Clustering-Based Spectrum Sharing Strategy for Cognitive Radio Networks

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***Abstract*— In this paper, we propose a clustering-based resource allocation (RA) scheme for the multiuser orthogonal frequency division multiplexing (OFDM)-based cognitive radio network, where we aim to maximize the sum capacity of the secondary users (SUs) subject to practical constraints in wireless environment. Our general RA optimization task leads to a challenging mixed integer programming problem that is computationally intractable. We first introduce a simple and efficient clustering method to divide all the SUs into multiple groups based on their mutual interference degrees, where the SUs in different groups can share the same OFDM subchannels to improve spectrum utilization efficiency, while the SUs with heavy mutual interference cluster together in the same group and employ different subchannels to alleviate their mutual interference. Then we develop efficient radio RA algorithms to maximize the sum rate of the SUs in each cluster. A user-oriented subchannel assignment method is presented to remove the awkward integer constraints of the formulated RA problem, followed by a fast power distribution algorithm that can work out optimal solutions with an approximate linear complexity. Simulation results indicate that our proposed RA scheme can improve the throughput of the SUs significantly as compared with other methods. Moreover, our proposed RA algorithms converge stably and quickly.**

***Index Terms*— Clustering, cognitive radio, convex optimization, resource allocation, spectrum sharing.**

I. Introduction

IN RECENT years telecommunication industry witnessed a boom in mobile wireless services, which are closely linked with our daily life including personal entertainment, studying, as well as finance, education and other industry sectors. The fourth generation (4G) mobile communication network can provide data rates of 1 Gb/s for low mobility and 100 Mb/s for high mobility. However, with the challenges of multi-form applications, huge numbers of subscribers,

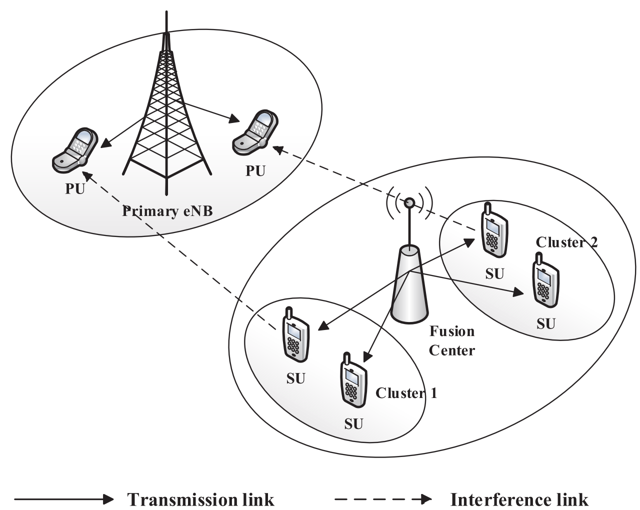

Fig. 1. Illustration of our considered system.

increased indoor traffic, massive power consumption and faster Internet access on the move, the 4G network can not satisfy the urgent need and advanced fifth generation (5G) mobile communication systems have been discussed in academia and industry [1]. Different types of network architectures, e.g., heterogeneous networks (HetNets) with densely deployed small cells, cloud radio access networks, and advanced signal processing technologies, e.g., massive MIMO, are introduced to meet the requirements mentioned above [2]–[5]. Besides, in the forthcoming 5G networks, we are also witnessing a dramatic growth in the demand of radio spectrum resources. Due to the limitation of spectrum availability, the need to lower the waste of spectrum resources and improve the spectrum utilization efficiency has gained accelerating interest.

Cognitive radio (CR) is a promising method to achieve this goal. The CR technology offers a natural solution to deal with random and diverse traffic demands in mobile networks, which can exploit scarce radio spectrum resource fully and alleviate the burden on mobile service providers. In essence, CR is a novel radio spectrum resource management paradigm where the secondary users (SUs) in the CR network can access vacant spectrum holes opportunistically without causing unacceptable interference to the primary users (PUs) in the licensed system. The SUs possess cognitive capability [6], [7] to collect spectrum sensing information and report sensing results to the fusion center (FC) in the CR network as shown in Fig. 1. Then the CR system is aware of its surrounding radio environment and uses radio resource in an intelligent

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manner [8]. Since the CR network usually coexists with the primary network, it is important to develop efficient cognitive radio resource management scheme [9] which jointly takes practical limitations into consideration to provide both SUs and PUs performance-guaranteed services.

The FC in the CR network can manage the transmission of the SUs and exchange signalling information with the access nodes in the primary network just like eNBs in the LTE-Advanced system. With the assistance of the FC and reliable spectrum sensing, the SUs can access vacant spectrum to transmit data opportunistically. However, as the number of subscribers increases explosively in the future, the CR network has to serve more and more SUs with limited vacant spectrum. If the CR users transmit over the same subchannel, it would lead to severe mutual interference just like the intercell interference in conventional cellular systems. More seriously, the SUs who suffer strong interference introduced by others can not properly perform radio environment cognitive procedure and yield wrong spectrum sensing results, which would deteriorate the performance of both the CR network and the primary one significantly. Thus, interference issue would be the bottleneck that limits the development of future CR network. Though there are many advanced techniques to tackle the intercell interference in the conventional cellular systems, however, as far as the authors have known, the interference management among the SUs in the CR network is still an open question, which is the motivation of this work.

In this paper, we investigate the scenario that the SUs with orthogonal frequency division multiplexing (OFDM) modulation can access the licensed spectrum used by the PUs opportunistically to satisfy their pre-defined transmission rate demands. A clustering technique is introduced to tackle the interference among the SUs by coordinating their transmissions which is motivated by the co-tier interference elimination techniques in the HetNet. Specifically, the SUs are divided into disjoint clusters where all subchannels are available to each cluster to enhance spectrum utilization efficiency. The subchannel and power allocation procedures are performed in each cluster to maximize the sum rate of the SUs while satisfying interference constraints of the PUs and the rate demands of the SUs. Since the optimization task we formulate is a mixed integer nonlinear programming (MINLP) that is hard to solve, we address it with a two-stage procedure: clustering and radio resource allocation. In the clustering procedure, the SUs with heavy mutual interference are grouped into the same cluster and use different subchannels to eliminate mutual interference. After obtaining the clustering configuration, subchannel allocation and power distribution are performed by a cluster center (CC) selected from the SUs in each cluster. The rate requirements of the SUs and a coarse proportional fairness among them can be roughly satisfied by the subchannel allocation procedure, then a fast algorithm is developed to yield optimal power distribution with near linear complexity. Numerical results validate the effectiveness and efficiency of our proposed resource allocation (RA) scheme.

The contributions of this work are summarized as follows:

- We propose a general interference management and RA scheme for the CR network, which can improve the system throughput significantly. The proposed scheme sheds insights on how to fulfill the potential of the CR technology to meet the ever-increasing traffic demands in future mobile networks.
- We introduce a simple and efficient clustering algorithm to address the mutual interference issue among the SUs and improve the spectrum utilization efficiency. The proposed clustering algorithm can adjust the number of clusters and change the cluster size to deal with different constraints arising in practical networks, which outperforms other clustering algorithms as can be seen from simulation results.
- We develop fast algorithms to tackle subchannel assignment and power distribution problems for each cluster with reasonable complexity, which is quite promising for practical applications.

The rest of this paper is organized as follows. Section II is the related works. In Section III, we illustrate system model and formulate optimization task. In Section IV, we discuss the clustering issue and introduce an efficient clustering algorithm. Section V and VI give efficient heuristic subchannel allocation and fast optimal power distribution algorithms, respectively. Simulation results and discussions are presented in Section VII and conclusions are drawn in Section VIII.

II. Related Work

As can be found in the literature, many RA algorithms for the CR networks have been exploited along with the progress of the CR technology during the past two decades [10]. An early survey on dynamic RA in the CR networks can be found in [11] and references therein give details about different algorithms. In [12], Lyapunov optimization is introduced to perform online RA algorithm that meets the desired objectives and provides explicit performance guarantees for a cognitive network with static PUs and mobile SUs. Ge and Wang [13] show that fast optimal power distribution for OFDM-based CR networks can be obtained by exploiting the structure of the problem. A quality of experience (QoE) driven channel allocation method is proposed in [14], where the SUs collect historical QoE data under different primary channels and send them to CR base stations so that the available channel resources can be assigned to the SUs based on their QoE expectations by these base stations. Imperfect spectrum sensing issue is investigated in [15], where a heterogeneous CR system is modeled to support diverse services required by the SUs. In [16], cooperative relays are introduced to enhance the performance of the CR networks and efficient RA algorithms are also developed. Due to the environment and operation expenditure issues arising from the sharply increasing energy consumption, energy-efficient RA for the CR network attracts attention recently [17], where energy efficiency of the CR system is usually taken into consideration [18], [19]. A chance-constrained energy-efficient RA scheme is proposed in [20], where the probability interference constraint is addressed by Bernstein approximation.

The issues investigated in these works mainly focus on how to yield promising solutions to the RA problems with different targets in the CR network where the SUs are generally served by a single cognitive base station. However, the throughput of the CR system can not be exploited fully due to the limited spectrum reuse efficiency. It is necessary to enable the SUs to share the same subchannels provided that the interference among them is light, just as the interference management in the cellular system which has been studied in the literature. In [21], the basic concept of the cooperative small cell network architecture, as well as the related technical aspects, are presented to provide high capacity for hotspots with interference mitigation. Clustering-based interference mitigation schemes have been discussed for the cellular networks. In [22], a semi-distributed hierarchical interference management scheme is proposed, which is based on joint clustering and radio resource allocation for the femtocells. In [23], an admission control algorithm based on clustering is proposed to meet the Quality of Service (QoS) requirements of users in an OFDMA femtocell network. Joint base station clustering and beamformer design is proposed to deal with the interference management problem in a multicell MIMO HetNet in [24], where a nonsmooth utility maximization task is formulated to select a few serving base stations for each user without incurring much loss in terms of system throughput and user fairness. In [25], two inter-cluster interference management methods are studied through spectrum reuse and user's power control.

Though there are quite a few works on the clustering-based interference management in the cellular systems, however, they can not be extended straightforwardly to the CR scenarios. First, the infrastructure of the CR system is low-cost and simpler as compared to that of the conventional cellular system so complex signal processing technique is usually unavailable in the CR system; second, in contrast with the critical coverage requirement in the cellular network, the CR system needs not to provide seamless coverage but ample opportunity for the SUs who request data transmission. In other words, it is profitable to employ proper clustering methods for the SUs to enhance the performance of the CR system. As a result, exploiting simple but efficient clustering and RA algorithms is necessary and promising to improve the performance of the CR networks, which is the motivation of this work.

III. System Model

A. Network Model

Consider a multiuser OFDM-based CR network with K SUs, denoted by $\mathcal{K} = \{1, 2, \ldots, K\}$, coexisting with L PUs in a licensed system as shown in Fig.1. There is a fusion center (FC) which performs channel state information (CSI) collection from the SUs and makes a decision on the presence or absence of the primary signals [26]. Specifically, each SU senses the primary signals periodically. When the SUs capture the signals, they report their observation to the FC. When the primary signals are absent, the CR network is allowed to utilize the channel for data transmission; otherwise, the channel is not available for the SUs in the time duration. Assume that perfect CSI is available at the transceivers of the SUs, which is sent to the subcarrier and power allocation module through FC. The whole spectrum W is divided into N OFDM subchannels in the CR system, denoted by $\mathcal{N} = \{1, 2, \ldots, N\}$. Denote the signal-to-interference-plus-noise (SINR) of the the kth SU on the nth OFDM subchannel with unit power as $h_{k,n}$,

$$h_{k,n} = \frac{g_{k,n}}{\Gamma(N_0 W/N + \sum_{l=1}^{L} I_{l,k,n}^{PS})}, \tag{1}$$

where $I_{l,k,n}^{PS}$ is the interference introduced to the kth SU on the nth OFDM subchannel by the lth PU with unit transmission power, N_0 is noise power of each subchannel, $g_{k,n}$ is the power gain of the kth SU on the nth OFDM subchannel with unit power. Γ is the SINR gap, which can be represented as $\Gamma = -\ln(5\text{BER})/1.5$ for an uncoded multilevel quadrature amplitude modulation (MQAM) with a specified bit-error-rate (BER) [27].

The transmission rate of the kth SU on the nth subchannel is

$$r_{k,n} = \frac{W}{N} \log_2(1 + p_{k,n} h_{k,n}), \tag{2}$$

where $p_{k,n}$ is the transmission power of the kth SU on the nth subchannel. Denote R_k as the sum rate of the kth SU,

$$R_k = \sum_{n=1}^{N} \rho_{k,n} \frac{W}{N} \log_2(1 + p_{k,n} h_{k,n}), \tag{3}$$

where $\rho_{k,n}$ can be either 1 or 0, informing whether the kth SU occupies the nth subchannel or not.

B. Interference Model

To reduce mutual interference among the SUs, the SUs in the CR network can be divided into disjunct clusters. Denote the set of clusters as $\mathcal{C}$. An SU cluster $\mathcal{C}_m \subseteq \mathcal{K}, \forall m \in 1, 2, \ldots, |\mathcal{C}|$, $\cup_{m=1}^{|\mathcal{C}|} \mathcal{C}_m = \mathcal{K}$, and $\cap_{m=1}^{|\mathcal{C}|} \mathcal{C}_m = \emptyset$. Note that the entire set of subchannels are available to the SUs in a single cluster and the SUs within the same cluster would transmit data over different subchannels simultaneously. That is, there is no mutual interference among the SUs in the same cluster. However, cluster size is an important parameter to make a trade-off between the share in the available spectrum and the co-tier interference among different clusters. If the cluster size is very small, the number of available subchannels for each user within a cluster is relatively large but the co-tier interference among clusters may be serious. In contrary, if the cluster size is larger, the co-tier interference between adjacent clusters could be minimized, however, the share of subchannels for each cluster would be smaller. Intuitively, the SUs with negligible mutual interference are grouped into different clusters so they can use the same subchannel for transmission. To simplify analysis, we can assume that the co-tier interference between two clusters is negligible.

To cope with the interference to the PUs introduced by the SUs, we adopt the concept of *reference user* [28]. For each SU cluster $\mathcal{C}_m$, we define the PU who receives the heaviest interference from the $\mathcal{C}_m$ as the *reference user* of the cluster, which is denoted as PU_m:

$$PU_m = \arg\max_{l \in \mathcal{L}} \sum_{k \in \mathcal{C}_m} \sum_{n \in \mathcal{N}} \frac{P_t \cdot |\mathcal{C}_m|}{N} \cdot |\tilde{h}_{l,n}^{k}|^2, \tag{4}$$

where $\tilde{h}^k_{l,n}$ is the channel gain of the interference link from the SU k to the PU l on the nth subchannel and $\frac{P_t \cdot |\mathcal{C}_m|}{N}$ represents the average power distribution on each subchannel in the cluster $\mathcal{C}_m$. For simplicity, let $\widetilde{H}^k_{l,n} = |\tilde{h}^k_{l,n}|^2$.

To guarantee the QoS of each PU, the interference received by PU_m cannot exceed a given threshold $I^{th}_{PU_m}$. The threshold $I^{th}_{PU_m}$ varies based on the scale of the cluster $\mathcal{C}_m$, that is,

$$I^{th}_{PU_m} = I^{th} \cdot |\mathcal{C}_m|, \tag{5}$$

where I^{th} the average interference power threshold of a PU.

C. Problem Formulation

We try to maximize the sum rate of the SUs while keeping the interference to each PU below its predefined threshold. Mathematically, the optimization problem can be formulated as follows:

$$\begin{aligned}
&\max_{\mathcal{C}_m, p_{k,n}, \rho_{k,n}} \sum_{\mathcal{C}_m \in \mathcal{C}} \sum_{k \in \mathcal{C}_m} \sum_{n \in \mathcal{N}} \rho_{k,n} r_{k,n} \\
&s.t. \mathrm{C1}: R_k \geq R_{min}, \quad \forall k \in \mathcal{K}, \\
&\quad \mathrm{C2}: \sum_{n=1}^{N} \rho_{k,n} p_{k,n} \leq P_T, \quad \forall k \in \mathcal{K}, \\
&\quad \mathrm{C3}: \sum_{k \in \mathcal{C}_m} \sum_{n \in \mathcal{N}_l} p_{k,n} \widetilde{H}^k_{PU_{m,n}} \leq I^{th}_{PU_m}, \forall l, \quad \forall \mathcal{C}_m \in \mathcal{C}, \\
&\quad \mathrm{C4}: \sum_{k \in \mathcal{C}_m} \rho_{k,n} = 1, \quad \forall n \in \mathcal{N}, \ \mathcal{C}_m \in \mathcal{C}, \\
&\quad \mathrm{C5}: \cup_{m=1}^{|\mathcal{C}|} \mathcal{C}_m = \mathcal{K}, \\
&\quad \mathrm{C6}: \cap_{m=1}^{|\mathcal{C}|} \mathcal{C}_m = \emptyset, \\
&\quad \mathrm{C7}: p_{k,n} \geq 0, \quad \forall k \in \mathcal{K}, \ n \in \mathcal{N}, \\
&\quad \mathrm{C8}: \rho_{k,n} \in \{0, 1\}, \quad \forall k \in \mathcal{K}, \ n \in \mathcal{N}.
\end{aligned} \tag{6}$$

R_{min} is the minimal rate constraint of the SUs in each cluster. $\rho_{k,n}$ can only be either 1 or 0, indicating whether the nth subchannel is occupied by the kth SU or not, P_T is the power budget of each SU. C1 is the rate requirement of the SUs. C2 is the power limitation. C3 is the interference constraint for each cluster, which enforces that the total received interference at PU_m below $I^{th}_{PU_m}$. C4 is the exclusion constraint, indicating the nth subchannel can only be occupied by at most one SU in the cluster $\mathcal{C}_m$. C5 means that the entire set of clusters $\mathcal{C}$ form the SU set $\mathcal{K}$. C6 indicates that the set of clusters are disjoint. C7 and C8 are intuitive.

IV. Efficient Clustering Algorithm

In this section, we introduce an efficient clustering scheme to reduce mutual interference among SUs in different clusters, which is inspired by the dynamic clustering method, isodata method, developed in [29]. The FC in the CR network gathers information about average channel gains of all the SUs and performs the clustering procedure for them, and then a group of candidate cluster configurations can be obtained. After this, the FC sends the clustering results to the SUs through common channels. Besides, there is an SU acting as cluster center (CC) within each cluster, who performs subchannel allocation and power distribution for the cluster members (CMs) and reports the sum achievable rate to the FC. The FC guarantees the cluster configuration yielding the highest sum rate be the best cluster configuration.

For a given number of SUs, all possible clustering configurations could be found by exhaustive search. With the subchannel allocation and power distribution, the cluster configuration which yields the highest system capacity is the optimal one. For K SUs, the number of possible ways to cluster them is given by the second kind of Stirling number [30]:

$$\sum_{i=1}^{K} \frac{1}{i!} \sum_{j=0}^{i} (-1)^{i-j} j^K \approx O(K^K).$$

Obviously, the number of possible cluster configurations (Bell Number) grows exponentially with the number of the SUs. Thus, it is impractical to obtain the optimal cluster configuration by exhaustive search even for medium size of SUs.

Our objective is to construct a weighted interference graph $G(V, E, W)$ on the basis of the topology of the given CR network. The vertex set is represented by $V = \{v_1, v_2, \ldots, v_K\}$ where each vertex denotes an SU node and $(i, j) \in E$ is the set of edges between two vertices. W is the weight set, every edge (i, j) is given a non-negative weight $w_{i,j}$, which represents the interference degree between SU i and SU j. In fact, two SUs are severely interfering to each other if they have high channel gain $g^n_{i,j}$ between each other. Therefore, we can make $w_{i,j}$ in a direct proportion to $g^n_{i,j}$ by setting $w_{i,j} = g^n_{i,j}$.

After obtaining an interference graph, the SUs should be assigned to disjoint clusters based on the weighted interference graph. As aforementioned, the number of clusters and the cluster size are important parameters to make a trade-off between the share in the available spectrum and the co-tier interference. Our proposed clustering scheme can change the number of clusters and cluster size as the SU density differs, which outperforms some traditional clustering algorithms based on a given number of clusters.

Given the weighted interference graph $G(V, E, W)$ with K SUs and the edge weight $w_{i,j}$ for each edge (v_i, v_j), the optimal clustering problem can be formulated as follows:

$$\begin{aligned}
&\max \sum_{v_i \in C_m, v_j \in C_n, m \neq n} w_{ij} \\
&s.t. \mathrm{C1}: \cup_{m=1}^{N_c} C_m = V, \\
&\quad \mathrm{C2}: C_m \cap C_n = \emptyset, \quad m, n \in 1, 2, \ldots, N_c,
\end{aligned} \tag{7}$$

where N_c is the number of clusters.

Eq. (7) has been proved to be an NP-hard problem which is intractable. We propose a heuristic clustering algorithm to obtain the clustering configuration. The procedure initializes by setting up the weighted interference graph and then a set of initial CCs $c_1, c_2, \ldots, c_{N_c}$ will be selected accordingly. The rest SUs are then attached to their own clusters as CMs. An SU x belongs to cluster i when $w_{x,i} > w_{x,j}, i \neq j$, where $w_{x,i}, w_{x,j}$ indicate the interference degree between SU x and CC i, SU x and CC j, respectively. After this, we update the

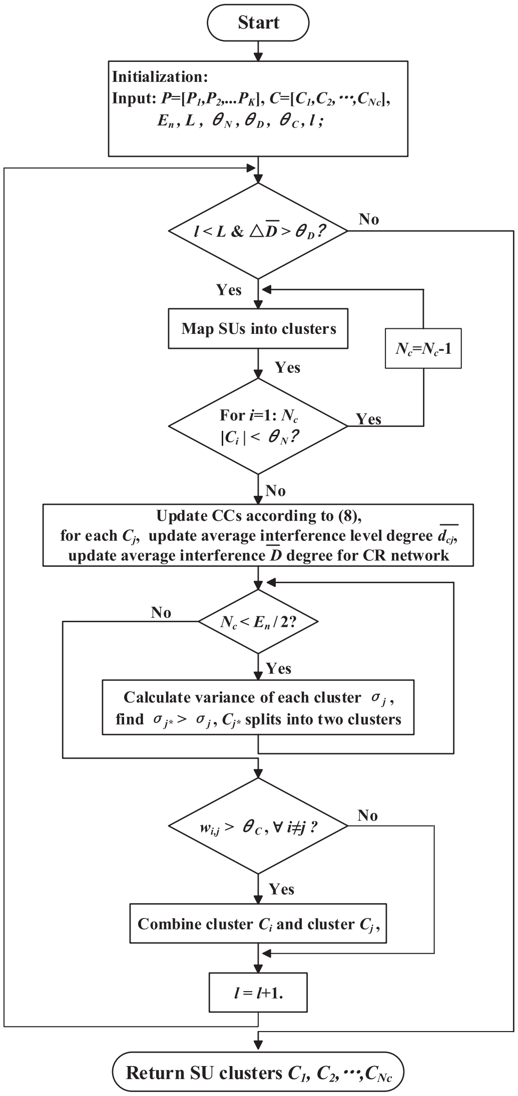

Fig. 2. Flowchart of the clustering algorithm.

CCs by

$$c_j = \frac{1}{\mid C_j \mid} \sum_{k \in C_j} P_k, \ \ j = 1, 2, \ldots, N_c, \tag{8}$$

where P_k represents the position of SU k in the weighted interference graph.

Then we perform merge or split mechanism. If the distance between two CCs is smaller than the previously set threshold, the two clusters will be merged into one cluster; otherwise, if the variance of a cluster or the cluster size is beyond the previously set threshold, we will divide the cluster into two clusters. The detailed description of our proposed clustering algorithm is given in Fig. 2 and the description of the parameters is given in Table I. As can be seen from Fig. 2, this process repeats until the stopping criteria is met: the maximum iterations have been reached or $\triangle\overline{D} \le \theta_D$, where $\overline{D} = \frac{1}{N_c}\sum_{j=1}^{N_c}\overline{d_{c_j}}$ represents the average interference degree of the CR network. $\overline{d_{c_j}} = \frac{1}{|C_j|}\sum_{k \in C_j} w_{k,c_j}$ represents the average interference degree between CMs and CC in the cluster C_j. The complexity of the proposed SUs clustering algorithm can be controlled by setting the number of maximum iterations and the average interference degree of the CR network. Furthermore, the FC can be equipped with power computing capacity, the proposed clustering scheme is practical for applications.

TABLE I
PARAMETER DESCRIPTION

E_n	Expected minimal cluster number
L	Maximal iterations
θ_N	Minimal cluster size
θ_D	Average interference degree threshold of CR network
θ_C	Allowed maximal interference degree between two CCs

V. SUBCHANNEL ALLOCATION SCHEME

When obtaining the clustering results, the *reference user* of each cluster and the interference threshold of it can be obtained by (4) and (5). Based on the assumption on the co-tier interference, the resource allocation for each cluster is independent of the other clusters. We try to maximize the sum rate of all SUs within each cluster while keeping the interference to each PU below its predefined threshold. For cluster $\mathcal{C}_m$, the resource allocation problem is

$$\begin{aligned} &\max_{r_{k,n}, \rho_{k,n}} \sum_{k \in \mathcal{C}_m} \sum_{n \in \mathcal{N}} \rho_{k,n} r_{k,n} \\ &s.t. \text{C1}: R_k \ge R_{min}, \forall k \in \mathcal{C}_m, \\ &\quad \text{C2}: \sum_{n \in \mathcal{N}} \rho_{k,n} p_{k,n} \le P_T, \quad \forall k \in \mathcal{C}_m, \\ &\quad \text{C3}: \sum_{k \in \mathcal{C}_m} \sum_{n \in \mathcal{N}_l} p_{k,n} \widetilde{H}_{l,n}^k \le I_{PU_m}^{th}, \forall l, \\ &\quad \text{C4}: \sum_{k \in \mathcal{C}_m} \rho_{k,n} = 1, \quad \forall n \in \mathcal{N}, \\ &\quad \text{C5}: p_{k,n} \ge 0, \quad \forall k \in \mathcal{C}_m, n \in \mathcal{N}, \\ &\quad \text{C6}: \rho_{k,n} \in \{0, 1\}, \quad \forall k \in \mathcal{C}_m, \ n \in \mathcal{N}. \end{aligned} \tag{9}$$

Intuitively, the binary variable $\rho_{k,n}$ makes (9) a mixed integer programming that is NP-hard. We propose a heuristic subchannel allocation method to remove the integer constraints, in which the SNR of a subchannel and the interference introduced to PUs are jointly taken into consideration in the OFDM-based CR network. Since each subchannel can be allocated to only one user, we prefer to allocate the subchannel to users over which they can achieve the highest possible rate among all available subchannels. The procedure is repeated until all subchannels are consumed. The detail of the proposed subchannel allocation scheme is given in Table II. The set of subchannels allocated to SU k is denoted as Ω_k. The highest achievable rate of subchannel n for SU k is given by

$$r_{k,n}^M = \frac{W}{N} \log_2(1 + p_{k,n}^M h_{k,n}), \tag{10}$$

where $p_{k,n}^M$ is the maximum power allocated to subchannel n for SU k [13], [15],

$$p_{k,n}^M = \min(P_T, \min_{l \in \mathcal{L}}(\frac{I_{PU_m}^{th}}{\widetilde{H}_{l,n}^k})), \tag{11}$$

TABLE II
SUBCHANNEL ALLOCATION

Algorithm: Subchannel Allocation

Initialization:
 Set $R_k = 0,\ \Omega_k = 0,\ \forall k \in \mathcal{C}_m,\ \mathcal{K}_t = \mathcal{C}_m,\ \mathcal{N}_t = \mathcal{N}$;
First round:
 for $k \in \mathcal{C}_m$
  Find k^*, n^* that $r^M_{k^*,n^*} \geq r^M_{k,n}, \forall k \in \mathcal{K}_t, \forall n \in \mathcal{N}_t$;
  $\Omega_{k^*} = \Omega_{k^*} \bigcup n^*,\ \mathcal{K}_t = \mathcal{K}_t \backslash k^*,\ \mathcal{N}_t = \mathcal{N}_t \backslash n^*$;
  $R_{k^*} = r^M_{k^*,n^*}$.
 end for
Second round
 while $\mathcal{N}_t \neq \varnothing$
  Find $k^* = \arg(\min_{k \in \mathcal{C}_m} R_k)$;
  Find n^* that $r^M_{k^*,n^*} \geq r^M_{k^*,n}, \forall n \in \mathcal{N}_t$;
  $\Omega_{k^*} = \Omega_{k^*} \bigcup n^*,\ \mathcal{N}_t = \mathcal{N}_t \backslash n^*$;
  $R_{k^*} = R_{k^*} + r_{k^*,n^*}$.
 end while

we can see that the constraints C2 and C3 in (9) are satisfied in (11), which means the power on subchannel n is always bounded by the power constraint P_T and the interference constraints laid by the PUs.

VI. FAST OPTIMAL POWER ALLOCATION

For a given subchannel assignment, the constraints C4 and C6 in (9) vanish, the optimization problem is transformed into the following form:

$$\begin{aligned} &\max_{p_{k,n}} \sum_{k \in \mathcal{C}_m} \sum_{n \in \Omega_k} r_{k,n} \\ &s.t.\ \text{C1}: R_k \geq R_{min}, \quad \forall k \in \mathcal{C}_m, \\ &\quad \text{C2}: \sum_{n \in \Omega_k} p_{k,n} \leq P_T, \quad \forall k \in \mathcal{C}_m, \\ &\quad \text{C3}: \sum_{k \in \mathcal{C}_m} \sum_{n \in \mathcal{N}_l} p_{k,n} \widetilde{H}^k_{l,n} \leq I^{th}_{PU_m}, \forall l, \\ &\quad \text{C4}: p_{k,n} \geq 0, \quad \forall k \in \mathcal{C}_m,\ n \in \mathcal{N}. \end{aligned} \tag{12}$$

Eq. (12) is easy to be proved as a convex optimization problem because the objective function is convex and all the constraints are affine [31]. Generally, such kind of optimizaiton problem can be solved by standard convex optimization techniques, in which barrier method [31] is widely used. However, the high computational complexity contributed by Newton iteration step prevents its online application of solving (12). The Newton method is described in Fig. 3. As can be seen from the figure, Newton step needs matrix inversion with a complexity of $O(N^3)$, where the number of subchannels N is always several thousand in practical systems and such a complexity is too high for the RA problem to be performed online. Thus, we develop an efficient fast barrier method by exploiting the structure of (12) to calculate Newton step.

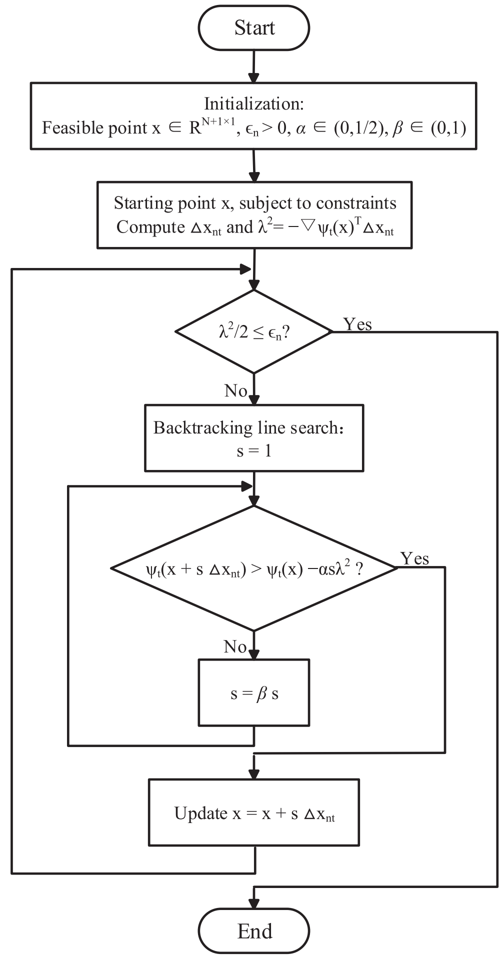

Fig. 3. Flowchart of Newton method.

The barrier function of (12) is

$$\begin{aligned} \phi(P) = &- \sum_{k \in \mathcal{C}_m} \log\Big(\sum_{n \in \Omega_k} \frac{W}{N} \log_2(1 + p_{k,n} h_{k,n}) - R_{min}\Big) \\ &- \sum_{k \in \mathcal{C}_m} \sum_{n \in \Omega_k} \log(p_{k,n}) - \log\Big(P_T - \sum_{k \in \mathcal{C}_m} \sum_{n \in \Omega_k} p_{k,n}\Big) \\ &- \sum_{l=1}^{L} \log\Big(I^{th}_{PU_m} - \sum_{k \in \mathcal{C}_m} \sum_{n \in \mathcal{N}_l} p_{k,n} \widetilde{H}^k_{l,n}\Big), \end{aligned} \tag{13}$$

where $P = (p_{1,1}, \ldots, p_{K,N})$. Denote

$$f(P) = \sum_{k \in \mathcal{C}_m} \sum_{n \in \Omega_k} \frac{W}{N} \log_2(1 + p_{k,n} h_{k,n}).$$

Then, by introducing a logarithmic barrier function with a parameter t, the optimal solution of (12) can be approximated by solving the following unconstrained minimization problem

$$\min \psi_t(P) = -t f(P) + \phi(P). \tag{14}$$

Newton step at P, denoted by ΔP_{nt}, is given by

$$\nabla^2 \psi_t(P) \Delta P_{nt} = -\nabla \psi_t(P), \tag{15}$$

where $\nabla^2 \psi_t(P)$ is the Hessian and $\nabla \psi_t(P)$ is the gradient of $\psi_t(P)$, respectively.

For simplicity, denote

$$f_0 = P_T - \sum_{k\in\mathcal{C}_m}\sum_{n\in\Omega_k} p_{k,n},$$
$$f_k = \sum_{n\in\Omega_k}\frac{W}{N}\log_2(1+p_{k,n}h_{k,n}) - R_{min},$$
$$g_l = I^{th}_{PU_m} - \sum_{k\in\mathcal{C}_m}\sum_{n\in\mathcal{N}_l} p_{k,n}\widetilde{H}^k_{l,n}.$$

The Hessian of $\psi_t(P)$ is

$$\begin{aligned}\nabla^2\psi_t(P) &= \begin{bmatrix} D_1 & & & \\ & D_2 & & \\ & & \ddots & \\ & & & D_N\end{bmatrix} \\ &\quad + \frac{\nabla f_0 \nabla f_0^T}{f_0^2} + \frac{\nabla^2 f_0}{f_0} \\ &\quad + \sum_{k\in\mathcal{C}_m}\frac{\nabla f_k\nabla f_k^T}{f_k^2} + \sum_{k\in\mathcal{C}_m}\frac{\nabla^2 f_k}{f_k} \\ &\quad + \sum_{l=1}^{L}\frac{\nabla g_l\nabla g_l^T}{g_l^2} + \sum_{l=1}^{L}\frac{\nabla^2 g_l}{g_l} \\ &= \mathbf{D} + \sum_{i=1}^{|\mathcal{C}_m|+L+1}\mathbf{q}_i\mathbf{q}_i^T, \end{aligned} \tag{16}$$

where

$$D_i = t\frac{W}{N}\frac{1}{\ln 2}(1+\frac{1}{f_k^*})(\frac{h_{k^*,i}}{1+h_{k^*,i}p_{k^*,i}})^2 + \frac{1}{p^2_{k^*,i}},$$
$$\mathbf{q}_i = \begin{cases} \frac{\nabla f_0}{f_0}, & i=1,\\ \frac{\nabla f_k}{f_k}, & k=1,\ldots,\mid\mathcal{C}_m\mid, i=k+1,\\ \frac{\nabla g_l}{g_l}, & l=\mid\mathcal{C}_m\mid+2,\ldots,\mid\mathcal{C}_m\mid+L+1,\\ & i=\mid\mathcal{C}_m\mid+1+l,\end{cases}$$

where $\mid\mathcal{C}_m\mid$ is the number of SUs in cluster m and Matrix $\mathbf{D}$ is positive definite and all $\mathbf{q}_i\mathbf{q}_i^T > 0$. Thus, we can find that the Hessian is positive definite and also invertible. Consider the Hessian of $\psi_t(P)$, an efficient algorithm can be developed to calculate the Newton step by exploiting its special structure. According to the decomposition in (16), the Hessian can be written into

$$\mathbf{\Lambda}_i = \mathbf{D} + \sum_{m=1}^{i}\mathbf{q}_m\mathbf{q}_m^T, \quad i=1,2,\ldots,M, \tag{17}$$

where $M=\mid\mathcal{C}_m\mid+L+1$. Then we propose an $(M+1)$-step iterative algorithm to quickly compute the Newton step. The detailed description of the algorithm is given in Table III. As can be seen from the table, after the Mth step, it produces $M+1$ matrix systems $\mathbf{\Lambda}_M u_i^M = \mathbf{q}_{i-1}$ and m variables $\mathbf{q}_i^{m-1}$, $i=1,\ldots,m$ in step $m-1$ can be obtained by the $m+1$ variables $\mathbf{q}_i^m$, $i=1,\ldots,m+1$ in step m. Hence, the Newton step can be indirectly worked out by an M-step reverse computation. Furthermore, since $\mathbf{D}$ is a diagonal, we can also solve each set of equations in step M to obtain $M+1$ variables u_i^M, $i=1,2,\ldots,M+1$.

TABLE III
FAST CALCULATING NEWTON STEP

Step 1 Decompose Λ_M, $\Lambda_M = \Lambda_{M-1} + \mathbf{q}_M\mathbf{q}_M^T$.
Then we have $u^0 = u_1^1 - \frac{\mathbf{q}_M^T u_1^1}{1+\mathbf{q}_M^T u_2^1}u_2^1$,
Where $\Lambda_{M-1}u_1^1 = -\bigtriangledown\psi_t(P)$ and $\Lambda_{M-1}u_2^1 = \mathbf{q}_M$
After Step 1, we can figure out the $\triangle P_{nt}$ by solving u_1^1 and u_2^1,
Step 2 Decompose Λ_{M-1} with $\Lambda_{M-1} = \Lambda_{M-2} + \mathbf{q}_{M-1}\mathbf{q}_{M-1}^T$
Similarly, u_1^1 and u_2^1 can be obtained by
$u_i^1 = u_i^2 - \frac{\mathbf{q}_{M-1}^T u_i^2}{1+\mathbf{q}_{M-1}^T u_i^2}u_3^2, i=1,2,$
where $\Lambda_{M-1}u_1^2 = -\bigtriangledown\psi_t(P)$, $\Lambda_{M-1}u_i^2 = \mathbf{q}_{M+2-i}, i=2,3.$
⋮
Continue this process to Step M,
Step M
We can obtain $M+1$ variables by solving $M+1$ liner equation,
$\mathbf{D}u_1^M = -\bigtriangledown\psi_t(P)$
$\mathbf{D}u_i^M = \mathbf{q}_{M+2-i}, i=2,3,\ldots,M+1.$

Theorem 1: Eq. (15) can be solved with complexity of $O(M^2N)$.

Proof: The computational complexity of our proposed algorithm can be calculated as follows. The proposed fast algorithm to solve (16) requires M decompositions, while each decomposition yields an additional matrix equation. First, we need to solve the matrix systems in step M to obtain $M+1$ variables with the computation complexity $O(MN)$. Then, a reverse substitution with M steps is required to figure out u^0. Thus, we can conclude the computational complexity of our proposed algorithm for the formulated problem (12) is $O(M^2N)$ and the number of $M \ll N$ in practical wireless systems.

VII. Simulation Results and Discussions

We evaluate the performance of our resource allocation algorithms with a series of numerical experiments. Consider the downlink of an OFDM-based CR system, where all users randomly locate in a 3×3 km area. Each PU occupies random bandwidth which spans continuous subchannels, and each receiver uniformly distributes in the circle within 0.5 km from its transmitter. The noise power is 10^{-13} W while the interference thresholds of all PUs are set to 5×10^{-13} W. The minimal rate requirement of SUs is 20 bits/symbol. The channel suffers from frequency selective fading. The path loss exponent is 4. The variance of logarithmic normal shadow fading is 10 dB and the amplitude of multipath fading is Rayleigh. The parameters of the barrier method are set to the typical values discussed in [31].

First, we present the clustering result of our proposed clustering algorithm in Fig. 4. There are 20 SUs and 1 PU in the system. As can be seen from Fig. 4, the SUs are divided into five clusters and we can find that our proposed clustering algorithm is reasonable and convincing intuitively. We also investigate the convergence of our proposed algorithms. As discussed in Section VI, the computational load mainly lies

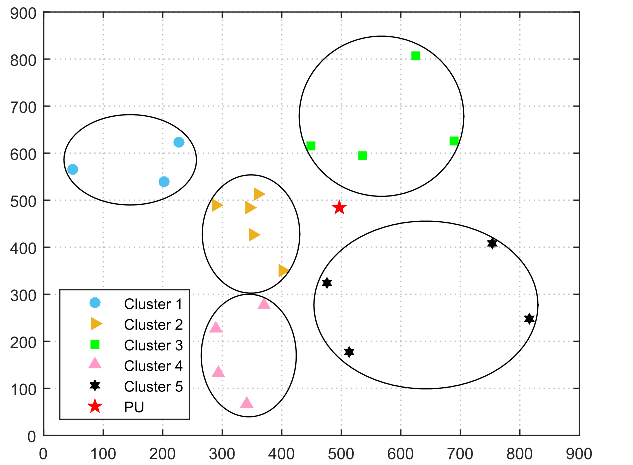

Fig. 4. Results of the proposed clustering algorithm. $K = 20$, $N = 32$, $L = 1$.

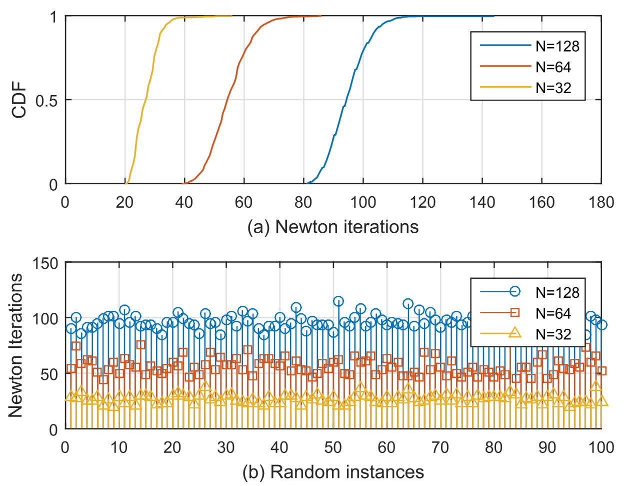

Fig. 5. CDF of Newton iterations (a); Random instances of Newton iterations (b). $N = 32$ and $P_T = 1$W.

in the computation of Newton step. Fig. 5 (a) and (b) shows the Cumulative Distribution Function (CDF) of the number of Newton iterations of our proposed algorithm and the number of Newton iterations for convergence in 100 random instances with different settings of N, respectively. As can be seen in Fig. 5, the number of Newton iterations is not large with given N and varies in a narrow range, indicating our proposed algorithm is very efficient.

Fig. 6 shows the average sum rate of SUs as a function of I^{th} achieved by our proposed algorithm. There are 32 subchannels with the total transmission power limit $P_T = 1$W. The number of SUs and PUs are 20 and 1, respectively, and we set $N_c = 5$. For comparison, we use the optimal solution to the relaxing form of (9) as an upper bound. From Fig. 6 we can see that the performance of our proposed algorithm is close to the upper bound. The gap is always less than 2%. We can conclude that our algorithm is close to the optimal solution. Note that the sum rate also increases with the increase of K, which is due to the user diversity gain. Besides, Fig. 7 shows further comparison of the average sum rate of SUs as a function of I^{th} achieved by our proposed algorithm with different

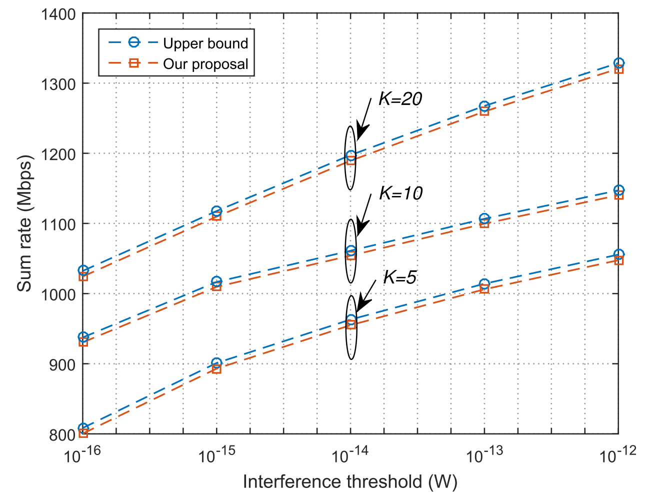

Fig. 6. Average sum rate as a function of interference threshold I^{th}. $N = 32$, $L = 1$.

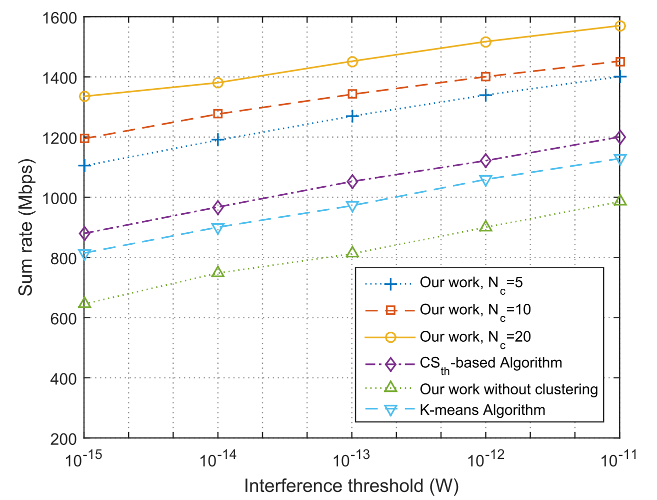

Fig. 7. Average sum rate as a function of interference threshold I^{th}. $N = 32$, $L = 1$ and $K = 20$.

setting of N_c and other clustering algorithms including CS_{th}-based clustering algorithm developed in [23] and classical K-means algorithm with $N_c = 5$. In the CS_{th}-based clustering algorithm, a cluster formation algorithm is proposed for a given cluster size threshold (CS_{th}), where clustering head is first elected with given cluster size threshold and the cluster is formed based on the interference degree step by step. As can be seen from the figure, our proposed dynamic clustering algorithm outperforms the other two clustering algorithms since we not only deal with the mutual interference between any two SUs but also consider the trade off between the share in the available spectrum resource and the co-tier interference among different clusters. Besides, the sum rate of the clusters increases as the number of clusters increases, this is because the whole subchannels can be used within each cluster on the assumption that there is no co-tier interference among clusters and the high frequency reuse leads to high system throughput.

Fig. 8 and Fig. 9 show the average sum rate as a function of the number of subchannels and the transmission power

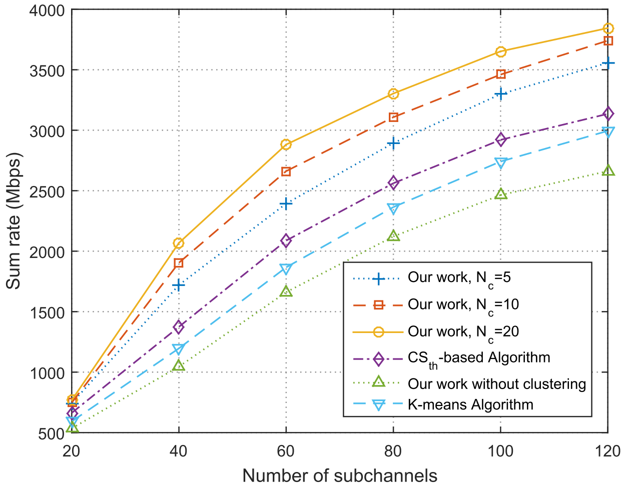

Fig. 8. Average sum rate as a function of number of subchannels with $K = 20$, $L = 1$ and $P_T = 1$W.

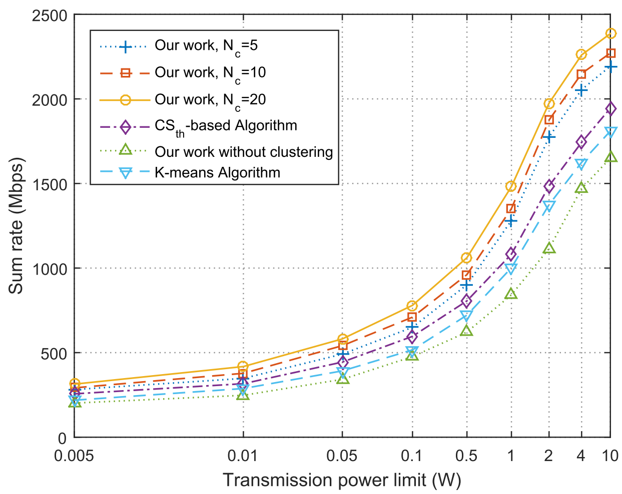

Fig. 9. Average sum rate as a function of transmission power limit with $K = 20$, $L = 1$ and $N = 32$.

limit obtained by our proposed algorithm for different number of N_c, respectively. The number of SUs and PUs are 20 and 1, respectively. We also choose two clustering algorithms for comparison: CS_{th}-based clustering algorithm and the classic K-means algorithm with $N_c = 5$. As can be seen from both Fig. 8 and Fig. 9, our proposed efficient clustering algorithm outperforms the other two. In Fig. 8, the average sum rate of the SUs increases as the number of subchannels increases, which can be explained as channel diversity in wireless environment. In Fig. 9, the sum rate of the SUs increases with the increase of the transmission power limit, this is because more power can be consumed to increase the transmission rate with the growth of transmission power limit. However, as can be seen from Fig. 9, the increase of sum rate slows down with the continuous growth of transmission power limit ($P_T > 2$ W), the reason is that the interference threshold limits the maximum transmission power of the SUs, which results the sum rate of SUs eventually. Besides, it can be also seen from both Fig. 8 and Fig. 9 that the sum rate increases with the increase of the number of clusters. It is intuitive because more clusters lead to higher area spectrum efficiency, which will finally increase the transmission rate of the SUs.

VIII. Conclusions

In this paper, we presented a novel clustering-based radio resource allocation scheme for an OFDM-based cognitive radio network. Our target is to maximize the sum rate of all SUs while controlling the interference to the PUs below their tolerable thresholds. The SUs with negligible mutual interference can share the same subchannels to improve the spectrum utilization efficiency. We tackle the formulated hard optimization task with a two-step procedure: clustering and resource allocation. The SUs with heavy mutual interference are grouped into a cluster and use different subchannels to avoid the mutual interference. Then the cluster center in each cluster performs subchannel and power allocation for the SUs in this cluster. A heuristic subchannel assignment method is proposed to remove the integer constraints in the resource allocation problem and a fast algorithm with low complexity is developed to yield optimal power distribution solution by exploiting the structure of the problem. Numerical results show that our clustering-based resource allocation proposal can achieve higher system capacity as compared with other methods, while the algorithm developed in this paper is robust for all considered scenarios.

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