Energy-Efficient Scheduling and Power Allocation for Energy Harvesting-Based D2D Communication

Ying Luo, Peilin Hong, and Ruolin Su

Key Laboratory of Wireless-Optical Communications, School of Information Science and Technology, University of Science and Technology of China, HeFei, Anhui 230027 China
Email: {yingluo@mail.ustc.edu.cn, plhong@ustc.edu.cn, ruolinsu@mail.ustc.edu.cn}

Abstract—Energy harvesting (EH)-based device-to-device (D2D) communication brings some challenges in resources management due to the joint influence of the volatility of available energy and the interference between cellular and D2D users. In this paper, we focus on improving the energy efficiency of EH-based D2D communication for the scenario where multiple EH-based D2D communication links multiplex the uplink channel resource of one cellular user (CU). Considering the variation of transmission requests based on available energy in different time slots, a short-term sum energy efficiency maximization problem for EH-based D2D communication is formulated to integrate the transmission scheduling and power allocation while maintaining a given transmission rate requirement for both CU and D2D links. The modeled problem is a non-convex mixed integer non-linear programming (MINLP) problem. In view of the NP-hardness property of the optimization problem, we develop a two-layer convex approximation iteration algorithm (CAIA) to obtain a feasible suboptimal solution. Finally, numerical simulation results indicate the performance of CAIA in aspects of average energy efficiency and transmission rate of D2D communication.

I. INTRODUCTION

The unprecedented expansion of mobile devices and traffic loads in cellular networks is driving the need to explore more energy and spectral efficient wireless communication technologies. Device-to-Device (D2D) communication, which enables devices to communicate directly with each other in close proximity bypassing the base station (BS), has been introduced to enhance network performance by offloading traffic from the cellular network [1]. However, along with hundreds or thousands of wireless devices making attempts to access the spectrum and set up communications, D2D-assisted wireless communication devices may be the low-powered devices (e.g., machine-type devices (MTDs) [2]), which are typically equipped with fixed energy supplies, such as batteries with limited operation life. Replacing batteries or charging power by a charger system for such devices is impractical or cost-prohibitive.

To prolong the limited lifetime, energy harvesting (EH) is emerging as an appealing technique to provide unlimited power supplies and achieve energy-efficient transmission for low-power wireless communication devices [3]. However, due to the intermittent and random nature of the renewable energy support technology, EH will also bring some challenges that are not considered in conventional battery or grid power-operated communications. Consequently, it is practically important to carefully manage the harvested energy for the purpose of satisfying the different transmission requirements in the EH-based D2D communication network.

A. Related Works and Motivations

Recent works have focused on developing efficient transmission and resource allocation schemes to achieve different transmission requirements for EH-based D2D communication. In terms of access control, a sub-band statistics online learning and mode selection scheme is designed in [4] to decide when to switch from D2D mode to EH mode and vice versa in order to lower sub-band switch cost and computational complexity. For cognitive D2D communication powered by EH, Ahmed H. S. et al. propose two different spectrum access policies, namely, random and prioritized access policies in [5]. The performance of the proposed system in both the transmission probability and the signal-to-interference-plus-noise ratio (SINR) outage probability is evaluated.

Moreover, some researchers have paid efforts to study the resource allocation in terms of power and spectrum for EH-based D2D communication. Authors of [6] consider the sum-rate optimal power allocation policy for energy harvesting transmitters in a Gaussian interference channel, which is similar to a single D2D communication model in [7]. To fully consider the effect of various practical constraints such as energy causality and battery capacity, Zhou et al. investigate the energy-efficient power allocation problem under the non-causal knowledge of energy arrival in [8]. For spectrum resource assignment problem, authors of [9] and [10] respectively aim to maximize sum rate and minimize energy cost in EH-based D2D communication underlaying cellular network.

These previous works have addressed many challenges caused by the unreliable and unstable power supply of EH to provide desired transmission requirements under a simple reusing mode where one D2D link multiplex one cellular user’s (CU’s) radio resource. In the reusing mode, the spectrum of the CU will be vacant when the EH-based D2D link is idle caused by its energy deprivation. Hence, to meet today’s requirement of spectrum efficiency, multiple EH-based D2D pairs can be scheduled to reuse the same radio resource by filling the channel gap caused by the energy deficiency of the single EH-based D2D pair.

However, when multiple EH-based D2D pairs multiplex the same spectrum resource, the transmission requests based on
available energy at different time slots may be unbalanced. Under the delay-tolerant network, balancing the transmission requests among different time slots can decrease the mutual interference between users, and eventually improve the system performance. Let us take two EH-based D2D pairs (EH-DPs) reusing channel resource of one CU as a simple example. Due to the available energy limitation, the two EH-DPs probably transmit at the same time slot, and idle at the next time slot under the real-time transmission scheme (RTS) (i.e., RTS chooses the EH-DPs whose available energy can satisfy its transmission rate requirements under the mutual interference, solves the power allocation problem, and immediately transmits data from source to destination [11, 12]). Scheduling any of the EH-DPs to transmit at the next time slot will decrease the interference between users and improve the energy efficiency. Based on above discussion, how to design an efficient scheduling strategy for multiple EH-based D2D pairs reusing the same spectrum resource is an significant research work that can improve both the energy and spectrum efficiency. As far as we know this work is an open research issue that has not been studied in the EH-Based D2D communication underlying cellular network.

B. Contributions and Organizations

In this paper, the scenario is assumed that multiple EH-based D2D pairs are already matched to share the uplink spectrum with a CU in a non-orthogonal way. With consideration of the variation of the available energy and channel state, an energy-efficient scheduling scheme of joint transmission scheduling and power allocation is designed. Therefore, our main contributions can be concluded as follows:

- Firstly, to realize the energy-efficient scheduling scheme, we study a short-term sum energy efficiency (stSEE) maximization problem of D2D communication while guaranteeing both the energy restriction and transmission rate constraint of both CU and D2D links.
- Subsequently, we propose a two-layer convex approximation iteration algorithm (CAIA) consisting of an outer-layer iteration algorithm (OLIA) and an inner-layer convex approximation algorithm (ILCA), and thus obtain a feasible suboptimal solution for the modeled stSEE maximization problem which is a non-convex mixed integer non-linear programming (MINLP) problem.

As a result, simulation results show that the short-term energy-efficient scheduling scheme outperforms conventional real-time transmission strategy in aspects of the average energy efficiency (EE) and transmission rate.

In Section II, we describe the system model and formulate the stSEE maximization problem. In Section III, the two-layer convex approximation iteration algorithm (CAIA) is designed to solve the stSEE maximization problem. The numerical analysis and simulation results of the proposed algorithm are demonstrated and discussed in Section IV. Finally, a concluding remark is given for this paper in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

Suppose that the spectrum matching has been already completed, and thus \( N \) EH-DPs can share the spectrum resource with one CU in a non-orthogonal way to transmit data. The uplink sharing mode only causes interference at the BS which generally has stronger processing abilities than user equipments [13]. Hence, as shown in Fig. 1, the \( N \) EH-DPs can multiplex the uplink spectrum resource of one CU. Each EH-DP has a transmitter and a receiver, and the transmission mode of each EH-DP is one-way. At the same time, the transmitter of each EH-DP is assumed to be equipped with an EH device and a battery. Besides, the D2D receiver is battery-supported, and its available power is not considered in this paper. In reality, the above EH-powered D2D transmitter may be an information distribution equipment (IDE) for a market, a conference center, etc., and the D2D receiver can be a passenger. The IDE can distribute useful information to adjacent passengers so that data transmission is from IDEs to passengers only. Thus we can simply assume that the transmission mode of each EH-DP is one-way. In what follows, let us suppose that \( B \) represents the BS, \( c \) is the CU, and \( d_i \) is a pair of D2D users in the EH-DPs set \( \Phi_D (|\Phi_D| = N) \). Moreover, the concepts of terms of energy and power are the same.

![Fig. 1: System model when CU and EH-DPs operate on uplink shared spectrum](image)

In general, any D2D link will cause interference to the cellular receiver BS and the other D2D communication link. Similarly, the interference from cellular communication will be received by D2D receivers. Assuming that the whole system operates in a time-slotted fashion. Therefore, the transmission rates of the cellular link and D2D links in an instantaneous time slot \( t \) can be given by \( r_c^t \) and \( r_{d_i}^t \), respectively:

\[
r_c^t = \log \left( 1 + \frac{p_c^t \eta_c d_c}{\sum_{d_j \in \Phi_D} x_{d_j}^t P_{d_j}^t g_{d_j, c} + n_0} \right),
\]

\[
r_{d_i}^t = \log \left( 1 + \frac{p_{d_i}^t g_{d_i, c}}{\sum_{d_j \in \Phi_D} x_{d_j}^t P_{d_j}^t g_{d_j, d_i} + n_0} \right).
\]
\[ r_{d_i}^t = \log \left( 1 + \frac{g_{d_i}^t \cdot P_{d_i}}{p_{c}^t + \sum_{d \in \Phi_D, \; d \neq d_i} x_{d_i}^t \cdot g_{d_i}^t} \right) \quad \forall d_i \in \Phi_D, \] (2)

As shown in the motivation section, balancing the transmission requests among different time slots can improve the system performance. Thus, we need to decide which EH-DPs to reuse the channel resource in each time slot. Therefore, \( x_{d_i}^t (d_i \in \Phi_D) \) is defined as the transmission indicator variable of \( d_i \)-th EH-DP in time slot \( t \), where \( 1 \) indicates chosen and \( 0 \) indicates not chosen. \( p_{c}^t \) and \( P_{d_i} \) are the transmission power of CU and EH-DP in time slot \( t \), respectively. \( g_{i,j} (i,j \in [c, \Phi_D]) \) denotes the channel gain between node \( i \) and node \( j \). \( n_0 \) is the noise power, which equals to \( B_W \cdot P_n \), where \( B_W \) is the uplink channel bandwidth and \( P_n \) is the noise density.

**B. Energy Model**

In D2D communication, D2D transmitter uses the harvested energy to finish transmission. Hence, the energy harvesting process is known causally by D2D transmitter, and is subjected to Bernoulli process:

\[ E_{d_i}^t = \begin{cases} E, & \text{with probability of } \delta \\ 0, & \text{with probability of } (1 - \delta) \end{cases} \] (3)

where (3) denotes that the harvested power of \( d_i \)-th EH-DP within discrete time slot \( t \) is \( E \) with probability \( \delta \). So, as illustrated by Fig. 2, in \( T \) time slots, \( E_{d_i}^t \) units of harvested energy is added to the battery and \( P_{d_i}^t \) units of energy is depleted from the battery for transmission of the \( d_i \)-th D2D link in each time slot. Suppose \( B_{d_i}^t (t = \{1, 2, \ldots, T\}) \) is the available energy in battery of \( d_i \)-th EH-DP, and the initial power in battery \( (B_{d_i}^0) \) is zero. This brings the following cumulative power constraint:

\[ \sum_{n=1}^{t} P_{d_i}^n \leq \sum_{n=1}^{t} E_{d_i}^n, (\forall d_i \in \Phi_D; t = 1, 2, \ldots, T) \] (4)

the constraint (4) indicates that the consumed energy \( P_{d_i}^n \) is subject to the constraint \( E_{d_i}^n \leq B_{d_i}^n + B_{d_i}^{n-1} \) in each time slot, where \( B_{d_i}^{n-1} \) is the available energy of battery in the last time slot. Likewise, \( P_{d_i}^t \) units of power is allocated for data transmission for cellular user under the constraint of maximum power.

**Fig. 2: Discrete-time transmission of \( d_i \)-th D2D pair with EH technology**

We assume that the energy stored and depleted from the battery are only for communication purposes. Existing energy in the battery can be retrieved without any loss and the battery capacity is large enough so that every quanta of incoming energy can be stored in the battery. This assumption is especially valid for the current state of the technology in which batteries have very large capacities compared to the rate of harvested energy flow [14]. Besides, it is assumed that the channel state information (CSI) of all the involved links, and the energy harvesting information of all EH-DPs are acquired by the BS so that the BS is capable of controlling the transmission scheduling and the power allocation.

**C. Problem Formulation**

In order to efficiently utilize energy to finish transmission requests, energy efficiency has been considered as the key mathematical optimization objective. Thus, a short-term sum energy efficiency (stSEE) of the D2D communication maximization problem as \( \mathbf{P}_1 \) is formulated:

\[
\begin{align*}
\mathbf{P}_1 : \max_{X_{C},P_D} & : \sum_{t=1}^{T} \sum_{d_i \in \Phi_D} x_{d_i}^t \cdot \left( \frac{r_{d_i}^t}{p_{d_i}^t} \right), \\
\text{s.t.} \quad & 0 \leq p_{c}^t \leq p_{c}^{\text{max}} \quad (t = \{1, 2, \ldots, T\}), \quad (5a) \\
& r_{c}^t \geq r_{c}^{t_{\text{th}}}, \quad (5b) \\
& \sum_{t=1}^{T} p_{d_i}^t \leq \sum_{t=1}^{T} E_{d_i}^t \quad (t = \{1, 2, \ldots, T\}; \forall d_i \in \Phi_D), \quad (5c) \\
& 0 \leq p_{d_i}^t \leq p_{d_i}^{\text{max}}, \quad (5d) \\
& r_{d_i}^t \geq r_{d_i}^{t_{\text{th}}} \quad (\forall x_{d_i}^t = 1), \quad (5e) \\
& x_{d_i}^t \in \{0, 1\}, \quad (5f)
\end{align*}
\]

where \( X = \{x_{d_i}^t (d_i \in \Phi_D; t = \{1, 2, \ldots, T\})\} \), \( P_{C} = \{p_{c}^t\} \) and \( P_{D} = \{p_{d_i}^t\} \) are the sets of indicating factors, transmission power of CU and EH-DPs, respectively. (5a) and (5d) represent the maximum transmit power constraints in each time slot of CU and EH-DPs, respectively. In this paper, \( N \) EH-DPs are allowed to reuse the channel resource of the dedicated CU to transmit. Thus, in order to satisfy the quality of service (QoS) of CU, we define a minimum transmission rate requirement for CU as (5b). Furthermore, (5e) is the transmission rate requirement for the chosen EH-DPs at the \( t \)-th time slot. (5c) is the available energy constraint of each EH-DP, which indicates that the available transmission power must be lower than the harvested energy in each time slot.

### III. THE PROPOSED TWO-LAYER CONVEX APPROXIMATION ALGORITHM

In above formulation, some of the optimization variables (the components of \( X \)) can take only binary values, whereas the other variables (the components of \( P_{C} \) and \( P_{D} \)) are real-valued. In addition, the objective (5) and constraints (5b), (5e) depend on the non-convex functions \( r_{c}^t \) and \( r_{d_i}^t \). Hence, (5) is a non-convex MINLP problem, which is non-deterministic polynomial-time (NP) hard. For immediate proof of NP-hardness, note that MINLP includes mixed integer linear programming (MILP) problem, which is NP-hard [15]. Despite the hardness of solving the optimization problem, we propose a two-layer convex approximation iteration algorithm (CAIA), which contains an outer-layer iteration algorithm (OLIA) and an inner-layer convex approximation algorithm (ILCA), to obtain a feasible suboptimal solution. The OLIA first equivalently transform
the fractional programming problem. Next, the ILCA is implemented to approximately convert the non-convex MINLP optimization objective into a convex one.

A. Outer-Layer Iteration Algorithm

We first handle the fractional objective in (5), which can be classified as a nonlinear fractional program [16]. For description convenience, let \( \Omega \) denote the feasible solution set defined by (5a)–(5f). Let \( q^{\text{OPT}} \) represent the maximum stSEE of D2D communication. Then, it can be defined as follows:

\[
q^{\text{OPT}} = \max_{\{X, P_C, P_D\} \in \Omega} \left( \frac{\sum_{t=1}^{T} \sum_{d \in \Phi_D} x^t_{d_i} \cdot r^t_{d_i}}{P^t_{d_i}} \right).
\]

(6)

We are now ready to present the following Theorem.

**Theorem 1:** The maximum stSEE \( q^{\text{OPT}} \) can be achieved if and only if:

\[
\max_{\{X, P_C, P_D\} \in \Omega} \left\{ \sum_{t=1}^{T} \sum_{d \in \Phi_D} x^t_{d_i} \cdot r^t_{d_i} - q^{\text{OPT}} \cdot \sum_{t=1}^{T} \sum_{d \in \Phi_D} x^t_{d_i} \cdot p^t_{d_i} \right\} = 0.
\]

(7)

**Proof:** The proof is similar to the proof in [16].

Therefore, the equivalent function (7) of the objective (5) can be solved by exploiting an iterative algorithm known as the Dinkelbach method [16]. Let \( k \) denote the number of iterations, \( q_k \) denote the instantaneous sum EE, and \( \varepsilon \) represent the convergence threshold. Thus, the corresponding OLIA can be summarized in Algorithm 1.

**Algorithm 1: Outer-Layer Iteration Algorithm (OLIA)**

**Initialization:** \( k = 1, q_0 = 0, \varepsilon = 10^{-2} \).

1. **step1:** For the given \( q_k \), solve the following optimization problem to obtain \( X^*, P^*_C \) and \( P^*_D \):

\[
F(q_k) = \max_{\{X, P_C, P_D\} \in \Omega} \left( \sum_{t=1}^{T} \sum_{d \in \Phi_D} x^t_{d_i} \cdot r^t_{d_i} - q_k \cdot \sum_{t=1}^{T} \sum_{d \in \Phi_D} x^t_{d_i} \cdot p^t_{d_i} \right).
\]

(8)

2. **step2:** Set \( q_{k+1} = \max_{\{X, P_C, P_D\} \in \Omega} \left( \sum_{t=1}^{T} \sum_{d \in \Phi_D} x^t_{d_i} \cdot r^t_{d_i} \right) / \left( \sum_{t=1}^{T} \sum_{d \in \Phi_D} x^t_{d_i} \cdot p^t_{d_i} \right) ;

If \( |F(q_k)| > \varepsilon \), \( k \leftarrow k + 1 \);

3. **step3:** Repeat the steps 1–2 until \( |F(q_k)| \leq \varepsilon \).

**Update:** return \( X = X^*, P_C = P^*_C \) and \( P_D = P^*_D \).

However, the equivalent objective problem (8) in Algorithm 1 is also a non-convex MINLP formulation. Thus, we convert the problem (8) into a convex problem by the following inner-layer convex approximation algorithm.

B. Inner-Layer Convex Approximation

For brevity, we denote \( q \) as \( q_k \) at the \( k \)-th iteration in OLIA. To find an accurate solution for the non-convex MINLP problem (8), we perform the following three steps. Before demonstrating the first step, we shall note that the allocated power is zero, i.e., \( p^t_{d_i} = 0 \), if the channel resource of CU is not allocated to EH-DP \( d_i \) at the \( t \)-th time slot, e.q., \( x^t_{d_i} = 0 \). Therefore, the first step is relaxing \( x^t_{d_i} \) into a continuous variable within \([0, 1]\) and rewriting the problem (8) by the substitution of \( S^t_{d_i} = x^t_{d_i} \cdot p^t_{d_i} \) as follows:

\[
\max_{X, P_C, S_D} \left\{ \sum_{t=1}^{T} \sum_{d \in \Phi_D} R^t_{d_i} - q \cdot \sum_{t=1}^{T} \sum_{d \in \Phi_D} S^t_{d_i} \right\},
\]

(9) 

**s.t.** (5a),

\[ R_c^t \geq e^{x^t_{d_i}}, \]

(9b)

\[ \sum_{n=1}^{T} S^t_{d_i} \leq \sum_{n=1}^{T} E^t_{n}, \]

(9c)

\[ 0 \leq S^t_{d_i} \leq p^t_{d_i} \max, \]

(9d)

\[ R^t_{d_i} \geq x^t_{d_i} \cdot r^t_{d_i} \]

(9e)

\[ x^t_{d_i} \in [0, 1], \]

(9f)

where \( R_c^t \) and \( R^t_{d_i} \) are the equivalent transformations of \( r^t_{d_i} \) and \( r^t_{d_i} \), according to \( S^t_{d_i} = x^t_{d_i} \cdot p^t_{d_i} \), respectively, and can be represented by (10) and (11).

\[
R_c^t = \log \left( 1 + \frac{p^t_{d_i} \cdot q_{d_i} B}{S^t_{d_i} \cdot g_{d_i} + n_0} \right).
\]

(10)

\[
R^t_{d_i} = \log \left( 1 + \frac{p^t_{d_i} \cdot S^t_{d_i} \cdot g_{d_i} \cdot x^t_{d_i} + n_0}{p^t_{d_i} \cdot S^t_{d_i} \cdot g_{d_i} + n_0} \right).
\]

(11)

Based on the above equivalent substitution, we can notice that the variables \( x^t_{d_i} \) and \( p^t_{d_i} \) are integrated by \( S^t_{d_i} \). The optimization problem (8) can be equivalently solved by finding the solutions about parameters of \( X, P_C, \) and \( S_D \).

The second step, our approach utilizes the same convex approximation approach as [17] used to obtain a tight approximation solution of the problem (9). The inequality (12) is set to obtain an approximation about the original sum rate.

\[
\alpha \log z + \beta \leq \log(1 + z).
\]

(12)

This approximation is proved to be tight and has low complexity at \( z = z_0 \) and \( \alpha = \frac{\log(1+\log z_0)}{\log z_0} \) in [17].

The third step, the optimization problem can be converted to a convex optimization problem by duality with a new objective of the problem (9) can be equivalently converted into the following convex optimization problem through the above three steps as follows:

\[
\max_{X, P_C, S_D} \left\{ \sum_{t=1}^{T} \sum_{d \in \Phi_D} \tilde{R}^t_{d_i} - q \cdot \sum_{t=1}^{T} \sum_{d \in \Phi_D} \tilde{S}^t_{d_i} \right\},
\]

(13) 

**s.t.** (13a)

\[ p^t_{c} \leq e^{p^t_{c} \max}, \]

(13b)

\[ r^t_{d_i} - R^t_{d_i} \leq 0, \]

(13c)

\[ \sum_{n=1}^{T} \tilde{S}^t_{d_i} - \sum_{n=1}^{T} E^t_{n} \leq 0, \]

(13c)

\[ \tilde{p}^t_{d_i} \leq e^{\tilde{p}^t_{d_i} \max}, \]

(13d)

\[ x^t_{d_i} \cdot r^t_{d_i} - \tilde{R}^t_{d_i} \leq 0, \]

(13e)

\[ x^t_{d_i} \in [0, 1], \]

(13f)
where $\tilde{R}_c^i$ and $\tilde{R}_{d_i}$ are the tight approximation about $R_c^i$ and $R_{d_i}$ after the second and third steps, and are denoted as follows:

$$\tilde{R}_c^i = \alpha_{z_0} \left( \log(g_{c,d}) + \tilde{p}_c^i - \log \left( \sum_{d_i \in D_i} e^{\tilde{s}^i_d} \cdot g_{d_i,B} + n_0 \right) \right) + \beta_{z_0},$$

$$\tilde{R}_{d_i} = \alpha_{z_0} \left( \log(g_{d_i}) + \tilde{p}_{d_i} - \log \left( \sum_{d_j \in D_j, j \neq i} e^{\tilde{s}^j_{d_j}} \cdot g_{d_j,d_i} + n_0 \right) \right) + \beta_{z_0},$$

where the $\alpha_{z_0}$ and $\beta_{z_0}$ are set as the same as in [17]. Notably, the above optimization problem (13) can be easily proved as a convex problem by the convexity of log-sum-exp. Therefore, we can use the conventional convex optimization algorithms to solve it. Once the solution is obtained, we may transform the power allocation variables back with $p_c^i = e^{\tilde{p}_c^i}$, $p_{d_i}^j = e^{\tilde{s}^j_{d_i}}$, $x_{d_i}^j = 1$ when $p_{d_i}^j$ is greater than zero, and otherwise $x_{d_i}^j = 0$.

### IV. Simulation Results

To assess the effectiveness of CAIA, we compare the performance between the proposed CAIA and the RTS in terms of average EE and transmission rate of EH-DPs under different scenarios. In RTS, the EH-DPs which have enough power to meet its transmission rate requirement will be chosen in each time slot, the power allocation of the CU and the chosen EH-DPs is also executed, and the data will be transmitted immediately from source to destination. Additionally, the average represents the mean of all EH-HPs’ performance in whole time slots. For example, the average EE equals to $(\text{sum EE}/(N \times T))$.

#### A. Simulation Setup

Above all, the detailed cellular network simulation scenario should be illustrated. We consider a cellular network as shown in Fig. 1. The radius of the cellular network is 800 meters. The BS is always located at the center of the circle. The position of CU and EH-DPs, which is known by the BS, is randomly distributed in the area. Besides, the distance between receiver and sender of each EH-DP is randomly distributed in the range of 20 meters to 50 meters. Because the spectrum matching between the CU and EH-DPs has been already finished, the distance between CU and each D2D pairs is simply set greater than 200 meters for the purpose of avoiding serious interference. Similarly, the distance between different D2D pairs is at least 100 meters. The other network parameters used in this paper are presented by Table I.

For each simulation scenario with different numbers of EH-DPs or different energy arrival probabilities, for example a scenario has 2 EH-DPs, we generate the corresponding random scenario of 100 times and average the results. Furthermore, the energy arrival process for every EH-DP is supposed to be i.i.d random sample obeying the same $E$ and $\delta$ in each scenario.

#### B. Performance Results

Fig. 3 and Fig. 4 depict the average EE and transmission rate of EH-DPs for CAIA and RTS algorithm. As shown in Fig. 3, it can be clearly seen that the CAIA obtains better EE than RTS no matter under how many numbers of EH-DPs with different energy arrival probabilities. However, the growth rate of average EE between CAIA and RTS algorithm gradually becomes smaller with the increase of $\delta$. That is because the time slots available to be scheduled are reduced with the rise of energy arrival probability. Besides, please note that the average EE is slowly declined when the node number of EH-DPs is greater than 5 when $\delta$ is 0.8. This phenomenon is mainly caused by the fact that the more available energy is, the more request transmission D2D pairs are. This will result in that more energy will be consumed to obtain the target transmission rate. Finally, the average EE will decline.

![Fig. 3: Average energy efficiency of EH-DPs](image)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Path loss, CU link</td>
<td>128.1+37.6log(d_i[Km]) dB</td>
</tr>
<tr>
<td>Path Loss, DU link</td>
<td>148+40log(d_i[Km]) dB</td>
</tr>
<tr>
<td>CU max Tx power (P_{max}^c)</td>
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<tr>
<td>D2D max Tx power (P_{max}^d)</td>
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<td>Harvested power (E)</td>
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<td>Energy arrival prob. ($\delta$)</td>
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<tr>
<td>Channel bandwidth (BW)</td>
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<tr>
<td>Noise density ($\rho_n$)</td>
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</tr>
<tr>
<td>Number of EH-DPs (N)</td>
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</tr>
<tr>
<td>Min trans. rate, CU link ($r_{th}^c$)</td>
<td>2 bps/Hz</td>
</tr>
<tr>
<td>Min trans. rate, DU link ($r_{th}^d$)</td>
<td>4 bps/Hz</td>
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<tr>
<td>Sum time slots (T)</td>
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</tr>
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</table>

### TABLE I: Simulation parameters of the model
that the proper sum time slots are preferably set to 200.

C. Proper Sum Time Slots

Although the short-term scheduling consideration helps network to obtain better performance, the longer the sum time slots are, the more computational complexity of the proposed algorithm is. Therefore, we study the proper sum time slots, which can lower the computational complexity as well as keep the network performance. As shown in Fig. 5, we study the relationship between average EE and sum time slots \( T \) under the numbers of EH-DPs \( N \) are 3 and 4, and the energy arrival probability \( \delta \) is 0.4. According to the real-time choosing and transmission properties, the time slots will not influence the performance of RTS. However, for the short-term scheduling algorithm CAIA, the average EE keeps stable when the sum time slots reaches 200 no matter how many EH-DPs. It means that the proper sum time slots are preferably set to 200.

![Fig. 4: Average rate of EH-DPs](image)

![Fig. 5: Average EE of EH-DPs vs. sum time slots under the energy arrival probability \( \delta \) is 0.4](image)

V. CONCLUSION

In this paper, we have devoted to doing some researches on energy harvesting-based D2D communication underlaying cellular network with consideration of the diversity of available energy and channel state. Thus, for delay-tolerant network, a short-term sum energy efficiency maximization problem (stSEE) of joint transmission scheduling and power allocation has formulated. The stSEE is a non-convex mixed integer non-linear programming (MINLP) problem. Thus, we transform the stSEE problem into a convex problem and obtain a feasible suboptimal solution by the proposed two-layer convex approximation iteration algorithm (CAIA). Through simulation results, the performance of CAIA is assessed and compared with real-time transmission scheme in the aspects of average energy efficiency and transmission rate of EH-based D2D pairs. Moreover, the proper sum time slots for the short-term scheduling scheme, which can maintain network performance and lower the computational complexity, have been investigated.

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