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A Social-Aware Resource Allocation for 5G Device-to-Device Multicast Communication

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ABSTRACT With the ever-increasing demands for popular content sharing among humans, device-to-device (D2D) multicast communication, as a promising technology to support wireless services within a local area, is introduced in a 5G cellular network. However, the existing resource allocation approaches for D2D multicast communication usually consider only physical domain constraints but neglect social domain factors, which would result in ineffective D2D links between users unwilling to share interests. Different from existing works, the D2D multicast scheme proposed in this paper will produce effective D2D multicast links by sufficiently utilizing both the physical and social properties of mobile users, with the goal to maximize the throughput of the overall social-aware network and guarantee fairly allocation of the channel between different D2D multicast clusters. The scheme mainly consists of two parts, the formation of D2D multicast clusters and joint optimization of power and channel allocation. In the formation of D2D multicast clusters, members and head in each cluster are selected by taking into account both social attributes and physical factors, such as community, ties, and geographical closeness. In the joint optimization, a two-step scheme is designed to first calculate the optimal power allocation by geometric proximity and then select suitable cellular channels for each D2D multicast cluster utilizing an extended one-to-many bipartite graphs matching algorithm. Simulation results demonstrate that, compared with heuristic algorithm and stochastic algorithm, the proposed scheme can increase the throughput of the overall social-aware network by about 5% and 50%, respectively.

INDEX TERMS D2D multicast communication, resources allocation, power control, social-aware.

I. INTRODUCTION

With smart phones and tablets becoming increasingly popular, the past few years have witnessed a tremendous growth of new applications in wireless systems [1], [2]. The proliferation of wireless applications, e.g. high-quality wireless video and massively multiplayer mobile game, will lead to an explosion of the mobile traffic. Cisco Visual Index reports that mobile traffic will surpass 15 exabytes per month in 2018 [3]. To meet the huge network traffic demands, it is urgent to make better use of limited spectrum resources in 5G wireless network [4]. Considering that most of traffic is generated in local areas such as sharing multimedia files in workplaces, colleagues and stadiums, the main concern is how to greatly improve local area services [5]. In addition, social attributes have become non-ignorable factors in wireless communication since mobile terminals are held by human beings and social information reflects the interactions between them in real life. For example, content sharing is more likely to take place among friends.

Device-to-device (D2D) communication is proposed as a key component in the 5G cellular network to satisfy the emerging demands of higher data rates for local area services [6]. It can make geographically proximate devices directly communicate with each other by reusing the licensed spectrum resources, without accessing a base station [7]. Due to physical proximity and frequency reuse, D2D communication can effectively improve spectrum utilization, offload traffic and reduce delay. Among other technologies, multicast communication plays an important role in local area services. It is an efficient data streaming paradigm for radio resource leveraging the broadcasting nature of wireless transmissions. It can deliver the same service traffic to multiple mobile users simultaneously [8]. As a combination of D2D and multicast, D2D multicast communication enables multiple proximate users to share the contents of their common interests directly, which greatly reduces power consumption and improves spectral efficiency. Due to the effectiveness, D2D multicast communication gains increasing attention in local area wireless services. Note that D2D multicast is divided into multi-rate multicast and single-rate multicast, this paper focuses on single-rate multicast, which means D2D multicast rate depends on the worst one of all the multicast recipients channel conditions. Then an appropriate resource allocation is necessary.

Due to no desired contents or low trust levels between some users, the establishment of D2D links might be hampered in the mobile network while satisfying physical transmission conditions. Therefore, the knowledge of social characteristics derived from underlying social network will play an important role in improving the performance of mobile networks. In sociology, a social network refers to the structure made up of a set of entities and a set of ties between them, and it is mainly characterized by community, centrality and social tie [9]. Here in the social-aware mobile network, a community is composed of sets of mobile users sharing common interests. Centrality indicates the social importance of a mobile user, and the higher centrality typically implies a user has stronger capability of connecting other users in the network [10]. Social tie is used to reflect the strength of social connections between two users. With the knowledge of social ties, it can avoid forming ineffective D2D links, for instance, the links between users unwilling to share contents. Thus the knowledge of social information will have strong impacts on the D2D multicast cluster formation and further influence the performance of D2D multicast underlay social-aware mobile network.

As is demonstrated above, an effective D2D multicast scheme in the socially-aware mobile network should take factors in both physical and social domains into account. The network parameters in the physical domain play an important role in both D2D multicast establishment and resource allocation strategy. For example, user density and geographical location determine how many D2D multicast links can be set up, and channel quality and transmission power determine for the D2D multicast link. The factors in the social domain, such as users' social relations, their willingness to join and consistency of their desired data contents, also have an impact on D2D cluster formation strategy, which would further influence the effectiveness of resource allocations in D2D multicast communications underlying cellular networks.

In this paper, we exploit social information to ensure the availability and reliability of D2D links. In this way, resources allocation can be performed accordingly to improve the overall users' throughput and the spectrum efficiency for multiple D2D multicast clusters and cellular users (CUs). Different social communities are formed according to the users' interested contents. In each community, a graph model is utilized to represent the social ties and physical distance, respectively. Based on the two-tier graph models, we design a greedy iterative method to obtain D2D multicast clusters and the transmitters (cluster heads) in them. Then, we study resource allocation optimization problem considering the quality-of-service requirements of both D2D clusters and CUs. To reduce the computation complexity, a two-step scheme is proposed. In the first step, it calculates the optimal power allocation for each D2D cluster and each cellular user. In the second step, a maximum weight bipartite matching model is developed to choose suitable CUs for each D2D cluster to share their resource to maximize the overall network throughput while guaranteeing the fairly allocation of resources among D2D clusters. Here, D2D multicast clusters are stimulated to share uplink resources of cellular users. Our contributions are summarized as follows.

- We utilize the knowledge derived from social domain information of mobile users in the social-aware mobile network, such as community and social ties, to improve the effectiveness of forming D2D multicast clusters which is a prerequisite for D2D resource allocation. We also extend the one-to-one matching method to a one-to-many version for solving resource allocation problem in D2D multicast underlay mobile network.
- To solve D2D multicast clustering problem, a greedy iterative method is designed, which maximizes the number of admitted D2D users and selects the best D2D user as cluster head. This method is implemented based on a physical-social graph, a union of a physical graph and a social graph. The social graph is modeled to reveal the real social ties of the users and physical graph is utilized to reflect the geographical closeness of the users.
- Based on the result of D2D multicast clustering, a joint power and channel resource allocation model is formulated to maximize system throughput and minimize the channels gap among different D2D multicast clusters. It is solved by a two-step scheme: one is optimal power allocation solved by geometric programming techniques and the other is channel assignment solved by Hungarian algorithm.

The rest of this paper is organized as follows. Section II gives a brief review of the related work. Section III presents the system architecture and an exemplified scenario. Section IV describes the two-layer graph model depicting the factors in both social and physical domains, and an optimization problem for power-channel joint allocation is also derived and presented in this section. Section V presents the two-step method to solve the problem. Simulation results together with their analyses are demonstrated in section VI, and some conclusions are drawn in Section VII.

II. RELATED WORK

Several works have been done on D2D multicast communication underlaying cellular networks. Meshgi *et al.* [11] presented a joint channel and power allocation scheme to maximize total throughput, where a heuristic algorithm was used to solve the channel assignment problem. Wu *et al.* [12] proposed an interference-coordinated optimal channel allocation method and a distance-constrained suboptimal channel allocation method for D2D underlaid multicast communication based on cognitive radio. Bhardwaj and Agnihotri [13] designed a QoS-ware resource allocation approach to minimize the interferences among D2D and CUs. A joint power and channel allocation scheme based on bipartite graph matching was proposed by Bhardwaj and Agnihotri [14] to handle mutual interferences among multiple CUs and D2D groups. Bo *et al.* [15] devised an efficient resource allocation strategy to maintain the fairness of among each D2D multicast group. A distance-constrained round-robin resource sharing scheme was studied by Gong *et al.* [16] for D2D multicast communications underlay single frequency network. The above works consider either one D2D link only reuses one orthogonal cellular channel [11]–[15] or multiple D2D links reuse one same CU channels [16]. Different from existing, we propose a method to assign multiple orthogonal channels for each D2D cluster. And the extended one to many bipartite graph matching is proposed to achieve optimal channel allocation, which not only improves system performance but also ensures fair allocation of the channel between D2D multicast clusters.

Moreover, social-aware D2D communication has obtained attention in recent researches [17]–[25]. Li *et al.* [17] introduced a social-aware enhanced D2D communication architecture by exploiting social networking characteristics. Zhao *et al.* [18] designed a social-aware D2D resource sharing scheme based on cooperative game theory to maximize the performance of both social and physical domains. Wang *et al.* [19] devised a two-step coalition game for social-community-aware D2D resource allocation. A joint mode selection and link allocation for social-aware D2D communications was proposed by Yang *et al.* [20] to improve the energy efficiency. Cao *et al.* [21] designed an efficient device-to-device cooperative strategy based on social trust and social reciprocity characteristics for video multicast system. Zhao *et al.* [22] proposed a novel social-community-aware long-range links establishment strategy to reduce multi-hop transmission delay. Zhang *et al.* [23] considered the mobile social and network knowledge jointly to suggest a cluster formation scheme for D2D communications. Jiang *et al.* [24] gave two social-aware energy harvesting D2D communication schemes for local data dissemination. Alim*et al.* [25] proposed a least cost D2D multi-hop path selection approach by leveraging social communities for real-time content delivery. Above literatures consider only the effect of a single social attribute on D2D communication, either social community or social ties. In addition, most of them concentrated on the study of D2D pair scenarios.

Different from existing works, we focus on multicast case of social-aware D2D resource allocation in cellular system, in which social attributes like communities and trust ties are jointly considered. We mainly address the following issues: 1) the reasonable formation of D2D multicast clusters in the social-aware D2D multicast underlying mobile network; 2) the optimal power and spectrum allocation to maximize the total data rate of system.

III. SYSTEM OVERVIEW

A. SYSTEM ARCHITECTURE

In this work, we concentrate on social-aware resource allocation for D2D multicast communication in an OFDMA-based cellular network. A scenario of uplink resource sharing is considered, since uplink spectrum is under-utilized comparing to that of downlink in the FDD system which means a lower interference on the signal. As is illustrated in Fig. 1, it combines physical domain and social domain. Each user in the physical domain corresponds to a node in the social domain. In the physical domain, the users access the network via cellular link or established a D2D communication link, subject to physical communication constraints. In the social domain, these users form a social network composed of some stable communities. To gain a comprehensive understanding of this system, we will introduce the functions of each component in these two domains.

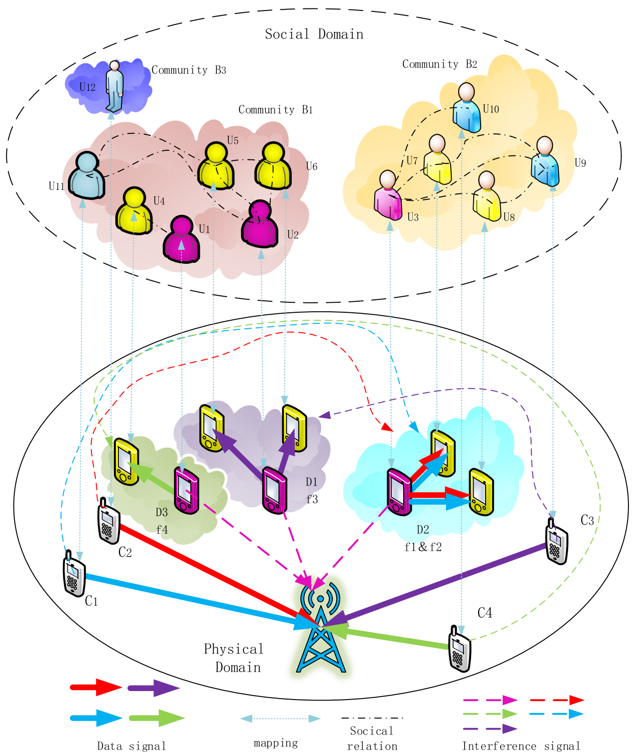

FIGURE 1. System model of cluster-based D2D multicast communication.

1) SOCIAL DOMAIN

1) Community stands for a set of nodes having the same interested contents to download in this paper. Obviously, only the members in the same community could build D2D multicast cluster. Due to physical and ties constraints, not all user can be served in D2D mode. There will be cellular users and D2D users at the same time. *2)* Social tie information not only reflects the degree of communication requirements but also the degree of trust among nodes. The links correlated to strong ties are more likely to be trustful and efficacious and the corresponding users are more expected to communicate in D2D mode. Thus social ties should be leveraged reasonably in order to attain higher throughput and achieve better privacy and security.

2) PHYSICAL DOMAIN

1) eNB: We consider the scenario of one eNB in the physical domain, where there is no corresponding a node in the social network. The eNB collects channel information and requests from all users and allocates the power and spectrum resources to each user. *2)* User: There are two types of users in the physical domain. One is cellular user who can communicate with others through the eNB. And they are assigned orthogonal resources for communication. The others are D2D users including D2D transmitters and D2D receivers. D2D multicast means the data is delivered from one D2D transmitter to multiple D2D receivers over direct wireless links by reusing uplink resources of cellular users.

In this paper, we focus on content sharing among mobile D2D users with multicast technologies. This proposed scheme can be carried out in a centralized manner. Firstly, the eNB collects the mobile information of all users, such as physical distances and social ties among users and generate the physical-social graph. Then, the involved users are divided into different communities according to content interests. It is noted that the social ties information is obtained from historical encounters recorded in the mobile network. Cellular users and potential D2D multicast clusters are derived by clustering scheme in Section IV-B, and resources will allocated accordingly in Section V. Table I lists main symbols used in the paper.

B. EXAMPLE SCENARIO

We use the scenario in Fig. 1 as the example to illustrate the system architecture. From Fig. 1 we can see that in the social domain mobile users are divided into different social communities. Users in each social community have different social ties with each other, which is decided by the degree of social trust. As shown in Fig. 1, there are three communities denoted by Community B_1, Community B_2, and Community B_3, which are represented by dark pink, orange and navy blue clouds in the social domain, respectively. In social communities, there are three types of users. The red users, (U_1, U_2, U_3) represent the important nodes with high centralities i.e. the one owns strong social ties with other users. The yellow users, ($U_4, \ldots, U_8$)represent the general multicast receivers whose social ties with the central node (user) are above the social threshold, and it gets the sharing contents from the central node. The blue users, ($U_9, \ldots, U_{12}$) represent the ones who can not form D2D cluster with others, e.g. those who have no common service content with other users, or whose social ties with the other interests users could not satisfy the requirement of social closeness threshold, or whose physical distance is too far away from other users. Note that there are two clusters in Community B_1, this is because some people in the same community may have weak social ties or long physical distance between each other, which makes them impossible to form one multicast cluster.

TABLE 1. Parameters of the system.

Notation	Meanings
$\mathcal{K}$ and K	The set and number of system users
$\mathcal{B}$ and B	The set and number of system users
$\mathcal{Y}_b$ and Y_b	The set and number of users in social community $\mathcal{B}_b$
$\mathcal{C}$ and M	The set and number of CUs in system
$\mathcal{D}$ and N	The set and number of D2D clusters in system
$g_b^s \triangleq (\mathcal{Y}_b, \varepsilon_b^s)$	Social graph in social community$\mathcal{B}_b$
$g_b^p \triangleq (\mathcal{Y}_b, \varepsilon_b^p)$	Physical graph in social community $\mathcal{B}_b$
$g_b^{ps} \triangleq (\mathcal{Y}_b, \varepsilon_b^{ps})$	Physical-Social graph in social community$\mathcal{B}_b$

In the physical domain, there are some users who are in close physical proximity to form a D2D multicast cluster in the same community with meeting social tie constraints. The other users are in the cellular communication mode. As illustrated in Fig. 1, there are four regular cellular users $\{\mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3, \mathcal{C}_4\}$ and three D2D multicast clusters $\{\mathcal{D}_1, \mathcal{D}_2, \mathcal{D}_3\}$. D2D multicast links reuse the spectrum occupied by cellular links. Thus, two types of interference exist, i.e. interference between eNB and D2D transmitter and interference between D2D receiver and cellular users. In order to avoid intensive interference, we assume that one CU's resource can be utilized at most by one D2D cluster while one D2D cluster can reuse the resources of multiple CUs. For example, the D2D cluster $\mathcal{D}_2$ reuses the resource f_1 of $\mathcal{C}_1$ and the resource f_2 of $\mathcal{C}_2$. However, it cannot reuse the f_3 of $\mathcal{C}_3$ or the resource f_4 of $\mathcal{C}_4$ because they have been reused by other D2D clusters.

IV. PROBLEM FORMULATION

A. SYSTEM MODEL

Assume that there are K original users in system denoted by the set $\mathcal{K} = \{\mathcal{K}_k \,|k = 1, 2, \ldots, K\}$. We use $\mathcal{C}$ and $\mathcal{D}$ to represent the set of cellular users and the D2D multicast clusters respectively. According to different interested content, some users form B communities denoted by the set $\mathcal{B} = \{\mathcal{B}_b \,|b = 1, 2, \ldots, B\}$. And some users with strong ties in the same social community form the D2D multicast cluster if the physical distance condition of D2D communication can be satisfied.

For the community $\mathcal{B}_b$, there are Y_b active users, denoted by the set $\mathcal{Y}_b = \left\{\mathcal{Y}_{b,\tau} \,|\tau = 1, 2, \ldots, Y_b\right\}$. However, due to the location constraint, only some of them are close enough to form D2D multicast clusters. Taking such location constraint into account, we introduce the physical graph $g_b^p \triangleq (\mathcal{Y}_b, \varepsilon_b^p)$ to reflect the physical connections among users in the community $\mathcal{B}_b$, where $\mathcal{Y}_b$ is the vertex set and $\varepsilon_b^p \triangleq \left\{(m, n) : e_{m,n}^p = 1, \forall m, n \in \mathcal{Y}_b\right\}$ is the edge set. And $e_{m,n}^p = 1$ if and only if user m and user n are capable of forming a D2D link i.e. the physical distance $l_{m,n}^p$ between device m and n is smaller than the certain threshold l_{thrd}^p.

We also introduce the social graph $g_b^s \triangleq (\mathcal{Y}_b, \varepsilon_b^s)$ to show the strength of social ties among the nodes in the community $\mathcal{B}_b$ where $\varepsilon_b^s \triangleq \left\{(m, n) : e_{m,n}^s \in [0, 1], \forall m, n \in \mathcal{Y}_b\right\}$ represents the edge set and $e_{m,n}^s$ reflects the social tie closeness between user m and n in the social network. Considering the ownership of files (i.e. privacy and security), we set a threshold e^s_{thrd}. If the social strength $e^s_{m,n}$ is bigger than threshold e^s_{thrd}, it means trust exists between user m and n for a strong social tie; otherwise, there is no trust between user m and n for a weak social tie. By considering the physical and social domains together in community, we obtain the physical-social graph $g^{ps}_b \triangleq \left(\mathcal{Y}_b, \varepsilon^{ps}_b\right)$, where $\varepsilon^{ps}_b \triangleq \left\{(m,n) : e^{ps}_{m,n} = e^p_{m,n} * e^s_{m,n}, \forall m,n \in \mathcal{Y}_b\right\}$. If and only if $e^{ps}_{m,n} \geq e^s_{thrd}$, the social D2D communication link can be established between user m and n.

B. CLUSTER FORMATION

We provide a greedy iterative method to form different D2D multicast clusters in each community, which includes the following main steps. As is shown in Fig. 2, a simple example is provided.

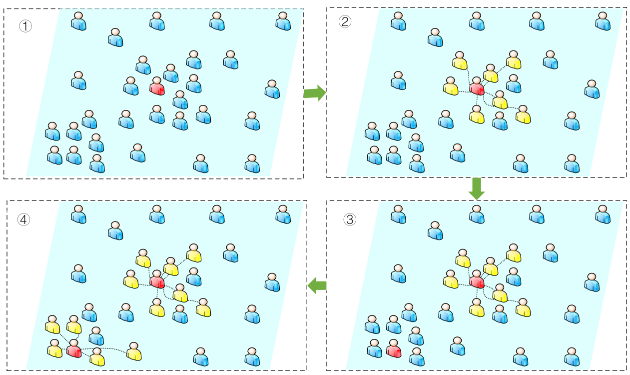

FIGURE 2. Cluster formation of D2D multicast.

Step 1: First we get the social communities set $\mathcal{B}$ according to the interesting contents of users. For each community $\mathcal{B}_b$, we get the set $\mathcal{Y}_b$ and initialize the set $\mathcal{U}^b = \mathcal{Y}_b$.

Step 2: For each community $\mathcal{B}_b$, the user $\widetilde{y}$ in set $\mathcal{U}^b$ can be selected as the multicast cluster head from the candidate users, if the following condition can be satisfied: The user $\widetilde{y}$ should have the closest physical-social relationship with the other users in the set $\mathcal{U}^b$, which means the condition $\widetilde{y} = \arg\max_{y \in \mathcal{Y}_b} \varepsilon^{ps}_b$ is achieved.

Step 3: For the user $x \neq \widetilde{y}$ in cluster $\mathcal{U}^b$, if the following two conditions are simultaneously satisfied, the user x added to multicast cluster $\mathcal{W}(\widetilde{y})$ whose cluster head is user $\widetilde{y}$. Firstly, the social tie strength $e^{ps}_{x,\widetilde{y}}$ between user x and cluster head $\widetilde{y}$ is bigger than e^s_{thrd}. Secondly, the physical distance between user x and cluster head $\widetilde{y}$ is in proximity to meet distance threshold $l^p_{m,n} \leq l^p_{thrd}$. It means condition $e^{ps}_{x,\widetilde{y}} \geq e^s_{thrd}$, $e^p_{x,\widetilde{y}} = 1, \forall x \in \mathcal{U}^b - \{\widetilde{y}\}$ is satisfied. It ends until all users are traversed. If $|\mathcal{W}(\widetilde{y})| > 1$, then, $\mathcal{W}(\widetilde{y}) \in \mathcal{D}$, otherwise, $\mathcal{W}(\widetilde{y}) \in \mathcal{C}$.

Step 4: Set $\mathcal{U}^b = \mathcal{U}^b - \mathcal{W}_{\widetilde{y}}$. If $\left|\mathcal{U}^b\right| > 1$, turn to **Step 2**. Otherwise, the cluster formation terminates.

Based on the above results, we further denote the set of cellular users as $\mathcal{C} = \{\mathcal{C}_i \,|i = 1, 2, \ldots, M\}$ and the set of D2D multicast clusters as $\mathcal{D} = \left\{\mathcal{D}_j \,|j = 1, 2, \ldots, N\right\}$, where M and N are the number of cellular users and D2D multicast clusters, respectively. Here, assume that $M > N$ because the number of cellular users are usually larger than D2D clusters in practical networks. In D2D cluster $\mathcal{D}_j$, D2D transmitter and D2D receiver are denoted as $d^t_{j,\widetilde{y}}$ and $d^r_{j,x}$, $x \in \mathcal{D}_j / \left\{\widetilde{y}_j\right\}$, and the number of D2D receivers is represented as X_j. According to 3GPP technical report and standard, A resource block is the smallest unit for resources scheduling that occupies 12 subcarriers and one time slot. Limited by the radio ability of terminal equipment, the D2D side-link connection use the Single Carrier-Frequency Division Multiple Access modulation, which consists of one or several RBs with continuous spectrum. We assume there are a total W resource blocks (RBs), CUs share these RBs uniformly and each D2D cluster will reuse some CUs' allocated resources to facilitate and simplify the analysis of interferences between cellular users and D2D clusters.

C. PROBLEM DESCRIPTION

Let $G_{j,d^r_{j,x}}$ denotes the channel gain between $d^t_{j,\widetilde{y}}$ and $d^r_{j,x}$, $G_{i,d^r_{j,x}}$ denotes the interference channel gain from $\mathcal{C}_i$ to $\mathcal{D}_j$, $G_{i,B}$ denotes the channel gain between $\mathcal{C}_i$ and eNB, $G_{j,B}$ denotes the interference channel gain from d^t_j to the eNB. Let $P^C_{i,j}$ represent the transmit power of cellular user $\mathcal{C}_i$ whose resources are shared with D2D cluster $\mathcal{D}_j$, $P^D_{i,j}$ represents transmit power of D2D cluster $\mathcal{D}_j$ who shares the resource of cellular user $\mathcal{C}_i$. Then the channel quality SINR of $\mathcal{C}_i$ is

$$SINR^C_{i,j} = \frac{P^C_{i,j} G_{i,B}}{P^D_{i,j} G_{j,B} + N_0}, \tag{1}$$

where N_0 is noise.

$$\begin{aligned} &SINR^D_{i,j} \\ &= \min_{x \in \mathcal{D}_j / \{\widetilde{y}_j\}} \frac{P^D_{i,j} G_{j,d^r_{j,x}}}{P^C_{i,j} G_{i,d^r_j} + N_0} \\ &= \min\left(\frac{P^D_{i,j} G_{j,d^r_{j,1}}}{P^C_{i,j} G_{i,d^r_{j,1}} + N_0}, \frac{P^D_{i,j} G_{j,d^r_{j,2}}}{P^C_{i,j} G_{i,d^r_{j,2}} + N_0}, \ldots, \frac{P^D_{i,j} G_{j,d^r_{j,x}}}{P^C_{i,j} G_{i,d^r_{j,x}} + N_0}\right). \end{aligned} \tag{2}$$

According to Shannon's theorem, the transmission rate $R^D_{i,j}$ of D2D cluster $\mathcal{D}_j$ reusing the channels of $\mathcal{C}_i$, the transmission rate $R^C_{i,j}$ of $\mathcal{C}_i$ whose resources are shared with D2D cluster $\mathcal{D}_j$ and the transmission rate R^C_i of $\mathcal{C}_i$ whose resources are not shared can be obtained, respectively. P^C_i represents the transmit power of cellular user $\mathcal{C}_i$ without resources sharing.

$$R^C_{i,j} = \frac{W}{M} \log_2\left(1 + SINR^C_{i,j}\right), \tag{3}$$

$$R^D_{i,j} = \frac{W}{M} \cdot X_j \cdot \log_2\left(1 + SINR^D_{i,j}\right), \tag{4}$$

$$R^C_i = \frac{W}{M} \log_2\left(1 + \frac{P^C_i G_{i,B}}{N_0}\right). \tag{5}$$

We define a $M \times N$ matrix $\Im = [\zeta_{i,j}]_{M\times N}$ to represent the resources allocation scheme of D2D clusters, where $\zeta_{i,j}$ is a binary variable, and $\zeta_{i,j} = 1$ if the D2D cluster D_j reuses the resource of $\mathcal{C}_i$, otherwise $\zeta_{i,j} = 0$. Let $R_{i,j}$ represent the total throughput of the resources occupied by $\mathcal{C}_i$, it consists of the throughput sum of cellular users and D2D clusters with resource sharing, and the throughput of cellular users without resource sharing.

$$\begin{aligned} R_{i,j} &= \zeta_{i,j}\left(R_{i,j}^C + R_{i,j}^D\right) + (1-\zeta_{i,j})\,R_i^C \\ &= \zeta_{i,j}\left(R_{i,j}^C + R_{i,j}^D - R_i^C\right) + R_i^C \\ &= \zeta_{i,j}\Delta R_{i,j} + R_i^C \end{aligned} \tag{6}$$

As R_i^C is a constant value, $R_{i,j}$ is only related to the value of $\zeta_{i,j}$ and the value of $\Delta R_{i,j}$. Let $\Delta R_{i,j}$ denotes the increased throughput after D2D reusing the channels of $\mathcal{C}_i$, e.g. $\Delta R_{i,j} = R_{i,j}^C + R_{i,j}^D - R_i^C$. Thus, $R_{i,j}$ can be further stated as the increased system throughput after D2D communication occurs.

D. PROBLEM FORMULATION

Our objective is to maximize the overall throughput and minimize the channel gap among D2D clusters while guaranteeing the QoS of both D2D clusters and the cellular users sharing channel resources with them.

Let $P_j^{D,MAX}$ and $P_i^{C,MAX}$ denote the maximum transmit power of D2D cluster and CU, respectively. $\Gamma_{D,j}$ and $\Gamma_{C,i}$ denote the minimum SINR threshold required by D2D clusters and CUs, respectively. Then the optimization problem can be mathematically formulated as **P1:**

$$\arg\max_{\zeta_{i,j}} \sum_{i=1}^{M}\sum_{j=1}^{N} R_{i,j}\left(P_{i,j}^D, P_{i,j}^C\right), \tag{7}$$

$$\min_{j\neq j'\in\mathcal{D}} \left|\sum_{i=1}^{M}\zeta_{i,j} - \sum_{i=1}^{M}\zeta_{i,j'}\right|, \tag{8}$$

$$s.t.\ R_{i,j} = \zeta_{i,j}\Delta R_{i,j} + R_i^C, \tag{9}$$

$$0 \le \sum_{i=1}^{M}\sum_{j=1}^{N}\zeta_{i,j} \le M, \quad 0 \le \sum_{j=1}^{N}\zeta_{i,j} \le 1, \tag{10}$$

$$\begin{aligned} &SINR_{i,j}^C\left(P_{i,j}^D, P_{i,j}^C\right) \ge \Gamma_{C,i}, \\ &SINR_{i,j}^D\left(P_{i,j}^D, P_{i,j}^C\right) \ge \Gamma_{D,j}, \end{aligned} \tag{11}$$

$$0 \le P_{i,j}^D \le P_j^{D,MAX}, \quad 0 \le P_{i,j}^C \le P_i^{C,MAX}. \tag{12}$$

Equation (7) and (8) are the objective function, it is designed to attain the maximum system throughput with minimum gap of resources allocated between different D2D multicast clusters, where $P_{i,j}^D$ and $P_{i,j}^C$ represent the optimal transmission power of D2D cluster $\mathcal{D}_j$ and CU $\mathcal{C}_i$ when $\mathcal{D}_j$ shares the resource of $\mathcal{C}_i$, respectively. Constraint (9) indicates that system throughput is related to the resource allocation of D2D cluster and the throughput gain of each channel. Constraints (10) ensures that a cellular user's channel resources can be shared by at most one D2D cluster while one D2D cluster can reuse multiple CUs' channel resources, but no more than the total amount of channels. Constraint (11) indicates that resource reused occurs only when both CUs and D2D users meet the service quality requirements. Constraint (12) is the limit of maximum transmit power for each channel.

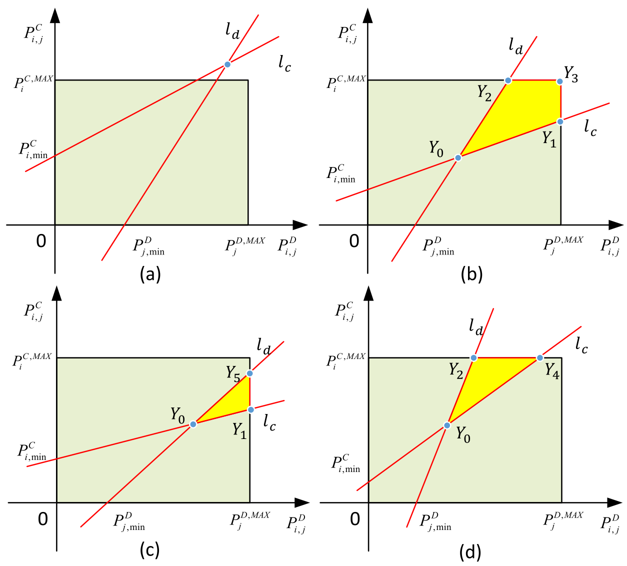

FIGURE 3. Possible feasible regions with different situations. (a) $P_{i,j}^{C,Y_0} > P_{i,j}^{C,MAX}$ or $P_{i,j}^{D,Y_0} > P_{i,j}^{D,MAX}$, (b) $P_{i,j}^{C,Y_0} \le P_{i,j}^{C,MAX}$ and $P_{i,j}^{D,Y_0} \le P_{i,j}^{D,MAX}$, and $P_{i,j}^{D,Y_2} < P_{i,j}^{D,MAX}$ and $P_{i,j}^{C,Y_1} < P_{i,j}^{C,MAX}$, (c) $P_{i,j}^{C,Y_0} \le P_{i,j}^{C,MAX}$ and $P_{i,j}^{D,Y_0} \le P_{i,j}^{D,MAX}$, and $P_{i,j}^{D,Y_2} < P_{i,j}^{D,MAX}$ and $P_{i,j}^{D,Y_1} > P_{i,j}^{D,MAX}$, (d) $P_{i,j}^{C,Y_0} \le P_{i,j}^{C,MAX}$ and $P_{i,j}^{D,Y_0} \le P_{i,j}^{D,MAX}$, and $P_{i,j}^{C,Y_1} < P_{i,j}^{C,MAX}$ and $P_{i,j}^{C,Y_5} < P_{i,j}^{C,MAX}$.

V. RESOURCES ALLOCATION

In this section, we will solve the original optimization problem in **P1** by splitting it into two steps. The first step is the power allocation. The second step is the channel allocation.

A. POWER ALLOCATION

In order to further improve the throughput, it is necessary to make reasonable power control for cellular users and D2D users. The optimization problem **P1** contains a power optimization sub-problem. It is shown in (13) with the range of channel transmission power limitation and the minimum SINR constraints of D2D and cellular users.

$$\begin{aligned} (P_{i,j}^{D*}, P_{i,j}^{C*}) = &\arg\max_{(P_{i,j}^D, P_{i,j}^C)\in\Re} R_{i,j} \\ \Re = &\Big\{(P_{i,j}^D, P_{i,j}^C) : 0 \le P_{i,j}^D \le P_j^{D,MAX}, \\ &0 \le P_{i,j}^C \le P_i^{C,MAX} \\ &SINR_{i,j}^C \ge \Gamma_{C,i}, SINR_{i,j}^D \ge \Gamma_{D,j}\Big\}, \end{aligned} \tag{13}$$

where $\Re$ is the feasible region of $(P_{i,j}^D, P_{i,j}^C)$. It is a convex optimization problem [26] which can be solved by geometric programming techniques with computation of $O(5MN)$. As is shown in Fig. 3, feasible region varies obviously in the four situations according to different values of the channel gain, target SINR and other related parameters.

Let $Y_0(P_{i,j}^{D,Y_0}, P_{i,j}^{C,Y_0})$ represent the intersection with SINR restrictions of $SINR_{i,j}^C = \Gamma_{C,i}$ and $SINR_{i,j}^D = \Gamma_{D,j}$. $Y_1(P_j^{D,MAX}, P_{i,j}^{C,Y_1})$ denotes the intersection of $SINR_{i,j}^C = \Gamma_{C,i}$ and $P_j^{D,MAX}$. $Y_2(P_{i,j}^{D,Y_2}, P_i^{C,MAX})$ as the intersection of $SINR_{i,j}^D = \Gamma_{D,j}$ and $P_i^{C,MAX}$. $Y_3 = (P_j^{D,MAX}, P_i^{C,MAX})$ is the intersection of $P_i^{C,MAX}$ and $P_j^{D,MAX}$, $Y_4(P_{i,j}^{D,Y_4}, P_i^{C,MAX})$ is the intersection of $SINR_{i,j}^C = \Gamma_{C,i}$ and $P_i^{C,MAX}$. $Y_5(P_{i,j}^{C,Y_5}, P_j^{D,MAX})$ is expressed as the intersection of $SINR_{i,j}^D = \Gamma_{D,j}$ and $P_j^{D,MAX}$. And the value of $P_{i,j}^{C,Y_0}$, $P_{i,j}^{D,Y_0}$, $P_{i,j}^{C,Y_1}$, $P_{i,j}^{D,Y_2}$ $P_{i,j}^{D,Y_4}$, $P_{i,j}^{C,Y_5}$ are shown as follows.

$$P_{i,j}^{C,Y_0} = \frac{\left(G_{j,d_{j,x}^r} + G_{j,B}\Gamma_{D,j}\right)\Gamma_{C,i}N_0}{G_{j,d_{j,x}^r}G_{i,B} - \Gamma_{C,i}\Gamma_{D,j}G_{i,d_{j,x}^r}G_{j,B}}, \tag{14}$$

$$P_{i,j}^{D,Y_0} = \frac{\left(G_{i,d_{j,x}^r}\Gamma_{C,i} + G_{i,B}\right)\Gamma_{D,j}N_0}{G_{j,d_{j,x}^r}G_{i,B} - \Gamma_{C,i}\Gamma_{D,j}G_{i,d_{j,x}^r}G_{j,B}}, \tag{15}$$

$$P_{i,j}^{C,Y_1} = \frac{\Gamma_{C,i}(P_j^{D,MAX}G_{j,B} + N_0)}{G_{i,B}}, \tag{16}$$

$$P_{i,j}^{D,Y_2} = \frac{\Gamma_{D,j}(P_i^{C,MAX}G_{i,d_{j,x}^r} + N_0)}{G_{j,d_{j,x}^r}}, \tag{17}$$

$$P_{i,j}^{D,Y_4} = \frac{P_i^{C,MAX}G_{i,B} - \Gamma_{C,i}N_0}{\Gamma_{C,i}G_{j,B}}, \tag{18}$$

$$P_{i,j}^{C,Y_5} = \frac{G_{j,d_{j,x}^r}P_j^{D,MAX} - \Gamma_{D,j}N_0}{\Gamma_{D,j}G_{i,d_{j,x}^r}}. \tag{19}$$

Since the all channel gains are greater than zero, we can prove the following lemma.

Lemma 1: At least one of optimal transmission power is equal to the maximum power i.e. $(P_{i,j}^{D*}, P_{i,j}^{C*}) = (P_{i,j}^{D*} = P_j^{D,MAX})$ or $(P_{i,j}^{C*} = P_i^{C,MAX})$. The proof is given in Appendix A.

Lemma 2: The optimal transmit power allocation $\left(P_{i,j}^{D*}, P_{i,j}^{C*}\right)$ over a D2D multicast cluster and CU only exists on the corners of feasible region $\Re$. The proof is given in Appendix B.

According to *Lemma 1*, the optimal power pair resides on line $\overline{Y_1Y_2}$ *or* $\overline{Y_1Y_3}$ in Fig. 3b or line $\overline{Y_1Y_5}$ in Fig. 3c or line $\overline{Y_2Y_4}$ in Fig. 3d. Based on *Lemma 2*, it is known that the optimal solution is located at one end point of the above lines. For situation (a), $(P_{i,j}^{D*}, P_{i,j}^{C*}) = \emptyset$ since $\Re = \emptyset$. For situation (b), $(P_{i,j}^{D*}, P_{i,j}^{C*})$ falls in the set $\{Y_1, Y_2, Y_3\}$. For situation (c), $(P_{i,j}^{D*}, P_{i,j}^{C*})$ falls in the set $\{Y_1, Y_5\}$. For situation (d), $(P_{i,j}^{D*}, P_{i,j}^{C*})$ falls in the set $\{Y_2, Y_4\}$. So the optimal power pair is located at one point in $\{Y_1, Y_2, Y_3, Y_4, Y_5\}$. We traverse all the collection to get $R_{ij}^*(P_{i,j}^{D*}, P_{i,j}^{C*})$. Therefore, the original optimization problem can be further simplified into the following equation:

$$\begin{aligned}
&\arg\max_{\zeta_{i,j}} \sum_{i=1}^{M}\sum_{j=1}^{N} R_{i,j}\left(P_{i,j}^{D*}, P_{i,j}^{C*}\right)\\
&\min_{j\neq j'\in\mathcal{D}} \left|\sum_{i=1}^{M}\zeta_{i,j} - \sum_{i=1}^{M}\zeta_{i,j'}\right|\\
&s.t.\ R_{i,j} = \zeta_{i,j}\Delta R_{i,j} + R_i^C\\
&\quad 0 \le \sum_{i=1}^{M}\sum_{j=1}^{N}\zeta_{i,j} \le M, \quad 0 \le \sum_{j=1}^{N}\zeta_{i,j} \le 1.
\end{aligned} \tag{20}$$

where (20) is quite similar to **P1**, except that $R_{i,j}$ is based on the optimal power allocation $(P_{i,j}^{D*}, P_{i,j}^{C*})$. Since the SINR restriction has already been considered in (13), it is not embodied in (20).

B. CHANNEL ALLOCATION VIA BIPARTITE MATCHING

We can get all feasible mapping of resources reusing between D2D clusters and cellular users by exploiting the power control results $(P_{i,j}^{D*}, P_{i,j}^{C*})$. Since the channel of one CU can share resource with at most one D2D cluster and one D2D cluster can reuse multiple CUs' resources, we need to find the optimal solution on channel assignment from all feasible mappings. This optimal resource allocation can be obtained by the maximum weight bipartite matching method in graph theory.

As Fig. 4 shows, we construct bipartite graph G , whose two groups of vertices are the set of cellular users $\mathcal{C}$ and the set of D2D clusters $\mathcal{D}$, respectively. If cellular user $\mathcal{C}_i$ is a reuse candidate of D2D cluster $\mathcal{D}_j$, there is an edge with weight $\Delta R_{i,j}$ connecting vertex j and vertex i. Otherwise, there is a virtual edge with zero weight.

Hungarian algorithm is a typical method to solve this kind of bipartite matching problem [27], [28], but it requires the bipartite graph to be completely symmetric. Therefore, we need to transform the original non-symmetric bipartite matching problem into an absolute symmetric one. As illustrated in Fig.4, it can be achieved by: 1) if M is ∂ times of N i.e. $M = \partial \times N$, we add $(\partial - 1) \times N$ vertices in the set $\mathcal{D}$ with original weighted edges, which is exactly ∂ copies of the original clusters. 2) If $M = \partial \times N + \bar{\lambda}$, we add $\partial \times N$ vertices in the set $\mathcal{D}$ with original weighted edges and add $N - \bar{\lambda}$ virtual vertices in the set $\mathcal{C}$ with zero weighted edges. Another advantage brought in by the vertices of copied clusters is that it compels uniform resource allocation between different clusters, which satisfies the objective of minimizing the gap of allocated resource. Then the Hungarian algorithm can be appropriate for finding the solution in such a one-to-many bipartite matching graph.

The main idea of Hungarian algorithm is to find a perfect matching with minimum cost. Our goal is max-

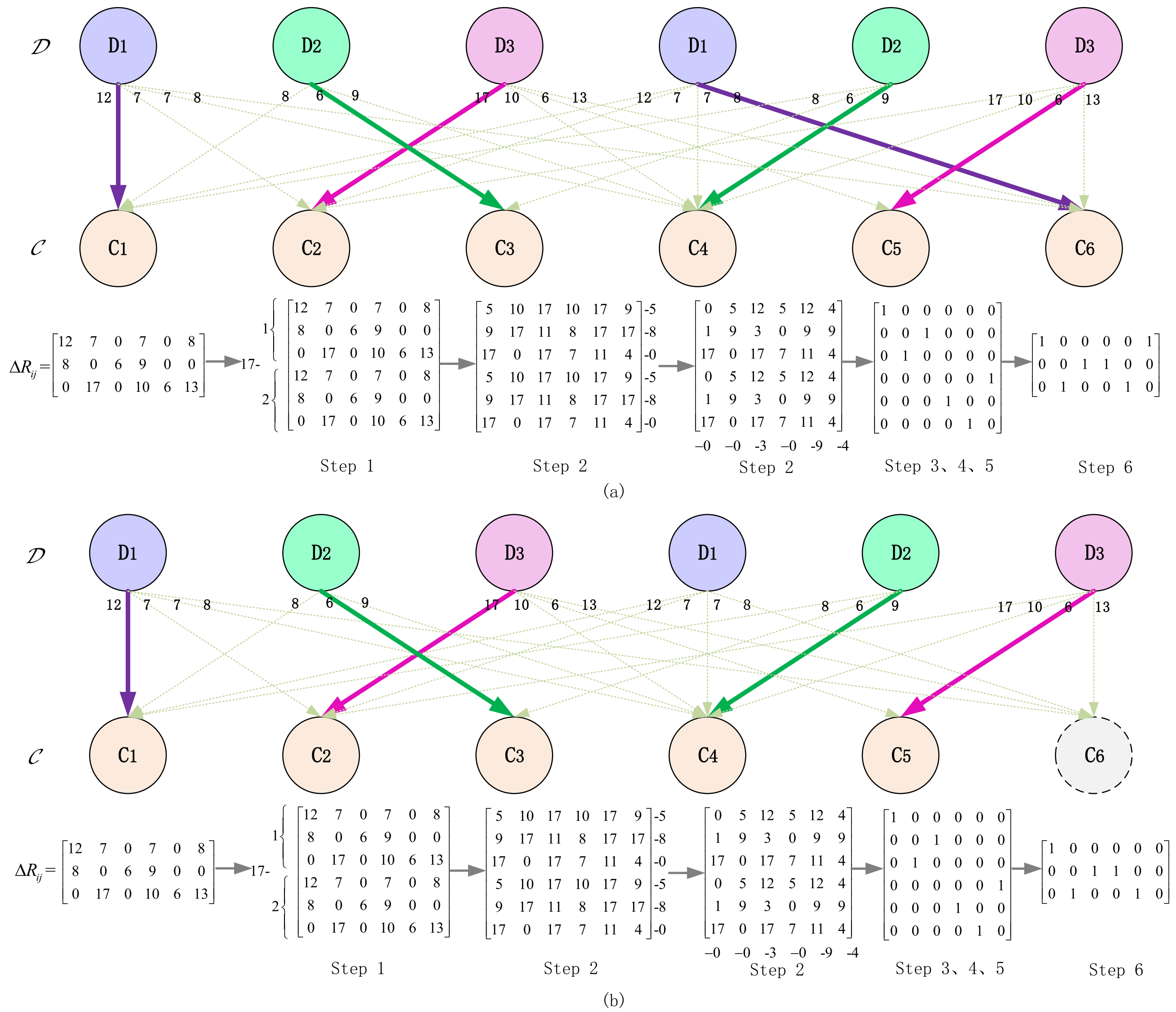

FIGURE 4. **Illustration of bipartite matching between D2D clusters and cellular users: (a) bipartite matching in the case of $M = \partial \times N$ and (b) bipartite matching in the case of $M = \partial \times N + \bar{\lambda}$.**

imized the sum of throughput increment $R_{i,j}(P_{i,j}^{D*}, P_{i,j}^{C*})$. To this end, we firstly make a weight transformation edge between vertices i and j. Then, the one-to-one matchings between D_j and C_i are performed heuristically. Details of the implementation of Hungarian algorithm are shown in the following steps. For better understanding, we provide a simple example in Fig. 4.

Step 1: Generate efficiency matrix $\mathcal{R} = [\Delta R_{i,j}]_{\partial N \times \partial N}$ or $\mathcal{R} = [\Delta R_{i,j}]_{(\partial+1)N \times (\partial+1)N}$ according to the extension of the binary graph G and its edge weights. Then find the largest element $\Phi = \max\{\Delta R_{i,j}\}$ in matrix $\mathcal{R}$, and get a new matrix $H = [h_{i,j}]$, $h_{i,j} = \Phi - \Delta R_{i,j}$.

Step 2: Find out the minimum value of the matrix H in each row, $u_i = \min\limits_{\forall j} \hat{h}_{i,j}$, $i, j = 1, 2, \ldots, M$, get a new matrix $\hat{H} = [\hat{h}_{i,j}]_{\partial N \times \partial N}$ or $\hat{H} = [\hat{h}_{i,j}]_{(\partial+1)N \times (\partial+1)N}$ by $h_{i,j} - u_i$. Find out the minimum value of the matrix $\hat{H}$ in each column $v_j = \min\limits_{\forall i} \hat{h}_{i,j}$, $i, j = 1, 2, \ldots, M$, get a new matrix $H^* = [h_{i,j}^*]_{\partial N \times \partial N}$ or $H^* = [h_{i,j}^*]_{(\partial+1)N \times (\partial+1)N}$ by $\hat{h}_{i,j} - v_j$. As shown in Fig. 4, u_i and v_j are marked on the right and down of the matrix respectively.

Step 3: Create a subgraph G^* with vertices i and j which satisfies $h_{i,j}^* = 0$ and the edge with weight $\Delta R_{i,j}$. Select the edge with maximum weight in graph G^* and get optimal matching $\mathcal{M}_{\max}$. $\mathcal{M}_{\max}$ is the subset of edges of sub-graph G^*, the two nodes of any edges in $\mathcal{M}_{\max}$ are different and any two edges in $\mathcal{M}_{\max}$ share no common nodes. If $\mathcal{M}_{\max}$ is the perfect matching, i.e. the nodes of edges cover all nodes of the graph G, go to **Step 5**, otherwise, go to **Step 4**.

Step 4: Let V be a vertex cover of G^*, and let $Q = \mathcal{C} \cap V$, $\mathcal{T} = \mathcal{D} \cap V$. Then Find out θ satisfies $\theta = \min\left\{h_{i,j} : \mathcal{C}_i \in \mathcal{C} - Q, \mathcal{D}_j \in \mathcal{D} - \mathcal{T}\right\}$, and increase u_i by θ for the rows of Q and decrease v_j by θ for the columns of $\mathcal{T}$. Go back to **Step 2**.

Step 5: If $\mathcal{M}_{\max}$ is a perfect matching, delete the virtual nodes with the corresponding edge in $\mathcal{M}_{\max}$, then get the

TABLE 2. Parameters of the system.

Parameter	Value
Cell radius	0.5km
Number of users, K	20,40,$\cdots$,100
Number of social community, B	3
Social-ties threshold, e^s_{thrd}	0.3,0.5,0.7
D2D physical distance threshold, l^p_{thrd}	10,20,$\cdots$,100m
Maximum transmission power	24dBm
Uplink bandwidth	5MHz
Noise spectral density	-174dBm/Hz
Path loss model for cellular links	128.1+37.6log(d[km])
Path loss model for D2D links	148+40log(d[km])
$\Gamma_{C,i}, \Gamma_{D,j}$	3dB

optimal allocation results. Then find the element $h^*_{i,j} = 0$ and the corresponding matrix position (i^*, j^*). Consequently, we derived that the relative element $\zeta_{i^*,j^*} = 1$ and other $\zeta_{i,j} = 0$. Remove the virtual nodes and their edges in $\mathcal{M}_{\max}$ to obtain the optimal allocation results.

Step 6: The dimension of resource allocation matrix in **Step 5** is transformed and the result of resource allocation matrix $[\zeta_{i,j}]_{M\times N}$ is obtained.

From above, Hungarian algorithm can get the optimal solution of resources allocation, while guaranteeing the fairness for different D2D multicast clusters.

VI. SIMULATION RESULT

In this section, we present and analyze the simulation results. Our simulations are carried out in a single cell scenario within a 500m × 500m area with one eNB located in the center and some social communities without geographical overlapping. All original users are distributed randomly in the physical area of social communities corresponding within the cell. We establish the social tie matrix for the users in each social community by setting the degree of closeness between users randomly within the range 0 and 1. We suppose that all the CUs share the total bandwidth equally and satisfy the QoS requirements before resources reusing. The simulation parameters are shown in TABLE 2.

The performance of our proposed D2D multicast scheme is closely related to the formation of D2D multicast clusters and the joint allocation of power and spectrum resources. Thus, the effects of detailed clustering method and resource allocation algorithm are respectively analyzed in this paper. Firstly, the results of D2D multicast clusters formation are analyzed with respect the number of remaining cellular users M and that of D2D multicast clusters N, as well as the average size of D2D multicast clusters, which is defined as the average amount of members in the formed clusters, considering the impacts of total amount of users K, physical distance proximity threshold d and social closeness threshold s. Secondly, we evaluate the performance of our proposed resource allocation scheme by comparing it with two classic schemes, denoted as Heuristic and Stochastic respectively. In the heuristic algorithm, each D2D cluster searches the most beneficial channel in turn. In the stochastic scheme, a random reusable resource allocation matrix of the cluster is developed as long as it satisfies the boundary restriction listed in (13). Three aspects of the performance are analyzed including throughput, D2D access rate and D2D access fairness. We first evaluate the throughput gain of the overall system, together with the throughput degradation of the resource-shared cellular users (RCUs). The throughput gain will indicate the advantages of the proposed D2D multicast scheme, mainly the ultra high reuse gain, while the throughput decrement of RCUs is used to assess the performance sacrifice to obtain the reuse gain. Then we evaluate the performance in D2D access rate, which is defined as the ratio of D2D multicast clusters where D2D multicast communication is applicable after resource allocation to the candidate clusters formed in the clustering stage. In addition, D2D fairness index is defined as the variation of channel resource allocation among D2D clusters. So a smaller index means better fairness.

For the sake of convenience, we use s and d to represent the social closeness and physical proximity threshold respectively. All the results were averaged over 200 random trials.

A. THE PERFORMANCE OF CLUSTERING SCHEME

In Fig. 5, we evaluate the performance of the proposed clustering scheme for different numbers of original users K on four aspects of metrics, the number of cellular users M, the ratio of potential D2D users in K, the number of formed clusters N and the average size of the formed clusters. The effects of both physical proximity threshold and social closeness threshold are considered. In general, it can be seen that, given specific values of s and d, the values of the four metrics get larger with the increase of K, due to the enlarged group of original users. The increase of M following K in Fig. 5(a) does not necessarily mean a drop of potential D2D users, as can be validated in Fig. 5(b) and further explained in Fig. 5 (c) and (d). Moreover, social closeness threshold s and physical proximity threshold d show strongly joint but distinctive impacts to the clustering results, which contributes to the varied shapes of curves.

In Fig. 5(a), the curves for $d = 70$m are always below the curves for $d = 30$m, because more original users will meet this physical proximity criterion and are grouped into clusters, causing the reduction of M for larger d. Correspondingly a considerable increment of potential D2D users ratio can be observed in Fig. 5(b). These analyses are also suitable for s. From Fig. 5 (c) and (d), in the high physical proximity requirement ($d = 30$m) case, the number of formed clusters N and the average size of them simply go down with the increase of s for all K. Because $d = 30$m sets a strong limit to the physical coverage area of a cluster, and the grown social closeness threshold s just raises the requirement for D2D link establishment. However, it is not the same in the $d = 70$m case, where N goes up with the increase of s for large K, while N drops for small K. Because, with low social closeness requirement ($s = 0.3$), large K leads to the constraint of physical proximity threshold become weak, and more users

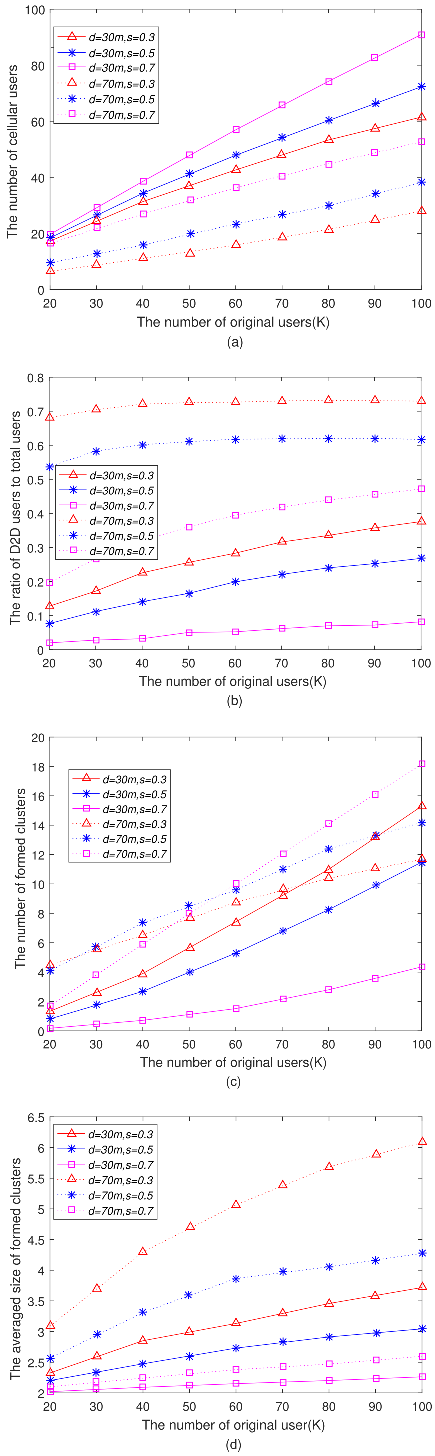

FIGURE 5. The performance of clustering for different user scales. (a) the number of cellular users versus user scales, (b) the ratio of D2D users versus user scales, (c) the number of D2D clusters versus user scales, (d) the averaged size of D2D cluster versus user scales.

will be grouped into clusters. Increasing s will just make users out of these clusters and form new but small clusters, resulting in the enlarged N and diminished average cluster size. Alternatively, when K is small, the constraining effect of d is strengthened due to enlarged distance between original

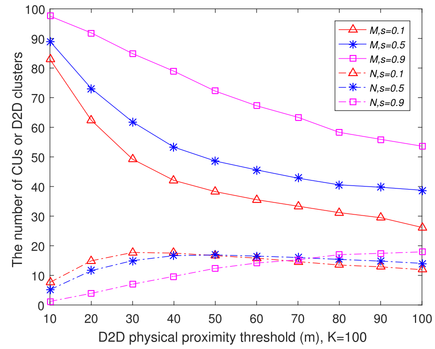

FIGURE 6. The number of CUs and D2D clusters versus D2D physical proximity threshold.

users, and there will be fewer users in each formed cluster. Raising the social closeness requirement just invalidates some of the clusters, causing the drop of average cluster size. These are consistent with what we observed in Fig. 5(c) and (d). Fig. 6 will give further analyses on the joint effects of s and d on the clustering results.

Fig. 6 illustrates how the physical proximity threshold d affects M and N in the cases of low, medium and high social closeness thresholds for s being 0.3, 0.5 and 0.7 respectively. In all three cases, we observe M decreases with the increase of d, and smaller s results in fewer cellular users. This goes along with our intuition because smaller s means weaker social closeness is required between users to form a cluster and more initial users become potential D2D users. As to the number of D2D clusters, Fig. 6 clearly shows that both s and d take effect, however, with altered significance. In $s = 0.7$ case, the N curve monotonically stretches up as d increases 10m to 100m. In $s = 0.3$ and 0.5 cases, the N curve goes up and then down with the increase of d. That is probability because N is decided by both the number of potential D2D users and the cluster size. In $s = 0.7$ case where strong social closeness is required to form a cluster, s is the key factor that limits the size of D2D multicast cluster. With d increasing, the cluster size will stay almost unchanged, while the limit on physical proximity becomes weak and more initial users become potential D2D users, leading to the constant increase of N. In other two cases, s and d compete to be the dominating factor. If d is small, d dominates the effect and we observe a sharp increase of N before d reaches 40m, and then N curve becomes flat or even goes down due to the cluster size getting larger.

B. THE PERFORMANCE OF RESOURCES ALLOCATION

In Fig. 7, the performance of three algorithms is compared for different physical proximity thresholds in the cases of adopting low, medium and high social closeness thresholds. From the figure, the throughput increments of all approaches increase with the rising of physical proximity threshold. This is because larger physical proximity threshold makes original users much easier to join D2D multicast clusters, thus leading to the increased amount of D2D users and the enlarged cluster size, which is consistent with the fact in Fig. 6. As a

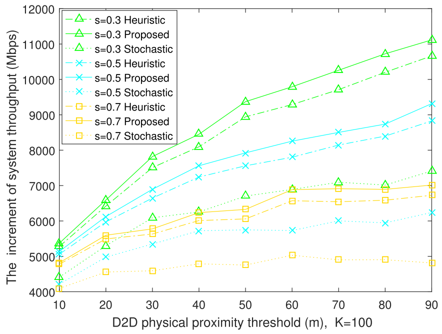

FIGURE 7. The increment of system throughput versus D2D physical proximity threshold.

result, each D2D cluster can reuse more cellular resources and the resource multiplexing gain is even larger, which jointly contribute to the total throughput improvement. In addition, the social closeness threshold also shows interesting impact on throughput improvement. From Fig. 7, the increment of throughout using small s is always larger than using a large s for the same algorithm, and the margin between them gets larger with the increase of d. Because s gradually dominates the effect with d getting larger. In whatever cases, the proposed algorithm gains more throughput than the other two algorithms. When $d = 90$m, the proposed scheme produces 50% more throughput than Stochastic and 5% more than Heuristic. Because the proposed algorithm considers all possible channels allocation permutations and selects the one that optimized the system throughout, while the stochastic algorithm randomly selects channel from the set of allowed-reusing channels and heuristic algorithm pursues the maximum benefit of each D2D cluster individual without considering the global optimal.

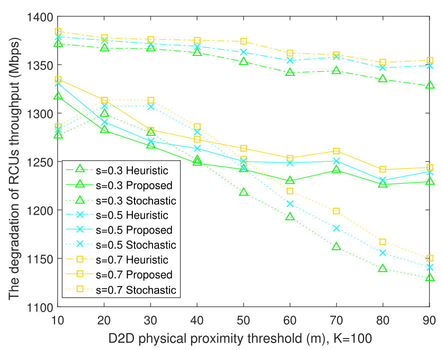

FIGURE 8. The drop of RCUs throughput versus D2D physical proximity threshold.

Fig. 8 evaluates the main side effect of introducing D2D multicast in cellular, which primarily refers to the throughput performance degradation of cellular users that share channels with D2D multicast clusters. In general, the curves are all above zero, indicating that the throughput performance of cellular users is alway impacted. However, despite this throughput decrement, the overall system throughput grows significantly, validating the effectiveness of our proposed D2D multicast scheme. Moreover, the resource allocation is based on the clustering results. As a result, both social closeness threshold s and physical proximity threshold d affect the decrement, which is mainly owing to the decrease of M, the number of remaining cellular users. In addition, resource allocation scheme really exerts direct impact to the throughput decrement. From Fig. 8, three resource allocation schemes produce apparently different curves. The reasons for this lie in two aspects, the D2D access rate and the interference caused by sharing channel resources. The three schemes (Proposed, Heuristic and Stochastic) take reduced care of the interference, so the proposed scheme would have the least throughput decrement; however, the observation results appear to be different, because with better interference consideration, the proposed and heuristic schemes would make more formed clusters into D2D multicast clusters and increase the interference again. This also accounts for the occasionally higher decrement of the proposed scheme than the heuristic, and the fluctuation of curves. The detailed D2D access rate of the three algorithm is depicted and analyzed in the following part.

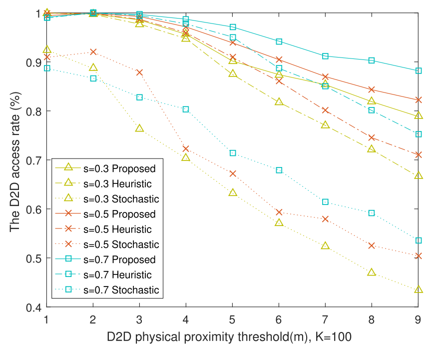

FIGURE 9. The D2D access rate versus D2D physical proximity threshold.

Fig. 9 compares the performance of our proposed algorithms with Heuristic and Stochastic on D2D access rate under different level of threshold requirements. It shows that D2D access rate generally decreases with the increase of physical proximity threshold or the reduction of social closeness requirement. To put some explanation here, we know from earlier analyses that there will be more cellular users when lower social closeness is required or d gets larger, which leads to the lower criterion in D2D multicast clusters planning, and it is increasingly hard for these clusters to meet some prerequisites in D2D multicast communication, low interference to the proximate cellular users such as. The interference between D2D clusters and channel-shared cellular users is closely related to the effectiveness of resource allocation scheme. To our satisfaction, the proposed scheme keeps much larger D2D access rate than the compared existing schemes. This means more D2D multicast communication will be established through the proposed scheme, and the system throughput thus enjoys a boost by a much larger channel reuse gain, which is consistent with the observation in Fig. 7.

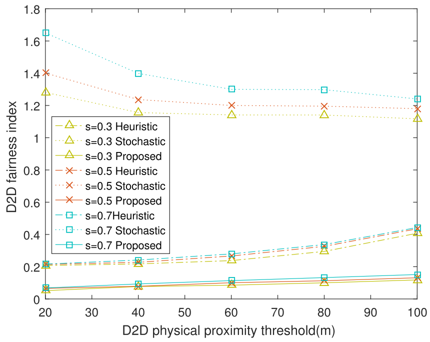

FIGURE 10. The D2D fairness index of different schemes.

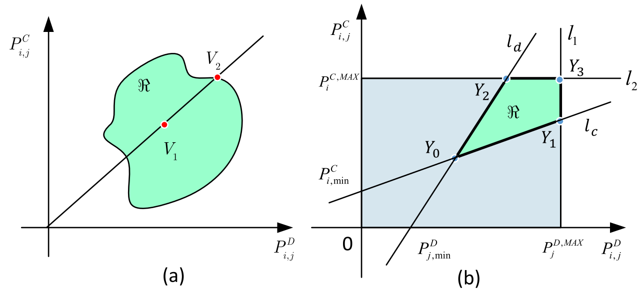

FIGURE 11. The optimal power allocation $(P^{D*}_{i,j}, P^{C*}_{i,j})$ and the boundary of $\Re$. (a) the optimal power allocation $(P^{D*}_{i,j}, P^{C*}_{i,j})$ achieved on the boundary of $\Re$, (b) feasible region $\Re$.

The fairness index of each compared algorithm is ploted in Fig. 10 against the physical proximity threshold d and the effects of social closeness requirement are also considered. From the figure, our proposed scheme has obviously advantages over the compared schemes. And it is easy to notice that its fairness index is almost steady with the change of both d and s, which demonstrates the fairness-guaranteeing property of our proposed scheme. It is partially due to the design principle of minimizing the resource distribution, and on the other hand, the extend one-to-many matching algorithm is used to specifically solve the resource allocation. As to the other two schemes, the statistic scheme shows the worst fairness performance, while the heuristic only has slightly larger fairness index than the proposed one. That is because, the former just arbitrarily picks a channel without good consideration of fairness, and the latter chooses a shared channel for each D2D multicast cluster with the strategy to iteratively maximize the throughput gain or minimize the mutual interference. This strategy works well in one-to-one cases; however, it can not properly deal with the one-to-many case as investigated in this paper, which also become a driving factor and motivation for conducting the research in this paper.

Summarizing the results obtained from above figures, we observe that, our proposed scheme obtains a much better system sum rate than the other two algorithms while incurring very little increased of CUs throughout and also ensures a larger D2D access rate and fair allocation of channels among the D2D clusters.

VII. CONCLUSION

In this paper, we propose a social-aware resource allocation for 5G D2D multicast communications. Firstly, we design a novel D2D multicast cluster formation scheme which simultaneously takes account of physical communication distance and social trust ties between mobile users. Considering factors in both physical and social domains ensures the availability and rationality of D2D multicast links, which form the basis for further resource allocation. Secondly, a joint power and channel resource allocation scheme are proposed not only to achieve maximum system throughput but also to maintain fairness for different D2D multicast clusters. We formulate the joint optimization problem and then find the solution through two steps: the optimal power control for each D2D cluster and each cellular user, and the optimal channel allocation obtained through an extended one-to-many maximum weighted matching algorithm. At last, we conduct extensive simulations to evaluate the performance of our proposed schemes. Numerical results demonstrate that our solution allows a good balance between throughput performance and fairness among multicast clusters and has significant advantages over other algorithms.

APPENDIX A
PROOF OF LEMMA 1

Proof: We prove the Lemma 1 using contradiction. According to constraints in (13), $\Re$ is a closed and bounded set or empty. For non-empty $\Re$, let $\partial\Re$ be the boundary region of $\Re$, then $\Re' = \{\Re\}\setminus\{\partial\Re\}$. Further assuming a point $V_1(P^{D*}_{i,j}, P^{C*}_{i,j})$ in $\Re'$ as depicted in Fig. 11(a), a line is drawn through point V_1 which intersects the boundary at $V_2(P^{D,b}_{i,j}, P^{C,b}_{i,j})$ with slope $\ell = P^{C*}_{i,j}/P^{D*}_{i,j} \geq 0$. Let $P^{C,b}_{i,j} = \delta P^{C*}_{i,j}$ and $\delta > 1$. Since ℓ is $\frac{P^{C,b}_{i,j}-P^{C*}_{i,j}}{P^{D,b}_{i,j}-P^{D*}_{i,j}}$, so $P^{D,b}_{i,j} = \delta P^{D*}_{i,j}$ By putting value $(\delta P^{D}_{i,j}, \delta P^{C}_{i,j})$ in (6), for $\delta > 1, \delta \in R^+$ and $(P^{D}_{i,j}, P^{C}_{i,j}) \in \Re$, we get

$$
\begin{aligned}
R_{i,j}(\delta P^{D}_{i,j}, \delta P^{C}_{i,j}) &= \frac{W}{M}\log_2\left((1+\alpha_1)(1+\alpha_2)^{X_j}\right)\\
&> R_{i,j}(P^{D}_{i,j}, P^{C}_{i,j})
\end{aligned}
$$

where $\alpha_1 = \frac{P^{C}_{i,j}G_{i,B}}{P^{D}_{i,j}G_{j,B}+N_0/\delta}$ and $\alpha_2 = \min\limits_{x\in\mathcal{D}_j/\{\widetilde{y}_j\}} \frac{P^{D}_{i,j}G_{j,d^r_{j,x}}}{P^{C}_{i,j}G_{i,d^r_j}+N_0/\delta}$. With increasing δ, $R_{i,j}(\delta P^{D*}_{i,j}, \delta P^{C*}_{i,j}) > R_{i,j}(P^{D*}_{i,j}, P^{C*}_{i,j})$ which contradicts the assumption that $(P^{D*}_{i,j}, P^{C*}_{i,j})$ is the optimal solution, thus $(P^{D*}_{i,j}, P^{C*}_{i,j}) \in \partial\Re$ holds. Thus the optimal transmit power allocation will have $P^{D*}_{i,j} = P^{D,MAX}_{j}$ or $P^{C*}_{i,j} = P^{C,MAX}_{i}$.

Thus, Lemma 1 is proved.

APPENDIX B
PROOF OF LEMMA 2

Proof: The contour of $\Re$ and $\partial\Re$ varies with the merits of constrained parameters. However, according to formulation (13), $\partial\Re$ is bounded by the four edges illustrated in Fig. 11(b). These edges $l_1 : P^C_{i,j} = P^{C,MAX}_i$, $l_2 : P^D_{i,j} = P^{D,MAX}_j$, $l_d : SINR^D_{i,j} \geq \Gamma_{D,j}$, $l_c : SINR^C_{i,j} = \Gamma_{C,i}$. Let $l'_n : l_n \cap \partial\Re\ (n = 1\ to\ 4)$ and $R_{i,j}(P^D_{i,j}, P^C_{i,j}) = \frac{W}{M}\log_2((1 + SINR^C_{i,j})(1 + SINR^D_{i,j})^{X_j})$. If $(P^D_{i,j}, P^C_{i,j}) \in l'_2$ then $\frac{\partial^2\Re}{\partial(P^C_{i,j})^2} \geq 0$. If $(P^D_{i,j}, P^C_{i,j}) \in l'_1$, $\frac{\partial^2\Re}{\partial(P^D_{i,j})^2} \geq 0$. If $(P^D_{i,j}, P^C_{i,j}) \in l'_d \cup l'_c$, then $R_{i,j}$ is always an increasing function. Furthermore, it has been proved that $R_{i,j}(P^D_{i,j}, P^C_{i,j})$ is a convex function in [14], and the logarithm is a monotonically increasing function, we can deduce that $(P^{D*}_{i,j}, P^{C*}_{i,j})$ only resides on the corners of $\Re$. The proof of convexity of $R_{i,j}(P^D_{i,j}, P^C_{i,j})$ is omitted for sake of brevity.

Thus, Lemma 2 is proved.

REFERENCES

[1] F. Xia, L. T. Yang, L. Wang, and A. Vinel, "Internet of Things," *Int. J. Commun. Syst.*, vol. 25, no. 9, pp. 1101–1102, 2012.

[2] H.-G. Yoon, W.-G. Chung, H.-S. Jo, J. Lim, J.-G. Yook, and H.-K. Park, "Spectrum requirements for the future development of IMT-2000 and systems beyond IMT-2000," *J. Commun. Netw.*, vol. 8, no. 2, pp. 169–174, 2006.

[3] Cisco, San Jose, CA, USA. (2015). *Global Mobile Data Traffic Forecast Update, 2014–2019*. [Online]. Available: http://www.cisco.com

[4] T. O. Olwal, K. Djouani, and A. M. Kurien, "A survey of resource management toward 5G radio access networks," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 3, pp. 1656–1686, 3rd Quart., 2016.

[5] H. Zhang, C. Jiang, N. C. Beaulieu, X. Chu, X. Wen, and M. Tao, "Resource allocation in spectrum-sharing OFDMA femtocells with heterogeneous services," *IEEE Trans. Commun.*, vol. 62, no. 7, pp. 2366–2377, Jul. 2014.

[6] K. Doppler, M. Rinne, C. Wijting, C. B. Ribeiro, and K. Hugl, "Device-to-device communication as an underlay to LTE-advanced networks," *IEEE Commun. Mag.*, vol. 47, no. 12, pp. 42–49, Dec. 2009.

[7] G. Fodor *et al.*, "Design aspects of network assisted device-to-device communications," *IEEE Commun. Mag.*, vol. 50, no. 3, pp. 170–177, Mar. 2012.

[8] J. M. Vella and S. Zammit, "A survey of multicasting over wireless access networks," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 2, pp. 718–753, 2nd Quart., 2013.

[9] K.-C. Chen, M. Chiang, and H. V. Poor, "From technological networks to social networks," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 9, pp. 548–572, Sep. 2013.

[10] N. Vastardis and K. Yang, "Mobile social networks: Architectures, social properties, and key research challenges," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1355–1371, 3rd Quart., 2013.

[11] H. Meshgi, D. Zhao, and R. Zheng, "Joint channel and power allocation in underlay multicast device-to-device communications," in *Proc. IEEE Int. Conf. Commun.*, Jun. 2015, pp. 2937–2942.

[12] X. Wu, Y. Chen, X. Yuan, and M. E. Mkiramweni, "Joint resource allocation and power control for cellular and device-to-device multicast based on cognitive radio," *IET Commun.*, vol. 8, no. 16, pp. 2805–2813, 2014.

[13] A. Bhardwaj and S. Agnihotri, "A resource allocation scheme for device-to-device multicast in cellular networks," in *Proc. IEEE Int. Symp. Pers., Indoor, Mobile Radio Commun.*, Aug./Sep. 2015, pp. 1498–1502.

[14] A. Bhardwaj and S. Agnihotri, "A resource allocation scheme for multiple device-to-device multicasts in cellular networks," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Apr. 2016, pp. 1–6.

[15] B. Peng, C. Hu, T. Peng, Y. Yang, and W. Wang, "A resource allocation scheme for D2D multicast with QoS protection in OFDMA-based systems," in *Proc. IEEE 24th Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC)*, Sep. 2013, pp. 12383–12387.

[16] W. Gong, X. Wang, M. Li, and Z. Huang, "Round-robin resource sharing algorithm for device-to-device multicast communications underlying single frequency networks," in *Proc. Int. Conf. Telecommun.*, 2014, pp. 191–195.

[17] Y. Li, T. Wu, P. Hui, D. Jin, and S. Chen, "Social-aware D2D communications: Qualitative insights and quantitative analysis," *IEEE Commun. Mag.*, vol. 52, no. 6, pp. 150–158, Jun. 2014.

[18] Y. Zhao, Y. Li, Y. Cao, T. Jiang, and N. Ge, "Social-aware resource allocation for device-to-device communications underlaying cellular networks," *IEEE Trans. Wireless Commun.*, vol. 14, no. 12, pp. 6621–6634, Dec. 2015.

[19] F. Wang, Y. Li, Z. Wang, and Z. Yang, "Social-community-aware resource allocation for D2D communications underlaying cellular networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 5, pp. 3628–3640, May 2016.

[20] L. Yang, D. Wu, S. Xu, and Y. Cai, "Social-aware energy-efficient joint mode selection and link allocation in D2D communications," in *Proc. Int. Conf. Wireless Commun. Signal Process.*, Oct. 2016, pp. 1–6.

[21] Y. Cao, T. Jiang, X. Chen, and J. Zhang, "Social-aware video multicast based on device-to-device communications," *IEEE Trans. Mobile Comput.*, vol. 15, no. 6, pp. 1528–1539, Jun. 2016.

[22] Y. Zhao, Y. Li, H. Mao, and N. Ge, "Social-community-aware long-range link establishment for multihop D2D communication networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 11, pp. 9372–9385, Nov. 2016.

[23] G. Zhang, K. Yang, and H.-H. Chen, "Socially aware cluster formation and radio resource allocation in D2D networks," *IEEE Wireless Commun.*, vol. 23, no. 4, pp. 68–73, Aug. 2016.

[24] L. Jiang *et al.*, "Social-aware energy harvesting device-to-device communications in 5G networks," *IEEE Wireless Commun.*, vol. 23, no. 4, pp. 20–27, Aug. 2016.

[25] M. A. Alim, T. Pan, M. T. Thai, and W. Saad, "Leveraging social communities for optimizing cellular device-to-device communications," *IEEE Trans. Wireless Commun.*, vol. 16, no. 1, pp. 551–564, Jan. 2017.

[26] D. Feng, L. Lu, Y. Yuan-Wu, G. Y. Li, G. Feng, and S. Li, "Device-to-device communications underlaying cellular networks," *IEEE Trans. Commun.*, vol. 61, no. 8, pp. 3541–3551, Aug. 2013.

[27] H. W. Kuhn, "The Hungarian method for the assignment problem," *Naval Res. Logistics Quart.*, vol. 2, nos. 1–2, pp. 83–97, Mar. 1955.

[28] J. Munkres, "Algorithms for the assignment and transportation problems," *J. Soc. Ind. Appl. Math.*, vol. 5, no. 1, pp. 32–38, 1957.

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