Optimal Relay Selection and Power Control for Energy-Harvesting Wireless Relay Networks

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***Abstract*—Ambient energy harvesting (EH) has emerged as a promising technique to improve the energy efficiency and reduce the total greenhouse gas emissions for green relay networks. In this paper, we study the joint relay selection and power control problem for the decode-and-forward EH wireless relay network. In particular, the problem formulation is to maximize the end-to-end system throughput by a deadline under the limitations of data and energy storage. To solve the problem under an offline optimization framework, we decompose such an optimization problem into two subproblems: 1) the joint time scheduling and power control subproblem and 2) the relay selection subproblem. Due to the convex nature of the joint time scheduling and power control subproblem, we derive the optimal solution via the primal decomposition. Based on the obtained system throughput, we can quickly select the best relay that achieves the maximum throughput. For the practical implementation, we further design the sub-optimal online joint time scheduling and power control algorithm. Specifically, the best relay is first obtained based on the statistical knowledge of energy arrivals and channel states, and then the best relay decides the time scheduling and power control that maximizes the total throughput according to the instantaneous state of channel fading, energy arrival, and queue data in each time slot. Simulation results show that the proposed offline algorithm can guarantee the maximum system throughput. Moreover, the simulation results show that compared to the optimal offline algorithm, the sub-optimal online algorithm suffers only a small degradation in performance.**

***Index Terms*—Ambient energy harvesting, relay wireless network, relay selection, power control, throughput maximization.**

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I. Introduction

Recently, mobile data traffic has been experiencing exponential growth due to the proliferation of wireless devices and emerging multimedia services [1], [2]. This trend has been accomplished by more and more indoor and edge users, which might been experiencing the low quality of services (QoS) due to channel impairments such as path-loss, shadowing and small-scale fading. To overcome such impairments, the relay-assisted access technique as a potential application of wireless relay networks has been proposed as a promising solution of exploiting energy efficiency and spatial diversity to improve the QoS of indoor and cell-edge users [3], [4]. It is known that the relay stations act as relays to transfer the information from edge users to the macro-cell base station.

Therefore, the topic on wireless relay networks has received a lot of research interests [5]–[12], which can be divided into two threads. The first thread is mainly concerned with the design of relaying transmission policy. For example, [5] and [6] studied the amplify-and-forward (AF) and the decode-and-forward (DF) as two most relaying protocols. In [7], an opportunistic buffered decode-wait-and-forward protocol was proposed to improve the system throughput and the end-to-end packet delay through exploiting both relay buffering and relay mobility. In [8], a unequal error protection distributed network coding transmission scheme based on fountain codes was proposed for wireless relay networks. The second thread is mainly concerned with relay selection, as the network performance can be substantially improved through appropriately choosing the relays. For example, the optimal outage probability and diversity gain were studied in [9] for the wireless MIMO relay network over Rayleigh fading channels when the greedy opportunistic user scheduling and the best relay selection are both taken into account. In [10], the outage probability performance and outage diversity in the single-carrier spectrum sharing wireless relay network were derived. In [11], the optimal user scheduling and relay selection scheme was proposed to minimize the total power consumption under the constraints of minimum data rate requirements for wireless relay networks. In [12], the next-hop-relay selection scheme based on a symbol error probability analysis and geographic information was developed for wireless relay networks. Although a significant amount of efforts have been spent on wireless relay networks, the conventional on-grid power supply was applied for relays in most prior work.

However, the dense population of relays and wireless devices renders high energy consumption and considerable greenhouse gas (such as carbon) emissions [13]–[15]. To deal with the environmental and financial concerns, energy harvesting (EH) technology has been introduced to wireless relay networks. Specifically, the wireless devices and relays in wireless relay networks are powered by harvesting renewable ambient energy, such as solar, wind, thermoelectric, electromechanical, and ambient radio frequency energy [15]. Due to the intermittent nature of energy arrivals, it is of practical importance to carefully manage the energy supply and select forwarding relays in order to guarantee the transmission reliability and throughput of the network.

Driven by the benefits of EH relay networks, there have been several studies on power control for two-hop EH wireless relay networks under the multi-fold randomness of energy arrival, data arrival and channel fading [16]–[19]. In [16], the offline optimal solutions based on the guideline of directional water-filling was studied for the short-term throughput maximization and transmission completion time minimization in a half-duplex Decode-and-Forward (DF) relay network system with EH source and non-EH relay nodes. Optimal offline, optimal online, and sub-optimal online power control schemes were proposed in [17] and [18] for the Gaussian relay fading channel with EH source and relay nodes. Under the constraint of finite data buffers, optimal transmission power control policies were developed in [19] for throughput maximization by a deadline over the half-duplex DF relay static channel with EH source and relay nodes. These previous works mainly studied the power control policies, either offline or online, for the EH wireless relay network with either infinite data and energy storage, finite energy storage, or finite data buffer.

However, due to the inherent randomness of energy arrivals at each relay, relay selection planning is also essential to improve the energy efficiency and service quality of users. Therefore, considerable research interests have been devoted to the study on joint relay selection and power control for EH wireless relay networks [20]–[23]. For example, a distributed solution to the relay selection problem was proposed in [20], based on the repeated Bayesian Stackelberg Game under the assumption that each relay always forwards information with all harvested energy at each time slot. In [21], the relay selection decision scheme was designed for EH wireless relay networks in the joint framework of the college admission market and the interactive partially observable Markov decision process. In [22], offline optimal and sub-optimal online joint relay selection and power control schemes were proposed for maximizing the throughput of an amplify-and-forward EH wireless relay network subject to the finite energy storage. In [23], the optimal relay selection was investigated in EH wireless relay networks with different assumptions on the availability of channel side information and energy side information. Although lots of efforts have been spent on joint relay selection and power control for EH wireless relay networks, to the best of the authors' knowledge, joint relay selection and power control has not been addressed for an EH wireless relay network with limited data and energy storage before in the literature.

In this paper, we study an EH wireless relay network consisting of one source node, multiple EH relays operating in DF mode, and one destination node. Each relay is equipped with a finite-size battery and a finite-size data buffer for storing the harvested energy and the received data, respectively. Also, each relay is powered by the energy stored in the battery. We aim to obtain the optimal offline, and sub-optimal online joint relay selection and power control scheme that maximize the end-to-end system throughput delivered to the destination node by a deadline subject to the data buffer and battery storage limitations. We note that the optimal offline algorithm is of interest when the knowledge of energy arrivals and channel fading levels is known a priori for all relays in all transmission slots. However, in practice, due to the randomness of energy arrivals and channel fading, it is difficult to predict all energy arrivals and channel fading levels in advance. This calls for online algorithms that only require causal information of energy arrivals and channel fading levels. Nevertheless, it is still of importance to design the optimal offline algorithm as it provides the performance upper bound that can be used as a benchmark to evaluate the proposed online algorithm. In particular, the following summarizes our contributions and key results:

- *Problem formulation:* The joint relay selection and power control problem is defined to maximize the total throughput by a deadline through the joint relay selection, time scheduling and power allocation while meeting the causality and storage constraints on energy and data.
- *Offline algorithm design:* Under the offline optimization framework, the defined optimization problem is solved in two phases: the joint time scheduling and power allocation phase followed by the optimal relay selection phase. Due to the convex nature, the optimal solution to the joint time scheduling and power allocation can be obtained via the primal decomposition. Then, we can quickly select the best relay that maximizes the end-to-end system throughput by a deadline based on the system throughput obtained by each relay.
- *Online algorithm design:* Under the online optimization framework, the defined optimization problem is solved in two phases: the online relay selection phase followed by the online joint time scheduling and power allocation phase. Specifically, at the beginning of transmission period, the best relay is obtained based on the statistical knowledge of energy arrivals and channel fading levels from relays. After that, the best relay decides a new time scheduling and power level according to the instantaneous states of channel fading levels, energy arrival, and queue data in each time slot.

The remainder of this paper is organized as follows. In Section II, we introduce the DF EH wireless relay network model and present the problem formulation. In Section III, we propose an efficient algorithm to solve the joint relay selection and power control problem in the offline optimization framework. For the practical implementation, Section IV presents a sub-optimal online algorithm. In Section V, we evaluate the performance of the proposed schemes through several simulations. Finally, Section VI concludes the paper.

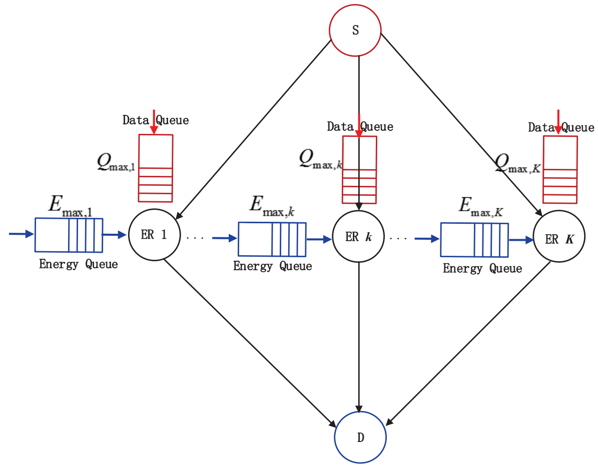

Fig. 1. A wireless relay network with a set of energy harvesting relay nodes.

II. System Model and Problem Formulation

A. System Model

We consider an EH wireless relay network as shown in Fig. 1, which consists of a non-EH source node (S), a destination node (D), and a set $\mathcal{K} = \{1, \ldots, K\}$ of EH relay nodes (ERs). The source node is powered by a battery with E_s units of available energy, and has available bits to be transmitted all the time. Each EH relay node is equipped with two queues: the data queue (i.e., the data buffer) which stores data bits from the source node, and the energy queue (i.e., the battery) which stores the energy harvested from nature, e.g., solar, wind, or electro-mechanical energy. In particular, the data queue and energy queue of EH relay node k can store at most $Q_{\max,k}$ bits of data and $E_{\max,k}$ units of energy, respectively. The transmission operates in slotted time with L-length unit slots.[1] Let t and t_0 denote the tth slot with the time interval $[t, t+1)$, and the time instant at the beginning of slot t, respectively. We model the energy replenishment process of each EH relay node k as a discrete process with E_{kt} units of energy harvested at time instant t_0. All harvested energy must first be buffered in the battery before it is used by the relay, and the relay is allowed to use the battery energy only for data transmission. Accordingly, if the harvested energy E_{kt} is larger than the available battery space of relay k at time t_0, the battery is charged to the maximum capacity and the remainder of harvested energy is discarded due to finite battery storage capacity. Therefore, let e_{kt} denote the battery energy of relay k at time instant t_0, and the relay k has the available battery energy equal to $\min\{E_{\max,k}, e_{kt} + E_{kt}\}$ at time slot t. Furthermore, it is reasonable to assume that $E_{kt} \leq E_{\max}$ for all k and t, as no more than an $E_{\max}$ amount of harvested energy can be utilized by the relay node k.

Each relay node operates in the half-duplex mode which cannot transmit and receive data simultaneously. Our relaying scheme employs the two-hop DF transmission, in which every time slot is divided into two mini-slots for respectively transmitting and forwarding. Suppose that the source node selects a relay node k for forwarding its information to the destination node at time slot t. The source node transmit a symbol with transmit power of $p_{s,t}$ during the first time fraction τ_{kt}, and the relay node k first decodes the received symbol and then forwards it to the destination node with the transmit power of $p_{r,kt}$ during the left time fraction $1-\tau_{kt}$. We consider fading channels, and let $\tilde{h}_{s,kt}$ and $\tilde{h}_{r,kt}$ denote the channel gain from the source node to the relay node k and the channel gain from the relay node k to the destination node at time slot t, respectively, which are determined by various factors such as path loss, shadowing and fading effects. Let $h_{s,kt}$ and $h_{r,kt}$ be the actual channel gains divided by the noise power n_0, respectively, i.e., $h_{s,kt} = \frac{\tilde{h}_{s,kt}}{n_0}$ and $h_{r,kt} = \frac{\tilde{h}_{r,kt}}{n_0}$. Therefore, assuming that the relay node k is selected to forward the transmission of the source node at time slot t, the average rates of the source node and the relay node k at time slot t are calculated as

$$r_{s,kt} = W\tau_{kt}\log(1 + h_{s,kt}p_{s,t}) \tag{1}$$

and

$$r_{r,kt} = W(1-\tau_{kt})\log(1 + h_{r,kt}p_{r,kt}) \tag{2}$$

based on the Shannon capacity formula, respectively, where W is the system bandwidth.

B. Problem Formulation

We aim at maximizing the end-to-end system throughput over T time slots (calculated as the total number of bits delivered by a deadline T) through the joint relay selection, time scheduling and power allocation for the wireless relay network. For simplicity, the transmit power of the source node is set to be fixed at any time, say p_s satisfying $p_s \leq \frac{E_s}{LT}$. If the relay node k is selected to forward the transmission of the source node by the deadline T, we denote $x_k = 1$, and $x_k = 0$ otherwise. Further, the source node must be assisted by the same unique relay station during the period T, and we have the following constraint as[2]

$$\sum_{k=1}^{K} x_k = 1. \tag{3}$$

Due to energy harvesting and finite battery storage capacity, there exists a causality constraint on $p_{r,kt}$ satisfying

$$p_{r,kt}(1-\tau_{kt}) \leq \frac{\min\{E_{kt} + e_{kt}, E_{\max,k}\}}{L}, \forall t \in \{1, 2, \ldots, T\}, \tag{4}$$

and an energy conservation constraint satisfying

$$e_{kt+1} = \min\{E_{kt} + e_{kt}, E_{\max,k}\} - p_{r,kt}(1-\tau_{kt})Lx_k. \tag{5}$$

Without loss of generality, let the battery of relay node k be empty at the beginning, and thus e_{k1} can be set to be 0. On the

[1] In this paper, we assume that the channel state information keep constant during every time slot, and thus the time length L is generally set to be less than the coherence time of channel fading.

[2] We can strike the balance between the system performance and system complexity through setting the frequency of updating relay selection during the time duration T.

other hand, due to data arrivals and data buffer size limitation, there exists a causality constraint on the data rate, i.e.,

$$r_{r,kt} \le \min\left\{ r_{s,kt} + \frac{d_{kt}}{L}, \frac{Q_{\max,k}}{L} \right\}, \forall t \in \{1, 2, \ldots, T\}, \tag{6}$$

and a flow balance equation satisfying

$$d_{kt+1} = \min\{ r_{s,kt}L + d_{kt}, Q_{\max,k} \} - r_{r,kt}Lx_k, \tag{7}$$

where d_{kt} denotes the queue data of relay node k at time instant t_0. Similarly, we assume the data buffer to be empty for each relay node at the beginning, i.e., $d_{k1} = 0$ for all k.

Considering these constraints above, we formulate the throughput maximization problem as

$$\begin{aligned} \max \quad & \sum_{k=1}^{K} \sum_{t=1}^{T} r_{r,kt} x_k \\ \text{s.t.} \quad & \text{constraints} \quad (3) - (7), \\ & 0 \le \tau_{kt} \le 1, \forall t \in \{1, 2, \ldots, T\}, \forall k \in \mathcal{K}, \\ \text{vars.} \quad & \tau_{kt}, x_k, p_{r,kt}, e_{kt}, d_{kt}, \forall t \in \{1, 2, \ldots, T\}, \forall k \in \mathcal{K}. \end{aligned} \tag{8}$$

Note that the problem in (8) is a complex combinatorial and integer problem, and thus is difficult to solve. In the following sections, we will propose an efficient offline algorithm to solve the problem in (8) via decomposition.

III. Optimal Offline Algorithm Design

In this section, we aim to find the optimal relay selection, and optimal time scheduling and power allocation by optimizing multiple variables sequentially. In particular, we first decompose the optimization problem (8) into two subproblems: the joint time scheduling and power allocation subproblem and the relay selection subproblem. Then, the necessary properties of the optimal solution for joint time scheduling and power allocation subproblem are established. Finally, we develop an efficient optimal algorithm to solve the problem (8).

A. Decomposition

Since the objective in the problem (8) is to maximize the total throughput by the deadline T, the relay node that can guarantee the maximum total throughput by the deadline is selected to assist the transmission of the source node. Therefore, the problem (8) can be equivalently decomposed into

Sub-1: Joint Time Scheduling and Power Allocation

$$\begin{aligned} R_k^* = \max \quad & \sum_{t=1}^{T} r_{r,kt} \\ \text{s.t.} \quad & p_{r,kt}(1 - \tau_{kt})L \le \min\{E_{kt} + e_{kt}, E_{\max,k}\}, \\ & e_{kt+1} = \min\{E_{kt} + e_{kt}, E_{\max,k}\} - p_{r,kt}(1 - \tau_{kt})L, \\ & r_{r,kt} \le \min\{r_{s,kt} + d_{kt}/L, Q_{\max,k}/L\}, \\ & d_{kt+1} = \min\{r_{s,kt}L + d_{kt}, Q_{\max,k}\} - r_{r,kt}L, \\ & 0 \le \tau_{kt} \le 1, \forall t \in \{1, 2, \ldots, T\} \\ \text{vars.} \quad & \tau_{kt}, p_{r,kt}, e_{kt}, d_{kt}, \forall t \in \{1, 2, \ldots, T\} \end{aligned} \tag{9}$$

and

Sub-2: Relay Selection

$$k^* = \underset{k}{\operatorname{argmax}}\ R_k^* \text{ and } x_{k^*} = 1, x_k = 0, \forall k \ne k^*. \tag{10}$$

Note that (9) corresponds to the subproblem that maximizes the total throughput by the deadline when selecting the relay node k, and (10) corresponds to the subproblem that selects the best relay node for maximizing the total throughput by the deadline.

B. Optimality Conditions

The following Propositions show the properties of the optimal solution to the subproblem (9).

Lemma 1: For the maximum throughput of (9), the battery of the relay k does not overflow when energy arrival happens, and the data buffer can not overflow either at any time slot.

Proof: We start by assuming that the battery of relay node k overflows at energy arrival instant t_0. Let the power allocation allowing this overflow be $p_{r,kt-1}$ in time slot $t-1$ before t_0. E_{kt} is less than or equal to $E_{\max,k}$ by the system model and causes an overflow, and thus the battery energy is strictly positive right before t_0. This implies that $p_{r,kt-1}$ can be increased by an infinitesimal amount δ without violating energy-feasibility. Furthermore, the time fraction τ_{t-1} can be increased by consuming the same amount of energy for the guarantee of throughput-feasibility. Due to the fact that the throughput increases with the energy consumption while decreasing with the time fraction, these doings can guarantee the increase of throughput while avoiding the energy overflow.

We then assume that the data buffer of relay node k overflows when the source node transmits information to the relay node k at time slot t. On one hand, if the overflow is caused due to the non-empty data buffer right before t_0, we can decrease the time fraction with the same amount of energy at time slot $t-1$ to recover the data overflow. Since the throughput decreases with the time fraction when given the energy consumption, this doing strictly increases the throughput. On the other hand, if the overflow is caused by the transmission of the source node at time slot t, we can decrease the time fraction and the energy consumption at time slot t to resolve the data overflow. Since the throughput decreases with the time fraction while increasing with the energy consumption, this doing will not reduce the throughput.

Therefore, neither the battery nor the data buffer will overflow when we maximize the total throughput in (9). ■

We introduce one variable $\bar{\tau}_{kt}$, and define it as $\bar{\tau}_{kt} = 1 - \tau_{kt}$. For the brevity, we set $u_{kt} = W \log(1 + h_{s,kt}p_s)$. Without loss of optimality, the equality $r_{r,kt} = W\bar{\tau}_{kt} \log(1 + h_{r,kt}p_{r,kt})$ can be replaced with $r_{r,kt} \le W\bar{\tau}_{kt} \log(1 + h_{r,kt}p_{r,kt})$. This is because that the optimal solution always occurs for achieving the maximum when such an inequality is satisfied with equality. Therefore, we can rewrite the problem (9) as (11) by Lemma 1.

$$R_k^* = \max \sum_{t=1}^{T} r_{r,kt}$$

$$\begin{aligned}
\text{s.t.}\quad & \sum_{i=1}^{t} p_{r,ki}\bar{\tau}_{ki} \le \sum_{i=1}^{t} E_{ki}/L, \\
& \sum_{i=1}^{t-1} p_{r,ki}\bar{\tau}_{ki} \ge \sum_{i=1}^{t} E_{ki}/L - E_{\max,k}/L, \\
& \sum_{i=1}^{t} \bar{\tau}_{ki}u_{ki} + \sum_{i=1}^{t} r_{r,ki} \le \sum_{i=1}^{t} u_{ki}, \\
& \sum_{i=1}^{t} \bar{\tau}_{ki}u_{ki} + \sum_{i=1}^{t-1} r_{r,ki} \ge \sum_{i=1}^{t} u_{ki} - Q_{\max,k}/L, \\
& r_{r,kt} \le W\bar{\tau}_{kt}\log(1 + h_{r,kt}p_{r,kt}), \\
& 0 \le \bar{\tau}_{kt} \le 1, \\
\text{vars.}\quad & \bar{\tau}_{kt}, p_{r,kt} \ge 0, r_{r,kt} \ge 0, \forall t \in \{1, 2, \ldots, T\}. \qquad (11)
\end{aligned}$$

The following Theorem 1 shows the convex nature of the problem in (11).

Theorem 1: The equivalent problem of (**Sub-1**) (i.e., Problem (11)) can be transformed into a convex optimization problem, and thus there exists a unique optimal solution.

Proof: Let $q_{kt} = \bar{\tau}_{kt}p_{r,kt}$. It is clear that q_{kt} corresponds to the actual amount of power allocated to the relay node k at time slot t. Therefore, Problem (11) can be rewritten as problem (P).

Since the Hessian matrix of $W\bar{\tau}_{kt}\log(1 + \frac{h_{r,kt}q_{kt}}{\bar{\tau}_{kt}})$ with $\bar{\tau}_{kt}$ and q_{kt} is positive-definite, the function $W\bar{\tau}_{kt}\log(1 + \frac{h_{r,kt}q_{kt}}{\bar{\tau}_{kt}})$ is concave [24]. Thus, the inequality constraint in (17) is convex. Further, the constraints in (13)-(16) are all affine. Thus, the feasible set of this optimization problem (P) is convex. Together with the linear objective function, the problem (P) is a convex optimization problem, and there exists a unique optimal solution, which can be obtained in polynomial time. ∎

$$P : R_k^* = \max \sum_{t=1}^{T} r_{r,kt} \tag{12}$$

$$\text{s.t.} \quad \sum_{i=1}^{t} q_{ki} \le \sum_{i=1}^{t} E_{ki}/L, \tag{13}$$

$$\sum_{i=1}^{t-1} q_{ki} \ge \sum_{i=1}^{t} E_{ki}/L - E_{\max,k}/L, \tag{14}$$

$$\sum_{i=1}^{t} \bar{\tau}_{ki}u_{ki} + \sum_{i=1}^{t} r_{r,ki} \le \sum_{i=1}^{t} u_{ki}, \tag{15}$$

$$\sum_{i=1}^{t} \bar{\tau}_{i}u_{ki} + \sum_{i=1}^{t-1} r_{r,ki} \ge \sum_{i=1}^{t} u_{ki} - Q_{\max,k}/L, \tag{16}$$

$$r_{r,kt} \le W\bar{\tau}_{kt}\log\left(1 + \frac{h_{r,kt}q_{kt}}{\bar{\tau}_{kt}}\right), \tag{17}$$

$$0 \le \bar{\tau}_{kt} \le 1, \tag{18}$$

$$\text{vars.} \quad \bar{\tau}_{kt}, q_{kt} \ge 0, r_{r,kt} \ge 0, \forall t \in \{1, 2, \ldots, T\} \tag{19}$$

C. Optimal Algorithm

Due to the convex nature, the primal decomposition can be used to solve the problem (11) by separating its optimization into two levels of optimization [25] and then alternatively optimizing variables $p_{r,kt}$'s and $\bar{\tau}_{kt}$'s in the two levels of optimization. At the lower level, we optimize variables $p_{r,kt}$'s and $r_{r,kt}$'s by solving the problem (11) related to variables $p_{r,kt}$'s and $r_{r,kt}$'s when $\bar{\tau}_{kt}$'s are fixed. Due to the convex nature, the problem in (11) at the lower level can be solved with the canonical convex optimization algorithms (e.g., interior-point method [26]). At the higher level, we optimize the coupling variables $\bar{\tau}_{kt}$'s with the updated $p_{r,kt}$'s and $r_{r,kt}$'s. Assume the optimal $p_{r,kt}$ and $r_{r,kt}$ to be $p_{r,kt}(n)$ and $r_{r,kt}(n)$ at the nth iteration, respectively. Due to the convex nature, the updating $\bar{\tau}_{kt}$'s can be obtained with a projected subgradient method as

$$\begin{aligned}
\bar{\tau}_{kt}(n+1) = \Bigg[\bar{\tau}_{kt}(n) + s_t\Bigg(&\left(\sum_{i=t}^{T}\lambda_{1i} + \sum_{i=t}^{T-1}\lambda_{2i}\right)p_{r,kt}(n) \\
&+\left(\sum_{i=t}^{T}\lambda_{3i} + \sum_{i=t}^{T-1}\lambda_{4i}\right)u_{kt} \\
&+ \lambda_{5t}\big(W\log(1 + h_{r,kt}p_{r,kt}(n)) - r_{r,kt}(n)\big)\Bigg)\Bigg]_0^1,
\end{aligned} \tag{20}$$

where $[x]_a^b$ means $\min\{\max\{x, a\}, b\}$, $s_t > 0$ is the nth step size, and λ_{mt} is the optimal multiplier variable corresponding to the mth constraint in problem (9) at the nth iteration.

In summary, we have the following Algorithm 1 to solve problem (11). Note that when every relay node obtains its maximum throughput R_k^* through Algorithm 1, the best relay can be selected by (10).

Algorithm 1 Optimal Algorithm to Solve the Problem (11)

- **Input:** The relay node k needs its channel gains $h_{r,kt}$'s, energy arrivals E_{kt}'s, battery capacity $E_{\max,k}$, buffer size $Q_{\max,k}$, the instantaneous rates of the source node (i.e., u_{kt}'s), the deadline T, and the tolerance error ϵ.
- **Output:** The relay node k obtains the optimal transmit power and time fraction allocated to each time slot t (denoted by $p_{r,kt}^*$ and $\bar{\tau}_{kt}^*$, respectively), and the maximum total throughput R_k^* (i.e., $R_k^* = \sum_{t=1}^{T} W\bar{\tau}_{kt}\log(1+h_{r,kt}p_{r,kt})$).

1: **Initialization:** Set the iteration index n to be $n = 1$, and $\tau_{kt}(1)$ equal to some feasible value for all t.
2: Update $p_{r,kt}(n+1)$ by solving the problem (11) related to variables $p_{r,kt}$'s and $r_{r,kt}$'s with the interior-point method for given $\bar{\tau}_{kt}(n)$'s.
3: Update $\bar{\tau}_{kt}(n+1)$ by (20).
4: Set $n \leftarrow n+1$ and go to step 2 (until satisfying termination criterion $\sum_{t=1}^{T} |p_{r,kt}(n) - p_{r,kt}(n-1)| + |\bar{\tau}_{kt}(n) - \bar{\tau}_{kt}(n-1)| \le \epsilon$).

D. Computational Complexity

The following theorem shows the computational complexity of the proposed offline joint time scheduling and power control algorithm.

Theorem 2: Let the step size be $\frac{1}{t}$ at the nth iteration. The computational complexity of the proposed offline joint time scheduling and power control algorithm (i.e., Algorithm 1) is of $O(T^{0.5}\log(T)e^{1/\epsilon})$ iterations.

Proof: We adopt the primal decomposition with the projected subgradient method to find the optimal solution to problem (9). Recall that a convex programming at the lower level is solved via the interior-point algorithm at each iteration, and its computational complexity is $O(T^{0.5}\log(T))$. Further, the project subgradient method is performed to update the time scheduling at each iteration, which gives the computational complexity of $O(1)$. Therefore, the per-iteration computational complexity of the offline joint time scheduling and power control algorithm is $O(T^{0.5}\log(T)) + O(1) = O(T^{0.5}\log(T))$. On the other hand, $O(e^{1/\epsilon})$ iterations are needed when the offline joint time scheduling and power control algorithm obtains the ϵ-optimal solution. For the detailed proof, interested readers are referred to [28, Propagation 2]. Therefore, we have that the computational complexity of the offline joint time scheduling and power control algorithm is $Q(T^{0.5}\log(T)e^{1/\epsilon})$. ■

Remark 1: Together with the number of relays being K, the total computational complexity of the offline joint time scheduling and power control algorithm across all relays is $Q(KT^{0.5}\log(T)e^{1/\epsilon})$. Further, the computational complexity of relay selection in (10) is $Q(K)$. Therefore, the computational complexity of the proposed offline relay selection and power control algorithm is $Q(KT^{0.5}\log(T)e^{1/\epsilon}) + Q(K) = Q(KT^{0.5}\log(T)e^{1/\epsilon})$.

IV. Online Algorithm Design

In practice, due to the randomness of energy arrivals and channel fading, it is difficult to predict all energy arrivals and channel fading levels in advance. In this section, we therefore propose a online relay selection and power control algorithm that only requires causal information of energy arrivals and channel fading levels.

Recall that the throughput maximization problem in (8) covers the relay selection and the joint time scheduling and power allocation, and thus we propose a online relay selection and power control algorithm including two key parts as follows.

1) *Relay selection:* The source node selects the best relay based on the statistical knowledge of energy arrivals and channel fading levels from relays when staring the data transmission.
2) *Joint time scheduling and power allocation:* In each time slot, the best relay decides a new power level and time allocation according to the instantaneous states of its battery energy and queue data.

In the following, we shall introduce every key part in details.

A. Relay Selection

With the goal of maximizing the end-to-end throughput by a deadline, the source node selects the relay that can forward the most data according to the predicated channel fading levels and energy arrivals as the best relay. In particular, the relay selection has three key ingredients as follows.

1) When the source node starts the data transmission, it asks every relay for its forwarding capacity.
2) When the relay k receives the request from the source node, it predicts its forwarding capacity according to the estimation of channel fading levels and energy arrivals in the following transmission period, and informs the source node of the result.
3) The source node decides the best relay based on the feedback from relays.

In the following, we shall introduce every key ingredient in details. In particular, the proposed online relay selection algorithm works as follows.

First: the relay k estimates the channel levels $h_{s,kt}$ and $h_{r,kt}$ as $h_{s,k}$ and $h_{r,k}$ for $t = 1, \ldots, T$, respectively, according to the channel state information in N time slots before the transmission period. Considering the coherence nature of the channel in the time domain, $h_{s,k}$ and $h_{r,k}$ can be respectively expressed as

$$h_{s,k} = \sum_{n=1}^{N} \omega_{-n} h_{s,k(-n)},$$
$$h_{r,k} = \sum_{n=1}^{N} \omega_{-n} h_{r,k(-n)}, \tag{21}$$

where $h_{s,k(-n)}$ and $h_{r,k(-n)}$ denote the channel gain between the source node and relay k and the channel gain between the relay k and destination node in the nth time slot before the transmission period, respectively. Here, the coefficient ω_{-n} indicates the weight of $h_{s,k(-n)}/h_{r,k(-n)}$ for the estimation of $h_{s,k}/h_{r,k}$, satisfying

$$\omega_{-n} = \frac{2^{-n}}{1 - 2^{-N}}. \tag{22}$$

Similarly, the energy arrival E_{kt} is estimated as E_k for all $t = 1, \ldots, T$, satisfying

$$E_k = \sum_{n=1}^{N} \omega_{-n} E_{k(-n)}, \tag{23}$$

where $E_{k(-n)}$ is the amount of energy harvested in the nth time slot before the transmission period.

Second: based on the estimation results of channel fading levels and energy arrivals, each relay k evaluates its forwarding capacity without taking account into the data and energy storage limits. Specifically, the forwarding capacity of relay k, denoted by F_k, is obtained by the following formula:

$$\begin{aligned} F_k = \max \quad & W\hat{\tau}_k TL \log\big(1 + h_{r,k}\hat{p}_{r,k}\big) \\ \text{s.t.} \quad & WTL\big(1 - \hat{\tau}_k\big)\log\big(1 + h_{s,k}p_s\big) + d_{k1} \\ & \geq WTL\hat{\tau}_k \log\big(1 + h_{r,k}\hat{p}_{r,k}\big), \\ & p_{r,k}TL\hat{\tau}_k \leq TE_k + e_{k1}, \\ & 0 \leq \hat{\tau} \leq 1, \hat{p}_{r,k} \geq 0, \\ \text{vars.} \quad & \hat{\tau}_k, \hat{p}_{r,k}, \end{aligned} \tag{24}$$

where variables $\hat{\tau}_k$ and $\hat{p}_{r,k}$ mean the time fraction and transmit power used by relay k for forwarding, respectively. Since the function $W\hat{\tau}_k TL\log(1+h_{r,k}\hat{p}_{r,k})$ is increasing with $\hat{\tau}_k$ and $\hat{p}_{r,k}$

while the function $(1-\hat{\tau}_k)\log(1+h_{s,k}p_s)$ is decreasing with $\hat{\tau}_k$, we can easily obtain the optimal solution to (24) as follows:

$$(\hat{\tau}_k^*, \hat{p}_{r,k}^*) = \begin{cases} \left(\frac{TE_k+e_{k1}}{TL}, 1\right), & \text{if } \log\left(1 + h_{r,k}\frac{TE_k+e_{k1}}{TL}\right) \leq \frac{d_{k1}}{WTL} \\ \left(\frac{TE_k+e_{k1}}{TL\tilde{\tau}_k}, \tilde{\tau}_k\right), & \text{otherwise,} \end{cases} \tag{25}$$

where $\tilde{\tau}_k$ is the root of the equation $(1-\tilde{\tau}_k)\log(1+h_{s,k}p_s) + \frac{d_{k1}}{WTL} = \tilde{\tau}_k \log(1 + h_{r,k}\frac{TE_k+e_{k1}}{\tilde{\tau}_k TL})$. Due to the monotonic nature, $\tilde{\tau}_k$ can be obtained via bisection searching [27]. After that, the relay k has $F_k = W\hat{\tau}_k^* TL\log(1+h_{r,k}\hat{p}_{r,k}^*)$, and informs it to the source node.

Finally: when the source node receives the forwarding capacity from each relay, it decides the best relay k^* by

$$k^* = \underset{k}{\operatorname{argmax}}\ F_k^* \text{ and } x_{k^*} = 1, x_k = 0, \forall k \neq k^*, \tag{26}$$

which is used for forwarding by a deadline T.

B. Joint Time Scheduling and Power Allocation

The best relay k^* adopts the best-effort transmission policy to help the source node forward the data to the destination node according to the battery energy and queue data in each time slot. In particular, the best-effort transmission policy works as follows. **First**, the best relay k^* estimates the channel levels (i.e., h_{s,k^*t} and h_{r,k^*t}), the battery energy (i.e., $\min\{E_{\max,k^*}, e_{k^*t}+E_{k^*t}\}$), and the queue data (i.e., d_{k^*t}) at each time slot t. **Second**, the best relay k^* predicts the optimal time scheduling and power allocation used in time slot t by maximizing the total throughput subject to the causality constraints of battery energy and queue data, i.e.,

$$\begin{aligned} \max\quad & r_{r,k^*t} \\ \text{s. t.}\quad & p_{r,k^*t}(1-\tau_{k^*t}) \leq \frac{\min\left\{E_{\max,k^*}, e_{k^*t}+E_{k^*t}\right\}}{L}, \\ & r_{r,k^*t} \leq \min\left\{r_{s,k^*t} + \frac{d_{k^*t}}{L}, \frac{Q_{\max,k^*}}{L}\right\} \\ & 0 \leq \tau_{k^*t} \leq 1 \\ \text{vars.}\quad & \tau_{k^*t}, p_{r,k^*t} \geq 0. \end{aligned} \tag{27}$$

Finally: the best relay k^* informs the optimal time scheduling $\tau_{k^*t}^*$ to the source node, and then the source node transmits its data to the best relay during $\tau_{k^*t}^* L$.

In the implementation, we can obtain the optimal solution to problem (27) as shown in Theorem 3.

Theorem 3: The optimal solution to problem (27), denoted by $(p_{r,k^*t}^*, \tau_{k^*t}^*)$, can be calculated by

$$(p_{r,k^*t}^*, \tau_{k^*t}^*) = \begin{cases} \left(\frac{Eb_t}{L}, 0\right), & \text{if } \log\left(1+\frac{h_{r,k^*t}Eb_t}{L}\right) \leq \frac{d_{k^*t}}{WL}, \\ (\tilde{p}_t, 1-\Gamma_t), & \text{if } \log\left(1+\frac{h_{r,k^*t}Eb_t}{L\Gamma_t}\right) \geq \frac{Q_{\max,k^*}}{WL\Gamma_t}, \\ \left(\frac{Eb_t}{L\tilde{\Gamma}_t}, 1-\tilde{\Gamma}_t\right), & \text{otherwise.} \end{cases} \tag{28}$$

Here, $Eb_t = \min\{E_{\max,k^*}, e_{k^*t}+E_{k^*t}\}$, $\Gamma_t = \max\{0, 1 - \frac{Q_{\max,k^*}-d_{k^*t}}{WL\log(1+p_s h_{s,k^*t})}\}$, $\tilde{p}_t$ is the root such that $WL\Gamma_t \log(1 + h_{r,k^*t}\tilde{p}_t) = Q_{\max,k^*}$, and $\tilde{\Gamma}_t$ is the root such that $WL\tilde{\Gamma}_t\log(1+\frac{h_{r,k^*t}Eb_t}{L\tilde{\Gamma}_t}) = (1-\tilde{\Gamma}_t)\log(1+h_{s,k^*t}p_s) + d_{k^*t}$, which can be obtained by the bisection searching [27].

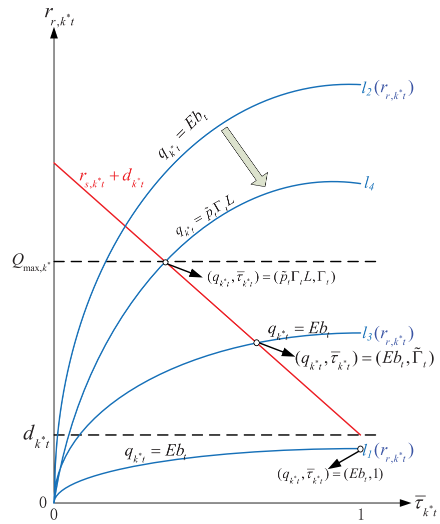

Fig. 2. The curves of r_{r,k^*t} and $r_{s,k^*t} + d_{k^*t}$.

Proof: To obtain the optimal solution to (27), we need to introduce new variables $\bar{\tau}_{k^*t} = 1-\tau_{k^*t}$ and $q_{k^*t} = p_{r,k^*t}\bar{\tau}_{k^*t}L$ to (27). In this doing, the function r_{r,k^*t} is increasing with $\bar{\tau}_{k^*t}$ and q_{k^*t}, while the function r_{s,k^*t} is decreasing with $\bar{\tau}_{k^*t}$. Therefore, when q_{k^*t} is set to be Eb_t, we have the curves of r_{r,k^*t} and $r_{s,k^*t}+d_{k^*t}$ as shown in Fig. 2, where the curve of r_{r,k^*t} is one of curves l_1, l_2 and l_3. From Fig. 2, we can find that if the curve l_1 is satisfied such that the best relay k^* cannot forward all data d_{k^*t} in the queue with all energy Eb_t (i.e., $\log(1+\frac{h_{r,k^*t}Eb_t}{L}) \leq \frac{d_{k^*t}}{WL}$), we have that due to the monotonic nature, the maximum total throughout is obtained when the optimal $\bar{\tau}_{k^*t}$ and q_{k^*t} are equal to 1 and Eb_t, respectively. In this case, $(p_{r,k^*t}^*, \tau_{k^*t}^*)$ satisfies $(\frac{Eb_t}{L}, 0)$ accordingly. On the other hand, if the best relay k^* can forward all data d_{k^*t} in the queue with all energy Eb_t, the curve of r_{r,k^*t} is either l_2 or l_3. If the curve l_2 is satisfied, the best relay cannot forward the data from the source node and the data in the queue due to the limited data queue $Q_{\max,k^*}$ (i.e., $\log(1+\frac{h_{r,k^*t}Eb_t}{L\Gamma_t}) \geq \frac{Q_{\max,k^*}}{WL\Gamma_t}$). In this case, the maximum total throughput must be equal to $Q_{\max,k^*}$, and the best relay k^* forwards $Q_{\max,k^*}$ data by reducing energy consumption to $\tilde{p}_t\Gamma_t L$, i.e., the curve l_4 in Fig. 2. Therefore, the optimal $\bar{\tau}_{k^*t}$ and q_{k^*t} are equal to Γ_t and $\tilde{p}_t\Gamma_t L$, and hence the optimal solution to problem (27) being $(\tilde{p}_t, 1-\Gamma_t)$. On the contrary, if the curve l_3 is satisfied, the best relay k^* needs to forward the data from the source node and the data in the queue with Eb_t energy when maximizing the total throughput. Therefore, the optimal $\bar{\tau}_{k^*t}$ and q_{k^*t} are equal to $\tilde{\Gamma}_t$ and Eb_t, and hence the optimal solution to problem (27) being $(\frac{Eb_t}{L\tilde{\Gamma}_t}, 1-\tilde{\Gamma}_t)$. ■

In summary, the proposed online relay selection and power control algorithm can realize the online relay selection by running the online relay selection algorithm, and the joint time scheduling and power allocation by running the best-effort transmission policy.

TABLE I
SIMULATION PARAMETERS

Simulation parameters	Value chosen
Carrier frequency	2000 MHz
Path loss model	$(128.1 + 37.6\log_{10}(d))$ dB (d in km)
Channel fading	Rayleigh fading
Bandwidth	180 kHz (i.e., 12 subcarriers)
Noise power spectral density	-174 dBm/Hz
Energy arrival	unif(0, $E_{k,\max}$) for all k
p_s	20 dBm
The length of time slot (i.e., L)	1 sec
The deadline T	10 secs

C. Computational Complexity

The following theorem shows the computational complexity of the proposed online relay selection and power control algorithm.

Theorem 4: Given the error tolerance of bisection searching, say δ, the computational complexity of the proposed online relay selection and power control algorithm is of $\log_2(\delta^{-1})(K+T)+K$ iterations in the worst case.

Proof: The proposed online relay selection and power control algorithm includes the online relay selection and joint time scheduling and power control. The best relay is obtained by solving (25) for all relays and (26). The computational complexity of solving (25) is equal to the computational complexity of bisection searching in the worst case, i.e., of $\log_2(\delta^{-1})K$ iterations, and the computational complexity of solving (26) is of K iterations. Thus, the computational complexity of relay selection is of $\log_2(\delta^{-1})K + K$. Since the online joint time scheduling and power control is achieved by solving (28) at each time slot, its computational complexity is of $\log_2(\delta^{-1})T$ in the worst case. As a result, the total computational complexity of the proposed online relay selection and power control algorithm is of $\log_2(\delta^{-1})(K + T) + K$ iterations in the worst case, and Theorem 4 follows. ■

V. NUMERICAL RESULTS

In this section, we will evaluate the maximum throughput by a deadline T and the optimal relay selection when using the proposed algorithms. According to the Macro cell parameters in [29], we set the simulation parameters in Table I. We set every $E_{k,\max}$ to be on the order of 1 J for an illustration target, since a fictitious battery that carries energy is assumed for only communication purposes. We use the Clarke's model [30] to generate the fading level with considering the approximal coherence time being 1 second. Suppose that the changes in the fading level occur relatively slowly during one time slot. In the following simulations, we consider a set of EH wireless relay networks as shown in Fig. 3, where K relays are randomly deployed in a 200m-by-400m rectangle, and the source and destination nodes are placed in (0,200m) and (1000m, 200m), respectively.

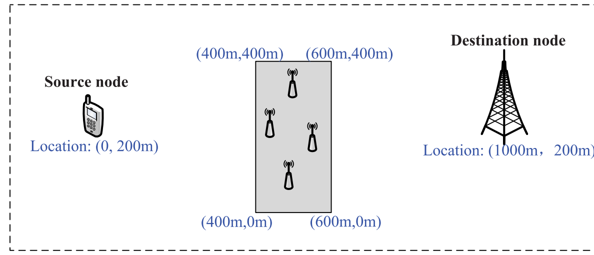

Fig. 3. The network topology used for simulations, where K relays are randomly deployed in the shadowing area.

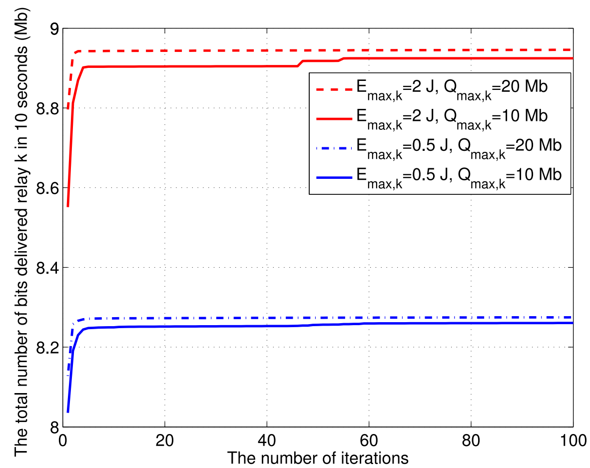

Fig. 4. The optimality and convergence of the proposed offline algorithm with $\epsilon = 10^{-4}$ under different settings of $E_{\max,k}$ and $Q_{\max,k}$.

Example 1: We start with examining the optimality and convergence of the proposed offline algorithm when running it in the Rayleigh fading scenario with the following channel gains[3] in (29), as shown at the bottom of the next page, for the relay node k in (500m, 200m). Fig. 4 shows the optimality and convergence of the proposed offline algorithm with $\epsilon = 10^{-4}$ under different settings of the battery capacity and the data buffer size of relay node k (i.e., $Q_{\max,k}$ and $E_{\max,k}$, respectively). It can be seen that the proposed algorithm can always converge to the maximum throughput quickly. We can also find that the maximum throughput increases with the increasing of $Q_{\max,k}$ and $E_{\max,k,}$. This is because that the relay is more likely to forward data bits in the time slots with good channel situation when increasing $Q_{\max,k}$ and $E_{\max,k}$.

Example 2: In this simulation example, we want to compare the average total throughput obtained by the proposed offline algorithm and the proposed online algorithm. We consider a set of EH wireless relay networks as shown in Fig. 3. We vary the number of relays from 10 to 50. For the comparison with our proposed algorithms, we therefore introduce two baseline algorithms: the random selection algorithm and the max-SINR selection algorithm. The random selection algorithm assumes that the source node randomly selects one relay with uniform distribution, and the chosen relay forwards the information

[3] These channel gains are one sample when considering the Rayleigh fading with the mean of path loss.

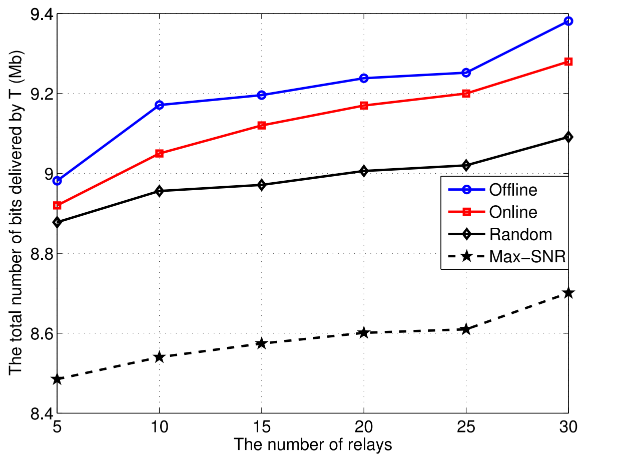

Fig. 5. The total number of bits delivered by the deadline T when using the proposed offline algorithm, the proposed online algorithm, the random relay selection scheme, and the max-SINR relay selection scheme, respectively.

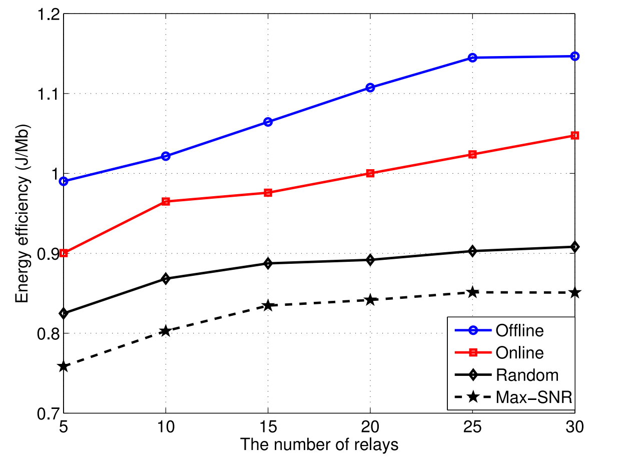

Fig. 7. The energy efficiency when using the proposed offline algorithm, the proposed online algorithm, the random relay selection scheme, and the max-SINR relay selection scheme, respectively.

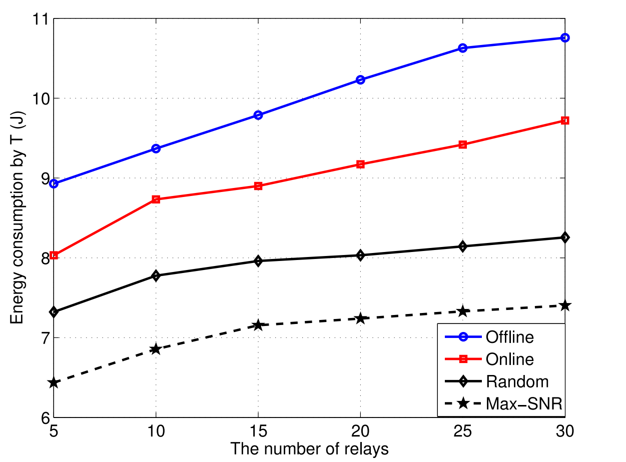

Fig. 6. The total energy consumption by the deadline T when using the proposed offline algorithm, the proposed online algorithm, the random relay selection scheme, and the max-SINR relay selection scheme, respectively.

to the destination node via the best-effort transmission policy. The max-SINR relay selection algorithm means that the source node selects the relay that poses the best channel gain averaging over the period T, and the chosen relay forwards the information to the destination node via the best-effort transmission policy.

Figs. 5, 6, and 7 show the performance of these four algorithms in terms of the total number of bits delivered, the total energy consumption needed, and the energy efficiency obtained, respectively, in which each point is obtained by averaging over 100 different topologies with the same density of relays. It can be seen that the performance of these four algorithms increases with the increase of the number of relays. It is not surprising to see that the proposed offline algorithm always outperforms the other three algorithms. This is because that the offline algorithm can always make the optimal decisions of relay selection, time scheduling and power control according to the prefect information of energy arrivals and channel fading levels. Furthermore, we can find that using any algorithm, the more bits can be delivered to the destination node with the more energy consumption when increasing the density of relays. This is because that more appropriate relay can be elected as the best relay with the increase of the number of relays. On the other hand, it can be seen that the proposed online algorithm achieves better performance in comparison with the two baseline algorithms, although it suffers a small degradation from the proposed offline algorithm. Specifically, the degradation is at most 1.5% of total throughput delivered and 11% of energy efficiency. Therefore, the proposed online algorithm may be a viable policy for practical implementation.

VI. Conclusion

This paper addressed the joint relay selection and power control problem in the DF EH wireless relay network with finite data and energy storage. In particular, we first solved such an optimization problem under an offline optimization framework by decomposing it into subproblems: the joint time scheduling and power control subproblem and the relay selection problem. Due to the convex nature, the optimal solution to the joint time scheduling and power control problem was obtained via the primal decomposition. After that, the best relay was determined based on the obtained system throughput for each relay. For the practical implementation, we further proposed a sub-optimal online joint time scheduling and power control algorithm. For specific, we first decided the best relay based on the statistical knowledge of energy arrivals and channel states, and then decided the time

$$\begin{bmatrix} h_{s,kt} \\ h_{r,kt} \end{bmatrix}_T = \begin{bmatrix} 3.2219 & 3.9216 & 5.2155 & 4.1177 & 4.2498 & 3.6772 & 4.3517 & 1.7038 & 1.6988 & 1.5511 \\ 0.7877 & 3.9465 & 2.5211 & 1.8201 & 0.7894 & 3.8728 & 3.1068 & 1.3141 & 2.3216 & 0.8936 \end{bmatrix} \times 10^3 \quad (29)$$

scheduling and power control of the best relay that maximizes the total throughput according to the instantaneous state of channel fading, energy arrival, and queue data in each time slot. After analyzing the computational complexity of two proposed algorithms, we presented numerical results to show that compared to the optimal offline algorithm, the sub-optimal online algorithm suffers only a small degradation in performance.

For the future work, we will study the joint relay selection and power control problem for a multi-source multi-relay communication system, where all source nodes and relays are powered by harvesting renewable ambient energy, and are subject to the finite data and energy storage.

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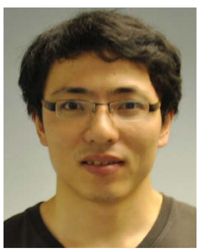

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