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Spectrum Estimation and Optimal Secondary User Selection in Cognitive Radio Networks

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Abstract: The high-speed development of wireless communication technology has emerged in the surging insistence on optimal spectrum resources. Nevertheless, in consonance to a contemporary study, most of the assigned frequency encounters notable underutilization as far as Cognitive Radio Network (CRN) is concerned. One important issue correlated with spectrum management is how to properly estimate and allocate the spectrum to a Secondary User (SU) for a highly dynamic environment in an optimal manner with minimum sensing delay. In this paper, a Chebyshev Vector Dynamic Spectrum and Kolmogorov-Smirnov Convolutional Network (CVDS-KSCN) method for dynamic spectrum estimation and optimal secondary user selection in CRN is developed. First, it is proposed to tackle the dynamic spectrum access issue with minimum sensing delay in CRN attaining robust spectrum channel throughput with minimum sensing delay. The spectrum estimation is modeled using the Chebyshev distance-based Harmonious Vector Spectrum Estimation model in a dynamic manner. With the dynamic spectrum estimated results, a Kolmogorov-Smirnov Convolutional Neural Network-based Secondary User Selection model is applied to retrieve optimal secondary users in CRN. The performance of CVDS-KSCN is assessed over numerous key aspects, where simulation results confirm the efficiency of the proposed method in achieving high reliable spectrum estimation and Secondary User selection. It is expressive in the simulation results that the proposed CVDS-KSCN method can achieve a good probability of throughput and reduction in sensing delay during Secondary User Selection with low probability of false alarm. The results show that the proposed method outperfroms the DRS and EFAHP algorithms quantitatively in terms of four parameters, namely throughput, sensing delay, false alarm percentage and Secondary User Selection Time.

Keywords: Chebyshev distance; cognitive radio network; harmonious vector; Kolmogorov-Smirnov; spectrum estimation; spectrum management

1 INTRODUCTION

One of the conventional types of wireless network communications that makes use of unused spectrum bands from licensed users with authorization or license is referred to as the Cognitive Radio Network (CRN). Here, the licensed users are also referred to as the Primary Users (PU) and on the other hand the users who are accessing available un-used spectrum are referred to as the Cognitive Radio (CR) users or Secondary Users (SU). With the elevating demand for spectrum the underutilized spectrum necessitates to be utilized in an effective manner. Hence CRN is one of the optimistic methods to complement the spectrum prerequisite of the future generation. A Deadline-based cross-layer Routing and Spectrum allocation (DRS) was proposed in [1] with the objective of utilizing the available resources to estimate the optimal routing, session and spectrum to dispatch optimal number of data packets to their considered destination within the designated limit. In DRS, a Weighted Virtual Queue (VQ) was utilized for cross-layer optimization, therefore ensuring optimal session management. Next, the Virtual Queue Length (VQL) was employed to consider the limits corresponding to each data packet. Finally, the integrated routing and spectrum allocation was also included to ensure optimality in allocating the resources, therefore contributing to throughput and reliability. Despite improvement observed in terms of both throughput and reliability, with a highly dynamic environment, fast convergence is said to be compromised, therefore affecting the sensing delay. To address this issue, in this work, Chebyshev distance-based Harmonious Vector Spectrum Estimation is proposed that with the aid of Chebyshev distance and Support Vector machine learning model reduces the sensing delay, therefore also improving throughput. Some of the unfolding wireless applications necessitate more spectrum space to handle the swift heightening of users. One of the paramount issues to be handled is channel selection in an optimal manner with the purpose of ensuring data transmission in un-interrupted fashion. In [2], a significant channel selection method for enhancing the quality of service (QoS) in CRNs was proposed and called Efficient Feedback Analytic Hierarchy Process (EFAHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), therefore contributing to minimal computational time and number of handoffs. Despite improvement observed both in terms of computational time and number of handoffs, with the dynamic changes and absence of probability distribution, therefore compromising the Secondary User selection time. To address this issue, a Kolmogorov-Smirnov Convolutional Neural Network-based Secondary User Selection model is employed that with the aid of Kolmogorov-Smirnov test and CNN sees to that not only the Secondary User selection time is reduced but the false alarm rate is also reduced. In this paper, Chebyshev Vector Dynamic Spectrum and Kolmogorov-Smirnov Convolutional Network (CVDS-KSCN) method for dynamic spectrum estimation and optimal secondary user selection in CRN is considered, in which an estimation of spectrum is first made and then with the estimated spectrum Secondary Users are selected for utilization of the available spectrum unused by the Primary Users. The objective is attaining the maximum of throughput in CVDS-KSCN while reducing the sensing delay and false alarm rate of SU, without affecting PU spectrum utilization. Three contributions are summarized in this paper.

- First, a novel Graph Cognitive Radio Network model for Spectrum Estimation and Secondary User Selection is formulated as a nonlinear integer programming problem under certain constraints, which is different from the works that design the paradigm to enhance spectrum allocation using Weighted Virtual Queue [1]. To be more specific, it takes advantage of the neighbourhood channel availability after formed spectrum estimation, which validates more elasticity to SUs and contemplates the application scenario.
- Second, to ensure the QoS of SU, taking only throughput and reliability constraints into consideration for optimizing spectrum allocation is not sufficient. The advantage of having a maximum throughput and minimum

sensing delay of SU in the constraint conditions is utilised to study the spectrum estimation problem using Chebyshev distance-based Harmonious Vector Spectrum Estimation algorithm.

- Third, in order to optimize the Secondary User selection, Max Empirical Kolmogorov-Smirnov Neural Network-based Secondary User selection algorithm based on empathise convolution and Max Empirical Probable Pooling is proposed to obtain the optimal solution, with the features of fast convergence and minimum false alarm rate.

The rest of this paper is organized as follows. Section 2 reviews the related works on spectrum estimation and Secondary User selection in CRN. Section 3 introduces the system model and the proposed CVDS-KSCN method. Section 4 analyses the convergence and simulation result of the proposed algorithm followed by an in-depth discussion in Section 5. Section 6 concludes the paper.

2 RELATED WORKS

Dynamic Spectrum Sharing (DSS) in CRNs has been extensively considered as an efficient means to permit the Secondary Users in accessing the licensed spectrums in a dynamic manner and to inevitably control the issue of spectrum under-utilization because of static spectrum allocation. A Radio Frequency (RF) energy saving mechanism using hardware-based underlay cognitive radio network (RH-CRN) was proposed in [3]. Here, the Secondary Transmitter (ST) initially collected energy from RF signals and then communicated with the Secondary Receiver (SR) employing the harvested energy for fast convergence. A survey of spectrum sharing in CRN was designed in [4]. Yet another method utilizing confidence level and Support Vector Machine to significantly perform energy harvesting and improve total primary capacity was proposed in [5]. However, quality of service was not focused. To address this issue, a multi-objective optimization framework that embodies two objectives, i.e., power minimization and the leased time minimization was proposed in [6]. This objective was achieved by employing convex optimization and by applying the Lagrangian dual method, therefore obtaining tradeoff between the transmit power and leased time. With the heightening awareness on wireless communications, radio spectrum insufficiency has become present-days ultimatum. Increased spectral bandwidth demand is shooting utilization of spectrum to paramount limits. However, the disadvantages of conventional wireless technology results in wastage of spectrum, appealing aggressive utilizations of those profitable unutilized resources. A novel multi-channel (*m*-channel) allocation and maximization of performance algorithm concerning low-power mobiles was proposed in [7]. The objective was achieved by employing Maximum Independent Sets (MIS). However, the complexity involved was found to be high. To address upon this concept, enhanced energy detection-based cooperative spectrum sensing was designed in [8]. With this not only the complexity was found to be reduced but also false alarm rate was also improved. However, with multiple radio access networks, selection of optimal network out of available networks is said to be higher. To concentrate upon this issue, Multiple Attribute Decision Making (MADM) scheme was proposed in [9] for spectrum handoff and optimal network convergence. The swift expansion of smart mobile devices and the steady control of the spectral band in the radio communication system have emerged in scarcity of frequencies. A cooperative spectrum detection scheme utilizing multi user diversity to smooth sharing between PU and SU ensuring efficient spectrum sharing was investigated in [10]. A survey of spectrum allocation using machine learning was presented in [11]. With the CRN focused or positioned at reinforcing the system via learning and updating by discovering and estimating the resource availability, a consensus performance and spectrum sharing power control mechanism in CRN was proposed in [12]. With this large-scale sensing delay in the CRN was focused. Efficient utilization of unutilized licensed spectrum by SUs without giving rise to any unfavorable intervention to the Pus is one of the difficult jobs and in [13] a comprehensive representation of integrated spectrum sensing and resource allocation in CRN was discussed in detail by employing Random Walk Gray Wolf Optimization (RW-GWO) algorithm. However, fast convergence in dynamic environment still remains an open issue. To concentrate on this aspect, genetic algorithm on the basis of state of the art crossover and mutation operators was proposed in [14]. In CRNs allocation of spectrum becomes complicated when multiple SUs coincidentally required to be assigned new and pertinent bands upon return of the PU. Several existing methods concentrate on the advantage of individual users, disregarding the influence of an allocation on other users and heavily depend on the sensing channel in a periodic manner and transmission cycle that minimizes the utilization of spectrum in an efficient manner. A method that utilizes the cooperation between users for efficiently detecting PU's return which alleviates CRs from sensing hence enhancing spectrum utilization was proposed in [15]. Auction is frequently applied in CRNs on account of its effectiveness and fairness effects. A predominant issue while designing auction mechanism is the efficient utilization of constrained spectrum resource. In [16], a predictive double spectrum auction was proposed that initially obtained the range concerning bidding via statistical analysis, and then employed Markovian prediction based algorithm to produce requirements for bidding primary and secondary users, respectively, therefore improving utilization ratio. Yet another novel intelligent dynamic spectrum allocation model with bandwidth flexibility was proposed in [17], therefore concentrating on average packet loss and average delay. Quality of Service (QoS) via pricing and distributed power control utilizing Nash Equilibrium, therefore contributing to significant minimization in power consumption and high improvement in speed of convergence was proposed in [18]. An Optimum Relay Selection and Accurate Cooperative Spectrum Sensing to reduce interference in terms of delay and delivery ratio were investigated in [19]. As presented, there were certain efforts put in the literature addressing the issue of selecting secondary user in CRN. The most critical issue in CRN is to design a proper spectrum estimation method in the presence of dynamic environment and optimal selection of secondary user. Most work in literature either ignores the delay involved in estimating the spectrum or else ignores the false alarm rate involved in selecting the secondary user. To address these issues in this paper, Chebyshev Vector Dynamic Spectrum and Kolmogorov-Smirnov Convolutional Network is proposed. The description of this method is provided in the forthcoming sections.

3 METHODOLOGIES

The proposed Chebyshev Vector Dynamic Spectrum and Kolmogorov-Smirnov Convolutional Network (CVDS-KSCN) are split into two phases. In the first phase, spectrum estimation is made by means of Chebyshev distance-based Harmonious Vector machine learning model. With the resultant spectrums obtained, in the second phase, Secondary User selection is developed by employing Kolmogorov-Smirnov Convolutional Neural Network model.

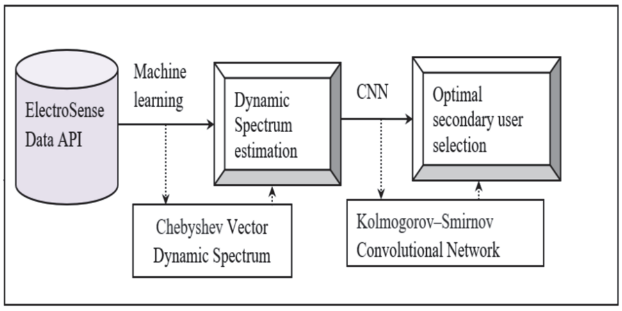

Figure 1 Block diagram of CVDS-KSCN

As shown in the above Fig. 1, the CVDS-KSCN method is designed with the estimation of spectrum in a dynamic manner to ensure minimum sensing delay with respect to iterations and improved throughput, followed by which selection of Secondary User is performed in an optimal manner to minimize false alarms and secondary user selection time. In the subsequent sections, the network model is presented followed by which the description of the CVDS-KSCN method is designed.

3.1 Graph Cognitive Radio Network Model

A Graph Cognitive Radio Network model for Spectrum Estimation and Secondary User Selection in CRNs is considered. Fig. 2 shows a sample Graph Cognitive Radio Network model used for the proposed method.

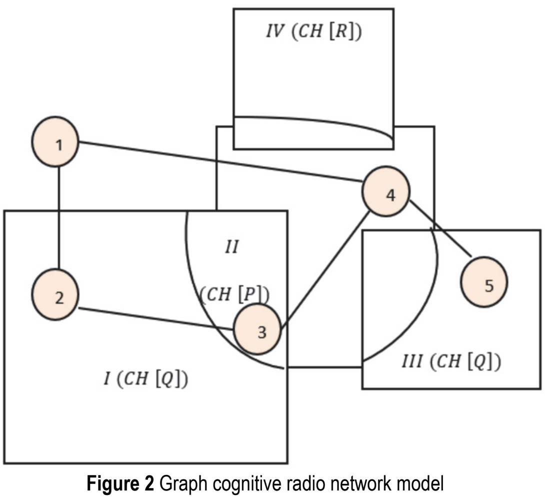

Figure 2 Graph cognitive radio network model

As shown in the above figure, the network model is engrossed as graph "$G = (V, E, A)$". Here, "V" denotes the vertices or users, "E" represents interference, so that no channels can be allocated in a simultaneous manner to any adjoining nodes, and finally "A" represents channel availability for the corresponding graph "G". Further, it is assumed that "N" denotes the total number of Secondary Users with the edges formulated as given below.

$$E = \begin{cases} e_{ij} = 1, \text{if edge between vertices } V_i \text{ and } V_j \\ e_{ij} = 0, \text{vertices } V_i \text{ and } V_j \text{ use same channel} \end{cases} \tag{1}$$

Moreover, "C" represents the number of channels available in graph "G".

$$A = \begin{cases} A_{ic} = 1, \text{ Channel C is availale at vertexi} \left[c \in C \right] \\ A_{ic} = 0, \text{ Channel C is notavailale at vertexi} \left[c \in C \right] \end{cases} \tag{2}$$

Fig. 2 shows four different Primary Users "PU" denoted by "I" to "IV" employing channel bands "P", "Q" and "R". Also, five distinct Secondary Users "SU" are also present in the CRN denoted by numerals "1-5" respectively. This infers that the channels cannot be used by "SU" in the neighbourhood and hence the nodes within a certain limit of each "PU" cannot make use of the similar channel for allocation. On the other hand, if a "SU" is within the blocked circle of a designated "PU", the channel cannot be utilized by this designated "PU". For example, node "3" is within the interference of "PU" "I", who utilized channel "Q", and is within the interference of "PU" "II", who utilizes channel "P". Hence, it cannot reuse channels "P" and "Q". Due to this, each node has access to a different set of channels. Therefore, the channels available at CRN vertex "1" are "$\{P, Q, R\}$", and "$\{P, R\}$", at CRN vertex "5" respectively. Then, the objective of the proposed channel allocation is to maximize the Spectrum Utilization that is formulated as nonlinear integer programming as given below.

$$\begin{aligned} &\text{Max} \sum_{i=1}^{N} \sum_{c=1}^{C} SU_{ic} \rightarrow \\ &\rightarrow \begin{cases} \text{if } SU_{ic} = 1, A_{ic} = 1 c\text{hannel is assigned to } 'i' \\ \text{if } SU_{ic} = 0, A_{ic} = 0 \,\text{channel is not assigned to } 'i' \end{cases} \end{aligned} \tag{3}$$

The proposed Graph Cognitive Radio Network Model can be expanded in a similar manner to any number of PUs and SUs us in a network with respective channel bands.

3.2 Chebyshev Distance-Based Harmonious Vector Spectrum Estimation

Several spectrum sensing or spectrum estimation models have been proposed to recognize the existence of the "PU" signal transmission. With these spectrum estimation models more spectrum utilization changes have been provided to the "SUs" with minimal interferences to the "PUs". In this work, a Chebyshev distance-based Harmonious Vector Spectrum Estimation model is proposed to obtain robust spectrum channel throughput with minimum sensing delay even in the highly dynamic environment with fast convergence. Fig. 3 shows the block diagram of Chebyshev distance-based Harmonious Vector Spectrum Estimation model.

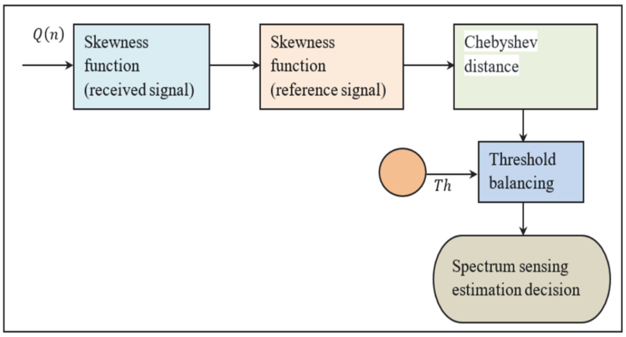

Figure 3 Chebyshev distance-based harmonious vector spectrum estimation

As shown in Fig. 3, the secondary users "*SUs*" learn about the CRN environment by means of basic formulation as given in Eq. (4).

$$Q(n)=\begin{cases} AW(n), PU \text{ signal is absent} \\ CG*RS(n)+AW(n), PU \text{ signal is present} \end{cases} \tag{4}$$

From the Eq. (4), secondary received signal "$Q(n)$" is sensed by means of the additive white noise "AW", channel gain "CG" and the respective PU signal "$RS(n)$" and accordingly, the presence or absence of "PU" signal is made. Followed by which Chebyshev distance is estimated that measures the distance taking into consideration only the most significant relevant dimension. It is also specifically based on the skewness of the received "SU" signal. This detector performs by computing the Chebyshev distance between the skewness of the received "SU" signal and a reference "SU" signal. The skewness of the received signal is then mathematically formulated as given in Eq. (5).

$$S_{RS}(\alpha)=\sum_{n=1}^{N} RS(n)*RS'(n-\alpha) \tag{5}$$

From the Eq. (5), the skewness "S" of the received "SU" signal "RS" at a corresponding iteration "α" is estimated based on the received signal "RS" and the number of sensors (i.e., samples) "N" respectively. The skewness of the reference signal is then mathematically formulated as given in Eq. (6).

$$S_{\text{RefS}}=\left[\frac{1}{\text{Freq}(\alpha)}\right]*T+1 \tag{6}$$

From the Eq. (6), the skewness "S" of the reference signal "RefS" is measured on the basis of the frequency of iterations "Freq(α)" at the respective time "T". The Chebyshev distance "$Dis_{\text{Chebyshev}}$" is the difference between the skewness of the received signal and the skewness of the reference signal with the most significant relevant dimension. This is mathematically formulated as given in Eq. (7).

$$Dis_{\text{Chebyshev}}\left[S_{RS}(\alpha), S_{\text{RefS}}\right]= =\max_{n}\left\{\left(S_{RS}(\alpha)\right)_n-\left(S_{\text{RefS}}\right)_n\right\} \tag{7}$$

With the obtained distance to concentrate on the sensing delay for highly dynamic environment easing fast convergence Harmonious Support Vector Spectrum Estimation must be made. This observation leads to the idea of harmonious support vector spectrum estimation that necessitates association between all "*SUs*" in a CRN to reduce sensing delay and improve the detection performance even in case of highly dynamic environment, therefore ensuring fast convergence. As we cannot acquire a linear separable hyperplane that can estimate the spectrum, a slack variable "H" is introduced for possible estimation as given below. Then, the probability of detection, probability of missed detection and the probability of false alarm of harmonious spectrum sensing are mathematically formulated as given in Eqs. (8), (9) and (10).

$$Prob_{d,n}=Prob\left(Dis\langle\lambda|H_0\right) \tag{8}$$

$$Prob_{m,n}=\left(1-Prob_{d,n} \mid H_1\right) \tag{9}$$

$$Prob_{fa,n}=Prob\left(Dis\geq\lambda \mid H_2\right) \tag{10}$$

From the Eqs. (8), (9) and (10), the final spectrum estimation decision corresponding to "H_0" is detected if all "N" participating "*SUs*" in a CRN indicated that the "SU" is absent whereas decision corresponding to "H_1" is made if there is at least one out of "N" "*SUs*" reports that the "PU" is present and finally decision corresponding to "H_2" is made upon false alarm. Fig. 4 shows the Spectrum Estimation via Hyperplane Classification.

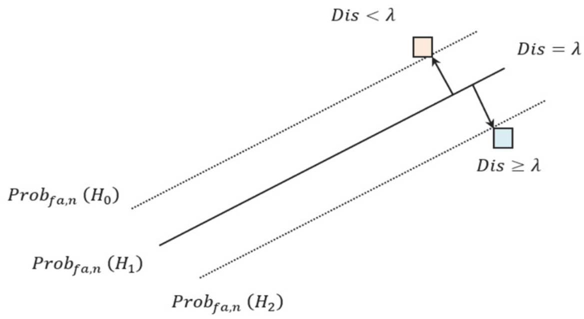

Figure 4 Spectrum estimation via hyperplane classification

As shown in Fig. 4, the hyper plane is considered optimal if it can separate the spectrums without error, and the distance of the closest spectrums to the hyper plane is maximal. A typical hyper plane estimating spectrums via classification of the channels or spectrums into two classes is shown. With harmonious flow, with the aid of support vector machine solves the optimization issue by maximizing the margin while reducing the sum of errors. The pseudo code representation of Chebyshev distance-based Harmonious Vector Spectrum Estimation is given as Algorithm 1.

Input: Primary Users "$PU = PU_1, PU_2, \ldots, PU_n$", Secondary Users "$SU = SU_1, SU_2, \ldots, SU_n$"
Output: Robust spectrum channel throughput with minimum sensing delay
Step 1: **Initialize** graph "$G = (V, E, A)$", Threshold "Th", iterations "α" Step 2: **Begin** Step 3: **For** each iteration "α" Step 4: Estimate the skewness of the received signal as in Eq. (5) Step 5: Estimate the skewness of the reference signal as in equation (6) Step 6: Estimate the most significant relevant dimension using Chebyshev distance as in Eq. (7) Step 7: Evaluate probability of detection, probability of missed detection and probability of false alarm as in Eqs. (8), (9) and (10) Step 8: **Return** (spectrum channel "SC") Step 9: **End for** Step 10: **End**

Algorithm 1 Chebyshev distance-based harmonious vector spectrum estimation

As given in Chebyshev distance-based Harmonious Vector Spectrum Estimation algorithm, the objective remains in designing a spectrum estimation model with minimum sensing delay and maximum throughput or detection accuracy. To achieve these objectives first a skewness measure is made for both the received and reference signals. With this obtained skewness value, most significant relevant dimension is obtained by means of Chebyshev distance, therefore contributing to minimum sensing delay, followed by which, the probability measure is made for three different factors via learning processing by means of support vector. According to the results of these factors, finally decision corresponding to spectrum identification or estimation is made therefore contributing to detection accuracy.

3.3 Kolmogorov-Smirnov Convolutional Neural Network Based Secondary User Selection

With the estimated spectrum in consideration, the next step in our work is to focus on the optimal selection of secondary users which can guarantee reliable selection while reducing the false alarms and time consumed. In this work, a Kolmogorov-Smirnov Convolutional Neural Network-based Secondary User Selection model is proposed. A convolutional neural network comprises an input layer "(PU, SU, α, SC)", hidden layers and an output layer. In our work, the hidden layers include layers that perform convolutions and pooling. This is followed by the output layer, called the fully connected layer that provides the selection of secondary user made using our Max Empirical Kolmogorov-Smirnov Neural Network-based Secondary User selection algorithm.

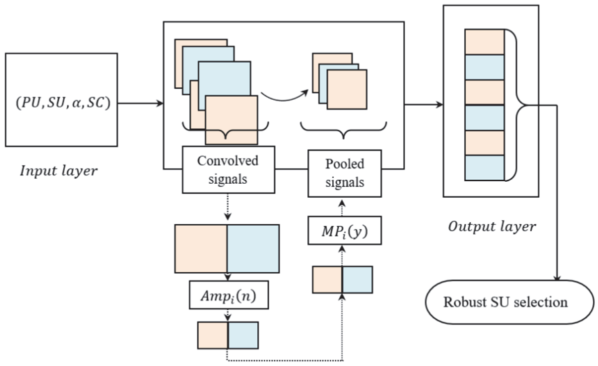

Figure 5 Kolmogorov-Smirnov CNN - based secondary user selection

Fig. 5 shows the Kolmogorov-Smirnov Convolutional Neural Network-based Secondary User Selection model.

As shown in Fig. 5, to start with, the input layers consist of inputs mainly comprising the number of iterations "α" and the spectrum channel estimation made "SC" for each secondary user "SU" in the presence of primary user "PU" in the CRN. These inputs are then fed into the hidden layer, i.e., convolved signals and pooled signals. In the proposed work, a depth wise convolution is made use of by measuring the amplitudes of the received signal trails formulated as given in Eq. (11).

$$Amp_i(n) = \sqrt{RS_{I,i}^2(n) + RS_{Q,i}^2(n)} \tag{11}$$

From the Eq. (11) "$RS_{I,i}^2(n)$" and "$RS_{Q,i}^2(n)$" represent the received signals imaginary and real part respectively, followed by which Max Empirical Probable Pooling is applied to the amplitude of the received signal trials for pooling. This is mathematically formulated as given in Eq. (12).

$$MP_i(y) = \frac{1}{N}\sum_{n=1}^{N} I\left(Amp_i(n) \le y\right) \tag{12}$$

From the above Eq. (12), "MP_i" denotes the max empirical probability distribution of the received signal from "i-th - SU", with "$I(\delta)$" representing the benchmark signal function. Here "$I(\delta)$" equals "1" if "δ" is true, otherwise "$I(\delta)$" equals "0". Finally, to low complexity and high efficiency, the effectiveness, Kolmogorov-Smirnov (KS) test is utilized to measure the co-existence between two "SUs". The KS test is established as follows.

$$D_{a,b} = \sum_{n=1}^{N} \sup\left|Amp_{i,a}(n) - Amp_{i,b}(n)\right| \tag{13}$$

Based on KS test, as given in equation (13), the SU selection mechanism is proposed as: if "$D_{a,b} \ge \eta$" two "SUs" are selected, otherwise, one of them is selected, where "η" is the specified threshold. The pseudo code representation of Max Empirical Kolmogorov-Smirnov Neural Network-based Secondary User selection is given in Algorithm 2.

As given in the Max Empirical Kolmogorov-Smirnov Neural Network-based Secondary User selection algorithm, the objective remains in selecting the secondary user on the basis of the target probability. In the proposed work, with the primary user, secondary user, spectrum and iterations fed as inputs to the input layer, the convolution and pooling are performed in the hidden layer to obtain the convolved and pooled signals with minimum false alarms by employing depth wise convolution and max pooling. Next, the proposed method is sufficient to distributed networks without the prerequisite of any intermediate coordinators, wherein the resultant Secondary User selection is made via Kolmogorov–Smirnov (KS) test, therefore contributing to minimization of Secondary User selection time.

Input: Primary Users "$PU = PU_1, PU_2, \ldots, PU_n$", Secondary Users "$SU = SU_1, SU_2, \ldots, SU_n$", spectrum channel "$SC$"

Output: Minimum false alarm-based optimal secondary user selection

Step 1: **Initialize** iterations "α", "η"
Step 2: **Begin**
Step 3: **For** each estimated spectrum channel "SC"
Step 4: **For** each iteration "α" and received signal trails
Step 5: Estimate depth wise convolution as in Eq. (11)
Step 6: Measure Max Empirical Probable Pooling as in Eq. (12)
Step 7: Estimate Kolmogorov-Smirnov (KS) test as in Eq. (13)
Step 8: **If** "$D_{a,b} \geq \eta$"
Step 9: **Then** two "SUs" are selected.
Step 10: **End if**
Step 11: **If** "$D_{a,b} < \eta$"
Step 12: **Then** "$ith - SU$" are selected.
Step 13: **End if**
Step 14: **End for**
Step 15: **End for**
Step 16: **End**

Algorithm 2 Max empirical Kolmogorov-Smirnov neural network-based secondary user selection

4 EXPERIMENTAL SETUP

In this section, the simulation results to evaluate the performance of CVDS-KSCN method in terms of efficient spectrum estimation and optimal secondary user allocation in cognitive radio network for spectrum access is presented. The CVDS-KSCN method is compared with two other methods, Deadline-based cross-layer Routing and Spectrum allocation (DRS) [1] and Efficient Feedback Analytic Hierarchy Process (EFAHP) Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [2] to measure four parameters, sensing delay, throughput, false alarm, Secondary User selection time. DRS and EFAHP-TOPSIS have been studied widely for various network scenarios and for a variety of traffic like text, voice and video. The performance evaluation is done by means of Python using ElectroSense Data API, a Web API for retrieval of raw and aggregated spectrum data. In this API, the information is extracted by default by means of current state of the sensor.

Table 1 Request parameters

Name	Description
Sensor	Sensor serial number
timeBegin	Start time in seconds since epoch
timeEnd	End time in seconds since epoch
freqMin	Lower bound for frequency in Hz
freqMax	Higher bound for frequency in Hz
aggFreq	Frequency resolution
aggTime	Time resolution
aggFun	Aggregation function
serial	sensor serial number
time	Time to retrieve meta information in seconds since epoch (Unix time), default is the time of the method call
noiseFloor	An estimation for the noise floor. See the external documentation
startFreq	Frequency of the first entry in "values"

Consequently, by changing the location and sensor, information state is subject to change. With this, the meta-information for the subsequent device is retrieved for an arbitrary point in a specified time. In this manner, data is retrieved for a single sensor within a time window, based on timeBegin and timeEnd corresponding to a frequency range given by freqMin and freqMax. Moreover, the aggregation also occurs according to time and frequency domain for given resolutions aggTime and aggFreq. Some of the request parameters are given in Tab. 1.

5 PERFORMANCE ANALYSIS
5.1 Sensing Delay

The spectrum access sensing delay refers to the time delay taken in responding to spectrum estimation for the corresponding Secondary Users. Lower the spectrum sensing delay, higher the number of Secondary User responses are said to be accomplished. This is mathematically expressed as given in Eq. (14).

$$SD = \sum_{i=1}^{n} D_i \left[SEReq_t - SERes_t \right] \quad (14)$$

From the Eq. (14), the spectrum access sensing delay "SD" is measured based on the spectrum estimation request time "$SEReq_t$" and the spectrum estimation response time "$SERes_t$" with respect to the different numbers of secondary users "SU". It is measured in terms of milliseconds (ms). Tab. 2 shows the results of sensing delay for three different methods, CVDS-KSCN, DRS [1] and EFAHP-TOPSIS [2].

Table 2 Tabulation of sensing delay

Number of secondary users	Sensing delay / ms		
	CVDS-KSCN	DRS	EFAHP-TOPSIS
25	625	750	1125
50	800	950	1015
75	915	1055	1090
100	1025	1085	1125
125	1055	1135	1185
150	1095	1185	1235
175	1125	1245	1285
200	1150	1315	1355
225	1185	1525	1725
250	1205	1785	2025

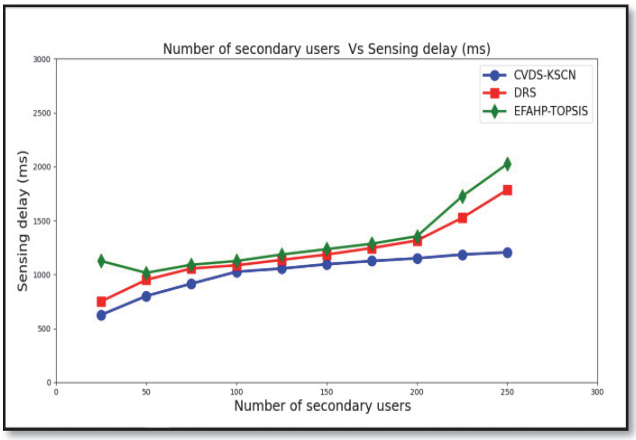

Figure 6 Graphical representation of sensing delay

Fig. 6 illustrates the sensing delay involved in CRN during spectrum estimation. A significant amount of delay is said to occur while estimating the spectrum as the number of Primary Users, Primary Users utilizing the channel and the number of Secondary Users waiting to be allotted with the spectrum must be measured. Hence, the sensing delay observed in Fig. 6 is found to be directly proportional to the number of Secondary Users waiting to be allocated with the spectrum or channel. In other words, increasing the Secondary Users causes an increase in the sensing delay also. However, simulations conducted with "25" Secondary Users considered for simulation and the difference between spectrum estimation request and response time being "25 ms" using CVDS-KSCN, "30 ms" using [1] and "45 ms" using [2], the overall sensing delay was observed to be 625 ms, 750 ms and 1125 ms respectively. With these results the sensing delay using CVDS-KSCN was found to be comparatively lesser than [1] and [2]. The reason behind the minimization of sensing delay is due to the Chebyshev distance employed to measure the difference between the skewness of the received signal and the skewness of the reference signal. As a result, the most significant relevant dimension signals are retrieved, therefore reducing the sensing delay using CVDS-KSCN by 14% compared to [1] and 21% compared to [2].

5.2 Throughput

The throughput is defined as the ratio of allocated channel (in terms of Kbps) to the available channel (in terms of Kbps). This is expressed as given in Eq. (15).

$$Throughput = \frac{CH_{\text{alloc}}}{CH_{\text{avail}}} \tag{15}$$

From the Eq. (15) the throughput rate "Th" is measured based on the allocated or identified channel "CH_{alloc}" and the available channel "CH_{avail}". It is measured in terms of kilo bits per seconds (Kbps). Tab. 3 shows the results of throughput for three different methods, CVDS-KSCN, DRS [1] and EFAHP-TOPSIS [2].

Table 3 Tabulation of throughput

Number of channels	Throughput / Kbps		
	CVDS-KSCN	DRS	EFAHP-TOPSIS
20	66	55	44
40	57	47	37
60	55	42	37
80	52	47	33
100	47	42	29
120	42	37	27
140	37	32	22
160	39	27	17
180	37	25	20
200	35	28	22

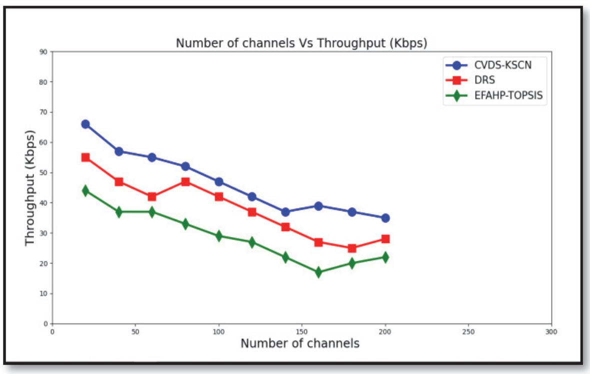

Figure 7 Graphical representation of throughput

Fig.7 shows the throughput rate for 200 different channels. From Fig. 7, x axis refers to the number of channels in use for simulation in the range of 20 and 200 and y axis refers to the throughput rate. However, with "20" channels selected for simulation, the available channel (in terms of Kbps) being "18 Kbps" and the allocated channel (in terms of Kbps) being "12 Kbps" using CVDS-KSCN, "10 Kbps" using [1] and "8 Kbps" using [2], the overall throughput rate was observed to be 66 Kbps, 55 Kbps and 44 Kbps respectively. From this it is inferred that the throughput rate using CVDS-KSCN is said to be better than upon comparison with [1] and [2].

5.3 Secondary User Selection Time

A significant amount of time is said to be consumed during the process of selecting the secondary users in CRN. This is mathematically expressed as given in Eq. (16).

$$SU_{st} = \sum_{i=1}^{n} SU_i * Time\left[D_{a,b}\right] \tag{16}$$

From the above Eq. (16), the secondary user selection time "SU_{st}" is measured based on the number of secondary users involved during the simulation "SU_i" and the time consumed in secondary user selected via Kolmogorov-Smirnov (KS) test "$Time[D_{a,b}]$". It is measured in terms of milliseconds (ms). Tab. 4 shows the results of secondary user selection time using the state-of-the-art methods, CVDS-KSCN, DRS [1] and EFAHP-TOPSIS [2].

Table 4 Tabulation of Secondary User selection time

Number of secondary users	Secondary user selection time / ms		
	CVDS-KSCN	DRS	EFAHP-TOPSIS
25	3.375	4.125	4.875
50	5.325	7.325	10.155
75	7.955	12.535	18.135
100	11.355	18.155	25.215
125	15.925	25.325	40.325
150	20.155	30.135	55.135
175	25.325	35.155	60.235
200	31.544	41.325	65.125
225	40.325	50.215	70.315
250	45.815	65.325	85.215

Fig. 8 shows the graphical representation of Secondary User selection time with respect to different numbers of secondary users in the range of 25 to 250. However, with "25" numbers of Secondary Users to be allocated with the intended channels and the time consumed in selecting optimal secondary users being "0.135 ms" using CVDS-KSCN, "0.165 ms" using [1] and "0.195 ms" using [2], the overall secondary user selection times were observed to be 3.375 ms, 4.125 ms and 4.875 ms respectively. From the results it is inferred that the secondary user selection time is found to be comparatively lesser using CVDS-KSCN upon comparison with [1] and [2]. The reason behind the minimization of time was due to the Kolmogorov-Smirnov (KS) test applied in CVDS-KSCN for measuring the co-existence between two "SUs". According to the result of the co-existence only, SU selection mechanism is made. Also, the test possesses the advantages of the statistic distribution not depending on cumulative distribution function being tested and therefore reducing the time consumed in selecting the secondary user in CRN using CVDS-KSCN by 29% compared to [1] and 51% compared to [2].

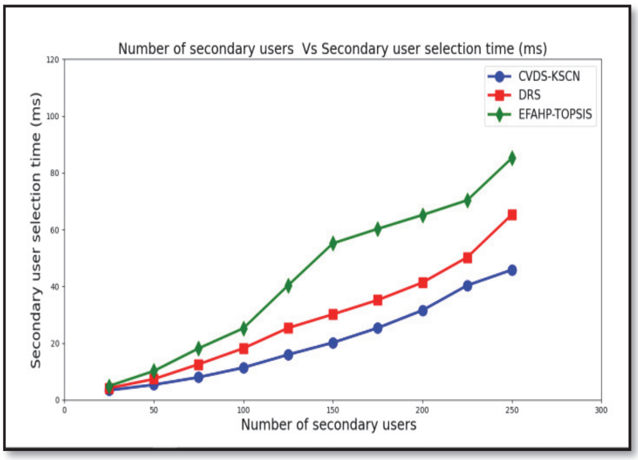

Figure 8 Graphical representation of secondary user selection time

5.4 False Alarm

For secondary user selection test**,** the false alarm rate denotes the number of false positives (test signals which are not selected receiving a false signal selection) versus the total number of positive signal selection. This is mathematically formulated as given in Eq. (17).

$$FA = \frac{FS_{SU}}{AS_{SU}} * 100 \tag{17}$$

From the Eq. (17), the false alarm "FA" is measured based on the falsified selection of Secondary User "FS_{SU}" to the actual selection of Secondary User "AS_{SU}". It is measured in terms of percentage. Tab. 5 tabulates the false alarm rate for CVDS-KSCN, DRS [1] and EFAHP-TOPSIS [2].

Table 5 Tabulation of false alarm

Number of channels	False alarm / %		
	CVDS-KSCN	DRS	EFAHP-TOPSIS
20	87.5	81.25	75
40	85.25	81	74.25
60	84.35	80	73.15
80	84	79.15	72.55
100	83.25	79	72.15
120	83.15	80	73
140	85	81.35	73.55
160	86.25	82	74
180	87	82.55	74.55
200	85.15	81	75

Finally, Fig. 9 shows the false alarm rate with respect to 200 different channels. Also from the figure a steady amount of false alarm is reported. In other words, increasing the number of channels neither increases nor decreases the false alarm rate. But, with "16" number of actual selection of secondary user from a simulation set of secondary user "25" and the falsified selection of them being "12" using CVDS-KSCN, "13" using [1] and "14" using [2], the overall false alarm rates were observed to be 75%, 81.25% and 87.5% respectively.

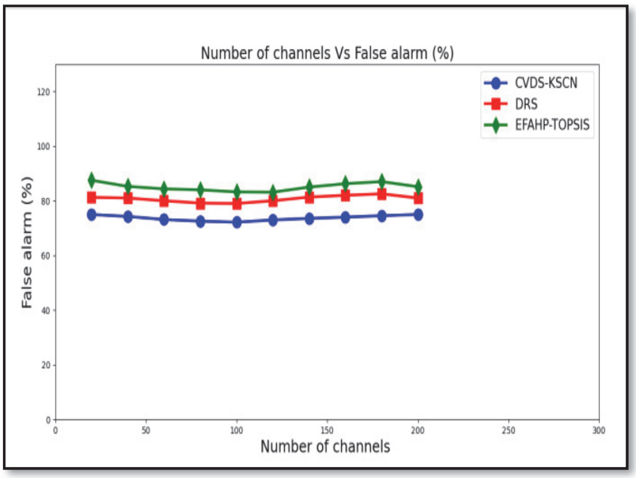

Figure 9 Graphical representation of false alarm (%)

From the results, the false alarm rate using CVDS-KSCN was found to be comparatively lesser than [1] and [2]. The reason behind the improvement was due to the application of Max Empirical Kolmogorov-Smirnov Neural Network-based Secondary User selection algorithm. By applying this algorithm, depth wise convolution was used for measuring the amplitudes of the received signal trails and Max Empirical Probable Pooling to the amplitude of the received signal trials for pooling. With this, the falsified selection was reduced, therefore improving the false alarm rate using CVDS-KSCN by 9% compared to [1] and 13% compared to [2].

6 CONCLUSION

In this paper, a method to estimate the spectrum for highly dynamic environment and selection of optimal number of Secondary Users in cognitive radio networks is proposed, in such a way that the sensing delay and false alarm incurred when every SU taking part in the sensing operation could be reduced. First, the spectrums are estimated on the basis of the skewness between the received and reference signal in order to minimize the convergence effect on cooperative sensing. Second, with the estimated channels being in use for the Secondary User, an entirely distributed mechanism is utilized employing KS test that measures the harmonious function of different SUs. It is representative in the simulation results that high probability of throughput and low false alarm with the optimal minimal sensing delay is achieved by the proposed method. It is noted that the sensing delay is improved around 14%-21% and an improvement in throughput of about 45% in average with a minimal sensing delay and a reduction in false alarm up to 13% is obtained when compared to DRS and EFAHP-TOPSIS methods. In the future, the proposed work can be expanded to a test bed based scenario and some more machine learning models can be used for improvising the Secondary User Selection.

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