Optimizing Network Sustainability and Efficiency in Green Cellular Networks

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***Abstract*—In this paper, we study the resource allocation in a device-to-device (D2D) communication underlaying green cellular network, where the base station (BS) is powered by sustainable energy. Our objective is to enhance the network sustainability and efficiency by introducing power control and cooperative communication. Specifically, we propose optimal power adaptation schemes to maximize the network efficiency under two practical power constraints. We then take the dynamics of the charging and discharging processes of the energy buffer into consideration to ensure the network sustainability. To this end, the energy buffer is modeled as a G/D/1 queue where the input energy has a general distribution. Power allocation schemes are proposed based on the statistics of the energy buffer to enhance the network efficiency and sustainability. Both theoretical analysis and numerical results demonstrate that our proposed power allocation schemes can improve the network throughput drastically while maintaining the network sustainability at a certain level.**

***Index Terms*—Green cellular networks, D2D communications, cooperative communications, network sustainability, spectrum efficiency, power allocation.**

I. Introduction

THE rapid growth of Information and Communications Technology (ICT) industry has boosted the development of wireless communication, which has raised over 6 billion cellular users worldwide [1]. With astronomical escalation of mobile terminals, the cellular industry has unprecedented growth of data traffic requirement, which leads to enormous energy consumption. In 2011, more than 4 million base stations have been deployed to provide services for mobile users, causing an extremely high energy consumption of 25MWh per year in average [2]. Among the devices of cellular networks, the BSs occupy almost 60% of the whole network's energy consumption [3]. Nowadays, the energy cost of cellular networks has become a significant portion of the operational expenditure with the increase of energy price. For example, the operational cost of a BS powered by electrical grid is approximately 3000 US dollars per year, and the cost may be ten times more if the BS is powered by diesel power generators in the rural area [2]. Therefore, it is essential to consider how to decrease the energy consumption, especially the energy consumption of BSs, to fulfill the ever growing users' requirement and reduce the operational cost in cellular networks.

To provide sustainable and clean power, eco-friendly green energy, e.g., solar, wind and hydro, is emerging as a popular substitute of traditional energy. Green wireless devices, i.e., wireless devices powered by green energy, are anticipated to be widely deployed to construct the next-generation wireless networks. In traditional electricity grid based wireless networks, the network devices are generally powered by limited yet stable resources, e.g., coal, petroleum and natural gas. One of the most critical research issues in this field is to maximize the energy efficiency, such that the energy utilization can be improved. However, unlike traditional energy, green energy charging capability highly depends on its location, local weather and time, which is naturally sustainable and highly dynamic. For example, the harvested energy by solar panels is different in daytime and night within the same day, which also varies at different locations depending on the intensity of solar radiation. The dynamic charging capability and availability of green energy may cause intermittent power support for green wireless devices, which have shifted the fundamental design criterion and the main performance metric of green wireless communication networks from energy efficiency to energy sustainability. Therefore, how to efficiently allocate the harvested energy to ensure the network sustainability and fulfill the explosively increasing user demand has become an essential research issue. On one hand, many works [4]–[7] have addressed the energy sustainability issue of green wireless communication networks. In [4], a stochastic framework to model the dynamics of green energy buffer is designed, and a distributed admission control strategy is proposed to guarantee high resource utilization and to improve energy sustainability. In [5], [6], network planning in green wireless networks is considered, and the minimum network device deployment problem is formulated. Heuristic algorithms are proposed to fulfill users' QoS requirement and guarantee network sustainability by using the minimal number of network devices. In [7], a hybrid utilization of wind and solar power is considered. Authors find that the combined use of wind and solar power can provide more stable and lower-cost green energy for WLAN mesh nodes in certain geographic locations, i.e., Toronto, Seattle, Phoenix, etc., compared with using wind or solar power only.

On the other hand, to fulfill the ever growing users' re-

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quirement of high-data-rate communications, various promising technologies, e.g., device-to-device communication and cooperative communication, have been introduced to cellular networks. By utilizing D2D communication, cellular devices can transmit data with each other directly without BSs, and the network throughput of wireless cellular networks can be significantly improved [8]–[11]. However, D2D communication normally shares the same spectrum with regular cellular transmissions, which limits the performance of the whole network. To further enhance the network performance, cooperative communication is emerging as a promising technology. With the help of relays, cooperative communication can significantly increase the network throughput by taking advantage of the broadcast nature of wireless channels. Considering the unique features of the relay channel, wireless relay networks have been studied from various perspectives, including transmission framework [12], [13], cooperative protocol [14], [15], and relay positioning [16], [17], etc. Among these, resource allocation, including power allocation is one of the most efficient methods to maximize the utilization of the existing limited resources and improve the network performance [18]. For example, [19], [20] study the resource allocation schemes when the source and the relay occupy orthogonal channels. With the assumption that the source and the relay transmit in the same channel, [21] focuses on the power allocation schemes to improve the achievable rate with the relay adopting the amplify-and-forward scheme. [22], [23] investigate the power allocation schemes for decode-and-forward relays.

In this paper, we aim at improving the network's overall throughput by exploiting the benefits of D2D and cooperative communication, while maintaining the network sustainability in green cellular networks. Specifically, we consider a green device-to-device communication underlaying cellular network where the BS is powered by sustainable energy. Cooperative communication is utilized to improve the transmission efficiency, and the BS helps to relay the source's signal to the destination. The cooperative BS adopts the decode-and-forward protocol and transmits in the same channel with the source. This type of cooperation can better exploit the broadcast nature of wireless signals while improving the utilization of existing allocated spectral resources. We focus on designing efficient power allocation schemes and make the following contributions:

- Both green energy and wireless communication technologies are considered to provide an efficient transmission regime in a device-to-device communication underlaying cellular network, where a BS powered by sustainable energy is deployed in the network. To improve the network throughput, the BS is equipped with cooperation devices to assist the communication between the source and the destination.
- Efficient power allocation schemes are proposed to maximize the overall throughput under two practical types of power constraints depending on whether users are able to adjust their transmission power. Our power allocation schemes can effectively improve the network throughput while ensuring that the energy harvested from the environment can sustain the wireless communication without any node outage.
- An analytical framework to model the dynamics of the green energy charging and discharging processes is presented. The energy buffer can be approximated as a G/D/1 queue where the energy charging process has a general distribution. The distribution of the buffer storage is derived, which sheds some light on the green network designs.

The remainder of the paper is organized as follows. Section II introduces the system model and the relay channel achievable rate. In Section III, we discuss the power adaptation schemes to maximize the achievable rate of each single-user channel. Depending on whether the source node is able to adjust its power levels, we solve the optimization problem under two types of power constraints: total power constraint and BS power constraint. Section IV further takes the dynamics of the sustainable energy into consideration. The energy buffer is modeled as a G/D/1 queue and power allocation schemes that can ensure the network sustainability are proposed. Section V contains some numerical results, and Section VI provides concluding remarks and possible future work.

II. System Configuration

A. Network Model

The structure of the D2D communication underlaying cellular network considered in this paper is shown in Fig. 1. The network consists of a set of wireless users and a single BS, where all the users are located within the transmission range of the BS. The wireless channels of cellular network and D2D communication are orthogonal with each other, thus the interference between cellular network and D2D communication is ignorable. Wireless users can communicate with each other by either cellular network through the BS or by direct data transmission through device-to-device communication. As the BS occupies almost 60% energy consumption of the whole network, a green BS, i.e., a BS powered by renewable energy, is equipped in the network. Since the renewable energy is by nature intermittent and variable, the BS is associated with a rechargeable battery with large capacity to buffer the dynamically charged energy and to provide a constant power output. To ensure the network connectivity, a back up energy source, such as power grid or battery is also available at the BS to provide temporary power supply in some extreme cases when the harvested renewable energy cannot support reliable communication.

For D2D communication in the network, each wireless user can communicate with all other users within the network, and has the same time period for transmission. The green BS can act as a relay and is capable of cooperation with the source nodes to transmit data to the destinations. The cooperative protocols most commonly used are Amplify-and-Forward (AF) and Decode-and-Forward (DF). AF relays simply amplify the received signals and forward them to the destination. To avoid propagating the interference and noise from the source-relay channel, relay would employ extra resources such as time slots or frequency bands for orthogonal transmission. On the other hand, DF could completely eliminate the noise since the relay decodes the received signal before forwarding it, so the source and the relay are able to transmit at the same time and on the

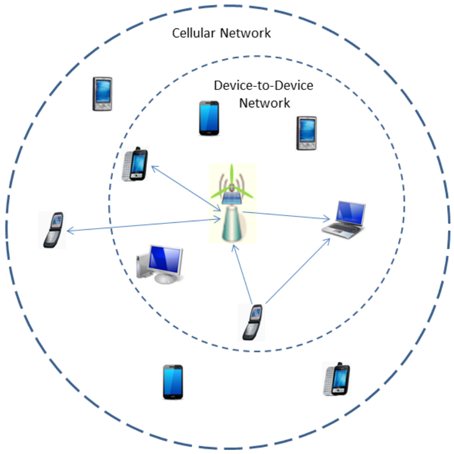


Fig. 1. A green device-to-device communication underlaying cellular network.

same frequency band to improve the spectral efficiency. In this work, considering that each user only has a short period for transmission, we adopt DF protocol at the BS to better exploit the broadcast nature of wireless signals.

In order to maintain fairness, each user has the same time period T for data transmission, which is scheduled by the BS through Time Division Multiple Access (TDMA) in a synchronized manner. During each time period, only one source-destination pair, i.e., one communication channel is permitted for transmission in the network. Suppose there are m pairs in the network, represented by $\mathcal{M} = \{1, \ldots, m\}$. Let i be the current active channel, $i = 1, \ldots, m$. The source node, destination node and the BS for channel i are denoted as s_i and d_i and r, respectively. As only one source-destination pair is allowed to transmit, each transmission channel in this network forms a three-terminal relay channel. To avoid the confusion, in the rest of this paper, the term "BS" and "relay node" will be used interchangeably.

With the help of the BS as the relay node, a single-hop and long-distance transmission can be changed into two-hop and shorter-range transmissions. The presence of an intermediate node can significantly enhance the transmission performance by the two-phase communication, i) source node s_i transmits to relay node r and ii) relay node r transmits to the destination d_i along with node s_i.

B. Achievable Rate

The highest information theoretic achievable rate of the discrete memoryless DF relay channel when channel i is active is given by:

$$R^{(i)} \leq \max_{p(x_{s_i}, x_r)} \min\{I(X_{s_i}; Y_r|X_r), I(X_{s_i}, X_r; Y_{d_i})\}, \quad (1)$$

where x_{s_i}, y_{d_i}, y_r and x_r are denoted as the input to the channel, the output of the channel, the observation by the relay node and the input symbol chosen by the relay, respectively.

The first term $I(X_{s_i}; Y_r|X_r)$ is the largest rate that the relay node can decode the signal, and the second term $I(X_{s_i}, X_r; Y_{d_i})$ is to ensure that the destination can decode. The highest achievable rate of the relay channel is obtained with an optimal joint probability between the codes sent by the source and the relay.

In the D2D network, assume that all wireless channels are independent Rayleigh fading channels with path loss. The channel gain coefficients are denoted by h_{s_ir}, h_{rd_i} and $h_{s_id_i}$, representing the channel conditions for the source-BS, BS-destination and source-destination channels, respectively. The channel gain coefficients can be obtained through a feedback channel in cellular networks. In this paper, we assume that these coefficients can be estimated accurately at the BS. As some research works have addressed the resource allocation with imperfect channel state information, e.g. [24], [25], this issue can be investigated in the future.

The received signals at the relay node and at the destination node at time t are given by

$$\begin{aligned} y_r(t) =& h_{s_ir}x_{s_i}(t) + z_r(t), \\ y_{d_i}(t) =& h_{s_id_i}x_{s_i}(t) + h_{rd_i}x_r(t) + z_{d_i}(t), \end{aligned} \quad (2)$$

where $z_r(t)$ and $z_{d_i}(t)$ are independent zero-mean Gaussian noises received at the relay node r and at the destination node d_i both with variance σ^2.

During each user's transmission period, both the user and the relay send a sequence of length n. The input sequence at the source node is subject to the following average power constraint:

$$\frac{1}{n}\sum_{t=1}^{n} x_{s_i}^2(t) \leq P_s^{(i)}, \quad (3)$$

and the transmitting power constraint at the relay node when channel i is active is given by

$$\frac{1}{n}\sum_{t=1}^{n} x_r^2(t) \leq P_r^{(i)}. \quad (4)$$

When channel i is active, the highest achievable rate of the relay channel is given by

$$\begin{aligned} R^{(i)} &= \max_{p(x_{s_i}, x_r)} \min\{I(X_{s_i}; Y_r|X_r), I(X_{s_i}, X_r; Y_{d_i})\} \\ &= \max_{0\leq\beta\leq 1} \min\left\{\frac{1}{2}\log\left(1 + \frac{|h_{s_ir}|^2\beta P_s^{(i)}}{\sigma^2}\right), \frac{1}{2}\log\left(1 + \frac{1}{\sigma^2}\cdot\right.\right. \\ &\left.\left.\left(|h_{s_id_i}|^2\beta P_s^{(i)} + \left(\sqrt{|h_{s_id_i}|^2\bar{\beta}P_s^{(i)}} + \sqrt{|h_{rd_i}|^2 P_r^{(i)}}\right)^2\right)\right)\right\}. \end{aligned} \quad (5)$$

Rate (5) is achieved by the joint superposition encoding process among the source node s_i and the relay node r, which consists of consecutive blocks of transmission. During each block, two codes are generated: one code $\underline{u}$ containing the subsequent block's message and the other code $\underline{x_r}$ for the current block's message. During each transmission block, the relay node r sends $\underline{x_r}$ containing the current block's message with its maximum transmission power $P_r^{(i)}$. The source node s_i, on the other hand, divides its total transmission power $P_s^{(i)}$ into two parts, $\beta P_s^{(i)}$ and $\bar{\beta} P_s^{(i)}$ with different purposes, where $\bar{\beta} = 1 - \beta$. $\beta P_s^{(i)}$ is used for transmitting $\underline{u}$ and $\bar{\beta} P_s^{(i)}$ is devoted to cooperate with the relay for transmitting $\underline{x_r}$ to the destination. The code $\underline{x_{s_i}}$ sent by s_i is the superposition of $\underline{u}$ and $\underline{x_r}$.

III. Rate Maximization for a Single-User Channel

It can be observed from (5) that the achievable rate $R^{(i)}$ is a function of the transmission powers $P_s^{(i)}$ and $P_r^{(i)}$ when the location of the BS is fixed. Therefore, each single user's achievable rate can be improved by optimally adapting the transmission powers. In this section, we consider two types of transmission power constraints and discuss the optimal power adaptation schemes and the maximum single user's achievable rates separately.

- Both wireless users and the BS can adopt different power levels for data transmission. Therefore, we aim to maximize the transmission efficiency, i.e., to maximize the overall transmission rate of the channel under a total power constraint.
- Only BS can adjust its power level and all users transmit with a fixed power. In this scenario, we will derive the optimal transmission power at the BS in terms of maximizing the transmission rate.

A. Rate Maximization under Total Power Constraint

The objective is to allocate $P_s^{(i)}$ and $P_r^{(i)}$ under a total power consumption constraint $P_{tot}^{(i)}$, which is the maximum available transmission power for channel i. The problem is formulated as an optimization problem:

$$\max_{P_s^{(i)},P_r^{(i)}} \; R^{(i)} \qquad \text{subject to } P_s^{(i)} + P_r^{(i)} \leq P_{tot}^{(i)}. \tag{6}$$

In the achievable rate expression (5), the first term is the relay decoding rate and the second represents the destination decoding rate. For any given $P_s^{(i)}$ and $P_r^{(i)}$, the largest achievable rate is attained by optimally choosing β by the source. Since the highest achievable rate is obtained when the relay decoding rate equals the destination decoding rate, our optimal power allocation scheme tries to balance these two rates by jointly designing $P_s^{(i)}$, $P_r^{(i)}$ and β.

Depending on whether relay decoding rate or destination decoding rate is the bottleneck, there are two power allocation strategies for the source node.

- If the destination decoding rate is the bottleneck, the source node can reduce β until the relay decoding rate equals the destination decoding rate.
- If the relay decoding rate is the bottleneck, the source node will set $\beta = 1$.

Note that when $\beta = 1$, the source node and the relay node will transmit independent codes. Therefore, the second cooperation mode between the source and the relay is also known as the "asynchronous case" while the first mode is referred to as the "synchronous case". For our optimization problem, we will jointly allocate $P_s^{(i)}$, $P_r^{(i)}$ and β for both cases.

1) Synchronous Case: The destination decoding rate is the bottleneck, and $\beta < 1$. Denote $P_{s_1}^{(i)} = \beta P_s^{(i)}$ and $P_{s_2}^{(i)} = \bar{\beta} P_s^{(i)}$ as the two components of $P_s^{(i)}$. Since the signal received at the destination contains a combined strength, we first maximize the destination decoding rate with fixed $P_0^{(i)}$, $P_0^{(i)} = P_{s_2}^{(i)} + P_r^{(i)}$. Then, we can allocate $P_{s_1}^{(i)}$ and $P_0^{(i)}$ under the total power constraint. The destination decoding rate is given by:

$$I(X_{s_i}, X_r; Y_{d_i}) = \frac{1}{2}\log\left(1 + \frac{1}{\sigma^2}\cdot \left(|h_{s_id_i}|^2 P_{s_1}^{(i)} + \left(\sqrt{|h_{s_id_i}|^2 P_{s_2}^{(i)}} + \sqrt{|h_{rd_i}|^2 (P_0^{(i)} - P_{s_2}^{(i)})}\right)^2\right)\right). \tag{7}$$

Since (7) is a concave function of $P_{s_2}^{(i)}$, the first-order condition results in the optimum power allocation between $P_{s_2}^{(i)}$ and $P_r^{(i)}$, which is given by

$$P_{s_2}^{(i)} = \frac{|h_{rd_i}|^2}{|h_{s_id_i}|^2 + |h_{rd_i}|^2} P_0^{(i)}, \qquad P_r^{(i)} = \frac{|h_{s_id_i}|^2}{|h_{s_id_i}|^2 + |h_{rd_i}|^2} P_0^{(i)}, \tag{8}$$

and the destination decoding rate becomes:

$$I(X_{s_i}, X_r; Y_{d_i}) = \frac{1}{2}\log\left(1 + \frac{\frac{4|h_{s_id_i}|^2|h_{rd_i}|^2}{|h_{s_id_i}|^2 + |h_{rd_i}|^2} P_0^{(i)} + |h_{s_id_i}|^2 P_{s_1}^{(i)}}{\sigma^2}\right). \tag{9}$$

For the optimization problem (6), the optimum of rate $R^{(i)}$ is achieved when $P_{s_1}^{(i)} + P_{s_2}^{(i)} + P_r^{(i)} = P_{tot}^{(i)}$ and when the relay decoding rate equals the destination decoding rate, i.e.,

$$\frac{|h_{s_ir}|^2 P_{s_1}^{(i)}}{\sigma^2} = \frac{4|h_{s_id_i}|^2|h_{rd_i}|^2 P_0^{(i)}}{(|h_{s_id_i}|^2 + |h_{rd_i}|^2)\sigma^2} + \frac{|h_{s_id_i}|^2 P_{s_1}^{(i)}}{\sigma^2}. \tag{10}$$

The above constraints lead to the optimal solution when $|h_{s_id_i}| \leq |h_{s_ir}|$:

$$P_{s_1}^{(i)} = \frac{|h_{s_id_i}|^2 + |h_{rd_i}|^2}{|h_{s_ir}|^2 + |h_{rd_i}|^2} P_{tot}^{(i)}, \qquad P_0^{(i)} = \frac{|h_{s_ir}|^2 - |h_{s_id_i}|^2}{|h_{s_ir}|^2 + |h_{rd_i}|^2} P_{tot}^{(i)}. \tag{11}$$

The highest achievable rate in the synchronous case is given by

$$R_{sync}^{(i)} = \frac{1}{2}\log\left(1 + \frac{|h_{s_ir}|^2(|h_{s_id_i}|^2 + |h_{rd_i}|^2)}{|h_{s_ir}|^2 + |h_{rd_i}|^2} \cdot \frac{P_{tot}^{(i)}}{\sigma^2}\right). \tag{12}$$

If $|h_{s_id_i}| > |h_{s_ir}|$, the source-destination channel has a better channel condition than the source-relay channel. In this case, any direct transmission is more reliable than cooperative transmission. Therefore, the source transmits to the destination directly to avoid the waste of resources, and the highest end user rate (channel capacity) for non-cooperative transmission is

$$R_{dir}^{(i)} = \frac{1}{2}\log\left(1 + \frac{|h_{s_id_i}|^2 P_{tot}^{(i)}}{\sigma^2}\right). \tag{13}$$

2) Asynchronous Case: In this case, the source and the relay employ independent codes, so that $\beta = 1$.

The achievable rate for channel i becomes

$$R^{(i)} = \min\left\{\frac{1}{2}\log\left(1+\frac{|h_{s_ir}|^2P_s^{(i)}}{\sigma^2}\right),\right.$$
$$\left.\frac{1}{2}\log\left(1+\frac{|h_{s_id_i}|^2P_s^{(i)}+|h_{rd_i}|^2P_r^{(i)}}{\sigma^2}\right)\right\}. \quad (14)$$

By the same argument, the maximum achievable rate is obtained when the relay decoding rate equals the destination decoding rate, i.e.,

$$|h_{s_ir}|^2P_s^{(i)} = |h_{s_id_i}|^2P_s^{(i)} + |h_{rd_i}|^2P_r^{(i)}. \quad (15)$$

When $|h_{s_id_i}| \le |h_{s_ir}|$, the optimal power allocation in the asynchronous case is given by:

$$P_s^{(i)} = \frac{|h_{rd_i}|^2}{|h_{s_ir}|^2-|h_{s_id_i}|^2+|h_{rd_i}|^2}P_{tot}^{(i)},$$
$$P_r^{(i)} = \frac{|h_{s_ir}|^2-|h_{s_id_i}|^2}{|h_{s_ir}|^2-|h_{s_id_i}|^2+|h_{rd_i}|^2}P_{tot}^{(i)}, \quad (16)$$

and the highest achievable rate is given by

$$R_{asyn}^{(i)} = \frac{1}{2}\log\left(1+\frac{|h_{s_ir}|^2|h_{rd_i}|^2}{|h_{s_ir}|^2-|h_{s_id_i}|^2+|h_{rd_i}|^2}\cdot\frac{P_{tot}^{(i)}}{\sigma^2}\right). \quad (17)$$

Remark 1. *The optimal cooperation strategy and power adaptation scheme to maximize the achievable rate depends on the channel conditions and the locations of the users. For example, in the AWGN channel with path loss, if BS is closer to the source, the power allocation in the synchronous case achieves higher rate; otherwise, the power allocation scheme in the asynchronous case achieves higher rate.*

B. Rate Maximization under BS Power Constraint

Suppose all users have a fixed transmission power $P_s^{(i)} = P_s$ and only the BS can adjust its power level based on the harvested energy and the QoS requirement. Then, the rate maximization problem under BS power constraint is formulated as:

$$\begin{aligned}\max_{P_r^{(i)}}\ & R^{(i)}\\ \text{subject to } & P_s^{(i)} = P_s\\ & P_r^{(i)} \le P_r,\end{aligned} \quad (18)$$

where P_r is the maximum transmission power at the BS.

Intuitively, the achievable rate $R^{(i)}$ improves with the BS transmission power. However, since the relay decoding rate is independent of $P_r^{(i)}$, in this problem, we are interested in how $R^{(i)}$ changes with BS transmission power $P_r^{(i)}$. When the power level at the BS is known, the source node will adapt its transmission power accordingly by choosing proper β to maximize the achievable rate.

As shown in Section III-A, when $|h_{s_id_i}| > |h_{s_ir}|$, the source transmits to the destination directly. Therefore, we only discuss the power adaptation scheme for the source and the BS to maximize the achievable rate when $|h_{s_id_i}| \le |h_{s_ir}|$.

In the synchronous case, the relay decoding rate is the dominant one, so the source node will choose $0 < \beta < 1$ to balance the relay decoding rate and the destination decoding rate. In this case, $R^{(i)}$ increases with $P_r^{(i)}$, so the maximum is achieved when $P_r^{(i)} = P_r$. In the asynchronous case, the relay decoding rate becomes the bottleneck, so $\beta = 1$.

1) Synchronous Case: In this case, the maximum rate is achieved when $P_r^{(i)} = P_r$ and

$$|h_{s_ir}|^2\beta P_s = |h_{s_id_i}|^2\beta P_s + \left(\sqrt{|h_{s_id_i}|^2\bar{\beta}P_s}+\sqrt{|h_{rd_i}|^2P_r}\right)^2. \quad (19)$$

Solving (19) for β, we can get

$$\beta = \frac{|h_{s_id_i}|^2|h_{rd_i}|^2}{|h_{s_ir}|^4P_s}\cdot\left(\sqrt{\frac{|h_{s_ir}|^2P_s-|h_{rd_i}|^2P_r}{|h_{rd_i}|^2}}+\sqrt{\frac{(|h_{s_ir}|^2-|h_{s_id_i}|^2)P_r}{|h_{s_id_i}|^2}}\right)^2. \quad (20)$$

The condition for this case to happen is

$$P_r < \frac{|h_{s_ir}|^2-|h_{s_id_i}|^2}{|h_{rd_i}|^2}P_s. \quad (21)$$

Therefore, the maximum rate is given by

$$R_{sync}^{(i)} = \frac{1}{2}\log\left(1+\frac{|h_{s_id_i}|^2|h_{rd_i}|^2}{|h_{s_ir}|^2\sigma^2}\cdot\left(\sqrt{\frac{|h_{s_ir}|^2P_s-|h_{rd_i}|^2P_r}{|h_{rd_i}|^2}}+\sqrt{\frac{(|h_{s_ir}|^2-|h_{s_id_i}|^2)P_r}{|h_{s_id_i}|^2}}\right)^2\right). \quad (22)$$

2) Asynchronous Case: When $P_r \ge \frac{|h_{s_ir}|^2-|h_{s_id_i}|^2}{|h_{rd_i}|^2}P_s$, $\beta = 1$. Since the bottleneck is the relay decoding rate, improving $P_r^{(i)}$ cannot increase the achievable rate. In this case, the maximum transmission rate is a constant and given by

$$R_{asyn}^{(i)} = \frac{1}{2}\log\left(1+\frac{|h_{s_ir}|^2P_s}{\sigma^2}\right), \quad (23)$$

and the optimal transmission power at the BS is given by

$$P_r^{(i)} = \frac{|h_{s_ir}|^2-|h_{s_id_i}|^2}{|h_{rd_i}|^2}P_s. \quad (24)$$

In conclusion, depending on the BS's power output as well as its location, the maximum achievable rate for the optimization problem (18) is given by

$$R^{(i)} = \begin{cases}\frac{1}{2}\log\left(1+\frac{|h_{s_id_i}|^2|h_{rd_i}|^2}{|h_{s_ir}|^2\sigma^2}\cdot\left(\sqrt{\frac{|h_{s_ir}|^2P_s-|h_{rd_i}|^2P_r}{|h_{rd_i}|^2}}+\sqrt{\frac{(|h_{s_ir}|^2-|h_{s_id_i}|^2)P_r}{|h_{s_id_i}|^2}}\right)^2\right), & \text{if } P_r < \frac{|h_{s_ir}|^2-|h_{s_id_i}|^2}{|h_{rd_i}|^2}P_s;\\ \frac{1}{2}\log\left(1+\frac{|h_{s_ir}|^2P_s}{\sigma^2}\right), & \text{if } P_r \ge \frac{|h_{s_ir}|^2-|h_{s_id_i}|^2}{|h_{rd_i}|^2}P_s.\end{cases} \quad (25)$$

IV. Power Allocation Considering Energy Buffer Dynamics

In green cellular network, the BS is equipped with a rechargeable energy battery to store and release the harvested renewable energy. In this section, we take the dynamic energy charging/discharging processes into consideration to allocate the maximum power output $P_r^{(i)}$ for each channel i.

A. Energy Buffer Model

Since the renewable energy is intrinsically intermittent, the charging process is a stochastic process. Denote $N(t)$ as the total harvested energy over time $[0, t]$. $N(t)$ is non-decreasing and its corresponding charging rate is $\lambda(t)$. Considering the intermittency of the renewable energy sources, we assume that the charging rate changes over time and the charging process is described as a non-homogeneous random process in this paper. As the transmission time for each channel is relatively short compared with the process, the charging rate of the process during channel i's transmission can be approximated as a constant $\lambda^{(i)}$.

The harvested energy at the BS is consumed for signal processing, coding and forwarding the information to the destination. The total transmission energy when channel i is active can be calculated by

$$E^{(i)} = P_r^{(i)} T, \tag{26}$$

where T is the transmission time for channel i.

Suppose the energy used for signal processing and coding is a constant E_0 for all time periods. Denote $V(t)$ as the total energy discharged over $[0, t]$. Then,

$$V(t) = \frac{E_0 t}{T} + \int_0^t P_r(s) ds, \tag{27}$$

where $P_r(s) = P_r^{(i)}$ when channel i is active at time s. The discharging rate of channel i is thus a constant given by

$$\mu^{(i)} = P_r^{(i)} + E_0/T. \tag{28}$$

Denote C as the battery capacity, which is assumed to be large enough to store the energy harvested within a time period. Then, the energy stored in the buffer at time t is given by

$$Q(t) = \min[\max[N(t) - V(t), 0], C]. \tag{29}$$

Define $D(Q_0^{(i)})$ as the energy depletion time of the energy buffer with initial buffer length $Q_0^{(i)}$,

$$D(Q_0^{(i)}) = \inf(t \geq 0 | Q(t) = 0, Q(0) = Q_0^{(i)}), \tag{30}$$

where $\inf\{t \in \mathcal{T}\}$ denotes the infimum of set $\mathcal{T}$.

Our objective is to design the maximum transmission power for each channel while preventing the D2D communication network from battery energy depletion. Specifically, we intend to avoid energy buffer vacancy during each transmission period by deciding the transmission power at the beginning of the period.

To achieve this goal, we investigate the relationship between the energy depletion time of the energy buffer $D(Q_0^{(i)})$ and the discharging rate $\mu^{(i)}$. Let $f_D(t; Q_0^{(i)})$ denote the probability density function of the energy depletion time. Based on the start up delay analysis in [26], we have

$$f_D(t; Q_0^{(i)}) = -\frac{d}{dt} \int_0^\infty p^Q(q, t) dq, \tag{31}$$

where $p^Q(q, t)$ is the probability density function of the buffer energy storage $Q(t)$ at time t.

In the following, we intend to obtain $p^Q(q, t)$, which is denoted as

$$p^Q(q, t) = \mathrm{E}[\delta(q - Q(t))], \tag{32}$$

where $\mathrm{E}[\cdot]$ calculates the expectation of the input function.

During each transmission period, the energy buffer has a random input and a constant rate output. Without loss of generality, suppose the arrival process during channel i's transmission is a random process with a general distribution. Thus, the temporal evolution of the energy buffer during a small time interval Δ can be described by

$$dQ(t) = Q(t + \Delta) - Q(t) = \eta(\Delta) - \mu^{(i)} \Delta, \tag{33}$$

where $\eta(\Delta) = N(t + \Delta) - N(t)$ denotes the the summation of energy charged during Δ.

The charging process with a general distribution can be approximated as a Wiener process with a drift [27], [28]. The drift during channel i's transmission is at rate $\lambda^{(i)}$. The variance of the charging process $\nu^{(i)}$ is determined by the Wiener process. In a Wiener process, the increment within a time duration Δ is normally distributed with zero mean and a variance, which is linearly proportional to the time duration Δ [29]. As a result, let $\nu^{(i)} = 2\gamma\Delta$, where 2γ is a scaling factor determined by the specific charging technology. The probability density function for $\eta(\Delta) = x + \lambda^{(i)}\Delta$ is given by

$$p^\eta(x, \Delta) = \frac{1}{\sqrt{4\pi\Delta\gamma}} e^{-(x)^2/(4\Delta\gamma)}. \tag{34}$$

Since the analysis of probability density function with a constant drift rate is complex, to facilitate analysis, we adopt the techniques in [30] to obtain $p^Q(q, t)$ through Fourier transform. Let $\mathcal{F}\{u(x)\}$ denote the Fourier transform of a function $u(x)$, we have

$$\mathcal{F}\{u(x)\} := \hat{u}_\xi = \int_{-\infty}^{\infty} u(x) e^{-j\xi x} dx, \tag{35}$$

where $\hat{u}_\xi$ is the transformed function, and ξ is the transform variable. The Fourier transform of the probability density function is a characteristic function of the random variable. Thus, the Fourier transform preserves all the random variable's statistic information. This feature guarantees the accuracy of our analysis.

Let $\hat{p}_\xi^Q(t)$ and $\hat{p}_\xi^\eta(\Delta)$ denote the Fourier transform of $p^Q(q, t)$ and $p^\eta(x, \Delta)$, respectively. Performing Fourier transform on (33) and taking $\Delta \to 0$, we can get

$$\frac{\partial}{\partial t} \hat{p}_\xi^Q(t) = \mu^{(i)} \mathcal{F}\{\frac{\partial}{\partial q} p^Q(q, t)\} + \hat{p}_\xi^Q(t) \phi_\xi, \tag{36}$$

where

$$\phi_\xi = \lim_{\Delta \to 0} \frac{1}{\Delta} [\hat{p}_\xi^\eta(\Delta) - 1]. \tag{37}$$

To get $\hat{p}^{\eta}_{\xi}(\Delta)$ in (37), we perform Fourier transform on the probability density function $p^{\eta}(x,\Delta)$, which is given by (34), and obtain

$$\hat{p}^{\eta}_{\xi}(\Delta) = e^{-\gamma\Delta\xi^2} e^{-j\xi\lambda^{(i)}}. \tag{38}$$

Thus, ϕ_ξ is given by

$$\phi_\xi = -\gamma\xi^2 - j\xi\lambda^{(i)}. \tag{39}$$

Based on the time derivative property of Fourier transform, (36) could be further reformed as

$$\begin{aligned}\frac{\partial}{\partial t}\hat{p}^{Q}_{\xi}(t) &= j\xi\mu^{(i)}\hat{p}^{Q}_{\xi}(t) + \hat{p}^{Q}_{\xi}(t)\phi_\xi \\ &= (j\xi\mu^{(i)} + \phi_\xi)\hat{p}^{Q}_{\xi}(t).\end{aligned} \tag{40}$$

To solve this first order ordinary differential equation (40), we need to determine initial values. The initial condition of (40) could be obtained at time $t = 0$. At time $t = 0$, the energy buffer length is $Q_0^{(i)}$, namely $p^Q(q = Q_0^{(i)}, 0) = 1$. The Fourier transform of this condition is $\hat{p}^{Q}_{\xi}(0) = e^{-j\xi Q_0^{(i)}}$. With this initial condition and (39), the solution to (40) can be obtained as

$$\hat{p}^{Q}_{\xi}(t) = e^{-j\xi Q_0^{(i)}} e^{(j\xi(\mu^{(i)}-\lambda^{(i)})-\gamma\xi^2)t}. \tag{41}$$

Finally, $p^Q(q,t)$ can be obtained by performing the inverse Fourier transform on (41). Replacing $p^Q(q,t)$ in (31), the probability density function of the energy depletion time with initial buffer length $Q_0^{(i)}$ is given by

$$f_D(t; Q_0^{(i)}) = \frac{Q_0^{(i)}}{\sqrt{4\gamma\pi t^3}} \exp\left\{-\frac{(Q_0^{(i)} + (\lambda^{(i)} - \mu^{(i)})t)^2}{4\gamma t}\right\}. \tag{42}$$

B. Power Allocation Schemes

We have modeled the energy buffer and provided the probability density function of energy depletion time in the previous subsection. Based on our theoretical analysis, in this subsection, we design power allocation schemes to maximize the transmission efficiency while ensuring the network sustainability. Assume that the initial energy storage in the buffer and the statistical parameters of the charging process can be estimated and are available at the beginning of each transmission period. The BS can adjust the discharging rate by choosing transmission power $P_r^{(i)}$ during channel i's transmission period. The objective of our power allocation scheme is to maximize each single channel's transmission rate while maintaining the sustainability of the network at a certain level. We still consider two different network scenarios depending on whether users are able to adjust the transmission power. In the first network scenario, both the BS and users can adjust transmission power. Thus, our scheme can allocate power for both the BS and users to improve the transmission efficiency. Then, we consider the case that users can not adjust transmission power due to equipment constraints, which means that only the BS can choose various powers for data transmission. In the following, we present the transmission power allocation frameworks under both total power constraint and BS power constraint cases.

1) Power Allocation under Total Power Constraint: We first consider the situation that both the BS and users can adjust their transmission power levels. In the proposed network scenario, since improving the transmission rate is at the expense of consuming more transmission power, the communication network may not be sustainable over time due to power depletion. To tackle this issue, our design objective is to improve the transmission efficiency of each channel while maintaining the whole network's sustainability. Our proposed scheme allocates both BS transmission power and user transmission power on a slot-by-slot basis.

At the beginning of channel i's transmission period, the remaining energy in the buffer is $Q_0^{(i)}$. In order to maintain the network sustainability, the maximum transmission power $P_r^{(i)^*}$ for the BS on channel i is determined by numerically solving the following equation:

$$E[D(Q_0^{(i)})] = T + \delta, \tag{43}$$

where δ denotes a constant to guarantee the sustainability of green wireless networks. δ is decided according to the tolerance level of the transmission or the available volume of backup energy. If there is sufficient backup energy or the transmission has high tolerance level, i.e., the network tolerates a high transmission latency like data transmission, δ can be set to a small value. If the available volume of the backup energy is not enough and the transmission does not tolerate a high transmission latency, such as voice/video, a large δ is chosen.

Based on our analysis in Section IV-A, the expectation of the depletion time can be calculated by

$$E[D(Q_0^{(i)})] = \int_0^\infty \frac{Q_0^{(i)}}{\sqrt{4\gamma\pi t}} \exp\left\{-\frac{(Q_0^{(i)} + (\lambda^{(i)} - (P_r^{(i)} + E_0/T))t)^2}{4\gamma t}\right\} dt. \tag{44}$$

Then, we can obtain the optimal P_s to maximize the transmission efficiency based on the value of $P_r^{(i)^*}$. In the total power constraint case, the user is able to adjust its own transmission power to cooperate with the BS to improve the transmission efficiency. Based on (8) and (11) in Section III-A, in the synchronous case, the optimal transmission power for the user is given by

$$P_s^{(i)^*} = \frac{|h_{s_i d_i}|^2(|h_{s_i d_i}|^2 + |h_{r d_i}|^2) + |h_{r d_i}|^2(|h_{s_i r}|^2 + |h_{r d_i}|^2)}{|h_{s_i d_i}|^2(|h_{s_i r}|^2 - |h_{s_i d_i}|^2)} P_r^{(i)^*}. \tag{45}$$

In the asynchronous case, according to (16), the optimal user transmission power is given by

$$P_s^{(i)^*} = \frac{|h_{r d_i}|^2}{|h_{s_i r}|^2 - |h_{s_i d_i}|^2} P_r^{(i)^*}. \tag{46}$$

2) Power Allocation under BS Power Constraint: We further consider the case that users can not adjust their transmission power level due to the device constraints. In this case, users transmit with fixed power while BS adapts its transmission power to meet our design objective.

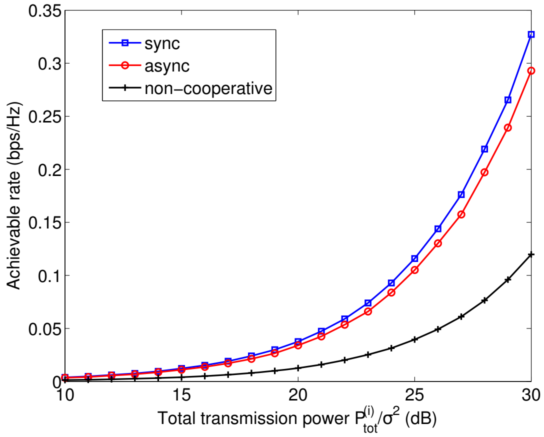


Fig. 2. Rate comparison under the total power constraint for a single-user channel.

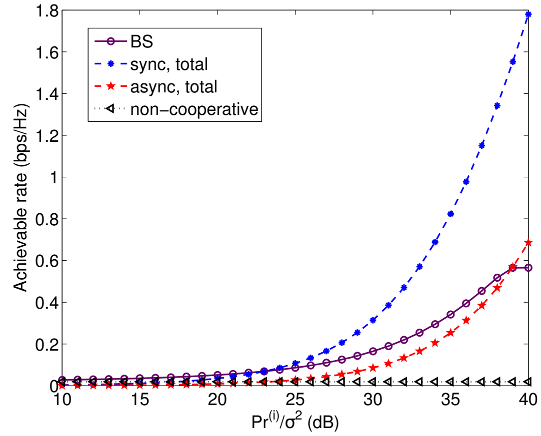


Fig. 3. Rate comparison for a single-user channel.

According to (25), the maximum rate for the optimization problem (18) is achieved when $P_r^{(i)} = P_r$ if $P_r < \frac{|h_{s_ir}|^2-|h_{s_id_i}|^2}{|h_{rd_i}|^2}P_s$, and $P_r^{(i)} = \frac{|h_{s_ir}|^2-|h_{s_id_i}|^2}{|h_{rd_i}|^2}P_s$ if $P_r \geq \frac{|h_{s_ir}|^2-|h_{s_id_i}|^2}{|h_{rd_i}|^2}P_s$.

Therefore, the power allocation scheme performs as follows: at the begining of channel i's transmission period, based on the remaining buffer energy $Q_0^{(i)}$, the BS first calculates a transmission power $P_r^{(i)^*}$ such that

$$E[D(Q_0^{(i)})] = T + \delta, \tag{47}$$

which is the same as the first step of the power allocation scheme in the total power constraint case.

Then, the BS compares $P_r^{(i)^*}$ with $\min\{P_r, \frac{|h_{s_ir}|^2-|h_{s_id_i}|^2}{|h_{rd_i}|^2}P_s\}$ and chooses the minimum of the two values as the optimal transmission power.

V. Numerical Results

To verify the above theoretical analysis and to evaluate our power allocation schemes, we provide some numerical results in this section. We assume that all wireless channels are independent Rayleigh fading channels with path loss.

Firstly, in order to illustrate the rate enhancement by the cooperative communication in a single-user channel, we compare the optimal rate achieved by our proposed cooperative power adaptation schemes with the non-cooperative transmission rate under the total power constraint as shown in Fig. 2. The transmission power for the non-cooperative communication is set to be $P_{tot}^{(i)}$, which is the maximum total transmission power for channel i. Suppose $P_{tot}^{(i)}/\sigma^2$ ranges from 10dB to 30dB, and the path loss exponent α is 2. The distances between the source and the BS, between the BS and the destination, and between the source and the destination are 75 meters, 80 meters and 150 meters, respectively.

It can be observed that cooperative transmission can achieve higher rate than non-cooperative transmission in both synchronous case and asynchronous case. In a high SNR environment, the spectrum efficiency can be doubled.

Fig. 3 depicts the rate comparison employing different power adaptation schemes for both total power constraint and BS power constraint problems. Suppose $P_r^{(i)}/\sigma^2$ ranges from 10dB to 40dB. For the total power constraint problem, the source would adapt its own transmission power based on the available BS's transmission power. For the BS power constraint problem, the transmission power at the source is set to be 20dB and the maximum BS transmission power P_r is 40dB. The rest of the simulation parameters remain unchanged. To illustrate the rate improvement, we also set the capacity of the non-cooperative transmission as a baseline for comparison, where the user transmission power is 20dB.

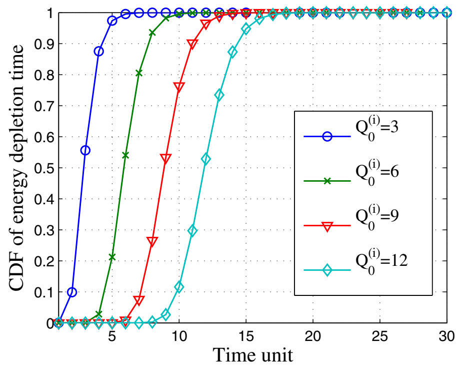
It can be observed that the power adaptation schemes under the total power constraint can achieve higher rate, which is at the expense of higher transmission power at the source. Under the BS power constraint, the channel rate reaches a constant when $P_r^{(i)}$ is large, which is bounded by the limited transmission power at the source.

Secondly, we evaluate our proposed power allocation schemes considering the energy buffer dynamics. The cumulative distribution function (CDF) of energy depletion time is shown in Fig. 4, where Fig. 4(a) illustrates the CDF with different initial buffer storage and Fig. 4(b) depicts the CDF with different discharging rate.

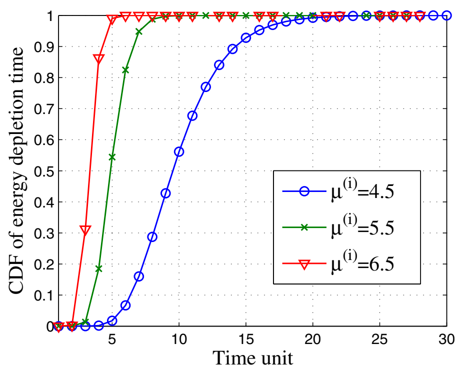
It can be seen from Fig. 4(a) that the CDF curve of the energy depletion time shifts right as the initial buffer energy $Q_0^{(i)}$ grows, which means that the BS is more likely to provide energy output for a longer time if $Q_0^{(i)}$ is large. As shown in Fig. 4(b), the CDF curve shifts left as the discharging rate $\mu^{(i)}$ grows, which means that the BS is more likely to deplete its energy soon with the increase of the discharging rate.

The depletion time expectation $E[D(Q_0^{(i)})]$ of the green energy buffer model shown in Subsection IV-A is depicted in Fig 5. The charging rate $\lambda^{(i)}$ is set to be 3.5. It can be seen that $E[D(Q_0^{(i)})]$ decreases with depletion rate $\mu^{(i)}$ and increases with the initial energy storage $Q_0^{(i)}$ from both analytical results and simulation results.

Fig. 6 and Fig. 7 illustrate the performance of our proposed power allocation schemes in a practical network containing 20 consecutive transmissions. The user transmission power in the BS constraint case is set to be 2dB and the maximum BS transmission power is 10dB. The battery capacity is 100. The renewable energy charging rate at the BS during



(a) $\lambda^{(i)} = 3.5$, $\mu^{(i)} = 5.5$



(b) $Q_0^{(i)} = 10$, $\lambda^{(i)} = 3.5$

Fig. 4. CDF of energy depletion time.

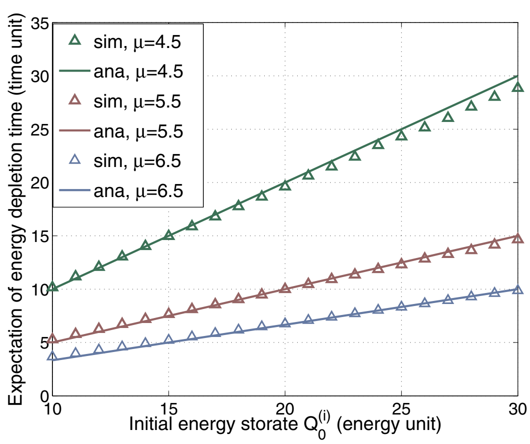
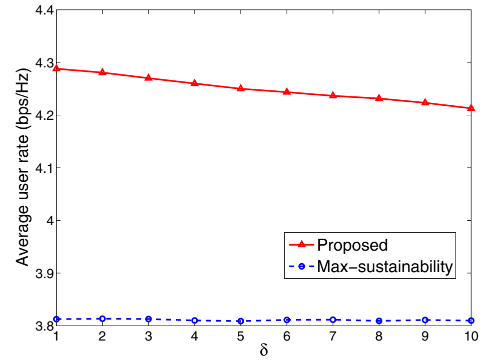
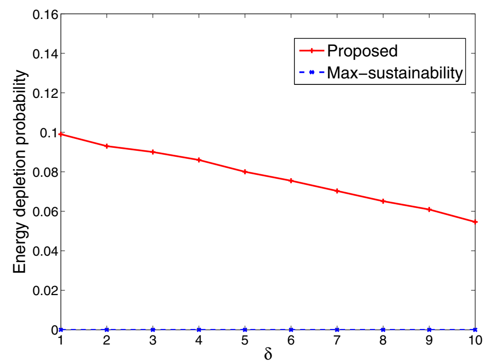


Fig. 5. Expectation of depletion duration ($\lambda^{(i)} = 3.5$).

each transmission period is random and time-variant. Suppose that the energy charging rate can be forecasted based on some historical data, e.g. data from the previous day or year. To demonstrate the energy efficiency of our proposed schemes, we compare with a max-sustainability scheme where $P_r^{(i)} = \frac{Q_0^{(i)} - E_0}{T}$ in total power constraint case and $P_r^{(i)} = \min\{\frac{Q_0^{(i)} - E_0}{T}, P_r^{(i)*}, P_r\}$ in BS power constraint case. We calculate both the energy depletion probability and the average transmission rate of all channels according to the reference max-sustainability scheme and our proposed power allocation schemes derived in Subsection IV-B. The comparison in the total power constraint case is shown in Fig. 6 and the result in the BS power constraint case is shown in Fig. 7.



(a) Average channel rate



(b) Energy depletion probability

Fig. 6. Total power constraint case (channel number=20).

It can be observed that our proposed power allocation schemes can improve the average transmission rate drastically for both total power constraint case and BS power constraint case. The reason is that our schemes exploit the dynamic charging process of the renewable energy to improve the energy efficiency. Compared with the max-sustainability power allocation scheme which has zero energy depletion probability, our proposed method is associated with very low depletion probability.

VI. Conclusion

In this paper, we have proposed several power allocation schemes to maximize the throughput while maintaining the network sustainability in a D2D communication underlaying green cellular network. The results should shed some light on the green wireless network design with energy efficiency and energy sustainability as critical design criteria. For the future work, we will consider more network scenarios including various mobility patterns and QoS requirement of users to optimize the network efficiency and sustainability in green wireless communication networks.

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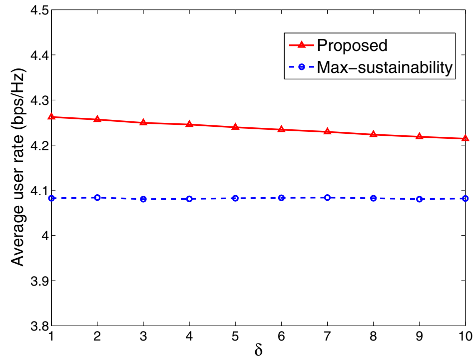
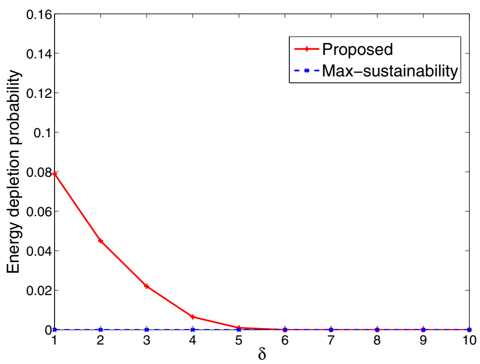


(a) Average channel rate



(b) Energy depletion probability

Fig. 7. BS power constraint case (channel number=20, $P_s = 2dB$).

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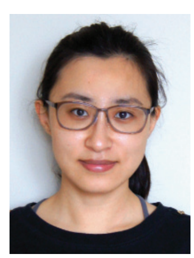

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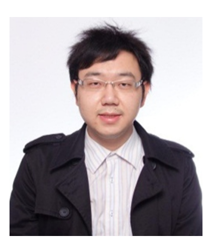

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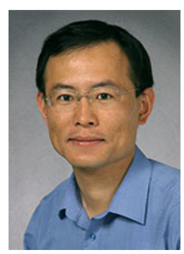

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