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DSACSS: Deep Learning-based spectrum allocation with cooperative spectrum sensing for cognitive WSNs

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ABSTRACT

The incorporation of intelligence into wireless sensors is a contemporary paradigm for boosting the effectiveness of wireless sensor networks (WSNs) and the effective use of radio frequency spectrum. The existing traditional distribution of radio frequencies leads to coexistence issues or resource underutilization. Cognitive sensors with adjustable spectrum sharing might be used to solve this problem. In this field, spectrum management includes spectrum sensing and allocation. Several techniques have been developed to address these issues but complexity and throughput remains a challenging task for these networks. In this work, these issues has been addressed and developed a combined approach for spectrum sensing, spectrum allocation and cluster head selection to improve the overall spectrum utilization and improve the energy utilization. Moreover, the proposed scheme also adapts the deep learning scheme to identify the spectrum information based on historical pattern. The comparative analysis shows that the proposed approach shows better spectrum detection performance in comparison with KMeans, GMM, KNN, DAG-SVM approach.

Keywords *– Spectrum Sensing, Clusterhead Selection, Cognitive Radio Networks, Deep Learning*

1. INTRODUCTION

Currently, tremendous growth in the purview of wireless data exchange is noticed.This increased demand urges for utilization of faster computation, processing and data transfer technologies by the means of efficient communication strategies [1]. Thus, wireless communication technologies have gained research interests due to their important role in current communication circumstances.The high-speed communication technology plays an important role for various applications such as remote surveillance monitoring, health care, industrial automation, IP-TV, online streaming and many more [2]. However, to achieve the high speed communication, availability of radio spectrum in one of the prime and most important requirement. The intensified demand for bandwidth consuming wireless applications has led towards the overcrowding of radio frequency (RF) spectrum [3].

Moreover, efficient management of these available channels also plays a significant role because of its scarcity. Recently, Federal Communications Commission (FCC) has raised the issue regarding the inefficient use of available spectrum [4]. According to FCC, small portion of available spectrum is used whereas the rest of the portion is unused or underused which lead to wastage of spectrum. Nowadays, research communities have focused on coping up the issues spectrum scarcity and adopted the cognitive radio based system to efficiently utilize the available spectrum [5].

Cognitive radio is considered as an intelligent technique which regulates itself according to the surrounding to the radio environment based on its knowledge [6]. It has the nature of efficient spectrum access intelligently, and opportunistically, helping to improve the overall utilization of available spectrum. A cognitive radio comprises of primary user which is also known as licensed user, secondary user which is also known as unlicensed user and base station. The cognitive radios initialize spectrum sensing task to obtain the information about vacant spectrum which helps to utilize spectrums efficiently. Similarly, the CRs play important role because of its opportunistic spectrum sensing characteristics [7].

The vacant spectrums are also known as spectrum holes. This technique enables the secondary users to access the spectrum in the absence of primary users. The spectrum sensing performance of CRs depends on the probability of detection [8] (Pd) and probability of false alarm (Pf) [9] i.e. higher Pd and lower Pf improves the performance of communication system. Similarly, spectrum sharing also played an important role to improve the performance of cognitive radio networks [10]. In [11], Li et al. presented two approach for spectrum sensing where first approach follows the traditional method of spectrum sharing where PU can coexist with SU and interference is restricted to a threshold value where the performance of SU is not influenced. Similarly, the other scheme follows the opportunistic spectrum access where sensed spectrum is allowed to access to the secondary users.

Nowadays, the demand of wireless sensor networks also has increased dramatically because these networks are used widely in various real-time applications. Wireless sensor networks are comprised of several number of tiny sensor nodes which are deployed for specific applications in unattended environments. These senor nodes are resource constrained in terms of battery capacity, computations, transmission range etc. moreover, these networks operate in unlicensed band (ISM band) which are already crowded thus spectrum management for these networks become an important aspect. Generally, the cognitive WSN boosts the channel utilisation while maintaining the successful packet delivery. Moreover, energy efficiency, minimum interference and collision occurrence are the prime concerns for this. Several techniques have been developed to deal with this issue of spectrum sensing, and management in cognitive radio enabled wireless sensor networks such as in [12] Carie et al. developed a novel approach to combine cognitive radio with wireless sensor networks to transmit the data from source to sink via a routing path. Moreover, this scheme also addressed the issue of energy scarcity, Alghazzawi et al. [13] discussed the use of WSN for agriculture application and presented a new approach where the cognitive radios are applied to carry out the congestion control mechanism. Deng et al. [14] focused on energy harvesting related issues and presented a resource allocation mechanism by using Q-learning techniques.

The aforementioned studies have reported the significance of integrating the cognitive radio with WSN which shows that it can help to confront bottlenecks in WSN by efficient utilisation of spectrum holes to boost the spectrum utilization, and minimise the interference with other communication technologies in the same band. However, some characteristics of sensor nodes pose several challenges and necessitates to handle the additional tasks such as spectrum sensing, sharing, and movement.

Thus, in this work, the main focus is on combination of cognitive radio and WSN which is used further to study the issue of spectrum sensing and allocation in these networks. Thus, the main aims in this study are as follows:

- To study the possibilities, current progress and challenges in assimilating the CR and WSN
- To develop a novel approach for spectrum sensing
- To develop a new energy efficient approach for spectrum allocation to improve the communication performance and reduce the wastage of spectrum.

2. LITERATURE SURVEY

These networks play important role in various applications due to their efficient scheme of spectrum management and utilisation to improve the performance of communication system. Several techniques are described in this context, some of the recent techniques are discussed in this section. The study is divided into two phases as (a) spectrum sensing and (b) spectrum allocation.

(a) Spectrum sensing

Cao et al. [15] focused on solving the issue of spectrum scarcity which occurs in traditional sensor networks. The efficient utilisation of these spectrum hole is pivotal task to improve the communication performance. Moreover, the resource limited issues of WSN cause more complexities to achieve the desired performance. To deal with these issue, authors developed a new approach which uses particle swarm optimization along with the Cauchy mutation function to mitigate the issue of local problem solving. Chen et al. [16] developed a non-cooperative spectrum sensing algorithm which is a combination of phase space reconstruction, multi-resolution and singular spectrum entropy techniques to sense the narrowband wireless signals. Stephan et al. [17] introduced ESUR which is an energy and spectrum aware unequal clustering based routing scheme to mitigate the clustering related issues in cognitive WSN. In cluster formation phase, it considers the residual energy, and spectrum awareness. The spectrum awareness is measured based on common data channel for primary user appearance probability. Sofia et al. [18] discussed that auctioning mechanism in cognitive radio help cognitive users to efficiently utilize the part of unused license band. Auction method helps to share the spectrum with other users at a trivial mutual interference. However, traditional algorithms are not suitable to perform the desired operation for multi-winner auction strategy thus authors introduced interference based constraints to obtain the winner of the formulated game. This scheme focuses to enhance the revenue of primary user thus it motivates to least the bands for communication. The SU in traditional SS, i.e. signal detection, applies a test statistic (TS) to the received signal and compares it to a predetermined limit to determine the PU status. When the TS exceeds a particular level, the PU is deemed functional. In fact, this initiative presupposes that the statistical distribution of TS is known in order to set the optimal threshold that meets the target detection and false alarm rates, which is not always feasible due to volatile, and possibly unknown, statistical characteristics of the clutter, the PU signal, or the transmission medium.

However, to deal with this issue of statistical problem in tradition spectrum sensing schemes, several techniques have been introduced [19, 20]. Most of the recent techniques are based on the machine learning. In this line of spectrum management, Solanki et al. [20] developed a deep machine learning spectrum sensing mechanism called as “DLSenseNet” which uses structural information of received modulate signal to obtain the channel information and based on that spectrum sensing is performed.Obite et al. [21] focused on deep reinforcement learning approach for spectrum sensing in cognitive radio networks. Authors reported that the conventional methods are prone to noise uncertainty and it relies on the partial prior knowledge of primary users which may lead to inaccurate spectrum detection. Thus, to mitigate this issue author presented a combined deep learning and reinforcement learning approach to extract the features from given data. This deep learning scheme is based on the cooperative spectrum sensing method. However, there are several issues present in deep learning scheme while training the huge dataset which can be addressed by incorporating optimization schemes to pave the way for effective solutions. Luo et al. [22] discussed the advantage of cooperative spectrum sensing scheme to deal with spatial diversity gain in cognitive radio sensor networks. Moreover, the security in these networks remains a challenging task. To overcome these issues, to resist the aforesaid type of attack, the authors suggest to incorporate the security paradigm during spectrum sensing mechanism. This scheme is based on a reputation system for cognitive WSN. A trust management methodology for this study for cooperative spectrum management is built using the beta reputation model to award reputation value to cognitive sensor nodes based on their past sensing activity. To increase the accuracy of the sensing findings, the fusion centre assigns a fair weight value based on the examination of the provided findings in the final choice.

Deng et al. [23] reported the issues of spectrum scarcity and the network throughput related issues. Furthermore, changes in network topological structure are caused by node mobility. As a result, a significant quantity of data transmission is utilized, resulting in an increase in system power requirements and a significant impression on network longevity to perform the desired task. Opportunistic spectrum access is used to alter the transmit power of sensor nodes and the data transfer velocity in large-scale wireless mobile sensor networks to tackle the real-time communication challenge. To investigate joint optimum cognitive forwarding while optimising system throughput and network lifespan, a novel routing approach with cognition control along with optimization strategy based on multiple channels is introduced along with a cross-layer architecture.

(b) Spectrum allocation

Wu et al. [24] reported that the opportunistic spectrum access of these networks is a promising technique to improve the communication performance of Cognitive WSN. However, several issues are prevalent such as battery-driven design, availability of spectrum, communication coverage, large-scale network architecture and complicated topology of these networks. Furthermore, the dispersed structure of sensor networks compels all sensor node to cooperate in order to maximise the total network's performance. The Multi-agent Reinforcement Learning (RL) approach is an appealing alternative because of the beneficial qualities of CWSN. A reinforcement learning-based approach is presented to deal with power consumption related issues while data exchange and spectrum selection, which enables multiple sensors to adjust and adapt from existing past decisions as well as those of their neighbours. The suggested approach is multi-agent distributed and adaptable to end-to-end source-to-sink data needs as well as the amount of residual power in the network's sensors.

Zhou et al. [25] describe some important challenges in cognitive WSN. CWMSN is likewise restricted in terms of energy and spectrum. As a result, a spectrum allocation model is proposed in this study. In addition, to tackle the bandwidth allocation difficulty in CWMSN, a novel binary quantum-behaved elite particle swarm optimization method (BQEPSO) based on the integration of quantum operator, elite operator, and binary particle swarm optimization (BPSO) is presented. The method may ensure that spectrum resources are used without interference in the CWMSN and that spectrum allocation is as efficient as possible.

Xu et al. [26] suggested to incorporate energy harvesting schemes to improve the network lifetime. Moreover, incorporation of cognitive capability helps to improve the transmission by accessing unauthorized spectrum resources opportunistically. In this process, the secondary users request the spectrum from primary user on lease to accomplish their communication task. However, this method increases the cost. In order to maintain the overall cost in a limit and maximize the spectrum utilization, a game theory based approach is presented with energy harvesting capacity. The SUs are considered as game players.

Similar to [26], Liu et al. [27] developed a sub-channel and resource allocation scheme. This approach considers the spectrum leasing mechanism in CR to improve the overall performance. The CRSN with spectrum leasing mode is discussed in this work. Secondary Users (SUs) convey information to Primary Users (PUs) in the CRSN, and PUs lease some spectrum usage time to SUs as a payment. To enhance system performance, a hybrid subchannel, energy, and leasing optimal scheduling method that takes into account wireless energy harvesting and transmission outage probability limitations has been offered. An alternating optimization approach is used in the joint optimization process, and the CVX solver is used to resolve scalability issue.Han et al. [28] discussed the cognitive radio enabled WSN with IoT systems. In the cognitive-radio-based IoT, this article tackles the spectrum allocation problem in terms of spectrum usage and network throughput. On the one hand, each link in a transmission line aspires to increase transmission performance on the assigned spectrum channel in order to achieve maximum end-to-end throughput. On the other hand, these linkages use the same frequency channel to send as much data as possible at the same time in order to maximise spectrum usage. The authors present a network sequential channel model that highlights the restrictions of mutual interference and resource rivalry in links contemporaneous communications to solve the issue.

3. PROPOSED MODEL

In previous sections, the need of cognitive radio and its diverse applications has been described . Due to current demand of wireless sensor network and inadequate spectrum availability for WSN has raised a new challenge in this field of WSN. Thus, energy consumption minimization, spectrum sensing and spectrum allocation are the important aspects in these network. By addressing these issues, the overall performance of cognitive radio enabled wireless sensor network can be improved. In order to achieve these objectives, a novel combined spectrum sensing, cluster formation and spectrum allocation scheme is introduced.

3.1 Spectrum sensing

Consider a cognitive WSN which consist of N number of Cognitive Sensors and a FC (Fusion centre) which makes the final decision about the channel occupancy. Below given figure 2 depicts the overall architecture of the network. The cluster head communicates with the fusion center.

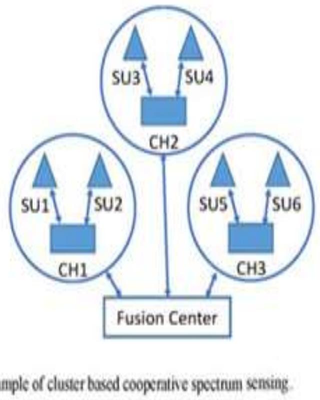

Fig.1. Cooperative Spectrum Sensing in Cognitive WSN

Initially, it is presuppose that all sensor nodes have the identical spectrum sensing period denoted as T and spectrum sensing period of cognitive capable sensor nodes is denoted as δ, $0 < \delta < T$. The secondary user j, $\forall_j \in N$ receives the signal from primary user at the frequency f_s. Each sensor node has capacity to observe the channel status which is decided by evaluating $X_j[k], k = 1,2, \dots \delta$. Generally, the observation is obtained by evaluating two hypothesis which are denoted as H_1 and H_0. The H_1 denotes that the primary user is active and H_0 denotes that the primary user is inactive. The hypothesis can be represented as:

$$H_1: X_j[k] = s_j[k] + u_j[k]$$
$$H_0: X_j[k] = u_j[k] \tag{1}$$

Where $s_j[k]$ denotes the signal of primary user at the j^{th} sensor which is a random zero mean process with a variance σ_{sj}^2. The $u_j[k]$ is the Gaussian noise. The considered Gaussian noise is independent and identically distributed using a random process with zero mean and it has variance as σ_u^2. Under hypothesis H_1, the received signal-to-noise ratio (SNR) is measured denoted as γ_j of (PU) primary user which is measured at the j^{th} sensor node.

In this process of channel or spectrum sensing, two important parameter P_d probability of detection and P_f probability of false alarm are used for hypothesis H_0 and H_1. These probabilities help to determine the occupancy of channels as busy or idle channels. If the P_d is high then it prevents the primary user from interference from secondary user whereas lower P_f helps secondary users to access the available spectrum hole for communication. Thus, for any cognitive enabled network, the ideal conditions are higher P_d and low P_f. The energy detector uses rules for sensor j as:

$$E_j = \frac{1}{\delta f_s} \sum_{k=1}^{\delta f_s} X_{jk}^2 \lessgtr_{H_0}^{H_1} \epsilon : \{ \begin{matrix} D_j = 0 \; if \; H_0 \\ D_j = 1 \; if \; H_1 \end{matrix} \tag{2}$$

Here, ϵ denotes the detection threshold to make the decision, D_j is the outcome of decision for j^{th} sensor node. This decision is made in the form of 1 or 0 based on the primary user signal. For a selected threshold value ϵ, the false alarm probability for spectrum in j^{th} cognitive sensor is expressed as

$$P_{f_j} = P(E_j > \epsilon | H_0) = Q(\left(\frac{\epsilon}{\sigma_u^2} - 1\right) \sqrt{\delta f_s} \tag{3}$$

However, the performance of this stage is degraded due to deep fading and shadowing thus cooperative spectrum sensing plays an important role to overcome this issue. According to this approach, the cognitive sensor decides the information about channel and send this information to fusion centre which makes final decision whether to allocate the spectrum or not. Based on this, the probabilities can be computed as:

$$P_f(\delta) = 1 - \prod_{j=1}^{N} \left(1 - P_{f_j}(\delta)\right)$$
$$P_d(\delta) = 1 - \prod_{j=1}^{N} \left(1 - P_{d_j}(\delta)\right) \tag{4}$$

Several algorithms have reported that number of participating nodes doesn't have impact on the spectrum sensing performance. The advantage of this is taken and selected the nodes which are having higher probabilities of detection and located near to fusion centre. Thus, the probability values can be described as:

$$P_f(\delta) = 1 - \prod_{j=1}^{N} \left(1 - \rho_j P_{f_j}(\delta)\right)$$
$$P_d(\delta) = 1 - \prod_{j=1}^{N} \left(1 - \rho_j P_{d_j}(\delta)\right) \tag{5}$$

Here, ρ_j is the index to provide information about occupancy and availability of channels. The value of this index varies as $\rho \in \{0,1\}$ where 1 represents the sensing and 0 is used to denote the not sensing.

3.2 Spectrum allocation

This section presents the proposed approach for spectrum allocation. In these networks, the primary and secondary users must operate in the same frequency bands to conduct the successful data transmission. However, the activity channel slots may vary from time slot due to communication activities of primary users. Thus, for the considered time slot, it is compulsory task for sensor nodes to utilize the current available information and select one or more idle channel as working channel. Thus, selecting the suitable working frequency band for source and destination is the important task of spectrum management scheme.
In order to represent the spectrum availability, binary variables and the spectrum availability is used by using these variables can be expressed as:

$$c_{i,j}^{s} = \begin{cases} 1, if\ channel\ j\ is\ avilable\ for\ i^{th} sender \\ 0, otherwise \end{cases}$$
$$c_{i,j}^{d} = \begin{cases} 1, if\ channel\ j\ is\ avilable\ for\ i^{th} destination \\ 0, otherwise \end{cases} \tag{6}$$

This information about channel availability can be obtained by using cooperative spectrum sensing methodology as described in previous section. However, co-channel interference is a tedious task for these scenarios. In order to mitigate the co-channel interference, an inference matrix is defined which is represented as:

$$\mathcal{A}_{i1,i2,j} = \begin{cases} 1, if\ channel\ conflict\ between\ source - destination\ link \\ 0, otherwise \end{cases} \tag{7}$$

Here, $\mathcal{A}_{i1,i2,j} = 1$ denotes that if two pairs from source to destination are identified as i_1 and i_2 suffer from interference, thus, these channels cannot be allocated to each other simultaneously. Considering that the Δ_i^s and Δ_i^d denotes the set of available channel at secondary sender and destination of S-D pair, these sets can be expressed as:

$$\Delta_i^s = \{j | c_{i,j}^s = 1, \forall_j \in \mathcal{M}\}$$
$$\Delta_i^d = \{j | c_{i,j}^d = 1, \forall_j \in \mathcal{M}\} \tag{8}$$

In this stage, for each source to destination pair, the spectrum allocation can be determined with the help of two vectors, which are expressed as:

$$\alpha_s = \{s_{i,j}, \forall_i \in \mathcal{N}, j \in \mathcal{M}\}$$
$$\alpha_d = \{d_{i,j}, \forall_i \in \mathcal{N}, j \in \mathcal{M}\} \tag{9}$$

Here, α_s denotes the channel allocated to secondary user and α_d is the channel allocation for destination node.

3.3 Node preference benchmarks

For simplification, a scenario for cognitive sensor nodes is considered where average energy depletion in spectrum sensing can be monitored into two main fragments: (a) energy requirements for channel sensing, and energy depletion during signal processing tasks such as modulation, pulse shaping etc. (b) energy consumption to transmit the data to fusion centre. Based on these assumptions, the energy consumption can be expressed as:

$$C_T = \sum_{j=1}^{N} \rho_j (Cs_j + C_{tj}) \tag{10}$$

Cs_j denotes the energy consumed during signal processing tasks and C_{tj} denotes the energy consumption for data transmission to fusion centre. Here, it is considered that Cs_j is same for all whereas the C_{tj} depends on distance between transmitter and receiver. However, the power attenuation relies on distance to be travelled by data packet. Thus, C_{tj} can be expressed as:

$$C_{tj}(d_j) = C_{electrical} + r_{amp} d_j^2 \tag{11}$$

r_{amp} denotes the obligatory augmentation, d is the distance between node and envisaged fusion centre.
Further, based on probability detection, probability of false alarm and index, the detection and energy consumption performance can be enhanced based on the following problem:

$$\min_{\rho_j} C_T = \sum_{j=1}^{N} \rho_j \left(C_{s_j} + C_{tj}\right) \ \ s.t. P_f \leq \Omega\ , P_d \geq \Psi \tag{12}$$

According to this analysis, the small value of Ω and high values of Ψ are obtained to utilize the spectrum efficiently and mitigate the inference.

3.4 Cluster formation and deep learning

To further enhance the performance of proposed approach, a clustering mechanism is incorporated which is adopted from [19]. According to this, the total power consumption is expressed as:

$$E(P_{total}) = C_0 P_r \left(\frac{N^2}{3\rho K} + K d_{max}^2 \right) \tag{13}$$

By solving it further, the optimal number of clusters can be obtained as:

$$K_{opt} = \left\lfloor \frac{N}{d_{max}\sqrt{3\rho}} + 0.5 \right\rfloor \tag{14}$$

Further, for cluster head selection, the spectrum availability is considered as the criteria .
Finally, a deep learning based approach is presented where H_1 and H_0 are used as the input for deep learning model. The CNN model uses energy consumption, distance, and spectrum occupancy parameters which are obtained from the previous stages. Below given figure 3 depicts the overall architecture of deep learning.

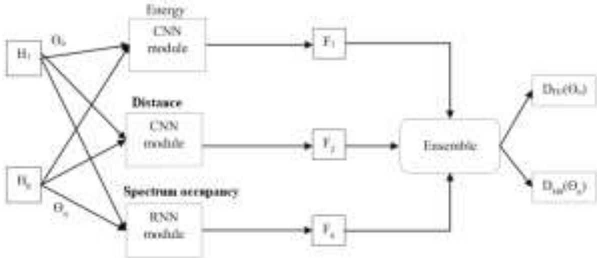

Fig.2. Deep Learning Architecture

The main aim of this training process is to maximize the likelihood outcome according to their corresponding categories as $L(\odot)$, it can be expressed as:

$$L(\odot) = P(L|X;\odot) = \prod_{k=1}^{k} \left(D(\odot)H - 1\,(x_N)\right)^{l_n} \left(D(\odot)H_0(x_N)\right)^{l-l_n} \tag{15}$$

4. RESULTS AND DISCUSSION

This section describes the implementation of proposed approach and outcome of this approach is compared with other existing schemes. The proposed approach is based on the deep learning strategy which uses historical data pattern to proliferate the spectrum sensing performance. In this work, a deep learning based scheme is developed along with LSTM networks to improve the spectrum sensing performance. This work uses a Monte-Carlo simulation method where 100 iterations of this experiment are performed and average performance measured. The M number of primary users and N number of secondary users are deployed in a 2D geographical region 0f 500mx200m. The probability on the presence of the PU $P_r = 0.5$, the received SNR=-10db to 10dB, the transmission power Pt = 10W, the noise power $\sigma_n^2 = 0.1$W .. The power consumption bounds are $p_{min} = 10mW$ and $P_{max} = 30mW$. The antenna gains are $G_i^T = G_j^{Rx} = 1$, path loss exponent is $\alpha = 3$ and channel bandwidth is considered as 5MHz. the performance is measured in terms of detection accuracy for varied number of user, training data size and power consumption ratio.

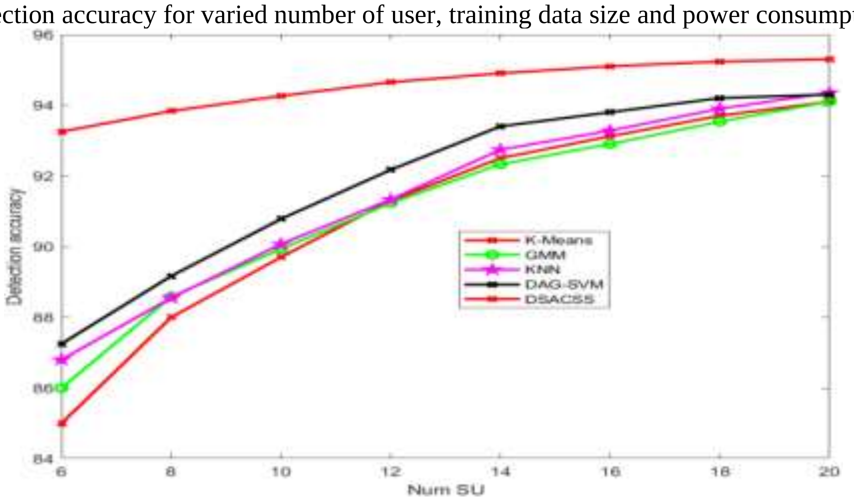

Fig 3. Detection Accuracy

Figure 4 depicts spectrum sensing performance for varied number of secondary users. In this experiment, it is considered that the secondary users vary from 6 to 20. The comparative study shows that proposed approach achieves better performance for spectrum sensing. As the number of secondary users are increasing, the detection performance also increases. The average performance for this experiment is obtained as 91.20%, 91.28%, 91.50%, 92.06% and 94.62% by using KMeans, GMM, KNN, DAG-SVM and proposed DSACSS approach.

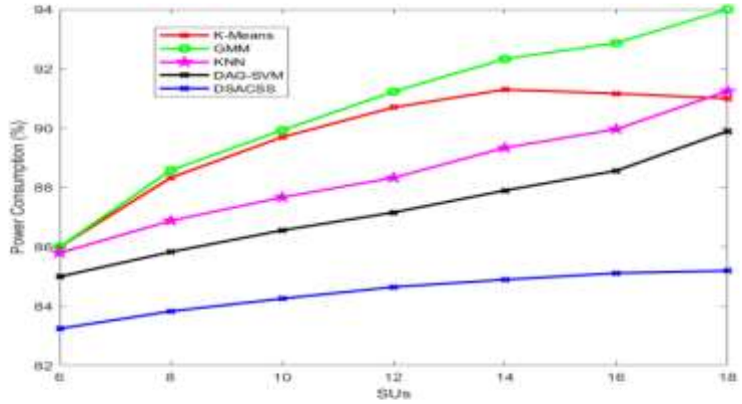

Fig.4. Energy Consumption Performance

Figure 5 demonstrates the average energy consumption performance for varied number of secondary users. T Conventional machine learning techniques use more energy, and insufficient comprehension of complex patterns uses more energy, reducing the entire lifespan of the network. In this experiment, it is illustrated that overall power usage for a variety of users using existing and suggested approaches. The comparative analysis shows that the average power consumption is obtained as 90.87,90.07, 88.38, 87.24 and 84.25% by using KMeans, GMM, KNN, DAG-SVM and proposed DSACSS approach.

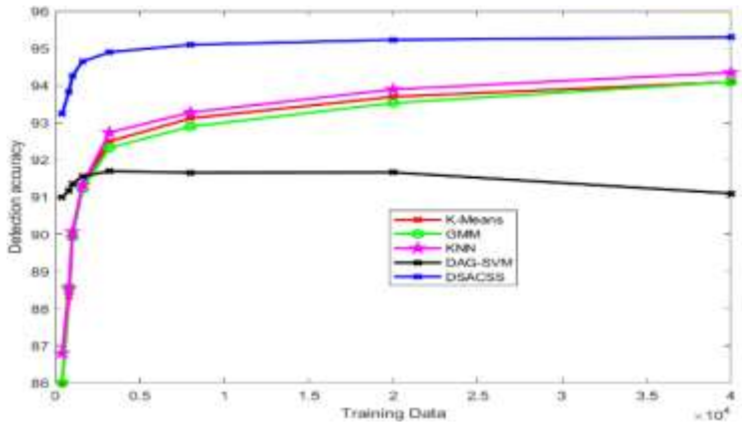

Fig.5. Spectrum Sensing Accuracy For Varied Size Of Training Data

The deep learning scheme is based on the pattern learning approach. To measure its efficiency, the performance for different set of training dataset is measured, which contains different number of samples in figure 6. In this experiment, the overall power consumption is demonstrated by using existing and proposed approach for varied number of users. The comparative analysis shows that the average power consumption is obtained as 85.55, 86.35, 87.36, 93.10 and 94.65% by using KMeans, GMM, KNN, DAG-SVM and proposed DSACSS approach. Further, figure 7 shows the time required for training and testing process. The time required for testing is less when compared with training.

Fig.6. Training and Testing Time.

The overall outcome of these experiments is presented in below given table 2

Table.1. The Overall Performance Comparison

PUs	DAGSVM	GMM	Kmeans	KNN	DSACSS
6	91	86	86	86.8	93.25
8	91.2	88.5	88	87.2	93.95
10	91.3	91.25	91	91.65	94.3

12	91.5	91.8	92	92.15	94.85
14	91.8	92.1	92.5	92.55	94.95
16	92	92.5	93	93.1	95.2
18	91.9	94	94	94.25	95.2
20	91.1	94.1	94.1	94.35	95.3

5. CONCLUSION

In this work, spectrum sensing and allocation in cognitive radio enabled WSN has been focused. The proposed scheme uses cooperative spectrum sensing and deep learning for spectrum allocation. The comparative study shows the average detection performance is obtained as 85.10%, 86.23%, 86.80%, 87.25%, and 93.25% by using k-means, GMM, KNN, DAGSVM and proposed DSACSS approach, respectively.

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