ENERGY HARVESTING AND RESOURCE ALLOCATION OPTIMAZATION IN IOT DEVICES

BY

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ABSTRACT

In the Beyond-5G (B5G) era, the massive deployment of Internet of Things (IoT) devices faces a critical bottleneck regarding dynamic energy availability and limited battery lifespans. This project addresses the fundamental inefficiencies in existing Energy Harvesting (EH) IoT networks, specifically the severe performance degradation caused by stochastic energy arrivals and the reliance on Fixed Power Splitting (FPS) ratios in Simultaneous Wireless Information and Power Transfer (SWIPT) architectures. The methodology adopts a mathematical system model that integrates a normalized Lyapunov optimization framework with an Adaptive SWIPT mechanism. By executing low-complexity, real-time centralized scheduling through an Access Point, the system dynamically manages both uplink transmission power and downlink power-splitting ratios. The research process involved rigorous MATLAB simulations evaluating the framework against standard FPS baselines under normal and extreme environmental energy droughts. Results demonstrate that the proposed adaptive model successfully prevents data queue explosions under heavy traffic loads, achieves superior energy efficiency, and dynamically shifts between maximizing downlink throughput and harvesting life-saving energy. Notably, during simulated physical energy droughts, the adaptive framework maintained a 60% network survival rate, whereas aggressive fixed policies suffered total system outages. In conclusion, the integrated algorithmic model effectively extends network lifetime and guarantees queue stability, offering a sustainable resource allocation solution for future zero-maintenance IoT deployments.

Area of Study (Minimum 1 and Maximum 2): Internet of Things, Wireless Communications

Keywords (Minimum 5 and Maximum 10): Energy Harvesting, Lyapunov Optimization, Resource Allocation, SWIPT, Queue Stability, B5G Networks, Network Survivability

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS

α	Alpha
η	Eta (efficiency)
λ	Lambda
ρ	Rho (ratio)
τ	Tau

LIST OF ABBREVIATIONS

AoI	Age of Information
AP	Access Point
AWGN	Additive White Gaussian Noise
B5G	Beyond-5G
CSI	Channel State Information
DRL	Deep Reinforcement Learning
EE	Energy Efficiency
EH	Energy Harvesting
FPS	Fixed Power Splitting
IoT	Internet of Things
ISAC	Integrated Sensing and Communication
MAC	Media Access Control
MEC	Mobile Edge Computing
MRC	Maximal Ratio Combining
PS	Power Splitting
QoS	Quality of Service
RIS	Reconfigurable Intelligent Surface
RF	Radio Frequency
STAR-RIS	Simultaneously Transmitting and Reflecting RIS
SWIPT	Simultaneous Wireless Information and Power Transfer
TS	Time Splitting
WSN	Wireless Sensor Network

Chapter 1

Introduction

1.1 Problem Statement and Motivation

In the future Beyond-5G (B5G) era, enormous numbers of Internet of Things (IoT) devices will be in use, and there is a critical need to use the technology of Energy Harvesting (EH) to eliminate the reliance on battery replacements. However, there are some non-negligible problems in current EH-based IoT systems. The primary problem is dynamic and unpredictable energy availability. [1] pointed out that dynamic energy availability heavily depends on environmental conditions, while existing energy management scheduling and control algorithms often fail to adapt to this variability. They are either designed assuming fixed energy arrivals [2] or take excessive time to adapt to sudden fluctuations [3]. Therefore, researchers in communications and networking have the urgency to develop an appropriate algorithm to adapt to the sudden changes in energy harvesting. Otherwise, this inefficient power usage will result in a severe waste of energy or system outages even worse.

Secondly, the balance between data queue stability and energy usage is insufficiently addressed. For example, many approaches, such as those presented in [4] and [5], isolatedly optimize for either maximizing throughput or maximizing energy efficiency, without jointly considering them together under a mathematically rigorous framework. The indefinite growth of a data queue will increase transmission delay and fail to meet the requirement of Quality of Service (QoS). On the other hand, the insufficient use of energy in a node will also directly degrade the overall throughput of the system. Therefore, maintaining a dynamic balance between data queue stability and energy preservation is crucial for preventing system performance degradation.

Thirdly, the limited lifetime of IoT nodes is another major concern regarding the scalability of the system. It is because even with energy harvesting, every single IoT node experiences different channel conditions and traffic loads; hence, uneven energy distribution across nodes causes some of them to deplete their energy faster than others. In this situation, network lifetime and reliability are heavily reduced. Cooperative energy transfer mechanisms, such as Simultaneous Wireless Information and Power Transfer (SWIPT)-enabled sharing, can be introduced as a backup energy supply for low-energy nodes to greatly improve the lifetime of IoT devices. However, traditional SWIPT architectures predominantly rely on Fixed Power Splitting (FPS) ratios [6]. This characteristic restricts the system's flexibility. A system adopting a conservative splitting ratio will waste possible spectrum capacity during healthy energy states, whereas system adopting an aggressive ratio will accelerate battery depletion during energy droughts. Although recent studies have explored dynamic ratio adjustments, they often rely on computationally heavy methods such as Deep Reinforcement Learning (DRL) or complex mixed-integer programming [7], which are impractical for the case of resource-constrained IoT microcontrollers.

Solving these interconnected problems is absolutely important in terms of both technical and societal development. For future wireless networks in the B5G era, IoT is ubiquitous to perform critical functions. At the same time, massive deployments of wireless sensors can cause huge energy depletion during operation. This is not aligned with global sustainability goals due to the generation of electronic waste and carbon emissions. The proposal of EH offers a sustainable alternative by leveraging ambient power. Minimizing the use of batteries means less mining of rare materials and lower greenhouse gas emissions from production and shipping. The way to reduce the carbon footprint is to create a sustainable, greener environment coexisting within the future B5G era.

Some potential functional benefits are also considered. In remote or hostile environments, such as disaster zones or massive agricultural properties, self-powered devices can collect data and operate autonomously without human interference. This is considered highly practical when replacing batteries is physically impossible. Likewise, in industrial settings, it reduces downtime and minimizes maintenance, hence eliminating a large proportion of operational costs. We can boldly conclude that eliminating the need to replace batteries is the first fundamental step towards true full automation without human intervention.

Finally, from a business and technology perspective, the successful optimization of EH-IoT networks will highly encourage the development of B5G. Currently, the high energy demand of large-scale IoT networks acts as the primary bottleneck of B5G deployment. If the demonstration of an EH-IoT network can meet strict performance and coverage requirements while showing its feasibility using renewable energy, it will highly encourage investment from the industries and organizations. Hence, companies will confidently adopt IoT at a scale that they can sustain.

1.2 Objectives

The main objective of this project is to design, implement, and validate an integrated IoT resource allocation framework that combines normalized Lyapunov optimization with an Adaptive SWIPT-based energy harvesting module. We will demonstrate its effectiveness through rigorous simulation using standard performance metrics. We breakdown this main objective into three specific sub-objectives to provide a more clear direction to validate this research.

The first sub-objective is optimizing energy expenditure while ensuring queue stability under dynamic traffic loads. Normally, IoT system struggle to decide whether increasing uplink throughput to improve QoS or decreasing uplink throughput to save energy. This objective is achieved by implementing a normalized Lyapunov optimization policy. It utilizes the drift-plus-penalty method to mathematically balance the trade-off between minimizing uplink transmission energy usage and preventing data queue explosions. By acting as a context-aware scheduler, it prevents excessive energy expenditure without requiring future channel state information.

The second objective is dynamically balancing downlink information throughput and energy harvesting capabilities. If an EH-enabled IoT system allocates too much energy to maximize throughput, it will quickly drain the harvested battery. Conversely, conserving too much energy results in high delays and spectrum waste. This objective is met by developing an Adaptive SWIPT ratio module that dynamically adjusts the power-splitting parameter ρ based on real-time evaluations of the node's virtual energy deficit queue, ensuring queues remain within acceptable limits while simultaneously avoiding early energy depletion.

The third sub-objective is maximizing node survivability and extending network lifetime under severe environmental constraints. By integrating the adaptive SWIPT mechanism with the Lyapunov scheduler, the framework provides a robust backup energy supply. This objective aims to validate the proposed model's ability to sustain operations during simulated physical energy droughts. The effectiveness of extending the node lifetime will be proven by benchmarking the adaptive approach against established Fixed Power Splitting policies (e.g., aggressive, balanced, and conservative static ratios).

1.3 Project Scope and Direction

By the end of this project, we will deliver an energy-effective and highly stable algorithmic model that can be utilized in real-world EH-IoT networks. The scope is strictly focused on the algorithmic design, mathematical formulation, and software simulation of the resource allocation scheduler. The framework is primarily integrated with a normalized Lyapunov optimization approach to establish centralized scheduling for remote sensor nodes. The scope encompasses an Adaptive SWIPT-enabled wireless energy harvesting module to provide sustained viability for the EH-IoT system.To examine the improvements in terms of energy efficiency, queue stability, and system survivability, a comprehensive comparison between Fixed SWIPT baselines and the proposed adaptive scheme will be conducted via MATLAB simulations. The related metrics, such as average queue backlog, cumulative battery level, and smoothed downlink information throughput, will be measured. During the simulation, the mathematical model will be tested under highly realistic and harsh physical constraints. This includes the integration of static circuit power consumption P_{circ}, stochastic Poisson traffic arrivals, Rayleigh fading channels, and a specifically modeled "energy drought" phase to thoroughly evaluate the robustness of the node's survivability.

Our direction is to solve the inefficiencies in current EH-enabled IoT systems. These inefficiencies are due to ignoring the imbalance between stochastic energy arrivals, queue dynamics, and static wireless energy transfer configuration. Therefore, by re-engineering these constraints through a strictly normalized Lyapunov function, our proposed framework can provide a systematic solution to reduce unnecessary energy consumption, balance traffic utility with energy deficits, and extend the operational lifetime of IoT devices. We expect this research to significantly facilitate the development of B5G networks, where sustainable, zero-maintenance, and scalable IoT deployment is a critical requirement.

1.4 Contributions

IoT devices are ubiquitous in our daily lives. Ranging from smart homes to smart factories, and from critical medical equipment to urban transportation. However, IoT monitoring devices commonly face a serious problem: continuously replacing batteries not only brings high maintenance costs but also can cause severe environmental contamination. Furthermore, some real-time IoT systems are impossible to accept sudden power outages from their end nodes. Although EH-enabled IoT devices help to reduce the dependency on physical batteries, the unstable nature of ambient energy does not completely eliminate the risk of energy management failure. Therefore, there is a distinct need to propose an integrated algorithmic framework for EH-IoT networks that systematically addresses energy consumption, queue stability, and node lifetime simultaneously.

By advancing the sustainability and reliability of future wireless systems, users in the B5G era will have less worries regarding hardware maintenance. Future industries will benefit from a comparably stable system with an extremely low risk of downtime. By dynamically reducing unnecessary energy consumption and harvesting RF energy intelligently, our model contributes to a greener society by directly reducing the technological carbon footprint. Specifically, a resilient IoT system is crucial in smart healthcare, disaster rescue operations, and agriculture automation—areas where continuous data transmission directly impacts human lives. Finally, the algorithms developed in this model will greatly foster the development of B5G networks, which require reliable large-scale IoT deployments.

1.5 Report Organization

This report is organised into 5 chapters: Chapter 1 Introduction, Chapter 2 Literature Review, Chapter 3 System Model, Chapter 4 System Simulation and Performance Evaluation, Chapter 5 Conclusion and Recommendation. The first chapter introduces the foundational problem statement, the motivation behind the research, specific project objectives, the defined scope and direction, and the expected technical contributions. The second chapter is the literature review critically examines existing academic literature regarding SWIPT architectures, EH models, and Lyapunov optimization techniques. It highlights the current limitations of static resource allocation and substantiates the necessity for an adaptive approach. The third chapter is establishing the theoretical framework. It provides the detailed mathematical equations for queue dynamics, battery state updates, and the precise formulation of the normalized Lyapunov Drift-Plus-Penalty objective function used for the optimization. Simultaneously, it elaborates on the system architecture, including figure of system design and the algorithmic step-by-step flowchart. It details how the central Access Point interacts with the IoT nodes and processes the Adaptive SWIPT logic. Furthermore, the fourth chapter outlines the configuration of the simulation environment. It details the physical parameter specifications, the construction of the energy drought scenarios, and the resolutions to implementation challenges encountered during development. Hence presents the quantitative results generated from the simulations. It provides an in-depth analysis of the system's performance metrics—comparing the Adaptive SWIPT model against multiple Fixed SWIPT baselines—and evaluates the successful completion of the project's objectives. The fifth chapter summarizes the major findings of the project and provides strategic recommendations for future research scaling and physical layer integration.

Chapter 2
Literature Review

2.1 Previous Works on Energy Harvesting in IoT

2.1.1 Foundations of SWIPT and EH Models

The conceptual foundation of transmitting both energy and information simultaneously over a single line was initially established by Varshney in 2008 [8]. This work provided the fundamental of information theory for Simultaneous Wireless Information and Power Transfer (SWIPT) by mathematically calculating the trade-off between the transmission rates of energy and data. This original concept also catalyzed subsequent research into the feasibility of harvesting energy directly from ambient Radio-Frequency (RF) signals while maintaining active data communication.

Building upon this foundation, [6] rigorously analyzed the achievable rate-energy trade-offs in practical scenarios. They proposed the receiver operations of dynamic power splitting (PS) and time splitting (TS), with the architectural designs for separated and integrated receivers to optimize performance across different operational states. Their contributions were critical to the early development of EH-enabled IoT systems by proving that energy acquisition and data transmission could be jointly optimized rather than treated as mutually exclusive processes. However, these foundational studies show limitations in practical IoT environments due to the reliance on idealized linear energy harvesting models and the assumption of perfect Channel State Information (CSI).

To acquire a more comprehensive understanding of RF-EH networks, an extensive survey elaborating on various architectural design issues is provided in [2]. Besides than analyzing the mathematical constraints within different RF-EH models, the study highlighted the potential of RF-EH to extend the operational lifetime of wireless sensor networks and IoT devices by up to 70%. Noticeably, critical metrics such as resource allocation efficiency and queue stability were largely marginalized in these early works. Thus, while the initial development of EH and SWIPT offered robust theoretical support, hidden practical issues—such as excessive delay and system instability due to queue backlogs under stochastic energy arrivals—remained unresolved.

2.1.2 Advances in Nonlinear EH Modeling and Optimization

Subsequently, researchers proposed more sophisticated EH models to directly address the physical nonlinearity of practical energy harvesting circuits. As a significant advancement, [9] introduced the concept of robust outage capacity to mitigate the challenges of unknown CSI, successfully optimizing the ratio settings for both PS and TS schemes. Their mathematical proofs demonstrated that the PS scheme systematically outperforms the TS scheme in terms of the rate-energy trade-off. From a different perspective, [10] extended this by considering nonlinear EH models into IoT systems with Integrated Sensing and Communication (ISAC), proposing a transmit power optimization method to maximize energy efficiency under realistic physical constraints. Interestingly, [10] reached a conclusion similar to [9], confirming that TS receiver architectures comparatively limit overall system performance. Figure 2.1 shows the detailed operations of TS receiver and PS receiver.

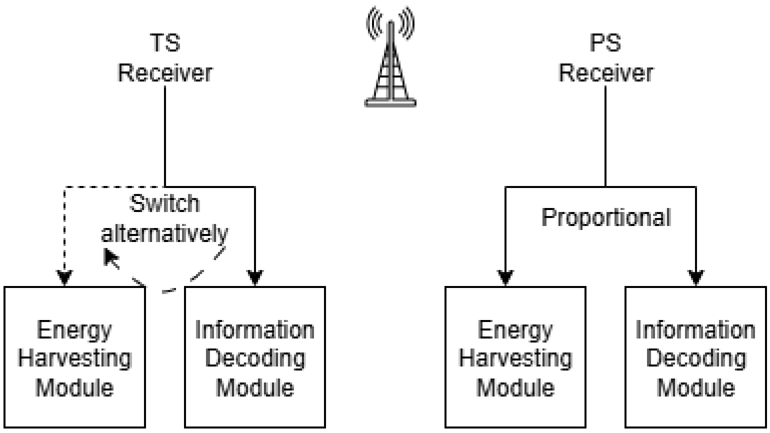

Figure 2.1 Operations of TS receiver and PS receiver

Concurrently, recent studies have explored the integration of intelligent surfaces to facilitate energy-efficient SWIPT. [11] investigated Reconfigurable Intelligent Surface (RIS)-assisted SWIPT IoT systems, concluding that RIS deployments effectively enhance both spectral and energy efficiency. Building upon these results, [12] further investigated Simultaneously Transmitting and Reflecting RIS (STAR-RIS), an upgraded architecture capable of providing 360-degree coverage to improve SWIPT performance, specifically addressing the challenge of under severe channel uncertainty.

Focusing strictly on solutions constrained by nonlinear EH, [13] developed an energy-saving optimization framework combining relay transmitting modes with power-time-splitting, achieving a recorded efficiency improvement of at least 26.4%. Similarly, [4] designed an algorithm for energy efficiency maximization under imperfect channel knowledge by jointly optimizing sub-channel matching and power allocation. Furthermore, [14] introduced an alternative approach utilizing α-fair resource allocation for nonlinear EH, bypassing the traditional multiple access channel-broadcast channel duality used for linear models.

These works represent significant progress in optimizing power efficiency under the physical limitations of nonlinear EH systems. Nevertheless, the majority of these studies remain heavily skewed towards energy-saving maximization, often ignoring the strict requirements for queue stability across distributed nodes, which is paramount for ensuring Quality of Service (QoS) in real-time IoT applications.

2.2 Previous Works on Resource Allocation in IoT

Resource allocation techniques in IoT networks are extensive and can be categorized based on their primary optimization targets. As illustrated in [15], resource allocation mechanisms are typically divided into efficiency-aware, QoS-aware, and power-aware classifications, and more shown in Figure 2.2. In the context of this project, our proposed methodology can be classified into QoS-aware (which concerning queue stability) and power-aware (which concerning energy sustainability) resource allocation.

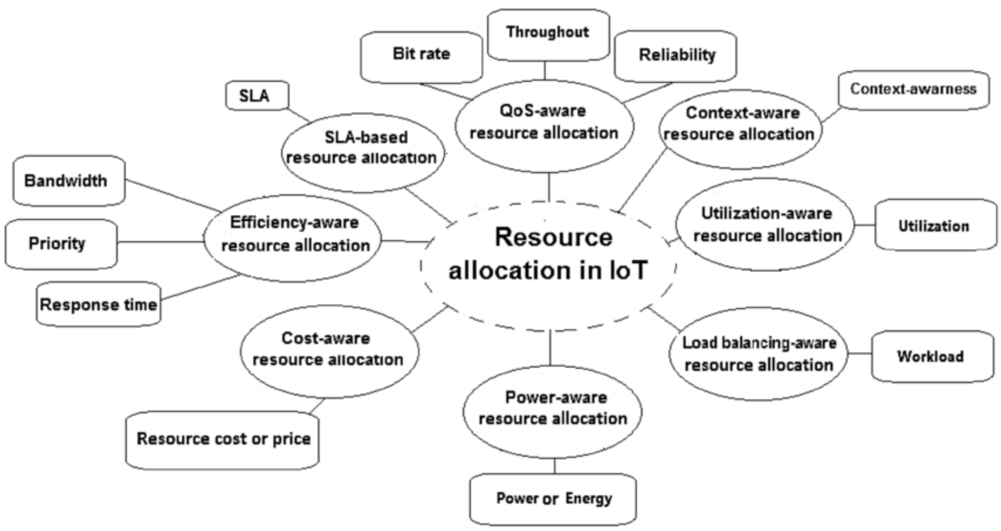

Figure 2.2 Categorization of Resource Allocation in IoT [15]

2.2.1 Lyapunov Optimization

Among stochastic resource allocation techniques, Lyapunov optimization is uniquely positioned to fulfill the contradictory requirements of balancing throughput, bounding delay, and ensuring energy sustainability simultaneously. [5] systematically detailed the stochastic network optimization framework utilizing the Lyapunov drift-plus-penalty method. This algorithm is highly prevalent in dynamic wireless systems because it guarantees queue stability while driving long-term system performance towards near-optimality, smoothly handling stochastic traffic arrivals and time-varying channel conditions. Figure 2.3 demonstrates working flow of Lyapunov optimization in centralized scheduling.

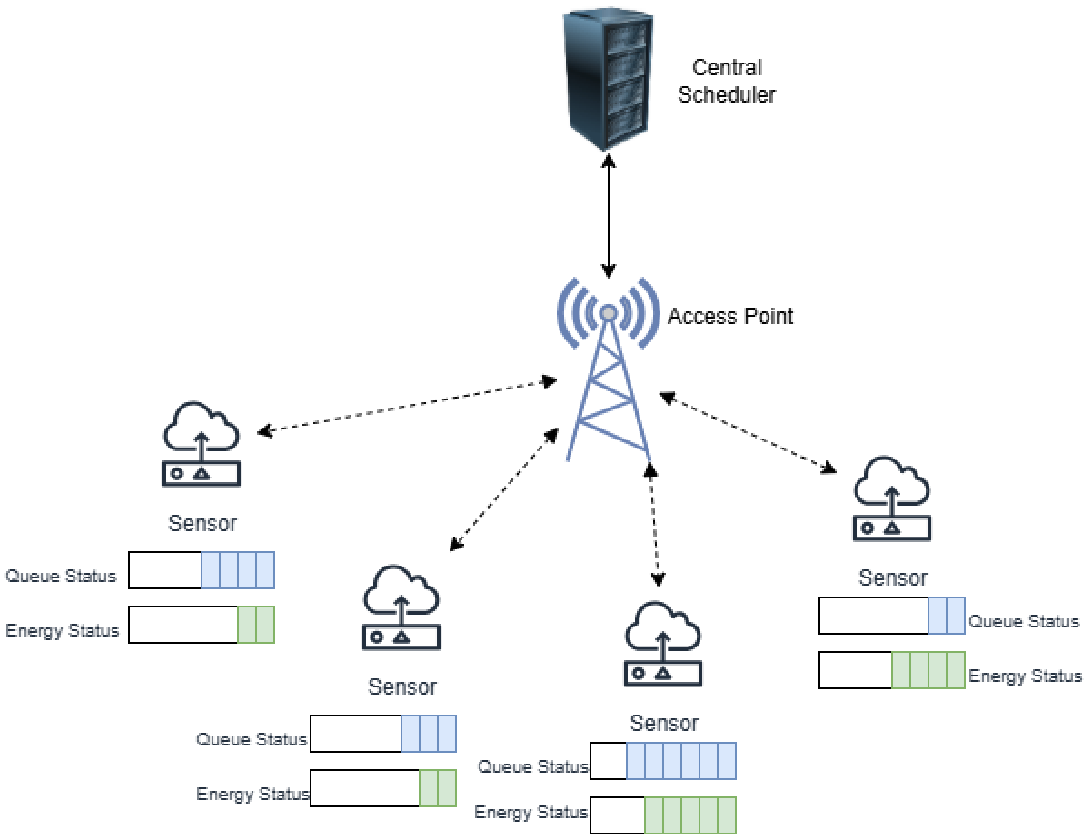

Figure 2.3 Working flow of Lyapunov optimization

In the specific context of EH-enabled IoT, Lyapunov optimization is exceptionally useful for balancing energy consumption against queue dynamics. By mathematically controlling the Lyapunov drift, data queues are strictly kept within bounded limits—a mathematical guarantee that conventional heuristic optimization methods cannot provide. Furthermore, the drift-plus-penalty method executes an *O(1)* complexity decision per time slot without requiring future CSI or a priori knowledge of energy generation profiles. However, existing studies applying

Lyapunov techniques to EH systems frequently focus narrowly on the throughput-delay trade-off, lacking an integrated mechanism (like dynamic SWIPT) to actively replenish the energy deficit, thereby limiting the maximum achievable network lifetime.

2.2.2 Stochastic and Heuristic Optimization Methods

Beyond Lyapunov frameworks, researchers have extensively explored other stochastic optimization and heuristic approaches. For example, [4] proposed a two-stage algorithm utilizing relaxation methods to decompose and solve a probabilistic mixed non-convex optimization problem. While their results demonstrated an energy efficiency improvement of up to 84.69%, the method incurs unavoidably high computational overhead and deployment complexity. Similarly, the relay-assisted optimization models introduced by [13] achieved significant energy savings but required centralized processing with full deterministic system knowledge. These examples highlight that algorithms which achieve absolute mathematical maximums often demand computational resources that far exceed the capabilities of low-power IoT microcontrollers.

2.2.3 Deep Reinforcement Learning (DRL) Approaches

Recently, Deep Reinforcement Learning (DRL) has emerged as a prominent tool for handling dynamic resource allocation in complex EH environments. For instance, [7] proposed a DRL approach for joint resource management in UAV-assisted SWIPT Mobile Edge Computing (MEC) networks. Their framework utilized advanced neural networks to map environmental states directly to resource allocation actions, demonstrating superior adaptability in highly mobile and unpredictable settings. However, similar to complex convex optimization, DRL architectures require extensive offline training phases, consume massive memory footprints, and lack rigorous mathematical guarantees for worst-case queue stability. Consequently, while DRL represents the state-of-the-art in adaptive learning, low-complexity deterministic algorithms like Lyapunov optimization still remain highly preferable for continuous real-time scheduling on constrained IoT devices.

2.3 Previous Works on Combined Approaches

2.3.1 Integration of EH, Resource Allocation, and SWIPT

Recent literature has increasingly attempted to fuse EH, resource allocation, and SWIPT to achieve holistic network sustainability. [16] investigated a cooperative IoT network utilizing SWIPT-enabled relay nodes. Their approach managed to balance throughput and energy efficiency using a low-complexity algorithm which favours great scalability. However, it relied on static traffic assumptions, significantly reducing its generalizability to bursty IoT networks. Conversely, [17] examined a SWIPT-assisted Wireless Sensor Network (WSN) reliant on hybrid access points, utilizing Maximal Ratio Combining (MRC) to maximize system reliability, though their research lacked depth regarding queue backlog management.

Addressing the timeliness of energy replenishment, [18] successfully proposed a novel SWIPT channel model incorporating Age-of-Information (AoI) optimization. This research improved AoI minimization by 30%, ensuring the freshness of harvested energy for persistent operation. Additionally, recent advancements have focused heavily on STAR-RIS-based resource management for 6G IoT, with [20] utilizing STAR-RIS and SWIPT alternatively to maximize spectrum efficiency and balance power consumption. While these integrations offer highly valuable insights, they are predominantly limited to specific physical-layer scenarios and rely on fixed or heuristic power splitting ratios.

2.3.2 Joint Application of Lyapunov Optimization and SWIPT

Despite the individual maturity of Lyapunov optimization in handling queue stability and SWIPT in providing RF energy, literature integrating both paradigms remains sparse, particularly regarding dynamic ratio adaptation. Existing works that attempt this integration typically apply Lyapunov optimization strictly for controlling uplink transmit power or binary scheduling decisions, while treating the SWIPT power-splitting ratio ρ as a static physical constant [21]. For instance, [21] effectively maximized the long-term communication capacity of a SWIPT-enabled relay system using Lyapunov optimization. However, their framework was confined to static power splitting factors, explicitly leaving dynamic ratio adaptation as an unresolved future challenge.

The reliance on Fixed Power Splitting (FPS) under a Lyapunov framework creates a severe logical bottleneck. For the nodes facing critical energy deficits cannot dynamically request a higher energy harvesting ratio, and fully charged nodes waste RF signals that could otherwise be used for decoding downlink data. The performance bottlenecks of static FPS have been rigorously exposed in recent literature. For an instance, [22] demonstrated that dynamic power splitting architectures achieve massive rate-energy region gains over FPS schemes in cooperative networks, proving that fixed ratios severely restrict system adaptability. To date, very few studies have formulated the SWIPT splitting ratio ρ as a direct, dynamic control variable embedded within the Lyapunov drift-plus-penalty objective function. This represents a critical research gap. By actively bounding the ratio decision to a virtual energy deficit queue, an Adaptive SWIPT mechanism can be achieved without the computational burden of DRL [7], thus presenting a mathematically guaranteed pathway to Pareto-optimal IoT survivability.

2.4 Critical remarks of previous works

From the comprehensive review above, the key contributions and distinct limitations of existing studies can be clearly summarized, revealing the critical research gap this project addresses.

Firstly, the foundational studies of [2], [6] and [8] established the theoretical boundaries for EH and SWIPT, providing fundamental rate-energy trade-offs. However, they heavily relied on idealized linear models and perfect channel assumptions, failing to align with realistic IoT environments where queue delays and battery lifetimes are major concerns.

Secondly, advanced physical layer designs described in [4], [9], [10], [13], [14] improved practical relevance through nonlinear EH models, while [11], [12], [19], and [20] introduced RIS/STAR-RIS to boost spectral efficiency. Despite these physical-layer improvements, these works predominantly focus on maximizing instantaneous energy efficiency, frequently overlooking MAC-layer metrics like stochastic queue stability.

Thirdly, modern resource allocation methods demonstrate a stark divergence in computational complexity. While [5] proved that Lyapunov optimization perfectly balances queue stability and energy efficiency with low computational overhead, recent adaptive SWIPT solutions, such as the approach by [7], rely on Deep Reinforcement Learning (DRL). Although DRL provides excellent environmental adaptability, its massive computational overhead and offline training requirements make it highly impractical for resource-constrained IoT nodes.

Finally, the most critical limitation lies in the current integration of Lyapunov optimization and SWIPT. Existing integrated approaches, such as the framework proposed in [21], successfully maximize long-term capacity but strictly rely on Fixed Power Splitting (FPS) ratios. As demonstrated in [22], static ratios create severe performance bottlenecks, failing to adapt to dynamic channel fading and energy droughts. A highly comprehensive framework that actively embeds a low-complexity, dynamic SWIPT ratio directly into the Lyapunov drift-plus-penalty equation remains evidently absent. This project directly targets this gap to simultaneously optimize energy consumption, queue stability, and node survivability.

Table 2.1 Literature Review Summary Table

Ref.	**Year**	**Theme**	**Contribution**	**Limitations**	**Related to Obj.**
[2], [6], [8]	2008–2015	SWIPT foundation	Established theoretical basis for joint information and power transfer; surveyed core EH architectures.	Assumed linear EH and ideal CSI; largely ignored system-level queue and node lifetime issues.	1,2
[4], [9], [10], [13], [14]	2018–2025	Nonlinear EH & optimization	Proposed robust power allocation under nonlinear EH, fading uncertainty, and fairness constraints.	Computationally complex; limited network scalability; lacked explicit mechanisms for queue stability.	1,2
[11], [12], [19], [20]	2024–2025	RIS / STAR-RIS SWIPT	Demonstrated massive spectral and energy efficiency gains using intelligent reflecting surfaces.	Scenario-specific implementations; primarily utilized static SWIPT ratios; overlooked node lifetime.	1,3
[16], [17], [18]	2019–2025	Cooperative SWIPT & AoI	Showed significant system reliability and data freshness (AoI) gains via cooperative EH.	Relied heavily on static traffic assumptions, reducing generalizability to bursty IoT networks.	3

Ref.	Year	Theme	Contribution	Limitations	Related to Obj.
[4], [5], [7]	2010–2025	Resource allocation	Utilized Lyapunov for queue stability and Deep Reinforcement Learning (DRL) for adaptive resource management.	DRL imposes impractical computational overhead for IoT; traditional stochastic models lack adaptive SWIPT.	1,2
[21], [22]	2017–2024	Lyapunov & Dynamic SWIPT Integration	Maximized long-term capacity via Lyapunov; proved massive rate-energy gains of dynamic SWIPT over fixed ratios.	Existing Lyapunov frameworks strictly rely on Fixed Power Splitting (FPS), causing rapid node death during energy droughts.	1,2,3

Chapter 3

System Model

This chapter formulates the mathematical system model for the proposed IoT network. To provide a clear conceptual foundation before detailing the equations, this chapter begins with an operational overview of the algorithm, followed by the rigorous definitions of the physical network boundaries, the queue and battery dynamics, the Adaptive SWIPT mechanism, and the normalized Lyapunov objective functions.

3.1 System Operation Overview and Flowchart

The proposed resource allocation framework operates as a continuous, discrete-time algorithm driven by a central Access Point (AP) acting as the main scheduler. Unlike simulation life-cycle flowcharts that possess definitive start and end points, the algorithmic flowchart depicts the persistent, slot-by-slot decision-making logic executed by the system during its operation. The comprehensive workflow within a single time slot t is illustrated in Figure 3.1.

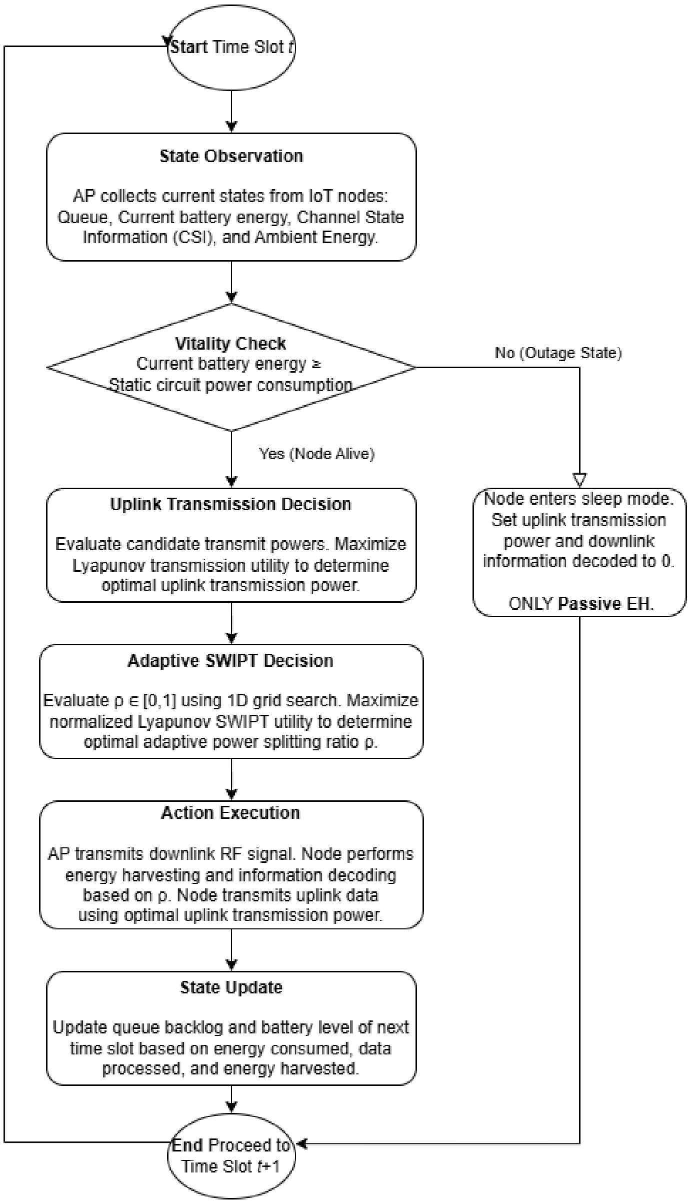

Figure 3.1 System Flowchart

As depicted in the flowchart, the central scheduler performs a deterministic sequence of operations at the beginning of every time slot t. The AP gathers the real-time operational states from all associated IoT nodes. This includes the current data queue backlog, the available battery energy, the instantaneous Channel State Information (CSI) for both uplink and downlink, and the available ambient energy. Before any optimization occurs, the system evaluates the physical survival of each node. If a node's remaining battery is lower than the required static circuit power leakage, the node is deemed "Dead" or in an outage state. For such nodes, uplink transmission and downlink information decoding are forcefully halted, and the node relies purely on passive energy harvesting to recover in subsequent slots. For active nodes, the scheduler evaluates the possible transmission power levels. It balances the urgency of clearing the queue backlog against the penalty of draining the battery by maximizing the Lyapunov transmission utility function, ultimately yielding the optimal transmit power. Concurrently, the scheduler determines the optimal power splitting ratio ρ. It iterates through discrete candidates within the range of [0, 1] and calculates the normalized Lyapunov SWIPT utility. This step mathematically dictates whether the node should aggressively decode downlink data or conservatively harvest RF energy based on its current energy deficit constraint. The AP broadcasts the downlink RF signal, and the nodes execute their assigned transmission and SWIPT actions. Consequently, the data queue and battery level are updated based on the physical expenditures and harvesting gains. The algorithm then seamlessly advances to the next time slot, repeating the adaptive loop to ensure long-term network sustainability.

3.2 System Architecture and Basic Assumptions

We consider a centralized Beyond-5G (B5G) Internet of Things (IoT) network consisting of one central Access Point (AP) and a set of N energy-harvesting IoT nodes, denoted by the set $\mathcal{N} = \{1,2,\dots,N\}$. The system operates in discrete time slots indexed by $t \in \{1,2,\dots,T\}$, where each time slot has a constant duration of τ seconds.

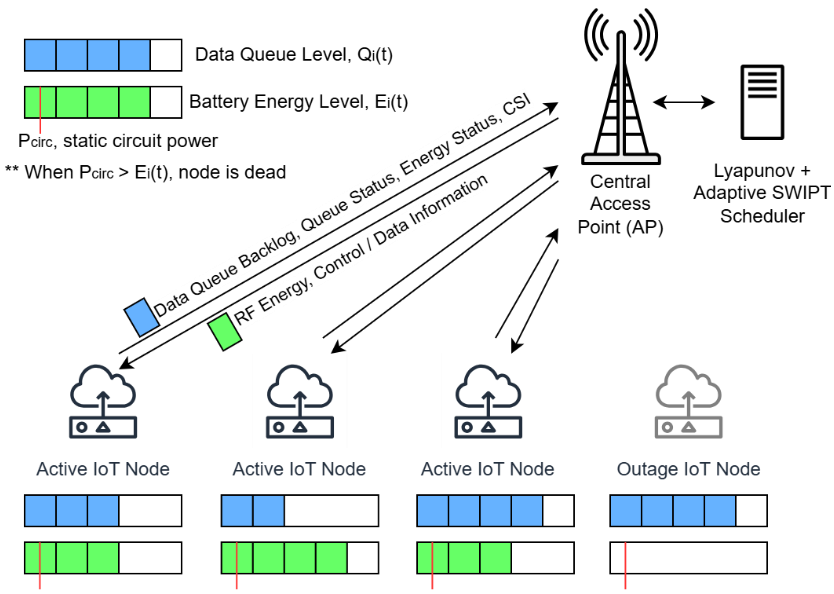

Figure 3.2 System Model

In Figure 3.2, it shows that the AP serves as both the central data receiver for uplink transmissions and the continuous Radio-Frequency (RF) energy transmitter for downlink SWIPT. All wireless channels are subjected to stochastic Rayleigh fading and additive white Gaussian noise (AWGN). The channel power gains from node i to the AP (uplink) and from the AP to node i (downlink) at time slot t are denoted as $h_i(t)$ and $g_i(t)$, respectively.

3.3 Queue and Energy Dynamics

In each time slot, each IoT node maintains and updates two critical physical states: the data queue backlog and the battery energy level.

3.3.1 Data Queue Model

Data packets arrive stochastically at each IoT node following a Poisson distribution. The data queue backlog evolves dynamically based on the newly arrived data and the successfully transmitted data. The queue updating equation is formulated as:

$$Q_i(t+1) = \max\left[Q_i(t) - R_{ul,i}(t), 0\right] + A_i(t) \tag{3.1}$$

where $Q_i(t+1)$ is the data queue backlog of node i at the beginning of the next time slot $t+1$ (in bits), $Q_i(t)$ is the current data queue backlog of node i at time slot t (in bits), $R_{ul,i}(t)$ is the amount of uplink data successfully transmitted by node i to the AP during time slot t (in bits), and $A_i(t)$ is the randomly arrived data volume for node i during time slot t (in bits)

3.3.2 Energy State Model

Unlike idealized systems, realistic IoT nodes suffer from constant static circuit power leakage. A node is considered to be in a "Dead" (outage) state if its battery level falls below the operational threshold required for circuit maintenance. The energy level of node i evolves as follows:

$$E_i(t+1) = \min\left[E_{max}, E_i(t) - P_{tx,i}(t)\tau - P_{circ}\tau + H_{env,i}(t) + S_{harv,i}(t)\right] \tag{3.2}$$

where $E_i(t+1)$ is the available battery energy of node i at time slot $t+1$ (in Joules), E_{max} is the maximum physical battery capacity of the IoT node (in Joules), $E_i(t)$ is the current battery energy of node i at time slot t (in Joules), $P_{tx,i}(t)$ is the uplink transmission power selected by node i at time slot t (in Watts), τ is the duration of a single time slot (in seconds), P_{circ} is the constant static circuit power consumption required to keep the node's baseband hardware alive (in Watts), $H_{env,i}(t)$ is the stochastic ambient energy harvested from the physical environment during time slot t (in Joules), and $S_{harv,i}(t)$ is the dedicated energy harvested from the AP's RF signal via SWIPT during time slot t (in Joules).

3.4 Adaptive SWIPT and Transmission Model

As like [22] has proven the effectiveness of adaptive SWIPT, our proposed system employs a Power Splitting (PS) SWIPT architecture. At each time slot, node i dynamically determines a power splitting ratio $\rho_i(t) \in [0, 1]$ to divide the incoming RF signal from the AP.

3.4.1 Downlink SWIPT Operations

In Beyond-5G (B5G) IoT environments, since nodes are typically deployed in areas where frequent battery replacement is impractical, utilizing Radio-Frequency (RF) signals emitted by the Access Point (AP) for Wireless Power Transfer is critical for sustaining system operation. The proposed system employs a Power Splitting (PS) architecture. The core physical logic behind this is that current hardware circuits cannot perform highly efficient energy harvesting and information decoding on the exact same RF signal simultaneously. Therefore, the received signal power must be divided into two streams using a proportional splitting factor $\rho_i(t)$. The objective of introducing this model is to achieve a dynamic balance between spectral efficiency and energy acquisition. When the RF signal enters the node's antenna, a proportion ρ of the power is directed to the rectenna circuit for energy harvesting to relieve battery constraints. The remaining proportion $(1 - \rho_i(t))$ is routed to the information decoding circuit to process downlink instructions or data.

Based on this physical architecture, the RF energy $S_{harv,i}(t)$ harvested by node i during time slot t is formulated as:

$$S_{harv,i}(t) = \eta \cdot \rho_i(t) \cdot P_{ap} \cdot g_i(t) \cdot \tau \tag{3.3}$$

where $S_{harv,i}(t)$ is the energy harvested via SWIPT (in Joules), η is the energy conversion efficiency of the rectenna circuit $(0 < \eta \leq 1)$, $\rho_i(t)$ is the adaptive power splitting ratio selected by node i at time slot t, P_{ap} is the constant transmission power of the central AP (in

Watts), $g_i(t)$ is the downlink channel power gain from the AP to node i, and τ is the duration of a single time slot (in seconds).

Simultaneously, to measure the communication quality of the downlink, the achievable downlink information throughput decoded by node i is calculated based on Shannon capacity:

$$R_{dl,i}(t) = B\log_2(1 + \frac{(1-\rho_i(t))\cdot P_{ap}\cdot g_i(t)}{N_0})\cdot\tau \tag{3.4}$$

where $R_{dl,i}(t)$ is the downlink information decoded during time slot t (in bits), B is the system communication bandwidth (in Hertz), $(1-\rho_i(t))$ is the fraction of the RF signal dedicated to information decoding, and N_0 is the additive white Gaussian noise (AWGN) power (in Watts).

3.4.2 Uplink Transmission

The uplink transmission model is directly associated with the Quality of Service (QoS) of the system. In IoT applications, data generated by sensors must be promptly transmitted to the AP for processing; otherwise, local buffer overflows will occur. The selection logic for the uplink transmit power $P_{tx,i}(t)$ follows an "on-demand allocation" principle: to ensure queue stability, when there is a large backlog of data, the node must increase its transmit power to achieve a higher transmission rate $R_{ul,i}(t)$.

From an engineering perspective, maximizing the uplink rate is the primary mechanism for maintaining low latency. If the clearance rate $R_{ul,i}(t)$ consistently remains below the data arrival rate λ, the data queue will grow infinitely, leading to system failure. If node i has sufficient energy $(E_i(t) > P_{circ}\tau)$, it starts to select an uplink transmission power constrained by its remaining battery. The successful uplink transmission volume for the node is determined by:

$$R_{ul,i}(t) = B\log_2(1 + \frac{P_{tx,i}(t)\cdot h_i(t)}{N_0})\cdot\tau \tag{3.5}$$

where $R_{ul,i}(t)$ is the uplink data successfully transmitted (in bits), $P_{tx,i}(t)$ is the uplink transmission power (in Watts), subject to $\left(0 \le P_{tx,i}(t) \le P_{tx\_max}\right)$, and $h_i(t)$ is the uplink channel power gain from node i to the AP.

3.5 Normalized Lyapunov Objective Formulation

Lyapunov optimization is included in this project because it is important in the field of energy harvesting. It helps to stabilize the uplink queue in a stochastic EH environment [22]. During integrating Lyapunov optimization with physical EH models, we faced a significant challenge which is the "Magnitude Imbalance" (Scale Imbalance). In the objective function, data rates (often in tens of thousands of bps) will mathematically overshadow battery energy levels (often fractions of a Joule). To resolve this, we strictly normalized all parameters to a dimensionless $[0, 1]$ scale.

3.5.1 Virtual Energy Deficit Queue

To trigger the Lyapunov penalty, we construct a virtual energy deficit queue that measures the node's "starvation level":

$$X_i(t) = E_{max} - E_i(t) \tag{3.6}$$

where $X_i(t)$ is the energy deficit of node i at time slot t (in Joules). A larger $X_i(t)$ implies the battery is nearly empty, E_{max} is the maximum battery capacity, and $E_i(t)$ is the current battery energy.

3.5.2 Uplink Transmission Utility Function

In stochastic optimization theory, the core of the Lyapunov drift-plus-penalty algorithm lies in transforming long-term stability constraints into a deterministic utility maximization problem for each individual time slot. For the uplink, the system must resolve a classic "energy-stability" trade-off.

The necessity of introducing the uplink utility function $U_{tx,i}(t)$ is that the system requires an objective mathematical criterion to determine whether consuming energy for transmission is worthwhile in the current time slot. If the system solely prioritizes high throughput, the node will rapidly deplete its battery; if it over-conserves energy, the data queue will explode. By constructing a utility function, the algorithm can dynamically evaluate two conflicting states, which are queue states and energy deficit states. For the queue states, the more severe the backlog, the higher the marginal utility of clearing data. For the energy deficit states, the emptier the battery, the higher the marginal penalty of consuming energy. Therefore, the criterion for node i to select the optimal uplink power $P_{tx,i}(t)$ is to maximize the following utility function:

$$U_{tx,i}(t) = Q_{norm,i}(t) \cdot R_{ul,norm,i}(t) - V_{tx} \cdot X_{norm,i}(t) \cdot P_{norm,i}(t) \tag{3.7}$$

where $U_{tx,i}(t)$ is the calculated utility for evaluating candidate uplink transmission powers, $Q_{norm,i}(t)$ is the normalized data queue backlog (dimensionless), acting as a dynamic weight for R_{ul}. When the queue is dangerously long, it forces the system to transmit at higher power to restore stability. $R_{ul,norm,i}(t)$ is the normalized achievable uplink data rate (dimensionless), representing the positive gain from transmission. V_{tx} is the Lyapunov trade-off control parameter for transmission, represemting mathematical sensitivity to energy consumption. For example, a larger V_{tx} imposes a stricter penalty on power consumption. $X_{norm,i}(t)$ is the normalized energy deficit ($\frac{X_i(t)}{E_{max}}$) (dimensionless). When the battery approaches depletion, X_{norm} approaches 1, heavily magnifying the penalty term for power consumption. And, $P_{norm,i}(t)$ is the normalized candidate transmission power ($\frac{P_{tx,i}(t)}{P_{tx\_max}}$) (dimensionless), representing the physical energy cost of transmission.

Through this formulation, when a low Q_{norm} and a high X_{norm} are observed (i.e., low queue pressure combined with a severe power shortage), the penalty term exceeds the gain term, resulting in $U_{tx} < 0$. In this scenario, the system automatically selects $P_{tx} = 0$, halting transmissions to ensure node survival.

3.5.3 Downlink SWIPT Utility Function

The optimization logic for the downlink differs from the uplink, focusing exclusively on the resource contention between "energy replenishment" and "downlink throughput". In each time slot, the RF signal power emitted by the AP is finite, and the node must decide what proportion to allocate for "survival" (energy harvesting) versus "functionality" (data decoding).

The introduction of the downlink utility function $U_{p,i}(t)$ is necessary to achieve adaptive SWIPT splitting. Traditional fixed ratio (Fixed PS) approaches cannot adapt to environmental volatility; for instance, during an "energy drought", nodes must exhibit a strong survival mechanism. Here, the energy deficit X_{norm} acts as a dynamic regulator: it automatically elevates the priority of energy harvesting based on the battery's starvation severity. Node i

maximizes the following utility function by iteratively searching for the optimal $\rho_i(t)$ within the continuous range of [0, 1]:

$$U_{p,i}(t) = X_{norm,i}(t) \cdot S_{norm,i}(t) + V_\rho \cdot R_{dl,norm,i}(t) \tag{3.8}$$

where $U_{p,i}(t)$ is the calculated utility for evaluating candidate SWIPT ratios ρ_i, $X_{norm,i}(t)$ acts as the dynamic weight. When the node is starving, $X_{norm,i}(t)$ approaches 1, prioritizing energy harvesting, $S_{norm,i}(t)$ is the normalized harvested SWIPT energy (dimensionless), V_ρ is the Lyapunov trade-off control parameter for information decoding. It controls how aggressively the node pursues downlink data when the battery is safe, and $R_{dl,norm,i}(t)$ is the normalized achievable downlink data rate (dimensionless).

Under this logic, when the node possesses sufficient energy ($X_{norm} \approx 0$), the first term approaches zero, and the system prioritizes maximizing R_{dl} to enhance spectral efficiency and communication performance. Conversely, when entering an energy drought, the drop in battery level causes X_{norm} to increase, prompting the system to rapidly raise the ρ ratio. This sacrifices the downlink data rate in exchange for extended node lifetime. This mechanism mathematically guarantees that the system operates on the Pareto optimal frontier regardless of physical environmental constraints.

Chapter 4

System Simulation and Evaluation

4.1 Overview

This chapter details the simulation configurations, performance metrics, and the comprehensive evaluation of the proposed Lyapunov-guided Adaptive SWIPT framework. To rigorously validate the system's robustness, the algorithmic model was translated into a discrete-time simulation environment using MATLAB. The simulation continuously monitors the behavior of the IoT network across normal conditions and severe environmental energy droughts.

Table 4.1: System Simulation Parameters and Specifications

Parameter	**Symbol**	**Value**	**Unit**
IoT Node	N	10	N/A
Simulation Length	T	1500	N/A
Slot Duration	τ	1	s
System Bandwidth	B	1	kHz
Max Transmission Power	P_{tx_max}	35	mW
Static Circuit Power	P_{circ}	15	mW
Maximum Battery Level	E_{max}	0.5	J
Initial Battery Level	E_{init}	0.5	J
AP Transmit Power	P_{ap}	150	mW
Energy Conversion Efficiency	η	0.5	N/A
Data Arrival Rate	λ	1.0	pkts/s
Packet Size	S_{pkt}	3000	bits
Noise Power	N_0	10^{-9}	W
Lyapunov Trade-off Weight	V	0.6	N/A

Table 4.1 presents the complete list of system parameters, symbols, values, and their respective interpretations used throughout the simulation. These parameters have been mathematically balanced to accurately reflect the physical constraints of real-world Beyond-5G (B5G) IoT devices, including realistic rectenna conversion efficiencies and constant static baseband circuit power leakages.

4.2 Performance Evaluation and Discussion

The system's performance is benchmarked against three conventional Fixed Power Splitting (FPS) policies: Fixed $\rho = 0.3$ (Aggressive throughput), Fixed $\rho = 0.6$ (Balanced), and Fixed $\rho = 0.9$ (Conservative survival). The evaluation is categorized into three specific sub-sections corresponding directly to the project objectives.

4.2.1 Ensuring Queue Stability and Optimizing Energy Expenditure

In stochastic IoT networks, unmanaged data queues lead to buffer overflows, severe packet drops, and unacceptable latency. Simultaneously, aggressive data transmission without considering energy costs drains the battery prematurely. Ensuring strict queue stability while optimizing energy expenditure is the fundamental requirement for reliable QoS in B5G networks.

The proposed framework achieves this by incorporating the queue backlog $Q(t)$ into the Lyapunov drift equation. By independently scheduling concurrent transmissions only when the transmission utility U_{tx} is positive, the algorithm deterministically bounds the queue length without requiring future channel knowledge.

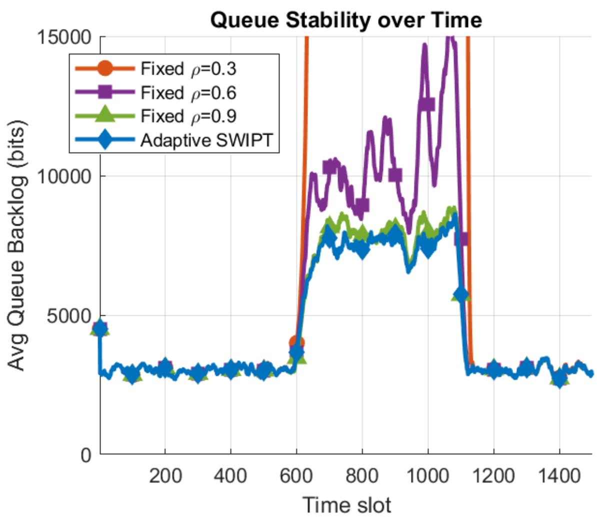

Figure 4.1 Queue Stability over Time

As illustrated in the Figure 4.1, we can observe that during the energy drought phase (t=600 to 1100), the aggressive Fixed 0.3 policy suffers from power outage, completely halting transmissions and causing its queue to explode exponentially. In contrast, the Adaptive SWIPT algorithm maintains a stable and heavily bounded queue trajectory comparable to the conservative policies. By optimizing uplink throughput at suitable stage, queue backlog can be controlled at a comparatively low level, hence maintaining a healthy level of QoS.

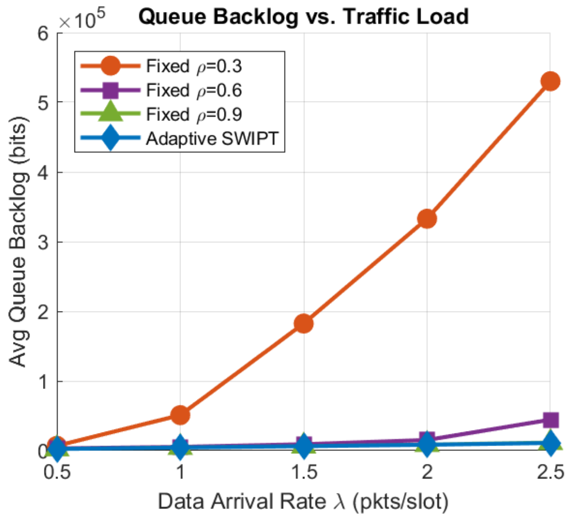

Figure 4.2 Average Queue Backlog vs. Arrival Rate

As the network traffic load λ scales from 0.5 to 2.5, the queue backlog of the Adaptive SWIPT model grows linearly and remains stable, whereas fixed policies fail to sustain the clearance rate under heavy loads, proving the superior congestion control of the Lyapunov scheduler. It is because of adaptive SWIPT policy immediately increases the uplink throughput to clear the buffer according to Equation (3.7) to cope with situation of high data arrival rate while detecting accumulated data queue.

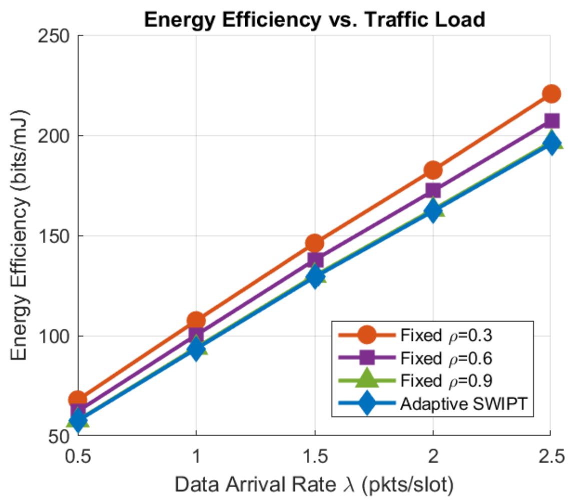

Figure 4.3 Energy Efficiency vs. Traffic Load

While the Fixed 0.3 policy numerically displays a higher Energy Efficiency (EE) metric in Figure 4.3, this represents a system failure state driven by widespread power outages and transmission halts during the energy drought, leading to queue explosions. When strictly constrained by the requirements of continuous network survivability and queue stability, the Adaptive SWIPT policy exhibits the highest sustainable overall Energy Efficiency. It allocates just enough power to clear the backlog without engaging in wasteful transmissions or risking node depletion, demonstrating superior practical power-awareness compared to the rigid FPS strategies.

4.2.2 Dynamically Balancing Downlink Throughput and Energy Harvesting

SWIPT architectures possess a fundamental physical trade-off: RF signals dedicated to energy harvesting cannot be used for information decoding, and vice versa. Utilizing a static splitting ratio ρ inevitably leads to spectrum waste when the battery is full or rapid node death when the battery is empty. Dynamic balancing is crucial for maximizing spectral efficiency.

This objective is fulfilled through the normalized SWIPT utility function U_ρ. The scheduler continuously calculates the normalized energy deficit $X(t)$. When $X(t)$ is small, the utility favors information decoding; when $X(t)$ approaches 1, the utility heavily penalizes data rates to force emergency energy harvesting.

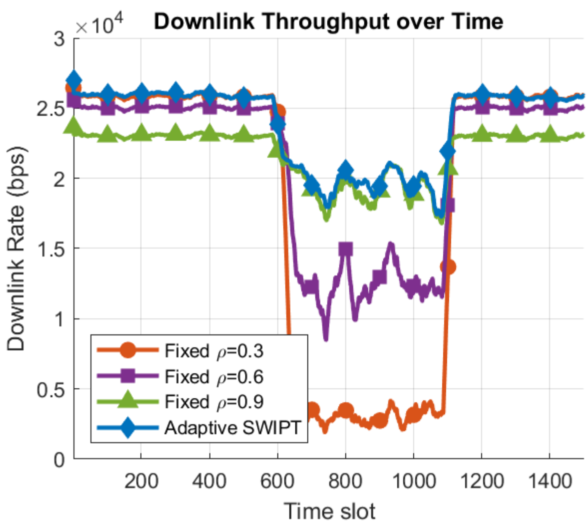

Figure 4.4 Downlink Throughput over Time

During healthy environmental states, the Adaptive algorithm matches the peak throughput of the aggressive Fixed 0.3 policy. However, when entering the harsh drought phase, the Adaptive algorithm intelligently initiates a "strategic dip," sacrificing downlink throughput (matching the Fixed 0.9 trajectory) to harvest life-saving energy. Once the environment recovers, it instantly regains maximum throughput.

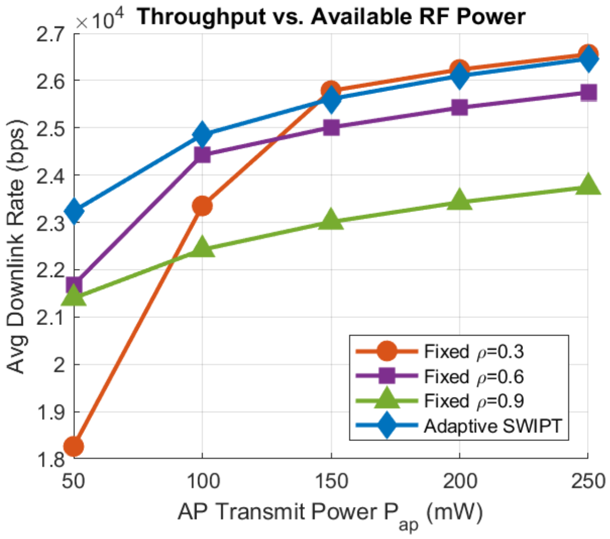

Figure 4.5 Average Downlink Rate vs. AP Transmit Power

As the available AP RF power increases, the Adaptive SWIPT model exponentially scales its throughput, outperforming all fixed baselines by dynamically shifting its ratio towards data decoding once the baseline energy threshold is satisfied.

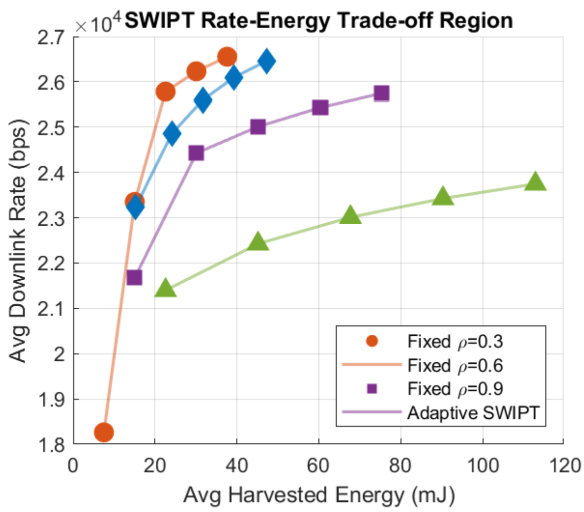

Figure 4.6 Rate-Energy Trade-off Region

Plotting the Average Downlink Rate against Average Harvested Energy reveals the Pareto frontier of the system. The Adaptive SWIPT strategy completely breaks the linear constraints of fixed ratios, achieving a significantly expanded performance envelope that maximizes both metrics concurrently.

4.2.3 Maximizing Node Survivability and Extending Network Lifetime

The ultimate metric of sustainability in EH-IoT is node lifetime. Replacing remote sensors is economically and physically unviable. IoT nodes face static circuit power leakages P_{circ} even when idling. If a node cannot harvest enough energy to counter this leakage during an environmental drought (e.g., night time or severe physical blockages), it will suffer a fatal outage.

The algorithm prevents node death by enforcing a strict physical vitality check $(E(t) \geq P_{circ}\tau)$ integrated with the Lyapunov energy deficit penalty. In severe states, the algorithm forces $P_{tx} = 0$ and $\rho \approx 1$, entering a deep survival mode to counter the static leakage.

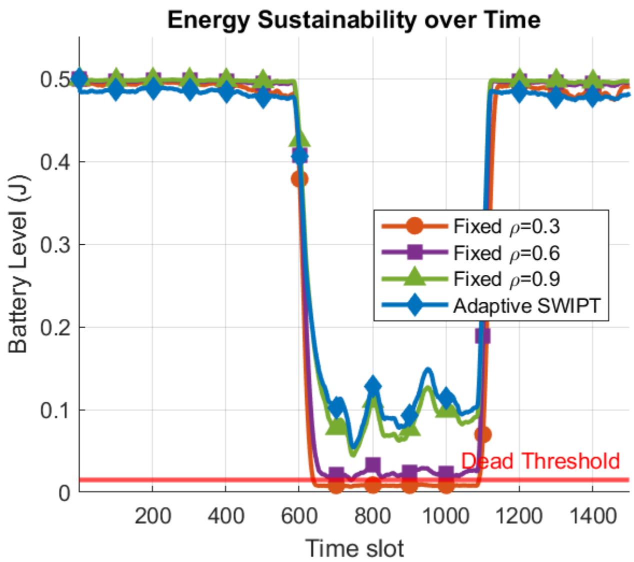

Figure 4.7 Energy Sustainability over Time

The time-series simulation confirms that during the extreme drought, Fixed 0.3 and Fixed 0.6 rapidly cross the "Dead Threshold" (15 mW) and perish. The Adaptive SWIPT strictly maintains its battery level above the critical threshold, showcasing flawless survival mimicking the ultra-conservative Fixed 0.9.

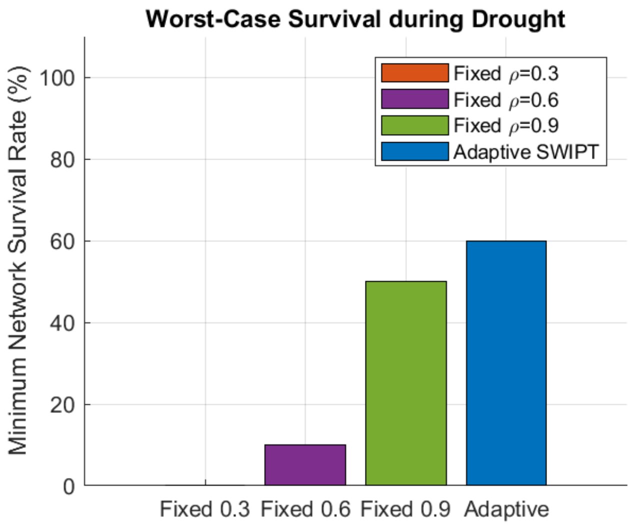

Figure 4.8 Worst-Case Survival Rate during Drought

Examining the minimum percentage of alive nodes during the drought window provides stark evidence of vulnerability. Static Fixed 0.3 crashes to a 0% survival rate, whereas the Adaptive policy maintains best network survival rate, which is 60%, guaranteeing possibly uninterrupted network coverage.

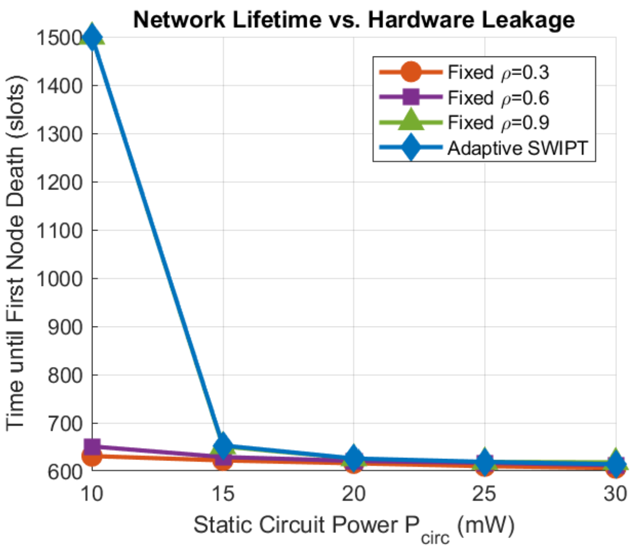

Figure 4.9 Network Lifetime vs. Static Circuit Power

As the static hardware power consumption increases (simulating more power-hungry sensors), the time until the first node death drops sharply for fixed policies. The Adaptive SWIPT mechanism consistently delays network failure to the maximum theoretical physical limit, proving its practical superiority for long-term B5G IoT deployments.

Chapter 5

Conclusion

5.1 Conclusion

This project successfully designed, simulated, and validated an integrated resource allocation framework for Energy Harvesting IoT networks, directly addressing the critical challenges of battery dependency in B5G deployments. The mathematical integration of a normalized Lyapunov optimization scheduler with an Adaptive SWIPT module achieved all defined objectives. Firstly, the framework strictly maintained data queue stability while avoiding premature energy depletion, utilizing the U_{tx} utility function to dynamically adjust uplink transmission power. Secondly, the Adaptive SWIPT algorithm eliminated the spectrum waste inherent in Fixed Power Splitting (FPS) architectures. By dynamically evaluating the virtual energy deficit queue, the system intelligently shifted between maximizing downlink data decoding during healthy states and enforcing emergency energy harvesting during energy droughts. Finally, rigorous MATLAB simulations proven the robustness of the model. Compared to traditional static policies which suffered 0% survival rates during severe environmental energy droughts, the proposed adaptive methodology maintained a 60% network survival rate and continuously maximized the overall operational lifetime of the resource-constrained nodes.

5.2 Recommendation

While the current normalized Lyapunov framework achieves deterministic stability with minimal computational overhead, future iterations of this research can be expanded through the integration of Artificial Intelligence (AI) and Machine Learning techniques.

First possible improvement is Deep Reinforcement Learning (DRL) Integration. Future studies are recommended to incorporate DRL agents (such as Deep Q-Networks or Proximal Policy Optimization) to handle highly complex, multi-dimensional state spaces where explicit mathematical formulations become intractable. DRL could learn hidden channel fluctuation patterns and user mobility behaviors over time, potentially achieving tighter convergence bounds than standard Lyapunov drift mechanisms.

Second possible advancement is Multi-Agent Decentralized Scheduling. The current model assumes a centralized Access Point. Future works can explore distributed Deep Learning algorithms deployed directly on Edge computing gateways, allowing IoT nodes to perform cooperative, multi-agent resource allocation autonomously without relying on a single central scheduler.

Finally, there is a need for physical-layer prototype validation. Moving beyond discrete-time software simulations, implementing the proposed adaptive algorithm on physical Software Defined Radios (SDR) and real-world rectenna circuits will be a crucial next step to validate hardware-in-the-loop efficiency and true circuit conversion nonlinearities.

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APPENDIX

```
%
=====================================================================
=======
% FYP2 Matlab Code: Lyapunov + Adaptive SWIPT
%
=====================================================================
=======

clear; close all; clc;

%% =================== 1. BASE SYSTEM PARAMETERS
==========================
params.N = 10;                   % Number of IoT nodes
params.T = 1500;                 % Simulation time slots
params.slot_duration = 1;        % Slot duration (s)
params.B = 1e3;                  % Bandwidth (Hz)
params.noise = 1e-9;             % AWGN power (W)
params.P_tx_max = 0.035;         % Max uplink Tx power (35mW)
params.P_circ = 0.015;           % Static circuit power (15mW)
params.E_max = 0.5;              % Battery capacity (J)
params.E_init = 0.5 * ones(params.N,1); % Initial full battery
params.P_ap = 0.15;              % AP transmit power (150mW)
params.eta = 0.5;                % Energy conversion efficiency
params.V = 0.6;                  % Lyapunov trade-off parameter
params.lambda = 1.0;             % Poisson arrival rate (packets/slot)
params.packet_size = 3000;       % Packet size (bits)
params.seed = 42;                % Random seed for reproducibility

policies = {@policy_fixed_03, @policy_fixed_06, @policy_fixed_09, @policy_adaptive};
policy_names = {'Fixed \rho=0.3', 'Fixed \rho=0.6', 'Fixed \rho=0.9', 'Adaptive SWIPT'};
colors = [0.8500 0.3250 0.0980; 0.4940 0.1840 0.5560; 0.4660 0.6740 0.1880; 0 0.4470
0.7410];
line_styles = {'-', '-', '-', '-'};
markers = {'o', 's', '^', 'd'};

%% =================== 2. PART A: TIME-SERIES SIMULATION
==================
rng(params.seed);
A_seq = poissrnd(params.lambda, params.T, params.N) * params.packet_size;
h_seq = exprnd(1, params.T, params.N);
g_seq = exprnd(1, params.T, params.N);

% Generate environmental energy with a harsh drought from t=600 to 1100
time_vector = (1:params.T)';
env_base = 0.030 + 0.005 * sin(2*pi*time_vector/800);
env_base(600:1100) = 0.002; % Extreme ambient drought (2mW)
Henv_seq = max(0, env_base + 0.002*randn(params.T, params.N));
```

```
% Dynamic AP Power to simulate severe blockage during drought
Pap_seq = params.P_ap * ones(params.T, 1);
Pap_seq(600:1100) = 0.04; % AP power drops severely to 40mW

% Run time-series simulation
ts_metrics = cell(length(policies),1);
for i = 1:length(policies)
    ts_metrics{i} = run_core_simulation(params, A_seq, h_seq, g_seq, Henv_seq, Pap_seq,
policies{i});
end

%% =================== 3. PART B: PARAMETER SWEEPS
======================
% Sweep 1: Arrival Rate (Lambda) for Objective 1
lambda_range = 0.5:0.5:2.5;
sweep_lambda_Q = zeros(length(policies), length(lambda_range));
sweep_lambda_EE = zeros(length(policies), length(lambda_range)); % Energy Efficiency

for idx = 1:length(lambda_range)
    p_temp = params; p_temp.lambda = lambda_range(idx);
    A_temp = poissrnd(p_temp.lambda, params.T, params.N) * params.packet_size;
    for i = 1:length(policies)
        m = run_core_simulation(p_temp, A_temp, h_seq, g_seq, Henv_seq, Pap_seq,
policies{i});
        sweep_lambda_Q(i, idx) = mean(m.queue_over_time);
        % Calculate Energy Efficiency: Total bits transmitted / Total Joules consumed
        sweep_lambda_EE(i, idx) = sum(m.uplink_throughput) /
sum(m.energy_consumed_over_time);
    end
end

% Sweep 2: AP Transmit Power for Objective 2
Pap_range = 0.05:0.05:0.25;
sweep_Pap_Rdl = zeros(length(policies), length(Pap_range));
sweep_Pap_Harv = zeros(length(policies), length(Pap_range));

for idx = 1:length(Pap_range)
    p_temp = params;
    Pap_temp_seq = Pap_range(idx) * ones(params.T, 1); % Constant for sweep
    for i = 1:length(policies)
        m = run_core_simulation(p_temp, A_seq, h_seq, g_seq, Henv_seq, Pap_temp_seq,
policies{i});
        sweep_Pap_Rdl(i, idx) = mean(m.downlink_rate);
        sweep_Pap_Harv(i, idx) = mean(m.harvested_energy_over_time);
    end
end

% Sweep 3: Static Circuit Power for Objective 3
```

```
Pcirc_range = 0.01:0.005:0.03;
sweep_Pcirc_life = zeros(length(policies), length(Pcirc_range));

for idx = 1:length(Pcirc_range)
   p_temp = params; p_temp.P_circ = Pcirc_range(idx);
   for i = 1:length(policies)
      m = run_core_simulation(p_temp, A_seq, h_seq, g_seq, Henv_seq, Pap_seq,
policies{i});
      sweep_Pcirc_life(i, idx) = m.time_to_first_death;
   end
end

%% =================== 4. PLOTTING THE 3 OBJECTIVE FIGURES
================
smooth_window = 30;
mk_idx = 1:100:params.T;

% ---------------------------------------------------------------------
% Objective 1 - Queue Stability & Energy Efficiency
% ---------------------------------------------------------------------
figure('Name', 'Obj 1: Queue & Energy', 'Units','normalized','Position',[0.05 0.3 0.9 0.4]);

subplot(1,3,1); hold on;
for i=1:length(policy_names)
   sq = movmean(ts_metrics{i}.queue_over_time, smooth_window); sq(1) =
ts_metrics{i}.queue_over_time(1);
   plot(sq, 'Color', colors(i,:), 'LineStyle', line_styles{i}, 'LineWidth', 2, ...
      'Marker', markers{i}, 'MarkerIndices', mk_idx, 'MarkerFaceColor', colors(i,:));
end
xlim([1, params.T]); ylim([0, 15000]); xlabel('Time slot'); ylabel('Avg Queue Backlog
(bits)');
title('Figure 4.1: Queue Stability over Time'); legend(policy_names, 'Location', 'best'); grid
on;

subplot(1,3,2); hold on;
for i=1:length(policy_names)
   plot(lambda_range, sweep_lambda_Q(i,:), 'Color', colors(i,:), 'LineWidth', 2, ...
      'Marker', markers{i}, 'MarkerFaceColor', colors(i,:), 'MarkerSize', 8);
end
xlabel('Data Arrival Rate \lambda (pkts/slot)'); ylabel('Avg Queue Backlog (bits)');
title('Figure 4.2: Queue Backlog vs. Traffic Load'); legend(policy_names, 'Location', 'best');
grid on;

subplot(1,3,3); hold on;
for i=1:length(policy_names)
   % Convert to bits/mJ for readability
   plot(lambda_range, sweep_lambda_EE(i,:)/1000, 'Color', colors(i,:), 'LineWidth', 2, ...
      'Marker', markers{i}, 'MarkerFaceColor', colors(i,:), 'MarkerSize', 8);
end
```

```
xlabel('Data Arrival Rate \lambda (pkts/slot)'); ylabel('Energy Efficiency (bits/mJ)');
title('Figure 4.3: Energy Efficiency vs. Traffic Load'); legend(policy_names, 'Location',
'best'); grid on;

% ----------------------------------------------------------------------
% Objective 2 - Dynamic SWIPT Balancing
% ----------------------------------------------------------------------
figure('Name', 'Obj 2: SWIPT Throughput', 'Units','normalized','Position',[0.05 0.3 0.9 0.4]);

subplot(1,3,1); hold on;
for i=1:length(policy_names)
    sr = movmean(ts_metrics{i}.downlink_rate, smooth_window); sr(1) =
ts_metrics{i}.downlink_rate(1);
    plot(sr, 'Color', colors(i,:), 'LineStyle', line_styles{i}, 'LineWidth', 2, ...
        'Marker', markers{i}, 'MarkerIndices', mk_idx, 'MarkerFaceColor', colors(i,:));
end
xlim([1, params.T]); xlabel('Time slot'); ylabel('Downlink Rate (bps)');
title('Figure 4.4: Downlink Throughput over Time'); legend(policy_names, 'Location', 'best');
grid on;

subplot(1,3,2); hold on;
for i=1:length(policy_names)
    plot(Pap_range.*1000, sweep_Pap_Rdl(i,:), 'Color', colors(i,:), 'LineWidth', 2, ...
        'Marker', markers{i}, 'MarkerFaceColor', colors(i,:), 'MarkerSize', 8);
end
xlabel('AP Transmit Power P_{ap} (mW)'); ylabel('Avg Downlink Rate (bps)');
title('Figure 4.5: Throughput vs. Available RF Power'); legend(policy_names, 'Location',
'best'); grid on;

subplot(1,3,3); hold on;
for i=1:length(policy_names)
    scatter(sweep_Pap_Harv(i,:).*1000, sweep_Pap_Rdl(i,:), 100, colors(i,:), markers{i},
'filled');
    plot(sweep_Pap_Harv(i,:).*1000, sweep_Pap_Rdl(i,:), 'Color', [colors(i,:) 0.5],
'LineWidth', 1.5);
end
xlabel('Avg Harvested Energy (mJ)'); ylabel('Avg Downlink Rate (bps)');
title('Figure 4.6: SWIPT Rate-Energy Trade-off Region'); legend(policy_names, 'Location',
'best'); grid on;

% ----------------------------------------------------------------------
% Objective 3 - Survivability & Lifetime
% ----------------------------------------------------------------------
figure('Name', 'Obj 3: Survivability', 'Units','normalized','Position',[0.05 0.3 0.9 0.4]);

subplot(1,3,1); hold on;
for i=1:length(policy_names)
    se = movmean(ts_metrics{i}.energy_over_time, smooth_window); se(1) =
ts_metrics{i}.energy_over_time(1);
```

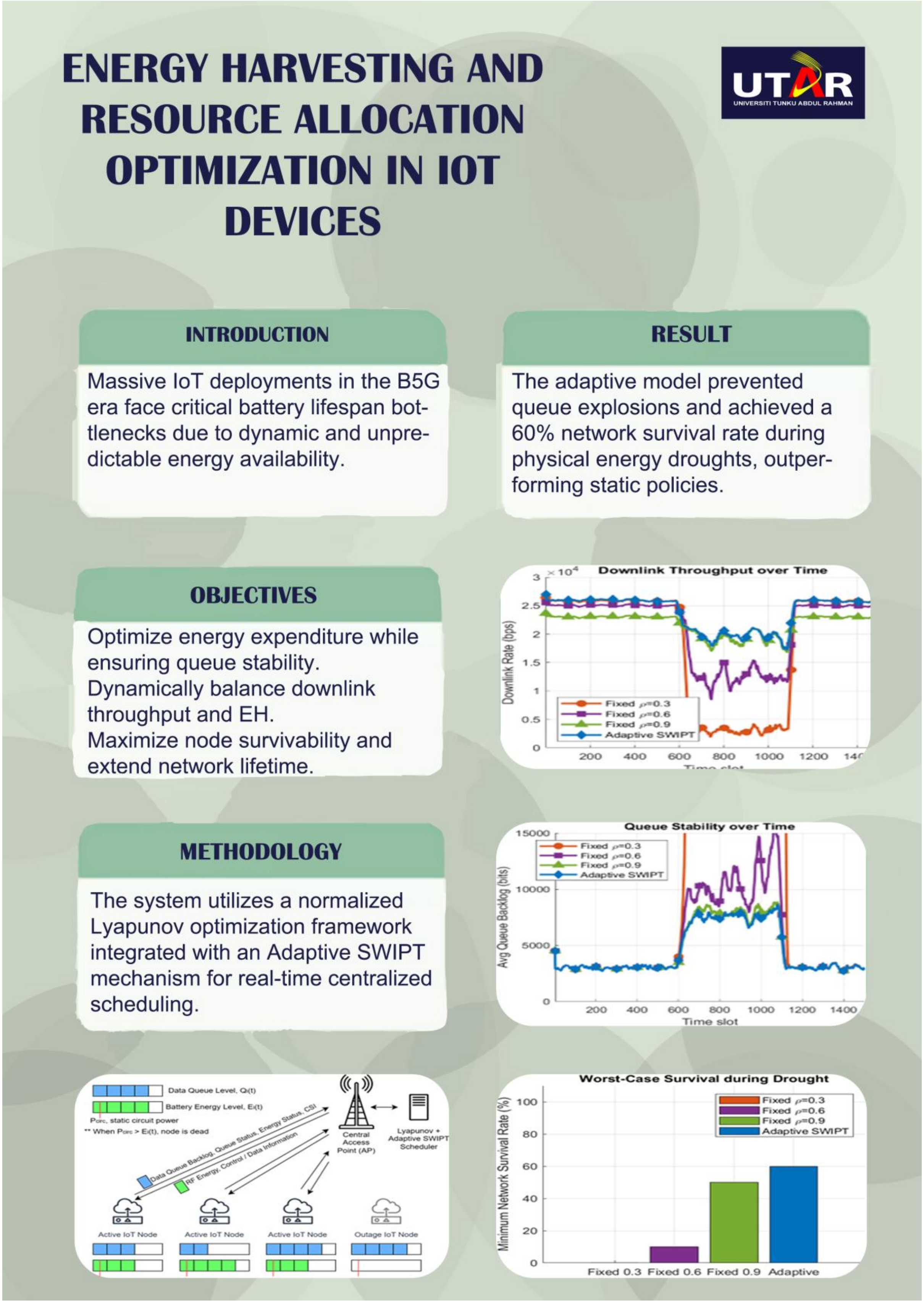
```
    plot(se, 'Color', colors(i,:), 'LineStyle', line_styles{i}, 'LineWidth', 2, ...
        'Marker', markers{i}, 'MarkerIndices', mk_idx, 'MarkerFaceColor', colors(i,:));
end
xlim([1, params.T]); ylim([0, 0.55]); yline(params.P_circ, 'r-', 'Dead Threshold', 'LineWidth',
2);
xlabel('Time slot'); ylabel('Battery Level (J)');
title('Figure 4.7: Energy Sustainability over Time'); legend(policy_names, 'Location', 'best');
grid on;

subplot(1,3,2); hold on;
drought_idx = 600:1100;
for i=1:length(policy_names)
    % Calculate WORST-CASE survival rate during drought
    min_survival = min(ts_metrics{i}.alive_nodes_over_time(drought_idx)) / params.N * 100;
    bar(i, min_survival, 'FaceColor', colors(i,:));
end
set(gca, 'XTick', 1:4, 'XTickLabel', {'Fixed 0.3', 'Fixed 0.6', 'Fixed 0.9', 'Adaptive'});
ylabel('Minimum Network Survival Rate (%)'); ylim([0, 110]);
title('Figure 4.8: Worst-Case Survival during Drought'); legend(policy_names, 'Location',
'best'); grid on;

subplot(1,3,3); hold on;
for i=1:length(policy_names)
    plot(Pcirc_range.*1000, sweep_Pcirc_life(i,:), 'Color', colors(i,:), 'LineWidth', 2, ...
        'Marker', markers{i}, 'MarkerFaceColor', colors(i,:), 'MarkerSize', 8);
end
xlabel('Static Circuit Power P_{circ} (mW)'); ylabel('Time until First Node Death (slots)');
title('Figure 4.9: Network Lifetime vs. Hardware Leakage'); legend(policy_names, 'Location',
'best'); grid on;


%% =================== 5. CORE SIMULATION ENGINE
==========================
function metrics = run_core_simulation(params, A_seq, h_seq, g_seq, Henv_seq, Pap_seq,
policy_fn)
    N = params.N; T = params.T;
    Q = zeros(N,1);
    E = params.E_init;

    Q_hist = zeros(T, N);
    E_hist = zeros(T, N);
    Rdl_hist = zeros(T, N);
    Rul_hist = zeros(T, N);
    Econs_hist = zeros(T, N);
    Harv_hist = zeros(T, N);
    Alive_hist = zeros(T, 1);

    time_to_first_death = T;
    death_recorded = false;
```

```
for t = 1:T
    params.P_ap = Pap_seq(t); % Inject dynamic AP power

    state.Q = Q; state.E = E; state.h = h_seq(t,:)';
    state.g = g_seq(t,:)'; state.H_env = Henv_seq(t,:)';

    action = policy_fn(state, params);

    is_dead = (E < params.P_circ);
    Alive_hist(t) = N - sum(is_dead);

    if any(is_dead) && ~death_recorded
        time_to_first_death = t;
        death_recorded = true;
    end

    actual_p_circ = min(params.P_circ, E);
    E_rem = E - actual_p_circ;

    actual_p_tx = min(action.p_tx, E_rem / params.slot_duration);
    actual_p_tx(is_dead) = 0;

    SINR = (actual_p_tx .* state.h) ./ params.noise;
    R_ul = params.B * log2(1 + SINR) * params.slot_duration;
    transmitted = min(Q, R_ul);
    transmitted(is_dead) = 0;

    P_rx = params.P_ap .* state.g;
    S_harv = params.eta .* action.rho .* P_rx * params.slot_duration;

    R_dl = params.B * log2(1 + ((1 - action.rho) .* P_rx) ./ params.noise);
    R_dl(is_dead) = 0;

    energy_consumed = actual_p_tx * params.slot_duration + actual_p_circ;
    Q = max(Q - transmitted, 0) + A_seq(t,:)';
    E = min(params.E_max, E - energy_consumed + state.H_env + S_harv);
    E(E < 0) = 0;

    Q_hist(t,:) = Q'; E_hist(t,:) = E'; Rdl_hist(t,:) = R_dl';
    Rul_hist(t,:) = transmitted';
    Econs_hist(t,:) = energy_consumed'; Harv_hist(t,:) = S_harv';
end

metrics.queue_over_time = mean(Q_hist, 2);
metrics.energy_over_time = mean(E_hist, 2);
metrics.downlink_rate = mean(Rdl_hist, 2);
metrics.uplink_throughput = mean(Rul_hist, 2);
metrics.energy_consumed_over_time = mean(Econs_hist, 2);
```

```
    metrics.harvested_energy_over_time = mean(Harv_hist, 2);
    metrics.alive_nodes_over_time = Alive_hist;
    metrics.time_to_first_death = time_to_first_death;
end

%% ================== 6. POLICY DEFINITIONS
==============================
function action = policy_fixed_03(state, params)
    action = calc_uplink_power(state, params); action.rho = 0.3 * ones(params.N, 1);
end

function action = policy_fixed_06(state, params)
    action = calc_uplink_power(state, params); action.rho = 0.6 * ones(params.N, 1);
end

function action = policy_fixed_09(state, params)
    action = calc_uplink_power(state, params); action.rho = 0.9 * ones(params.N, 1);
end

function action = policy_adaptive(state, params)
    action = calc_uplink_power(state, params);
    action.rho = zeros(params.N, 1);
    rho_grid = linspace(0, 1, 20);
    P_rx = params.P_ap .* state.g;
    X = params.E_max - state.E;

    for i = 1:params.N
        S_cand = params.eta .* rho_grid .* P_rx(i) .* params.slot_duration;
        Rdl_cand = params.B * log2(1 + ((1 - rho_grid) .* P_rx(i)) ./ params.noise);

        X_norm = X(i) / params.E_max;
        S_norm = S_cand / (params.eta * params.P_ap * params.slot_duration);
        Rdl_norm = Rdl_cand / (params.B * 30);

        U_rho = X_norm .* S_norm + params.V .* Rdl_norm;
        [~, best_idx] = max(U_rho);
        action.rho(i) = rho_grid(best_idx);
    end
end

function action = calc_uplink_power(state, params)
    X = params.E_max - state.E;
    p_cand = min(state.E / params.slot_duration, params.P_tx_max);
    R_ul_cand = params.B * log2(1 + (p_cand .* state.h) ./ params.noise);

    Q_norm = state.Q / 5000;
    X_norm = X / params.E_max;
    R_ul_norm = R_ul_cand / (params.B * 25);
    p_norm = p_cand / params.P_tx_max;
```

```
    V_tx = 3.0;
    U_tx = Q_norm .* R_ul_norm - V_tx .* X_norm .* p_norm;

    action.p_tx = zeros(params.N, 1);
    transmit_mask = (U_tx > 0) & (p_cand > 0);
    action.p_tx(transmit_mask) = p_cand(transmit_mask);
end
```

POSTER


ENERGY HARVESTING AND RESOURCE ALLOCATION OPTIMIZATION IN IOT DEVICES
UTAR
UNIVERSITI TUNKU ABDUL RAHMAN
INTRODUCTION
Massive IoT deployments in the B5G era face critical battery lifespan bottlenecks due to dynamic and unpredictable energy availability.
RESULT
The adaptive model prevented queue explosions and achieved a 60% network survival rate during physical energy droughts, outperforming static policies.
OBJECTIVES
Optimize energy expenditure while ensuring queue stability.
Dynamically balance downlink throughput and EH.
Maximize node survivability and extend network lifetime.
METHODOLOGY
The system utilizes a normalized Lyapunov optimization framework integrated with an Adaptive SWIPT mechanism for real-time centralized scheduling.
Downlink Throughput over Time
Downlink Rate (bps)
Fixed ρ=0.3
Fixed ρ=0.6
Fixed ρ=0.9
Adaptive SWIPT
Queue Stability over Time
Avg Queue Backlog (bits)
Time slot
Data Queue Level, Qi(t)
Battery Energy Level, Ei(t)
Central Access Point (AP)
Lyapunov + Adaptive SWIPT Scheduler
Data Queue Backlog, Queue Status, Energy Status, CSI
RF Energy, Control / Data Information
Active IoT Node
Outage IoT Node
Worst-Case Survival during Drought
Minimum Network Survival Rate (%)
Fixed 0.3
Fixed 0.6
Fixed 0.9
Adaptive