Statistical Performance Evaluation for Energy Harvesting Communications based on Large Deviation Theorem

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I dedicate this thesis to my paternal grandparents Vishnu Prasad Beohar - Kamla Beohar and maternal grandparents Dr. R.P Shrivasatva - Nirmala Shrivastava

Abstract

Energy harvesting (EH) is a promising technology for enhancing a network's quality of service (QoS). EH-based communication systems are studied by tackling the challenges of energy-outage probability and energy conditioning. These issues motivate this research to develop new solutions for increasing the lifetime of device batteries by leveraging renewable energy sources available in the surrounding environment, for instance, from solar and radio-frequency (RF) energy through harvesting. This dissertation studies an energy outage problem and user QoS requirements for energy harvesting communications.

In the first part of this dissertation, the performance of an energy harvesting communication link is analysed by allowing a certain level of energy-outage. In EH systems, energy consumed from the battery depends on the QoS required by the end user and on the channel state information. At the same time, the energy arrival to the battery depends on the strength of the power source, solar in this case, and is independent of the fading channel conditions and the required QoS. Due to the independence between the energy arrival into the battery and the energy consumed from there, it is challenging to estimate the exact status of the available energy in the battery. An energy outage is experienced when there is no further energy for the system to utilise for data transmission. In this part, a thorough study was carried out to analyse the required energy harvesting (EH) rate for satisfying the QoS requirements when a level of energy-outage is allowed in a point-to-point EH-based communication system equipped with a finite-sized battery. Furthermore, an expression relating the rate of the incoming energy with the fading channel conditions and the minimum required QoS of the system was provided to analyse the performance of the EH-based communication system under energy constraints. Finally, numerical results confirm the proposed mechanism's analytical findings and correctness.

In the second part of this dissertation, the performance of point-to-point communications is investigated in which the source node can harvest and store energy from RF signals and then use the harvested energy to communicate with its end destination. The continuous availability of RF energy has proved advantageous as a wireless power source to support low-power devices, making RF-based energy harvesting an alternative and viable solution for powering next-generation wireless networks, particularly for Internet-of-Things (IoT) applications.

Specifically, the point-to-point RF-based energy-harvesting communication is considered, where the transmitter, which can be an IoT sensor, implements a time-switching protocol between the energy harvesting and the information transfer, and we focus on analysing the system performance while aiming to guarantee the required QoS of the end user subject to system constraint energy outage. The time-switching circuit at the source node allows the latter to switch between harvesting energy from a distant RF energy source and transmitting data to its target destination using the scavenged energy. Using a duality principle between the physical energy queue and a proposed virtual energy queue and assuming that a certain level of energy outage can be tolerated in the communication process, the system performance was evaluated with a novel analytical framework that leverages tools for the large deviation principle.

In the third and last part of this dissertation, an empirical study of the RF-EH model is presented for ensuring the QoS constraints during an energy-outage for Simultaneous Wireless Information and Power Transfer (SWIPT) network. We consider a relay network over a Rayleigh fading channel where the relay lacks a permanent power source. Thus, we obtain energy from wireless energy harvesting (EH) of the source's signals to maintain operation. This process is performed using a time-switching protocol at the relay for enhancing the quality of service (QoS) in SWIPT networks. A numerical approach is incorporated to evaluate the performance of the proposed RF-EH model in terms of different evaluation parameters such as time-switching protocol, transmit power and outage. The assumptions of the large deviation principle are satisfied using a proposed virtual energy queuing model, which is then used for the performance analysis. We established a closed-form expression for the system's probability of experiencing an energy outage and the energy consumed by the relay battery.

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Publications

Journal Papers

1. **D. Beohar**, L. Musavian, and S. Aissa, "Novel Mathematical Framework for Performance Analysis of Energy Harvesting Based Point-to-Point Communications," submitted in *IEEE ACCESS*. (Under Review)

Conference Papers

1. **D. Beohar**, L. Musavian, and S. Aissa, "RF Energy Harvesting Communications Using Time-Switching Protocol with QoS Guarantee," in *International Wireless Commun. and Mobile Comput. Conference (IWCMC)*, Dubrovnik, Croatia, June 2022.

2. **D. Beohar**, L. Musavian, and S. Aissa, "Low-Complexity Framework for Performance Analysis of Energy Harvesting Communications," in *30th Biennial Symp. on Commun. (BSC)*, Saskatoon, SK, Canada, June 2021.

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Nomenclature

Acronyms / Abbreviations

Ai-BSF Aluminum Back Surface Field

AoI Age of Information

CU Cellular User

D2D Device to Device

DFP Distributed Fractional Power

DUE Device to Device User Equipment

EE Energy Efficiency

EH-WSN Energy-Harvesting Wireless Sensor Network

EH Energy Harvesting

EIE Effective Incoming Energy

EOE Effective Outgoing Energy

FFR Firm Frequency Response

FTT Fixed Threshold Transmission

GW Gigawatt

HGWO Hybrid Grey Wolf Optimizer

IID Independent and Identical Distributed

IIPV Infrastructure Integrated Photovoltaic

IoT Internet of Things

IPV Integrated Photovoltaic

LAN Local Area Network

LDP Large Deviation Principle

MAC Media Access Control

MDP Markov Decision Process

MGF Moment Generating Function

NOMA Non-Orthogonal Multiple Access

OFDM Orthogonal Frequency Division Multiplexing

OP Outage Probability

PDF Probability Density Function

PERC Passivated Emitter and Rear Cell

PS Power Splitting

PSR Power Splitting Relaying Protocol

PV Photo Voltaic

QoS Quality of Service

RF-EH Radio Frequency Energy Harvesting

RF Radio Frequency

SARSA State Action Reward State Action

SEH Solar Energy Harvesting

SiNx Silicon Nitride

Si Silicon

SNR Signal to Noise Ratio

SWIPT Simultaneous Wireless Information and Power Transfer

TSR Time Switching Relaying Protocol

TS Time Switching

UAV Unmanned Aerial Vehicle

WBAN Wireless Body Area Network

WET Wireless Energy Transfer

WPT Wireless Power Transmission

WSN Wireless Sensor Network

WSN Wireless Sensor Networks

List of Symbols

$h(t)$	Rayleigh Block Fading Channel
t	Time Index
T	Block Duration
$x(t)$	Transmitted Signal
$n(t)$	Gaussian Random Noise
$A(t)$	Energy Accumulated in the Battery
$E(t)$	Empty Portion of the Battery
$B_{\max}$	Maximum Level of Battery
$\mu_{\mathrm{i}}(t)$	Rate of Incoming Energy
$\mu_{\mathrm{o}}(t)$	Rate of Outgoing Energy
$r(t)$	Instantaneous Rate
N_0B	Noise Density Per Unit Bandwidth
$P_{\max}T$	Maximum Transmission Power
P_{out}	Energy-Outage of Battery
ε	Probability of Non-Empty Virtual Buffer
u	QoS exponent
$\mathbb{E}$	Expectation Operator
$\mu_{\mathrm{i_{fix}}}$	Constant Rate of Energy $\mu_{\mathrm{i}}(t)$
$R_{\min}$	Minimum Required Rate
h_1	Channel Coefficient Between RF Energy Source and Sensor Node
h_2	Channel Coefficient Between Sensor Node and Destination
d_1	Distance from RF Energy Source to Sensor Node
d_2	Distance from Sensor Node to Destination
αT	Time Interval During Sensor Node Harvests Energy
P_s	Transmit Power of RF Energy Source
η	Energy Conversion Efficiency
m	Path Loss Exponent
$\mu_{\mathrm{o_{fix}}}$	Constant Rate of Energy $\mu_{\mathrm{o}}(t)$
$p\left(\lvert h_1\rvert^2\right)$	Probability Density Function of $\lvert h_1\rvert^2\rvert$
γ	Distribution of Channel Power Gain
$\mu_{\max}T$	Maximum Power of Relay
v	Random Variable

Chapter 1

Introduction

1.1 Motivation

This part will briefly explain the study's contextual background by introducing the concepts of energy harvesting systems and their performance analysis in maximising energy performance. This section also discusses prediction-based and various energy harvesting techniques and their significance in wireless information and power transfer. Increase in the frequency level of weather events noticed all over the place world in modern times confirms further than ever the real-time aspect of climate change; as such, it is pretty essential to intervene for minimising global level carbon discharges. For this concern, it is appropriate to enhance effective and low-cost renewable expertise to reduce fossil fuel reliance and correspondingly carbon emissions.

Currently, renewable resources have emerged as an essential alternative to electrical energy sources as they have proved to be a fundamental potential aspect for instituting several issues, such as an increase in energy requirement, changes in climate and global warming, which empower the remarkable progress of the human society. Since the Photo Voltaic (PV) market is exponentially increasing at a yearly rate of 35% to 40%, the Si-based solar cells have extended their peak point, with the PV fixing nearly 25 GW in 2012. High-efficiency technologies chiefly target increasing the efficiency level, which is generated power per unit area, and it has stayed as the utmost adversary study topic. Si-centred PV procedure incorporates photons concentration, transfer of an electron from photons to electron-hole pairs, isolation and carrying of charges to the external electrodes. High-efficiency technology generally embraces new design parameters for solar cells, optimisation of light absorption, and loss of photo-created carriers. The highly productive passivated emitter and rear cell (PERC) devices are developed as an enhanced scheme of typical industrialised screen printed p-type Si solar cells as it could reduce electrical and optical losses. General losses in the PV design are optical and electrical losses. Optical losses are the loss of photons that could have generated electron hole pairs in the cell. Electrical losses are the photons that got absorbed in the cell but were not capable of contributing to the cell power output. The comprehensive assembly progression of the PERC cells was somewhat diverse from the industrial stock Ai-BSF cells since earlier texturing and phosphorus dispersion, dielectric protection cover for example, SiNx is dropped on the rear side of the solar cell. The Photovoltaic (PV) community pays vital attention to improvements in the energy conversion efficiency of solar cells.

These days, PV based technologies denote one such procedures that could improve renewable energies share and it signifies a huge potential to supply around 5% global electricity demand by 2030 and 11% by 2050. Several research works has been conducted in this field earlier since it could offer higher power output than regular PV. Also, they could be cost effective if thermal component is found to be cheaper. Moreover, it is identified that PVT technology possess the gain to cool PV cells and formerly upsurge their electrical output [21]. Capability to create valuable means of energy from solar irradiation is confined by land constraint owing to its discrete way of nature. By means of harvesting incident solar energy from roadways, it is probable to exploit exploitation of land devoted towards transportation. Grid dependence could be minimized explicitly by using infrastructure integrated PV (IIPV) technology for driving the roadway loads while also dropping the distribution losses and requirements for copper. Thus provides economic level gain. IPV might also contribute in moderating concerns related to suitable infrastructure up-gradation in distribution grids owing to high forecast with advent of electric vehicles (EVs) [99]. Depending on sensors, distribution schemes, sensing based prototypes, energy efficacy level and exposure in wireless sensor based networks, numerous issues and methods were examined and survey was conducted centred on four diverse viewpoints for instance,

1. Energy efficiency and diverse groups of WSN environmental based sensors;

2. Sensing prototypes, coverage and distribution based policies;

3. Kinds of coverage, energy efficiency, sensor types and its prototypes and deployment approaches; and

4. Energy efficiency appliances.

Research in [7] could be mainly considered as an inventiveness for research scholars in the field of wireless sensor networks and numerous problems in research which range from kinds of sensors to reportage, energy efficacy are upcoming areas for further research study in wireless networks.

Wireless sensor networks (WSNs) are the focus to the constraint check of energy storage at every mobile node and saving on energy consumption or prolonging the battery life for sensor nodes has turned into an imperative research concern in wireless sensor networks. In recent times, energy harvesting (EH) has fascinated massive attention from researchers as a hopeful cost-effective method to exploit energy efficiency of a wireless network, particularly in wireless sensor networks. Numerous energy harvesting bases have been considered, such as natural sources (solar, wind, thermal, etc.), powerfully coupled magnetic resonances [72]. In the 5th generation period, the prevalent uses of Internet of Things and enormous machine-type communications have introduced growing research comforts on the backscatter wireless powered communication (B-WPC) method owing to its ultra-high energy efficiency and low cost. The universal B-WPC network is categorized by nodes with active spatial locations and erratic short packets, of which the performance has not been completely inspected. An inclusive examination of a multi-antenna B-WPC network is carried out in [138] with irregular short packets beneath a stochastic geometry background. By developing a time-space Poisson point process model, the behaviour of the network is well seized in a decentralized and asynchronous transmission manner of approach.

IoT devices are anticipated to be interrelated by means of wireless communication based techniques in smart towns, primarily 5G. Hence, it stays vital to explore IoT in 5G connection based networks, which is estimated to offer substantial connectivity laterally by means of high data rates. Owing to huge amount of consumers, wireless spectrum would be inadequate to provide necessities of all IoT devices and this could be alleviated by accepting intelligent frequency spectrum allocation systems. Similarly, IoT applications could employ cognitive proficiencies for actual spectrum exploitation affording to the accessible bandwidth and application necessities [6].

Studies aim the expansion of EE and cost minimization of the scheme by minimization of transfer powers of base stations and grid energy consumption with support of traffic shaping and EH and green energy management correspondingly [20]. Major objective is to evaluate the performance of “EH-based” communications beneath energy-outage restraints. These kind of breakdown is very much stimulating, as the harvested energy and energy used for the communication are found to be independent with the latter dependent on quality-of-service (QoS) constraint and, in turn, on the channel state data; and the prior dependent on power of the solar energy for harvesting. It is, consequently, challenging to assess the precise real-time battery position at the transmitter.

1.2 Aims and Objectives

The aforementioned challenges above are now factored into the following key aim and objectives for this thesis:

- Analyze the performance of an energy harvesting communication link by allowing a certain level of energy-outage.
- Study the dependence of energy consumption on the required QoS and channel state information in EH systems.
- Investigate the dependence of energy arrival on the strength of the power source and its independence from fading channel conditions and QoS requirements.
- Examine the challenges of estimating the available energy in the battery due to the independence between energy arrival and consumption.
- Determine the required energy harvesting rate to satisfy QoS requirements when allowing a certain level of energy-outage in a point-to-point EH-based communication system with a finite-sized battery.
- Provide an expression that relates the incoming energy rate with fading channel conditions and the minimum required QoS of the system to analyze the performance of the EH-based communication system under energy constraints.
- Verify the analytical findings and correctness of the proposed mechanism through numerical results.

1.3 Challenges

The following research challenges must be overcome:

- **Research Challenge 1**: How to determine the minimum energy harvesting rate to meet Quality of Service (QoS) requirements while allowing for energy outage in a point-to-point communication system with a limited battery.
- **Research Challenge 2**: How to evaluate a point-to-point energy-harvesting communication system with a time-switching circuit at the source node for switching between energy harvesting and data transmission using the RF energy.

- **Research Challenge 3**: How to assess the performance of the proposed RF-EH using a time-switching protocol at the relay for enhancing the quality of service (QoS) in SWIPT networks.

This dissertation examines and addresses these research problems. The contributions in the next section briefly describes how the earlier issues were resolved.

1.4 Thesis Contributions

Applications of the fifth generation (5G) networks and beyond include massive sensing, holographic telepresence, mixed reality, and virtual reality. These cutting-edge applications require extremely high data rates, which raises the requirement for extremely high energy resources. Higher carbon dioxide gas emissions and a requirement for powerful batteries may follow from this. However, device battery lifespan is still constrained in comparison to the growing demand for faster data rate connectivity. In actuality, the gap between battery advancements and the rising energy consumption is growing. However, it can be expensive or impossible to replace non-rechargeable batteries in severe and isolated environments. These problems have spurred researchers to create fresh approaches for extending the lifespan of device batteries by utilising renewable energy sources present in the immediate environment, such as solar and wind energy, through harvesting. The following are the contributions made by the thesis work in addressing the aforementioned goals:

- To develop a mathematical framework for the performance analysis of EH communications. The framework is developed based on a concept of energy-outage probability. Energy outage is experienced when there is no further energy for the system to utilize for the data transmission. We use the randomness property of energy-outage occurrence in the system to develop the mathematical framework. Specifically, the LDP theorem is used to model queuing system for the EH battery. A virtual battery queuing model is used to facilitate providing the assumptions needed for using LDP. Building upon the above two fundamental new ideas, we obtain a formulation that relates the channel capacity to the rate of the energy arrival. This gives a unique mathematical framework that directly relates the two concepts together, which are rather independent by nature. The performance of point-to-point EH communication is investigated using this mathematical tool. Simulation results are provided in order to understand how this mathematical framework performs.

  The publication addressing this contribution are the following:

  - **D. Beohar**, L. Musavian, and S. Aissa, "Novel Mathematical Framework for Performance Analysis of Energy Harvesting Based Point-to-Point Communications," submitted in *IEEE ACCESS*. (Under Review)
  - **D. Beohar**, L. Musavian, and S. Aissa, "Low-Complexity Framework for Performance Analysis of Energy Harvesting Communications," in *30th Biennial Symp. on Commun. (BSC)*, Saskatoon, SK, Canada, June 2021.

- To develop a mathematical framework for the investigation of the system performance under energy-outage constraints. Deriving closed-form analytical expressions for the rate of the energy that is consumed from the battery of the transmit node and for the energy-outage probability. Obtaining a formulation for the transmit power of the sensor node so that a target energy-outage probability remains satisfied. Also, a virtual energy queuing model is proposed to make use of the large deviation principle theorem, as a powerful tool for the performance evaluation conducted here. Investigating the effects of key parameters, such as the RF source power, and the distance between the RF source and the sensor node, on performance, via numerical results that also corroborate the analytical findings.

  The publication addressing this contribution is the following:

  - **D. Beohar**, L. Musavian, and S. Aissa, "RF Energy Harvesting Communications Using Time-Switching Protocol with QoS Guarantee," in *International Wireless Commun. and Mobile Comput. Conference (IWCMC)*, Dubrovnik, Croatia, June 2022.

- The last contribution of this work is to develop a mathematical framework, in order to study the performance of SWIPT networks when a desired energy-outage at the transmitter is taken into account. When we need to transmit with a given quantity of energy yet the battery is short on power, such a situation occurs. High transmission power is necessary to achieve a certain QoS, such as a minimum throughput level. Also, it is difficult to determine the actual condition of the available energy in the battery because of the independence between the energy entering the battery and the energy leaving it. Energy outages are unavoidable in such circumstances. We provide a analytical framework for evaluating the RF energy harvesting model to enhance the QoS, presuming that the system can withstand some degree of energy-outage to occur.

1.5 Background

1.5.1 Energy Harvesting Networks

This section will give a brief description of the influence of energy harvesting in wireless networks and its role in enhancing energy efficiency. Due to the increase in the power demand these days, the energy harvesting (EH) from the unexploited form of natural waste energy resource is quite common and these sources possess the prospective of micro to milli watts power reliant on ambient environments. For providing power to micro devices in distant location, several scholars have been focusing on micro level energy harvesting and this concept mainly leads to radical cost minimization. As far as the assembly is recognized, it could create electricity with cost minimization or effort such as renewable form of resources. Research in [95] reviews main key areas of piezoelectric energy harvesting system (PEHS) such as electrical and mechanical based methodologies introduced by various researchers. From the survey, it was considered that the current methodologies could more or less enhance energy harvesting with the support of piezoelectric aspects and however reliability and solidity of models were not up to mark. Rapid rate of urban growth and progress in population mentions significance of urban areas in context of general energy consumption and greenhouse gas emissions. With the support of special research methods, energy performance study spans diverse research extents and some of the concepts like zero energy or low energy highlight diverse phases of energy performance in the assembled environs particularly at the district scale which is studied in this research [2].

Apart from the standard RF EH system, where merely a source node data conveyed over intermediary EH relaying node, this research work [87] considered to transfer data of IoT relay node beside source node data by means of Non-orthogonal multiple access (NOMA) protocol. This is carried out with the manifestation of interfering signal to appropriate end point. Generally with the occurrence of interfering signal, the grouping of two prevalent energy harvesting relaying architecture models - time switching (TS) relaying and power splitting (PS) relaying with NOMA protocol for IoT relay schemes were studied.

Both in industry and academic based domain, the Wireless Body Area Networks (WBANs) have gained huge attention for the purpose of continuous monitoring and control of functional hints of human body. An energy effectual means of resource allocation system is vital to extend the period of the networks, as the sensors in WBANs are classically battery-driven and inopportune to recharge, whereas certifying the rigid necessities of quality of service (QoS) of the WBANs in nature.

Energy harvesting (EH) technology with the proficiency of harvesting energy from ambient bases could possibly decrease the dependence on the battery supply as a probable substitute resolution to state the energy efficiency problem. In research work [132] discusses the resource distribution problem for EH-powered WBANs (EH-WBANs). Major aim of this research is to increase energy efficacy level of EH-WBANs with joint collaboration of transmission mode, relay selection range, assigned time slot, transmission power and the energy constraint of each sensor. System throughput in D2D underlying network systems is confined by means of battery lifespan budget and to extend the lifetime of networks, the harvesting of energy has been realistic to D2D underlying networks. In D2D underlying cellular networks, time allocation and joint power control was considered in which the D2D users were driven by means of energy harvested from uplink transmission of a CU. Moreover, the energy harvested is reduced by means of restricted transmit power and lifetime of CU is reduced without harvesting of energy. Here in [83], a novel scheme is considered wherever both CUs and D2D transmitter (Tx) harvest energy from hybrid access point (HAP). Energy Harvesting-based D2D communication Heterogeneous Networks (EH-DHNs) is a heterogeneous means of cellular network, where DUEs harvest energy from innumerable kinds of energy bases and usages the harvested energy for D2D communication, and multiplex the spectrum resource block of Cellular User Equipments (CUEs) in the underlay mode. In EH-DHNs, the DUEs using EH function could harvest energy from the ambient RF source, conversely, the amount of the harvested energy or the interval of energy harvesting is associated to the energy efficacy of D2D links [47]. Also, the energy saving has become vital factor for UAV communications particularly in IoT based applications. To extend the life period of sensor network, wireless energy consumption was reduced and under a further concrete means of energy consumption model of UAV, it was pointed out that propulsion energy is quite large than communication based energy. Hence for reducing the dominating aspect of energy consumption, researchers adopted minimal flight time of UAV while permitting sensors to upload magnificently particular amount of data [140].

1.5.2 Wireless Power Transfer

This section will provide a brief overview about the implementation of wireless power transfer techniques.

Enhanced use of wireless sensor nodes are proficient of collecting and transmitting information by means of wireless communication channels whereas frequently located in places that are demanding to admit. This drives the research area into innovative means of results concerning energy harvesting (EH) and wireless power transfer (WPT). This basically adopts battery free means of sensor nodes. RF EH and WPT are significant technologies with the prospective to power IoT devices and smart sensing designs comprising nodes that requisite to be wireless, maintenance free, and adequately low in cost to support their usage practically everywhere owing to the omnipresence of radio frequency (RF) energy. Research in [50] introduces an ultra-low power 2.5 μW extremely assimilated assorted signal system on chip (SoC), for multi-source energy harvesting. A comprehensive review of the wide range of WPT systems that have been examined in previous research works which could enhance the overall performance of the system [44].

Novel design approaches to electromagnetic field manipulation based systems were introduced in [109]. This could create the progressive forms of wireless power transfer. At this time the expansion process of innovative physical effects and constituents for wireless power transfer were reviewed and explored the techniques depending on coherent perfect absorption, parity–time symmetry and exceptional points, and on-site power generation. Similarly examines the use of meta-materials and meta-surfaces in wireless power transfer and moreover, the use of acoustic power transfer technology. Owing to the drawbacks of low power density, high cost and heavy weight, the development and application of battery powered devices faces unprecedented technical challenges. Wireless power transfer (WPT) offers a band novel approach to the energy achievement for electric-driven devices, therefore assuaging the over-dependence on the battery challenges as a novel array of energization. An overview of the WPT techniques were presented in [147] with an importance on operational mechanisms, technical based challenges and classical applications.

1.6 Thesis Organization

The rest of this thesis is divided into the following sections. Chapter 2 gives an overview of the existing work on energy harvesting networks, importance of energy harvesting in wireless sensor networks and performance analysis of energy harvesting systems. Wireless power transmission techniques are introduced and explaining how the energy can be stored in different system for various applications and finally the large deviation theorem.

In Chapter 3, a detailed investigation was carried out to analyze the required energy harvesting (EH) rate for satisfying the QoS requirements when a level of energy-outage is allowed in a point-to-point EH-based communication system equipped with a finite-sized battery. The amount of energy used from the battery is determined by the end user's desired QoS as well as by channel state information. The strength of the power source in this case, solar determines how much energy is stored the battery, which is independent of the fading channel conditions and the desired QoS. It is difficult to determine the exact status of the available energy in the battery since energy entering the battery and energy leaving it are independent processes. Energy outages are unavoidable in such circumstances. A simple analytical framework is introduced for evaluating the effectiveness of EH communications, presuming that the system can withstand some degree of energy-outage to occur.

In Chapter 4, a mathematical framework is developed for the investigation of system performance under energy-outage limitations using time-switching circuit. Derived a closed-form analytical expression for the possibility of an energy outage and the rate at which the transmit node's battery is being depleted of energy. Obtaining a formulation for the sensor node's transmit power that satisfies the target energy-outage probability. A virtual energy queuing model is also suggested as a strong tool for the performance assessment carried out, making use of the large deviation principle theorem. Analytical and numerical results are used to investigate the influence of important variables on performance, such as the RF source power and the distance between the RF source and the sensor node.

In Chapter 5, an RF-EH model using a time-switching protocol is implemented to enhance the quality of service (QoS) in SWIPT networks. Also, a numerical approach is incorporated to evaluate the performance of the proposed RF-EH model in terms of different evaluation parameters such as time-switching protocol, transmit power and outage.

Finally, Chapter 6 contains a discussion of potential future study directions as well as the dissertation's final remarks.

Chapter 2

Related Works

The previous chapter provided the background of the research study, motivation, significance, aim and objectives of the study. It also provided an overview of energy harvesting (EH) networks and wireless power transfer (WPT) systems. In this chapter, existing studies on EH, techniques exploited for EH in wireless networks, techniques exploited for WPT and performance analysis of existing EH for wireless systems will be investigated.
The primary energy harvesting technologies can be classified by the hierarchy shown in Fig.2.1 [18]. The figure shows the four main energy harvesting systems: solar EH, thermal EH, RF EH and motion EH. Each method has its harvesting component, such as PV cells for solar EH, thermoelectric generators for thermal EH, RF-electromagnetic for RF EH and mechanical-electromagnetic for motion EH. This thesis focuses explicitly on solar EH and RF EH harvesting techniques.

2.1 Energy Harvesting Batteries

Energy harvesting batteries are a type of rechargeable battery that can extract and store energy from their surrounding environment, such as solar, thermal, or mechanical energy. These batteries are increasingly becoming popular as they eliminate the need for constant battery replacements or recharging by conventional methods. They can be used in various applications such as wireless sensor networks, wearable devices, and remote monitoring systems, where it may be challenging or inconvenient to change the battery or recharge it regularly.

The performance of energy-harvesting batteries largely depends on the strength and stability of the energy source and the efficiency of the energy conversion mechanism [17]. The battery capacity and its ability to store energy are crucial factors determining the system's overall energy harvesting efficiency. However, it is challenging to estimate the exact status

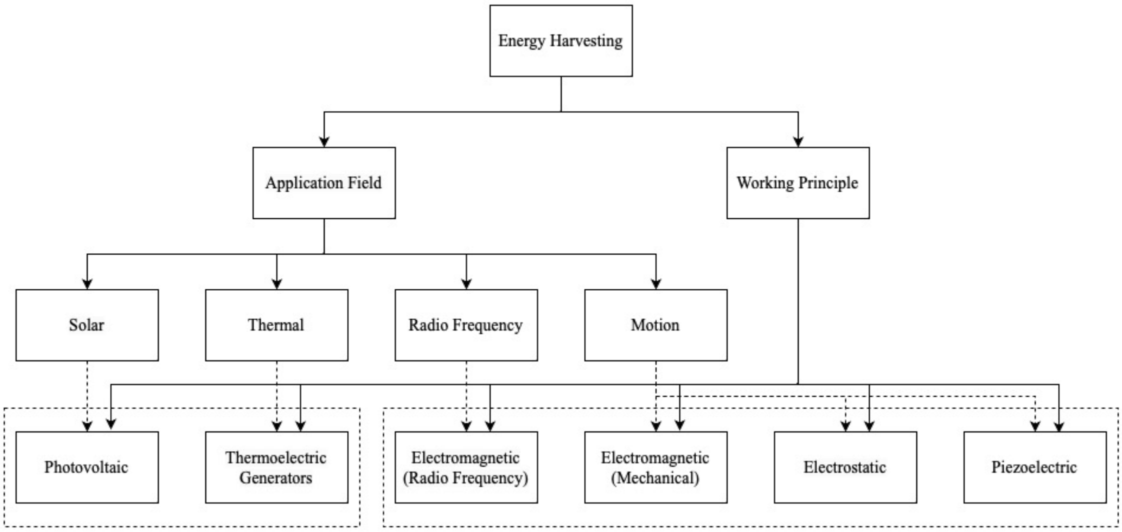


Fig. 2.1 Hierarchy of primary energy harvesting methods [18].

of the available energy in the battery due to the independence between energy arrival and consumption. As a result, careful consideration is required when designing an energy harvesting system to ensure that the required energy is available when needed.

Despite the challenges, energy-harvesting batteries offer several advantages over conventional batteries, such as reduced maintenance, increased reliability, and decreased environmental impact. With advancements in energy harvesting technologies, these batteries are expected to become more efficient, cost-effective, and widely used in various applications that require sustainable and autonomous power solutions [37].

2.2 Fading Channels

Fading channels are a common phenomenon in wireless communication systems, where the signal strength fluctuates due to variations in the propagation environment. These variations can be caused by several factors, such as reflection, diffraction, and signal scattering as it travels through the channel. As a result, the received signal at the receiver end experiences random variations in amplitude, phase, and frequency. This randomness can result in distortion, attenuation, and even complete signal loss, reducing system performance and reliability.

Fading channels can be classified into two categories, slow fading and fast fading, based on the rate of signal variations. Slow fading occurs over a more extended period, typically caused by environmental changes, such as the user's movement or terrain, and can be compensated for using equalization techniques. On the other hand, fast fading occurs rapidly and is usually caused by multipath interference, where multiple copies of the signal reach the receiver with different delays and phases. Fast fading can be mitigated by using diversity techniques, such as frequency diversity, time diversity, and space diversity.

Fading channels are a significant challenge in wireless communication systems, and several techniques have been developed to mitigate their effects, such as error correction codes, interleaving, and modulation schemes. Wireless communication systems can provide reliable and robust communication links by understanding the characteristics of fading channels and developing suitable mitigation techniques, even in challenging environments [135].

2.3 Battery and User QoS

Battery quality of service (QoS) and user quality of service are two critical factors impacting energy-harvesting communication systems' performance. Battery QoS refers to the amount and availability of energy stored in the battery, directly affecting the system's ability to transmit data. The energy consumed by the system depends on the required user QoS and the channel state information. Therefore, the energy harvesting rate must be adjusted to meet the user's QoS requirements while ensuring that the battery is not depleted, causing an energy outage.

User QoS, on the other hand, refers to the level of service provided to the end user, such as data rate, latency, and reliability. The QoS requirements vary depending on the application, and ensuring that these requirements are met while operating under energy constraints is crucial. Energy harvesting communication systems must optimize energy consumption and harvesting rates to provide the required QoS while maintaining the battery's energy levels.

Estimating the exact battery status in energy harvesting systems is challenging due to the independence between energy arrival and consumption. Therefore, sophisticated algorithms and mechanisms are required to dynamically regulate energy harvesting and consumption rates. By considering both battery and user QoS, energy-harvesting communication systems can operate optimally under energy constraints and provide reliable and sustainable communication solutions [22].

2.4 Principles of Energy Harvesting

In this section existing EH networks for wireless systems are reviewed.

A solar EH with wireless charging framework for wireless sensor networks (WSNs) is presented in [122]. In the presented framework, the cluster heads were supplemented with solar panels for scavenging solar energy while the remaining nodes were powered through wireless charging. This framework reduced battery exhaustion by 20% and achieved 25% savings in vehicles' moving price. Moreover, it receded the number of expensive mobile chargers through deploying more cheaper solar-powered systems. [91] discussed EH in WSNs. The authors proposed a neoteric EH clustering protocol depending on hierarchical clustering. The proposed EH protocol exploited solar EH. Exploitation of solar energy enhanced the WSN's lifetime and outperformed the available clustering protocols. Simulations affirmed that this approach boosted the network efficacy and moreover displayed a robust ability for balancing energy consumption. [23] presented a double-polarized electromagnetic EH system involving a rectifier and an absorber surface. The absorber's unit cell was developed using channeling features and bow-tie dipoles which made it suitable for efficiently integrating and transferring the gathered power from several unit cells. This system displayed effective EH performance and achieved greater than 60% of efficacy. [8] presented a solar cell antenna for EH and wideband communication. The presented design contained an EH array employed for achieving both optical EH and wireless communication simultaneously. This design would be promising for clean energy, environmental protection and green communication. [42] discussed solar EH using MAC protocol in WSNs. The presented approach eliminated the necessity of frequent battery replacement. Experimental investigations affirmed that this approach displayed remarkable performance when compared to available EH-based protocols with regard to delay, collision rate, energy consumption and throughput.

A smart solar EH system for WSNs is proposed in [56]. The presented system comprised a control circuitry, lithium (Li) battery and a solar panel. It exploited hardware rather than software for charge regulation of Li battery. This system exploited solar energy under adequate sunshine conditions and adopted the Li battery as a supplementary power supply under no sunshine, rain and overcast conditions. The exploited Li battery charging policy ingeniously prevented the charging-discharging cycle and thereby led to prolonged battery lifetime. Experimental investigations indicated that this system offered high efficacy, less power loss and high reliability. [144] proposed a cooperative fusion of RF EH and devoted WPT. It exploited a low-threshold constricted dynamic range rectifier for optimizing ambient EH and simultaneously reflecting a devoted power incidence. Experimental investigations confirmed its effectiveness for WSN operations. [45] discussed EH using MAC protocol in WSNs. The presented protocol here exploited the channel's idle time for autocharging sensor batteries. Under data unavailability conditions, the sensors were autocharged through the energy emitted by energy transmitters. Simulations manifested that the presented protocol enhanced the EH rate by 150% compared to previously reported MAC protocol. Additionally, it augmented the WSN's lifetime owing to active energy transmission technique. [51] presented an augmented hierarchical clustering scheme for EH mobile WSNs. In this scheme, the EH rate was considered in the cluster head selection procedure. The conducted simulations declared that the presented clustering scheme performed better with regard to EH and WSN's lifetime enhancement compared to previously reported clustering techniques. [148] described EH in WSNs. Extensive experiments were executed for achieving EH. Simulations manifested that this approach offered 15% amelioration in EH.

A novel form of energy management system is established to effectively collaborate a hybrid form of energy storage system positioned on the pumped hydro storage system along with batteries [75]. Suitable arrangement and forecast way of energy storage system for the congestion managing is offered in [77]. At this time the supreme imperative aspects measured were the capacity and rated power. To improve the energy efficiency and battery lifespan time for the battery semi-active hybrid management, an optimization centered control methodology is offered in [100]. Model Predictive Control based method is proficient in [113] to exploit the battery lifespan and the storage capacity. Non dominated-Sorting-Genetic-Algorithm II has been organized for planning an optimal observation of electrical energy storage scheme for prevalent island distributed network [123]. A mathematical epitome of the arrangement of the battery storage systems were projected with several types of batteries in which the effects of battery brands and the capacity deficiency topographies on the optimal capacity features of the battery energy storage systems and the power forecast patterns of the hybrid power systems were studied [125].

For the finest location of the battery energy storage system in the delivery system to diminish the distribution system losses, a loss sensitivity centered system has been estimated. Correspondingly contributes an effective technique for stipulating the optimal extent of the battery energy storage system with the support of particle swarm optimization procedure [145]. By embracing a multi objective optimization process positioned on an amplified way a decision sustenance tool for energy storage choice standards is recommended in [80]. The prospective use of LiFePO4 battery energy storage systems were defined to contribute in the FFR market of the UK National Grid. To enhance the energy stowage dispatch program for demand charge management in a grid connected and united photovoltaic battery storage system, a linear programming routine has been applied. Here the optimization system is outlined as a linear program and it controls day ahead PV power output and the load estimations with reliable updates to describe the appropriate time to charge or discharge the battery focus to fundamental dynamical and electrical performance bounds of PV+

system [82]. The energy management approach is generally combined with optimization to certify the stability of load supply demand and to decline the cost of energy production rate [25]. For reducing overall energy storage system size and extend the battery life cycle, the ultracapacitor hybrid energy storage has been suggested as a solution where ultracapacitor acts as a power buffer to charge or discharge the peak power [126]. Two scenarios of community energy storage ownership were proposed in [139] which demonstrates a cost-effective system policy for all Lithium ion batteries and vanadium redox flow battery for both Energy Arbitrage and Energy Arbitrage - Peak Shaving scenarios. An affine arithmetic-based multi-objective optimization method was suggested for the optimal action of energy storage systems in dynamic distribution networks with certain uncertainties.

2.5 Energy Harvesting Enabled Communication Systems

In this section existing works or techniques exploited for performance analysis of EH systems are presented.

The cognitive radio (CR) network's performance is investigated in [73]. This work assumed that the CR node performed EH using RF signal and spectrum sensing simultaneously through energy splitting component. Throughout the study, it was presumed that CR harvested energy from the preliminary user (PU) signal. This work captured the PU's behavior in terms of disappear and re-appear probabilities through monitoring its influence on the total energy harvested and CR performance. Here, sensing method under Nakagami-m fading channel was inspected through deriving false alarm probability and detection probability. Furthermore, performance of adopted system framework was examined in terms of surplus energy remaining for further transfer and outage probability while taking into account the collision parameter in PU. Performance was also investigated with regard to net energy harvested, outage probability (OP), average throughput and net rewarded energy. Through varying distinct sorts of parameters like sensing time, decision threshold, collision probability, etc. a graphical investigation of energy harvesting problem was presented for throughput maximization. By correlating transmission power with OP it was noticed that the augmentation in transmission power over a certain time interval reduced the OP keeping other variables constant. [71] discussed performance assessment of EH directed wireless relay networks. For enhancing coverage and capacity, a relay-supported network with EH and spectrum sensing was adopted for delivering better service quality. The relay was deployed for assisting communication between source-destination entities and decoding data/harvest energy from approaching signals simultaneously through a power partitioning scheme. Two strategies were proposed for EH relaying structure with regard to amount of relay transfers and EH capacity. The validity of achieved analytical results was manifested using numerical simulations.

A graph-oriented approach for EH-WSNs performance analysis is proposed in [97]. Here, system topology was molded by arbitrary graph and throughput of EH-WSNs was described using this graph function. In the exploited arbitrary graph, the selection of likelihoods for edges and nodes was dependent on traffic intensity, transmission range, monitoring requirements, intrusion details, and EH intensity. It was manifested from simulations that this approach effectively analyzed the EH system's performance. [70] presented an approach for assessing the performance of EH systems. The employed EH-WSN framework contained several source nodes (SNs), power stations, a jammer, base station and several passive eavesdroppers. The employed power stations transferred RF energy to SNs while the SNs transmitted data to their respective base stations. A jammer generated jamming signals against several eavesdroppers. Performance inspection of the presented approach clarified that it outperformed the classical approaches. [36] presented a performance investigation of EH multi-antenna relay systems with distinct antenna selection methods. In the presented work, the energy-constrained relay initially harvested the energy from the acquired signal using a power partitioning technique and further exploited that energy for broadcasting the acquired signal to its destination. For evaluating the EH network's performance, OP expressions were derived under dissimilar Rayleigh fading channels. Experimental findings declared that the relay position had a vast impact on optimal power-partitioning ratio and outage performance.

The performance of EH-based bidirectional multi-relay network is analyzed in [106]. In this work, the chosen amplify-and-transmit relay nodes harvested energy through time-switch relaying from destination and source nodes by adopting the 'harvest-and-utilize' approach without preserving it. The network performance parameters like ergodic sum-rate, throughput and outage probability were investigated considering two instances of relay selection. It was clarified from simulation outputs that through appropriate relay selection and optimal time-switching variable, better outage and throughput performance could be gained. [67] presented an adaptive EH method and evaluated the secondary wireless network's performance with regard to throughput and OP. The impacts of EH efficacy on secondary network's throughput and outage performance was explored. Contrary to fixed duration harvesting, the harvesting duration in proposed method was adaptively adjusted based on harvesting circuit's efficiency, channel state of interfering links and channel state of harvesting links. Experimental and simulatory outputs clearly substantiated that the presented adaptive EH method outperformed the fixed duration based EH approach with regard to outage performance. [110] analyzed an EH based multi-antenna relaying network's performance. The analysis executed in this work considered a realistic fading scenario wherein the destination-relay and source-relay links experienced independent Rician and Nakagami-m fading respectively. Furthermore, the EH network's ergodic throughput and outage performance were examined. Results ascertained that the presented multi-antenna relaying network was capable of augmenting the EH capability and thereby ameliorating the overall network performance. [118] examined the EH-based bi-directional relay network's performance under Nakagami-m fading channel. Here, a bi-directional relay system was considered wherein two sources interchanged data through a wireless powered relay. Here, data transmission was accomplished in three stages through adopting a time switching structure. Numerical results illustrated that the presented approach could be a promising candidate for WSNs.

The outage performance of cognitive EH relaying system is investigated over fading channel (Nakagami-m) in [141]. For ensuring transmission reliability, cognitive transmitter communicated with the receiver through the relay selected using an expedient relay selection technique. Furthermore, two EH protocols namely time switching and power splitting were exploited. Cognitive EH relaying system's OP was derived and impact of time switching rate, data rate, amount of PUs and fading coefficients on cognitive system was analyzed. Findings clarified that system performance could be ameliorated through augmenting the amount of relays and fading coefficients. Additionally, transmission quality could be enhanced through diminishing the time switching rate. [85] analyzed the multihop EH cognitive relay system's outage performance. Presuming the multihop system as secondary network, this work derived an expression for outage probability experienced by the secondary user (SU) considering the impact of interference power from PU. The developed OP framework was also utilized for assessing the influence of certain key variables on SU link's reliability in an EH network. Furthermore, effect of diverse parameters like path loss index, harvest-to-transfer time duration rate, transmit power and EH efficiency on optimal relay position was analyzed. It was identified from analysis that the outage amelioration was achieved upon placing the relay at the optimum position. [72] presented a rigorous investigation of time-switching based EH approach's performance for a bidirectional half-duplex WSN in Rician fading channel. This work considered the hardware detriments at relay and source nodes and derived asymptotic and exact forms of OP, error-rate and achievable throughput at every destination node. Numerical algorithms helped in identifying the best EH strategy. [104] analyzed the performance of an EH-equipped double-hop relaying network. Here, solar energy was considered as the EH source at the transmitter and interference energy within the radio frequency as the EH source at the relay node. Further, time switching method was employed for switching between decoding data and EH. In this work, the 'harvest-utilize' approach was implemented and effects of EH in ameliorating the relaying system's performance was analyzed. Experimental findings declared that the EH at the relay and source led to substantial amelioration in throughput.

The performance of collaborative cognitive network employing an EH bi-antenna relay system is analyzed in [108]. Here, energy from secondary source's RF signals was harvested before simultaneously executing the broadcasting and receiving processes. This work considered Rayleigh fading for deriving asymptotic expressions of OP and throughput. Experimental investigations confirmed that the developed EH approach outperformed the competing collaborative cognitive networks without EH structure with regard to throughput and OP. [121] explored the wireless EH multihop cluster-dependent network's performance over Nakagami-m channels. In this work, three relay selection methods were presented. The first method was exploited chiefly for selecting the relay capable of harvesting the colossal energy for data forwarding. The second one was utilized mainly for choosing relay capable of providing supreme information channel gain and the third method for choosing relays in consecutive clusters depending on the optimum data link and optimum EH link. Performance assessment with regard to OP of three methods in Nakagami-m fading scenario illustrated the efficacy and superiority of this approach. [15] investigated the wireless EH network's performance. This work considered Rayleigh fading condition for deriving an expression for achievable system throughput and OP. The effect of relay nodes on ergodic capacity and OP was also analyzed. Simulation outputs illustrated the optimum EH duration for which system achieved minimum OP and maximum throughput. [30] investigated the performance of collaborative NOMA with EH system. In this work, the energy efficacy, ergodic rate and coverage probability were derived using stochastic geometry approach. Numerical outputs validated the deduced expressions and manifested the adopted EH system's effectiveness in ameliorating the energy efficacy, ergodic rate and coverage probability.

2.6 Simultaneous Wireless Information and Power Transfer Communication Systems

In this section existing works on or techniques exploited for WPT are reviewed.

An energy switch (Wireless Power Transmission) is a breakthrough generation that gives electricity to communique gadgets without the strength devices. With the tremendous improvement being made currently, this period has been attracting a wireless of attention of worldwide scientists and R&D firms. These days, the use of cell appliances which consist of cellular telephones, PDAs, laptops, drugs, and other handheld gadgets, geared up with rechargeable batteries has been appreciably spreading as an energy harvesting concern. It is called as electromagnetic strength is related to the transmission of electromagnetic waves. Tentatively, we can use all electromagnetic surfs for a wireless power transmission (WPT) [40].

The distinction among the wireless power transmission (WPT) and verbal exchange schemes is the simplest WiFi. Maxwell's theory and Equations suggest that the electromagnetic place and its strength disperse to all hints. Although we can transmit the power in a communication device, the transmitted electricity is suitable to all directions. Even though the received energy is WiFi for a transmission of facts, the overall performance from the transmitter to receiver is quite low. Therefore, we do no longer name it the wireless power transmission system [151]. Wireless technology time in the future wireless of the previous couple of many years, improved trouble over the environmental effect of the global warming-based transportation system, collectively with the hazard of top oil's has caused come back interest in an electric powered transportation system. Battery-powered electric motors (EVs) seem like a great option to trade in with the energy disaster and international warming because they have zero oil consumption and zero emission. Furthermore, we're pretty abruptly attaining the quilt of the cheap oil technology. Therefore, the want for possibility growing and the charge opposition of options towards oil is turning into more and more sensible [11].

Electric powered cars vary from one to another fossil gasoline-powered motors in that the energy they consume can be sourced from a sizeable variety of property, which includes fossil-fuels, nuclear energy assets together with the grading strength, solar-energy, and the wind-energy are aggregate of these. But it's so far generated, this strength is then transmitted to the vehicle through use of overhead strains, an energy transfer along with inductive charging, or a right way connection via an electrical cable [93].

The power may also be stored on board the car using a battery system, flywheel system, or incredible capacitors. Automobiles using engines operating on the working principle of fuel combustion can generally simply obtain their power from a one or multiple resources, normally non-sustainable natural sources. A key gain of electrical or hybrid electric powered motors is regenerative braking and suspension, their capacity to recover energy generally misplaced all through braking as power to be rearranged to the consigned battery system. But EVs are especially trusted the external energy guide.

The identification of OFDM signal using neural network based model is discussed in [146]. The identification of the OFDM signal is amongst different other signals such wavelet signal, single carrier signal and an OFDM signal. The algorithm used in this proposition is

HGWO algorithm whereby the algorithm is responsible for optimisation of the weights and threshold. There is a need for manual determination of formation of network in this approach. [48] details a deep learning based wireless signal identification method based on data of spectrum towards monitoring values in spectrum. [89] briefs a method based on convolution neural networks deep learning for radio fingerprinting using I/Q sequences as examples. This particular design helps in finding particular devices and the features which are involved in finding transformations of wireless signals.

The disadvantage of the method involved in the research is that the procedure is time consuming and can result in over fitting which is to be avoided. The available downtime in the bursty communications of a wireless LAN based on semi-markov model is being depicted in [27]. The method discussed in above paper displays trade-off between accuracy of prediction and complexity of computation. The work in [133] involves finding spectrum of structure for defining signal in applications involving Cognitive Radio. This approach involves combination of cyclo-stationary feature map along with coherence function towards achieving classification effectively. This method is capable of good performance at medium Signal to Noise ratio and ineffective in higher SNRs. [112] introduces finding the wireless standard based signals which exists in the absence of any previous data with the use of Fast Fourier Transforms, Power Spectral Density. The technique used in the approach is Support Vector Machines using different parameters for configuration such as type of kernel, volume of I/Q samples and quantity of training input. [54] presents a summary of identification of modulation and recognition of various wireless technologies. This paper involves review of different methods used for recognition of signals. [96] discusses method on deep convolution neural networks for identification of signals. The validation of the evaluation is done in the boundaries of industrial surroundings.

The energy-effective mobile charging for WPT in Internet of things (IoT) systems is introduced in [69]. An efficient technique called best charging efficacy was proposed for diminishing energy consumption. It was identified from experimental investigations that the presented approach outperformed the available algorithms with regard to delay, charging cost and efficacy. [58] presented a neoteric effective sandwiched WPT system for battery recharging. The presented design exploited different sandwiched topology for receiver and transmitter coils. Furthermore, a bilateral coil pattern was exploited in the receiver which assisted in harnessing greater power within the constrained size. Experimental observations indicated that this system provided 88% transmission efficiency and higher power (about 5W). [131] presented a magnetic resonance coupling-dependent WPT system. The presented WPT system contained a perpendicular transmitter-receiver structure and a bipolar transmitter. The bipolar transmitter assisted in substantially diminishing the output power variation. Furthermore, the presented WPT system was even capable of effectively handling the power zero phenomenon and achieving greater power transfer efficacy (about 80% under properly aligned operating situations and 70% under misaligned operating situations). [107] introduced a WPT system with an elevated power transfer density (PTD). It achieved an elevated PTD through operating at 6.78 MHz switching frequency and by exploiting innovatively devised matching networks which utilized parasitic capacitances as part of WPT mechanism. It was noticed from results that this system was capable of transferring 589 W power and achieving 19.6 kW/m2 PTD.

2.7 Large Deviation Theorem

Large deviation theoretical approach mainly includes the possibilities of rare such occurrences which could be exponentially small as a function of several parameters like number of random elements of a system, time over which a stochastic system is noticed.

The theory has applications in several diverse scientific fields, extending from queuing theory to statistics and from finance to engineering level. It is furthermore increasingly deployed in statistical physics for learning both equilibrium and non-equilibrium systems. The initial part of these notes presents the rudimentary features of large deviation theory at a level suitable for advanced undergraduate and graduate students in “physics, engineering, chemistry, and mathematics” [114].

The main focus there is on the modest but powerful concepts behind large deviation theory, specified in non-technical terms, and on the application of these ideas in simple stochastic practices, such as sums of independent and identically dispersed “random variables and Markov processes”. Certain physical applications of these processes are enclosed in exercises controlled at the end of each segment.

Secondly, the problem of statistically estimating large deviation probabilities is treated at a very basic level. The ultimate idea of prominence sampling is presented there together with the exponential change of measure. Other numerical methods based on sample means and generating functions, with applications to “Markov processes”, are also covered.

Let $Y_1, Y_2, \ldots$, be a sequence of independent and identically distributed (i.i.d.) random variables with mean $\mu = \mathbb{E}[Y_1] < 1$ and let $M_t = \frac{1}{t}(Y_1 + \ldots + Y_t)$ denote the empirical mean. From the Weak Law of Large Numbers, it is known that for any $a > \mu, \lim_{x \to 2} P(M_t > a) = 0$. But how fast is this convergence sustained remains a question. This falls into the range of the theory of large deviations. Large deviation theory includes a set of techniques for turning difficult probability problems dealing with a class of rare events into analytic problems in the calculus of variations.

To find out the convergence rate of the above problem, we provide the following calculations. For an integer s (such that t/s is an integer), we can divide the set $Y_1, Y_2, Y_3, \ldots, Y_t$ into multiple subsets of $\{Y_{q\frac{t}{s}+1}, Y_{q\frac{t}{s}+2}, ..., Y_{(q+1\frac{t}{s})}\}, q = 0, ..., s-1$.

For each integer s,

$$P(Y_1 + Y_2 + Y_3, ..., Y_t > at) \tag{2.1}$$

$$\geq P\left(Y_1 + Y_2 + ... + Y_{\frac{t}{s}} > a\frac{t}{s}, ..., Y_{n-\frac{n}{k+1}} + ... + Y_t > a\frac{t}{s}\right) \tag{2.2}$$

$$= P\left(Y_1 + Y_2 + ... + Y_{\frac{t}{s}} > a\frac{t}{s}\right)^s \tag{2.3}$$

Owing to the i.i.d. property. Therefore, the conclusion is that convergence rate is at the most exponential manner. Then, by means of fixing positive parameter $\theta > 0$,

$$P\left(\sum_{1 \leq i \leq n} Y_i > at\right) = P\left(e^{\theta \sum_{1 \leq i \leq t} Y_i} \geq e^{\theta at}\right) \tag{2.4}$$

$$\geq \frac{\mathbb{E}\left[e^{\theta \sum_{1 \leq i \leq t} Y_i}\right]}{e^{\theta at}} \tag{2.5}$$

$$= \frac{\mathbb{E}\left[\prod_i e^{\theta Y_i}\right]}{(e^{\theta a})^t} \tag{2.6}$$

$$= \left(\frac{\mathbb{E}[e^{\theta Y_1}]}{e^{\theta a}}\right)^t. \tag{2.7}$$

From (2.4) and (2.5), it is derived by utilizing the Markov inequality. From (2.6) and (2.7), it is due to the reason that the random variables $Y_i, i = \in [1, n]$ are i.i.d. Hence, (7) is attained, which is an upper bound for the tail probability. For the bound to be meaningful and useful, $\mathbb{E}[e^{\theta Y_1}]$ needs to exist and $\frac{\mathbb{E}[e^{\theta Y_1}]}{e^{\theta a}}$ needs to be less than 1.

Here, the $\mathbb{E}[e^{\theta Y_1}]$ is a moment generating function (MGF) of Y_1 and it could be described by $M_Y(\theta^2)$. As the moment generating function plays a significant role in understanding level of effective bandwidth and effective capacity. The following definition is provided.

Let Y be any random variable and the moment generating function (MGF) of Y is denoted as,

$$M_Y(\theta) = \mathbb{E}[e^{\theta Y}] = \begin{cases} \sum_y e^{\theta y} A_Y(y), & \text{if Y is discrete with PMF } A_Y(y), \\ \\ \int_{-\infty}^{\infty} e^{\theta y} f_Y(y) dy, & \text{if Y is continuous with PDF } f_Y(y). \end{cases}$$

Here, the $M_Y(\theta)$ exists only when sum or integral could converge. Reason behind calling $M_Y(\theta)$ moment generating function is due to the Taylor expansion of $e^{\theta Y}$.

If assumed that it converges, then,

$$M_Y(\theta) = \mathbb{E}[e^{\theta Y}] = \mathbb{E}[1 + \theta Y + \frac{1}{2}\theta^2 Y^2 + \frac{1}{3!}\theta^3 Y^3 + ...] = \sum_{i=0}^{\infty} \frac{1}{i!}\theta^i \mathbb{E}[Y^i].$$

Moments, also referred to the term $\mathbb{E}X^i$, contain crucial information about the distribution. We can determine each moment of this distribution using the MGF. The one-to-one correspondence between MGF and the probability distribution of the random variable is another crucial characteristic of MGF. For any such distribution, there exists unique moment generating function which could characterize it. Also, for each moment generating function, there is a unique probability distribution it characterizes.

Let us recollect that we have found that $P\left(\sum_{1\leq i\leq n} Y_i > at\right) \leq \left(\frac{M_Y(\theta)}{e^{\theta}a}\right)^n$ in (2.7) is to be estimated $P\left(\sum_{1\leq i\leq n} Y_i < at\right)$, for some $a < \mu$. Then, by fixing negative $\theta < 0$, the following is attained,

$$P\left(\sum_{1\leq i\leq n} Y_i < at\right) = P\left(e^{\theta \sum_{1\leq i\leq t} Y_i} \geq e^{\theta at}\right) \leq \left(\frac{M_Y(\theta)}{e^{\theta}a}\right)^n. \tag{2.8}$$

2.8 Summary

This chapter discussed the diverse EH networks, existing techniques for EH in WSNs, WPT techniques and existing works on performance analysis of EH systems. Reviewing the existing works it could be inferred that though existing EH networks offered satisfactory performance, limited efforts were made in these studies towards analyzing the EH-based communication network's performance under energy-outage constraints. Since the harvested energy and the energy used for the communication are independent, with the latter depending on the quality-of-service (QoS) requirement and, in turn, on the channel state information, performance analysis of such EH networks could be extremely challenging. Therefore, estimating the exact real-time battery status at the transmitter could be tedious. To surmount this challenge, better approaches or mathematical models are required which are capable of effectively and precisely analyzing the performance of EH-based communication network's performance under energy-outage constraints.

Chapter 3

Performance Analysis of Solar Energy Harvesting Communications

3.1 Introduction

Massive sensing, holographic telepresence, and mixed or virtual reality, are few to name applications of the fifth generation (5G) networks and beyond [90]. These futuristic applications demand very high data rates, which in turn increases the need for very high energy resources [90]. This can result in higher carbon dioxide gas emission, and the need for long-lasting batteries. However, compared to the increasing need for higher data rate communication, device battery lifetime remains limited [90]. In fact, the gap between the battery enhancements and the increasing demand for energy continues to widen up. At the same time, in harsh and remote environments, replacing the non-rechargeable batteries of devices is either costly or not possible. These issues have motivated researchers to develop new solutions for increasing the lifetime of device batteries by leveraging renewable energy sources available in the surrounding environment, for instance, from solar and wind energy, through harvesting.

Indeed, energy harvesting (EH) has the potential to prolong the lifetime of energy-limited devices and networks, and improve their performance. By using rechargeable batteries, EH communication systems can have extended lifetime and, hence, are economical, efficient, and carbon-friendly. In general, EH-based systems are studied by tackling the challenges related to improving energy efficiency, power allocation and overall energy management [65]. In fact, most of the power allocation strategies designed for conventional communication systems without EH may not be optimal in EH-based communication systems [98].

Several works have been carried out by researchers to develop efficient power allocation algorithms better energy management strategies for EH communication systems, see e.g. [78] and [32], and references therein. In particular, the work in [78] advanced an energy management strategy for EH communication systems, with an optimal power allocation strategy to minimize the transmission completion time and maximize throughput. Therein, both offline and online transmission policies are proposed. In the offline policy, the arrival time and the amount of harvested energy are known to the transmitter before starting communication, whereas the online policy assumes that the arrival time and the amount of harvested energy are within the scope of knowledge of the transmitter during the course of transmission. For the offline policy, the said work proposed a directional water-filling algorithm to maximize throughput. For the online policy, the problem of minimizing the transmission completion time was addressed by using stochastic dynamic programming. Later in [32], an advanced power allocation algorithm for EH communication was proposed. In that work, maximizing throughput subject to the time-varying energy sources and the varying channel conditions was studied. Specifically, two forms of channel state information and harvested energy information were assumed at the transmitter, namely, causal and full, and a staircase water-filling algorithm was proposed based on the conventional water-filling algorithm with dynamic programming to achieve optimal energy allocation.

Using offline power allocation has received significant attention. In the literature, different system models were investigated to improve various performance metrics [137, 120, 119]. Particularly, an offline algorithm based on dynamic programming to minimize the transmission completion time under infinite battery capacity setting was proposed in [137]. Therein, the random arrival of data packets and the harvested energy at the source were considered. Optimal offline algorithms for EH communication under limited energy storage capacity and energy replenishment constraints are studied in [120]. Particularly, the short-term throughput maximization problem subject to deadline constraint is solved for a single-user scenario. The work in [120] was then extended to the multi-user Gaussian interference channel case in [119], where throughput maximization was solved via an iterative algorithm.

The focus of the above-mentioned works is mainly within the scope of having complete knowledge of the arrival time and the amount of harvested energy, which are unrealistic assumptions in practical scenarios. Indeed, one cannot ignore the fact that getting complete information of the dynamics of the EH process is not possible in practice. To make the problems tractable, online power allocation strategies for realistic EH communication systems were studied in different papers [104, 129, 41, 52]. Specifically, for different EH system models, various algorithms were discussed to optimize different performance metrics such as throughput. Particularly in [104], the performance of an EH-based relaying system equipped with both an EH battery and a fixed battery was analyzed, and closed-form expressions for the cumulative distribution function of the end-to-end signal-to-noise ratio (SNR) was derived. In [129], a competitive online algorithm was proposed, and its efficiency was verified to meet the requirement of maximizing throughput. Therein, trade-offs between high-rate and low-rate energy transmissions in fading channels as well as in static channels were developed and compared. In [41], online throughput maximization with EH source was developed as a Markov decision process (MDP) with “transmit" and “defer" actions. The ensuing policy, which depends upon the channel state and the energy queue length, was proven optimal over the set of actions where the source chooses to transmit or to defer transmission. Minimization of the packet loss in an EH communication system was investigated in [52], while considering that the available harvested energy must fulfill the power requirement to guarantee the real-time transmission success. Therein, a MDP and a stochastic online algorithm were applied to achieve optimal energy allocation.

More recently, advanced works on online transmission policies were carried out [46, 68, 9, 13, 5, 150, 4]. In [46], an optimal power control scheme in multi-user setting is modeled by a predictive approach using MDP. The Bellman dynamic programming equation was solved to minimize the distortion over a fading channel by estimating the energy used to transmit data. In the same work, a practical Q-learning algorithm was also proposed, providing a sub-optimal solution for the power management problem. It is to be noted, however, that dynamic programming suffers from limited scalability. In [68], throughput maximization in EH based communication was addressed by developing online sub-optimal power allocation policy. A Q-learning based SARSA (State-Action-Reward-State-Action) algorithm was proposed, and compared with an approximation SARSA based allocation policy developed to study the problem of computation and dimension associated with large systems. In [9], minimization of the average age of information (AoI) in EH communication systems online policy, was analyzed. The AoI denotes the amount of time elapsed since the most recent information is delivered to the end point. The said work tackled the problem by sending an update signal only if the AoI exceeds a certain threshold, and developed an optimal renewal policy by using Lagrangian approach for different system models. In [13], considering EH multiple access channels, a distributed fractional power (DFP) scheme was proposed to develop a lower bound for synchronized Bernoulli energy arrivals. Correlation between the throughput of asynchronous and synchronous Bernoulli energy arrivals was studied, and the DFP policy was proven to be near-optimal in increasing throughput. Energy overflow is considered under storage modeling by using the large deviation theory with Markov decision process to study the throughput of EH communication in [5]. The work in [150] presented the asymptotically optimal online power allocation solution that enhances the performance of the EH communication for infinite time slots and battery capacity. [4] proposed the statistical energy underflow limitation, and an energy management method to limit the battery from falling under a certain level.

The aforementioned works [78, 32, 120, 119] have an underpinning assumption that the resources are allocated in such a way that they guarantee the availability of a sufficient amount of energy in the battery for transmission at a given rate. This assumption is not always feasible, particularly when the fading channel is severely weak, or that energy available for the data transmission is not sufficient. When the transmissions have to be done with significantly high transmit powers, guaranteeing the QoS, e.g., throughput requirement, becomes very challenging. Hence, it is inevitable that energy-outage will happen, i.e., energy available in the battery is not sufficient. In such scenarios, the EH communication system cannot accommodate the required QoS. However, and as will be detailed shortly, we look at the problem from a different perspective by limiting the energy-outage to a very small value.

The energy-outage constraint was considered in several works [39, 149, 24, 53]. In [39], outage probability minimization of an EH system with strict delay constraints was studied by providing a fixed threshold transmission (FTT) scheme supporting online transmission policy. Therein, results of outage probability were shown to be close to a lower-bound on the admissible EH rates. The work in [149] extended the idea of [39] by proposing three power control policies, namely, linear power levels policy, joint threshold-based policy, and disjoint threshold-based policy, and investigated minimization of the outage probability. These policies were investigated to compare the energy arrivals between the source and the destination for finite-sized and infinite-sized batteries. In [24], two power allocation schemes were studied and compared using exhaustive search, and an upper-bound expression was derived using monotonic optimization for the outage probability of the considered EH system. The work in [53] made use of MDP to attain less battery outage in the considered EH system. The problem was studied under channel and battery status constraints for high SNR requirements.

3.1.1 Contributions

With regard to the previously discussed studies, a mathematical framework that can provide a useful tool to analyze the performance of EH communication systems when considering energy-outage at the transmitter is yet to be developed. As discussed, developing such a framework is difficult due to the independent randomness in the energy arrival for the harvesting and the fading channel conditions. Motivated by the above discussions, and in order to obtain more insight for analyzing the performance of EH-based communication, in this work we develop a simple and novel mathematical framework in which we expand the idea of energy-outage. Such an event happens when we need to transmit with a certain amount of energy, but that the battery does not have sufficient resources. To satisfy a target QoS, e.g., a minimum throughput level, high transmission power is required. In EH systems, energy consumed from the battery depends on the QoS required by the end user, and on the channel state information. At the same time, the energy arrival to the battery depends on the strength of the power source, solar in this case, and is independent of the fading channel conditions and the required QoS. Due to the independence between the energy arrival into the battery and the energy consumed from there, it is challenging to estimate the exact status of the available energy in the battery. In such conditions, energy-outage is inevitable. Assuming that the system can tolerate some level of energy-outage to take place, we introduce a simple analytical framework for analyzing the performance of EH communications. To the best of our knowledge, this is the first work that takes into account the aforementioned practical limitations to develop a simple mathematical framework in the context of energy-outage under QoS constraint, by invoking tools of LDP, to study the performance of EH-based communications. In more detail, the major contributions of this work are summarized as follows:

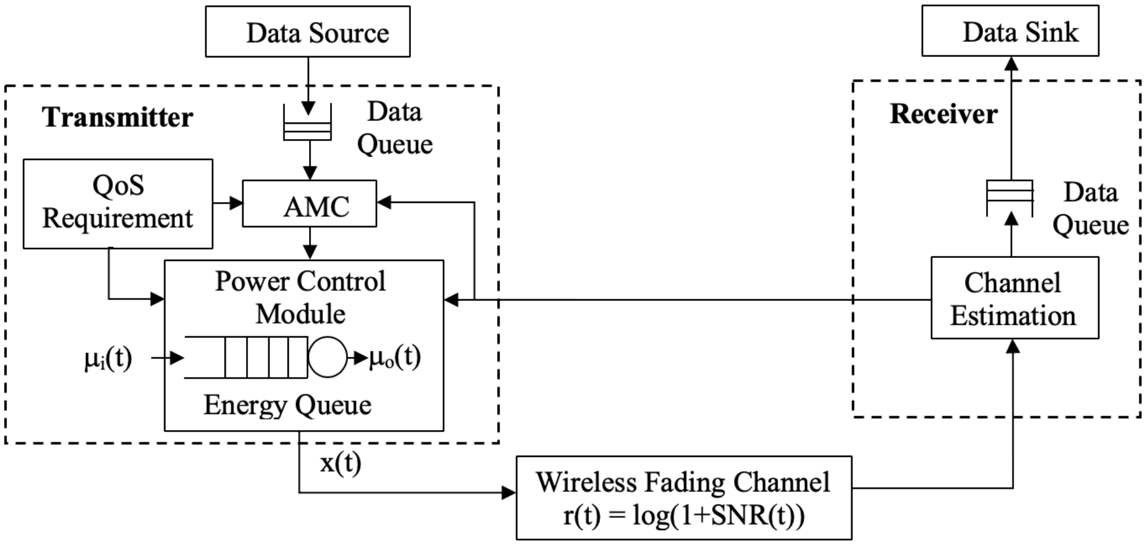
- A novel mathematical framework is proposed for the performance analysis of EH communications. The framework is developed based on a concept of energy-outage probability. Energy outage is experienced when there is no further energy for the system to utilize for the data transmission.

- We use the randomness property of energy-outage occurrence in the system to develop the mathematical framework. Specifically, the LDP theorem is used to model a virtual queuing system for the EH battery. The proposed virtual battery queuing model facilitates providing the assumptions needed for using LDP.

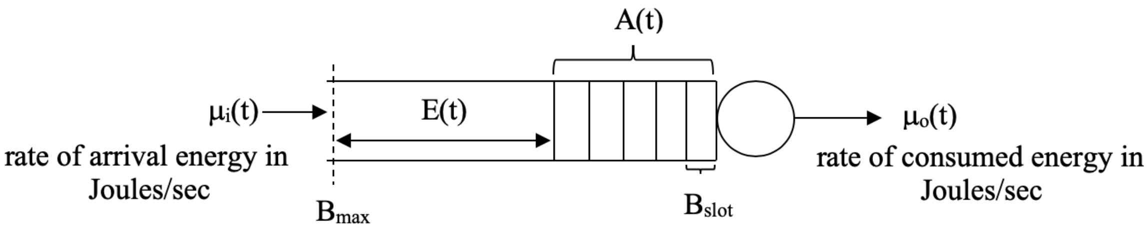
- Building upon the above two fundamental new ideas, we obtain a formulation that relates the channel capacity to the rate of the energy arrival. This gives a unique mathematical framework that directly relates the two concepts together, which are rather independent by nature. The performance of point-to-point EH communication is investigated using this mathematical tool.

- Simulation results are provided in order to understand how this mathematical framework performs.

The remainder of this chapter is organized as follows. Section 3.2 explains the system model in detail. The proposed mathematical framework is developed in Section 3.3. Then,



(a) System model.



(b) Battery structure within the power control module in (a).

Fig. 3.1 The energy-harvesting based communication system.

numerical results are presented and discussed in Section 3.4, followed by concluding remarks provided in Section 3.5.

3.2 System Model

We consider point-to-point EH-based communication as illustrated in Fig. 3.1. At the transmitter, data packets are stored in a data queue, and a battery is used to store the harvested energy. The energy arrival process and the source-to-destination fading channel are considered to be stationary and ergodic. We assume that the channel is Rayleigh block fading, and refer to it by coefficient $h(t)$, where t is to the time index. With the block fading model, the channel remains constant during a fading block, but varies independently from one fading block to another. The block duration is denoted by T.

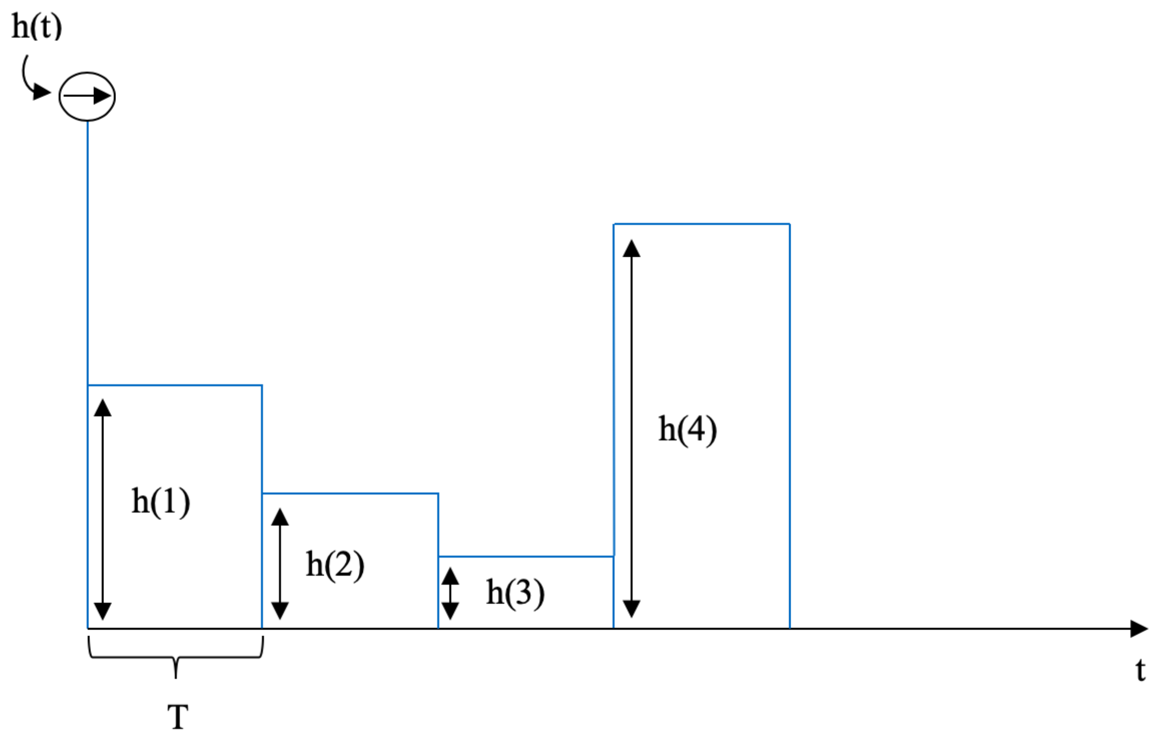


Fig. 3.2 Illustration of the channel coefficient variation in consecutive time slots.

At the destination node of the EH-based communication system under consideration, the signal captured by the receive antenna is given by

$$y(t) = h(t)x(t) + n(t),$$

where $x(t)$ is the transmitted signal, and $n(t)$ is the Gaussian random noise, assumed of zero mean and unit variance [78], [117].

Figure 3.2 illustrates how the channel coefficients $h(t)$ can vary in consecutive time slots.

3.2.1 Physical Battery Storage Model

Physical battery storage model for the EH source is considered. The model has an energy queue, where the arriving (harvested) energy is stored. Energy accumulated in the battery at time t is denoted by $A(t)$, and the empty portion of the battery is denoted by $E(t)$. The physical battery storage model represents the EH as the energy arrival process, and the energy consuming as the departure process. The model is depicted in Fig. 3.1(b), in which the empty portion of the battery can be mathematically represented by

$$E(t) = B_{\max} - A(t), \tag{3.1}$$

where $B_{\max}$, in Joules, denotes the maximum level of energy that the battery can withhold.

Energy accumulated in the battery at time $t+1$ can be formulated as

$$A(t+1) = \max\{0, \min\{B_{\max}, A(t) + \mu_{\mathrm{i}}(t)T - \mu_{\mathrm{o}}(t)T\}\}, \tag{3.2}$$

where $\mu_{\mathrm{i}}(t)$ is the rate of incoming energy into the battery, in the unit of Joules/sec, and where $\mu_{\mathrm{o}}(t)$ is the rate of energy spent out from the battery, in the unit of Joules/sec.

With the described model, the instantaneous rate, $r(t)$ in nats/s/Hz, can be expressed as

$$r(t) = \log\left(1 + \frac{h(t)\mu_{\mathrm{o}}(t)}{N_0 B}\right), \tag{3.3}$$

where N_0B is the noise density per unit bandwidth and B is system bandwidth.

The transmission power of the system is constrained by a maximum permissible level, $P_{\max}T$. Therefore, the outgoing power can never go beyond this level. The end user, on the other hand, has a QoS requirement that needs to be met, in terms of the minimum service throughput. Since the channel fading is a random process, meeting the QoS target requires that the transmission be done with high transmit power when the channel is severely weak.

However, it is challenging to guarantee that the required amount of transmit power is always available in the EH battery of the transmitter, not to mention that the said amount of power is difficult to measure given that the incoming energy into the battery is harvested from the environment, e.g., solar, and that it is difficult to predict whether it can be sufficient to allow proper adaptation of the data transmission to the variations of the channel so as to meet the user's QoS, or not.

Given that the accumulated energy in the battery is a complex function of all these parameters, it is challenging to estimate the exact battery status, and guarantee that the required QoS can be maintained during the whole data transmission process.

3.2.2 Problem Statement and Approach

As discussed above, due to the unknown status of the available energy in the battery, the required QoS cannot be guaranteed all the time. However, it is possible to meet the demand for at least a high percentage of time by allowing a small amount of energy-outage to happen in the system. Accordingly, a probabilistic approach is taken in our performance analysis problem, in which we leverage the LDP theorem to examine the probability of energy-outage occurrence in the battery. Large deviation theory is mainly concerned with the study of the asymptotic behavior of probabilities of rare events [102]. The theory proves that the decline of the probability of rare/tail events is exponential [102].

Let us assume $S_1, S_2, \ldots$ to be a sequence of independent and identically distributed (i.i.d.) random variables with mean $m = \mathbb{E}[S_1] < \infty$, and let $M(N) = \frac{1}{N}(S_1 + \ldots + S_n)$ denote the empirical mean. From the law of large numbers and the central limit theorem, we note that $\lim_{N\to\infty} \Pr\{M(N) > b\} = 0$ for any $b > m$. As N grows, the distribution of $M(N)$ converges to the expected value of the random variable. However, the convergence of the tail event probabilities when $N \to \infty$ is not provided by the law of large numbers and the central limit theorem. To fill the gap, convergence when $N \to \infty$ is examined by using the theory of large deviation.

Based on the LDP theorem, for a dynamic queuing system with stationary ergodic arrival and transmission processes [19], the accumulated portion of the queue length process $M(N)$ converges in distribution to a steady state queue length $M(\infty)$, leading to

$$\lim_{N\to\infty} \frac{\log\big(\Pr\{M(\infty) \geq b\}\big)}{b} = -I, \tag{3.4}$$

where I is the so-called rate function. The probability decays exponentially as $N \to \infty$ at a rate that depends on b [102], [143].

In the LDP theorem, the probabilities of events that are exponentially small are taken into account. Hence, invoking the tools of LDP in the current work is useful to find a statistical expression for the energy-outage under QoS constraint in the EH-based communication system. This inequality, which is based on the LDP theorem, can be estimated only when the battery capacity threshold is very large, using

$$\Pr\{M(\infty) \geq b\} \approx e^{-Ib}. \tag{3.5}$$

In our proposed design, we assume that energy-outage happens when the amount of energy needed to transmit the data packets is less than the outgoing energy $\mu_{\mathrm{o}}(t)T$.[1] We define the battery's energy-outage status P_{out} statistically, that is

$$\Pr\{A(t) < \mu_{\mathrm{o}}(t)T\}, \tag{3.6}$$

which explains the condition where the available energy/power is not sufficient to transmit the data, in which case the system suffers energy-outage.

[1] If energy accumulated in the battery exceeds the storage capacity, then battery overflow will occur, leading to energy waste. Hence, we need to deal with the problem of an unstable queuing system, which makes the analysis of the system under study, and EH-based communication in general, a challenging task, especially that many powerful tools and results from the queuing theory cannot be applied due to the instability. For smooth operation of the system, it is required to avoid energy loss due to battery overflow. Also, the battery overflow probability is equal to the probability of the virtual battery being non-empty. As our focus in this paper is on considering the event of energy-outage, situations with battery overflow are left for investigation in future work.

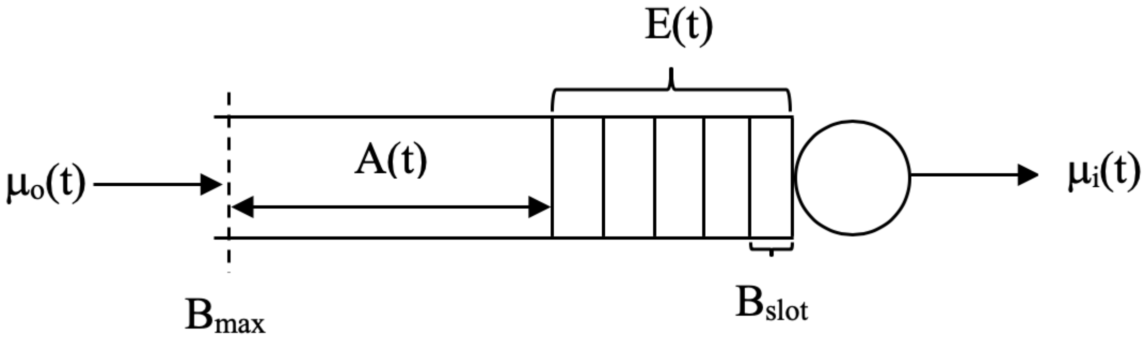


Fig. 3.3 The virtual battery queuing model.

Based on the physical battery storage model, the LDP tools and assumptions explained above can only work if the following inequality holds:

$$\Pr\{A(\infty) \leq \mu_{\mathrm{o}}(t)T\} \leq P_{\mathrm{out}}. \tag{3.7}$$

As per (3.7), when the accumulated energy is less than the minimum required outgoing energy, energy-outage takes place in the system. Hence, according to the LDP theorem, the inequality is inverse of what we want to implement in the framework, as discussed above. To solve the inverse inequality problem, we look into the empty part of the battery so that we can reverse this inequality and use the assumptions of the LDP theorem. Specifically, we introduce a virtual battery queuing model to use the inverse inequality. This helps us to investigate the system performance which is discussed in the next section.

3.3 Proposed Mathematical Framework

We aim to develop a simple mathematical framework based on assumptions of the LDP theorem. In order to implement the assumptions, we further propose a virtual battery queuing model. Using the proposed model, we estimate the energy-outage probability under QoS constraint. Also, the theory of effective energy harvesting is proposed to derive statistical relations between the QoS component, the Rayleigh fading channel conditions, and the level of incoming energy into the battery of the data transmitter.

3.3.1 Virtual Battery Queuing Model

The virtual battery queuing model is shown in Fig. 3.3. This model is basically a representation of the physical battery storage model with interchanged parameters such that tools of the LDP theorem can be invoked.

In the proposed queuing model, the roles of the harvested energy and the consumed energy are reciprocated to have a steady queue. Specifically, we exchange the roles of the EH process and the energy-consuming process, which were discussed in the conventional physical battery storage model in Section II. By exchanging the roles, the model allows for a flexible approach to energy storage and consumption, thereby improving energy systems' overall efficiency and sustainability. The virtual battery queuing model achieves this using inverse inequality and the LDP theorem. The inverse inequality states that the probability of an event occurring is greater than or equal to the exponential of the negative of its upper bound. This provides a useful tool for analyzing the behaviour of the virtual battery queuing model. In this way, the proposed virtual battery queuing model can be implemented to use the inverse inequality so as to make use of the LDP theorem.

Under this setup, the queue length, $E(t)$, can be explained by the energy consumption instead of the level of energy left in the battery. Correspondingly, energy left in the battery is given by

$$A(t) = B_{\max} - E(t). \tag{3.8}$$

As shown in Fig. 3.3, the energy arrival to the virtual queue is denoted as $\mu_{\text{o}}(t)$, $\mu_{\text{i}}(t)$ indicates the energy departure from the queue, and the threshold level of the queue is $B_{\max}$. Similar to (3.8), $E(t)$ for the virtual queue model can be defined as

$$E(t) = B_{\max} - A(t). \tag{3.9}$$

Also, the number of empty energy slots in the battery at time $t+1$ can be approximated as

$$E(t+1) = \max\{0, \min\{B_{\max}, E(t) + \mu_{\text{o}}(t)T - \mu_{\text{i}}(t)T\}\}, \tag{3.10}$$

Our goal is to estimate and analyze the energy-outage probability in the proposed virtual battery queuing model in order to examine the performance of the EH-based communication system under QoS constraint.

3.3.2 Analysis of the Energy-Outage Probability

We analyze the energy-outage probability to theoretically evaluate the performance of the EH-based communication system. According to the physical limitation of the system, we define the energy-outage condition as the probability when the harvested energy is not sufficient enough to sustain the active power consumption process. That is, situations where the harvested energy is unavailable for transmission or that the harvested energy is below the outgoing energy $\mu_o(t)T$, should be very limited. Otherwise, the system remains inactive and no transmission takes place. Specifically, once the accumulated energy, $A(t)$, is below the threshold $\mu_o(t)T$, the transmitter enters into the battery-low status or an energy-outage event occurs, and then the system will hibernate until the battery gets recharged to a satisfying level.

With the aid of proposed virtual battery queuing model by considering the empty side of the battery, the energy-outage probability is estimated with the probability of empty portion of queue at time t. At the same time, the occurrence of energy-outage should be minimum, i.e.,

$$\Pr\big\{E(t) \geq (B_{\max} - \mu_o(t)T)\big\} \leq P_{\text{out}}. \tag{3.11}$$

The formula shown in (3.11) expresses the probability that the virtual buffer is not full at a given time t.

Next, we derive and estimate the energy-outage probability under QoS constraint by invoking tools of the LDP theorem.

3.3.3 Statistical QoS Guarantees

Based on the LDP theorem [19], we can show that for a dynamic queuing system with stationary ergodic arrival and transmission processes, a simpler and tighter formulation can be found to to calculate the energy-outage probability. An assumption is made that the battery's maximum power $P_{\max}T$ can be used at each time slot. The empty portion of queue length process, $E(t)$ $(t \geq 0)$, converges in distribution to a finite random variable $E(\infty)$ that satisfies

$$\lim_{B_{\max}\to\infty} \frac{\log\Big(\Pr\big\{E(\infty) \geq (B_{\max} - P_{\max}T)\big\}\Big)}{B_{\max} - P_{\max}T} = -u, \tag{3.12}$$

which states that the probability of the queue length exceeding threshold $(B_{\max} - P_{\max}T)$ decays exponentially fast as $B_{\max}$ increases.

Further, for large values of $B_{\max}$, we have

$$\Pr\big\{E(\infty) \geq (B_{\max} - P_{\max}T)\big\} \approx e^{-u(B_{\max} - P_{\max}T)}. \tag{3.13}$$

For small values of $B_{\max}$, a more accurate approximation is given by

$$\Pr\big\{E(\infty) \geq (B_{\max} - P_{\max}T)\big\} \approx \varepsilon e^{-u(B_{\max} - P_{\max}T)}, \tag{3.14}$$

where ε denotes the probability of non-empty virtual buffer, i.e.,

$$\Pr\{E(t) > 0\} = \varepsilon, \tag{3.15}$$

which can be approximated by the ratio between the average incoming rate and the fixed outgoing rate pertaining to the virtual battery queue model, namely, as $\varepsilon \approx \frac{\mathbb{E}(\mu_{\mathrm{o}}(t))}{\mu_{\mathrm{i_{fix}}}}$[128].

In the above formulation, the constant u $(u \geq 0)$ is termed as QoS exponent, which acts as a significant aspect for statistical QoS guarantee requirement, shows the exponential decreasing rate of the QoS violation probabilities. Larger value of u results into a faster decay rate supporting a more stringent QoS requirement, while a smaller value of u leads to a slower decay rate, which illustrates that the EH-based communication system can provide a looser QoS requirement. Specifically, when u is close to 0, a longer decay can be tolerated by the communication system. On the other hand, when u is tends to ∞, the system cannot endure any delay [19].

3.3.4 Theory of Effective Energy Harvesting

The proposed theory of effective energy harvesting states that the stochastic behaviour of the arrival energy traffic process can be modelled by its effective EH asymptotically.

An arrival energy process to the queue is considered, which gets to the empty side of it, or we can simply say that the empty slot accumulation of the battery , i.e., $\mu_{\mathrm{o}}(t)$, which is defined for $t \geq 0$, represents the rate of outgoing energy or energy spent (in Joules per second) from the battery over the time interval $[0,t)$.

The asymptotic log moment generating function (MGF) of $\mu_{\mathrm{o}}(t)$ is assumed, which is expressed as

$$\Lambda(u) = \lim_{t\to\infty} \frac{1}{t} \log\left(\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right), \tag{3.16}$$

and exists for all $u \geq 0$. Here, $\mathbb{E}[\cdot]$ denotes the expectation operator.

Further, assume that $\mu_{\mathrm{i}}(t)$, which is the rate of energy exiting from the virtual queue, i.e., the rate of energy coming into the battery of the physical model, is fixed. As such, $\mu_{\mathrm{i}}(t)$ is fixed, say to $\mu_{\mathrm{i_{fix}}}$ as shown in Fig. 3.4.

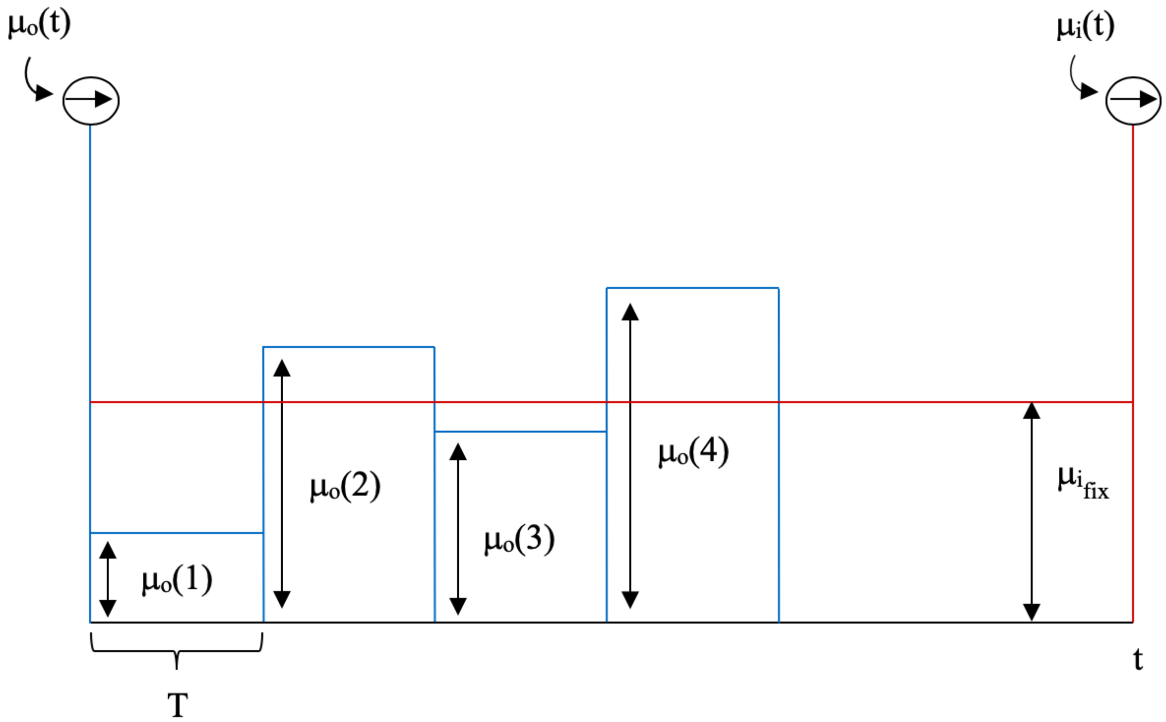


Fig. 3.4 Energy arrival $\mu_{\mathrm{i}}(t)$ and energy spent $\mu_{\mathrm{o}}(t)$.

The effective EH function of $\mu_{\mathrm{o}}(t)$ is defined as

$$\alpha(u) = \frac{\Lambda(u)}{u}. \tag{3.17}$$

By substituting the asymptotic log MGF (3.16) into (3.17), we get

$$\frac{\Lambda(u)}{u} = \frac{1}{u} \lim_{t \to \infty} \frac{1}{t} \log\left(\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)} \right] \right). \tag{3.18}$$

Then simplifying further, we obtain

$$\begin{aligned}
\frac{\Lambda(u)}{u} &= \lim_{t\to\infty} \frac{1}{ut} \log\left(\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right) \\
&= \lim_{t\to\infty} \frac{1}{ut} \log\left(\mathbb{E}\left[e^{u\Sigma_{i=0}^{t}\mu_{\mathrm{o}}(t)}\right]\right) \\
&= \lim_{t\to\infty} \frac{1}{ut} \log\left(\mathbb{E}\left[\prod_{i=0}^{t} e^{u\mu_{\mathrm{o}}(t)}\right]\right) \\
&= \lim_{t\to\infty} \frac{1}{ut} \log\left(\prod_{i=0}^{t} \mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right) \\
&= \lim_{t\to\infty} \frac{1}{ut} \log\left(\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right)^{t}.
\end{aligned} \tag{3.19}$$

Hence, a simplified expression for the effective EH function is obtained as follows:

$$\frac{\Lambda(u)}{u} = \frac{1}{u} \log\left(\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right). \tag{3.20}$$

3.3.5 Formulation of an Upper Bound for $\mu_{\mathrm{i_{fix}}}$

According to the energy arrival process and the expression shown in (3.3), by assuming the rate of energy $\mu_{\mathrm{i}}(t)$ to be constant, namely, $\mu_{\mathrm{i_{fix}}}$, we can write

$$\mu_{\mathrm{i_{fix}}} \leq \frac{\Lambda(u)}{u} = \frac{1}{u} \log\left(\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right). \tag{3.21}$$

Let us recall that the goal is to achieve a minimum required rate $R_{\min}$. Hence, $R_{\min}$, in the unit of nats/s/Hz, can be expressed as

$$r(t) = \log\left(1 + \frac{\mu_{\mathrm{o}}(t)h^2(t)}{N_0 B}\right) \geq R_{\min}, \tag{3.22}$$

which leads to

$$\mu_{\mathrm{o}}(t) = \frac{(e^{R_{\min}} - 1)N_0 B}{h^2(t)}. \tag{3.23}$$

Now, substituting (3.23) into (3.21), we find the expression for $\mu_{\mathrm{i_{fix}}}$ as

$$\mu_{\mathrm{i_{fix}}} \leq \frac{1}{u} \log\left(\mathbb{E}\left[e^{u\left(\frac{(e^{R_{\min}}-1)N_0 B}{h^2(t)}\right)} \right]\right). \tag{3.24}$$

The simple and final analytical expression shown in (3.24) establishes the relationship between the channel state information, $h^2(t)$, the minimum required rate by the user, R_{min}, and the rate of the solar energy, $\mu_{\text{i}_{\text{fix}}}$. At the same time, this inequality also satisfies and relates the energy-outage probability calculated in (3.13). With the help of the statistical expressions shown in (3.13) and (3.24), we can analyze the energy-outage probability in the EH-based communication system, namely, determining the probability that the battery will not have the required amount of energy that is needed for the data transmission.

In the context of the proposed mathematical framework for EH-based communication systems, Monte Carlo simulation is used to confirm the analytical findings and investigate the impact of different system parameters on system performance. To perform Monte Carlo simulation in this context, we generate many random input values for the system parameters, such as the QoS component u and the Rayleigh fading channel. These random values can be used as inputs to the developed framework, which will produce corresponding output values for energy-outage probability P_{out} from (3.13) and $\mu_{\text{i}_{\text{fix}}}$ from (3.24) for the required rate of EH for achieving the target QoS. By repeating this process multiple times with different random input values, we generated a large number of output values and used statistical analysis to understand the distribution of these values and draw conclusions about the overall system performance.

This helps us to identify trends and patterns in the data, as well as to assess the impact of different system parameters on the required rate of EH for achieving the target QoS. Overall, the Monte Carlo simulation provides a powerful tool for evaluating the performance of the proposed framework for EH-based communication systems. Using this technique, we gain insights into the system's behaviour under different conditions and make informed decisions about system design and optimization.

Input:[N_0B, R_{min}, B_{max}, P_{max}, u]
Step 1:
Defining the range of QoS
for loop of QoS (which applies Monte Carlo for 100000 iterations)
generating Rayleigh fading channel
Step 2:
Calculate μ_{o} from (3.23)
Calculate $\mu_{\text{i}_{\text{fix}}}$ from (3.24)
Calculate P_{out} from (3.13)

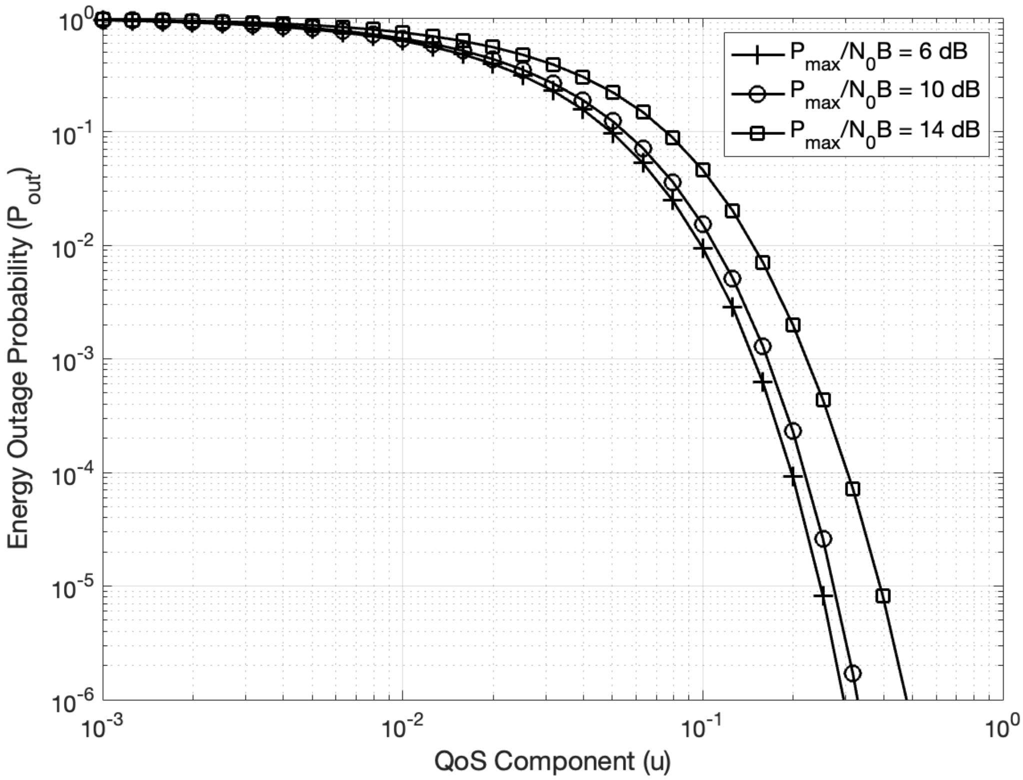


Fig. 3.5 Energy-outage probability versus the QoS component for various values of $P_{\max}$.

3.4 Numerical Results and Validation

With the proposed mathematical framework, numerical results pertaining to the required rate of EH for achieving the target QoS in the EH-based communication system are now presented and discussed. Simulations are used to confirm the analytical findings through the developed framework, particularly with respect to the expressions obtained in (3.13) and (3.24), and also to investigate the impact of the energy-outage probability P_{out}, the QoS component u, and the amount of incoming energy $\mu_{\text{i}_{\text{fix}}}$, on the system performance.

In the simulations, the number of independent Monte-Carlo runs is set to 10^5. Unless otherwise stated, the following parameter setting is used: the noise density $N_0B = 1$, the maximum level of energy that the transmitters's battery can withhold is $B_{\max} = 50$ Joules, the minimum rate requirement $R_{\min} = 0.5$ nats/s/Hz, the maximum transmission power $P_{\max} = 10$ dB, and the duration of one time slot is $T = 1$ sec.

Firstly, Fig. 3.5 shows the energy-outage probability, P_{out}, versus the QoS component, u, for various values of the maximum transmission power $P_{\max}$. As observed, when the QoS component increases, the energy-outage probability decreases. This confirms the theory that

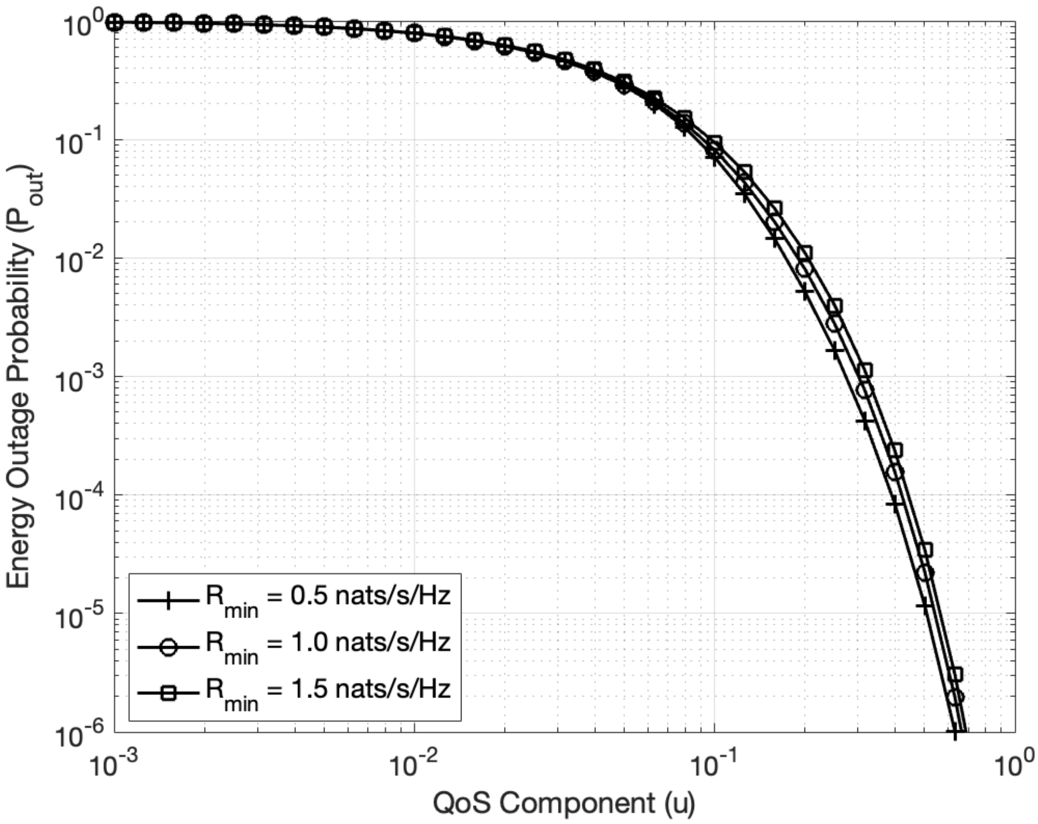


Fig. 3.6 Energy-outage probability versus the QoS component for various values of the minimum required rate $R_{\min}$.

larger u gives a more stringent QoS guarantee, i.e., the system will tolerate less energy-outage, which also confirms our design approach. The figure's results also demonstrate that when $P_{\max}$ increases from 6 dB to 14 dB, P_{out} decreases, which is a favorable condition for the EH-based communication system to be more sustainable.

Figure 3.6 illustrates the energy-outage probability versus the QoS component, for different values of the minimum required rate $R_{\min}$. As observed, when u increases, P_{out} decreases. This confirms the theory that larger u gives a stricter QoS guarantee, i.e., the system will tolerate less energy-outage and, as such, will be more efficient to increase throughput and decrease energy-outage as per the required performance measures. Fig. 6 also demonstrates that when $R_{\min}$ increases from 0.5 nats/s/Hz to 1.5 nats/s/Hz, then P_{out} increases, which proves the correctness of our design approach and confirms as well the desired output result according to the paper's analysis.

Figure 3.7 plots the rate of the incoming energy, $\mu_{i_{\text{fix}}}$, versus the QoS component, for various values of $P_{\max}$. From this figure, we notice that when $P_{\max}$ varies from 5 dB to 15

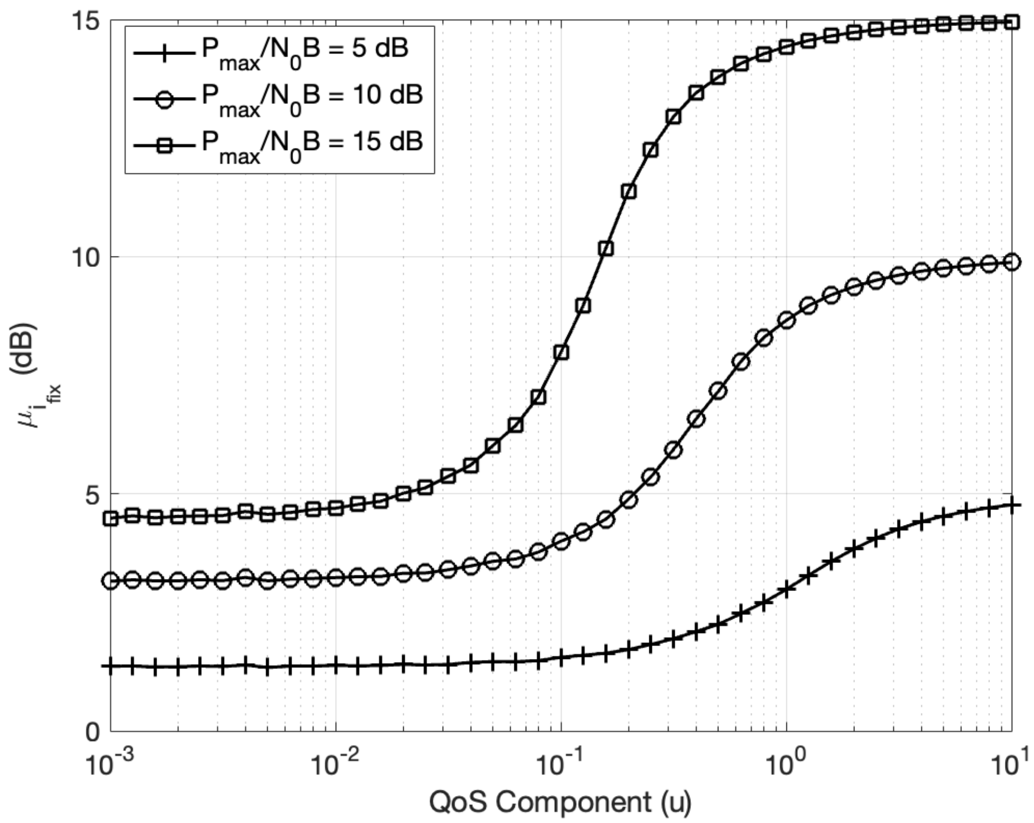


Fig. 3.7 Rate of incoming energy versus the QoS component for various values of $P_{\max}$.

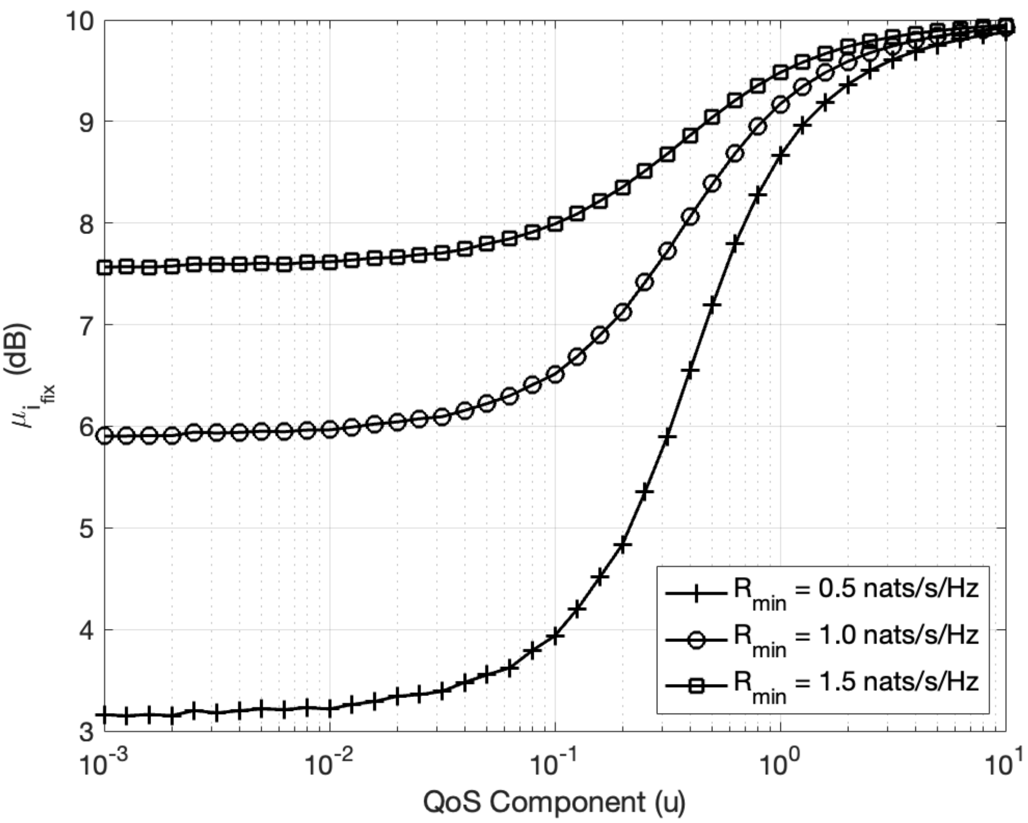


Fig. 3.8 Rate of incoming energy versus the QoS component for various values of the minimum required rate $R_{\min}$.

dB, $\mu_{i_{\text{fix}}}$ first remains stable and, then, increases gradually to become stable eventually after a break-point for increased values of the QoS component. This behavior can be explained by the fact that the amount of incoming energy into the battery also increases at higher rate with higher values of $P_{\max}$, for stringent QoS guarantee. That is, higher rate of incoming energy will be required to support maximum transmission power.

Figure 3.8 shows the variations of the rate of incoming energy $\mu_{i_{\text{fix}}}$ versus the QoS component for various values of minimum required rate $R_{\min}$. As observed, $\mu_{i_{\text{fix}}}$ increases with the increase of the QoS component u as $R_{\min}$ increases from 0.5 nats/s/Hz to 1.5 nats/s/Hz. This proves that higher QoS can be guaranteed with the increase in the rate of the incoming energy into the battery of the data transmitter. If we consider the QoS component to be 10^{-2}, then for a minimum required data rate of 0.5 nats/s/Hz, the rate of the incoming energy $\mu_{i_{\text{fix}}}$ is 3.2 dB. For a minimum required data rate of 1.0 nats/s/Hz, $\mu_{i_{\text{fix}}}$ is almost 6 dB, whereas for data rate requirement of 2.0 nats/s/Hz, $\mu_{i_{\text{fix}}}$ is between 7 dB and 8 dB. This shows that as $R_{\min}$ gets higher, the rate of incoming energy $\mu_{i_{\text{fix}}}$ will also be high in order to satisfy the required QoS.

Figure 3.9 shows the energy-outage probability P_{out} versus the rate of incoming energy $\mu_{i_{\text{fix}}}$, for various values of the minimum required rate $R_{\min}$. When $\mu_{i_{\text{fix}}}$ is relatively large, e.g., 7.5 dB, then P_{out} shows a consistently downward trend with the increase of $\mu_{i_{\text{fix}}}$ for all the considered rate values. This shows that a higher rate of incoming energy can be harvested and, at the same time, the system will face less energy-outage events.

Figure 3.10 illustrates the energy-outage probability versus the rate of the incoming energy for various values of the transmission power ($P_{\max}$). As it can be noticed, the energy-outage probability P_{out} decreases rapidly. In particular, $P_{\max} = 12$ dB provides the least values of P_{out} and $\mu_{i_{\text{fix}}}$. A higher rate of incoming energy shows that the transmission power can also be increased, which means that more data can be transmitted. With the increase in the incoming energy, the system will face less energy-outage, which is obviously beneficial for the system.

Figure 3.11 shows the variation of P_{out} as a function of $\mu_{i_{\text{fix}}}$, for various values of the battery capacity $B_{\max}$. To explain in detail, if we consider the rate of the incoming energy ($\mu_{i_{\text{fix}}}$) to be 7 dB, then for a battery capacity of at least 30 Joules, the energy-outage probabaility lies between 10^{-1} and 10^{-2}. Similarly, for a battery capacity of 40 Joules and 50 Joules, the energy-outage probability lies between 10^{-2} and 10^{-3}, and between 10^{-3} and 10^{-4}, respectively. This indicates that an increase in the battery capacity will allow more energy to be stored, which will help reduce the energy-outage probability.

We further plot results of the energy-outage probability versus the QoS component for different values of the battery capacity $B_{\max}$. Here in Fig. 3.12, $P_{\max} = 10$ dB is considered.

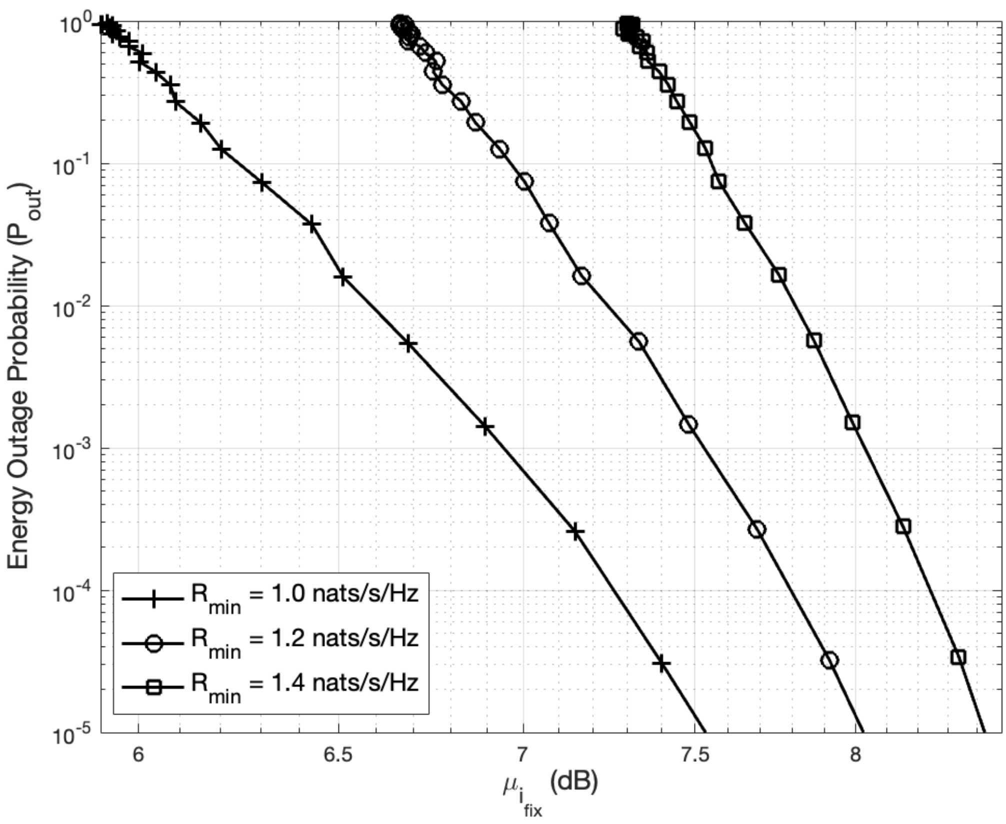


Fig. 3.9 Energy-outage probability versus the rate of incoming energy for various values of the minimum required rate $R_{\min}$.

The figure indicates that for small values of the QoS component, e.g., $u = 10^{-3}$, different values of $B_{\max}$ will not affect the energy-outage probability P_{out}. When u increases, changes in $B_{\max}$ yield energy-outage events. This shows that with the increase in battery capacity, the required QoS can be maintained and, also, the system faces less energy-outage.

The energy-outage probability, P_{out}, is analyzed in Fig. 3.13 a function of the rate of incoming energy, $\mu_{\text{i}_{\text{fix}}}$. From the result of derivation, we obtained the value of P_{out} to be approximatively 10^{-1}, and $\mu_{\text{i}_{\text{fix}}}$ is approximated as 10.6 dB. From the system simulation output, P_{out} is approximated as 10^{-2}, and $\mu_{\text{i}_{\text{fix}}}$ is approximated as 10.4 dB. Therefore, we can say that the energy-outage probability with the proposed mechanism is less than 10^{-5} in the system simulation. Also, we can see that the value of P_{out} obtained from the proposed framework is higher than the one obtained with the system simulation, which can be explained by the tighter measure of outage probability being needed in the framework for the QoS constraint to be satisfied.

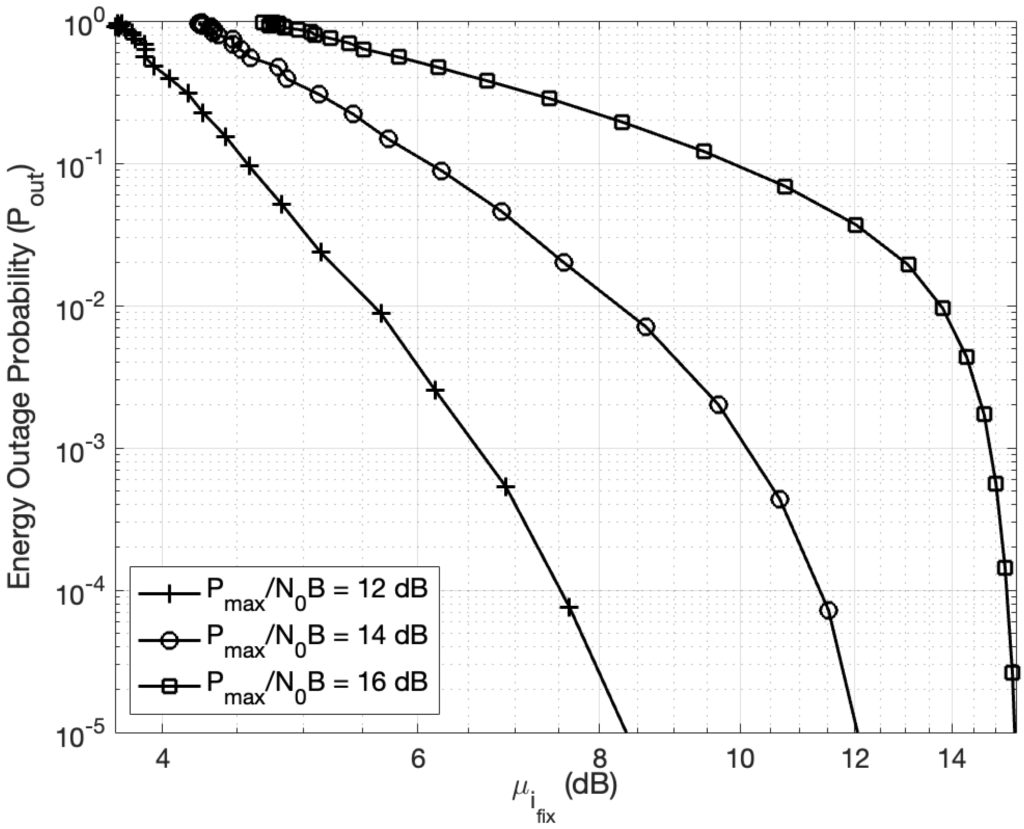


Fig. 3.10 Energy-outage probability versus the rate of incoming energy for various values of $P_{\max}$.

In Fig. 3.14, the plot in the system-level simulation is derived by comparing the outage probabilities of two different scenarios: the energy harvesting system and the baseline scenario. The plot shows how the outage probability varies with the QoS Component u for both scenarios.

- Parameters and Initialization for developed framework and system simulation: Parameters like noise density N_0B, rate rt, battery threshold $B_{\max}$, and maximum transmission power in dB $P_{\max}$ are defined.

- Energy Harvesting System and Baseline Initialization: Variables are initialised to store simulation results for both energy harvesting. Battery levels are set to the initial battery capacity $B_{\max}$ for both systems.

- Main Loop for QoS Component u: The code iterates over the array of QoS components u to evaluate system performance at different data collection priorities.

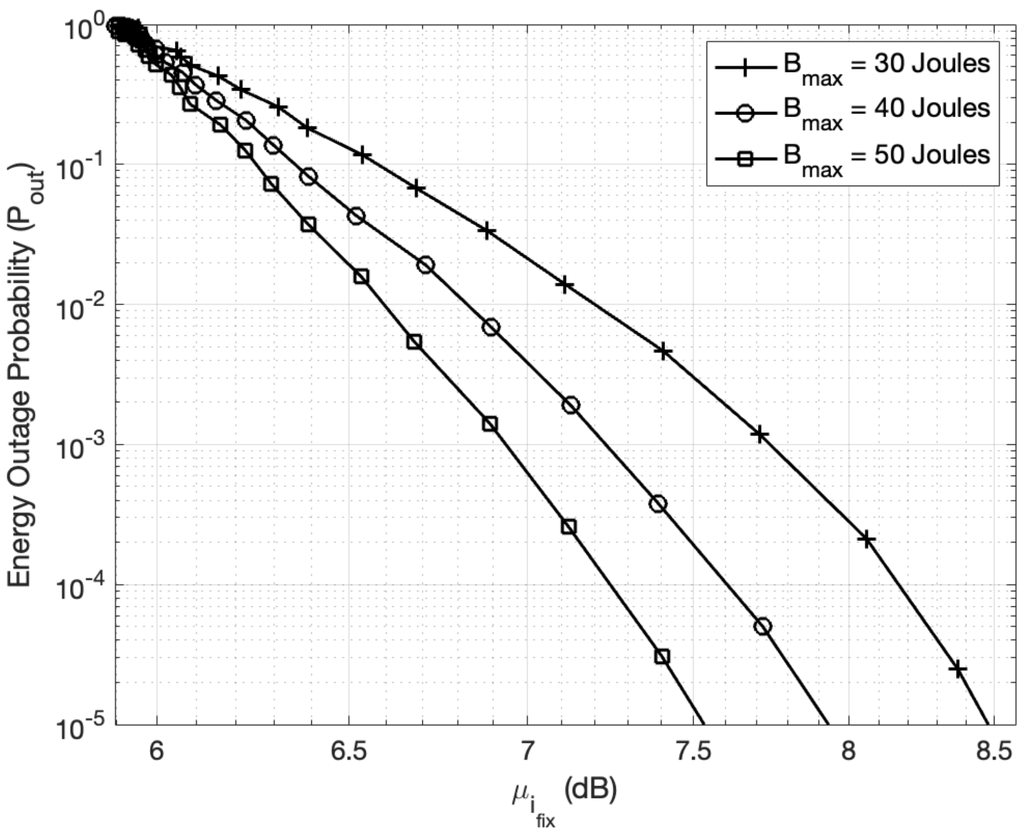


Fig. 3.11 Energy-outage probability versus the rate of incoming energy for various values of $B_{\max}$.

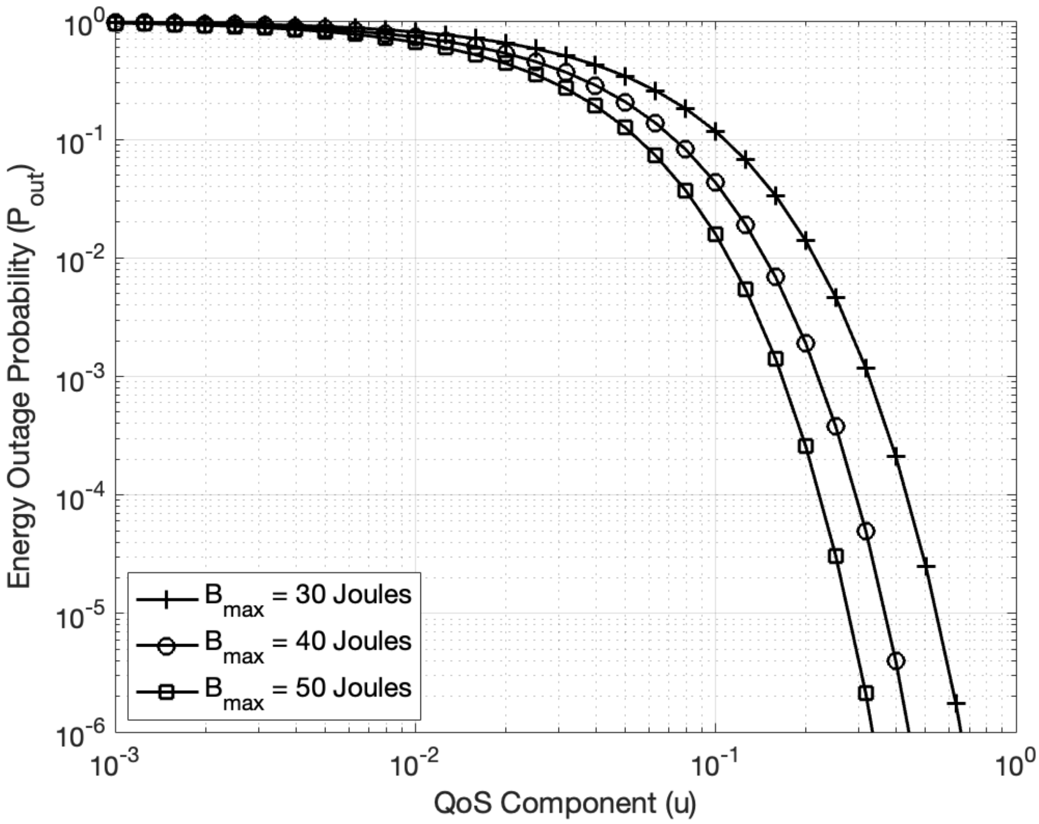


Fig. 3.12 Energy-outage probability versus the QoS component for various values of $B_{\max}$.

- Monte Carlo Simulations: For each u, Monte Carlo simulations (100,000 iterations in this case) are performed to estimate system behaviour under random Rayleigh fading channel conditions. The harvested energy and transmission power for the energy harvesting system is calculated based on the channel conditions and the energy harvesting formula (3.24).

- Battery Management for Baseline Scenario: The battery status of the energy harvesting system undergoes modification in response to both the energy gathered through harvesting and the power utilised for data transmission. This adjustment considers the upper limit of the battery's capacity, denoted as the maximum battery threshold $B_{\max}$. Consequently, the battery's state evolves by adding the harvested energy and subtracting the consumed energy.

- Outage Probability Calculation: After the Monte Carlo simulations, the outage probabilities are computed for the energy harvesting system P_{out} and the baseline scenario at different QoS u. Outage probability represents insufficient battery energy.

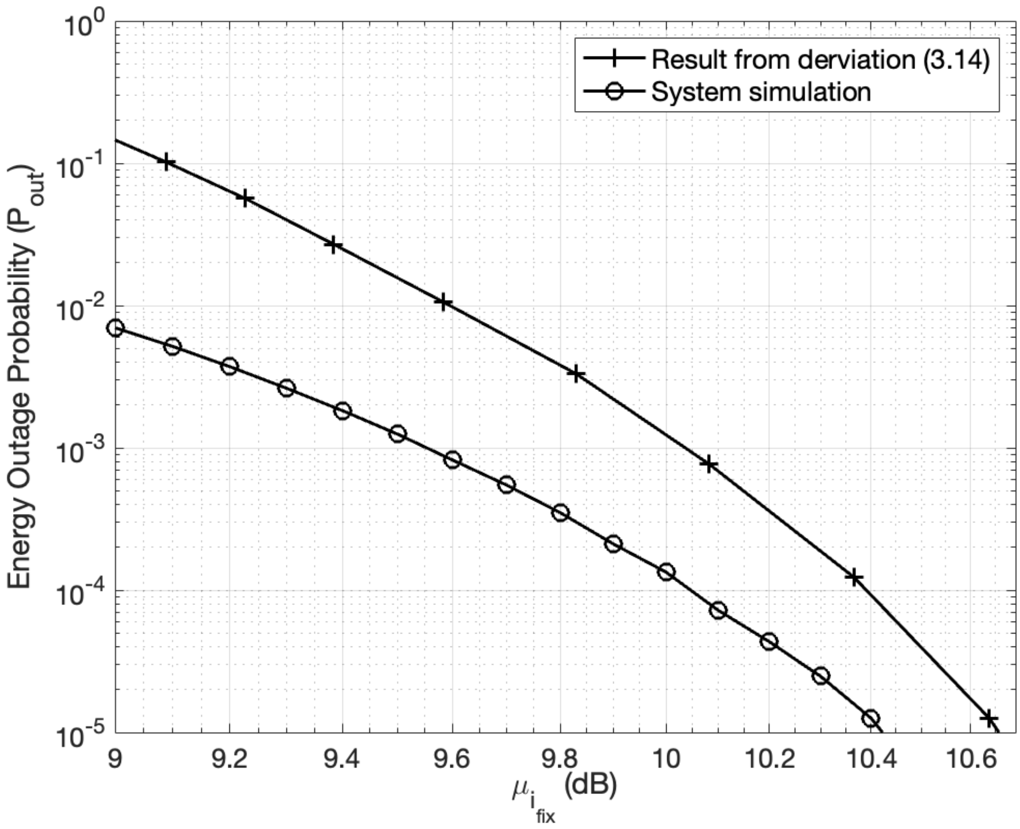


Fig. 3.13 Confirmation of the correctness of the proposed mechanism.

- Log-Log Plot Generation: A log-log plot is generated to compare the outage probabilities of the energy harvesting system and the baseline scenario. It considers channel fading, harvested energy, and battery constraints to calculate outage probabilities and demonstrates the benefits of the developed framework in improving the system's performance. The plot visually compares the two scenarios based on outage probabilities at various QoS levels.

The developed framework serves as a valuable design tool for engineers, enabling them to determine the optimal size of a solar panel to meet a specific minimum energy requirement, for example, 95% of the time. By utilising this formulation, engineers can calculate the necessary incoming energy rate related to the solar panel size to achieve the desired outage probability, thereby ensuring optimal system performance. However, it is essential to note that the outage probability derived from the developed framework is higher than the actual outage performance of the baseline system. The figure demonstrates the disparity in outage probabilities. For instance, when the Quality of Service (QoS) component is set to 10^{-1}, the outage probability for the developed framework reaches 13%. In contrast, the baseline

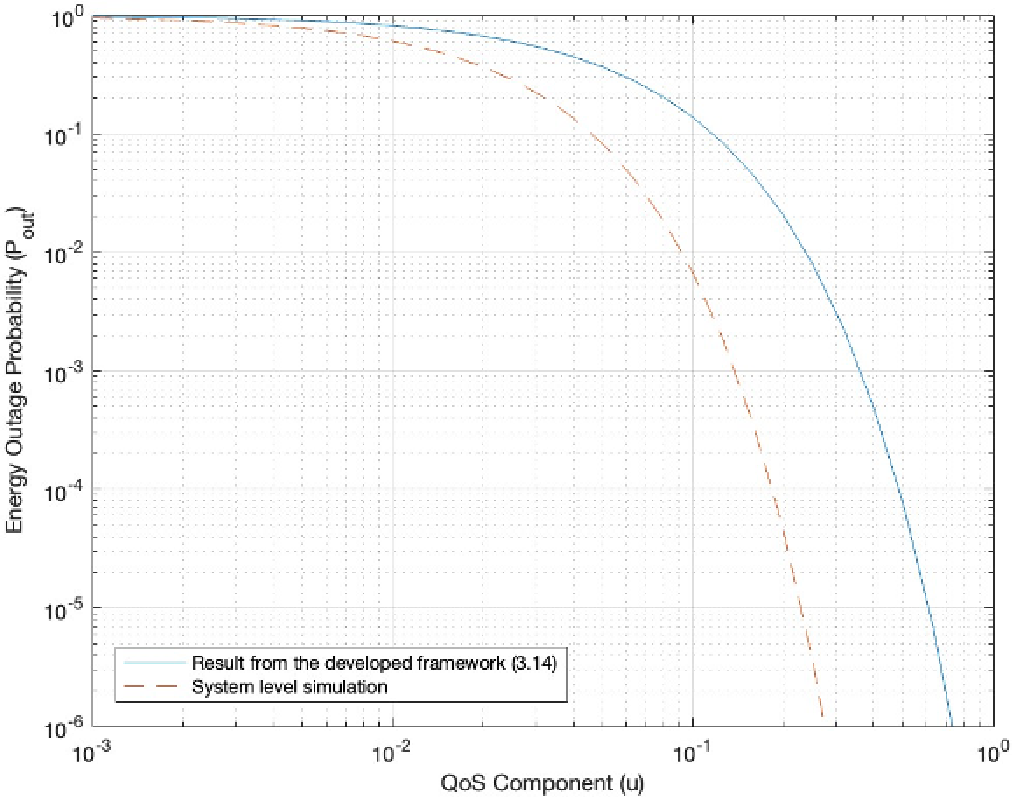


Fig. 3.14 Comparison between developed framework and system-level simulation.

system achieves a superior outage probability of 0.6%. Despite this difference, the provided solution satisfies the requirements of the actual system. This theory and methodology are applied and expanded upon in subsequent chapters of the study.

3.5 Conclusion

In this chapter, a thorough study was carried out to analyze the required energy harvesting (EH) rate for satisfying the QoS requirements when a level of energy-outage is allowed in point-to-point EH-based communication system equipped with a finite-sized battery. A probabilistic approach was taken, and a novel yet simple mathematical framework using large deviation principle (LDP) was developed. In particular, a virtual battery queuing model was proposed so that the LDP can be used and adapted. Furthermore, an expression relating the rate of the incoming energy with the fading channel conditions and the minimum required QoS of the system was provided to analyze the performance of the EH-based communication system under energy constraint. Numerical results were provided to validate the proposed analytical framework and discuss the system performance in different scenarios.

Chapter 4

RF Energy Harvesting Communications using Time-Switching Protocol

4.1 Introduction

An early definition of transmitting energy in the Earth's atmosphere without using any stringing wires by converting the wireless energy to usable electric current power was proposed by the great visionary Nikola Tesla [35]. Recently, energy harvesting and wireless power transfer technologies have attracted considerable attention, owing to their ability to maintain longer battery and network lifetimes as compared to the conventional operations with limited capacities of the devices' batteries [66]. The concept of energy harvesting consists in scavenging energy from renewable energy sources available in the surrounding environment including solar energy, radio-frequency (RF) energy, etc. This technique promises tremendous scope for the replacement of small batteries in low-power electrical devices and systems [104, 92, 79, 105].

In this regard, it is known that each source of energy for the harvesting has its own advantages and limitations. For example, solar energy can only be harvested during daytime in an outdoor environment, with no access during night times or in bad weather conditions [64]. On the other hand, the continuous availability of RF energy has proved to be advantageous as a wireless power source to support low-power devices remotely [64], making RF-based energy harvesting an alternative and viable solution for powering next-generation wireless networks, particularly for Internet-of-Things (IoT) applications. Such wireless powering can be implemented in different ways. For instance, through dedicated power beacons, or by leveraging the abundance of RF signals in the air from ambient sources such as TV towers, cellular base stations, WiFi, satellite communications, etc. [116, 55, 38].

Several research works have clearly shown that RF-based energy harvesting does improve the performance of wireless communications from different viewpoints [74, 10, 86, 61]. For instance, a wireless sensor network powered by a green energy beacon is investigated in [74]. Ambient RF energy is also known to be sufficient for powering sensors via energy harvesting in many applications [10]. RF energy-harvesting with decode-and-forward relaying is used in [86] to increase the throughput performance of wireless sensor networks. In the RF-based energy-harvesting communication network considered in [61], the uplink scheduling problem for maximizing the network throughput is analyzed when channel state information is not available.

The benefits of RF-based energy harvesting in wireless communication systems are well discussed in the literature. The concept of RF energy harvesting for transmitting information has also been the focus of many research studies. Generally, the time-switching protocol is assumed at the hybrid energy-data device, where the circuit switches between harvesting energy for a fraction of the time interval, and transmitting information in the rest of the available time. In [103], time-switching energy harvesting was used to investigate the performance of a point-to-point communication system equipped with a fixed battery. The authors in [57] studied the throughput maximization problem of a point-to-point communication system implementing time-switching protocol, and the optimizing of the information transmission rate by balancing the energy harvesting time and the information transmission time. In [60], the authors studied abnormal scenarios in multi-point wireless body area networks with a time-switching protocol and investigated the maximum achievable throughput of the network. The performance of time switching (TS) and power splitting (PS) energy harvesting technologies in a two-hop cooperative network with a battery supported was investigated in [3]. Expressions for throughput with selective decode-and-forward relaying with the direct link (SDFDL) and incremental relaying (IR) are developed under the assumption of the direct connection, optimal combining at the destination, and a practical non-linear model for EH.

Despite the significant impact of RF energy harvesting using time-switching protocol in a wireless communication system, so far, research on RF energy harvesting using time-switching protocol in wireless communication systems has mainly assumed the energy in the battery to be always available for the data transmission. This assumption is not always feasible, especially when the system operates in weak fading channel conditions, given that higher transmit power levels would be needed in order to guarantee the required quality-of-service (QoS) of the end user in these conditions. In fact, when the status of energy level in the battery is unknown, guaranteeing the necessary power levels for the information transmission becomes very challenging, and generally leads to energy outage, thus making it difficult to maintain the user's QoS at the target levels. In this paper, we look into this problem through a probabilistic approach, while considering that a small amount of energy-outage is allowed to happen in the system.

Specifically, we consider point-to-point RF-based energy-harvesting communication, where the transmitter, which can be an IoT sensor, implements time-switching protocol between the harvesting and the information transfer, and we focus on analyzing the system performance while aiming to guarantee the required QoS of the end user for maximum time subject to system constraint on the energy outage. The practical challenge of operating the system with unknown battery status is tackled. Particularly, considering that the rate of the energy that is consumed from the sensor's battery is fixed, and the channels to be subject to Rayleigh fading, we derive the analytical formulae for the rate of the outgoing energy from the transmitter and for the energy-outage probability. Closed-form expressions are provided accordingly. The contributions of the chapter can hence be summarized as follows:

- Developing a mathematical framework to investigate the system performance under energy-outage constraints.
- Deriving closed-form analytical expressions for the rate of the energy consumed from the battery of the transmit node and for the energy-outage probability.
- Obtaining a formulation for the transmit power of the sensor node so that a target energy-outage probability remains satisfied. Also, a virtual energy queuing model is proposed to make use of the large deviation principle theorem, as a powerful tool for the performance evaluation conducted here.
- Investigating the effects of key parameters such as the RF source power, and the distance between the RF source and the sensor node.
- Numerical results are also provided to corroborate the analytical findings.

The remainder of this chapter is organized as follows. The system model is detailed in Section 4.2. The queuing models and the performance evaluation are elaborated in Section 4.3. Numerical results are presented and in Section 4.4, followed by the chapter's conclusion in Section 4.5.

4.2 The RF Energy-Harvesting Based Communication System

4.2.1 System Model

The RF energy harvesting point-to-point communication system as illustrated in Fig. 4.1(a). Energy for the harvesting at the sensor device, S, originates from a distant RF source, and assumed to be stochastic, resulting in varying input energy level at the rectifying circuit of the sensor. The harvested energy is stored in an energy queue, and then used for the transmission of the data queued in the information circuit of the sensor towards the end destination, D. The transmit and receive nodes, S and D, are equipped with single antennas, and the switching between the harvesting and the data transmission at node S takes places according to a time-switching protocol as shown in Fig. 4.1(a).

All radio channels are assumed to be subject to Rayleigh fading. The channel coefficient between the RF energy source and the sensor node is denoted by h_1, whereas the communication link between the two nodes, i.e., S and D, is assumed to be a block fading channel having coefficient h_2. The distance from the RF energy source to the sensor node is denoted by d_1, and the distance between the sensor node and the destination node is denoted by d_2.

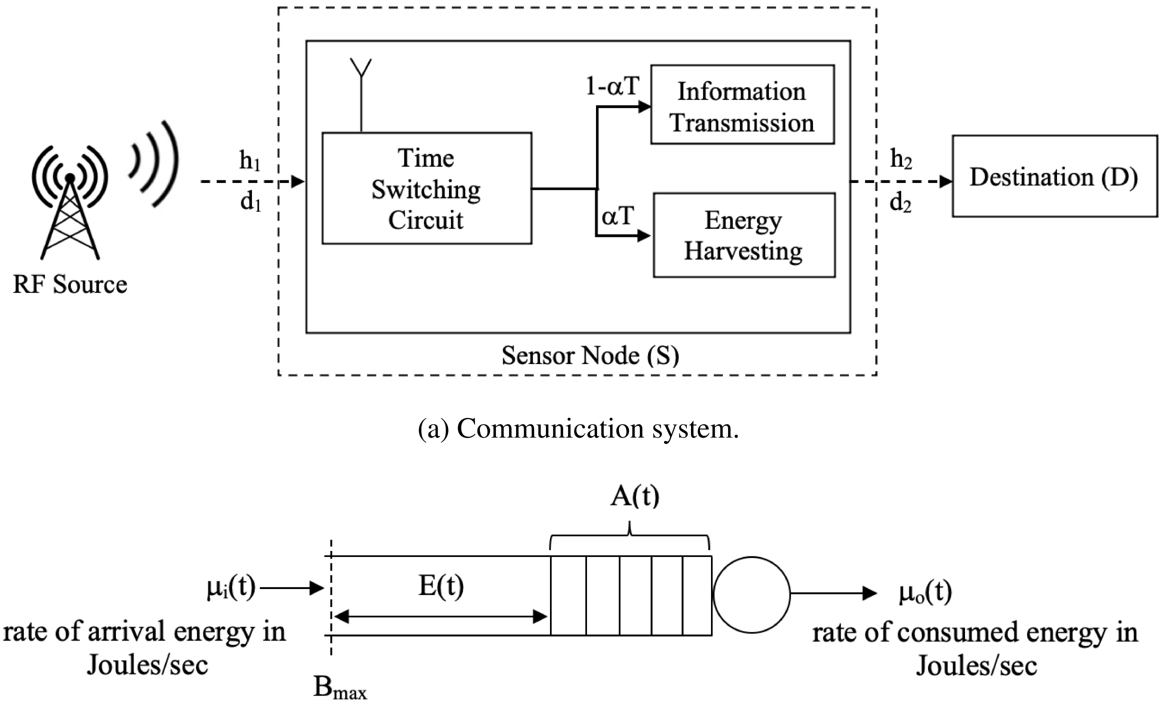
4.2.2 Time-Switching Protocol

The time-switching protocol assures the functioning of the sensor node as an energy harvester and information transmitter (Fig. 4.2). Let T be the length of the fading block within which these two functions take place. Then, the fraction of time αT, where $0 \leq \alpha \leq 1$, denotes the time interval during which the sensor node harvests energy from the RF source, and the remaining block time, i.e., $(1-\alpha)T$, is used for the information processing and transmitting it from node S to node D.

The signal originating from the distant RF energy source is received at the sensor node in the form

$$y(t) = \sqrt{\frac{P_s}{d_1^m}} h_1 x(t) + n(t), \tag{4.1}$$

where P_s is the transmit power of the RF energy source, and $x(t)$ is the source signal transmitted with power $\mathbb{E}[|x(t)|]^2 = 1$, where $\mathbb{E}[\cdot]$ is the expectation operator and $|\cdot|$ is the absolute value operator, and where m is the path-loss exponent pertaining to the link between



(a) Communication system.

(b) Energy queue structure within the power control module of the system illustrated in (a).

Fig. 4.1 The RF energy-harvesting based communication system.

the said energy source and the sensor, and $n(t)$ is the additive white Gaussian noise at node S, having zero mean and unit variance,

From (4.1), the harvested energy $\mu_{\mathrm{i}}(t)$ at the sensor node can be found using

$$\mu_{\mathrm{i}}(t) = \frac{\eta P_s |h_1|^2 \alpha T}{d_1^m}, \tag{4.2}$$

where $0 < \eta < 1$ is the energy conversion efficiency of the rectifying circuit [130].

4.3 Modeling and Performance Evaluation

Two queuing models are considered in this paper. As we know, during severely weak channel conditions, or when the sensor battery lacks the amount of energy that is required for the data transmission, the data transmission can be interrupted and it will be challenging to guarantee the required QoS u, to the user. Hence, due to the unknown status of the resource level of the sensor's battery, the system can go into an energy-outage state. By using tools from the well-known large deviation principle (LDP) theorem, we take a probabilistic approach

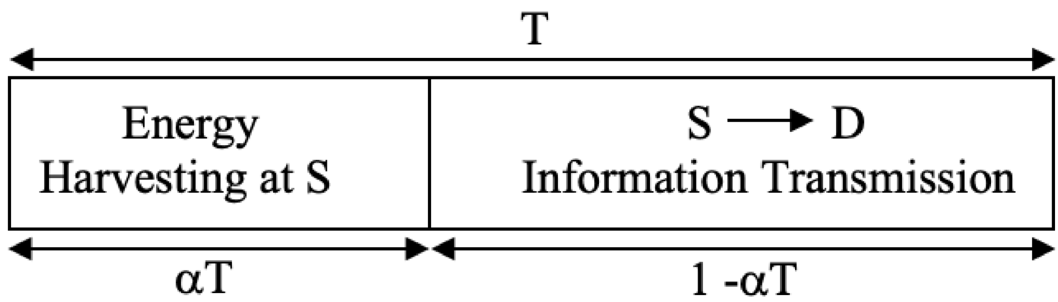


Fig. 4.2 Time-switching protocol for energy harvesting and information processing at the sensor node S.

in which a very small percentage of energy-outage is allowed to happen in the system. To incorporate LDP, two queuing models are introduced in this section.

4.3.1 Queuing Model for Physical Energy

At the sensor node, a physical energy queue model is considered part of the energy harvesting circuit, as illustrated in Fig. 4.1(b). The model consists of an energy queue, where energy that is harvested from the distant RF source is accumulated. The battery has a storage capacity of $B_{\max}$ in Joules. Energy stored in the battery is denoted by $A(t)$, and the empty portion of the battery is $E(t)$. Energy coming into the battery is $\mu_{\mathrm{i}}(t)$ (Joules/sec), and energy spent from the battery is denoted by $\mu_{\mathrm{o}}(t)$ (Joules/sec). Please refer (3.2) for further information.

At the destination, a given QoS requirement (in the form of throughput) has to be fulfilled in order to have a successful communication.

As discussed above, to guarantee the target QoS for maximum time, we adopt a probabilistic approach by tolerating a low level of energy-outage to occur in the system. In this direction, principles from the LDP theorem are considered. The inequality followed by LDP as shown in (4.3) can be estimated only when the battery capacity is very large, by using [14]:

$$\Pr\left\{M(\infty) \geq b\right\} \approx e^{-Ib}, \tag{4.3}$$

where $M(\infty)$ is the convergence of the steady queue length at ∞, I is the so-called rate function, and b denotes the battery capacity.

Based on the physical battery storage model, the LDP tools and assumptions explained above can only work if the following inequality holds:

$$\Pr\left\{A(\infty) \leq \mu_{\mathrm{o}}(t)T\right\} \leq P_{\mathrm{out}}, \tag{4.4}$$

where P_{out} denotes the energy-outage probability.

As discussed briefly in [14], due to the inverse inequality problem as seen when comparing (4.3) and (4.4), the LDP in the physical energy queuing model cannot be used. To solve this problem, we look into the empty portion of the battery and propose a virtual energy queuing model, which will allow us to use tools from LDP.

4.3.2 Queuing Model for Virtual Energy

We propose a virtual energy queuing model, please refer Fig.3.3. The roles of the harvested energy and the spent energy are reversed in the suggested queuing model to maintain a stable queue. We specifically swap the functions of the EH process and the energy-consuming process, which were covered in Section 4.2 discussion of the traditional physical battery storage architecture. The paradigm enables a flexible approach to energy storage and consumption by switching roles, enhancing energy systems' overall efficiency and sustainability. This is accomplished through the virtual battery queuing model employing the LDP theorem and inverse inequality. According to the inverse inequality, the chance of an event occurring is larger than or equal to the exponential of the negative of its upper bound. This is a helpful tool for understanding how the virtual battery queuing model behaves. In this way, the inverse inequality can be used to apply the LDP theorem to the suggested virtual battery queuing model.

Now, the RF energy coming into the sensor's battery is denoted by $\mu_{\mathrm{o}}(t)$ (Joules/sec) and the RF energy spent out from the battery is denoted as $\mu_{\mathrm{i}}(t)$ (Joules/sec). Please refer (3.10) for further information.

Basically, the virtual energy queuing model is proposed to eliminate limitations occurring in the physical energy queuing model. Firstly, the assumptions of the LDP theorem were invoked with the help of this model. Secondly, the problem of inverse inequality is addressed, as discussed earlier.

With the aid of the proposed virtual energy queuing model via the consideration of the empty side of the sensor's battery as opposed to its full side, the energy-outage probability can be estimated with the probability of the empty portion of the queue at time t. At the same time, the occurrence of energy-outage should be minimum. Please refer (3.11) for further information. We assume $\mu_{\mathrm{o}}(t)$ to be fixed at the level $\mu_{\mathrm{o_{fix}}}$.

4.3.3 Energy Harvesting Function

In the virtual energy queuing model, the empty side is assumed to have stationary and ergodic incoming energy at $t \geq 0$. The incoming rate of energy can be modelled by its effective energy harvesting, asymptotically. Asymptotic Log moment generating function (MGF) of $\mu_\mathrm{i}(t)$ is assumed, which is expressed as

$$\Lambda(-u) = \lim_{t\to\infty} \frac{1}{t} \log\left(\mathbb{E}\left[e^{-u\mu_\mathrm{i}(t)}\right]\right), \tag{4.5}$$

and exists for all $u \geq 0$.

Wireless power transmission function of $\mu_\mathrm{i}(t)$ is defined as

$$\alpha(u) = \frac{-\Lambda(-u)}{u}. \tag{4.6}$$

By substituting the asymptotic MGF shown in (4.5) into (4.6), we get

$$\frac{-\Lambda(-u)}{u} = -\frac{1}{u} \lim_{t\to\infty} \frac{1}{t}\log\left(\mathbb{E}\left[e^{-u\mu_\mathrm{i}(t)}\right]\right). \tag{4.7}$$

Simplifying further, we obtain

$$\begin{aligned}
\frac{\Lambda(u)}{u} &= -\lim_{t\to\infty} \frac{1}{ut}\log\left(\mathbb{E}\left[e^{-u\mu_\mathrm{i}(t)}\right]\right) \\
&= -\lim_{t\to\infty} \frac{1}{ut}\log\left(\mathbb{E}\left[e^{-u\Sigma_{i=0}^{t}\mu_\mathrm{i}(t)}\right]\right) \\
&= -\lim_{t\to\infty} \frac{1}{ut}\log\left(\mathbb{E}\left[\prod_{i=0}^{t} e^{-u\mu_\mathrm{i}(t)}\right]\right) \\
&= -\lim_{t\to\infty} \frac{1}{ut}\log\left(\prod_{i=0}^{t}\mathbb{E}\left[e^{-u\mu_\mathrm{i}(t)}\right]\right) \\
&= -\lim_{t\to\infty} \frac{1}{ut}\log\left(\mathbb{E}\left[e^{-u\mu_\mathrm{i}(t)}\right]\right)^{t}.
\end{aligned} \tag{4.8}$$

Hence, we obtain the simplified expression as

$$\frac{-\Lambda(-u)}{u} = -\frac{1}{u}\log\left(\mathbb{E}\left[e^{-u\mu_\mathrm{i}(t)}\right]\right). \tag{4.9}$$

4.3.4 Formulation of $\mu_{\mathrm{o_{fix}}}$

An upper bound on $\mu_{\mathrm{o_{fix}}}$ is formulated as

$$\mu_{\mathrm{o_{fix}}} \leq \frac{-\Lambda(-u)}{u} = -\frac{1}{u}\log\left(\mathbb{E}\left[e^{-u\mu_{\mathrm{i}}(t)}\right]\right). \tag{4.10}$$

Next, we derive a closed-Form expression for $\mu_{\mathrm{o_{fix}}}$. First, we have

$$\mu_{\mathrm{o_{fix}}} \leq -\frac{1}{u}\log\left(\int_0^\infty e^{-u\mu_{\mathrm{i}}(t)} p\left(|h_1|^2\right) d\left(|h_1|^2\right)\right), \tag{4.11}$$

where $p\left(|h_1|^2\right)$ is the probability density function (PDF) of $|h_1|^2|$.

Substituting the value of $\mu_{\mathrm{i}}(t)$ from (4.2) into (4.11), we can write

$$\mu_{\mathrm{o_{fix}}} \leq -\frac{1}{u}\log\left(\int_0^\infty e^{-u\left(\frac{\eta P_s |h_1|^2 \alpha T}{d_1^m}\right)} p\left(|h_1|^2\right) d\left(|h_1|^2\right)\right). \tag{4.12}$$

Since we assume Rayleigh fading channels, the distribution of the channel power gain $|h_1|^2 = \gamma$ is exponential. Hence, we have

$$\mu_{\mathrm{o_{fix}}} \leq -\frac{1}{u}\log\left(\int_0^\infty e^{-u\left(\frac{\eta P_s \gamma \alpha T}{d_1^m}\right)} p(\gamma) d\gamma\right). \tag{4.13}$$

Next, with the PDF of γ given by

$$p(\gamma) = e^{-\gamma}; \gamma \geq 0,$$

the above expression of $\mu_{\mathrm{o_{fix}}}$ becomes

$$\mu_{\mathrm{o_{fix}}} \leq -\frac{1}{u}\log\left(\int_0^\infty e^{-u\left(\frac{\eta P_s \gamma \alpha T}{d_1^m}\right)} e^{-\gamma} d\gamma\right). \tag{4.14}$$

Finally, solving the definite integral, we obtain

$$\begin{aligned}\mu_{\mathrm{o_{fix}}} &\leq -\frac{1}{u}\log\left(\frac{d_1^m}{\alpha\eta P_s T u + d_1^m}\right)\\ &\leq \frac{\frac{-1}{u}\log\left(\frac{d_1^m}{\alpha\eta P_s T u + d_1^m}\right)\alpha T}{(1-\alpha)T}.\end{aligned} \tag{4.15}$$

4.3.5 Energy-Outage Probability

Now, the energy-outage probability is analyzed to measure the performance of the RF energy-harvesting based communication system.

In the proposed virtual energy queuing model, energy that is accumulated in the battery, $A(t)$, should not be less than the required outgoing energy for transmission, $\mu_{o_{\text{fix}}}$. If this is not the case, then the system will be stagnant and no further transmission can occur. The data transmission is possible only when the available energy in the battery exceeds $\mu_{o_{\text{fix}}}$. With the help of the proposed virtual energy queuing model, a relationship between an energy-outage event and the probability of empty portion exceeding $B_{\max}$ and $\mu_{o_{\text{fix}}}$ is obtained. From (3.11), the energy-outage probability can be formulated as

$$P_{\text{out}} = \varepsilon\, e^{-u\left(B_{\max}-\mu_{o_{\text{fix}}}\right)\left(1-\alpha T\right)}, \tag{4.16}$$

where ε is the probability of non-empty virtual buffer, which is estimated as $\varepsilon \approx \frac{\mu_{o_{\text{fix}}}}{\mathbb{E}(\mu_{\text{i}}(t))}$.

4.4 Numerical Results and Discussion

In this section, numerical results are presented to examine the performance of the RF energy-harvesting based point-to-point communication system in terms of the energy-outage probability P_{out}, the QoS component u, and the amount of incoming energy $\mu_{\text{i}}(t)$.

In the simulations, we assume the noise density power $N_0B = 1$, equal time duration for the energy harvesting and data transmission via the choice of $\alpha = 0.5$, and a maximum energy battery storing capability of $B_{\max} = 300$, unless otherwise stated. The energy conversion efficiency is set to unity.

In Fig. 4.3, we show the variation of the energy-outage probability P_{out} versus the QoS component u, for various values of the RF energy source power P_s. The plot shows that for stringent QoS, the system will face less energy outage, whereas looser QoS will make the system face more energy outage for different values of P_s.

Figure 4.4 illustrates the energy-outage probability P_{out} versus the QoS component u for various values of the distance d_1 between the RF energy source and the sensor node. We note that for a given value of u, the energy-outage probability increases with the increase in the distance d_1. For instance, if we consider u to be 10^{-2}, then when the sensor node is 5 m away from the RF energy source the energy-outage probability is 1%. When the distance d_1 increases, the system faces more energy outage. For instance, when $d_1 = 15$ m, the energy-outage probability increases to about 3%.

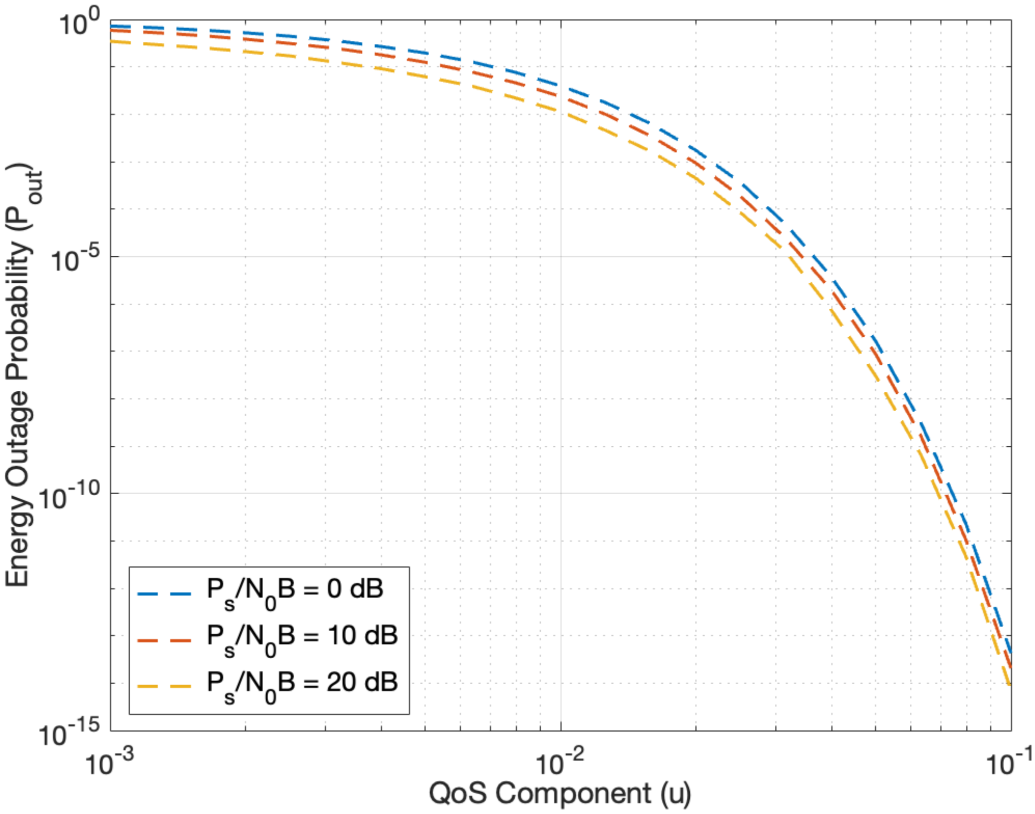


Fig. 4.3 Energy-outage probability versus the QoS component u for various values of P_s.

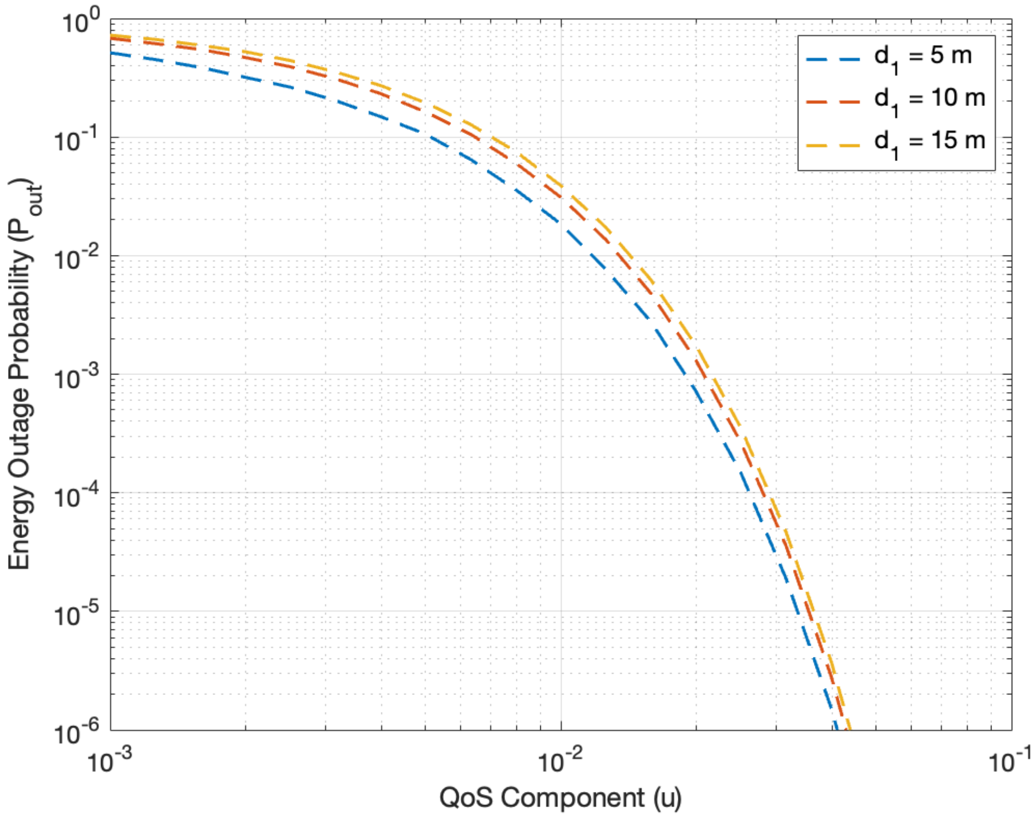


Fig. 4.4 Energy-outage probability versus the QoS component u for various values of d_1.

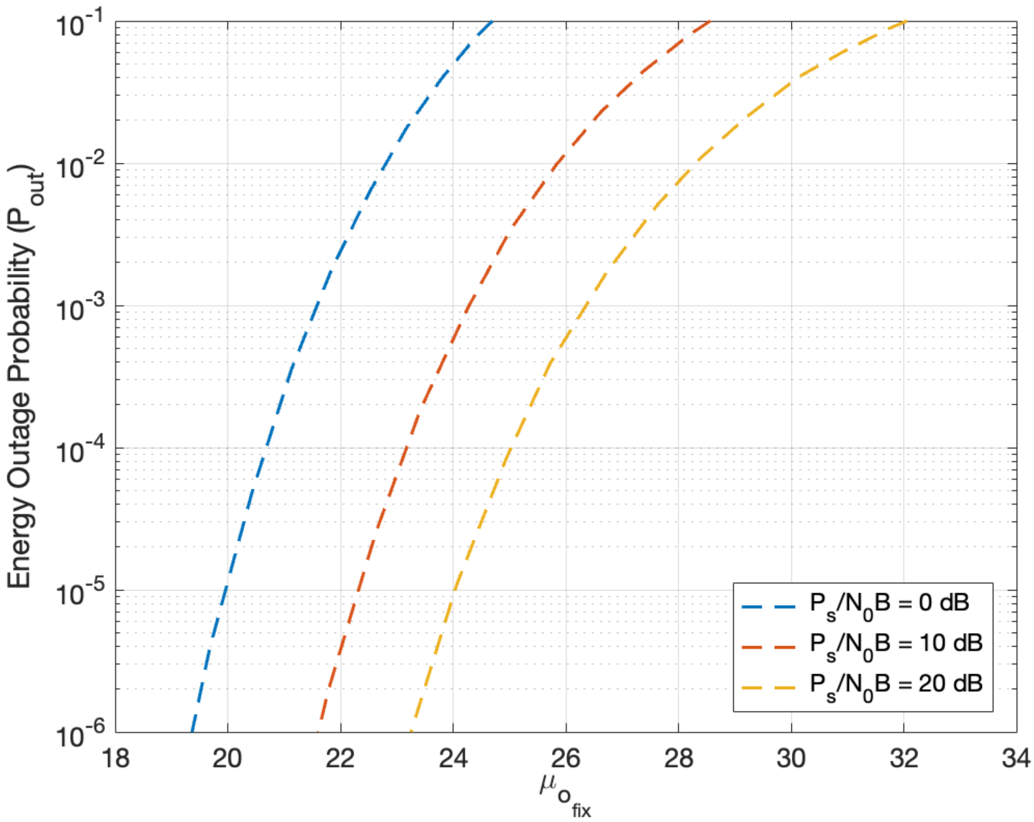


Fig. 4.5 Energy-outage probability versus the fixed rate of energy spent from the battery for various values of P_s.

Figure 4.5 depicts the relationship between the energy-outage probability P_{out} and the fixed rate of energy spent from battery, i.e., $\mu_{o_{\text{fix}}}$, for various values of P_s. It is observed from the figure that with an increase in the value of P_s, i.e., from 0 dB to 20 dB, the fixed rate of energy spent from battery $\mu_{o_{\text{fix}}}$ also increases. That is, the higher the transmit power of the RF energy source, the higher the rate of the energy spent from the battery will be. Also, if we consider $\mu_{o_{\text{fix}}}$ to be 24 dB, the energy-outage probability decreases with the increase in P_s.

Figure 4.6 shows the impact of the distance between the RF energy source and the sensor node, d_1, on the QoS component, u. As the plot shows, the QoS component increases as the distance between the RF source and the sensor node increases. For instance, when $d_1 = 6$ m, then u is approximately $10^{-2.8}$, while for the distance 16 m, the value of u is approximately $10^{-1.2}$. Hence, for lower values of d_1, the QoS component is loose, whereas for the higher values of d_1, the QoS component u is stringent.

Figure 4.7 shows a comparison of the analytical results pertaining to the energy-outage probability and the QoS component against Monte-Carlo simulation results. In the sim-

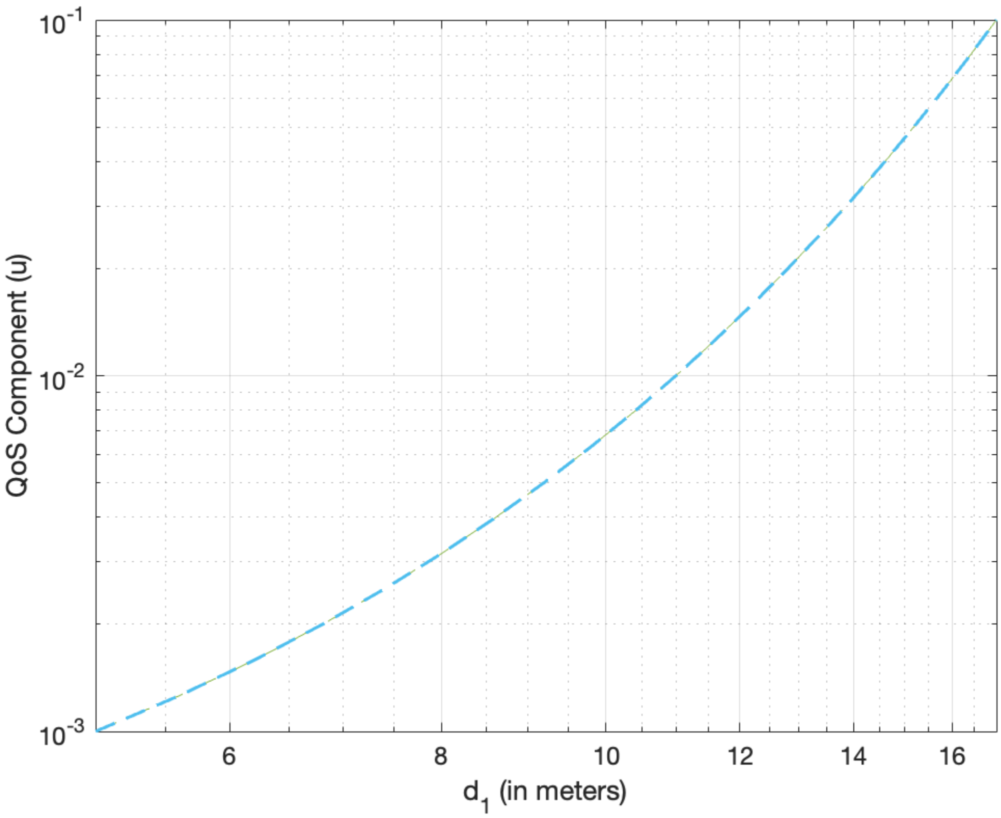


Fig. 4.6 QoS component, u, versus the distance between the RF energy source and the sensor node, d_1.

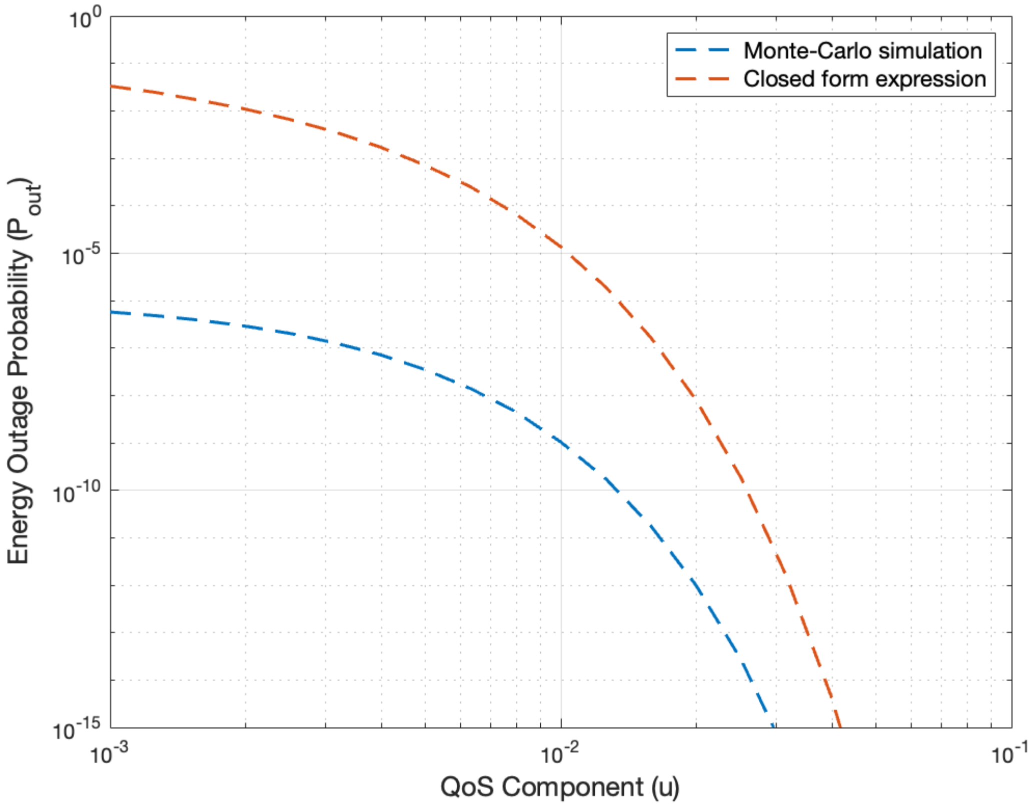


Fig. 4.7 Validation of the theoretical analysis.

ulations, the chosen set-up is such that the theoretical analysis is validated. From the Monte-Carlo simulation, P_{out} is approximately 10^{-6} and the QoS component u is approximately 0.03. From the closed-form expression, P_{out} is approximately 10^{-2} and the QoS component u is approximately 0.04. The figure demonstrates that the value of P_{out} obtained from the closed-form expression is higher than the value of P_{out} that is obtained from the Monte-Carlo simulation. This confirms that for stringent QoS requirements to be satisfied, tighter measure of P_{out} is needed.

Please refer to Figure 3.14 for the system-level simulation plot, which illustrates the comparison of outage probabilities between two distinct scenarios: the energy harvesting system and the baseline scenario.

4.5 Conclusion

In this chapter, we analyzed the performance of point-to-point energy-harvesting point-to-point communication, in which the time-switching circuit at the source node allows the latter to switch between harvesting energy from a distant RF energy source, and transmitting data to its target destination by using the scavenged energy. Using a duality principle between the physical energy queue and a proposed virtual energy queue, and assuming that a certain level of energy outage can be tolerated in the communication process, the system performance was evaluated with a novel analytical framework that leverages tools for the large deviation principle. The effects of various system parameters on the performance of the communication system were studied and analyzed. As an increase in the distance between the sensor node and the RF energy source can impact the energy-outage probability significantly, the proposed analysis can help determine the distance dependency for a feasible harvesting, and the permissible energy-outage to guarantee the QoS requirements.

Chapter 5

QoS Guarantee for SWIPT network with Energy Harvesting Model

5.1 Introduction

Wireless communication networks have become increasingly popular and essential due to the widespread use of communication devices. However, these devices are often battery-operated and have limited lifespans, which can decrease their efficiency and increase costs. To address this issue, energy harvesting technologies can extend the lifespan of wireless devices and reduce battery dependency [12, 115].

Recently, EH using radio frequency (RF) signals has gained prominence among researchers [144]. RF EH is considered as a potential solution for improving the lifetime of energy constrained wireless networks [1, 88]. RF EH is one of the most propitious candidates as an alternative power source which can reduce the battery dependency. RF EH can overcome the limitations of traditional EH techniques such as lower power conversion efficiency, low power density, larger size and increased power loss. In comparison to conventional energy supplying devices, such as batteries which are characterized by their limited operation time and energy constraint nature, RF EH ensures seamless wireless communication without the need of using external energy sources [43]. In addition, RF energy is one of the easily available energy for wireless sensors all the time compared to other EH techniques such as solar, thermal, and piezoelectric energies. This is because of the electromagnetic waves which are originating from radar stations, cell phone towers, various Wi-Fi routers, and satellites, is abundantly available in environment for information exchange. An advantage of using RF signals for EH is its ability to allow simultaneous data and energy transmission which ensures fast and swift communication in wireless networks [94]. The amount of energy extracted in RF harvesting depends on various factors such as the wavelength of RF signal, and power transmitted. Several research investigations have been proposed for maximizing energy efficiency of wireless networks using RF EH techniques [33, 55, 124]. In general, there are two main protocols which are widely used in RF EH networks for data transmission and information processing namely Time switching based relaying (TSR) [101] protocol and Power splitting based relaying (PSR) protocol [76]. In TSR protocol, the receiver shifts between EH and information processing while in PSR, the signal is split into two parts by the receiver for EH and information processing.

Recently there is a great attention for wireless energy transfer (WET) because of its ability to improve the energy efficiency of these networks. In general, the WET can be categorized into three main types namely magnetic resonant coupling [124], inductive coupling [26] and RF based WET [62]. Among these, magnetic resonance and inductive coupling depend on near field magnetic fields and are not suitable for EH devices due to the mobility of the sensor nodes. In addition, the short distance between wireless charging devices and non-alignment of the magnetic fields affects the performance of these two WETs. On the contrary, RF based WETs make use of electromagnetic waves which allows wireless charging and communication in wireless networks over long distances. In addition, the broadcasting nature of RF based energy transfer extends can be used for multiple charging devices which eliminates the requirement of manual recharging and power cords for wireless networks. Hence, the concept of simultaneous wireless information and power transfer (SWIPT) becomes more appropriate for communication networks [84, 63]. The emergence of SWIPT technology to communication networks has transformed the architecture of the wireless communication networks and resource allocation process. In SWIPT systems, the energy of the signal carrying information can be increased to match the magnitude of RF energy harvested at the receivers. However, the power density of the RF energy harvesters is quite small and the need for an efficient EH model for maximizing the energy efficiency is still persistent. Several research works have proposed different approaches for improving the energy efficiency in SWIPT networks via different EH techniques [31, 111, 134]. An energy maximization of EH technique is proposed in [136] wherein an under laid cellular network is optimized by obtaining an optimal resource allocation and power efficiency. The study incorporated a pre matching algorithm for segmenting device links into a SWIPT network and it was observed that the non-EH groups cannot meet the sensitivity of the EH models. In addition, a two-layered architecture composed of an iterative algorithm is discussed for optimizing the power splitting ratio for maximizing the energy efficiency for each SWIPT network. In [59], the authors offer a closed-form analysis of the outage probability for a nonlinear TS-based receiver. The numerical analysis adopts the use of Gaussian-Chebyshev quadrature formulae. The results demonstrate that an upper limit of transmission power exists due to the EH circuit's nonlinear effect. The authors in [49] examined a novel transmission protocol and the operation of the network. The outage probability (OP) and block error rate (BLER) performances for Rayleigh distributed fading channels are assessed, taking into account the non-linear energy harvesting (EH) mechanism at power-constrained nodes and direct and cooperative phase transmissions. In [34], the outage probability performance for uplink and downlink NOMA systems with multi-antenna energy harvesting aerial base stations, which serve as mobile relays, is evaluated under faulty successive interference cancellation (SIC). In [81], An H-SWIPTMS energy harvesting technique is proposed to improve the energy harvesting capacity for multiple sources. Following the simultaneous wireless information and power transfer (SWIPT) principle for radio frequency (RF) energy harvesting (EH)-enabled cooperative cognitive radio network (CCRN), the hybrid power time switching (HPTS) technique is adopted for harvesting energy from RF signals at Internet-of-Things devices in [28] .The works in [142] and [16] assume that the resources are allocated for maximizing energy efficiency in such a way that it ensures the availability of sufficient energy in batteries for data transmission. However, this assumption is not suitable for all conditions, especially when the communication channel is extremely weak. Wireless energy transfers have to be performed with high power transmissions and guaranteeing the QoS of EH in terms of different parameters such as throughput and outage probability can be highly challenging. It can be inferred from existing literary works that the energy outage can happen when sufficient energy is not available in batteries and in such cases, the EH communication cannot achieve desired QoS. Despite the availability of different energy maximization and QoS enhancing techniques, there is still a lack of an efficient RH energy harvesting model which can maximize the energy efficiency in wireless networks considering the QoS parameters.

This research aims to ensure QoS in SWIPT networks based on RF EH model and TSR protocol.

5.1.1 Contributions

The main contributions of this chapter can be summarized as follows:

- This chapter presents a RF EH model to enhance the QoS in SWIPT networks wherein the source node harvests and stores energy from RF signals and uses the harvested energy for communication.

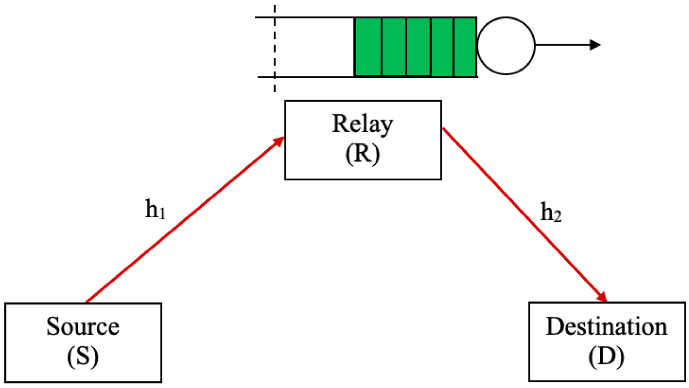
- A time-switching protocol is considered where the relay nodes harvest energy from the received signal during the time fraction. Information is transmitted using the remaining time fraction, with the first half being used to send information from the source to the relay and the remaining time used to send information from the relay to the destination.

- A novel mathematical framework is employed for the performance evaluation of the proposed RF EH model for communication, considering the energy outage at the relay. Developing the mathematical framework, we used the randomness property of the system's energy-outage occurrence. The queuing system for the EH battery is modelled using the LDP theorem. A virtual battery queuing model is used to facilitate providing the assumptions needed for using LDP.
- We provide a closed-form solution for the possibility of an energy outage and the rate of energy flowing in and out from the relay node's battery.
- The performance of this work is validated in terms of different evaluation metrics such as optimal EH time, QoS component, RF source power and outage probability.

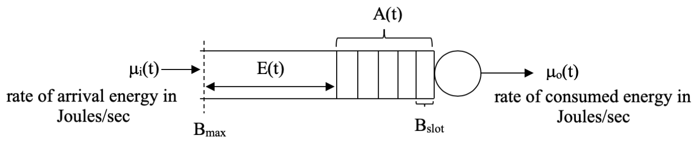
The organization of the chapter is as follows: Section 5.2 discusses the framework of the proposed RF model and different steps involved in the implementation. Section 5.3 will discuss the relay EH network. Numerical results are discussed in Section 5.4. Section 5.5 concludes the chapter.

5.2 System Model

The proposed RF-EH model implements a time switching protocol which considers a wireless relay network with a source (S) transmitting data to its destination (D) through a relay (R) as shown in Fig. 5.1. It is assumed that the source and destination are not linked to each other directly and all channels are independent of each other. The coefficients of the fading channels h_1 and h_2 are defined by the channels from the source to the relay and from the relay to the destination, respectively and the block period of transmission is denoted as T. A finite sized EH battery at relay is used for evaluating the performance. The distance from source to relay and relay to destination is referred as d_1 and d_2, respectively. It is assumed that the source, relay and destination all are equipped with a single antenna. The switching between harvesting energy and transmitting information takes place at relay following time switching protocol.



(a) System model.



(b) Battery structure within the power control module in (a).

Fig. 5.1 The energy-harvesting based communication system.

5.2.1 Time Switching Protocol

Fig.5.2 shows the parameters responsible for functioning time switching protocol performing EH and information processing at relay. Let T represent the size of the fading block that contains these functions. The proposed relay network consist of three steps namely;

- Step 1: The energy harvesting from the RF signal source to the relay with a time duration of αT, where $0 \leq \alpha \leq 1$.
- Step 2: The source communicates with the relay for a time duration of $(1-\alpha)T/2$.
- Step 3: In this step, remaining $(1-\alpha)T/2$ is used by the relay to communicate with the destination.

The RF-EH based communication system is characterized by the signal captured by the receiving antenna at the relay. Please refer (4.1) and (4.2) for further information.

5.2.2 Physical Battery Storage Model

The battery storage model used in this research for RF EH employs an energy queue which stores the harvested energy. The energy stored in the battery at time t is represented as $A(t)$

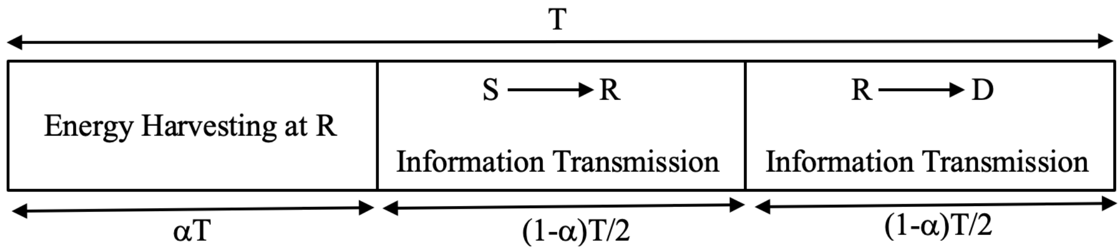


Fig. 5.2 Time-switching protocol for energy harvesting and information processing at the sensor node R.

and the empty portion of the battery is represented as $E(t)$. In the battery storage model, the RF based EH signifies EH as the incoming process and energy consumption as the outgoing process. $B_{\max}$ denotes the maximum level of energy that the battery can withhold in Joules. $\mu_{\mathrm{i}}(t)$ defines the rate of energy flowing into the battery and $\mu_{\mathrm{o}}(t)$ is the rate of energy flown out of the battery. Both these terms are measured as Joules/sec. Please refer (3.1) and (3.2) for further information.

The power of signal transmission in relay is restricted by defining a threshold value also known as maximum permissible level, $\mu_{\max}T$. This level states that the value of the transmitted power should not exceed the value of $\mu_{\max}$. Here, the Rayleigh channel fading is considered as a random process and to satisfy the QoS constraints it is essential to maintain a high transmission power while transmitting the signal when the channel is significantly weak. However, guaranteeing the availability of energy required for high power transmission is a difficult task and it is also challenging to determine the amount of energy flowing into the battery which is harvested from the external environment. Specifically RF energy which enables the fast adaptation of the data transmission process in order to satisfy the QoS.

Considering the fact that it is difficult to estimate the energy stored in the battery and to predict the battery status, it is also complicated to ensure that a desired QoS is maintained during the entire data transmission process.

5.3 Analysis of relay EH network

A novel mathematical approach is formulated for evaluating the performance of the RF-EH based on the assumptions of the (Large Deviation Principle) LDP theorem. A virtual queuing model is proposed for implementing the assumptions and for estimating the probability of energy outage on the QoS. In addition, the theory of effective RF-EH is proposed for obtaining the statistical relation between different factors such as amount of energy flowing into the battery, Rayleigh fading channel conditions, and QoS constraints. According to the proposed theory of effective energy harvesting, the arriving energy traffic process' stochastic behaviour can be asymptotically described by its effective EH [14].

5.3.1 Virtual Battery Queuing Model

A Virtual Battery Queuing Model is proposed, please refer Fig.3.3. The proposed queuing model maintains a steady queue by reversing the roles of the captured and expended energy. The EH process and the energy-consuming process, which were addressed in Section 5.2's exposition of the conventional physical battery storage design, are precisely swapped. By rotating roles, the paradigm provides a flexible approach to energy storage and consumption, increasing energy systems' overall efficiency and sustainability. This is achieved using the inverse inequality and LDP theorem in the virtual battery queuing model. According to the inverse inequality, the probability of an event occurring is greater than or equal to the exponential of the negative of its upper bound. This is a useful tool for comprehending the operation of the virtual battery queuing model. The proposed virtual battery queuing model can then be subjected to the LDP theorem using the inverse inequality.

In this model, the length of the battery queue $E(t)$ can be used to determine the energy consumption and the amount of energy left in the battery. Please refer (3.8) for further information.

As shown in Fig.3.3, the incoming flow of energy into the virtual queue and the corresponding energy outflow are represented as $\mu_{\mathrm{o}}(t)$ and $\mu_{\mathrm{i}}(t)$ respectively and $B_{\max}$ is the maximum permissible value. Please refer (3.9) for further information.

The queue model can also formulate the number of empty energy slots in the battery at time $t+1$. Please refer (3.10) for further information.

The virtual queue model helps in analyzing and predicting the probability of the energy outage in the proposed virtual battery queuing model for evaluating the performance of the RF-EH based communication systems to ensure the QoS in SWIPT networks.

5.3.2 Source and Relay Transmission Rate

According to the suggested theory of RF EH, the incoming energy process' stochastic behaviour can be asymptotically described by its efficacious RF EH.

The transmission rate of 1^{st} hop i.e. from source to relay is r_1 in nats/sec/Hz

$$r_1 = \log\left(1 + |h_1|^2 \frac{P_s}{nd_1^m}\right)\left((1-\alpha)\frac{T}{2}\right) \tag{5.1}$$

The transmission rate of 2^{nd} hop i.e. from relay to destination is r_2 in nats/sec/Hz

$$r_2 = \log\left(1 + |h_2|^2 \frac{\mu_o}{nd_2^m}\right)\left((1-\alpha)\frac{T}{2}\right) \tag{5.2}$$

It is assumed that the rate of first hop is equal to rate of second hop, $r_1 = r_2$. Also, the distance between source and relay d_1 and the distance between relay and destination d_2 are equal. Hence,

$$\begin{aligned} &\log\left(1 + |h_1|^2 \frac{P_s}{nd_1^m}\right)\left((1-\alpha)\frac{T}{2}\right) \\ &= \log\left(1 + |h_2|^2 \frac{\mu_o}{nd_2^m}\right)\left((1-\alpha)\frac{T}{2}\right) \end{aligned} \tag{5.3}$$

Further simplifying (5.3),

$$\mu_o = \frac{|h_1|^2 P_s}{|h_2|^2} \tag{5.4}$$

5.3.3 RF Energy Harvesting

The empty slot accumulation of the battery, denoted by $\mu_o(t)$, which is specified for $t \geq 0$, reflects the rate of outgoing energy or energy expenditure (in Joules per second). An arrival energy process to the queue is considered, which arrives to the empty side of it.

It is assumed that $\mu_o(t)$ has an asymptotic log moment generating function, which is written as

$$\Lambda(u) = \lim_{t\to\infty} \frac{1}{t} \log\left(\mathbb{E}\left[e^{u\mu_o(t)}\right]\right), \tag{5.5}$$

valid for all $u \geq 0$. Here, $\mathbb{E}[\cdot]$ represents the expectation operator.

The following is a definition of the effective EH function of $\mu_o(t)$:

$$\alpha(u) = \frac{\Lambda(u)}{u}. \tag{5.6}$$

The asymptotic log MGF (5.5) is substituted into (5.6), we obtain

$$\begin{aligned}\frac{\Lambda(u)}{u} &= \lim_{t\to\infty}\frac{1}{ut}\log\left(\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right)\\ &= \lim_{t\to\infty}\frac{1}{ut}\log\left(\mathbb{E}\left[\prod_{i=0}^{t}e^{u\mu_{\mathrm{o}}(t)}\right]\right)\\ &= \lim_{t\to\infty}\frac{1}{ut}\log\left(\prod_{i=0}^{t}\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right)\end{aligned}$$

Inferring that $\{\mu_{\mathrm{o}}[\mathrm{i}], \mathrm{i} = 0, 1, 2, ...\}$ is independent and that the service process is stable, ergodic, and holds under the assumption of a block fading channel, we obtain

$$\begin{aligned}\frac{\Lambda(u)}{u} &= \lim_{t\to\infty}\frac{1}{ut}\log\left(\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right)\\ &= \lim_{t\to\infty}\frac{1}{ut}\log\left(\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right)^{t}.\end{aligned} \tag{5.7}$$

Consequently, the simplified expression is derived as

$$\frac{\Lambda(u)}{u} = \frac{1}{u}\log\left(\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right). \tag{5.8}$$

Also, it is assumed that $\mu_{\mathrm{i}}(t)$ has the following asymptotic log moment generating function:

$$\Lambda(-u) = \lim_{t\to\infty}\frac{1}{t}\log\left(\mathbb{E}\left[e^{-u\mu_{\mathrm{i}}(t)}\right]\right), \tag{5.9}$$

valid for all $u \geq 0$. Here, $\mathbb{E}[\cdot]$ represents the expectation operator.

The following is a definition of the effective EH function of $\mu_{\mathrm{o}}(t)$:

$$\alpha(u) = \frac{-\Lambda(-u)}{u}. \tag{5.10}$$

The asymptotic log MGF (5.9) is substituted into (5.10), we obtain

$$\begin{aligned}\frac{-\Lambda(-u)}{u} &= \lim_{t\to\infty}-\frac{1}{ut}\log\left(\mathbb{E}\left[e^{-u\mu_{\mathrm{i}}(t)}\right]\right)\\ &= \lim_{t\to\infty}-\frac{1}{ut}\log\left(\mathbb{E}\left[\prod_{i=0}^{t}e^{-u\mu_{\mathrm{i}}(t)}\right]\right)\\ &= \lim_{t\to\infty}-\frac{1}{ut}\log\left(\prod_{i=0}^{t}\mathbb{E}\left[e^{-u\mu_{\mathrm{i}}(t)}\right]\right)\end{aligned}$$

By assuming a block fading channel and deducing that $\{\mu_{\mathrm{i}}[\mathrm{i}], \mathrm{i} = 0, 1, 2, ...\}$ is independent and the service process is stable and ergodic, we attain

$$\begin{aligned}\frac{-\Lambda(-u)}{u} &= \lim_{t\to\infty}\frac{1}{ut}\log\left(\mathbb{E}\left[e^{-u\mu_{\mathrm{i}}(t)}\right]\right)\\ &= \lim_{t\to\infty}\frac{1}{ut}\log\left(\mathbb{E}\left[e^{-u\mu_{\mathrm{i}}(t)}\right]\right)^{t}.\end{aligned} \tag{5.11}$$

Consequently, the simplified expression is derived as

$$\frac{-\Lambda(-u)}{u} = \frac{1}{u}\log\left(\mathbb{E}\left[e^{-u\mu_{\mathrm{i}}(t)}\right]\right). \tag{5.12}$$

5.3.4 Upper Bound of μ_{i}

As per the energy arrival process, upper bound of μ_{i} is,

$$\mu_{\mathrm{i}} \leq \frac{\Lambda(u)}{u} = \frac{1}{u}\log\left(\mathbb{E}\left[e^{u\mu_{\mathrm{o}}(t)}\right]\right). \tag{5.13}$$

Further, a closed-form expression for μ_{i} can be obtained as follows:

$$\mu_{\mathrm{i}} \leq \frac{1}{u}\log\left(\int_{0}^{\infty} e^{u\mu_{\mathrm{o}}(t)}p\left(|h_1|^2\right)d\left(|h_1|^2\right)\right), \tag{5.14}$$

where $p\left(|h_1|^2\right)$ is the probability density function (PDF) of $|h_1|^2|$.

Substituting μ_{o} from (5.4) in (5.14),

$$\mu_{\mathrm{i}} \leq \frac{1}{u}\log\left(\int_{0}^{\infty} e^{u\frac{|h_1|^2(P_s)}{|h_2|^2}} p\left(|h_1|^2\right)d\left(|h_1|^2\right)\right), \tag{5.15}$$

Note that only the ratio $\frac{|h_1|^2}{|h_2|^2}$ determines how the integration in (5.15) depends on the random variables $|h_1|^2$ and $|h_2|^2$. Now, the random variable v is defines as $v = \frac{|h_1|^2}{|h_2|^2}$.

$$\mu_{\mathrm{i}} \leq \frac{1}{u}\log\left(\int_{0}^{\infty} e^{uvP_s}p(v)d(v)\right), \tag{5.16}$$

The distribution of random variable v can be found as

$$p(v) = \frac{1}{(v+1)^2} \tag{5.17}$$

and the result is shown in [29].

The relay has a cutoff value $\mu_{\max}$ such that the transmission is suspended when $\frac{\mu_{\max}}{P_s} \leq \frac{|h_1|^2}{|h_2|^2}$, the outgoing energy can be found as,

$$\mu_{\mathrm{o}} = \begin{cases} \frac{|h_1|^2 P_s}{|h_2|^2} & 0 \leq \frac{|h_1|^2}{|h_2|^2} \leq \frac{\mu_{\max}}{P_s} \\ \\ \mu_{\max} & \frac{\mu_{\max}}{P_s} \leq \frac{|h_1|^2}{|h_2|^2} < \infty \end{cases}$$

By inserting (5.17) into (5.16), the expression for μ_{i} becomes

$$\mu_{\mathrm{i}} \leq \frac{1}{u} \log \left(\int_{0}^{\frac{\mu_{\max}}{P_s}} \frac{e^{uvP_s}}{(v+1)^2} dv + \int_{\frac{\mu_{\max}}{P_s}}^{\infty} \frac{e^{u\mu_{\max}}}{(v+1)^2} dv \right), \tag{5.18}$$

Performing integration by parts,

$$\int_{0}^{\frac{\mu_{\max}}{P_s}} \frac{e^{uvP_s}}{(v+1)^2} dv = -\frac{e^{uvP_s}}{v+1} - \int_{0}^{\frac{\mu_{\max}}{P_s}} -\frac{P_s u e^{uvP_s}}{v+1} dv$$

and

$$\int_{\frac{\mu_{\max}}{P_s}}^{\infty} \frac{e^{u\mu_{\max}}}{(v+1)^2} dv = \frac{e^{u\mu_{\max}}}{\frac{\mu_{\max}}{P_s} + 1}$$

Further, evaluating the integration as follows:

$$\frac{1}{u}\log\left(\int_{0}^{\frac{\mu_{\max}}{P_s}} \frac{e^{uvP_s}}{(v+1)^2}dv + \int_{\frac{\mu_{\max}}{P_s}}^{\infty} \frac{e^{u\mu_{\max}}}{(v+1)^2}dv\right)$$
$$= -\frac{e^{u\mu_{\max}}}{u\mu_{\max}+P_s u}P_s u(-P_s u) - e^{-P_s u}P_s u - Ei(u\mu_{\max}+P_s u)$$
$$+e^{-P_s u} + e^{-P_s u} + Ei(P_s u) + \frac{e^{u\mu_{\max}}}{\frac{\mu_{\max}}{P_s}+1} \tag{5.19}$$

5.3.5 Upper Bound of μ_{o}

As per the energy arrival process, upper bound of μ_{o} is,

$$\mu_{\mathrm{o}} \leq \frac{-\Lambda(-u)}{u} = \frac{-1}{u}\log\Big(\mathbb{E}\big[e^{-u\mu_{\mathrm{i}}(t)}\big]\Big). \tag{5.20}$$

Further, a closed-form expression for μ_{o} can be obtained as follows:

$$\mu_{\mathrm{o}} \leq \frac{-1}{u}\log\left(\int_{0}^{\infty} e^{-u\mu_{\mathrm{i}}(t)} p\left(|h_1|^2\right) d\left(|h_1|^2\right)\right), \tag{5.21}$$

where $p\left(|h_1|^2\right)$ is the probability density function (PDF) of $|h_1|^2|$.

Substituting μ_{i} from (4.2) in (5.21),

$$\mu_{\mathrm{o}} \leq \frac{-1}{u}\log\left(\int_{0}^{\infty} e^{-u\left(\frac{\eta P_s |h_1|^2 \alpha T}{d_1^m}\right)} p\left(|h_1|^2\right) d\left(|h_1|^2\right)\right), \tag{5.22}$$

The distribution of the channel power gain, $|h_1|^2 = \gamma$, is exponential since it is believed that the channels are subject to Rayleigh fading. Thus, we have

$$\mu_{\mathrm{o}} \leq -\frac{1}{u}\log\left(\int_{0}^{\infty} e^{-u\left(\frac{\eta P_s \gamma \alpha T}{d_1^m}\right)} p(\gamma)d\gamma\right), \tag{5.23}$$

with the PDF of γ provided by

$$p(\gamma) = e^{-\gamma}; \gamma \geq 0.$$

Consequently, the above μ_o expression becomes

$$\mu_o \leq -\frac{1}{u}\log\left(\int_0^\infty e^{-u\left(\frac{\eta P_s \gamma \alpha T}{d_1^m}\right)} e^{-\gamma} d\gamma\right). \tag{5.24}$$

Lastly, by resolving the definite integral of the aforementioned equation, we arrive at

$$\mu_o \leq -\frac{1}{u}\log\left(\frac{d_1^m}{\alpha\eta P_s T u + d_1^m}\right). \tag{5.25}$$

5.3.6 Energy-Outage Probability

The probability of energy outage is evaluated to determine the performance efficiency of the RF-EH based communication systems. The probability is calculated considering the physical constraints of the communication systems and is defined as the energy outage condition when the energy harvested is not sufficient to maintain an active energy consumption mechanism. In simple words, it can be said that the conditions when the harvested energy is not available for information transmission or when the harvested energy is below the outgoing energy $\mu_o(t)T$ and this value is maintained as low as possible in order to prevent the system from becoming inactive. Once the energy flowing into the battery $A(t)$ falls below the threshold value $\mu_o(t)T$, the transmitter shows the low battery status and the system goes into hibernation condition when the energy outage occurs and this status continues till the battery is recharged to a specific level. The virtual battery queuing model is designed based on the empty side and the probability of energy outage occurrence is calculated and predicted based on the probability of empty portion queue at a time t. Simultaneously, the occurrence of energy outage is expected to be low as illustrated,

$$\Pr\big\{E(t) \geq (B_{\max} - \mu_o(t)T)\big\} \leq P_o. \tag{5.26}$$

Where, P_o is defined as the maximum probability of energy outage which the system can tolerate. The term $Pr\{E(t)\}$ signifies the probability at which the virtual buffer is restricted at a time t. Further, the probability of energy outage is estimated following the QoS constraints as discussed in the next section.

5.3.7 QoS Guarantees

The LDP theorem discussed previously can be used to illustrate that it requires a robust formulation for a dynamic queuing system with an appropriate transmission process for calculating the probability of energy outage. Here, it is assumed that the maximum power of the battery $\mu_{\max}T$ can be employed for different time slots and the length of empty portion process $E(t)$ $(t \geq 0)$ converges in distribution to a finite random variable $E(\infty)$ which satisfies the following criteria:

$$\lim_{B_{\max}\to\infty} \frac{\log\Big(\Pr\big\{E(\infty) \geq (B_{\max} - \mu_{\max}T)\big\}\Big)}{B_{\max} - \mu_{\max}T} = -u, \tag{5.27}$$

(5.27) defines the probability of the queue length which exceeds the threshold value $(B_{\max} - \mu_{\max}T)$ and then reduces exponentially as fast as $B_{\max}$ increases. For large values and of $B_{\max}$, (5.28) provides the constraints.

$$\Pr\big\{E(\infty) \geq (B_{\max} - \mu_{\max}T)\big\} \approx e^{-u(B_{\max} - \mu_{\max}T)}. \tag{5.28}$$

Correspondingly, the accurate approximation for smaller values of $B_{\max}$ is given in (5.29).

$$\Pr\big\{E(\infty) \geq (B_{\max} - \mu_{\max}T)\big\} \approx \varepsilon e^{-u(B_{\max} - \mu_{\max}T)}, \tag{5.29}$$

where ε denotes the probability of non-empty virtual buffer, i.e.,

$$\Pr\{E(t) > 0\} = \varepsilon, \tag{5.30}$$

The probability can be determined by calculating the ratio of the average incoming rate to the fixed outgoing rate corresponding to the virtual battery queue model. The ratio is given as follows [127]:

$$\varepsilon \approx \frac{\mathbb{E}(\mu_{\mathrm{o}}(t))}{\mathbb{E}(\mu_{\mathrm{i}}(t))} \tag{5.31}$$

In the aforementioned formulation, the constant $u(u \geq 0)$ is defined as the QoS exponent, which is highly important for guaranteeing the QoS. The decrease in the exponential value also decreases the probability rate of QoS violation. Larger the value of u faster is the rate of decay which assists in attaining better QoS and the smaller value of u reduces the decay rate and this signifies that the RF-EH based communication system can achieve a lower QoS requirement.

It is essential to incorporate potentially suitable channel models which can effectively represent practically relevant network conditions and help in developing an appropriate analytical model for determining the performance of the RF-EH based communication networks.

5.4 Validation and Discussion

This section discusses the results of the simulation analysis based on the proposed energy harvesting framework discussed in section III. As discussed in the previous section, the energy transmission process and the fading channel between source and destination is assumed to be static. The proposed RF EH model is simulated with respect to different performance evaluation metrics namely QoS which is measured in terms of effective incoming energy and effective outgoing energy, outage probability, and maximum energy stored in the battery. In the proposed model, energy harvesting is performed to enhance the QoS in SWIPT networks which enables the source node to harvest and store the energy from RF signals and use the same energy for communication to improve the energy efficiency. The performance of statistical QoS can be analyzed by evaluating the outgoing and incoming processes. RF EH has a greater role in determining the potential capability and lifespan of wireless networks, specifically SWIPT networks. Though EH systems are advantageous, they suffer from various issues such as lack of energy availability from harvesting sources, ineffective harvesting techniques, and power management. The dependency on the batteries restricts the adaptability of WSNs. Hence it is essential to focus more on QoS enhancement and maximize the energy efficiency of batteries in wireless networks in order to overcome the drawbacks.

The performance of RF EH in terms of QoS is shown in Fig. 5.3. In the plot, the curves represented in blue and red lines signifies the effective outgoing energy (EOE) and effective incoming energy (EIE) respectively (see Appendix A). As inferred from the above figure, the effective outgoing energy can be increased by increasing the outgoing process which in turn results in the larger QoS exponent solution and is denoted as u^*. This is defined by the arrow at the lower position. This also indicates that the higher outgoing process can help in obtaining a more regulated QoS for a particular incoming process. On the other hand, increasing the incoming process as denoted by the arrow at the upper position, increases the effective incoming energy which results in the generation of a smaller QoS exponent solution u^* for a specific outgoing process. This process is in contrast with the increase in the outgoing process. This validates the fact that with the increase in the incoming process, a lower QoS can be guaranteed which is not appropriate for most of the wireless networks. With the increase in the bandwidth of the arrival process such that $EIE > EOE$, no particular solution can be obtained for the condition $u^* > 0$ existing. In this case, the service process

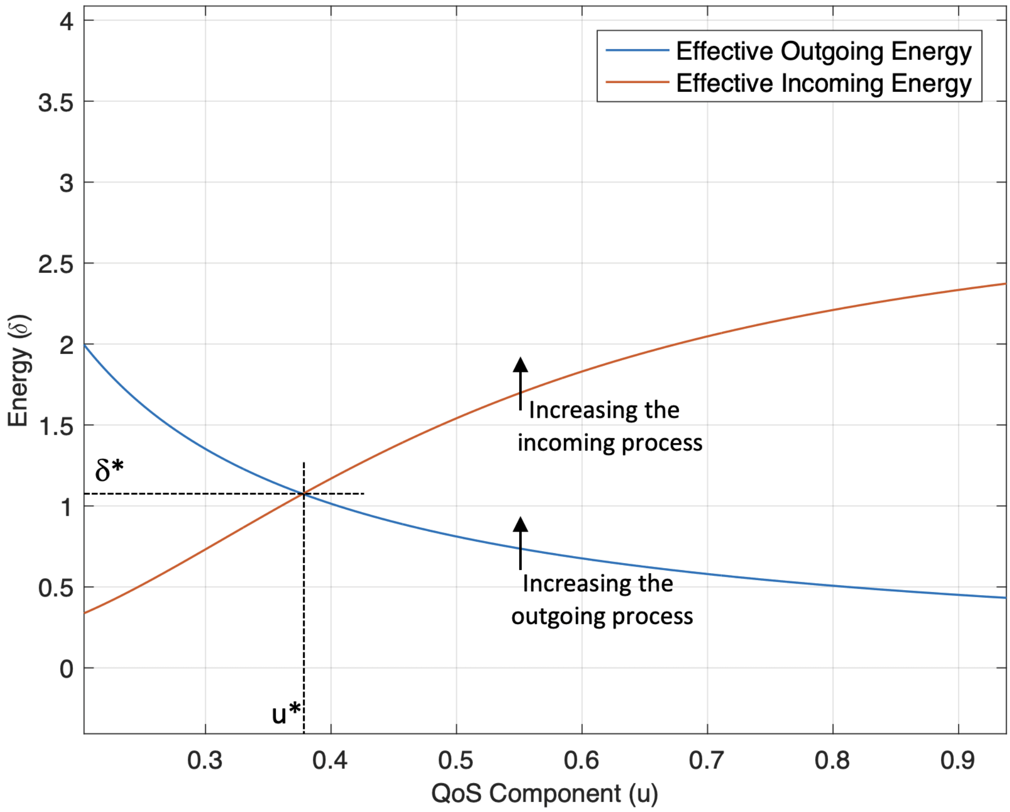


Fig. 5.3 The relationship between effective incoming energy and effective outgoing energy as a function of the QoS exponent u.

cannot support any QoS for the given arrival process which is consistent with the queuing theory. For other conditions, if $EIE > EOE$, both queue length and the queuing delay will tend to infinity. The results of the simulation analysis depend on the expressions for outage probability as shown in (5.35), which is calculated by evaluating the maximum probability of energy outage which the system can tolerate. The energy outage is realized by carrying out certain random realizations of the Rayleigh fading channels of h_1 and h_2.

The QoS component for the RF EH model with respect to the energy harvesting factor α is illustrated in Fig. 5.4. The QoS component is realized for different values and the performance of the QoS component is observing a steady decline with the increase in the number of realizations. Here the variation in the curve denotes that when the energy harvesting factor is 0.05, the value of the QoS component is 1.15. The QoS component can be determined by analyzing whether the QoS component values are stringent or not. In general, the EH in battery based wireless networks is restricted due to the limited battery capacity

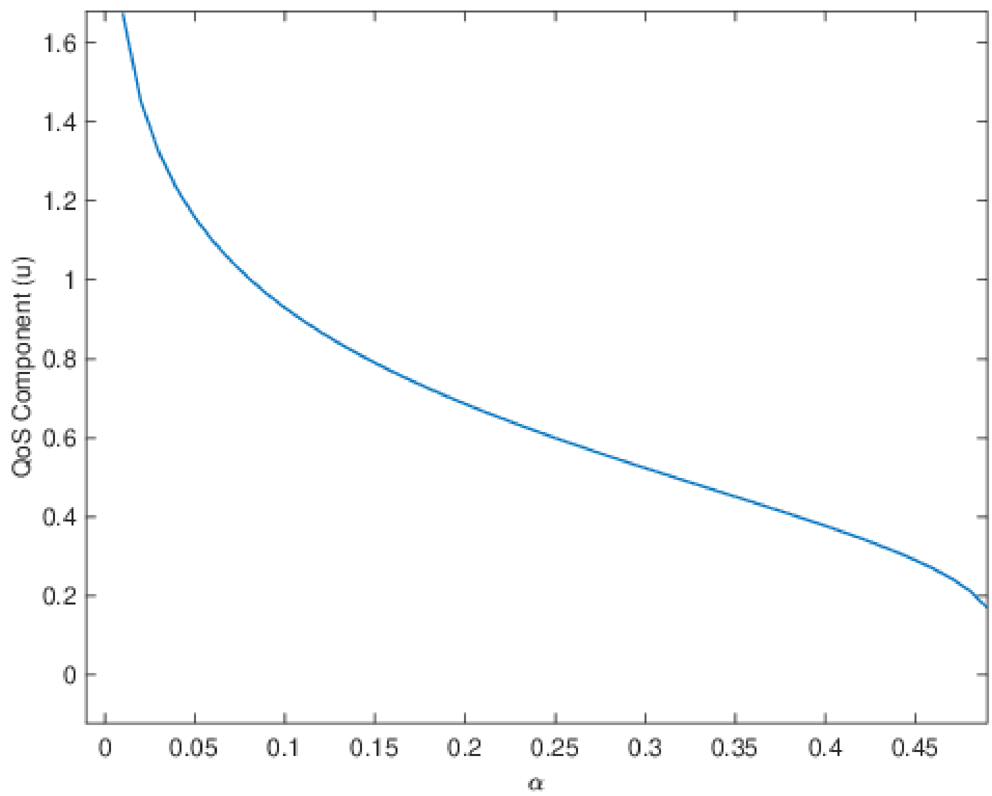


Fig. 5.4 QoS component versus α.

in the high SNR region where the QoS component is very low and the QoS component is stringent in the lower SNR region.

In Fig. 5.5, we show the variation of the energy-outage probability P_{out} versus the RF energy source power P_{s}. for various values of the battery capacity B_{max}. The outage probability is simulated considering different battery capacities as shown in figure. Here the outage probability is considered as a point at which the power of the receiver falls below the threshold value. It can be observed from the plot, that the outage probability increases with the increase in the maximum battery capacity. Also, with the increase in battery capacity, will enable more energy to be stored, hence lowering the likelihood of an electricity outage.

Fig. 5.6, plots the energy-outage probability versus energy harvesting factor for various values of battery capacity B_{max}. The likelihood of an energy outage drops when α rises to an optimal level, but it then begins to rise as α rises from this optimal level. This is because there is less time for energy harvesting for α values that are smaller than the optimal α. As a result, less energy is captured and an increased likelihood of outages is seen. On the

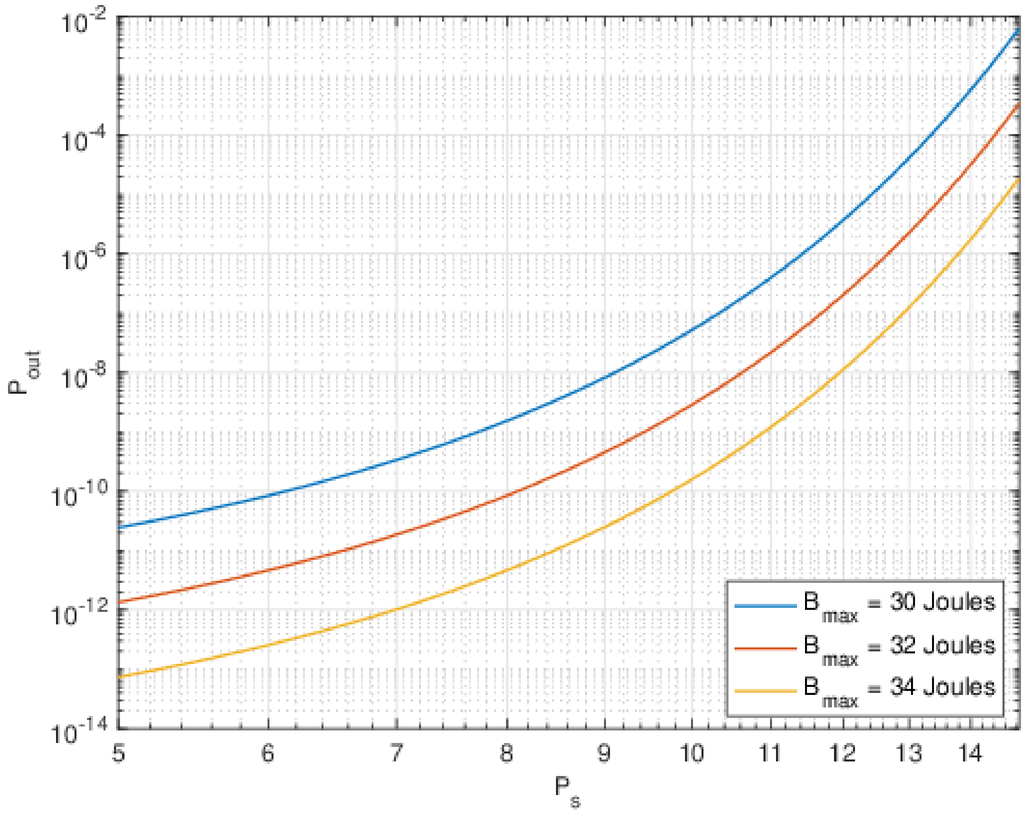


Fig. 5.5 Energy outage probability versus the RF transmit source for various values of $B_{\max}$.

other hand, with α values higher than the optimal α, less time is available for information transmission and more time is wasted on energy harvesting.

Fig. 5.7 defines the relationship between the energy-outage probability P_{out} and the RF energy source power, i.e., P_s, for various values of $\mu_{\max}$. The graph shows that the energy-outage probability P_{out} increases as the value of P_s increases. Also, with the increase in relay transmission cutoff value $\mu_{\max}$, energy outage probability decreases. For instance, if we consider P_s to be 7 dB then for $\mu_{\max} = 12$ dB, the P_{out} is approximate 10^{-12}, for $\mu_{\max}$ $= 14$ dB, the P_{out} is approximate 10^{-14} and for $\mu_{\max} = 16$ dB, the P_{out} is approximate 10^{-15}.

Further, the effect of battery capacity $B_{\max}$ on the energy-outage probability P_{out} is shown in Fig. 5.8. The figure shows that the P_{out} decreases with the increase in $B_{\max}$. For example, P_{out} is approximately 10^{-2} when $B_{\max}$ is 32 Joules, whereas P_{out} is approximately 10^{-8} when $B_{\max}$ is 42 Joules. As a result, there is less chances of an outage when the battery capacity is high, whereas there is more energy-outage when the battery capacity is low.

For the system-level simulation, refer to Fig. 3.14, which compares the likelihood of an outage under the energy harvesting system with the baseline scenario.

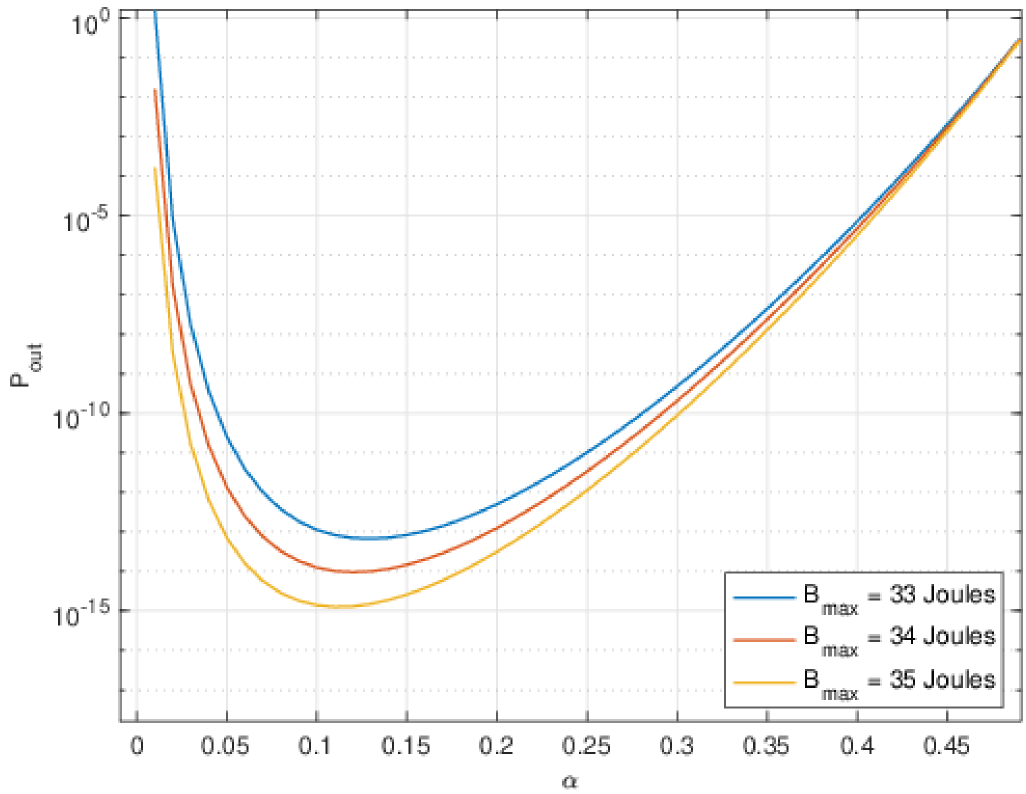


Fig. 5.6 Energy outage probability versus the energy harvesting factor α for various values of $B_{\max}$.

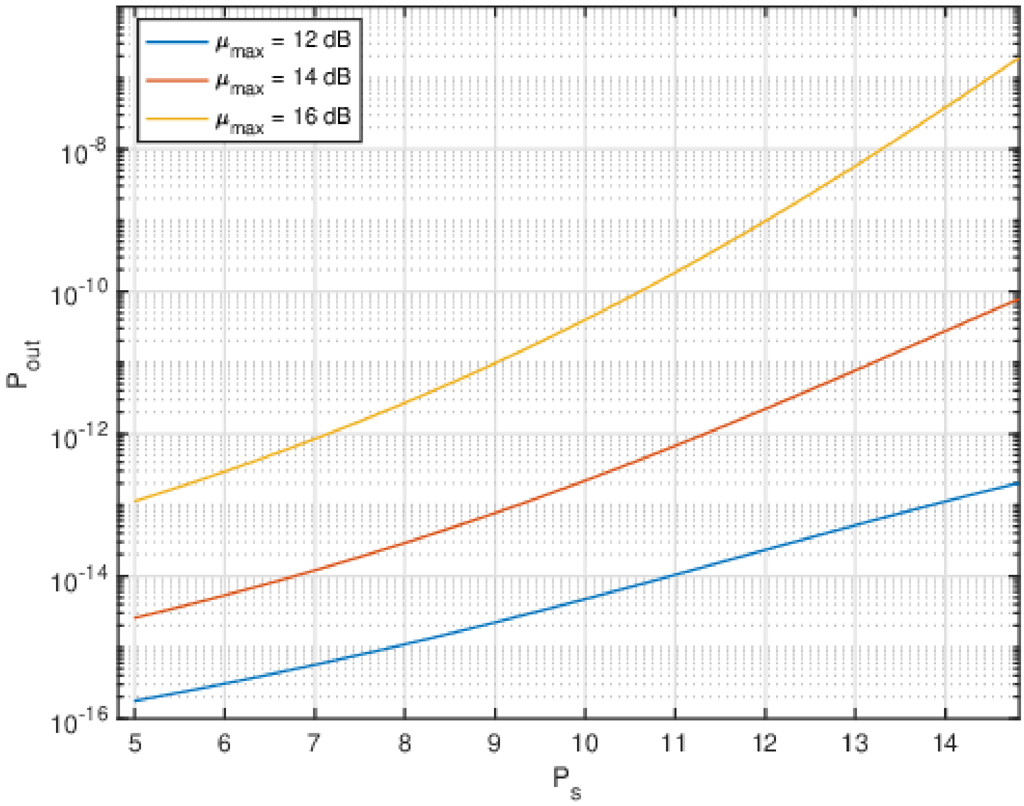


Fig. 5.7 Energy-outage probability versus the RF transmit source for various values of μ_{max}.

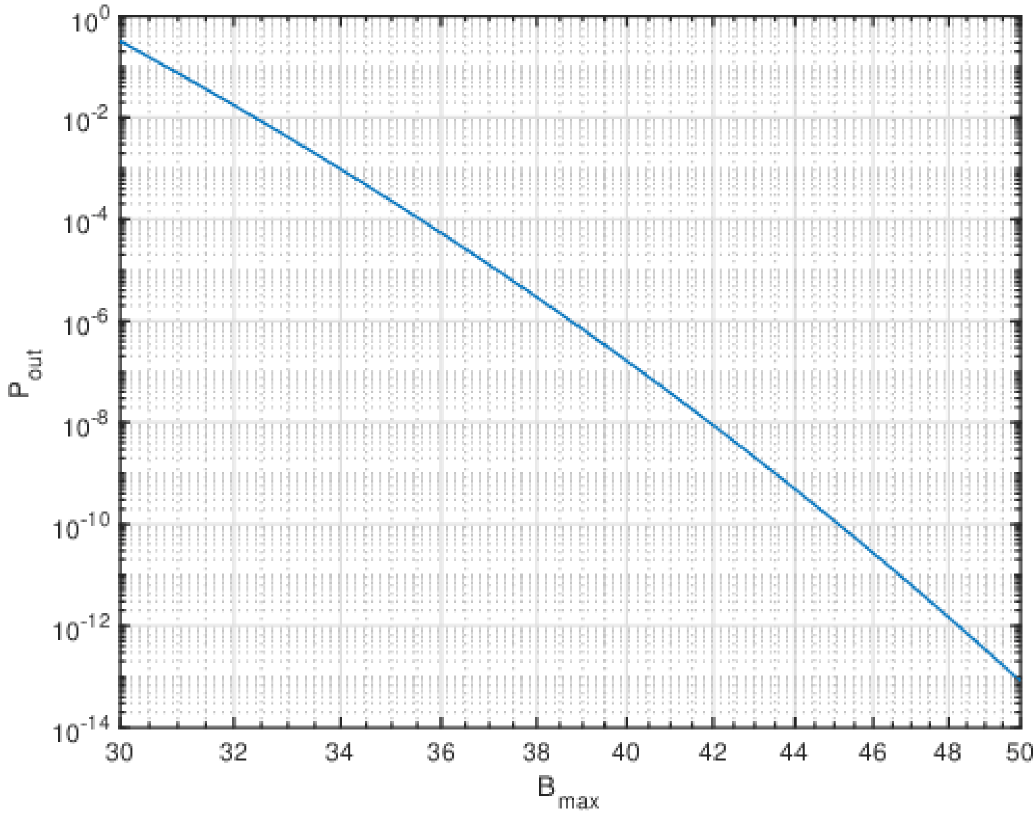


Fig. 5.8 Energy-outage probability versus the battery capacity $B_{\max}$.

5.5 Conclusion

This chapter presents an empirical study of the RF-EH model for ensuring the QoS constraints during energy outage. A point to point RF-EH based communication system is implemented and the modeling of the physical battery storage model and the virtual battery queuing model is discussed wherein these two models assist in formulating the statistical QoS parameters. The proposed approach is a probabilistic approach which uses a mathematical analysis based on LDP and the virtual battery queuing model was used in accordance with the adaptation of the LDP framework. The mathematical expressions defining the rate of the incoming energy and energy outflow from the battery is evaluated and are used to calculate the probability of energy outage. The fading channel conditions and the QoS constraints of the RF-EH based communication system determines the performance of the communication systems with an emphasis on QoS constraints.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This research work discusses the implementation of an energy harvesting (EH) model for improving energy efficiency in wireless communication networks. The main objective of this research is to develop a low complex mathematical model for evaluating the performance of different energy harvesting models such as solar energy harvesting systems (SEH), RF energy harvesting (RF-EH), wireless power transmission (WPT) and simultaneous wireless information and power transmission in wireless networks. To achieve the research objectives, this research conducted a comprehensive analysis of the existing EH systems, emphasising SEH and RF EH systems. Various current prediction-based techniques and energy harvesting techniques with their significance in wireless-based information and power transfer were analysed, and the impact of EH techniques on the energy efficiency of wireless networks. The performance of the proposed EH approach in communication systems was determined using a common complex mathematical framework.

It can be inferred from existing studies that solar energy harvesting-based energy management models are being developed for powering sensor nodes in wireless sensor networks (WSNs) by various networking organizations. In general, WSNs communicate via sensor nodes connected through wireless links and due to this, the sensor nodes consume more energy than desired. The excess energy consumption reduces the lifetime of the sensor nodes, and replacing or charging nodes frequently is a challenging and tedious task. Hence it is essential to develop efficient energy harvesting systems such as solar energy and RF energy harvesting systems to increase the battery storage capacity and increase the WSN systems' efficiency. The SEH models operate based on the solar energy extracted from the sun, which is converted into electrical energy using photovoltaic cells. The nodes in the wireless networks are charged using the electrical energy of the SEH. This reduces the need for the replacement of batteries in sensor nodes in communication networks. Experimental analysis shows that the deployment of SEH for communication networks involves a lot of complexities, such as difficulty in handling the dynamic characteristics of EH systems, time-varying attributes, and problems in predicting their performance and the availability of ambient solar energy. However, the performance of these systems can be controlled using various advanced techniques, such as energy-aware protocols. The controlling techniques control the duty cycle of the EH systems, and their operation can be adjusted according to the environmental conditions. In addition to the SEH model, this research also analyzed the deployment of the RF EH model and wireless power transfer (WPT) for supplying energy to the sensor nodes. The adoption of wireless power transfer (WPT) is highly advantageous since they are independent of the manual intervention for charging the batteries of the sensor nodes. Additionally, WPT systems enhance the adaptability of wireless communication networks for long-range applications while simultaneously reducing the size of the batteries and increasing the feasibility of communication.

In this research, the RF EH model is designed and simulated to improve the quality of service (QoS) in simultaneous wireless information and power transfer (SWIPT) networks. In SWIPT networks, the source node harvests and stores energy from radio-frequency (RF) signals and the harvested energy is used for communicating with other systems. The operating process of the RF EH model is controlled using a time-switching protocol which equally shifts the energy transmission between different stages of operation, such as information processing and energy harvesting. The energy efficiency is based on the energy output measured at the transmission side. The simulation was carried out to evaluate the performance of the proposed RF EH model using different performance metrics such as optimal EH time, throughput, QoS, effective outgoing energy and effective incoming energy, maximum energy stored in the battery and outage probability. It can be said that the proposed approach achieves better QoS when the communication between the service and arrival process is enhanced. Simulation results revealed that the RF EH plays a significant role in maximising the capacity and lifespan of the SWIPT networks. A few challenges and complexities were observed during the experimental evaluation, such as lack of energy availability from energy sources, difficulty in arriving at an optimal solution, and challenges in determining the energy distribution among different stages of operation. The proposed approach aimed to minimise or possibly eliminate the dependency of the SWIPT network on the batteries for power supply and storage. In this context, energy efficiency maximisation and enhancement of power transmission in these networks play an important role. The proposed RF-EH model was able to resolve the drawbacks of the conventional RF EH techniques and achieve better conversion efficiency, power density, reduced network size, and low power loss. These factors are highly significant in determining the QoS in wireless networks, and hence the evaluation of these parameters was emphasised. Energy conversion efficiency holds the highest prominence because of its ability to assess the performance of harvesting techniques.

A low complex and structured mathematical model was developed to evaluate the performance of the RF EH model, and the mathematical model was formulated based on certain constraints and assumptions which were made according to the LDP theorem. In addition to this, the assumptions were implemented using a virtual queuing model, which was also used for estimating the probability of an energy outage on the QoS. Other parameters were also analysed, such as the amount of energy flowing into the battery, Rayleigh fading channel conditions, and QoS constraints. The probability of an energy outage was calculated based on the physical constraints. It was observed from the simulation analysis that the energy outage helps in determining the amount of energy harvested required for maintaining the active energy state in the communication systems. It elaborates on the energy available for exchanging information from one source to another. The value of energy outage probability is maintained at a lower value when the amount of energy harvested is lesser than the outgoing energy.

The outage probability value is maintained at a lesser value to keep the system active. The active or inactive state of the battery is determined by evaluating the amount of energy flowing into the battery for charging. If the energy inflow is below the threshold value, then a low battery signal is flagged by the transmitter, and in this case, the system moves into hibernation mode, and in this case, the energy outage was observed. This stage of the battery is continued until the charge of the battery reaches a particular level. In addition to the energy outage probability, a virtual battery queuing model was designed considering the occurrence of an energy outage and the empty side of the queuing model. Based on these scenarios, the probability of an empty portion queue at a particular instance is calculated for further analysis.

Results of the simulation analysis show that the effective outgoing energy of the RF EH model can be increased by increasing the outgoing process, which maximises the QoS exponent solution. Besides, results also validate the efficacy of the proposed approach in terms of achieving desired performance.

The QoS constraints have a more significant role in improving the efficacy of wireless communication systems. This research investigated different mechanisms available for improving the QoS using RF EH, SEH, and WPT techniques. The SWIPT networks majorly rely on batteries as their energy backup. Since batteries have a limited lifespan, it needs frequency charging or replacement which affects the efficiency of the system and increases the system cost. By utilizing suitable energy harvesting technologies, the lifespan of sensors in the SWIPT networks can be maximized. As inferred from existing literary works, the amount of energy extracted in RF harvesting depends on various factors, such as the wavelength of the RF signal and the power transmitted. In addition, the adoption of antennas also significantly influences energy extraction using energy harvesting techniques. However, it is challenging to design an optimal antenna to assist energy harvest in SWIPT networks. The complexity is mainly due to the dynamic nature of SWIPT networks and the challenges associated with the size of the antennas. Most of the existing studies that implemented antennas in the RF EH process lack an effective approach which uses antennas with reduced size and greater power efficiency. In this context, there is an excellent scope of research.

6.2 Future Direction

Research in the aforementioned areas could result in more significant contributions to IoT networks in the future. Hence, the following study paths are suggested as interesting next stages, building on the methodologies suggested in the current thesis:

- **Meta Surface-based RF Antennas and SWIPT Networks**: The main objective behind this is to overcome the limitations of conventional antennas such as microstrip antennas, monopole antennas, slot antennas, and dielectric resonator antennas and to achieve better power conversion efficiency. Furthermore, Meta surface antennas are advantageous in their ability to perform complex tasks such as ambient and microwave energy harvesting and lower power loss. The study intends to explore more on achieving high energy efficiency considering the dynamic behaviour of SWIPT networks. The application of RF modules with compact antennas, energy-efficient devices and reliable radio technology can yield excellent results in terms of maximizing energy efficiency. The combination of these elements can be used for effectively processing data and improving the performance efficiency of RF EH systems.

- **Improved Energy Management in SWIPT Networks**: As a part of further research, this study intends to investigate the WPT technology using advanced sensor techniques, communication modules, and control strategies. The current research does not focus on reducing or preventing power leakage in communication networks. There is a great demand for controlling power leakage using advanced power electronic converters integrated with energy harvesting systems. The controllers can also be deployed to control the operating cycle. In this context, this research also focuses on implementing power electronic converters with suitable pulse modulation techniques for energy management in SWIPT networks. Another vital research objective for future research is to enhance energy efficiency by minimizing the power consumption by power electronic converters and to supply maximum energy to the SWIPT networks using the harvested energy. It is also recommended that the current research work can design an efficient mathematical approach suitable for networks other than SWIPT and harvest more energy in future fifth-generation (5G) wireless networks and beyond. Furthermore, the research can extend to SWIPT-enabled WSN-assisted Internet of Things (IoT) applications. For this, the proposed energy harvesting approach can be optimized using optimization algorithms in terms of transmitted power, harvest weight factor and offloading weight factor to improve energy efficiency.

- **Battery Outage Prediction using Machine Learning**: The development of smart power management methods that may dynamically modify battery-powered device power consumption by the quality of service criteria represents another significant area for future research. This can be done by forecasting future energy demand using machine learning algorithms and adjusting power use accordingly. Machine learning algorithms can be trained on data from various sensors on the device to predict the battery life. Research is also required to determine how to efficiently power battery-operated devices using renewable energy sources like solar and RF power considering energy overflow. This can reduce our reliance on fossil fuels and offer a sustainable power supply to wireless communication devices.

Appendix A

The statistical QoS performance changing according to the outgoing and incoming process shown in Fig. 5.4 can be calculated in the following algorithm.

$Step1:$ Find the effective-incoming energy function EIE(u) and effective-outgoing energy function EOE(u) based on the statistical characteristics of the incoming and outgoing process. Find the rate of energy and QoS-exponent pair solution ($\delta^* u^*$) such that EIE(u)= EOE(u)=δ^*.

$Step2:$ Estimate the probability of non-empty virtual buffer ε by using

$$\varepsilon \approx \frac{\mathbb{E}(\mu_{\mathrm{o}}(t))}{\mathbb{E}(\mu_{\mathrm{i}}(t))}$$

.

$Step3:$ The delay-bound violation probability can be calculated using

$$\Pr\big\{E(\infty) \geq (B_{\max} - \mu_{\max} T)\big\} \approx \varepsilon e^{-u(B_{\max} - \mu_{\max} T)}$$

and

$$\varepsilon \approx \frac{\mathbb{E}(\mu_{\mathrm{o}}(t))}{\mathbb{E}(\mu_{\mathrm{i}}(t))}$$

for any predetermined delay-bound $(B_{\max} - \mu_{\max} T)$ and $(\delta^* u^*)$ obtained in $Step2$.

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