On Throughput Maximization of Time Division Multiple Access with Energy Harvesting Users

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Abstract—In this paper, we consider a multiple access channel, where multiple users equipped with energy harvesting batteries communicate to an access point. To avoid consuming extra energy on competition for the channel, the users are supposed to share the channel via Time Division Multiple Access (TDMA). In many existing works, it is commonly assumed that the users’ energy harvesting processes and storage status are known to all the users before transmissions. In practice, such knowledge may not be readily available. To avoid excessive overhead for real-time information exchange, we consider the scenario where the users schedule their individual transmissions according to the users’ statistical energy harvesting profiles. We first study the optimal transmission scheme in the case where each node has an infinite-capacity battery. By optimization theory, we show that to maximize the average system throughput, all the users should transmit at an identical optimal power, which solely depends on the energy harvesting rate per timeslot. We then study the equal-power TDMA scheme in the case where each node is equipped with a battery of finite capacity. The system is formulated as a polling system consisting of multiple energy queues and one server. By the Markov chain modeling method, we derive the performance of equal-power TDMA in terms of the energy loss ratio and the average system throughput. In addition, we develop an algorithm to efficiently compute the optimal transmission power for each user. We also consider an equal-time TDMA scheme, which assigns equal-length subslots to each user, and analyze its system performance. It is found that equal-power TDMA always outperforms equal-time TDMA in the infinite-capacity battery case, while equal-time TDMA exhibits compatible or even slightly better performance in some scenarios when the batteries have finite capacities.

I. INTRODUCTION

Energy harvesting based communication has attracted much research attention in recent years. Equipped with energy harvesting devices, wireless users are able to gather energy from surrounding environments [1]–[4]. Thus, the network mobility can be greatly enhanced and the network lifetime can be extended, if wireless users can utilize the harvested energy to transmit their data. Energy harvesting can also help reduce carbon emission and environmental pollution, as well as reliance on traditional energy resources. Thus, energy harvesting has been regarded as a key technology leading to wireless green communications.

In the past few years, efficient power allocation and energy management have been the focus of green communications with energy harvesting capacities. Recent works fall into two major categories: offline (deterministic) and online (stochastic) algorithms. When developing offline algorithms, the energy harvesting profile, including the arrival times and associated amount of harvested energy, and data arrival times and sizes are assumed to be known to the users before each transmission starts. [5]–[7] studied the optimal transmission problem for an energy harvesting wireless link with batteries of either finite or infinite capacity. Offline scheduling algorithms were developed to minimize the transmission time or maximize the short term throughput. This line of work has been extended to wireless fading channels [8], broadcast channels [9] and two-hop networks [10]. Battery imperfections, such as time-varying battery capacity and energy leakage, were considered in [11].

Though the offline assumption seems too ideal in practice, the offline solutions provide bounds on performance of online algorithms and usually lead to heuristic but efficient online algorithms [8]. Online optimal scheduling was considered in [12] for a time varying channel, where a source with energy harvesting capacity adopted an adaptive transmission policy based on the random energy arrivals and channel state variations. The optimal scheduling policy over a Gilbert-Elliot channel was considered in [13], where an energy harvesting source chose whether to transmit a packet or defer the transmission in each slot. A save-then-transmit protocol was proposed in [14] to minimize the delay constrained outage probability by using two alternating batteries.

In this paper, we consider an energy harvesting Multiple Access Channel (MAC) where multiple users transmit to an access point (AP) using harvested energy. Some exemplary works on energy harvesting MAC can be found in [15]–[19] etc. Among these works, [15] and [16] studied the optimal power policy and the optimal packet scheduling policy, respectively, for a two-user Gaussian multiple access channel under deterministic system settings. Taking lossy energy storage into account, [15] proposed a double-threshold based power allocation policy. In [16], the transmission powers and rates are scheduled for both users to minimize the delivery time from the users to the destination. In [18], the authors proposed an iterative dynamic water-filling algorithm to maximize the channel sum-rate for fading MAC with finite-capacity energy harvesting batteries. It was assumed that the information of channel states and energy harvesting states for $K$ time slots is known a priori and the maximum energy consumption per slot is bounded. Without the knowledge of the energy harvesting processes and users’ battery states, online optimal scheduling for a multiple access channel was studied in [17],
where one of the $K$ users is scheduled to transmit in each slot, through the modeling of a partially observable Markov decision process. Long-term average sum-throughput of a multiple access communication system with energy harvesting nodes was studied in [19] in the continuous time regime.

In contrast to existing works, we study the optimal transmission problem on an energy harvesting MAC where multiple users share the channel via Time Division Multiple Access (TDMA) for low complexity and low energy consumption. Assuming that the users do not exchange their energy harvesting states and energy storage states in real time, we study efficient transmission schemes based on the users’ statistical energy harvesting profiles and the battery capacities. We consider two cases: 1) each user has a battery of infinite capacity; 2) each user is equipped with a finite-capacity battery. In the infinite-capacity battery case, all the harvested energy is consumed for data transmission. In this case, we show that equal-power TDMA scheme is optimal as far as the maximum average system throughput is concerned, and the optimal transmission power is solely determined by the total average amount of energy harvested by all the users in each slot, i.e., the energy harvesting rate. We also study the performance of the equal-power TDMA scheme in the finite-capacity battery case. With the assistance of Markov chain modeling, we derive the energy loss ratio, and the average system throughput as functions of the transmission power. By analyzing the property of the throughput function, we develop an efficient algorithm to compute the optimal transmission power under the equal-power TDMA framework. We also consider a simple equal-time TDMA scheme, which divides each slot into equal-length subslots and assigns one subslot to each user, allowing them to transmit with all the energy storage in each slot. We prove that equal-power TDMA always outperforms equal-time TDMA when the battery capacity is infinite. However, this conclusion does not hold when the battery’s capacity is finite. Equal-time TDMA exhibits compatible or even slightly better performance in different scenarios, depending on the system parameters. Simulations are carried out to validate the theoretical results.

The rest of this paper is organized as follows. Section II presents the system model and briefly introduces the queuing model. Section III studies the optimal transmission problem in the case with infinite-capacity batteries, and proves the optimality of the equal-power TDMA scheme. In the finite-capacity battery case, the performance of equal-power TDMA is evaluated using the Markov chain model, and an algorithm is developed to find the optimal transmission power in Section IV. Section V demonstrates simulation results and Section VI concludes this paper.

II. SYSTEM MODEL

A. System Description

We consider a multiple access channel (MAC) with $K$ energy harvesting users communicating to one AP, as shown in Fig. 1. Each user, denoted by $k (k \in K = \{1, \cdots, K\})$, is equipped with a battery, and transmits using the harvested energy supply stored in this battery. The harvested energy is generally sporadically and randomly available. The users will rely on the harvested energy to transmit their own data. Assuming that the data buffer of each user is saturated and there are always available data packets for transmission.

In this work, we consider the scenarios where no real-time energy information is shared between the users and the AP. That is, each user does not have the knowledge of the energy harvesting status and energy storage status of other users. Instead, the users’ statistical energy harvesting profiles are shared between the users once for all. In this scenario, we assume that the users share the channel via TDMA and access the channel one by one in a fixed order, as shown in Fig. 2. As a low-complexity and low energy consumption, TDMA has been widely and easily implemented in wireless cellular/local/ad-hoc networks. The user occupying the channel will schedule the transmission (power and time) based on its own energy storage along with the statistical energy harvesting profiles. After the transmission, it will send an ending signal to notify the next user. Thus, the users do not need to consume a proportion of limited energy to compete for the channel.

The system is assumed to be time-slotted, and the length of each slot is equal to $T$ seconds. We suppose that each battery is recharged once by energy harvesting devices at the beginning of each slot $n (n = 1, 2, \cdots)$. $E^{(n)} = [E^{(n)}_1, E^{(n)}_2, \cdots, E^{(n)}_K]$ represents the energy-harvesting status at slot $n$, as shown in Fig. 2. In accordance to discrete-time energy arrivals, user $k$ receives $m_k^{(n)}$ energy packets in each slot $n$ with one energy packet containing a fixed amount of $\bar{e}_s$ (Joule) energy, where $m_k^{(n)} \in \{0, 1, \cdots\}$ is a random number. Thus, a total amount of $E_k^{(n)} = m_k^{(n)} \bar{e}_s$ (Joule) energy is harvested by user $k$ in slot $n$. This assumption facilitates our queuing analysis later. And the continuous situation can be well approximated when $\bar{e}_s$ is sufficiently small. The newly harvested energy will be
stored in the battery and used for data transmission. The energy storage process can be modeled as an energy queue. Suppose that \( E_k^{(n)} \)'s are independent and identically distributed (i.i.d.) across all the slots \( n \) and all the nodes \( k \), and the probability mass function of \( E_k^{(n)} (m_k^{(n)}) \) is denoted by

\[
f_k(m) = \Pr\{m_k^{(n)} = m\}.
\]

\( f_k(m) \) \( k \)

**B. Queueing Model**

As mentioned above, the \( K \) users access the same channel via TDMA. The whole system can thus be regarded as a polling system, where one server station visits \( K \) energy queues cyclically in a fixed order, as shown in Fig. 2. Let us denote by \( Q_k \) the capacity of energy queue \( k \); \( Q_k = \infty \) and \( Q_k < \infty \) indicate that the battery at user \( k \) has an infinite and finite capacity, respectively. Let \( a_k[n] \) and \( v_k[n] \) denote the number of energy packets harvested and consumed, respectively, by user \( k \) in slot \( n \). For each queue \( k \), \( a_k[n] = m_k^{(n)} \) energy packets arrive at the beginning of slot \( n \), and the amount of energy storage in the battery accumulates to

\[
q_k[n] = \min\{q_k[n-1] + a_k[n], Q_k\},
\]

where \( q_k[n-1] \) denotes the length of queue \( k \) at the end of slot \( n-1 \). If the battery at user \( k \) has an infinite capacity, all the harvested energy can be stored in the battery. Otherwise, a portion of energy may have to be discarded, when the battery of finite capacity is full. At the end of slot \( n \), the length of queue \( k \) is updated as

\[
q_k[n] = q_k^{(n)} - v_k[n].
\]

The service process \( v_k[n] \) of each queue \( k \) is determined by the service discipline applied in the polling system and the service rate at which the stored energy is consumed. Typically, the service disciplines are divided into two categories: exhaustive service and gated service [20], [21]. In the former case, the current queue shall be emptied before the server moves to the next queue. In the later case, at most a certain number of customers who wait in the queue before the polling starts will be served. In the case with \( Q_k = \infty \), it does not matter whether to apply the exhaustive or gated service discipline, since all the harvested energy can be efficiently used. When \( Q_k < \infty \), energy loss may be induced due to the limited capacity of the battery. In this case, the service process \( v_k[n] \) and the system performance could be affected. In this work, we will mainly consider the exhaustive service discipline. As will be seen later, the gated service case can be analyzed in a similar way. Subject to the amount of energy storage in the battery, the energy consumption rate depends on the transmission power, which in turn affects the system throughput.

**C. System Throughput**

In slot \( n \), the transmission time and transmission power of the user \( k \) are denoted by \( t_k^{(n)} \) and \( P_k^{(n)} \), respectively. They are related to each other as \( t_k^{(n)} P_k^{(n)} = \tilde{E}_k^{(n)} \), where \( \tilde{E}_k^{(n)} = v_k[n] \cdot \tilde{e}_k \) denotes the amount of energy consumed in this slot. And the data rate can be computed as \( C_k^{(n)} = W \log(1 + |h_k^{(n)}|^2 P_k^{(n)}/N_0 W) \), where \( h_k^{(n)} \) is the channel gain of user \( k \) that is assumed to stay constant in each slot. \( W \) denotes the bandwidth of the channel, and \( N_0 \) denotes the noise spectral density. Without loss of generality, we assume that \( t_k^{(n)} = 1 \) for all \( k \) and \( n \). Thus, the overall throughput of the MAC channel in the \( n \)-th slot is given by

\[
\tau^{(n)} = K \sum_{k=1}^{K} C_k^{(n)} = \sum_{k=1}^{K} W \log(1 + P_k^{(n)}/N_0 W) t_k^{(n)}.
\]

User \( k \) relies on its local energy storage \( \tilde{q}_k^{(n)} \) and the users’ statistical energy harvesting profiles to choose the transmission parameters \( P_k^{(n)} \) and \( t_k^{(n)} \) if this user is allowed to access the channel in slot \( n \). With i.i.d. energy arrivals across all the slots \( n \), the index \( n \) can be omitted. In the sequel, we first study the optimal TDMA transmission scheme to maximize the average system throughput per slot \( \tau(\mathcal{T}) \) in the case when the batteries have infinite capacities. Then, we extend our study of TDMA schemes to the finite-capacity battery case.

**III. OPTIMAL TRANSMISSION FOR THE INFINITE CAPACITY BATTERY CASE**

If all the users have infinite capacities, all the harvested energy is stored and consumed on data transmission. In this case, we do not need to be concerned with the details of energy storage and thus the queueing process.

All the users share the channel based on the statistical multiplexing. Without considering energy storage status, each user \( k \) can schedule the transmission power \( P_k \) and time \( t_k \) based on the number of energy packets \( m \) harvested each time. In this sense, the transmission power and time of user \( k \) can be expressed as \( P_k(m) \) and \( t_k(m) \), respectively. By taking the expectation over the random number \( m \), the average system throughput per slot is given by

\[
\tau = \sum_{k=1}^{K} \sum_{m=0}^{\infty} W \log(1 + P_k(m)/N_0 W) t_k(m) f_k(m).
\]

1From [21], the users spend less time waiting for the next service under the exhaustive service discipline and thus achieve a higher throughput.

2The channel capacity is used as an ideal approximation for the real data rate.

3The scenarios with time varying channel fading can be analyzed using the same method considered in this work.
Meanwhile, the average transmission time is equal to
\[ \bar{t} = \sum_{k=1}^{K} \sum_{m=0}^\infty t_k(m) f_k(m). \]

(6)

Our objective is to maximize the average system throughput \( \mathcal{T} \) by optimizing \( P_k(m) \) and \( t_k(m) \) subject to the long-term average transmission time constraint \( \bar{t} \leq T \). According to Loynes’s theorem [22], the energy consumption rate must be equal to or greater than the energy arrival rate \( \bar{P} \) so that the energy storage does not increase to infinity. Hence, the average service time satisfies \( \bar{t} \leq T \). Here, we assume that in the long run, the average total amount of energy harvested per slot is consumed within one slot. By this means, we may easily assure from scheduling algorithm perspective that no energy will be wasted at all. Accordingly, the optimization problem is formulated as

\[
\begin{align*}
\max_{P_k(m), t_k(m)} & \quad \sum_{k=1}^{K} \sum_{m=0}^\infty W \log(1 + P_k(m) / N_0 W) t_k(m) f_k(m) \\
\text{s.t.} & \quad \sum_{k=1}^{K} \sum_{m=0}^\infty t_k(m) f_k(m) \leq T.
\end{align*}
\]

(7)

In the sequel, we will study the optimal transmission policy through convex optimization theory.

We first define the average amount of energy arriving at user \( k \) per slot as
\[ \bar{E}_k = \bar{e}_k \sum_{m=0}^\infty m f_k(m), \]
and its average transmission time per slot as
\[ \bar{t}_k = \sum_{m=0}^\infty t_k(m) f_k(m). \]

(8)

(9)

Then, we reveal the optimal transmission power \( P_k^*(m) \) and the optimal transmission time \( t_k^*(m) \) in the following theorem.

**Theorem 1.** The optimal average transmission power and time of user \( k \) are given by

\[
P_k^*(m) = P^* = \frac{\sum_{k=1}^{K} \bar{E}_k}{T}
\]

(10)

and

\[
t_k^*(m) = \bar{t}_k = \frac{T \bar{E}_k}{\sum_{k=1}^{K} \bar{E}_k}.
\]

(11)

respectively.

**Proof:** Using Jensen’s inequality, the average throughput of user \( k \) per slot satisfies
\[
\mathcal{T}_k = \sum_{m=0}^\infty W \log(1 + P_k(m) / N_0 W) t_k(m) f_k(m)
\]
\[
= \bar{t}_k \cdot \sum_{m=0}^\infty W \log(1 + P_k(m) / N_0 W) \frac{t_k(m) f_k(m)}{t_k}
\]
\[
\leq \bar{t}_k \cdot W \log(1 + \sum_{m=0}^\infty \frac{P_k(m) t_k(m) f_k(m)}{N_0 W \frac{t_k}{t_k}})
\]
\[
= \bar{t}_k \cdot W \log(1 + \frac{1}{N_0 W \frac{t_k}{t_k}}),
\]

(12)

where the inequality holds since \( \log(\cdot) \) is a concave function, and the last equality is due to \( P_k(m) t_k(m) = m \bar{E}_k \), since no energy loss is induced during energy storage and consumption and all the available energy is fully used for transmission. The inequality becomes equality when \( P_k(m) = \bar{E}_k \) is constant. In this case, we get \( \mathcal{T} = \sum_{k=1}^{K} \bar{t}_k W \log(1 + \frac{1}{N_0 W \frac{t_k}{t_k}}) \). And the constraint in (7) becomes \( \sum_{k=1}^{K} \bar{t}_k \leq T \).

With Jensen’s inequality again, we have
\[
\begin{align*}
\mathcal{T} &= \sum_{k=1}^{K} \bar{t}_k W \log(1 + \frac{1}{N_0 W \frac{t_k}{t_k}})
\leq \sum_{k=1}^{K} \bar{t}_k W \log(1 + \frac{1}{N_0 W \frac{\sum_{k=1}^{K} \bar{E}_k}{\sum_{k=1}^{K} \bar{t}_k}})
\end{align*}
\]
\[
= \sum_{k=1}^{K} \bar{t}_k W \log(1 + \frac{1}{N_0 W \frac{\sum_{k=1}^{K} \bar{E}_k}{\sum_{k=1}^{K} t_k}})
\]
\[
\leq T W \log(1 + \frac{1}{N_0 W \frac{\sum_{k=1}^{K} \bar{E}_k}{T}})
\]

(13)

where the first inequality becomes an equality when \( \bar{E}_k = \cdots = \bar{E}_k \) and \( \alpha \) holds, the last inequality is due to the constraint \( \sum_{k=1}^{K} \bar{t}_k \leq T \) and \( \sum_{k=1}^{K} \bar{E}_k / \sum_{k=1}^{K} \bar{t}_k = \alpha \), and it becomes an equality when \( \sum_{k=1}^{K} \bar{t}_k = T \). Hence, all the \( K \) users have the same optimal transmission power given by (10). Accordingly, the average transmission time of user \( k \) per slot is proportional to the average amount of harvested energy, as given by (11).

From this theorem, the optimal TDMA scheme is the equal-power scheme, which requires all the users to transmit at an identical power \( P^* \). The optimal power \( P^* = \sum_{k=1}^{K} \bar{E}_k / T \) solely depends on the statistical energy harvesting profiles of all the users. By substituting (10) into (5), we obtain the maximum average system throughput as
\[
\mathcal{T}^* = T W \log(1 + \frac{P^*}{N_0 W}),
\]

(14)

which can be regarded as a throughput upper bound for this system.

Notice that the transmission power \( P^* \) meets exactly the minimum power requirement. When the users transmit at an identical power \( P \) (not necessarily equal to \( P^* \)), the average system throughput is given by
\[
\mathcal{T}(P) = W \log(1 + \frac{P}{N_0 W} \frac{\sum_{k=1}^{K} \bar{E}_k}{P}),
\]

(15)

and the average transmission time in each round is \( \bar{t}(P) = \frac{T}{N_0 W \frac{P}{P}} \). When \( P < P^* \), the average transmission time satisfies \( \bar{t}(P) > T \), and the amount of energy storage increases to infinity, since the system cannot consume all the harvested energy in time.

Alternatively, the users can share the channel through the equal-time TDMA scheme, which simply assigns one subslot of \( \frac{T}{N} \) seconds to each user per slot. Thus, each user can adjust its transmission power based on its energy storage per slot. In this way, all the energy harvested per slot will be depleted within this slot. When the equal-time TDMA scheme
is applied, the average system throughput per slot is obtained as
\[ \mathcal{T}_{ct} = K \sum_{k=1}^{\infty} \sum_{m=0}^{\infty} W \log(1 + \frac{1}{N_0W} \frac{m \tilde{e}_s}{T/K} f_k(m)). \] (16)

From the proof of Theorem 1, we know that our proposed equal-power TDMA scheme always outperforms the equal-time TDMA scheme regardless of the energy harvesting profiles. That is, \( \mathcal{T}_{ct} \) ≥ \( \mathcal{T}_{ct} \) holds for any distribution \( f_k(m) \). This owes to the fact that the equal-power TDMA scheme schedules the users’ transmission power and time simultaneously according to their statistical energy harvesting profiles.

In the case when the battery capacities are finite, it is not trivial to find the optimal transmission scheme for each user based on their individual energy storage status. Based on the insights obtained in the infinite-capacity battery case, we will extend our study on the equal-power TDMA scheme to the finite-capacity battery case and leave the study on the optimal transmission scheme for the future work.

IV. EQUAL-POWER TDMA FOR THE FINITE CAPACITY BATTERY CASE
When the battery capacities are finite, part of harvested energy may have to be discarded due to limited space. In this case, we should take the users’ energy storage status into consideration. Thus, we first discuss the service process of the polling system in details. Then, we formulate a Markov chain model to analyze the performance of the equal-power TDMA scheme. We also develop an algorithm to obtain the optimal transmission power. Finally, we briefly discuss the performance of the equal-time TDMA scheme when the battery capacity is finite.

A. Service Process
As described in Section II-B, the system consists of \( K \) energy queues and one server, and the server visits the queues in a fixed and cyclic order, referred to as a polling system [20]. The system state can be expressed as \( (s[n], q[n]) \), where \( s[n] \) denotes the index of the energy queue the server is to visit and \( q[n] = [q_1[n], \ldots, q_K[n]] \) denotes the energy storage status at the end of slot \( n \). The iteration process of the system state is discussed in the following.

With the exhaustive service discipline, the server continues to serve the queue \( s[n-1] \) until this queue is empty and then moves to the next queue in each round. When all the users transmit with the optimal power \( P^* \) given by (10), the server can serve at most \( M \) energy packets in one slot, where \( M = \frac{P^*}{\gamma_0} = \sum_{k=1}^{K} \tilde{e}_k \). Let \( \tilde{q}^{(n)} = (\tilde{q}^{(n)}_1, \ldots, \tilde{q}^{(n)}_K) \) be the energy storage state after one new energy arrival at the beginning of slot \( n \). Let us define \((k + i) = \text{mod}(k + i, K) \) \((k + i) \in \{1, 2, \ldots, K\}\). Given \( s[n-1] \) and \( \tilde{q}^{(n)} \), we define a function
\[ \zeta(s[n-1], q^{(n)}) = \begin{cases} 0, & \text{if } \tilde{q}^{(n)}_s < 1, \\ \max_{m=0}^{\infty} \tilde{q}^{(n)}_s - 1 + m, & \text{otherwise}, \\ \infty, & \text{if } \tilde{q}^{(n)}_s \geq 1. \end{cases} \] (17)

to measure how many queues have been polled. For simplicity, we express \( \zeta^{(n)} = \zeta(s[n-1], q^{(n)}) \). If \( \sum_{k=1}^{K} \tilde{q}^{(n)}_k < M \), the service capability outperforms the current energy storage in slot \( n \). In this case, all the energy stored in the batteries is consumed and the energy packets in one slot. In particular, \( \zeta^{(n)} \) queues with their indices in \( K_0 = \{s[n-1], (s[n-1] + 1), \ldots, (s[n-1] + \zeta^{(n)} - 1)\} \) are emptied, queue \( s[n] \) may be partially served, and the rest queues with their indices denoted by \( K_1 = K - K_0 - \{s[n]\} \) get no service at all. After serving \( M \) energy packets in a row, the server happens to visit the energy queue \( s[n] = (s[n-1] + \zeta^{(n)}) \). For ease of expression, we denote by
\[ e^{(n)}_s = \sum_{i=0}^{\zeta^{(n)}-1} \tilde{q}^{(n)}_{s[n-1]+i} \] (18)
the total number of energy packets consumed before the server polls queue \( s[n] \). From the above description, the service process \( v_k[n] \) of queue \( k \) can be expressed as
\[ v_k[n] = \begin{cases} \tilde{q}^{(n)}_k, & k \in K_0, \\ M - e^{(n)}_v, & k = s[n], \\ 0, & k \in K_1. \end{cases} \] (19)

At the end of each slot \( n \), the system state is updated as
\[ s[n] = s[n-1] \oplus \zeta^{(n)} \], \[ q_k[n] = q_k[n] - v_k[n] \quad (\forall k \in K). \] (20)

Specifically when \( \sum_{k=1}^{K} q_k[n] \leq M \), the system state becomes
\[ s[n] = s[n-1], \quad q[n] = [0, \ldots, 0]. \] (21)

From (20) and (17), the system state \( (s[n], q[n]) \) is determined by its previous state \( (s[n-1], q[n-1]) \), the energy arrival status \( a[n] = [a_1[n], \ldots, a_K[n]] \), and the service capacity \( M \), which are mutually independent. Hence, the system states \( \{(s[n], q[n])\} \) constitute a multi-dimensional Markov chain. In the sequel, we discuss the corresponding Markov chain and its transition probabilities.
B. Markov Chain Model

With \( s[n] \in \{1, \ldots, K\} \) and \( q_k[n] \in \{0, \ldots, Q_k\} \), there are totally \( K \prod (Q_k + 1) \) system states. And the transition between the system states is expressed by (20). Let \( \Pr \{ (s', q'| (s, q) \} \) denote the one-step transition probability of the Markov chain, which is homogeneous by the system description. To express the transition probability, we define the probability that the queue length increases from \( m_1 \) to \( m_2 \) due to one energy arrival as

\[
\tilde{f}_k(m_1, m_2) = \begin{cases} 
\tilde{f}_k(m_2 - m_1), & m_2 < Q_k, \\
\sum_{m=m_2-m_1} \tilde{f}_k(m), & m_2 = Q_k.
\end{cases}
\]

(22)

According to the above description, the server polls through \( \zeta(s, q) \) (c.f.(17)) queues and serves totally \( M \) energy packets in one slot. If \( \zeta(s, q) > 0 \), totally \( M \) energy packets in queues \( K_0 \cup \{s\} \) are served. Here, \( K_0 = \{s, (s + 1), \ldots, (s + \zeta(s, q) - 1)\} \). Equivalently the energy arrival process \( a = [a_1, a_2, \ldots, a_K] \) (c.f.(2)) should satisfy

\[
\sum_{k \in K \cup \{s\}} \min\{q_k + a_k, Q_k\} - q_k = M,
\]

(23)

where \( q_k = 0 \) for all \( k \in K_0 \). Accordingly, the transition probability can be computed as

\[
\Pr \{ (s', q'| (s, q) \} = \prod_{k \in K} \tilde{f}_k(q_k, q_k') \times \sum_{\bar{a}} \prod_{k \in K \cup \{s\}} \tilde{f}_k(q_k, \min\{q_k + a_k, Q_k\}),
\]

(24)

where \( \bar{a} = [a_s, a_{s+1}, \ldots, a_s'] \) is any energy arrival status for queues \( K_0 \cup \{s\} \) that should satisfy the equation (23). Specifically, when the service capacity is larger than the current energy storage capacity, \( i.e., \sum_{k=0}^{M} \min\{q_k + a_k, Q_k\} \leq M, \) all the energy queues will be emptied at the end of the slot. In this case, \( \zeta = K, \) and the corresponding transition probability is equal to

\[
\Pr \{ (s', q'| (s, q) \} = \prod_{k \in K} \tilde{f}_k(q_k, \min\{q_k + a_k, Q_k\}).
\]

(25)

If \( \zeta = 0 \), only queue \( s \) is polled and \( M \) energy packets in this queue are served and hence \( s' = s \). This case only happens when \( Q_s \geq M \). The transition probability is given by

\[
\Pr \{ (s', q'| (s, q) \} = \tilde{f}_{s'}(q_s, q_s' + M) \prod_{k \in K \cup \{s\}} \tilde{f}_k(q_k, q_k').
\]

(26)

According to the exhaustive service discipline, the service process \( \nu \) depends on the service capacity \( M \) and is updated as (19). Hence, the relationship between the system states varies with \( M \) and some states may become transient. The set of recurrent states \( \{(s[n], q[n])\} \) can be determined by substituting all possible energy arrivals \( a[n] \) into (20) with \( s[n-1] \in \{1, \ldots, K\} \) and \( q_k[n] \in \{0, \ldots, Q_k\} \). For illustration purpose, consider an example shown in Fig. 4 for a symmetric polling system, where two queues of finite capacity \( Q_k = 2 \) are polled and the service capacity is \( M = 2 \). In this case, the system states outside the dotted rectangular are transient states. Some transient states, such as \( (1, 0, 1), (1, 0, 2), \) and \( (1, 1, 1) \), are grouped together, since they all transfer to the same states. Then, we discuss the probabilities of transitions between recurrent states of the Markov chain in Fig. 4. From (24), the state \((1, 0, 0)\) will transfer to state \((2, 0, 1)\) and state \((2, 0, 2)\) with probabilities \( \eta_1 = \tilde{f}_1(0, a_1) \tilde{f}_2(0, a_2) \) and \( \eta_2 = \tilde{f}_1(0, 2) \tilde{f}_2(0, 2) \), respectively. From (25), the state \((1, 0, 0)\) will stay at itself with the probability \( 1 - \eta_1 - \eta_2 = \tilde{f}_1(0, a_1) \tilde{f}_2(0, a_2) \). When the total number of arriving energy packets satisfies \( a_1 + a_2 \leq M = 2 \). Similarly, from (24), the state \((1, 0, 0)\) transfers to state \((2, 0, 1)\) with probability \( \eta_3 = \tilde{f}_1(1, 1 + a_1) \tilde{f}_2(0, a_2) \). And the condition \( \min\{a_1, 1\} \) is 2 comes from (23). And it transfers to state \((2, 0, 2)\) and state \((1, 0, 0)\) with probabilities \( \eta_4 = \tilde{f}_1(1, 2) \tilde{f}_2(0, 2) \), and \( 1 - \eta_1 - \eta_3 = \tilde{f}_1(1, 2) \tilde{f}_2(0, 2) \), respectively. Likewise, the probabilities of transition from state \((1, 0, 0)\) to state \((2, 0, 1)\), state \((2, 0, 2)\), and state \((1, 0, 0)\) are \( \eta_5 = \tilde{f}_1(2, 2) \tilde{f}_2(0, 2) \), \( \eta_6 = \tilde{f}_1(2, 2) \tilde{f}_2(0, 2) \), and \( 1 - \eta_2 - \eta_5 = \tilde{f}_1(2, 2) \tilde{f}_2(0, 0) \), respectively. Since the Markov chain is symmetric, the other transition probabilities of the Markov chain can be obtained in the same way, as shown in Fig. 4.

To study the stationary distribution of the Markov chain, we only care about recurrent system states. Let \( S_r \) be the set of the recurrent states and \( N_r \) be the cardinality of this set. We then denote by \( \phi \) the \( N_r \times N_r \) transition probability matrix. Let \( \pi \) denote the \( 1 \times N_r \) column vector containing steady-state probabilities, and by \( 1 \) the \( N_r \times 1 \) column vector with all the elements equal to one. Once obtaining the transition probability matrix \( \phi \), we can compute the steady-state probability vector by solving the following linear equations

\[
\phi^T \pi = 1, \quad 1^T \pi = 1.
\]

(27)

As soon as the steady-state probabilities \( \pi(s, q) \) are obtained, we can easily analyze the system performance as follows.

C. System Performance

When the batteries have finite capacities, energy loss is inevitable during the storage stage, which may greatly affect the system throughput. In the following, we compute the energy loss ratio and the system throughput based on the Markov reward process.

We denote by \( r_{\text{loss}} \) and \( p_{\text{idle}} \) the energy loss ratio and the probability that the channel remains idle, respectively. The energy loss ratio is the ratio of the average amount of discarded energy and the total amount of harvested energy. Given the system state \((s, q)\), the number of energy packets discarded by user \( k \) due to overflow is computed as

\[
ev_k(q_k, a_k) = \max\{q_k + a_k - Q_k, 0\},
\]

(28)

which is a function of \( q_k \) and \( a_k \). Using the law of total
probability, the energy loss ratio is
\[ r_{\text{loss}} = \frac{\sum_{(s,q)} \sum_{a} \sum_{k=1}^{K} c_k(q_k, a_k)\pi(s,q) \prod_{k} f_k(a_k)}{\sum_{k=1}^{\infty} E_k}, \quad (29) \]
where \( \prod_{k} f_k(a_k) \) is the joint probability that \( a_k \) energy packets arrive at each queue \( k \). Intuitively, the minimum energy loss ratio is achieved, when the energy packets stored in the queues are all served in one slot. In this case, the steady-state loss ratio is achieved, when the energy packets stored in each queue are empty. Conceivably, this gap will be diminished, when the system state become all zero \( q = [0, \ldots, 0] \). By substituting \( q_k = 0 \) into (29), we can obtain the minimum energy loss ratio
\[ r_{\text{loss},\min} = \frac{1}{\sum_{k=1}^{K} E_k (a)} \sum_{k=1}^{K} \max(a_k - Q_k, 0) \prod_{k} f_k(a_k). \quad (30) \]

Given the system state \( (s,q) \), the idle time in one slot is equal to \( t_{\text{idle}}(q) = \max\{0, \sum_{m=M}^{\infty} f_k(m) \} \). Using the law of total probability again, the idle probability is equal to
\[ p_{\text{idle}} = \sum_{(s,q)} \max\{0, 1 - \sum_{k=1}^{K} q_k \} \pi(s,q). \quad (31) \]
Since the average data transmission time per slot is equal to \( (1 - p_{\text{idle}})T \), the average system throughput can be obtained as
\[ \mathcal{T}_q = (1 - p_{\text{idle}})TW \log(1 + \frac{P^*}{N_0W}). \quad (32) \]
Compared with the system performance given by (14) in the infinite capacity battery case, the average system throughput \( \mathcal{T}_q \) is decreased by a factor of \( (1 - p_{\text{idle}}) \). This is due to the fact that the total amount of energy storage is reduced due to overflow and thus the server is idle from time to time when the queues are empty. Conceivably, this gap will be diminished, when the battery capacities \( Q_k (k \in K) \) go to infinity and the idle probability approaches zero.

### D. Optimal Transmission Power

Till now, we have analyzed the average system performance based on the assumption that all the users adopt transmission power \( P^* \) given by (10), which is not necessarily optimal when the battery capacities are finite. Specifically, the idle probability \( p_{\text{idle}} \) is a function of the transmission power \( P \), since the number of energy units served per slot \( M \) and the steady-state probability vector \( \pi \) are both determined by the transmission power \( P \). As a result, \( \mathcal{T}_q \) is a function of the transmission power \( P \) and can be expressed as \( \mathcal{T}_q(P) \). In the sequel, we will discuss the optimal transmission power for the finite capacity battery case.

Let us denote \( P^*_q \) the optimal transmission power under the equal-power TDMA framework. It can be obtained by solving the problem
\[ \max_{\mathcal{T}_q(P)} \mathcal{T}_q(P) = (1 - p_{\text{idle}}(P))TW \log(1 + \frac{P}{N_0W}). \quad (33) \]

It is not trivial to solve the problem (33), since the idle probability \( p_{\text{idle}}(P) \) given by (31) is an implicit function of \( P \). In the sequel, we first discuss two special cases before getting into the details on how to compute \( P^*_q \) numerically.

1) **Special Case I**: When the capacity of each queue \( k \) is sufficiently large or the amount of energy harvested each time is small enough, \( \sum_{m=0}^{\infty} f_k(m) \approx 1 \), the energy loss is negligible and we can evaluate the average system throughput using the formula (5) for the infinite-capacity battery case. In this case, the optimal transmission power \( P^*_q \) is approximate to \( P^* \) given by (10).

2) **Special Case II**: When the energy arrival satisfies 
\[ \sum_{m=0}^{\infty} f_k(m) \approx 1 \] for any queue \( k \), the energy storage for the corresponding user per slot is equal to \( Q_k \varepsilon_k \) with almost probability one. In this case (with the i.i.d. energy arrival assumption), the idle probability becomes \( p_{\text{idle}} = \max\{0, 1 - \sum_{k=1}^{K} Q_k \varepsilon_k \} \). Let \( P_{th} \) be a power threshold defined as
\[ P_{th} = \frac{\sum_{k=1}^{K} Q_k \varepsilon_k}{T}. \quad (34) \]
From (32), we have
\[ \mathcal{T}_q(P) = \begin{cases} \frac{E_{\text{idle}}}{T} & P > P_{th}; \\
TW \log(1 + \frac{P}{N_0W}) & P \leq P_{th}. \end{cases} \quad (35) \]
For any \( P \leq P_{th} \), we have
\[ \mathcal{T}_q(P) = TW \log(1 + \frac{P}{N_0W}) \leq TW \log(1 + \frac{P_{th}}{N_0W}), \quad (36) \]
since \( \log(x) \) is a monotonically increasing function. Hence, the maximum average throughput can only be achieved within \([P_{th}, \infty)\). In this case, the maximum average throughput \( \mathcal{T}_q \) and the optimal power \( P^*_q \) can be obtained by solving the problem
\[ \max_{P \in [P_{th}, \infty)} \mathcal{T}_q(P) = \frac{P_{th}}{P}TW \log(1 + \frac{P}{N_0W}). \quad (37) \]
This problem is equivalent to maximize \( \mathcal{T}_q(P) = \sum_{k=1}^{K} Q_k \varepsilon_k \log(1 + \frac{P}{N_0W}) \) under the constraint \( \sum_{k=1}^{K} Q_k \varepsilon_k \leq T \). Similar to the infinite-capacity battery case, the optimal transmission power is obtained as
\[ P^*_q = P_{th} = \frac{\sum_{k=1}^{K} Q_k \varepsilon_k}{T}. \quad (38) \]
And the maximum average throughput is equal to
\[ \mathcal{T}^*_q = TW \log(1 + \frac{1}{N_0W} \sum_{k=1}^{K} Q_k \varepsilon_k). \quad (39) \]
Hence, the optimal power \( P^*_q \) totally depends on the amount of energy storage per slot \( \sum_{k=1}^{K} Q_k \varepsilon_k \).

3) **The General Case**: In the sequel, we will discuss the optimal identical power to maximize the average throughput \( \mathcal{T}_q(P) \) in the general scenario. In particular, we first show that the optimal power \( P^*_q \) can be found within the range \([0, P_{th}]\) and then develop an algorithm to compute the power \( P^*_q \).

**Theorem 2**: The optimal solution \( P^*_q \) to Problem (33) lies within the range \([0, P_{th}]\).
Proof: To prove $P^*_{q} \in (0, P_{th})$, it is sufficient to prove $P_{th} = \arg \max_{P \in (P_{th}, \infty)} T_q(P)$. In the case when $P \geq P_{th}$, the service capacity of the polling system outperforms the energy storage capacity, since $\sum_{k=1}^{K} \bar{\epsilon}_k \leq \sum_{k=1}^{K} Q_k \bar{\epsilon}_s \leq PT$ holds for any energy storage status $q = \{q_1, \cdots, q_K\}$. Hence, the $K$ queues will be emptied at each slot. Given the energy storage status $q$, the service time is equal to $\sum_{k=1}^{K} \bar{\epsilon}_k$, and the idle time is $T = \frac{\sum_{k=1}^{K} q_k \bar{\epsilon}_s}{PT}$, Averaging over the energy storage profile, the idle probability is given by

$$p_{idle}(P) = 1 - \frac{\sum_{k=1}^{K} f_k^q(m)}{PT}, \quad (40)$$

where $f_k^q(m)$ is the probability mass function for the finite capacity battery case:

$$f_k^q(m) = \begin{cases} f_k(m), & m < Q_k, \\ \sum_{m \geq Q_k} f_k(m), & m = Q_k, \end{cases} \quad (41)$$

and $\bar{E}_k^q$ is the average amount of energy storage in queue $k$ per slot, defined as

$$\bar{E}_k^q = \bar{\epsilon}_s \sum_{m=0}^{Q_k} m f_k^q(m). \quad (42)$$

As a result, the average throughput becomes

$$T_q(P) = W \log(1 + \frac{P}{N_0 W}) \sum_{k=1}^{K} \bar{E}_k^q P. \quad (43)$$

$$T_q(P) = W \log(1 + \frac{P}{N_0 W}) \sum_{k=1}^{K} \frac{Q_k \bar{\epsilon}_s P}{PT}. \quad (44)$$

Subject to the constraint $P \geq P_{th}$ or $\sum_{k=1}^{K} Q_k \bar{\epsilon}_s \leq T$, we have. Similar to special case II, we can obtain the optimal power $P^*_{q}$ to maximize the average throughput $T_q(P)$ within $P \in [P_{th}, \infty)$. Accordingly, the maximum system throughput is equal to $T_q(P_{th})$.

Based on the above discussion, the optimal power $P^*_{q}$ can be found within the range $(0, P_{th}]$. In this case, we shall compute the idle probability $p_{idle}(P)$ and the average throughput $T_q(P)$ approximately based on the Markov chain model. Notice that both the data rate $W \log(1 + \frac{P}{N_0 W})$ and the idle probability $p_{idle}(P)$ monotonically increases with the transmission power $P$, since the service capacity per slot is enhanced with $P$. As a product of the data rate $W \log(1 + \frac{P}{N_0 W})$ and the average transmission time $(1-p_{idle}(P))T$, the average throughput $T_q(P)$ turns out to be a unimodal function of $P$. By exploiting this property, we develop a low-complexity Golden-section search algorithm, Algorithm 1.

Algorithm 1 A search algorithm for getting $P^*_{q}$

1: Set a small $\epsilon$, $P_1 = \epsilon$, $P_2 = P_{th}$, $\kappa = 1.618034$.
2: $x = (P_2 - P_1)/\kappa$, $P_a = P_2 - x$, $P_b = P_1 + x$.
3: Compute $T_q(P) \forall P \in \{P_1, P_a, P_b, P_2\}$.
4: repeat
5: $x = x/\kappa$.
6: if $T_q(P_{a}) > T_q(P_{b})$ then
7: $P_a = P_b$, $P_b = P_a P_a = P_2 - x$.
8: $T_q(P_{a}) = T_q(P_{a})$ and compute $T_q(P_{a})$.
9: else
10: $P_1 = P_a$, $P_a = P_b, P_b = P_1 + x$.
11: $T_q(P_{a}) = T_q(P_{b})$ and compute $T_q(P_{b})$.
12: end if
13: until $P_a - P_1 \leq \epsilon$.
14: Obtain $T_q = \max_{P \in (P_1, P_a, P_b, P_2)} T_q$.

As discussed in Section IV-D, we can easily understand that equal-power TDMA is superior to equal-time TDMA in special case I, which is similar to the infinite-capacity battery case. In special case II, the total amount of energy storage per slot is equal to $\sum_{k=1}^{K} Q_k \bar{\epsilon}_s$. Using Jensen’s inequality, we have

$$T_{et.q} = \sum_{k=1}^{K} W \log(1 + \frac{Q_k \bar{\epsilon}_s}{N_0 W}) \frac{K \bar{\epsilon}_s}{T} f_k^q(m). \quad (45)$$

Hence, equal-power TDMA is still superior to equal-time TDMA in special case II. In the other cases, it is not straightforward to compare the performance between the equal-power and equal-time TDMA schemes theoretically. We will make a comparison of the two schemes by simulations in the next section.

V. Simulation Results

In this section, we demonstrate the performances of the equal-power and equal-time TDMA schemes by simulation results. Suppose that $K$ users access the same channel one by one according to a fixed order. The network parameters are set as $N_0 = 1$, $W = 1$ Hz, and $T = 1$s. Without loss of generality, we assume that the number of energy packets arriving at user $k$ follows a Poisson process with the parameter $\lambda_k$ and each packet contains $\bar{\epsilon}_s = 0.05$ Joule energy. That is, at the beginning of each time slot, $m$ energy packets are harvested by user $k$ with probability $f_k(m) = \frac{N_0 \exp(-\lambda_k)}{m!}$. In the infinite-capacity battery case with $Q_k = \infty$, the users transmit at the same optimal power $P^*_q$ given by (10). In the finite-capacity battery case, the optimal transmission power $P^*_q$ is computed
Conceivably, the energy loss ratio decreases with the increase of the battery capacity $Q_k$, since the amount of energy lost due to overflow is reduced.

Then, we discuss the curves of the average throughput in Fig. 6. It is observed that with infinite-capacity batteries, i.e., $Q_k = \infty$, the average throughput $\overline{T}(P)$ monotonically decreases with the increase of the transmission power, and the maximum average throughput $\overline{T}^\ast$ is obtained at the optimal power $P^\ast$. When $Q_k = \infty$, no energy loss happens and all the harvested energy is efficiently used for data transmission, while the energy loss is inevitable when the battery capacities are finite. Hence, it’s not surprising to see that the average throughput with $Q_k = \infty$ is higher than those with finite-capacity batteries. In the latter case, the average system throughput $\overline{T}_q(P)$ is a unimodal function of the transmission power $P$, and achieves its maximum at $P^\ast_q$, as shown in Fig. 6.

When $P$ is increased within the range $(0, P^\ast_q)$, less harvested energy is wasted due to overflow and more energy can be used to increase the average throughput. When $P$ is larger than $P^\ast_q$, the energy storage is rapidly exhausted and the channel may keep silent for too long. This situation becomes worse with the increase of $P$, and hence $\overline{T}_q(P)$ monotonically decreases in this region. Together with the results shown in Fig. 5, the transmission power should be adjusted to strike a good balance between the data rate and energy loss in the finite-capacity battery case.

In Figs. 7, 8 and 9, we demonstrate how the maximum average throughput, the optimal transmission power, and the average energy loss ratio change with the parameter $\lambda$, respectively. In this experiment, $K = 5$, $\lambda_1 = \lambda_2 = \lambda$, and the battery capacities $Q_k$ are the same. In the infinite-capacity battery case, the maximum average throughput $\overline{T}$ gradually increases without bound, as the optimal transmission power $P^\ast$ increases without bound with $\lambda$, as can be seen in Fig. 8. In the finite-capacity battery case with $Q_k = 1, 2, 3$, the average amount of energy storage per slot increases with the increase of the parameter $\lambda$ at the beginning. Accordingly, the optimal transmission power $P^\ast_q$ is increased to accelerate the energy consumption, as can be seen in Fig. 8. As a result, and the maximum average throughput $\overline{T}_q$ increases with the
The growth of $\lambda$, since more energy can be efficiently used for data transmission. When $\lambda$ is sufficiently high, all batteries are fully charged in each slot, corresponding to special case II in Section IV-D. In this case, the optimal transmission power $P_{th}^*$ reaches its maximum $P_{th}$ and the maximum average throughput $\mathbb{T}_g$ remains constant. As shown in Fig. 9, the energy loss ratio $r_{loss}$ always monotonically increases with the increase of $\lambda$, since more energy is harvested and a higher proportion of the energy has to be discarded due to overflow.

In Fig. 7, we also compare the throughput performance of the equal-power and equal-time TDMA schemes. Observed from this figure, one can see that equal-power TDMA always outperforms equal-time TDMA in the infinite-capacity battery case. This is due to the fact that equal-power TDMA can efficiently exploit all the harvested energy by selecting the optimal transmission power and time simultaneously according to the statistical energy harvesting profiles, while equal-time TDMA assigns fixed-length subslots to each user under any circumstance. In the finite-capacity battery case, equal-power TDMA is superior to equal-time TDMA, when $\lambda$ is relatively small. In this case, the optimal transmission power can strike a good balance between the data rate and the transmission time, when the energy loss ratio is also relatively small, as shown in Fig. 9. However, with the further increase of $\lambda$, more and more energy loss is induced, and the performance gap between equal-power TDMA and equal-time TDMA is diminished. As shown in Fig. 7, equal-time TDMA is even slightly better than equal-power TDMA for the middle range of $\lambda$, when $Q_k = 2$ or $Q_k = 3$. When $\lambda$ is sufficiently large, the two TDMA schemes achieve the same average throughput, i.e., $\mathbb{T}_{et,q} = \mathbb{T}_g$. In Fig. 10, we demonstrate the performance comparison between the two TDMA schemes for the case when the battery capacities are different. In this experiment, we set $K = 5$, $\lambda_k = \lambda$, and $Q_k = k$ for $k = 1, 2, \ldots, 5$. In this case, we can see that equal-power TDMA is superior to equal-time TDMA for almost the whole range of $\lambda$. In contrast to the result shown in Fig. 7, equal-power TDMA achieves a higher throughput than equal-time TDMA when $\lambda$ is sufficiently large, i.e., $\mathbb{T}_g > \mathbb{T}_{et,q}$, corresponding to our theoretical analysis for special case II in Section IV-E.

VI. CONCLUSIONS

In this paper, we studied the optimal transmission problem for the energy harvesting MAC channel, where multiple users with energy harvesting capacities share the channel via TDMA. In the infinite-capacity battery case, we proved that the equal-power TDMA scheme is optimal, and the optimal transmission power is only determined by the total average amount of energy harvested per slot. We then extended our study to the finite-capacity battery case under the equal-power TDMA framework. To analyze the performance of the queueing based polling system, we formulated a multi-dimensional Markov chain. The energy loss ratio and the average system throughput were derived according to the Markov reward process. We discussed the derivation of the optimal transmission power in two special cases, and found the optimal transmission power numerically for the general scenario. When the battery capacity is finite, the optimal transmission power depends
on the energy harvesting rate as well as the limited battery capacity. It was found that equal-power TDMA always outperforms equal-time TDMA in the infinite-capacity battery case, while equal-time TDMA exhibits compatible or even slightly better performance in some scenarios when the batteries have finite capacities, depending on the system parameters. We will extend this work to the scenario where the users’ transmissions are scheduled based on the energy harvesting status, battery storage status, and time-varying wireless channel conditions.

REFERENCES


