Chapter 1

Simultaneous Wireless

Information and Power

Transfer in UDN with

Caching Architecture

Sumit Gautam, Thang X. Vu*, Symeon Chatzinotas, and Bjorn Ottersten

Interdisciplinary Centre for Security, Reliability and Trust, University of Luxembourg, Luxembourg

*Corresponding Author: Thang X. Vu; thang.vu@uni.lu

In this chapter, we investigate the performance of cache-assisted simultaneous wireless information and power transfer (SWIPT) cooperative systems, in which one source communicates with one destination via the aid of multiple relays. In order to prolong the relays' serving time, the relays are assumed to be equipped with a cache memory and energy harvesting (EH) capability. Based on the time-splitting mechanism, we analyze the effect of caching on the system performance in terms of the serving throughput and the stored en-

ergy at the relay. In particular, two optimization problems are formulated to maximize the relay-destination throughput and the energy stored at the relay subject to some quality-of-service (QoS) constraints, respectively.

1.1. Introduction

The exponential increase in the usage of wireless devices like smart-phones, wearable gadgets, or connected vehicles, has not only posed substantial challenges to meet the performance and capacity demands [1], but also revealed some serious environmental concerns with alarming energy consumption and CO₂ emissions [2]. These concerns become more significant as the forecast number of devices will exceed 50 billions by the end of 2020 [3]. Recent developments in the upcoming paradigm of Internet-of-Things (IoT) emphasize the interconnection between equipments, commodities, functionalities, and customers, with or without human mediation. Since most of these connecting operations involve wireless sensor nodes or equivalent battery-limited devices that may not be continuously powered, energy becomes a sparse and pivotal resource. These challenges require the future communication networks to have not only efficient energy management but also capability of being self-powered from redundant energy sources, which is known as energy harvesting (EH).

Among potential EH techniques, simultaneous wireless information and power transfer (SWIPT) has received much attention as the key enabling technique for future IoT networks. The basic premise behind SWIPT is to allow concurrent data reception and EH from the same radio frequency (RF) input signal. Considering rapid drainage of battery sources in wireless devices, it has almost become essential to take up such techniques in order to compensate

for this issue. Since the conventional receiver architectures are capable of performing information decoding with focus on increasing the data rate only and are unable to harvest energy, this calls for alternative receiver architectures to support SWIPT [4], [7]-[11]. Two notable architectures have been proposed based on time switching (TS) and power splitting (PS) schemes [5, 6]. In the former, the received signal is switched between the information decoder and energy harvester. It is noted in the TS scheme that full received power is used for either information decoding or energy harvesting. In the latter, both the information decoder and energy harvester are active simultaneously, each of them receives parts of the signal power. A comprehensive review on SWIPT is presented in [12].

Another major problem the future networks have to face is network congestion, which usually occurs during peak hours when the network resource is scarce. The cause of this congestion is mainly due to the fact that replicas of a common content may be demanded by various mobile users. A promising solution to overcome network congestion is to shift the network traffic from peak hours to off-peak times via content placement or caching [13]. In (off-line) caching, there is usually a placement phase and a delivery phase. In the placement phase, which usually occurs during off-peak times when the network resources are abundant, popular content is prefetched in distributed caches close to end users. The latter usually occurs during peak hours when the actual users' requests are revealed. If the requested content is available in the user's local storage, it can be served without being requested from the core network. Various advantages brought by caching have been observed in terms of backhaul's load reduction [13, 14] and system energy efficiency improvement [15].

Furthermore, densification of these networks is also crucial for the future of wireless networks in order to tackle heavy congestion scenarios. However, ultra dense networks (UDNs) inflict significant issues in terms of dynamic system foundation and implementation of algorithmic models [16]. Recent studies reveal that UDNs within macro-cells are expected to provide not only an extended coverage with enhanced system capacity, but also an appreciable quality of experience (QoE) to the end-user [17]. In addition, targeting the enhancement of system performance at the end-user, which is assisted by a chosen relay from a pool of cooperative sub-network of relays, within the UDNs, is an interesting problem. In this vein, by leveraging the concept of cooperative systems within UDNs, where relays are superficially equipped with energy harvesting and caching capabilities, we propose a framework for relay selection to serve the end-user.

A generic concept outlining joint EH and caching has recently been proposed for 5G networks to exploit the benefits of both techniques. A so-called framework GreenDelivery is proposed in [2], which enables efficient content delivery in small cells based on energy harvesting small base stations. In [18], an online energy-efficient power control scheme for EH with caching capability is developed. In particular, by adopting the Poisson distribution for the energy sources, a dynamic programming problem is formulated and solved iteratively by using numerical methods. The authors in [19] propose a caching mechanism at the gateway for the energy harvesting based IoT sensing service to maximize the hit rate. In [20], the authors investigate the performance of heterogeneous vehicular networks with renewable energy source. A network planning problem is formulated to optimize cache size and energy harvesting rate subject to backhaul capacity limits. We note that these works either address an abstract EH

with general external energy sources or consider EH separated from caching.

In this chapter, we investigate the performance of EH based cooperative networks within the UDNs, in which the relay nodes are equipped with both SWIPT and caching capabilities. In particular, we aim at developing a framework to realize the integration of SWIPT with caching architectures. The considered system is assumed to operate in the TS based mode, since the PS counterpart imposes complex hardware design challenges of the power splitter [6]. The main contributions of this chapter are three-fold, listed as follows.

- Firstly, we introduce a novel architecture for cache-assisted SWIPT relaying systems under the TS-based and decode-and-forward (DF) relaying protocol and study the interaction between caching capacity and SWIPT in the considered system.
- 2. Secondly, an optimization problem is formulated to maximize the throughput of the (serving) link between the relay and destination, taking into account the caching capacity, minimum harvested energy and quality-of-service (QoS) constraints. By using the Karush-Kuhn-Tucker (KKT) conditions with the aid of the Lambert function, a closed-form solution of the formulated problem is obtained. Based on this result, the best relay will be selected for cooperation.
- 3. Thirdly, we formulate an optimization problem to maximize the energy stored at the relay subjected to the QoS constraint. Similar to the previous problem, a closed-form solution is obtained by using the KKT conditions and the Lambert function. The effectiveness of the proposed schemes are demonstrated via intensive numerical results, through which the impacts of key system parameters are observed.

The remainder of this chapter is organized as follows. Section 1.2 describes

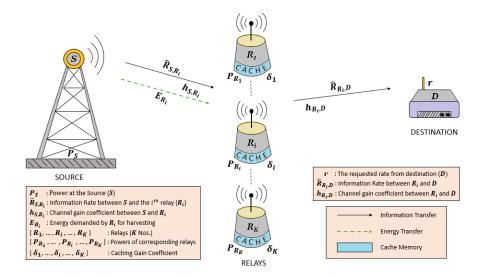


Figure 1.1: System model for SWIPT with caching.

the system model and relevant variables. Section 1.3 presents the problem for maximization of link throughput between the relay and destination. Section 1.4 maximizes the stored energy at the relay. In Section 1.5, numerical results are presented to demonstrate the effectiveness of the proposed architectures. Finally, Section 1.6 concludes the chapter.

1.2. System Model

We consider a generic TS based SWIPT system, which consists of one source, K relays, and one destination, as depicted in Fig. 1.1. Due to limited coverage, e.g., transmit power limit or blockage, there is no direct connection between the source and the destination. The considered model can find application on the downlink where the base station plays the source's role and sends information to a far user via a small- or femto- cell base station. The relays operate in DF mode and are equipped with single antenna. We consider a general cache-aided

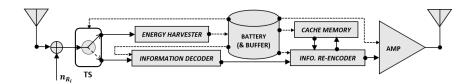


Figure 1.2: Proposed DF relay transceiver design for hybrid SWIPT and caching with time switching (TS) architecture.

SWIPT model, in which each relay contains an information decoder, an energy harvester, and a cache in order to store or exchange information. The block diagram of a typical relay architecture is shown in Fig. 1.2.

We consider block Rayleigh fading channels, in which the channel coefficients remain constant within a block (or coherence time), and independently change block to block. One communication session (broadcasting and relaying) takes place in T seconds (T does not exceed the coherence time). In the broadcasting phase, the source-relay links are active for information decoding (at the relay) and energy harvesting. The relays employ the TS scheme so that the received signal is first provided to the the energy harvester for some fraction of the time allocated for transmitter-relay communication link, and then to information decoder for the remaining fraction. This mechanism is also known as harvest-then-forward protocol [21]. In the relaying phase, the selected relay forwards the information to the destination. Full channel state information (CSI) is assumed to be available at a centralized base station which performs all the computations and inform the relevant devices via adequate signaling. The relay with the best reward will be selected for sending information to the destination. Details on relay selection will be presented in the next sections.

Fig. 1.3 presents a convention for allocation of time fractions in the TS scheme: i) energy harvesting at the relay, ii) information processing at the

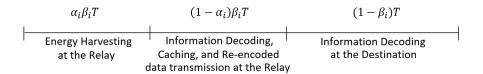


Figure 1.3: Convention assumed for distribution of time to investigate the rate maximization problem.

relay, and <u>iii)</u> information forwarding to the destination. The link between the transmitter and *i*-th relay with cache is active for a fraction of $\beta_i T$ seconds, while the link between the *i*-th relay and destination is active for the remaining $(1-\beta_i)T$, where $0 \le \beta_i \le 1$. Furthermore, we assume that the energy harvesting at the relays takes place for a fraction of $\alpha_i \beta_i T$ seconds and the information decoding at the relay takes place for a fraction of $(1-\alpha_i)\beta_i T$ seconds, where $0 \le \alpha_i \le 1$. For ease of representation, we assume normalized time to use energy and power interchangeably without loss in generality.

Signal model. We define the information transfer rates from the source to the *i*-th relay as \hat{R}_{S,R_i} , and from the *i*-th relay to the destination as $\hat{R}_{R_i,D}$, with $1 \leq i \leq K$, where $i \in \mathbb{Z}$.

Let h_{S,R_i} and $h_{R_i,D}$ denote the channel coefficients between the source and the *i*-th relay and between the *i*-th relay and the destination, respectively, and d_{S,R_i} and $d_{R_i,D}$ denote the distance between the source and *i*-th relay, and the distance between the *i*-th relay and destination, respectively. Furthermore, P_S and P_{R_i} denote the transmit power at the source and the *i*-th relay, respectively.

Let $x \in \mathbb{C}$ be the transmitted symbol by the source satisfying $E\{|x|^2\}=1$. The signal received at the *i*-th relay is given by

$$y_{R_i} = \sqrt{P_S} \ d_{S,R_i}^{-\vartheta/2} \ h_{S,R_i} \ x + n_{R_i},$$
 (1.1)

where ϑ is the path loss exponent, n_{R_i} is the additive white Gaussian noise (AWGN) at the relay, which is an independent and identically distributed (i.i.d.) complex Gaussian random variable with zero mean and variance $\sigma_{n_{R_i}}^2$.

Upon receiving the desired signal from the source, the relay decodes to obtain the estimate of the original signal. Then the (selected) relay re-encodes and forwards it to the destination. The signal received at the destination as transmitted by the *i*-th relay is given by

$$y_D = \sqrt{P_{R_i}} d_{R_i,D}^{-\vartheta/2} h_{R_i,D} \tilde{x} + n_D,$$
 (1.2)

where \tilde{x} is the transmit symbol from the relay, and n_D is the AWGN at the destination node which is an i.i.d. complex Gaussian random variable with zero mean and variance $\sigma_{n_D}^2$. We note that in the proposed cached-aid architecture, the relayed symbol can be either decoded source symbol or from the relay's cache.

The effective signal-to-noise ratio (SNR) of the source-relay and relaydestination links are given as

$$\gamma_{S,R_i} = \frac{P_S \ d_{S,R_i}^{-\vartheta} \ |h_{S,R_i}|^2}{\sigma_{n_{R_i}}^2}; \ \gamma_{R_i,D} = \frac{P_{R_i} \ d_{R_i,D}^{-\vartheta} \ |h_{R_i,D}|^2}{\sigma_{n_D}^2}. \tag{1.3}$$

By assuming a Gaussian codebook, the achievable information rate on the source-relays link is

$$\hat{R}_{S,R_i} = B \log_2(1 + \gamma_{S,R_i}), \quad \forall i,$$
 (1.4)

and the achievable information rate at the destination is

$$\hat{R}_{R_i,D} = B \log_2(1 + \gamma_{R_i,D}), \forall i,$$
 (1.5)

where B is the channel bandwidth.

Caching model. A general caching model is considered at the relays. In particular, in addition to the information sent from the source, the relays have access to the information stored in their individual caches to serve the destination. For robustness, we assume that for i = 1, ..., K, the *i*-th relay does not have information about the content popularity. Therefore, it will store $0 \le \delta_i \le 1$ parts of every file in its cache [13, 15] ¹. For convenience, we call δ_i as the caching coefficient throughout the chapter. This caching scheme will serve as the lower bound benchmark compared to the case where priori information of content popularity is available. When the destination requests a file from the library, δ_i parts of that file are already available at the *i*-th relay's cache. Therefore, the source need to send only the remaining of that file to the relay.

Power assumption at the relay. For robustness, we assume that the relays are powered by an external source, E_{ext} , on top of the harvested energy. This general model allows to analyze the impact of various practical scenarios. As an usecase, the purely SWIPT relay is obtained by setting E_{ext} to zero. The harvested energy at the *i*-th relay is given by

$$E_{R_i} = \zeta \alpha_i \beta_i (P_S d_{S,R_i}^{-\vartheta} |h_{S,R_i}|^2 + \sigma_{n_{B_i}}^2), \tag{1.6}$$

where ζ is the energy conversion efficiency of the receiver.

In the following couple of sections, we address the problems for maximizing the serving information rate between the relay and the destination, and

¹This caching method is also known as probabilistic caching.

1.3. Maximization of the serving information rate

In this section, we aim at maximizing the serving information data between the selected relay and the destination, by taking into consideration the caching capacity at the relay, while assuring the predefined QoS constraint and that the total transmit power at the source does not exceed the limit. The corresponding optimization problem (P1) is stated as follows

$$(P1): \max_{i \in \mathcal{K}, \alpha_i, \beta_i, P_{R_i}} (1 - \beta_i) \hat{R}_{R_i, D}$$

$$(1.7)$$

subject to :(C1) :
$$(1 - \alpha_i)\beta_i(\hat{R}_{S,R_i} + (\delta_i \cdot r)) \ge (1 - \beta_i)\hat{R}_{R_i,D},$$
 (1.8)

$$(C2): (1 - \beta_i) P_{R_i} \le E_{R_i} + E_{ext}, \tag{1.9}$$

$$(C3): 0 < P_S \le P^*, \tag{1.10}$$

$$(C4): 0 \le \alpha_i \le 1, \tag{1.11}$$

$$(C5): 0 \le \beta_i \le 1, \tag{1.12}$$

where $\mathcal{K} = \{1, \dots, K\}$, E_{R_i} is given in (1.6), E_{ext} is the external energy required at the relay for further transmission of the signal, P^* is the maximum power limit at the transmitter, and r is the QoS constraint. The objective in (1.7) is to maximize the transferred data to the destination, since the relay-destination link is active only in $1 - \beta_i$ (active times normalized by T). Constraint (1.8) is to assure non-empty buffer at the relay. Constraint (1.9) is to assure that the used energy at the relay cannot exceed the input.

This is a mixed-integer programming problem implying that relay selection along with joint computations of α_i , β_i , and P_{R_i} is a difficult task. Therefore, we recast (P1) into a pair of coupled optimization problems namely, outer optimization for choosing the best relay, and inner optimization for joint computations of α_i , β_i , and P_{R_i} . In the following sections, we address the optimal solutions to the inner and outer optimizations, respectively.

Optimization of TS Factors and the Relay Transmit Power. In this subsection, we address the inner optimization problem of (P1) involving joint computations of α_i , β_i , and P_{R_i} , assuming that the *i*-th relay is active. The result sub-problem is formulated as follows

$$(P2): \max_{\alpha_{i}, \beta_{i}, P_{R_{i}}} (1 - \beta_{i}) \hat{R}_{R_{i}, D}$$
subject to: $(1.8) - (1.12)$.

This is a non-linear programming problem involving joint computations of α_i , β_i , and P_{R_i} , which is challenging to find the exact solution. Since the constraints are partially convex on each variable while fixing the others, we propose to solve this problem using the KKT conditions.

The Lagrangian corresponding to (P2) can be denoted as follows

$$\mathcal{L}(\alpha_i, \beta_i, P_{R_i}; \lambda_1, \lambda_2, \lambda_3, \lambda_4) = F(\alpha_i, \beta_i, P_{R_i}) - \lambda_1 G(\alpha_i, \beta_i, P_{R_i})$$
$$-\lambda_2 H(\alpha_i, \beta_i, P_{R_i}) - \lambda_3 I(\alpha_i, \beta_i, P_{R_i}) - \lambda_4 J(\alpha_i, \beta_i, P_{R_i}), \quad (1.14)$$

where

$$F(\alpha_{i}, \beta_{i}, P_{R_{i}}) = (1 - \beta_{i})B \log_{2}(1 + \gamma_{R_{i},D}), (1.15)$$

$$G(\alpha_{i}, \beta_{i}, P_{R_{i}}) = (1 - \beta_{i})B \log_{2}(1 + \gamma_{R_{i},D}) - (1 - \alpha_{i})\beta_{i}[B \log_{2}(1 + \gamma_{S,R_{i}}) + (\delta_{i} \cdot r)] \leq 0, (1.16)$$

$$H(\alpha_{i}, \beta_{i}, P_{R_{i}}) = (1 - \beta_{i})P_{R_{i}} - \zeta \alpha_{i}\beta_{i}(P_{S}d_{S,R_{i}}^{-\vartheta}|h_{S,R_{i}}|^{2} + \sigma_{R_{i}}^{2}) - E_{ext} \leq 0, (1.17)$$

$$I(\alpha_{i}, \beta_{i}, P_{R_{i}}) = \alpha_{i} - 1 \leq 0, (1.18)$$

$$J(\alpha_{i}, \beta_{i}, P_{R_{i}}) = \beta_{i} - 1 \leq 0, (1.19)$$

For (local) optimality, it must hold $\nabla \mathcal{L}(\alpha_i, \beta_i, P_{R_i}; \lambda_1, \lambda_2, \lambda_3, \lambda_4) = 0$. Thus, we can represent the equations for satisfying the optimality conditions as

$$\frac{\partial \mathcal{L}(\alpha_i, \beta_i, P_{R_i}; \lambda_1, \lambda_2, \lambda_3, \lambda_4)}{\partial \alpha_i} \implies -\lambda_1 [\beta_i (B \log_2 (1 + \gamma_{S,R_i}) + (\delta_i \cdot r))]$$

$$-\lambda_2 [-\zeta \beta_i (P_S d_{S,R_i}^{-\vartheta} |h_{S,R_i}|^2 + \sigma_{n_{R_i}}^2)] - \lambda_3 = 0, \quad (1.20)$$

$$\frac{\partial \mathcal{L}(\alpha_{i}, \beta_{i}, P_{R_{i}}; \lambda_{1}, \lambda_{2}, \lambda_{3}, \lambda_{4})}{\partial \beta_{i}} \implies -B \log_{2}(1 + \gamma_{R_{i}, D}) - \lambda_{1}[-B \log_{2}(1 + \gamma_{R_{i}, D})] - (1 - \alpha_{i})[B \log_{2}(1 + \gamma_{S, R_{i}}) + (\delta_{i} \cdot r)] - \lambda_{2}[-P_{R_{i}} - \zeta \alpha_{i}(P_{S} d_{S, R_{i}}^{-\vartheta} |h_{S, R_{i}}|^{2} + \sigma_{R_{i}}^{2})] - \lambda_{4} = 0, \quad (1.21)$$

$$\frac{\partial \mathcal{L}(\alpha_{i}, \beta_{i}, P_{R_{i}}; \lambda_{1}, \lambda_{2}, \lambda_{3}, \lambda_{4})}{\partial P_{R_{i}}} \Longrightarrow \frac{\ln(2) d_{R_{i},D}^{-\vartheta} |h_{R_{i},D}|^{2}}{\sigma_{n_{D}}^{2} + P_{R_{i}} d_{R_{i},D}^{-\vartheta} |h_{R_{i},D}|^{2}} \\
- \lambda_{1} \left(\frac{\ln(2) d_{R_{i},D}^{-\vartheta} |h_{R_{i},D}|^{2}}{\sigma_{n_{D}}^{2} + P_{R_{i}} d_{R_{i},D}^{-\vartheta} |h_{R_{i},D}|^{2}} \right) - \lambda_{2} = 0. \quad (1.22)$$

The conditions for feasibility are as expressed in (1.16), (1.17), (1.18), and

(1.19). Complementary slackness expressions can be represented as follows

$$\lambda_1 \cdot G(\alpha_i, \beta_i, P_{R_i}) = 0, \tag{1.23}$$

$$\lambda_2 \cdot H(\alpha_i, \beta_i, P_{R_i}) = 0, \tag{1.24}$$

$$\lambda_3 \cdot I(\alpha_i, \beta_i, P_{R_i}) = 0, \tag{1.25}$$

$$\lambda_4 \cdot J(\alpha_i, \beta_i, P_{R_i}) = 0. \tag{1.26}$$

The conditions for non-negativity read $\alpha_i, \beta_i, P_{R_i}, \lambda_1, \lambda_2, \lambda_3, \lambda_4 \geq 0$. It is straightforward to verify that if $\lambda_3 \neq 0$, then $I(\alpha_i, \beta_i, P_{R_i}) = 0$ implying that $\alpha_i = 1$. Since this is not a feasible solution, therefore $\lambda_3 = 0$. Similarly, it can be shown that $\lambda_4 = 0$. From further analysis, we find that the solutions corresponding to the binding cases of KKT yields either zero, negative, or unbounded values of the optimization variables, thereby violating the nonnegativity constraints. The final solution can be postulated in the following theorem, following the non-binding case.

Theorem 1.1: For $\lambda_1 \neq 0 \implies G(x, P_{R_i}) = 0$; $\lambda_2 \neq 0 \implies H(x, P_{R_i}) = 0$, we obtain the following optimal values

$$P_{R_i} = \left(\exp\left(\mathcal{W}(\mathcal{A}\exp(-\log^2(2)) + \log(2)) + \log^2(2)\right) - 1\right) \left(\frac{\sigma_{n_D}^2}{d_{R_i,D}^{-\vartheta} |h_{R_i,D}|^2}\right),$$
(1.27)

where $\mathcal{A} = \frac{(\ln(2)d_{R_i,D}^{-\vartheta}|h_{R_i,D}|^2)(\zeta(P_Sd_{S,R_i}^{-\vartheta}|h_{S,R_i}|^2 + \sigma_{n_{R_i}}^2))}{\sigma_{n_D}^2}$ and $\mathcal{W}(\cdot)$ is the Lambert W function [22].

$$\beta_{i} = \frac{\varphi - E_{ext}(B \log_{2}(1 + \gamma_{S,R_{i}}) + (\delta_{i} \cdot r))}{\varphi - \zeta(P_{S}d_{S,R_{i}}^{-\vartheta}|h_{S,R_{i}}|^{2} + \sigma_{n_{R_{i}}}^{2})(B \log_{2}(1 + \gamma_{S,R_{i}}) + (\delta_{i} \cdot r))},$$
(1.28)

where
$$\varphi = P_{R_i}(B \log_2(1 + \gamma_{S,R_i}) + (\delta_i \cdot r)) - \zeta(P_S d_{S,R_i}^{-\vartheta} |h_{S,R_i}|^2 + \sigma_{n_{R_i}}^2) B \log_2(1 + \gamma_{S,R_i}) + (\delta_i \cdot r) + (\delta_i \cdot$$

$$\gamma_{R_{i},D}).$$

$$\alpha_{i} = \frac{(1 - \beta_{i})P_{R_{i}} - E_{ext}}{\zeta \beta_{i} (P_{S} d_{S,R_{i}}^{-\vartheta} |h_{S,R_{i}}|^{2} + \sigma_{n_{R_{i}}}^{2})}.$$
(1.29)

From an economic view-point, the Lagrange Multipliers λ_1 and λ_2 can be expounded as the prices for data and energy in cost/bit and cost/Joule, respectively. Leveraging the results from our mathematical analysis, we find that $\lambda_1 = \frac{f_1(P_S)}{f_2(P_S,\delta_i,r)} \cdot \lambda_2$, where $f_1(P_S) = \zeta(P_S d_{S,R_i}^{-\vartheta}|h_{S,R_i}|^2 + \sigma_{n_{R_i}}^2)$, and $f_2(P_S,\delta_i,r) = B \log_2(1+\gamma_{S,R_i}) + (\delta_i \cdot r)$. Correspondingly, it is clear that if more data rate is demanded by the user provided the caching capacity is fixed, then we are enforced to compensate for the request by using the energy metric per cost unit in order to satisfy the respective data and energy constraints in (P2). This action would however add more to the energy price. Similarly, it is apparent that increasing the transmit power will readily add to the cost of data transfer in addition to an increased energy price. In the context of caching, it would be needless to mention that the higher the cache capacity is, the lower will be the prices for data and energy transmissions.

Relay Selection. In this subsection, we consider optimal selection of a relay to address the solution of outer optimization of (P1). Based on the above developments, we find the best relay which provides maximum throughput corresponding to (1.7). The best relay index is selected as $j^* = \arg\max_{j \in \{1,...,K\}} (1 - \beta_j^*) \hat{R}_{R_j,D}^*$, where β_j^* and $\hat{R}_{R_j,D}^*$ are the solutions of problem (1.13). It is worth to mention that this relay selection is based on exhausted search and provides the best performance with high cost of complexity. Finding a compromise relay selection is of interest in the future research.

1.4. Maximization of the Energy Stored at the Relay

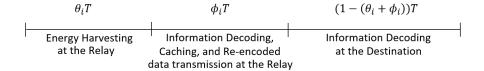


Figure 1.4: Convention assumed for distribution of time to investigate the stored energy maximization problem.

In this section, we aim at maximizing the energy stored at the relay. The stored energy is calculated by subtracting the input energy, e.g., E_{ext} plus the harvested energy, by the output energy, e.g., used for forwarding information to the destination. Our motivation behind this section is that the stored energy at the relay can be used to perform extra processing task, e.g., sensing, or to recharge a battery for future use. In particular, an optimization problem is formulated to jointly select the best relay and maximize the stored energy, while satisfying a given QoS.

For convenience, we introduce a new convention for fraction of times in the TS scheme, as shown in Fig. 1.4. The link between the transmitter and relay with cache is considered to be active for a fraction of $(\theta_i + \phi_i)T$ seconds, while the link between the relay and destination is active for the remaining $(1 - (\theta_i + \phi_i))T$, where $0 \le \theta_i + \phi_i \le 1$. As mentioned earlier, since the relay adopts a TS type of scheme for SWIPT, we assume that the energy harvesting at the relay takes place for a fraction of $\theta_i T$ seconds and the information decoding at the relay takes place for a fraction of $\phi_i T$ seconds. Similarly, we assume normalized time to use energy and power interchangeably without loss

in generality. We remind that the harvested energy at the relay i is given as

$$E_{R_i} = \zeta \theta_i (P_S d_{S,R_i}^{-\vartheta} |h_{S,R_i}|^2 + \sigma_{n_{R_i}}^2), \tag{1.30}$$

where ζ is the energy conversion efficiency of the receiver.

We now consider the problem of relay selection for maximization of the energy stored at the relay, while ensuring that the requested rate between relay-destination is above a given threshold and that the total transmit powers at the transmitter and relay does not exceed a given limit. The corresponding optimization problem (P3) can be expressed as

$$(P3): \max_{i \in \mathcal{K}, \theta_i, \phi_i, P_{R_i}} \left[\zeta \theta_i (P_S d_{S, R_i}^{-\vartheta} |h_{S, R_i}|^2 + \sigma_{n_{R_i}}^2) + E_{ext} - (1 - (\theta_i + \phi_i)) P_{R_i} \right]^+$$

$$(1.31)$$

subject to:
$$(C1): \phi_i(\hat{R}_{S,R_i} + (\delta_i \cdot r)) \ge (1 - (\theta_i + \phi_i))\hat{R}_{R_i,D}, (1.32)$$

$$(C2): (1 - (\theta_i + \phi_i))P_{R_i} \le E_{R_i} + E_{ext}, \tag{1.33}$$

$$(C3): (1 - (\theta_i + \phi_i))\hat{R}_{R_i, D} \ge r, \tag{1.34}$$

$$(C4): 0 < P_S \le P^*, \tag{1.35}$$

$$(C5): 0 \le \theta_i + \phi_i \le 1, \tag{1.36}$$

where the objective in (1.31) is non-zero and the constraint (1.34) is to satisfy the QoS requirement.

The problem (P3) is difficult to solve, since it is a mixed-integer programming problem involving relay selection along with joint computations of θ_i , ϕ_i , and P_{R_i} . So, we recast (P3) into pair of coupled optimization problems for performing the outer optimization to choose the best relay, and inner optimization for joint computations of θ_i , ϕ_i , and P_{R_i} . In the following subsec-

tions, we address the optimal solutions to the inner and outer optimizations, respectively.

Optimization of TS Factors and the Relay Transmit Power. In this subsection, we consider the inner optimization problem of (P3). We determine the technique for joint computations of θ_i , ϕ_i , and P_{R_i} , for maximizing the energy stored at the relay while ensuring that the requested rate between relay-destination is above a given threshold and that the total transmit powers at the transmitter and relay does not exceed a given limit. Correspondingly, the sub-problem (P4) can be formulated as

$$(P4): \max_{\theta_{i}, \phi_{i}, P_{R_{i}}} \left[\zeta \theta_{i} (P_{S} d_{S, R_{i}}^{-\vartheta} |h_{S, R_{i}}|^{2} + \sigma_{n_{R_{i}}}^{2}) + E_{ext} - (1 - (\theta_{i} + \phi_{i})) P_{R_{i}} \right]^{+}$$

$$(1.37)$$

subject to:
$$(C1): \phi_i(\hat{R}_{S,R_i} + (\delta_i \cdot r)) \ge (1 - (\theta_i + \phi_i))\hat{R}_{R_i,D},$$
 (1.38)

$$(C2): (1 - (\theta_i + \phi_i))P_{R_i} \le E_{R_i} + E_{ext}, \tag{1.39}$$

$$(C3): (1 - (\theta_i + \phi_i))\hat{R}_{R_i, D} \ge r, \tag{1.40}$$

$$(C4): 0 < P_S \le P^*, \tag{1.41}$$

$$(C5): 0 \le \theta_i + \phi_i \le 1. \tag{1.42}$$

This is a non-linear programming problem involving joint computations of θ_i , ϕ_i , and P_{R_i} , which introduces intractability. Therefore, we propose to solve this problem using the KKT conditions.

The Lagrangian for (P4) can be expressed as follows

$$\mathcal{L}(\theta_i, \phi_i, P_{R_i}; \mu_1, \mu_2, \mu_3, \mu_4) = F(\theta_i, \phi_i, P_{R_i}) - \mu_1 \ G(\theta_i, \phi_i, P_{R_i})$$
$$-\mu_2 \ H(\theta_i, \phi_i, P_{R_i}) - \mu_3 \ I(\theta_i, \phi_i, P_{R_i}) - \mu_4 \ J(\theta_i, \phi_i, P_{R_i}), \tag{1.43}$$

where

$$F(\theta_{i}, \phi_{i}, P_{R_{i}}) = \left[\zeta \theta_{i} (P_{S} d_{S,R_{i}}^{-\vartheta} | h_{S,R_{i}}|^{2} + \sigma_{n_{R_{i}}}^{2}) + E_{ext} - (1 - (\theta_{i} + \phi_{i})) P_{R_{i}}\right]^{+}, \quad (1.44)$$

$$G(\theta_{i}, \phi_{i}, P_{R_{i}}) = (1 - (\theta_{i} + \phi_{i})) B \log_{2}(1 + \gamma_{R_{i},D}) - \phi_{i} \left[B \log_{2}(1 + \gamma_{S,R_{i}}) + (\delta_{i} \cdot r)\right] \leq 0, \quad (1.45)$$

$$H(\theta_{i}, \phi_{i}, P_{R_{i}}) = (1 - (\theta_{i} + \phi_{i})) P_{R_{i}} - \zeta \theta_{i} (P_{S} d_{S,R_{i}}^{-\vartheta} | h_{S,R_{i}}|^{2} + \sigma_{n_{R_{i}}}^{2}) - E_{ext} \leq 0, \quad (1.46)$$

$$I(\theta_{i}, \phi_{i}, P_{R_{i}}) = r - (1 - (\theta_{i} + \phi_{i})) B \log_{2}(1 + \gamma_{R_{i},D}) \leq 0, \quad (1.47)$$

$$J(\theta_{i}, \phi_{i}, P_{R_{i}}) = (\theta_{i} + \phi_{i}) - 1 \leq 0. \quad (1.48)$$

with $\mu_1, \mu_2, \mu_3, \mu_4$ being the Lagrange Multipliers for the corresponding constraints (C1), (C2), (C3), and (C5).

For optimality, $\nabla \mathcal{L}(\theta_i, \phi_i, P_{R_i}; \mu_1, \mu_2, \mu_3, \mu_4) = 0$. Thus, we can represent the equations for satisfying the optimality conditions as

$$\frac{\partial \mathcal{L}(\theta_{i}, \phi_{i}, P_{R_{i}}; \mu_{1}, \mu_{2}, \mu_{3}, \mu_{4})}{\partial \theta_{i}} \Longrightarrow \left[\zeta (P_{S} d_{S,R_{i}}^{-\vartheta} |h_{S,R_{i}}|^{2} + \sigma_{n_{R_{i}}}^{2}) + P_{R_{i}} \right]
- \mu_{1} \left[-B \log_{2}(1 + \gamma_{R_{i},D}) \right] - \mu_{2} \left[-P_{R_{i}} - \zeta (P_{S} d_{S,R_{i}}^{-\vartheta} |h_{S,R_{i}}|^{2} + \sigma_{n_{R_{i}}}^{2}) \right]
- \mu_{3} \left[B \log_{2}(1 + \gamma_{R_{i},D}) \right] - \mu_{4} = 0, \quad (1.49)$$

$$\frac{\partial \mathcal{L}(\theta_{i}, \phi_{i}, P_{R_{i}}; \mu_{1}, \mu_{2}, \mu_{3}, \mu_{4})}{\partial \phi_{i}} \implies P_{R_{i}} - \mu_{1}[-B \log_{2}(1 + \gamma_{R_{i},D}) - (B \log_{2}(1 + \gamma_{S,R_{i}}) + (\delta_{i} \cdot r))] - \mu_{2}[-P_{R_{i}}] - \mu_{3}[B \log_{2}(1 + \gamma_{R_{i},D})] - \mu_{4} = 0, \quad (1.50)$$

$$\frac{\partial \mathcal{L}(\theta_{i}, \phi_{i}, P_{R_{i}}; \mu_{1}, \mu_{2}, \mu_{3}, \mu_{4})}{\partial P_{R_{i}}} \implies -(1 - (\theta_{i} + \phi_{i}))$$

$$- \mu_{1} \left[(1 - (\theta_{i} + \phi_{i})) \left(\frac{\ln(2) d_{R_{i},D}^{-\vartheta} |h_{R_{i},D}|^{2}}{\sigma_{n_{D}}^{2} + P_{R_{i}} d_{R_{i},D}^{-\vartheta} |h_{R_{i},D}|^{2}} \right) \right]$$

$$- \mu_{2} (1 - (\theta_{i} + \phi_{i})) - \mu_{3} \left[- (1 - (\theta_{i} + \phi_{i})) \left(\frac{\ln(2) d_{R_{i},D}^{-\vartheta} |h_{R_{i},D}|^{2}}{\sigma_{n_{D}}^{2} + P_{R_{i}} d_{R_{i},D}^{-\vartheta} |h_{R_{i},D}|^{2}} \right) \right] = 0.$$
(1.51)

The conditions for feasibility are as expressed in (1.45), (1.46), (1.47), and (1.48). Complementary slackness expressions can be represented as follows

$$\mu_1 \cdot G(\theta_i, \phi_i, P_{R_i}) = 0,$$
 (1.52)

$$\mu_2 \cdot H(\theta_i, \phi_i, P_{R_i}) = 0,$$
(1.53)

$$\mu_3 \cdot I(\theta_i, \phi_i, P_{R_i}) = 0,$$
 (1.54)

$$\mu_4 \cdot J(\theta_i, \phi_i, P_{R_i}) = 0.$$
 (1.55)

The conditions for non-negativity are: θ_i , ϕ_i , P_{R_i} , μ_1 , μ_2 , μ_3 , $\mu_4 \geq 0$. It is clear that if $\mu_4 \neq 0$, then $J(\theta_i, \phi_i, P_{R_i}) = 0$ implying that $\theta_i + \phi_i = 1$. Since this is not a feasible solution, therefore $\mu_4 = 0$. From further analysis, we find that the solutions corresponding to the binding cases of KKT yields either zero, negative, or unbounded values of the optimization variables, thereby violating the non-negativity constraints. The two possible solution are as mentioned in the following theorems, respectively.

Theorem 1.2: If $\mu_1 \neq 0 \implies G(\theta_i, \phi_i, P_{R_i}) = 0$; $\mu_2 = 0 \implies H(\theta_i, \phi_i, P_{R_i}) \neq 0$; $\mu_3 \neq 0 \implies I(\theta_i, \phi_i, P_{R_i}) = 0$, then we obtain the following optimal values

$$P_{R_i}^{\dagger} = (\nu - 1) \left(\frac{\sigma_{n_D}^2}{d_{R_i,D}^{-\vartheta} |h_{R_i,D}|^2} \right),$$
 (1.56)

$$\phi_i^{\dagger} = \frac{r}{B \log_2(1 + \gamma_{S.B.}) + (\delta_i \cdot r)},\tag{1.57}$$

$$\theta_{i}^{\dagger} = 1 - r \left(\frac{1}{B \log_{2}(1 + \gamma_{S,R_{i}}) + (\delta_{i} \cdot r)} + \frac{1}{B \log_{2}\left(1 + \frac{P_{R_{i}}^{\dagger} d_{R_{i},D}^{-\vartheta} |h_{R_{i},D}|^{2}}{\sigma_{n_{D}}^{2}}\right)} \right), \tag{1.58}$$

where

$$\nu = \exp\left(\mathcal{W}(-A\exp(-\log^2(2)) + \log(2)) + \log^2(2)\right) \tag{1.59}$$

with
$$\mathcal{A} = \ln(2) - \left(\frac{\zeta}{\sigma_{n_D}^2}\right) (\ln(2) d_{R_i,D}^{-\vartheta} |h_{R_i,D}|^2) (P_S d_{S,R_i}^{-\vartheta} |h_{S,R_i}|^2 + \sigma_{n_{R_i}}^2)$$

Theorem 1.3: If $\mu_1 \neq 0 \implies G(\theta_i, \phi_i, P_{R_i}) = 0$; $\mu_2 \neq 0 \implies H(\theta_i, \phi_i, P_{R_i}) = 0$; $\mu_3 \neq 0 \implies I(\theta_i, \phi_i, P_{R_i}) = 0$, then the following values are optimal

$$P_{R_i}^* = (\eta_L - 1) \left(\frac{\sigma_{n_D}^2}{d_{R_i,D}^{-\vartheta} |h_{R_i,D}|^2} \right), \tag{1.60}$$

$$\phi_i^* = \frac{r}{B \log_2(1 + \gamma_{S.R.}) + (\delta_i \cdot r)},$$
(1.61)

$$\theta_i^* = \frac{r P_{R_i}^* - E_{ext} B \log_2 \left(1 + \frac{P_{R_i}^* d_{R_i,D}^{-\vartheta} |h_{R_i,D}|^2}{\sigma_{n_D}^2} \right)}{\zeta(P_S d_{S,R_i}^{-\vartheta} |h_{S,R_i}|^2 + \sigma_{n_R}^2)}, \tag{1.62}$$

where $\eta_L = \text{Largest Root of } [\mathcal{A} + B \log_2(\eta) \left(\mathcal{B} + \mathcal{C} \eta + \mathcal{D} B \log_2(\eta) \right) = 0]$, with $\mathcal{A} = a \cdot b \cdot r$, $\mathcal{B} = -a \cdot b - b \cdot r \cdot \left(\frac{\sigma_{n_D}^2}{d_{R_i,D}^{-\vartheta} |h_{R_i,D}|^2} \right) + a \cdot r$, $\mathcal{C} = b \cdot r \cdot \left(\frac{\sigma_{n_D}^2}{d_{R_i,D}^{-\vartheta} |h_{R_i,D}|^2} \right)$, and $\mathcal{D} = -b \cdot E_{ext}$, where $a = \zeta(P_S d_{S,R_i}^{-\vartheta} |h_{S,R_i}|^2 + \sigma_{n_R_i}^2)$, and $b = B \log_2(1 + \gamma_{S,R_i}) + (\delta_i \cdot r)$.

To summarize the solutions obtained above, we propose the following algorithm to maximize the stored energy in the relay supporting SWIPT - Caching system (MSE-WC Algorithm)

Input: The parameters h_{S,R_i} , $h_{R_i,D}$, δ_i , r, and E_{ext} .

Output: The maximized value of energy stored at the relay: $\{E_S\}$.

- 1. : Initialize: $\zeta\in(0,1],\ P_T\in(0,\varepsilon P_{Max}],\ 0.5<\varepsilon<1,\ \sigma^2_{n_{R_i}}=1,$ and $\sigma^2_{n_D}=1.$
- 2. : Compute $P_{R_i}^{\dagger}$, ϕ_i^{\dagger} , and θ_i^{\dagger} using (1.56), (1.57), and (1.58) respectively.
- 3. : Define: $E_S^\dagger = \zeta \theta_i^\dagger (P_S d_{S,R_i}^{-\vartheta} |h_{S,R_i}|^2 + \sigma_{n_{R_i}}^2) + E_{ext} (1 (\theta_i^\dagger + \phi_i^\dagger)) P_{R_i}^\dagger.$
- 4. : Compute $P_{R_i}^*$, ϕ_i^* , and θ_i^* using (1.60), (1.61), and (1.62) respectively.
- 5. : Define: $E_S^* = \zeta \theta_i^* (P_S d_{S,R_i}^{-\vartheta} |h_{S,R_i}|^2 + \sigma_{n_{R_i}}^2) + E_{ext} (1 (\theta_i^* + \phi_i^*)) P_{R_i}^*$
- 6. $: E_S = \max(E_S^{\dagger}, E_S^*).$
- 7. : return E_S .

The algorithm proposed above returns the maximized value of the objective function as its output. First, we initialize all the necessary values as indicated in 1). Then, we compute the optimal values of $P_{R_i}^{\dagger}$, ϕ_i^{\dagger} , and θ_i^{\dagger} in 2), and define the energy stored at the relay in 3). 2) and 3) corresponds to the solutions obtained for Case VI during the analysis. Similarly, we find the optimal values of $P_{R_i}^*$, ϕ_i^* , and θ_i^* in 4), and define the energy stored at the relay in 5) accordingly. 4) and 5) corresponds to the solutions obtained for Case VIII during the analysis. Next, we find the maximum of the two computed local optimal solutions for the energy stored at the relay, which in turn maximizes the objective function. It should also be noted that the solutions proposed in (P2) for maximizing the energy stored at the relay are not necessarily global optimum, as the problem is non-linear in nature. However, the KKT conditions guarantees the local optimal solutions.

In order to analyze the proposed approach from an economic perspective,

we denote the equivalent relationship between the Lagrange Multipliers μ_1 and μ_3 as μ_R and rename μ_2 as μ_E which corresponds to the the prices for data and energy, respectively, in cost units. Using the results from our mathematical analysis, we find that $\mu_E = \frac{f_1(P_S, \delta_i, r)}{f_2(P_S)} \cdot \mu_R$, where $f_1(P_S, \delta_i, r)$, and $f_2(P_S)$ are functions computed as per the illustrated technique. Correspondingly, if more energy is required by the relay with fixed caching capacity, then we are forced to compensate for the request by using the energy metric per cost unit at the source in order to satisfy the respective data and energy constraints in (P2). This action would however add more to the data price as well. Similarly, it is apparent that increasing the transmit power will readily add to the cost of energy transfer in addition to an increased data price. Furthermore in the context of caching, it is worth mentioning that extra cache capacity implies subordinate prices for data and energy transmissions per cost unit.

Relay Selection. From the methods proposed above, optimal TS ratios and the relay transmit power can be computed easily. Herein, we propose to find the best relay which provides maximized harvested power corresponding to (1.31). In this context, the index of the optimally selected relay can be expressed as $j^* = \arg\max_{j \in \{1,\dots,K\}} E_{S_j}^*$, where $E_{S_j}^*$ is the optimal energy stored at the j-th relay as the solution of problem (1.37).

1.5. Numerical Results

In this section, we evaluate the performance of the proposed system for the solutions presented in this chapter. We consider a total bandwidth of B=1 MHz, $\zeta=0.80$, $\sigma_{n_{R_i}}^2=0$ dBW, and $\sigma_{n_D}^2=0$ dBW [23]. Throughout the simu-

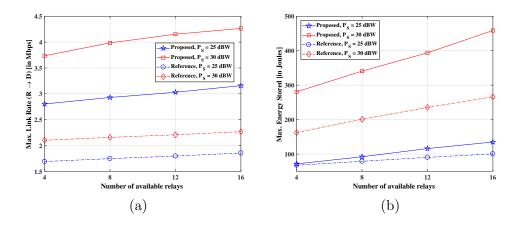


Figure 1.5: Performance comparison between the proposed cache-aided SWIPT and the reference scheme for different number of available relays with $\delta=0.5$ and $E_{ext}=30$ Joules. (a) Link rate performance, r=1 Mbps. (b) Stored energy performance, r=1 Mbps.

lations, we assume that the channel coefficients are i.i.d. and follows Rayleigh distribution. The path loss is considered to be 3 dB [24]. Additionally, all the relays have the same caching coefficient, i.e., $\delta_i = \delta, \forall i$. All the results are evaluated over 500 Monte-Carlo random channel realizations. The proposed architecture is compared with a reference scheme using a fix time-splitting. The reference scheme spends the first half period for information broadcasting and energy harvesting, and uses the second half period for relaying.

Fig. 1.5 plots the performance of the cache-aided SWIPT as a function of the total number of relays. The result is calculated based on the best relay selected as in Section 1.3 and Section 1.4. In both cases, $\delta = 0.5$, $E_{ext} = 30$ Joules. It is observed from Fig. 1.5a that the proposed architecture significantly outperforms the reference and the gain is larger as the number of available relays increases. In particular, the proposed architecture achieves a performance gain of 15% for $P_S = 25$ dBW and 20% for $P_S = 30$ dBW over the reference scheme. This result confirms the effectiveness of the proposed optimization

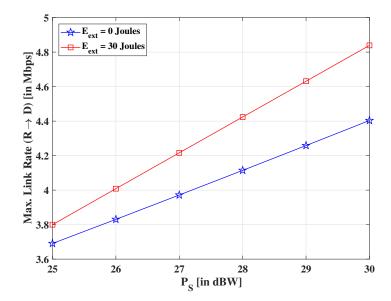


Figure 1.6: Maximized link rate versus the total source transmit power P_S with various E_{ext} . The total number of available relays K = 8, caching coefficient $\delta = 0.5$, and r = 1 Mbps.

framework. It is also shown that having more relays results in a better serving rate thanks to inherent diversity gain brought by the relays. The harvested energy comparison between the proposed and the reference is plotted in Fig. 1.5b. A similar conclusion is observed that the proposed architecture surpasses the reference in all cases. In addition, having more available relays improves the harvested energy.

Fig. 1.6 illustrates the results corresponding to the solutions proposed for the rate maximization problem, assuming that an optimal relay is chosen as per the solutions corresponding to the outer optimization of (1.7). It is observed from the figure that the source transmit power has a significant influence on the achievable rate. In particular, by increasing the source transmit power by 5 dBW, the serving rate is increased by 30%. This result can be explained from the fact that for a given caching coefficient, the source does not have to send the

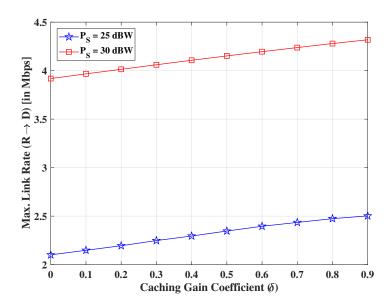


Figure 1.7: Maximized link rate versus the caching coefficient with various P_S . The total number of available relays K=8, $E_{ext}=30$ Joules, and r=3 Mbps.

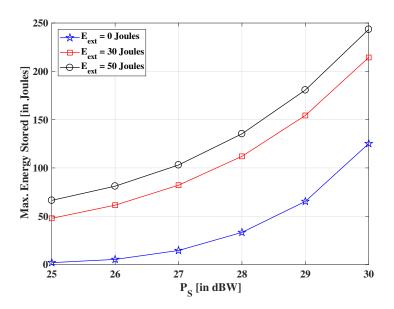


Figure 1.8: Stored energy performance as a function of the source transmit power for various values of E_{ext} . K=8 relays, $\delta=0.5$ and r=3 Mbps.

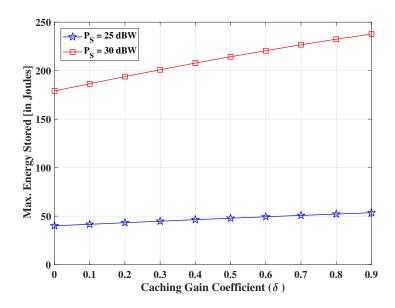


Figure 1.9: Stored energy performance as a function of the caching coefficient for various values of P_S . K=8 relays, $E_{ext}=30$ Joules, and r=3 Mbps.

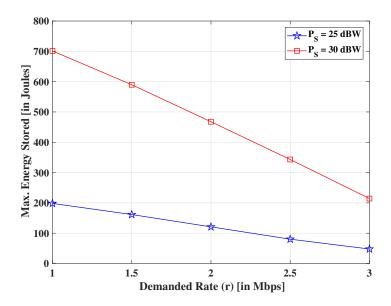


Figure 1.10: Stored energy performance as a function of QoS requirements with different source transmit power. K=8 relays, $\delta=0.5$ and $E_{ext}=30$ Joules.

whole requested content to the relay. In this case, having a larger source power results in more harvested energy, which in turn increase the relay's transmit power. Especially, this observation is also obtained when there is not external energy source, e.g., $E_{ext} = 0$, which shows the effectiveness of the proposed cache-aided SWIPT architecture.

Fig. 1.7 plots the maximum throughput as a function of the caching gain coefficient with $E_{ext} = 30$ Joules and r = 3 Mbps. It is observed that the caching gain has similar impact on the achievable throughput for different values of P_S . In general, a larger cache size (or equivalent larger caching coefficient) results in a higher serving rate. This result together with result in Fig. 1.6 suggest an interactive role of the caching capacity and the transmit power. In particular, a smaller source power system can still achieve the same throughput by increasing the cache size.

Fig. 1.8 presents the stored energy at the chosen relay, according to the solution of outer optimization of (1.31), as a function of the source's transmit power and different external energy values. It is shown from the results that the source transmit power has large impacts on the stored energy at the relay. In particular, increasing the source's transmit power by 2 dBW will double the stored energy at the relay. It is also observed that increasing the external energy can significantly improve the stored energy at high P_S values. However, when P_S is small, increasing E_{ext} does not bring considerable improvement. This is because at low P_S values, most of the time is used for information transfer from the source to the relay.

Fig. 1.9 depicts the plot of the energy stored at the selected relay as a function of the cache capacity δ , with $E_{ext} = 30$ Joules and r = 3 Mbps. The case with $\delta = 0$ implies that there is no caching at the relay. It is shown that

caching helps to increase the saved energy at the relay for all P_S values. And the increased stored energy are almost similar for different P_S . This is because of the linear model of the caching system.

Fig. 1.10 presents an evaluation of the energy stored at the chosen relay against the increasing values of r. It is seen that the energy stored at the relay decreases with increasing values of requested rate (r), for $\delta = 0.5$ and $E_{ext} = 30$ Joules. On the other hand, it is clear that with increasing values of P_S , the energy stored at the relay increases non-linearly. The former variation is due to the fact that in order to meet the demand of requested rate at the destination, more energy would be required for resource allocation at the relay which utilizes the harvested energy.

1.6. Conclusion

In this chapter, we proposed and investigated relay selection strategy in a novel time switching (TS) based SWIPT with caching architecture involving half duplex relaying systems where the relay employs the DF protocol. We addressed the problem of relay selection to maximize the data throughput between the relay and destination under constraint on minimum energy stored at the relay; and relay selection for maximizing the energy stored at the relay under constraints on minimum rate and harvested energy, guaranteeing a good performance in both the cases with regards to the QoS constraints. Besides, both the problems were formulated according to two separate yet distinct conventions over the time period. We presented the closed-form solutions for the proposed relay system to enable SWIPT with caching. With the help of simulations, we illustrated the results corresponding to the solutions obtained for

the aforementioned problems with parameter variations. This work can be further extended to many fascinating directions like multiuser and multicarrier scenario, and relaying with full duplexing mode.

Acknowledgment

This work is supported, in parts, by the Luxembourg National Research Fund (FNR) under the project FNR CORE ProCAST, FNR-FNRS bitateral InWIP-NET, and in parts, by the European Research Council (ERC) under project AGNOSTIC.

Bibliography

- [1] S. Gautam, E. Lagunas, S.K. Sharma, S. Chatzinotas, and B Ottersten, "Relay Selection Strategies for SWIPT-Enabled Cooperative Wireless Systems", in 28th Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), October 2017.
- [2] S. Zhou, J. Gong, Z. Zhou, W. Chen, and Z. Niu, "GreenDelivery: proactive content caching and push with energy-harvesting-based small cells", IEEE Commun. Mag., 53(4):142–149, April 2015.
- [3] ERICSSON white paper, "More than 50 Billion Connected Devices," 2011.
- [4] S. Gautam and P. Ubaidulla. "Simultaneous transmission of information and energy in OFDM systems", in Proc. 18th Wireless Personal Multimedia Communications (WPMC), December 2015.

- [5] X. Zhou, R. Zhang, and C. K. Ho, "Wireless Information and Power Transfer in Multiuser OFDM Systems," *IEEE Trans. Wireless Commun.* 13(4):2282–2294, April 2014.
- [6] X. Zhou, R. Zhang, and C. K. Ho. "Wireless Information and Power Transfer: Architecture Design and Rate-Energy Tradeoff," IEEE Trans. Commun., 61(11):4754–4767, November 2013.
- [7] Q. Gu, G. Wang, R. Fan, Z. Zhong, K. Yang, and H. Jiang. "Rate-Energy Tradeoff in Simultaneous Wireless Information and Power Transfer over Fading Channels with Uncertain Distribution", *IEEE Trans. Veh. Tech*nol., PP(99):1–1, 2017.
- [8] J. Park, B. Clerckx, C. Song, and Y. Wu. "An Analysis of the Optimum Node Density for Simultaneous Wireless Information and Power Transfer in Ad Hoc Networks," *IEEE Trans. Veh. Technol.*, PP(99):1–1, 2017.
- [9] Bruno Clerckx. "Waveform and Transceiver Design for Simultaneous Wireless Information and Power Transfer," *CoRR*, abs/1607.05602, 2016.
- [10] I. Bang, S. M. Kim, and D. K. Sung, "Adaptive Multiuser Scheduling for Simultaneous Wireless Information and Power Transfer in a Multicell Environment," *IEEE Trans. Wireless Commun.*, 16(11):7460–7474, Nov. 2017.
- [11] S. Mahama, D. K. P. Asiedu, and K. J. Lee. "Simultaneous Wireless Information and Power Transfer for Cooperative Relay Networks With Battery," *IEEE Access*, 5:13171–13178, 2017.
- [12] J. Huang, C. C. Xing, and C. Wang. "Simultaneous Wireless Informa-

- tion and Power Transfer: Technologies, Applications, and Research Challenges," *IEEE Commun. Mag.*, 55(11):26–32, Nov. 2017.
- [13] S. Borst, V. Gupta, and A. Walid. "Distributed Caching Algorithms for Content Distribution Networks," in *Proc. IEEE Int. Conf. Comput. Com*mun., pages 1–9, Mar. 2010.
- [14] M. A. Maddah-Ali and U. Niesen. "Fundamental Limits of Caching," *IEEE Trans. Inf. Theory*, 60(5):2856–2867, May 2014.
- [15] T. X. Vu, S. Chatzinotas, and B. Ottersten. "Edge-Caching Wireless Networks: Performance Analysis and Optimization," *IEEE Trans. Wireless Commun.*, PP(99):1–1, 2018.
- [16] W. Peng, M. Li, Y. Li, W. Gao, and T. Jiang. "Ultra-dense heterogeneous relay networks: A non-uniform traffic hotspot case," *IEEE Network*, 31(4):22–27, July 2017.
- [17] C. Yang, J. Xiao, J. Li, X. Shao, A. Anpalagan, Q. Ni, and M. Guizani. "Disco: Interference-aware distributed cooperation with incentive mechanism for 5g heterogeneous ultra-dense networks," *IEEE Comm. Mag.*, PP(99):1–7, 2018.
- [18] A. Kumar and W. Saad. "On the tradeoff between energy harvesting and caching in wireless networks," in 2015 IEEE International Conference on Communication Workshop (ICCW), pages 1976–1981, Jun. 2015.
- [19] D. Niyato, D. I. Kim, P. Wang, and L. Song. "A novel caching mechanism for Internet of Things (IoT) sensing service with energy harvesting," in *Proc. IEEE Int. Conf. Commun.*, pages 1–6, May 2016.

- [20] S. Zhang, N. Zhang, X. Fang, P. Yang, and X. S. Shen, "Cost-effective vehicular network planning with cache-enabled green roadside units," in *Proc. IEEE Int. Conf. Commun.*, pages 1–6, May 2017.
- [21] S. Lohani, R. A. Loodaricheh, E. Hossain, and V. K. Bhargava, "On Multiuser Resource Allocation in Relay-Based Wireless-Powered Uplink Cellular Networks," *IEEE Trans. Wireless Commun.*, 15(3):1851–1865, March 2016.
- [22] Robert M Corless, Gaston H Gonnet, David EG Hare, David J Jeffrey, and Donald E Knuth. "On the LambertW function," Advances in Computational mathematics, 5(1):329–359, 1996.
- [23] V. Havary-Nassab, S. Shahbazpanahi, A. Grami, and Z. Q. Luo. "Distributed Beamforming for Relay Networks Based on Second-Order Statistics of the Channel State Information," *IEEE Trans. Signal Process.*, 56(9):4306–4316, Sept 2008.
- [24] D. Green, Z. Yun, and M. F. Iskander. "Path Loss Characteristics in Urban Environments Using Ray-Tracing Methods," *IEEE Antennas Wireless Propag. Lett.*, 16:3063–3066, 2017.