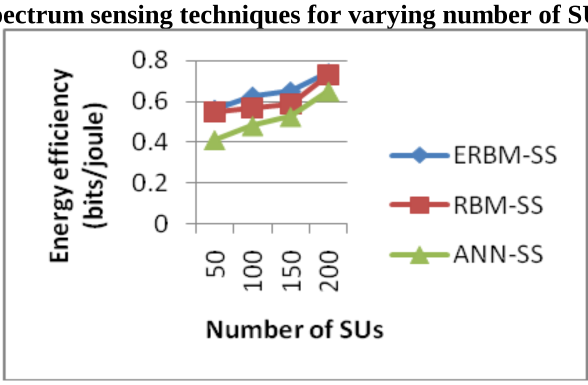

Fig.4 Comparison of energy efficiency of different spectrum sensing techniques for varying number of SUs

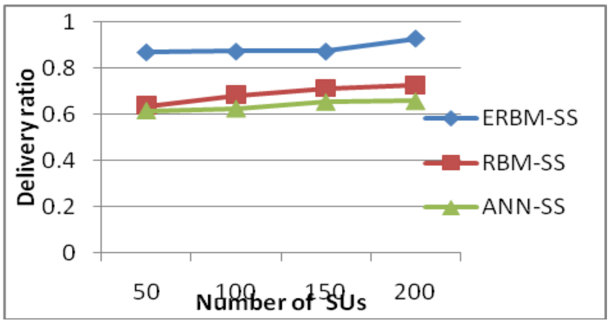

Fig.5 Comparison of delivery ratio of different spectrum sensing techniques for varying number of SUs

C. Performance analysis based on varying simulation time

The comparison of performance metrics of different spectrum sensing techniques for varying simulation times is shown in figure 6-9. Figure 6 shows the comparison of throughput of different techniques by varying simulation time. Compared to RBM-SS and ANN-SS, throughput of the proposed ERBM-SS is increased to 25% and 96% respectively. Tradeoff between the detection probability and simulation time for different spectrum sensing techniques is shown in Figure 7. As shown in the figure, detection probability is increased when the simulation time increases. Besides this, detection probability of the proposed ERBM-SS is increased to 13% and 24% than that of the existing RBM-SS and ANN-SS respectively. Energy efficiency and delivery ratio of different spectrum sensing techniques are shown in figures 8 and 9 respectively. As shown in Figure 8, the proposed ERBM-SS increases the energy efficiency of the network than RBM-SS and ANN-SS by 60% and 93% respectively. Compared to RBM-SS and ANN-SS, delivery ratio of the proposed ERBM-SS is increased to 15% and 45% respectively as shown in Figure 9.

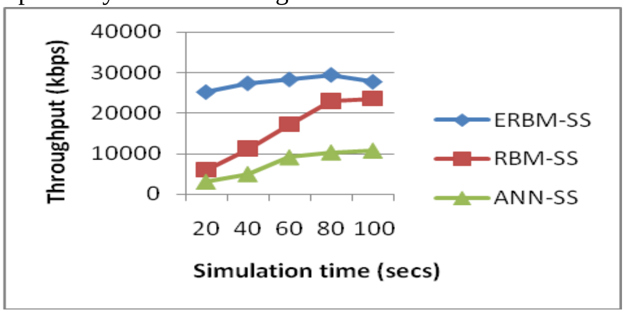

Fig.6 Comparison of throughput of different spectrum sensing techniques for varying simulation time

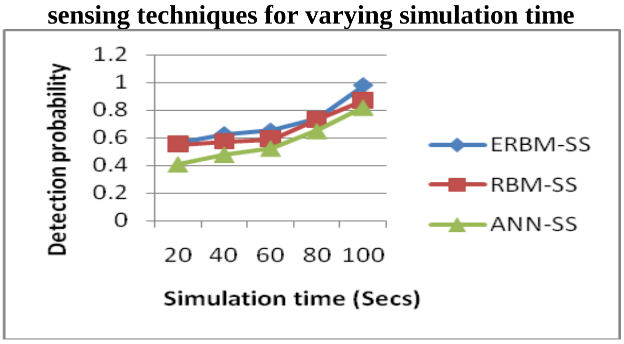

Fig.7. Comparison of detection probability of different spectrum sensing techniques for varying simulation time

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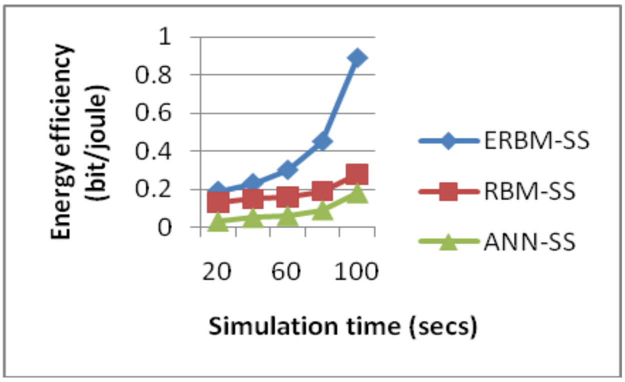

Fig.8. Comparison of energy efficiency of different spectrum sensing techniques for varying simulation time

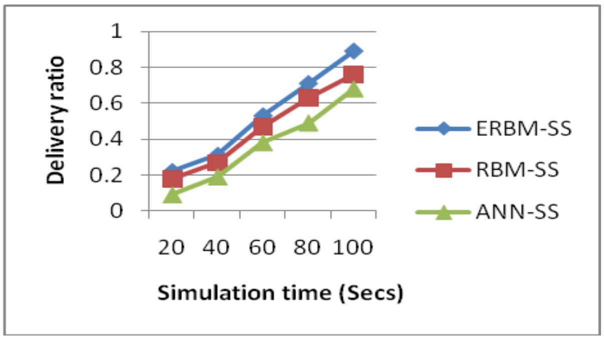

Fig.9. Comparison of delivery ratio of different spectrum sensing techniques for varying simulation time

VI. CONCLUSION

In this paper, an enhanced restricted Boltzmann machine (ERBM) is presented for spectrum sensing based on RBM and Particle Swarm Optimization (PSO).The performance metrics of is compared with that of existing spectrum sensing techniques ANN-SS and RBM-SS by varying number of SUs and simulation time. Simulation results showed that throughput of the proposed ERBM-SS is increased to 83% and 96% than that of RBM-SS and ANN-SS respectively. Detection probability of the proposed ERBM-SS reaches 0.9 when number of users are 20 but decreases when number of SU increases however in comparison of RBM-SS and ANN-SS it is improved to 88% and 97%. Energy efficiency is improved by 12% and 30% and delivery ratio is improved by 27% and 37% in comparison of existing techniques. Simulation results establish that proposed spectrum sensing technique offer better results than the existing techniques up to 100 Secondary Users.

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