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Spectrum Sensing and Resource Allocation for Proficient Transmission in Cognitive Radio with 5G

M. Meena and V. Rajendran

Department of ECE, Vels Institute of Science, Technology & Advanced Studies (VISTAS), Pallavaram, Chennai, Tamil Nadu 600117, India

ABSTRACT
In orthogonal frequency division multiplexing (OFDM)-based cognitive radio network–cooperative spectrum sensing (CRN-CSS), resource allocation is critical due to the introduction of interference during spectrum sensing and transmission. This paper resolves this problem of interference through proficient spectrum sensing and resource allocation to improve data transmission. CRN-CSS network is integrated with 5G supported by multiple-input–multiple-output equipped fusion center (FC) to handle massive number of users without loss in connectivity. OFDM-based data transmission is adapted in CRN-CSS to achieve a better transmission rate. In the integrated network, grouping process is initiated by a balanced K-means clustering algorithm to preserve cooperation among secondary users (SUs). Dynamic slot allocation scheme, two-stage multi-slot channel assignment method, is proposed to avoid interference during spectrum sensing. Sensing errors are minimized with the assistance of the energy spectral density-based energy detection spectrum sensing method. For global decision-making, the channel state weighted graph scheme is introduced in which spectrum agent plays a vital role. Finally, resource allocation is carried out by the FC by utilizing efficient Karush–Kuhn–Tucker (EKKT) conditions. Through EKKT method spectrum, transmission powers are allocated to SUs together in such a way that interference with primary user is avoided. Meanwhile, OFDM-based transmission with quadrature phase shift keying modulation scheme reduces peak-to-average-power ratio that leads to high transmission rate. The proposed network is extensively simulated in the NS-3.26 simulation tool and the performance is evaluated from the following performance metrics: throughput, capacity, network utility, transmission power, and transmission rate.

KEYWORDS
CRN-CSS; 5G; MIMO; OFDM; PAPR reduction; Resource allocation; Spectrum agent

1. INTRODUCTION

With the extensive advancements in wireless communication, a number of devices are connected seamlessly in today's world [1,2]. Provisioning of wireless spectrum for seamless connectivity is a major issue which raises the problem of spectrum scarcity. On the other hand, federal communications commission (FCC) confirms that a large amount of spectrum is underutilized by licensed users, which increases the spectrum holes. This conflict in spectrum availability results in the rise of cognitive radio network (CRN). Cognitive radio is a software defined radio (SDR) with the additional abilities of sensing its environment, tracking changes, and adapting upon findings [3]. These advantages of CRN are utilized in the fifth generation (5G) network with massive multiple-input–multiple-output (MIMO) technology by adapting orthogonal frequency division multiplexing (OFDM)-based transmission [4,5]. Involvement of OFDM-based transmission results in spectral efficiency and high transmission rate. However, OFDM-based CRN met with the following issues: peak-to-average-power ratio (PAPR), synchronization, spectrum sensing, interference avoidance, and power requirements.

The primary functions of CRN are spectrum sensing, spectrum analysis, spectrum decision, and resource allocation [6]. Many research works held on spectrum sensing and one of the major solutions to minimize sensing errors is cooperative spectrum sensing (CSS). Further spectrum sensing can be performed by the energy detection (ED) method which is simple and efficient. Some research works focused on improving the ED method [7–9]. Kernelized ED (KED) is designed to improve detection accuracy in Gaussian and non-Gaussian noise environments. Noise uncertainty problem is addressed by the blind ED method and the maximum–minimum ratio-based ED method. In CSS, interference during spectrum sensing is resolved by spectrum sensing scheduling [10,11]. Minimization of interference through CSS scheduling increases throughput, fairness, energy efficiency, and sensing accuracy. The channel assignment and scheduling algorithms are classified based on the 0following characteristics: coordination mechanisms, objectives, solving approaches, network types, and number of radios. Based on these characteristics, a majority of research works assign channels for spectrum sensing. The spectrum availability decision is made based on the spectrum-sensing results. For decision-making, hard fusion (such as AND rule, OR rule, K out N rule) and soft fusion methods are adapted in CRN [12]. Fusion center (FC) is also contributed in decision-making by making use of the fusion rule [13]. Here the involvement of the FC in decision-making improves energy efficiency. Majority voting rule and maximal ratio combining rule are also adapted for decision-making in FC [14].

Spectrum sensing and decision-making function detect the available spectrum, which can be used by secondary users (SUs). Then resource allocation is followed by decision-making to make better use of the available spectrum [15]. Resource allocation includes both spectrum allocation and transmission parameters such as transmission power. Some research works concentrated on spectrum allocation [16,17]. Bee colony algorithm is utilized for spectrum allocation which aims to maximize the overall quality of experience (QoE). The double auction-based method uses Markovian prediction algorithm for spectrum allocation. To improve energy efficiency and the quality of service, both frequency and power allocation are performed by relaxation and quantization algorithm [18] in OFDMA-based CRN-CSS network. Channel state information (CSI) is considered as major metric in resource allocation (both spectrum and transmission power) for OFDMA-based CRN network [19]. Here iterative successive convex algorithm (SCA) is adapted for resource allocation.

1.1 Major Contributions

The major contributions of this paper in CRN-CSS are listed as follows:

- To support huge users without loss in spectrum efficiency CRN-CSS is integrated with 5G. High transmission rate was achieved by adapting OFDM. Our proposed network supports both short-range and long-rage application with the involvement of 5G coverage.
- CSS in CRN involves with grouping of SUs by the balanced K-means (BK-means) algorithm which performs based on distance and node degree of SUs.
- To minimize interference among SUs, multi-slot channel assignment is performed by the proposed novel two-stage multi-slot channel assignment (TMSCA) algorithm. Further sensing errors are minimized by the energy spectral density-based energy detection (ESD-ED) method.
- Accurate spectrum sensing decision on primary user (PU) activity is made by FC supported by spectrum agent (SA). We propose channel state weighted graph (CSWG) for global decision-making which minimizes decision-making errors and improves spectrum utilization
- Finally, the available spectrum is allocated to SUs along with transmission power based on efficient Karush–Kuhn–Tucker (EKKT) conditions. The resource allocation considers power and interference constraints to avoid interference with PU signal.
- PAPR reduction followed by adapting the quadrature phase shift keying (QPSK) scheme and also by selecting signal with high signal to noise ratio (SNR) for transmission. Reduction of PAPR leads to increased transmission rate.

1.2 Organization of the Paper

The rest of this paper is organized as follows: in Section 2, we surveyed previous works held on CRN-CSS with OFDM. Section 3 highlights the major problems involved in the current research work. In Section 4, we elaborate the proposed OFDM-based CRN-CSS with novel algorithms. Finally in Section 5, the experimental model of our proposed OFDM-based CRN-CSS is considered and our proposed work is evaluated in terms of significant performance metrics. In Section 6, we conclude our contributions.

2. RELATED WORKS

In this section, significant research works held on CRN-CSS are surveyed. This section addresses challenges and issues faced by previous research works in OFDM-based CRN-CSS.

2.1 Related Works on CRN-CSS

In CRN-CSS, sensing channel assignment and sensing scheduling was vital since it mitigates the interference among SUs. An adaptive assignment strategy was introduced to assign sensing channel for group-based CSS [20]. Here two-channel selection then best user assignment (CSBUA) and best user assignment and channel selection (BUACS) algorithms were involved in sensing the channel assignment. Upon the assigned channel, SU performs ED method-based spectrum sensing to make decision on spectrum availability. However, in both algorithms SU is allowed to sense only one channel in each round which increases waiting time. In [21], CSS scheduling was formulated as integer linear programming (ILP) problem and the distributed solution was presented based on the coalitional game theory. In this approach, SUs were allowed to form coalition for each channel and each coalition was included with a cluster head (CH). The best sensing channel was identified by CH with the knowledge of number of SUs that were presented in coalition for that channel. Channel with more number of SUs was selected as the optimal channel by CH. Here we can see that optimal sensing channel involves with more number of SUs for sensing. Assigning additional SUs for this optimal channel increases the possibility of interference.

Spectrum sensing accuracy was further improved by the multi-agent architecture framework that was most suitable for 5G network [22]. In a multi-agent architecture, multiple SAs were deployed in the network for the purpose of spectrum sensing. In this work, SA had switched between two modes such as SA mode and SU mode. In SA mode, it performs spectrum sensing for other SUs, *i.e.* whenever a SU requires spectrum it requested to SA for sensing the report. Then the SA performs spectrum sensing for that particular user with the sensing report. The major aim of this work was to minimize energy consumption in SUs. It is difficult to manage multiple agents and also it increases the number of SAs with an increase in the number of SUs. Cluster formation was also performed to improve sensing efficiency in the presence of malicious users in CRN [23]. Here the network was grouped into small clusters and each cluster was elected with CH. CH was responsible to aggregate sensing reports from its cluster members (CMs) and to transmit the sensing reports to FC. To avoid interference during sensing report transmission, all CHs were allowed to access FC in a sequential order all the time. Furthermore, maximum likelihood (ML) estimator was involved in FC to detect malicious nodes. Perhaps, this method minimizes interference at FC; it increases waiting time for each CH due to sequential order access.

In cluster-based CRN-CSS, time division multiple access (TDMA)-based reporting framework was designed [24]. Clusters were formed by the K-means clustering algorithm based on SU location. Each cluster was provided with TDMA reporting slot to report sensing information to FC. The authors suggested that the involvement of TDMA framework minimizes reporting time and increases transmission time. In addition, K-out-of-N rule was adapted in decision-making at CH and OR rule was adapted in decision-making at FC. However, the cluster formation by k-means algorithm produces unbalanced clusters which lead to inefficient spectrum sensing. Furthermore, the involvement of OR rule in FC results in inaccurate decision. Spectrum allocation was followed by decision-making and performed using a game theoretic approach [25]. A two-tier multi-user CRN was introduced in which SUs were divided into real-time users and non-real-time users. The idea was to utilize the intervals introduced by the real-time user's transmission for non-real-time user's transmission. The key concept behind this work was that real-time data transmission followed by the voice over internet protocol (VoIP) packets which left intervals during transmission. Both real-time and non-real-time SUs were selected by an auction game. If non-real-time user requires spectrum more than that left by real-time user, then data transmission of non-real-time user is not efficient.

2.2 Related Works on OFDM-based CRN

Virtual clustering distributed coordination (VCDC) scheme was presented in OFDM-based CRN-CSS network [26]. Here neighbor discovery time was decreased and inter-cluster communication was supported by discrete-OFDM (D-OFDM). Clusters were formed based on the similarity between spectrum availability observed by SUs. Additionally, the following control packets were exchanged for cluster formation: coordination request, coordination response, coordination decision, and activated shared channel. Although this method preserves coordination among SUs, it increases control packet overhead in the network. In wireless networks, MIMO-OFDM was presented with an index modulation for minimum mean square error detectors to improve spectral efficiency [27]. Here multiple detectors, such as ML, MMSE, and ordered successive interference cancellation-based MMSE detectors, were involved. In MIMO-OFDM-based CRN, cyclostationary detection method was adapted for spectrum sensing [28]. The main aim of this work was to evaluate the network based on mean square error and successful reconstruction rate. However, in both works high PAPER is presented which degrades the overall network performance.

Artificial bee colony (ABC) with crossover operator was involved in the cognitive MIMO-OFDM system to achieve optimal power allocation [29]. In this approach, eight crossover operators were applied to resolve power allocation problem. The optimal crossover rate was determined with eight operators over multiple trials and an optimal rate was adapted for power allocation. However, computational complexity and time consumption are high in order to apply eight crossover operators.

To allocate transmission power and spectrum together, the robust power allocation (RPA) method was introduced in OFDM-based CRN [30]. Both channel uncertainty and imperfect sensing error were considered for resource allocation. Furthermore, relay selection was performed upon average interference power in each hop. ABC method and RPA method support only a single user for resource allocation.

For multi-user resource allocation, location-aware spectrum access was presented in underlay and overlay CRN [31]. Here the network was divided into underlay CRN and overlay CRN based on the coverage area. SUs presented in overlay region were suggested to use overlay spectrum access techniques and SUs presented in the hybrid region were suggested to use sensing-free spectrum access techniques. In this method, interference between SU and PU is a major problem which degrades the network performance. A robust power allocation scheme, based on switched affine-based control approach, was introduced for OFDM-based CRN [32]. The objective of this method was to maximize the data rate in channel uncertainties. This method also fails to avoid interference between SUs and PUs. Furthermore, water-filling algorithm was adapted for resource allocation in PU localization-based resource allocation [33] and in the underlay model [34]. In both resource allocation schemes, the location of PU was estimated with the interference of PU. Then resource allocation was performed by the water-filling algorithm. But the major issue associated with water-filling algorithm is high computational complexity.

3. PROBLEM FORMULATION

In CRN-CSS, utility-based CSS scheduling was performed with energy efficiency [35]. Here each SU was allowed to make decision about sensing, *i.e.* whether participated in sensing or not. SUs involved in sensing were denoted as contributors and other SUs were considered as free-riders. The sensing channel was selected by the contributor based on channel uncertainty. Here a major problem in spectrum utilization occurs, when the network has free-riders more than contributors. In this situation, the spectrum was underutilized by the cognitive network. Furthermore, decentralized selection of sensing channel leads to large sensing interference. In the cluster-based CRN, global decision on spectrum availability was made in a centralized manner by FC [36]. Optimal location for FC was determined by the general center scheme. OR rule was adapted for global decision-making problem. However, in OR rule if anyone of the SUs report was erroneous, then the decision was incorrect which leads to spectrum underutilization.

To minimize interference and to improve spectral efficiency in resource allocation, an interference alignment (IA) with frequency clustering was introduced [37]. Here initially frequency clustering was performed to enable CSS and then power allocation was performed for each SU. Perhaps this method minimizes interference; this method relatively depends upon SNR and CSI which limit the performance in low SNR scenarios. In addition, it is not ensured that the knowledge of CSI is available every time. Dynamic spectrum allocation was presented in OFDM-based cognitive femtocell network [38]. The resource allocation problem was resolved by the dual decomposition method. The spectrum efficiency was improved by saving a part of spectrum. However, saving a part of available spectrum leads to spectrum underutilization since the PU appearance is dynamic. In addition, the optimal solution determination is not able to minimize interference between PU and SU since interference constraint is not considered. Computational complexity was minimized by decoupling resource allocation process in two steps [39]. In the first step, adaptive algorithm was introduced to assign subcarriers to SUs based on power allocated initially. Then in the next step, optimal power allocation process was realized. Perhaps this method minimizes computational complexity; it consumes large time for resource allocation in two steps in an iterative manner.

Thus the major problems addressed in the previous research works are ineffectual CSS with inaccurate decision-making. Further interference between SUs and PUs, computational complexity, and time consumption are still challenging issues in OFDM-based CRN-CSS.

In addition, we formulate our objective in resource allocation to improve network capacity such that throughput can be improved. Optimal resource allocation problem was formulated as non-convex problem. Our major objective function can be summarized as the following optimization problem.

$$\text{maximise } C = \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{n_{min}} \alpha_{ki} C_{kij}(P_{kj}(i)) \tag{1}$$

$$\text{Subject to } \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{n_{min}} \alpha_{ki} \cdot P_k(i) \cdot I_i^g \leq I_{TH}^g,$$

$$\times\, g = 1, 2, \ldots, G$$

$$\sum_{k=1}^{K} \alpha_{ki} \leq 1 \quad \forall i, \alpha_{ki} \in \{0, 1\} \quad \forall i, k$$

$$\alpha_{ki} \cdot P_k(i) \geq 0 \quad \forall i, \text{and } k$$

The above optimization problem has an objective to maximize the capacity of the network subject to transmit power constraint, interference constraint, and assignment constraint. Here the capacity of cognitive network with K number of SUs and N number of channels is considered. The assignment constraint to assign ith channel to kth user is denoted as α_{ki}. Similarly, the power constraint is represented as $P_k(i)$ and I_i^g represents interference constraint.

4. PROPOSED OFDM-BASED CRN-CSS WITH 5G

In this section we briefly discuss about our proposed novel OFDM-based CRN-CSS with 5G network. Our proposed network comprises the following entities: K number of SUs as $SU = \{SU_1, SU_2, \ldots, SU_K\}$, M number of primary users as $PU = \{PU_1, PU_2, \ldots, PU_M\}$, and N number of channels, FC, and SA as shown in Figure 1. The overall process is comprised of eight sequential steps. Here we design FC with MIMO technology to support huge number of SUs without a reduction in the transmission rate. Integration of CRN-CSS with 5G is achieved to support high data rate and to preserve connectivity among a vast number of SUs. Initially the network is decomposed into small groups by BK-means algorithm. Then each group is assigned with optimal sensing slots using the novel TMSCA method which avoids sensing interference. Upon the assigned channel SUs perform an ESD-ED based spectrum sensing which identifies the available spectrum in a wide band.

Global decision is made by FC with the assistance of the CSWG method supported by SA. Finally resource allocation, *i.e.* jointly power, and channel allocation are carried out by considering EKKT conditions under power, interference, and assignment constraints. Without interference and with optimal resources, the transmission performance is improved in the network which leads to high-throughput efficiencies. Furthermore, OFDM is adapted to preserve high transmission rate and the problem of PAPR is resolved by utilizing QPSK modulation. Each significant process is explained in the following sections.

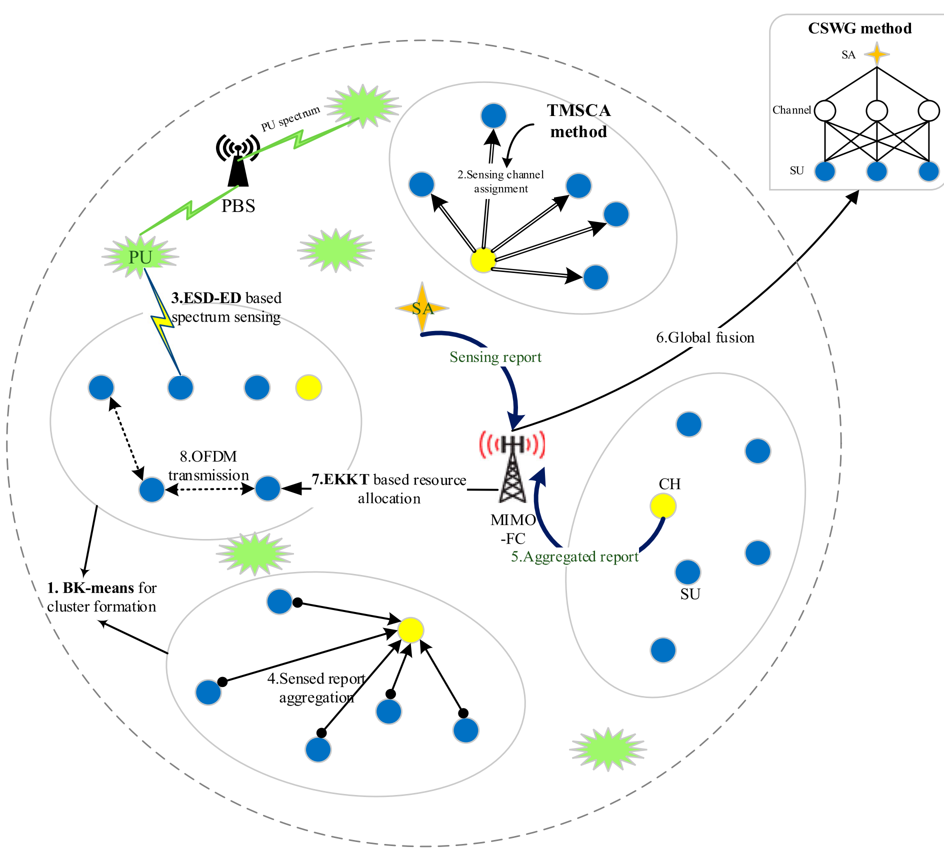

Figure 1: Overall architecture of the proposed OFDM-based CRN-CSS with 5G scenario

4.1 Group Formation: BK-means Algorithm

Group formation is the initial process in our work which supports CSS in CRN. For efficient group formation, BK-means algorithm is presented. BK-means algorithm decomposes the network into small groups in a balanced manner, *i.e.* each group with equal number of SUs. The key idea behind BK-means algorithm is to divide the network into equal size clusters (or) groups. The cluster formation process is carried out by FC in the following steps.

Step 1: Initialize number of clusters $\mathbb{K}$, and cluster size $Size(Cl)$. Here our major aim is to balance the clusters in the network, so that we select a number of clusters using some existing methods. For instance, the value of $\mathbb{K}$ is determined by the elbow method and the cluster size is optimized by our proposed BK-means algorithm. Cluster size can be expressed as follows:

$$Size(Cl) = \frac{K}{\mathbb{K}} \tag{2}$$

Cluster size is determined based on a number of SUs in the network (K) and a number of clusters $\mathbb{K}$.

Step 2: Randomly initialize $\mathbb{K}$ number of centroids as follows:

$$Centroids = \{\mathbb{C}_1, \mathbb{C}_2, \ldots, \mathbb{C}_{\mathbb{K}}\} \tag{3}$$

Step 3: Assign SUs to closest centroid based on distance. Here *Manhattan distance*, which gives absolute distance, is determined between SUs and centroids. We use Manhattan distance instead of Euclidean distance since Euclidean distance is influenced by unusual values and not able to provide accurate distance. In order to obtain accurate distance between centroids and SUs, Manhattan distance is computed. Accurate distance computation leads to robust result in group formation. Manhattan distance between SU and centroid is computed as follows:

$$D(SU_1, \mathbb{C}_2) = |x_2 - x_1| + |y_2 - y_1| \tag{4}$$

Here (x_1, y_1) represents points of SU and (x_2, y_2) represents points of centroid. Involvement of Manhattan distance also minimizes the measurement errors which lead to accurate distance calculation. Then the SU assignment process follows:

$$If\,(D(SU_1, \mathbb{C}_2) = \text{Small, then assign } SU_1 \rightarrow \mathbb{C}_2 \tag{5}$$

This process is iterated until all SUs are assigned to at least one centroid.

Step 4: In this step all centroids are updated, *i.e.* recomputed. Then step 2 and step 3 are performed with new (or) updated centroid until optimal groups are formed. In this step $\mathbb{K}$ numbers of clusters (Cl) are formed as follows:

$$Cls = \{Cl_1, Cl_2, .., Cl_{\mathbb{K}}\} \tag{6}$$

Step 5: In the final step, for each cluster CH is selected based on node degree and distance with FC and average distance with other SUs in cluster. The CH is responsible to aggregate sensing reports from all of its cluster members (CM).

Thus BK-means algorithm forms clusters with equal size, which balances overall network in spectrum sensing. It also preserves cooperation among SUs to realize CSS in CRN. Since all clusters have the same number of SUs, it is possible to obtain the same opportunities for spectrum sensing. Cluster formation also minimizes interference during spectrum sensing which degrades the data transmission. All SUs perform sensing and report the sensing information to their CH and then CH transmits the aggregated reports to FC. Here CH is required not to wait since FC is equipped with MIMO.

4.2 Multi-slot Channel Assignment: TMSCA Method

In CSS-based CRN, introduction of interference is a major issue still that is not resolved. To resolve this issue, we propose a dynamic multi-slot channel assignment process based on the TMSCA method. In this method, channel assignment is performed in two stages. In the first stage, each cluster is provided with a set of channel for sensing in the given round. In the next stage, each round is segmented into multiple slots and each SU is assigned with a sensing channel at each slot. It is worth to note that in our network cluster size is equal so that the slot duration is also equal. Thus each SU is given with same sensing duration in the network. Consider $\mathbb{K}$ number of channel sets $\{CS_1, CS_2, .., CS_{\mathbb{K}}\}$ and $\mathbb{K}$ number of clusters$\{Cl_1, Cl_2, \ldots, Cl_{\mathbb{K}}\}$. Each channel set has five sensing channels and each cluster has five SUs. Then in the first stage each cluster is provided with a channel set. This scheduling is performed by FC with the knowledge of SA since for each channel set SA provides sensing reports. In round 1 R_1, channel set assignment process is performed as follows:

$$R_1 : \{CS_1 \rightarrow Cl_1\}, \{CS_2 \rightarrow Cl_2\}, .., \{CS_{\mathbb{K}} \rightarrow Cl_{\mathbb{K}}\} \tag{7}$$

Further in each round the channel sets are rotated among clusters. This scheduling is performed with the assistance of FC and SA.

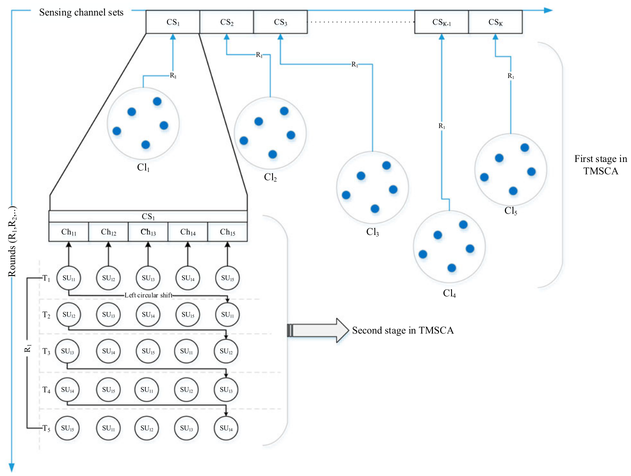

Figure 2: TMSCA-based sensing channel assignment

In Figure 2, the process of TMSCA method with two stages is illustrated. When the first stage is completed, the second stage is followed by CH. Consider channel assignment in Equation (7), in which CS_1 is assigned to Cl_1. In the second stage, round R_1 is divided into multiple time slots based on the number of sensing channels. Here we have CS_1 with five sensing channels $CS_1 = \{Ch_{11}, Ch_{12}, Ch_{13}, Ch_{14}, Ch_{15}\}$, and Cl_1 with five SUs $Cl_1 = \{SU_1, SU_2, SU_3, SU_4, SU_5\}$. Then R_1 has five time slots as $R_1 = \{T_1, T_2, T_3, T_4, T_5\}$. In each time slot, SU is assigned by CH to sense each channel in left circular manner. Thus in each time slot sensing channels are assigned in following manner.

$$\begin{aligned}
&Ch_{11} : \{SU_1 \to T_1, SU_2 \to T_2, SU_3 \to T_3, SU_4 \\
&\quad \to T_4, SU_5 \to T_5\} \\
&Ch_{12} : \{SU_1 \to T_5, SU_2 \to T_1, SU_3 \to T_2, SU_4 \\
&\quad \to T_3, SU_5 \to T_4\} \\
&Ch_{13} : \{SU_1 \to T_4, SU_2 \to T_5, SU_3 \to T_1, SU_4 \\
&\quad \to T_2, SU_5 \to T_2\} \\
&Ch_{14} : \{SU_1 \to T_3, SU_2 \to T_4, SU_3 \to T_5, SU_4 \\
&\quad \to T_1, SU_5 \to T_2\} \\
&Ch_{15} : \{SU_1 \to T_2, SU_2 \to T_3, SU_3 \to T_4, SU_4 \\
&\quad \to T_5, SU_5 \to T_1\}
\end{aligned}$$

In the above left circular shift method, each SU is assigned with each sensing channel in each time slot. Furthermore, TMSCA method ensures each channel is sensed by all SUs in the network without interference. Here we can see that no interference is introduced among SUs during spectrum sensing. Minimizing interference leads to improve spectrum sensing which results in high spectrum efficiency. When the available spectrum is accurately identified, then the network is able to transmit more data results in high throughput.

Upon assigned sensing channel each SU perform spectrum sensing through the proposed ESD-ED method. ESD measures energy of a signal over a frequency, while the conventional ED method measures the energy of signal in a piece of frequency. Thus, ESD can able to identify more amount of spectrum than the conventional ED method. Furthermore, the threshold computation is performed with the knowledge of noise uncertainty which improves the accuracy of spectrum sensing. In the conventional ED method, PU status is detected based on the following two hypotheses.

$$X(n) = \begin{cases} w(n), & H_0 \\ s(n) + w(n), & H_1 \end{cases} \tag{8}$$

The hypothesis test is made on the received signal $X(n)$. Energy is computed for the received signal and compared with threshold value. If the energy of the signal is higher than the threshold value, then it can be concluded that the signal contains both PU signal $s(n)$ and noise signal $w(n)$, *i.e.* PU is active on that channel. Otherwise, PU is absent, *i.e.* the received signal contains only noise signal. The energy of the received signal is computed by SU as follows:

$$E = \int_{-\infty}^{\infty} |x(t)|^2 \tag{9}$$

Energy of the signal is the sum of energy in all signal samples in the received signal in a time domain. However, this part is modified in our work to achieve better sensing accuracy. We compute ESD instead of energy level for the received signal in the proposed ESD-ED method. ESD defines the measure of signal energy over a frequency. ESD of signal is computed as follows:

$$\psi_x(f) = |X(f)|^2 \tag{10}$$

ESD is the energy per unit bandwidth of spectral components of $x(t)$ at center frequency f as in Equation (10). Then the threshold computation is followed by ESD computation to perform a hypothesis test. Threshold computation is performed as follows:

$$\lambda_{new} = \frac{\lambda}{\sum \wp_i} \tag{11}$$

Here a new threshold λ_{new} is computed in terms of conventional threshold (as in conventional ED method) (λ) and noise uncertainty factor $\wp_k$ which can be computed as follows:

$$\rho_k = \frac{\max\limits_{1 \le q \le Q} \sigma_k^2(q)}{\frac{1}{Q}\sum_{q=1}^{Q} \sigma_k^2(q)} \tag{12}$$

Noise uncertainty factor is computed in terms of noise frequency σ of each signal sample where Q signal samples are considered. Based on the computed threshold value PU activity on the channel is determined. Local decision on the channel status is taken by SU as follows:

$$Decision = \begin{cases} PU\ is\ present & ES \ge \lambda_{new} \\ PU\ is\ absent & ESD < \lambda_{new} \end{cases} \tag{13}$$

CH aggregates sensing report from each SU at each time slot and transmit the sensing report to FC at the end of each round, *i.e.* SU reports to CH at each time slot and CH reports to FC at each round.

Algorithm 1 details the overall process involved in CRN-CSS spectrum sensing. The CSS process is initiated with the clustering of SUs and then each SU is assigned with sensing channel in cooperative manner.

Algorithm 1. Proposed CRN-CSS with TMSCA

Input: $SU = \{SU_1, SU_2, .., SU_K\}, \{CS_1, CS_2, .., CS_{\mathbb{K}}\}$
Output: Optimal sensing scheduling
Begin
Initialize network with SUs and PUs
Initialize number of clusters $\mathbb{K}$
Find $Size(cl)$
Select random centroids $Centroids = \{\mathbb{C}_1, \mathbb{C}_2, .., \mathbb{C}_{\mathbb{K}}\}$
For all $SU_x \in SU$
  Find $D(SU_x, \mathbb{C}_y)$
  If $D(SU_x, \mathbb{C}_y) = Small$
    Assign $SU_x \rightarrow Cl_y$
  Else
    Goto→ 7
  Update $\mathbb{C}_y \in Centroids$
  End if
Do
Until convergence
Return
$Cls = \{Cl_1, Cl_2, .., Cl_{\mathbb{K}}\}$
End for
For each $Cl_y \in Cls$
  Assign $CS_z \in CS$ at R_1
  For each $SU_x \in Cl_y$
    Divide $R_1 \rightarrow T_1, T_2, T_3, ..T_t$
    Assign $SU_x \rightarrow Ch_h \in CS_z$ at T_1
    Do until no SU without Ch at T_1
  End for
For $Cl_y withCS_z$
  Do left circular shift in $Ch_h \in CS_z$ at T_2
  Rotate CS at R_2
  Do until
  All channels are sensed
End for
For each channel
  SU performs $ESD - ED$
  $SU(sensing\ report) \rightarrow CH$ at T_t
  $CH(Aggregated\ report) \rightarrow FC$ at R_r
End for
End

4.3 Global Fusion: CSWG Method

Global decision-making process is followed by spectrum sensing. For global decision-making, FC considers sensing reports aggregated from SUs as well as the sensing report obtained from SA. We introduce a SA which is a new entity in the network to improve sensing accuracy. SA is only working for FC in spectrum sensing. SA performs spectrum sensing on each channel set and reports to FC about each channel state in the channel set. Here it is assumed to be that SA always provides an accurate status of the channel at any given time. Global decision is made by comparing the sensing report of SU with that of SA. This comparison is made in order to identify the SUs which performs accurate sensing on PU status. SUs, which provide accurate sensing report, are only considered for spectrum allocation to improve the network performance. The sensing reports from SUs have two hypotheses on channel status in binary representation, as shown in Table 1.

Aggregated sensing reports are analyzed by FC with the help of SA. To speed up the process CSWG is adapted for decision-making in FC. In the CSWG method a undirected graph is constructed between each channel and SUs and SA based on sensing reports. For each group an undirected graph is constructed with the channel set at each round. Then the link between channel and SU is given with a weight value based on the sensing report. At the end of R_1, FC constructs CSWG between channels in CS_1 and SUs in Cl_1. Consider sensing reports for CS_1, as shown in Table 2.

Based on the aggregated sensing reports, FC builds a CSWG graph. For sensing reports illustrated in Table 1, the constructed CSWG is shown in Figure 3. In CSWG,

Table 1: Sensing reports

Hypothesis	Report	PU status
H_0	1	PU is absent, *i.e.* Channel is idle
H_1	0	PU is presented, *i.e.* channel is busy

Table 2: Aggregated sensing results for CS_1

SU/Ch	Ch_1	Ch_2	Ch_3	Ch_4	Ch_5
SU_1	1	0	0	1	0
SU_2	0	1	1	1	0
SU_3	1	0	0	1	0
SU_4	1	0	1	1	0
SU_5	1	1	0	0	0
SA	1	1	0	1	0

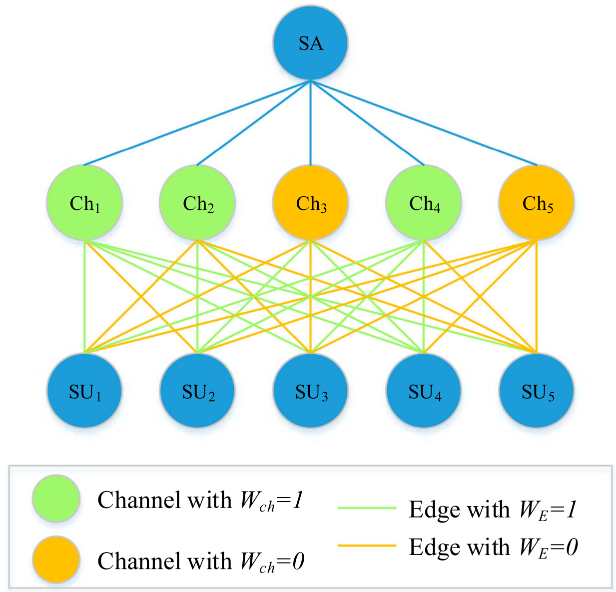

Figure 3: CSWG construction

an undirected graph $G(V, E)$ is constructed with V vertices and E edges. Here V represents channels presented in the channel set and SUs presented in cluster. Similarly, E represents edges between SUs and channels. Channels are given with weight value W_{Ch} based on the sensing report from SA that represents the state of the channel. This weight value can be 'zero' or 'one'.

After assigning the weight values, each edge between SU and channel is given with a weight value based on the sensing report of SU on a particular channel. SUs, which provide accurate sensing reports, are identified by the following criteria.

$$Report(SU) = \begin{cases} True, & if(W_{ch} = W_E) \\ False, & Otherwise \end{cases} \tag{14}$$

From the CSWG, FC made global decision accurately and also identified the SUs which provide false-sensing reports. Then the SUs are informed by FC about the improper sensing report so that SUs can improve their spectrum-sensing process. When an accurate sensing decision is made, then the spectrum availability is accurately identified by the cognitive network. Thus by utilizing the available spectrum the network throughput can be enhanced.

4.4 Resource Allocation: EKKT Conditions

In our OFDM-based CRN-CSS, resource allocation process considers joint spectrum and power allocation for multi-user multi-channel scenario. Joint spectrum allocation and power allocation problem are formulated as in Equation (1). Our proposed system model comprises K number of users and N number of subcarriers in the available spectrum. Upon the formulated problem, the available subcarrier and power to particular SU with the aim of maximizing network capacity. Here the capacity of SU link gives the ability of SU to transmit more data successfully, *i.e.* high throughput. This can be computed as follows:

$$C_k(i) = \sum_{j=1}^{n_{\min}} log_2 \left(1 + \frac{P_{kj}(i)\lambda_{kj}^2(i)}{N_0}\right) \tag{15}$$

where $P_{kj}(i)$ represents the kth user at the jth antenna of ith subcarrier. Furthermore, $\lambda_{kj}(i)$ is the jth diagonal element of a diagonal matrix. The problem formulated in Equation (1) is a non-convex problem and can be converted into a convex one by introducing a new variable as follows:

$$S_{kj}(i) = \alpha_{ki}.P_{kj}(i) \tag{16}$$

Thus the problem can be rewritten as follows:

$$\text{maximise } C = \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{n_{\min}} \alpha_{ki} C_{ki}\left(\frac{S_{kj}(i)}{\alpha_{ki}}\right) \tag{17}$$

$$\text{Subject to} \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{n_{\min}} S_{kj}(i) \cdot I_i^g \leq I_{TH}^g, \quad g = 1, 2, \ldots, G$$

$$\sum_{k=1}^{K} \alpha_{ki} \leq 1 \quad \forall i, \alpha_{ki} \in \{0, 1\} \quad \forall i, k$$

$$S_{kj}(i) \geq 0 \quad \forall i, j \text{ and } k$$

when $\alpha_{ki} \neq 0$, then this problem can be solved by KKT conditions. To improve resource allocation we introduce the EKKT method in which optimal SU is assigned with the optimal channel. For this purpose, we sorted all SUs based on their spectrum efficiency and all channels based on their capacity. The resource allocation process is initiated with optimal SU and optimal channel. Then over iteration, spectrum allocation is performed for each SU with reasonable transmission power. The Lagrangian of Equation (1) is given as

$$\mathcal{L}(\alpha_{ki}, S_{kj}, \mu_{kj}(i), \rho_{ki}, \xi_{ki}, \psi_g)$$
$$= -\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{n_{\min}} \alpha_{ki} \cdot C_{kij}\left(\frac{S_{kj}(i)}{\alpha_{ki}}\right)$$
$$+ \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{n_{\min}} \mu_{kj}(i)(0 - S_{kj}(i))$$

$$+\sum_{i=1}^{N} v_i\left(\sum_{k=1}^{K}\alpha_{ki}-1\right)+\sum_{k=1}^{K}\sum_{i=1}^{N}\rho_{ki}(\alpha_{ki}-1)$$
$$+\sum_{k=1}^{K}\sum_{i=1}^{N}\xi_{ki}(0-\alpha_{ki})$$
$$+\sum_{g=1}^{M}\psi_g\left(\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{n_{\min}}S_{kj}(i)\cdot I_{ij}^{g}-I_{TH}^{g}\right) \tag{18}$$

Here $\mu_{kj}(i), \rho_{ki}, \xi_{ki}, \psi_g$ are non-negative Lagrangian multipliers. The KKT conditions are

$$\partial_{S_{kj}(i)}L = C'_{kij}\left(\frac{S_{kj}(i)}{\alpha_{ki}}\right)-\mu_{kj}(i)+\sum_{g=1}^{M}\psi_g\cdot I_{ij}^{g}=0 \tag{19}$$

$$\partial_{\alpha_{ki}}L=-\sum_{j=1}^{n_{\min}}\left[C_{kij}\left(\frac{S_{kj}(i)}{\alpha_{ki}}\right)-\frac{S_{kj}(i)}{\alpha_{ki}}\cdot C'_{kij}\left(\frac{S_{kj}(i)}{\alpha_{ki}}\right)\right]$$
$$+v_i+\rho_{ki}-\xi_{ki}=0 \tag{20}$$

$$\mu_{kj}(i)\cdot(0-S_{kj}(i))=0 \tag{21}$$

$$v_i\cdot\left(\sum_{k=1}^{K}\alpha_{ki}-1\right)=0 \tag{22}$$

$$\rho_{ki}\cdot(\alpha_{ki}-1)=0 \tag{23}$$

$$\xi_{ki}\cdot(0-\alpha_{ki})=0 \tag{24}$$

$$\psi_g\cdot\left(\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{n_{\min}}S_{kj}(i)\cdot I_{ij}^{g}-I_{TH}^{g}\right)=0 \tag{25}$$

By utilizing (1) and (19) $S^{*}_{kj}(i)$ is expressed as follows:

$$S^{*}_{kj}(i)=\alpha_{ki}\cdot\left(\frac{1}{Ln2\cdot\left(\sum_{g=1}^{G}\psi_g\cdot I_{ij}^{g}-\mu_{kj}(i)\right)}-\frac{N_0}{\lambda_{kj}^{2}(i)}\right) \tag{26}$$

Here $\mu_{kj}(i)=0$ in the following cases

$$\frac{N_0}{\lambda_{kj}^{2}(i)}\le\frac{1}{Ln2\cdot\left(\sum_{g=1}^{G}\psi_g\cdot I_{ij}^{g}\right)} \tag{27}$$

Thus Equation (26) can be written as

$$S^{*}_{kj}(i)=\alpha_{ki}\cdot\left(\frac{1}{Ln2\cdot\left(\sum_{g=1}^{G}\psi_g\cdot I_{ij}^{g}\right)}-\frac{N_0}{\lambda_{kj}^{2}(i)}\right) \tag{28}$$

If

$$\frac{N_0}{\lambda_{kj}^{2}(i)}>\frac{1}{Ln2\cdot\left(\sum_{g=1}^{G}\psi_g\cdot I_{ij}^{g}\right)} \tag{29}$$

$$S^{*}_{kj}(i)=0 \tag{30}$$

Then in this considered case we can conclude as follows:

$$S^{*}_{kj}(i)=\alpha_{ki}\cdot\left(\frac{1}{Ln2\cdot\left(\sum_{g=1}^{G}\psi_g\cdot I_{ij}^{g}\right)}-\frac{N_0}{\lambda_{kj}^{2}(i)}\right) \tag{31}$$

From Equation (31), transmission power can be computed as follows:

$$P^{*}_{kj}(i)=\left(\frac{1}{Ln2\cdot\left(\sum_{g=1}^{G}\psi_g\cdot I_{ij}^{g}\right)}-\frac{N_0}{\lambda_{kj}^{2}(i)}\right) \tag{32}$$

Joint spectrum and power assignment constraint can be defined from Equation (20) as follows:

$$G_{ijk}=-\sum_{j=1}^{n_{\min}}\left[C_{kij}\left(\frac{S_{kj}(i)}{\alpha_{ki}}\right)-\frac{S_{kj}(i)}{\alpha_{ki}}\cdot C'_{kij}\left(\frac{S_{kj}(i)}{\alpha_{ki}}\right)\right]$$
$$=v_i+\rho_{ki}-\xi_{ki} \tag{33}$$

Furthermore when $\alpha_{ki}=1$, then $\xi_{ki}=0$, and $\rho_{ki}\ge 0$. Similarly if $0<\alpha_{ki}<1$, then $\xi_{ki}=0$ and $\rho_{ki}=0$. Thus Equation (33) can be written as follows:

$$G_{ijk}=\begin{cases}v_i, & if\ 0<\alpha_{ki}<1\\ \ge v_i, & if\ \alpha_{ki}=1\end{cases} \tag{34}$$

Finally, the subcarrier allocation is performed effectually by

$$\alpha_{ki}=\begin{cases}1 & if\ k^{*}=\operatorname{argmax}(G_{ijk})\\ 0 & \text{Else}\end{cases} \tag{35}$$

Based on Equation (35), spectrum for data transmission is allocated to SU which has the maximum spectrum efficiency and the transmission power is optimized based on Equation (31). Optimal channel allocation and transmission power allocation improve the data transmission rate in the network. The proposed EKKT method resolves the problem of interference. In addition, the problem of PAPR is reduced by adapting the QPSK modulation scheme. The PAPR is further minimized by selecting an optimal signal for transmission based on signal-to-noise ratio value. Thus the involvement of effective signal selection minimizes PAPR significantly.

Our proposed OFDM-based CRN-CSS with 5G network improves network throughput with transmission rate. This objective is achieved by eliminating interference in the network and by allocating optimal resource for data transmission.

5. PERFORMANCE EVALUATION

In this section, we evaluate our proposed OFDM-based CRN-CSS with 5G in terms of performance metrics. Our proposed OFDM-based CRN-CSS is modeled using the network simulator (NS-3.26) which is an event-based network simulator. This section comprises two subsections: simulation environment and comparative analysis. Each subsection can explained further.

5.1 Simulation Environment

As mentioned earlier, NS-3.26 simulation tool is utilized to analyze our proposed work. NS-3.26 supports the simulation of various types of networks and different communication protocols. Due to the high support in dynamic network simulation, we adapt NS-3.26 for our work. Implementation in NS-3 is realized with the assistance of C++ and python languages. The NS-3 library is wrapped by Python that delegates the parsing of C++ headers. Here users are allowed to interact with NS models through C++ while they interact with the core through python scripts. Our network environment comprises PUs, SUs, PBS, MIMO-FC, and SA.

The majority of significant simulation parameters are illustrated in Table 3. On the whole, our proposed work is performed over a frequency band which is assumed to be 5 GHz. In OFDM, 256 fast Fourier Transform (FFT) is considered. We have 192 subcarriers over 25 channels. Each channel bandwidth is varied from 10 to 20 MHz. 5 dB of noise figure is considered with a downlink distance of 300 m. Frame duration is 10 ms and OFDM symbol duration is 0.8s. Furthermore, QPSK modulation scheme with 2bits/symbol is adapted for OFDM transmission. The block size computed for QPSK scheme is 48. Channels are independent and identically distributed by Gaussian distribution with *zero mean* and *unit variance*. Noise variance assumed in our work is10^{-6}. Our proposed OFDM-based CRN-CSS with 5G network is designed by considering all the above parameters. Overall simulation environment of OFDM-based CRN-CSS with 5G network is illustrated in Figure 4.

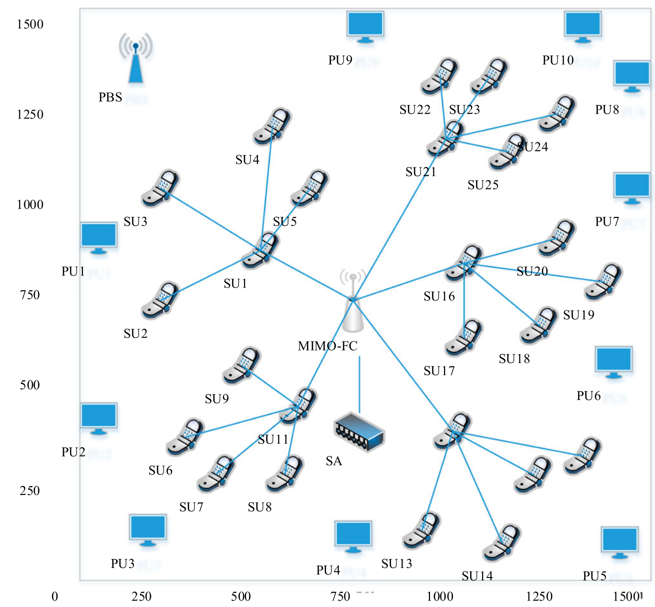

Figure 4: OFDM-based CRN-CSS with 5G scenario

Table 3: Simulation environment of OFDM-based CRN-CSS

Parameter			Value
Simulation area			1500×1500 m
Network entities	Number of PUs		10
	Number of SUs		25
	Number of PBS, SA		1
	MIMO-FC	Number of FC	1
		Number of antennas	4×4
Mobility model of SU			Random waypoint
Mobility speed			100 Mbps
Total time slot			1000
Sensing duration	Minimum		1 μs
	Maximum		10 μs
Noise figure			5 dB
Channel bandwidth			20 MHz
Number of channels			25
Transmission scheme			OFDM
Number of subcarriers			192
Modulation scheme			QPSK
Average transmission power			Up to 30 dBm
Packet size			50 KB
Total number of packets			500
Packet interval			100 ms
Simulation time			5 sec

Our considered simulation scenario has 25 SUs and 10 PUs with a single PBS and a single FC. Here five clusters are formed by the BK-means algorithm and each cluster consists of five SUs, *i.e.* equal cluster size. The cluster size is a variable and the number of clusters is also variable in accordance with the cluster size.

5.2 Comparative Analysis

In this subsection, we compare our OFDM-based CRN-CSS with significant previous research works such as RPA [30], location aware allocation [31], switched affine method [32], IA method [37], localization method [33], water-filling method [34], utility-based method [35], dynamic access method [38], and adaptive algorithm [39]. Comparisons are made in terms of detection probability, network utility, transmission rate, transmission power, capacity, and throughput.

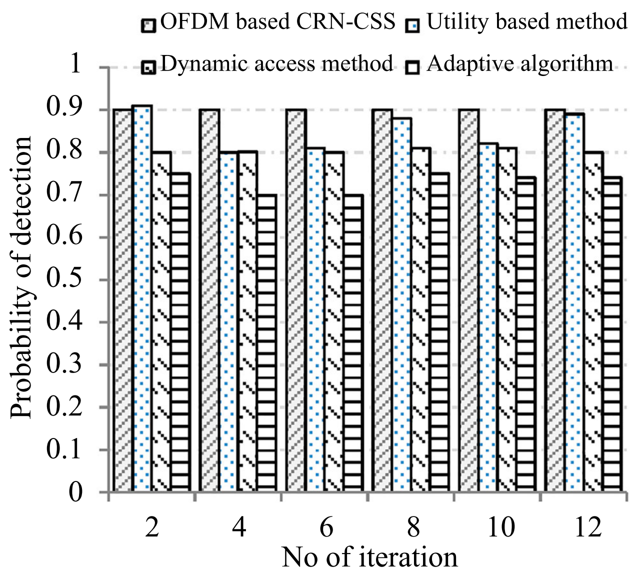

Figure 5: Analysis on Detection probability

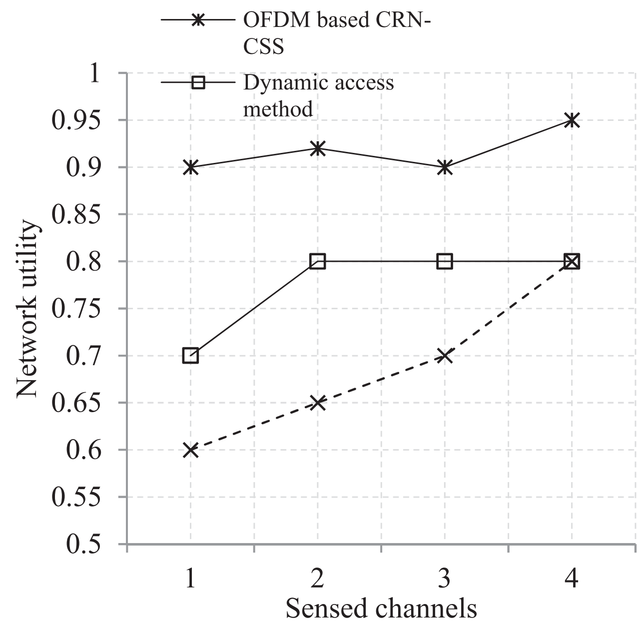

Figure 6: Analysis on Network utility

5.2.1 Effectiveness in Detection Probability

Detection probability measures the accuracy of spectrum-sensing method involved in CRN-CSS. Detection probability increases when idle channels are identified accurately by SUs. This metric measures the efficiency of spectrum-sensing method and the sensing channel assignment algorithm. When there is no interference is introduced during spectrum sensing, then the probability of its detection is high.

In Figure 5, detection accuracy is compared between the proposed OFDM-based CRN-CSS and the existing utility-based CSS. We can see that OFDM-based CRN-CSS achieves consistent detection probability about 0.9, *i.e.* 90% of detection accuracy. But in utility-based CSS, detection probability is oscillated between values of 0.8 and 0.9. In the second iteration, the result of utility-based CSS is 1% better than that of the proposed work. This shows that in the second iteration, the number of contributors is large in the network. However, when number of iteration increases the detection probability is minimized since the work strongly depends upon the number of contributors. In addition, the involvement of interference during spectrum sensing is also a major problem in this work. Besides, the dynamic access method and adaptive algorithm adopts the conventional spectrum sensing method which is not suitable for noisy environment. Thus both works achieve lower probability detection which is lower than 0.8. All of these limitations are resolved in our OFDM-based CRN-CSS with 5G network which improves detection accuracy. On the whole, the proposed OFDM-based CSS achieves 5% better detection probability than the previous work.

5.2.2 Effectiveness on Network Utility

Network utility is defined as the measure of SU satisfactory level. When all available resources, *i.e.* of PU network are utilized effectively by the SU network, then this metric is high. This metric evaluates the proposed CSS and resource allocation scheme jointly since the spectrum sensing and spectrum allocation play a vital role in network utility.

Figure 6 analyses the network utility in accordance with sensed channels. Here the proposed OFDM-based CRN-CSS achieves better network utility than the existing dynamic access method. This method shows the inability of dynamic access method in spectrum sensing and resource allocation. In OFDM-based CRN-CSS, the network utility is greater than 0.9 regardless of the number of sensed channels. In order to improve network utility it is necessary to identify idle channels accurately and also it is necessary to allocate required resource for transmission.

Likewise, adaptive algorithm-based resource allocation process consumes more time for power allocation. Thus this method is unable to achieve better network utility. In the proposed work, ESD-ED with TMSCA method improves sensing accuracy and EKKT method improves resource allocation efficiency. Thus OFDM-based CRN-CSS utilizes network resources in an effective manner.

5.2.3 Effectiveness on Transmission Rate

Transmission rate is the measure of number of bits transmitted per second over the network. Transmission rate

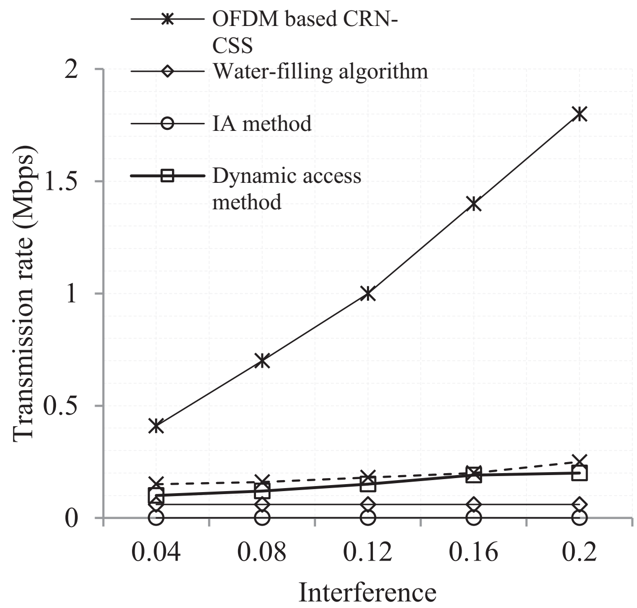

Figure 7: Achieved transmission rate

strongly depends upon available bandwidth and allocated spectrum resources.

In Figure 7, the achieved transmission rate in OFDM-based CRN-CSS is compared with that of the previous research works. Our proposed OFDM-based CRN-CSS outperforms all other previous works in transmission rate. Even with the increase in the probability of interference, transmission rate is increased in our work. This analysis shows the ability of our network to handle interference. This is because we allocate resource for data transmission in accordance with interference constraint which eliminates the problem of interference in the network. Furthermore, all idle channels are identified by our work accurately which increases the transmission rate. On average 1.1 Mbps transmission rate is achieved by the proposed work, whereas water filling algorithm provides 0.06 Mbps, RPA scheme provides 0.055 Mbps, and IA method provides 0.00015 Mbps transmission rate. The dynamic access method and adaptive algorithm achieve better transmission rate than that of other existing works, but fail to achieve better result than the proposed work. Involvement of effectual resource allocation process aids in better transmission rate. But the absence of effectual spectrum sensing and decision-making leads to inefficiency.

In Table 4, transmission rate is analyzed in terms of the number of bits transmitted per second in the network. Our proposed work achieves relatively higher transmission rate compared with other works. This analysis shows that proposed work has the ability to identify idle spectrum accurately, and allocation of reasonable resources without interference leads to high transmission rate.

Table 4: Transmission rate analysis

Method	Number of bits transmitted per second
RPA scheme	55,000
IA method	550
Water-filling algorithm	60,000
Dynamic access method	152,000
Adaptive algorithm	188,000
OFDM-based CRN-CSS	1,100,000

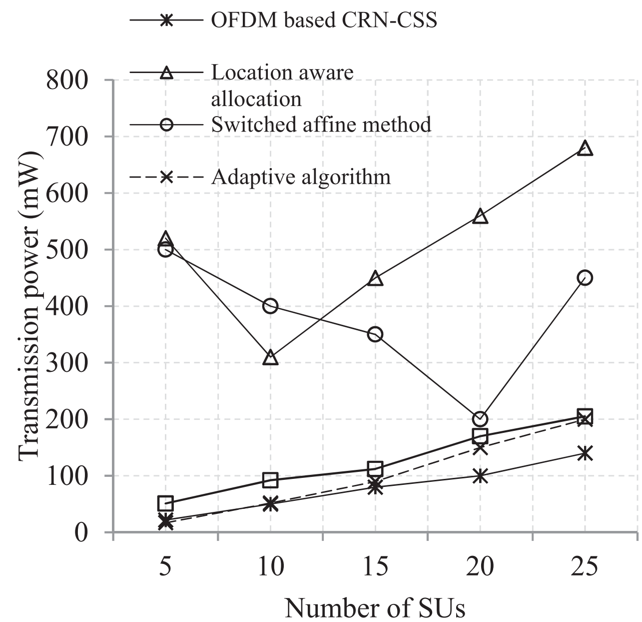

Figure 8: Allocated transmission power for SUs

5.2.4 *Effectiveness on Transmission Power*

This metric measures the power allocated for each SU for data transmission in the network. SU requires high transmission power when the available bandwidth is low and the involvement of interference and noise are high. When these problems, such as idle channel detection, interference, and noise are resolved, then SU transmission can be performed even with a minimum transmission power.

In Figure 8, the transmission power allocated for SUs is analyzed and compared with the previous works. In the proposed OFDM-based CRN-CSS, SUs require a small amount of power to achieve better transmission rate. Requirement of a small amount of power shows that the proposed work completely mitigates the interference problem and allocates optimum resource for data transmission. In addition, transmission is also improved by reducing PAPR through QPSK modulation scheme and effective signal selection. Average transmission power required by SU in OFDM-based CRN-CSS is 5.6 mW. In

Table 5: Transmission power allocated for five SUs

SUs	Transmission power (mW)
SU_1	4.4
SU_2	5.6
SU_3	6
SU_4	4
SU_5	8

the previous works, location-aware allocation, switched affine method, adaptive algorithm, and dynamic access method, SU requires transmission power 27.2, 18, 8, and 20 mW, respectively.

In Table 5, the transmission power allocated for five SUs in a cluster is illustrated. Transmission power required by SU in our work is low since there is no interference during transmission and an optimal spectrum is allocated for transmission. Even with a small amount of transmission power, our proposed work achieves a better transmission rate.

5.2.5 *Effectiveness on Capacity*

Network capacity is defined as the amount of traffic that can be handled by the network at given time. When network is able to support a large amount of data, then the network capacity will be increased. Network capacity is increased with the decrease in congestion and interference.

The analysis on network capacity is illustrated in Figure 9. The capacity of the proposed OFDM-based CRN-CSSS network increases with an increase in distance between PU and SU which minimizes interference during data transmission. Existing localization method fails to achieve better capacity since it involves with localization errors which leads to ineffectual spectrum utilization. Optimal resource allocation improves network capacity even in large distance. However, even with optimal resource allocation process, dynamic access method and adaptive algorithm are not able to achieve better capacity. This is because, network capacity depends upon network management, spectrum sensing, and resource allocation. Thus the absence of any effectual process will affect the network capacity. When the distance between PU and SU is 1 km, then the capacity achieved by localization method is 1.8 Mbps, while the proposed work achieves capacity up to 9 Mbps. Thus the proposed work achieves better results in the network capacity.

5.2.6 *Effectiveness in Throughput*

Throughput is an important measure of network performance which defines the amount of data transmitted from source to destination in a given period of time.

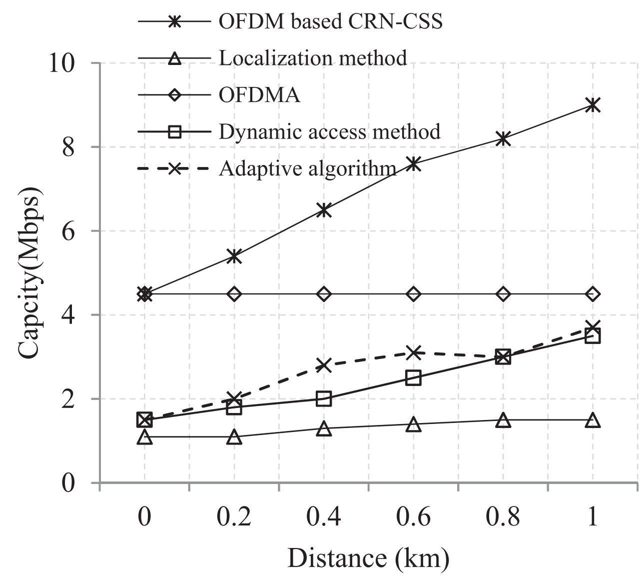

Figure 9: Network capacity analysis

Table 6: Throughput result obtained

Work	Number of packets transmitted	Number of packets received successfully
RPA	500	130
Dynamic access	500	220
Adaptive algorithm	500	150
Proposed	500	400

When the throughput is high, then it can be found that transmission is efficient in the network.

Throughput efficiency of the proposed work is analyzed in Figure 10. From the graphical analysis, we can see that proposed work achieves better throughput efficiency than that of previous works. It shows gradual increase in throughput with an increase in sensing time. The increase in sensing time results in high sensing accuracy which leads to high throughput. In detail, to achieve better throughput it is necessary to identify available spectrum and requires optimal resource for data transmission. However, previous works are not able to achieve better throughput due to the lack of sensing efficiency and resource allocation efficiency.

A brief analysis on throughput efficiency is depicted in Table 6. Here throughput efficiency is measured for 500 data packets. In our work, 80% of packets reached their destination without any packet loss. Thus our network minimizes interference between SU and PU. However, the previous works are not able to transmit half the amount of packet successfully. Our proposed OFDM-based CRN-CSS is twice time better than the previous research works.

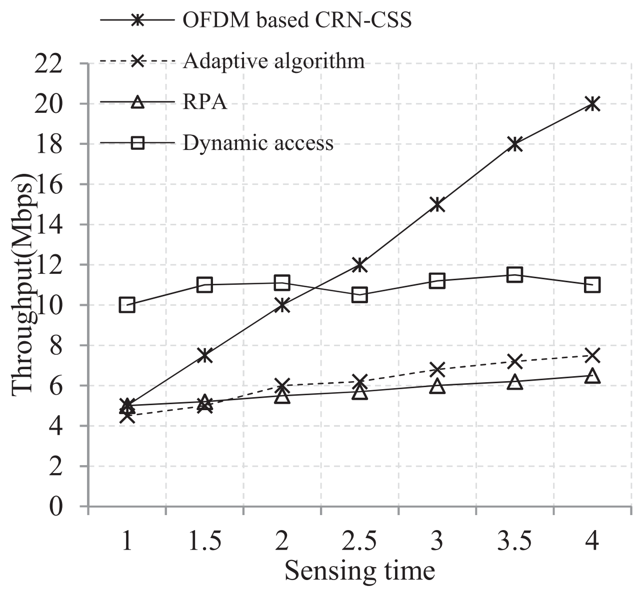

Figure 10: Throughput efficiency based on sensing time

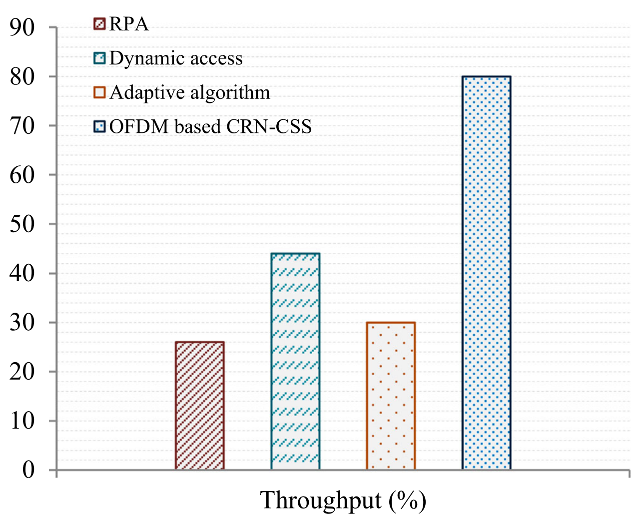

Figure 11: Analysis on throughput efficiency

Table 7: Overall analysis

Parameter	Dynamic access method	Adaptive algorithm	OFDM-based CRN-CSS
Detection probability	0.8	0.73	0.9
Network utility	0.75	0.68	0.91
Transmission rate (Mbps)	0.152	0.18	1.06
Transmission power (mW)	25.2	20.36	15.65
Capacity (Mbps)	2.4	2.7	6.9
Throughput (%)	44	30	80

Throughput efficiency of the proposed work is shown in Figure 11. Here the proposed OFDM-based CRN-CSS achieves high throughput compared with the previous works. Thus our proposed CRN-CSS network supports high throughput with a high transmission rate.

In Table 7, overall analysis on the proposed and existing work is illustrated, here we can see that the proposed OFDM-based CRN-CSS achieves better results in all aspects than dynamic access, method, and adaptive algorithm. Involvement of efficient cluster formation, spectrum sensing, decision-making, and resource allocation improve the network performance.

6. CONCLUSION

In this paper, we proposed a novel OFDM-based CRN-CSS with 5G network to improve the transmission performance of cognitive network. The proposed network comprises MIMO-FC that supports a huge number of users with high data rate. To preserve cooperativeness among SUs, BK-means algorithm is proposed in which equal size clusters are formed. For each cluster, a set of channels are assigned and each SU is provided with sensing channel at each slot by the TMSCA method. Involvement of the TMSCA method ensures interference-free spectrum sensing for SUs. ESD-ED method improves sensing accuracy even in noise uncertainties. With accurate sensing reports of SUs, FC made global decision by CSWG with the support of sensing report of SA. Finally, resource allocation is carried out by EKKT method with joint multiuser spectrum and power allocation. Resource allocation is performed with the knowledge of channel state, interference constraint, and power constraint. Furthermore, OFDM transmission with QPSK modulation scheme is adapted to reduce PAPR and to improve transmission rate. Extensive simulation in ns-3 shows promising results in detection probability, network utility, transmission rate, transmission power, capacity, and throughput. In future, we have interested to extend this work in large scale environment. We are also intended to reduce PAPR further reduced by signaling methods to achieve high throughput.

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Authors

M. Meena received the ME degree in Applied Electronics Engineering from Anna University. She is currently an Assistant Professor and a part-time PhD research scholar at Vels University. Her research interests include computer networks, wireless networking, cognitive radio network, and software defined radio, etc. She has published 11 papers in Scopus-indexed journal.

Corresponding author. Email: meena.se@velsuniv.ac.in.

Dr. V. Rajendran received his MTech in Physical Engineering from Indian Institute of Science, Bangalore, India and received hid PhD degree on Electrical and Electronics Engineering from Chiba University, Japan in 1981 and 1993, respectively. He is currently, a professor and the head of the department of Electronics and Communication Engineering in Vels Institute of Science and Technology, Pallavaram, Chennai, India. He was awarded MONBUSHO Fellowship, Japanese Govt. Fellowship (1988–1989) through the Ministry of Human Resource and Development, Govt. of India. He was elected twice as Vice Chairman – Asia of Execution Board of Data Buoy Co-operation Panel (DBCP) of Inter-Governmental Oceanographic Commission (IOC)/World Meteorological Organization (WMO) of UNSCO, in October 2008 and September 2009, respectively. He was a Life fellow of Ultrasonic Society of India, India (USI)in January 2001. He was a Life fellow of Institution of Electronics and Telecommunication Engineering (IETE), India, in January 2012. His area of interest includes cognitive radio and software-defined radio communication, antennas and propagation and wireless communication, under water acoustic signal processing and under water wireless networks. He has published 52 papers in web of science and Scopus-indexed journal.

Email: director.ece@velsuniv.ac.in.