Joint Resource Allocation Algorithm for Energy Harvest-based D2D Communication Underlaying Cellular Networks Considering Fairness

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***Abstract*—In this paper, we aim to maximize the minimum data volume for the energy harvest (EH)-based D2D communication underlaying cellular network. The formulated problem is a mixed integer nonlinear programming (MINLP), which we split into two sub-problems to solve separately. We first employ the Successive Convex Approximation (SCA) method to solve the time and power allocation, while putting the spectrum multiplexed pairs as fixed. Then, we develop a fair allocation mechanism to allocate spectrum resources. Numerical results show that our developed algorithm outperforms other benchmark schemes in terms of the minimum and overall data volumes.**

***Index Terms*—D2D communication, Energy harvesting, Resource allocation, Time splitting**

I. INTRODUCTION

WITHIN the 5G framework, there are some major challenges hindering the development of the 5G enhanced Internet of Everything applications [1]. Two typical challenges are network congestion and energy consumption constraint issues. D2D communication and energy harvest (EH) technologies have been proposed as the techniques to address these two challenges [2]. Recently, D2D communication working with EH has attracted enormous research interest. EH enables the end device to harvest renewable energy such as solar, wind, etc., and radio frequency (RF) energy from the environment. In such advanced EH-based D2D communication, the limitation of battery capacity of end devices therefore can be released. There have been numbers of work done on such EH-enabled D2D communication.

In [3]–[5], the resource allocation algorithms for EH-based D2D networks have been studied. Literature [3] studied maximizing total throughput by using joint time scheduling and power control method. Literature [4] proposed a stable matching algorithm to optimize spectral resources and power allocation to improve the average energy efficiency. Those works in [3], [4] however solved simple problems under some simplified assumptions. In [5], Hamdi et al. studied the joint task allocation and power problem for D2D offload communication with EH, where energy arrival is modeled as a Poisson process. In addition, the works in [6]–[8] have further investigated multidimensional optimization, such as joint time slot, power, and spectrum resource block allocation for cellular user equipment (CUE) and D2D user equipment (DUE), to improve system performance. In [6], Gupta et al. studied joint optimization algorithms to maximize the total rate of a D2D link, where only the quality of service (QoS) requirements of CUE are considered. In [7], Meng et al. focused on improving the spectral efficiency of D2D networks under cellular networks and designed a matching-based resource allocation algorithm. In [8], Kuang et al. studied to maximize the average energy efficiency of all D2D links while maintaining the QoS for CUE and EH. However, current existing work has not considered the problem of this letter.

In this letter, we propose an optimization algorithm in EH assisted D2D communication underlaying cellular networks considering fairness. Overall, the innovations of this study include: i) we proposed a joint resource allocation algorithm for the EH-based D2D underlying cellular network focuses on fairness. ii) The QoS of DUE and CUE is considered, which was less simultaneously considered in EH-based D2D scenarios before. iii) We jointly optimize the EH and transmission time slots, CUE and DUE transmit power and spectrum allocation.In specific, a Successive Convex Approximation (SCA) based iterative algorithm with an improved Hungarian-based matching method is designed to solve the formulated mixed integer nonlinear programming (MINLP) problem.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

We consider a single cellular cell with a base station (BS) and multiple mobile devices equipped with energy harvesting modules, as shown in Fig. 1. The mobile device supports both cellular and D2D communication and adaptively selects one of them depending on the communication status. At this point, there are M CUE and N DUE pairs, where the DUE pair consists of a DUE transmitter (DUE-T) and a DUE receiver (DUE-R). The set of DUE pairs is $\mathcal{N} = \{1, ..., N\}$ and CUE is $\mathcal{M} = \{1, ..., M\}$. M CUEs are assigned M uplink orthogonal resource blocks. We assume that one CUE shares the spectrum with one DUE pair.

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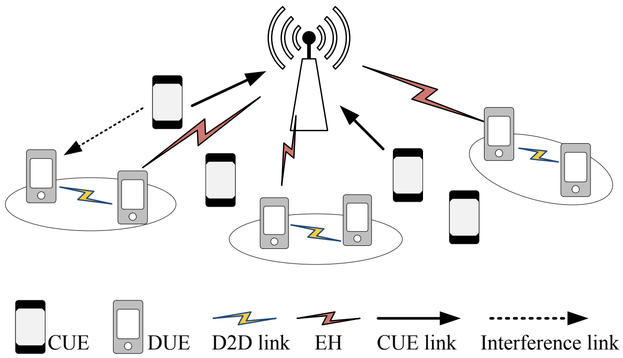

Fig. 1. System model.

In this scenario, we propose that DUE collects RF energy from the BS to replenish the energy consumed by the transmission. A harvest-storage-use protocol is adopted where the storage time is ignored. The DUE harvests energy in time slot t_n^e for the information transmission in time slot t_n^i, while the energy consumed by the circuit is provided by the pre-stored power. Assume E_n^d is the energy harvested by DUE-T n at t_n^e, which is expressed as

$$E_n^d = \eta P_B g_{B,n} t_n^e \tag{1}$$

where η is the conversion efficiency of the EH circuit, and P_B denotes the transmit power of the BS. Particularly, the channel gain $g_{B,n}$ between the BS and the DUE-T n is $\beta_{B,n} d_{B,n}^{-\alpha}$. $d_{B,n}$ is the distance between the BS and DUE-T n; α is the decay exponent; $\beta_{B,n}$ is the small-scale fading component and obeys the Rayleigh distribution of unit parameters. The transmit power of DUE-T n is expressed as

$$P_n^d = \frac{E_n^d}{t_n^i} \tag{2}$$

In time slot t_n^i, the communication interference occurs when the n-th D2D pair shares the uplink spectrum resources of the m-th CUE. In this case, the signal-to-interference-to-noise ratio (SINR) of the channel between the n-th DUE-R and BS can be expressed as

$$\gamma_n^d = \frac{P_n^d h_n}{\sigma^2 + \sum\limits_{m \in M} \rho_{m,n} P_m^c h_{m,n}} \tag{3}$$

$$\gamma_m^c = \frac{P_m^c h_{m,B}}{\sigma^2 + \sum\limits_{n \in N} \rho_{m,n} P_n^d h_{n,B}} \tag{4}$$

where P_m^c and P_n^d are the transmit power of the CUE and DUE-T respectively; $h_{m,B}$ and h_n are the channel gains; σ^2 is the noise power; $\rho_{m,n}$ is a spectrum multiplexing indicator representing whether the n-th DUE pair multiplexes the spectrum of the m-th CUE. Correspondingly, the information transmission rate of DUE and CUE can be expressed as

$$R_n^d = \log_2(1 + \gamma_n^d) \tag{5}$$

$$R_m^c = \log_2(1 + \gamma_m^c) \tag{6}$$

B. Problem Formulation

Based on the system model, we aim to maximize minimum amount of data exchanged among all users by jointly optimizing the time slot, transmit power of CUE and DUE, and the spectrum resource allocation during period time T. In particular, the communication quality of CUE and DUE has to be ensured during this time. The optimization problem is formulated as

$$\max_{t_n^e, t_n^i, P_m^c, P_n^d, \rho_{m,n}} \min_{n \in \mathcal{N}} \ t_n^i R_n^d \tag{7}$$

$$s.t.\ R_m^c \geq R_{th}^c,\ \forall m \in \mathcal{M} \tag{7a}$$

$$R_n^d \geq R_{th}^d,\ \forall n \in \mathcal{N} \tag{7b}$$

$$t_n^e + t_n^i \leq T,\ 0 \leq t_n^e, t_n^i \leq T,\ \forall n \in \mathcal{N} \tag{7c}$$

$$E_{th}^d \leq E_n^d \leq E_{\max}^d,\ \forall n \in \mathcal{N} \tag{7d}$$

$$0 \leq P_n^d \leq P_{\max}^d,\ \forall n \in \mathcal{N} \tag{7e}$$

$$0 \leq P_m^c \leq P_{\max}^c,\ \forall m \in \mathcal{M} \tag{7f}$$

$$\sum_{n \in N} \rho_{m,n} \leq 1,\ \rho_{m,n} \in \{0,1\},\ \forall m \in \mathcal{M} \tag{7g}$$

$$\sum_{m \in M} \rho_{m,n} = 1,\ \rho_{m,n} \in \{0,1\},\ \forall n \in \mathcal{N} \tag{7h}$$

where (7a) and (7b) are the constraints ensuring the communication quality of CUE and DUE, where R_{th}^c and R_{th}^d are the required minimum transmission rate for CUE and DUE respectively. (7c) refers to the time constraint. (7d) means that the collected energy is within the upper and lower boundaries. The upper bound $E_{\max}^d$ is the battery capacity of the device, and the lower bound E_{th}^d is the minimum energy required by the device to complete the information transmission. (7e) and (7f) are the transmit power constraints for DUE and CUE. Finally, (7g) and (7h) are the constraints of the spectrum reuse indicator factor. Specifically, (7g) indicates that one CUE spectrum can only be shared with one DUE pair, and (7h) indicates that each D2D link can at least find one spectrum.

III. Joint Optimization Algorithm

The problem defined in (7) is a MINLP problem and is difficult to solve. First, the target function in (7) and constraint functions in (7a) and (7b) are nonlinear. The optimization variables $\rho_{m,n}$ for the spectrum multiplexing are binary and the variables in (7g)-(7h) are discrete ones, making the optimization problem a mixed integer problem. To solve this problem, we split into two more tractable sub-problems to solve separately.

A. Time and Power Allocation for Each CUE-DUE Pair

While not considering the communication quality of DUE and putting $\rho_{m,n}, \forall m, n$ as fixed, the optimization problem in (7) can be rewritten as

$$\max_{t_n^e, t_n^i, P_n^d, P_m^c} t_n^i \log_2(1 + \frac{P_n^d h_n}{\sigma^2 + P_m^c h_{m,n}}) \tag{8}$$
$$s.t.\ (7a), (7c), (7d), (7e), (7f)$$

which is a simpler sub-problem and only considers the allocations of time and power.

The optimal time allocation of problem (8) follows

$$t_n^e + t_n^i = T \tag{9}$$

which is proved in Appendix A. Thus, t_n^e can be rewritten as $t_n^{e\,*} = T - t_n^i$.

Therefore, with (1) and (9), the variable P_n^d in (2) can be rewritten as

$$P_n^{d\,*} = \frac{A}{t_n^i} - B \tag{10}$$

where $A = T\eta P_B g_{B,n},\ B = \eta P_B g_{B,n}$. Accordingly, with (4) and (6), constraints (7a) can be transformed into

$$\frac{(2^{R_{th}^c} - 1)(\sigma^2 + P_n^d h_{n,B})}{h_{m,B}} \le P_m^c \tag{11}$$

In addition, with (1) and (9), constraints (7d) can be transformed into

$$T - \frac{E_{\max}^d}{B} \le t_n^i \le T - \frac{E_{th}^d}{B} \tag{12}$$

According to (9)-(12), then problem (8) can be simplified as

$$\max_{t_n^i, P_m^c} \ t_n^i \log_2 (1 + \frac{(\frac{A}{t_n^i} - B) h_n}{\sigma^2 + P_m^c h_{m,n}}) \tag{13}$$

$$s.t.\ (11), (12)$$

$$0 \le t_n^i \le T,\ \forall n \in \mathcal{N} \tag{13c}$$

$$\frac{A}{P_{\max}^d + B} \le t_n^i \le T,\ \forall n \in \mathcal{N} \tag{13e}$$

$$0 \le P_m^c \le P_{\max}^c,\ \forall m \in \mathcal{M} \tag{13f}$$

where (13e) is obtained by bringing (10) into (7e).

Note that the problem (13) is monotonically decreasing with respect to P_m^c. The optimal P_m^c can be given by

$$P_m^{c\,*} = a + b\frac{1}{t_n^i} \tag{14}$$

where $a = \frac{(2^{R_{th}^c} - 1)(\sigma^2 - B h_{n,B})}{h_{m,B}}$, $b = \frac{(2^{R_{th}^c} - 1) A h_{n,B}}{h_{m,B}}$. Based on (14), constraint (13f) can be rewritten as

$$\frac{b}{P_{\max}^c - a} \le t_n^i \tag{15}$$

To make the problem (13) more tractable, we utilize logarithmic transformation to reformulate object function (13) as

$$\max_{t_n^i} f(\ t_n^i) = \max_{t_n^i} f_1(\ t_n^i) - f_2(\ t_n^i) \tag{16}$$

where $f_1(t_n^i) = t_n^i \log_2 (a_1 \frac{1}{t_n^i} + b_1)$, $f_2(t_n^i) = t_n^i \log_2 (c_1 \frac{1}{t_n^i} + d_1)$ and $a_1 = b h_{m,n} + A h_n$, $b_1 = \sigma^2 + a h_{m,n} - B h_n$, $c_1 = b h_{m,n}$, $d_1 = \sigma^2 + a h_{m,n}$. Note that object function in (16) is still non-convex. However, it is easy to prove that $f_1(\ t_n^i)$ and $f_2(t_n^i)$ are convex functions, then the objective function of (16) is the difference between two convex functions (D.C.) [9]. By applying the first-order Taylor expansion at the given point t^k, $f_2(t_n^i)$ can be expanded to $f_2(t^k) + \langle \nabla f_2(t^k),\ \ (t_n^i - t^k) \rangle$. Then the problem (16) can be approximated as

$$\max_{t_n^i} \ f_1(t_n^i) - f_2(t^k) - \langle \nabla f_2(t^k), (t_n^i - t^k) \rangle \tag{17}$$

$$s.t.\ (12), (13c), (13e), (15)$$

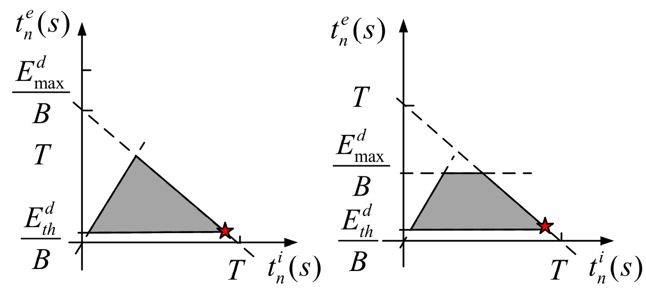

Fig. 2. The feasible region of feasibility check problem.

where t^k is the value of the k-th iteration, $\nabla f_2(t^k)$=$\log_2 (c_1 \frac{1}{t^k} + d_1) - \frac{c_1}{\ln 2 (c_1 + d_1 t^k)}$ is the gradient vector of $f_2(\ t_n^i)$.

If we initialize the t^k and $f(t^k)$, for given t^k, the optimal solution t_n^i in the problem (17) can be obtained by a standard convex optimization solver like *cvx*. Next, we update the t^k to t_n^i. After continuously solving and updating t^k to approximate t_n^i, the optimal solutions of (17) and (16) are approximately equal. Then the sub-optimal $t_n^{i\,*}$ can be obtained. Therefore, we proposed a SCA method to solve time and power allocation in an iterative method.

B. Feasible Check for Time and Power Allocation

Considering the complexity of the constraints of the problem (8) there may be no feasible solution. Therefore, a feasibility check is necessary to exclude unsatisfied CUE-DUE pairs before solving the sub-problem. The feasibility check must consider a problem that can confirm the existence of the feasible solution to the problem (8), which can be expressed as

$$\max_{t_n^e, t_n^i, P_n^d, P_m^c} \ R_m^c \tag{18}$$

$$s.t.\ (7c), (7d), (7e), (7f)$$

where a feasible solution exists only when the maximum value $R_m^{c\,\prime}$ is greater than R_{th}^c.

Problem (18) can be easily solved. Obviously, the optimal P_m^c in (18) is $P_{\max}^c$, because the object function of (18) decreases monotonically with respect to the variable P_m^c. In addition,with (1) and (2), (7d) and (7e) can be transformed into

$$\frac{E_{th}^d}{B} \le t_n^e \le \frac{E_{\max}^d}{B} \tag{19}$$

$$0 \le t_n^e \le \frac{P_{\max}^d}{B} t_n^i \tag{20}$$

which indicates the solution of feasible check problem lies in a bounded region. Moreover, the problem (18) is monotonically increasing with respect to the t_n^i and decreasing with respect to the t_n^e. In specific, as shown in Fig. 2, the optimal solution is obtained at the boundary of the feasible region. Therefore, the optimal solution to the feasibility check problem is $P_m^{c\,\prime} = P_{\max}^c, t_n^{e\,\prime} = \frac{E_{th}^d}{\eta P_B g_{B,n}}, t_n^{i\,\prime} = T - t_n^{e\,\prime}$. As a result, when we get the maximum value $R_m^{c\,\prime}$ and then check the feasibility condition $R_m^{c\,\prime} \ge R_{th}^c$, the CUE-DUE pairs that do not meet the condition can be excluded, i.e., $\rho_{m,n} = 0$, vice versa.

C. Spectrum Allocation for Multiple CUE-DUE Pairs

For any given time and transmit power $\{t_n^e, t_n^i, P_m^c, P_n^d\}$, the spectrum allocation of problem (7) can be optimized by solving the following problem

$$\max_{\rho_{m,n}} \min_{n\in\mathcal{N}} \; t_n^i R_n^d \qquad (21)$$
$$s.t. (7b), (7g), (7h)$$

Considering the constraint (7b), CUE-DUE pairs with $R_{m,n}^d$ greater than R_{th}^d will be retained, otherwise, they will be excluded, which can be expressed as

$$R_{m,n}^d{}^* = \begin{cases} R_{m,n}^d(P_m^c{}^*, P_n^d{}^*), & \text{if } R_{m,n}^d(P_m^c{}^*, P_n^d{}^*) \geq R_{th}^d \\ -\infty, & \text{otherwise.} \end{cases} \qquad (22)$$

where $R_{m,n}^d(P_m^c{}^*, P_n^d{}^*) = \log_2(1 + \frac{P_n^d{}^* h_n}{\sigma^2 + P_m^c{}^* h_{m,n}})$.

Let $D_{m,n}{}^* = t_n^i{}^* R_{m,n}^d{}^*$, then the spectrum resource reuse problem can be expressed as

$$\max_{\rho_{m,n}} \min_{n\in\mathcal{N}} \sum_{m\in\mathcal{M}} \rho_{m,n} D_{m,n}{}^* \qquad (23)$$
$$s.t. (7g), (7h)$$

which is a binary matching problem, where $D_{m,n}^d{}^*$ can be regarded as a weight. Here, we propose a fair spectrum allocation mechanism to obtain $\rho_{m,n}{}^*$ by combining binary search and the Hungarian method.

We use $D_{m,n}^d{}^*$ as the weight, and then use the algorithm in the literature [10] to find the maximum minimum (max-min) value Φ_{mid}. According to [10], we perform the following operations. $M \times N$ $D_{m,n}^d{}^*$ are stored in vector $\mathbf{\Phi}$ in ascending order. Initialize the binary search boundary which left is $\Phi_l = \Phi_0$ and the right is $\Phi_r = \Phi_{M\times N}$. The index position in the middle is $mid = l + (r - l)/2$. Φ_{mid} is compared with each $D_{m,n}^d{}^*$ and the result is recorded in the matrix $\boldsymbol{K}$. When Φ_{mid} is greater than $D_{m,n}^d{}^*$, $K_{m,n} = 1$, otherwise it is $K_{m,n} = 0$. Next, Hungarian algorithm is applied to $\boldsymbol{K}$ to get the lowest cost denoted as x. x being 0 denotes that the value of the Φ_{mid} is not greater than the searched max-min. Let the left boundary be updated to the middle, i.e., $\Phi_l = \Phi_{mid}$. Conversely, if x is 1, let $\Phi_r = \Phi_{mid}$. Repeat the above search until $\Phi_l = \Phi_r$. The last Φ_{mid} is the max-min amount of data.

Subsequently, we utilize Φ_{mid} to filter out the candidate CUE-DUE pairs and then assign them using the Hungarian algorithm. Specifically, if $D_{m,n}^d{}^*$ smaller than Φ_{mid}, $K_{m,n}$ are set to positive infinity. The Hungarian algorithm is then applied to $\boldsymbol{K}$ to obtain the spectrum assignment $\rho_{m,n}{}^*$.

D. Joint Resource Allocation Algorithm

Based on the subsection *A*, *B* and *C*, we propose an overall joint resource allocation algorithm, as **Algorithm 1**. In step3-step15, if feasibility conditions in subsection *B* are met, we employ the SCA method proposed in subsection *A* to find the time and power optimal allocation. In step16-step24, $D_{m,n}^d{}^*$ is obtained, and then the spectrum is allocated with a fair spectrum allocation mechanism developed in subsection *C*.

The computational complexity of SCA method is $O(\log \frac{1}{\varepsilon})$ where ε is the iterative precision and spectrum allocation mechanism is $O(M^3 \log(MN))$. Therefore, the total computational complexity of **Algorithm 1** is $O(M^3 \log(MN) + MN \log \frac{1}{\varepsilon})$.

Algorithm 1 Joint resource allocation algorithm

1: **Input**: N; M; P_B; η; γ_{th}^c; T; ε
2: **Output**: $t_n^i{}^*$; $t_n^e{}^*$; $P_m^c{}^*$; $P_n^d{}^*$; $\rho_{m,n}{}^*$
3: **for** m=1:M **do**
4:   **for** n=1:N **do**
5:     **if** $R_m^c{}' \geq R_{th}^c$ **then**
6:       Initialize $k = 1$, t^1, $f(t^0)$
7:       **while** $f(t^k) - f(t^{k-1}) > \varepsilon$ **do**
8:         Get $f(t^k)$
9:         Solve problem (17) to obtain t_n^i
10:         $k = k + 1$, $t^k = t_n^i$
11:       **end while**
12:       $t_n^i{}^* = t_n^i$, get $t_n^e{}^*$, $P_n^d{}^*$, $P_m^c{}^*$ from (9), (10), (14)
13:     **end if**
14:   **end for**
15: **end for**
16: Get $D_{m,n}{}^*$ and max-min value Φ_{mid} refer to [10]
17: **for** m=1:M **do**
18:   **for** n=1:N **do**
19:     **if** $D_{m,n}{}^* < \Phi_{mid}$ **then**
20:       $K_{m,n} = \infty$
21:     **end if**
22:   **end for**
23: **end for**
24: Apply the Hungarian method for $\boldsymbol{K}$ to get $\rho_{m,n}{}^*$.

IV. Numerical Results

In this section, numerical results are provided to evaluate the joint optimization algorithm. The radius of the cell is 200 m, and the mobile devices are randomly generated with a normal distribution. The simulation parameters are given as $\sigma^2 = -174$ dBm, $\eta = 0.8$, $E_{\max}^d = 100$ mJ, $E_{\max}^d = 0.5$ mJ, $P_B = 40$ dBm, $P_{\max}^d = 23$ dBm, $P_{\max}^c = 23$ dBm, $N = 10$, $M = 20$, $R_{th}^c = 2$ bps/Hz, $R_{th}^d = 0.5$ bps/Hz, $\varepsilon = 1 \times 10^{-4}$. Partial parameters are from reference [3], [7]. The simulation platform is MATLAB 2017a on a 64-bit system with a 3.10GHz CPU and 16GB RAM.

The proposed algorithm is compared with four algorithms. The genetic algorithm (labeled as Gen) utilizes MATLAB's *ga* solver, where the problem (8) is set as a fitness function and other parameter settings follow the default values. AveTime indicates the power optimization of the average time slot allocation. The Hungarian algorithm maximizes the total cost. The algorithm that maximizes the minimum (labeled as MAX-MIN) is designed in the literature [10].

Fig. 3(a) and 3(b), the time and power are optimized using the Proposed algorithm, the AveTime, and the Gen algorithm, respectively. When $P_B = 40$ dBm, our proposed algorithm achieves a higher minimum data amount which is about 70% higher than AveTime and about 25% better than Gen. The amount of data at $P_B = 42$ dBm is greater than $P_B = 40$ dBm because the higher BS transmit power contributes to energy harvesting. In Fig. 3(a), the higher R_{th}^c causes the transmit

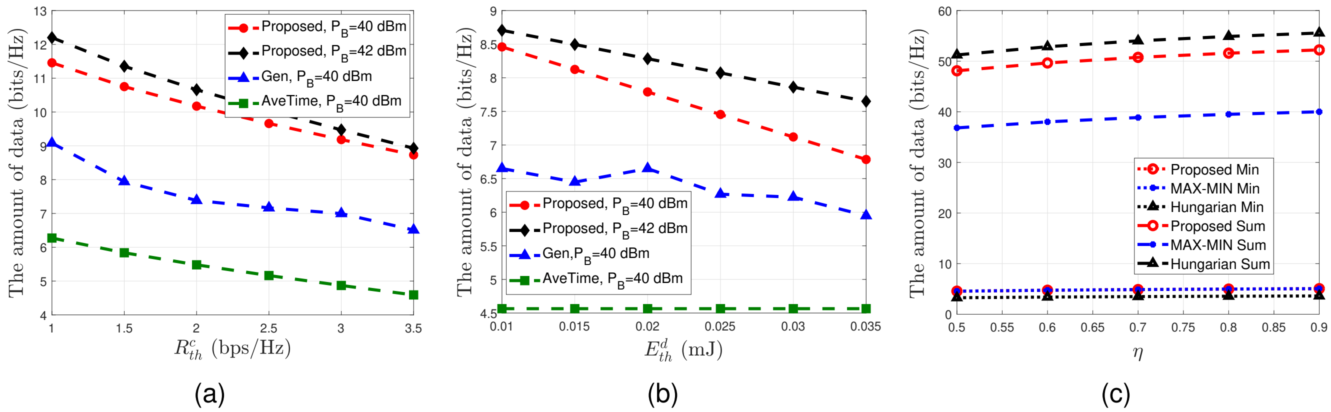

Fig. 3. The amount of data with different parameters. (a) The minimum amount of data for DUE with vary R^c_{th}. (b) The minimum amount of data for DUE with vary E^d_{th}. (c) The amount of data for DUE with vary η.

power of DUE to decrease. As R^c_{th} goes from 1 to 3.5 bps/Hz, the minimum amount of data reachable decreases by 24%. In Fig. 3(b), all algorithms reduce the amount of data accordingly as E^d_{th} increases, except for the AveTime algorithm, because E^d_{th} affects the time slot allocation. However, the AveTime algorithm may not be able to satisfy the higher E^d_{th}.

In Fig. 3(c), we compare the proposed fair spectrum allocation algorithm with the Hungarian and the MAX-MIN algorithm in terms of the sum of data and the minimum amount of data. In the case of the sum of data volume, the Proposed is larger than the MAX-MIN but lower than the Hungarian algorithm. In terms of minimum data size, the Proposed is equal to the MAX-MIN and higher than the Hungarian algorithm. Specifically, when $\eta = 0.8$, the sum of the data volume Proposed exceeds the MAX-MIN by 30% and the minimum data volume Proposed exceeds Hungarian by 28%. Therefore, our proposed fair algorithm balances the total amount of data with the minimum amount of data. Fig. 3(c) also denotes that the amount of data increases with η.

V. Conclusions

In this paper, we studied the joint optimization problem in the EH powered D2D underlaying cellular network. In terms of time and power allocation, we design an iterative optimization problem to find an approximate optimal solution for a single multiplexed CUE-DUE pair. Next, we proposed an improved algorithm by binary search and Hungarian algorithm. It can not only achieve the maximum minimum data volume, but also reach a great total data amount. The simulation results show that the algorithm proposed in this paper has obvious effects in increasing the amount of data transmitted in the system and ensuring fairness among users.

Appendix A
Proof of (9)

Suppose there is an optimal solution $\{t^{i\,*}_n, t^{e\,*}_n, P^{d*}_n, P^{c\,*}_m\}$ that satisfies $t^{e\,*}_n + t^{i\,*}_n < T$, and the optimal value is $D^*_{m,n} = t^{i\,*}_n \log_2(1+\frac{P^{d\,*}_n h_n}{\sigma^2+P^{c}_m{}^* h_{m,n}})$. Construct another optimal solution $\{\widetilde{t^i_n}, \widetilde{t^e_n}, P^{d*}_n, P^{c\,*}_m\}$, where $\widetilde{t^i_n} = \frac{t^{i\,*}_n T}{t^{i\,*}_n + t^{e\,*}_n}$, $\widetilde{t^e_n} = \frac{t^{e\,*}_n T}{t^{i\,*}_n + t^{e\,*}_n}$. $\widetilde{t^i_n} + \widetilde{t^e_n} = T$ and constraints (7a-7f) are still hold. The optimal value is $\widetilde{D_{m,n}} = \frac{T}{t^{i\,*}_n + t^{e\,*}_n} * t^{i\,*}_n \log_2(1+\frac{P^{d\,*}_n h_n}{\sigma^2+P^{c}_m{}^* h_{m,n}})$, i.e., $\widetilde{D_{m,n}} = \frac{T}{t^{i\,*}_n + t^{e\,*}_n} D^*_{m,n}$. If $t^e_n + t^i_n < T$ contradicts the assumptions. The unique optimal solution $\widetilde{D_{m,n}} = D^*_{m,n}$ can be obtained when $t^e_n + t^i_n = T$. It is proved that the optimal solution is always obtained at $t^e_n + t^i_n = T$.

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