Relay Selection and Power Allocation for Cooperative Communication Networks with Energy Harvesting

Fei Wang, Songtao Guo, *Member, IEEE,* Yuanyuan Yang, *Fellow, IEEE* and Bin Xiao, *Senior Member, IEEE.*

***Abstract*—This paper addresses the joint relay, power splitting ratio, and transmission power selection problem for an energy harvesting (EH) cooperative network, where the source and the relays can harvest energy from natural sources (e.g., solar) and radio frequency (RF) signals, respectively. To effectively use the harvested energy of the source, the relays are designed to employ the power splitting technique to scavenge energy from RF signals radiated by the source. The addressed problem is considered in both offline and online settings, with the objective to maximize system payoff, which is defined as the difference between system transmission benefit and system energy cost, and meanwhile to minimize system outage probability. In particular, direct transmission is considered in our study and relay transmission is selected dynamically based on network channel conditions and the available energy of EH nodes. Our simulation results reveal that it is necessary to consider direct transmission and select relay transmission and power splitting ratio dynamically in some cases, which can greatly improve system performance. Besides, simulations also verify that considering system energy consumption is also meaningful for EH relaying systems, which can lead to a desired system performance by choosing some related parameters appropriately. In addition, we also show that the resource allocation models and the corresponding resource allocation schemes proposed can be extended to more general communication scenarios, for instance, when some relays scavenge energy from natural sources and others from RF signals.**

***Index Terms*—Energy harvesting, cooperative networks, simultaneous information and energy transfer, power allocation, relay and power splitting ratio selection, generalized outer approximation (GOA).**

I. Introduction and Related Work

In cooperative communication networks, sources and cooperating relays are connected to the power grid or equipped with pre-charged batteries conventionally. However, running the power grid to supply energy is often impractical or cumbersome in several scenarios, while the limited storage capacity of pre-charged batteries always leads to the limited lifetime of networks. Therefore, introducing energy harvesting (EH) nodes is attractive due to their long lifetime without continuous monitoring and maintenance [1].

EH nodes use energy harvesting technologies to scavenge energy so as to carry out their communication tasks [2]. Energy can be harvested from natural sources such as solar and vibration, and can also be obtained using the wireless power transfer (WPT) technology [3]. However, since the amount of energy harvested by EH nodes is unpredictable and only the energy available in batteries can be used in the current time, EH communication networks motivate the need for the design of novel transmission policies to meet specific network requirements.

Recently, transmission policies for EH cooperative networks have been provided in the literature, such as [4]-[11]. The use of EH relays in cooperative communication was first introduced in [4] for a relay selection EH network. In [5]-[7], assuming a deterministic EH model under which the energy arrival time and the amount of harvested energy are known prior to transmission, several power allocation policies were proposed for the classical three-node relay system. However, the deterministic EH model is impractical because the energy arrival time and the harvested amount are random in nature. Therefore, several transmission policies were given in [8]-[11] under more general energy harvesting profiles. In [8], several joint relay selection and power allocation schemes were proposed under the assumption that the energy harvesting process is ergodic and stationary. Similarly, in [9]-[10], several power allocation schemes were given for cooperative EH networks under the assumption that energy can be harvested during any time of data transmission. The work in [9]-[10] was extended in [11] for the buffer-aided link adaptive EH relay system, which was shown to be more robust to the change of EH rates.

However, [4]-[11] all focused on networks harvesting energy from natural sources. In communication scenarios without access to natural sources, this type of energy harvesting technology is not applicable. Therefore, a new energy harvesting technology, i.e., WPT technology, has recently received considerable attention [12], [13]. In WPT, energy can be harvested through (i) strongly coupled magnetic resonances, or (ii) radio frequency (RF) signals. But, energy transfer based on magnetic resonances has some limitations. For example, it requires that each energy receiver must mount a coil tuned to resonate at exactly the same frequency as the coil on the energy transmitter, and it is usually activated by near field induction from very powerful nodes (e.g., base stations and vehicles).

Compared to strongly coupled magnetic resonances, energy

F. Wang and S. Guo are with the College of Electronic and Information Engineering, Southwest University, Chongqing, 400715, P. R. China.

Y. Yang is with the Department of Electrical & Computer Engineering, Stony Brook University, Stony Brook, NY 11794, USA.

B. Xiao is with Department of Computing, The Hong Kong Polytechnic University, Kowloon, Hong Kong.

This work was supported by the National Natural Science Foundation of China (No. 61170248, 61373179, 61373178, 61402381), Natural Science Key Foundation of Chongqing (cstc2015jcyjBX0094), Science and Technology Leading Talent Promotion Project of Chongqing (cstc2013kjrc-ljrccj40001) and Fundamental Research Funds for the Central Universities (XDJK2013C094, XDJK2013A018).

transfer based on RF signals does not have the above limitations and more importantly RF signals can carry energy and information concurrently. Thus, a RF-based energy harvesting technique, called simultaneous wireless information and power transfer (SWIPT) has attracted much attention recently, since network nodes can scavenge energy from incoming RF signals and process the carried information simultaneously [14] by using SWIPT. The concept of SWIPT was first proposed in [14] for point-to-point communication networks with discrete memoryless channels, and the work was extended in [15] for point-to-point networks with frequency-selective channels. However, the study in [14]-[15] is based on an ideal receiver design which can observe and extract power simultaneously from the same received signal, while practical circuits for harvesting energy cannot decode the carried information directly [16]. Thus, [16]-[17] proposed a practical receiver design with separate information decoding and energy harvesting receivers, where receivers for information decoding and energy harvesting are operated in a time switching or power splitting manner.

Based on the receiver design in [16]-[17], SWIPT for cooperative communication networks has also been studied in [18]-[24]. In [18], two relaying protocols were proposed to enable energy harvesting and information processing at the relay. In [19]-[20], for cooperative EH networks using SWIPT, several power allocation strategies for the relay were put forward to distribute the harvested energy among multiple source-destination pairs. In [21], Krikidis considered the application of SWIPT for large-scale cooperative networks, and a cooperative protocol was proposed. In [22]-[23], SWIPT has been applied to multi-antenna cooperative systems, and information and energy cooperation problem was considered. In [24], Wang, et. al. studied the power allocation and rate adaption problem for relay-assisted SWIPT systems where only imperfect channel state information (CSI) is known at transmitters.

Although [4]-[11] and [18]-[24] have made significant contributions on EH cooperative networks, there are still some formidable shortcomings in these works. Firstly, all these works only study the scenarios where all EH nodes can harvest energy either from natural sources or RF signals. Therefore, it is meaningful to consider the scenarios when some EH nodes can scavenge energy from natural sources while others from RF signals due to hardware design or environment limitations. Secondly, direct transmission, which may be more efficient than relay transmission sometimes, is generally not taken into account, e.g, in [6]-[9], [18]-[20], [22]-[24]. However, in fact, whether to use direct transmission or relay transmission should be dynamically determined by network channel conditions and the available energy of network nodes. Thirdly, the power splitting ratio which determines the power used for energy harvesting and information processing is usually taken as a constant value, e.g., in [18] or is allowed to take any value in the interval [0,1], e.g., in [19]-[22], but this parameter may take only discrete levels in practice and should also be optimized dynamically according to network conditions so as to maximize system performance. Finally, the problem of energy consumption is not sufficiently considered. Nevertheless, since the amount of energy harvested by EH nodes is random and is affected by many factors, such as weather, location, and channel conditions, it is necessary to efficiently use the harvested energy to combat some unpredictable events (e.g., rainy days) so that network lifetime can be prolonged.

In this paper, we jointly consider all the above issues and our contributions can be summarized as follows.

- We consider a relaying network with one EH source, one destination, and multiple EH decode-and-forward relays, where the source and the relays can harvest energy from natural sources (e.g., solar) and RF signals, respectively, because of their hardware design or surrounding environment limitations. To maintain normal network operation, we integrate the above two energy harvesting technologies together. Therefore, the source is designed to replenish energy from natural sources, while the relays use the power splitting strategy to scavenge energy from RF signals radiated by the source.
- We study the joint relay, power splitting ratio, and transmission power selection problem, which is considered in both offline and online settings with only imperfect CSI at hand. Particularly, direct transmission is taken into account, and whether to use direct transmission or relay transmission together with suitable power splitting ratio selection is dynamically determined according to network channel conditions and the available energy of network nodes. In addition, the system energy consumption is taken into consideration to efficiently use the harvested energy and prolong the network lifetime.
- We obtain an offline and two online resource allocation schemes, even though the proposed offline and online problems are non-convex with integer variables. Simulation results show that system performance can be greatly improved by considering direct transmission in some cases and dynamically choosing power splitting ratio. Furthermore, simulations also show that considering system energy consumption is also meaningful for EH cooperative networks, which can lead to a desired system performance by selecting some related parameters properly.
- In addition, we also show that the resource allocation models and the corresponding resource allocation schemes proposed have better scalability, and they can be extended to more general communication scenarios, for example, when part of relays replenish energy from natural sources while others from RF signals.

The remainder of this paper is organized as follows. Section II presents the system model. Section III formulates the offline problem and designs an offline scheme. Section IV gives two online schemes, and Section V provides numerical results. Finally, Section VI concludes this paper.

II. System Model

A. Network Model

Consider an EH decode-and-forward cooperative communication network with one source S, one destination D, and J

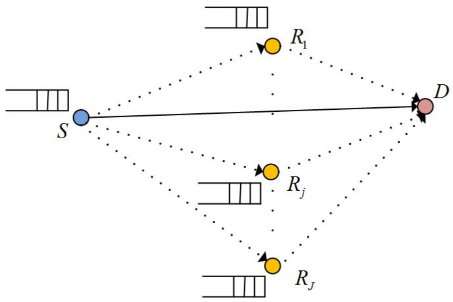


Fig. 1. Network model with one EH source and multiple EH relays.

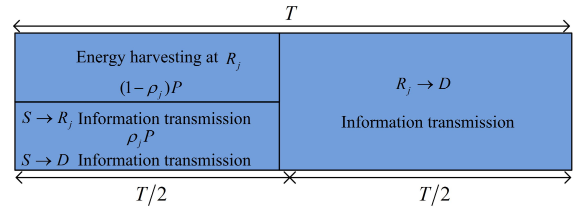


Fig. 2. Illustration of cooperation between network nodes, where T is the duration of each interval k.

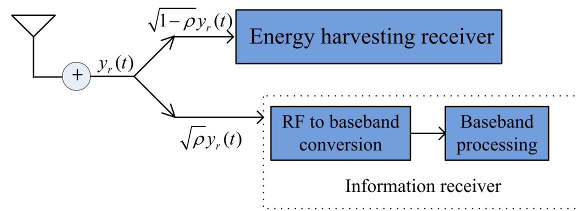


Fig. 3. Block diagram of the relay receiver.

relays $R_j (1 \leq j \leq J)$ as shown in Fig. 1, where each node has a single antenna. We assume that S and R_j can harvest energy from natural sources and RF signals respectively due to their hardware design or surrounding environment limitations[1], while D is not an EH node and has continuous supply of energy. A potential communication scenario, for instance, when an outdoor transmitter communicates with its receiver via some indoor nodes in a smart-home system or some nodes embedded in buildings. In fact, we will show in Section IV that the optimization models and the resource allocation schemes proposed in the paper can also be extended to more general scenarios, for example, when some relays harvest energy from natural sources while others from RF signals.

As mentioned, S can harvest energy from natural sources, such as solar and thermoelectric, while each relay R_j can replenish energy from its surrounding RF signals. Therefore, to efficiently use the energy harvested by S and at the same time help S forward information, we assume that the transmission is carried out by the following two phases for each time interval k (see Fig. 2). Particularly, the direct link between S and D is considered and only one suitable relay is selected for transmission when necessary.

Phase I: In the first time slot, S transmits while R_j and D receive. All relays are half-duplex, which means that each relay cannot transmit and receive data simultaneously. Besides, each relay receiver consists of an energy harvesting unit and a conventional signal processing core unit, as shown in Fig. 3. In particular, each relay receiver employs the power splitting technique [16]-[17] to harvest energy from RF signals radiated by S, where the received signals are splitted into two power streams with power splitting ratios $1-\rho_j$ and ρ_j, and the two power streams are used for energy harvesting and the source to relay information transmission, respectively. Note that since at most one relay R_ζ is selected to help S forward data in each interval k, other relays only harvest energy from the received source signal (i.e., $\rho_j = 0, j \neq \zeta$) and the harvested energy is reserved for future use.

Phase II: In the second time slot, the selected relay R_ζ (if such a node exists and it successfully decodes the received source message) transmits, and D exploits Maximum Ratio Combining (MRC) [25] to receive the signals from S in the first time slot and from R_ζ in the second time slot, pertaining to the same message.

The above mentioned single-relay selection scheme is reasonable. The underlying reason is that it is much easier to be implemented than traditional distributed space-time coding or beamforming which requires the tight synchronization among multiple geographically separated relays [4], since only one relay is selected for data forwarding in the single-relay selection scheme.

Define $h_{SR_j,k}$, $h_{R_jD,k}$, and $h_{SD,k}$ as the channel gains of the $S-R_j$, R_j-D, and $S-D$ links in the kth interval, respectively. In particular, large scale path loss will be considered only in the simulation section so as to simplify the analytical expressions, but this does not affect our analytical process. All channels are assumed to be quasi-static and independent of each other within each interval k, and they need not be identically distributed. Besides, define $\sigma^2_{R_j,k}$ and $\sigma^2_{D,k}$ as the variances of Additive White Gaussian Noise (AWGN) at R_j and D respectively. As shown in [18], such noise consists of the baseband AWGN as well as the sampled AWGN due to RF band to baseband signal conversion, as shown in Fig. 3.

Since perfect channel state information (CSI) is often unavailable due to channel estimation errors, quantization errors and so on [26]-[27], we will consider imperfect CSI in the paper. To estimate network CSI, S can first transmit training signals before data transmission in phase I, and then D and each relay R_j can evaluate channel gains $h_{SD,k}$ and $h_{SR_j,k}$ respectively. Similarly, R_j can transmit training signals to D so that D is able to estimate $h_{R_jD,k}$. Then, S can obtain all the measured channel gains by feedback from R_j and D.

In the paper, the dynamic power splitting ratio selection is considered. Since the relay receiver can only split the received signal into two power streams based on a finite discrete set of power splitting ratios in practice [28], we assume that ρ_j can

[1]Note that in practice S and R_j may also be able to extract energy from traditional power supply, such as pre-charged batteries, and the harvested energy from natural sources or RF signals may be used as a supplement for the total energy consumption so as to prolong the lifetime of S and R_j.

take value from the following set:

$$\rho_j \in \left\{\rho_{R_j}^1, \ldots, \rho_{R_j}^n, \ldots, \rho_{R_j}^N\right\}. \tag{1}$$

A reasonable choice of ρ_j is very important for system performance, because it determines the reliability of data reception at R_j in Phase I and the energy of R_j reserved for Phase II.

B. System Throughput

With the above assumptions, the achievable end-to-end rate $r_{S,k}^1$ when one relay is selected to assist the source transmission can be expressed as [25]

$$\begin{aligned} r_{S,k}^1 = \min \tfrac{1}{2}\{&\log(1+\textstyle\sum_{j=1}^J \sum_{n=1}^N w_{R_j,k}^n \rho_{R_j}^n P_{S,k}\tau_{SR_j,k}),\\ &\log(1+P_{S,k}\tau_{SD,k}+\textstyle\sum_{j=1}^J \sum_{n=1}^N w_{R_j,k}^n P_{R_j,k}^n \tau_{R_jD,k})\}, \end{aligned} \tag{2}$$

where $\tau_{SR_j,k} = |h_{SR_j,k}|^2/\sigma_{R_j,k}^2$, $\tau_{SD,k} = |h_{SD,k}|^2/\sigma_{D,k}^2$, and $\tau_{R_jD,k} = |h_{R_jD,k}|^2/\sigma_{D,k}^2$. $w_{R_j,k}^n$ is a binary variable to indicate whether relay $R_j(1 \le j \le J)$ is selected for transmission in interval k with power splitting factor $\rho_{R_j}^n(1 \le n \le N)$. $P_{S,k}$ and $P_{R_j,k}^n$ are the transmission powers for S and R_j, respectively. Specifically, if $w_{R_j,k}^n = 1$, then $P_{R_j,k}^n > 0$; otherwise $P_{R_j,k}^n = 0$. Besides, since the decode-and-forward relay strategy is considered, the selected relay R_ζ must be able to decode the source signal successfully. That is to say, the SNR of $S - R_\zeta$ link must be no less than γ_{min}, where γ_{min} is the SNR threshold for correct decoding at R_ζ. In general, some relay may be used if S itself cannot transmit data to D successfully, for example, when the channel gain $h_{SD,k}$ is weak or the harvested energy of S is inadequate.

On the other hand, if no relay is selected to forward the source information and only the direct transmission between S and D is employed, the achievable end-to-end rate $r_{S,k}^2$ can be given by [25], [32]-[33]

$$r_{S,k}^2 = \log(1+P_{S,k}\tau_{SD,k}). \tag{3}$$

This scenario may occur, for instance, when $h_{SD,k}$ is very good and S has sufficient energy so that D can decode the source information correctly, where the SNR threshold required for successful decoding at D is also assumed to be γ_{min}.

Note that for mathematical tractability, we combine (2) and (3) together and write the achievable end-to-end rate as $r_{S,k}$ by introducing a virtual relay R_0 with $\tau_{SR_0,k} = \tau_{R_0D,k} = \tau_{SD,k}$, where $r_{S,k}$ is given by

$$r_{S,k} = \min \tfrac{1+w_k^0}{2}\{\log(1+SNR_{1,k}), \log(1+SNR_{2,k})\}, \tag{4}$$

$$\begin{aligned} SNR_{1,k} = &\, w_k^0 P_{S,k}\tau_{SD,k}\\ &+\textstyle\sum_{j=1}^J \sum_{n=1}^N w_{R_j,k}^n \rho_{R_j}^n P_{S,k}\tau_{SR_j,k}, \end{aligned} \tag{5}$$

and

$$\begin{aligned} SNR_{2,k} = &\,(1+w_k^0)P_{S,k}\tau_{SD,k}\\ &+\textstyle\sum_{j=1}^J \sum_{n=1}^N w_{R_j,k}^n P_{R_j,k}^n \tau_{R_jD,k}. \end{aligned} \tag{6}$$

In (4), w_k^0 is a 0-1 binary variable and $w_k^0 + \sum_{j=1}^J \sum_{n=1}^N w_{R_j,k}^n \le 1$. If $w_k^0 = 1$, (4) reduces to (3) and R_0 is selected, meaning that only direct transmission is employed. If $\sum_{j=1}^J \sum_{n=1}^N w_{R_j,k}^n = 1$, (4) reduces to (2) and some relay $R_j(1 \le j \le J)$ is chosen to assist the transmission of S. In the following, unless otherwise specified, when the term "relay" is involved, it also includes node R_0.

C. Battery Dynamics

Denote the battery energy of a node $\mathcal{N} \in \{S, R_1, \ldots, R_J\}$ at the beginning of each interval k as $B_{\mathcal{N},k}$. In general, the battery energy is updated as follows [34]

$$B_{\mathcal{N},k+1} = f(B_{\mathcal{N},1},...,B_{\mathcal{N},k},P_{\mathcal{N},1},...,P_{\mathcal{N},k},H_{\mathcal{N},1},...,H_{\mathcal{N},k}), \tag{7}$$

where the function f depends on the battery dynamics, such as the storage efficiency and memory effects, and then $B_{\mathcal{N},k+1}$ may not increase linearly with respect to the variables in (7), e.g., $H_{\mathcal{N},k}$. However, intuitively, $B_{\mathcal{N},k+1}$ should increase or remain the same if $B_{\mathcal{N},k}$ or $H_{\mathcal{N},k}$ increases or if $P_{\mathcal{N},k}$ decreases. Therefore, similar to [1], [8]-[9], [16], [34], we assume that $B_{\mathcal{N},k+1}$ increases and decreases linearly in the extremely short time period T (duration of each interval k), provided that the maximum storage capacity $B_{\mathcal{N}}^{max}$ is not exceeded, that is,

$$B_{\mathcal{N},k+1} = \min(B_{\mathcal{N},k} + H_{\mathcal{N},k} - P_{\mathcal{N},k}T/2 - P_C^{\mathcal{N}}T, B_{\mathcal{N}}^{max}), \tag{8}$$

where $P_{\mathcal{N},k} \in \left\{P_{S,k}, P_{R_1,k}^1, \ldots, P_{R_j,k}^n, \ldots, P_{R_J,k}^N\right\}$. $P_C^{\mathcal{N}}$ is the constant circuit power consumption at node $\mathcal{N}$, which is used for maintaining the routine operations, for example, filters and frequency synthesizer. Moreover, $H_{\mathcal{N},k}$ is the harvested energy at node $\mathcal{N}$ within interval k. In our work, $H_{\mathcal{N},k}$ is modeled as an ergodic random process with mean $H_{\mathcal{N}} = E\{H_{\mathcal{N},k}\}$, where $E\{.\}$ denotes the expectation. No other limiting assumptions are made about it in our analysis. Therefore, this general model can encompass several energy harvesting profiles in the literature [29]-[30], for example, the Markov model-based profile in [29]. Besides, $B_{\mathcal{N},1} = H_{\mathcal{N},0}$ denotes the available energy at node $\mathcal{N}$ before transmission starts. Specifically, for relay R_j, due to imperfect CSI, the estimated energy[2] $H_{R_j,k}$ harvested from source S during the first time slot can be given by [16]

$$H_{R_j,k} = \eta(1-\textstyle\sum_{n=1}^N w_{R_j,k}^n \rho_{R_j}^n)P_{S,k}|h_{SR_j,k}|^2 T/2, \tag{9}$$

where $0 < \eta < 1$ is the energy conversion efficiency which depends on the rectification process and the energy harvesting circuitry [18].

[2]Although relays can scavenge energy from RF signals emitted by different energy providers, we still assume that S is the main renewable energy provider in the considered time interval because it needs to transmit data in the above mentioned time interval and then nearby relays can replenish energy from it. In fact, if the energy harvested from other energy providers is considered, we only need to plus this part of energy to (9), and this does not affect our proposed resource allocation schemes below. Moreover, the energy replenished from antenna noise is neglected, because antenna noise, whose variance is generally much smaller than the average power of RF signals radiated by S and other energy providers, has little impact on energy harvesting [31].

III. Offline Case

In this section, we aim at designing an offline resource allocation scheme to provide a performance benchmark for the system and to effectively use the harvested energy of S and R_j. Our objective is to maximize system payoff, which is defined as the difference between system transmission benefit and system energy cost, and meanwhile to minimize system outage probability by jointly selecting suitable relay, power splitting factor, and transmission power.

A. Problem Formulation

We assume that non-causal knowledge of energy arrivals at S and the estimated CSI of all network links is available. However, since the harvested energy $H_{R_j,k}$ of each relay is connected with the source power $P_{S,k}$ and the estimated CSI $h_{SR_j,k}$, $H_{R_j,k}$ cannot be known in advance but can be calculated using (9). Thus, the offline optimization problem can be formulated as

$$
\begin{aligned}
&\max \quad \nu_{S,r}\sum_{k=1}^{K} r_{S,k}T-\nu_{S,P}U_{TE}(P,W),\\
&s.t.\\
&(C1)\sum_{k=1}^{l}(P_{S,k}1/2+P_C^S)T\le\sum_{k=0}^{l-1}H_{S,k},\forall l,\\
&(C2)\sum_{k=1}^{l}(\sum_{n=1}^{N}w_{R_j,k}^{n}P_{R_j,k}^{n}1/2+P_C^{R_j})T\le\sum_{k=0}^{l}H_{R_j,k},\forall j,\forall l,\\
&(C3)\sum_{k=0}^{m}H_{S,k}-\sum_{k=1}^{m}(P_{S,k}1/2+P_C^S)T\le B_S^{max},\forall m,\\
&(C4)\sum_{k=0}^{m}H_{R_j,k}-\sum_{k=1}^{m}(\sum_{n=1}^{N}w_{R_j,k}^{n}P_{R_j,k}^{n}1/2+P_C^{R_j})T\\
&\qquad\le B_{R_j}^{max},\forall j,\forall m,\\
&(C5)w_k^0+\sum_{j=1}^{J}\sum_{n=1}^{N}w_{R_j,k}^{n}\le 1,\forall k,\\
&(C6)w_k^0,w_{R_j,k}^{n}\in\{0,1\},\forall j,\forall n,\forall k,\\
&(C7)SNR_{1,k}\le(w_k^0+\sum_{j=1}^{J}\sum_{n=1}^{N}w_{R_j,k}^{n})\gamma_{max},\forall k,\\
&(C8)(w_k^0+\sum_{j=1}^{J}\sum_{n=1}^{N}w_{R_j,k}^{n})\gamma_{min}\le SNR_{1,k},\forall k,\\
&(C9)SNR_{2,k}\le(w_k^0+\sum_{j=1}^{J}\sum_{n=1}^{N}w_{R_j,k}^{n})\gamma_{max},\forall k,\\
&(C10)(w_k^0+\sum_{j=1}^{J}\sum_{n=1}^{N}w_{R_j,k}^{n})\gamma_{min}\le SNR_{2,k},\forall k,\\
&(C11)P_{S,k}\le(w_k^0+\sum_{j=1}^{J}\sum_{n=1}^{N}w_{R_j,k}^{n})P_S^{max},\forall k,
\end{aligned}
\tag{10}
$$

where $W=\left\{w_k^0,w_{R_j,k}^n,\forall k,\forall j,\forall n\right\}$, $P=\{P_{S,k},P_{R_j,k}^n,\forall k,$ $\forall j,\forall n\}$, and $U_{TE}(P,W)$ is the overall system consumption given by

$$
\begin{aligned}
U_{TE}(P,W)=&\sum_{k=1}^{K}(P_{S,k}T/2+(P_C^S+\sum_{j=1}^{J}P_C^{R_j})T\\
&+\sum_{j=1}^{J}\sum_{n=1}^{N}w_{R_j,k}^{n}P_{R_j,k}^{n}T/2).
\end{aligned}
\tag{11}
$$

Moreover, similar to [32]-[33], $\nu_{S,r}$ and $\nu_{S,P}$ are defined as the equivalent revenue per unit throughput and the equivalent cost per unit transmission energy[3], respectively. Correspondingly, $\nu_{S,r}\sum_{k=1}^{K} r_{S,k}T$ and $\nu_{S,P}U_{TE}(P,W)$ are defined as system transmission benefit and system energy cost, respectively. The purpose of considering system energy consumption is to save energy due to the intermittent and unpredictable nature of energy arriving at S and $R_j(1\le j\le J)$ so that network lifetime can be prolonged. $C1$ is the energy neutrality constraint for S which mandates that the energy used by S so far cannot exceed the energy harvested by it. $C3$ is the battery capacity constraint for S which states that the energy level in the battery of S should never exceed B_S^{max} so as to prevent energy overflow. For $R_j(1\le j\le J)$, $C2$ and $C4$ can be similarly explained as $C1$ and $C3$. respectively. γ_{max} is the maximum SNR constraint, which can model the scenarios when D or R_j has limited choices of modulation and coding schemes.

Furthermore, $C7-C10$ are the SNR constraints for all relays and D. If $w_k^0+\sum_{j=1}^{J}\sum_{n=1}^{N}w_{R_j,k}^{n}=1$, then D can receive signals successfully regardless which relay (R_0 or $R_j(1\le j\le J)$) is selected. However, if $w_k^0+\sum_{j=1}^{J}\sum_{n=1}^{N}w_{R_j,k}^{n}=0$, then no relay is chosen. This means whichever relay is selected, the reception rate $r_{S,k}$ at D cannot be guaranteed to be larger than or equal to the target rate r_0, which corresponds to the minimum SNR γ_{min}. Therefore, a system outage occurs. This may occur, for instance, when the network suffers from poor channel conditions or S and $R_j(1\le j\le J)$ do not have adequate energy. In such cases, it can be seen from $C11$ that S stops transmitting in the current interval k and in the meantime reserves the newly harvested energy for future use. In this way, the system outage probability, i.e., $Prob(r_{S,k}<r_0)$ can be reduced as much as possible.

B. Iterative Algorithm for Offline Optimization

Problem (10) is a non-convex mixed integer and nonlinear program (MINLP), which involves both integer variables and real variables. The non-convexity arises due to the min function in the objective function and the multiplicative form of integer variables (i.e., w_k^0's and $w_{R_j,k}^n$'s) and real variables (i.e., $P_{S,k}$'s and $P_{R_j,k}^n$'s) in the constraints and the objective function. In general, it is very hard to solve this type of problem and high-complexity algorithms are usually required. Therefore, to make problem (10) easily solvable, we need to transform it into a convex problem. We handle this issue by taking the following two steps.

First, we define some new variables $\widetilde{P}_{S,k}^{R_0}=w_k^0P_{S,k}$, $\widetilde{P}_{R_j,k}^{n}=w_{R_j,k}^{n}P_{R_j,k}^{n}$, and $\widetilde{P}_{SR_j,k}^{n}=w_{R_j,k}^{n}P_{S,k}$, and add following constraints

$$C12 \qquad \widetilde{P}_{S,k}^{R_0}\le P_{S,k},\widetilde{P}_{S,k}^{R_0}\le w_k^0P_S^{max}, \tag{12}$$

$$C13 \qquad \widetilde{P}_{SR_j,k}^{n}\le P_{S,k},\widetilde{P}_{SR_j,k}^{n}\le w_{R_j,k}^{n}P_S^{max}, \tag{13}$$

$$C14 \qquad \widetilde{P}_{R_j,k}^{n}\le w_{R_j,k}^{n}P_{R_j}^{max}, \tag{14}$$

where constraints $C12-C14$ are used to ensure the efficiency of new variables $\widetilde{P}_{S,k}$, $\widetilde{P}_{R_j,k}^{n}$, and $\widetilde{P}_{SR_j,k}^{n}$. In addition, variables $\widetilde{P}_{S,k}$ and $\widetilde{P}_{R_j,k}^{n}$ represent the actual transmission powers of R_0 and $R_j(1\le j\le J)$ respectively, and $\widetilde{P}_{SR_j,k}^{n}$ coupled with $\rho_{R_j}^n$ (i.e., $\widetilde{P}_{SR_j,k}^{n}\rho_{R_j}^n$) represents the actual consumed power of $R_j(1\le j\le J)$ used for the source to relay information reception.

[3]Similar to [33], $\nu_{S,r}$ and $\nu_{S,P}$ can be defined as concave functions of $r_{S,k}$ and $U_{TE}(P,W)$, respectively, and then the two parameters can be determined dynamically according to system resource allocation. However, this will make problem (10) more difficult to be solved. Therefore, like [32], we take $\nu_{S,r}$ and $\nu_{S,P}$ as constants, and assume that they can be determined offline on the basis of different weather and channel conditions and/or users' QoS requirements because these factors affect system resource allocation significantly.

Second, we address the min function in the objective function by introducing several extra auxiliary variables z_k's and ξ_k's, $k \in \{1, 2, \ldots, K\}$ and transforming problem (10) into its equivalent form (15):

$$
\begin{aligned}
&\max \quad \nu_{S,r} \textstyle\sum_{k=1}^{K} \widetilde{r}_{S,k} T - \nu_{S,P} \widetilde{U}_{TE}(\widetilde{P}, W),\\
&s.t.\\
&C1, C3, C5, C6, C11, C12, C13, C14,\\
&(C2) \textstyle\sum_{k=1}^{l} (\sum_{n=1}^{N} \widetilde{P}^{n}_{R_j,k} 1/2 + P_C^{R_j}) T \le \sum_{k=0}^{l} \widetilde{H}_{R_j,k}, \forall j, \forall l,\\
&(C4) \textstyle\sum_{k=0}^{m} \widetilde{H}_{R_j,k} - \sum_{k=1}^{m} (\sum_{n=1}^{N} \widetilde{P}^{n}_{R_j,k} 1/2 + P_C^{R_j}) T\\
&\qquad\qquad \le B^{max}_{R_j}, \forall j, \forall m,\\
&(C7) \widetilde{SNR}_{1,k} \le (w_k^0 + \textstyle\sum_{j=1}^{J} \sum_{n=1}^{N} w^n_{R_j,k}) \gamma_{max}, \forall k,\\
&(C8) (w_k^0 + \textstyle\sum_{j=1}^{J} \sum_{n=1}^{N} w^n_{R_j,k}) \gamma_{min} \le \widetilde{SNR}_{1,k}, \forall k,\\
&(C9) \widetilde{SNR}_{2,k} \le (w_k^0 + \textstyle\sum_{j=1}^{J} \sum_{n=1}^{N} w^n_{R_j,k}) \gamma_{max}, \forall k,\\
&(C10) (w_k^0 + \textstyle\sum_{j=1}^{J} \sum_{n=1}^{N} w^n_{R_j,k}) \gamma_{min} \le \widetilde{SNR}_{2,k}, \forall k,\\
&(C15) z_k \le \widetilde{SNR}_{1,k}, \forall k,\\
&(C16) z_k \le \widetilde{SNR}_{2,k}, \forall k,
\end{aligned} \tag{15}
$$

where $\widetilde{P} = \left\{P_{S,k}, \widetilde{P}^{R_0}_{S,k}, \widetilde{P}^{n}_{R_j,k}, \widetilde{P}^{n}_{SR_j,k}, \forall k, \forall j, \forall n\right\}$, $\xi_k = z_k w_k^0$,

$$\widetilde{r}_{S,k} = \tfrac{1}{2} \log(1 + z_k) + \tfrac{w_k^0}{2} \log(1 + \xi_k / w_k^0), \tag{16}$$

$$
\begin{aligned}
\widetilde{U}_{TE}(\widetilde{P}, W) = &\textstyle\sum_{k=1}^{K} (P_{S,k} T/2 + (P_C^S + \sum_{j=1}^{J} P_C^{R_j}) T\\
&+ \textstyle\sum_{j=1}^{J} \sum_{n=1}^{N} \widetilde{P}^{n}_{R_j,k} T/2),
\end{aligned} \tag{17}
$$

$$\widetilde{H}_{R_j,k} = \eta (P_{S,k} - \textstyle\sum_{n=1}^{N} \widetilde{P}^{n}_{SR_j,k} \rho^n_{R_j}) |h_{SR_j,k}|^2 T/2, \tag{18}$$

$$
\begin{aligned}
\widetilde{SNR}_{1,k} = &\widetilde{P}^{R_0}_{S,k} h_{SD,k}\\
&+ \textstyle\sum_{j=1}^{J} \sum_{n=1}^{N} \rho^n_{R_j} \widetilde{P}^{n}_{SR_j,k} \tau_{SR_j,k},
\end{aligned} \tag{19}
$$

and

$$
\begin{aligned}
\widetilde{SNR}_{2,k} = &(P_{S,k} + \widetilde{P}^{R_0}_{S,k}) \tau_{SD,k}\\
&+ \textstyle\sum_{j=1}^{J} \sum_{n=1}^{N} \widetilde{P}^{n}_{R_j,k} \tau_{R_j D,k}.
\end{aligned} \tag{20}
$$

Now, problem (15) is a convex MINLP, that is, it is convex when all integer variables, (i.e., w_k^0's and $w^n_{R_j,k}$'s) are allowed to take vales from the interval [0, 1]. Therefore, we can apply the generalized outer approximation (GOA) algorithm to solve this problem [34, pp. 175-182]. GOA decomposes problem (15) into two sub-problems: a primal problem and a master problem. The primal problem gives rise to Z, Γ, and $\widetilde{P}$ for the fixed integer assignment W, where $Z = \{z_k, \forall k\}$ and $\Gamma = \{\xi_k, \forall k\}$. On the other hand, solving the master problem gives the new W for previously obtained Z, Γ, and $\widetilde{P}$. GOA iteratively solves the primal problem and the master problem until their solutions converge. For the first iteration, a feasible initial vector is given for the integer assignment W. In the following, we describe the primal problem and the master problem for a given iteration $t \in \{1, 2, \ldots, Ite\}$, where Ite is the total number of iterations required for the convergence of GOA.

Primal Problem (the t_{th} iteration): The primal problem corresponds to fixing the W variables in problem (15) to a particular 0-1 combination. Then, for the given optimal W obtained from iteration $t-1$, i.e., W^{t-1}, the primal problem can be formulated as follows:

(**PP**(W^{t-1}))

$$
\begin{aligned}
&\max \quad \nu_{S,r} \textstyle\sum_{k=1}^{K} \widetilde{r}_{S,k}(Z, \Gamma, W^{t-1}) T - \nu_{S,P} \widetilde{U}_{TE}(\widetilde{P}, W^{t-1}),\\
&s.t.\\
&C1, C2, C3, C4, C11, C12, C13, C14, C15, C16,\\
&(C7) \widetilde{SNR}_{1,k} \le (w_k^{0,t-1} + \textstyle\sum_{j=1}^{J} \sum_{n=1}^{N} w^{n,t-1}_{R_j,k}) \gamma_{max}, \forall k,\\
&(C8) (w_k^{0,t-1} + \textstyle\sum_{j=1}^{J} \sum_{n=1}^{N} w^{n,t-1}_{R_j,k}) \gamma_{min} \le \widetilde{SNR}_{1,k}, \forall k,\\
&(C9) \widetilde{SNR}_{2,k} \le (w_k^{0,t-1} + \textstyle\sum_{j=1}^{J} \sum_{n=1}^{N} w^{n,t-1}_{R_j,k}) \gamma_{max}, \forall k,\\
&(C10) (w_k^{0,t-1} + \textstyle\sum_{j=1}^{J} \sum_{n=1}^{N} w^{n,t-1}_{R_j,k}) \gamma_{min} \le \widetilde{SNR}_{2,k}, \forall k.
\end{aligned} \tag{21}
$$

It can be observed that problem (21) is a convex optimization problem, thus it can be optimally solved by any standard algorithm, e.g., Lagrangian dual method [1]. However, the primal problem may be infeasible for some W, that is, some constraints may be violated. In this case, instead of solving problem (21), a feasibility problem will be considered [35]-[36]. To formulate this problem, we first write the original problem (15) into the following form:

$$
\begin{aligned}
&\max \quad f(Z, \Gamma, \widetilde{P}, W),\\
&s.t. \quad\; g(Z, \Gamma, \widetilde{P}, W) \le 0,
\end{aligned} \tag{22}
$$

where $f(Z, \Gamma, \widetilde{P}, W)$ stands for the objective function in problem (15) and $g(Z, \Gamma, \widetilde{P}, W) \le 0$ is a vector which represents all constraints of (15).

Then, the feasibility problem can be formulated as:

$$
\begin{aligned}
&\min \quad \textstyle\sum_{i \in I'} \theta_i g_i^{+}(Z, \Gamma, \widetilde{P}, W^{t-1}),\\
&s.t. \quad\; g_i(Z, \Gamma, \widetilde{P}, W^{t-1}) \le 0, \forall i \in I,
\end{aligned} \tag{23}
$$

where θ_i is the nonnegative weight, $g_i^{+}(Z, \Gamma, \widetilde{P}, W^{t-1}) = max(0, g_i(Z, \Gamma, \widetilde{P}, W^{t-1}))$ is a component of $g(Z, \Gamma, \widetilde{P}, W)$, I is the set of feasible inequality constraints, and I' is the set of infeasible inequality constraints. Note that problem (23) is also convex since $g_i^{+}(Z, \Gamma, \widetilde{P}, W^{t-1})$ which is the maximum of two convex functions is convex [37]. Infeasibility in the primal problem (21) is detected when the solution of problem (23) is obtained for which its objective value is greater than zero [36]. Moreover, by solving (23), the constraints indexed by $i \in I'$ may be driven to be feasible gradually, whist maintaining feasibility for constraints indexed by $i \in I$.

Master Problem (the t_{th} iteration): The master problem is derived using primal information which consists of the previously obtained Z, Γ, and $\widetilde{P}$ within the first t iterations, and is based on an outer approximation (linearization) of the nonlinear objective and constraints around the primal solutions obtained within the first t iterations. Since all constraints in problem (15) are linear, the master problem can be formulated as follows: (**MP**)

$$
\begin{aligned}
&\max_{Z,\widetilde{P},W,\mu_{GOA}} \quad \mu_{GOA},\\
&s.t. \;\; \mu_{GOA} \le f(Z^m,\Gamma^m,\widetilde{P}^m,W^{m-1})\\
&\qquad\qquad +\nabla f(Z^m,\Gamma^m,\widetilde{P}^m,W^{m-1})^{\mathrm{T}} \begin{pmatrix} Z-Z^m \\ \Gamma-\Gamma^m \\ \widetilde{P}-\widetilde{P}^m \\ W-W^{m-1} \end{pmatrix},\\
&\qquad LBD^t < \mu_{GOA},\\
&\qquad g(Z,\Gamma^m,\widetilde{P},W) \le 0,
\end{aligned} \tag{24}
$$

where $LBD^t = \{\max f^m, m \le t, m \in F^t\}$,

$$F^t = \{\, m|\, m \le t : \mathbf{PP}(W^{m-1}) \text{ is feasible}\}, \tag{25}$$

and $(Z^m,\Gamma^m,\widetilde{P}^m)$ is an optimal solution to $\mathbf{PP}(W^{m-1})$.

By solving the master problem (24), a new integer assignment W^t to be used in the next primal problem can be obtained. Besides, any previously obtained integer assignment W is prevented from becoming the solution of problem (24) due to the second and third constraints in this problem [36]. The detailed description of the GOA algorithm can be seen in Algorithm 1.

In Algorithm 1, on the one hand, it is worth noting that since solving the primal problem (21) or the feasibility problem (23) (if (21) is infeasible) gives rise to the variable vector $\widetilde{P}$ for fixed integer assignment W, the network power allocation, i.e., the value of variables $P_{S,k}$'s and $P^n_{R_j,k}$'s can be obtained for fixed W. On the other hand, since solving the master problem (24) gives a new integer vector W, the new joint relay and power splitting selection, that is, a new selection of relay R_ζ, which forwards information for S, and the corresponding power splitting ratio ρ^n_ζ can be known. Therefore, when Algorithm 1 converges, the solution for the offline problem (10) can be obtained.

As for the computational complexity, we note that due to the convexity, problems (21) and (23) can be solved in polynomial time, and the complexity increase linearly with the relay number J, the number of power splitting ratios N, and the interval number K. However, the master problem (24) may have non-polynomial complexity as it is a mixed integer linear program (MILP) for K time intervals. Fortunately, we can use the efficient optimization software, such as Mosek, Cplex, or Gurobi, to solve problem (24) offline. In these softwares, there exist some embedded functions which can be used to effectively solve MILP problems with up to hundreds of thousands of variables.

Remark 1: As shown in [35], the master problem (24) provides an upper bound, denoted as μ^t_{GOA} on the solution of problem (15) at each iteration t. Moreover, due to the first constraint in (24), the newly obtained μ^t_{GOA} is always less than or equal to the previously obtained μ_{GOA} within the first $t-1$ iterations; thus the upper bound sequence is non-increasing. On the other hand, the primal problem (21) provides the solution for a given integer assignment W and thus its solution (if feasible) can always provide a lower bound on the solution of the original problem (15). In this paper, we let the lower bound

TABLE I
ALGORITHM 1: GENERALIZED OUTER APPROXIMATION METHOD FOR OFFLINE CASE

1: Initialization: initial integer assignment W^0, converge parameter ϵ, $\Delta \leftarrow \emptyset$ and $t \leftarrow 1$.
2: `flag` $\leftarrow 1$.
3: **while** `flag`$\neq 0$ **do**
4: Solve the primal problem (21), or the feasible problem (23) if (21) is infeasible. Denote the solution as $(Z^t,\Gamma^t,\widetilde{P}^t)$ and the lower bound as LBD^t.
5: $\Delta \leftarrow \Delta \cup \{t\}$.
6: Solve the master problem (24), and obtain the new integer assignment W^t and the upper bound UBD^t.
7: **if** the master problem (22) is infeasible or $\lvert LBD^t - UBD^t\rvert \le \epsilon$ **then**
8: `flag` $=0$.
9: **end if**
10: Set $t \leftarrow t+1$.
11: **end while**

at each iteration equals the maximum of the lower bounds of the previous iterations and the lower bound of the current iteration. Therefore, the sequence of the updated lower bound is non-decreasing. In such a case, the GOA algorithm can be shown to converge within a finite number of iterations [35].

IV. Online Case

In practice, the offline scheme proposed above may not be applicable since the future CSI and the upcoming harvested energy are not available. Therefore, in the following, we consider the more practical case when only causal information of CSI and energy arrivals is known. In principle, the optimal online solution can be obtained by using the dynamic programming. However, dynamic programming suffers from the "curse of dimensionality" and thus it is very difficult to be implemented [1]. Therefore, we propose two suboptimal online schemes, i.e., the current-information-based online algorithm (CI-OA) and the statistic-property-based online algorithm (SP-OA) in this section.

A. CI-OA

In this scheme, we assume that S is the central node. At the beginning of each interval, it executes the online algorithm only on the basis of the evaluated instantaneous CSI and the estimated stored energy of each node, as well as the potential harvested energy $H_{R_j,k}$ of each relay $R_j (1 \le j \le J)$ in the current interval. Then, S broadcasts the optimal transmission power and the optimal power splitting factor to each relay $R_j (1 \le j \le J)$ before data transmission. Specifically, in order to guarantee that network nodes have sufficient energy for data transmission (with high probability), system energy consumption in the current interval is also considered. Therefore, for CI-OA, the optimization problem for time interval k can be formulated as follows:

$$
\begin{aligned}
&\max \quad \nu_{S,r} r_{S,k} T - \nu_{S,P} U_{TE,k}(P_k,W_k),\\
&s.t. \;\; (C1)(P_{S,k}T/2 + P_C^S T) \le B_{S,k},\\
&\qquad (C2)(\textstyle\sum_{n=1}^N w^n_{R_j,k} P^n_{R_j,k} T/2 + P_C^{R_j} T)\\
&\qquad\qquad\qquad \le \min\{H_{R_j,k} + B_{R_j,k}, B^{max}_{R_j}\}, \forall j,\\
&\qquad C5, C6, C7, C8, C9, C10, C11,
\end{aligned} \tag{26}
$$

where $C5-C11$ are the same as those in the offline optimization problem (15), and

$$U_{TE,k}(P_k,W_k)=(P_{S,k}T/2+(P_C^S+\sum_{j=1}^{J}P_C^{R_j})T + \sum_{j=1}^{J}\sum_{n=1}^{N}w_{R_j,k}^{n}P_{R_j,k}^{n}T/2). \quad (27)$$

Moreover, $C1$ states that the total consumed energy at S in interval k cannot exceed the current available energy $B_{S,k}$ stored in the source battery. $C2$ can be similarly explained as $C1$ except that the potential harvested energy $H_{R_j,k}$ of each relay $R_j(1\le j\le J)$ is also considered. This is because the selected relay needs this part of energy to forward the source information in the second time slot of interval k. Moreover, $H_{R_j,k}$ is a function of the source transmission power $P_{S,k}$ and the estimated CSI $h_{SR_j,k}$, and thus it needs to be calculated dynamically. However, the harvested energy $H_{S,k}$ which is generally unknown at the beginning of interval k needs not to be considered.

Similar to the offline problem (10), the online problem (26) can also be solved using the GOA algorithm. But the complexity of the involved GOA algorithm for solving problem (26) is much lower than that for problem (10). First, for (26), the complexity of the primal problem and the feasibility problem, which are also convex similar to problems (21) and (23), only increases linearly with the relay number J and the number of power splitting ratios N but not the interval number K, because problem (26) only considers the resource allocation for one fixed time interval k. Besides, for the same reason, the master problem of (26) can be much more easily solved by using the function *mosekopt* in Mosek, even though the above mentioned master problem is also a MILP problem like problem (24).

B. SP-OA

For comparison purpose, similar to [8], we also consider another online scheme (i.e., SP-OA) which is based on the statistical property of the harvested energy of each node. Specifically, to guarantee that S has sufficient energy for transmission, we further limit the consumed energy of S based on its transmission probability Pb_S and the average harvested energy H_S. Then, another energy consumption constraint of S can be given and expressed as

$$P_{S,k}T/2+P_C^ST\le \alpha H_S/Pb_S, \quad (28)$$

where α is a scaling factor.

However, since it is generally difficult to determine Pb_S, we approximate $\alpha H_S/Pb_S$ in (28) by σH_S, where σ is also a scaling factor. Similarly, another energy constraint (29) for $R_j(1\le j\le J)$ is also given. In (29), the transmission probability Pb_{R_j} of $R_j(1\le j\le J)$ is approximated by $1/J$ for simplicity, and the scaling factor τ is similar to σ. Furthermore, it is worth noting that as it is hard to know the average energy H_{R_j} for each relay $R_j(1\le j\le J)$, we use the average harvested energy within the first $k-1$ intervals instead of H_{R_j} in (29).

$$\sum_{n=1}^{N}w_{R_j,k}^{n}P_{R_j,k}^{n}T/2+P_C^{R_j}T\le\tau\sum_{l=1}^{k-1}H_{R_j,l}/((k-1)Pb_{R_j}), \quad (29)$$

where the harvested energy $H_{R_j,l}(l\le k-1)$ within the first $k-1$ intervals has already been known in the current interval k. And, for given energy harvesting statistics, parameters σ and τ can be optimized offline to improve system performance.

C. Model Extension

As mentioned in Section II, the proposed offline model (10) and the online models, e.g., (26) can also be extended to more general scenarios. For example, when some relays harvest energy from natural sources and others from RF signals, or all relays harvest energy from natural sources. In these scenarios, we only need to make the following small changes. First, set $N=1$ and $\rho_{R_j}^n=1$ in the optimization models, e.g., (10) and (26) for relays replenishing energy from natural sources, since these nodes do not harvest energy from RF signals. Second, set the energy constraints, e.g., $C2$ in (10) and (26), the battery capacity constraints, e.g., $C4$ in (10), and the harvested energy $H_{R_j,k}$ in each time interval k similar to those for the source. On the other hand, if the source is not an EH node, then we only need to delete the energy constraint and the battery capacity constraint for it. Correspondingly, resource allocation schemes similar to Algorithm 1 can be used for the above scenarios.

V. Performance Evaluation

In this section, we evaluate the performance of the proposed offline and online resource allocation schemes through simulations.

A. Simulation Environment and Parameters

As shown in Section II, we consider a scenario where an outdoor transmitter communicates with its receiver through some deployed indoor relays, for example in a smart-home system. We assume that the distance from the source to the destination is d_1 m, and all relays are randomly distributed within a circular area with a radius of $d_1/2$ m, where the center of the circular area is just the midpoint of the line segment connecting the source and the destination. Since many obstructions may exist between different nodes, all channels are assumed to be Rayleigh fading and large scale path loss is considered.

In the following experiments, unless otherwise specified, the parameters are set as follows: d_1=20 m, since RF-based energy harvesting may only be possible for short-distance communication nowadays. The energy conversion efficiency η is taken as $\eta=0.5$ similar to [16], [28], because it is affected by antenna and rectenna circuit design and can only be achieved as high as $\eta=0.7$ [22]. Besides, for our considered scenario, we assume all nodes are in small to medium size. Therefore, similar to [28] which considers an indoor communication scenario, we assume that $P_S^{max}=P_{R_1}^{max}=\cdots=P_{R_J}^{max}=5$ W, $B_S^{max}=B_{R_1}^{max}=\cdots=B_{R_J}^{max}=25$ Joule, and the power splitting ratio $\rho_{R_j}^n$ takes value from the set $\{0,0.25,0.5,0.75,1\}$. Furthermore, just as shown in Section II, T takes a small value which is set as $T=1$ s and totally $K=100$ intervals are considered. For $H_{S,k}$, which stands the energy harvested by the source in each interval k, we assume that it independently and randomly takes value in [0, 1] with the average harvesting rate being $H_S = 0.5$ Joule just as in [8], [11]. In addition, we set $\gamma_{max} = 22$ dB, and the number of indoor relays $J = 8$ which is enough for our considered scenario. Specifically, $\nu_{S,r}$ and $\nu_{S,P}$ are taken as 1.5 and 1 respectively so as to balance system throughput and system energy consumption and meanwhile to make these conflicting objectives comparable, a common way which is adopted to treat multi-criteria optimization problems [37].

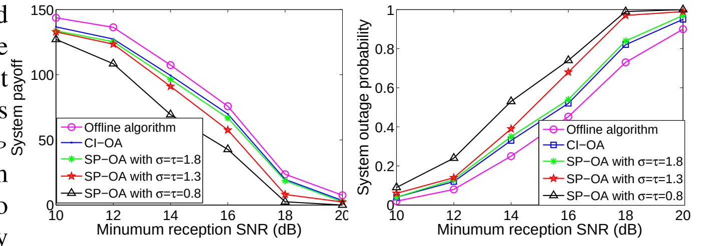
B. Performance Comparison of Proposed Algorithms

In this part, we will compare the performance of the proposed offline and online algorithms by choosing different network parameters, such as the minimum SNR γ_{min}, the maximum transmission power $P_{\mathcal{N}}^{max}, \mathcal{N} \in \{S, R_1, \ldots, R_J\}$, and the average harvesting rate H_S of S. In addition, the effect of these parameters on the performance of the proposed algorithms will also be studied.

1) Algorithm performance versus γ_{min}: Fig. 4(a) shows the difference between system transmission benefit and system energy cost, which is defined as system payoff, versus the minimum SNR γ_{min}. And, Fig. 4(b) shows system outage probability as γ_{min} changes. We can observe that for all considered algorithms, system payoff decreases and system outage probability increases when γ_{min} increases. The reason for this is that the destination (i.e., D) may not be able to decode signals successfully for large γ_{min}, especially when network channels are in deep fading, and then in this situation S stops transmitting and system performance becomes poor. In addition, we can also see that the offline algorithm achieves the best performance, and it provides a performance bound for both online algorithms. This is because we assume that the non-causal knowledge of channel gains of all network links and energy arrivals at S is available in the offline algorithm, whereas the online algorithms are based mainly on the causal information of the harvested energy and the CSI.

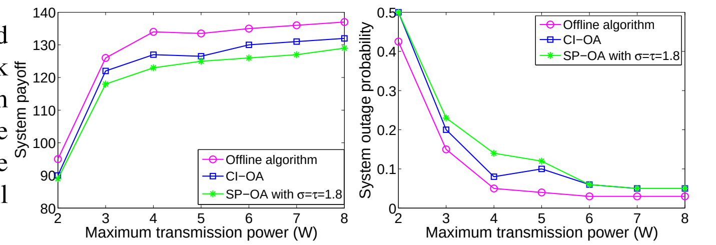
However, it is surprising to see that CI-OA performs close to the offline algorithm, and it has a better performance compared to SP-OA especially when σ and τ take small values, e.g., 0.8. Moreover, the performance gain obtained by CI-OA over SP-OA gradually degrades as σ and τ increase for all considered γ_{min}. The reasons for these are that (i) system energy consumption has already been taken into account in CI-OA similar to the offline algorithm, so for maximizing system payoff, the network will transmit as much data as possible while saving as much energy as possible; (ii) SP-OA limits the transmission powers of network nodes by considering the statistical property of the harvested energy (see (28) and (29)), so the required minimum SNR γ_{min} at D may not be satisfied when σ and τ are small, and then system performance becomes very poor. However, the effect of (28) and (29) becomes less and less evident with σ and τ increasing, and therefore the performance of SP-OA becomes close to that of CI-OA.

2) Algorithm performance versus $P_{\mathcal{N}}^{max}$: Fig. 5 depicts system payoff and system outage probability when the maximum



(a) (b)

Fig. 4. Algorithm performance versus minimum SNR γ_{min} (a) System payoff; (b) System outage probability.

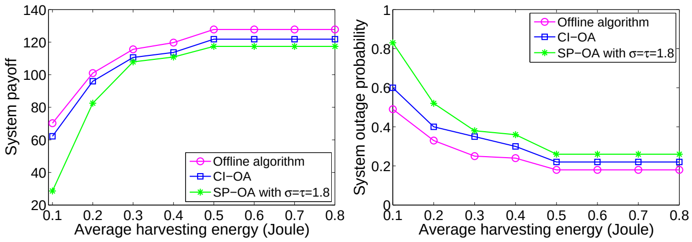


(a) (b)

Fig. 5. Algorithm performance versus maximum transmission power $P_{\mathcal{N}}^{max}$ (a) System payoff; (b) System outage probability.

transmission power $P_{\mathcal{N}}^{max}, \mathcal{N} \in \{S, R_1, \ldots, R_J\}$ changes, where γ_{min} is set as 12 dB. Similar to the results in Fig. 4, the offline algorithm has the best performance and CI-OA generally performs better than SP-OA. In particular, we can observe that for all the three algorithms, system performance is first improved obviously with increasing $P_{\mathcal{N}}^{max}$, but starting at a certain value of $P_{\mathcal{N}}^{max}$, system performance becomes almost unchanged. This can be explained by the facts that (i) small values of $P_{\mathcal{N}}^{max}$ limit the performance of all algorithms since the required minimum SNR γ_{min} at D may not be satisfied in this situation even when channel states are not very weak; (ii) the network nodes stop increasing the transmission powers if the system throughput gain due to higher transmission powers cannot neutralize the associated energy consumption increase. Therefore, the constant system payoff and system outage for large $P_{\mathcal{N}}^{max}$ indicate that, for given parameters, only increasing $P_{\mathcal{N}}^{max}$ beyond a certain value may not improve system performance.

3) Algorithm performance versus H_S: Fig. 6 shows system payoff and system outage probability versus the average harvesting rate H_S of S, where we take $\gamma_{min} = 12$ dB and $P_{\mathcal{N}}^{max} = 3$ W as an example. As expected, we can see that system performance is improved as H_S increases for all the considered algorithms. However, the slope of the system payoff curves is large for small H_S and gradually decreases to zero with increasing H_S, and similarly system outage probability first decreases sharply with increasing H_S but remains unchanged after H_S goes beyond a certain value. This is due to the fact that the performance of all considered algorithms is limited by the finite storage capacity of the batteries. For large H_S, additional harvested energy cannot be stored in the batteries and therefore the extra amount of energy is wasted.



(a) (b)

Fig. 6. Algorithm performance versus average harvesting rate H_S (a) System payoff; (b) System outage probability.

Furthermore, it can also be observed that the difference gap between CI-OA and SP-OA is very large at small H_S even when σ and τ are both taken as a large number 1.8. The reason for this is that in SP-OA, the constraints (28) and (29) further limit the consumed energy of network nodes especially at small H_S, and then the performance of SP-OA is limited ulteriorly. Furthermore, as mentioned in section III, relays may also replenish energy from RF signals emitted by other energy providers. In fact, like the effect of H_S on system performance, a similar performance trend can be seen if this part of energy is considered.

C. Effect of Dynamic Selection of Direct Transmission and Relay Transmission on System Performance

In this subsection, we verify the effect of dynamic selection of direct transmission and relay transmission on system performance. We consider short-distance communication and take d_1=10 m as an example[4]. For comparison, a baseline algorithm (i.e., baseline I) similar to CI-OA but without considering direct transmission is considered. Fig. 7 illustrates system payoff, system outage probability, and direct transmission probability. It can be seen that our proposed algorithms provide significant performance gain compared to baseline I for small γ_{min} and the performance advantage becomes smaller for large γ_{min}. This is due to the fact that compared to baseline I, direct transmission is taken into consideration in our proposed algorithms, and thus direct transmission instead of relay transmission can be used (seen from Fig. 7(c)), for example, when the channel gain of $S-D$ link is much better than that of R_j-D link or the relays do not have enough energy. However, if the minimum reception SNR γ_{min} also cannot be satisfied through direction transmission for large γ_{min}, the performance of our algorithms becomes close to that of baseline I. Therefore, simulation results confirm that in some cases[5], it is necessary to take account of direct transmission, and select direct transmission and relay transmission dynamically for the EH decode-and-forward cooperative communication networks.

[4]In fact, d_1 can also be set as other values. However, we find the advantage of our algorithms over Baseline I decreases with the increase of d_1. Therefore, for RF-based energy harvesting, a representative and medium size value is taken for d_1, i.e., d_1=10 m similar to [28].

[5]As mentioned above, the advantage of our proposed algorithms over Baseline I decreases as d_1 increases. The reason is that the channel condition of $S-D$ link decreases with the increase of d_1, and then direct transmission may not be considered in some cases. Therefore, we conjecture that direct transmission needs to be considered especially for small d_1.

D. Effect of Parameters $\nu_{S,r}$ and $\nu_{S,P}$ on System Performance

In this part of simulation, we examine the effect of parameters $\nu_{S,r}$ and $\nu_{S,P}$ on system performance. Specifically, only the typical algorithm, CI-OA, is studied. Fig. 8 illustrates the simulation results for different pairs of $\nu_{S,r}$ and $\nu_{S,P}$. It can be observed that system throughput and system consumed energy generally increase as the ratio of $\nu_{S,r}$ and $\nu_{S,P}$ increases, while system outage probability first decreases for small γ_{min} and then keeps almost unchanged for large γ_{min}. The reasons for these are: (i) the increase of the ratio between $\nu_{S,r}$ and $\nu_{S,P}$ means that energy cost is not the main factor needing to be considered and less attention is paid on energy saving. Therefore, much energy will be consumed generally, and correspondingly system throughput will increase and system outage probability will not increase; (ii) However, as γ_{min} becomes large, the transmitters may not increase transmission powers in time intervals if channel gains are not very good so as to save energy. Thus system outage probability remains almost unchanged in this situation. Anyway, a desired system performance can be achieved by a reasonable choice of $\nu_{S,r}$ and $\nu_{S,P}$. For instance, if energy is insufficient and/or user's QoS requirement is not strict, then a high $\nu_{S,P}$ can be chosen; otherwise, a relatively high $\nu_{S,r}$ may need to be chosen. Generally, this can be obtained by the offline algorithm for different weather and channel conditions and/or QoS requirements.

E. Effect of Dynamic Power Splitting Ratio Selection on System Performance

We now examine whether it is necessary to select the power splitting ratio $\rho^n_{R_j}$ dynamically. For the purpose of comparison, another baseline algorithm (i.e., baseline II), which is similar to CI-OA but uses a fixed power splitting ratio for the selected relay in all cases, is also considered. Fig. 9 depicts the simulation results for different γ_{min}. We can observe that no matter what $\rho^n_{R_j}$ is, baseline II always has the worst performance among all the considered algorithms. This is due to the fact that the power splitting ratio $\rho^n_{R_j}$ is selected dynamically for all relays in our three proposed algorithms according to the CSI and the stored energy of nodes, so as to achieve the best system performance. However, baseline II cannot adjust the parameter $\rho^n_{R_j}$ so that a suboptimal resource allocation strategy has to be chosen sometimes, and thus system performance is degraded. Therefore, simulation results verify that choosing an appropriate power splitting ratio dynamically is required for EH decode-and-forward cooperative communication systems. Moreover, since information and energy receivers operate with very different sensitivity in practice (e.g., -10dBm for energy receivers versus -60dBm for information receivers [16]) and wireless transmission may suffer deep channel fading especially in dense urban areas, we conjecture that a relatively large $\rho^n_{R_j}$ may be needed in dense urban areas considering the energy/information receiver power sensitivity difference. In this way, the energy receiver may be able to harvest enough energy

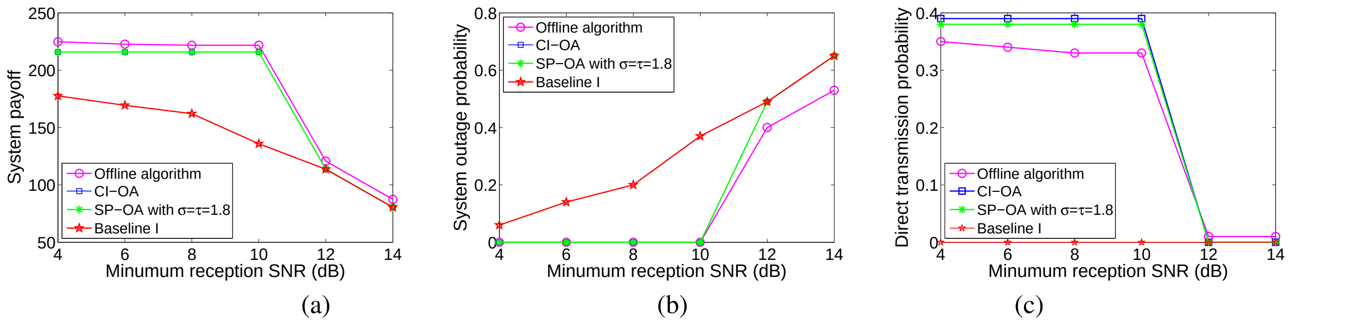


Fig. 7. System performance comparison between algorithms with and without direct transmission (a) System payoff; (b) System outage probability; (c) Direct transmission probability.

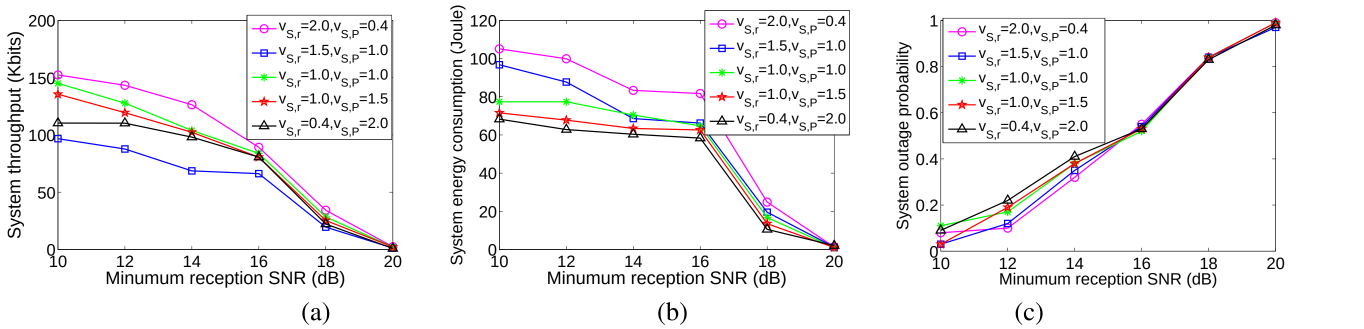


Fig. 8. System performance for different $\nu_{S,r}$ and $\nu_{S,P}$ (a) System throughput; (b) System energy consumption; (c) System outage probability.

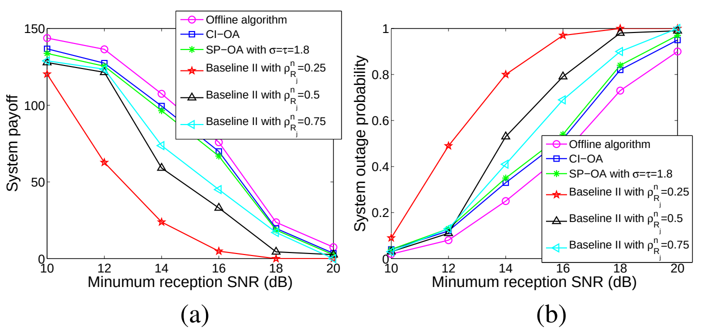


Fig. 9. System performance comparison between algorithms with and without dynamic splitting ratio selection. (a) System payoff; (b) System outage probability.

for data transmission; contrarily, a relatively small $\rho^n_{R_j}$ may be needed in non-dense areas.

VI. Conclusions

In this paper, the problem of joint relay and power splitting ratio selection along with power allocation is studied for an EH relaying system, where the source and the relays can harvest energy from natural sources and RF signals, respectively. To effectively use the harvested energy of the source, the relays are designed to employ the power splitting technique to scavenge energy from RF signals radiated by the source. The addressed problem is considered in both offline and online settings, with the objective to maximize system payoff and meanwhile to minimize system outage probability. In particular, direct transmission is considered, and whether to use a relay for transmission is determined by network channel states and available energy of EH nodes. An offline and two online resource allocation schemes are proposed. Simulations show that system performance can be improved by choosing suitable power splitting ratios and dynamically selecting direct transmission and relay transmission. Moreover, simulations also show that considering system energy consumption is also necessary for EH relaying systems, where a desired system performance can be achieved by choosing energy related parameters, i.e., $\nu_{S,r}$ and $\nu_{S,P}$ appropriately.

Finally, in future, we will consider some more complex scenarios, such as the scenario with multiple EH sources and multiple EH relays, where sources and/or relays can harvest energy from both natural sources and RF signals simultaneously. For these scenarios, we will further address the joint relay, power splitting ratio, and power allocation problem along with considering some other aspects, such as network admission control.

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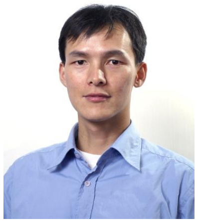
Fei Wang received her B.S. degree in Mathematics from Liaocheng University, Liaocheng, China, in 2005, her M.S. degree from Wuhan University, Wuhan, China, in 2007, and her Ph.D. degree in Computer Science of Chongqing University in 2012. She is currently a lecturer of Southwest University, Chongqing, China. Her research interests include congestion control and cross-layer optimization and distributed algorithm design in wireless ad hoc networks.

Songtao Guo received his B.S., M.S. and Ph.D. degrees in Computer Software and Theory from Chongqing University, Chongqing, China, in 1999, 2003 and 2008, respectively. He was a professor from 2011 to 2012 at Chongqing University. At present, he is a professor at Southwest University, China. His research interests include wireless sensor networks, ad hoc networks and parallel and distributed computing. He has published more than 40 scientific papers in leading refereed journals and conferences. He has received many research grants from National Science Foundation of China and Chongqing and Postdoctoral Science Foundation of China.

Yuanyuan Yang received the BEng and MS degrees in computer science and engineering from Tsinghua University, Beijing, China, and the MSE and PhD degrees in computer science from Johns Hopkins University, Baltimore, Maryland. She is a professor of computer engineering and computer science at Stony Brook University, New York. Her research interests include wireless networks, data center networks, optical networks and high-speed networks. She has published over 300 papers in major journals and refereed conference proceedings and holds seven US patents in these areas. She has served as an Associate Editor-in-Chief and an Associated Editor for IEEE Transactions on Computers and an Associate Editor for IEEE Transactions on Parallel and Distributed Systems. She is an IEEE Fellow.



Bin Xiao received the BSc and MSc degrees in electronics engineering from Fudan University, China, in 1997 and 2000, respectively, and the PhD degree in computer science from the University of Texas at Dallas in 2003. Currently, he is an associate professor in the Department of Computing at The Hong Kong Polytechnic University, Hong Kong. His research interests include wireless sensor networks and RFID systems. He is a recipient of the Best Paper Award of IEEE/IFIP EUC 2011. He is a senior member of the IEEE.