Optimum Power Allocation Policies for an Energy Harvesting Wireless Transmission System Under Energy Storage Losses

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Declaration

I, *Abdul Basit* declare that this thesis titled “Optimum Power Allocation Policies for an Energy Harvesting Wireless Transmission System Under Energy Storage Losses” has not been submitted already for a degree or some other qualification at NUST or some other institution.

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I dedicate this thesis to my dearest mother *Late Nasreen Naz* and father *Muhammad Din*, who supported me in all ups and downs.

Abstract

This research work presents an energy harvesting model in which the transmitter harvests energy from the surrounding environment and stores it in an imperfect battery. Inevitably, this harvested energy has two kinds of extra consumption: battery storage losses and circuit power consumption. Towards this end, a single-user channel model is considered to determine the optimum power allocation policies for static and fading channels. The objective is to maximize the average throughput of an energy harvesting wireless transmission system within a finite time fraction during which transmission occurs. The throughput maximization problem is formulated with joint constraints viz., finite sized battery, circuit power consumption and limited amount of transmit power and solved using convex optimization techniques. Specifically, Lagrange multiplier method and Karush-Kuhn-Tucker (KKT) conditions are used to solve the proposed optimization problem. An optimum offline power allocation policy is proposed and an algorithm is provided to find optimum thresholds for power allocation. Moreover, an online power allocation policy is derived and an algorithm is provided with harvested energy available causally at the transmitter. For online algorithm, we consider adaptive thresholds that varies with storage efficiency and value of epoch. Simulation results show that the proposed offline and online algorithms have outperformed the earlier work focused on considering energy storage losses for energy harvesting wireless transmission systems.

Keywords: *Energy harvesting, green communication, optimum power allocation, energy storage losses.*

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List of Abbreviations and Symbols

EH	Energy Harvesting
KKT	Karush-Kuhn-Tucker
AWGN	Additive White Gaussian Noise
$\mathbf{\Gamma}$	Storage Efficiency
$\mathcal{H}$	Harvested Energy
ε	Circuit Power Consumption

Chapter 1

Introduction

Due to tremendous increase in energy utilization by wireless transmission systems, the research interests in green communication has increased significantly [1]. Towards this end, two methods are used to attain green communication: energy efficiency and energy harvesting. Energy efficiency refers to the optimized use of energy for data transmission [2, 3]. On the other hand, energy harvesting is the extraction of energy from ambient environments, such as solar energy, thermal energy, tidal energy and wind energy [4, 5]. This energy's hunt is focused on obtaining clean energy from the surrounding energy resources. The energy can be harvested from multiple renewable energy resources, referred to as hybrid energy harvesting [6]. Energy harvesting is not only limited to wireless sensor networks with energy harvesting sensor nodes but can be extended to cellular networks with base stations powered by hybrid renewable energy resources [7, 8].

1.1 Energy Harvesting

With advancement in new technologies and proliferation of physical devices, the energy requirement has increased significantly. Most of these devices are powered by batteries that need to be replaced after some time. However, their replacement in various remote applications is not feasible. To deal with the battery replacement issues, energy harvesting (EH) from the ambient environment is a

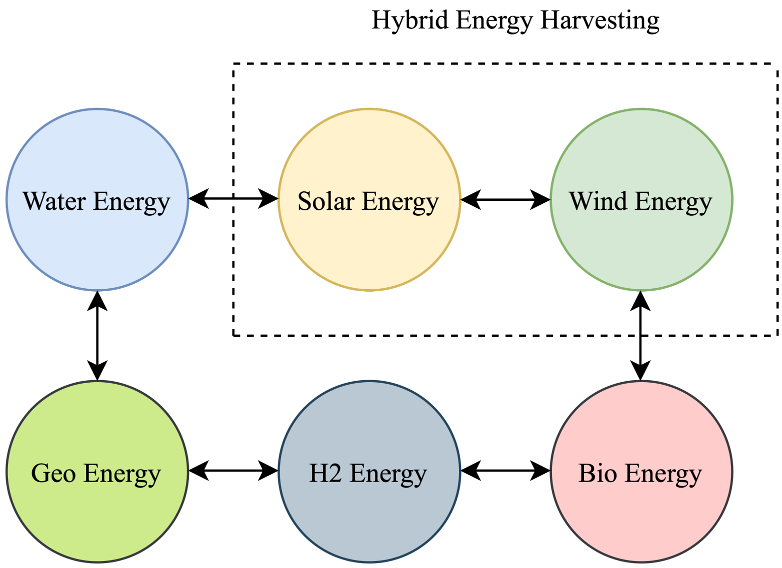

Figure 1.1: Renewable energy sources for harvesting clean energy form ambient environment.

better alternative to increase the lifetime of an energy harvesting transmitting node [11, 12]. There are two types of energy resources i.e., non-renewable and renewable [13]. Non-renewable energy resources include oil, coal and natural gas. These resources are limited in extent and will be exhausted in the near future. While renewable energy resources include wind, solar and water etc., which are not limited and readily available for use. These resources are clean and environment friendly. However, the renewable energy resources are not as efficient as the non-renewable ones. Fig. 1.1 illustrates different renewable energy resources for harvesting clean energy from ambient environment. Research communities in the field of communication believe that these renewable resources are useful for future wireless transmission systems.

There are several key benefits of using energy harvesting [14, 15] techniques as compared to the traditional wireless communication systems. These benefits include self-sustainability, low carbon emissions and easy implementation. Therefore, energy harvesting wireless communication networks have been studied extensively in the literature [16–20]. Other benefits include the increased life expectancy of energy harvesting devices, environment friendly as compared to the traditional non-renewable energy resources, reliability, and low cost in some applications such as wireless sensor networks. Contrary to these benefits, the deployment of energy harvesting transmission systems is expensive. Although these systems are environment friendly, but some of the energy resources i.e., bio energy has some adverse effects on the environment. There are various challenges regarding energy harvesting transmission systems that need to be addressed.

1.2 Related Work

As compared to the traditional wireless communication systems with abundant supply of energy [9], the energy available to the energy harvesting transmission systems is limited and time-varying [32]. Moreover, the energy consumption is always lower than or equal to the energy harvested from the environment, because energy is stored in storage devices with limited capacity. This leads to energy leakage, energy overflow and energy storage losses. Considering solar energy harvesting, there is a constraint on the size of solar panel and number of batteries attached with it [7, 10]. Additionally, there are battery leakage currents and shortfalls due to inefficiency of energy storage devices [21, 22]. The repetitive charging and discharging of batteries is another factor that adversely effects the performance of energy harvesting transmission systems [23]. Efficient energy scheduling is the performance metric for an energy harvesting transmission system [24–27]. There are two types of energy scheduling techniques: *offline* and *online*. Former is based on the non-causal knowledge of harvested energy at the transmitter whereas later is based on causal knowledge of harvested energy. Moreover channel and battery states information are also considered for offline energy scheduling [28]. Huang et. al. [29] investigated the optimum power allocation policies for a fading channel. A global optimum offline power allocation algorithm is proposed. The objective was to minimize the outage probability. Similar to the offline algorithm, an online power allocation algorithm is derived and solved through dynamic programming. In [30], power allocation policies are studied to minimize the outage probability under finite battery storge constraint. Sum-rate maximization problem with constrained utility function is proposed for wireless senor networks. An intuitive algorithm solution is presented considering complex nature of constrained utility maximization problems [31]. For sum-rate maximization, an optimal offline power allocation algorithm is proposed for broadcast channels under battery storage and permissible transmit power constraints. The optimization problem is formulated by considering random data arrivals and harvested energy [35]. For online energy scheduling , the power allocation policies are modeled as Markov Decision Process (MDP). A throughput maximization problem is modeled as an MDP for an energy harvesting transmission system [33]. It is constrained by maximum power permissible for transmission. In comparison, the offline power allocation policies outperforms the online policies [34].

Energy harvesting wireless transmission systems bring new constraints on harvested energy for optimal power allocation [36–41]. Additional constraints include quality of service, delay in data transmission and varying channel states for a fading channel [42–45]. In [46], an optimization problem is formulated to minimize data transmission time under energy causality constraint. An offline power allocation solution is presented to solve the optimization problem. Tutuncuoglu et. al. [47] formulated an optimization problem to maximize the throughput under finite battery size and energy causality constraints. Two related optimization problems are solved: maximizing short term throughput and minimizing transmission completion time. For a single-user communication channel, the optimal transmission policies are derived to balance the data queue and minimize information transmission delay [48]. Water-filling algorithms are used to model the energy flow in fading channels. An algorithm with directional water-level thresholds is developed for energy flow in fading channels [49, 50], where direction of the energy (water) flow is towards right. It means that the energy cannot be used before it is harvested. In [51], two water-filling algorithms are proposed: geometric water filling (GWF) algorithm and recursively geometric water-filling (RGWF) algorithm. Former is based on sum power constraint and later is based on energy causality constraint. The energy scheduling policies are not limited to single-user channels but have been extended to broadcast channels [52–54], multiple access channels [55], interference channels [56] and two-hop relay channels [57–63]. In bidirectional water-filling for multiple access channels [68–70], the users transfer energy to one another by mutual energy cooperation on a two-way multiple access channel. All these studies are based on a common assumption i.e., the energy is not lost during storage or retrieval.

There are many different manifestations of the energy loss i.e., imperfections due to charging/discharging, energy leakage, degradation of battery's size [71, 72] and circuit power consumption [64–67]. Such imperfections also effects duty-cycling in energy harvesting wireless transmission systems [73, 74]. In [75], the authors formulated throughput maximization problem under two types of battery imperfections i.e., energy leakage with time and degradation of battery due to repetitive charging and discharging. However, these imperfections are long term effects of energy storage on energy harvesting transmission systems. A throughput maximization problem is formulated with circuit power consumption constraint for a fading channel [76]. Both energy and spectrum harvesting are considered to develop optimal power allocation algorithm. In [77], the authors formulated throughput maximization problem under circuit power consumption constraint for both static and fading channels. Orhan et. al. [78] proposed an optimization problem with three objectives: throughput maximization, energy maximization for delivering all data packets and reduction of transmission completion time. Offline and online algorithms are developed for optimal power allocation. Loss due to energy storage/retrieval is considered for static and fading channels with single and multiple users [79]. A double-threshold power allocation policy is proposed considering limited battery storage constraint.

1.3 Research Gaps

The capability of harvesting the energy from ambient environment imposes new constraints on the communication. The first constraint is that the energy retrieved from the battery during a time fraction is less than the energy stored at that time. The second constraint is that the energy cannot be used before it is harvested.

The third constraint contradicts the assumption that storage devices have infinite capacity. Furthermore, the harvested energy is limited and random in nature, which makes it critical to allocate transmit power effectively. Power allocation for wireless transmission systems with energy harvesting transmitters has been studied widely in the literature but there is room for improvement. The optimum power allocation policies with energy storage losses and joint constraints i.e., finite battery size, circuit power consumption and finite transmit power are not studied to the best of our knowledge.

1.4 Contributions

The investigations in this research work are providing the following contributions to fill in the aforementioned research gaps.

1) The optimization problem is formulated as an average throughput maximization within a finite time fraction under energy storage losses and joint constraints i.e., finite sized battery, circuit power consumption and limited amount of transmit power.

2) An offline algorithm is proposed for optimum power allocation for both static and fading channels.

3) A low-complexity online algorithm with adaptive energy storage and retrieval thresholds is proposed for both static and fading channels.

Chapter 2

System Model and Proposed Methodology

2.1 System Model

The system model of a wireless transmission system with energy harvesting transmitter is shown in Fig. 2.1. Assuming that the data transmission has a finite communication session of $\mathcal{T}$ epochs, each with slot length $t = 1s$. Let $\mathcal{H}_i = \xi_i - \varsigma_i + \varrho_i - \varepsilon_i$ represents the amount of harvested energy available for transmission in epoch i, where ξ_i represents harvested energy in epoch i, ς_i represents the stored energy in epoch i, ϱ_i represents energy retrieved from battery in epoch i and ε_i is the circuit energy consumption in epoch i. Here $\varepsilon_i = \varepsilon\Theta_i$, where ε is the circuit power consumption and Θ_i $(0 < \Theta_i \leq 1)$ is the finite time fraction during which transmission occurs. At the beginning of each epoch i, the transmitter harvests ξ_i units of energy. It retrieves ϱ_i units of energy from the battery and stores ς_i units for future use. We represent p_i as the transmit power available for data transmission in epoch i. The transmit power p_i is defined as follows.

$$p_i = \frac{\mathcal{H}_i}{\Theta_i} \tag{2.1.1}$$

Considering the battery storage efficiency Γ $(0 \leq \Gamma \leq 1)$. If energy is not stored or retrieved from the battery in an epoch, then there are no energy storage losses,

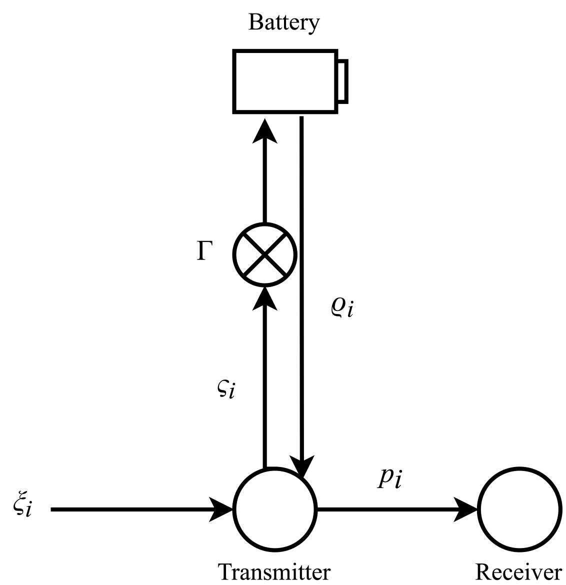

Figure 2.1: Single-user wireless transmission system with energy harvesting transmitter over an Additive White Gaussian Noise (AWGN) channel.

otherwise only $\Gamma\varsigma_i$ units are stored in the battery and $(1-\Gamma)\varsigma_i$ units are lost due to storage inefficiency.

2.1.1 Constraints

The energy retrieved from the battery in an epoch i is less than the energy stored in that epoch. This constraint is referred to as energy causality constraint. Let $\mathcal{B}_i$ is the amount of energy available in epoch i and is written as follows

$$\mathcal{B}_i = \sum_{j=1}^{i}(\Gamma\varsigma_j - \varrho_j) \geq 0, \quad i = 1, ..., \mathcal{T}. \tag{2.1.2}$$

The size of energy storage batteries is not infinite. The amount of energy greater than the size of battery is lost and cannot be stored, resulting in energy overflow. It is sub-optimal to ignore these energy overflows [47, 79]. This constraint is termed as no-energy-overflow constraint and can be written as

$$\mathcal{B}_i = \sum_{j=1}^{i}(\Gamma\varsigma_j - \varrho_j) \leq \xi_{max}, \quad i = 1, ..., \mathcal{T}. \tag{2.1.3}$$

where ξ_{max} is the maximum amount of energy that can be stored in the battery. Let $\mathcal{P}_{max}$ be the maximum amount of power that can be used by transmitter for data transmission. The optimum transmission policy is constrained by a limited amount of power and this constraint can be written as

$$p_i = \xi_i - \varsigma_i + \varrho_i - \varepsilon_i \leq \mathcal{P}_{max}, \quad i = 1, ..., \mathcal{T}. \tag{2.1.4}$$

2.1.2 Objective Function

The instantaneous transmission rate of AWGN channel for an epoch i, channel fading coefficient g_i and transmit power p_i is given by

$$\mathcal{R}(p_i) = \frac{1}{2}\log(1 + g_i p_i), \quad i = 1, ..., \mathcal{T} \tag{2.1.5}$$

We aim to maximize average throughput within a finite time fraction during which transmission occurs. The objective function R_{avg} is written as follows

$$\mathcal{R}_{avg} = \frac{1}{\mathcal{T}} \sum_{i=1}^{\mathcal{T}} \Theta_i \mathcal{R}(p_i) \tag{2.1.6}$$

2.2 Offline Energy Scheduling Policy for a Static Channel

In this section, the optimal offline energy scheduling policy for a static channel is proposed. For a static channel, the channel state is same throughout the duration of data transmission i.e., $g_i = g, i = 1, ..., T$. We first formulate the optimization problem with infinite sized battery and transmit power available for data transmission. After that the optimization problem constrained by finite battery size and limited amount of transmit power is formulated and optimal power allocation policies are derived.

2.2.1 Throughput maximization with infinite sized battery and transmit power

The average throughput maximization problem for an energy harvesting wireless transmission system shown in Fig. 2.1, with infinite sized battery and transmit power is written as

$$\mathcal{P}1: \max_{(\varsigma_i, \varrho_i, \Theta_i)} \mathcal{R}_{avg} \tag{2.2.1}$$

subject to

$$\begin{aligned}
&\mathcal{C}1: \mathcal{B}_i \geq 0, \quad i = 1, ..., \mathcal{T}. \\
&\mathcal{C}2: p_i = \xi_i - \varsigma_i + \varrho_i - \varepsilon_i \geq 0, \quad i = 1, ..., \mathcal{T}. \\
&\mathcal{C}3: \varsigma_i \geq 0, \quad i = 1, ..., \mathcal{T}. \\
&\mathcal{C}4: \varrho_i \geq 0, \quad i = 1, ..., \mathcal{T}. \\
&\mathcal{C}5: 0 < \Theta_i \leq 1, \quad i = 1, ..., \mathcal{T}.
\end{aligned} \tag{2.2.2}$$

where $\mathcal{C}1$ and $\mathcal{C}2$ correspond to non-negativity of stored energy and transmit power, respectively. The amount of energy stored or retrieved from the battery cannot be negative, as enforced by constraints $\mathcal{C}3$ and $\mathcal{C}4$, respectively. Constraint $\mathcal{C}5$ shows the time fraction during which transmission occurs in epoch i. The optimal power allocation policy satisfies $\varsigma_i \varrho_i = 0$ i.e., energy cannot be stored and retrieved from the battery at the same time [79].

The objective function of $\mathcal{P}1$ is concave in p and all constraints are linear. Therefore, $\mathcal{P}1$ is a convex optimization problem and is solved by Lagrangian method. Moreover, the KKT conditions are necessary and sufficient for finding optimal solution. The Lagrangian function of $\mathcal{P}1$ is

$$\begin{aligned}
\mathcal{L} = \sum_{i=1}^{\mathcal{T}} \Big(&\mathcal{R}_{avg} + \zeta_i \Big(\sum_{j=1}^{i} (\Gamma \varsigma_j - \varrho_j) \Big) + \vartheta_i (\xi_i - \varsigma_i + \varrho_i - \varepsilon_i) \\
&+ \delta_i \varsigma_i + \omega_i \varrho_i + \varphi_i \Theta_i + \varpi_i (1 - \Theta_i) \Big)
\end{aligned} \tag{2.2.3}$$

where $\zeta_i, \vartheta_i, \delta_i, \omega_i, \varphi_i, \varpi_i, i = 1, ..., \mathcal{T}$ are non-negative Lagrange multipliers. By taking derivative of (2.2.3) with respect to $\varsigma_i, \varrho_i, \Theta_i$, we find KKT conditions for optimality.

$$\Gamma \sum_{j=i}^{\mathcal{T}} \zeta_j - \frac{g}{1 + g p_i} - \vartheta_i + \delta_i = 0, \quad i = 1, ..., \mathcal{T} \tag{2.2.4}$$

$$\frac{g}{1 + g p_i} - \sum_{j=i}^{\mathcal{T}} \zeta_j + \vartheta_i + \omega_i = 0, \quad i = 1, ..., \mathcal{T} \tag{2.2.5}$$

$$\mathcal{R}(p_i) - \frac{g(p_i + \varepsilon)}{2(1 + g p_i)} - \varepsilon \vartheta_i + \varphi_i - \varpi_i = 0, \quad i = 1, ..., \mathcal{T} \tag{2.2.6}$$

The complementary slackness conditions are

$$\zeta_i\Big(\sum_{j=1}^{i}(\Gamma\varsigma_j - \varrho_j)\Big) = 0, \quad i = 1, ..., \mathcal{T} \tag{2.2.7}$$

$$\vartheta_i(\xi_i - \varsigma_i + \varrho_i - \varepsilon_i) = 0, \quad i = 1, ..., \mathcal{T} \tag{2.2.8}$$

$$\delta_i\varsigma_i = 0, \quad \omega_i\varrho_i = 0, \quad i = 1, ..., \mathcal{T} \tag{2.2.9}$$

$$\varphi_i\Theta_i = 0, \quad \varpi_i(1 - \Theta_i) = 0, \quad i = 1, ..., \mathcal{T} \tag{2.2.10}$$

The optimal value of transmit power p_i is derived from (2.2.4) and (2.2.5) as

$$\begin{aligned} p_i &= \frac{1}{\Gamma\sum_{j=i}^{\mathcal{T}}\zeta_j - \vartheta_i + \delta_i} - \frac{1}{g}, \quad i = 1, ..., \mathcal{T} \\ p_i &= \frac{1}{\sum_{j=i}^{\mathcal{T}}\zeta_j - \vartheta_i - \omega_i} - \frac{1}{g}, \quad i = 1, ..., \mathcal{T} \end{aligned} \tag{2.2.11}$$

Rearranging (2.2.6) as

$$\mathcal{R}(p_i) = \frac{g(p_i + \varepsilon)}{2(1 + gp_i)} + \varepsilon\vartheta_i - \varphi_i + \varpi_i, \quad i = 1, ..., \mathcal{T} \tag{2.2.12}$$

First we analyze (2.2.11), the optimal solution cannot be obtained through water-filling algorithm due to energy storage losses [79]. We define two thresholds: energy storage threshold $\chi_{\varsigma i}$ and retrieval threshold $\chi_{\varrho i}$. When $p_i > 0$, then to satisfy (2.2.8), we get $\vartheta_i = 0$. When energy is stored in the battery i.e., $\varsigma_i > 0$ then to satisfy (2.2.9), we get $\delta_i = 0$. The transmit power p_i in (2.2.11) (first equality) becomes equal to $\chi_{\varsigma i}$. Similarly, when energy is retrieved from the battery i.e., $\varrho_i > 0$ then to satisfy (2.2.9), we get $\omega_i = 0$. The transmit power p_i in (2.2.11) (second equality) becomes equal to $\chi_{\varrho i}$. The optimal transmit power is limited to these two thresholds i.e., $\chi_{\varrho i} \leq p_i \leq \chi_{\varsigma i}$.

$$\chi_{\varsigma i} = \frac{1}{\Gamma\sum_{j=i}^{\mathcal{T}}\zeta_j} - \frac{1}{g} \tag{2.2.13}$$

$$\chi_{\varrho i} = \frac{1}{\sum_{j=i}^{\mathcal{T}}\zeta_j} - \frac{1}{g} \tag{2.2.14}$$

The storage threshold should be greater than or equal to the retrieval threshold i.e., $\chi_{\varsigma i} \geq \chi_{\varrho i}$. These two thresholds have the following relationship.

$$\frac{1 + g\chi_{\varrho i}}{1 + g\chi_{\varsigma i}} = \Gamma, \quad i = 1, ..., \mathcal{T} \tag{2.2.15}$$

Following the above analysis, when $\varsigma_i > 0$ and $\varrho_i = 0$, the optimal transmit power from (2.2.11) (first equality) is equal to the storage threshold i.e., $p_i = \chi_{\varsigma i}$. When $\varrho_i > 0$ and $\varsigma_i = 0$, the optimal transmit power from (2.2.11) is equal to the retrieval threshold i.e., $p_i = \chi_{\varrho i}$. The optimal transmission policy is based on aforementioned storage and retrieval thresholds and is written as follows

$$p_i = \min(\max(\chi_{\varrho i}, [\xi_i/\Theta_i - \varepsilon]^+), [\chi_{\varsigma i}]^+) \tag{2.2.16}$$

$$\varsigma_i = [\xi_i/\Theta_i - \varepsilon - p_i]^+, \quad \varrho_i = [p_i - (\xi_i/\Theta_i - \varepsilon)]^+ \tag{2.2.17}$$

For an epoch i, the problem $\mathcal{P}1$ can be rewritten as

$$\mathcal{P}2 : \max_{(\varsigma_i, \varrho_i, \Theta_i)} \Theta_i \mathcal{R}(p_i) \tag{2.2.18}$$

subject to $\mathcal{C}1 - \mathcal{C}5$.

where $\Theta_i = \frac{\xi_i}{p_i + \varepsilon}$. By taking derivative of (2.2.18) with respect to Θ_i, we get

$$\mathcal{R}(p_i) = \frac{g(p_i + \varepsilon)}{2(1 + gp_i)} \tag{2.2.19}$$

For transmit power $p_i > 0$, to satisfy (2.2.8), we get $\vartheta_i = 0$ and for Θ_i $(0 < \Theta_i \leq 1)$, to satisfy (2.2.10) we get $\varphi_i = 0$, $\varpi_i = 0$. Therefore, (2.2.12) becomes similar to (2.2.19). Suppose χ_0 is the optimal solution of $\mathcal{P}2$, we determine χ_0 from circuit power consumption ε and channel fading coefficient g. The optimal transmission policy for $\mathcal{P}2$ is expressed as

$$p_i = \max(p_i, \chi_0) \tag{2.2.20}$$

$$\Theta_i = \frac{\xi_i - \varsigma_i + \varrho_i}{p_i + \varepsilon} \tag{2.2.21}$$

Theorem 1: The optimal power allocation policy for $\mathcal{P}1$ depends on three thresholds: $\chi_{\varsigma i}, \chi_{\varrho i}$ and χ_0.

Proof: We consider three cases i.e., $\chi_0 > \chi_{\varsigma i}$, $\chi_{\varrho i} \leq \chi_0 \leq \chi_{\varsigma i}$ and $\chi_0 < \chi_{\varrho i}$, and prove each case separately.

1) When $\chi_0 > \chi_{\varsigma i}$, then $p_i = \chi_0$. If $\xi_i - \varepsilon > \chi_0$ then $\varsigma_i = \xi_i - \varepsilon - \chi_0, \varrho_i = 0$ and $\Theta_i = \frac{\xi_i - \varsigma_i}{\chi_0 + \varepsilon} = 1$. If $\chi_{\varrho i} \leq \xi_i - \varepsilon \leq \chi_0$ then $\varsigma_i = 0, \varrho_i = 0$ and $\Theta_i = \frac{\xi_i}{\chi_0 + \varepsilon}$. If $\xi_i - \varepsilon < \chi_{\varrho i}$ then $\varsigma_i = 0, \varrho_i = \min(\mathcal{B}_{i-1}, \chi_{\varrho i} - (\xi_i - \varepsilon))$ and $\Theta_i = \frac{\xi_i + \varrho_i}{\chi_0 + \varepsilon}$.

2) When $\chi_{\varrho i} \leq \chi_0 \leq \chi_{\varsigma i}$. If $\xi_i - \varepsilon > \chi_{\varsigma i}$ then $p_i = \chi_{\varsigma i}$, $\varsigma_i = \xi_i - \varepsilon - \chi_{\varsigma i}$, $\varrho_i = 0$ and $\Theta_i = \frac{\xi_i - \varsigma_i}{\chi_{\varsigma i} + \varepsilon} = 1$. If $\chi_{\varrho i} \leq \xi_i - \varepsilon \leq \chi_{\varsigma i}$ then $p_i = \max(\chi_0, \xi_i - \varepsilon)$, $\varsigma_i = 0$, $\varrho_i = 0$ and $\Theta_i = \frac{\xi_i}{p_i + \varepsilon}$. If $\xi_i - \varepsilon < \chi_{\varrho i}$ then $p_i = \chi_0$, $\varsigma_i = 0$, $\varrho_i = \min(\mathcal{B}_{i-1}, p_i - (\xi_i - \varepsilon))$ and $\Theta_i = \frac{\xi_i + \varrho_i}{p_i + \varepsilon}$.

3) When $\chi_0 < \chi_{\varrho i}$, the optimal power allocation policy is similar to the double-threshold policy, and optimal solution can be found by (2.2.16).

From the above analysis, we conclude that the optimal power allocation policy is based on three thresholds, which are non-decreasing until value of $\mathcal{B}_i = 0$, and battery should deplete at the last epoch of a finite communication session [79]. We propose an algorithm to find optimal thresholds.

Algorithm 1: Calculate χ_0 from channel fading coefficient g and circuit power consumption ε. Start from an epoch $j = 1$, find the largest value of storage threshold χ_s by doing a linear search, then using (2.2.15) find the value of retrieval threshold χ_r, that makes the power allocation policy in (2.2.16) and (2.2.17) feasible. Now find the smallest epoch k such that $k > j$, for which the value of $\mathcal{B}_i = 0$. Assign the optimal thresholds to epochs $i = j, ..., k$. Repeat the above process until $k < \mathcal{T}$. Finally, compare the values of χ_0 with $\chi_{\varsigma i}$ and $\chi_{\varrho i}$, adjust the values of $p_i, \varsigma_i, \varrho_i, \Theta_i$ and calculate $\mathcal{B}_i$. The optimal power in the last time epoch is calculated from

$$p_{\mathcal{T}} = \max(\chi_0, \xi_{\mathcal{T}} - \varepsilon + \mathcal{B}_{\mathcal{T}-1}) \tag{2.2.22}$$

$$\Theta_{\mathcal{T}} = \frac{\xi_{\mathcal{T}} + \mathcal{B}_{\mathcal{T}-1}}{p_{\mathcal{T}} + \varepsilon} \tag{2.2.23}$$

2.2.2 Throughput maximization constrained by finite sized battery and transmit power

In practical scenarios, the size of battery and transmit power is finite. We extend our optimization problem $\mathcal{P}1$ with additional constraints i.e., no-energy-overflow and finite transmit power. The battery size is ξ_{max} and maximum power permissible for transmission is $\mathcal{P}_{max}$. The average throughput maximization problem is expressed as

$$\mathcal{P}3 : \max_{(\varsigma_i, \varrho_i, \Theta_i)} \mathcal{R}_{avg} \tag{2.2.24}$$

subject to

$$\begin{aligned}
&\mathcal{C}1-\mathcal{C}5\\
&\mathcal{C}6:\mathcal{B}_i\leq\xi_{max},\quad i=1,...,\mathcal{T}.\\
&\mathcal{C}7:p_i=\xi_i-\varsigma_i+\varrho_i-\varepsilon_i\leq\mathcal{P}_{max},\quad i=1,...,\mathcal{T}.
\end{aligned}\tag{2.2.25}$$

The Lagrangian function of $\mathcal{P}3$ is

$$\begin{aligned}
\mathcal{L}=&\sum_{i=1}^{\mathcal{T}}\Big(\mathcal{R}_{avg}+\zeta_i\Big(\sum_{j=1}^{i}(\Gamma\varsigma_j-\varrho_j)\Big)+\gamma_i(\xi_{max}-\sum_{j=1}^{i}(\Gamma\varsigma_j-\varrho_j))\\
&+\vartheta_i(\xi_i-\varsigma_i+\varrho_i-\varepsilon_i)+\psi_i(\mathcal{P}_{max}-(\xi_i-\varsigma_i+\varrho_i-\varepsilon_i))+\delta_i\varsigma_i\\
&+\omega_i\varrho_i+\varphi_i\Theta_i+\varpi_i(1-\Theta_i)\Big)
\end{aligned}\tag{2.2.26}$$

where γ_i and ψ_i are non-negative Lagrange multipliers. Taking derivative of (2.2.26) with respect to ς_i, ϱ_i and Θ_i, we get

$$\Gamma\sum_{j=i}^{\mathcal{T}}(\zeta_j-\gamma_j)-\frac{g}{1+gp_i}-\vartheta_i+\psi_i+\delta_i=0,\quad i=1,...,\mathcal{T}\tag{2.2.27}$$

$$\frac{g}{1+gp_i}-\sum_{j=i}^{\mathcal{T}}(\zeta_j-\gamma_j)+\vartheta_i-\psi_i+\omega_i=0,\quad i=1,...,\mathcal{T}\tag{2.2.28}$$

$$\mathcal{R}(p_i)-\frac{g(p_i+\varepsilon)}{2(1+gp_i)}+(-\vartheta_i+\psi_i)\varepsilon+\varphi_i-\varpi_i=0,\quad i=1,...,\mathcal{T}\tag{2.2.29}$$

The complementary slackness conditions corresponding to γ_i and ψ_i are

$$\gamma_i(\xi_{max}-\sum_{j=1}^{i}(\Gamma\varsigma_j-\varrho_j))=0,\quad i=1,...,\mathcal{T}\tag{2.2.30}$$

$$\psi_i(\mathcal{P}_{max}-(\xi_i-\varsigma_i+\varrho_i-\varepsilon_i))=0,\quad i=1,...,\mathcal{T}\tag{2.2.31}$$

These conditions together with conditions in (2.2.7), (2.2.8), (2.2.9) and (2.2.10) are the complementary slackness conditions for $\mathcal{P}3$. The optimal value of transmit power p_i is written as

$$\begin{aligned}
p_i&=\frac{1}{\Gamma\sum_{j=i}^{\mathcal{T}}(\zeta_j-\gamma_j)-\vartheta_i+\psi_i+\delta_i}-\frac{1}{g},\quad i=1,...,\mathcal{T}\\
p_i&=\frac{1}{\sum_{j=i}^{\mathcal{T}}(\zeta_j-\gamma_j)-\vartheta_i+\psi_i-\omega_i}-\frac{1}{g},\quad i=1,...,\mathcal{T}
\end{aligned}\tag{2.2.32}$$

Rearranging (2.2.29) as

$$\begin{aligned}
\mathcal{R}(p_i)=\frac{g(p_i+\varepsilon)}{2(1+gp_i)}-(-\vartheta_i+\psi_i)\varepsilon-\varphi_i+\varpi_i,\\
i=1,...,\mathcal{T}
\end{aligned}\tag{2.2.33}$$

With the addition of two new Lagrange multipliers γ_i and ψ_i, the new thresholds are

$$\chi_{\varsigma i} = \frac{1}{\Gamma \sum_{j=i}^{\mathcal{T}} (\zeta_j - \gamma_j)} - \frac{1}{g} \tag{2.2.34}$$

$$\chi_{\varrho i} = \frac{1}{\sum_{j=i}^{\mathcal{T}} (\zeta_j - \gamma_j)} - \frac{1}{g} \tag{2.2.35}$$

Analyzing (2.2.32), when $0 < p_i < \mathcal{P}_{max}$ then to satisfy (2.2.8) and (2.2.31), we get $\vartheta_i = 0, \psi_i = 0$. When energy is stored in the battery, $\varsigma_i > 0$ and to satisfy (2.2.9) we get $\delta_i = 0$. Similarly, for the case of energy retrieval, $\varrho_i > 0$ and we get $\omega_i = 0$ to satisfy (2.2.9). Now analyzing (2.2.33), when $0 < \Theta_i \leq 1$, then to satisfy (2.2.10), we get $\varphi_i = 0, \varpi_i = 0$ and solution of (2.2.33) is obtained similar to (2.2.19). The value of new thresholds does not change until the battery reaches its maximum capacity or is depleted [79]. We propose an algorithm to find optimal power allocation policy with no-energy-overflow and finite transmit power constraints.

Algorithm 2: Calculate χ_0 from channel fading coefficient g and circuit power consumption ε. Start from an epoch $j = 1$, find the largest value of storage threshold $0 \leq \chi_\varsigma \leq \mathcal{P}_{max}$ by doing a linear search, then using (2.2.15) find the value of retrieval threshold χ_ϱ, that makes the power allocation policy in (2.2.16) and (2.2.17) feasible. Now find the smallest epoch k such that $k > j$, for which the value of $\mathcal{B}_i = 0$ or $\mathcal{B}_i = \xi_{max}$. Assign the optimal thresholds to epochs $i = j, ..., k$. Repeat the above process until $k < \mathcal{T}$. Finally, compare the values of χ_0 with $\chi_{\varsigma i}$ and $\chi_{\varrho i}$, adjust the values of $p_i, \varsigma_i, \varrho_i, \Theta_i$ and calculate $\mathcal{B}_i$.

2.3 Offline Energy Scheduling Policy for a Fading Channel

For fading channels, the channel fading coefficient g_i is constant during an epoch i, but varies from one epoch to another. The transmitter has non-causal knowledge of channel fading coefficients $g_i, i = 1, ..., \mathcal{T}$.

2.3.1 Throughput maximization with infinite sized battery and transmit power

The average throughput maximization problem for a fading channel with infinite sized battery and transmit power is expressed as

$$\mathcal{P}4: \max_{(\varsigma_i, \varrho_i, \Theta_i)} \frac{1}{\mathcal{T}} \sum_{i=1}^{\mathcal{T}} \Theta_i \mathcal{R}(p_i, g_i) \tag{2.3.1}$$

subject to

$$\begin{aligned} \mathcal{C}8 &: \mathcal{B}_i \geq 0, \quad i = 1, ..., \mathcal{T}. \\ \mathcal{C}9 &: p_i = \xi_i - \varsigma_i + \varrho_i - \varepsilon_i \geq 0, \quad i = 1, ..., \mathcal{T}. \\ \mathcal{C}10 &: \varsigma_i \geq 0, \quad i = 1, ..., \mathcal{T}. \\ \mathcal{C}11 &: \varrho_i \geq 0, \quad i = 1, ..., \mathcal{T}. \\ \mathcal{C}12 &: 0 < \Theta_i \leq 1, \quad i = 1, ..., \mathcal{T}. \end{aligned} \tag{2.3.2}$$

The KKT conditions for optimality are

$$\Gamma \sum_{j=i}^{\mathcal{T}} \zeta_j - \frac{g_i}{1 + g_i p_i} - \vartheta_i + \delta_i = 0, \quad i = 1, ..., \mathcal{T} \tag{2.3.3}$$

$$\frac{g_i}{1 + g_i p_i} - \sum_{j=i}^{\mathcal{T}} \zeta_j + \vartheta_i + \omega_i = 0, \quad i = 1, ..., \mathcal{T} \tag{2.3.4}$$

$$\mathcal{R}(p_i) - \frac{g_i(p_i + \varepsilon)}{2(1 + g_i p_i)} - \varepsilon\vartheta_i + \varphi_i - \varpi_i = 0, \quad i = 1, ..., \mathcal{T} \tag{2.3.5}$$

The complementary slackness conditions are same as for $\mathcal{P}1$. We define two water-level thresholds: $\kappa_{\varsigma i}$ and $\kappa_{\varrho i}$ for energy storage and retrieval, respectively. For a fading channel, these thresholds can be written as

$$\kappa_{\varsigma i} = \frac{1}{\Gamma \sum_{j=i}^{\mathcal{T}} \zeta_j}, \ \kappa_{\varrho i} = \frac{1}{\sum_{j=i}^{\mathcal{T}} \zeta_j}, \quad i = 1, ..., \mathcal{T} \tag{2.3.6}$$

These water-level thresholds have the following relationship

$$\kappa_{\varrho i} = \Gamma \kappa_{\varsigma i}, \quad i = 1, ..., \mathcal{T} \tag{2.3.7}$$

The optimal power allocation policy is expressed as

$$p_i = \min(\max(\kappa_{\varrho i} - 1/g_i, [\xi_i/\Theta_i - \varepsilon]^+), [\kappa_{\varsigma i} - 1/g_i]^+) \tag{2.3.8}$$

$$\varsigma_i = [\xi_i/\Theta_i - \varepsilon - p_i]^+, \quad \varrho_i = [p_i - (\xi_i/\Theta_i - \varepsilon)]^+ \tag{2.3.9}$$

The analysis of (2.3.5) is similar to the static channel case. The value of χ_0 changes during each time slot due to varying channel states g_i. The optimal power allocation policy is expressed as

$$p_i = \max(p_i, \chi_0(g_i)) \tag{2.3.10}$$

$$\Theta_i = \frac{\xi_i - \varsigma_i + \varrho_i}{p_i + \varepsilon} \tag{2.3.11}$$

We can find the optimal water-level thresholds from Algorithm 1 by replacing the power allocation policy in (2.2.16) and (2.2.17) with (2.3.8) and (2.3.9), respectively. The $\chi_{\varsigma i}$ and $\chi_{\varrho i}$ are replaced with $\kappa_{\varsigma i}$ and $\kappa_{\varrho i}$, respectively.

2.3.2 Throughput maximization constrained by finite sized battery and transmit power

The average throughput maximization problem for a fading channel with finite sized battery and limited amount of transmit power is expressed as

$$\mathcal{P}5: \max_{(\varsigma_i, \varrho_i, \Theta_i)} \frac{1}{\mathcal{T}} \sum_{i=1}^{\mathcal{T}} \Theta_i \mathcal{R}(p_i, g_i) \tag{2.3.12}$$

subject to

$$\begin{aligned} &\mathcal{C}8 - \mathcal{C}12 \\ &\mathcal{C}13: \mathcal{B}_i \leq \xi_{max}, \quad i = 1, ..., \mathcal{T}. \\ &\mathcal{C}14: p_i = \xi_i - \varsigma_i + \varrho_i - \varepsilon_i \leq \mathcal{P}_{max}, \quad i = 1, ..., \mathcal{T}. \end{aligned} \tag{2.3.13}$$

The KKT conditions for optimality are

$$\begin{aligned} \Gamma \sum_{j=i}^{\mathcal{T}} (\zeta_j - \gamma_j) - \frac{g_i}{1 + g_i p_i} - \vartheta_i + \psi_i + \delta_i = 0, \\ i = 1, ..., \mathcal{T} \end{aligned} \tag{2.3.14}$$

$$\begin{aligned} \frac{g_i}{1 + g_i p_i} - \sum_{j=i}^{\mathcal{T}} (\zeta_j - \gamma_j) + \vartheta_i - \psi_i + \omega_i = 0, \\ i = 1, ..., \mathcal{T} \end{aligned} \tag{2.3.15}$$

$$\mathcal{R}(p_i) - \frac{g_i(p_i+\varepsilon)}{2(1+g_ip_i)} + (-\vartheta_i + \psi_i)\varepsilon + \varphi_i - \varpi_i = 0, \quad i = 1, ..., \mathcal{T} \tag{2.3.16}$$

The complementary slackness conditions are similar to $\mathcal{P}3$. We define new water-level thresholds for a fading channel with finite sized battery and limited amount of transmit power constraints.

$$\kappa_{\varsigma i} = \frac{1}{\Gamma\sum_{j=i}^{\mathcal{T}}(\zeta_j - \gamma_j)}, \;\; \kappa_{\varrho i} = \frac{1}{\sum_{j=i}^{\mathcal{T}}(\zeta_j - \gamma_j)}, \quad i = 1, ..., \mathcal{T} \tag{2.3.17}$$

These thresholds have following relationship

$$\kappa_{\varrho i} = \Gamma\kappa_{\varsigma i}, \quad i = 1, ..., \mathcal{T} \tag{2.3.18}$$

With new water-level thresholds, the optimal power allocation policy is expressed as

$$p_i = \min(\max(\kappa_{\varrho i} - 1/g_i, [\xi_i/\Theta_i - \varepsilon]^+), [\kappa_{\varsigma i} - 1/g_i]^+) \tag{2.3.19}$$

$$\varsigma_i = [\xi_i/\Theta_i - \varepsilon - p_i^+, \quad \varrho_i = [p_i - (\xi_i/\Theta_i - \varepsilon)]^+ \tag{2.3.20}$$

We can find optimal water-level thresholds from Algorithm 2 by replacing the power allocation policy in (2.2.16) and (2.2.17) with (2.3.19) and (2.3.20), respectively. The $\chi_{\varsigma i}$ and $\chi_{\varrho i}$ are replaced with $\kappa_{\varsigma i}$ and $\kappa_{\varrho i}$, respectively.

2.4 Online Energy Scheduling Policies

For offline power allocation policy, the information about harvested energy is known prior to the start of communication session. This approach is used in application where harvested energy can be controlled or predicted [80]. In this section, we propose energy scheduling policies for static and fading channels, that require causal knowledge of the harvested energy.

2.4.1 Static Channel

For static channel, we consider an online double-threshold policy [79] with constant energy storage and retrieval thresholds i.e., $\chi_{\varsigma i} = \chi_\varsigma$ and $\chi_{\varrho i} = \chi_\varrho$, $i = 1, ..., \mathcal{T}$.

The energy storage threshold is predicted as follows

$$\Gamma \int_{\chi_\varsigma}^{\infty} (e-\chi_\varsigma) f_\xi(e) de - \int_0^{\chi_\varrho} (\chi_\varrho - e) f_\xi(e) de = 0 \tag{2.4.1}$$

where $f_\xi(\xi)$ is the stationary probability distribution with Markovian harvested energy ξ_i. When storage efficiency $\Gamma = 0$, (2.4.1) ensures that no energy is stored i.e., $p_i = \xi_i - \varepsilon_i$, which is optimal in this case.

The fixed thresholds are not feasible for all epochs. We propose an adaptive energy storage threshold. The value of this threshold varies with storage efficiency Γ and value of epoch i. The new threshold is written as

$$\chi_{\varsigma i} = \chi_\varsigma(\Gamma, i) \tag{2.4.2}$$

With this threshold the energy harvesting transmitter will not store energy when storage efficiency is small or the communication session is about to end. The value of retrieval threshold $\chi_{\varrho i}$ is calculated from (2.2.15). The optimal online power allocation policy is expressed as

$$p_i = \begin{cases} \max(\chi_0, \chi_{\varsigma i}), & \xi_i - \varepsilon > \chi_{\varsigma i} \\ \max(\chi_0, \xi_i - \varepsilon), & \chi_{\varrho i} \leq \xi_i - \varepsilon \leq \chi_{\varsigma i} \\ \max(\chi_0, \xi_i + \min(\varrho_i, \mathcal{B}_{i-1})), & \xi_i - \varepsilon < \chi_{\varrho i} \end{cases} \qquad i = 1, ..., \mathcal{T} \tag{2.4.3}$$

$$\Theta_i = \frac{\xi_i - \varsigma_i + \min(\varrho_i, \mathcal{B}_{i-1})}{p_i + \varepsilon}, \qquad i = 1, ..., \mathcal{T} \tag{2.4.4}$$

2.4.2 Fading Channel

For fading channel, the value of channel fading coefficient g_i varies with time. The energy storage threshold is predicted as follows [79]

$$\int\int_0^{\infty} \left[e - \left[\kappa_\varsigma - \frac{1}{g}\right]^+ \right]^+ - \left[\kappa_\varrho - \frac{1}{g} - e\right]^+ f_{\xi,G}(e,g) de dg = 0 \tag{2.4.5}$$

where $f_{\xi,G}(\xi, G)$ is the joint stationary probability distribution of Markovian harvested energy ξ_i and channel fading coefficients g_i. The new adaptive water-level storage threshold is written as

$$\kappa_{\varsigma i} = \kappa_{\varsigma}(\Gamma, i) \tag{2.4.6}$$

The energy storage threshold is written as

$$\chi_{\varsigma i} = \kappa_{\varsigma i} - \frac{1}{g_i} \tag{2.4.7}$$

The water-level retrieval threshold is calculated from (2.3.7). The optimal online power allocation policy is expressed as

$$p_i = \begin{cases} \max(\chi_0(g_i), \chi_{\varsigma i}), & \xi_i - \varepsilon > \chi_{\varsigma i} \\ \max(\chi_0(g_i), \xi_i - \varepsilon), & \chi_{\varrho i} \leq \xi_i - \varepsilon \leq \chi_{\varsigma i} \\ \max(\chi_0(g_i), \xi_i + \min(\varrho_i, \mathcal{B}_{i-1})), & \xi_i - \varepsilon < \chi_{\varrho i} \end{cases} \qquad i = 1, ..., \mathcal{T} \tag{2.4.8}$$

$$\Theta_i = \frac{\xi_i - \varsigma_i + \min(\varrho_i, \mathcal{B}_{i-1})}{p_i + \varepsilon}, \qquad i = 1, ..., \mathcal{T} \tag{2.4.9}$$

Chapter 3

Results

3.1 Results & Discussion

This section provides a detailed discussion of the simulation results. All the simulations are done in MATLAB 2019b for a finite session of $\mathcal{T} = 10$ epochs, with each epoch of length $t = 1s$. We consider an AWGN channel with noise spectral density $\mathcal{N}_0 = 10^{-19}$W/Hz. The bandwidth is 1MHz and path loss is $PL(dB) = -100$ [79]. The energy harvesting transmitter in Fig. 2.1 has a finite sized battery i.e., $\xi_{max} = 10$mJ and maximum power permissible for transmission is $\mathcal{P}_{max} = 20$mW. The circuit power consumption is $\varepsilon = 5$mW.

Referring to Fig. 3.1, it shows the variation of throughput with storage efficiency for a static channel. The clean energy is harvested in an independent and identically distributed (i.i.d.) manner, following a uniform random distribution in the range [5,20] mJ. When storage efficiency is below 50%, the proposed offline and online policies are not storing any energy, which is optimal in this case due to large energy storage losses. Overall, the proposed policies outperforms the earlier work [79] on energy storage losses. Fig. 3.2 shows the variation of throughput with storage efficiency for a static channel when clean energy is harvested as random bursts of energy, generating energy values uniformly in range [5,20] mJ. The energy harvesting process is modelled as a Markov Decision Process (MDP) i.e., the amount of harvested energy remains constant with a probability of 0.5, and generates a

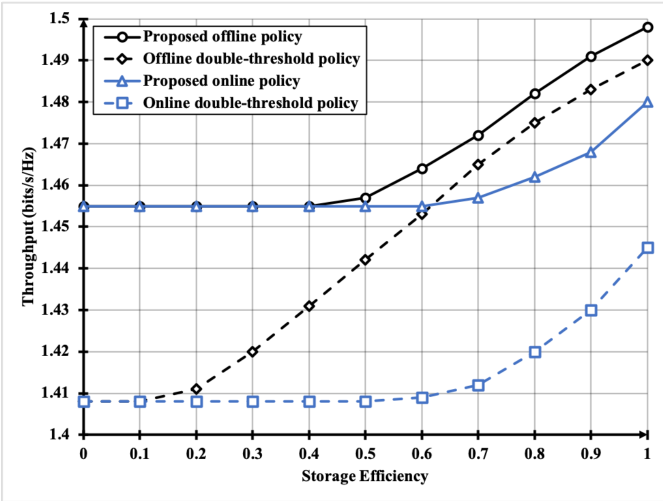

Figure 3.1: Throughput variations of a static channel with non-decreasing storage efficiency and i.i.d. energy arrivals. The harvested energy values are generated uniformly in range [5,20] mJ.

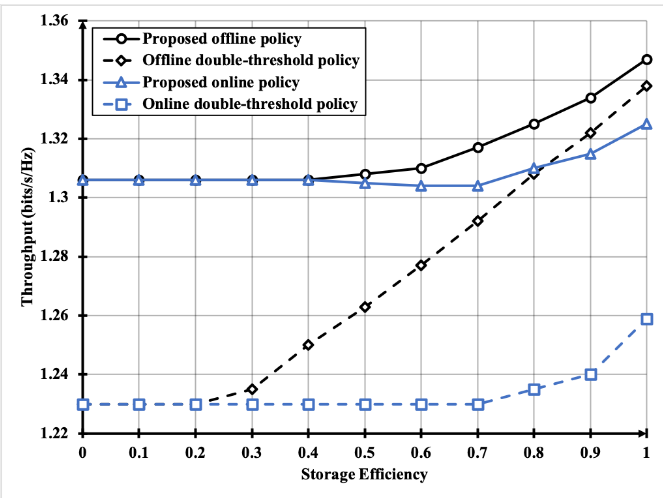

Figure 3.2: Throughput variations of a static channel with non-decreasing storage efficiency and Markov (*bursty*) energy arrivals. The harvested energy values are generated uniformly in range [5,20] mJ.

new value with same probability. The proposed policies adapt to storage efficiency values greater than 50%. Similarly simulations are also done for a time-varying channel, following an exponential distribution. The variations of throughput with storage efficiency are shown in Fig. 3.3 & 3.4, respectively. Referring to Fig. 3.3, the proposed power allocation policies behave as non-storage policies when storage efficiency is less than 20% to reduce the affect of energy storage losses. Similar

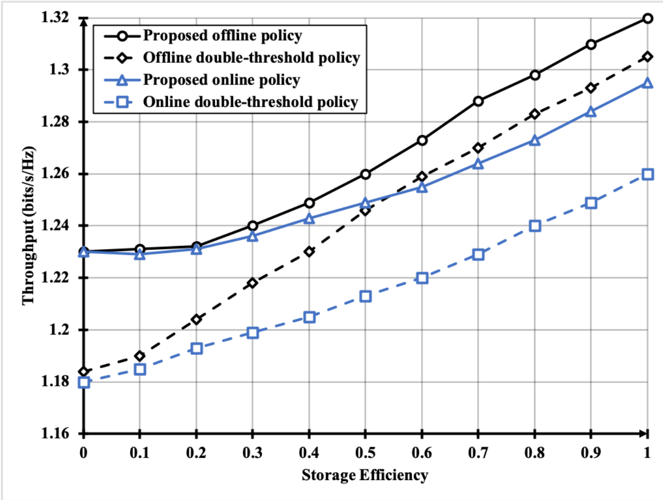

Figure 3.3: Throughput variations of a fading channel with non-decreasing storage efficiency and i.i.d. energy arrivals. The harvested energy values are generated uniformly in range [5,20] mJ.

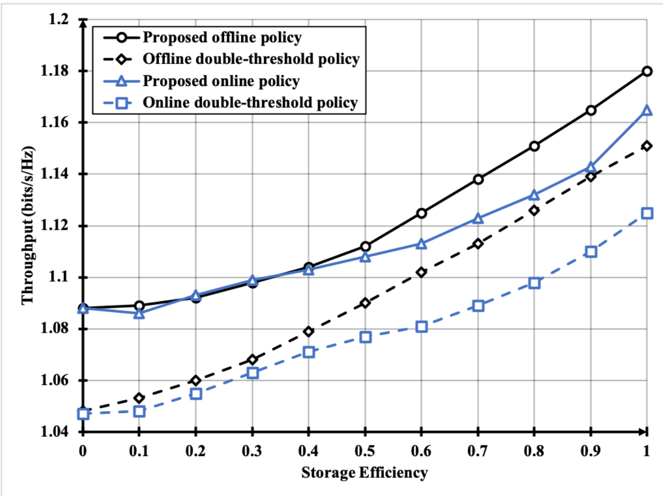

Figure 3.4: Throughput variations of a fading channel with non-decreasing storage efficiency and Markov (*bursty*) energy arrivals. The harvested energy values are generated uniformly in range [5,20] mJ.

to the static channels case, it outperforms the double-threshold policy. In Fig. 3.4, there is a performance improvement for random energy arrivals and varying channel states. It shows the adaptive capability of the proposed offline and online policies, respectively.

To analyze the performance of proposed power allocation policies for random en-

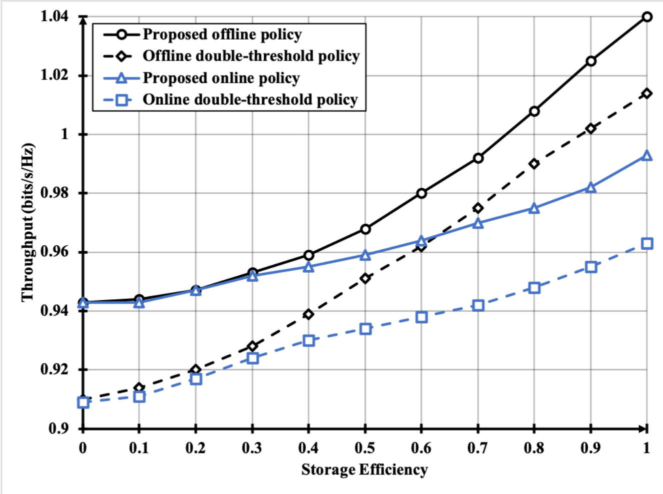

Figure 3.5: Throughput variations of a fading channel with non-decreasing storage efficiency and Markov (*random walk*) energy arrivals. The harvested energy values are generated uniformly in range [5,20] mJ.

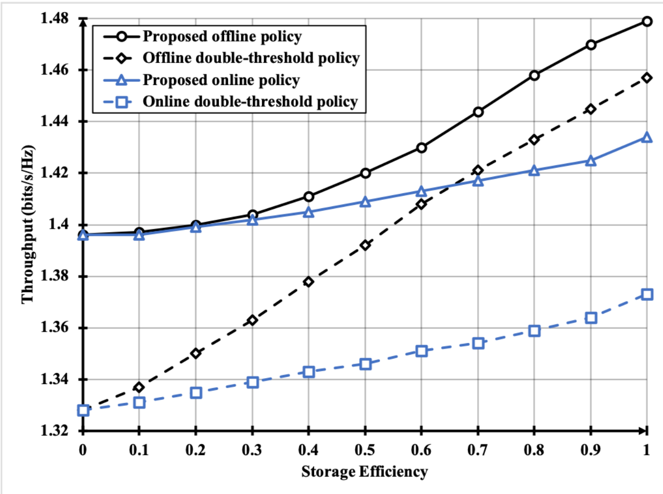

Figure 3.6: Throughput variations of a fading channel with non-decreasing storage efficiency and i.i.d. energy arrivals. The harvested energy values are generated uniformly in range [5,15] mJ.

ergy arrivals, we modelled the energy arrival process as Markov random-walk. The harvested energy performs a random walk uniformly in range [5,20] mJ. It increases/decreases the amount of harvested energy by 1 with a probability of 0.6 and remains constant with a probability of 0.4. The variations of throughput with storage efficiency for a fading channel are shown in Fig. 3.5. The proposed policies outperforms the double-threshold policies. We also change the dynamic

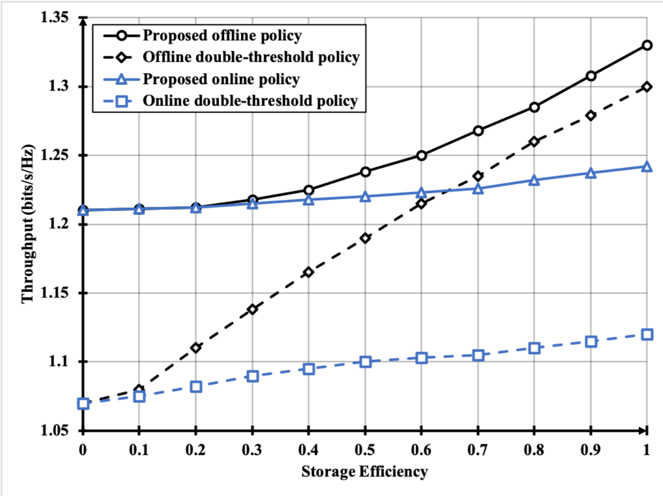

Figure 3.7: Throughput variations of a fading channel with non-decreasing storage efficiency and Markov (*bursty*) energy arrivals. The harvested energy values are generated uniformly in range [5,15] mJ.

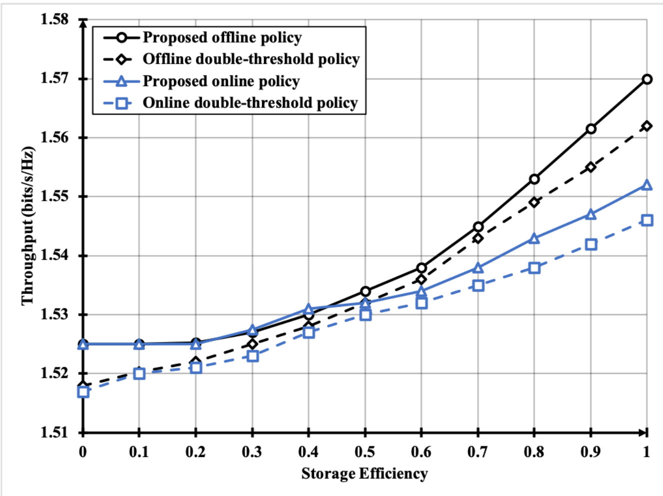

Figure 3.8: Throughput variations of a fading channel with non-decreasing storage efficiency and Markov (*random walk*) energy arrivals. The harvested energy values are generated uniformly in range [5,15] mJ.

range of harvested energy to highlight the performance of proposed methodology. The simulations are done for a fading channel and harvested energy is generated randomly in range [5,15] mJ. These results are shown in Fig. 3.6, 3.7 & 3.8.

Now, we consider the storage efficiency in between $60 - 70\%$ to analyze the performance of all power allocation policies discussed in this paper. Simulations are

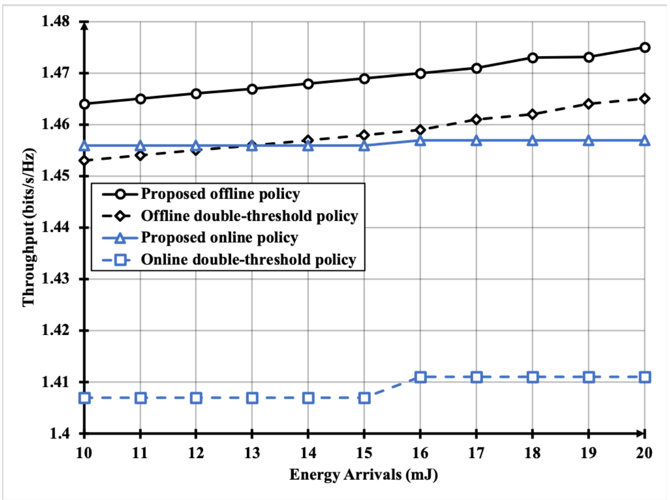

Figure 3.9: Throughput variations of a static channel with harvested energy values and i.i.d. energy arrivals. Storage efficiency is $60 - 70\%$ and the harvested energy values are generated uniformly in range [5,20] mJ.

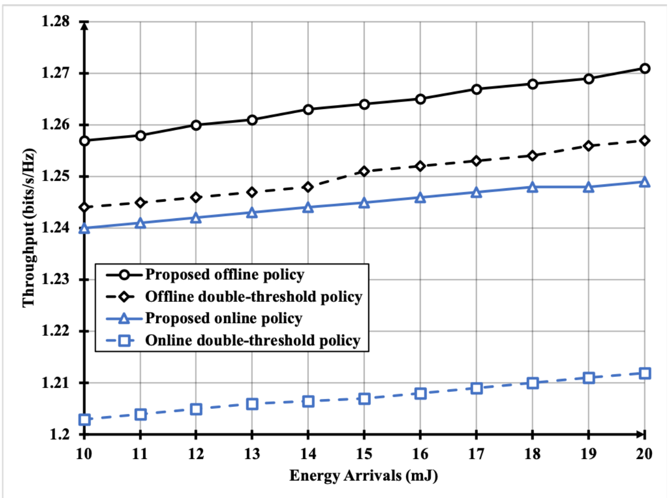

Figure 3.10: Throughput variations of a fading channel with harvested energy values and i.i.d. energy arrivals. Storage efficiency is $60 - 70\%$ and the harvested energy values are generated uniformly in range [5,20] mJ.

done for both static and fading channels and energy is harvested in an i.i.d. manner, following a uniform random distribution in range [5,20] mJ. The variations of throughput with storage efficiency are shown in Fig. 3.9 & 3.10, respectively. Generally, the performance of all power allocation policies is improved, with proposed policies outperforming the double-threshold policies.

Chapter 4

Conclusion

Green communication has attracted the research community by utilizing renewable energy resources for data transmission. In this paper, we present an energy harvesting wireless transmission system considering energy storage losses comprehensively. These energy storage losses arise due to imperfect energy storage devices. In this regard, we consider a single-user static and fading channels model to determine the power allocation policies. First, the optimal offline power allocation problem is formulated and solved by using convex optimization techniques i.e., Lagrangian method and KKT conditions for static and fading channels. The optimization problem considered energy storage losses and joint constraints such as finite battery size, circuit power consumption and finite power permissible for transmission. An offline algorithm is proposed to find optimal offline power allocation policy. Results show the performance improvement of proposed offline policy. Secondly, the online power allocation problem is formulated for both static and fading channels. An online algorithm with causal knowledge of harvested energy is proposed. It considers storage efficiency and value of time slot for finding optimum power allocation thresholds. The proposed online policy outperforms the online double-threshold policy. In future, the energy storage losses due to battery imperfections can be further combined with other types of imperfections i.e., battery degradation and energy leakage with time. Moreover, other communication overheads can be considered, that will lead to practical implementation of energy harvesting wireless transmission systems.

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