Author(s): Xu, Chen; Gao, Caixia; Zhou, Zhenyu; Chang, Zheng; Jia, Yunjian

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Social Network-Based Content Delivery in Device-to-Device Underlay Cellular Networks Using Matching Theory

Chen Xu, *Member, IEEE,* Caixia Gao, Zhenyu Zhou, *Member, IEEE,*
Zheng Chang, *Member, IEEE,* Yunjian Jia, *Member, IEEE*

***Abstract*—With the popularity of social network-based services, the unprecedented growth of mobile date traffic has brought a heavy burden on the traditional cellular networks. Device-to-device (D2D) communication, as a promising solution to overcome wireless spectrum crisis, can enable fast content delivery based on user activities in social networks. In this paper, we address the content delivery problem related to optimization of peer discovery and resource allocation by combining both the social and physical layer information in D2D underlay networks. The social relationship, which is modeled as the probability of selecting similar contents and estimated by using the Bayesian nonparametric models, is used as a weight to characterize the impact of social features on D2D pair formation and content sharing. Next, we propose a three-dimensional iterative matching algorithm to maximize the sum rate of D2D pairs weighted by the intensity of social relationships while guaranteeing the quality of service (QoS) requirements of both cellular and D2D links simultaneously. Moreover, we prove that the proposed algorithm converges to a stable matching and is weak Pareto optimal, and also provide the theoretical complexity. Simulation results show that the algorithm is able to achieve more than 90% of the optimum performance with a computation complexity one thousand times lower than the exhaustive matching algorithm. It is also demonstrated that the satisfaction performance of D2D receivers can be increased significantly by incorporating social relationships into the resource allocation design.**

***Index Terms*—social network, device-to-device communication, content delivery, Bayesian nonparametric models, matching theory.**

I. Introduction

A. Background and Motivation

WITH the popularity of high-performance intelligent terminals and the emergence of new mobile multimedia services, the demand on wireless high data rate has been growing continuously [1]. The contradiction between the growing service demands of users and the limited network bandwidth has become increasingly prominent [2]. The existing wireless network architecture needs to be upgraded [3].

Researchers in academia and industry therefore attempt to explore new valuable communication technologies that can improve the system capacity by spectrum reuse. Device-to-device (D2D) communication, as one of the key solutions for future 5G system, allows mobile devices to transmit data signals over local peer-to-peer links instead of through a traditional infrastructure, i.e., the base station (BS) of cellular network. By reusing cellular spectrum resources under the control of the BS, D2D communication can dramatically increase the spectrum efficiency and network capacity [4], [5]. Moreover, because of the proximity effect of direct connections, D2D is expected to enhance the data transmission rates and promote new applications [6], [7].

According to the analytical data results [1], a large amount of data traffic is generated from hotspots, where the distribution of mobile users is extremely dense, such as a subway train, a concert hall, and other public places. From another perspective, the users located in the hotspots may have "relationships" with other ones, which can be obtained from their social data on the social platforms. The social relationship, generally speaking, includes real friend relations and virtual relations associated with interests in similar contents. In practice, multiple users may request for the same content, while the BS has to transmit the content to these users by multiple repeated transmissions in the traditional way. For this case, it is reasonable to apply D2D technique to push or share the same content from the content holder to users with tight social relationships. It is worth noting that the appropriate cellular spectrum resources need to be reused by the D2D links. As a result, the heavy data traffic is offloaded from the cellular infrastructure, and at the same time the spectrum efficiency is increased.

There exist some works on cellular data offloading by integrating D2D communications with social networks [8]–[11]. In such a scenario, the BS pushes the content to a set of seed users, who then transmit the content to other users in proximity by D2D links. The relationships between the seed and non-seed users are defined as "social ties", which reflect the similarity of users' preferences on the content. The core objective is to spread the popular content in as short a

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C. Xu, C. Gao and Z. Zhou are with the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China, 102206. (E-mal: chen.xu@ncepu.edu.cn, caixia_gao@ncepu.edu.cn, zhenyu_zhou@ncepu.edu.cn)

Z. Chang is with Department of Mathematical Information Technology, University of Jyväskylä, FIN-40014 Jyväskylä, Finland. (E-mail: zheng.chang@jyu.fi)

Y. Jia is with the College of Communication Engineering, Chongqing University, Chongqing, China 400044. (E-mail: yunjian@cqu.edu.cn)

time period as possible. However, in practice, there is another situation that users in the hotspots may not be interested in the same content. For instance, two passengers on a subway train are using Facebook to browse pictures posted by their mutual friend, while another passenger has just downloaded a video that other passengers around him may be interested in. Therefore, in order to implement effective content delivery and achieve good user satisfactions, it is necessary to consider the different preferences of users on the contents based on historical data obtained from the social platforms.

The above consideration brings challenges to the system. First, the social relationships that reflect the close degree of users, i.e., the consistency degree of preferences on similar contents, are required for determining the transmitter and receiver of D2D communication, which can be regarded as a process of peer discovery. Second, since the D2D transmitters push contents to the receivers by reusing the cellular spectrum, the co-channel interference cannot be ignored, which requires an efficient resource management to optimize the system performance and guarantee the quality of service (QoS) as well. Combining these two aspects, the strategy of content delivery should consider the system status information from both social layer and physical layer. On the one side, the content delivered to the user is expected to be what he just wants; on the other side, the reused spectrum is hoped to be the best choice for maximizing the system sum rate.

B. Contributions

In this paper, in order to implement effective content delivery, we study a joint peer discovery and resource allocation approach, with the objective of maximizing the system sum rate weighted by the intensity of users' social relationships, and at the same time guaranteeing the QoS of both cellular and D2D links. Due to the uncontrollability and uncertainty of users' activities in social network [12], we utilize the probabilities of selecting similar contents, which can be estimated by Bayesian nonparametric models [13], to obtain the social relationships among users. Considering the different preferences of users on the contents and spectrum resources, we focus on solving the joint optimization problem by matching theory [14], which attempts to describe the formation of mutually beneficial relationships. Some works have already employed matching theory to allocate limited resources to users that maximize resource efficiency [15]–[18], and some works have proposed energy-efficient resource management schemes based on matching theory for D2D communications [19], [20]. Note that in our problem, the matching between D2D transmitters and receivers, and the matching between D2D pairs and resource blocks (RBs), should be jointly considered. Thus, we propose a three-dimensional matching process to achieve the coordinated allocation of users, contents, and spectrum resources, based on the social layer and phasical layer information. The main contributions of this paper are summarized as follows:

- We propose a social network-based content delivery approach to offload the cellular data traffic by D2D links. Specifically, we define the intensity of two users' social relationship as the normalized correlation of the probabilities of selecting similar contents that estimated by the Bayesian nonparametric models. Moreover, a joint peer discovery and spectrum resource allocation problem, which involves the matching between content providers (transmitters) and content consumers (receivers), and the matching between D2D links and spectrum resources, respectively, is proposed and formulated as a three-dimensional matching that maximizes the system sum rate weighted by the intensity of social relationships.
- Due to its combinatorial nature, the joint allocation problem is intractable and belongs to the class of NP-hard problems. We simplify the problem based on pricing strategy and give a sub-optimal solution, which can approach the performance of the exhaustive optimal algorithm with a much lower complexity. First, we transform the three-dimensional matching into a two-sided matching, in which the preference lists of transmitters from one side over the combinations of receivers and resources from the other side are established based on the achievable weighted rates. Then we introduce a pricing strategy to decide the winner when more than one transmitter propose towards the same combination. In the algorithm, we also consider the power control for D2D transmissions to avoid excessive interference to cellular users.
- The properties of the proposed three-dimensional matching algorithm including convergence, stability, optimality and complexity are analyzed theoretically. In the simulation, we compare the proposed matching algorithm with the exhaustive optimal and random matching algorithm in terms of the achieved weighted sum rate for D2D communications under different scenarios. Numerical results show that our proposed scheme can achieve a considerable performance gain, and the satisfactions of users on the shared contents are substantially improved with the consideration of social relationships.

The rest of this paper is organized as follows. In Section II, we provide a brief review of the related works. The system model consisting of physical layer and social layer is given in Section III, and the formulation of the social network-based content delivery problem is introduced in Section IV. Section V describes the three-dimensional matching algorithm with relevant theoretical concepts and analysis. The simulation results and discussions are presented in Section VI. Finally, we conclude the paper in Section VII.

II. Related Works

Our previous works mainly focused on the resource allocation problem and provided a theoretical analysis on the tradeoff between energy efficiency and spectrum efficiency [21], [22]. However, the peer discovery problem has not been taken into consideration. In comparison, this paper aims to solve the joint peer discovery and resource allocation problem with power control in D2D communications underlaying cellular networks by exploring both social and physical layer information. Utilizing the location information of users, a centralized D2D discovery scheme, which can adaptively allocate resource blocks for the discovery to avoid the underutilization of spectrum resources based on the random access procedure in LTE-A system, was proposed in [23]. In [24], the authors proposed a social-aware peer discovery scheme for D2D communications based on an established paradigm, in which mobile users are divided into groups by utilizing the social domain information including location, interest and background. A code-based discovery protocol that studied in [25] utilizes the discovery code containing the compressed information of mobile applications to find the nearby devices that have interests on the mobile applications, and thus to realize proximity-based services. The above works mainly solve the peer discovery issue of D2D communications considering physical location information, social information or interests on mobile applications, etc.

In addition, social information in social network is utilized to enhance various performance metrics of D2D communications. For instance, clustering schemes with an admission policy were proposed to increase system rate in [26] with consideration of social interaction. While in [27], it was proposed to improve the system throughput and energy efficiency based on the Chinese Restaurant Process (CRP). Mode selection of content downloading for D2D users and relay selection for social-trust-based and social-reciprocity-based cooperative D2D communications were studied in [8] and [28], respectively. Sharing strategies utilizing social relationship were proposed in [9] and [10] with consideration of minimum delay and formation of a practical network, respectively.

Besides, resource allocation issue for D2D pairs with consideration of the social relationship were studied in different scenarios, such as a single community in [29]–[31], cooperative communities in [32] and a slotted system in [33]. In a single community, D2D pairs can simply reuse the RBs occupied by the cellular users that are in the same community. While in the scenario of cooperative communities, D2D pairs can reuse the RBs of the cellular users that are in the community coalition, namely the aggregation of the cooperative communities. Due to the human mobility in a slotted system, a D2D link can be considered for resource allocation only when the two users encounter and the contact time is long enough to complete a meaningful transmission. Focus on different methods, the allocation of RBs to D2D pairs was solved using the matching game in [29], two-step coalitional game in [32] and other maximization games in [30]–[33] with different objective functions. Resource allocation problem can be modeled as a two-sided matching problem using matching theory. Such that the problem is formulated as a matching game in which D2D pairs and RBs rank one another based on the utility functions that consider both physical and social metrics in [29]. Also, matching theory has been utilized to solve resource allocation problems considering two-dimensional matching with mutual preferences in D2D communications [20], [34], heterogeneous cellular networks [15], [17], cognitive radios [16], and etc.

However, the previous works have not employed social information to solve the joint peer discovery and resource allocation problem, which actually involves a three-dimensional matching among D2D transmitters, D2D receivers and RBs in the content delivery process.

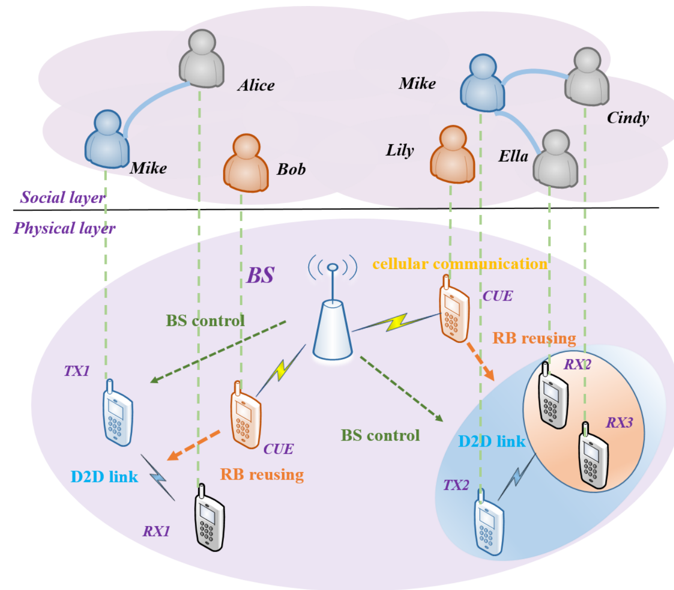

Fig. 1. System model of social network-based content delivery in D2D underlay cellular networks.

III. System Model

We consider a cellular network with one BS and multiple users involving traditional cellular user equipments (CUEs) and potential D2D pairs. Each user can receive data from either the BS, or another user through potential D2D links. In this paper, the mode selection problem is left out of consideration, and thus we assume that there exist some users satisfying the physical requirement of D2D, such as the constraint of transmission distance. Once it is found that two users can be matched to form a D2D pair, the content holder transmits signals to the requester. Here, we focus on two key problems: 1) How to match the content transmitter (TX) with the receiver (RX) so that the RX would be satisfied with the received content; 2) How to design an efficient resource allocation scheme for D2D pairs to maximize the system performance.

An illustration of social-aware D2D underlay network is shown in Fig. 1. The architecture can be divided into two layers consisting of social layer and physical layer. In the social layer, users' behaviors in social network reflect their real social connections, which can be obtained from social platforms, such as Microblog, Facebook, Twitter, etc. Thus, we can derive the real close degree of user relationships by exploring their behaviors in such platforms. In the physical layer, the establishment of D2D links are mainly determined by transmission distance between two mobile nodes, namely smart terminals, such as smartphones and tablets. For each user in the social layer, there exists a corresponding terminal in the physical layer. To achieve successful message pushing or content sharing through D2D links, both the social relations and the physical locations need to be taken into account.

In general, if two users have a stronger social relationship, the probability of establishing direct link between them would be higher, which is because their content preferences are more similar than that of users with weak social connections.

Meanwhile, a better channel quality between users promotes an establishment of D2D link. In this section, we introduce the system model of social-aware D2D underlay network. The physical transmission model is first described, and then, the social relationship between users is quantified.

A. Physical Layer Model

In the system, we assume that D2D links share uplink (UL) resource blocks (RBs) occupied by cellular users, and for simplicity, one RB is allocated to one CUE and can be reused by at most one D2D pair. Furthermore, we assume that there are N D2D TXs (content providers) and N D2D RXs, which are denoted by the set $\mathcal{N}_T$=$\{1,\cdots,i,\cdots,N\}$ and $\mathcal{N}_R$=$\{1,\cdots,j,\cdots,N\}$, respectively. K RBs and the corresponding cellular users are denoted by the set $\mathcal{N}_K$=$\{N_1,\cdots,N_k,\cdots,N_K\}$ and $\mathcal{K}$=$\{1,2,\cdots,k,\cdots,K\}$, respectively. For the channel model, we use the Rayleigh fading to model the small-scale fading, and employ the free space propagation path-loss to model the large-scale fading. The received power of D2D link between transmitter $i\in\mathcal{N}_T$ and receiver $j\in\mathcal{N}_R$, and the received power of cellular link between CUE $k\in\mathcal{K}$ and the BS, can be expressed as

$$P_{r,j}=P_i^D h_{ij}^2=P_i^D d_{ij}^{-\alpha}h_{0,ij}^2, \tag{1}$$

$$P_{r,k}=P_k^C h_k^2=P_k^C d_k^{-\alpha}h_{0,k}^2, \tag{2}$$

where P_i^D and P_k^C are the transmit power of D2D TX i and CUE k, respectively. h_{ij} and h_k denote the channel response of the D2D link and the cellular link. d_{ij} is the transmission distance between TX i and RX j while d_k represents the transmission distance between CUE k and the BS. α is the path-loss exponent corresponding to the large-scale fading of the transmission channel, and $h_{0,ij}$, $h_{0,k}$ are the Rayleigh channel coefficient, which obeys the complex Gaussian distribution $\mathcal{CN}(0,1)$.

As a result of uplink spectrum reusing, both D2D receivers and the BS suffer from co-channel interference. When D2D pair D_{ij} that composed of TX $i\in\mathcal{N}_T$ and RX $j\in\mathcal{N}_R$ reuses the uplink RB $N_k\in\mathcal{N}_K$, RX j receives interference from CUE $k\in\mathcal{K}$, and the BS is exposed to interference from D2D TX i. The signal to interference plus noise ratio (SINR) of user j on RB N_k and the SINR of BS are

$$\gamma_{D_{ij},k}=\frac{P_i^D h_{ij}^2}{P_k^C h_{kj}^2+N_0}=\frac{P_i^D d_{ij}^{-\alpha}h_{0,ij}^2}{P_k^C d_{kj}^{-\alpha}h_{0,kj}^2+N_0}, \tag{3}$$

$$\gamma_{k,i}=\frac{P_k^C h_k^2}{P_i^D h_{iB}^2+N_0}=\frac{P_k^C d_k^{-\alpha}h_{0,k}^2}{P_i^D d_{iB}^{-\alpha}h_{0,iB}^2+N_0}. \tag{4}$$

Here, h_{kj} and h_{iB} are the channel responses of the interference links between CUE k and D2D RX j, between D2D TX i and the BS, respectively. N_0 is the one-sided power spectral density of the additive white Gaussian noise (AWGN) at the receivers. Based on the above expressions, the channel rate of D2D pair D_{ij} reusing RB N_k and the rate of cellular link between k and the BS are obtained by

$$r_{D_{ij},k}=\log_2\left(1+\frac{P_i^D h_{ij}^2}{P_k^C h_{kj}^2+N_0}\right), \tag{5}$$

$$r_{k,i}=\log_2\left(1+\frac{P_k^C h_k^2}{P_i^D h_{iB}^2+N_0}\right). \tag{6}$$

B. Social Layer Model

In social network, users' behaviors reflect the close degree of their relationships. Therefore, it is extremely important to analyze users' social behaviors during the process of social layer modeling. However, it is hard to find an appropriate model to describe the properties of social behaviors due to their uncontrollability and uncertainty. Thus, we utilize the probability of selecting similar contents to represent the similarity of users' behaviors, which determines the intensity of their social relationships. Bayesian model is an efficient model that apply Probability and Statistics into complex area to handle the uncertainty reasoning. Integrating the prior information and sample information, it is easy to obtain the posterior probability distribution. It means that the system can obtain the probability distributions of users' content selections by integrating the history records collected from different social network platforms using the Bayesian technique [35]–[37]. After that, the intensity of social relationship, i.e., the consistency degree of preferences on similar contents, can be quantified.

Statistical modeling is a useful tool which models the process as a stochastic variable with a correlative probability density function (pdf) in a feature space. A particular statistical distribution, which is supposed to approximate the practical distribution with the parameters estimated from the sample, is used to represent the pdf parametrically. In this process, we have to find an appropriate model that approximates the actual distribution to estimate the associated parameters. However, Bayesian nonparametric models can estimate the pdf directly from the samples without making any assumptions for the underlaying distribution so as to avoid the parameter estimation process and the accuracy of the estimation would be improved as more data are observed. Dirichlet processes [38], [39], which are a family of stochastic processes, are often used in Bayesian nonparametric statistics since the prior and posterior distributions in Bayesian nonparametric models are stochastic processes rather than parametric distributions. In the following paragraph, We will introduce the theoretical basis and the process to build the social relationship among users in details.

1) Theoretical Basis: Dirichlet distribution, the infinite-dimensional generalization of which is Dirichlet process, is a multivariate generalization of the beta distribution. Based on the theoretical meaning of the beta distribution, we assume that Y_f has been observed ς_f-1 times, $f=1,2,\cdots,F$. y_f can be viewed as the probability of Y_f. Then the Dirichlet distribution of order $F\geq 2$ with parameters $\varsigma_1,\cdots,\varsigma_F>0$

has a pdf with respect to Lebesgue measure on the Euclidean space $\mathbb{R}^{F-1}$ that obtained by

$$\begin{aligned} & Dir(\varsigma_1, \cdots, \varsigma_F) \\ & = f(y_1, \cdots, y_{F-1}; \varsigma_1, \cdots, \varsigma_F) = \frac{1}{B(\varsigma)} \prod_{f=1}^{F} y_f^{\varsigma_f - 1}. \end{aligned} \tag{7}$$

For all $y_1, \cdots, y_{F-1} > 0$, they satisfy $y_1 + y_2 + \cdots + y_F - 1 < 1$ while y_F is an abbreviation for $1 - y_1 - \cdots - y_{F-1}$. The density is zero outside this open $(F-1)$ dimensional simplex. The normalizing constant $B(\varsigma)$ can be expressed according to the gamma function as it is the multivariate beta function:

$$B(\varsigma) = \frac{\prod_{f=1}^{F} \Gamma(\varsigma_f)}{\Gamma(\Sigma_{f=1}^{F} \varsigma_f)}, \varsigma = (\varsigma_1, \cdots, \varsigma_F). \tag{8}$$

We define $\varsigma_0 = \Sigma_{f=1}^{F} \varsigma_f$. The beta distributions, which are the marginal distributions of the Dirichlet distribution, are given by

$$y_f \sim Beta(\varsigma_f, \varsigma_0 - \varsigma_f). \tag{9}$$

Then, for the Dirichlet process (DP) over a set Θ, we introduce a base distribution H and a concentration parameter α, which is a positive real number. We denote that the random distribution X is Dirichlet process distributed with H and α, denoted as $X \sim DP(\alpha, H)$, if for every finite measurable partition $G_1, \cdots, G_U$ of Θ, we have

$$(X(G_1), \cdots, X(G_U)) \sim Dir(\alpha H(G_1), \cdots, \alpha H(G_U)). \tag{10}$$

The base distribution H is basically the mean of the DP and the parameter α can be viewed as an inverse variance, which means that for any measurable partition $G \subset \Theta$, $E[X(G)] = H(G)$, $V[X(G)] = H(G)(1 - H(G))/(\alpha + 1)$. We regard α as the strength parameter corresponding to the strength of the prior when utilizing the DP as a prior information in Bayesian nonparametric models. The variance would decrease with α growing, and thus, the DP would concentrate more on the mean.

Let $X \sim DP(\alpha, H)$. Since X is a random distribution over Θ, we can draw the independent samples in turn from X, which are written as a sequence $\chi_1, \cdots, \chi_n$ and we note that the values of χ_s are in Θ. Let $n_u = \#\{s : \chi_s \in G_u\}$ be the number of the observed values in G_u, $u = 1, \cdots, U$. Based on the conjugacy between the Dirichlet and multinomial distributions, we have:

$$\begin{aligned} & (X(G_1), \cdots, X(G_U)) \mid \chi_1, \cdots, \chi_n \\ & \sim Dir(\alpha H(G_1) + n_1, \cdots, \alpha H(G_U) + n_U). \end{aligned} \tag{11}$$

The above is true for all finite measurable partitions, thus the posterior distribution over X must be a DP and can be expressed as

$$X \mid \chi_1, \cdots, \chi_n \sim DP(\alpha + n, \frac{\alpha}{\alpha + n} H + \frac{n}{\alpha + n} \frac{\Sigma_{s=1}^{n} \omega_{\chi_s}}{n}). \tag{12}$$

ω_s is the point mass located at χ_s and $n_u = \Sigma_{s=1}^{n} \omega_s(G_u)$. We can see that the posterior DP update α as $\alpha + n$ and update H as $\frac{\alpha H + \Sigma_{s=1}^{n} \omega_{\chi_s}}{\alpha + n}$. The posterior base distribution is a weighted average between the prior base distribution H, whose weight is proportional to α, and the empirical distribution $\frac{\Sigma_{s=1}^{n} \omega_{\chi_s}}{n}$, whose weight is proportional to the number of observations n. Thus, we can utilize α as the strength associated with the prior base distribution. When $\alpha \to 0$, the prior distribution H becomes meaningless such that the posterior distribution is just obtained from the empirical distribution. Namely that with the number of observations increasing, the posterior is mainly determined by the empirical distribution, which closely approximates the real underlying distribution.

We consider the predictive distribution of χ_{n+1} when given the sequence $\chi_1, \cdots, \chi_n$. Since $\chi_{n+1} \mid X, \chi_1, \cdots, \chi_n \sim X$, for a measurable $G \subset \Theta$, we have

$$\begin{aligned} & P(\chi_{n+1} \in G \mid \chi_1, \cdots, \chi_n) = E[X(G) \mid \chi_1, \cdots, \chi_n] \\ & = \frac{1}{\alpha + n} (\alpha H(G) + \Sigma_{s=1}^{n} \omega_{\chi_s}(G)), \end{aligned} \tag{13}$$

in which the last step follows from X's posterior base distribution when given the prior n observations. With X marginalized out,

$$\chi_{n+1} \mid \chi_1, \cdots, \chi_n \sim \frac{1}{\alpha + n} (\alpha H + \Sigma_{s=1}^{n} \omega_{\chi_s}). \tag{14}$$

Hence, the posterior base distribution is also the predictive distribution of χ_{n+1} when given $\chi_1, \cdots, \chi_n$. However, the distribution drawn form the DP is discrete, thus we use kernel [40]–[42] to smooth out the distribution to obtain its density distribution. That is, when $X \sim DP(\alpha, H)$ and $f(x \mid \phi)$ indexed by ϕ is used as a family of densities (kernels), we can smooth out the distribution drawn from the DP and get the nonparametric density of x as follows:

$$p(x) = \int f(x \mid \phi) X(\phi) d\phi. \tag{15}$$

2) Estimation of Probability Distribution: We assume that the users in our system are denoted by the set C. For a certain user $c \in C$, q observation sets which involve the probabilities of selecting the similar contents can be obtained from social network platforms in several time periods. And we denote the q observation sets as the set $\mathcal{Q}$. At a certain time, for observation set $Q \in \mathcal{Q}$, user c selects the similar contents with the probability p_{Qc}. Hence, the value of p_{Qc} is a random variable with a pdf $P_{Qc}(p_{Qc})$ over the state space $\Theta = [0, 1]$. In each observation set $Q \in \mathcal{Q}$, Z_{Qc} observations are performed, which are denoted by $\mathcal{Z}_{Qc}$=$\{p_{Qc}^1, p_{Qc}^2, \cdots, p_{Qc}^{Z_{Qc}}\}$, $\forall c \in C$, $Q \in \mathcal{Q}$. Employing the DP, the predictive pdf of the next observation $p_{Qc}^{Z_{Qc}+1}$ can be obtained by using the following formula based on the observation set $\mathcal{Z}_{Qc}$:

$$\begin{aligned} & P_{Qc}(p_{Qc}^{Z_{Qc}+1} \in \mathcal{E} \mid p_{Qc}^1, p_{Qc}^2, \cdots, p_{Qc}^{Z_{Qc}}) \\ & = \frac{1}{\varpi + Z_{Qc}} (\varpi G(\mathcal{E}) + \Sigma_{z=1}^{Z_{Qc}} \omega_{p_{Qc}^z}(\mathcal{E})), \end{aligned} \tag{16}$$

where $\mathcal{E}$ is a measurable partition of Θ. G is the base distribution as the prior and ϖ is viewed as the strength associated with the prior base distribution for the estimation of the posterior. With the DP marginalized out, the predictive distribution of the next observation $p_{Qc}^{Z_{Qc}+1}$ conditioned on the observation set $\mathcal{Z}_{Qc}$ can be expressed as:

$$p_{Qc}^{Z_{Qc}+1}|p_{Qc}^1, p_{Qc}^2, \cdots, p_{Qc}^{Z_{Qc}} \sim \frac{1}{\varpi + Z_{Qc}}(\varpi G + \Sigma_{z=1}^{Z_{Qc}} \omega_{p_{Qc}^z}). \quad (17)$$

When the base distribution G and the concentration parameter ϖ of the DP are unknown, we express the predictive pdf of the next observation $p_{Qc}^{Z_{Qc}+1}$ as follows based on (16),

$$P_{Qc}(p_{Qc}^{Z_{Qc}+1} \in \mathcal{E} \mid p_{Qc}^1, p_{Qc}^2, \cdots, p_{Qc}^{Z_{Qc}}) = \frac{\Sigma_{z=1}^{Z_{Qc}} \omega_{p_{Qc}^z}(\mathcal{E})}{Z_{Qc}}. \quad (18)$$

$\omega_{p_{Qc}^z}$ is the point mass located at p_{Qc}^z and $\omega_{p_{Qc}^z}(\mathcal{E}) = 1$ when $p_{Qc}^z \in \mathcal{E}$; $\omega_{p_{Qc}^z}(\mathcal{E}) = 0$ otherwise. Then we use kernel to smooth out the distribution drawn from the DP to get the continuous estimate $\tilde{P}_{Qc}$ of P_{Qc}. However, as the number of the available observations Z_{Qc} is small, we consider another approach to improve the estimates.

For user $c \in C$, given the subset $\mathcal{W} \subseteq \mathcal{Q}$ and the observation set $Q \in \mathcal{Q}$, we denote that the rest observation sets in subset $\mathcal{W}$ except Q as $\mathcal{W}_{Qc} = \mathcal{W} \setminus \{Q\}$, which represents the priors. Then, we can integrate the observation set Q with the set of validated priors $\mathcal{W}_{Qc}$ to derive the pdf of any new observation $p_{Qc}^{Z_{Qc}+1}$ using the following expression:

$$P_{Qc}^{\mathcal{W}} = \varphi_Q \tilde{P}_{Qc}(\mathcal{E}) + \sum_{L \in \mathcal{W}_{Qc}} \varphi_L \tilde{P}_{Lc}(\mathcal{E}). \quad (19)$$

The contribution of the observation set Q for the generation of the pdf $P_{Qc}^{\mathcal{W}}$ is quantified by φ_Q while that of $L \in \mathcal{W}_{Qc}$ is quantified by φ_L. In practice, we set the weights φ_Q and φ_L to be proportional to the number of observations, which are expressed as:

$$\varphi_Q = \frac{Z_{Qc}}{\sum_{V \in \mathcal{W}} Z_{Vc}}, \varphi_L = \frac{Z_{Lc}}{\sum_{V \in \mathcal{W}} Z_{Vc}}, \forall L \in \mathcal{W}_{Qc}. \quad (20)$$

With the consideration of the equal availability of observation sets, we define that $P_c = P_{Qc}^{\mathcal{W}}$.

3) Intensity of Social Relationship: Due to the fact that the social relationship close degree of any two users is measured by the similarity of their selection on contents, the probability corresponding to the selection of similar contents is utilized to derive the normalized correlation that indicates the intensity of the social relationship. For D2D TX $i \in \mathcal{N}_T$ and RX $j \in \mathcal{N}_R$, the intensity of their social relationship can be expressed as:

$$\rho_{ij} = (corr(p_i, p_j) + 1)/2, \quad (21)$$

where $p_i \sim P_i(p)$ and $p_j \sim P_j(p)$. P_i and P_j represent the estimated correlative pdfs. And ρ_{ij} varies from 0 to 1, namely $\rho_{ij} \in [0, 1]$.

IV. Problem Formulation

The purpose of our work is to achieve content delivery with high satisfactions of users by employing social-aware D2D techniques, while at the same time, maximizing the transmission sum rate of D2D links. Hence, we need to consider an optimization problem involving both the social layer and the physical layer. Furthermore, we formulate the objective function as a weighted channel rate, i.e., the rate weighted by the intensity of social relationship. The weighted rate of the link between D2D TX i and RX j when reusing RB N_k can be obtained by

$$R_{D_{ij},k} = I(\rho_{ij})\rho_{ij} r_{D_{ij},k}. \quad (22)$$

In practice, TX i is approved to share contents with RX j only when the intensity of social relationship between them is no less than a threshold δ, that is to say, it is potential for i and j to form a D2D link when $\rho_{ij} \geq \delta$. Hence, we define $I(\rho_{ij})$ as an indicator function of ρ_{ij} that $I(\rho_{ij}) = 1$ when $\rho_{ij} \geq \delta$; $I(\rho_{ij}) = 0$ otherwise.

To maximize the weighted sum rate of all the D2D pairs, we need to design an efficient mechanism for pairing the content provider (TX) with the content consumer (RX) and allocating the spectrum resource to the transmission link. In other word, it is an issue of joint peer discovery and resource allocation for D2D communication. To avoid excessive interference to cellular links, power control for D2D TX should be also taken into account. We use a set of binary variables $X = \{x_{i,j,k}\}$ to formulate the user pairing and resource allocation. $x_{i,j,k} = 1$ denotes that a D2D link is established between TX i and RX j reusing RB N_k. Accordingly, we jointly design the binary decision variables $\{x_{i,j,k}\}$ and the continuous power variables P_i^D to optimize the system performance. A mixed integer programming problem is formulated as

$$\begin{aligned}
\max_{\{X, P_i^D\}} \quad & \sum_{k=1}^{K}\sum_{j=1}^{N}\sum_{i=1}^{N} x_{i,j,k} R_{D_{ij},k} \\
\text{s.t.} \quad & C1: \ 0 \leq P_i^D \leq P_{max}, \\
& C2: \ x_{i,j,k} \in \{0,1\}, \forall i \in \mathcal{N}_T, j \in \mathcal{N}_R, N_k \in \mathcal{N}_K, \\
& C3: \ \sum_{j \in \mathcal{N}_R, N_k \in \mathcal{N}_K} x_{i,j,k} \leq 1, \forall i \in \mathcal{N}_T, \\
& \qquad \sum_{i \in \mathcal{N}_T, N_k \in \mathcal{N}_K} x_{i,j,k} \leq 1, \forall j \in \mathcal{N}_R, \\
& \qquad \sum_{i \in \mathcal{N}_T, j \in \mathcal{N}_R} x_{i,j,k} \leq 1, \forall k \in \mathcal{N}_K, \\
& C4: \ r_{D_{ij},k} \geq r_{min}^d, \forall i \in \mathcal{N}_T, j \in \mathcal{N}_R, N_k \in \mathcal{N}_K, \\
& C5: \ r_{k,i} \geq r_{min}^c, \forall i \in \mathcal{N}_T, j \in \mathcal{N}_R, N_k \in \mathcal{N}_K.
\end{aligned} \quad (23)$$

Here, constraint $C1$ gives the transmit power range of D2D TXs, which ensures the power would not exceed the maximum P_{max}. The three inequalities in $C3$ ensures that each TX can only be paired with at most one RX and vice versa, while each RB can only be assigned to at most one D2D pair and vice versa. $C4$ and $C5$ guarantee the QoS requirements of D2D links and cellular links, respectively.

V. Social Network-Based Content Delivery Matching Algorithm for D2D Underlay Networks

In this section, we investigate a three-dimensional matching approach to solve the mixed integer programming problem (23). First, we introduce some concepts of matching theory which are the basis of our algorithm. Then, we give the establishment process of the preference list, which is the critical component of matching model. The preference list is mainly based on maximizing the weighted channel rate, which is coupled with a power control problem. Afterwards we introduce a pricing strategy to simplify the three-dimensional matching problem, and propose an iterative algorithm to derive a stable matching among D2D TXs, D2D RXs and RBs. Finally, the properties of the proposed matching approach, including convergence, stability, optimality and complexity, are analyzed in details.

A. Matching Concepts

In a formal matching model, there are two finite and disjoint sets denoted by M=$\{m_1, m_2, \cdots, m_i, \cdots, m_n\}$ and W=$\{w_1, w_2, \cdots, w_j, \cdots, w_p\}$, respectively. Each $m_i \in M$ has its own preferences over the set W and the same as $w_j \in W$ over M. The individual preferences represent the priorities of its selection among different alternatives. If m_i prefers w_1 to w_2, we express it as $w_1 >_{m_i} w_2$. $w_1 \geq_{m_i} w_2$ represents that w_1 is liked at least as well as w_2 by m_i. It is rational for the preferences of each individual to have properties involving complete ordering and transitive. Complete ordering means that each individual will never confront with an indeterminable choice, i.e., any two alternatives can be compared for an individual to get a preferred one. The property of transitive represents that if w_1 is liked at least as well as w_2 and w_2 is liked at least as well as w_3 for m_i, thus w_1 is liked at least as well as w_3 for m_i. Given the preferences of the individuals involved, we define that:

Definition 1: A matching μ is a one-to-one correspondence from the set $M \cup W$ onto itself, denoted by μ: $M \cup W \rightarrow M \cup W$, such that $\mu(m) = w$ means that m and w are paired and $\mu(m) = m$ means that m is not matched. We refer to $\mu(m)$ as the mate of m.

We consider a matching μ where individuals m and w are not matched with each other but prefer each other to their mates at μ, namely $w >_m \mu(m)$ and $m >_w \mu(w)$. Thus, m and w form a *blocking pair* for matching μ, namely that (m, w) *blocks* the matching. We say that matching μ is not stable because m and w would prefer to disrupt the matching in order to pair with each other.

Definition 2: A matching μ is stable if there is not any blocking pair.

In our system, we attempt to solve the problem (23) by employing the three-dimensional matching that pairs D2D TXs, D2D RXs and RBs with each other. For its high complexity, we transform it to a two-sided matching. First, we define a RX-RB unit which is composed of one RX and one RB. Due to the assumption that there is one CUE on each RB, we then rewrite the RX-RB unit as RX-CUE (RC) unit. Owing to the existence of N RXs and K CUEs, there are $N \times K$ different RC units, denoted by $\mathcal{RC} = \{RC_{j,k}\}_{j=1,k=1}^{j=N,k=K}$. Thus, the three-dimensional matching problem can be simplified to a two-sided matching with N TXs on one side and $N \times K$ RC units on the other side. We have the definition as below:

Definition 3: A matching Φ is a one-to-one correspondence $\mathcal{N}_T \cup \mathcal{RC} \rightarrow \mathcal{N}_T \cup \mathcal{RC} \cup \{\emptyset\}$ and such that $\Phi(i) = RC_{j,k}$ means that TX i is matched with the unit $RC_{j,k}$ consisting of RX j and CUE k.

Because of the constraint that the matching among TXs, RXs and RBs is a three-dimensional one-to-one correspondence, when $\Phi(i) = RC_{j,k}$, for $\forall i^{'} \in \mathcal{N}_T \setminus \{i\}$, $\Phi(i^{'}) = \{\mathcal{RC} \setminus \{RC_{j,k}\}\} \cup \{\emptyset\}$. The matching Φ is stable when there is not any blocking pair, that is to say, there is no pair consisting of TX i and RC unit $RC_{j,k}$ that is not matched with each other but prefer each other to be their mates under matching Φ.

B. Preference Establishment

In a matching process, individuals on one side propose to establish pairs with ones on the other side based on their own preference lists. Since the three-dimensional matching problem is transformed to a two-sided matching problem with N TXs on one side and NK RC units on the other side, the essential issue is to find the preference lists of TXs on RC units. For TX i, when paired with different RC units, it can achieve different channel rates and different content satisfactions of RX, due to the different physical and social layer information. Therefore, the preference of TX on RC units can be formulated as the weighted channel rate (22) with the optimization of power variables P_i^D. In the process of preference lists establishment, we need to temporarily pair each TX ($\forall i \in \mathcal{N}_T$) with each RC units ($\{RC_{j,k}\}_{j=1,k=1}^{j=N,k=K}$), and thus to obtain the weighted channel rate corresponding to each three-dimensional combination TX-RX-CUE with the transmit power of TX being restricted to meet the QoS of CUE. Let $T_i = \{t_1, t_2, \cdots, t_{N \times K}\}$ denote the achieved maximum weighted rate of TX i paired with each RC units in descending order, and $O_i = \{o_1, o_2, \cdots, o_{N \times K}\}$ denote the corresponding RC units, which can be defined as the preference list of TX i. Then, we define $\mathcal{T}$=$\{T_1, T_2, \cdots, T_i, \cdots, T_N\}$ as the weighted rate set of all the TX-RC pairs, $\mathcal{O}$=$\{O_1, O_2, \cdots, O_i, \cdots, O_N\}$ as the preference list set of TX $i, \forall i \in \mathcal{N}_T$ on $\mathcal{RC}$ corresponding to $\mathcal{T}$. To obtain the maximum weighted channel rate for each TX-RC pair, we formulate the following problem:

$$\begin{aligned} \max_{\{P_i^D\}} \quad & R_{D_{ij},k} \\ \text{s.t.} \quad & C1: 0 \leq P_i^D \leq P_{max} \\ & C2: r_{D_{ij},k} \geq r_{min}^d, \\ & C3: r_{k,i} \geq r_{min}^c. \end{aligned} \tag{24}$$

Thus, the preference list of D2D TX i on RC units $RC_{j,k}$ can be derived by solving problem (24), and a detailed preference establishment algorithm is summarized in Algorithm 1, which constitutes the basis of the matching algorithm. An illustration of the preference lists establishment and a stable matching that we expected is shown in Fig. 2.

C. Three-dimensional Matching Algorithm

Based on the established preference lists, TXs could propose towards the RC units in their own first order. However, there exists a situation that more than one TX propose towards the same RC unit. Here, we propose a pricing strategy to decide

Algorithm 1 Preference Establishment Algorithm

Input: $\mathcal{N}_T$, $\mathcal{N}_R$, $\mathcal{N}_K$, $\mathcal{K}$, ρ_{ij}, r_{min}.
Output: $\{P_i^D\}$, $\mathcal{O}$, $\mathcal{T}$.
for $i \in \mathcal{N}_T$ **do**
  for $j \in \mathcal{N}_R$ **do**
    for $k \in \mathcal{K}$ **do**
      Calculate the maximum weighted rate $R_{D_{ij},k}$ by using (24) with the optimization of transmit power P_i^D.
    end for
  end for
end for
for $i \in \mathcal{N}_T$ **do**
  Obtain T_i by sorting the achieved maximum weighted rates $R_{D_{ij},k}$, $\forall j \in \mathcal{N}_R$, $k \in \mathcal{K}$ in descending order. Establish the preference list O_i of TX i on RC units by sorting each RC unit $RC_{j,k}$ in descending order based on T_i.
end for

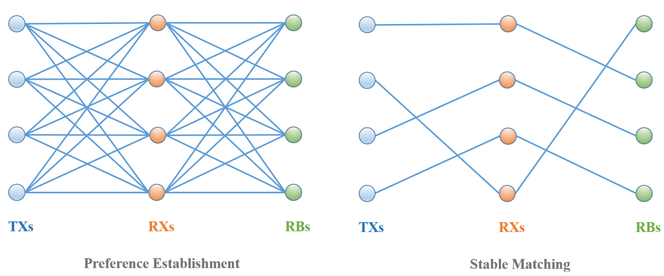

Fig. 2. Graphical expressions of preference establishment and a stable three-dimensional matching.

the winner. The proposed matching algorithm is described briefly as follows.

- First of all, we introduce the concept of *price* for each RC unit which represents the matching cost for each TX. These prices are set to be zero at the beginning and they are virtual money without any physical significance. Let $\mathcal{CR}$=$\{CR_1, \cdots, CR_j, \cdots, CR_N\}$, $\forall j \in \mathcal{N}_R$ and $\mathcal{CK}$=$\{CK_1, \cdots, CK_k, \cdots, CK_K\}$, $\forall k \in \mathcal{K}$ denote the price sets of RXs and CUEs, respectively. The prices of RC units are denoted by $\mathcal{C}$=$\{C_{j,k}\}_{j=1,k=1}^{j=N,k=K}$ where the price $C_{j,k}$ of $RC_{j,k}$ is the sum of RX j's price CR_j and CUE k's price CK_k.
- The proposed algorithm proceeds iteratively. In each iteration, any TX i that has not been matched with any RC unit would propose to its most preferred RC unit in O_i based on its payoff, which is equal to the achieved maximum weighted rate minus the matching cost, i.e., the current price of the RC unit. If any RX or CUE receives request from only one TX, the requested RC units would be directly matched with the TXs that initiate requests, and thus to form a stable matching.
- Otherwise, the conflicting elements set consisting of RXs and CUEs that have received requests from more than one TX is denoted by Ω. Then, the elements in Ω would raise their prices with the price step s, which is determined by the minimum of the differences between any two adjacent values in the ordered weighted rate set. Accordingly, each TX that has proposed updates its preference list and renews its request. The process of rising prices continues until there is only one request received for the RC units.
- The algorithm would end if there exists no new request from TXs, i.e., all the TXs are matched when $K \geq N$ or all the CUEs are matched when $N \geq K$.

Algorithm 2 The Three-Dimensional Matching Algorithm

Input: $\mathcal{N}_T$, $\mathcal{N}_R$, $\mathcal{K}$, $\mathcal{O}$, $\mathcal{T}$, $\mathcal{CR}$, $\mathcal{CK}$, $\mathcal{C}$, Ω, s.
Output: Φ, $\{x_{i,j,k}\}$.
Initialization:
Every TX $i \in \mathcal{N}_T$ builds its preference list on $\mathcal{RC}$ by using Algorithm 1.
Set Φ=$\emptyset$, Ω=$\emptyset$, s=0.1.
while $\exists \Phi(i) = \emptyset$ **do**
  if $O_i \neq \emptyset$ **then**
    for $i \in \mathcal{N}_T$ **do**
      TX i which has not been matched proposes to its most preferred RC unit in updated O_i.
    end for
    Count the amount of RXs and CUEs that have received requests and put the conflicting elements that have received more than one request into Ω.
    if $\Omega = \emptyset$ **then**
      Match the RC unit with its requestor TX directly.
    end if
    if $\Omega \neq \emptyset$ **then**
      for $RC_{j,k} \in \mathcal{RC}$ **do**
        if RX j and CUE k receive requests from more than one TX **then**
          RX j and CUE k in Ω increase their prices CR_j and CK_k with the price step s, and then TXs would update their preference lists and change their choices on RC units according to the price $C_{j,k}$. After this process, RX j and CUE k would be matched with the last remaining TX i that proposes to them, which is denoted by $\Phi(i) = RC_{j,k}$.
        end if
      end for
    end if
    Update: Update $\mathcal{O}$ and $\mathcal{T}$ by deleting the RC units involving the matched RX j or CUE k and the corresponding achieved weighted rate respectively. Set $\mathcal{CR} = \{0\}$, $\mathcal{CK} = \{0\}$, $\mathcal{C} = \{0\}$.
  else
    break
  end if
end while

The above steps can lead to a stable matching that is proved in subsection V-D. We summarize the proposed three-dimensional matching algorithm in Algorithm 2.

In D2D underlay cellular network, the BS is the controller of resource management and link establishment, and thus the global channel state information (CSI) should be available at the BS for the matching approach. However, it is unnecessary for D2D users to obtain the global CSI but just to feedback detected CSI by receiving detection signals at each terminal to the BS.

D. Properties of the Three-dimensional Matching Algorithm

In this subsection, the properties involving convergence, stability, optimality, and complexity of the proposed three-dimensional matching algorithm are analyzed in details.

1) Convergence: We define the achieved maximum weighted rate $R_{D_{ij},k}$ as valuation $v_{i,j,k}$ of $RC_{j,k}$ for TX i, and the price $C_{j,k}$ of $RC_{j,k}$ as the matching cost for TXs. Then the payoff of TX i being matched with $RC_{j,k}$ can be written as $v_{i,j,k} - C_{j,k}$. In addition, it is denoted that there exists contention among TXs when any RX or CUE receives requests from more than one TX. At the start of each contention, the prices of RXs and CUEs are set to be zero and they would gradually increase by the step size s in the process of the contention. Any $i \in \mathcal{N}_T$ that has proposed to the conflicting elements would change its choice with the increase of the prices, which is based on its current maximum payoff:

$$(j,k) = arg \max_{j \in \mathcal{N}_R, k \in K} (v_{i,j,k} - C_{j,k}) \tag{25}$$

The matching rules from Algorithm 2 show that the conflicting elements would be assigned to the TX that is the last one remaining in the request queue with the increase of the conflicting elements' prices. Assuming that TX i is matched with the conflicting RC unit $RC_{j,k}$, the contention must come to an end within $v_{i,j,k}/s$ steps. Hence, we can conclude the matching process within finite iterations.

2) Stability: ***Theorem 1:*** The proposed Algorithm 2 can converge to a two-sided stable matching Φ in finite iterations.

Proof: According to Definition 2, the matching Φ is said to be stable if there exists no blocking pair. In order to prove the stability of the proposed matching algorithm, we first assume that there exists $i \in \mathcal{N}_T, j \in \mathcal{N}_R, k \in \mathcal{N}_K$ that TX i and RC unit $RC_{j,k}$ are not matched with each other under matching Φ but prefer to be mutually matched, i.e., $\Phi(i) \neq RC_{j,k}$, and $RC_{j,k} >_i \Phi(i)$, $i >_{RC_{j,k}} \Phi(RC_{j,k})$.

In the matching, since each TX attempts to maximize its own payoff, the maximization problem for each TX can be written as $\max_{j \in \mathcal{N}_R, k \in K}(v_{i,j,k} - C_{j,k}), \forall i \in \mathcal{N}_T$. On account of the assumption that $RC_{j,k} >_i \Phi(i)$, TX i must have proposed to RC unit $RC_{j,k}$ based on the matching rules. However, considering the pricing strategy in Algorithm 2, the inexistence of $\Phi(i) = RC_{j,k}$ in the matching result represents that the final payoff for TX i matched with $RC_{j,k}$ is zero, and it has given up the request to $RC_{j,k}$ during the process of rising prices. Moreover, the winner in the contention for $RC_{j,k}$ is $\Phi(RC_{j,k})$, i.e., $\Phi(RC_{j,k}) >_{RC_{j,k}} i$. Therefore, the condition $i >_{RC_{j,k}} \Phi(RC_{j,k})$ cannot hold when $RC_{j,k} >_i \Phi(i)$, which means TX i and $RC_{j,k}$ cannot form a blocking pair. The analysis result contradicts the assumption. Thus, the matching Φ obtained from Algorithm 2 is stable. ■

3) Optimality: ***Theorem 2:*** The content delivery one-to-one matching Φ is weak Pareto optimal for D2D transmitters on combinations of D2D receivers and spectrum resources.

Proof: Before the proof, we give the concept of Pareto improvement: if a change of assignment can improve one's payoff and the change can be approved by others, then it is a Pareto improvement. Moreover, if there exists no Pareto improvement, the current assignment is said to be weak Pareto optimal.

First, we assume that there exists a Pareto improvement for matching Φ. We define the improvement for TX i as $RC_{j,k}$, thus we have $RC_{j,k} >_i \Phi(i)$. One case is that $RC_{j,k}$ has not been matched under Φ, i.e., $\Phi(RC_{j,k}) = \emptyset$. It is obvious that $i >_{RC_{j,k}} \Phi(RC_{j,k})$. That is, TX i and $RC_{j,k}$ prefer to be matched with each other and form a blocking pair. This contradicts with Theorem 1 that Φ is stable. The other case is that $RC_{j,k}$ has already been matched with TX i', which does not approve i to be matched with $RC_{j,k}$. Then, the contention between i and i' lead to a process of rising prices. The payoff of i would reduce, and $RC_{j,k} >_i \Phi(i)$ would not hold any more.

Based on the above cases, we can conclude that there exists no Pareto improvement, and the matching Φ is weak Pareto optimal for D2D transmitters. ■

4) Complexity: In the process of preference establishment, the computational complexity for any TX $i \in \mathcal{N}_T$ to obtain the preferences is $\mathcal{O}(NK)$ since that each TX has to find its preference value for each RC unit, which is corresponding to the achieved weighted rate. The computational complexity to derive the preference list by sorting the preference values for each TX is $\mathcal{O}(NK\log(NK))$. In Algorithm 2, the complexity of each process, in which TXs that have not been matched propose to their most preferred RC units, is $\mathcal{O}(N^{loop})$ [43]. N^{loop} is the required number of iterations in the process of rising prices based on the step size s, i.e., during N^{loop} iterations, the assignment of the conflicting elements are finished when $\Omega \neq \emptyset$. We have $N^{loop} = 1$ when $\Omega = \emptyset$. Then, the computational complexity of the matching process is $\mathcal{O}(NN^{loop})$ $(N \geq K)$ or $\mathcal{O}(KN^{loop})$ $(K \geq N)$.

For the centralized exhaustive search, the total number of possible matching results is $N! \times K!$. The complexity of the algorithm can be written as $\mathcal{O}(N! \times K!)$. It is obvious that the proposed matching algorithm results in a much lower complexity for sufficient large values of N and K.

VI. Numerical Results

In this section, the performance of the proposed iterative matching algorithm and impacts of the social relationships on D2D receivers' satisfactions are validated through simulations. The simulation parameters are summarized in Table I [10], [20]–[22]. We consider a single cellular network with a radius of $R = 200$ m, in which K CUEs are randomly distributed. N D2D transmitters and N receivers are randomly deployed in a circular hot spot area with the radius of $r = 30$ m. Fig. 3 shows a snapshot of UEs' locations with $K = N = 6$. In the circular hot spot area represented by the blue dotted circle, D2D TXs and RXs that satisfy both the physical and social

TABLE I
SIMULATION PARAMETERS.

Simulation Parameter	Value
Cell radius R	200 m
Radius of the hot zone r	30 m
Max D2D transmission distance d_{max}	50 m
Pathloss exponent α	4
Max transmission power of D2D TXs P_{max}	23 dBm
Transmission power of cellular users P_k^C	23 dBm
Noise power N_0	-114 dBm
Number of D2D transmitters and receivers N	$1 \sim 6$
Number of resource blocks and cellular users K	$1 \sim 6$
QoS requirement r_{min}	0.5 bit/s/Hz
Step size s	0.1

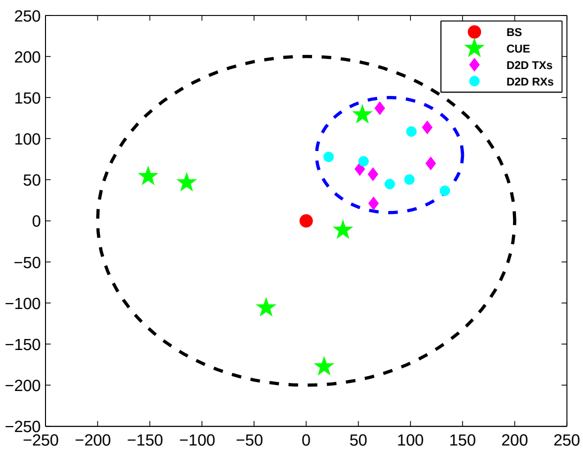

Fig. 3. A snapshot of user locations for a single cellular network with K CUEs, N D2D TXs and N D2D RXs ($K = 6$, $N = 6$, d_{max}=50 m, the cell radius is 200 m and the size of the spot hot is 30 m, respectively).

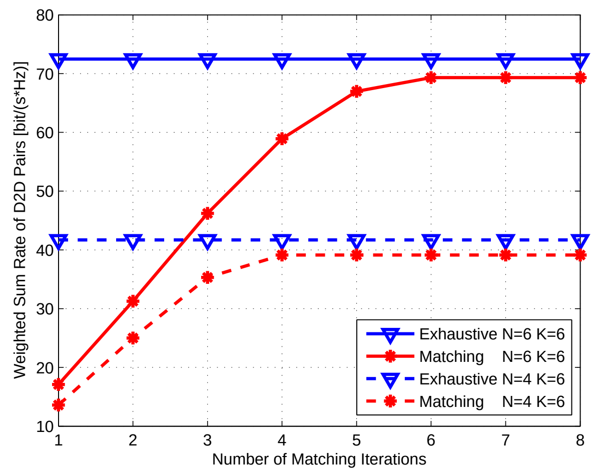

Fig. 4. Weighted sum rate of D2D pairs vs. number of matching iterations (N=6).

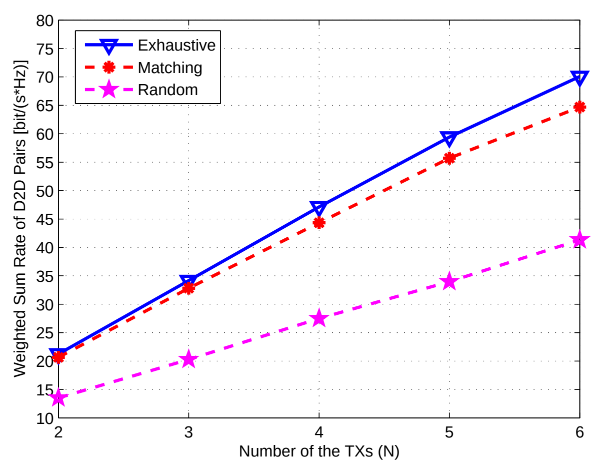

Fig. 5. Weighted sum rate of D2D pairs vs. number of TXs (K=6).

requirements of D2D communication can form a D2D pair to directly exchange contents.

A. Convergence

The proposed algorithm is compared with two heuristic algorithms, i.e., the exhaustive and random matching algorithms. In particular, the exhaustive matching algorithm which examines every possible solution to find the optimum one is used to serve as an upper performance benchmark, while the random matching algorithm is used to serve as a lower performance benchmark. The convergence of the proposed matching algorithm is shown in Fig. 4, which represents the weighted sum rate of D2D pairs versus the matching iterations. In Algorithm 2, we denote that at least one TX-RX-CUE pair would be formed in each iteration, thus we can derive that the number of the iterations required for the proposed algorithm to converge is related with the number of the TXs, RXs and CUEs. Given $K = 6$, we can see that it only takes 4 and 6 matching iterations for the proposed algorithm to converge when $N = 4$ and $N = 6$, respectively. Moreover, it can be seen that the performance of matching is quite close to that of the exhaustive algorithm after the convergence.

B. Weighted Sum Rate

Fig. 5 shows the weighted sum rate of all D2D pairs versus the number of TXs, while Fig. 6 shows the weighted sum rate of all D2D pairs versus the number of CUEs. It is observed that the performance gaps between the proposed algorithm and the optimum exhaustive matching algorithm in Fig. 5 and Fig. 6 are small. For instance, in Fig. 5, the proposed algorithm is able to achieve 94.92% of the optimum performance, and outperforms the random matching algorithm by as much as 74.89% when $N = 5$ and $K = 6$. In Fig. 6, the corresponding values of the performance compared with the optimum performance and the random performance are 93.33% and 74.61%, respectively, when $N = 6$ and $K = 5$. On the other hand, the computational complexity of the proposed matching algorithm is an order of magnitude lower than that of the exhaustive algorithm. For example, when $N = K = 6$, it takes 5.184×10^5 iterations for the exhaustive matching algorithm to find the optimum solution, while the

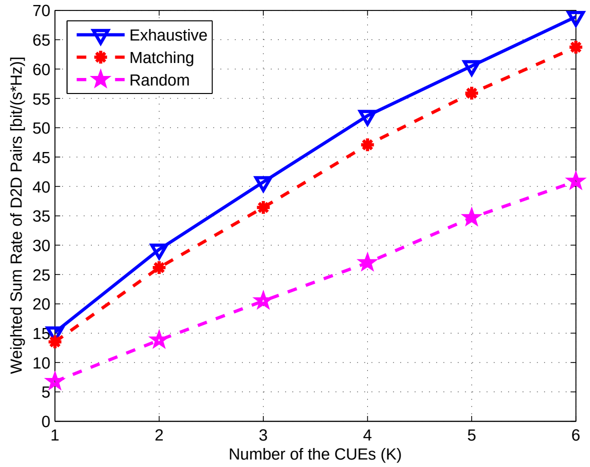

Fig. 6. Weighted sum rate of D2D pairs vs. number of CUEs (N=6).

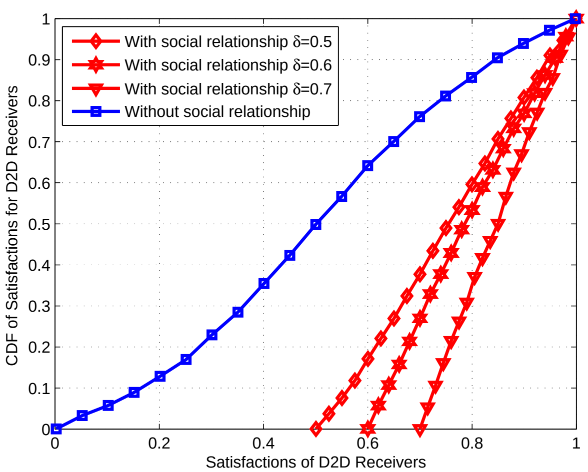

Fig. 7. Distribution of content satisfactions for D2D receivers.

proposed algorithm only requires 600 iterations, which reduces the complexity by nearly a thousand times. Compared with the exhaustive matching, the proposed algorithm does not need to achieve every possible matching result, which significantly reduces the computational complexity.

From another perspective, we can find that the weighted sum rate raises up with both the number of D2D TXs and the number of CUEs (RBs) increasing. On one hand, when the amount of RBs is fixed, more D2D pairs contribute to a higher sum rate of D2D links. On the other hand, as the amount of RBs increases, the system supports to establish more D2D links. In Fig. 6, it is obvious that the increment of weighted sum rate decreases continuously as the number of RBs increases. The reason is that the probability of accessing to the most preferred RB for a D2D pair becomes lower as more D2D pairs access to the network.

C. User Satisfaction

Fig. 7 shows the cumulative distribution functions (CDFs) of the satisfactions for D2D RXs, namely the similarity of users' preferences on the content which is reflected by the intensity of social relationships between the mutually matched D2D TXs and RXs. To evaluate the impacts of the social relationships on D2D RXs' satisfactions, both the social-aware and social-unaware matching algorithms are compared by varying the threshold of social relationships. Simulation results show that for the social-unaware algorithm, the proportion of D2D RXs whose satisfaction is greater than 0.8 is 15%, while the corresponding proportions achieved by the proposed algorithm are much higher, i.e., 41%, 47% and 65% for $\delta = 0.5$, $\delta = 0.6$ and $\delta = 0.7$, respectively. It is noted that when the threshold δ decreases, the satisfaction performance also becomes worse. The reason is that it is much easier for D2D TXs and RXs with weak intensity of social relationship to from a D2D pair when the threshold is lower, which in turn degrades the satisfaction performance.

VII. Conclusions

In this paper, we studied the content delivery problem in social network-based D2D communications with uplink spectrum reusing. Both the social layer and the physical layer information were exploited in the optimization of the matching among users, contents, and spectrum resources. First, we modeled the social relationship between two users as the probability of selecting similar contents, which was estimated by using Bayesian nonparametric models. Then, we proposed a three-dimensional iterative matching algorithm to maximize the sum rate of D2D pairs weighted by the intensity of social relationships while guaranteeing the quality of service (QoS) requirements of both cellular and D2D links simultaneously. Finally, the proposed algorithm was validated through simulations and compared with exhaustive optimal and random matching algorithms. Simulation results demonstrated that the performance of the proposed iterative matching algorithm is much better than that of the random matching algorithm, and is very close to that of the optimum exhaustive matching but with a much lower computational complexity. Furthermore, the content satisfactions of D2D receivers are dramatically improved if social layer information is considered during the matching process. In future works, we will focus on the design of social-aware resource allocation algorithms for D2D communication by incorporating distributed caching schemes.

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