Opportunistic Multi-Channel Access in Heterogeneous Networks with Renewable Energy Supplies

Hang Li, Chuan Huang, Fuad Alsaadi, Abdullah M. Dobaie, and Shuguang Cui

Abstract

The heterogeneous system, where small networks (e.g., femtocell or WiFi) boost the system capacity under the umbrella of a large network (e.g., cellular systems), is a promising architecture for the next generation wireless communication systems. In addition, energy harvesting (EH) based green communication is one key next-generation technology. In this paper, we study an uplink transmission scenario under such a heterogeneous network hierarchy, where each mobile user (MU) is powered by a sustainable energy supply and has deterministic access to the large network via one private channel, but only dynamic access to a small network with certain probability via one common channel shared by multiple MUs. Considering a general EH model, i.e., energy arrivals are time-correlated, we study an opportunistic transmission scheme and aim to maximize the average throughput for each MU, which jointly exploits the statistics and current states of the channel, battery, and EH rate, together with the availability to the common channel. Applying a simple yet efficient “save-then-transmit” scheme, the throughput maximization problem is cast as a “rate-of-return” optimal stopping problem. The optimal solution is investigated for the general Markovian channel states and energy arrivals, followed by the independent and identically distributed (i.i.d.) case. As performance benchmarks, the optimal and some suboptimal power allocation schemes with conventional constant power supplies are also examined.
Finally, numerical results are presented, and a new concept of “EH diversity” is discussed.

Index Terms

Heterogeneous networks, femtocell, energy harvesting, opportunistic transmission, optimal stopping.

I. INTRODUCTION

A. Motivations

Heterogeneous networks (HetNets), where small networks (e.g., femtocell or WiFi) composed of low-power access points (APs) are placed under the coverage of a large network (e.g., cellular network), evolve into a new type of network deployment that could enhance the overall system capacity with reasonable cost and power consumption [1], [2]. Standardization bodies, such as ETSI and 3GPP, have paid much attention to this shifting of network paradigm and have made femtocells part of the current and future cellular standards, like UMTS and LTE/LTE-A. Now, commercial femtocell deployments could be found globally, operated by various cellular carrier companies [3].

In a cellular network, a mobile user (MU) is usually assigned a dedicated channel to access the base station (BS), while this link may experience bad channel conditions due to the possible severe path loss and fading between the MU and the BS. In such cases, however, the desired quality-of-service (QoS) could still be satisfied by allowing the MU to access a nearby AP in an underlying small network via a common channel, whose channel condition is relatively good. Essentially, the MU in the above HetNet constructs a multi-channel access scheme: The messages from MU could be directly delivered to the cellular BS, or if available, to a nearby low-power AP as well [4]. In general, there are two modes of access control for small networks (e.g., for femtocells): restricted access, i.e., only pre-registered users could access the corresponding AP [3], [4]; and open access, i.e., any local users in the small network
could gain the access. It is worth noting that the small network could either share the same band with the large network, or operate over a band orthogonal to the large network: e.g., WiFi uses the unlicensed band [6] and femtocells could be allocated with different bands from the large network via orthogonal frequency division multiple access (OFDMA) or time division multiple access [3], [5]. In practice, the MU may fail to establish a dedicated link to the small network due to the limited spectrum resources or the relatively large distance to the AP, which introduces another type of channel randomness beyond channel fading in the conventional cellular system.

Another significant advantage enabled by the afront-mentioned HetNet is that the MU could potentially enjoy a longer lifetime since its power consumption is reduced by communicating with the local AP instead of the far away BS. However, since the lifetime of an MU is still limited by the stored energy in the batteries [7], the MU should seek an “active” way to recharge itself, especially in a green fashion. Such renewable energy powered nodes will play critical roles in the next generation wireless system, which is designed to be environment friendly and to support diversified applications such as machine-to-machine communications and Internet of things (IoT). A promising “self-charging” technology is energy harvesting (EH), which can efficiently convert certain renewable energy sources (e.g., solar, radiation, and vibration) to electric energy [3]. In this way, the MU could prolong the battery life almost infinitely, and fulfil the increasing demands of green systems [9]. Compared with the conventional constant power supply, such a renewable energy supply raises a new design constraint: The consumed energy up to any time should be bounded by the harvested energy until this point, which is named as the EH constraint [7].

In this paper, we study a simple uplink HetNet scenario depicted in Fig. 1, where each EH-based MU has an individual link, namely a private channel, to the large network BS for deterministic access. Moreover, a local AP of a small network offers a common channel, which is randomly shared by all nearby MUs. Here we consider a scenario that each MU could access the common channel with a certain
probability at each time slot. Thus, based on this multi-channel access setup, the MU could fulfil a transmission by using the harvested energy via either its private channel solely or via both the private and common channels simultaneously.

On the MU side, there are two types of state information that could be causally known before the transmission: the channel state information (CSI) of the links to the large network and the small network (if the AP was successfully occupied by the MU); and the energy state information (ESI), i.e., the EH rate (the harvested energy per unit time) at the MU. Therefore, the MU could decide when to start a transmission with both CSI and ESI at hand. Obviously, a longer time to probe those information may lead to a higher transmission power, a higher chance of good channel condition, and a higher likelihood to secure the common channel, while it may reduce the average effective throughput since the probing time is increased. Thus, this leaves us an interesting tradeoff to optimize: channel-energy probing time vs. transmission time. In addition, we consider a “save-then-transmit” scheme such that the transmission would consume all the harvested energy at the MU. This suboptimal power utilization scheme is able to maximize the instant transmit power such that the instant transmission rate is maximized, and is more tractable for the analysis as well.
B. Contributions

First, we propose an opportunistic transmission scheme for the multi-channel HetNet uplink powered by sustainable energy supplies, and aim to maximize the average throughput for each user by jointly exploiting the stochastic CSI and ESI. More precisely, the throughput maximization is cast as a “rate-of-return” optimal stopping problem. With Markovian private channel and EH models, the optimal stopping rule is shown to exist and have a state-dependent threshold-based structure with both finite and infinite battery capacities. The optimal throughput is shown to be strictly increasing over the access probability of the common channel.

Moreover, we study the case when the private channel gains and the EH rates are respectively independent and identically distributed (i.i.d.) across different communication blocks. The corresponding optimal stopping rule is proved to be a pure-threshold policy, i.e., the threshold does not change over time, which could be found via a one-dimension search. With such a fixed threshold, the mean delay (i.e., the mean probing time) is proved to be decreasing polynomially over the access probability of the common channel. We also show via simulations that the randomness of EH rates, termed “EH diversity”, influences the throughput performance and could be exploited by our proposed pure-threshold policy. Specifically, we find that the more dynamically the EH rate varies, the higher the average throughput that the MU could achieve.

Finally, we study the case with conventional constant power supplies, showing that the optimal power allocation has a “water-filling” structure, where the water level is jointly determined by the statistics of both the private and common channels, and the common channel access probability. For a practical setup, e.g., code-division multiple access (CDMA) based cellular networks [10], [11], we also study the channel inversion based transmission scheme where the receiving power is required to be constant: Different from the single channel access [10], our case reveals that jointly adjusting the receiving power levels at both the BS and local AP could achieve the maximum throughput under this inversion scheme.
C. Related Works and Organization

Most of existing works related to the uplink of heterogeneous cellular networks (HCNs) assume certain deterministic access control of the underlying small networks [3], [5], [12], [13]. From the views of both the femtocell owner and the overall network operator, authors in [5] evaluated the femtocell performance with open and restricted accesses. It was shown that with nonorthogonal (in terms of frequency or time) multiple access, i.e., CDMA, for mobile users, the open access benefits both the femtocell owner and the network operator; and for the orthogonal case, time-division multiple access (TDMA) or orthogonal frequency-division multiple access (OFDMA), the femtocell access control (open or restricted) is closely related to the user density. In [12], by adopting open access, the outage behaviors of both femtocell and macrocell users were analyzed by using the stochastic geometry to model the locations of both the femtocell APs and the cellular users. The authors also presented several interference avoidance methods to enhance the per-user capacity. In [13], each macrocell user was assumed one direct link to the macrocell BS, and one relay link to the femtocell AP. Playing a non-cooperative game against the others, each user could seek its preferred open-access femtocell and split the rates between the BS and the AP to maximize its own utility. In contrast to these existing works, here we consider users with random, not deterministic, access to the local AP, which is more realistic in WiFi based HetNets.

On the other hand, the study of wireless transmitters powered by renewable energy has also drawn a lot of attention in recent years. Particularly, with noncausal (i.e., offline) knowledge on energy arrival processes, the throughput maximization problem was investigated for both non-fading and fading channels in [7], [14], in addition to the classic three-node Gaussian relay channel [15]. With causal (i.e., online) knowledge, the optimal throughput in fading channels over finite-time horizons was obtained via dynamic programming techniques in [7], [14]. A save-then-transmit protocol was proposed in [16], where each communication block is divided into two parts: the first one for harvesting energy and the other for data transmission. In our paper, on the contrary, we consider the save-then-transmit strategy over infinite
number of communication blocks.

In some cases, wireless users may first potentially ask for more channel resources and then transmit. In [17], the authors discussed how a transmitter probes a relay channel with some additional time cost when its direct channel is undesirable. In addition, similar channel selection problems for WiFi and cognitive radio were investigated in [18] and [19], respectively. For [17]–[19], the key idea is that the sender may spend time on probing the channel quality before starting a transmission. We here adopt a similar idea; however, we need to face a different and more challenging scenario: Besides the large network channel quality, we also need to probe the resource availability in the small network, and the local battery status that is dynamic due to the energy arrival and withdrawal.

The remainder of this paper is organized as follows. The specific system model and the problem formulation are described in Section II. The throughput optimization problem is solved for both Markovian and i.i.d. models in Section III. The optimal power allocation and suboptimal channel inversion with traditional power supplies are discussed in Section IV. Numerical results are provided in Section V. Finally, Section VI concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

As shown in Fig. 1, an uplink HetNet communication scenario is considered: One private channel to the large network BS is assigned to each EH-based MU, and one common channel to a given small network AP is randomly accessed by all nearby users. All private and common channels are orthogonal in frequency, slotted equally in time, and synchronized. Moreover, an MU could access at most one local AP through the common channel in each slot, and if successful, the MU is required to release the common channel to the network at the end of this slot.

At the beginning of each time slot, an MU first obtains the CSI of the private channel through some
Fig. 2. A realization of the proposed multi-channel access system.

handshaking mechanism. Meanwhile, it could access to the common channel with probability $p_s$, called the *access probability*. If the MU secured the common channel, it then obtains the corresponding CSI. Here, the time for channel acquiring and estimation is negligible compared to the duration of each time slot. In addition, when entering a new time slot, each MU is assumed to know its ESI. Thus, based on the ESI and CSI, the MU decides between the following two operations:

1) transmit immediately during the current time slot via the private channel, or both the private and common channels as long as the common channel is secured; or

2) continue to probe the CSI and ESI for one more time slot, and release the common channel if it has been secured by the MU.

In Fig. 2, we show one realization of the probing and access process, in which two users are assigned with two private channels, respectively, and share one common channel. In particular, MU 1 transmits only through its private channel at time $T$ and MU 2 transmits via both its private and the common channel at time $K$.

Next, we introduce the channel model. Define an indicator $\phi$ following Bernoulli distribution such that $\phi = 0$ with probability (w.p.) $1 - p_s$ and $\phi = 1$ w.p. $p_s$, where $p_s$ is a constant. Thus, at time slot $t$, there are two cases:

- If $\phi_t = 0$, i.e., only the private channel is available, the received signal in the $t$-th time slot at the
BS is given by

\[ y_t = h_t \sqrt{P_t} x_t + z_t, \]  

(1)

where \( h_t \) is the channel gain from the MU to the BS, \( P_t \) is the transmit power over the private channel, \( x_t \) is the transmitted signal with zero mean and unit variance, and \( z_t \) is the circularly symmetric complex Gaussian (CSCG) noise with zero mean and unit variance. Define \( \{ H_t = |h_t|^2 \} \) on a state space \( \mathcal{H} \) with finite mean and variance.

- If \( \phi_t = 1 \), i.e., both the private and common channels are available, the received signal in the \( t \)-th time slot at the BS is the same as (1), and that at the AP is given by

\[ y^c_t = h^c_t \sqrt{P^c_t} x^c_t + z^c_t, \]  

(2)

where \( h^c_t \) is the channel gain from the MU to the AP, \( P^c_t \) is the transmit power over the common channel, \( x^c_t \) and \( z^c_t \) are defined similar as (1). Define \( \{ H^c_t = |h^c_t|^2 \} \) on a space \( \mathcal{H}_c \) with finite mean and variance.

Here, we assume that \( H_t \) follows a more general Markovian model [20] while \( H^c_t \) follows an i.i.d. model, due to the fact that the MU-to-BS link usually experiences a much longer distance such that the channel may be under correlated shadowing, while the MU-to-AP link does not, given its much shorter distance. Note that the CSI includes both \( H_t \) and \( H^c_t \).

In general, the energy used for data transmission is only a portion of the total harvested energy. If the hardware has a constant power consumption [16], it is reasonable and convenient to consider the “net” harvested energy for transmission usage, i.e., the total harvested energy subtracts a constant value. With such a simplification, we assume that the referred harvested energy is all used for data transmission, i.e., in our paper, the harvested energy is already the net harvested energy. We use \( \{ B_t \}_{t \geq 1} \) to denote the energy level at the battery for the considered MU at the beginning of time slot \( t \), and the energy level is
quantified into unit steps, i.e., \( B_t \in \mathcal{B} = \{0, \delta, 2\delta, \ldots, B_{\text{max}}\delta\} \), where \( \delta \) is the smallest energy unit, and \( B_{\text{max}} \) could be either a finite integer or infinity. For the case of \( B_{\text{max}} = +\infty \), it is a good approximation when the battery capacity is large enough compared with the EH rate, e.g., an AA-sized NiMH battery has a capacity of 7.7 kJ, which requires a couple of hours to be fully charged by some commercial solar panels [21]. During time slot \( t \), the MU can harvest \( E_t \) amount of energy. The sequence \( \{E_t\}_{t \geq 1} \) is modeled as a homogeneous Markov process. Due to hardware limitations, the EH rate is represented over a finite state space \( \mathcal{E} \subseteq \{E : E = k\delta, k \in \mathbb{N}\cup\{0\}\} \).

In addition, the MU works in a “save-then-transmit” pattern over multiple time slots: The MU is probing and harvesting simultaneously, and then uses up the total available energy in the battery for each transmission. Note that such a scheme has the nature of maximizing the instant transmit power, and is more reasonable for the low-EH-rate scenarios. Therefore, the available energy at the battery at the beginning of time slot \( t \) is given by:

\[
B_t = \min\left\{\sum_{i=0}^{t-1} E_i, B_{\text{max}}\delta\right\} \quad \text{for} \quad t \geq 1, \quad \text{and when} \quad t = 1, \quad \text{we set} \quad B_1 = 0.
\]

**B. Problem Formulation**

For simplification, denote the first time slot after one data transmission as the starting of a new save-then-transmit period, and let \( t = 1 \). We use Shannon capacity formula to represent the instant transmission rate \( R_t \) of the MU at time slot \( t \). Then, based on the above channel model and applying a joint decoder at the receivers, the rate \( R_t \) with unit bandwidth is expressed as

\[
R_t = \log (1 + H_t P_t) + \log (1 + \phi_t H_t^c P_t^c).
\]  

(3)

Due to the adopted save-then-transmit scheme, it is easy to see that \( P_t + \phi_t P_t^c = B_t \). When \( \phi_t = 0 \), it follows \( P_t = B_t \), since only the private channel is available; and when if \( \phi_t = 1 \), the power allocation follows the “water-filling” scheme given in the next lemma.
**Lemma 2.1:** When the MU can access both the private and common channels, i.e., $\phi_t = 1$, it is optimal to allocate power as follows:

- If $|\frac{1}{H_t} - \frac{1}{H_c} - B_t| < B_t$, we have that $P_t = \frac{1}{2} \left( B_t + \frac{1}{H_t} - \frac{1}{H_c} \right)$ and $P_c = \frac{1}{2} \left( B_t + \frac{1}{H_t} - \frac{1}{H_c} \right)$;
- If $|\frac{1}{H_t} - \frac{1}{H_c} - B_t| \geq B_t$ and $H_t > H_c$, we have $P_t = B_t$ and $P_c = 0$;
- If $|\frac{1}{H_t} - \frac{1}{H_c} - B_t| \geq B_t$ and $H_t < H_c$, we have $P_t = 0$ and $P_c = B_t$.

Lemma 2.1 can be proved by using standard convex optimization techniques and thus the proof is omitted for brevity. For notation simplicity, we define state of the MU, including CSI and ESI, at time $t$ as $F_t = \{\phi_t, B_t, E_{t-1}, H_t, H_c\} \in \mathcal{F} = \{0, 1\} \times B \times E \times H \times H_c$. In this way, $R_t = R(F_t)$ is uniquely determined by $F_t$.

If we let $T$ be some stopping rule, which indicates the time slot to stop probing and to start the transmission, the transmission rate at the time slot $T$ would be $R(F_T)$. Denote the duration of each time slot as $\tau$; and then the number of transmitted bits during this save-then-transmit period is $R(F_T)\tau$ and the length of this period is $T\tau$. If such a process repeats $L$ times and at each time, the MU starts with some fixed initial state $F_1 \in \mathcal{F}$, we obtain

$$\frac{\sum_{l=1}^{L} R(F_T)\tau}{\sum_{t=1}^{L} T\tau} \rightarrow \lambda_{F_1} = \frac{\mathbb{E}[R(F_T) | F_1]}{\mathbb{E}[T | F_1]}$$

almost surely (a.s.), as $L \rightarrow \infty$ by the renewal theory [22], where $\lambda_{F_1}$ is the average throughput per save-then-transmit period given that the initial state is $F_1$. Then, we define the maximum throughput $\lambda_{F_1}^*$ and the optimal stopping rule $T_{F_1}^*$ as

$$\lambda_{F_1}^* \triangleq \sup_{T \geq 1} \frac{\mathbb{E}[R(F_T) | F_1]}{\mathbb{E}[T | F_1]}, \quad T_{F_1}^* \triangleq \arg \sup_{T \geq 1} \frac{\mathbb{E}[R(F_T) | F_1]}{\mathbb{E}[T | F_1]}.$$  \hspace{1cm} (4)

In the next section, we will solve problem (4) to fine $T_{F_1}^*$ and $\lambda_{F_1}^*$. Note that if we could solve problem (4) for any fixed initial state $F_1$, we can deal with the general case of a randomly generated $F_1$, which will be discussed in the next section as well.
III. Optimal Stopping Rule and Throughput

The problem defined in (4) is a “rate-of-return” problem and could be converted into a standard optimal stopping problem \cite{23}, \cite{24}. For a certain \( \lambda > 0 \), we let \( G_T = R(F_T) - \lambda T \), and consider a new problem with some initial state \( F_1 \):

\[
\sup_{T \geq 1} \mathbb{E}[G_T | F_1].
\]  

(5)

The following lemma, which is directly from Theorem 1 of chapter 6 in \cite{24}, connects problems (4) and (5):

\textbf{Lemma 3.1:} i) If (4) holds, it follows that when \( \lambda = \lambda_{F_1}^* > 0 \), \( \sup_{T \geq 1} \mathbb{E}[G_T | F_1] = 0 \) and the supremum is attained at the same \( T_{F_1}^* \) in (4); and ii) conversely, if for some \( \lambda = \lambda_{F_1}^* > 0 \), \( \sup_{T \geq 1} \mathbb{E}[G_T | F_1] = 0 \) and it is attained by some \( T_{F_1}^* \), then (4) holds.

Therefore, we will focus on finding the optimal stopping rule \( T_{F_1}^* \) for problem (5) and \( \lambda = \lambda_{F_1}^* > 0 \) such that \( \sup_{T \geq 1} \mathbb{E}[G_T | F_1] = 0 \). In the rest of this section, we first solve problem (5) with Markovian private channel states and EH rates. Then, we consider the corresponding i.i.d. case.

A. Solutions for Markovian Case

Given some \( \lambda > 0 \), we define the remaining expected maximum reward starting at time \( t \) as

\[
V_t(F_t) = \sup_{T \in T_t} \mathbb{E}[R(F_T) - \lambda T | F_t],
\]  

(6)

where \( T_t = \{ T \geq t : \mathbb{E}[T] < \infty \} \). Under this interpretation, \( R(F_T) \) can be regarded as the offer at time \( T \), \( \lambda T \) is the cost, and \( G_T \) is the net reward. We let \( G_{\infty} = -\infty \) since it is irrational that a transmitter does not send any data forever. By replacing the set \( \{ t \geq 1 \} \) with \( T_t \), problem (5) is equivalent to \( V_1(F_1) \), i.e.,

\[
\sup_{T \in T_t} \mathbb{E}[G_T | F_1] = V_1(F_1).
\]  

(7)
Note that the optimal stopping rule $T^*_{F_1}$ is required to be finite a.s. If $T^*_{F_1} \notin \mathcal{T}_1$, we just claim that it does not exist. The following proposition shows the form of the optimal stopping rule, whose proof is given in Appendix A.

**Proposition 3.1:** Given the initial information $F_1 \in \mathcal{F}$, the optimal stopping rule for problem (7) exists with either $B_{\text{max}} < +\infty$ or $B_{\text{max}} = +\infty$. Moreover, it has the following form

$$T^*_{F_1} = \min \left\{ t \geq 1 : R(F_t) - \lambda^*_F = V_1(F_t) \right\}, \tag{8}$$

where

$$\lambda^*_F = \max \left\{ R(F_1), E[V_1(F_2) \mid F_1] \right\}. \tag{9}$$

**Remark 3.1:** It is observed from (8) that the optimal stopping rule is state-dependent and has a threshold-base structure with a parameter $\lambda^*_F$. The structure is derived based on the optimality equation [23], [24], or equivalently, the dynamic programming equation [25], [26]. From (9), we also observe that the optimal throughput depends on the initial $F_1$.

**Remark 3.2:** In practice, it is more reasonable to treat the initial state information $F_1$ as a random vector, i.e., $F_1$ is defined over the space $\mathcal{F}_1 \subseteq \mathcal{F}$ with a certain stationary distribution. Then, problem (4) becomes

$$\lambda^*_F \triangleq \sup_{T \in \mathcal{T}_1} \frac{E_{F_1}[E[R(F_T) \mid F_1]]}{E_{F_1}[E[T \mid F_1]]},$$

$$T^*_{F_1} \triangleq \arg \sup_{T \in \mathcal{T}_1} \frac{E_{F_1}[E[R(F_T) \mid F_1]]}{E_{F_1}[E[T \mid F_1]]},$$

where the outer expectation is taken over the stationary distribution of $F_1$ on space $\mathcal{F}_1$. By Lemma 3.1, we should find $\lambda^*_F$ such that $\sup_{T \in \mathcal{T}_1} E_{F_1}[E[G_T \mid F_1]] = 0$. By a similar argument to that for Proposition
the optimal stopping rule $T_{F_1}^*$ has the same form as (8), and the optimal throughput $\lambda_{F_1}^*$ is given as

$$\lambda_{F_1}^* = \mathbb{E}_{F_1} \left[ \max \{ R(F_1), \mathbb{E} [V_1(F_2) | F_1] \} \right].$$ (10)

Compared to $\lambda_{F_1}^*$ in (9), $\lambda_{F_1}^*$ is just the expected value of $\lambda_{F_1}^*$.

Moreover, the next proposition shows the strict monotonicity of the optimal throughput $\lambda_{F_1}^*$ over the access probability $p_s$, which implies that the common channel is helpful for sure in general.

**Proposition 3.2:** $\lambda_{F_1}^*$ is strictly increasing over $p_s$.

**Proof:** Please see Appendix B. \hfill \blacksquare

**B. Solutions for i.i.d. Case**

In this subsection, we focus on the case when $\{H_t\}_{t \geq 1}$ and $\{E_t\}_{t \geq 1}$ are both i.i.d., respectively. As a special case of the one studied in the previous subsection, the optimal stopping rule of this case still exists. Taking one step further, the corresponding optimal stopping rule is simplified to bear a pure-threshold structure.

**Proposition 3.3:** When $\{H_t\}_{t \geq 1}$ and $\{E_t\}_{t \geq 1}$ are i.i.d. with finite means and variances, respectively, the optimal stopping rule $T_{F_1}^*$ for problem (7) has the following form:

$$T_{F_1}^* = \min \{ t \geq 1 : R(F_t) \geq \gamma \}. $$ (11)

where $\gamma$ is a fixed real number.

The proof is given in Appendix C. Moreover, we note that the expected value of $T_{F_1}^*$ corresponds to the average length of the save-then-transmit period, i.e., the mean delay. The next proposition (proved in Appendix D) shows that for a fixed threshold, the delay performance is improved with the proposed multi-channel access.

**Proposition 3.4:** Given a fixed $\gamma > 0$, $\mathbb{E} [T_{F_1}^*]$ is decreasing polynomially over $p_s$. 
Following Proposition 3.3 and Lemma 3.1, we have

\[ 0 = V_1(F_1) = \sup_{T \in T_i} E[R(F_T) - \lambda^*_F, T \mid F_1] \]

\[ = E \left[ R \left( F_{T^*_F} \right) I \left( R(F_{T^*_F}) \geq \gamma \right) \mid F_1 \right] - \lambda^*_F, E[|T^*_F'] \mid F_1], \]

where \( I(\cdot) \) is the indicator function. Then, we obtain

\[ \lambda^*_F, = \max_{\gamma \geq 0} \frac{E \left[ R \left( F_{T^*_F} \right) I \left( R(F_{T^*_F}) \geq \gamma \right) \mid F_1 \right]}{E \left[ |T^*_F'| \mid F_1 \right]} . \] (12)

**Conjecture:** \( \lambda^*_F, \) is a quasi-concave function over \( \gamma \).

Our conjecture will be validated via numerical results in Section V. Such a conjecture provides us a guideline for adjusting \( \gamma \): if the throughput is getting smaller as \( \gamma \) increases, any larger \( \gamma \) will lead to a lower throughput. Thus, a simple searching method could be given as: Let \( \gamma \) increase from zero, and set a tolerant length as the increment for each step; the searching should stop at \( \gamma_0 \), where the next step after \( \gamma_0 \) indicates a lower throughput than that at \( \gamma_0 \); then the optimal \( \gamma \) is the one within \([0, \gamma_0]\) that achieves the maximum of \( \lambda \).

**Remark 3.3:** The i.i.d. system models result in the pure-threshold policy that could also work as a suboptimal scheme when EH rates behave as a Markovian process. Moreover, this pure-threshold policy is able to explore the “EH diversity”, which is built upon the randomness of EH rates with different transition probability matrices. Such diversity could result in the throughput improvement, which will be further discussed via simulations in Section V.

**IV. THROUGHPUT WITH CONSTANT POWER SUPPLY**

In this section, we investigate the throughput of the MU with a constant power supply (i.e., a conventional battery) in the discussed multi-channel access system, which will serve as performance benchmarks for our proposed schemes. Note that we only need to change the EH constraints into the average power...
constraints, and keep the same channel and access models as before.

Under a constant power supply, the MU does not need to work in a save-then-transmit cycle. Accordingly, now the target is to find the average throughput over the entire operation time. With the instant transmission rate $R_t$ given by (3), finding the optimal power allocation is equivalent to solving the following optimization problem:

$$\max_{P_t, P_t^c} \lim_{K \to \infty} \frac{1}{K} \sum_{t=1}^{K} \left( \log (1 + H_t P_t) + \log (1 + \phi_t H_t^c P_t^c) \right)$$

s.t. $$\lim_{K \to \infty} \frac{1}{K} \sum_{t=1}^{K} (P_t + \phi_t P_t^c) \leq B;$$

$$P_t, P_t^c \geq 0, \text{ for } t = 1, \ldots, K,$$  \hspace{1cm} (13)

where $B$ is the average power limit. In the following two subsections, we first find the optimal solution for problem (13); then we consider the channel inversion scheme which is commonly used in cellular networks.

A. Optimal Power Allocation

By applying a similar technique as in [10], we could solve problem (13) and obtain the optimal power allocation scheme as

$$P_t^* = \left( \frac{1}{\xi} - \frac{1}{H_t} \right)^+, \quad P_t^{c,*} = \left\{ \begin{array}{l} \left( \frac{1}{\xi} - \frac{1}{P_{t}^c} \right)^+, \quad \text{if } \phi_t = 1, \\ 0, \quad \text{if } \phi_t = 0, \end{array} \right.$$  \hspace{1cm} (14)

where $\xi$ satisfies

$$B = \int_{H \cap [\xi, +\infty)} \left( \frac{1}{\xi} - \frac{1}{x} \right) dF_{H_t}(x)$$

$$+ p_s \int_{H_c \cap [\xi, +\infty)} \left( \frac{1}{\xi} - \frac{1}{y} \right) dF_{H_c}(y).$$  \hspace{1cm} (15)
Note that the integral region for the private channel gain is \( \mathcal{H} \cap [\xi, +\infty) \) since \( H_t \in \mathcal{H} \) and \( H_t \) should be no smaller than \( \xi \). The integral region of the common channel power gain follows a similar argument.

Therefore, by taking (14) into the objective function of problem (13), the maximum MU throughput is given by

\[
C_{\text{max}} = \int_{\mathcal{H} \cap [\xi, +\infty)} \log \left( \frac{x}{\xi} \right) dF_H(x) \\
+ p_s \int_{\mathcal{H}_c \cap [\xi, +\infty)} \log \left( \frac{y}{\xi} \right) dF_{H_c}(y).
\]

The optimal solution is in a “water-filling” form similar to the optimal power allocation of the single fading channel case. However, the water level is jointly determined by the probability \( p_s \) and the statistics of both private and common channels. Next, we present one example on how to efficiently compute the water-level for some typical channel distributions.

**Example 4.1:** Suppose that \( H \) and \( H_c \) are i.i.d. with an exponential distribution of means \( 1/\eta \) and \( 1/\eta^c \), respectively. The water level \( \xi \) is obtained by solving the following equation:

\[
B + \int_{\xi}^{+\infty} \left( \frac{\eta}{x} e^{-\eta x} + \frac{p_s \eta^c}{x} e^{-\eta^c x} \right) dx = \frac{1}{\xi} \left( e^{-\eta \xi} + p_s e^{-\eta^c \xi} \right).
\]

Then, it is followed by the next lemma whose proof is given in Appendix E.

**Lemma 4.1:** There exists a unique \( \xi \) on \( \mathbb{R}^+ \) that makes (17) hold.

As such, the maximum of the throughput is given as

\[
C_{\text{max}} = \int_{\xi}^{+\infty} \left( \log \left( \frac{x}{\xi} \right) \frac{\eta}{x} e^{-\eta x} dx + \log \left( \frac{y}{\xi} \right) \frac{p_s \eta^c}{y} e^{-\eta^c y} dy \right).
\]

Since \( \xi \) is determined by \( p_s \), it is hard to figure out how the maximum throughput \( C_{\text{max}} \) given in
either (16) or (18) behaves as \( p_s \) changes. Intuitively, \( C_{\text{max}} \) should be strictly increasing over \( p_s \) due to the benefit of the proposed multi-channel access scheme, which will be verified numerically in Section V.

**B. Channel Inversion**

Now, we consider the channel inversion scheme that is common in a spread-spectrum system such as the CDMA-based cellular network, where the signal received at the BS is always required to be at a constant level \[10, 11\]. Suppose that the power of the received signal over the private channel is required to be at least \( \alpha = H_t P_t \), and that over the common channel is required to be at least \( \beta = H_c P_c \) for \( 1 \leq t \leq K \). In this case, the transmit power should adapt according to the channel inversion, i.e., \( P_t = \alpha / H_t \) and \( P_c^\phi = \beta / H_c^\phi \) when \( \phi_t = 1 \), otherwise \( P_c^\phi = 0 \). Due to the power constraint at the transmitter side, \( \alpha \) and \( \beta \) should satisfy

\[
B = \int_{H} \frac{\alpha}{x} dF_H(x) + p_s \int_{H_c} \frac{\beta}{y} dF_{H_c}(y) \nonumber
\]

\[
= \alpha E\left[\frac{1}{H}\right] + \beta E\left[p_s H_c\right].
\]

Thus, instead of optimizing the transmit power to maximize the throughput of the MU, we could adjust the received power levels \( \alpha \) and \( \beta \) based on the channel statistic information, and find the maximum of the MU throughout by solving the following convex optimization problem:

\[
C_{\text{inver}} = \max_{\alpha, \beta} \left( \log \left(1 + \alpha \right) + p_s \log \left(1 + \beta \right) \right), \quad (19)
\]

for which the optimal solution is given as:

- if \( p_s = 0 \), \( \alpha^* = \frac{B}{E\left[\frac{1}{H}\right]} \) and \( \beta^* = 0 \);
• if $0 < p_s \leq 1$, we have

\[
\begin{align*}
\alpha^* &= \left( \frac{1}{\xi \mathbb{E}[\frac{1}{H}]} \ln 2 - 1 \right)^+; \\
\beta^* &= \left( \frac{1}{\xi \mathbb{E}[\frac{1}{H_c}]} \ln 2 - 1 \right)^+,
\end{align*}
\]

(20)

where $\xi$ satisfies the equation

\[
B = \left( \frac{1}{\xi} - \mathbb{E}\left[\frac{1}{H}\right]\right)^+ + p_s \left( \frac{1}{\xi} - \mathbb{E}\left[\frac{1}{H_c}\right]\right)^+.
\]

(21)

Remark 4.1: Different from the single fading channel case (i.e., $p_s = 0$ [10], if multi-channel access is available, the receiver side has the freedom to adjust the required receive power at different receivers based on a water level of $1/\xi$, which is jointly determined by the channel statistics and the access probability. Thus, the overall achievable throughout of the MU could be maximized with the optimal $\alpha^*$ and $\beta^*$ given in (20).

We observe from (19) that $C_{\text{inver}}$ may be increasing over $p_s$. However, when $0 < p_s \leq 1$, (20) also implies that the optimal $\alpha^*$ and $\beta^*$ are determined by $\xi$, which could be regarded as a function of $p_s$ and uniquely obtained from (21). Thus, the relationship between $C_{\text{inver}}$ and $p_s$ is not that straightforward. To better understand their relationship, we consider an interesting example below.

Example 4.2: Suppose that $\mu = \mathbb{E}\left[\frac{1}{H}\right] = \mathbb{E}\left[\frac{1}{H_c}\right] > 0$. By the result above, when $p_s = 0$, we have $\alpha^* = \frac{B}{\mu}$; when $0 < p_s \leq 1$, we have $\alpha = \beta = \frac{B}{\mu(1 + p_s)}$ by (20) and (21). It follows that the maximum throughput is given as

\[
C_{\text{inver}} = (1 + p_s) \log \left( 1 + \frac{B}{\mu(1 + p_s)} \right),
\]

(22)

where $p_s \in [0, 1]$. Then, we have the following proposition whose proof is given in Appendix F.

Proposition 4.1: $C_{\text{inver}}$ given by (22) is strictly increasing and concave over $p_s$ for all $\frac{B}{\mu} \in (0, +\infty)$.

Remark 4.2: So far, we have considered the opportunistic transmission scheme for EH-based MUs, and the optimal power allocation and channel inversion schemes for conventional MUs. In general, the
respective throughputs are strictly increasing over the access probability $p_s$, which proves the benefits of exploring the multi-channel access.

V. NUMERICAL RESULTS

In this section, we present some numerical results to validate our analysis. In the simulation, the length of each time slot is 1 ms and the energy step is set to be $\delta = 10^{-3}$ J.

A. Markovian Private Channel Gains

First, we consider the renewable energy supply at the MU with the time-correlated private channel, which corresponds to Section III-A. Here, we use a simple model to illustrate. The capacity of the battery is $B_{\text{max}} = 1$ and the EH rate is $E_t = \delta$, which is equivalent to $B_t = \delta$ for all $t \geq 1$. The common channel is static with a constant power gain $H_c^c = 2^5$ for $t \geq 1$. The gain of the private channel has two states $\{0.1, 2^4\}$ with transition probability 1 from state 0.1 to $2^4$ and probability 0.5 from state $2^4$ to 0.1. As a comparison, we choose the method of best-effort delivery [29], i.e., the transmitter keeps transmitting in each time slot without any channel-energy probing. With the best-effort delivery, the MU
will transmit when the private channel is at state 0.1, even though the MU knows that the channel will change into state $2^4$ for sure in the next time slot.

In Fig. 3, we show the optimal average throughput $\lambda^*$ with the opportunistic scheme proposed in Section III-A under the impact of access probability $p_s$. We let $\lambda_0$ be the average throughput under the method of best-effort delivery. First, we observe that the throughput increases as $p_s$ increases, which agrees with Proposition 3.2. Second, $\lambda^*$ is higher than $\lambda_0$ when $0 \leq p_s < 1$. It agrees with our intuition that when the transmitter experiences a bad channel ($H_t = 0.1$), it skips the transmission immediately and seeks for a better channel state, which leads to a higher average throughput. Third, $\lambda^*$ and $\lambda_0$ are the same at $p_s = 1$. Since the transmitter is able to deterministically access the common channel in this case, and the transmission rate will not be harmed even though the private channel is bad. Thus, the transmitter does not need to skip any transmission, which results in the same average throughput. It also implies that only when the difference of the rewards between the good and bad channel conditions is large enough, does the opportunistic scheme perform significantly better.

**B. I.I.D. Private Channel Gains**

Next, we show some simulation results related to Section III-B. We apply a two-state EH model (similar to that in [28]), where the EH rate can be either zero (“BAD”) or $4\delta$ (“GOOD”) with probability 0.5 for each state. The channel gains in either the private or the common channel are i.i.d. following an exponential distribution with unit mean. In addition, in order to obtain smoother curves to observe, we allow the transmitter to keep harvesting energy during transmissions (i.e., full duplex energy operation).

In Fig. 4, we show how the threshold $\gamma$ influences the average throughput with different access probability $p_s$. We observe that the average throughput could be optimized by adjusting the threshold $\gamma$, which validates the results in [12] and our conjecture in Section III-B. In addition, the optimal throughput $\lambda^*$ is always greater than $\lambda_0$, and the throughput gain is approximately $10\% \sim 20\%$. 
Fig. 4. Average throughput vs. threshold $\gamma$.

Fig. 5. Mean delay vs. probability $p_s$.

We also show how the mean delay varies over the access probability $p_s$ in Fig. 5. Since the optimal threshold is different when $p_s$ changes, we choose two typical values for comparison: $\gamma = 1.5$, which is optimal for $p_s = 0$; and $\gamma = 2$, which is optimal for $p_s = 0.5, 0.75, 1$ based on our results in Fig. 4. For either $\gamma = 1.5$ or $\gamma = 2$, we observe from Fig. 5 that the mean delay decreases as $p_s$ increases, which agrees with Proposition 3.4. The mean delay with the optimal $\gamma$ is roughly increasing over $[0, 0.5]$ and decreasing over $[0.5, 1]$. Our intuition is that the multi-channel access setup is with the most uncertainty
when $p_s = 0.5$, such that the transmitter may need more time to spend on channel-energy probing.

The throughput performance of the MU with different power supplies and transmission schemes is shown in Fig. 6. Note that we have four schemes in total: With the renewable energy supply, we have the proposed opportunistic transmission scheme and the best-effort delivery; with the constant energy supply, we have the “water-filling” allocation and channel inversion schemes. To make them comparable, we assume that the average power constraint for the conventional MU is 2 W. Also, since the opportunistic transmission scheme maximizes the throughput per transmission, we also present the throughput per transmission for the “water-filling” scheme, rather the average transmission rate of all time. The EH-based transmitter with the opportunistic transmission scheme could only achieve about 70% of the throughput with the optimal power allocation, which is mainly caused by the following facts. The EH-based transmitter spends a certain amount of time on channel-energy probing and greedily uses all stored energy at one time. The channel inversion scheme suffers from the throughput penalty when $E[\frac{1}{P}]$ and $E[\frac{1}{H}]$ are large (e.g., Rayleigh fading in our simulations), which is even worse than the EH-based MU with the opportunistic scheme or the best-effort delivery method.
C. EH Diversity

Finally, we want to show the existence of EH diversity and the proposed opportunistic scheme is able to explore this type of diversity. For better illustration, we focus on the pure-threshold policy discussed in Section III-B. The access probability is set to be 0.5. The Markovian EH model (a) in Fig. 7 is the benchmark, which is equivalent to an i.i.d. EH model with probability 0.5 to be either “GOOD” or “BAD”. To compare, we choose EH models (b) and (c) as shown in Fig. 7 which have the same stationary distribution as that of model (a), while bearing different “randomness”: Model (b) changes from one state to the other with a higher frequency compared with model (a), and model (c) changes...
with a lower frequency such that the EH rate is likely to stay in one state and rarely change over time. In addition, we also consider model (d), which represents the case that the EH rate has a higher stationary probability to be “GOOD”.

In Fig. 8, we show the average throughput over different threshold values for the four EH models with the pure-threshold opportunistic scheme depicted in Fig. 7. We first observe that for both Markov and i.i.d. EH rates, the pure-threshold stopping rule is able to exploit the channel and energy conditions such that the throughput could be improved. Second, EH model (d) achieves the highest throughput, since model (d) has the largest stationary probability for the EH rate to be in the “GOOD” state. Third, we observe the throughput differences across EH models (a), (b) and (c). When $\gamma = 0$, these three models lead to the same throughput performance, for $\gamma = 0$ implies that the opportunistic transmission scheme is not applied such that the average throughput is mainly determined by the stationary characteristics. When $\gamma$ increases until the optimal value that leads to the maximum average throughput, we observe that the EH model (b) could make the transmitter achieve a slightly higher throughput than model (a). Similarly, model (a) is able to achieve a higher throughput than that of model (c). Note that among models (a), (b) and (c), EH model (b) is more likely to shift from one state to the other, while model (c) is likely to keep staying in either “BAD” or “GOOD” state. The EH model (a) behaves in between. The observation is that when the EH rate varies in a more dramatic way, it has larger randomness, where we could claim a higher EH diversity. Accordingly, our proposed opportunistic scheme would take advantage of such EH diversity by exploiting the EH variation, where the transmitter could opportunistically wait or start the transmission depending on the energy state.

VI. CONCLUSION

In this paper, we considered a HetNet uplink with multi-channel access, where each EH-powered MU has deterministic access to a private channel linked to the cellular BS, and random access to a
common channel linked to a local AP. As such, the MU could fulfil a transmission via its private channel or both private and common channels. By jointly taking advantage of channel-energy variation and common channel sharing, we proposed an opportunistic transmission scheme that allows the transmitter to properly probe the channel-energy state, such that the average transmission rate is maximized. In particular, we formulated the average throughput maximization problem as an optimal stopping problem of rate-of-return. By applying the optimal stopping theory, we proved that the optimal stopping rule exists and has a state-dependent and threshold-based structure in general. Moreover, when the private channel gains and EH rates are i.i.d., respectively, the optimal stopping rule turned out to be a simple pure-threshold policy. We also found the optimal power allocation scheme for the transmitter powered by a conventional power supply, to serve as performance benchmarks. Numerical results validated the analysis with both Markovian and i.i.d. statistical models for the private channel gains and EH rates. We showed that under the renewable energy supply, the proposed opportunistic transmission scheme could achieve a higher throughput than the method of best-effort delivery. Also, our simulation results revealed the throughput gap between the conventional and renewable energy supplies. Furthermore, the EH diversity was discussed, which could be explored by the proposed pure-threshold policy such that the throughput performance could be further enhanced.

APPENDICES

A. Proof of Proposition 3.1

According to the optimal stopping theory \cite{23,24}, the existence of the optimal stopping rule could be proved by checking the following two conditions: For a given \( \lambda > 0 \),

\[
\text{C1: } \mathbb{E} \left[ \sup_{T \geq 1} G_T \mid F_1 \right] < \infty;
\]

\[
\text{C2: } \limsup_{T \to \infty} G_T < G_\infty = -\infty \text{ a.s.}
\]

We first check C1 and C2 for \( B_{max} < +\infty \) and \( B_{max} = +\infty \), respectively.
• $B_{\text{max}} < +\infty$: For C1, we have $\sup_{T \geq 1} G_T \leq \sup_{T \geq 1} R(F_T)$. Since the channel gains are finite a.s., and the battery capacity is finite, the expectation of the transmission rate is finite as well, which proves that C1 holds. For C2, we only need to show that for any large negative real number $\nu < 0$, there exists a $K \geq 0$ a.s. such that for all $T \geq K$, $G_T = R(F_T) - \lambda T < \nu$. In fact, for any $T$, $E[R(F_T)] < \infty$, which implies that $\mathbb{P}\{R(F_T) = \infty\} = 0$. However, the term $\lambda T$ will increase to infinity as $T \to \infty$. Thus, when $T \geq K$, $R(F_T) - \lambda T$ can be as small as we want a.s., i.e., $R(F_T) - \lambda T < \nu$ a.s., which proves that C2 holds.

• $B_{\text{max}} = +\infty$: For this case, we check C2 first. Recall the expression of $R(F_T)$ in (3), we have

$$
R(F_T) - \lambda T \\
\leq \log \left( \frac{1 + H_T B_T}{2\lambda T/2} \right) + \log \left( \frac{1 + H_T \phi_T B_T}{2\lambda T/2} \right) \\
\leq \log \left( \frac{1 + H_T E_{\text{max}} T}{2\lambda T/2} \right) + \log \left( \frac{1 + H_T \phi_T E_{\text{max}} T}{2\lambda T/2} \right).
$$

(23)

By noticing the maximum EH rate $E_{\text{max}} < +\infty$ and using L’Hôpital’s rule [30], the first term in (23) satisfies

$$
\lim_{T \to \infty} \frac{1 + H_T E_{\text{max}} T}{2\lambda T/2} = \lim_{T \to \infty} \frac{H_T E_{\text{max}}}{\lambda \ln 2} = 0.
$$

We could apply a similar check for the second term of (23). Thus, C2 holds. For C1, we could use the above results of C2 and obtain that $\forall \epsilon > 0$, there exists an $N > 0$ such that $\mathbb{E}[\sup_{T \geq 1} G_T | F_1] < \mathbb{E}[\sup_{1 \leq T \leq N} (R(F_T) - \lambda T) | F_1] + \epsilon$. Since the channel gains are finite a.s., and for all $1 \leq T \leq N$, $E[B_T] = E\left[\sum_{t=1}^{T-1} E_t\right] < \infty$, we obtain $\mathbb{E}[\sup_{1 \leq T \leq N} (R(F_T) - \lambda T) | F_1] < \infty$, which implies that C1 holds.

Therefore, both C1 and C2 hold for either $B_{\text{max}} < +\infty$ or $B_{\text{max}} = +\infty$, which implies that the optimal stopping rule exists.
Next, we derive the optimal stopping rule. Consider the remaining maximum expected reward \( V_t(F_t) \) given by (6), which is further rewritten as

\[
V_t(F_t) = \sup_{T \in T_t} \mathbb{E}[R(F_T) - \lambda(T - (t - 1)) \mid F_t] - \lambda(t - 1)
\]

\[
= \sup_{T \in T_t} \mathbb{E}[R(F_T) - \lambda T] - \lambda(t - 1)
\]

\[
= V_1(F_t) - \lambda(t - 1).
\]  

(24)

Meanwhile, \( V_t(F_t) \) satisfies the dynamic programming equation [25], [26]:

\[
V_t(F_t) = \max \{ R(F_t) - \lambda t, \mathbb{E}[V_{t+1}(F_{t+1}) \mid F_t] \}.
\]  

(25)

Therefore, the optimal stopping rule has the following form

\[
T_{F_1}^* = \min \{ t \geq 1 : R(F_t) - \lambda t = V_t(F_t) \}
\]

\[
= \min \{ t \geq 1 : R(F_t) - \lambda t = V_1(F_t) - \lambda(t - 1) \}
\]

\[
= \min \{ t \geq 1 : R(F_t) - \lambda = V_1(F_t) \},
\]

where the second equation holds due to (24). By letting \( \lambda = \lambda_{F_1}^* \), we obtain the form of \( T_{F_1}^* \) as shown in (8).

Finally, we compute \( \lambda_{F_1}^* \). By Lemma 3.1, \( \lambda_{F_1}^* \) makes the following equation hold:

\[
0 = \sup_{T \in T_t} \mathbb{E}[G_T \mid F_1] = V_1(F_1)
\]

\[
= \max \{ R(F_1) - \lambda_{F_1}^*, \mathbb{E}[V_2(F_2) \mid F_1] \}
\]

\[
= \max \{ R(F_1) - \lambda_{F_1}^*, -\lambda_{F_1}^* + \mathbb{E}[V_1(F_2) \mid F_1] \}.
\]

Thus, we could obtain \( \lambda_{F_1}^* \) by some simple rearrangements.
B. Proof of Proposition 3.2

Recalling Proposition 3.1 and Remark 3.2 that the optimal stopping rule $T^*_F$ has the same form as (8) and thus is finite a.s.. Then, given some $\epsilon > 0$, there exists an $M \geq 2$ such that for all $t \geq M$, we have $\mathbb{P}(T^*_F = t) < \epsilon$. Therefore, when we consider the expected value of $V_1(F)$ (defined in (7)), we could just focus on a finite horizon, i.e., $1 \leq t \leq M$. Then, by the dynamic programming algorithm [24]–[26], we have

$$V_1(F_t) = \max \{R(F_t), \mathbb{E}[V_1(F_{t+1}) | F_t] - \lambda^*_F\}, \text{ for } t = 1, 2, \ldots, M - 1$$

$$V_1(F_M) = R(F_M) - \lambda^*_F.$$ 

Now, we show that $\lambda^*_F$ is strictly increasing over $p_s$ by contradiction. First, we fix $\lambda^*_F$, and let $p_s$ increase to $p_s + \Delta$, where $\Delta$ is a small positive real number. Then, we move backward. Note that at step $t = M$, $V_1(F_M)$ only depends on $F_M$ and does not change with $p_s$. At $t = M - 1$, we observe that

$$\mathbb{E}[V_1(F_M) | F_{M-1}] = (p_s + \Delta)\mathbb{E}[R(H_M, H_M^c) - R(H_M, 0) | F_{M-1}] + \mathbb{E}[R(H_M, 0) | F_{M-1}] - \lambda^*_F.$$ 

Note that the private channel could not be strictly better than the common channel [3], i.e., it is unrealistic that $\min_{H_M \in \mathcal{H}} H_M > \max_{H_M \in \mathcal{H}} H_M^c$. It follows that $\mathbb{E}[R(H_M, H_M^c) - R(H_M, 0) | F_{M-1}] > 0$. Thus, we have that $\mathbb{E}[R(F_M) - \lambda^*_F | F_{M-1}]$ strictly increases as $p_s$ increases to $p_s + \Delta$.

Suppose that at $t = k$ for $2 \leq k \leq M - 1$, $\mathbb{E}[V_1(F_{k+1}) | F_k]$ strictly increases as $p_s$ increases to $p_s + \Delta$. Since the expected value of $R(F_k)$ also strictly increases following a similar argument as we discussed at step $t = M - 1$, we have that the expected value of $\max \{R(F_k), \mathbb{E}[V_1(F_{k+1}) | F_k]\}$ strictly
increases. Then, at \( t = k - 1 \), we have

\[
\mathbb{E} \left[ V_1(F_k) \mid F_{k-1} \right] = \mathbb{E} \left[ \max \{ R(F_k), \mathbb{E} \left[ V_1(F_{k+1}) \mid F_k \right] \} \mid F_{k-1} \right] - \lambda^*_F,
\]

which strictly increases and thus implies that such an increment holds for all \( t = 1, 2, \ldots, M - 1 \).

At the step \( t = 1 \), we have

\[
\mathbb{E}[V_1(F_1)] = \mathbb{E} [ \max \{ R(F_1), \mathbb{E} [ V_1(F_2) \mid F_1] \} ] - \lambda^*_F,
\]

where \( \mathbb{E} [ \max \{ R(F_1), \mathbb{E} [ V_1(F_2) \mid F_1] \} ] \) should also strictly increase as \( p_s \) increase to \( p_s + \Delta \). However, we recall from Proposition 3.1 and Remark 3.2 that \( \mathbb{E}[V_1(F_1)] = 0 \), which is attained by \( T^*_F \) and \( \lambda^*_F \).

It implies that in order to make \( \mathbb{E}[V_1(F_1)] = 0 \), the value \( \lambda^*_F \) should not be fixed and must strictly increase accordingly, which contradicts the assumption in the first step that \( \lambda^*_F \) is fixed. Thus, \( \lambda^*_F \) strictly increases as \( p_s \) increases. Finally, this proposition is proved by letting \( \epsilon \to 0 \) (i.e., \( M \) is large enough).

C. Proof of Proposition 3.3

Since the optimal stopping rule is given by (8) based on Proposition 3.1 we could further rearrange the rule as

\[
T^*_F = \inf \{ t \geq 1 : V_1(F_t) - R(F_t) + \lambda^*_F = 0 \}
= \inf \{ t \geq 1 : \Lambda(F_t) = 0 \}.
\]

The function \( \Lambda(\cdot) \) is defined by \( \Lambda(F_t) = V_1(F_t) - R(F_t) + \lambda^*_F \), where \( F_t = \{ \phi_t, B_t, E_{t-1}, H_t, H^c_t \} \in \mathcal{F} \).

The following properties of \( \Lambda(F_t) \) play a key role in the proof of this proposition:

1) \( \Lambda(F_t) \geq 0 \) for all \( F_t \);
2) $\mathbb{E}[\Lambda(F_t) \mid B_t] < +\infty$ for all $B_t \geq 0$. Moreover, $\mathbb{E}[\Lambda(F_t) \mid B_t] = 0$ when $B_t$ is large enough;

3) $\mathbb{E}[\Lambda(F_{t+1}) \mid F_t] < +\infty$ for all $B_t \geq 0$. Moreover, $\mathbb{E}[\Lambda(F_{t+1}) \mid F_t] = 0$ when $B_t$ is large enough;

4) $\Lambda(F_t) = 0$ when $R(F_t)$ is large enough.

If all the above properties are true, it follows that $\forall \epsilon > 0$, there exists $\gamma \geq 0$ such that $\Lambda(F_t) \leq \epsilon$ whenever $R(F_t) > \gamma$, which implies that the stopping rule $T^*_F$ has the form given by (11) (similar to the technique used in [23]). In the following, we prove the four properties.

For Property 1), it is straightforward to see that

$$\Lambda(F_t) = V_1(F_t) - R(F_t) + \lambda^*_F,$$

$$= \max \{ R(F_t) - \lambda^*_F, -\lambda^*_F + \mathbb{E}[V_1(F_{t+1}) \mid F_t] \} - R(F_t) + \lambda^*_F,$$

$$= \max \{ 0, \mathbb{E}[V_1(F_{t+1}) \mid F_t] - R(F_t) \} \geq 0. \quad (28)$$

For Property 2), suppose that the transmitter does not stop channel-energy probing until time $t$; then starting at $t$, we should have $T \in T_t = \{ T \geq t : \mathbb{E}[T] < \infty \}$. Thus, $\mathbb{E}[\Lambda(F_t) \mid B_t]$ could be written as

$$\mathbb{E}[\Lambda(F_t) \mid B_t] = \sum_{n \geq t} P(T = n) \mathbb{E}[\Lambda(F_t) \mid B_t, T = n] < \infty,$$

due to $\mathbb{P}(T = +\infty) = 0$. Then, with a fixed $T = n$ such that $t \leq n < \infty$, along with Property 1), $\mathbb{E}[\Lambda(F_t) \mid B_t, n]$ is expanded as

$$0 \leq \mathbb{E}[\Lambda(F_t) \mid B_t, n]$$

$$= \mathbb{E} \left[ R(F_n) - R(F_t) - \lambda^*_F n \mid B_t \right] + \lambda^*_F,$$

$$\leq (1 - p_s) \mathbb{E} \left[ \log \left( \frac{1 + HB_n}{1 + HB_t} \right) \right]$$

$$+ p_s \left( \mathbb{E} \left[ \log \left( \frac{1 + HP_n}{1 + HP_t} \right) + \log \left( \frac{1 + H^cP^c_n}{1 + H^cP^c_t} \right) \right] \right), \quad (29)$$

$$(30)$$
where the second inequality holds due to $-\lambda_{F,1}^* n + \lambda_{F,1}^* \leq 0$ for $n \geq t$. Note that we do not put the time index $n$ on $H$ and $H^c$ since $\{H_t\}_{t \geq 1}$ and $\{H_t^c\}_{t \geq 1}$ are i.i.d., respectively. Next, we want to show that both (29) and (30) are finite and could be as small as we want with a large $B_t$, which would complete the proof for 2).

• For (29): by plugging $B_n = B_t + \sum_{j=t}^{n-1} E_j$, we obtain

$$\text{[29]} = (1 - p_s) \mathbb{E} \left[ \log \left( 1 + \frac{H \sum_{j=t}^{n-1} E_j}{1 + HB_t} \right) \right] < +\infty$$

since $H$ has finite mean and $\{E_j\}_{t \leq j \leq n-1}$ are i.i.d. with finite mean as well. Moreover, if $B_t \to \infty$, (29) $\to 0$.

• For (30): Since $P_n + P_n^c = B_n = B_t + \sum_{j=t}^{n-1} E_j$, and both $H$ and $H^c$ have finite means, respectively, it follows that (30) is finite. When the transmitter occupies the common channel at time $T \geq t$, there are three possible events by Lemma 2.1: If $\left| \frac{1}{H^c} - \frac{1}{H} \right| \geq B_n$, allocating all power to one of the two channels; otherwise, allocating the power to both channels at a certain ratio. Note that the probability of any above event happening does not depend on $n$ if $B_t$ is large enough. To see this point, we let $Q = \mathbb{P} (\left| \frac{1}{H^c} - \frac{1}{H} \right| < B_t)$, $q_1 = \mathbb{P} (\left| \frac{1}{H^c} - \frac{1}{H} \right| \geq B_t, H > H^c)$, and $q_2 = \mathbb{P} (\left| \frac{1}{H^c} - \frac{1}{H} \right| \geq B_t, H < H^c)$. When $B_t$ is large, there is

$$\mathbb{P} \left( \left| \frac{1}{H^c} - \frac{1}{H} \right| < B_t + \sum_{j=t}^{n-1} E_j \right) \approx Q,$$

and similarly, we have $\mathbb{P} (\left| \frac{1}{H^c} - \frac{1}{H} \right| \geq B_n, H > H^c) \approx q_1$, $\mathbb{P} (\left| \frac{1}{H^c} - \frac{1}{H} \right| \geq B_n, H < H^c) \approx q_2$. 
Then, by applying $Q$, $q_1$ and $q_2$, we can expand (30) as

$$
(30) \approx p_s q_1 E \left[ \log \left( \frac{1 + H \B_n}{1 + h \B_t} \right) \right] + q_2 E \left[ \log \left( \frac{1 + H^c \B_n}{1 + h^c \B_t} \right) \right] + p_s Q E \left[ \log \left( \frac{1 + H \B_n + H^c \B_n}{1 + H \B_n + H^c \B_n} \right) \right].
$$

Similarly as the reasoning in (29), we obtain that (30) → 0 as $B_t → ∞$.

Therefore, we conclude that $E[Λ(F_t + 1) | B_t]$ is finite and could be arbitrarily small when $B_t$ is large enough.

For 3), we expend $E[Λ(F_t+1) | F_t]$ as

$$
E[Λ(F_t+1) | F_t] = E[Λ(F_{t+1}) | B_t] = \sum_{e \in \mathcal{E}} P(E_t = e)E[Λ(F_{t+1}) | B_{t+1} = B_t + e],
$$

since only $B_t$ is correlated over time. By Property 2), we know $E[Λ(F_{t+1}) | B_{t+1} = B_t + e]$ is finite and thus $E[Λ(F_{t+1}) | F_t]$ is finite since $\mathcal{E}$ is a finite space. Moreover, by Property 2), we have $E[Λ(F_{t+1}) | B_{t+1} = B_t + e] → 0$ as $B_t → ∞$. Therefore, it follows that $E[Λ(F_{t+1}) | F_t]$ could be as small as we want when $B_t$ is large enough.

By now, we are ready to show Property 4). We could rewrite (28) as

$$
Λ(F_t) = \max \{0, E[V_1(F_{t+1}) | F_t] - R(F_t)\}
$$

$$
= \max \{0, E[Λ(F_{t+1}) + R(F_{t+1}) - λ^*_{F_t} | F_t] - R(F_t)\}.
$$

Next, we show Property 4) by contradiction. Suppose that $Λ(F_t) > 0$ for all $R(F_t) ≥ 0$, then we have

$$
E[Λ(F_{t+1}) + R(F_{t+1}) | F_t] > R(F_t) + λ^*_{F_t}.
$$

(31)
For the left-hand side (LHS) of (31), \( \mathbb{E} [R(F_{t+1}) \mid F_t] \) is finite for any fixed \( B_t \), and \( \mathbb{E} [\Lambda(F_{t+1}) \mid F_t] \) is either a finite number or an arbitrarily small positive number if \( B_t \) is large enough. Then, we choose \( K < +\infty \) and \( B_t = B_{\text{max}} \) such that the LHS of (31) is upper-bounded by \( K \). With such \( K \) and \( B_t \), we have

\[
K > \mathbb{E} [\Lambda(F_{t+1}) + R(F_{t+1}) \mid F_t] > R(F_t) + \lambda^*_{F_1}.
\] (32)

However, for the right-hand side (RHS) of (31) with the same \( B_t \), \( R(F_t) \) could be arbitrarily large if \( H_t \) and \( H^c_t \) are large enough. Then, there always exists an \( M > 0 \) such that when \( H_t, H^c_t > M \), \( R(F_t) > K \), which leads to the contradiction with the inequality (32). Therefore, we obtain that \( \Lambda(F_t) = 0 \) when \( R(F_t) \) is large enough.

Overall, we have shown that all four properties hold, and we conclude that the optimal stopping rule has a pure-threshold structure given by (11).

D. Proof of Proposition 3.4

Given some \( \gamma > 0 \), we let \( q_t(p_s) = \mathbb{P} (R(H_t, \phi_t H^c_t) \geq \gamma) \). Based on the form of the stopping rule \( T_{F_1}^* \) given by (11), we obtain

\[
\mathbb{E} [T_{F_1}^*] = q_1(p_s) + \sum_{t=2}^{\infty} t q_t(p_s) \prod_{n=1}^{t-1} (1 - q_n(p_s)).
\]

Since \( \mathbb{E} [T_{F_1}^*] < \infty \), it follows that \( \forall \epsilon, \epsilon_0 > 0 \), there exists \( N > 0 \) such that \( \mathbb{P} (T_{F_1}^* = t) = q_t(p_s) \prod_{n=1}^{t-1} (1 - q_n(p_s)) < \epsilon \) for all \( t \geq N \), and \( \sum_{t=N}^{\infty} t q_t(p_s) \prod_{n=1}^{t-1} (1 - q_n(p_s)) < \epsilon_0 \). Note that the generality still holds
to let $q_N(p_s) = \epsilon$ since $\mathbb{P}(T^{*}_{F_1} = N) = \epsilon \prod_{n=1}^{N-1} (1 - q_n(p_s)) < \epsilon$. Then, we have

$$\mathbb{E} \left[ T_{F_1}^* \right] = q_1(p_s) + \sum_{t=2}^{N} t q_t(p_s) \prod_{n=1}^{t-1} (1 - q_n(p_s)) + \epsilon_0$$

$$= \epsilon_0 + q_1(p_s) + (1 - q_1(p_s)) \cdot (2q_2(p_s) + (1 - q_2(p_s))) \cdot \cdots \cdot ( (N - 1)q_{N-1}(p_s) + (1 - q_{N-1}(p_s))N \epsilon ) \cdots .$$

We introduce $U_t = t q_t(p_s) + (1 - q_t(p_s)) U_{t+1} = t + (1 - q_t(p_s)) (U_{t+1} - t)$, where we notice $U_{t+1} - t > 0$.

With this notation, we have $\mathbb{E} \left[ T_{F_1}^* \right] = \epsilon_0 + U_1$.

Next, we show the monotonicity of $\mathbb{E} \left[ T_{F_1}^* \right]$ by using the mathematical induction in a “backward” fashion: From a very large number $N$ back to $t = 1$. First, we check $U_N$. It is true since $U_N = N \epsilon$, which is independent with $p_s$. Then, suppose that $U_{k+1}$ is decreasing over $p_s$ for $k = 2, \ldots, N - 1$; we check $U_k = k + (1 - q_k(p_s)) (U_{k+1} - k)$. For $q_k(p_s)$, we have

$$q_k(p_s) = \mathbb{P} (R(H_k, 0) \geq \gamma) + p_s \left( \mathbb{P} (R(H_k, H_k^c) \geq \gamma) - \mathbb{P} (R(H_k, 0) \geq \gamma) \right),$$

where $\mathbb{P} (R(H_k, H_k^c) \geq \gamma) \geq \mathbb{P} (R(H_k, 0) \geq \gamma)$ due to $R(H_k, H_k^c) \geq R(H_k, 0)$. It follows that $q_k(p_s)$ is an increasing linear function of $p_s$, and then $1 - q_k(p_s)$ is deceasing. Since both $(1 - q_k(p_s))$ and $(U_{k+1} - k)$ are nonnegative and decreasing, $U_k$ is decreasing as well. Moreover, $U_k$ is a polynomial function of $p_s$ due to the linearity of $q_k(p_s)$ and the iteration function, i.e., $U_k = k + (1 - q_k(p_s)) (U_{k+1} - k)$. Thus, we obtain that $\mathbb{E}[T_{F_1}^*] = U_1 + \epsilon_0$ is a polynomial function and decreasing over $p_s$. By letting $\epsilon_0 \to 0$, we are done with the proof for this proposition.
E. Proof of Lemma 4.1

We observe that the LHS of (17) is a function of $\xi$ over $\mathbb{R}^+$, denoted by $\text{LHS}(\xi)$, which is strictly decreasing since the interval $[\xi, +\infty)$ is decreasing as $\xi$ increases. When $\xi = 0$, we have

\[
\text{LHS}(0) = B + \int_0^{+\infty} \left( \frac{\eta}{x} e^{-\eta x} + \frac{ps\eta^c}{x} e^{-\eta^c x} \right) dx
= B + (\eta + ps\eta^c)\Gamma(0) = +\infty,
\]

where $\Gamma(0) = \int_0^{+\infty} x^{-1} e^{-x} dx = +\infty$. In addition, as $\xi \to \infty$, we have $\text{LHS}(\xi) \to B$. For the RHS of (17), denoted by $\text{RHS}(\xi)$, it is strictly decreasing from $+\infty$ to zero. Thus, there exists a $\xi_0$ such that for all $\xi \geq \xi_0$, we have $\text{LHS}(\xi) \geq \text{RHS}(\xi)$.

Next, we show that on $(0, \xi_0]$, if we let $\xi$ decrease starting from $\xi_0$, the function $\text{RHS}(\xi)$ increases faster than $\text{LHS}(\xi)$, which proves that there exists a unique point making (17) hold. Suppose that given some $\xi \in (0, \xi_0]$, we take the following partition such that $\xi = x_0 < x_1 < x_2 \ldots$, and $x_{i+1} - x_i = \Delta x$ for $i = 0, 1, 2, \ldots$. Then, when $\Delta x$ is small, we have

\[
\text{LHS}(\xi) \approx \sum_{i=0}^{\infty} \left( \frac{\eta}{x_i} e^{-\eta x_i} + \frac{ps\eta^c}{x_i} e^{-\eta^c x_i} \right) \Delta x. 
\]

Thus, we obtain that

\[
\text{LHS}(\xi) - \text{LHS}(\xi + \Delta x) = \left( \frac{\eta}{x_0} e^{-\eta x_0} + \frac{ps\eta^c}{x_0} e^{-\eta^c x_0} \right) \Delta x
= \frac{1}{\xi} \left( \eta e^{-\eta \xi} + ps\eta^c e^{-\eta^c \xi} \right) \Delta x
\]
Since RHS$(\xi)$ is differentiable, we have

\[
\text{RHS}(\xi) - \text{RHS}(\xi + \Delta x) = -\left( \frac{d\text{RHS}(x)}{dx} \right)_{x=\xi} \Delta x \\
= \frac{1}{\xi} \left( \eta e^{-\eta \xi} + p_s \eta e^{-\eta \xi} \right) \Delta x \\
+ \frac{1}{\xi^2} \left( e^{-\eta \xi} + p_s e^{-\eta \xi} \right) \Delta x.
\]

It follows that \( \text{RHS}(\xi) - \text{RHS}(\xi + \Delta x) > \text{LHS}(\xi) - \text{LHS}(\xi + \Delta x) \) since \( \frac{1}{\xi^2} (e^{-\eta \xi} + p_s e^{-\eta \xi}) \Delta x > 0 \).

Therefore, we conclude that RHS$(\xi)$ is increasing faster than LHS$(\xi)$ on $(0, \xi_0]$ as $\xi$ decreases. Since both RHS$(\xi)$ and LHS$(\xi)$ go to $+\infty$ as $\xi \to 0$, there must exist one point $\xi^* \in (0, \xi_0]$ such that LHS$(\xi^*) = \text{RHS}(\xi^*)$.

\[F. \text{ Proof of Proposition 4.1}\]

First, we consider the monotonicity of $C_{\text{inver}}$. By checking the first-order derivative of $C_{\text{inver}}$ on $(0, 1]$, we obtain

\[
\frac{dC_{\text{inver}}}{dp_s} = \log \left( 1 + \frac{B}{\mu + p_s} \right) - \frac{B}{\mu + p_s}
= f \left( p_s, \frac{B}{\mu} \right) - g \left( p_s, \frac{B}{\mu} \right).
\]

(34)

It remains to show $f \left( p_s, \frac{B}{\mu} \right) > g \left( p_s, \frac{B}{\mu} \right)$ over $p_s \in [0, 1]$ for all $\frac{B}{\mu} \in (0, +\infty)$. Since $\log(1 + x) \approx x$ when $x$ is small, we have

\[
\lim_{\frac{B}{\mu} \to 0} f \left( p_s, \frac{B}{\mu} \right) \approx \frac{B}{\mu + p_s} > \frac{B}{\mu + 1 + p_s} = g \left( p_s, \frac{B}{\mu} \right).
\]

Thus, $f > g$ when $\frac{B}{\mu}$ is small. Moreover, we note that

\[
\frac{df}{d\frac{B}{\mu}} = \frac{1}{1 + p_s + \frac{B}{\mu}} > \frac{1}{1 + p_s + \frac{B}{\mu}} \cdot \frac{1 + p_s}{1 + p_s + \frac{B}{\mu}} = \frac{dg}{d\frac{B}{\mu}} > 0,
\]
which implies that both $f$ and $g$ are strictly increasing over $\frac{B}{\mu}$, and $f$ is increasing faster than $g$. Thus, we conclude that $f > g$ for all $\frac{B}{\mu} \in (0, +\infty)$.

Next, we consider the concavity of $C_{\text{inver}}$, which could be shown by check the second-order derivative of $C_{\text{inver}}$ as

$$\frac{d^2 C_{\text{inver}}}{(dp_s)^2} = \frac{d}{dp_s} (f - g) = -\frac{\left(\frac{B}{\mu}\right)^2}{(1 + p_s)(1 + p_s + \frac{B}{\mu})^2} < 0.$$ 

Thus, the proposition is proved.

REFERENCES

[1] J. G. Andrews, “Seven ways that HetNets are a cellular paradigm shift,” *IEEE Commun. Mag.*, vol. 51, no. 3, pp. 136-144, Mar. 2013.

[2] A. Ghosh, N. Mangalvedhe, R. Ratasuk, B. Mondal, M. Cudak, E. Visotsky, T. A. Thomas, J. G. Andrews, P. Xia, H. S. Jo, H. S. Dhillon and T. D. Novlan, “Heterogeneous cellular networks: From theory to practice,” *IEEE Commun. Mag.*, vol. 50, no. 6, pp. 54-64, June 2012.

[3] J. G. Andrews, H. Claussen, M. Dohler, S. Rangan and M. C. Reed, “Femtocells: Past, present, and future,” *IEEE J. Sel. Areas Commun.*, vol. 30, no. 3, pp. 497-508, Apr. 2012.

[4] D. López-Pérez, I. Güvenç, G. de la Roche, M. Kountouris, T. Q. S. Quek and J. Zhang, “Enhanced intercell interference coordination challenges in heterogeneous networks,” *IEEE Wireless Commun. Mag.*, vol. 18, no. 3, pp. 22-30, June 2011.

[5] P. Xia, V. Chandrasekhar and J. G. Andrews, “Open vs. closed access femtocells in the uplink,” *IEEE Trans. Wireless Commun.*, vol. 9, no. 12, pp. 3798-3809, Dec. 2010.

[6] M. Bennis, M. Simsek, A. Czyliwic, W. Saad, S. Valentin and M. Debbah, “When cellular meets WiFi in wireless small cell networks,” *IEEE Commun. Mag.*, vol. 51, no. 6, pp. 44-50, June 2013.

[7] C. K. Ho and R. Zhang, “Optimal energy allocation for wireless communications with energy harvesting constraints,” *IEEE Trans. Signal Process.*, vol. 60, no. 9, pp. 4808-4818, Sep. 2012.

[8] S. Sudevalayam and P. Kulkarni, “Energy harvesting sensor nodes: survey and implications,” *IEEE Commun. Surveys Tuts.*, vol. 13, no. 3, pp. 443-461, Third Quarter 2011.

[9] X. Wang, A. V. Vasilakos, M. Chen, Y. Liu and T. T. Kwon, “A survey of green mobile networks: opportunities and challenges,” *ACM J. Mob. Netw. Appl.*, vol. 17, no. 1, pp. 4-20, Feb. 2012.
[10] A. J. Goldsmith, P. P. Varaiya, “Capacity of fading channels with side information,” *IEEE Trans. Inf. Theory*, vol. 43, no. 6, pp. 1986-1992, Nov. 1997.

[11] K. S. Gilhousen, I. M. Jacobs, R. Padovani, A. J. Viterbi, L. A. Weaver, Jr. and C. E. Wheatley, III, “On the capacity of a cellular CDMA system,” *IEEE Trans. Veh. Technol.*, vol. 40, no. 2, pp. 303-312, May 1991.

[12] V. Chandrasekhar and J. G. Andrews, “Uplink capacity and interference avoidance for two-tier femtocell networks,” *IEEE Trans. Wireless Commun.*, vol. 8, no. 7, pp. 3498-3509, July 2009.

[13] S. Samarakoon, M. Bennis, W. Saad and M. Latva-aho, “Enabling relaying over heterogeneous backhauls in the uplink of femtocell networks,” in *Proc. WiOpt’12*, Paderborn, Germany, pp. 75-80, May 2012.

[14] O. Ozel, K. Tutuncuoglu, J. Yang, S. Ulukus, and A. Yener, “Transmission with energy harvesting nodes in fading wireless channels: optimal policies,” *IEEE J. Sel. Areas Commun.*, vol. 29, no. 8, pp. 1732-1743, Sept. 2011.

[15] C. Huang, R. Zhang, and S. Cui, “Throughput maximization for the Gaussian relay channel with energy harvesting constraints,” *IEEE J. Sel. Areas Commun.*, vol. 31, no. 8, pp. 1469-1479, Aug. 2013.

[16] S. Luo, R. Zhang, and T. J. Lim, “Optimal save-then-transmit protocol for energy harvesting wireless transmitters,” *IEEE Trans. Wireless Commun.*, vol. 12, no. 3, pp. 1196-1207, Mar. 2013.

[17] X. Gong, C. Thejaswi P. S., J. Zhang, and H. V. Poor, “Opportunistic cooperative networking: to relay or not to relay?” *IEEE J. Sel. Areas Commun.*, vol. 30, no. 2, pp. 307-314, Feb. 2012.

[18] V. Kanodia, A. Sabharwal, and E. W. Knightly, “MOAR: a multi-channel opportunistic auto-rate media access protocol for ad hoc networks,” in *Proc. IEEE BROADNETS*, San Jose, USA, pp. 600-610, Oct. 2004.

[19] T. Shu and M. Krunz, “Throughput-efficient sequential channel sensing and probing in cognitive radio networks under sensing errors,” in *Proc. ACM MobiCom’09*, Beijing, China, pp. 37-48, Sept. 2009.

[20] Q. Zhang and S. A. Kassam, “Finite-state Markov model for Rayleigh fading channels,” *IEEE Trans. Commun.*, vol. 47, no. 11, pp. 1688-1692, Nov. 1999.

[21] V. Sharma, U. Mukherji and V. Joseph, “Optimal energy management policies for energy harvesting sensor nodes,” *IEEE Trans. Wireless Commun.*, vol. 9, no. 4, pp. 1326-1336, April 2010.

[22] P. Billingsley, *Probability and Measure*, 3rd ed., New York: John Wiley & Sons, Inc., 1995.

[23] T. S. Ferguson and J. B. MacQueen, “Some time-invariant stopping rule problems,” *Optimization*, vol. 23, no. 2, pp. 155-169, Jan. 1992.

[24] T. S. Ferguson, *Optimal stopping and applications*, 2006 [Online]. Available: [http://www.math.ucla.edu/~tom/Stopping/Contents](http://www.math.ucla.edu/~tom/Stopping/Contents)

[25] H. Wang, *Introduction to Stochastic Control Theory*, 2006 [Online]. Available:
[26] N. Bäuerle and U. Rieder, *Markov Decision Processes with Applications to Finance*, Heidelberg: Springer, 2011.

[27] M. Beaudin, H. Zareipour, A. Schellenberglabe, and W. Rosehart, “Energy storage for mitigating the variability of renewable electricity sources: an updated review,” Energy for Sustainable Development, vol. 14, no. 4, pp. 302-314, Dec. 2010.

[28] N. Michelusi, K. Stamatiou, and M. Zorzi, “Transmission policies for energy harvesting sensors with time-correlated energy supply,” *IEEE Trans. Commun.*, vol. 61, no. 7, pp. 2988-3001, July 2013.

[29] D. D. Clark and W. Fang, “Explicit allocation of best-effort packet delivery service,” *IEEE/ACM Trans. Netw.*, vol. 6, no. 4, pp. 362-373, Aug. 1998.

[30] D. Chatterjee, *Real Analysis*, 2nd ed., New Delhi: PHI Learning Pvt. Ltd., 2005.