Energy Efficient D2D Communications: A Perspective of Mechanism Design

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***Abstract*— The energy consumption of a base station (BS) has attracted much attention in the study of wireless communication. Device-to-device communication, which can be utilized to offload the traffic from the BS, provides an effective way to increase network energy efficiency. How to optimally coordinate users to redistribute the traffic so as to minimize the energy consumption is an important issue. In this paper, we study two problems that are critical to this issue. First, considering that relaying data to others incurs costs to the users and different users have different costs, we propose a contract theoretical approach to design the mechanism for pricing the contributions of users. The second problem is to make a proper matching between users who demand data and users who are willing to relay data. Matching theory is exploited to deal with this problem. Specifically, we consider both interference-free and interference scenarios and develop matching algorithms, which can achieve stable matching and weak stable matching, respectively. Simulation results demonstrate the effectiveness of the proposed algorithms.**

***Index Terms*— Green cellular networks, device-to-device communication, contract theory, adverse selection, matching theory.**

I. INTRODUCTION

AS THE predominant mobile communication architecture, cellular network has encountered a tremendous growth of data traffic in recent years, mainly due to the increase of mobile users and the proliferation of smart phone-based applications. The energy cost and carbon footprint coming along with the growth of traffic have led to an emerging research area called "green cellular networks", which aims at addressing energy efficiency amongst the network operators and regulatory bodies [1]–[3]. Device-to-device (D2D) communication, which enables two proximity devices[1] to transmit signal directly without going through the base station (BS), can significantly increase network energy efficiency and has been considered one of the key techniques for the LTE (Long Term Evolution)-based cellular networks [4]–[6].

The advantage of D2D communication with respect to energy efficiency is two-fold. On one hand, due to the short distance transmission, lower power and shorter time will be feasible for mobile users to get the desired data. On the other hand, D2D communication can offload the traffic from the cellular tier, thus the energy consumption of the BS can be reduced. In this paper, we focus on the issue that how to optimize the energy consumption of the BS in D2D communications underlying cellular networks. The basic idea is to establish a D2D link between the user who requests data from the BS and the user who is elaborately selected by the BS as the relay for the former user. In such way, the traffic over the cellular link between the BS and a distant user may be transferred to the cellular link between the BS and a less distant user and the D2D link, which is beneficial to the BS in terms of energy consumption.

The idea of utilizing D2D communications to balance the traffic in cellular networks has been explored in some previous studies [7]–[9]. Many of these studies are based on an underlying assumption that all cellular users will act as relays whenever they are requested to. However, such an assumption no longer holds if we consider a more practical scenario where relaying data to others comes with a cost and users are self-interested, in the sense that they seek to maximize their own utilities. To motivate the self-interested users to relay data for others, the network operator, or the BS, needs to pay some incentives, such as monetary rewards or tokens [10], [11], to users. Usually, a pricing mechanism [12] is essential for the operator to determine the payments. The use of pricing mechanism can be found in some literatures on D2D communications [11]–[16]. Different from those previous works, in this paper we propose a contract theoretical approach to optimally determine the monetary rewards paid to different users. The reason we apply contract theory [17] is that the unit cost perceived by users, who act as relays for others, are different from one another. The cost of each user is generally unknown to the BS, which means there is *information asymmetry*

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[1]Throughout this paper, we use the two terms "user" and "device" interchangeably.

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between the BS and users. And contract theory provides an elegant way to deal with such problems.

The contract-based pricing mechanism guarantees the participation of users. In other words, when the BS applies the contract mechanism, there should be no problem to assume that users will accept the data relay task when they are chosen by the BS. Then the BS can focus on the other important question, which is how to select the relay user for each user who has a request for data, so that the total energy consumption can be minimized. If we treat the users who demand data as *buyers* and the users who are capable of providing a data relay service as *sellers*, then the BS actually plays the role of a *market maker* between the two parties. Considering that matching theory [18] is a useful tool in market design, in this paper we exploit methodologies from matching theory to coordinate the users. Specifically, a stable matching algorithm is proposed to deal with the situation where the intracell interference is negligible. In practice, the channel resource available for a BS is limited, which means it is very likely that a pair of D2D users who directly communicate with each other have to share the channel with another pair of D2D users. As a result, the transmission quality perceived by the buyer will be interfered by the seller from the other pair. The stable machining algorithm is modified to deal with the interference problem, and the modified algorithm can achieve a weak stable matching between buyers and sellers. We have conducted simulations to demonstrate the effectiveness of the proposed algorithms.

The rest of this paper is organized as follows. Section II briefly introduces some studies that are related to our work. The system model is presented in Section III. In Section IV, we describe the contract theoretical approach proposed for pricing the data relay task. Based on the pricing mechanism, two matching algorithms are proposed in Section V, and performance of the algorithms is evaluated in Section VI. Finally, the paper is concluded in Section VII.

II. Related Work

A. D2D Assisted Energy Saving

D2D-assisted energy saving methods have been widely investigated in the study of cellular networks [19]–[21]. As described in [22], device and service discovery is the first step to establish a network assisted D2D link. In [19], Doppler *et al.* proposed an energy efficient discovery scheme which is based on the LTE beacon structure and utilizes the OFDMA (orthogonal frequency division multiple access) principle. In [20], Wang *et al.* studied the radio resource and power allocation problem. They treated energy efficiency as the optimization objective and introduced a reverse iterative combinatorial auction game to solve the problem. To reduce of the energy consumption of the BS in a video transmission and sharing scenario, Shen *el al.* [21] proposed to construct inband underlaying D2D clusters where the total energy consumption of each cluster is constrained. In this paper we also focus on the energy consumption of the BS, and we apply contract theory and matching theory to design mechanisms to configure the D2D links.

B. Pricing Mechanism and Contract Theory

Gizelis and Vergados provide a comprehensive survey of pricing schemes proposed for wireless services in [12]. Methodologies from game theory [23] and contract theory [17] have been applied to the pricing problem. In [24], Wei *et al.* investigated the pricing-based energy efficient optimization problem for wireless network virtualization. They formulated the problem as a market competition and employed a non-cooperative game to search the optimal pricing function. In [13], Yin *et al.* proposed a decentralized framework of joint spectrum allocation and power control to coordinate interference between the D2D layer and the cellular layer in D2D communications systems. They applied a pricing based game theoretical approach to mitigate the interference from D2D pairs to the BS. In [25], Zhang *et al.* proposed a contract-theoretic approach to address the problem of incentivizing access points to offload traffic for the base stations in an SDN (software defined network)-at-edge. In [26], contract theory was applied to solve the problem of incentivizing users to participate in D2D communications. This is similar to our work. However, different from the model proposed in [26] where a user's type was defined to be the user's preference towards joining D2D communications, in this paper we treat the unit cost that the user pays for data transmission as the user's type.

C. Matching Theory

Matching theory [18] is often used in the study of economical market design [27]. Researchers have applied matching theory to wireless networks [28]–[30]. In [28], Feng *et al.* studied the spectrum sharing problem among multiple primary users and multiple secondary users. They modeled the network as a one-to-one matching market and proposed two distributed matching algorithms. In [29], Hamidouche *et al.* formulated the caching problem in small cell networks as a many-to-many matching game between small base stations and service providers' servers, and proposed a matching algorithm that can reach a pairwise stable outcome. In [30], Gu *et al.* modeled the resource allocation problem in D2D communications underlying cellular networks as a stable marriage problem, and proposed two matching algorithms to find a stable matching between admissible D2D pairs and cellular users. Inspired by these studies, we model the coordination between buyers and sellers as a one-to-one matching game and propose algorithms to find an energy-efficient stable matching.

III. System Model

A. Data Redistribution

As depicted in Fig. 1, we consider a single-cell scenario of an OFDMA-based cellular network, where a base station (BS) equipped with an omnidirectional antenna is located at the center of the cell. Assuming that time is slotted into discrete intervals, and during each time interval t, the set of users located within the coverage area of the BS, denoted as $\mathcal{N}_t$, remains unchanged. Moreover, similar to previous studies [7], [9], [30], we consider a static transmission environment. That is, the

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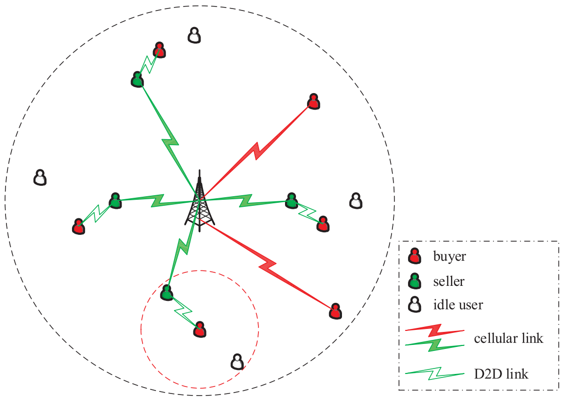

Fig. 1. An illustration of the D2D-assisted data redistribution. The black dotted line marks the coverage area of the BS, and red dotted line marks the communication range of a user. When a user (red colour) sends a data request to the BS, the BS can select a relay user (green color) who gets data from the BS via a cellular link and then transmits the data to the destination user via a D2D link.

locations of the users are assumed to be unchanged within a time interval. At any given time t, a number of users, referred to as *buyers*, send their requests for data to the BS. Let $\mathcal{B}_t$ denote the set of buyers. Upon receiving the request of a buyer $b_j \in \mathcal{B}_t$, the BS can directly transmit data to b_j, or it can choose a *seller* s_i from $\mathcal{S}_t \triangleq \mathcal{N}_t \backslash \mathcal{B}_t$ as a relay. In the latter case, the BS first transmits the requested data to s_i, then the data is transmitted through the D2D link established between s_i and b_j.

From the perspective of the BS, since the D2D transmission incurs no consumption of energy, much energy can be saved if s_i is much closer to the BS than b_j. In this sense, utilizing D2D communications to redistribute data traffic is energy efficient for the BS. Given the users' requests, the energy consumption of the BS depends on both the transmission power of the BS and the distances between the BS and data receivers (i.e. the buyers or the selected sellers). In this paper we assume that the transmission power of the BS is fixed and focus on how to select proper data receivers to reduce the energy consumption of the BS.

Specifically, given the set of buyers $\mathcal{B}_t$ and the set of potential sellers $\mathcal{S}_t$, the BS applies a matching algorithm to find a proper seller for each buyer, with the purpose of minimizing the total energy consumption. Let σ denote the mapping from buyers to sellers, i.e. $\sigma\left(b_j\right)$ represents the seller assigned to the buyer b_j. The problem of the BS can be formalized as

$$\min_{\sigma \in \Lambda} P_{BS} \left(\sum_{\substack{b_j \in \mathcal{B}_t, \\ \sigma(b_j) \in \mathcal{S}_t}} T\left(BS, \sigma\left(b_j\right)\right) + \sum_{\substack{b_j \in \mathcal{B}_t, \\ \sigma(b_j) = \varnothing}} T\left(BS, b_j\right) \right), \tag{1}$$

where Λ denotes the set of all possible mappings, P_{BS} denotes the transmission power of the BS, $\sigma\left(b_j\right) \in \mathcal{S}_t$ means the matching algorithm successfully finds a seller for b_j, and $T\left(BS, \sigma\left(b_j\right)\right)$ denotes the transmission time corresponding to the transmission between the BS and the seller $\sigma\left(b_j\right)$. For some reasons, e.g. the buyer is far away from other users, the matching algorithm may fail to find a seller for the buyer. In such a case (i.e. $\sigma\left(b_j\right) = \varnothing$), data is directly transmitted from the BS to the buyer. The corresponding transmission time is $T\left(BS, b_j\right)$. Intuitively, users' locations would be the first consideration of the BS when constructing the mapping σ. Nevertheless, there are some constraints associated with the choosing of sellers. A mapping σ is feasible only if all the constraints described in the following subsections are satisfied.

B. Interference Management

There are two types of communications co-existing in the network, namely the cellular communication between the BS and the user, and the D2D communication. Suppose that the BS uses frequency division duplex (FDD) technology to manage the channel resources. The D2D communications reuse the *uplink* resources of the cellular users, and there are two types of interference need to be taken care of. On one hand, the uplink transmission between a cellular user and the BS will be interfered by the D2D transmission which shares the same channel. On the other hand, the D2D communication between a seller and a buyer will be interfered by the cellular user and other D2D transmitters that share the same channel.

More specifically, let $\mathcal{C} \triangleq \{c_1, \cdots, c_K\}$ denote the set of K orthogonal channels available for the BS. Denote the number of buyers as N_B and the number of potential sellers as N_S. Given a mapping $\sigma : \mathcal{B}_t \rightarrow \mathcal{S}_t$, we use a $N_S \times N_B$ matrix M_σ to represent the allocation of channels. For any $i \in \{1, \cdots, N_S\}$ and $j \in \{1, \cdots, N_B\}$, denote the entry at the ith row and the jth column as $M_\sigma(i, j)$. Define $M_\sigma(i, j) = 0$ if the D2D link between s_i and b_j is not established, and $M_\sigma(i, j) = k$ ($k \in \{1, \cdots, K\}$) if the channel c_k is allocated to the D2D pair $\left(s_i, b_j\right)$. There is at most one non-zero entry in each row and column of M_σ, which means each user is allowed to establish at most one D2D link with another user.

Consider a seller s_i that transmits data to a buyer b_j via a D2D link. The D2D pair $\left(s_i, b_j\right)$ may share the channel with some user u_C that communicates with the BS via a cellular link. The SINR (Signal to Interference plus Noise Ratio) at the BS, denoted as Γ_{BS}, is given by

$$\Gamma_{BS} = \frac{g_{u_C} P_{u_C}}{n_0 + \delta_{c-ij}\, g_{s_i} P_{s_i}}, \tag{2}$$

where P_{u_C} denotes the transmission power of u_C, P_{s_i} denotes the transmission power of s_i, n_0 denotes the power of the additive white Gaussian noise, g_{u_C} denotes the channel gain between u_C and the BS, g_{s_i} denotes the channel gain of the interference link from s_i to the BS, the indicator $\delta_{c-ij} = 1$ if the D2D pair shares the same channel with u_C, otherwise $\delta_{c-ij} = 0$. Similar to [30], we consider both the fast fading due to multipath propagation and slow fading due to shadowing effect. The channel gain g_{u_C} is defined as

$$g_{u_C} = \beta \eta_C \zeta_C d_C^{-\alpha}, \tag{3}$$

where β is a constant depending on system parameters, η_C is the fast fading gain, ζ_C is the slowing fading gain, α is the path loss exponent, and d_C is the distance between u_C

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and the BS. The channel gain of the interference link can be defined similarly. To ensure the transmission quality of the cellular link, it is required that Γ_{BS} is no less than a pre-specified threshold γ_C.

The SINR at the buyer depends on which transmission mode the buyer uses. If the buyer gets data directly from the BS via a cellular link, then due to the orthogonality of resources in OFDMA, the interference from other cellular users can be ignored. If the buyer gets data from a seller via a D2D link, the interference mainly comes from users that share the same channel with the buyer. Consider a pair of D2D users (s_i, b_j). Let $S_{Int}(s_i)$ denote the set of sellers that use the same channel with s_i, i.e.

$$S_{Int}(s_i) = \left\{ s_l | s_l \in S_t, \sum_{b_m \in \mathcal{B}_t} M_\sigma(l, m) = M_\sigma(i, j) \right\}. \quad (4)$$

The SINR perceived by b_j, denoted as Γ_{b_j}, is given by

$$\Gamma_{b_j} = \frac{g_{ij} P_{s_i}}{n_0 + \delta_{c-ij} g_{u_C - b_j} P_{u_C} + \sum_{s_l \in S_{Int}(s_i)} g_{lj} P_{s_l}}, \quad (5)$$

where g_{ij} is the channel gain between s_i and b_j, $g_{u_C - b_j}$ is the channel gain of the interference link from some cellular user u_C to b_j, g_{lj} is the channel gain of the interference link from s_l to b_j, P_{s_l} is the transmission power of s_l. The channel gain of the interference link is defined in a similar way as before (see (3)). Considering that the D2D link is established over relatively short distance, we model the D2D link as a single-slope distance dependent path loss channel [8]. The channel gain between s_i and b_j is defined as

$$g_{ij} = \beta d_{ij}^{-\alpha}, \quad (6)$$

where d_{ij} denotes the distance between the two users. The transmission rate of the D2D link is

$$R(s_i, b_j) = \omega \log\left(1 + \Gamma_{b_j}\right), \quad (7)$$

where ω is the bandwidth. It is assumed that the transmission rate should be no less than a pre-specified threshold γ_{rate}. The threshold γ_{rate} imposes a constraint on the matching between buyers and sellers. Intuitively, either the distance between the seller and the buyer is large or the transmission power of the seller is low, the seller cannot be matched with the buyer.

C. User Participation

Utilizing D2D communications to offload data traffic from the cellular tier can save the BS's energy, while users who transmit data to others have to pay additional cost for the time and energy consumption. To ensure that the user will undertake the data transmission task whenever needed, the BS must pay the user sufficient rewards to compensate the cost. Here we consider monetary rewards. Given a pair of users (s_i, b_j), let r_{ij} denote the reward that the BS pays to the seller s_i for transmitting one unit of data to the buyer b_j. The cost of s_i, denoted as c_{ij}, is defined as

$$c_{ij} = \theta_i \frac{P_{s_i}}{R(s_i, b_j)}, \quad (8)$$

where $\frac{P_{s_i}}{R(s_i, b_j)}$ represents the energy consumption of s_i for transmitting one unit of data to b_j. To monetize the energy loss perceived by s_i, we introduce the parameter θ_i. Large θ_i indicates that a high reward is required to encourage the user to transmit data to others. Hence in subsequent discussions, we sometimes refer to θ_i as the seller's *resistance*.

According to (5) and (7), the transmission rate between s_i and b_j is influenced by the users that share the same channel. Consider an extreme case where all users share the same channel, and all the chosen sellers, except s_i, as well as the cellular user u_C, transmit data with the maximal power $P_{\max}$. In such a case, the transmission rate between s_i and b_j is

$$Rate_{worst}(s_i, b_j) = \omega \log\left(1 + \frac{g_{ij} P_{s_i}}{n_{\max}}\right), \quad (9)$$

where $n_{\max} \triangleq n_0 + g_{u_C - b_j} P_{\max} + P_{\max} \sum_{b_k \in \mathcal{B}_t, \sigma(b_k) = s_l \in S_t} g_{lj}$ denotes the maximum possible power of the noise and interference. And the utility of s_i is defined as

$$U_{ij} = r_{ij} - \theta_i \frac{P_{s_i}}{Rate_{worst}(s_i, b_j)}. \quad (10)$$

To meet the buyer's requirement on transmission rate, the seller has to set a larger power than it would under normal circumstances. To ensure that the seller will undertake the data transmission task in any cases, this worst-case utility should be non-negative. This is the *participation constraint* that the BS must take account of.

The rewards offered to sellers can be seen as the extra cost that the BS pays for energy saving. So long as the participation constraints can be satisfied, the BS prefers to pay as less as possible. The seller's resistance θ_i depends on both objective factors (e.g. the performance of the battery) and subjective factors (e.g. the user's willingness to relay data to others) inherent to the user, which means θ_i varies from one user to another. Moreover, θ_i is generally unknown to the BS, or we can say, there is *information asymmetry* between the sellers and the BS. This makes it difficult for the BS to decide the optimal reward paid to each seller. To deal with the information asymmetry problem, we resort to *contract theory* [17]. Specifically, it is assumed that the BS designs a menu of contracts to define the transmission power of the seller and the corresponding reward. With the elaborately designed contracts, the BS can incentivize the desired sellers to undertake the transmission tasks. In the following section, we will present the formulation of the contract problem and the design of the optimal contract.

IV. Encourage User Participation for Energy Saving

As defined in Section III-B, each potential seller can relay data to at most one buyer. Considering that there may be multiple buyers, the BS needs to carefully match the buyers with the sellers so as to reduce the total energy consumption. In case that the seller chosen by the BS refuses to relay data to the designated buyer, the BS should first ensure the seller a non-negative utility. Therefore, before we investigate the matching algorithms, in this section we propose a contract

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theoretical approach to design a mechanism to price the contribution of the sellers in such a way that user participation is guaranteed and the reward paid by the BS is minimized.

A. Contract With Adverse Selection

Following the contract theory terminology, we refer to θ_i as the *type* of seller s_i. The BS, which plays the role of the *principal*, delegates the data transmission tasks to multiple *agents*, namely the sellers. In this paper, we consider the case of *adverse selection* [17], i.e. the seller's type θ_i is unknown to the BS. Suppose that a buyer b_j requests one unit of data from the BS and the BS chooses the seller s_i as a candidate relay for b_j, then the BS can offer a menu of contracts $\left\{\left(r_{ij}(\theta), p_{ij}(\theta)\right)\right\}$ to the seller, where the contract $\left(r_{ij}(\theta), p_{ij}(\theta)\right)$ is designated for the seller with type θ. If the seller accepts the contract, then it will transmit data to b_j and the transmission power is $p_{ij}(\theta)$. In return, the BS pays a reward $r_{ij}(\theta)$ to the seller. Define

$$e_{ij}(P) = \frac{P}{\omega \log\left(1 + \frac{g_{ij} P}{n_{\max}}\right)}, \quad 0 \le P \le P_{\max}. \tag{11}$$

It can be verified that $e_{ij}(P)$ increases monotonously with P. Further, we define $t_{ij}(\theta) = e_{ij}\left(p_{ij}(\theta)\right)$, then the utility of the seller with type θ can be written as

$$U_{ij}(\theta) = r_{ij}(\theta) - \theta t_{ij}(\theta). \tag{12}$$

Notice that the reciprocal of $e_{ij}(P)$, namely the ratio of the transmission rate to the transmission power, has a similar form with the *energy efficiency* defined in [31]. We refer to e_{ij} as *inverse energy efficiency*. And in subsequent discussions, we first investigate the design of $t_{ij}(\theta)$. The transmission power $p_{ij}(\theta)$ can be determined by using the monotonicity of $e_{ij}(P)$.

To make the contract design problem tractable, we assume that the sellers' types are drawn independently and identically from $\left[\underline{\theta}, \bar{\theta}\right]$, and the corresponding probability density function $f(\theta)$ is known to the BS. Given the distribution of sellers' types, the objective of the BS is to design a menu of contracts to minimize the expected rewards paid to sellers. To be a feasible menu of contracts, $\left\{\left(r_{ij}(\theta), t_{ij}(\theta)\right)\right\}$ should satisfy the following constraints.

1) Participation Constraints: As described in Section III-C, the contracts should bring a non-negative utility to each type of seller. That is,

$$U_{ij}(\theta) \ge 0, \quad \forall \theta \in \left[\underline{\theta}, \bar{\theta}\right]. \tag{13}$$

2) Incentive Compatibility Constraints: To ensure that the seller will accept the contract designated for it rather than choosing other contracts, the following condition must be satisfied:

$$r_{ij}(\theta) - \theta t_{ij}(\theta) \ge r_{ij}\left(\tilde{\theta}\right) - \theta t_{ij}\left(\tilde{\theta}\right), \quad \forall \left(\theta, \tilde{\theta}\right) \in \left[\underline{\theta}, \bar{\theta}\right]^2 \tag{14}$$

3) Boundary Constraint: As mentioned in Section III-B, the transmission rate $R\left(s_i, b_j\right)$ should be no less than the threshold γ_{rate}. To ensure that $Rate_{worst}\left(s_i, b_j\right) \ge \gamma_{rate}$, the transmission power of s_i should be no less than $P_{\min}^{(ij)} \triangleq \frac{n_{\max}}{g_{ij}}\left(2^{\frac{\gamma_{rate}}{\omega}} - 1\right)$. And there is $p_{ij}(\theta) \le P_{\max}$. Then by using the monotonicity of $e_{ij}(P)$, we can get

$$\frac{P_{\min}^{(ij)}}{\gamma_{rate}} \le t_{ij}(\theta) \le \frac{P_{\max}}{\omega \log\left(1 + \frac{g_{ij} P_{\max}}{n_{\max}}\right)}, \quad \forall \theta \in \left[\underline{\theta}, \bar{\theta}\right], \tag{15}$$

For ease of description, define

$$e_{\max}^{(ij)} = \frac{P_{\max}}{\omega \log\left(1 + \frac{g_{ij} P_{\max}}{n_{\max}}\right)} \tag{16}$$

and

$$e_{\min}^{(ij)} = \frac{P_{\min}^{(ij)}}{\gamma_{rate}}. \tag{17}$$

4) Isoperimetric Constraint: Though the reward paid to the seller can compensate its energy cost, it is still important for the BS to keep the energy efficiency of the seller at a certain level so that the whole system is energy-efficient. Here for simplicity and without loss of generality, we assume that the expected inverse energy efficiency of the seller should satisfy

$$\int_{\underline{\theta}}^{\bar{\theta}} t_{ij}(\theta) f(\theta) d\theta = e_{req}, \tag{18}$$

where $e_{req} > 0$ is specified by the BS.

Denote the set of all feasible menus of contracts as $\mathcal{C}$. The BS's problem can be formulated as

$$\begin{aligned} (\mathbf{P}) \quad & \min_{\left\{\left(r_{ij}(\theta), t_{ij}(\theta)\right)\right\} \in \mathcal{C}} \int_{\underline{\theta}}^{\bar{\theta}} r_{ij}(\theta) f(\theta) d\theta, \\ & \text{subject to } (13) \sim (18). \end{aligned} \tag{19}$$

Next we will discuss how to solve this optimization problem.

B. Contract Design

1) Simplifying Constraints: The participation constraints described in (13) and the incentive compatibility constraints described in (14) are important for the optimization problem **P**. Though described with one inequality, (13) actually contains an infinity of constraints, each of which corresponds to a certain θ. Similarly, (14) should be treated as an infinity of constraints, each of which corresponds to a certain pair of θ and $\tilde{\theta}$. To find the optimal solution to **P**, we need to express the constraints in a concise way.

Following a similar approach proposed in [17], we reduce the infinity of incentive constraints in (14) to a differential equation

$$\frac{dr_{ij}(\theta)}{d\theta} - \theta \frac{dt_{ij}(\theta)}{d\theta} = 0 \tag{20}$$

and a monotonicity constraint

$$-\frac{dt_{ij}(\theta)}{d\theta} \ge 0. \tag{21}$$

Further, by using (12) we can express (20) in a simpler way:

$$\frac{dU_{ij}(\theta)}{d\theta} = -t_{ij}(\theta). \tag{22}$$

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According to (15) and (22), participation constraints in (13) can be simplified to $U_{ij}\left(\bar{\theta}\right) \geq 0,\ \forall\theta \in \left[\underline{\theta},\bar{\theta}\right]$. Further, we can predict that this constraint must be binding at the optimum, i.e.

$$U_{ij}^{*}\left(\bar{\theta}\right) = 0. \tag{23}$$

Suppose that $U_{ij}^{*}\left(\bar{\theta}\right) > 0$, then the BS could reduce $U_{ij}^{*}\left(\bar{\theta}\right)$ by a small amount while keeping $t_{ij}^{*}\left(\bar{\theta}\right)$ unchanged. As a result, the expected reward is reduced, which contradicts with the optimality of $U_{ij}^{*}\left(\bar{\theta}\right)$.

2) Integration by Parts: By using (22) and (23), we can get

$$U_{ij}\left(\theta\right) = \int_{\theta}^{\bar{\theta}} t_{ij}\left(\tau\right)d\tau. \tag{24}$$

Then the objective function of problem **P** can be rewritten as

$$\begin{aligned}
&\int_{\underline{\theta}}^{\bar{\theta}}\left[U_{ij}\left(\theta\right)+\theta t_{ij}\left(\theta\right)\right]f\left(\theta\right)d\theta \\
&= \int_{\underline{\theta}}^{\bar{\theta}} f\left(\theta\right)\left[\int_{\theta}^{\bar{\theta}} t_{ij}\left(\tau\right)d\tau\right]d\theta + \int_{\underline{\theta}}^{\bar{\theta}}\theta t_{ij}\left(\theta\right)f\left(\theta\right)d\theta \\
&= \int_{\underline{\theta}}^{\bar{\theta}} F\left(\theta\right)t_{ij}\left(\theta\right)d\theta + \int_{\underline{\theta}}^{\bar{\theta}}\theta t_{ij}\left(\theta\right)f\left(\theta\right)d\theta,
\end{aligned} \tag{25}$$

where the last equation is obtained via integration by parts.

Based on above discussions, the optimization problem **P** can be reformulated as

$$\left(\mathbf{P}'\right)\ \min_{t_{ij}(\theta)} \int_{\underline{\theta}}^{\bar{\theta}} t_{ij}\left(\theta\right)f\left(\theta\right)\left[\theta+\frac{F\left(\theta\right)}{f\left(\theta\right)}\right]d\theta, \tag{26}$$

subject to

$$\frac{dt_{ij}\left(\theta\right)}{d\theta} \leq 0,$$

$$\int_{\underline{\theta}}^{\bar{\theta}} t_{ij}\left(\theta\right)f\left(\theta\right)d\theta = e_{req},$$

$$e_{\min}^{(ij)} \leq t_{ij}\left(\theta\right) \leq e_{\max}^{(ij)},\quad \forall\theta\in\left[\underline{\theta},\bar{\theta}\right].$$

Once we have determined the optimal $t_{ij}^{*}\left(\theta\right)$, the optimal reward function can be defined as

$$\begin{aligned}
r_{ij}^{*}\left(\theta\right) &= U_{ij}^{*}\left(\theta\right)+\theta t_{ij}^{*}\left(\theta\right) \\
&= \int_{\theta}^{\bar{\theta}} t_{ij}^{*}\left(\tau\right)d\tau + \theta t_{ij}^{*}\left(\theta\right).
\end{aligned} \tag{27}$$

3) Optimal Contract: To derive the analytic form of the optimal $t_{ij}^{*}\left(\theta\right)$, we assume that the distribution of seller's type satisfies the following condition

$$\frac{d}{d\theta}\left[\theta+\frac{F\left(\theta\right)}{f\left(\theta\right)}\right] \geq 0. \tag{28}$$

For example, suppose that sellers' types are uniformly distributed within $\left[\underline{\theta},\bar{\theta}\right]$, then there is $\frac{d}{d\theta}\left[\theta+\frac{F(\theta)}{f(\theta)}\right] = 2 > 0$. Following a similar analysis in [32], we make the following proposition.

Proposition 1: If the distribution of seller's type satisfies (28), then the solution to the optimization problem **P** is

$$t_{ij}^{*}\left(\theta\right) = \begin{cases} e_{\max}^{(ij)}, & \underline{\theta} \leq \theta \leq \theta_{th}^{(ij)} \\ e_{\min}^{(ij)}, & \theta_{th}^{(ij)} < \theta \leq \bar{\theta}, \end{cases} \tag{29}$$

$$r_{ij}^{*}\left(\theta\right) = \begin{cases} \theta_{th}^{(ij)}\left(e_{\max}^{(ij)}-e_{\min}^{(ij)}\right)+\bar{\theta}e_{\min}^{(ij)}, & \underline{\theta} \leq \theta \leq \theta_{th}^{(ij)} \\ \bar{\theta}e_{\min}^{(ij)}, & \theta_{th}^{(ij)} < \theta \leq \bar{\theta}, \end{cases} \tag{30}$$

where $\mathbb{I}\left(\cdot\right)$ is an indicator function, and $\theta_{th}^{(ij)}$ is the solution to

$$\left(e_{\max}^{(ij)}-e_{\min}^{(ij)}\right)\int_{\underline{\theta}}^{\theta_{th}^{(ij)}} f\left(\theta\right)d\theta = e_{req}-e_{\min}^{(ij)}. \tag{31}$$

Proof: It can be easily verified that $t_{ij}^{*}\left(\theta\right)$ and $r_{ij}^{*}\left(\theta\right)$ satisfy (27). Hence, to prove **Proposition1**, it suffices to show that $t_{ij}^{*}\left(\theta\right)$ in (37) is the solution to problem **P'**.

It can be verified that $t_{ij}^{*}\left(\theta\right)$ satisfies all the constraints described in **P'**, hence $t_{ij}^{*}\left(\theta\right)$ is a feasible solution. To show its optimally, consider an arbitrary function $t_{ij}\left(\theta\right)$ that satisfies the constraints of **P'**. Define $\delta_t\left(\theta\right) = t_{ij}^{*}\left(\theta\right)-t_{ij}\left(\theta\right)$. Then for any $\theta\in\left[\underline{\theta},\theta_{th}\right]$,$\delta_t\left(\theta\right)\geq 0$; for any $\theta\in\left[\theta_{th},\bar{\theta}\right]$,$\delta_t\left(\theta\right)\leq 0$. And there is

$$\int_{\underline{\theta}}^{\theta_{th}}\delta_t\left(\theta\right)f\left(\theta\right)d\theta + \int_{\theta_{th}}^{\bar{\theta}}\delta_t\left(\theta\right)f\left(\theta\right)d\theta = 0. \tag{32}$$

Moreover, since the distribution satisfies $\frac{d}{d\theta}\left[\theta+\frac{F(\theta)}{f(\theta)}\right] \geq 0$, for any $\theta_1\in\left[\underline{\theta},\theta_{th}\right]$ and $\theta_2\in\left[\theta_{th},\bar{\theta}\right]$,

$$\theta_1+\frac{F\left(\theta_1\right)}{f\left(\theta_1\right)} \leq \theta_{th}+\frac{F\left(\theta_{th}\right)}{f\left(\theta_{th}\right)} \leq \theta_2+\frac{F\left(\theta_2\right)}{f\left(\theta_2\right)}. \tag{33}$$

Then we get

$$\begin{aligned}
&\int_{\underline{\theta}}^{\theta_{th}}\delta_t\left(\theta\right)f\left(\theta\right)\left[\theta+\frac{F\left(\theta\right)}{f\left(\theta\right)}\right]d\theta \\
&\leq \left[\theta_{th}+\frac{F\left(\theta_{th}\right)}{f\left(\theta_{th}\right)}\right]\int_{\underline{\theta}}^{\theta_{th}}\delta_t\left(\theta\right)f\left(\theta\right)d\theta,
\end{aligned} \tag{34}$$

and

$$\begin{aligned}
&\int_{\theta_{th}}^{\bar{\theta}}\delta_t\left(\theta\right)f\left(\theta\right)\left[\theta+\frac{F\left(\theta\right)}{f\left(\theta\right)}\right]d\theta \\
&\leq \left[\theta_{th}+\frac{F\left(\theta_{th}\right)}{f\left(\theta_{th}\right)}\right]\int_{\theta_{th}}^{\bar{\theta}}\delta_t\left(\theta\right)f\left(\theta\right)d\theta.
\end{aligned} \tag{35}$$

Adding above two inequalities yields

$$\begin{aligned}
&\int_{\underline{\theta}}^{\bar{\theta}} t_{ij}^{*}\left(\theta\right)f\left(\theta\right)\left[\theta+\frac{F\left(\theta\right)}{f\left(\theta\right)}\right]d\theta \\
&\leq \int_{\underline{\theta}}^{\bar{\theta}} t_{ij}\left(\theta\right)f\left(\theta\right)\left[\theta+\frac{F\left(\theta\right)}{f\left(\theta\right)}\right]d\theta,
\end{aligned} \tag{36}$$

which implies that $t_{ij}^{*}(\theta)$ is the solution to the optimization problem **P'** and thus concludes the proof.

According to (29) and the definition of $t_{ij}\left(\theta\right)$, the power function in the optimal contract $\left(r_{ij}^{*}\left(\theta\right),p_{ij}^{*}\left(\theta\right)\right)$ can be formulated as

$$p_{ij}^{*}\left(\theta\right) = \begin{cases} P_{\max}, & \underline{\theta} \leq \theta \leq \theta_{th}^{(ij)} \\ P_{\min}^{(ij)}, & \theta_{th}^{(ij)} < \theta \leq \bar{\theta}. \end{cases} \tag{37}$$

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An intuitive explanation to the optimal contract is that sellers who are of low resistance will be incentivized to work at the maximum power, and sellers of high resistance only tries to meet the lowest requirement on transmission rate. It should be noted that the constrains (15) and (18) imply that $e_{\min}^{(ij)} \leq e_{req} \leq e_{\max}^{(ij)}$. Both $e_{\max}^{(ij)}$ and $e_{\min}^{(ij)}$ depend on the distance between the seller and the buyer. When the distance is larger than some threshold, the condition $e_{\min}^{(ij)} \leq e_{req} \leq e_{\max}^{(ij)}$ will not hold. In such a case, the seller will not be considered as a candidate relay for the buyer, and there is no need for the BS to offer contracts to the seller. Moreover, given e_{req}, the threshold $\theta_{th}^{(ij)}$ is determined by $e_{\max}^{(ij)}$ and $e_{\min}^{(ij)}$, which are determined by the distance between the seller and the buyer. The smaller the distance is, the higher $\theta_{th}^{(ij)}$ is. That is to say, for a given buyer, it is possible that a seller of high resistance is chosen by the BS, as long as the seller is close enough to the buyer.

V. Coordinate Users for Energy Saving

In the above section we have proposed a contract theoretical approach for the BS to determine the rewards paid to sellers. By applying the derived optimal contract, the BS can ensure that the seller is willing to participate whenever it is required to relay the data to some buyer. With the guarantee of user participation, the BS can further investigate how to coordinate the buyers and the sellers to minimize the total energy consumption. To this end, a utility-based matching algorithm is proposed. In this section, we first introduce the utility functions of sellers and buyers, then we describe the details of the matching algorithm.

A. Utility Function

Upon receiving a buyer's request, the BS announces the optimal contract to all the potential sellers. According to (10), the utility of the seller is related to the buyer assigned to it. To incorporate the influence of the assignment of buyers, we reform the utility function in the following way. Assuming that each buyer requests one unit of data. Then given the allocation matrix M_σ, the utility of the seller s_i can be written as

$$U_{s_i}(M_\sigma) = \sum_{\substack{b_j \in \mathcal{B}_t,\\ M_\sigma(i,j)>0}} U_{ij}^{high} \mathbb{I}\left(\underline{\theta} \leq \theta_i \leq \theta_{th}^{(ij)}\right) + \sum_{\substack{b_j \in \mathcal{B}_t,\\ M_\sigma(i,j)>0}} U_{ij}^{low} \mathbb{I}\left(\theta_{th}^{(ij)} < \theta_i \leq \bar{\theta}\right) \quad (38)$$

where $U_{ij}^{high} = \left(\theta_{th}^{(ij)} - \theta_i\right) e_{\max}^{(ij)} + \left(\bar{\theta} - \theta_{th}^{(ij)}\right) e_{\min}^{(ij)}$ and $U_{ij}^{low} = \left(\bar{\theta} - \theta_i\right) e_{\min}^{(ij)}$.

As for the buyer, the utility is measured in terms of quality of experience (QoE). The evaluation of QoE is complicated [33]. Here for simplicity and without loss of generality, we focus on the influence of the transmission rate on user experience. If the buyer gets data directly from the BS via a cellular link, the transmission rate is

$$R\left(BS, b_j\right) = \omega \log\left(1 + \frac{g_{b_j} P_{BS}}{n_0}\right), \quad (39)$$

where ω is the bandwidth, n_0 denotes the power of the additive while Gaussian noise, P_{BS} denotes the transmission power of the BS, g_{b_j} is the channel gain from the BS to b_j. As we have done before, we define the channel gain as

$$g_{b_j} = \beta \eta_{b_j} \zeta_{b_j} d_{b_j}^{-\alpha}, \quad (40)$$

where η_{b_j} and ζ_{b_j} denote the fast fading gain and the slow fading gain respectively, d_{b_j} denotes the distance between the BS and the buyer.

If the buyer gets data from a seller via a D2D link, the transmission rate is given by (7). Intuitively, the buyer will get higher QoE by using the D2D transmission mode. Given the matrix M_σ, the utility of a buyer b_j is defined as

$$U_{b_j}(M_\sigma) = \sum_{s_i \in S_t, M_\sigma(i,j)>0} \left(R\left(s_i, b_j\right) - R\left(BS, b_j\right)\right). \quad (41)$$

As introduced in Section III, the ultimate goal of the BS is to minimize the total energy consumption. For each buyer b_j, there may be more than one seller nearby that is willing to act as the relay for the buyer. Among the candidate sellers, the BS prefers to match the buyer to the one that is located closer to the BS. After the BS applies the matching algorithm, if a buyer far from the BS is matched with a seller that is relatively close to the BS, then much energy can be saved for the BS. With this in mind, we introduce a parameter $\mu_{ij} \triangleq \left(\frac{d_{b_j}}{d_{s_i}}\right)^\kappa$, where d_{s_i} denotes the distance between the BS and the seller s_i, the positive constant κ is a system parameter. Then we revise the buyer's utility as

$$U_{b_j}(M_\sigma) = \sum_{s_i \in \mathcal{S}_t, M_\sigma(i,j)>0} \mu_{ij} \left(R\left(s_i, b_j\right) - R\left(BS, b_j\right)\right). \quad (42)$$

As discussed in Section III-B, the buyer has a minimum requirement on the transmission rate. Given a buyer b_j and a seller s_i, if the distance between the two users is large, then the seller has to increase the transmission power to meet the buyer's requirement. Thus, from the perspective of energy saving, the buyer located nearby is more preferred by the seller. Considering this, we introduce the parameter $\rho_{ij} \triangleq \left(\frac{1}{d_{ij}}\right)^\kappa$ and revise the seller's utility as

$$U_{s_i}(M_\sigma) = \sum_{\substack{b_j \in \mathcal{B}_t,\\ M_\sigma(i,j)>0}} \rho_{ij} U_{ij}^{high} \mathbb{I}\left(\underline{\theta} \leq \theta_i \leq \theta_{th}^{(ij)}\right) + \sum_{\substack{b_j \in \mathcal{B}_t,\\ M_\sigma(i,j)>0}} \rho_{ij} U_{ij}^{low} \mathbb{I}\left(\theta_{th}^{(ij)} < \theta_i \leq \bar{\theta}\right). \quad (43)$$

B. Energy Saving Stable Matching

Above we have discussed how to measure the utilities of buyers and sellers. Both buyers and sellers desire high utilities. By using the utility functions, the BS can compute a *preference list* for each buyer. The preference list is an ordering of potential sellers, where the seller that can bring higher utility to the buyer ranks higher. Similarly, the BS can compute a preference list for each potential seller. Based on

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the preference lists, the BS can make a match between buyers and sellers via greedy search. This is the basic idea of the proposed matching algorithm. As discussed in Section III-B, if a matched buyer-seller pair shares the same channel with other users, the interference among users should be taken into account. Here, as a start, we ignore the interference and propose a basic matching algorithm. In the following subsection, we'll discuss how to modify the algorithm to deal with the problem caused by channel sharing.

Before presenting the details of the matching algorithm, we first introduce several basic concepts.

Definition 1: Given a set of buyers $\mathcal{B}_t$ and a set of potential sellers $\mathcal{S}_t$, a matching function $\varphi(\cdot)$ is a mapping from $\mathcal{B}_t \cup \mathcal{S}_t$ to $2^{\mathcal{B}_t \cup \mathcal{S}_t}$ such that:

1) $\forall b_j \in \mathcal{B}_t$, $\varphi(b_j) \in \mathcal{S}_t$ or $\varphi(b_j) = \varnothing$, and $|\varphi(b_j)| \le 1$;

2) $\forall s_i \in \mathcal{S}_t$, $\varphi(s_i) \in \mathcal{B}_t$ or $\varphi(s_j) = \varnothing$, and $|\varphi(s_i)| \le 1$;

3) $\varphi(b_j) = s_i$ if and only if $\varphi(s_i) = b_j$.

Given the matching function φ, the mapping $\sigma : \mathcal{B}_t \to \mathcal{S}_t \cup \varnothing$ used in previous sections is determined. That is, $\forall b_j \in \mathcal{B}_t$, $\sigma(b_j) = \varphi(b_j)$. Also the positions of the non-zero entries in the channel allocation matrix M_σ are determined. It should be noted that if all the non-zero entries in M_σ take distinct values, i.e. each channel is used by at most one pair of D2D users, then there will be no interference among users. Otherwise, the transmission quality perceived by the buyer will be affected by the interference, and a different matching function may be more preferred by the BS. The matching algorithm applying to this case will be discussed later.

Definition 2: For any seller $s_i \in \mathcal{S}_t$, a preference relation $\succ_{s_i}$ is defined over the set $\mathcal{B}_t$ such that for any $b_j, b'_j \in \mathcal{B}_t$, $b_j \succ_{s_i} b'_j$ if and only if $U_{s_i}(b_j) > U_{s_i}(b_{j'})$, where $U_{s_i}(b_l)$ ($l = j, j'$) is defined as

$$U_{s_i}(b_l) = r^*_{il}(\theta_i) - \theta_i e^*_{il}(\theta_i). \quad (44)$$

And for any buyer $b_j \in \mathcal{B}_t$, a preference relation $\succ_{b_j}$ is defined over the set $\mathcal{S}_t$ such that for any $s_i, s_{i'} \in S_t$, $s_i \succ_{b_j} s_{i'}$ if and only if $U_{b_j}(s_i) > U_{b_j}(s_{i'})$, where $U_{b_j}(s_l)$ ($l = i, i'$) is defined as

$$U_{b_j}(s_l) = \mu_{lj}\left(R(s_l, b_j) - R(BS, b_j)\right). \quad (45)$$

Definition 3: A matching φ is blocked by the pair (s_i, b_j) if $\varphi(b_j) \ne s_i$, while $s_i \succ_{b_j} \varphi(b_j)$ and $b_j \succ_{s_i} \varphi(s_i)$. A matching is called stable if it is not blocked by any (s_i, b_j) pair.

Based on above definitions, we propose the following matching algorithm. Initially, the buyers send their requests to the BS. Based on the locations of the buyers, the BS first computes the threshold $\theta^{(ij)}_{th}$ (see (31)) for each potential seller. Then the BS sends the optimal contract $\left(r^*_{ij}(\theta), p^*_{ij}(\theta)\right)$ to corresponding seller. Based on the feedbacks (accept or reject) of sellers, the BS can determine the set of available sellers. Then for each buyer b_j, the BS computes the utility $U_{b_j}(s_i)$ corresponding to each candidate seller and constructs a preference list $PLIST_S(b_j)$. Similarly, for each candidate seller s_i, the BS computes the utility $U_{s_i}(b_j)$ corresponding to each buyer and constructs a preference list $PLIST_B(s_i)$. Based on these preference lists, the BS adopts an iterative approach to select sellers for buyers. At each iteration, the

Algorithm 1 D2D Matching for Interference-Free Model

Buyers in $\mathcal{B}_t$ sends requests to the BS. The BS announces the contract to other users and determines the set of available sellers $\mathcal{S}_t$.
$\forall b_j \in \mathcal{B}_t$, the BS computes the preference list $PLIST_S(b_j)$ and sets $\mathcal{S}(b_j) = \emptyset$;
$\forall s_i \in \mathcal{S}_t$, the BS computes the preference list $PLIST_B(s_i)$ and sets $\mathcal{B}(s_i) = \emptyset$.
$\mathcal{B}' \leftarrow \mathcal{B}_t$, $PairCount \leftarrow 0$.
while $\mathcal{B}' \ne \emptyset$ **do**
  for $b_j \in \mathcal{B}'$ **do**
    $s_i \leftarrow top\ of\ PLIST_S(b_j)$,
    $\mathcal{B}(s_i) \leftarrow \mathcal{B}(s_i) \cup \{b_j\}$,
  end for
  for $s_i \in \mathcal{S}$ **do**
    if $\mathcal{B}(s_i) \ne \emptyset$ **then**
      $b_j \leftarrow$ the buyer in $\mathcal{B}(s_i)$ that is most preferred by s_i,
      $\mathcal{B}(s_i) \leftarrow \{b_j\}$.
    end if
  end for
  $\tilde{\mathcal{B}} \leftarrow \mathcal{B}' \setminus \cup_i \mathcal{B}(s_i)$, $\mathcal{B}' \leftarrow \emptyset$.
  for $b_j \in \tilde{\mathcal{B}}$ **do**
    Remove the top seller in $PLIST_S(b_j)$,
    if $PLIST_S(b_j) \ne \emptyset$ **then**
      $\mathcal{B}' \leftarrow \mathcal{B}' \cup \{b_j\}$.
    end if
  end for
end while
for $s \in \mathcal{S}_t$ **do**
  if $\mathcal{B}(s_i) \ne \emptyset$ **then**
    $\varphi(s_i) \leftarrow b_j$ (the only element in $\mathcal{B}(s_i)$), $\varphi(b_j) \leftarrow s_i$.
    $PairCount \leftarrow PairCount + 1$.
    $M_\sigma(i, j) \leftarrow PairCount$.
  end if
end for

BS first chooses the seller that is most preferred by a buyer as the candidate relay for the buyer. If the seller is desired by multiple buyers, then the BS selects the buyer that is most preferred by the seller as the match of the seller. As for the rest of the buyers, this most preferred seller is no longer available, and the seller is moved from the corresponding preference list. Then the matching process goes to the next round. A detailed description of the matching algorithm is given in Algorithm1. Regarding to the stability of the matching result, we make the following proposition.

Proposition 1: Given the set of buyers and the set of sellers, Algorithm 1 provides a stable matching between buyers and sellers.

Proof: Assuming that after applying Algorithm1, the matching result is blocked by a pair (s_i, b_j). According to Algorithm1, when a seller is preferred by multiple buyers, or we can say, there is a list of candidate buyers for the seller,

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Algorithm 2 D2D Matching for Interference Model

The BS applies Algorithm1 to get a pre-matching result φ_0, and the corresponding allocation matrix is M_{σ_0}.
Check if swapping matching occurs: $I_{SM} \leftarrow \mathbb{I}$ (swapping matching occurs).
Check if self-enhancing matching occurs: $I_{SEM} \leftarrow \mathbb{I}$ (self-enhancing matching occurs).
$\varphi \leftarrow \varphi_0$, $M_\sigma \leftarrow M_{\sigma_0}$.
while $I_{SEM} \neq 0$ or $I_{SM} \neq 0$ **do**
  $I_{SEM} \leftarrow 0, I_{SM} \leftarrow 0$.
  // Check Self-Enhance Matching:
  for $b_j \in \mathcal{B}_t$ **do**
    $s_i \leftarrow \varphi(b_j)$, $k \leftarrow M_\sigma(i, j)$.
    for $k' \in \{1, \cdots, k-1, k+1, \cdots, K\}$ **do**
      $M_{\sigma'} \leftarrow M_\sigma$, $M_{\sigma'}(i, j) \leftarrow k'$.
      if b_j and $M_{\sigma'}$ satisfy (48) and (49) **then**
        $I_{SEM} \leftarrow 1$, $M_\sigma(i, j) \leftarrow k'$, break;
      end if
    end for
  end for
  // Check Swap Matching:
  for $(b_{j1}, b_{j2}) \in \mathcal{B}_t \times \mathcal{B}_t$ **do**
    $s_{i1} \leftarrow \varphi(b_{j1})$, $s_{i2} \leftarrow \varphi(b_{j2})$.
    $\varphi' \leftarrow \varphi$, $\varphi'(b_{j1}) \leftarrow s_{i2}$, $\varphi'(b_{j2}) \leftarrow s_{i1}$.
    $M_{\sigma'} \leftarrow M_\sigma$, $M_{\sigma'}(i1, j2) \leftarrow M_\sigma(i1, j1)$, $M_{\sigma'}(i2, j1) \leftarrow M_\sigma(i2, j2)$.
    if φ' and (b_{j1}, b_{j2}) satisfy (46) and (47) **then**
      $I_{SM} \leftarrow 1$, $\varphi \leftarrow \varphi'$, $M_\sigma \leftarrow M_{\sigma'}$.
      continue;
    end if
    $M_{\sigma'} \leftarrow M_\sigma$, $M_{\sigma'}(i2, j1) \leftarrow M_\sigma(i1, j1)$, $M_{\sigma'}(i1, j2) \leftarrow M_\sigma(i2, j2)$
    if φ' and (b_{j1}, b_{j2}) satisfy (46) and (47) **then**
      $I_{SM} \leftarrow 1$, $\varphi \leftarrow \varphi'$, $M_\sigma \leftarrow M_{\sigma'}$.
    end if
  end for
  $\forall b_j \in \mathcal{B}_t$, the BS computes $U_{b_j}(M_\sigma)$; $\forall s_i \in \mathcal{S}_t$, the BS computes $U_{s_i}(M_\sigma)$.
end while

the BS always chooses the buyer that is most beneficial to the seller, and other buyers are "rejected". If there is a pair (s_i, b_j) that satisfies $b_j \succ_{s_i} \varphi(s_i)$, then from the result that the buyer $\varphi(s_i)$, rather than b_j is assigned to the seller s_i we can conclude that b_j is not a candidate buyer of s_i. On the other hand, the buyer is always assigned to its most preferred seller unless it is rejected. For the pair (s_i, b_j) that satisfies $s_i \succ_{b_j} \varphi(b_j)$, the result that the buyer b_j is assigned to the seller $\varphi(b_j)$, rather than the seller s_i, implies that b_j used to be the candidate buyer of s_i but is rejected by s_i. This conclusion contradicts to the one stated before. Therefore, the assumption about the existence of the block pair (s_i, b_j) is invalid, which proofs that Algorithm1 can provide a stable matching result. ∎

Proposition 2: The computation complexity of Algorithm1 is $O(N_S N_B)$.

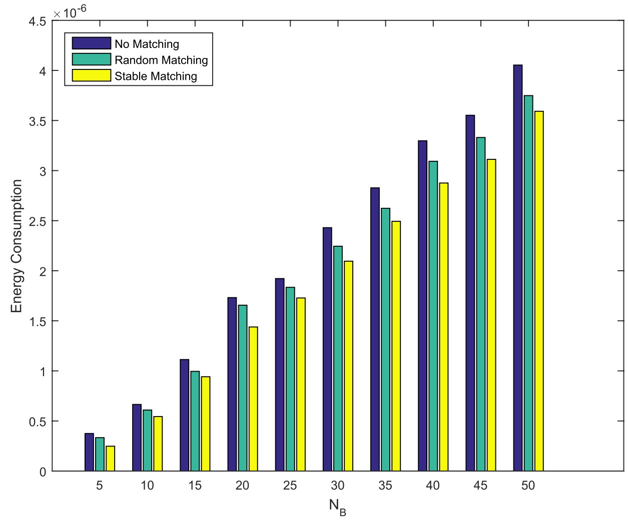

Fig. 2. The total energy consumption of the BS (without interference). The purple color denotes the setting where D2D communication is not allowed. The green color denotes the random matching algorithm. The yellow color denotes the proposed matching algorithm.

Proof: The complexity analysis mainly concerns the iterative part of Algorithm1. In each round, each buyer selects its favorite seller with complexity $O(1)$. After each seller determines its matched buyer with complexity $O(1)$, each buyer that has not been matched update its list of candidate sellers with complexity $O(1)$. Since each buyer performs the above operation for at most N_S rounds, the algorithm has complexity $O(N_S N_B)$. ∎

C. Energy Saving Matching With D2D Interference

The matching algorithm described in Algorithm1 is based on the assumption that there is no interference among the D2D users. Considering that the channel resource is limited, it is very likely that two or more pairs of D2D users have to share the same channel. In such a case, the interference among users cannot be ignored, and Algorithm1 is not applicable. To deal with the channel-sharing situation, we introduce the concept of weak stable matching and propose an algorithm that can provide a weak stable matching result.

1) Weak Stable Matching: The concept of weak stable matching is derived from two types of operations on the matching result, namely *swap* [34] and *self-enhance*.

*Definition 4: Given a matching function φ and the corresponding allocation matrix M_σ, **swap matching** occurs when there are two pairs of users (s_{i1}, b_{j1}) and (s_{i2}, b_{j2}) that satisfy $\varphi(s_{i1}) = b_{j1}$, $\varphi(s_{i2}) = b_{j2}$, and swapping the paired sellers of buyers causes no decline of the utility of any involved user. Let φ' denote the modified matching where the two pairs swap their matches, i.e. $\varphi'(b_{j1}) = s_{i2}$, $\varphi'(b_{j2}) = s_{i1}$. Let $M_{\sigma'}$ denote the corresponding allocation matrix. Swap matching occurs when*

$$U_{b_l}(M_{\sigma'}) - U_{b_l}(M_\sigma) \geq \delta_U, \quad b_l = b_{j1},\ b_{j2}, \tag{46}$$

$$U_x(M_{\sigma'}) \geq U_x(M_\sigma), \quad \forall x \in \mathcal{S}_t \cup \mathcal{B}_t, \tag{47}$$

where δ_U is a positive constant.

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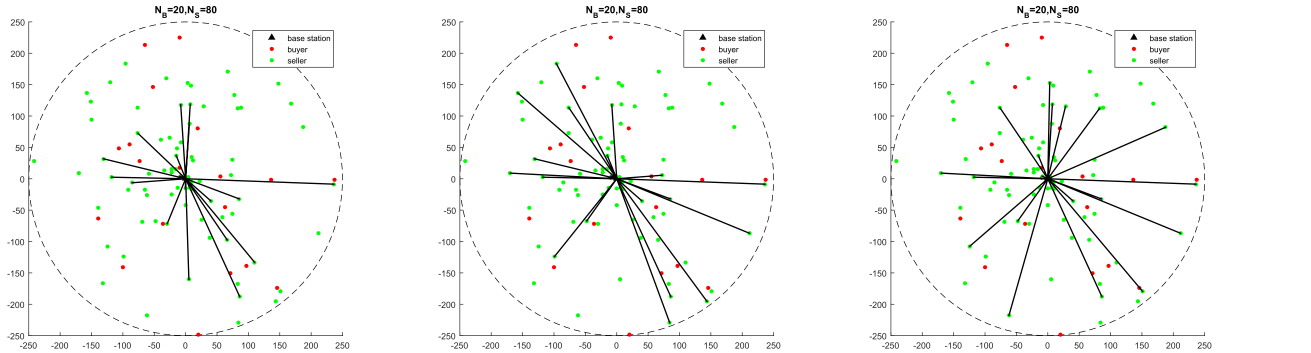

(a) (b) (c)

Fig. 3. An illustration of the energy consumption of the BS (without interference): (a) result of the proposed matching algorithm; (b)(c) two sample results of the random matching algorithm. The red point and the green point denote the buyer and the seller respectively. The black triangle denotes the BS. The black solid line denotes the cellular link between the BS and the seller that is chosen as the relay for a buyer. There are 20 buyers and 80 potential sellers.

Definition 5: Given a matching function φ and the corresponding allocation matrix M_σ, ***self-enhance matching*** *occurs when the change of the channel allocated to a pair of users (s_i, b_j) results in an increment of the users' utility without harming other users' utility. Let $M_{\sigma'}$ denote the matrix where $M_{\sigma'}(i, j) \neq M_\sigma(i, j)$, then self-enhance matching occurs when*

$$U_{b_j}(M_{\sigma'}) - U_{b_j}(M_\sigma) \geq \delta_U, \tag{48}$$

$$U_x(M_{\sigma'}) \geq U_x(M_\sigma), \quad \forall x \in \mathcal{S}_t \cup \mathcal{B}_t. \tag{49}$$

Definition 6: A matching function φ is called ***weak stable*** *if neither swap matching nor self-enhance occurs in the result.*

2) Algorithm of D2D Matching With Interference: Based on above definitions, we propose a matching algorithm that can achieve *weak stability*. A detailed description of the algorithm is given in Algorithm2. The BS first applies Algorithm1 to get a pre-matching result. Notice that different from the interference-free case where each D2D pair is allocated a distinct channel, now the available channel resource is limited. Thus the 28th Line in Algorithm1 is revised to $M_\sigma(i, j) \leftarrow \bmod(PairCount, K) + 1$, where K denotes the number of channels. If the pre-matching result is not weak stable, the BS then uses an iterative approach to modify the matching result, including changing the channel allocated to the matched users and swapping the pre-assigned sellers of two buyers, until no swapping matching or self-enhancing matching can be found. During the iteration, whenever the matching result changes, utilities of the involved users are updated accordingly.

Regarding to the stability of the matching, we make the following proposition.

Proposition 3: Given the set of users and the set of available channels, the iterative process described in Algorithm 2 converges to a weak stable matching.

Proof: Algorithm 2 checks self-enhancing matching and swapping matching iteratively. According to (46) $\sim$ (49), either swapping matching or self-enhancing matching occurs, the resulted update of the matching function and the corresponding allocation matrix will improve the utilities of users. Considering that the number of users and the number of available channels is finite, the possible values of each user's utility is finite, which implies that the iterative process will not continue indefinitely. In other words, the algorithm will converge to a weak stable result. ■

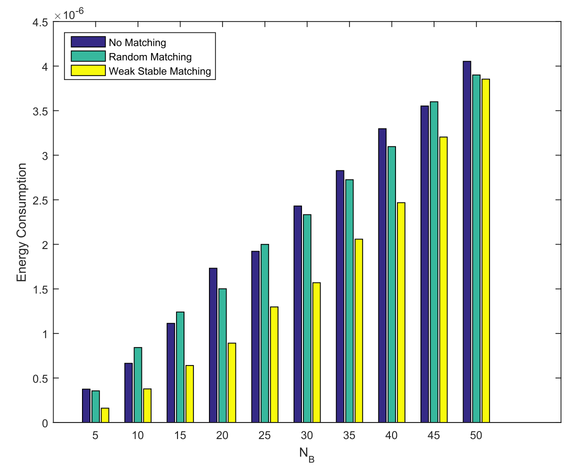

Fig. 4. The total energy consumption of the BS (with interference). The purple color denotes the setting where D2D communication is not allowed. The cyan color denotes the random matching algorithm. The yellow color denotes the proposed matching algorithm.

The computation complexity of Algorithm2 is mainly determined by the iterative process. The check of self-enhancing matching and swapping matching has complexity $O(N_S N_B K)$. And as defined in (46) and (48), after the check of self-enhancing matching and swapping matching, there is at least one buyer whose utility increases by δ_U, which can be controlled by the BS. Hence, the iteration process in Algorithm2 will converge within about $\frac{N_B \Delta U}{\delta_U}$ rounds, where ΔU denotes the maximum achievable improvement of the buyer's utility.

VI. Simulation

In previous sections, we have proposed a contract-based pricing mechanism and developed two matching algorithms for D2D communications. To evaluate whether the proposed algorithms can help to reduce the energy consumption of the BS, we conduct a series of simulations. In this section, we first describe the settings of the simulations, then we present the simulation results corresponding to interference-free

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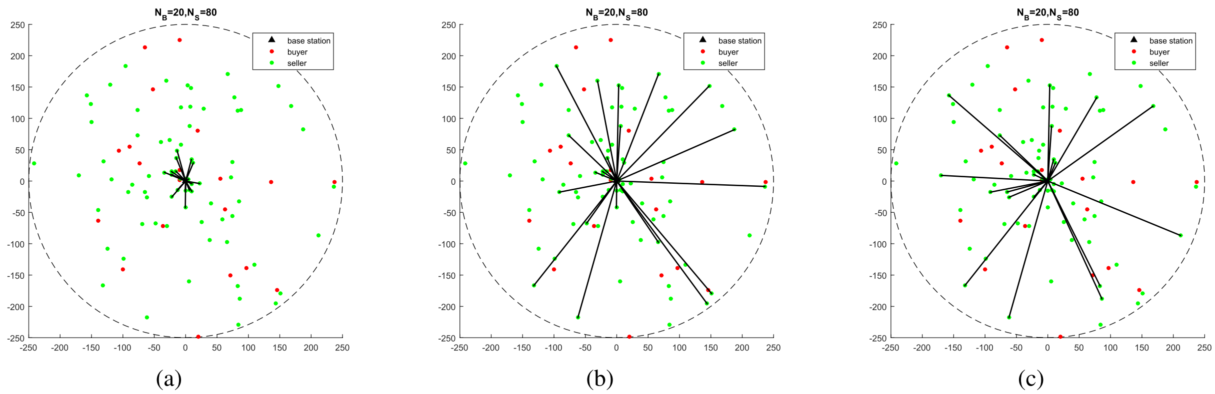

Fig. 5. An illustration of the energy consumption of the BS (with interference): (a) result of the proposed matching algorithm; (b)(c) two sample results of the random matching algorithm. The red point and the green point denote the buyer and the seller respectively. The black triangle denotes the BS. The black solid line denotes the cellular link between the BS and the seller that is chosen as the relay for a buyer. There are 20 buyers and 80 potential sellers.

model and interference model respectively. After that, a simple analysis of the influence of the pricing mechanism is presented.

A. Experiment Setting

Consider a set of $N = 100$ users that are randomly distributed within a circular area with the BS at the center of the circle. The radius of the circular area is set to 250m. We randomly choose $N_B \in \{5, 10, 15, \cdots, 50\}$ users from the N users as buyers, and the rest users are potential sellers. Each buyer demands one unit of data. The resistances of sellers are uniformly distributed within [0, 1]. The bandwidth for wireless transmission is set as $\omega = 200$kHz. The power density of the Gaussian noise is -174dBm/Hz. The number of channels is set as $K = 10$. As for the channel gain, the pass loss constant β is set to 0.01 and the path loss exponent α is set to 4. And similar to [30], we set the multipath fading gain as the exponential distribution with unit mean, and the shadowing gain as the log-normal distribution with 8dB deviation. Both the transmission power of the BS and the maximum transmission power of the user is set to 0.2W. Given above parameters, we can approximately determine the range of the transmission rate, which is 1Mbps$\sim$8Mbps. Hence we set the threshold of the transmission rate γ_{rate} as 2Mbps. And the BS's requirement on inverse energy efficiency is set as $e_{req} = 2.5 \times 10^{-8}$W/Mbps. As for the matching algorithm, the parameter κ used in (42) and (43) is set to 4, and the parameter δ_U used in (46) and (48) is set to 0.02.

In addition to the proposed matching algorithms, we implement a simple algorithm where each buyer is randomly matched to a buyer that is willing to act as a relay and can provide the required transmission rate. The performance of each algorithm is measured by the total energy consumption of the BS. Given a set of buyers and the corresponding sellers, we first compute the energy consumption of the BS when no D2D communication is established. Then we run each matching algorithm 10 times to reduce the influence of the randomness, and the average results are reported.

B. Stable Matching Without Interference

Fig. 2 shows the energy consumption of the BS in different settings. As we expected, the introduction of D2D communications dose reduce the energy consumption, and the proposed matching algorithm shows better performance than the random matching algorithm. To illustrate the difference between random matching and stable matching, in Fig. 3 we draw the cellular links between the BS and the sellers chosen for a given set of buyers. As we can see, most of the sellers chosen by the proposed matching algorithms lie close to the BS. While, when the buyers are randomly matched with the sellers, many sellers that are far away from the BS are chosen as the relays, which costs more energy of the BS for data transmission.

C. Weak Stable Matching With Interference

Fig. 4 shows the energy consumption of the BS in settings where the interference caused by channel sharing cannot be ignored. Similar as before, the energy consumption of the BS is reduced when D2D communications exist, and the proposed matching algorithm performs better than the random algorithm. Moreover, the advantage of the proposed algorithm are more obvious than that shown in Fig. 2. Again we draw the cellular links between the BS and the chosen sellers in Fig. 5. As we can see, all the sellers chosen by the proposed matching algorithm are quite close to the BS. In contrast, many of the sellers chosen by the random algorithm are far from the BS.

D. Different Pricing Mechanisms

In addition to comparing different matching algorithms, we also conduct simulations to investigate how the pricing mechanism affects the matching result and the energy consumption of the BS thereof. In Section IV we have described how to design the optimal contract to price the contribution of the sellers. Here for comparison purpose, we propose another pricing mechanism where sellers of different types are paid equally. More specifically, the contract for the seller of type θ is defined as

$$\begin{cases} p_{ij}(\theta) = p_{req} \\ r_{ij}(\theta) = \bar{\theta} \dfrac{p_{req}}{\omega \log\left(1 + \dfrac{g_{ij} p_{req}}{n_{\max}}\right)}, \end{cases} \tag{50}$$

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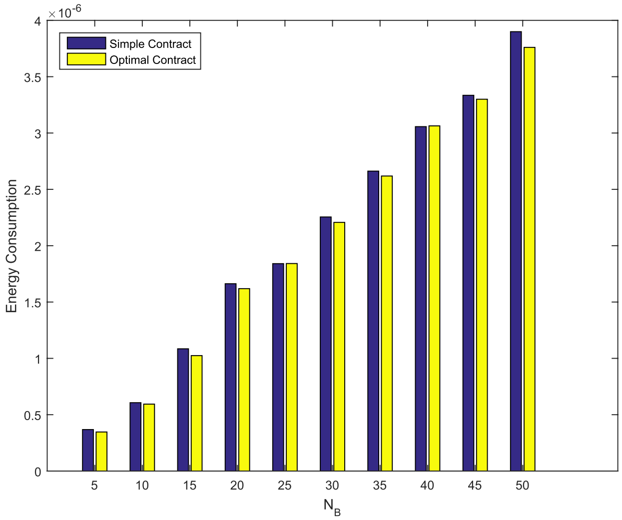

Fig. 6. The total energy consumption of the BS (without interference). The purple color denotes the proposed matching algorithm which uses the simple contract to compute the seller's utility. The yellow color denotes the proposed matching algorithm which uses the optimal contract to compute the seller's utility.

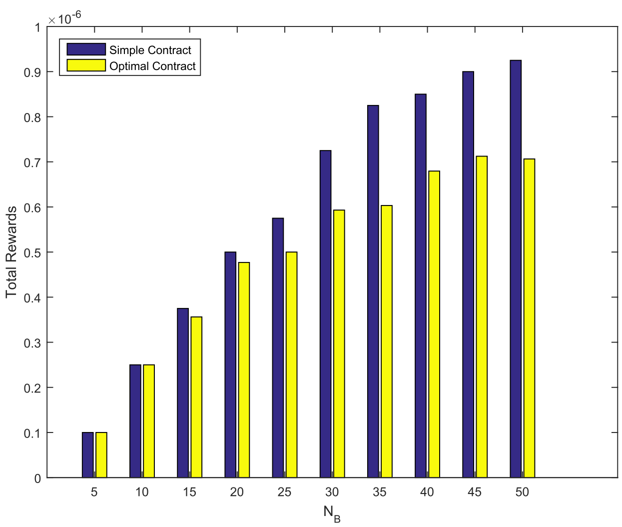

Fig. 7. The total rewards paid by the BS (without interference). The purple color denotes the proposed matching algorithm which uses the simple contract to compute the seller's utility. The yellow color denotes the proposed matching algorithm which uses the optimal contract to compute the seller's utility.

where p_{req} is the solution to the following equation

$$\frac{p_{req}}{\omega \log\left(1+\frac{g_{ij}p_{req}}{n_{\max}}\right)} = e_{req}. \tag{51}$$

It can be verified that above contract satisfies all the constraints described in Section IV-A. Similar to the optimal contract, if the minimum requirement on transmission rate cannot be satisfied, i.e. $\omega \log\left(1+\frac{g_{ij}p_{req}}{n_{\max}}\right) < \gamma_{rate}$, then the seller s_i will not be considered as a candidate relay for the buyer b_j. We refer to the above pricing mechanism as *simple contract*.

We repeat the simulations of the matching algorithms under the interference-free settings. Given a set of buyers, we use the optimal contract proposed in Section IV-B.3 and the simple contract to compute the seller's utility respectively, then we run Algorithm1 to get the matching results. Fig. 6 shows the energy consumption of the BS in different settings. As we can see, the optimal contract leads to a better selection of sellers with respect to energy saving, though the advantage of the optimal contract is not obvious. However, as mentioned in Section III-C, the total rewards paid to sellers can be seen as the extra cost that the BS pays for energy saving. Thus in addition to the total energy consumption, we also record the total rewards paid by the BS in each simulation. From the results shown in Fig. 7 we can see that, when the optimal contract is applied, the BS can pay less to the sellers than it would when applying the simple contract, especially when the proportion of buyers is high. The low payment demonstrates the advantage of the optimal contract.

VII. Conclusion

Utilizing D2D communications to offload the traffic over long-distance links is a promising way to reduce the energy consumption of base stations in cellular networks. To encourage the users to relay data for others, we proposed a contract-based mechanism for the BS to optimally determine which users should be chosen as the relays and how to pay them. Based on the contract, we proposed two matching algorithms to make a coordination between the users who demand data and the users who are willing to act as relays. Simulation results proved that the proposed algorithms are energy-efficient.

Currently, the contract-based pricing mechanism and the matching algorithm are studied separately. In future work, we will investigate how to incorporate the matching between buyers and sellers as well as the energy consumption of the BS into the design of pricing mechanisms, so that the energy efficiency can be further optimized.

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