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Joint Subcarriers and Power Allocation with Imperfect Spectrum Sensing for Cognitive D2D Wireless Multicast

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Abstract

Wireless multicast is considered as an effective transmission mode for the future mobile social contact services supported by Long Time Evolution (LTE). Though wireless multicast has an excellent resource efficiency, its performance suffers deterioration from the channel condition and wireless resource availability. Cognitive Radio (CR) and Device to Device (D2D) are two solutions to provide potential resource. However, resource allocation for cognitive wireless multicast based on D2D is still a great challenge for LTE social networks. In this paper, a joint sub-carriers and power allocation model based on D2D for general cognitive radio multicast (CR-D2D-MC) is proposed for Orthogonal Frequency-Division Multiplexing (OFDM) LTE systems. By opportunistically accessing the licensed spectrum, the maximized capacity for multiple cognitive multicast groups is achieved with the condition of the general scenario of imperfect spectrum sensing, the constraints of interference to primary users (PUs) and an upper-bound power of secondary users (SUs) acting as multicast source nodes. Furthermore, the fairness for multicast groups or unicast terminals is guaranteed by setting a lower-bound number of the subcarriers allocated to cognitive multicast groups. Lagrange duality algorithm is adopted to obtain the optimal solution to the proposed CR-D2D-MC model. The simulation results show that the proposed algorithm improves the performance of cognitive multicast groups and achieves a good balance between capacity and fairness.

Keywords: Cognitive radio, wireless multicast, orthogonal frequency-division multiple access, spectrum sensing, resource allocation

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1. Introduction

As a major part of mobile social networks, Long Time Evolution (LTE) systems support a great number of mobile social contact services. An important feature of social networks is the need of the same traffic contents by more than one terminal. Therefore, wireless multicast has the potential to support mobile social contacts because of its outstanding resource efficiency for transmitting packets from a single sender to multiple receivers at almost the same wireless resource as unicast [1]. However, wireless multicast performance is restricted by the terminal with the worst channel condition. Be aware of the scarce spectrum resource, resource allocation for wireless multicast is still open for more investigation.

D2D (device-to-device) technology is able to improve resource efficiency significantly in cellular networks by establishing direct links between terminals without BS forwarding in a cell. Meanwhile, cognitive radio (CR) is another excellent technology in improving spectrum resource utilization, which provides more potential spectrum resource by secondary user (SUs) properly sensing the spectrum conditions and seeking to overlay its signals with those of the primary users (PUs) without interfering with them [2][3]. It is natural to think that D2D with CR function is able to improve the spectrum resource utilization more effectively by dynamic establishment of the transmission links with the help of cognitive terminals. However, less works based on CR D2D resource allocation has been found in literature. In this paper, we focus on multicast, a more general transmission mode, and investigate the resource allocation algorithm for cognitive D2D multicast.

D2D links operate in a cognitive mode in the cellular networks, and share the spectrum resources with cellular users. It is well known that orthogonal frequency-division multiplexing/accessing (OFDM/OFDMA) has been standardized for LTE systems due to its flexibility in allocating spectrum. Considering the imperfect sensing conditions, we address the problem of resource allocation for cognitive multicast based on D2D technology. The imperfect spectrum sensing errors include misdetection and false alarm. A false alarm occurs when a CR user confuses an idle primary subcarrier as active and loses the opportunity to access the available channel. A misdetection occurs when a CR user confuses an active primary subcarrier as idle and can potentially cause harmful interference^[4]. In a cognitive cellular system, we introduce a model in which the users in a cell are under the control of a base station (BS), called PUs, and are characterized by a higher priority to access in a given frequency band than SUs employing D2D mode. In the meanwhile, SUs are characterized by CR capabilities, i.e. identifying spectrum opportunities, detecting the presence of PUs, and evaluating the SUs' source interference to the PUs' transceivers and access the spectrum channels shared with PUs [5][6][7]. The optimization objective is to maximize the capacity of the cognitive multicast network with the condition of maximum interference constraint and maximum power constraint, in which a risk-return function is adopted to describe the PUs' activities. To maintain a certain level of fairness, a minimum allowable number of subcarriers allocated to the multicast group is preset, which guarantees that the CR links with smaller channel gains are able to have the opportunities to possess some available subcarriers instead of being completely rejected. We formulate the joint subcarriers and power allocation as a non-linear programming problem, for which the optimal solution is known to be NP-hard [8]. We use the Lagrange duality algorithm to solve this problem.

The rest of the paper is organized as follows. The related work are presented in Section II. In section III, we describe the system model and formulate the proposed optimization problem.

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The optimization solution for the joint subcarriers and power allocation problem is provided in Section IV. Section V illustrates the simulation results. Finally, we conclude this paper in Section VI.

2. Related Work

Resource allocation is used to dynamically allocate limited resources, such as subcarriers, time slots and power in OFDM systems, in order to achieve the best quality of service at the lowest possible cost. In [9], an optimized model for joint spectrum allocation and scheduling has been proposed with the condition of interference characterization of Multi-Channel Contention Graphs to increase the throughput achieved by SUs in a multi-hop cognitive radio network. In [10], an OFDM-based CR system with one or more spectrum holes existing among the multiple PU frequency bands is considered. Subcarrier and power allocation optimization is formulated as a multi-dimensional 0-1 knapsack problem (MDKP) and a greedy max-min algorithm is proposed to solve it. In [11], two fair bandwidth-allocation problems based on a simple max-min fairness model and lexicographical max-min (LMM) fairness model are proposed to achieve the tradeoff between fairness and throughput in wireless mesh networks. In [12], two distributed algorithms to optimally allocate subcarriers and power in OFDMA ad hoc cognitive radio network have been proposed to offer either throughput maximization or energy efficiency subject to tolerable interference introduced to the primary network, and a joint subcarrier and power allocation method has been derived by Lagrange dual algorithm to maximize the capacity of the cognitive radio networks.

All the aforementioned works assumed that the spectrum sensing is perfect. In fact, the spectrum sensing is often imperfect due to the variations of channel fading and shadow effect, and limited CR receiver sensitivity [13][14][15]. A statistically robust resource allocation scheme for a decode-and-forward (DF) relay-assisted OFDMA network with imperfect channel state information has been proposed in [16], maximizing the sum rate of the overall network while solving the problem of the power leakage between neighboring subcarriers. However, the problem of resource allocation in cognitive multicast networks with D2D communication under imperfect sensing condition is still open for more investigation.

The major contributions of this paper are summarized as follows: 1) The proposed cognitive multicast scheme based on D2D technology is quite different from traditional D2D unicast with imperfect sensing condition. 2) The proposed optimized model CR-D2D-MC is a more general model and is well adapted multicast and unicast with imperfect sensing CR for D2D. This problem has not been addressed in literatures. 3) Lagrange dual method is adopted to obtain the optimal solution for the proposed problem CR-D2D-MC with low complexity.

3. System Model and Problem Formulation

3.1. System Model

The cognitive wireless multicast networks with D2D communication operate in the cellular system as illustrated in **Fig. 1**. Multiple cognitive multicast groups opportunistically access the spectrum licensed to the cellular network in a cell. Both of them are assumed to employ the OFDMA to access the system and each subcarrier has an equal bandwidth B_s which is much less than the coherent bandwidth of the channel and the channel response on each of subchannels is flat. The wireless channel is modeled as a frequency-selective Rayleigh fading channel. As a result of the spectrum sensing, there are *K* vacant subcarriers for SUs to

implement the opportunistic spectrum access. The primary BS transmits signals to its predefined *M* primary users and each primary user can use one subchannel (containing one or more subcarriers). Without loss of generality, we use a subcarrier as one allocated spectrum unit with bandwidth B_s . The CR network consists of *N* multicast groups while each multicast group contains one SU source node and several SU members. One source node can send data to multiple members over the allocated subcarriers at a time. The number of the members in the n^{th} multicast group is defined as $|U_n|$. If $|U_n|=1$ means the group is unicast while it is multicast if $|U_n|>1$. So our proposed framework can be applied to both unicast and multicast transmission. In addition, the set of subcarriers allocated to the n^{th} cognitive multicast group is denoted as K_n .



Fig. 1. D2D cognitive multicast system scenario

Consider that the channel link is composed of large-scale path loss and statistically independent small-scale quasi-static frequency selective Rayleigh fading, and the channel gain is $H_{ab} = L |h_{ab,k}|^2 d_{ab}^{-\theta}$, where $h_{ab,k}$ and d_{ab} are the channel coefficients on subcarrier k and the Euclidean distance between nodes a and b, respectively, L is a constant that depends on the environment, and θ is the path loss exponent. L and θ are assumed unchanged for all communication links.

Some parameters used in this paper are described and listed in Table 1.

$H_{n,k}^{PS}$	Channel gain array between Primary BS and n^{th} multicast group on subcarrier k
$H_n^{PS}(u,k)$	Channel gain between Primary BS and u^{th} member in n^{th} multicast group on subcarrier k
$H_n^{SS}(u,k)$	Channel gain between source node and u^{th} member in n^{th} multicast group on subcarrier k
$H_m^{SP}(n,k)$	Channel gain from n^{th} multicast group source node to m^{th} PU on subcarrier k
$P_{n,k}$	Power allocated to n^{th} multicast group source node on subcarrier k
$q^k_{\scriptscriptstyle md}$	Misdetection error of spectrum sensing

Table 1. List of parameters and their description

3.2 Problem Formulation

The coexistence of CR network and primary network will lead to mutual interference which can be divided into two types: one is caused by SUs to PUs which is caused by out-of-band leakage and imperfect spectrum sensing, and the other is caused by the primary BS to SUs which can lead to the reduction in the rate of cognitive users.

As mentioned above, the signal transmitted from the primary BS can also cause interference to the cognitive network, and this kind of interference is reflected in the rate decrease of SU. We denote $\Phi_{PU}^{(m)}(e^{jw})$ as the power spectral density (PSD) of the signal transmitted from the BS to m^{th} PU. The interference introduced to subcarrier k^{th} can be written as [12]

$$J(m,k) = \int_{(b-1/2)B_s}^{(b+1/2)B_s} \varepsilon \{I_K(\omega)\} d\omega$$
(1)

where constant b represents the number of subcarriers apart from the PU subband to SU subband, and

$$\varepsilon \left\{ I_{\kappa}(\omega) \right\} = \frac{1}{2\pi Q} \int_{-\pi}^{\pi} \Phi_{PU}^{(m)}(e^{jw}) \left(\frac{\sin((\omega - \phi)Q/2)}{\sin((\omega - \phi)/2)} \right)^2 d\phi$$
(2)

is the PSD of m^{th} PU's signal after the Q-FFT processing [17].

As the members in the n^{th} group use the same subcarriers to receive data from the source node, the interference introduced to u^{th} member in the n^{th} group on subcarrier k is

$$J_{m,n}(u,k) = H_{m,n}^{PS}(u,k) \sum_{m \in M} J(m,k)$$
(3)

where $H_{m,n}^{PS}(u,k)=L|h_{m,n}^{PS}(u,k)|^2 d_{mu}^{-\theta}$. The channel-to-interference-plus-noise ratio (CINR) of u^{th} member in the n^{th} group on subcarrier k can be expressed as

$$\gamma_{n,k}(u) = \frac{H_{m,n}^{PS}(u,k)P_{n,k}}{N_0 B_s + J_n(u,k)}$$
(4)

Assuming that QAM is adopted, the achievable maximum transmission rate of u^{th} member can be written as follows

$$R_{n,k}(u) = \frac{1}{K} \log_2 \left(1 + \frac{\gamma_{n,k}(u)}{\Gamma} \right) = \frac{1}{K} \log_2 \left(\frac{H_{m,n}^{PS}(u,k)P_{n,k}}{\Gamma(N_0 B_s + J_n(u,k))} \right)$$
(5)

where Γ is a function of the required BER which is $\Gamma = (0.2/BER - 1)/1.5$ for Rayleigh channel [18].

The achievable rates of members in n^{th} group are always different because of their channel conditions. However, the transmission rate from multicast source in a group is confined by the users with the worst channel state. Therefore, we can define the minimum rate of the users as the transmission rate $R_{n,k}$ for a multicast group given below

$$R_{n,k} = \min_{u \in U_n} \frac{1}{K} \log_2 \left(1 + \frac{\gamma_{n,k}(u)}{\Gamma} \right) = \frac{1}{K} \log_2 \left(1 + \frac{P_{n,k}}{\Gamma(N_0 B_s + J_n(u,k))} \min_{u \in U_n} H_{m,n}^{PS}(u,k) \right)$$
(6)

where U_n represents the set of receivers of n^{th} group.

In this paper, our objective is to optimize the allocation of subcarriers and power resources to each SU multicast group under the interference constraints and power constraints so that the

capacity of the cognitive multicast based on D2D (CR-D2D-MC) communication is maximized. We employ the risk-return expression [19] to describe the PU activities and assume a linear rate loss function $L(P_{n,k})$. The optimization problem CR-D2D-MC can be formulated as follows:

$$\max_{\{P_{n,k}\}} \sum_{n=1}^{N} \sum_{k \in \mathcal{K}_{n}} \frac{w_{k} |U_{n}|}{K} \log_{2} \left(1 + \frac{P_{n,k}}{\Gamma(N_{0}B_{s} + J_{n}(u,k))} \min_{u \in U_{n}} H_{m,n}^{PS}(u,k) \right) - \varphi_{k} L(P_{n,k})$$
(7)

S.t.
$$\sum_{n=1}^{N} \sum_{k \in \mathbb{N}_{n}} w_{k} P_{n,k} \tilde{I}_{n,k}^{(m)} + \alpha_{k} P_{n,k} g_{n,k} \le \overline{I}_{m}$$
(7a)

$$P_{n,k} \ge 0, P_{n,k} \cdot P_{n',k} = 0, \forall n' \neq n$$
(7b)

$$\sum_{k\in\mathbb{K}} P_{n,k} \le \overline{P}_n \tag{7c}$$

$$\left|\kappa_{n}\right| \geq L_{n} \tag{7d}$$

where formula (7) is the objective function of the optimization model, w_k indicates the probability that a subcarrier k is truly vacant and φ_k defines the probability that a subcarrier k is occupied by PU in the current frame.

Formula (7a) expresses the maximum interference constraint at m^{th} PU, and \overline{I}_m indicates the interference threshold at m^{th} PU. From the formula we can see that the interference introduced to m^{th} PU includes two parts: the interference caused by out-of-band leakage and the interference caused by imperfect spectrum sensing.

The PSD of the signal from the source node in n^{th} group on subcarrier k is expressed as [20]

$$\Phi_{n,k}^{SU}(f) = P_{k,n} T_s \left(\frac{\sin \pi f T_s}{\pi f T_s}\right)^2$$
(8)

where T_s is the OFDM symbol duration. The interference caused by this source in n^{th} multicast group to m^{th} PU can be written as

$$I_{1}^{(m)}(n,k) = P_{n,k}T_{s}H_{m}^{SP}(n,k) \int_{(a-1/2)B_{s}}^{(a+1/2)B_{s}} \left(\frac{\sin \pi fT_{s}}{\pi fT_{s}}\right)^{2} df = P_{n,k}P_{n,k}^{(m)}$$
(9)

where $H_m^{SP}(n,k) = L \left| h_m^{SP}(n,k) \right|^2 d_{mn}^{-\theta}$, $h_m^{SP}(n,k)$ is the corresponding channel coefficient, *a* is a constant representing the frequency distance between the corresponding CR and the PU in

multiples of
$$B_s$$
, and $\widetilde{P}_{n,k}^{(m)} = T_s H_m^{SP}(n,k) \int_{(a-1/2)B_s}^{(a+1/2)B_s} \left(\frac{\sin \pi f T_s}{\pi f T_s}\right)^2 df$

In addition to out-of-band emissions, imperfect spectrum sensing causes severe co-channel interference to PUs when SUs use the subcarriers that are occupied by PUs for transmission. This type of interference is defined as

$$I_{2}^{(m)}(n,k) = P_{n,k}H_{m}^{SP}(n,k) / N_{0}B_{s} = P_{n,k}g_{n,k}$$
(10)

where N_0 is the one-side PSD of AWGN.

To sum up, the total interferences to m^{th} PU on subcarrier k introduced by n^{th} source node can be expressed as

$$I_{n,k}^{(m)} = w_k I_1^{(m)}(n,k) + \alpha_k I_2^{(m)}(n,k) = w_k P_{n,k} I_{n,k}^{(m)} + \alpha_k P_{n,k} g_{n,k}$$
(11)

where α_k is the probability that a subcarrier k is truly occupied. Given that the cognitive network identified subcarrier k is vacant, α_k can be expressed as

$$\alpha_{k} = \Pr\left\{O_{K}\left|\hat{V}_{k}\right\} = \frac{\Pr(\hat{V}_{k}\left|O_{K}\right)\Pr(O_{K})}{\Pr(\hat{V}_{k}\left|O_{K}\right)\Pr(O_{K}) + \Pr(\hat{V}_{k}\left|V_{K}\right)\Pr(V_{K})} = \frac{q_{md}^{k}q_{pu}^{k}}{q_{md}^{k}q_{pu}^{k} + (1 - q_{fa}^{k})(1 - q_{pu}^{k})}$$
(12)

where V_k and O_k denotes the events that subcarrier k is actually vacant and occupied by PUs respectively, \hat{V}_k is the event that subcarrier k is sensed vacant, and q_{pu}^k is the probability that a PU transmits on subcarrier k.

Similarly, w_k can be expressed as

$$w_k = \Pr(V_k | \hat{V}_k) = 1 - \alpha_k \tag{13}$$

Formula (7b) represents the fact that each subcarrier can be allocated to at most one group, whereas (7c) represents the total transmit power at the source node of n^{th} multicast group and \overline{P}_n denotes the total power that the source node of n^{th} group can load. The minimum number limit of subcarriers allocation is represented in formula (7d) where L_n represents the minimum number of subcarriers allocated to n^{th} cognitive group.

4. Joint Subcarrier and Power Allocation Algorithm

With the absence of a centralized controller similar as the base station in cellular networks, cognitive multicast networks with D2D communication can not undertake a centralized resource allocation. Therefore it is necessary to find a distributed resource allocation algorithm. Lagrange dual method is one of the important distributed convex optimization algorithms for solving the resource optimization problem. In order to conveniently describe below, we let $\beta_{n,k}$ instead of $\frac{\min_{u \in U_n} H_{m,n}^{PS}(u,k)}{\Gamma(N_0 B_s + J_n(u,k))}$ in (7), and let $L(P_{n,k}) = C \cdot P_{n,k}$, where *C* is a constant. Then the

Lagrangian function can be expressed as

$$L(\bar{p}, \bar{\lambda}, \bar{\mu}) = \sum_{n=1}^{N} \sum_{k \in \mathbb{K}_{n}} \frac{w_{k} |U_{n}|}{K} \log_{2} \left(1 + \beta_{n,k} P_{n,k} \right) - \sum_{m=1}^{M} \lambda_{m} \left[\sum_{n=1}^{N} \sum_{k \in \mathbb{K}_{n}} P_{n,k} (w_{k} \tilde{I}_{n,k}^{(m)} + \alpha_{k} g_{n,k}) - \bar{I}_{m} \right] - C \varphi_{k} P_{n,k} - \sum_{m=1}^{N} \mu_{n} (\sum_{k \in \mathbb{K}} P_{n,k} - \bar{P}_{n})$$
(14)

where $\vec{\lambda} = [\lambda_1, \dots, \lambda_m]$, $\vec{\mu} = [\mu_1, \dots, \mu_n]$, $\vec{\lambda}$ and $\vec{\mu}$ are non negative dual variables associated with interference constraint and power constraint, respectively.

Therefore, the Lagrange dual objective is obtained as follows:

$$D(\vec{\lambda}, \vec{\mu}) = \max L(\vec{p}, \vec{\lambda}, \vec{\mu})$$
s.t. $P_{n,k} \ge 0$
(15)

Accordingly, the dual optimization problem is

$$\min_{\vec{\lambda} \ge 0, \vec{\mu} \ge 0} D(\vec{\lambda}, \vec{\mu}) \tag{16}$$

The Lagrange dual problem is a convex optimization problem, regardless of the convexity of the primal problem (7). The problem in (16) can be decomposed into K independent sub-problem, one for each subcarrier k:

$$D_{k}(\vec{\lambda},\vec{\mu}) = \max \sum_{n=1}^{N} \left\{ \frac{w_{k} |U_{n}|}{K} \log_{2} \left(1 + \beta_{n,k} P_{n,k}^{*} \right) - \left[\sum_{m=1}^{M} \lambda_{m}(w_{k} \tilde{I}_{n,k}^{(m)} + \alpha_{k} g_{n,k}) + C\varphi_{k} + \mu_{n} \right] P_{n,k}^{*} \right\}$$
(17)

Applying Karush–Kuhn–Tucker (KKT) conditions for Eq.(14), $P_{n,k}^*$ can be derived as:

$$P_{n,k}^{*} = \left(\frac{w_{k} |U_{n}|}{K \ln 2[\sum_{m=1}^{M} \lambda_{m}(w_{k} \tilde{I}_{n,k}^{(m)} + \alpha_{k} g_{n,k}) + C\varphi_{k} + \mu_{n}]} - \frac{1}{\beta_{n,k}}\right)$$
(18)

The right side in Eq. (18), $(\cdot)^+ = \max(\cdot, 0)$, and $\overline{\lambda}$ and $\overline{\mu}$ can be solved by sub-gradient method with guaranteed convergence as follows

$$\lambda_m(t+1) = \left(\lambda_m(t) - s(t) \left[\overline{I}_m - \sum_{n=1}^N \sum_{k \in K_n} P_{n,k} (w_k \widetilde{I}_{n,k}^{(m)} + \alpha_k g_{n,k}) \right] \right)^+$$
(19)

$$\mu_n(t+1) = \left(\mu_n(t) - \nu(t) \left[\overline{P}_n - \sum_{k \in \mathbb{K}_n} P_{n,k}\right]\right)^{*}$$
(20)

where s(t) and v(t) are the step size which are chosen sufficiently small to converge to the optimum value $\bar{\lambda}^*$ and $\bar{\mu}^*$, respectively.

The whole procedure of the proposed algorithm is summarized as **Table 2**.

 Table 2. Dual optimization algorithm

Initialize:

1. Find out the minimum channel gain between the source node and members for each multicast group;

2. Given $\overline{\lambda}$, $\overline{\mu}$, s(t), v(t), ε , $D^{(0)} = 0$, and t = 1;

Repeat:

- 3. Compute $P_{n,k}^*$ and $D_k^{(n)}(\vec{\lambda}, \vec{\mu})$ as in (18) and (17), and construct $\vec{D} := D_k^{(n)}(\vec{\lambda}, \vec{\mu})$;
- 4. Repeat:

Perform a 2-D search on \vec{D} , pick n^* , k^* that gives the maximum value of all $K \times N$ values in \vec{D} , if $|\kappa_{n^*}| < L_n$, allocated subcarrier k^* to group n^* , otherwise group n^* exit;

- Until $|\kappa_{n^*}| = L_n$;
- 5. Repeat:

Perform a 2-D search on \vec{D} , pick n^* , k^* that gives the maximum value of all $K \times N$ values in \vec{D} , allocated subcarrier k^* to group n^* ;

Until all the subcarriers have been allocated;

6. Compute $D^{(t)}$ and update $\vec{\lambda}$ and $\vec{\mu}$, t := t+1;

Until $|D^{(t+1)} - D^{(t)}| < \varepsilon$.

5. Simulation

In order to estimate the performance of the proposed optimization algorithm, the simulation is performed in MATLAB environment. An OFDM-based cognitive multicast network of K = 12 vacant subcarriers is assumed with N = 4 multicast SU groups, and the bandwidth of each subcarrier is $B_s = 10kHz$. The primary BS transmits downlink data to its M = 2 subscribed PUs. The channel coefficients are outcomes of independent Rayleigh distributed random variables with mean equal to 1, and the path loss exponent $\theta = 3$, the environment constant L = 1.

In **Fig. 2**, we present the performance comparison between our proposed algorithm and the global optimal exhaustive search algorithm. As shown in the figure, the dual optimization algorithm and the exhaustion search algorithm is almost impossible to distinguish in performance, When the number of OFDM subcarriers increases, the difference of system capacity (sum rate) between the original optimal value and its dual optimal value will become more and more small. In a real system, the number of subcarriers is usually relatively large, and the computational complexity is too high when using the exhaustive search algorithm, so it is suitable to use our proposed algorithm. And when the number of subcarriers tends to be infinity, the dual algorithm we proposed will become global optimal.

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Fig. 2. Performance comparison between the proposed algorithm and exhaustive search algorithm



Fig. 3. Convergence of the proposed algorithm with different step size

Fig. 3 shows the comparison of convergence processes of the proposed algorithm with different step sizes. Fig. 3 (a) and Fig. 3 (b) are obtained under the same conditions, e.g. the maximum power of each group $\overline{P}_n = 4W$, the maximum interference threshold $\overline{I}_m = 0.05W$, the number of multicast group $|U_n| = 4$ and tolerance $\varepsilon = 10^{-5}$. We choose $1/\sqrt{t}$ as the step size of Fig. 3 (a) and that of Fig. 3 (b) is 1/t. Clearly, Fig. 3 (a) converges in 30 iterations and performs much faster than Fig. 3 (b) while Fig. 3 (b) takes up to 600 iterations. It shows that the proposed algorithm has a very fast convergence speed and emphasizes the running time of the algorithm depending on the choice of the step size. It can also prove that this algorithm is especially suitable for optimization in wireless environment and can find the optimal solution in a very short period of time so as to overcome the channel variability.



Fig. 4. Capacity Comparison of dual optimization algorithm and average allocation algorithm



Fig. 5. Comparison of the proposed algorithm with considering fairness and without fairness. (a) Number of subcarriers allocated to each group; (b) Allocation of power on each subcarrier

As shown in **Fig. 4**, we compare the performance of the proposed algorithm and the average allocation algorithm. It is obvious that the performance of the proposed algorithm is much

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superior to that of the average allocation algorithm. The proposed algorithm performs a 2-D search on \vec{D} which involves searching through all *KN* values of $D_k^{(n)}(\vec{\lambda},\vec{\mu})$ to determine the optimal subcarrier matching for multicast groups, subsequently allocates power on each subcarrier to maximize the achievable rates of the groups. The algorithm combines the subcarrier allocation and the power allocation for optimal allocation, rather than consider them separately. Furthermore, our proposed algorithm considers the imperfect spectrum sensing, thus it can efficiently allocate the resources. Compared to the average allocation algorithm, it can make a good use of the subcarrier and power resources and obtain a better performance. Because the different environment conditions may cause inconsistent service performance for the different multicast groups, the proposed algorithm both considers the imperfect spectrum sensing and fairness between multicast groups, thus the achieved capacity is a little lower than that of the algorithm without considering the fairness and the scheme with perfect spectrum sensing.

However, we find from Fig. 5 (a) that the proposed scheme with fairness guarantees the spectrum requirements of each multicast group, specified by L_n and without considering the fairness the 2th group has not been allocated any subcarriers and will not meet their quality of service. It is not feasible as fairness is one of the major concerns in CR system. As illustrated in Fig. 5 (b), the subcarriers are not equally utilized because some subcarriers are allocated more power than others. Compared with the fairness case, the difference of power distribution on each subcarrier of the unfairness case is more apparent.



Fig. 6 shows the interference introduced to 1th primary user which is caused by the secondary transmission for fixed values of interference threshold $\overline{I_1}$ =0.05W. It is obvious that the interference increases with the power constraint and the number of multicast groups but never more than the interference threshold. When there is only one multicast group in the cognitive network, the interference curve is almost linear. As the number of groups increases, the interference become more complex, and the interference curve is no longer a linear increase.



Fig. 7. Capacity with the members in the multicast group

When the number of members in the multicast group increases, the performance of the multicast networks will also improve. From **Fig. 7**, we know that the capacity of the system almost linearly increases with the number of users in the multicast group. In addition, the result indicates that multicast technology can greatly improve the system capacity and make D2D communication more suitable for emergency communication and high data transmission services.

6. Conclusion

In this paper, we introduced a joint subcarrier and power allocation method CR-D2D-MC for cognitive multicast with D2D communication coexisting with cellular networks. The impact of imperfect spectrum sensing is considered in the proposed problem, which results in the capacity decrease of the cognitive multicast. In the proposed algorithm, the fairness is guaranteed by defining a lower bound of allowable number of subcarriers allocated to the multicast groups. The simulation results show that the proposed algorithm improves the spectrum efficiency and maintain a better tradeoff between capacity and fairness for cognitive networks in a low algorithm complexity. Therefore, employing cognitive multicast based on D2D is able to explore more potential spectrum resources adequately to improve the system performance, and make it possible to satisfy the requirements of multiple kinds of high rate transmission for mobile social contacts.

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