Resource Allocation in Cooperative and Heterogeneous Wireless Networks with Energy Harvesting

by

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A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

in

The Faculty of Graduate and Postdoctoral Studies

(Electrical and Computer Engineering)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

December 2017

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Abstract

The number of wireless connected devices is increasing rapidly, owing to the increasing applications of Internet of Things (IoT) devices. To address the coverage and capacity demand in the future, the fifth generation (5G) network will have heterogeneous architecture with densely deployed small cells and relay nodes for cooperative communication. Since dense deployment of base stations and relay nodes incur high energy consumption, renewable energy harvesting is a promising technique of reducing non-renewable energy consumption. Meanwhile, with increasing demand of IoT applications, self-sustaining battery life is direly needed in low power sensor-like devices. Since installation of bulky renewable energy harvesting infrastructure is not feasible in such miniature sensor-like devices, wireless energy harvesting is another promising technique that enables self-sustaining battery life of such devices. In this thesis, we address the challenges of resource allocation in cooperative and heterogeneous wireless communication networks with renewable and wireless energy harvesting.

First, we consider relay-based and user-based cooperation in uplink wireless-powered communication (WPC) to mitigate the “doubly near-far” problem. We propose algorithms to jointly optimize resource allocation for downlink energy harvesting and uplink information transmission in uplink WPC network with relay-based and user-based cooperation. Our algorithms improve throughput performance of user equipments that are far from access point. Next, we address new challenges of interference management in heterogeneous networks (Het-Nets) when downlink simultaneous information and power transfer (SWIPT) is enabled in small cells. We jointly maximize energy harvesting rate and throughput of small cell users while keeping interference within tolerable level. In time-switching approach of SWIPT, we
Abstract
demonstrate significant improvement in the energy harvesting rate by enabling flexible interference tolerance in macrocell users. Finally, we address the conflict between maximization of throughput and minimization of power cost in HetNets with renewable energy harvesting. We propose different online and offline algorithms to determine dynamic base station activation policy jointly with downlink resource allocation to optimize the trade-off between throughput performance and the associated power cost. Our algorithms demonstrate significant increase in throughput and decrease in non-renewable power consumption when compared to the baseline schemes. Performances of the proposed algorithms are analyzed through numerical simulations.
Lay Summary

Energy harvesting is envisioned as a key feature of future wireless networks. Wireless energy harvesting can elongate battery life of battery-constrained Internet of Things devices and renewable energy harvesting can lower non-renewable energy consumption of network equipments. In this thesis, we propose different algorithms for uplink/downlink resource allocation in cooperative and heterogeneous wireless communication networks with energy harvesting constraints. In wireless energy harvesting, we consider uplink wireless-powered communication (WPC) as well as downlink simultaneous information and power transfer (SWIPT). For uplink WPC, our algorithms improve throughput performance of user equipments that are far from access point by relay-based and user-based cooperation. For downlink SWIPT, our algorithms significantly improve the energy harvesting rate in small cells while satisfying minimum throughput requirements of macrocell users in heterogeneous networks (HetNets). For renewable energy harvesting HetNets, our algorithms improve the throughput performance while decreasing the power cost of serving the hotspot users.
Preface

Publications that resulted from the research presented in this thesis are as follows:


• S. Lohani, E. Hossain and V. K. Bhargava, “Resource allocation for wireless information and energy transfer in macrocell-small cell networks,” in *Proc. IEEE 84th Vehicular Technology Conference (VTC-Fall)*, Sep. 2016, pp. 1-5. (Linked to Chapter 4)

• S. Lohani, E. Hossain and V. K. Bhargava, “Downlink power allocation for wireless information and energy transfer in macrocell-small cell networks,” in *Proc. IEEE Wireless Communications and Networking Conference (WCNC)*, Apr. 2016, pp. 1-6. (Linked to Chapter 4)


I am the primary researcher and author for all the research contributions made in this thesis. I conducted the literature review to identify the research problems. I formulated the research problems, performed mathematical analysis, and carried out the numerical simulations. I also wrote the manuscripts for each publication. The contributions of the co-authors of my papers are as follows. Prof. Vijay K. Bhargava is my honorable supervisor. He has provided valuable guidance, technical suggestions, and constructive feedback for identifying the research problem, making the research progress, and preparing the associated manuscripts. Prof. Ekram Hossain is the co-supervisor of my research during my PhD. I consulted him during all my research works and he has provided valuable guidance, constructive technical feedback, and also helped in editorial corrections while preparing the corresponding manuscripts for publication. Dr. Shankhanaad Mallick was a post-doctoral fellow and Dr.
Roya Arab Loodarichech was a PhD student in our research group. They provided contribution in some of the above publications by offering technical feedback during the mathematical analysis and editorial feedback during preparation of the associated manuscripts.
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<tr>
<td>3GPP</td>
<td>3rd Generation Partnership Project</td>
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<tr>
<td>4G</td>
<td>Fourth Generation</td>
</tr>
<tr>
<td>5G</td>
<td>Fifth Generation</td>
</tr>
<tr>
<td>AP</td>
<td>Access Point</td>
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<tr>
<td>AWGN</td>
<td>Additive White Gaussian Noise</td>
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<tr>
<td>DBPSO</td>
<td>Discrete Binary Particle Swarm Optimization</td>
</tr>
<tr>
<td>DEH</td>
<td>Downlink Energy Harvesting</td>
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<td>DEPA</td>
<td>Downlink Equal Power Allocation</td>
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<td>EH</td>
<td>Energy Harvesting</td>
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<tr>
<td>HetNet</td>
<td>Heterogeneous Networks</td>
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<tr>
<td>HUE</td>
<td>Hotspot User Equipment</td>
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<tr>
<td>ID</td>
<td>Information Decoding</td>
</tr>
<tr>
<td>IoT</td>
<td>Internet of Things</td>
</tr>
<tr>
<td>KKT</td>
<td>Karush Kuhn Tucker</td>
</tr>
<tr>
<td>LTE-A</td>
<td>Long Term Evolution-Advanced</td>
</tr>
<tr>
<td>MBS</td>
<td>Macrocell Base Station</td>
</tr>
<tr>
<td>METIS</td>
<td>Mobile and wireless communications Enablers for the Twenty-twenty Information Society</td>
</tr>
<tr>
<td>MINLP</td>
<td>Mixed Integer Non-Linear Programming</td>
</tr>
<tr>
<td>MTC</td>
<td>Machine Type Communication</td>
</tr>
<tr>
<td>MUE</td>
<td>Macrocell User Equipment</td>
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<tr>
<td>Abbreviation</td>
<td>Description</td>
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<td>--------------</td>
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<tr>
<td>PSO</td>
<td>Particle Swarm Optimization</td>
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<tr>
<td>QoS</td>
<td>Quality of Service</td>
</tr>
<tr>
<td>RF</td>
<td>Radio Frequency</td>
</tr>
<tr>
<td>RFID</td>
<td>Radio Frequency Identification</td>
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<tr>
<td>RN</td>
<td>Relay Node</td>
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<td>RRSA</td>
<td>Random Relay and Subcarrier Assignment</td>
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<tr>
<td>SBS</td>
<td>Small cell Base Station</td>
</tr>
<tr>
<td>SNR</td>
<td>Signal-to-Noise Ratio</td>
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<tr>
<td>SUE</td>
<td>Small cell User Equipment</td>
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<tr>
<td>SWIPT</td>
<td>Simultaneous Wireless Information and Power Transfer</td>
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<tr>
<td>TN</td>
<td>Transmitting Node</td>
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<tr>
<td>UE</td>
<td>User Equipment</td>
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<tr>
<td>UIT</td>
<td>Uplink Information Transmission</td>
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<tr>
<td>WPC</td>
<td>Wireless-Powered Communication</td>
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Acknowledgments

I am very grateful to a number of people for their support and guidance in the journey of my PhD. Firstly, I would like to extend my deepest gratitude to my supervisor, Professor Vijay K. Bhargava and my co-supervisor, Professor Ekram Hossain for their incredible support and guidance. I consider myself very lucky to have had the opportunity of working under the supervision of such knowledgeable, supportive, and patient supervisors. This thesis would not have been possible without their invaluable advice, critical comments, and constant encouragement.

I would also like to thank Professor Vincent Wong, Professor Lutz Lampe, Professor Victor Leung, and Professor Alireza Nojeh for offering constructive suggestions and insightful feedback during my PhD qualifying exam and departmental exam.

I would also like to extend my gratitude towards all the colleagues of my research lab for their friendly support and the fruitful discussions. I appreciate the help and encouragement that I received from my senior colleagues, namely, Dr. Shankhanaad Mallick, Dr. Roya Arab Loodaricheh, Dr. Mai Hassan, Dr. Rindranirina Ramamonjison, and Dr. Hamidreza Boostanimehr. Special thanks go to Dr. Shankhanaad Mallick and Dr. Roya Arab Loodaricheh, with whom I had the chance to collaborate in some of my research works. Their technical suggestions and feedback have been very helpful in my research. This work was supported by Natural Sciences and Engineering Research Council of Canada (NSERC).
Dedication

I dedicate this thesis to my daughter, my husband, and my parents. My daughter, who was born just before I started writing my thesis, gave me a new dimension of encouragement and determination. I am eternally grateful to my mother for staying with me after the birth of my daughter, so that I could complete my thesis in time. I am thankful to both of my parents for laying a strong foundation for my education. Special thanks to my husband for all the support and sacrifices he made during the journey of my PhD.
Chapter 1

Introduction

The wireless communication industry has been expanding tremendously, both in terms of technology as well as subscribers. The journey of mobile communication has reached fourth generation (4G). Third Generation Partnership Project (3GPP) Release 10 known as Long Term Evolution-Advanced (LTE-A) was ratified as 4G technology by International Telecommunication Union in November 2010 [1]. It is now deployed in several parts of the world. Along the journey, subscriber demand has never failed to increase. For example, the number of wireless connected devices is expected to increase from 15 billion in 2015 to 28 billion in 2021 out of which 16 billion will be related to Internet of Things (IoT) [2]. With increasing application of IoT devices, there is increasing interest in incorporating IoT network under cellular communication technology [3, 4] and 1.5 billion IoT devices are expected to have cellular connectivity by 2021 [2]. Currently, researchers, users, and service providers are all looking forward to the fifth generation (5G) technology as a solution to support the increased capacity and coverage demand of the legions of connected devices and users of 2020 and beyond. For instance, Mobile and wireless communications Enablers for the Twenty-twenty Information Society (METIS) project [5] has concretized the requirements of 5G wireless communication networks and the research work towards standardization is on-going.

One of the major challenges imposed upon 5G networks is tremendous increase in traffic volume and legions of connected wireless devices. To address the coverage and capacity demand of legions of devices in the future, 5G network is expected to have heterogeneous architecture with macro cells overlaid or underlaid by large number of smaller cells along with relay nodes deployed for cooperative communication [6]. This will impose additional
resource management and interference management challenges. Moreover, increasing energy efficiency whilst achieving better performance is another challenging requirement of the 5G networks [5]. Increase of coverage and capacity leads towards higher consumption of energy [7]. Increasing energy consumption and consequent operational expenditure of the network operators have motivated researchers towards the concept of “Green Communication” which not only targets to reduce energy consumption in terms of environmental benefit but also in terms of economic benefit. Meanwhile, with increasing number of low power IoT devices, limited battery life of such miniature devices is another major performance bottleneck.

Lately, energy harvesting has received significant research attention in the field of wireless communications. As the name suggests, energy harvesting is a technique by which energy of ambient sources (solar, wind, wireless, and others) is converted into electrical energy and used to power user/network equipments. Harvesting energy from renewable energy sources (solar, wind, and others), which is termed as renewable energy harvesting, has emerged as one of the enabling technologies for Green Communication [8]. This technology makes use of perpetual renewable energy sources and reduces the consumption of high cost non-renewable energy sources. Since installing renewable energy harvesting infrastructure is not feasible in low-power miniature devices, wireless energy harvesting has also gained much attention in the field of energy harvesting as a potential technique of elongating the battery life of such battery-constrained IoT devices [6]. Hence, energy harvesting is envisioned as a key feature of future wireless networks [6,8].

In this thesis, we address some challenges imposed by energy harvesting constraints on resource allocation in heterogeneous and cooperative networks. In the next section, we provide brief overview of energy harvesting in wireless networks. We also provide a brief overview of heterogeneous and cooperative networks in Section 1.2.
1.1 Overview of Energy Harvesting in Wireless Networks

Depending upon the source of energy, energy harvesting can be broadly divided into two categories: wireless energy harvesting and renewable energy harvesting. In this section, we will discuss about these two energy harvesting technologies separately.

1.1.1 Wireless Energy Harvesting

The concept of harvesting energy from the received wireless signal, known as wireless energy harvesting, has gained much research attention in the field of wireless communication networks [9,10] because of its ability to extend the battery life of small network nodes. With the increasing demand of IoT applications, self-sustaining battery life is direly needed in sensor nodes [3,11]. Providing grid power or renewable energy harvesting infrastructure to each sensor node of a densely populated network may not be a viable option. Given the small size of the sensor nodes, they cannot have long battery life even if they are battery operated. Constantly changing or recharging the battery incurs high operational cost, requires constant human involvement, and may not be feasible in many network applications. Therefore, wireless energy harvesting is anticipated as one of the key features in the future of IoT [12]. Self-sustaining battery life of sensor nodes will allow full exploitation of several IoT applications such as embedded structure monitoring, industrial monitoring, environmental monitoring, and so on.

There are two major concerns in wireless energy harvesting technology. Firstly, due to the current hardware limitation, receiver circuits of UEs are not designed to harvest energy while decoding the information. The authors of [13] have proposed a receiver circuit that integrates the components of energy harvester and information decoder. However, the achievable throughput of such integrated receiver circuit is found to be much lower than that of the separated receiver. Therefore, receiver circuits of UEs need to have separate
1.1. Overview of Energy Harvesting in Wireless Networks

Figure 1.1: Simultaneous wireless information and power transfer in downlink. The UEs harvest energy from the same information signal transmitted on downlink by the access point (AP).

information decoding and energy harvesting circuit. Energy harvesting circuits such as P2110 Powerharvester receiver [14] has already been commercially available. Secondly, the receiver sensitivity of energy harvester is very poor (around $-20$ dBm) compared to that of an information receiver (around $-60$ dBm) [15,16]. If the received signal is significantly lower than $-20$ dBm, very little or no energy is harvested. This significantly reduces the range of wireless power transfer. For instance, in a certain experimental setting [15], wireless power transfer range is found to be around 11.38 meters for omnidirectional antenna and 37.51 meters for directional antenna. In the experiment, the power harvested at a distance of 10 m is found to be 12.94 $\mu$W with omnidirectional antenna and 140.73 $\mu$W with directional antenna. Since the received signal power is in the range of $\mu$W, wireless energy harvesting is applicable in very small nodes of wireless communication network with minimum power requirements, such as sensor nodes\(^1\) or RFID tags [15,18,19].

Wireless energy harvesting technology has been investigated in two different paradigms of wireless communication discussed separately in the following.

**Simultaneous wireless information and power transfer**

Simultaneous wireless information and power transfer (SWIPT) is used in downlink communication phase to transmit wireless energy to the UEs whilst transmitting downlink in-
1.1. Overview of Energy Harvesting in Wireless Networks

formation to them as shown in Fig. 1.1. For SWIPT, since current receiver circuits have separate information decoding and energy harvesting circuits, the received signal is shared, either by splitting the power of the received signal, called power-splitting approach, or by sharing the time of signal reception, called time-switching approach, among the information decoder and the energy harvester [13, 20]. In power-splitting approach, UEs use a radio frequency (RF) splitter [21] to split a fraction of the received signal to information decoding circuit and the rest to energy harvesting circuit (e.g., P2110 Powerharvester receiver [14]). In time-switching approach, UEs use a switch [22] to connect the RF input to energy harvesting circuit for a fraction of transmission time and to information decoding circuit for the remaining of transmission time. Refer to [23] and references therein for time-switching and power-splitting receiver circuit architectures for SWIPT.

Wireless-powered communication

When the UEs are making uplink transmission, it is not possible to transmit energy to them via SWIPT technique. Hence, another important paradigm of wireless energy harvesting is wireless-powered communication (WPC) in the uplink [24–26]. In this technique, uplink information transmission phase is preceded by downlink energy harvesting phase, where the wireless charging signal is transmitted by the access point to the UEs. The energy, harvested during downlink energy harvesting time, is utilized by the UEs to make uplink information transmission to the access point as shown in Fig. 1.2. It is termed as harvest-then-transmit protocol in [24].

In this thesis, we address the challenges of resource allocation in uplink WPC as well as downlink SWIPT.

1.1.2 Renewable Energy Harvesting

While wireless energy harvesting is suitable in small nodes of the network, renewable energy harvesting is a promising technique of reducing the power cost of bigger network nodes such
1.1. Overview of Energy Harvesting in Wireless Networks

![Wireless-powered communication in uplink. The AP makes downlink energy transmission first and then the UEs make uplink information transmission with the harvested energy.]

As base stations. In the era of rapidly increasing network density, and hence the energy demand, renewable energy harvesting has emerged as an enabling technology to lower the carbon footprint of wireless networks. There have been several studies in the literature considering solar or wind energy harvesting for the base stations \[27, 28\]. Some renewable energy sources can be more efficient in specific time and location only. For example, if solar energy harvesting is implemented, the system may not operate if it is cloudy for a long duration. Similar limitations apply to all natural sources of energy. Designing a device capable of harvesting energy from more than one sources can be a promising solution to that problem. One such hybrid energy harvesting model using solar energy and wind energy is presented in \[27\]. To ensure the continuous operation of the network equipments, it is better to add a constant energy source (power grid or battery) to the system. Fig. 1.3 depicts a base station powered by solar energy, wind energy, and constant energy source (power grid). However, the design should be such that energy consumption from the constant energy source is kept to minimum \[29\].

Due to the uncertainty of energy arrival in renewable energy harvesting systems, energy arrival becomes a random process to be considered in resource allocation schemes. The energy that will be harvested in future will not be of any use in the current packet transmission. Hence causality constraint is added in the resource allocation problem of renewable energy harvesting systems \[30, 31\]. In this thesis, we address the challenges of resource allocation in
1.2 Overview of Heterogeneous and Cooperative Wireless Networks

Heterogeneous networks (HetNets) comprise of different tiers of network overlaying or underlaying each other along with relay nodes as shown in Fig. 1.4. Typically larger cells, termed as macro cell are overlaid/underlaid by smaller cells. Although macro cells are usually designed to provide coverage to a larger area, there can be coverage holes due to different geographical obstructions and poor channel conditions. Also, there might be high demand in certain areas, called hotspots. Hence, smaller cells are designed to support the capacity demand of hotspots or serve the users in the coverage holes. Cooperative communication with relay nodes can also be used for providing coverage in the coverage holes, instead of deploying a small cell. In that case, the relay node receives the signal from the base station and forwards them to the users in the coverage holes. We will discuss more about relay-based and user-based cooperation in wireless communications subsequently. If macro cell and small cell base stations are powered by the same source of energy, deployment of smaller cells increases energy efficiency of the network as transmit power requirement of the base
1.2. Overview of Heterogeneous and Cooperative Wireless Networks

Figure 1.4: Heterogeneous network deployment. Solid line indicates wireless link while dashed line indicates backhaul link.

stations decreases significantly, owing to the reduced transmission distances [7].

While multi-tier architecture provides a low cost solution for increasing capacity and coverage, there are significant technical challenges in the design and deployment of such networks [32]. Different tiers of network can be overlaid with dedicated spectrum for each tier or underlaid to reuse the same spectrum, which is also called co-channel deployment. Deployment of different network tiers in dedicated channels results in an inefficient usage of spectrum whereas co-channel deployment gives rise to co-tier and cross-tier interferences [33–36]. However, co-channel deployment is essential to address the capacity demand of increasing number of UEs [6]. In this thesis, different challenges that arise in interference management and resource allocation in co-channel deployment of multi-tier network with wireless and renewable energy harvesting will be considered.

As mentioned previously, cooperative communication can also be used to serve the users in coverage holes. When direct link between the macro base station and a group of users in a certain geographical area is poor, a relay node can be installed such that channel gain of the link between the base station and the relay node as well as that between the relay node and the users are significantly better. The simplest form of cooperative communication can be demonstrated in a simple three terminal network with one source node, one relay node, and one destination node. With the promising concept of full-duplex communication,
source node to relay node communication can happen simultaneously while the received
signal is forwarded in the relay node to destination node link \[37\]. However, due to high
interference challenges, half-duplex relaying may be desirable where the source node to relay
node communication and relay node to destination node communication is separated in time
domain or frequency domain. In this thesis, we consider half-duplex relaying.

There are different forwarding policies defined for the relays \[38\]. The most commonly an-
alyzed forwarding policies in the literature are \textit{amplify-and-forward} and \textit{decode-and-forward}.
Amplify-and-forward is simple forwarding policy in which the relay amplifies the received sig-
nal and transmits it to the destination. This improves the signal-to-noise ratio of the signal
received at the destination. The main disadvantage of this forwarding policy is that the relay
amplifies the received noise signal along with the information signal, before forwarding them,
which curtails the resulting signal-to-noise gain at the destination. In decode-and-forward
policy, the relay first decodes the received message, and then makes the transmission of
the re-encoded message. In this case, channel gain of the link between the source and the
relay must be strong enough to ensure successful decoding at the relay. In this thesis, only
amplify-and-forward policy is considered.

For cooperative communication, instead of deploying dedicated relay nodes, different UEs
of the network can also be designed to cooperate by acting as a relay node for other UEs.
Since installing dedicated relay nodes can incur higher installation as well as operational
costs, cooperative communication among UEs of the network is gaining significant research
attention. With cooperation among UEs of the network, without added infrastructure, the
overall system capacity can be remarkably improved utilizing the spatial diversity due to
geographical separation of the cooperating UEs \[39\]. In this thesis, we consider relay-based
and user-based cooperation in wireless-powered networks.
1.3 Open Issues in Cooperative and Heterogeneous Wireless Networks with Energy Harvesting

Here, some open issues in the context of cooperative and heterogeneous wireless networks with energy harvesting are reviewed.

- Doubly Near-Far Problem in Uplink WPC
  The UEs far from the access point receive weak radio signal due to distance dependent attenuation and channel fading effects. In wireless energy harvesting systems, reception of weak signals not only hampers the achievable throughput, but also lowers the amount of harvested energy and the effect is more severe due to poor receiver sensitivity of energy harvester. If the uplink data transmission is powered by the harvested energy, deterioration of harvested energy implies lower uplink transmit power, which in turn further deteriorates the information rate. Therefore, severe “doubly near-far” problem has been noticed in uplink WPC networks since the UEs far from the access point suffer from distance dependent attenuation during downlink energy harvesting as well as uplink information transmission [24]. As in the case of traditional wireless networks, relay-based and user-based cooperation can enhance the performance of the UEs far from the access point. However, in such WPC networks, uplink information transmission is highly dependent on downlink energy harvesting phase and hence joint uplink and downlink resource allocation is of high importance. Joint consideration of uplink and downlink phase in such WPC network with relay-based and user-based cooperation increases complexity of the resource allocation problem.

- Interference Issues in HetNets with Downlink SWIPT
  With the foreseeable upsurge in IoT application and devices, joint investigation of SWIPT along with co-channel deployment of multi-tier HetNets will be significant in the design of future wireless networks. As discussed in Section 1.2, multi-tier network
architecture with co-channel deployment is essential to provide sustainable service to
the legions of wireless connected devices expected in the near future [6]. Also, as dis-
cussed in Section 1.1, wireless energy harvesting is a promising technology to elongate
battery life of the low power IoT devices. Hence, it is important to consider SWIPT in
HetNets. If SWIPT is enabled in HetNets, challenges associated with wireless power
transfer along with multi-tier network design converge into a common platform and
increase complexity of the resource allocation problem.

As discussed in Section 1.1, considering poorer receiver sensitivity of an energy har-
vester (around $-20$ dBm) in comparison to that of an information receiver (around
$-60$ dBm) [15,16], applicability of wireless power transfer is limited in small trans-
mission distances to serve low power miniature devices, like sensor nodes. In this context,
application of SWIPT in small cells to serve low-power sensor-like devices is promising.
However, due to poor receiver sensitivity of energy harvester, even with the small dis-
tance, in order to ensure significant wireless power transfer, the small cell base stations
need to transmit at a level much higher than that in traditional multi-tier communication
networks. High transmit power of small cell base stations increases undesired
co/cross-tier interference in co-channel deployment of multi-tier HetNets. Hence, we
face contradicting challenges, where interference mitigation demands transmit power of
small cell base stations to remain in lower range while wireless power transfer demands
the opposite. Therefore, interference management in multi-tier network needs to be
considered with a new approach to incorporate SWIPT in small cells.

- Rate-Energy Trade-off in Downlink SWIPT

As discussed in Section 1.1, due to current receiver circuit limitations, UEs need to
have separate information decoding and energy harvesting circuits for SWIPT and the
received signal has to be either switched in time domain or split in power domain [13,
20]. Therefore, resource allocation techniques significantly differ in downlink SWIPT
1.3. Open Issues in Cooperative and Heterogeneous Wireless Networks with Energy Harvesting

and uplink WPC. In uplink WPC, throughput directly depends on energy transmission in the downlink and hence maximizing the uplink throughput implies optimal sharing of time for downlink energy transmission and uplink information transmission [24]. However, in downlink SWIPT, allocating more time/power to energy harvesting process results in a lower throughput, whereas doing that to information decoding process results in lower harvested energy and hence, obtaining the optimal trade-off is critical. It is termed as rate-energy trade-off [13, 20]. Moreover, when SWIPT is enabled in small cells in a multi-tier network, co/cross-tier interference received by the small cell users acts as an additional source of energy and increases their harvested energy on one hand, while degrading their throughput performance on the other [40]. Therefore, it is important to design interference-aware resource allocation framework that jointly optimizes achievable throughput and energy harvesting rate.

- Rate-Energy Trade-off in HetNets with Renewable Energy Harvesting

Increasing throughput and reducing overall power cost of the network are among the key objectives set for future wireless networks [6, 8]. Intuitively, increasing throughput leads to increase in power cost and hence obtaining optimal rate-energy trade-off is one of the main design objectives in wireless networks. As discussed in Section 1.2, multi-tier HetNet architecture is envisioned as a key feature of future cellular networks to maximize total throughput of the system [6]. However, resource allocation in such networks needs to be carefully designed to mitigate cross and co-tier interferences [33–36]. If macrocell and small cell base stations rely on same source of energy, offloading users to small cell in a multi-tier network can also reduce overall power consumption of the network [7]. However, with the availability of diverse energy sources, the cost of different energy sources vary and hence, the network should be carefully designed to obtain optimal trade-off between throughput performance and power cost of the network. If the cost of energy source in small base stations is very high, multi-tier architecture may result in increased power cost of the network, which is not desirable.
There are several approaches, explored in the literature, for minimizing power cost of the network. As discussed in Section 1.1, renewable energy harvesting in base stations is one way of minimizing overall power cost of the network. Nevertheless, if base stations are designed to harvest energy from the nature, there are additional constraints in resource allocation, such as power allocation is constrained by the causality of energy arrival [30,31]. For robustness, energy harvesting base stations are also provided with a backup non-renewable power supply such as on-site generator or grid power supply [29]. In that case, increasing throughput may lead to higher consumption of non-renewable energy if the harvested energy is not sufficient. Therefore, obtaining optimal trade-off between throughput performance and power cost is a major research concern in such energy harvesting networks as well [41].

One way of optimizing throughput performance and power cost in energy harvesting HetNet is dynamically switching base stations on and off with varying availability of harvested energy and traffic condition of the network. It may be desirable to turn the energy harvesting base station off if its harvested energy is very low and/or the particular base station is under severe interference constraint, and/or number of active users in the corresponding cell is very low [42]. However, dynamic base station activation imposes challenges in ensuring quality of service (QoS) demand of the users in the switched off cells, which increases the complexity of resource allocation problem in HetNets with energy harvesting constraints.

1.4 Related Work, Motivation, and Objective

Here, the prior works regarding the open issues in the context of cooperative and heterogeneous wireless networks with energy harvesting are reviewed. The shortcomings in the existing literature are highlighted to provide the motivations and objectives of our research.
1.4.1 Doubly Near-Far Problem in Uplink WPC

As discussed in Section 1.3, “doubly near-far” problem arises in uplink WPC networks due to distance dependent attenuation in both downlink energy harvesting and uplink information transmission phases. There are several ways explored in the literature to overcome distance dependent attenuation in WPC networks. The authors in [43, 44] propose to overlay uplink communication networks with microwave power stations (called beacons) for wireless transmission of energy to the UEs. With even distribution of such power beacons, all UEs in a network can harvest comparable amount of energy. However, it requires the UEs to have dedicated antennas for microwave power receiver, which may not be desirable. Similarly, the authors in [45] propose regular periodic use of dedicated vehicular RF source that moves in optimal route to provide wireless energy to all UEs in the network. However, this solution approach increases the operational cost due to regular periodic vehicular movement.

It is well-known that relay-based and user-based cooperation improves end-to-end channel quality and capacity for UEs far from the access points, thus improving the coverage of communication networks [46–48]. Recently, relay-based and user-based cooperation has gained much research attention in both downlink SWIPT and uplink WPC [49–59]. There are various ways of cooperation for relay nodes in wireless communication networks with downlink SWIPT. The relay nodes can be designed to perform simultaneous information and energy relaying to enhance both the information capacity and harvested energy of the destination nodes by exploiting spatial diversity. In that case, the relay node needs to first harvest energy from the information it is going to relay, and then forward that information with the harvested energy. Such cooperation is needed in the network where both the destination nodes and the relay nodes are energy constrained. If the relay nodes have their own unconstrained power supply, they can be designed to perform simultaneous information relaying and power transfer to boost the information capacity and harvested energy of the destination nodes [49]. In this case, the relay nodes do not harvest energy from the information they are relaying. On the other hand, in the network where the destination
nodes are not energy constrained, the relay nodes can be designed to perform simultaneous information relaying and energy harvesting, which adds harvested energy as an incentive for relaying information signal [50]. This in turn increases the number of wireless nodes willing to serve as a relay. New relaying protocols, for relay nodes capable of harvesting energy from the received wireless signal, are proposed in [50-52] while power allocation strategies in such energy harvesting relay nodes are discussed in [53,54].

In WPC networks, the relay nodes can serve in both downlink energy harvesting and uplink information transmission phase. If the relay nodes do not want to utilize their own energy, they can be designed to forward energy signal from the access point to the destination nodes in downlink energy harvesting phase. In that case, the relay node needs to first harvest energy from the downlink signal and then forward it with the harvested energy, treating it like an information signal [55]. In this way, the destination nodes receive energy from multiple paths, which is known as multi-path energy routing [56], and thus the harvested energy in downlink energy harvesting phase is much higher.

However, if the relay nodes are willing to contribute their own energy, they can be designed as supplementary sources of energy signal during the downlink energy harvesting phase. Since the relay nodes do not spend any time in harvesting energy from transmission of the access point, the destination nodes receive much higher energy to harvest. In the uplink, the relay nodes simply act as traditional relay. However, using dedicated relay nodes to transmit wireless charging signal in the downlink has not been well investigated in the literature. The authors in [57-59] propose uplink cooperation among wireless-powered UEs to enhance their end-to-end channel capacity. This concept can also be applied to enhance throughput of UEs far from the access point. In such wireless-powered uplink cooperative networks, uplink information transmission is highly dependent on downlink energy harvesting phase and hence joint uplink and downlink resource allocation is of high importance. This increases the complexity of the resource allocation problems. However, the existing works simplify the problem by either assuming a simple three-node network or ignoring power
allocation in joint uplink and downlink resource allocation.

The shortcomings in the existing literature motivate us to pursue the following objectives in the context of uplink WPC:

- Design WPC network with dedicated relay nodes to broadcast wireless charging signal, for distant users, in the downlink and then relay their information signal to the access point in the uplink.

- Joint optimization of downlink and uplink resource allocation for multiuser uplink WPC networks with relay-based cooperation.

- Joint optimization of downlink and uplink resource allocation for multiuser uplink WPC network with user-based cooperation, for the scenarios where installing dedicated relay nodes is not feasible.

The contributions in Chapter 2 address the first two objectives. The third objective is tackled in Chapter 3. The contributions made regarding these objectives are explained at the beginning of the corresponding chapters.

1.4.2 Rate-Energy Trade-off and Interference Issues in HetNets with SWIPT

As we discussed in Section 1.3, considering limitation in service distance and energy harvesting rate of wireless power transfer, application of SWIPT in small cells to serve low-power sensor-like devices is promising. Wireless power transfer within small transmission distances has been widely investigated in the literature [13,18,20]. However, multi-tier network architecture is not considered in the aforementioned works. The authors of [15] propose integrating wireless power transfer capability in small cells of a HetNet to elongate the battery life of low power miniature devices and discuss different opportunities and challenges. However,
1.4. Related Work, Motivation, and Objective

out-of-band energy transmission is considered and the issues of rate-energy trade-off and interference management are not investigated.

As discussed in Section 1.3, it is important to optimize the rate-energy trade-off in SWIPT. Most of the existing works in SWIPT have proposed different resource allocation algorithms to maximize the throughput performance while ensuring minimum energy harvesting rate. The authors in [61] propose beamforming and resource allocation algorithm to maximize energy harvesting rate while ensuring minimum throughput, but consider spatially separated energy harvesting and information decoding UEs. To the best of our knowledge, joint optimization of energy harvesting rate and throughput together has not been considered in the literature. To attain the optimal rate-energy trade-off, it is important to optimize the power-splitting/time-switching factors in SWIPT. Comparison of time-switching and power-splitting approaches of SWIPT has been done in [13,20] by characterizing the rate-energy trade-off for these approaches. However, performance comparison of these two approaches has not been done in a multi-tier network setting under interference constraints.

As discussed in Section 1.3, when SWIPT is considered in small cells of HetNets, it is essential to address the cross and co-tier interference issues. While interference signals deteriorate the throughput in traditional networks, they improve energy harvesting rate in SWIPT networks. The concept of harvesting energy from intended signal as well as unintended noise/interference signal is considered in [40,62]. However, in the aforementioned works, interference signal is treated as a random variable. The authors in [63,64] demonstrate how transmit power allocation changes in a network with multiple transmitter-receiver pairs when the receivers harvest energy from both information and interference signal. However, the aforementioned works do not consider HetNet architecture.

Numerous research works have been done on interference-aware resource allocation in multi-tier HetNets with co-channel deployment [33,36]. The resource allocation scheme to mitigate co-tier interference in dense deployment of small cells is proposed in [33] where...
cross-tier interference is treated as white noise. Joint resource allocation and admission control scheme to optimize the performance of both macro-tier and small-tier users, assuming negligible co-tier interference, is proposed in [34]. The authors in [35] propose resource allocation algorithm based on game-theoretic approach where small cell users and macrocell users compete with each other to maximize their own performance. A low-complexity interference management scheme is proposed in [36] where the base stations in each tier evaluate the interference received from only one user, called ‘reference user’, to incorporate effect of overall cross-tier interference. However, the aforementioned works do not consider SWIPT in HetNets. As discussed in Section 1.3, when SWIPT is enabled in small cells of HetNets, we face contradicting challenges, where interference mitigation demands transmit power of small cell base stations to remain in lower range while wireless power transfer demands the opposite. Hence, interference management in multi-tier networks needs a new look to incorporate SWIPT in small cells. To the best of our knowledge, interference-aware resource allocation for SWIPT in small cells in a multi-tier HetNet has not been well investigated in the literature.

The shortcomings in the existing literature motivate us to pursue the following objectives in the context of downlink SWIPT in HetNet:

- Overcome the contradicting challenges of SWIPT in HetNets, where interference mitigation demands the transmit power of small cell base stations to remain in lower range while wireless power transfer demands the opposite.

- Joint optimization of energy harvesting rate and achievable throughput in SWIPT to obtain optimal rate-energy trade-off under interference constraints of the HetNets.

- Performance comparison of time-switching and power-splitting techniques of SWIPT in HetNets, under the interference constraints.

The aforementioned objectives are addressed in Chapter 4. The contributions made regarding these objectives are clarified at the beginning of the chapter.
1.4.3 Rate-Energy Trade-off in HetNets with Renewable Energy Harvesting

As discussed in Section 1.3, one way of optimizing throughput performance and power cost in energy harvesting HetNet is dynamically switching base stations on and off with varying availability of harvested energy and traffic condition of the network. Dynamic activation of base stations to minimize the power cost of traditional wireless networks is well-investigated in the literature. In [65], sleep duration of base station is optimized with varying traffic condition to minimize the power cost of a network. However, multi-tier architecture and energy harvesting capabilities are not considered in the work. The challenges of dynamic base station activation in wireless networks with multi-tier architecture and energy harvesting capability are discussed in [66].

Dynamic base station activation and resource allocation in multi-tier networks is well investigated in the literature [67–70]. To obtain optimal trade-off between throughput performance and power cost, in [69], maximization of energy efficiency is chosen as objective and base station activation is optimized. With a similar objective, the authors of [70] optimize base station activation jointly with user association. However, the aforementioned works do not consider energy harvesting capability in the base stations.

The concept of optimizing base station activation policy to overcome the temporal mismatch between traffic demand and energy arrival is proposed in [71] for energy harvesting networks. To minimize the cost of non-renewable energy consumption, the authors of [72] optimize energy purchase policy, while the authors of [73] optimize base station activation policy jointly with energy purchase policy, considering traffic load at the base station and arrival of renewable energy. However, aforementioned works do not optimize resource allocation along with base station activation policy. The authors of [74] propose optimal base station activation policy along with resource allocation to minimize grid power consumption of hybrid powered base stations while ensuring QoS provision to the users. However, the
1.4. Related Work, Motivation, and Objective

The aforementioned works do not consider multi-tier networks (or HetNets).

Joint resource allocation and dynamic base station activation in energy harvesting HetNets has not been well-investigated in the literature. In most areas, macro base stations are already deployed with grid power supply. However, there would be a need of deploying new small base stations to meet the growing demand of the hotspots. To reduce the consumption of non-renewable energy sources with increasing base station density, small base stations should be equipped with renewable energy sources. Therefore, consideration of energy harvesting capability in small base stations of a multi-tier network would be very important. In such a network, to minimize the non-renewable power consumption while maximizing the throughput performance, it is essential to jointly consider base station activation policy along with resource allocation considering both interference and energy harvesting constraints. To the best of our knowledge, joint optimization of interference-aware and energy-aware resource allocation with dynamic base station activation in energy harvesting HetNets has not been well-investigated in the literature. The authors of [75] optimize the “On” time of the energy harvesting base stations in a $K$-tier network. However, interference-aware resource allocation and energy-aware power allocation is not considered. Base station on/off strategies, user association, and power control is studied in a two-tier network with energy harvesting base stations in [76]. However, a greedy technique is adopted by considering only one time period, and interference-aware frequency reuse among different tiers is not considered. Characterization of different performance metrics in a multi-tier network consisting of energy harvesting base stations is presented in [77], where the energy harvesting base stations are active only when they have enough harvested energy. However, optimization of base station activation strategy is not considered.

The shortcomings in the existing literature motivate us to pursue the following objectives in the context of rate-energy trade-off in HetNets with energy harvesting:

- Optimize the trade-off between throughput performance and power cost in energy harvesting HetNets while ensuring QoS provision to all users.
• Design interference-aware and energy-aware resource allocation jointly with dynamic activation of energy harvesting base stations in HetNets.

The contributions made in Chapter 5 revolve around the aforementioned objectives. The contributions made regarding these objectives are clarified at the beginning of the chapter.

1.5 Thesis Outline

The rest of this thesis is organized as follows:

• In Chapter 2, we consider uplink WPC networks with relay-based cooperation where the relay node transmits energy charging signal in the downlink and relays the information signal in the uplink. Considering the limitation on available energy at the relay node and the total transmission time, we propose different resource allocation frameworks for two different relay-based harvest-then-transmit scenarios. First, we propose an iterative algorithm to optimize time and relay node power allocation (for downlink wireless charging and uplink data transmission/relaying) for both scenarios. Then, we jointly optimize time and power allocation for one scenario. Optimization problems are solved using convex optimization techniques. From the simulation results, we evaluate the throughput performance of the UEs, evaluate the fairness of the system using Jain's fairness index, and examine the resource allocated for downlink energy harvesting and uplink information transmission phases. It is observed that most of the available resources (transmission time and relay node energy) are allocated for wireless energy harvesting which is similar to that observed for downlink SWIPT in the existing literature. Simulation results on comparison of different relay-based scenarios reveal interesting insights and demonstrate remarkable improvement of throughput and fairness performance of uplink WPC networks in the presence of relay node.

• In Chapter 3, we study joint resource allocation for downlink energy transmission as
1.5. Thesis Outline

well as uplink information transmissions in a wireless-powered uplink cooperative network. To overcome the performance loss of the UEs that are far from the access point, cooperation among the UEs is considered in the uplink. As downlink power allocation affects the energy harvesting rate of the UEs and hence their uplink throughput, downlink and uplink resource allocation are jointly performed. The joint optimization problem of power allocation, subcarrier allocation, and relay selection is a mixed-integer nonlinear programming (MINLP) problem. Nevertheless, we obtain the optimal solution based on dual decomposition technique and relaxation of the binary integer constraints. From the simulation results, we evaluate the sum throughput and energy efficiency of the network. Simulation results show the effectiveness of our proposed scheme and performance improvements over the benchmark schemes.

- In Chapter [4] we perform downlink resource allocation for SWIPT in small cells underlaying a macrocell in a two-tier HetNet. We consider both time-switching and power-splitting approaches of SWIPT. We optimize downlink transmit power of small cell base stations along with time-switching/power-splitting variables for SWIPT to jointly maximize energy harvesting rate and achievable throughput of small cell users while ensuring minimum throughput of the macrocell user. To jointly optimize achievable throughput and energy harvesting rate of small cell users, we use scalarization technique of multi-objective programming. We formulate a resource allocation problem with the objective of maximizing weighted sum of normalized throughput and energy harvesting rate. In the time-switching approach, the resource allocation problem is a MINLP problem. To solve the MINLP problem, we relax the binary integer constraint and then identify the condition at which the obtained solution satisfies that constraint. In both the time-switching and power-splitting approaches, when co-tier interference is non-negligible, the formulated problem is solved sub-optimally by iteratively maximizing the minorant of the non-convex objective function. A special case with negligible co-tier interference is considered in time-switching approach and the
optimal solution is obtained by using convex optimization techniques. From the sim-
ulation results, we evaluate sum-throughput and sum-energy harvesting rate of small
cell users. Simulation results demonstrate that when macrocell users have flexible in-
terference tolerance levels in time-switching approach, energy harvesting rate of small
cell users is significantly enhanced. The results also highlight the improvement in en-
ergy harvesting rate in the presence of co-tier interference signal and reveal interesting
trade-off in achievable throughput and energy harvesting rate.

• In Chapter 5, we jointly optimize resource allocation with dynamic activation of en-
ergy harvesting base stations in a two-tier HetNet. We consider both energy harvesting
constraints and interference constraints along with time-variation in channel condition,
user activity, and energy arrival. We optimize the trade-off between throughput perfor-
mance of the small cell (or hotspot) users and the associated power cost by maximizing
the net reward, where positive reward is associated with achievable throughput of the
hotspot users and negative reward with the corresponding non-renewable power con-
sumption. QoS requirements of hotspot users as well as macrocell users are considered
in the optimization problem. Assuming the availability of non-causal information, we
propose offline resource allocation algorithm using discrete binary particle swarm op-
timization and dual decomposition technique. Assuming the availability of statistical
information of future values, we propose dynamic programming-based online algorithm.
Finally, we propose simple and greedy online algorithm assuming lack of any kind of
future information. From the simulation results, we evaluate the net reward generated
by different algorithms, throughput performance of hotspot users, and the correspond-
ing non-renewable power consumed. Simulation results demonstrate the performances
of the proposed offline, dynamic programming-based online, and greedy online algo-
rithms and highlight the scenarios where performance of the proposed algorithms are
significantly better than the baseline schemes.
1.5. Thesis Outline

• In Chapter 6, summary and concluding remarks are provided and possible future research directions are discussed.
Chapter 2

Resource Allocation in Uplink Wireless-Powered Communication Networks with Relay-based Cooperation

In this chapter, we consider uplink WPC network and address the challenge of joint allocation of resources for downlink energy harvesting and uplink information transmission when dedicated relay nodes are deployed to mitigate the “doubly near-far” problem. The accomplished works and research contributions of this chapter are briefly described in the following.

2.1 Accomplished Works and Research Contributions

In this chapter, we consider a network where the uplink communication of UEs is powered by wireless energy harvesting, based on the concept of harvest-then-transmit \[24\]. To enhance the performance of UEs far from the access point (far-UEs) and improve fairness (and thereby mitigate the doubly near-far problem), we utilize relay-based cooperation in such WPC network. Relay nodes are designed to independently broadcast wireless charging signal for far-UEs in the downlink and then relay their information signal to access point in the uplink. For such relay-based WPC, we propose resource allocation methods (i.e.,
2.1. Accomplished Works and Research Contributions

methods for allocation of downlink energy harvesting/uplink information transmission times and downlink/uplink transmit power of relay node) with the objective of maximizing total network throughput. Note that, without relays, fairness among the UEs (e.g., in terms of uplink capacity) can be maximized by using max-min or proportional fair objective function. However, it is well-known that, with such an objective, the overall sum-throughput would reduce \[24, 78, 79\]. Therefore, we utilize relay-based cooperation to improve performance of the far-UEs, which leads to better fairness without losing the overall throughput performance of the network. In the rest of the chapter, allocation of downlink energy harvesting and uplink information transmission times of the UEs is referred to as time allocation. Allocation of uplink and downlink relay node transmit power is referred to as power allocation.

We investigate resource allocation in two relay-based *harvest-then-transmit* scenarios depending on whether the far-UEs harvest energy from the RF transmission of both relay node and access point (Scenario I) or from the relay node only (Scenario II). In all cases, we formulate sum-throughput maximization problems for resource allocation. For Scenario I, due to computational intractability of joint power and time allocation problem, we propose an iterative power and time allocation algorithm. For Scenario II, we jointly optimize time along with transmit power of the relay node. Since the formulated problem for joint time and power allocation is non-convex, we convert it into a convex joint time and energy allocation problem by implementing change of variables. The problem is solved in closed-form by solving Karush-Kuhn-Tucker (KKT) conditions on the Lagrangian of the corresponding convex optimization problem. We also propose an iterative power and time allocation algorithm for this scenario. We analyze and compare the proposed resource allocation methods for WPC networks with relay-based cooperation under both Scenario I and Scenario II. Also, we compare the performance, of WPC networks with relay-based cooperation to that without the relay nodes, in terms of resource allocation, throughput, and fairness. To this end, we identify the suitable resource allocation method for WPC networks with relay-based cooperation.
2.2. System Model and Assumptions

The rest of the chapter is organized as follows. The system model and assumptions are explained in Section 2.2. Section 2.3 presents the problem formulation and solution approach. Performance evaluation results are presented and analyzed in Section 2.4.

2.2 System Model and Assumptions

Wireless-powered communication networks with relay-based cooperation

We consider an uplink communication network (Fig. 2.1) in which uplink transmission of UEs is powered by the energy harvested from wireless charging signal transmitted by the AP and/or the relay node. We particularly consider harvest-then-transmit protocol [24] to power uplink transmission of UEs. In this protocol, a fraction of each time frame is dedicated to transmit wireless charging signal from the AP/relay nodes and is termed as downlink energy harvesting (DEH) time. Uplink data transfer is then performed by UEs using the harvested energy in the remaining time termed as uplink information transmission (UIT) time. In the DEH phase, the energy harvesting circuit (e.g., P2110 Powercaster receiver [14]) harvests energy from the received wireless charging signal. The energy harvesting and conversion loss is indicated by energy harvesting efficiency $\eta_1$. $\eta_2$ fraction of the harvested energy is used for uplink transmission and remaining fraction is lost in receiver circuit power consumption\footnote{Note that we use fixed $\eta_2$ which causes the receiver circuit power consumption to become proportional to the harvested energy.}. For simplicity, we assume that all the energy harvested during DEH time is used for uplink transmission in UIT time.

An amplify-and-forward relay node is installed at a fixed distance from the AP to serve the far-UEs. The UEs served by the AP are termed as near-UEs from now on. We assume prior knowledge on the number of UEs with some data to transmit in the uplink. We consider that there are $N$ near-UEs and $K$ far-UEs. The total of DEH and UIT time is denoted by $T$. The DEH time, in which the AP and the relay node send wireless charging signal and the UEs harvest energy from it, is denoted by $t_{(d)}$. The remaining uplink transmission duration
2.2. System Model and Assumptions

Figure 2.1: Uplink WPC network with relay-based cooperation.

Figure 2.2: Relay-based harvest-then-transmit protocol.

is shared by both near and far-UEs to transmit their data to the AP. The time dedicated for UIT of each near-UE is denoted by $t_{i(n)}$, $i = 1, 2, ..., N$ and that of each far-UE is denoted by $t_{j(f)}$, $j = 1, 2, ..., K$, as shown in Fig. 2.2. Therefore,

$$t_{(d)} + \sum_{i=1}^{N} t_{i(n)} + \sum_{j=1}^{K} t_{j(f)} \leq T. \quad (2.1)$$

The transmit power of the AP is $P_A$. Energy available at the relay node per transmission block is $E_{\text{max}}$. Note that such a relay node may be operated by battery or by energy harvested from the nature. Therefore, transmit power of the relay node needs to be optimally allocated to maximally utilize its available energy. In this work, we assume to have prior knowledge of channel conditions. Channel power gains of the link between AP and $i_{th}$ near-UE, relay node and $i_{th}$ near-UE, AP and relay node, AP and $j_{th}$ far-UE, and relay node and $j_{th}$ far-UE are denoted by $g_{A,i}$, $g_{R,i}$, $g_{A,R}$, $h_{A,j}$, and $h_{R,j}$, respectively.
2.2. System Model and Assumptions

Relay-based harvest-then-transmit scenarios

We consider two different scenarios:

- **Scenario I**: The relay node transmits a power beacon in the downlink and acts as a traditional relay node in the uplink. In the downlink, both the AP and the relay node independently broadcast their own wireless charging signal in DEH time. Since the far-UEs receive signal from the AP transmission as well, they harvest energy from AP as well as relay node transmission. The near-UEs harvest energy from the AP transmission only since the relay node antenna directs the wireless charging signal towards far-UEs. In the uplink, the relay node simply amplifies and forwards the uplink information of each far-UE to the AP in their UIT time while near-UEs make direct uplink transmission to the AP in their UIT time.

- **Scenario II**: Similar to Scenario I, the relay node transmits a power beacon in the downlink and acts as a traditional relay node in the uplink. However, because of high path-loss in the link between the AP and far-UEs, the energy harvested by far-UEs from the AP transmission is assumed to be negligible. In other words, far-UEs are assumed to harvest energy only from the relay node transmission.

Since the relay node and the AP transmit wireless charging signal simultaneously, it is necessary to study the resource allocation and the network performance when far-UEs harvest energy from both the transmissions. Nevertheless, we will see later that the optimal solution of resource allocation problem in Scenario I is analytically intractable. Therefore, Scenario II is considered with a simplifying assumption to make the resource allocation problem computationally tractable. Next, we will discuss how to model the two scenarios.

**Modeling scenario I**

In Scenario I, the relay node transmits its own wireless charging signal along with the AP in the DEH time. Far-UEs harvest energy from both the relay node and the AP transmission.
whereas near-UEs harvest energy from the transmission from AP only. We will now discuss DEH and UIT processes separately in the following.

**Downlink wireless charging/energy harvesting:** In DEH time $t_{(d)}$, the AP broadcasts wireless charging signal with power $P_A$. At the same time, the relay node also broadcasts its wireless charging signal with power $P_{(rd)}$. Energy harvested by each near and far-UE are given by

\[
E_{i(n)} = \eta_1 P_A g_{A,i} t_{(d)}, \quad \forall i \tag{2.2}
\]

\[
E_{j(f)} = \eta_1 (P_A h_{A,j} + P_{(rd)} h_{R,j}) t_{(d)}, \quad \forall j. \tag{2.3}
\]

**Uplink information transmission:** Both near and far-UEs harvest certain amount of energy, given in (2.2) and (2.3), which they use for uplink transmission. In the following, we will discuss UIT of near and far-UEs separately.

**UIT of Near-UE:** The transmit power of a near-UE $i$ is given by: $P_{i(n)} = \eta_2 E_{i(n)}/t_{i(n)}, \forall i$. The throughput of that UE in bits/second/Hertz (bps/Hz) is thus given by

\[
R_{i(n)}^{(sc-I)} = \frac{t_{i(n)}}{T} \log_2 \left( 1 + \frac{g_{A,i} P_{i(n)}}{N_w} \right), \quad \forall i \tag{2.4}
\]

where $N_w$ is additive white Gaussian noise (AWGN) power at the AP. From (2.2) and (2.4), we can write

\[
R_{i(n)}^{(sc-I)} = \frac{t_{i(n)}}{T} \log_2 \left( 1 + \frac{\nu_i t_{(d)}}{t_{i(n)}} \right), \quad \forall i \tag{2.5}
\]

where $\nu_i = \frac{\eta P_A g_{A,i}^2}{N_w}$ and $\eta = \eta_1 \eta_2$.

**UIT of Far-UE:** The transmit power of each far-UE is given by: $P_{j(f)} = \frac{\eta_2 E_{j(f)}}{t_{j(f)}/2}, \forall j$, where the factor of 2 is introduced due to half-duplex relaying. In the second phase, signal received from each far-UE is amplified and forwarded to the AP by the relay node with power $P_{j(ru)}$. Signal-to-noise ratio (SNR) of the signal received at the AP, corresponding to
2.2. System Model and Assumptions

each far-UE is given by

$$\text{SNR}_{j(f)} = \frac{(P_{j(\text{ru})}P_{j(f)}g_{A,R}h_{R,j})}{(P_{j(f)}h_{R,j} + N_w)} \frac{1}{N_w}, \quad \forall j.$$ (2.6)

Assuming that the noise power is negligible in comparison to signal power, we ignore the higher order term ($N_w^2$) in the denominator. From (2.3) and (2.6),

$$\text{SNR}_{j(f)} = \frac{f_{\alpha(j)}(P_{(\text{rd})})f_{\beta}(P_{j(\text{ru})})t_{(d)}}{N_w(f_{\alpha(j)}(P_{(\text{rd})})t_{(d)} + f_{\beta}(P_{j(\text{ru})})t_{j(f)})}, \quad \forall j.$$ (2.7)

where $f_{\alpha(j)}(P_{(\text{rd})}) = 2\eta h_{R,j} (P_A h_{A,j} + P_{(\text{rd})} h_{R,j})$ is a function of power allocation variable $P_{(\text{rd})}$ and $f_{\beta}(P_{j(\text{ru})}) = P_{j(\text{ru})} g_{A,R}$ is a function of power allocation variable $P_{j(\text{ru})}$. Using (2.7),

the throughput of each far-UE in bps/Hz can thus be given by

$$R_{j(f)}^{(\text{sc-I})} = \frac{t_{j(f)}}{2T} \log_2 \left(1 + \text{SNR}_{j(f)}\right).$$ (2.8)

Since the available energy at the relay node is limited to $E_{\text{max}}$ in each transmission block, we have

$$P_{(\text{rd})} t_{(d)} + \sum_{j=1}^{K} P_{j(\text{ru})} \frac{t_{j(f)}}{2} \leq E_{\text{max}}.$$ (2.9)

Modeling scenario II

In Scenario II, we assume that the energy harvested by far-UE from the AP transmission is negligible in comparison to that harvested from the relay node transmission. The energy harvested by each near and far-UE in the DEH time are given by

$$E_{i(n)} = \eta_1 P_A g_{A,i} t_{(d)}, \quad \forall i.$$ (2.10)

$$E_{j(f)} = \eta_1 P_{(\text{rd})} h_{R,j} t_{(d)}, \quad \forall j.$$ (2.11)
2.2. System Model and Assumptions

The UEs make uplink transmission using the energy harvested during the DEH time. Following similar analysis as in the case of Scenario I, the uplink throughput of each near-UE is given by

\[ R^{(sc-II)}_i(n) = \frac{t_i(n)}{T} \log_2 \left( 1 + \frac{\nu_i t(d)}{t_i(n)} \right), \quad \forall i. \quad (2.12) \]

Similarly, SNR of the signal received at the AP (corresponding to each far-UE) is given by

\[ \text{SNR}_j(f) = \frac{2\eta h^2_{R,j} g_{A,R} P_{j(ru)} t(d)}{N_w (g_{A,R} P_{j(ru)} t(f)) + 2\eta h^2_{R,j} P_{r(d)} t(d)}, \quad \forall j. \quad (2.13) \]

Using (2.13), the throughput of each far-UE in bps/Hz can thus be given by

\[ R^{(sc-II)}_j(f) = \frac{t_j(f)}{2T} \log_2 \left( 1 + \text{SNR}_j(f) \right) = \frac{t_j(f)}{2T} \log_2 \left( 1 + \frac{\delta \alpha_j \beta P_{r(d)} P_{j(ru)} t(d)}{\alpha_j P_{r(d)} t(d) + \beta P_{j(ru)} t(f)} \right), \quad \forall j \quad (2.14) \]

where \( \alpha_j = 2\eta h^2_{R,j}, \beta = g_{A,R}, \) and \( \delta = \frac{1}{N_w}. \) Since the energy available at the relay node is limited to \( E_{max} \) in each transmission block, (2.9) defines the total energy constraint at the relay node.

In this chapter, we will determine the optimal allocation of DEH and UIT time along with downlink/uplink relay node transmit power by formulating an optimization problem with the objective of maximizing the sum-throughput of the network. For Scenario I, due to the complexity of the problem, we will use iterative algorithm for resource allocation, where time allocation is optimized for given power allocation and power allocation is optimized for given time allocation. For Scenario II, we will perform joint allocation of DEH and UIT time along with downlink/uplink transmit power. However, for fair comparison among the two scenarios, we use the iterative algorithm for resource allocation in Scenario II as well. In the rest of the chapter, power allocation refers to allocation of uplink and downlink transmit power at the relay node while time allocation refers to allocation of DEH time and UIT time of all UEs.
2.3 Problem Formulations and Solution Approaches

2.3.1 Joint Power and Time Allocation: Scenario I

In order to optimize DEH and UIT time along with relay node transmit power, we formulate the sum-throughput maximization problem as follows:

\[
\begin{align*}
\text{maximize} & \quad \sum_{i=1}^{N} R_{i(n)}^{(sc-I)} + \sum_{j=1}^{K} R_{j(f)}^{(sc-I)} \\
\text{subject to} & \quad C_1: t_{(d)} + \sum_{i=1}^{N} t_{i(n)} + \sum_{j=1}^{K} t_{j(f)} \leq T \\
& \quad C_2: P_{(rd)} t_{(d)} + \sum_{j=1}^{K} P_{j(ru)} \frac{t_{j(f)}}{2} \leq E_{\text{max}} \\
& \quad C_3: t_{i(n)} \geq 0, \quad \forall i; \quad t_{j(f)} \geq 0, \quad \forall j \\
& \quad C_4: P_{(rd)} \geq 0; \quad P_{j(ru)} \geq 0, \quad \forall j
\end{align*}
\]

(2.15)

where \(t_{(n)} = [t_{1(n)}, t_{2(n)}, \ldots, t_{N(n)}]\), \(t_{(f)} = [t_{1(f)}, t_{2(f)}, \ldots, t_{K(f)}]\), and \(P_{(ru)} = [P_{1(ru)}, P_{2(ru)}, \ldots, P_{K(ru)}]\). \(C_1\) is the constraint on total time (given by \(2.1\)) and \(C_2\) is energy constraint at the relay node (given by \(2.9\)). \(C_3\) and \(C_4\) are non-negativity constraints on time and power variables, respectively. The objective function of the problem in \(2.15\) is highly complicated in terms of the optimization variables and its optimal solution is analytically intractable.

We simplify the problem by setting \(P_{(rd)} = P_{j(ru)} = P_R\). The throughput of far-UE given in \(2.8\) can be re-written as:

\[
R_{j(f)}^{(sc-I)} = \frac{t_{j(f)}}{2T} \log_2 \left( 1 + \frac{2\eta h_{R,j} (P_A h_{A,j} + P_R h_{R,j}) P_{R} g_{A,R} t_{(d)}}{N_w \left( 2\eta h_{R,j} (P_A h_{A,j} + P_R h_{R,j}) t_{(d)} + P_{R} g_{A,R} t_{j(f)} \right)} \right), \quad \forall j.
\]

(2.16)

We can see that, the throughput expressions of far-UEs are still non-convex and intractable for joint power and time allocation. Thus, we propose to solve this problem in two phases iteratively. In one phase, for a given power allocation, optimal time allocation is performed while in another phase, for a given time allocation, optimal power allocation is performed.
2.3. Problem Formulations and Solution Approaches

Power allocation

For a given time allocation, the throughput expression of a far-UE given in (2.16) can be re-written as:

\[ R_{j(f)}^{(sc-I)} = \frac{t_j(f)}{2T} \log_2 \left( 1 + \frac{\alpha_{j(1)}P_R + \alpha_{j(2)}P_R^2}{\alpha_{j(3)} + \alpha_{j(4)}P_R} \right), \quad \forall j \]  
(2.17)

where

\[ \alpha_{j(1)} = 2\eta h_{R,j} h_{A,j} g_{A,R} P_A t(d) \]
\[ \alpha_{j(2)} = 2\eta h_{R,j}^2 g_{A,R} t(d) \]
\[ \alpha_{j(3)} = N_w 2\eta h_{R,j} P_A h_{A,j} t(d) \]
\[ \alpha_{j(4)} = N_w \left( 2\eta h_{R,j}^2 t(d) + g_{A,R} t_j(f) \right) . \]

We know that the throughput of near-UE does not depend on relay node transmit power. Therefore, the sum-throughput maximization problem in (2.15) becomes

\[
\begin{align*}
\text{maximize} & \quad \sum_{j=1}^{K} R_{j(f)}^{(sc-I)} \\
\text{subject to} & \quad \tilde{C}_2 : P_R \left( t(d) + \sum_{j=1}^{K} \frac{t_j(f)}{2} \right) \leq E_{\text{max}} \\
& \quad \tilde{C}_4 : P_R \geq 0 
\end{align*}
\]  
(2.18)

where \( \tilde{C}_2 \) is energy constraint at the relay node and \( \tilde{C}_4 \) is non-negativity constraint on the power allocation variable. The objective function is still non-convex in terms of the optimization variable. However, a careful inspection of the objective function and the constraint leads us to the optimal solution for power allocation.

**Lemma 1**: At optimality, the energy constraint \( \tilde{C}_2 \) of the optimization problem in (2.18) is tightly satisfied, i.e.,

\[ P_R = \frac{E_{\text{max}}}{\left( t(d) + \sum_{j=1}^{K} \frac{t_j(f)}{2} \right)} , \]  
(2.19)

**Proof**: The objective function is monotonically increasing in \( P_R \) which can be verified by showing \( \frac{\partial R_{j(f)}^{(sc-I)}}{\partial P_R} > 0 \). The constraint \( \tilde{C}_2 \) is also monotonically increasing in \( P_R \). Therefore, the constraint \( \tilde{C}_2 \) must hold with equality at optimality. This completes the proof. \( \Box \)

Thus, (2.19) is used to determine the optimal constant relay node transmit power. Next,
we will see how to determine optimal time allocation for given constant power allocation.

**Time allocation**

For given power allocation $P_R$, the throughputs of far-UEs given in (2.16) can be re-written as:

$$R_{j(f)}^{(sc-1)} = \frac{t_{j(f)}}{2T} \log_2 \left( 1 + \delta \frac{\alpha_j \beta t_{d(j)} + \beta t_{j(f)}}{\alpha_j t_{d(j)} + \beta t_{j(f)}} \right), \forall j,$$  \hspace{1cm} (2.20)

where

$$\alpha_j = 2 \eta h_{R,j} (P_R h_{A,j} + P_R h_{R,j}), \hspace{1cm} \beta = P_R g_{A,R}, \hspace{1cm} \delta = \frac{1}{N_w}. \hspace{1cm} (2.21)$$

Then the sum-throughput maximization problem in (2.15) becomes

$$\text{maximize} \sum_{i=1}^{N} R_{i(n)}^{(sc)} + \sum_{j=1}^{K} R_{j(f)}^{(sc-1)}$$

subject to $C_1, C_3$. \hspace{1cm} (2.22)

The throughput of near-UE given by (2.5) and far-UE given by (2.20) can be proven to be convex functions of optimization variables using the concavity of log function and the perspective operation [80]. Hence, the optimization problem in (2.22) is convex in terms of time variables and can be solved optimally by using convex optimization techniques [80].

The partial Lagrangian of the problem in (2.22) is given by

$$\mathcal{L}(t_{d}, t_{(n)}, t_{(f)}, \lambda) = \sum_{i=1}^{N} R_{i(n)}^{(sc-1)} + \sum_{j=1}^{K} R_{j(f)}^{(sc-1)} - \lambda \left( t_{d} + \sum_{i=1}^{N} t_{i(n)} + \sum_{j=1}^{K} t_{j(f)} - T \right) \hspace{1cm} (2.23)$$

where $\lambda$ is non-negative Lagrange multiplier corresponding to the constraint $C_1$. The constraint $C_3$ is not included in the Lagrangian and will be satisfied later (in Lemma 2). Using KKT stationarity conditions and differentiating (2.23) with respect to $t_{d}, t_{i(n)},$ and $t_{j(f)},$
we obtain the following equations, respectively:

\[
\sum_{i=1}^{N} \frac{\nu_i}{1+x_i} + \frac{\delta \alpha_j}{2(1 + \frac{\delta \beta y_j}{1+y_j})(1+y_j)^2} = \lambda^* T \ln(2)
\]

(2.24)

\[
\ln(1 + x_i) - \frac{x_i}{(1 + x_i)} = \lambda^* T \ln(2), \quad \forall i
\]

(2.25)

\[
\ln \left(1 + \frac{\delta \beta y_j}{1+y_j}\right) - \frac{\delta \beta y_j}{(1 + \frac{\delta \beta y_j}{1+y_j})(1+y_j)^2} = 2 \lambda^* T \ln(2), \quad \forall j
\]

(2.26)

where \(x_i = \frac{\nu_i t^{(d)}_{i(n)}}{t^{(n)}}, \quad \forall i\) and \(y_j = \frac{\alpha_j t^{(d)}_{j(f)}}{t^{(f)}}, \quad \forall j\). Also, \(t^{*}_{(d)}, t^{*}_{(n)}, t^{*}_{(f)}\), and \(\lambda^*\) are primal and dual optimal solutions of the problem in (2.22).

**Lemma 2**: \(x_i\) and \(y_j\) are both constants for all values of \(i\) and \(j\) if \(t^{*}_{(d)}, t^{*}_{(n)}, t^{*}_{(f)}>0\), i.e.,

\[
x = x_i = \frac{\nu_i t^{(d)}_{i(n)}}{t^{*}_{i(n)}}, \quad \forall i; \quad y = y_j = \frac{\alpha_j t^{(d)}_{j(f)}}{t^{*}_{j(f)}}, \quad \forall j.
\]

(2.27)

**Proof**: Let us define: \(f_1(x_i) = \ln(1 + x_i) - \frac{x_i}{1+x_i}\). Differentiating \(f_1(x_i)\) with respect to \(x_i\), we obtain: \(f'_1(x_i) = \frac{x_i}{(1+x_i)^2}\). If \(t^{*}_{(d)}, t^{*}_{(n)}>0\), then \(x_i > 0\) and \(f'_1(x_i) > 0\) which means \(f_1(x_i)\) is an increasing function. To satisfy \(f_1(x_i) = \lambda^* T \ln(2) = \text{constant}\), given in (2.25), \(x_i\) should be a constant. Similarly, we can prove that \(y_j\) should be a constant. This completes the proof.

Using Lemma 2, (2.24) to (2.26) can be re-written as

\[
\sum_{i=1}^{N} \frac{\nu_i}{1+x_i} + \frac{\delta \sum_{j=1}^{K} \alpha_j}{2(1 + \frac{\delta \beta y_j}{1+y_j})(1+y_j)^2} = \lambda^* T \ln(2)
\]

(2.28)

\[
\ln(1 + x_i) - \frac{x_i}{(1 + x_i)} = \lambda^* T \ln(2)
\]

(2.29)

\[
\ln \left(1 + \frac{\delta \beta y_j}{1+y_j}\right) - \frac{\delta \beta y_j}{(1 + \frac{\delta \beta y_j}{1+y_j})(1+y_j)^2} = 2 \lambda^* T \ln(2).
\]

(2.30)

Thus from the set of \(N + K + 1\) equations represented by (2.24) to (2.26), we obtain a set of three non-linear equations (2.28) to (2.30) for three unknown variables \(x, y, \lambda^*\) which can be uniquely solved. It should be noted that the number of equations to be solved is

\[36\]
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Lemma 3: The primal feasibility condition (constraint \( C_1 \)) is satisfied with strict equality, i.e.,

\[
t^*_d + \sum_{i=1}^{N} t^*_i(n) + \sum_{j=1}^{K} t^*_j(f) - T = 0.
\]  

(2.31)

Proof: We know that \( x, y > 0 \) (see Lemma 2). Since \( \nu_i, \alpha_j, \delta, \beta > 0, \forall i, j \), from (2.28), we can say that \( \lambda^* > 0 \). Then, to satisfy the KKT complementary slackness condition \( \left[ \lambda^*(t^*_d + \sum_{i=1}^{N} t^*_i(n) + \sum_{j=1}^{K} t^*_j(f) - T) = 0 \right] \), the primal feasibility condition must be satisfied with strict equality. This completes the proof.

□

Proposition 1: The optimal DEH and UIT time allocation, denoted by \( t^*_d, t^*_i(n), \) and \( t^*_j(f) \) are given by

\[
t^*_d = \frac{T}{1 + \sum_{i=1}^{N} \frac{\nu_i}{x^*} + \sum_{j=1}^{K} \frac{\alpha_j}{y^*}}, \quad t^*_i(n) = \frac{\nu_i t^*_d}{x^*}, \forall i, \text{ and } \quad t^*_j(f) = \frac{\alpha_j t^*_d}{\beta y^*}, \forall j
\]

(2.32)

where \( x^* \) and \( y^* \) are the unique solutions of (2.28) to (2.30).

Proof: When the solution of (2.28) to (2.30) are obtained, (2.27) can be used in (2.31) to obtain \( t^*_d \). Then, \( t^*_i(n) \) and \( t^*_j(f) \) are obtained from the definitions of \( x \) and \( y \) in (2.27). This completes the proof.

□

Hence, \( t^*_d \) gives the optimal DEH time, \( t^*_i(n) \) gives the optimal UIT times of near-UEs, and \( t^*_j(f) \) gives the optimal UIT times of far-UEs to maximize the sum-throughput of the network. We see that the UIT times of all UEs depend on channel power gain of their links to the AP and the relay node.

Iterative power and time allocation

Algorithm 1 summarizes the iterative power and time allocation procedure. Given the initial time allocation, relay node transmit power is optimally determined. Then the optimal time allocation is determined using the obtained relay node transmit power. This process is
2.3. Problem Formulations and Solution Approaches

repeated till convergence is reached.

Algorithm 1 Iterative Power and Time Allocation Algorithm

Require: Initialize $l = 0$, $t_{(d)}^{(l)}$, $t_{i(n)}^{(l)}$, and $t_{j(f)}^{(l)}$.
1: repeat
2: Determine relay node transmit power, $\mathcal{P}_{R}^{(l)}$ with (2.19)
3: Define $\nu_i$, $\alpha_j$, $\beta$, and $\delta$ using (2.21)
4: Solve (2.28) to (2.30) to find $x^*$ and $y^*$
5: Find $t_{(d)}^*$, $t_{i(n)}^*$, and $t_{j(f)}^*$ using (2.32)
6: Update $l \leftarrow l + 1$; $t_{(d)}^{(l)} = t_{(d)}^*$, $t_{i(n)}^{(l)} = t_{i(n)}^*$, and $t_{j(f)}^{(l)} = t_{j(f)}^*$
7: until Convergence of $\sum_{i=1}^{N} \mathcal{R}_{i(n)}^{(sc-II)} + \sum_{j=1}^{K} \mathcal{R}_{j(f)}^{(sc-II)}$

2.3.2 Joint Power and Time Allocation: Scenario II

In this section, we jointly allocate transmit power of the relay node along with DEH and UIT times of all UEs with the objective of maximizing sum-throughput in Scenario II of the proposed relay-based WPC network. The sum-throughput maximization problem is written as

$$\text{maximize} \quad t_{(d)}, t_{i(n)}^{(l)}, t_{j(f)}^{(l)}, P_{rd}, P_{ru} \sum_{i=1}^{N} \mathcal{R}_{i(n)}^{(sc-II)} + \sum_{j=1}^{K} \mathcal{R}_{j(f)}^{(sc-II)} \quad \text{(2.33)}$$

subject to $C_1$, $C_2$, $C_3$, $C_4$.

The objective function and constraint $C_2$ are not convex. We will see subsequently that it is possible to jointly allocate time and power optimally in Scenario II. However, for the sake of fair comparison between Scenarios I and II, we allocate time and power using same iterative algorithm proposed for Scenario I described here briefly.

Iterative power and time allocation

For a given initial time allocation, power allocation can be performed using the approach similar to that in Scenario I. Setting $P_{(rd)} = P_{(ru)} = P_{R}$, the optimal power allocation for Scenario II is determined by using (2.19).
With the given relay node transmit power $P_R$, the throughput of far-UEs given in (2.14) can be re-written as

$$R_{j(f)}^{\text{(sc-II)}} = \frac{t_j(f)}{2T} \log_2 \left( 1 + \frac{\delta \tilde{\alpha}_j \tilde{\beta} t_j(d)}{\tilde{\alpha}_j t_j(d) + \tilde{\beta} t_j(f)} \right), \quad \forall j$$

(2.34)

where $\tilde{\alpha}_j = 2\eta h^2_{R,j} P_R$ and $\tilde{\beta} = g_{A,R} P_R$. It should be noted that the throughput expression is similar to that of Scenario I given in (2.20). The throughput expression of near-UEs in Scenario II given in (2.12) is same as that of Scenario I given in (2.5). Hence the optimal time allocation can be obtained by using the similar approach as in Scenario I. Therefore, joint power and time allocation can be performed iteratively as defined in Algorithm [1].

Optimal power and time allocation

To solve the problem in (2.33) optimally, we implement the following changes of variables:

$$E_{(rd)} = P_{(rd)} t(d), \quad E_{j(ru)} = P_{j(ru)} t_j(f)/2, \quad \forall j.$$  

(2.35)

Here, $E_{(rd)}$ and $E_{j(ru)}$ are the energy allocated at relay node for transmitting wireless charging signal and relaying uplink information signal of each far-UE, respectively. Using (2.35), we can re-write (2.14) as

$$\tilde{R}_{j(f)}^{\text{(sc-II)}} = \frac{t_j(f)}{2T} \log_2 \left( 1 + \frac{\delta \alpha_j \beta E_{(rd)} E_{j(ru)} t_j(f)}{\alpha_j E_{(rd)} + 2\beta E_{j(ru)}} \right).$$

(2.36)
2.3. Problem Formulations and Solution Approaches

The sum-throughput maximization problem in (2.33) now becomes

\[
\begin{align*}
\text{maximize} & \quad \sum_{i=1}^{N} R_{i(n)}^{(\text{sc-II})} + \sum_{j=1}^{K} \tilde{R}_{j(f)}^{(\text{sc-II})} \\
\text{subject to} & \quad C_1, C_3 \\
C_2' : & \quad E_{(rd)} + \sum_{j=1}^{K} E_{j(ru)} \leq E_{\text{max}} \\
C_4' : & \quad E_{(rd)} \geq 0; \quad E_{j(ru)} \geq 0, \quad \forall j
\end{align*}
\]

(2.37)

where \( E_{(ru)} = [E_{1(ru)}, E_{2(ru)}, ..., E_{K(ru)}] \). The joint power and time allocation problem now becomes a joint energy and time allocation problem. \( C_2' \) is the energy constraint of the relay node equivalent to \( C_2 \) of problem in (2.33). \( C_4' \) is the non-negativity constraint on energy allocation variables. The objective function of the problem in (2.37) is concave. The proof of convexity is provided in Appendix A. The modified constraint \( C_2' \) as well as other constraints are affine in terms of the optimization variables. Therefore, it is a convex optimization problem and can be solved by using convex optimization techniques. The partial Lagrangian of the problem in (2.37) is given by

\[
\mathcal{L}(t_d, t_n, t_f, E_{(rd)}, E_{(ru)}, \mu_1, \mu_2) = \sum_{i=1}^{N} R_{i(n)}^{(\text{sc-II})} + \sum_{j=1}^{K} \tilde{R}_{j(f)}^{(\text{sc-II})} \\
- \mu_1 \left( t_d + \sum_{i=1}^{N} t_i(n) + \sum_{j=1}^{K} t_j(f) - T \right) \\
- \mu_2 \left( E_{(rd)} + \sum_{j=1}^{K} E_{j(ru)} - E_{\text{max}} \right)
\]

(2.38)

where \( \mu_1 \) and \( \mu_2 \) are non-negative Lagrange multipliers corresponding to constraints \( C_1 \) and \( C_2' \), respectively. The non-negativity constraints \( C_3 \) and \( C_4' \) are not included in the Lagrangian and will be satisfied later (in Lemma 4). Since the problem is convex, we can find its optimal solution by using KKT conditions [80]. Let us denote the primal and dual optimality values of the problem in (2.37) as \( t_d^*, t_n^*, t_f^*, E_{(rd)}^*, E_{(ru)}^*, \mu_1^*, \) and \( \mu_2^* \). By differentiating (2.38) w.r.t. \( t_d, t_i(n), t_j(f), E_{(rd)}, \) and \( E_{j(ru)} \), respectively and using KKT
2.3. Problem Formulations and Solution Approaches

stationarity conditions, we obtain

\[
\sum_{i=1}^{N} \frac{\nu_i}{1 + x_i} = \mu_1^* T \ln(2) \tag{2.39}
\]

\[
\ln(1 + x_i) - \frac{x_i}{1 + x_i} = \mu_1^* T \ln(2), \quad \forall i \tag{2.40}
\]

\[
\ln(1 + y_j) - \frac{y_j}{1 + y_j} = 2\mu_1^* T \ln(2), \quad \forall j \tag{2.41}
\]

\[
\sum_{j=1}^{K} \frac{\delta \alpha_j (1 - z_j)^2}{1 + y_j} = 2\mu_2^* T \ln(2) \tag{2.42}
\]

\[
\frac{2\delta \beta z_j^2}{1 + y_j} = 2\mu_2^* T \ln(2), \quad \forall j \tag{2.43}
\]

where \( x_i = \frac{\nu_i t^*_{(d)}}{t^*_{(n)}}, \quad a_j = \frac{1}{\alpha_j E^*_{(rd)}}, \quad y_j = \frac{\delta}{(a_j + b_j)t^*_{(f)}}, \quad b_j = \frac{1}{2\beta E^*_{(ru)}}, \quad z_j = \frac{b_j}{a_j + b_j}. \tag{2.44} \]

**Lemma 4**: \( x_i, y_j, \) and \( z_j \) are constant and independent of \( i \) or \( j \) if \( t^*_{(d)}, t^*_{(n)}, t^*_{(f)}, E^*_{(rd)}, E^*_{(ru)} > 0 \), i.e.,

\[
x = x_i = \frac{\nu_i t^*_{(d)}}{t^*_{(n)}}, \quad \forall i, \quad y = y_j = \frac{\delta}{(a_j + b_j)t^*_{(f)}}, \quad \forall j, \quad z = z_j = \frac{b_j}{a_j + b_j}, \quad \forall j. \tag{2.45}
\]

The proof is similar to the proof of Lemma 2 and is omitted. Using Lemma 4, (2.39) to (2.43) can be re-written, respectively, as

\[
\sum_{i=1}^{N} \frac{\nu_i}{1 + x} = \mu_1^* T \ln(2) \tag{2.46}
\]

\[
\ln(1 + x) - \frac{x}{1 + x} = \mu_1^* T \ln(2) \tag{2.47}
\]

\[
\ln(1 + y) - \frac{y}{1 + y} = 2\mu_1^* T \ln(2) \tag{2.48}
\]

\[
\sum_{j=1}^{K} \frac{\delta \alpha_j (1 - z)^2}{1 + y} = 2\mu_2^* T \ln(2) \tag{2.49}
\]
2.3. Problem Formulations and Solution Approaches

\[
\frac{2\delta\beta z^2}{1 + y} = 2\mu^*_2 T \ln(2). \tag{2.50}
\]

In this way, from \(N + 2K + 2\) equations represented in (2.39) to (2.43), we achieve five equations shown in (2.46) to (2.50) with five variables which can be solved in closed form. It should be noted that the number of equations to be solved remains constant regardless of the number of UEs. Next, we present the closed-form solution of the above mentioned equations.

**Lemma 5**: The solution of (2.46) to (2.50) is given by

\[
x^* = \frac{\sum_{i=1}^{N} \nu_i - 1}{\mathcal{W}(e^{-1}(\sum_{i=1}^{N} \nu_i - 1))} - 1, \quad \mu_1^* = \frac{\sum_{i=1}^{N} \nu_i}{(1 + x^*) T \ln(2)} \tag{2.51}
\]

\[
y^* = -1 - \frac{1}{\mathcal{W}(-e^{-2\mu^*_1 T \ln(2) + 1})}, \quad z^* = \frac{2 \sum_{j=1}^{K} \alpha_j - \sqrt{8 \sum_{j=1}^{K} \alpha_j \beta}}{2 \sum_{j=1}^{K} \alpha_j - 4 \beta} \tag{2.52}
\]

where \(\mathcal{W}(.)\) is Lambert W-function [81]. See Appendix B for the proof.

**Lemma 6**: The primal feasibility KKT conditions (constraints \(C_1\) and \(C'_2\)) are satisfied with strict equality, i.e.,

\[
t^*_d + \sum_{i=1}^{N} t^*_i(n) + \sum_{j=1}^{K} t^*_j(f) - T = 0, \quad E^*_{rd} + \sum_{j=1}^{K} E^*_j(ru) - E_{max} = 0. \tag{2.53}
\]

The proof is similar to that of Lemma 3 and is omitted. Using the results of Lemma 4, 5, and 6, we obtain the optimal time and energy allocation in closed-form in the following.

**Proposition 2**: The optimal time and relay node energy allocation denoted by \(t^*_d\), \(t^*_i\), \(t^*_j\), \(E^*_{rd}\), and \(E^*_{ru}\) are given by

\[
E^*_{rd} = \frac{2\beta z^* E_{max}}{2\beta z^* + (1 - z^*) \sum_{j=1}^{K} \alpha_j}, \quad E^*_j(ru) = \frac{(1 - z^*) \alpha_j E_{max}}{2\beta z^* + (1 - z^*) \sum_{j=1}^{K} \alpha_j}, \quad \forall j \tag{2.54}
\]
2.4. Performance Evaluation Results

\begin{equation}
    t^*_j(f) = \frac{z^*(1 - z^*) 2 \delta \beta \alpha_j E_{\text{max}}}{y^* \left(2 \beta z^* + (1 - z^*) \sum_{j=1}^{K} \alpha_j \right)}, \quad \forall j, \quad t^*_j(d) = \frac{T - \sum_{j=1}^{K} t^*_j(f)}{1 + \sum_{i=1}^{N} \nu_i}, \quad t^*_{i(n)} = \frac{\nu_i t^*_j(d)}{x^*}, \quad \forall i.
\end{equation}

(2.55)

See Appendix [C] for the proof. The solution shows that the time allocated for UIT of each far-UE and energy allocated at the relay node for information relaying are proportional to channel gain of the link between that UE and the relay node along with energy available at the relay node. Similarly, the time allocated for UIT of each near-UE is proportional to channel gain of the link between that UE and the AP along with the AP transmit power. Finally, we can obtain the optimal relay node power allocation from the optimal time and energy allocation as follows:

\begin{equation}
    P^*_{(rd)} = \frac{E^*_{(rd)}}{t^*_j(d)}, \quad P^*_{j(ru)} = 2 \frac{E^*_{j(ru)}}{t^*_j(f)}, \quad \forall j.
\end{equation}

Thus, we jointly obtain the optimal time and relay node power allocation solution in closed-form for Scenario II.

2.4 Performance Evaluation Results

We evaluate the performance of the resource allocation algorithms proposed for different scenarios of WPC networks with relay-based cooperation. We also compare the performance of the WPC networks with relay-based cooperation to that without the relay nodes [24].

2.4.1 Simulation Parameters

The channel gain for the link between source and destination is computed as \( h_{s,d} = 10^{-3} d^{-\alpha} \), where \( \alpha \) is path-loss attenuation factor, \( d \) is the distance, and reference path-loss at a distance of 1 m is 30 dB for operating frequency of 900 MHz [82]. Unless stated otherwise, \( \alpha = 2.7 \) is used for simulations considering urban environment [82]. AWGN power is assumed to be...
### 2.4. Performance Evaluation Results

![Graph showing performance evaluation results](image)

Figure 2.3: Convergence of Algorithm [I]

...90 dBm. The transmit power of the AP is 41 dBm and the energy available at the relay node is 20 J. The total transmission time is $T = 2 \text{ s}$. Energy harvesting efficiency is $\eta_1 = 50\%$ and $\eta_2 = 75\%$ due to receiver circuit power consumption. Relay node is fixed at a distance of 6 m from the AP. When two UEs are considered to be present in the system (i.e., $N = 1$ and $K = 1$), near-UE and far-UE are assumed to be at a distance of 6 m and 12 m from the AP, respectively. We also simulate the system model in the presence of multiple near and far-UEs. In this case, we randomly generate locations of near-UEs (maximum distance being 6 m) and far-UEs (maximum distance being 12 m) in each simulation and average the results over 1000 different random realizations. In each realization, the numbers of near and far-UEs are assumed to be equal.
2.4. Performance Evaluation Results

2.4.2 Simulation Results

Convergence of iterative algorithm

Fig. 2.3 presents the average sum-throughput of UEs determined by using Algorithm 1 in Scenarios I and II, plotted against iteration indices. \( N = 5 \) near-UEs and \( K = 5 \) far-UEs are considered in the system for the simulation. For both scenarios, the algorithm converges in 4 – 5 iterations. Also, the performance loss of Scenario II compared to Scenario I is found to be fairly small.

Resource allocation

The amount of allocated time for DEH and UIT is presented in Fig. 2.4 for varying energy harvesting efficiency \( \eta_1 \). In relay-based systems, energy allocated at relay node for transmitting wireless charging signal and relaying uplink information is presented in Figs. 2.5(a) and 2.5(b), respectively. For these results, \( N = 1 \) near-UE and \( K = 1 \) far-UE are considered in the network. Most of the available energy is allocated for wireless charging which is analogous to the result in downlink SWIPT \([13, 20]\) where most of the power is allocated to energy harvester. Energy allocated for wireless charging is the highest in Scenario II with optimal resource allocation which again shows that for optimality, maximum available energy is dedicated for wireless charging. Interestingly, introduction of relay node relaxes the time allocated for wireless charging which allows more time for transmission of far-UE. This is because relay node acts as an additional source of wireless charging signal. When its available energy is optimally utilized in Scenario II, DEH time decreases the most (Fig. 2.4(a)) and UIT time of far-UE increases the most (Fig. 2.4(c)). Increase in UIT time of far-UE is accompanied with slight decrease in UIT time of near-UE (Fig. 2.4(b)). With increasing energy harvesting efficiency, DEH time decreases and UIT time of near-UE increases as more energy can be harvested in less time when energy harvesting efficiency is higher. However, UIT time of far-UE decreases and relay nodes spend more energy in DEH phase.
Figure 2.4: Time allocated versus energy harvesting efficiency.
2.4. Performance Evaluation Results

Figure 2.5: Energy allocated at relay node versus energy harvesting efficiency.
2.4. Performance Evaluation Results

Table 2.1: Received, harvested, and transmit power of UEs

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Received Power (Downlink)</th>
<th>Harvested Energy</th>
<th>Transmit Power (Uplink)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P_{rx(n)}$ dBm</td>
<td>$P_{rx(f)}$ dBm</td>
<td>$E_{(n)}$ $\mu$J</td>
</tr>
<tr>
<td>Scenario II Optimal</td>
<td>-10.01</td>
<td>-3.67</td>
<td>18.39</td>
</tr>
<tr>
<td>Scenario II Iterative</td>
<td>-10.01</td>
<td>-5.24</td>
<td>20.59</td>
</tr>
<tr>
<td>Scenario I Iterative</td>
<td>-10.01</td>
<td>-5.05</td>
<td>20.53</td>
</tr>
<tr>
<td>No Relay</td>
<td>-10.01</td>
<td>-18.14</td>
<td>22.07</td>
</tr>
</tbody>
</table>

to compensate the loss in uplink throughput of far-UEs due to decrease in its UIT time.

In Table 2.1, we present the received power, harvested energy, and uplink transmit power of both near-UE and far-UE when $N = 1$, $K = 1$, $\eta_1 = 50\%$, and $\eta_2 = 75\%$. From the table, we see that the receiver sensitivity of energy harvesting circuit (around $-20$ dBm) is satisfied in both near-UE and far-UE in all the scenarios. It should be noted that the received power of far-UE is much lower in the scenario without the relay node. However, for fair comparison, we have assumed that the energy is harvested with efficiency of $\eta_1 = 50\%$ in all cases, irrespective of the received power level. We see that, the uplink transmit powers of both near-UE and far-UE are within the transmit power range (0 dBm to $-24$ dBm) of sensor nodes such as TelosB [17] and MICAz [83].

Throughput performance

In Fig. 2.6, we plot throughput of both near-UE and far-UE against varying energy harvesting efficiency $\eta_1$, when $N = 1$ and $K = 1$. We can see that far-UE throughput increases in both scenarios with relay-based cooperation. In Fig. 2.7, we plot the ratio of throughput of far-UE to that of near-UE. Significant increase in throughput ratio implies remarkable improvement in throughput of far-UE relative to the near-UE. The uplink throughput of near-UE increases while that of far-UE decreases with increasing energy harvesting efficiency which is in accordance with the variation in time allocation with energy harvesting efficiency.
2.4. Performance Evaluation Results

Energy harvesting efficiency ($\eta_1$) vs Throughput (bps/Hz)

Figure 2.6: Throughput versus energy harvesting efficiency.

Energy harvesting efficiency ($\eta_1$) vs Throughput ratio

Figure 2.7: Throughput ratio versus energy harvesting efficiency.
2.4. Performance Evaluation Results

In Fig. 2.8, the average sum-throughput is plotted against varying number of UEs. It is observed that the average sum-throughput increases with increasing number of UEs. In Fig. 2.9, the average sum-throughput is plotted against attenuation factor when $N = 5$ near-UEs and $K = 5$ far-UEs are present in the network. The sum-throughput decreases with increasing path-loss attenuation and the performance gain due to relay-based cooperation is more prominent when path-loss attenuation is high. From the simulation results, it is observed that the throughput performances of both Scenarios I and II with iterative resource allocation are very close to each other which validates our assumption (made in Scenario II) that energy harvested by far-UEs from the AP transmission is negligible. Scenario II has maximum performance gain when resources are optimally allocated.
2.4. Performance Evaluation Results

Figure 2.9: Average sum-throughput versus attenuation factor.

Fairness performance

We then evaluate fairness using Jain’s fairness index\(^3\) [84]. In Fig. 2.10, we plot Jain’s fairness index against varying energy harvesting efficiency when \(N = 1\) and \(K = 1\). In Fig. 2.11, we plot Jain’s fairness index against varying number of UEs. The figures show that fairness performance of both scenarios with relay-based cooperation is superior to that without relay node [24]. However, Jain’s fairness index decreases with increasing energy harvesting efficiency which due to increase in throughput of near-UE and decrease in that of far-UE. This shows that the effectiveness of relay-based cooperation in terms of fairness performance is more prominent when energy harvesting efficiency is low. The figures are consistent with the observations that Scenarios I and II have fairly similar performance with iterative resource allocation and that optimal resource allocation improves performance of Scenario II.

---

\(^3\)If \(x_i, i = 1, 2, ..., N\) is the throughput of each of \(N\) users, then Jain’s fairness index is given by: 
\[
 f(x) = \frac{\left(\sum_{i=1}^{N} x_i\right)^2}{N \sum_{i=1}^{N} x_i^2}.
\]
The fairness index has the range of \(0 < f(x) \leq 1\), where a higher number indicates a better fairness.
2.4. Performance Evaluation Results

![Graph 1](image1.png)

Figure 2.10: Jain’s fairness index versus energy harvesting efficiency.

![Graph 2](image2.png)

Figure 2.11: Jain’s fairness index versus number of UEs.
2.4.3 Summary of Observations

The simulation results demonstrate how the presence of relay nodes allows more uplink transmission time by reducing the downlink energy harvesting time. This causes improvement of throughput of far-UEs, sum-throughput, and fairness. Therefore, relay-based cooperation improves fairness without any loss in overall throughput performance. However, the effectiveness of relay-based cooperation in WPC networks is more prominent when path-loss attenuation is high and energy harvesting efficiency is low. With iterative power and time allocation, Scenario I provides a slightly better performance than that of Scenario II. However, the performance difference is negligible which validates our assumption (made in Scenario II) that energy harvested by far-UEs from the AP transmission is negligible. Simulation results demonstrate that the performance significantly improves due to optimal allocation of resources in Scenario II. Therefore, Scenario II is preferable in WPC networks with relay-based cooperation to maximize the throughput performance with lower computational complexity.
Chapter 3

Resource Allocation in Uplink Wireless-Powered Communication Networks with User-based Cooperation

In Chapter 2, we considered deployment of dedicated relay nodes for mitigating the “doubly near-far” problem in uplink WPC networks. However, deployment of dedicated relay nodes may not always be feasible or may incur high installation costs. Hence, in this chapter, we consider user-based cooperation in such uplink WPC network and perform joint resource allocation for downlink energy harvesting phase and uplink information transmission phase. The accomplished works and research contributions of this chapter are briefly described in the following.

3.1 Accomplished Works and Research Contributions

In this chapter, we consider an uplink WPC network where the uplink communication of UEs is powered by wireless energy harvesting. Based on the concept of harvest-then-transmit [24], UEs first harvest energy from the AP in DEH phase. Then, in UIT phase, the UEs, that do not have their own data to transmit, relay uplink information signal for the transmitting UEs. The transmission of different UEs are orthogonal in frequency. To optimize uplink
throughput performance of the transmitting UEs, we optimally allocate downlink transmit power of the AP for DEH phase jointly with relay selection, subchannel allocation, and power allocation for UIT phase. Although the formulated MINLP problem is solved by relaxing the integer constraints, the resulting solution is shown to always satisfy the constraints of the original problems, hence satisfying the condition of optimality.

The rest of the chapter is organized as follows. The system model and assumptions are presented in Section 3.2. In Section 3.3 the optimization problem is formulated and the solution approach is proposed. Numerical results are presented in Section 3.4.

3.2 System Model and Assumptions

Consider an uplink communication network as shown in Fig. 3.1. As in sensor network, let us assume there is an idle period before each uplink transmission. The idle period is dedicated for DEH where the AP transmits downlink wireless charging signal and all UEs harvest energy from the received signal. The AP is connected to the grid power. However, UEs are assumed to have no battery power and hence rely on harvested energy for their uplink transmissions. In the UIT period, the UEs, that are located closer to the AP and do not have any data to transmit are available to act as relay nodes (RNs) for other data-transmitting UEs which have poor channel quality to the AP. In the following, data-transmitting UEs will be referred as transmitting nodes (TNs). For simplicity we assume that we know which UEs have data to transmit and which are available as relay nodes and we also have their location information.

Let us assume that there are $K$ TNs with poor uplink channel quality and $R$ RNs with strong uplink channels. We consider that the available bandwidth is divided into $N$ subchannels, each with bandwidth of $B$. Channel gain of the links between AP to RN $r$ in subchannel $n$ are denoted by $h_{A,r}^n$, where $r \in \{1, 2, ..., R\}$ and $n \in \{1, 2, ..., N\}$. Channel gain of the links between RN $r$ to TN $k$ in subchannel $n$ are given by $h_{r,k}^n$, where $k \in \{1, 2, ..., K\}$. 
3.2. System Model and Assumptions

Channel gain of the links between AP and TN $k$ in subchannel $n$ are given by $g_{A,k}^n$. The DEH period is denoted by $\tau_e$ and the UIT period is denoted by $\tau_t$.

During the DEH period, the AP transmits wireless charging signal in all subchannels with power $P_A^n$. The energy harvested by the RNs and the TNs are given by:

\[
E_r = \sum_{n=1}^{N} P_A^n h_{r,k}^n \eta \tau_e, \quad \forall r, \\
E_k = \sum_{n=1}^{N} P_A^n g_{A,k}^n \eta \tau_e, \quad \forall k
\]

where $\eta$ is the energy harvesting efficiency.

In the UIT phase, each TN’s transmission is amplified and forwarded by their selected RNs in their selected subchannels. The subchannel and relay assignment variable is denoted by $s_{k,r}^n$. If an RN $r$ is selected as a relay for a TN $k$ in subchannel $n$, then $s_{k,r}^n = 1$ and otherwise $s_{k,r}^n = 0$. The achievable throughput in bits per second per Hertz (bps/Hz) of TN $k$, assisted by relay $r$ in subchannel $n$ is given as:

\[
R_{k,r}^n = \frac{1}{2} \log_2 \left( 1 + \frac{P_k^n h_{r,k}^n h_{A,r}^n}{N_w \left( P_k^n h_{r,k}^n + P_r^n h_{A,r}^n + N_w \right)} \right), \forall n, r, k
\]  

(3.1)

where $N_w$ is the AWGN power. $P_k^n$ is the uplink transmission power of the TN $k$ in the subchannel $n$ paired with the relay $r$. $P_r^n$ is the transmission power of the RN $r$. 

Figure 3.1: Uplink WPC network with user-based cooperation.
in the subchannel \( n \) in the second phase. The factor of \( \frac{1}{2} \) is due to half-duplex relaying\(^4\).

Assuming AWGN power to be much lower than the signal power, higher order term \((N_w)^2\) is ignored in the rest of this chapter. The total achievable throughput of TN \( k \) is given by

\[
R_k = \sum_{n=1}^{N} \sum_{r=1}^{R} s_{k,r}^n R_{k,r}^n, \forall k.
\]

In this chapter, to maximize uplink sum-throughput of all transmitting UEs, we will jointly optimize the following variables of the network: (i) downlink transmit power of the AP, (ii) uplink transmit power of the TNs and RNs, (iii) relay selection and subchannel assignment. It should be noted that uplink transmit power of the TNs and the RNs depend on their harvested energy which depends on downlink transmit power of the AP. Therefore, it is necessary to jointly allocate downlink transmit power of the AP along with uplink transmit power of the TNs and RNs. In addition, subchannel allocation and relay selection should be optimally performed in the uplink. Therefore, to jointly perform downlink/uplink power allocation, uplink relay selection and subchannel allocation, we will formulate an optimization problem with the objective of maximizing the sum-throughput of the network.

### 3.3 Problem Formulation and Solution Approach

In the following, we formulate an optimization problem to jointly perform downlink/uplink power allocation, uplink relay selection and subchannel allocation, as follows:

\[
\begin{align*}
\text{maximize} & \quad \mathbf{P}_{K, P_{R_A}, P_{S}} \sum_{K=1}^{K} R_k \\
\text{subject to} & \\
C_1 & : s_{k,r}^n \in \{0, 1\}, \forall r, k, n \\
C_2 & : \sum_{r=1}^{R} \sum_{k=1}^{K} s_{k,r}^n \leq 1, \forall n
\end{align*}
\]

\(^4\text{Note that, unlike our assumption, if DEH phase actually consumes some portion of the transmission time, the factor changes from } \frac{1}{2} \text{ to } \frac{\tau_1/2}{\tau_1 + \tau_2}.\)
3.3. Problem Formulation and Solution Approach

\[ C_3 : \sum_{r=1}^{R} \sum_{n=1}^{N} s_{k,r}^n P_{k,r}^{(1)} \leq \sum_{m=1}^{N} \frac{P_m g_{A,k}^m \eta \tau_e}{\Omega}, \forall k \]

\[ C_4 : \sum_{k=1}^{K} \sum_{n=1}^{N} s_{k,r}^n P_{r,A}^{(2)} \leq \sum_{m=1}^{N} \frac{P_m h_{A,r}^m \eta \tau_e}{\Omega}, \forall r \]

\[ C_5 : P_{k,r}^{(1)}, P_{r,A}^{(2)} \geq 0, \forall n, r, k \]

\[ C_6 : P_A^m \geq 0, \forall m \in \{1, 2, \ldots, N\} \]

\[ C_7 : \sum_{m=1}^{N} P_A^m \leq P_{A_{max}} \]

where \( P_K, P_R, P_A, \) and \( S \) denote uplink transmit power of the TNs, uplink transmit power of the RNs, downlink transmit power of the AP and subchannel and relay assignment variables, respectively. Constraint \( C_1 \) shows that \( s_{k,r}^n \) are binary integer variables as discussed previously. \( C_2 \) ensures that a subchannel is not used by more than one TN-RN pair, to eliminate the interference. \( C_3 \) and \( C_4 \) indicate that the total energy spent by TNs and RNs during the UIT period cannot be higher than that harvested during the DEH period. The factor of \( 1/2 \) is present in the constraints due to half-duplex relaying. Note that energy consumption at the transceiver circuit of UEs are assumed to be negligible and therefore not considered in the problem. \( C_5 \) and \( C_6 \) impose non-negativity constraint on the power variables. \( C_7 \) indicates total power budget of the AP during the DEH period.

The optimization problem (3.2) is an MINLP problem. The solution to such a problem is computationally very difficult to obtain in this form. Therefore, to solve the problem, we relax the binary integer subchannel allocation and relay selection variables to be continuous in the interval, i.e. \( s_{k,r}^n \in [0, 1] \). Next, we define following auxiliary variables:

\[ \tilde{P}_{k,r}^{(1)} = s_{k,r} P_{k,r}^{(1)}, \forall n, r, k \]

\[ \tilde{P}_{r,A}^{(2)} = s_{k,r} P_{r,A}^{(2)}, \forall n, r, k. \]
Using (3.3) and (3.4), the throughput expression given in (3.1) can be re-written as

\[
\tilde{R}_{k,r}^n = \frac{1}{2} \log_2 \left( 1 + \frac{\tilde{P}_{n}^{(1)} h_{r,k}^{n} h_{A,r}^{n}}{s_{n}^{n} \left( \tilde{P}_{n}^{(1)} + \tilde{P}_{n}^{(2)} h_{r,k}^{n} + h_{A,r}^{n} \right) N_w} \right), \forall n, r, k.
\] (3.5)

With the relaxation and change of variables, the problem (3.2) can be written as

\[
\begin{align*}
\text{maximize} & \quad \tilde{P}_{K}, \tilde{P}_{R}, P_{A}, S \\
\text{subject to} & \quad \tilde{C}_{1}, \tilde{C}_{2}, \tilde{C}_{3}, \tilde{C}_{4}, \tilde{C}_{5} \\
\tilde{C}_{1}: & \quad s_{n}^{n} \in [0, 1], \forall r, k, n \\
\tilde{C}_{3}: & \quad \sum_{r=1}^{R} \sum_{n=1}^{N} \tilde{P}_{k,r}^{(1)} \leq \sum_{m=1}^{N} 2 g_{A,k}^{m} P_{A}^m \eta_{r,t} / \tau_t, \forall k \\
\tilde{C}_{4}: & \quad \sum_{k=1}^{K} \sum_{n=1}^{N} \tilde{P}_{r,k,A}^{(2)} \leq \sum_{m=1}^{N} 2 h_{A,r}^{m} P_{A}^m \eta_{r,t} / \tau_t, \forall r \\
\tilde{C}_{5}: & \quad \tilde{P}_{k,r}^{(1)}, \tilde{P}_{r,k,A}^{(2)} \geq 0, \forall n, r, k
\end{align*}
\] (3.6)

where \( \tilde{R}_k = \sum_{r=1}^{R} \sum_{n=1}^{N} s_{n}^{n} \tilde{R}_{k,r}^n \). The objective function of the re-formulated problem (3.6) is concave, constraints \( \tilde{C}_{3} \) and \( \tilde{C}_{4} \) are affine, \( \tilde{C}_{1} \) is a boundary constraint, and hence the problem becomes convex optimization problem. The concavity of function \( f(\tilde{P}_{k,r}^{(1)}, \tilde{P}_{r,k,A}^{(2)}) = 1 + \frac{\tilde{P}_{n}^{(1)} h_{r,k}^{n} h_{A,r}^{n}}{\tilde{P}_{n}^{(1)} + \tilde{P}_{n}^{(2)} h_{r,k}^{n} + h_{A,r}^{n}} N_w \) in terms of power variables can be proven by computing its Hessian whose eigenvalues are non-positive. The throughput expression can be proven to be concave with respect to power as well as subchannel and relay assignment variables due to increasing concave nature of log function and by perspective operation \([80]\), similar to Appendix A. Therefore, the problem can be solved optimally using dual decomposition technique \([85]\), as explained in the following.
First, we define the following partial Lagrangian [80] for the problem:

\[
L(\tilde{P}_K, \tilde{P}_R, P_A, S, \lambda, \mu) = \\
\sum_{k=1}^{K} \tilde{R}_k - \sum_{k=1}^{K} \lambda_k \left\{ \sum_{r=1}^{R} \sum_{n=1}^{N} \tilde{P}_n^{(1)} - \sum_{m=1}^{N} 2P_A^m g_{A,k} \eta \tau_e / \tau_t \right\} \\
- \sum_{r=1}^{R} \mu_r \left\{ \sum_{k=1}^{K} \sum_{n=1}^{N} \tilde{P}_n^{(2)} - \sum_{m=1}^{N} 2P_A^m h_{A,r} \eta \tau_e / \tau_t \right\}
\]

(3.7)

where \( \lambda = \{\lambda_1, \lambda_2, ..., \lambda_k\} \) and \( \mu = \{\mu_1, \mu_2, ..., \mu_r\} \) are non-negative Lagrange multipliers for constraints \( \tilde{C}_3 \) and \( \tilde{C}_4 \), respectively. Then, Lagrangian dual function [80] of the problem is formulated as follows:

\[
g(\lambda, \mu) = \maximize_{\tilde{P}_K, \tilde{P}_R, P_A, S} L(\tilde{P}_K, \tilde{P}_R, P_A, S, \lambda, \mu) \\
\text{subject to } \tilde{C}_1, C_2, \tilde{C}_5, C_6, C_7.
\]

(3.8)

Maximization of the Lagrangian to obtain the dual function in (3.8) is our subproblem. After obtaining the dual function, the dual problem is formulated as follows:

\[
\minimize_{\lambda \geq 0, \mu \geq 0} g(\lambda, \mu).
\]

(3.9)

Since the primal problem is convex, strong duality holds and solution of the dual problem in (3.9) gives us the solution of the primal problem [80]. Next, we will discuss the solution approach of the subproblem as well as the dual problem.

Solving the subproblem

From careful inspection of the Lagrangian in (3.7), we know that maximization problem in (3.8) is a separable problem [85]. Therefore, the Lagrangian dual function can be decom-
posed into two functions as follows:

\[ g_1(\lambda, \mu) = \maximize_{\tilde{P}_K, \tilde{P}_R, S} \mathcal{L}_1(\lambda, \mu, \tilde{P}_K, \tilde{P}_R, S) \] (3.10)

subject to \( \tilde{C}_1, C_2, \tilde{C}_5 \)

\[ g_2(\lambda, \mu) = \maximize_{P_A} \mathcal{L}_2(\lambda, \mu, P_A) \] (3.11)

subject to \( C_6, C_7 \)

where \( g(\lambda, \mu) = g_1(\lambda, \mu) + g_2(\lambda, \mu) \) (3.12)

\[
\begin{align*}
\mathcal{L}_1(\lambda, \mu, \tilde{P}_K, \tilde{P}_R, S) &= \sum_{k=1}^{K} \tilde{R}_k - \sum_{k=1}^{K} \sum_{r=1}^{R} \sum_{n=1}^{N} \lambda_k \tilde{P}_n^{(1)} - \sum_{r=1}^{R} \sum_{k=1}^{K} \sum_{n=1}^{N} \mu_r \tilde{P}_n^{(2)} \\
\mathcal{L}_2(\lambda, \mu, P_A) &= \sum_{m=1}^{N} 2P_A^m \left\{ \sum_{k=1}^{K} \lambda_k g_{A,k}^m + \sum_{r=1}^{R} \mu_r h_{A,r}^m \right\} \eta \tau_t / \tau_t. 
\end{align*}
\] (3.13)

The maximization problem in (3.11) is a linear programming problem and can be solved by interior-point method [80]. Note that the constraints \( \tilde{C}_1 - C_2 \), and \( \tilde{C}_5 \) are incorporated in (3.10) and \( C_6 - C_7 \) are incorporated in (3.11). The maximization problem in (3.10) can be re-formulated as two step maximization problem as follows:

\[ g_1(\lambda, \mu) = \maximize_{S} \max_{\tilde{P}_K, \tilde{P}_R} \mathcal{L}_1(\lambda, \mu, \tilde{P}_K, \tilde{P}_R, S) \] (3.15)

subject to \( \tilde{C}_1, C_2, \tilde{C}_5 \).

To maximize \( \mathcal{L}_1(\lambda, \mu, \tilde{P}_K, \tilde{P}_R, S) \) in terms of power variables, let us apply KKT stationarity condition [80] as follows:

\[
\frac{\partial \mathcal{L}_1(\lambda, \mu, \tilde{P}_K, \tilde{P}_R, S)}{\partial \tilde{P}_n^{(1)}_{k,r}} = 0, \ \forall r, k, n
\] (3.16)
3.3. Problem Formulation and Solution Approach

\[
\frac{\partial L_1(\lambda, \mu, \tilde{P}_K, \tilde{P}_R, S)}{\partial \tilde{P}_{r_k,A}^{(2)}} = 0, \ \forall r, k, n. \quad (3.17)
\]

Solving (3.16) and (3.17) for the power variables, we get following relation between the subchannel and relay selection variables and power variables:

\[
\tilde{P}_{k,r}^{(1)} = s_{k,r}^n \left[ \frac{1}{2\lambda_k Y_{k,r}^n} \log_2 \left( \frac{N_w Y_{k,r}^n}{h_{r,k}^n} \right) \right]^+ \quad (3.18)
\]

\[
\tilde{P}_{r_k,A}^{(2)} = s_{k,r}^n \beta_{k,r}^n \left[ \frac{1}{2\lambda_k Y_{k,r}^n} \log_2 \left( \frac{N_w Y_{k,r}^n}{h_{r,k}^n} \right) \right]^+ \quad (3.19)
\]

where \( \beta_{k,r}^n = \sqrt{\frac{h_{A,r}^n h_{A,r}^n}{h_{k,r}^n h_{k,r}^n}} \), \( Y_{k,r}^n = \frac{\beta_{k,r}^n h_{k,r}^n + h_{A,r}^n}{h_{A,r}^n} \) and \( [x]^+ = \max(0, x) \). Using (3.18) and (3.19), the dual function in (3.15) can be re-written as:

\[
g_1(\lambda, \mu) = \max S_k \sum_{k=1}^{K} \sum_{r=1}^{R} \sum_{n=1}^{N} s_{k,r}^n X_{k,r}^n \quad (3.20)
\]

subject to \( C_1, C_2 \)

where

\[
X_{k,r}^n = \left\{ R_{k,r}^{n*} - \left( \lambda_k + \frac{\mu_r}{\beta_{k,r}^n} \right) Z_{k,r}^n \right\} \quad (3.21)
\]

\[
Z_{k,r}^n = \left[ \frac{1}{2\lambda_k Y_{k,r}^n} \log_2 \left( \frac{N_w Y_{k,r}^n}{h_{r,k}^n} \right) \right]^+ \quad (3.22)
\]

\[
R_{k,r}^{n*} = \frac{1}{2} \log_2 \left( 1 + \frac{Z_{k,r}^n h_{r,k}^n}{N_w Y_{k,r}^n} \right). \quad (3.23)
\]

The constraint \( C_5 \) is not included in (3.20) because it is already satisfied in (3.18) and (3.19). The maximization problem in (3.20) is a linear programming problem. However, it should be noted that, maximizing the objective function of the problem in (3.20) requires selection of the highest element of \( R \times K \) matrix \( [X_{k,r}^n] \) for each subchannel \( n \). Therefore, subchannel
and relay assignment variables are determined as follows:

\[
 s_{k,r}^n = \begin{cases} 
 1, & \text{if } (r^*, k^*) = \text{argmax}_{r,k} X_{k,r}^n \\
 0, & \text{otherwise.}
\end{cases} 
\] (3.24)

It should be noted that, despite the relaxation of subchannel and relay assignment variables, the optimal solution of the problem in (3.20) is always integer and hence, the obtained solution satisfies all constraints of our original problem in (3.2) [86].

Solving the dual problem

The dual problem is solved by subgradient method [87] as follows:

\[
\lambda_k^{(it+1)} = \left[ \lambda_k^{(it)} + \Delta_{\lambda_k} \left( \sum_{r=1}^{R} \sum_{n=1}^{N} \tilde{P}_{k,r}^{n(1)} - \sum_{m=1}^{N} 2P_{A}^{m} g_{A,k}^{m} \eta \tau_e / \tau_t \right) \right]^+, \forall k 
\] (3.25)

\[
\mu_r^{(it+1)} = \left[ \mu_r^{(it)} + \Delta_{\mu_r} \left( \sum_{k=1}^{K} \sum_{n=1}^{N} \tilde{P}_{r,k,A}^{n(2)} - \sum_{m=1}^{N} 2P_{A}^{m} h_{A,r}^{m} \eta \tau_e / \tau_t \right) \right]^+, \forall r 
\] (3.26)

where \(\Delta_{\lambda_k}\) and \(\Delta_{\mu_r}\) are positive constant step size for the subgradient method. For convex optimization problems, the subgradient method is guaranteed to converge for small step size and the proof of convergence can be found in [87]. The solution approach is summarized in Algorithm 2.

Algorithm 2 Proposed Joint Resource Allocation Scheme

Require: Initialize \(\lambda_k^{(it)}\), \(\mu_r^{(it)}\) for \(it = 1\).

1: repeat
2: Compute \(X_{k,r}^n\), \(\forall n, r, k\) using (3.21).
3: Determine \(s_{k,r}^n\), \(\forall n, r, k\) using (3.24).
4: Compute \(\tilde{P}_{k,r}^{n(1)}\) and \(\tilde{P}_{r,k,A}^{n(2)}\) using (3.18) and (3.19), respectively.
5: Determine \(P_{A}^{m}\) by solving the problem in (3.11) using interior-point method.
6: Compute \(\lambda_k^{(it+1)}\) and \(\mu_r^{(it+1)}\) using (3.25) and (3.26).
7: Assign \(it \leftarrow it + 1\).
8: until Convergence of \(g(\lambda, \mu)\).
3.4 Performance Evaluation Results

3.4.1 Simulation Parameters

Channel gain for the link between source and destination is computed as $h_{s,d} = R_f^2 10^{-3d - \alpha}$, where $d$ is the distance, path-loss attenuation factor is $\alpha = 2.7$ [82], and $R_f$ is Rayleigh distributed fading coefficient implying exponential distribution of $R_f^2$ with unit mean [88].

Reference path-loss at a distance of 1 m is 30 dB [82]. AWGN power is $10^{-11}$ W. The DEH time and the UIT time are defined as $\tau_e = 0.5$ and $\tau_t = 1$ second. Unless otherwise stated, energy harvesting efficiency is 50% and transmit power budget of the AP is 46 dBm. The maximum service distance of the network is 10 meters. Simulations are repeated over 1000 different random fading channels and the results are averaged.
3.4. Performance Evaluation Results

![Graph showing sum-throughput versus energy harvesting efficiency](image)

**Figure 3.3: Sum-throughput versus energy harvesting efficiency.**

### 3.4.2 Simulation Results

In Fig. 3.2, we analyze the sum-throughput performance of the proposed resource allocation scheme for different energy harvesting efficiency $\eta$, number of subchannels, and transmit power budget of the AP assuming $R = K = 4$. The sum-throughput performance of the system improves with increasing energy harvesting efficiency of the UEs. It is because, with higher energy harvesting efficiency, the nodes can harvest more energy and hence make uplink transmission/relaying with higher transmit power. Increase in transmit power budget of AP for downlink DEH phase leads to higher sum-throughput of the system. Similarly, the sum-throughput performance increases with increasing number of subchannels.

In Fig. 3.3, we plot the sum-throughput of the network against energy harvesting efficiency for $N = K = R = 4$. We also compare the performance of our proposed algorithm with two benchmark schemes. In downlink equal power allocation\[6\] (DEPA) scheme, transmit

---

6Note that, in comparison to the previous chapter, we have added Rayleigh distributed fading coefficient in computation of the channel gain in this chapter.

6Equal power allocation has been compared with optimal power allocation for UIT phase in the literature \[89\]. In this chapter, we compare the optimal power allocation with equal power allocation in downlink DEH phase.
3.4. Performance Evaluation Results

![System energy efficiency versus number of relays.](image)

**Figure 3.4: System energy efficiency versus number of relays.**

power of the AP is equally allocated among all subchannels and the uplink resource allocation is done optimally. In random relay and subchannel assignment (RRSA) scheme [89], the relay selection and subchannel assignment is performed randomly. We notice that, optimal relay selection and subchannel assignment remarkably improve the sum-throughput performance. In addition, joint downlink power allocation along with uplink resource allocation further improves the performance of the network. This shows the effectiveness of joint downlink and uplink resource allocation in wireless-powered networks.

In Fig. [3.4] the bar chart shows the average system energy efficiency for different number of relays in the network assuming $K = 4$ and $N = 8$. The performance of the proposed scheme is compared with the aforementioned benchmark schemes. System energy efficiency is mathematically defined as $R_{\text{sum}}/P_{\text{sum}}$, where $R_{\text{sum}}$ and $P_{\text{sum}}$ are the sum-throughput and sum-power consumption of the network, respectively. The total transmit power of the AP remains the same despite the increase in number of relays. However, with more relays present in the system, the achievable throughput of the network increases significantly. Therefore, the system energy efficiency improves with the increase in number of relay nodes.
3.4.3 Summary of Observations

Comparison of the proposed resource allocation algorithm with the benchmark schemes demonstrates the importance of joint consideration of DEH and UIT phase in resource allocation in the uplink WPC networks. Also the performance variation of the proposed algorithm with varying number of relays demonstrates the advantage of user-based cooperation in uplink WPC networks.
Chapter 4

Resource Allocation for Downlink SWIPT in Small Cells in a Two-Tier HetNet

As discussed in Chapter \[1\], wireless energy harvesting is studied in two different paradigms of wireless communication: (i) uplink WPC, and (ii) downlink SWIPT. In Chapters \[2\] and \[3\], we studied resource allocation in uplink WPC networks with relay-based and user-based cooperation. In this chapter, we consider downlink SWIPT and solve the resource allocation problem to obtain optimal rate-energy trade-off while addressing the interference management issues that arise when SWIPT is enabled in small cells of HetNets. The accomplished works and research contributions of this chapter are briefly described in the following.

4.1 Accomplished Works and Research Contributions

In this chapter, we investigate the problem of downlink resource allocation for SWIPT in small cells underlaying a macrocell (i.e. a co-channel deployment scenario) in a two-tier HetNet. Considering that current receiver circuits have separate information decoder and energy harvester, we consider both signal sharing approaches of SWIPT: time-switching and power-splitting. To obtain optimal rate-energy trade-off in SWIPT, we jointly allocate downlink transmit power of small cell base stations (SBSs) along with time-switching/power-splitting variables to optimize the throughput and energy harvesting rates of small cell UEs. To
4.1. Accomplished Works and Research Contributions

jointly optimize achievable throughput and energy harvesting rate of small cell UEs, we use scalarization technique of multi-objective programming. We formulate a resource allocation problem with the objective of maximizing the weighted sum of normalized throughput and energy harvesting rate.

In the time-switching approach, to address the challenge of interference management, we consider flexible interference tolerance levels in macrocell UEs to provide a degree of freedom for SBSs to adjust their transmit powers for information and power transfer. We jointly allocate downlink transmit power along with time-switching variables in two different scenarios: with negligible co-tier interference and with non-negligible co-tier interference. In both scenarios, the formulated problems are MINLP problems and we solve them by relaxing the binary integer constraint and then identifying the condition at which the obtained solution satisfies that constraint of the original problem. For the scenario with non-negligible co-tier interference, we propose a sub-optimal resource allocation framework based on iterative maximization of the minorant of the non-convex objective function. For the scenario with negligible co-tier interference, we determine the optimal resource allocation using convex optimization techniques. In the power-splitting approach, we propose a resource allocation framework, based on iterative maximization of the minorant of the non-convex objective function, to determine downlink transmit power and power-splitting variables, when co-tier interference is non-negligible.

The rest of the chapter is organized as follows. System model and assumptions are explained in Section 4.2. Sections 4.3 and 4.4 present problem formulations and solution approaches of resource allocation for the time-switching and power-splitting approaches of SWIPT. Performance evaluation results are presented in Section 4.5.
4.2 System Model and Assumptions

Two-tier HetNet model

We consider a two-tier HetNet with $S$ small cells underlaying a macrocell as shown in Fig. 4.1. We assume that small cells are deployed to serve sensor-like IoT devices with low power requirements while the macrocell UE may have high power requirement. The macrocell UE (MUE) is denoted by $u_m$ and served by the macrocell base station (MBS). The small cell UEs (SUEs) are denoted by $u_s$, $s \in \{1, 2, ..., S\}$ and served by an SBS in each small cell. We divide one transmission block of duration $T$ into $N$ time slots. The MUE and the SUEs are assumed to be active and associated to their serving base stations for the time period of consideration. Fading condition is assumed to be constant over each time slot. $h_{j,j}^t$ and $h_{j,k}^t$, $t \in \{1, 2, ..., N\}$, denote the channel gain of the link from base station $j$ to its UE $u_j$ and to UE $u_k$, served by base station $k$, respectively. MBS downlink transmit power is assumed to be $P_m^t = P_m$, $\forall t$. To simplify the exposition, without loss of generality, we assume that only one channel of bandwidth $B$ is available and hence shared by the macrocell and small cells to serve one UE in each cell during one transmission block.
4.2. System Model and Assumptions

SWIPT in small cells

As shown in Fig. [4.1], SWIPT is enabled in small cells. Assuming that the SUEs are sensor-like IoT devices with low power requirements, to elongate their battery life, they are considered to be capable of harvesting energy from the received signal. The energy harvested in one downlink transmission block can be stored in the battery for future or can be used in the next uplink transmission. Due to large transmission distance in macrocell and diverse power requirements of macrocell users, wireless energy harvesting is not considered in the MUE. With incorporation of SWIPT in small cells, we will investigate two signal sharing approaches: time-switching and power-splitting. As shown in Fig. [4.1] the MUE receives cross-tier interference from the SBS transmission (both information and power transmission). Therefore, to maximize wireless power transfer while guaranteeing QoS provisioning to the MUE, in time-switching approach, we assume flexible interference tolerance in MUE. To maximize the benefit of such flexible interference tolerance of MUE, we assume that energy harvesting (EH) and information decoding (ID) phase of all the SUEs are synchronized. If interference tolerance of MUE is high in EH phase and all SUEs are harvesting energy, then the transmit power of SBSs can be increased to allow significant wireless power transfer. The interference tolerance level of MUE can then be lowered in ID phase to ensure QoS provisioning to the MUE despite the corresponding loss of throughput in EH phase. However, optimal mode selection and resource allocation is crucial to ensure that minimum throughput requirement of MUE is satisfied while optimal trade-off is achieved for SUEs.

Next we will formulate the expressions of achievable throughput and energy harvesting rate of SUEs with time-switching and power-splitting approaches of SWIPT.

Time-switching approach

Let us assume that, in each time slot, the SUEs either decode information or harvest energy from the received signal. $\alpha_t^I$ and $\alpha_t^E$ are time-switching variables where $\alpha_t^I = 1$ in ID mode, and $\alpha_t^E = 1$ in EH mode such that $\alpha_t^I + \alpha_t^E \leq 1$, $\forall t$. $P_{s,t}^d$ denotes downlink transmit power
4.2. System Model and Assumptions

of SBS $s$ in time slot $t$ in ID mode and $P_{s,E}^t$ denotes that in EH mode. Let $R_{\text{tar}}$ and $E_{\text{tar}}$ denote the target throughput and energy harvesting rate of the SUEs in bits per second per Hertz (bps/Hz) and Joules per second (Jps), respectively. Let $R_{\text{min}}$ be the minimum throughput requirement of the MUE. In order to give an extra degree of freedom for SBSs to adjust the transmit powers in EH and ID mode, let us define following two parameters: $R_{\text{min,E}}$ is the minimum throughput ensured in the MUE during EH mode and $R_{\text{min,I}}$ is that during ID mode. The achievable throughput of the MUE over one transmission period is then given by

$$R_m = \sum_{t=1}^{N} \left( \alpha_t^I R_{\text{min,I}} + \alpha_t^E R_{\text{min,E}} \right).$$

Note that for a given transmit power of the MBS, to achieve the above rate, the interference caused by the SBSs will need to be controlled accordingly. The achievable throughput and energy harvesting rate of SUEs, over one transmission period, are given by

$$R_s = \sum_{t=1}^{N} \frac{\alpha_t^I}{N} \log_2 \left( 1 + \frac{P_{s,I}^t h_{s,s}^t}{\sum_{j=1,j\neq s}^{S} P_{j,I}^t h_{j,s}^t + \chi_{m,s}^t + N_{sp}} \right), \forall s \quad (4.1)$$

$$E_s = \sum_{t=1}^{N} \frac{\alpha_t^E \eta}{N} \left( \sum_{j=1}^{S} P_{j,E}^t h_{j,s}^t + \chi_{m,s}^t \right), \forall s \quad (4.2)$$

where $\chi_{m,s}^t = P_m h_{m,s}^t + N_w$, and $\eta$ is energy harvesting efficiency. $N_w$ and $N_{sp}$ are antenna noise power and signal processing noise power respectively. Note that SUEs harvest energy from signal transmitted by their serving SBSs, co-tier interference signal transmitted by other SBSs, cross-tier interference signal transmitted by the MBS (Fig. 4.1) as well as antenna noise.

**Power-splitting approach**

In power-splitting approach, each SUE splits power of the received signal into two fractions and shares it among information decoder and energy harvester. Let us assume that in each time slot, each SUE uses $\rho_{I(s)}^t$ fraction of signal power for ID process and $\rho_{E(s)}^t$ for EH process. Antenna noise and signal processing noise are both assumed to be AWGN. However, antenna noise is introduced in the RF band while signal processing noise is introduced during RF band to baseband conversion for information decoding [20].
such that $\rho^I_t(s) + \rho^E_t(s) \leq 1$, $\forall t, s$. $P^t_s$ denotes downlink transmit power of SBS $s$ in time slot $t$. To maintain consistency with time-switching approach, we assume that $\rho^I_t(s) = \rho^I_t$ and $\rho^E_t(s) = \rho^E_t$, $\forall s$. In this case, the achievable throughput and energy harvesting rate of SUEs are given by

\[
R_s = \sum_{t=1}^{N} \frac{1}{N} \log_2 \left( 1 + \frac{\rho^I_t P^t_s h^t_{s,s}}{\rho^I_t \left( \sum_{j=1, j\neq s}^{S} P^t_j h^t_{j,s} + \chi^t_{m,s} \right) + N_{sp}} \right), \forall s \tag{4.3}
\]

\[
E_s = \sum_{t=1}^{N} \frac{\rho^E_t \eta}{N} \left( \sum_{j=1}^{S} P^t_j h^t_{j,s} + \chi^t_{m,s} \right), \forall s. \tag{4.4}
\]

Note that, unlike time-switching approach, EH and ID processes are not separated in time domain in power-splitting approach, and hence $R_{(min)}$ is the minimum throughput that should be ensured for the MUE in each time slot. In other words, power-splitting approach lacks that additional degree of freedom which we have exploited in time-switching approach. The comparison of time-switching and power-splitting approaches is even more important in multi-tier network due to this inherent difference between the two approaches.

In this chapter, we optimize downlink transmit powers and time-switching/power-splitting variables to maximize the achievable throughput as well as energy harvesting rate of each SUE over one transmission block. This requires a multi-objective programming approach. In this work, we use scalarization method of solving multi-objective programming problem to formulate a single objective function \[90\]. The target throughput and energy harvesting rate of SUEs are $R_{(tar)}$ and $E_{(tar)}$, respectively. Following scalarization method, the combined single objective is to maximize the weighted sum of normalized throughput and energy harvesting rate where $R_{(tar)}$ and $E_{(tar)}$ are used for normalization. The weighted sum of normalized throughput and energy harvesting rate of each SUE is given by $w_{s,I} \frac{R_s}{R_{(tar)}} + w_{s,E} \frac{E_s}{E_{(tar)}}$, where $w_{s,I}$ and $w_{s,E}$ are weights that indicate the priority of each SUE for throughput performance and energy harvesting rate performance, respectively. The weights $w_{s,I}$ and $w_{s,E}$

\[8\]Note that the power splitter is assumed to be an ideal passive device that does not introduce any splitting loss or noise \[13,62\].
are assumed to remain constant over one transmission block and can be determined at the beginning of each transmission block, depending on various factors such as energy remaining in the battery, energy leakage in the battery, scheduled future uplink transmissions of the SUE, and so on.

Remark 1: Note that the proposed system model can be extended to multi-user and multichannel scenario in each cell. In that case, optimization of subcarrier allocation is also required along with downlink transmit power and time-switching/power-splitting variables. However, to simplify the exposition, we assume a single channel system without explicitly considering user scheduling.

Now that we have formulated the expressions of throughput and energy harvesting rate we will discuss resource allocation problems and the corresponding solution approaches for both time-switching and power-splitting approaches of SWIPT in the next sections.

4.3 Resource Allocation for Time-switching Approach: Problem Formulations and Solutions

In this section, we will formulate resource allocation problems to jointly optimize time-switching variables along with downlink transmit power of SBSs to maximize the weighted sum of normalized throughput and energy harvesting rate of SUEs over one transmission block. The optimization problem is formulated as follows:

\[
\text{maximize}_{P_I, P_E, \alpha_I, \alpha_E} \sum_{s=1}^{S} \left( w_s, I \frac{R_s}{R_{(t, r)}} + w_s, E \frac{E_s}{E_{(t, r)}} \right) \\
\text{subject to} \quad \begin{align*}
C_1 & : \alpha^t_I, \alpha^t_E \in \{0, 1\}, \forall t \\
C_2 & : \alpha^t_I + \alpha^t_E \leq 1, \forall t
\end{align*}
\]  

(4.5)
4.3. Resource Allocation for Time-switching Approach: Problem Formulations and Solutions

\[ C_3 : \alpha_t I \left( \sum_{s=1}^{S} P_{s,I} h_{s,m}^t - I_{max,I}^t \right) \leq 0, \forall t \]

\[ C_4 : \alpha_E I \left( \sum_{s=1}^{S} P_{s,E} h_{s,m}^t - I_{max,E}^t \right) \leq 0, \forall t \]

\[ C_5 : \sum_{t=1}^{N} \frac{1}{N} (\alpha_t^I R_{(min,I)} + \alpha_t^E R_{(min,E)}) \geq R_{(min)} \]

\[ C_6 : P_{s,I}^t, P_{s,E}^t \leq P_{s}(max), \forall s, t \]

\[ C_7 : P_{s,I}^t, P_{s,E}^t \geq 0, \forall s, t \]

where \( P_I = \{P_{s,I}^t, \forall s, t\} \), \( P_E = \{P_{s,E}^t, \forall s, t\} \), \( \alpha_I = \{\alpha_t^I, \forall t\} \), \( \alpha_E = \{\alpha_t^E, \forall t\} \), \( I_{max,I}^t = \frac{P_m h_{m,m}^t}{2^{R_{(min,I)}-1}} - N_w - N_{sp} \), and \( I_{max,E}^t = \frac{P_m h_{m,m}^t}{2^{R_{(min,E)}-1}} - N_w - N_{sp} \). \( C_1 \) is binary integer constraint on time-switching variables. \( C_2 \) ensures that SUEs are either in EH or ID mode, but not both. \( C_3 \) ensures that if SUEs are in ID mode, the sum interference received by the MUE is not higher than \( I_{max,I}^t \) in each time slot. \( C_4 \) imposes similar constraint in EH mode. \( C_5 \) ensures that throughput of the MUE over one transmission block is greater than or equal to \( R_{(min)} \). \( C_6 \) and \( C_7 \) are boundary constraints on power variables. The problem in (4.5) is not convex due to the presence of interference terms in \( R_s \) and is an MINLP problem due to constraint \( C_1 \). Such a problem is difficult to solve in its original form. To make the problem tractable, we relax the time-switching variables as \( 0 \leq \alpha_t^I, \alpha_t^E \leq 1 \). Note that this relaxation will allow the system to operate in both EH and ID mode in any time slot by sharing the time available in that slot, according to the factor \( \alpha_t^E \) and \( \alpha_t^I \), which is possible to implement. We also define auxiliary power variables as

\[ \tilde{P}_{s,I}^t = \alpha_t^I P_{s,I}^t, \quad \tilde{P}_{s,E}^t = \alpha_t^E P_{s,E}^t, \forall s, t. \] (4.6)

It should be noted that, despite the relaxation, the problem is still non-convex due to interference terms in the denominator. Now, we will solve the problem in two scenarios. Note that co-tier interference can be negligible due to heavy wall losses in indoor deployment of
small cells. First, we will solve the problem for the scenario where co-tier interference among small cells is negligible. However, co-tier interference may not be negligible in outdoor deployment of small cells. Therefore, we will also provide a sub-optimal solution approach for the case with non-negligible co-tier interference.

4.3.1 Scenario I: Negligible Co-tier Interference

Using (4.6) and discarding the co-tier interference terms, the throughput and energy harvesting rate of SUEs given in (4.1) and (4.2) can be respectively re-written as

\[
\tilde{R}_s = \sum_{t=1}^{N} \frac{\alpha^t}{N} \log_2 \left( 1 + \frac{\tilde{P}^t_{s,I} h^t_{s,m}}{\alpha^t I \left( \chi^t_{m,s} + N_{sp}^t \right)} \right), \quad \forall s
\]

\[
\tilde{E}_s = \sum_{t=1}^{N} \frac{\eta}{N} \left( \tilde{P}^t_{s,E} h^t_{s,m} + \alpha^t E \chi^t_{m,s} \right), \quad \forall s.
\]

Using (4.6) and (4.7), the optimization problem in (4.5) can be re-written as

\[
\begin{align*}
\text{maximize} & \quad \sum_{s=1}^{S} \left( w_{s,I} \frac{\tilde{R}_s}{R_{(tar)}} + w_{s,E} \frac{\tilde{E}_s}{E_{(tar)}} \right) \\
\text{subject to} & \quad C_2, C_5 \\
& \quad \tilde{C}_1 : 0 \leq \alpha^t_{I}, \alpha^t_{E} \leq 1, \quad \forall t \\
& \quad \tilde{C}_3 : \sum_{s=1}^{S} \tilde{P}^t_{s,I} h^t_{s,m} - \alpha^t_{I} P_{s(max)}^t \leq 0, \quad \forall t \\
& \quad \tilde{C}_4 : \sum_{s=1}^{S} \tilde{P}^t_{s,E} h^t_{s,m} - \alpha^t_{E} P_{s(max)}^t \leq 0, \quad \forall t \\
& \quad \tilde{C}_6 : \tilde{P}^t_{s,I} - \alpha^t_{I} P_{s(max)}^t \leq 0, \quad \forall s, t \\
& \quad \tilde{C}_7 : \tilde{P}^t_{s,E} - \alpha^t_{E} P_{s(max)}^t \leq 0, \quad \forall s, t \\
& \quad \tilde{C}_8 : \tilde{P}^t_{s,I}, \tilde{P}^t_{s,E} \geq 0, \quad \forall s, t
\end{align*}
\]

where \( \tilde{P}_I = \{ \tilde{P}^t_{s,I}, \forall s, t \} \) and \( \tilde{P}_E = \{ \tilde{P}^t_{s,E}, \forall s, t \} \). The constraints have been modified according to the definition of auxiliary variables in (4.6). Note that constraints \( \tilde{C}_6 \) and \( \tilde{C}_7 \)
4.3. Resource Allocation for Time-switching Approach: Problem Formulations and Solutions

ensure that auxiliary power variables $\tilde{P}_{s,I}$ and $\tilde{P}_{s,E}$ are zero if time-switching variables $\alpha_{t}^{I}$ and $\alpha_{t}^{E}$ are zero, respectively. Since $\log_2 \left( 1 + \frac{\tilde{P}_{s,I} h_{s,s}^{t}}{\lambda_{m,s} + N_{sp}} \right)$ is a concave function of $\tilde{P}_{s,I}$, $\frac{\alpha_{t}^{I}}{N} \log_2 \left( 1 + \frac{\tilde{P}_{s,I} h_{s,s}^{t}}{\alpha_{t}^{I} (\lambda_{m,s} + N_{sp})} \right)$ can be proven to be a concave function of $\tilde{P}_{s,I}$ and $\alpha_{t}^{I}$ by using perspective operation [80] and therefore $\tilde{R}_s$ becomes a sum of concave functions. Since $\tilde{R}_s$ is a concave function and $\tilde{E}_s$ is a linear function of the optimization variables, the objective function of the problem in (4.8) is concave, and the constraints are affine. Therefore, it is a convex optimization problem which can be solved optimally using convex optimization techniques [80]. The partial Lagrangian of the problem is given by

$$
\mathcal{L} \left( \tilde{P}_I, \tilde{P}_E, \alpha_I, \alpha_E, \lambda, \gamma \right) = \sum_{s=1}^{S} \left( w_{s,I} \frac{\tilde{R}_s}{R_{(tar)}} + w_{s,E} \frac{\tilde{E}_s}{E_{(tar)}} \right) - \sum_{t=1}^{N} \lambda^t \left( \alpha_{t}^{I} + \alpha_{t}^{E} - 1 \right) - \sum_{t=1}^{N} \gamma^t \left( \sum_{s=1}^{S} \tilde{P}_{s,I}^{t} h_{s,m}^{t} - \alpha_{t}^{I} I_{max,I}^{t} \right)
$$

(4.9)

where $\lambda, \gamma$ are non-negative Lagrange multipliers associated with constraints $C_2$ and $C_3$, respectively. Other constraints are not included in the Lagrangian and will be satisfied later. Since the problem in (4.8) is a convex optimization problem, the solution can be obtained by solving the following dual problem [80]:

$$
\min_{\lambda, \gamma} \max_{\tilde{P}_I, \tilde{P}_E, \alpha_I, \alpha_E} \mathcal{L} \left( \tilde{P}_I, \tilde{P}_E, \alpha_I, \alpha_E, \lambda, \gamma \right) \quad (4.10)
$$

subject to $C_1, C_4, C_5, C_6 - C_8, \lambda, \gamma \geq 0$.

The solution of the dual problem in (4.10) can be iteratively obtained by dual decomposition technique [85]. In each iteration, for given dual variables (Lagrange multipliers), the subproblems are solved to obtain the primal variables (power and time-switching variables). Then the master problem updates the dual variables using the solution of the subproblems. The iterative procedure is continued till convergence is attained.
4.3. Resource Allocation for Time-switching Approach: Problem Formulations and Solutions

Solving the subproblem

When the dual variables are known, to solve for the primal variables, we will exploit the fact that for a convex optimization problem, at optimality, KKT conditions must be satisfied [80]. Based on the KKT conditions, we can verify that, at optimality, time-switching variables $\alpha^t_I$, $\alpha^t_E$, and auxiliary power variables $\tilde{P}^t_{s,I}$ are related to each other as follows:

$$\alpha^t_E = 1 - \alpha^t_I, \forall t \quad (4.11)$$

$$\tilde{P}^t_{s,I} = \alpha^t_I \left[ \frac{w_{s,I}}{\gamma^t h^t_{s,m} N\log(2)} - \frac{\chi^t_m + N_{sp}}{h^t_{s,s}} \right]_0^{P_{s(max)}}, \forall s, t \quad (4.12)$$

where $[x]_a^b$ indicates $x = a$ if $x > a$ and $x = b$ if $x < b$. (4.11) and (4.12) are obtained by simplifying the KKT conditions and the details of derivation are shown in Appendix D. Note that boundary constraints $\tilde{C}_6$ and $\tilde{C}_8$ are included in (4.12).

Using the relation of optimization variables given in (4.11) and (4.12), we can re-write the subproblem of the dual problem given in (4.10) as

$$\begin{aligned}
\text{maximize} & \quad \sum_{t=1}^{N} \left( \alpha^t_I \tilde{R}^t_{sum} + \sum_{s=1}^{S} \tilde{P}^t_{s,E} H^t_{s,s} \right) \\
\text{subject to} & \quad \tilde{C}_1 : 0 \leq \alpha^t_I \leq 1, \forall t \\
& \quad \tilde{C}_4 : \sum_{s=1}^{S} \tilde{P}^t_{s,E} h^t_{s,m} \leq (1 - \alpha^t_I) I_{s(max),E}, \forall t \\
& \quad \tilde{C}_5 : \sum_{t=1}^{N} \alpha^t_I \geq \Upsilon_{(min)} \\
& \quad \tilde{C}_7 : \tilde{P}^t_{s,E} \leq (1 - \alpha^t_I) P_{s(max)}, \forall s, t \\
& \quad \tilde{C}_8 : \tilde{P}^t_{s,E} \geq 0, \forall s, t,
\end{aligned} \quad (4.13)$$


$$\tilde{R}^t_{sum} = \sum_{s=1}^{S} \left[ \frac{w_{s,I}}{NR_{(tar)}} \log_2 \left( 1 + \frac{\tilde{P}^t_{s,I} h^t_{s,s}}{w_{s,I} \chi^t_m + N_{sp}} \right) - \frac{w_{s,E} \chi^t_m \eta}{N E_{(tar)}} - \gamma^t h^t_{s,m} \tilde{P}^t_{s,I} \right] + \gamma^t I_{s(max),I}, \forall t,$$
4.3. Resource Allocation for Time-switching Approach: Problem Formulations and Solutions

\[ H_{s,s}^t = \frac{\eta_{w_s,E} h_{s,s}^t}{N E_{(\text{tar})}}, \forall s,t, \]
\[ \hat{P}_{s,t} = \left( \frac{w_{s,I}}{\gamma_{m,s} N \log(2) R_{(\text{tar})}} - \frac{\chi_{t,m,s} + N_{sp}}{h_{s,s}^t} \right)_0, \forall s,t, \]
\[ \Upsilon_{(\text{min})} = \frac{N \left( R_{(\text{min})} - R_{(\text{min,E})} \right)}{(R_{(\text{min,I})} - R_{(\text{min,E})})}, \]

and the constant terms are removed from the objective function. It should be noted that the constraints \( \hat{C}_1, \hat{C}_4, \hat{C}_5, \hat{C}_7, \) and \( \hat{C}_8 \) are derived from the constraints of the problem in (4.10) using (4.11). Note that the constraint \( \hat{C}_5 \) now dictates the minimum amount of time that should be allocated for ID process in order to ensure that minimum throughput requirement of the MUE is satisfied. The problem in (4.13) is a linear programming problem and can be solved optimally by using interior-point method.

**Lemma 7**: If \( \Upsilon_{(\text{min})} \) is an integer, then the resulting solution satisfies constraint \( C_1 \) of the original optimization problem in (4.5), and therefore, is the optimal solution of the original problem [91].

**Proof**: First, let us assume that the optimal solution has only one non-integer time-switching variable \( 0 < \alpha_t^t < 1 \), for \( t = t_1 \) and all the constraints are satisfied. In that case, if \( \Upsilon_{(\text{min})} \) is an integer and \( \hat{C}_5 \) has been satisfied, \( \sum_{t=1,t\neq t_1}^N \alpha_t^t = \Upsilon_{(\text{min})} \). To prove that the optimal solution always has integer time-switching variables, we will prove that the non-integer solution is not the optimal solution, by contradiction. Let us explore three different cases now.

**Case I**: Let us say \( \tilde{R}_{\text{sum}}^t > \alpha_t^t \tilde{R}_{\text{sum}}^t \sum_{s=1}^S \tilde{P}_{s,E}^t h_{s,s}^t \Rightarrow \tilde{R}_{\text{sum}}^t > \sum_{s=1}^S \frac{\tilde{P}_{s,E}^t}{1-\alpha_t^t} h_{s,s}^t \), then increasing \( \alpha_t^t \) to \( \alpha_t^{s_1} = 1 \) will force \( \tilde{P}_{s,E}^t \) to be \( \tilde{P}_{s,E}^t = 0, \forall s \) (due to constraint \( \hat{C}_7 \)) and will further maximize the objective function. It can be verified that the new solution will also satisfy all the constraints of the problem.

**Case II**: On the other hand, if \( \tilde{R}_{\text{sum}}^t < \alpha_t^t \tilde{R}_{\text{sum}}^t \sum_{s=1}^S \tilde{P}_{s,E}^t h_{s,s}^t \Rightarrow \tilde{R}_{\text{sum}}^t < \sum_{s=1}^S \frac{\tilde{P}_{s,E}^t}{1-\alpha_t^t} h_{s,s}^t \), then decreasing \( \alpha_t^t \) to \( \alpha_t^{s_1} = 0 \) zero will increase \( \tilde{P}_{s,E}^t \) to \( \tilde{P}_{s,E}^t = \frac{\tilde{P}_{s,E}^t}{1-\alpha_t^t}, \forall s \) (on account of constraint \( \hat{C}_7 \)) and will further maximize the objective function. It can be verified that the
new solution will also satisfy all constraints of the problem.

Case III: If $\tilde{P}_{t,1} = \alpha_{t,1} \tilde{P}_{sum} + \sum_{s=1}^{S} \tilde{P}_{t,s,E} H_{s,s}$, then setting either $\alpha_{t,1} = 0$ or $\alpha_{t,1} = 1$ will imply corresponding change in $\tilde{P}_{t,s,E}$, but the objective function will remain the same and all constraints of the problem will remain satisfied.

By these three cases, we prove by contradiction that the solution with one non-integer time-switching variable is not the optimal solution. Similar argument can be used to prove that the solution with two non-integer time-switching variables is also not the optimal solution, and so on. Therefore, we prove by contradiction, that the solution of the problem in (4.13) will satisfy binary integer constraint $C_1$ of the original optimization problem and hence is the optimal solution of the original problem, if $\Upsilon_{(min)}$ is an integer. This completes the proof.

□

Solving the master problem

The optimal value of dual variables can be obtained by using well-known subgradient method [87] to update the dual variables as follows:

$$
\gamma^{t(t+1)} = \left[ \gamma^{t(it)} + \Delta_{\gamma} \left( \sum_{s=1}^{S} \tilde{P}_{t,s,E} h_{s,m}^{t} - \alpha_{t,I} T_{max,I}^{t} \right) \right]^{+}, \forall t
$$

(4.14)

where $\Delta_{\gamma}$ is the step size and $[x]^{+}$ enforces the non-negativity constraint on dual variables. Updated dual variables are then used to obtain new solution for the subproblems. This process is iterated until convergence. Convergence of subgradient method to the globally optimal solution is guaranteed for convex optimization problem for small step size [87].

After obtaining optimal solution, the optimal power allocation can be recovered by using the relation in (4.6).
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4.3.2 Scenario II: Non-negligible Co-tier Interference

In this scenario, we assume that the co-tier interference is non-negligible. In this case, before relaxing the time-switching variables and using the auxiliary power variables given in (4.6), let us re-write the problem in (4.5) as

\[
\begin{align*}
\text{maximize} & \quad \sum_{t=1}^{N} \left( f(P_{1}^{t}, P_{E}^{t}, \alpha_{I}^{t}, \alpha_{E}^{t}) - g(P_{1}^{t}, \alpha_{I}^{t}) \right) \\
\text{subject to} & \quad C_{1} - C_{7}
\end{align*}
\]

where \( P_{1}^{t} = \{ P_{s,I}^{t}, \forall s \} \), \( P_{E}^{t} = \{ P_{s,E}^{t}, \forall s \} \), \( t \), and

\[
\begin{align*}
f(P_{1}^{t}, P_{E}^{t}, \alpha_{I}^{t}, \alpha_{E}^{t}) &= \sum_{s=1}^{S} \frac{w_{s,I}^{t} \alpha_{I}^{t}}{NR_{(tar)}} \log_{2} \left( \sum_{j=1}^{S} P_{j,I}^{t} h_{j,s}^{t} + \chi_{m,s}^{t} + N_{sp} \right) \\
&\quad + \frac{w_{s,E}^{t} \alpha_{E}^{t} \eta}{NE_{(tar)}} \left( \sum_{j=1}^{S} P_{j,E}^{t} h_{j,s}^{t} + \chi_{m,s}^{t} \right), \forall t
\end{align*}
\]

\[
\begin{align*}
g(P_{1}^{t}, \alpha_{I}^{t}) &= \sum_{s=1}^{S} \frac{w_{s,I}^{t} \alpha_{I}^{t}}{NR_{(tar)}} \log_{2} \left( \sum_{j=1, j \neq s}^{S} P_{j,I}^{t} h_{j,s}^{t} + \chi_{m,s}^{t} + N_{sp} \right), \forall t.
\end{align*}
\]

Now, let us relax the time-switching variables and use the definition of auxiliary power variables given in (4.6). With the auxiliary power variables, (4.16) and (4.17) can be re-written as

\[
\begin{align*}
f(\tilde{P}_{1}^{t}, \tilde{P}_{E}^{t}, \alpha_{I}^{t}, \alpha_{E}^{t}) &= \sum_{s=1}^{S} \frac{w_{s,I}^{t} \alpha_{I}^{t}}{NR_{(tar)}} \log_{2} \left( \sum_{j=1}^{S} \frac{\tilde{P}_{j,I}^{t} h_{j,s}^{t}}{\alpha_{I}^{t}} + \chi_{m,s}^{t} + N_{sp} \right) \\
&\quad + \frac{w_{s,E}^{t} \alpha_{E}^{t} \eta}{NE_{(tar)}} \left( \sum_{j=1}^{S} \frac{\tilde{P}_{j,E}^{t} h_{j,s}^{t}}{\alpha_{E}^{t}} + \chi_{m,s}^{t} \right), \forall t
\end{align*}
\]

\[
\begin{align*}
g(\tilde{P}_{1}^{t}, \alpha_{I}^{t}) &= \sum_{s=1}^{S} \frac{w_{s,I}^{t} \alpha_{I}^{t}}{NR_{(tar)}} \log_{2} \left( \sum_{j=1, j \neq s}^{S} \frac{\tilde{P}_{j,I}^{t} h_{j,s}^{t}}{\alpha_{I}^{t}} + \chi_{m,s}^{t} + N_{sp} \right), \forall t.
\end{align*}
\]

where \( \tilde{P}_{1}^{t} = \{ \tilde{P}_{s,I}^{t}, \forall s \} \) and \( \tilde{P}_{E}^{t} = \{ \tilde{P}_{s,E}^{t}, \forall s \}, \forall t \). It should be noted that \( f(\tilde{P}_{1}^{t}, \tilde{P}_{E}^{t}, \alpha_{I}^{t}, \alpha_{E}^{t}) \) and \( g(\tilde{P}_{1}^{t}, \alpha_{I}^{t}) \) can both be proven to be concave functions of \( \tilde{P}_{s,I}^{t}, \tilde{P}_{s,E}^{t}, \alpha_{I}^{t}, \) and \( \alpha_{E}^{t} \) due...
to concavity of perspective operation and concavity of log function. Therefore, problem
in (4.15) can be re-written, with difference of concave functions in the objective, as follows:

$$\max_{\tilde{P}_I, \tilde{P}_E, \alpha_I, \alpha_E} \sum_{t=1}^{N} \left( \tilde{f}(\tilde{P}_I, \tilde{P}_E, \alpha_I, \alpha_E) - \tilde{g}(\tilde{P}_I, \alpha_I) \right)$$

(4.20)

subject to $\tilde{C}_1, C_2, \tilde{C}_3, C_4, \tilde{C}_6 - \tilde{C}_8$. The constraints of the problem in (4.20) are same as that of the modified problem in (4.8) of Scenario I and derived in a similar manner. We know that the constraints are affine but
the objective function is neither concave nor convex. Finding the optimal solution to such
a problem is difficult in its original form. However, we can find suboptimal solution to the
problem in (4.20) by using successive convex approximation method where we iteratively
maximize the concave minorant [92–94] of the objective function. First of all, we will define
the concave minorant in the following definition.

**Definition 1**: Since $\tilde{g}(X^t)$ is a concave function, it is upper bounded by its first-order
Taylor approximation $\tilde{g}(X^t(k)) + \nabla \tilde{g}(X^t(k))^\top (X^t - X^t(k))$, and therefore, $\tilde{f}(X^t, Y^t) - \tilde{g}(X^t)$
is bounded below by its concave minorant $\tilde{f}(X^t, Y^t) - \tilde{g}(X^t(k)) - \nabla \tilde{g}(X^t(k))^\top (X^t - X^t(k))$ in
the neighborhood of $X^t(k)$ [92,94] as

$$\tilde{f}(X^t, Y^t) - \tilde{g}(X^t) \geq \tilde{f}(X^t, Y^t) - \tilde{g}(X^t(k)) - \nabla \tilde{g}(X^t(k))^\top (X^t - X^t(k))$$

(4.21)

where $X^t = \{\alpha^t_I, \tilde{P}_I^t, \forall s\}$, $Y^t = \{\alpha^t_E, \tilde{P}_E^t, \forall s\}$ are used for simplicity and conciseness of the
expression.

We know that

$$\nabla \tilde{g}(X^t(k))^\top (X^t - X^t(k)) = \sum_{s=1}^{S} U_s(\tilde{P}_I^t(k), \alpha_I^t(k)) (\tilde{P}_I^t - \tilde{P}_I^t(k)) + V(\tilde{P}_I^t(k), \alpha_I^t(k)) (\alpha_I^t - \alpha_I^t(k))$$
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where

\[ U_s(\tilde{P}_t^l, \alpha_t^l) = \frac{\partial \tilde{g}(\tilde{P}_t^l, \alpha_t^l)}{\partial \tilde{P}_{s,t}^l} = \sum_{l=1, l \neq s}^S \frac{w_{t,l} h_{t,l}^l}{NR_{(tar)}} \log(2) \left( \sum_{j=1, j \neq l}^S \frac{\tilde{P}_{t,j}^l h_{t,j}^l}{\alpha_t^l} + \chi_{t,m,l}^l + N_{sp} \right), \forall s \]

\[ V(\tilde{P}_t^l, \alpha_t^l) = \frac{\partial \tilde{g}(\tilde{P}_t^l, \alpha_t^l)}{\partial \alpha_t^l} = \sum_{s=1}^S \frac{w_{s,t}}{NR_{(tar)}} \left[ - \sum_{j=1, j \neq s}^S \frac{\tilde{P}_{t,j}^l h_{t,j}^s}{\alpha_t^l} \log(2) \left( \sum_{j=1, j \neq s}^S \frac{\tilde{P}_{t,j}^l h_{t,j}^s}{\alpha_t^l} + \chi_{t,m,s}^l + N_{sp} \right) \right. \\
+ \log(2) \left( \sum_{j=1, j \neq s}^S \frac{\tilde{P}_{t,j}^l h_{t,j}^s}{\alpha_t^l} + \chi_{t,m,s}^l + N_{sp} \right) \right]. \]

Therefore, we can write the concave minorant of the objective function as

\[ \Phi^{(k)}_{TS}(\tilde{P}_1^l, \tilde{P}_E^l, \alpha_I^l, \alpha_E^l) = \sum_{t=1}^N \left( \tilde{f}(\tilde{P}_1^l, \tilde{P}_E^l, \alpha_I^l, \alpha_E^l) - \tilde{g}(\tilde{P}_1^{(k)} I, \alpha_I^{(k)}) - \sum_{s=1}^S U_s(\tilde{P}_t^{(k)} I, \alpha_t^{(k)}) (\tilde{P}_{s,t}^l - \tilde{P}_{t,s}^{(k)}) - V(\tilde{P}_1^{(k)} I, \alpha_I^{(k)}) (\alpha_t^l - \alpha_t^{(k)}) \right). \] (4.22)

Now we will define the following convex subproblem to maximize the concave minorant of the objective function in the neighborhood of \((\tilde{P}_1^l, \alpha_I^l)\):

\[ \begin{align*}
\text{maximize} & \quad \Phi^{(k)}_{TS}(\tilde{P}_1^l, \tilde{P}_E^l, \alpha_I^l, \alpha_E^l) \\
\text{subject to} & \quad \tilde{C}_1, C_2, \tilde{C}_3, C_4, C_5, \tilde{C}_6 - \tilde{C}_8.
\end{align*} \] (4.23)

Maximizing the concave minorant

We know that subproblem defined in (4.23) is a convex optimization problem with affine constraints. Therefore, it can be solved optimally using convex optimization techniques \[80\].
Let us define the partial Lagrangian of the problem as

\[ L(k)(\tilde{P}_I, \tilde{P}_E, \alpha_I, \alpha_E, \lambda, \gamma) = \Phi_{TS}^{(k)}(\tilde{P}_I, \tilde{P}_E, \alpha_I, \alpha_E) - \sum_{t=1}^{N} \lambda^t (\alpha^t_I + \alpha^t_E - 1) - \sum_{t=1}^{N} \gamma^t \left( \sum_{s=1}^{S} \tilde{P}_{s,t}^t h_{s,m}^t - \alpha^t_I r_{\max,I}^t \right) \]  \hspace{1cm} (4.24)

where \( \lambda, \gamma \) are non-negative Lagrange multipliers associated with constraints \( C_2 \) and \( \tilde{C}_3 \) as in Scenario I. Other constraints are not included in the Lagrangian and will be satisfied later. Since the problem in (4.23) is convex, the solution can be obtained by solving the following dual problem [80]:

\[
\text{minimize} \quad \lambda, \gamma \quad \text{max} \quad \tilde{P}_I, \tilde{P}_E, \alpha_I, \alpha_E \quad L(k)(\tilde{P}_I, \tilde{P}_E, \alpha_I, \alpha_E, \lambda, \gamma) \\
\text{subject to} \quad \tilde{C}_1, \tilde{C}_4, C_5, \tilde{C}_6 - \tilde{C}_8, \lambda, \gamma \succeq 0. 
\]  \hspace{1cm} (4.25)

The solution of dual problem in (4.25) can be iteratively obtained by dual decomposition technique [85]. For given dual variables, the subproblems are solved to obtain the optimal power and time-switching variables. Then the master problem updates the dual variables using the solution of the subproblems. The iterative procedure is continued until convergence.

**Solving the subproblem**

As in Scenario I, to solve for the primal variables, we will exploit the fact that for convex optimization problem, at optimality, KKT conditions [80] must be satisfied. Based on the KKT conditions, we can verify that, at optimality, the time-switching variables and auxiliary power variables are related to each other as follows:

\[ \alpha^t_E = 1 - \alpha^t_I, \; \forall t \]  \hspace{1cm} (4.26)

\[ \tilde{P}_{s,t}^t = \alpha^t_I x_{s,t}^t P_s^{(\max)}, \forall s, t \]  \hspace{1cm} (4.27)
4.3. Resource Allocation for Time-switching Approach: Problem Formulations and Solutions

where \( x^t_s \) is the solution of \( S \times N \) equations given as

\[
\sum_{l=1}^{S} \frac{w_{t,I} h_{s,l}}{NR(tar) \log(2) \left( \sum_{j=1}^{S} x^t_j h_{j,l}^t + \chi_{m,l}^t + N_{sp} \right)} - U_s(\tilde{P}_1^{(k)}, \alpha_I^{(k)}) - \gamma^t h_{s,m}^t = 0, \forall s, t. \tag{4.28}
\]

(4.28) is obtained by simplifying the KKT conditions and the details of derivation are similar to that given in Appendix D for Scenario I. Note that boundary constraints \( \hat{C}_6 \) and \( \hat{C}_8 \) are included in (4.27).

Using the relations in (4.26) and (4.27), we can re-write the subproblem of the dual problem in (4.25) as

\[
\begin{align*}
\text{maximize} & \quad \sum_{t=1}^{N} \left( \alpha^t G^t + \sum_{s=1}^{S} \sum_{j=1}^{S} \tilde{P}_{j,s}^t H_{j,s}^t \right) \\
\text{subject to} & \quad \hat{C}_1, \hat{C}_4, \hat{C}_5, \hat{C}_7, \hat{C}_8
\end{align*}
\tag{4.29}
\]

where \( G^t = \sum_{s=1}^{S} \left[ \frac{w_{s,I} \log_2 \left( \sum_{j=1}^{S} P_{j,s}^t h_{j,s}^t + \chi_{m,s}^t + N_{sp} \right)}{NR(tar)} - U_s(\tilde{P}_1^{(k)}, \alpha_I^{(k)}) \tilde{P}_{s,I}^t - \frac{w_{s,E} h_{s,m,s}^t}{NE(tar)} - \gamma^t h_{s,m}^t \tilde{P}_{s,I}^t \right] + \gamma^t I_{max,I}^t - V(\tilde{P}_1^{(k)}, \alpha_I^{(k)}), \forall t, H_{j,s}^t = \frac{w_{s,E} h_{j,s}^t}{NE(tar)}, \forall j, t, s, \tilde{P}_{s,I}^t = [x^t_s]_{P_{s,max}}^t, \forall s, t, \text{and constant terms have been removed from the objective function. It should be noted that the constraints } \hat{C}_1, \hat{C}_4, \hat{C}_5, \hat{C}_7, \text{and } \hat{C}_8 \text{ are derived using (4.26) and are same as that of problem in (4.13) of Scenario I. Again, the problem in (4.29) is a linear programming problem and can be solved optimally using interior-point method. Lemma 7 holds true for the solution of the problem in (4.29) as well and it can be verified in a similar manner.}

Solving the master problem

As in Scenario I, optimal values of dual variables can be obtained by using subgradient method [87] to update the dual variables as given in (4.14).

Updated dual variables are then used to obtain new solution for primal variables. This process is iterated till convergence. Convergence of subgradient method to globally optimal
solution is guaranteed for a convex optimization problem. A new concave minorant is then defined in neighborhood of the optimal solution of the subproblem, using (4.22), and the process is iterated until convergence. Algorithm 3 summarizes the resource allocation framework described for Scenario II. Iterative maximization of concave minorant of the difference of concave functions is guaranteed to converge and the proof of convergence is similar to that in [95]. Note that, in both scenarios of time-switching approach, with the help of dual decomposition technique, a linear programming problem with reduced number of variables is rendered from the relaxed convex optimization problem to identify the condition at which solution of the relaxed convex optimization problem satisfies binary integer constraint of the original MINLP problem.

Algorithm 3 Resource Allocation Algorithm for Scenario II of Time-switching Approach

Require: Initialize $k = 0$ and $\tilde{P}_{s,I}^{t(k)}, \alpha_I^{t(k)}, \forall s,t$

1: repeat
2: Define concave minorant of objective function using (4.22)
3: Formulate convex subproblem as defined in (4.23)
4: Initialize dual variables $\gamma^t$, $\forall t$
5: repeat
6: Solve (4.28) for $x_s^t$, $\forall s,t$
7: Solve the problem in (4.29) for $\alpha_{s,I}^t$ and $\tilde{P}_{s,E}^t$, $\forall s,t$, using interior-point method
8: Compute $\alpha_E^t, \tilde{P}_{s,I}^t, \forall s,t$, using (4.27) and (4.26)
9: Update dual variables $\gamma^t$ using subgradient method as given in (4.14)
10: until Convergence
11: Update $k \leftarrow k + 1$; $\tilde{P}_{s,I}^{t(k)} = \tilde{P}_{s,I}^{t*}, \alpha_I^{t(k)} = \alpha_I^{t*}, \forall s,t$
12: until Convergence
13: Calculate $P_{s,I}^t$ and $P_{s,E}^t$ using the relation in (4.6)
4.4 Resource Allocation for Power-splitting Approach: Problem Formulation and Solution

Problem formulation

In power-splitting approach, SUEs split the received power into two fractions and share it among EH and ID circuits in each time slot. The resource allocation problem, to maximize weighted sum of normalized throughput and energy harvesting rate of the SUEs over one transmission block, is given by

$$\text{maximize } \sum_{s=1}^{S} \left( w_{s,I} \frac{R_s}{R_{(tar)}} + w_{s,E} \frac{E_s}{E_{(tar)}} \right)$$

subject to

$$C_a : \rho_I^t + \rho_E^t \leq 1, \forall t, \quad C_d : P_s^t \leq P_{s(max)}, \forall s, t$$

$$C_b : 0 \leq \rho_I^t, \rho_E^t \leq 1, \forall t, \quad C_e : P_s^t \geq 0, \forall s, t$$

$$C_c : \sum_{s=1}^{S} P_s^t b_{s,m} - I_{max}^t \leq 0, \forall t$$

where \(P \in \{ P_s^t, \forall s, t \}, \ \rho_I \in \{ \rho_I^t, \forall t \}, \ \text{and} \ \rho_E \in \{ \rho_E^t, \forall t \}\). Constraints \(C_a\) and \(C_b\) ensure that total power received by EH and ID circuits together cannot be greater than that received by power-splitter. Since EH and ID processes are not separated in time domain, \(R_{(min)}\) is the minimum throughput that should be ensured for MUE in each time slot to ensure that throughput of the MUE over one transmission block is greater than or equal to \(R_{(min)}\).

This requires maximum sum-interference received by the MUE to be less than or equal to

$$I_{max}^t = \frac{P_m h_{m,m}}{2^{R_{(min)}_m} - 1} - N_w - N_{sp}$$

in each time slot, as indicated by \(C_c\).\(^9\) \(C_d\) and \(C_e\) are boundary constraints on power variables. All constraints along with the objective of the problem in (4.30) can be separated in time domain. Therefore, from (4.30), \(N\) maximization problems

\(^9\)Note that constraint \(C_c\) of the problem formulated for power-splitting approach in (4.30) is equivalent to constraint \(C_5\) of the problem formulated for time-switching approach in (4.5) since both of them ensure that throughput of the MUE is greater than or equal to \(R_{(min)}\) over one transmission block, hence ensuring a fair comparison between these two approaches.
4.4. Resource Allocation for Power-splitting Approach: Problem Formulation and Solution

can be formulated and independently solved. Therefore, from now on, we will show the solution approach for one time-slot. We will simply eliminate superscript \( t \) from the defined variables and parameters.

**Solution approach**

Objective function of the problem in (4.30) is very complicated in terms of optimization variables. For tractability, we introduce auxiliary power variables: \( P_{s,I} = \rho_I P_s \) and \( P_{s,E} = \rho_E P_s, \forall s \). The achievable throughput and energy harvesting rate, given in (4.3) and (4.4), respectively, can be re-written as

\[
\tilde{R}_s = \frac{1}{N} \log_2 \left( 1 + \frac{P_{s,I} h_{s,s}}{\sum_{j=1, j \neq s}^S P_{j,I} h_{j,s} + \rho_I \chi_{m,s} + N_{sp}} \right) \\
\tilde{E}_s = \frac{\eta}{N} \left( \sum_{j=1}^S P_{j,E} h_{j,s} + \rho_E \chi_{m,s} \right), \forall s.
\]  

(4.31)

With introduction of auxiliary power variables, problem in (4.30) can be re-written as

\[
\text{maximize } \sum_{s=1}^S \left( \frac{w_{s,I} \tilde{R}_s}{R_{(tar)}} + \frac{w_{s,E} \tilde{E}_s}{E_{(tar)}} \right) \\
\text{subject to } C_a, C_b \\
\tilde{C}_{c1} : \sum_{s=1}^S P_{s,I} h_{s,m} - \rho_I I_{max} \leq 0 \\
\tilde{C}_{c2} : \sum_{s=1}^S P_{s,E} h_{s,m} - \rho_E I_{max} \leq 0 \\
\tilde{C}_{d1} : P_{s,I} - \rho_I P_{s(max)} \leq 0, \forall s \\
\tilde{C}_{d2} : P_{s,E} - \rho_E P_{s(max)} \leq 0, \forall s \\
\tilde{C}_e : P_{s,I}, P_{s,E} \geq 0, \forall s
\]  

(4.32)

where constraints \( \tilde{C}_{c1}, \tilde{C}_{c2}, \tilde{C}_{d1}, \tilde{C}_{d2}, \) and \( \tilde{C}_e \) are re-written using the definition of new auxiliary power variables, \( P_{I} = \{P_{s,I}, \forall s\} \), and \( P_{E} = \{P_{s,E}, \forall s\} \). The problem in (4.32) is
not convex but can be represented as a difference of concave functions as follows:

$$\sum_{s=1}^{S} \left( \frac{w_{s,I} R_s}{R_{(\text{tar})}} + \frac{w_{s,E} \tilde{E}_s}{E_{(\text{tar})}} \right) = f_{PS}(P_{1}, P_{E}, \rho_{I}, \rho_{E}) - g_{PS}(P_{1}, \rho_{I})$$

where

$$f_{PS}(P_{1}, P_{E}, \rho_{I}, \rho_{E}) = \sum_{s=1}^{S} \left[ \frac{w_{s,I}}{NR_{(\text{tar})}} \log_2 \left( \sum_{j=1}^{S} P_{j,I} h_{j,s} + \rho_{I} \chi_{m,s} + N_{sp} \right) \right. + \left. \frac{w_{s,E}}{NE_{(\text{tar})}} \left( \sum_{j=1}^{S} P_{j,E} h_{j,s} + \rho_{E} \chi_{m,s} \right) \right]$$

$$g_{PS}(P_{1}, \rho_{I}) = \sum_{s=1}^{S} \frac{w_{s,I}}{NR_{(\text{tar})}} \log_2 \left( \sum_{j=1, j \neq s}^{S} P_{j,I} h_{j,s} + \rho_{I} \chi_{m,s} + N_{sp} \right).$$

Following Definition 1, the concave minorant, $\Phi_{PS}^{(k)}(P_{1}, P_{E}, \rho_{I}, \rho_{E})$, of the objective function such that $\Phi_{PS}^{(k)}(P_{1}, P_{E}, \rho_{I}, \rho_{E}) \leq f_{PS}(P_{1}, P_{E}, \rho_{I}, \rho_{E}) - g_{PS}(P_{1}, \rho_{I})$, can be defined in the neighborhood of $(P_{1}^{(k)}, \rho_{I}^{(k)})$ as

$$\Phi_{PS}^{(k)}(P_{1}, P_{E}, \rho_{I}, \rho_{E}) = f_{PS}(P_{1}, P_{E}, \rho_{I}, \rho_{E}) - g_{PS}(P_{1}^{(k)}, \rho_{I}^{(k)})$$

$$- \sum_{s=1}^{S} U_{s(PS)}(P_{1}^{(k)}, \rho_{I}^{(k)}) \left( P_{s,I} - P_{s,I}^{(k)} \right) - V_{(PS)}(P_{1}^{(k)}, \rho_{I}^{(k)}) \left( \rho_{I} - \rho_{I}^{(k)} \right)$$

(4.33)

where

$$U_{s(PS)}(P_{1}, \rho_{I}) = \frac{\partial g_{PS}(P_{1}, \rho_{I})}{\partial P_{s,I}} = \sum_{l=1, l \neq s}^{S} \frac{w_{l,I} h_{s,l}}{NR_{(\text{tar})} \log(2) \left( \sum_{j=1, j \neq l}^{S} P_{j,I} h_{j,l} + \rho_{I} \chi_{m,l} + N_{sp} \right)}$$

$$V_{(PS)}(P_{1}, \rho_{I}) = \frac{\partial g_{PS}(P_{1}, \rho_{I})}{\partial \rho_{I}} = \sum_{s=1}^{S} \frac{w_{s,I} \chi_{m,s}}{NR_{(\text{tar})} \log(2) \left( \sum_{j=1, j \neq s}^{S} P_{j,I} h_{j,s} + \rho_{I} \chi_{m,s} + N_{sp} \right)}.$$
4.4. Resource Allocation for Power-splitting Approach: Problem Formulation and Solution

Therefore, the problem of maximizing concave minorant of the objective function in neighborhood of \((P_{I}^{(k)}, \rho_{I}^{(k)})\) can be written as

\[
\begin{align*}
\text{maximize} & \quad \Phi_{PS}(P_{I}, P_{E}, \rho_{I}, \rho_{E}) \\
\text{subject to} & \quad C_{a}, C_{b}, \tilde{C}_{c1}, \tilde{C}_{c2}, \tilde{C}_{d1}, \tilde{C}_{d2}, \tilde{C}_{e}.
\end{align*}
\] (4.34)

The problem in (4.34) has concave objective function and affine constraints and hence is a convex optimization problem which can be solved using convex optimization techniques discussed in the following.

Let us define the partial Lagrangian of the problem in (4.34) as follows:

\[
L^{(k)}(P_{I}, P_{E}, \rho_{I}, \rho_{E}, \lambda, \gamma_{1}, \gamma_{2}, \beta_{1}, \beta_{2}) = \Phi_{PS}(P_{I}, P_{E}, \rho_{I}, \rho_{E}) - \lambda (\rho_{I} + \rho_{E} - 1) - \gamma_{1} \left( \sum_{s=1}^{S} P_{s,I} h_{s,m} - \rho_{I} I_{\text{max}} \right) - \gamma_{2} \left( \sum_{s=1}^{S} P_{s,E} h_{s,m} - \rho_{E} I_{\text{max}} \right) - \sum_{s=1}^{S} \beta_{1s} (P_{s,I} - \rho_{I} P_{s,(\text{max})}) - \sum_{s=1}^{S} \beta_{2s} (P_{s,E} - \rho_{E} P_{s,(\text{max})})
\] (4.35)

where \(\lambda, \gamma_{1}, \gamma_{2}, \beta_{1}, \) and \(\beta_{2}\) are non-negative Lagrange multipliers associated with constraints \(C_{a}, \tilde{C}_{c1}, \tilde{C}_{c2}, \tilde{C}_{d1},\) and \(\tilde{C}_{d2},\) respectively. Constraints \(C_{b}\) and \(\tilde{C}_{e}\) are not included in the Lagrangian and will be satisfied later.

\textbf{Lemma 8:} At optimality, the auxiliary power allocation variables and power-splitting variables are related to each other as follows:

\[
\rho_{E}^{*} = 1 - \rho_{I}^{*}
\] (4.36)

\[
P_{s,E}^{*} = \frac{(1 - \rho_{I}^{*})}{\rho_{I}^{*}} P_{s,I}^{*}, \forall s.
\] (4.37)

\textbf{Proof:} Differentiating (4.35) with respect to \(\rho_{E}\) and applying the KKT stationarity conditions, we obtain \(\sum_{s=1}^{S} \frac{u_{s,E} y_{m,s}}{N E_{(\text{tar})}} - \lambda + \gamma_{2} I_{\text{max}} + \sum_{s=1}^{S} \beta_{2s} P_{s,(\text{max})} = 0.\) Since all the other terms in the left hand side of the equation are positive, in order to satisfy the stationarity
4.4. Resource Allocation for Power-splitting Approach: Problem Formulation and Solution

condition, $\lambda > 0$ is strictly satisfied. Then to satisfy the KKT slackness condition, the constraint associated with the Lagrange multiplier $\lambda$ must be tightly satisfied as given in (4.36). Then, (4.37) follows from (4.36) and the definition of auxiliary variables. This completes the proof.

Lemma 9: $P_{s,l}^*$ and $\rho_l^*$ are obtained by solving the following set of equations and inequalities:

$$
\sum_{l=1}^{S} \frac{w_{l,I}h_{s,l}}{NR_{(tar)} \log(2)} \left( \sum_{j=1}^{S} P_{j,l}h_{j,l} + \rho_l \chi_{m,l} + N_{sp} \right) + \frac{1 - \rho_l}{\rho_l} \sum_{l=1}^{S} \frac{w_{l,E} \eta h_{s,l}}{NE_{(tar)}} 
- U_s(PS)(P_{1}^{(k)}, \rho_{1}^{(k)}) - \gamma_l h_{s,m} = 0, \forall s
$$

(4.38)

$$
\sum_{l=1}^{S} \left[ \frac{w_{l,I} \chi_{m,l}}{NR_{(tar)} \log(2)} \left( \sum_{j=1}^{S} P_{j,l}h_{j,l} + \rho_l \chi_{m,l} + N_{sp} \right) - \frac{w_{l,E} \eta}{NE_{(tar)}} \left( \sum_{j=1}^{S} \frac{P_{j,l}h_{j,l}}{\rho_l^2} + \chi_{m,l} \right) \right]
- V_{(PS)}(P_{1}^{(k)}, \rho_{1}^{(k)}) + \gamma_l I_{max} = 0
$$

(4.39)

$$
P_{s,l} \geq 0, \quad 0 \leq \rho_l \leq 1.
$$

(4.40)

Proof: In the power-splitting approach, if maximum transmit power $P_{s(max)}$ is sufficiently high and maximum tolerable interference on MUE $I_{max}$ is sufficiently low, we can assume that the transmit power $P_{s,l}$ is always constrained by the interference constraint $C_{c1}$ and hence the boundary constraint $C_{d1}$ is never tightly satisfied. In that case $\beta_{1s}$ should be 0 to satisfy the slackness condition. Also, using relations given in (4.36) and (4.37) in Lemma 8, the partial Lagrangian given in (4.35) can be re-written in terms of $P_{s,l}, \forall s$ and $\rho_l$. Then, differentiating the new Lagrangian with respect to $P_{s,l}$ and $\rho_l$, and then using KKT stationarity conditions as shown in Appendix D for Scenario I, we obtain (4.38) and (4.39), respectively. It should be noted that the constraints $C_b$ and $\tilde{C}_e$ are satisfied in the

\footnote{Note that the assumption cannot be made in the time-switching approach because, by lowering the minimum rate requirement of MUE in the EH mode, the maximum tolerable interference of MUE is increased and hence transmit power of SBSs can be constrained either by the interference constraint or by the boundary constraint.}
solution by including the KKT primal feasibility conditions in (4.40). This completes the proof.

As in previous scenarios, the optimal value of dual variable $\gamma_1$ can be obtained by using subgradient method to update the dual variable \[87\]. Updated dual variable is then used to obtain new solution for primal variables. This process is iterated until convergence. The solution obtained is then used to obtain new concave minorant, defined in (4.33) and the process is repeated until convergence. Algorithm 4 summarizes the resource allocation framework described in this section. Note that with the help of dual decomposition technique, we identify the relationship between power-splitting and transmit power variables, and reduce the number of unknown variables to solve in each inner iteration of Algorithm 4.

Algorithm 4 Resource Allocation Algorithm for Power-splitting Approach

Require: Initialize $k=0$ and $P_{s,I}^{(k)}, \rho_I^{(k)}, \forall s$

1: repeat
2: Define concave minorant of objective function using (4.33)
3: Formulate convex subproblem defined in (4.34) and initialize dual variable $\gamma_1$
4: repeat
5: Solve (4.38)-(4.40) to obtain $P_{s,I}^*, \forall s$ and $\rho_I^*$
6: Compute $\rho_E^*$ and $P_{s,E}^*$, $\forall s$ using (4.36)-(4.37)
7: Update dual variable $\gamma_1$ using subgradient method as given in (4.14) for Scenario I
8: until Convergence
9: Update $k \leftarrow k + 1$; $P_{s,I}^{(k)} = P_{s,I}^*, \forall s$, $\rho_I^{(k)} = \rho_I^*$
10: until Convergence
11: Calculate $P_s = P_{s,I}/\rho_I, \forall s$

4.5 Performance Evaluation Results

In this section, we present and analyze simulation results for the proposed resource allocation models of different SWIPT scenarios in a two-tier HetNet and also compare them with the performance of the traditional two-tier communication network\[11\]. In particular, we evaluate

\[11\]Note that throughput expression and power allocation problem for traditional two-tier network model can be derived from that of SWIPT-based network with power-splitting approach by setting $\rho_I^* = 1$, $\rho_E^* = 0$ and the solution approach can be extracted accordingly.
sum-throughput \( R_{\text{sum}} = \sum_{s=1}^{S} R_s \) and sum-energy harvesting rate \( E_{\text{sum}} = \sum_{s=1}^{S} E_s \) of SUEs under different scenarios.

### 4.5.1 Simulation Parameters

We consider a single macrocell with the MBS at the origin. There are \( S = 2 \) small cells at a distance of 100 m from the MBS. Both small cells have an SUE at a distance of 3 to 10 m from the SBS. An MUE is located close to the small cells. The transmit power \( P_m \) of MBS and maximum transmit power \( P_{s(\text{max})} \) of SBSs are both assumed to be 46 dBm. Channel models from [96] are used to compute the channel gains. The path-loss, in dB, in the link from SBS to its SUE is \( 38.46 + 20\log D \), SBS to other UEs is \( 38.46 + 20\log D + L_w \), MBS to an SUE is \( 15.3 + 37.6\log D + L_w \), and MBS to MUE is \( 15.3 + 37.6\log D \), respectively, where \( D \) is the distance between the transmitter and the receiver in meters. \( L_w \) accounts for the losses due to walls and is assumed to be 1 dB in our simulations. The antenna noise power is assumed to be \( 10^{-13} \) W, signal processing noise power to be 3 dB stronger than the antenna noise power, each downlink time is divided into \( N = 4 \) time slots, and \( w_{s,I} \) and \( w_{s,E} \) are set to 1. Unless stated otherwise, energy harvesting efficiency \( \eta \) is 50\% \[^{12}\] minimum throughput requirement of MUE is 1 bps/Hz, and target throughput and energy harvesting rate of SUEs are 1 bps/Hz and 1 \( \mu \)Jps, respectively. Unless stated otherwise, in the scenarios with time-switching approach, the minimum throughput of MUE ensured in EH time is 0.05 bps/Hz and that in ID time is 2 bps/Hz. All the simulations are repeated for 1000 different Rayleigh fading channel realizations and the results are averaged.

\[^{12}\]Wireless energy harvesting efficiency is found to be as high as 65.2\% when the received RF power is \(-22\) dBm in [23,97]. However, for fair comparison, unless stated otherwise, we use \( \eta = 50\% \) in all scenarios.
4.5. Performance Evaluation Results

4.5.2 Simulation Results

Variation of $R_{\text{sum}}$ and $E_{\text{sum}}$ with energy harvesting efficiency $\eta$

When $\eta$ is very small, SUEs can harvest very little energy from the received signal which decreases the normalized energy harvesting rate. Therefore, more time is allocated to ID process to maximize the objective. For this reason, we notice higher $R_{\text{sum}}$ and lower $E_{\text{sum}}$ for lower $\eta$ (Figs. 4.2 and 4.3). With increasing $\eta$, time allocated to EH process increases because of which $E_{\text{sum}}$ increases and $R_{\text{sum}}$ decreases. However, beyond a certain value of $\eta$ (e.g. 20% when $R_{(\text{min},E)} = 0.05$ bps/Hz), the time allocated to ID process cannot be decreased further in order to satisfy the minimum throughput requirement of MUE (as indicated by constraint $\hat{C}_5$ in problem (4.13) and (4.29)). After that point, $R_{\text{sum}}$ saturates. However, $E_{\text{sum}}$ keeps improving with increasing $\eta$. In the case with power-splitting approach, $R_{\text{sum}}$ remains almost the same while $E_{\text{sum}}$ increases with increasing $\eta$.

We observe that, when $R_{(\text{min},E)} = 0.05$ bps/Hz, $E_{\text{sum}}$ is much higher in the time-switching approach compared to the power-splitting approach. This is because of the additional degree
4.5. Performance Evaluation Results

![Graph](image)

Figure 4.3: Sum-energy harvesting rate of SUEs versus $\eta$.

of freedom provided by isolating EH process from ID process in time domain and increasing the interference tolerance level of MUE during the EH phase. However, when $R_{(\text{min},E)}$ increases to 0.5 bps/Hz, interference tolerance of MUE in EH phase decreases and therefore $E_{\text{sum}}$ decreases significantly. In fact, $\eta$ must be very high (50 – 60%) for time-switching approach to have significant improvement over power-splitting approach in $E_{\text{sum}}$. The gain in $E_{\text{sum}}$, however, comes at the cost of lower $R_{\text{sum}}$ in comparison to the power-splitting approach. Comparing the two scenarios of time-switching approach, $E_{\text{sum}}$ is higher in the scenario with non-negligible co-tier interference at the cost of lower $R_{\text{sum}}$.

**Variation in $R_{\text{sum}}$ and $E_{\text{sum}}$ with target throughput of SUEs**

In the time-switching approach, with increasing $R_{(\text{tar})}$, the normalized throughput ($w_s I R_{(\text{tar})}$) decreases, and therefore, more time is allocated to EH process than ID process to maximize the objective (Fig. 4.6). Therefore, $R_{\text{sum}}$ decreases while $E_{\text{sum}}$ increases with increasing $R_{(\text{tar})}$ (Fig. 4.4 and 4.5). However, after a certain value, the sum-throughput of SUEs $R_{\text{sum}}$
### 4.5. Performance Evaluation Results

#### Figure 4.4: Sum-throughput of SUEs versus $R_{\text{tar}}$.

- **Power-splitting**: $E_{\text{tar}} = 1\mu\text{Jps}$
- **Time-switching: Sc-I**: $E_{\text{tar}} = 1\mu\text{Jps}$
- **Time-switching: Sc-II**: $E_{\text{tar}} = 1\mu\text{Jps}$
- **Power-splitting**: $E_{\text{tar}} = 10\mu\text{Jps}$
- **Time-switching: Sc-I**: $E_{\text{tar}} = 10\mu\text{Jps}$
- **Time-switching: Sc-II**: $E_{\text{tar}} = 10\mu\text{Jps}$

#### Figure 4.5: Sum-energy harvesting rate of SUEs versus $R_{\text{tar}}$.

- **Power-splitting**: $E_{\text{tar}} = 1\mu\text{Jps}$
- **Time-switching: Sc-I**: $E_{\text{tar}} = 1\mu\text{Jps}$
- **Time-switching: Sc-II**: $E_{\text{tar}} = 1\mu\text{Jps}$
- **Power-splitting**: $E_{\text{tar}} = 10\mu\text{Jps}$
- **Time-switching: Sc-I**: $E_{\text{tar}} = 10\mu\text{Jps}$
- **Time-switching: Sc-II**: $E_{\text{tar}} = 10\mu\text{Jps}$
4.5. Performance Evaluation Results

![Graph of Average fraction of time/power allocated for ID process versus R(tar).](image)

Figure 4.6: Average fraction of time/power allocated for ID process versus $R(tar)$.

Variation of $R_{sum}$ and $E_{sum}$ with transmit power of MBS

When $P_m$ increases from 46 dBm to 48 dBm, sum-energy harvesting rate $E_{sum}$ increases by about 1.5 times in all the scenarios (Fig. 4.7). With increase in $P_m$, SBSs can transmit higher power but SUEs will also suffer from higher cross/co-tier interference. Hence, sum-
4.5. Performance Evaluation Results

throughput of the SUEs $R_{\text{sum}}$ has been observed to remain unchanged with increase in $P_m$. The plot is omitted due to lack of interesting insights.

**Variation of $R_{\text{sum}}$ and $E_{\text{sum}}$ with minimum throughput requirements of MUE**

In the time-switching approach, with increasing $R_{(\text{min})}$, minimum time, that should be allocated to ID process to ensure that minimum throughput requirement of the MUE is satisfied, increases (constraint $\hat{C}_5$ of problem (4.13) and (4.29)). Therefore, $R_{\text{sum}}$ increases (Fig. 4.8) and $E_{\text{sum}}$ decreases (Fig. 4.9). On the other hand, in the power-splitting approach, with increasing $R_{(\text{min})}$, the interference tolerance of the MUE further decreases which restricts the transmit power of the SUEs. This causes both $E_{\text{sum}}$ as well as $R_{\text{sum}}$ to decrease with increasing $R_{(\text{min})}$. $E_{\text{sum}}$ increases with increasing $\eta$ while $R_{\text{sum}}$ decreases with increasing $\eta$ and then saturates which agrees with the result shown in Figs. 4.2 and 4.3. Interestingly, sum-throughput performance of traditional two-tier communication network is same as that of SWIPT network with power-splitting approach. It is mainly because, as long
4.5. Performance Evaluation Results

Figure 4.8: Sum-throughput of SUEs versus $R_{(min)}$.

Figure 4.9: Sum-energy harvesting rate of SUEs versus $R_{(min)}$. 
as the power-splitting factor $\rho_t^I$ is not arbitrarily small and the signal processing noise is negligible in comparison to the interference signal, throughput expression of the SUE with power-splitting approach is not affected by the power-splitting factor. This also indicates that, due to severe interference constraint imposed in the presence of macrocell UEs, energy harvesting rate is so small in power-splitting approach that downlink power is allocated to maximize the normalized throughput as in the case of a traditional two-tier network.

Due to the additional degree of freedom provided in the time-switching approach where the EH and ID processes are separated in time domain and the interference tolerance limit of MUE is increased in EH phase, the average received power of SUEs during EH process is much higher (equal to or more than $-15$ dBm) in time-switching approach, compared to power-splitting approach (below $-25$ dBm\textsuperscript{13}) as shown in Fig. 4.10. Given that the energy harvesting receiver sensitivity is one of the crucial issues in wireless energy harvesting systems, using time-switching approach opens up the possibility of successful wireless power transfer in small cells underlaying the macrocells. With increasing $R_{(\text{min},l)}$, $R_{\text{sum}}$ decreases

\textsuperscript{13}Note that, in our simulations, we use 50% energy harvesting efficiency, irrespective of the received power.
4.5. Performance Evaluation Results

Figure 4.11: Sum-throughput of SUEs versus $R_{(\text{min},I)}$.

Figure 4.12: Sum-energy harvesting rate of SUEs versus $R_{(\text{min},I)}$. 
and $E_{sum}$ increases (Figs. 4.11 and 4.12) because the minimum throughput requirement of MUE can be satisfied by allocating lesser time to ID process (constraint $\hat{C}_5$ of problem (4.13) and (4.29)). However, when $R_{(\min,E)}$ increases from 0.05 to 1 bps/Hz, it implies the interference tolerance level of MUE is not much high in the EH process which remarkably reduces $E_{sum}$. In fact, the time-switching approach results in even worse $E_{sum}$ performance than power-splitting approach, when $R_{(\min,I)} = R_{(\min,E)} = 1$. This demonstrates the importance of flexible interference tolerance levels in the MUE to maximize energy harvesting rate performance of SUEs in the time-switching approach.

**Performance and convergence analysis**

The value of the objective function in each iteration of maximizing the concave minorant in Algorithms 3 and 4 are plotted in Fig. 4.13 for $S = 2$ (for $R_{(\min,I)} = 2$ bps/Hz and $R_{\min,E} = 0.1$ bps/Hz). Both algorithms converge (upto 5 decimal digits) in around four iterations. The obtained value of the objective function upon convergence is compared with the result obtained by solving the non-concave problem directly with OPTI solver [98] which
4.5. Performance Evaluation Results

is a MATLAB toolbox to solve optimization problems. It is noted that the performance loss, due to approximation of the non-concave function by its concave minorant, is very small. Also, weighted sum of normalized throughput and energy harvesting rate of SUEs is higher in time-switching approach when compared to power-splitting approach.

4.5.3 Summary of Observations

From the simulation results, we observe that the achievable energy harvesting rate of SUEs is profoundly curbed by the minimum throughput requirement of MUE. In the time-switching approach, isolating the EH process from the ID process and increasing interference tolerance level of the MUE during EH process allow the SBSs to transmit higher power during the EH process. This increases the energy harvesting rate of SUEs. Since EH and ID process cannot be isolated in power-splitting approach, unlike the observation in [20], an inferior energy harvesting rate performance is observed, but a better throughput performance is attained. However, performance of the time-switching approach is worse if the MUE does not have flexible interference tolerance levels during EH and ID periods. Increasing $R_{(\text{min},I)}$ and decreasing $R_{(\text{min},E)}$ result in better sum-energy harvesting rate but increasing $R_{(\text{min},I)}$ lowers sum-throughput of SUEs. Hence these parameters should be carefully chosen to attain optimal rate-energy trade-off in SUEs. In the time-switching approach, while co-tier interference causes degradation in throughput performance of SUEs, it provides remarkable improvement in the energy harvesting rate.
Chapter 5

Joint Resource Allocation and Dynamic Activation of Energy Harvesting Small Cells in HetNets

In Chapters 2-4, we studied resource allocation in cooperative and heterogeneous networks with wireless energy harvesting. However, wireless energy harvesting is only applicable in low power miniature devices of the networks, such as sensor nodes, since the energy harvested is in the range of micro Watts. While wireless energy harvesting is a promising technique to elongate the battery life of small nodes in the network, renewable energy harvesting is a promising technique to reduce the power cost of bigger network nodes such as base stations. In this chapter, we consider renewable energy harvesting in small cells of HetNets and perform energy-aware and interference-aware resource allocation jointly with dynamic activation of energy harvesting base stations to optimize the trade-off between throughput performance and power cost of such network. The accomplished works and research contributions of this chapter are briefly described in the following.

5.1 Accomplished Works and Research Contributions

In this chapter, we consider a two-tier HetNet with co-channel deployment and renewable energy harvesting capability in the small base stations. To optimize the trade-off between throughput performance and power cost of serving the small cell (or hotspot) users, we
consider the problem of resource allocation and dynamic base station activation in such a network. Information about traffic demand or user activity of the network is needed to optimize dynamic base station activation and resource allocation in multi-tier networks [99]. When the base stations are energy harvesting in nature, information about arrival of harvested energy is also required along with that about user activity and traffic demand [71]. Therefore, in this chapter, considering variation in channel condition, user activity, and arrival of harvested energy, we investigate interference-aware and energy-aware resource allocation jointly with dynamic activation of SBSs in a two-tier network, where MBS is always activated for reliable operation.

To optimize the trade-off between throughput performance and power cost of serving the hotspot users, we associate positive reward for their attained throughput, negative reward (penalty) for corresponding non-renewable power consumption, and formulate an optimization problem to maximize the net reward over a number of time slots. Resource allocation is jointly performed to ensure interference-aware frequency reuse among macrocell and hotspot users when the SBS is activated, and the hotspot users are offloaded to the SBS, while ensuring orthogonal frequency allocation among them when the SBS is deactivated, and the hotspot users are served by the MBS. QoS provisioning is guaranteed by satisfying minimum throughput requirement of all macrocell and hotspot users in all time slots under consideration.

The formulated problem is solved as an offline problem assuming availability of non-causal information about channel condition, user activity, and energy harvested for the considered time period. Since non-causal information is unavailable in practice, we also solve the problem as an online problem using causal information only. The online problem is solved in two ways: using dynamic programming where statistical information of future values are available; and using greedy technique where no information of future values are available. Algorithms are proposed to solve the online and offline optimization problems in two stages: (i) determining base station activation variables; (ii) determining resource
5.2 System Model and Assumptions

allocation variables. We use discrete binary particle swarm optimization [100] to determine base station activation variables in offline algorithm. Numerical results are presented to analyze and compare the performances of the proposed algorithms with the baseline schemes. Three baseline schemes are used for comparison with the proposed algorithms: (i) Always On Scheme, where the SBSs are always activated, (ii) Always Off Scheme, where the SBSs are always deactivated, and (iii) Heuristic Scheme, where the SBS activation policy is determined heuristically.

The rest of the chapter is organized as follows. The system model and assumptions are explained in Section 5.2. Sections 5.3 and 5.4 present the offline and online problem formulations with solution approaches. Finally, performance evaluation results are presented and analyzed in Section 5.5.

5.2 System Model and Assumptions

Network model and user behavior

We consider downlink communication in a cellular network with one MBS and $N_T$ UEs. We consider a scenario where $H$ UEs are concentrated in a small area or hotspot and remaining $M$ UEs are distributed elsewhere, where $N_T = M + H$. An SBS is set up to serve HUEs in the hotspot, thus creating a two-tier network with co-channel deployment as shown in Fig. 5.1. The UEs in hotspot are referred to as hotspot UEs (HUEs) and denoted by $U_h$, $h \in \{1, 2, ..., H\}$. The UEs distributed elsewhere are called macrocell UEs (MUEs) and denoted by $U_m$, $m \in \{1, 2, ..., M\}$. Note that the UEs considered in our system model can be viewed as test points as in [67]. If a new user becomes active at the test point denoted by HUE $U_h$ inside the hotspot at time $t$, the activity indicator $H^t_h$ will be 1 and it will be 0 when the user leaves the hotspot. Similarly, $M^t_m$ is used as activity indicator of the test point denoted by MUE $U_m$. However, to retain the focus of our work on the problem of resource allocation in an energy harvesting HetNet, details of user mobility and hand-off are
5.2. System Model and Assumptions

The SBS is equipped with energy harvesting capability along with a non-renewable energy source. The source of renewable energy, for instance, can be solar panels as shown in Fig. 5.1. The energy harvesting rate in time slot $t$ is denoted by $E^t$ in joules per second (Jps). From here onward, the terms power and energy will be used interchangeably. If harvested energy is not enough, the SBS draws power from non-renewable energy source. If harvested energy is surplus to the requirement, the SBS stores it in a battery. Note that activation of the SBS increases throughput of HUEs, but also increases non-renewable power consumption if the harvested energy is not enough. Therefore, we assume that the SBS can be switched on or off, for optimal performance. $A^t$ is the SBS activation variable which is set to 1 if the SBS is activated in time slot $t$ and 0 otherwise. Hence, the network will be a two-tier network with co-channel deployment when the SBS is activated and a single tier network when the SBS is deactivated. Note that HUEs are offloaded to the SBS if it is activated and are served by

Figure 5.1: Two-tier HetNet with renewable energy harvesting in SBS.

not incorporated in the system model.

**Hybrid energy model and dynamic SBS activation**

The SBS is equipped with energy harvesting capability along with a non-renewable energy source. The source of renewable energy, for instance, can be solar panels as shown in Fig. 5.1. The energy harvesting rate in time slot $t$ is denoted by $E^t$ in joules per second (Jps). From here onward, the terms power and energy will be used interchangeably. If harvested energy is not enough, the SBS draws power from non-renewable energy source. If harvested energy is surplus to the requirement, the SBS stores it in a battery. Note that activation of the SBS increases throughput of HUEs, but also increases non-renewable power consumption if the harvested energy is not enough. Therefore, we assume that the SBS can be switched on or off, for optimal performance. $A^t$ is the SBS activation variable which is set to 1 if the SBS is activated in time slot $t$ and 0 otherwise. Hence, the network will be a two-tier network with co-channel deployment when the SBS is activated and a single tier network when the SBS is deactivated. Note that HUEs are offloaded to the SBS if it is activated and are served by
5.2. System Model and Assumptions

the MBS otherwise\(^{14}\)

**Channel model**

The available bandwidth is divided into \(N\) subchannels. \(h_{n,t}^{M,m}\) and \(h_{n,t}^{S,m}\) denote power gain of \(n\)th subchannel from MBS and SBS, respectively, to MUE \(U_m\), in time slot \(t\). Similarly, \(g_{n,t}^{M,h}\) and \(g_{n,t}^{S,h}\) denote power gain of \(n\)th subchannel from MBS and SBS, respectively, to HUE \(U_h\) in time slot \(t\). Channel power gain includes distance-dependent gain and multi-path fading gain.

**Statistical modeling of channel, energy, and user activity**

Channel gains, energy arrival, and user activities are modeled as independent random processes and their probability distribution are known via long term measurements. Channel gains and harvested energy have been widely assumed to follow Markov model \([30,101–103]\). Similarly, user activity can also be modeled as a two-state Markov model \([104,105]\).

**Resource allocation variables**

\[
P_S^{n,t} = P_{N_e}^{n,t} + P_{Re}^{n,t}
\]

denotes transmit power of the SBS in subchannel \(n\) in time slot \(t\) where \(P_{N_e}^{n,t}\) is power drawn from the non-renewable energy source and \(P_{Re}^{n,t}\) is that from the battery storing harvested energy. \(\sigma_{M,m}^{n,t}\), \(\rho_{M,h}^{n,t}\), and \(\rho_{S,h}^{n,t}\) are subchannel allocation variables. \(\sigma_{M,m}^{n,t}\) is 1 if subchannel \(n\) is allocated by MBS to MUE \(U_m\) in time \(t\) and \(\rho_{S,h}^{n,t}\) is 1 if it is allocated by SBS to HUE \(U_h\). Note that in case the SBS is deactivated, the network operates as a single tier network and HUEs associate with the MBS. \(\rho_{M,h}^{n,t}\) is 1 if subchannel \(n\) is allocated by MBS to UE \(U_h\) in time \(t\). The MBS transmits with power \(P_M\) in each subchannel.

\(^{14}\)Considering the amount of energy harvested, hotspot users can be partially offloaded to the active SBS to minimize non-renewable power consumption, which requires optimization of user association variables for optimal performance. However, optimization of user association is beyond the scope of this chapter.
5.2. System Model and Assumptions

Throughput reward and power consumption penalty

The throughput of an active MUE \( U_m \) is given by

\[
R^t_m = \sum_{n=1}^{N} \alpha_{M,m}^{n,t} \log_2 \left( 1 + \frac{P_{M}h_{M,m}^{n,t}}{A^t \sum_{h=1}^{H} H^{t}_{h} \rho_{S,h}^{n,t} (P_{Re}^{n,t} + P_{Re}^{n,t}) h_{S,m}^{n,t} + N_w} \right), \ \forall m, t, \text{ where } N_w \text{ is the AWGN power. Note that the interference terms will be present only when the SBS is activated and the network operates in two-tier mode. Similarly, throughput of an active HUE \( U_h \), when the SBS is switched on and off are, respectively, given by}
\]

\[
R^t_{h(on)} = \sum_{n=1}^{N} \rho_{S,h}^{n,t} \log_2 \left( 1 + \frac{P_{N}^{n,t} + P_{Re}^{n,t} g_{S,h}^{n,t}}{P_{M} g_{M,h}^{n,t} + N_w} \right), \ \forall h, t \tag{5.1}
\]

\[
R^t_{h(off)} = \sum_{n=1}^{N} \rho_{M,h}^{n,t} \log_2 \left( 1 + \frac{P_{M} g_{M,h}^{n,t}}{N_w} \right), \ \forall h, t. \tag{5.2}
\]

\( R^t_{h(on)} \) gives throughput of HUE \( U_h \) if the SBS is activated and \( R^t_{h(off)} \) gives its throughput if the SBS is deactivated and the HUE is associated to the MBS instead. Hence, at any time \( t \), throughput of an HUE is given by

\[
R^t_h = A^t R^t_{h(on)} + (1 - A^t) R^t_{h(off)}. \tag{5.4}
\]

Note that the reward function is defined as a linear function of throughput \[106\], ignoring the effect of diminished marginal utility.
in RF chain when the SBS is switched on [107]. Note that we do not consider static power consumption of the SBS because it is constant in both on and off states, thus becoming independent of resource allocation and SBS activation decisions. It is assumed to rely on non-renewable energy source for stable operation. From now onward, the power consumption will simply refer to dynamic power consumption of the active base station.

The non-renewable power expenditure at the SBS and the MBS for serving HUEs is given by

\[
P_{\text{SBS}}^t = A^t \sum_{h=1}^{H} \sum_{n=1}^{N} H_{h}^{t} P_{S,h}^{n,t} P_{N_c}^{n,t} \alpha_S, \quad P_{\text{MBS}}^t = (1 - A^t) \sum_{h=1}^{H} \sum_{n=1}^{N} H_{h}^{t} P_{M,h}^{n,t} P_{M} \alpha_M, \quad \forall t. \tag{5.5}
\]

Note that dynamic power consumption in the SBS becomes zero when it is deactivated due to inclusion of the variable \( A^t \) in (5.4) and (5.5). Power expenditure at the MBS for serving HUEs is \( \alpha_M \) times the transmit power accounting for RF transmission efficiency of the MBS. As the MBS is always activated, we do not consider its static power consumption which is independent of resource allocation and SBS activation decisions. The power consumption penalty incurred by serving HUEs is given by

\[
P_{\text{pen}}^t = r_g \left[ A^t \sum_{h=1}^{H} \sum_{n=1}^{N} H_{h}^{t} P_{S,h}^{n,t} P_{N_c}^{n,t} \beta + (1 - A^t) \sum_{h=1}^{H} \sum_{n=1}^{N} H_{h}^{t} P_{M,h}^{n,t} P_{M} \alpha_M \right], \quad \forall t \tag{5.6}
\]

where \( r_g \) is penalty per unit of non-renewable power consumed to serve HUEs. \( \beta \) is penalty increase factor assuming that cost of non-renewable energy source of the SBS is \( \beta \) times more than that of the MBS. We know that activating the SBS will increase the sum throughput of HUEs which increases the throughput reward. However, if the harvested energy is not enough, non-renewable power consumption may increase which increases associated power consumption penalty. Note that, non-renewable power is also consumed at the MBS to serve HUEs if the SBS is deactivated. Hence, it is important to determine whether it is optimal to activate or deactivate the SBS.

In this chapter, we will develop optimization problem to maximize the net reward of
5.3 Offline Optimization: Problem Formulation and Solution Approach

serving HUEs over $T$ time slots while ensuring QoS to all HUEs and MUEs. For this, we will consider three different scenarios. First, we will perform offline optimization for a deterministic scenario where the information of user activity, channel condition, and energy arrival of all time slots of consideration are available. Next, we will consider online optimization for a more practical scenario where the future information about user activity, channel condition, and energy arrival are not available but their statistics are known. Finally, we will consider a greedy online resource allocation framework where we maximize the reward function for one time slot at a time.

Remark 1: Note that the system model can be extended to a scenario with multiple hotspots. In that case, we have to consider co-tier interference among hotspots along with cross-tier interference. However, to simplify the exposition, we consider a single hotspot only.

5.3 Offline Optimization: Problem Formulation and Solution Approach

In this section, we assume the availability of future information about channel gains, renewable energy arrival, and user activity. Our objective is to determine SBS activation, downlink power, and subchannel allocation to maximize the net reward of serving HUEs $(R_{rew}^t - P_{pen}^t)$ over $T$ time slots. The problem can be written as

$$\begin{align*}
\text{maximize} & \quad \sum_{t=1}^{T} (R_{rew}^t - P_{pen}^t) \\
\text{subject to} & \quad C_1 : (R_m^t - R_{\min}) M_m^t \geq 0, \forall m, t \\
& \quad C_{2I} : A^t (R_{h(on)}^t - R_{\min}) H_h^t \geq 0, \forall h, t \\
& \quad C_{2II} : (1 - A^t) (R_{h(off)}^t - R_{\min}) H_h^t \geq 0, \forall h, t
\end{align*}$$

(5.7)

16 Focusing on maximizing the reward of serving the hotspot users could be important when hotspots with higher user density are generated in some events and maximizing their throughput is given higher priority in comparison to the macrocell users.
5.3. Offline Optimization: Problem Formulation and Solution Approach

\[ C_3 : \sum_{m=1}^{M} \sigma_{M,m}^{n,t} M_m^t + (1 - A^t) \sum_{h=1}^{H} \rho_{M,h}^{n,t} H_h^t \leq 1, \forall n, t \]

\[ C_4 : A^t \sum_{h=1}^{H} \rho_{S,h}^{n,t} H_h^t \leq 1, \forall n, t \]

\[ C_5 : \sum_{\tau=1}^{t} A^t \left( \sum_{h=1}^{H} \sum_{n=1}^{N} H_h^t \rho_{S,h}^{n,t} P_{Re}^{n,t} \rho_{S,h}^{n,t} \right) \leq \sum_{\tau=1}^{t} E^{\tau - 1}, \forall t \]

\[ C_6 : A^t \sum_{h=1}^{H} \left[ H_h^t \rho_{S,h}^{n,t} P_{Re}^{n,t} M_m^t \right] \leq I_{\text{max}}, \forall m, n, t \]

\[ C_7 : A^t, \rho_{S,h}^{n,t}, \rho_{M,h}^{n,t}, \sigma_{M,m}^{n,t} \in \{0, 1\}, \forall m, n, h, t \]

\[ C_8 : P_{Re}^{n,t}, P_{Ne}^{n,t} \geq 0, \forall n, t \]

where \( P_{Re} = \{P_{Re}^{n,t}, \forall n, t\} \), \( P_{Ne} = \{P_{Ne}^{n,t}, \forall n, t\} \), \( \rho_{M} = \{\rho_{M,h}^{n,t}, \forall n, t, h\} \), \( \rho_{S} = \{\rho_{S,h}^{n,t}, \forall n, t, h\} \), and \( \sigma_{M} = \{\sigma_{M,m}^{n,t}, \forall n, t, m\} \). Constraint \( C_1 \), \( C_2 \), and \( C_{2II} \) ensure QoS provisioning for all active UEs. \( C_3 \) and \( C_4 \) ensure orthogonal frequency allocation among active UEs by MBS as well as SBS to avoid intra-cell interference. Note that \( C_3 \) ensures that, if the SBS is deactivated, the MBS allocates one subchannel to only one UE out of all HUEs and MUEs, in one time slot. \( C_5 \) is energy causality constraint as given in (5.4). \( C_6 \) ensures that interference imposed on active MUEs by the SBS is not more than \( I_{\text{max}} \). Imposing a maximum interference constraint on transmit power of SBSs to protect MUEs is well adopted in the literature [108]. \( C_7 \) imposes binary integer constraint on subchannel allocation and SBS activation variables. \( C_8 \) imposes non-negativity constraint on power variables.

The problem is an MINLP problem due to the presence of binary integer SBS activation and subchannel allocation variables. Therefore, the optimal solution of such a problem is computationally intractable. To obtain the suboptimal solution, we can solve the problem in two stages iteratively. In the first stage, we can perform subchannel and power allocation for given SBS activation variables. In the next stage, we can optimize SBS activation variables for given subchannel and power allocation variables. To optimize SBS activation variables, we will use discrete binary particle swarm optimization (PSO) [100] due to its faster conver-
5.3. Offline Optimization: Problem Formulation and Solution Approach

In the following, we will solve the subchannel and power allocation problem for known SBS activation variables.

5.3.1 Subchannel and Power Allocation for Given SBS Activation Policy

For a given SBS activation policy, the SBS activation variables of the problem in (5.7) become known parameters. However, the problem still remains an MINLP problem due to the presence of binary integer subchannel allocation variables and is difficult to solve in its current form. To directly solve the problem, we can use OPTI [98], which is a free MATLAB toolbox capable of solving non-linear and discrete optimization problems. However, we are not able to obtain insightful analytical results. Therefore, we relax the subchannel allocation variables to take any value between 0 to 1 and define auxiliary power variables as

\[ \tilde{P}_{n,t}^{h,R} = \rho_{S,h} P_{n,t}, \quad \forall h, n, t. \]

Note that such a relaxation of subchannel allocation variables allows multiple UEs to share a subchannel in time domain within a transmission frame [34,41,111]. Although the relaxation gives an upper bound of the optimal solution, it is claimed in [41] that for a large number of subchannels, the solution of the relaxed problem is asymptotically optimal with respect to the original problem formulation.

Then, the throughput of an HUE \( U_h \) when the SBS is activated, given in (5.1), can be re-written as

\[
\bar{R}_{h(\text{on})} = \sum_{n=1}^{N} \rho_{S,h}^{n,t} \log_2 \left( 1 + \frac{(\tilde{P}_{n,t}^{h,R} + \tilde{P}_{n,t}^{h,N}) g_{S,h}}{\rho_{S,h}^{n,t}(P_{M} g_{M,h} + N_w)} \right), \quad \forall h, t.
\]

The throughput reward generated by HUEs is then given by

\[
\bar{R}_{\text{rew}} = r_{th} \left( A^t \sum_{h=1}^{H} H_{h}^t \bar{R}_{h(\text{on})} + (1 - A^t) \sum_{h=1}^{H} H_{h}^t R_{h(\text{off})} \right).
\]

The power consumption penalty incurred by serving HUEs, given
in (5.6), can be re-written as

\[
\bar{P}_{\text{pen}} = r_g \left[ A^t \sum_{t=1}^{H} \sum_{h=1}^{N} \sum_{n=1}^{N} H_h^t \tilde{P}_{n,t}^h, \rho_{n,t}^{m,t} \alpha_S + (1 - A^t) \sum_{t=1}^{H} \sum_{n=1}^{N} H_h^t \rho_{m,h}^{n,t} P_M \alpha_M \right], \forall t. \tag{5.9}
\]

Note that, due to the presence of subchannel and power allocation variables in the denominator, \( R_t^m \) cannot be rendered convex even with relaxation of subchannel allocation variables and introduction of auxiliary power variables. Hence, for analytical tractability, in our problem, we take a pessimistic approach and define the worst-case approximation of MUE throughput as \( \tilde{R}_t^m = \sum_{n=1}^{N} \sigma_{n,t}^{M,m} \log_2 \left( 1 + \frac{P_M h_{M,m}^t}{A^t I_{\text{max}} + N_w} \right) \), \( \forall m, t \) to ensure that minimum throughput requirement of active MUEs is satisfied even when the received interference is maximum. Note that such a worst-case approximation is commonly adopted in the literature for tractability of analysis [34,36,112]. Using the worst-case approximation of MUE throughput, relaxed subchannel allocation variables, auxiliary power variables, and (5.8)-(5.9), the optimization problem in (5.7) can be re-written as

\[
\begin{align*}
\text{maximize} & \quad \rho_S, \rho_M, \sigma_M, \tilde{P}_{\text{Re}}, \tilde{P}_{\text{Ne}} \sum_{t=1}^{T} \left( \tilde{R}_{\text{rew}}^t - \tilde{P}_{\text{pen}}^t \right) \\
\text{subject to} & \quad C_3, C_4, C_{2II} \\
\tilde{C}_1: & \quad \left( \tilde{R}_m^t - R_{\text{min}} \right) M_m^t \geq 0, \forall m, t \\
\tilde{C}_{2I}: & \quad A^t \left( \tilde{R}_{h(\text{on})}^t - R_{\text{min}} \right) H_h^t \geq 0, \forall h, t \\
\tilde{C}_5: & \quad \sum_{t=1}^{T} A^t \left( \sum_{h=1}^{H} \sum_{n=1}^{N} H_h^t \tilde{P}_{n,t}^{h,R} \alpha_S \right) \leq \sum_{t=1}^{T} E^t, \forall t \\
\tilde{C}_6: & \quad A^t \sum_{t=1}^{H} \left[ H_h^t \left( \tilde{P}_{n,t}^{h,R} + \tilde{P}_{n,t}^{h,N} \right) h_{S,m}^n M_m^t \right] \leq I_{\text{max}}, \forall m, n, t \\
\tilde{C}_7: & \quad 0 \leq \rho_{S,h}, \rho_{M,h}, \sigma_{M,m}^{n,t} \leq 1, \forall m, n, h, t \\
\tilde{C}_8: & \quad \tilde{P}_{n,t}^{h,R}, \tilde{P}_{n,t}^{h,N} \geq 0, \forall n, h, t 
\end{align*}
\]

(5.10)

where constraints \( \tilde{C}_1, \tilde{C}_{2I}, \tilde{C}_5 - \tilde{C}_8 \) are re-written form of the corresponding constraints of the problem in (5.7) using worst case approximation of MUE throughput, relaxed subchannel
allocation variables, auxiliary power variables, and (5.8). Since $\tilde{R}_t^{(on)}$ can be proven to be a concave function of optimization variables by using perspective operation [80] and $R_t^{(off)}$ and $P_{pen}$ are affine functions of optimization variables, the objective function of the problem in (5.10) is a concave function of the optimization variables and the constraints are either affine or convex. Therefore, solution of the problem can be obtained by solving its dual problem [80] discussed in the following.

The partial Lagrangian of the problem in (5.10) is given by [80]

$$L(\rho_S, \rho_M, \sigma_M, \tilde{P}_{R_e}, \tilde{P}_{N_e}, \lambda, \delta, \eta)$$

$$= \sum_{t=1}^{T} \left( \tilde{R}_t^{rew} - \tilde{P}_t^{pen} \right) - \sum_{h=1}^{H} \sum_{t=1}^{T} \lambda_{h,t} A^t \left( R_{min} - \tilde{R}_t^{(on)} \right) H_t^h$$

$$- \sum_{t=1}^{T} \delta_t \left[ \sum_{t=1}^{T} A^t \sum_{h=1}^{H} \sum_{n=1}^{N} H_t^h \tilde{P}_{h,R_e}^{n,t} \alpha_S - \sum_{\tau=1}^{t} E_{\tau-1} \right]$$

$$- \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{t=1}^{T} \eta_{m,n,t} \left[ A^t \sum_{h=1}^{H} h_{h,R_e}^{n,t} + \tilde{P}_{h,N_e}^{n,t} \right] h_{S,m}^{n,t} M_t^m - I_{max}$$

(5.11)

where $\lambda, \delta, \eta$ are non-negative Lagrange multipliers associated with constraints $\tilde{C}_2$, $\tilde{C}_5$, and $\tilde{C}_6$, respectively. Other constraints are not included in the Lagrangian and will be satisfied later. Using the Lagrangian given in (5.11), we can formulate the dual problem of the problem in (5.10) as follows:

\[
\text{minimize}_{\lambda, \delta, \eta} \max_{\rho_S, \rho_M, \sigma_M, \tilde{P}_{R_e}, \tilde{P}_{N_e}} L(\rho_S, \rho_M, \sigma_M, \tilde{P}_{R_e}, \tilde{P}_{N_e}, \lambda, \delta, \eta)
\]

(5.12)

subject to $\lambda, \delta, \eta \geq 0, \tilde{C}_1, C_2, C_3, C_4, \tilde{C}_5, \tilde{C}_6$.

We can use dual decomposition method [85] to solve (5.12). In the dual decomposition method, in each iteration, we will first solve the subproblem to obtain the primal variables (subchannel and power allocation variables) using the given value of dual variables (Lagrange multipliers). Then the master problem is solved to determine the dual variables using the obtained values of primal variables. The iteration is continued till convergence is attained.
Solving the subproblems

To solve for the primal variables, we exploit the fact that, for a convex optimization problem, the optimal solution must satisfy KKT conditions. Differentiating (5.11) with respect to $\tilde{P}_{n,t}^{h,R,e}$ and $\tilde{P}_{n,t}^{h,N,e}$, respectively, and using the KKT stationarity condition, we obtain

$$\tilde{P}_{n,t}^{h,R,e} + \tilde{P}_{n,t}^{h,N,e} = \rho_{S,h} \left[ \frac{r_{th} + \lambda_{h,t}^{(it)}}{(\log 2) \left\{ \sum_{\tau=t}^{T} \delta_{\tau}^{(it)} + \sum_{m=1}^{M} \eta_{m,n,t}^{(it)} h_{S,m}^{n,t} M_{m}^{t} \right\}} - \frac{P_{M} g_{M,h}^{n,t} + N_{w}}{g_{S,h}^{n,t}} \right]^{+}, \forall h, n, t$$  (5.13)

$$\tilde{P}_{n,t}^{h,N,e} + \tilde{P}_{n,t}^{h,R,e} = \rho_{S,h} \left[ \frac{r_{th} + \lambda_{h,b}^{(it)}}{(\log 2) \left\{ r_{g} \alpha_{S} + \sum_{m=1}^{M} \eta_{m,n,t}^{(it)} h_{S,m}^{n,t} M_{m}^{t} \right\}} - \frac{P_{M} g_{M,h}^{n,t} + N_{w}}{g_{S,h}^{n,t}} \right]^{+}, \forall h, n, t$$  (5.14)

where $[x]^{+}$ ensures non-negativity of transmit power of the SBS and $it$ is iteration index of dual decomposition method. We see that sum of $\tilde{P}_{n,t}^{h,R,e}$ and $\tilde{P}_{n,t}^{h,N,e}$ can be defined either by (5.13) or (5.14) and that power allocation variables are interdependent on each other.

To overcome the interdependency of power variables and to ensure maximum utilization of renewable power, we simplify (5.13) as [29,41]

$$\tilde{P}_{n,t}^{h,R,e} = \rho_{S,h}^{n,t} \tilde{P}_{n,t}^{h,R,e}, \forall h, n, t$$  (5.15)

where

$$\tilde{P}_{n,t}^{h,R,e} = \left[ \frac{r_{th} + \lambda_{h,t}^{(it)}}{(\log 2) \left\{ \sum_{\tau=t}^{T} \delta_{\tau}^{(it)} + \sum_{m=1}^{M} \eta_{m,n,t}^{(it)} h_{S,m}^{n,t} M_{m}^{t} \right\}} - \frac{P_{M} g_{M,h}^{n,t} + N_{w}}{g_{S,h}^{n,t}} \right]^{+}, \forall h, n, t. \quad (5.16)$$

However, the sum of $\tilde{P}_{n,t}^{h,R,e}$ and $\tilde{P}_{n,t}^{h,N,e}$ should strictly satisfy either (5.13) or (5.14). Therefore, using (5.14) and (5.15), we obtain

$$\tilde{P}_{n,t}^{h,N,e} = \rho_{S,h}^{n,t} \tilde{P}_{n,t}^{h,N,e}, \forall h, n, t$$  (5.17)
where

$$\tilde{P}_{h,N_e}^{n,t(it)} = \left[ \frac{r_{th} + \lambda_{h,t}^{(it)}}{(\log2) \{ r_{g} \alpha_{S} \beta + \sum_{m=1}^{M} r_{m,n,n,t} h_{S,m}^{n,t} M_{m} \}} - \frac{P_{M} g_{M,h}^{n,t} + N_w}{g_{S,h}^{n,t}} - \tilde{P}_{h,Re}^{n,t(it)} \right]^{+}, \forall h, n, t.$$ (5.18)

Note that the non-negativity constraint $\tilde{C}_8$ is satisfied in (5.16) and (5.18). The power allocations in (5.15) and (5.17) are in the form of multi-level water filling where

$$\frac{r_{th} + \lambda_{h,t}^{(it)}}{(\log2) \{ r_{g} \alpha_{S} \beta + \sum_{m=1}^{M} r_{m,n,n,t} h_{S,m}^{n,t} M_{m} \}}$$ and $$\frac{r_{th} + \lambda_{h,t}^{(it)}}{(\log2) \{ \sum_{t=1}^{T} r_{\delta_{S}^{(it)}} \alpha_{S} + \sum_{m=1}^{M} r_{m,n,n,t} h_{S,m}^{n,t} M_{m} \}}$$ are the water levels for $\tilde{P}_{h,N_e}^{n,t(it)}$ and $\tilde{P}_{h,Re}^{t,it}$, respectively.

Using (5.15) and (5.17) in (5.8) and (5.9), $\tilde{R}_{h(on)}^{t(it)}$ and $\tilde{P}_{pen}^{t(it)}$ become a linear function of subchannel allocation variables as

$$\tilde{R}_{h(on)}^{t(it)} = \sum_{n=1}^{N} \tilde{P}_{S,h}^{n,t(it)} \log_2 \left( 1 + \frac{\tilde{P}_{h,N_e}^{n,t(it)} + \tilde{P}_{h,Re}^{n,t(it)}}{P_{M} g_{M,h}^{n,t} + N_w} \right), \forall h, t$$ (5.19)

$$\tilde{P}_{pen}^{t(it)} = r_{f} \left[ A^{H} \sum_{h=1}^{H} \sum_{n=1}^{N} H_{h}^{t} \tilde{P}_{h,N_e}^{n,t(it)} \alpha_{S} \beta + (1 - A^{t}) \sum_{n=1}^{N} \sum_{h=1}^{H} H_{h}^{t} \tilde{P}_{M,h}^{n,t(it)} P_{M} \alpha_{M} \right] \forall t.$$ (5.20)

The throughput reward generated by HUEs is then given by $\tilde{R}_{rew}^{t(it)} = r_{th} \left( A^{t} \sum_{h=1}^{H} H_{h}^{t} \tilde{R}_{h(on)}^{t(it)} + (1 - A^{t}) \sum_{h=1}^{H} H_{h}^{t} R_{h(\text{off})}^{t(it)} \right)$. Using (5.15)-(5.20), the net reward we want to maximize becomes a linear function of $\tilde{P}_{S}^{t(it)}, P_{M},$ and $\sigma_{M}$ in each iteration and the subproblem in (5.12) can be re-written as

$$\max_{\tilde{P}_{S}^{t(it)}, P_{M}, \sigma_{M}} \sum_{t=1}^{T} \left( \tilde{R}_{rew}^{t(it)} - \tilde{P}_{pen}^{t(it)} \right) + \chi$$ (5.21)

subject to $\tilde{C}_1, C_{2H}, C_3, C_4, \tilde{C}_7$

where $\chi = \sum_{h=1}^{H} \sum_{t=1}^{T} \lambda_{h,t} A^{t} \tilde{R}_{h(on)}^{t(it)} H_{h}^{t} - \sum_{t=1}^{T} \delta_{t} \sum_{t=1}^{T} A^{t} \sum_{h=1}^{H} \sum_{n=1}^{N} H_{h}^{t} \tilde{P}_{S,h}^{n,t(it)} \alpha_{S} - \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{t=1}^{T} \eta_{m,n,t} A^{t} \sum_{h=1}^{H} H_{h}^{t} \tilde{P}_{S,h}^{n,t(it)} \chi_{S,m} M_{m}^{t}. \quad$ The objective function as well as the constraints of problem in (5.21) are now linear. Hence, the problem in (5.21) is a linear program and can be solved optimally using interior-point method. Once the subchannel allocation variables are known, the auxiliary power variables can be determined by using (5.15) and (5.17). Note that the constraints that were not considered in the
5.3. Offline Optimization: Problem Formulation and Solution Approach

partial Lagrangian are included in (5.21).

Solving the master problem

The master problem can be solved by using the subgradient method [87] to update dual variables in each iteration as follows:

\[
\lambda_{h,t}^{(i+1)} = \left[ \lambda_{h,t}^{(i)} + \Delta \lambda A^t \left( R_{\min} - \tilde{R}_{h,(on)}^{(i)} \right) H^t_h \right]^+ , \forall h,t
\]  
(5.22)

\[
\delta_t^{(i+1)} = \left[ \delta_t^{(i)} + \Delta \delta \left( \sum_{\tau=1}^{t} \sum_{h=1}^{T} \sum_{n=1}^{H} H^t_h \tilde{F}_{h,R_e}^{n,\tau(t)} + \tilde{F}_{h,N_e}^{n,\tau(t)} \right) \right]^+ , \forall t
\]  
(5.23)

\[
\eta_{m,n,t}^{(i+1)} = \left[ \eta_{m,n,t}^{(i)} + \Delta \eta \left( A^t \sum_{h=1}^{H} \left( \tilde{F}_{h,R_e}^{n,t} + \tilde{F}_{h,N_e}^{n,t} \right) H^t_h \tilde{n}_{S,m} M_{m} - I_{\max} \right) \right]^+ , \forall m,n,t
\]  
(5.24)

where \( \Delta \lambda, \Delta \delta, \) and \( \Delta \eta \) are step sizes and \( [x]^+ \) enforces non-negativity constraint on dual variables.

The master problem and the subproblems are iteratively solved until convergence. Convergence of subgradient method to the globally optimal solution is guaranteed for convex optimization problem for small step size [87]. Algorithm 5 summarizes the subchannel and power allocation framework, for given SBS activation policy. Note that the linear program given in (5.21) can also be separated into \( T \) linear programming problems and solved simultaneously. However, all of \( T \) optimization problems must be solved before updating the dual variables.

Remark 2: Note that, in the scenario with multiple hotspots, due to the presence of co-tier interference terms in throughput expression of the HUEs, subchannel and power allocation problem becomes highly complicated. However, if we use the worst-case approximation of throughput of HUEs by defining an upper bound on the received interference, as done for MUEs, the solution approach becomes similar to the one used in the scenario with single hotspot.
5.3. Offline Optimization: Problem Formulation and Solution Approach

Algorithm 5 Subchannel and Power Allocation Algorithm for Given SBS Activation Policy

**Require:** Offline information on channel gains, user activities, and energy arrivals

1. Initialize $\textit{it} = 1$ and $\lambda^{(\textit{it})}$, $\delta^{(\textit{it})}$, $\eta^{(\textit{it})}$

2. **repeat**

3. Compute $\hat{P}_{n,t}^{R}$ and $\hat{P}_{n,t}^{N}$, $\forall n, t, h$ using (5.16) and (5.18), respectively

4. Formulate the linear programming problem as given in (5.21) and solve it using interior-point method to determine $\rho_{S}^{(\textit{it})}$, $\rho_{M}$, and $\sigma_{M}$

5. Determine $\tilde{P}_{n,t}^{R}$ and $\tilde{P}_{n,t}^{N}$, $\forall n, t, h$ using (5.15) and (5.17)

6. Update dual variables $\lambda^{(\textit{it}+1)}$, $\delta^{(\textit{it}+1)}$, $\eta^{(\textit{it}+1)}$ using subgradient method as given in (5.22)-(5.24)

7. $\textit{it} \leftarrow \textit{it} + 1$

8. **until** Convergence

5.3.2 Discrete Binary PSO for Dynamic SBS Activation

In discrete binary PSO (DBPSO) [100], we first initialize an array of particles, corresponding to SBS activation variables, where position code of each particle $i$ is given as

$$A_{(i,\textit{it})} = \left[ A_{1(i,\textit{it})}, A_{2(i,\textit{it})}, \ldots, A_{T(i,\textit{it})} \right], \forall i \in \{1, 2, \ldots, P\} \quad (5.25)$$

where $A_{(i,\textit{it})}$ is SBS activation decision for time $t$ given by particle $i$ in the iteration $\textit{it}$ of the DBPSO algorithm and $\textit{it} = 1$ upon initialization. $T$ defines the dimension of the problem and $P$ is the swarm size. We also initialize arrays of velocities of particles as

$$V_{(i,\textit{it})} = \left[ v_{1(i,\textit{it})}, v_{2(i,\textit{it})}, \ldots, v_{T(i,\textit{it})} \right], \forall i. \quad (5.26)$$

The subchannel and power allocation framework given in the previous section is used to maximize the net reward function corresponding to each particle in each iteration. The personal best position code of each particle $A_{p\text{best}}(i)$ saves the position code of particle $i$ in the iteration $\textit{it}$ if it resulted in maximum net reward in comparison to all past iterations. The overall best position code of all particles $A_{g\text{best}}$ saves the position code of particle $i$ in iteration $\textit{it}$ if it resulted in maximum net reward in comparison to all particles in all past
5.4 Online Optimization: Problem Formulations and Solution Approaches

In this section, we optimize SBS activation, subchannel allocation, and power allocation variables using only the causal information of energy arrival, channel gains, and user activities. Since future values of these parameters are not known, we can follow two approaches: (i) if statistical information of future values are available through long term measurements, we

\[ v_{i,ip+1}^{t} = \left[ v_{i,ip}^{t} + \phi_{1}^{t} \left( A_{pbest}^{t}(i) - A_{ip}^{t} \right) + \phi_{2}^{t} \left( A_{gbest}^{t} - A_{ip}^{t} \right) \right] V_{max}, \forall i, t \]  

(5.27)

where \( \phi_{1}^{t} \) and \( \phi_{2}^{t} \) are the randomly generated positive number between 0 and 1. \( V_{max} \) and \( -V_{max} \) provide upper and lower bound on the velocity of the particles. Then the particles are updated in each iteration as follows [100]:

\[
\text{if } \text{rand}() < S(v_{i,ip+1}^{t}) \text{ then } A_{ip}^{t+1} = 1
\]

\[
\text{else } A_{ip}^{t+1} = 0
\]

(5.28)

where \( S() \) is a sigmoid function and \( \text{rand}() \) is quasirandom number selected from the range \([0, 1] \) [100]. Note that \( S(v_{i,ip+1}^{t}) \) gives the probability that \( A_{ip}^{t+1} \) will take on the value of 1 in the next iteration. The above described procedure is iterated until convergence is attained. Algorithm 6 summarizes framework for optimizing the SBS activation variables along with subchannel and power allocation variables.

**Remark 3**: Note that, in the scenario with multiple \((K)\) hotspots, the dimension of the DBPSO problem will increase from \( T \) to \( T \times K \). Hence, for higher values of \( K \), the dimension of the DBPSO problem will be large. However, we can use multiple variations of the PSO algorithm proposed in the literature for high dimensional problems [113, 114].
Algorithm 6 Offline Resource Allocation Algorithm

Require: Offline information on channel gains, user activities, and energy arrival
1: Initialize $P$ particles of $A_{(i,it_p)}$, $V_{(i,it_p)}$, $\forall i = 1, 2, ... P$ and iteration index $it_p = 1$
2: Initialize personal best value of each particle, $f_{\text{best}}(i)$ and overall best value of all particles, $f_{\text{best}}$ to a small value
3: repeat
4:   for $i = 1 : P$ do
5:       Determine subchannel and power allocation for $A = A_{(i,it_p)}$, using Algorithm 5 and let
6:       $f_{\text{max}}(i,it_p) = \max \sum_{t=1}^{T} \left( \hat{R}_{\text{rew}}^t - \hat{P}_{\text{pen}}^t \right) |A^t = A_{(i,it_p)}$
7:       Update personal best position of each particle
8:          if $f_{\text{max}}(i,it_p) > f_{\text{best}}(i)$, then $A_{p\text{best}}(i) = A_{(i,it_p)}$, $f_{\text{best}}(i) = f_{\text{max}}(i,it_p)$
9:          Update the overall best position of all particles
10:         if $f_{\text{max}}(i,it_p) > f_{\text{best}}$, then $A_{g\text{best}} = A_{(i,it_p)}$, $f_{\text{best}} = f_{\text{max}}(i,it_p)$
11:     end for
12: end repeat
13: Update the velocity using (5.27)
14: Update the position of the particles using (5.28)
15: $it_p \leftarrow it_p + 1$
16: until Convergence
17: Select $A_{g\text{best}}$ for SBS activation and the corresponding subchannel and power allocation for resource allocation.
can maximize the expected value of the net reward function for the considered time slots; (ii) in the absence of any kind of future information, we can maximize net reward of the current time slot using the causal information available. In the following, we will first provide a dynamic programming-based online solution to maximize expected value of net reward over a number of time slots [115]. Then we will provide a greedy online solution approach to maximize net reward of the current time slot.

5.4.1 Dynamic Programming-based Online Optimization

With the availability of causal information and statistics of future information, the SBS activation, subchannel allocation, and power allocation variables can be optimized to maximize the expected value of net reward function as

\[
\max_{A, \rho_S, \rho_M, \sigma_M, P_{Re}, P_{Ne}} \sum_{t=1}^{T} \mathbb{E}_{U,E,F} \{ R_t^{rew} - P_t^{pen} \}
\]

subject to \(C_1 - C_8\) \hspace{1cm} (5.29)

where \(U, E,\) and \(F\) denote random user activity, energy arrival, and channel fading, respectively. \(\mathbb{E}_{U,E,F}\{.\}\) denotes the statistical expectation with respect to user activity, energy arrival, and channel fading. Note that, in (5.29), the sum of the expected values of net reward function is maximized instead of the instantaneous values. The constraints are same as those of the offline problem in (5.7). However, if we define a new parameter \(B^t\) indicating the amount of energy available in the battery that stores the harvested energy in time slot \(t\), constraint \(C_5\) of the problem in (5.29) can also be written as

\[
C_{5a}: A^t \sum_{h=1}^{H} \sum_{n=1}^{N} H_h^{n,t} \rho_{S,h}^{n,t} P_{Re}^{n,t} \alpha_S \leq B^t, \ \forall t
\]

(5.30)
where \( B_t = E^{t-1} \), if \( t = 1 \) and the battery state has the following dynamics:

\[
B_t = \sum_{\tau=0}^{t-1} E^\tau - \sum_{\tau=1}^{t-1} A^\tau \left( \sum_{h=1}^{H} \sum_{n=1}^{N} H^\tau_h \rho_{S,h}^n \tau P_{R_e}^n, \alpha_S \right)
\]

or,

\[
B_t = B^{t-1} + E^{t-1} - A^{t-1} \sum_{h=1}^{H} \sum_{n=1}^{N} H^{t-1}_h \rho_{S,h}^{n,t-1} P_{R_e}^{n,t-1}, \alpha_S, \text{if, } t = 2, \ldots, T.
\]

Note that the system model can be characterized as a dynamic system where

- Random parameters are \( E^{t-1}, U^t, \) and \( F^t \), where \( E^{t-1} \) denotes energy arrived at the end of previous time slot, \( U^t = \{ M^t_m, \forall m, H^t_h, \forall h \} \) denotes user activity in the current time slot, and \( F^t = \{ f^{n,t}, \forall n \} \) denotes channel fading condition in the current time slot.

- State of the system is given by \( S^t = (B^t, E^{t-1}, U^t, F^t) \), where \( B^t \) denotes battery state in the current time slot which is updated according to (5.31).

- Decision variables to be selected in each time slot \( t \) are \( A^t, \rho_S^t, \rho_M^t, \sigma_M^t, P_{R_e}^t, P_{N_e}^t \).

- The net reward function in each time \( t \) is \( (R_{\text{rew}}^t - P_{\text{pen}}^t) \) where \( R_{\text{rew}}^t \) and \( P_{\text{pen}}^t \) are given in (5.3) and (5.6), respectively.

Our objective is to maximize expected value of the net reward over \( T \) time slots. The optimal solution can be obtained by using Bellman’s equation and backward induction [115]. For the last time slot, that is \( t = T \), the maximum reward can be computed as

\[
\text{For } t = T, \quad J^t(S^t) = \text{maximize}_{A^t, \rho_S^t, \rho_M^t, \sigma_M^t, P_{R_e}^t, P_{N_e}^t} \quad (R_{\text{rew}}^t - P_{\text{pen}}^t)
\]

subject to \( C_1 - C_4, C_5a, C_6 - C_8 \)

where constraint \( C_{5a} \) denotes the battery constraint as given in (5.30) and the remaining constraints are similar to those in (5.7) for time slot \( t \). Then, by backward induction, the
maximum reward of remaining time slots \( t = T - 1, T - 2, \ldots, 2, 1 \) can be computed as

\[
J^t(S^t) = \maximize_{A^t, \rho^t_S, \rho^t_M, \sigma^t_M, P^t_{Ra}, P^t_{Ne}} (R^t_{rew} - P^t_{pen}) + \tilde{J}^{t+1}(S^{t'}, A^t, P^t_{Ra}, \rho^t_S)
\]

subject to \( C_1 - C_4, C_5, C_6 - C_8 \)  

(5.33)

where

\[
\tilde{J}^{t+1}(S^t, A^t, P^t_{Ra}, \rho^t_S) = \mathbb{E}_{U,E,F}\{J^{t+1}(S^{t+1}|S^t, A^t, P^t_{Ra}, \rho^t_S)\}, \forall t.
\]

(5.34)

(5.34) can be calculated if the probability density functions of \( U, E \) and \( F \) are available.

Note that, in addition to the current state, future state also depends on SBS activation variable \( A^t \), power allocation variables \( P^t_{Ra} \), and subchannel allocation variables \( \rho^t_S \), due to the battery dynamics. The problems in (5.32) and (5.33) are still non-convex due to the coupling of binary integer SBS activation and subchannel allocation variables. However, in each time slot \( t \), we can solve the problem for \( A^t = 0 \) and \( A^t = 1 \) and choose the one that maximizes the reward for that time slot. Then, we can relax the binary integer constraint of subchannel allocation variables, \( 0 \leq \rho^{n,t}_{S,h}, \rho^{n,t}_{M,h}, \sigma^{n,t}_{M,m} \leq 1 \), introduce auxiliary power variables, \( \tilde{P}^{n,t}_{h,Ra} = \rho^{n,t}_{S,h} P^{n,t}_{Ra}, \forall h, n \) and \( \tilde{P}^{n,t}_{h,Ne} = \rho^{n,t}_{S,h} P^{n,t}_{Ne}, \forall h, n \), and use worst-case approximation of throughput of MUEs, as done in Section 5.3. With fixed \( A^t \), new auxiliary power variables, relaxed subchannel allocation variables, and worst-case approximation of throughput of MUEs, the problems in (5.32) and (5.33) are both convex optimization problems and can be optimally solved.

Using the dynamic programming method mentioned above, resource allocation is done in two phases: planning and implementation. In the planning phase, the problem in (5.32) is solved for all possible \( B^T, U^T, \) and \( F^T \) and the corresponding resource allocation decisions are stored in a look-up table. Then the problem in (5.33) is solved recursively for each time slot \( t = T - 1, T - 2, \ldots, 2, 1 \). In each time slot, the problem is solved for different possible \( B^t, U^t, \) and \( F^t \) and probability distribution of \( U, E \), and \( F \) are used to compute the expected future reward. The corresponding resource allocation decisions are stored in the
look-up table. In the implementation phase, at the beginning of each time slot, the resource allocation decision corresponding to the state $S^t$ at that time slot is extracted from the look-up table. The aforementioned resource allocation framework is summarized in Algorithm 7.

Algorithm 7 Dynamic Programming-based Online Resource Allocation Algorithm

1: **Planning**
2: \textbf{for} $x = 0 : 1$ \textbf{do}
3: \hspace{1em} Compute $J^T(S^T)|_{A^T=x}$ by solving the problem in (5.32), for $t = T$, $\forall B^T, U^T, F^T$
4: \hspace{1em} Denote optimal values as $(\rho^T_S, \rho^T_M, \sigma^T_M, P^T_{Re}, P^T_{Ne})|_{A^T=x}$
5: \textbf{end for}
6: Store $A^*^T = \text{argmax}_x J^T(S^T)|_{A^T=x}$, and $(\rho^*^T_S, \rho^*^T_M, \sigma^*^T_M, P^*^T_{Re}, P^*^T_{Ne})|_{A^T=A^*^T}$ on look-up table $\forall B^T, U^T, F^T$
7: \textbf{for} $t = T - 1 : 1$ \textbf{do}
8: \hspace{1em} Compute $J^t(S^t)|_{A^t=x}$ by solving the problem in (5.33), $\forall B^t, U^t, F^t$, using probability distribution of $U$, $E$, and $F$
9: \hspace{1em} Denote optimal values as $(\rho^*_S, \rho^*_M, \sigma^*_M, P^*_Re, P^*_Ne)|_{A^t=x}$
10: \textbf{end for}
11: Store $A^*^t = \text{argmax}_x J^t(S^t)|_{A^t=x}$, and $(\rho^*_S, \rho^*_M, \sigma^*_M, P^*_Re, P^*_Ne)|_{A^t=A^*^t}$ on look-up table $\forall B^t, U^t, F^t$
12: \textbf{end for}
13: **Implementation**
14: \textbf{for} $t = 1 : T$ \textbf{do}
15: \hspace{1em} Collect information on $E^{t-1}$, $U^t$, and $F^t$
16: \hspace{1em} Update $B^t$ using (5.31).
17: \hspace{1em} Return $(A^*^t, \rho^*_S, \rho^*_M, \sigma^*_M, P^*_Re, P^*_Ne)$ for $B^t, U^t, F^t$ from look-up table
18: \textbf{end for}

5.4.2 Greedy Online Optimization

Due to the curse of dimensionality, computational complexity in dynamic programming method discussed above increases exponentially with the number of users, subchannels, and time slots. Also, statistical information of the future values may not always be accurately available. Therefore, in this section, we present a greedy online optimization algorithm which has a much lower computational complexity and does not need any information on future
5.4. Online Optimization: Problem Formulations and Solution Approaches

values of user activity, channel fading, and energy arrival. In greedy online optimization technique, we simply maximize the net reward function of each time slot based on available causal information on battery level, user activity, energy arrival, and channel fading. The problem can be formulated as

\[
\begin{align*}
\text{maximize} & \quad A^t, \rho^t_S, \rho^t_M, \sigma^t_M, P^t_{\text{Re}}, P^t_{\text{Ne}} \left( R^t_{\text{rew}} - P^t_{\text{pen}} \right) \\
\text{subject to} & \quad C_1 - C_4, C_5a, C_6 - C_8
\end{align*}
\] (5.35)

where the constraints are same as those in (5.32) and (5.33). \( R^t_{\text{rew}} \) and \( P^t_{\text{pen}} \) are given in (5.3) and (5.6), respectively. The problem in (5.35) is non-convex due to the coupling of binary integer SBS activation and subchannel allocation variables. Therefore, as discussed in dynamic programming-based online algorithm, we will solve the problem for \( A^t = 1 \) as well as \( A^t = 0 \) and choose the value that maximizes the reward function. For fixed SBS activation variable, the problem in (5.35) becomes subchannel and power allocation problem.

Remark 4: Note that, in the scenario with multiple hotspots, there will be multiple SBS activation variables in each time slot and hence the online solution approach should also use the DBPSO algorithm to optimize the SBS activation variables.

Subchannel and power allocation for given SBS activation decision

For fixed SBS activation variable, the problem in (5.35) is still non-convex due to binary integer constraint on subchannel allocation variables, and non-convexity of \( R^t_{\text{h(on)}} \), \( R^t_{\text{m}} \), and \( P^t_{\text{pen}} \). Therefore, we relax the subchannel allocation variables, \( 0 \leq \rho^{n,t}_{S,h}, \rho^{n,t}_{M,h}, \sigma^{n,t}_{M,m} \leq 1 \), introduce auxiliary power variables, \( \tilde{P}^{n,t}_{h,\text{Re}} = \rho^{n,t}_{S,h} P^{n,t}_{\text{Re}}, \forall h, n \) and \( \tilde{P}^{n,t}_{h,\text{Ne}} = \rho^{n,t}_{S,h} P^{n,t}_{\text{Ne}}, \forall h, n \), and use worst-case approximation of throughput of MUEs, as done in Section 5.3. With fixed SBS activation variable, relaxed subchannel allocation variables, auxiliary power variables, \( \tilde{R}^t_{\text{h(on)}} \) and power consumption penalty \( \tilde{P}^t_{\text{pen}} \) become convex functions of optimization variables as given in (5.8) and (5.9), respectively, and hence the net reward function \( \tilde{R}^t_{\text{rew}} - \tilde{P}^t_{\text{pen}} \) is also
convex. Therefore, the problem in (5.35) can be transformed into a convex optimization problem similar to (5.10) and solved optimally [180]. As in Section 5.3, we solve this problem iteratively by dual decomposition technique. In each iteration of dual decomposition technique, we optimize the subchannel and power allocation variables using given values of Lagrange multipliers and then update the Lagrange multipliers using subgradient method.

**Solving the subproblem:** To optimize the subchannel and power allocation variables, using KKT conditions of optimality, we have

\[
\begin{align*}
\hat{P}_{h,R_e}^{n,t} &= \rho_{S,h}^{n,t} \hat{P}_{h,R_e}^{n,t}, \quad \hat{P}_{h,N_e}^{n,t} = \rho_{S,h}^{n,t} \hat{P}_{h,N_e}^{n,t}, \quad \forall h, n \quad \text{(5.36)} \\
\end{align*}
\]

where

\[
\begin{align*}
\hat{P}_{h,R_e}^{n,t} &= \left[ \frac{r_{th} + \gamma_h}{(\log 2) \left( \theta \alpha_S + \sum_{m=1}^{M} \mu_{m,n,h_{S,m}} M_m^t \right)} - \frac{P_M g_{M,h}^{n,t} + N_w}{g_{S,h}^{n,t}} \right]^{+}, \quad \forall h, n \quad \text{(5.37)} \\
\hat{P}_{h,N_e}^{n,t} &= \left[ \frac{r_{th} + \gamma_h}{(\log 2) \left( r \alpha_S \beta + \sum_{m=1}^{M} \mu_{m,n,h_{S,m}} M_m^t \right)} - \frac{P_M g_{M,h}^{n,t} + N_w}{g_{S,h}^{n,t}} - \hat{P}_{h,R_e}^{n,t} \right]^{+}, \quad \forall h, n \quad \text{(5.38)}
\end{align*}
\]

\(\gamma_h, \forall h, \theta,\) and \(\mu_{m,n}, \forall m, n\) are Lagrange multipliers associated with the convexified constraints similar to \(\tilde{C}_2,\tilde{C}_5,\) and \(\tilde{C}_6\) of the problem in (5.10). The details of derivation are similar to those for the offline optimization problem presented in Section 5.3. Power allocations given in (5.36) are also in multi-level water-filling form where the water levels for \(\hat{P}_{h,R_e}^{n,t}\) and \(\hat{P}_{h,N_e}^{n,t}\) are given by \((\log 2) \left( \theta \alpha_S + \sum_{m=1}^{M} \mu_{m,n,h_{S,m}} M_m^t \right)\) and \((\log 2) \left( r \alpha_S \beta + \sum_{m=1}^{M} \mu_{m,n,h_{S,m}} M_m^t \right)\), respectively. Note that the offline power allocation scheme considered Lagrange multipliers of causality constraint of all future time slots of consideration while the greedy scheme considers that of current slot only. Hence, offline power allocation scheme uses the harvested power more conservatively.

Using (5.36), \(\tilde{R}_{h(\text{on})}^t\) and \(\tilde{R}_{\text{pen}}^t\) given in (5.8) and (5.9) can be re-written as linear functions of subchannel allocation variables as given in (5.19) and (5.20), respectively. The reward
Online Optimization: Problem Formulations and Solution Approaches

for achievable throughput given in (5.3) becomes a linear function of subchannel allocation variables. Then, for each iteration, the problem in (5.35) can be transformed into a linear programming problem similar to (5.21) and solved optimally using interior-point method. Using the obtained subchannel allocation variables, power allocation variables are determined using (5.36).

Solving the master problem: Finally, the Lagrange multipliers can be updated using the well-known subgradient method similar to (5.22)-(5.24). Subgradient method is guaranteed to converge to the globally optimal solution for convex optimization problems [87].

After subchannel and power allocation variables are obtained, the battery level is updated for the next time slot, using (5.31). The greedy online resource allocation framework is summarized in Algorithm 8.

Algorithm 8 Greedy Online Resource Allocation Algorithm

for $t = 1 : T$
  Collect information on $E^{t-1}, U^t, F^t$ and update $B^t$ using (5.31).
  for $x = 0 : 1$
    Initialize dual variables $\gamma, \theta,$ and $\mu$.
    repeat
      Compute $\hat{P}_{n,R_e}^{t}$ and $\hat{P}_{n,N_e}^{t}$ using (5.37) and (5.38), respectively.
      Formulate the linear programming problem similar to (5.21) and solve it using interior-point method to determine $f_{\max}|_{A^t=x} = \max \rho_S^t, \rho_M^t, \sigma_M^t \left( \tilde{R}_{\text{rew}}^t - \tilde{P}_{\text{pen}}^t \right) |_{A^t=x}$ and let $(\rho_S^{\ast t}, \rho_M^{\ast t}, \sigma_M^{\ast t})|_{A^t=x}$ denote the subchannel allocation variables.
      Determine $(\hat{P}_{n,R_e}^{x,n,t}, \hat{P}_{n,N_e}^{x,n,t})|_{A^t=x}, \forall n, h$ using (5.36).
      Update dual variables $\gamma, \theta, \mu$ using subgradient method.
    until Convergence
  end for
  Select $A^t = \arg\max_x f_{\max}|_{A^t=x}$, and $(P_{R_e}^{x,t}, P_{N_e}^{x,t}, \rho_S^{x,t}, \rho_M^{x,t}, \sigma_M^{x,t})|_{A^t=A^t}$
end for
5.5 Performance Evaluation Results

We evaluate performances of the proposed offline/online algorithms and compare them with those of the baseline schemes. We choose three baseline schemes for comparison: (i) *Always On Scheme*, where $A^t = 1$, $\forall t$, (ii) *Always Off Scheme*, where $A^t = 0$, $\forall t$, and (iii) *Heuristic Scheme*, where $A^t = 0$ if $E^{t-1} = 0$, $A^t = 1$ if $E^{t-1} > E_{th}$, and $A^t = 0$ or $1$ with equal probability if $0 < E^{t-1} \leq E_{th}$, where $E_{th}$ is defined threshold. The resource allocation for these baseline schemes can be optimized using Algorithm 5 for given SBS activation policy.

We compare the net reward generated by different algorithms, throughput performance of HUEs, and non-renewable power consumed at SBS and MBS to serve HUEs (simply referred to as power consumption from here onward).

5.5.1 Simulation Parameters

We consider a single macrocell with the MBS at the origin. There is one hotspot at a distance of 100 m from the MBS with $H = 2$ HUEs. An SBS is installed at the center of the hotspot such that HUEs are located at distance of 3 to 10 m from the SBS. There are $M = 2$ MUEs located close to the hotspot. $T = 4$ consecutive time slots and $N = 4$ subchannels, each of bandwidth 20 KHz are considered in the simulations. In each time slot $t$, energy harvesting rate $E^t$ takes a value from the set \{0, $E_H$, $2E_H$\} with equal probability. For the *Heuristic Scheme*, we set the energy threshold $E_{th}$ to be $E_H$. The activity indicators of MUEs and HUEs take a value from the set \{0, 1\} with equal probability. The fading condition of any subchannel $n$ in a time $t$, $f^{n,t}$, follows exponential distribution with unit mean. Note that channel gain, energy harvesting rate, and activity indicators of the MUEs and HUEs are assumed to follow zeroth order Markov model in our simulations. The path-loss, in dB, in the link from SBS to the UEs is $38.46 + 20\log D$ and MBS to the UEs is $15.3 + 37.6\log D$, based on the channel models from [96], where $D$ is the distance between transmitter and receiver in meters. The minimum throughput requirement of MUEs and HUEs are set as
5.5. Performance Evaluation Results

Figure 5.2: Convergence of DBPSO algorithm.

$R_{\text{min}} = 50$ Kbps. Transmit power of the MBS is set to $P_M = 46$ dBm. We assume $r_{th}$ to be 0.01/Kbps while $r_g$ to be 0.1/Watt. Assuming cost of non-renewable energy source (e.g. on site energy generator) of the SBS is higher than that of the MBS (e.g. grid power), we set $\beta = 10$. The maximum interference tolerable to MUEs $I_{\text{max}}$ is $10^{-8}$ W and AWGN noise power $N_w$ is $10^{-13}$ W. Based on the results of [107], we set $\alpha_S = 25$, indicating that the transmit power is only 4% of the total dynamic power consumption in an SBS. However, unlike SBS, the signal processing and other power consumption overhead of the MBS can be assumed to be constant since they vary negligibly with the traffic load [107]. Therefore, considering 50% power amplifier efficiency, we set $\alpha_M = 2$.

5.5.2 Simulation Results

Convergence

Fig. 5.2 shows convergence behavior of the DBPSO algorithm used in Algorithm 6 for one particular realization of arrival of harvested energy, channel fading, and user activity, for $E_H = 4$ Jps. We observe that, the DBPSO algorithm converges to the same value when the number of particles $P = 4$ or $P = 6$ although convergence is faster when $P = 6$ as compared
5.5. Performance Evaluation Results

Table 5.1: Comparison among proposed algorithms (Scenario I)

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Net reward</th>
<th>SBS activation</th>
<th>Average throughput (Kbps)</th>
<th>Average power consumption in SBS (Watts)</th>
<th>Average power consumption in MBS (Watts)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Offline</td>
<td>2.7661</td>
<td>0, 1, 1, 1</td>
<td>77.204</td>
<td>0</td>
<td>4.6654</td>
</tr>
<tr>
<td>Dynamic</td>
<td>1.8634</td>
<td>0, 1, 1, 1</td>
<td>62.96</td>
<td>0.0043</td>
<td>4.7428</td>
</tr>
<tr>
<td>Greedy</td>
<td>1.7365</td>
<td>1, 1, 0, 1</td>
<td>59.879</td>
<td>0.2308</td>
<td>2.3347</td>
</tr>
</tbody>
</table>

to $P = 4$. The obtained value of the objective function upon convergence is compared with the result obtained by solving the original problem directly with the OPTI solver [98] which is a free MATLAB toolbox capable of solving non-linear and discrete optimization problems. It is noted that the performance loss in the proposed offline algorithm is small despite the approximations used in subchannel and power allocation algorithm.

**Comparison among the proposed algorithms**

We compare performances of the proposed algorithms by tabulating results obtained for each of the proposed algorithms for two different scenarios. We tabulate SBS activation decision made by the proposed algorithms, resulting average throughput of HUEs, average power consumption at the SBS and that at the MBS to serve HUEs, and the net reward, when $E_H = 4$ Jps. In Scenario I, we consider one random realization of energy arrival and user activity where energy harvesting rate in the 4 considered time slots are $E_H$, $2E_H$, 0, and $2E_H$, number of active MUEs are 2, 1, 1, and 2, while number of active HUEs are 2, 2, 1, and 1, respectively. To understand the effect of user activity variation, we consider that fading condition of all the subchannels remain same during the considered time slots. The results are presented in Table 5.1. The proposed offline algorithm and dynamic programming-based online algorithm turn the SBS off in the first time slot. It is because, with two MUEs active, the interference constraint is more severe which curbs throughput performance of HUEs hence resulting in lower net reward. However, the greedy online algorithm turns the SBS on whenever energy arrived is non-zero resulting in lower average throughput performance.
and higher power consumption at the SBS, and hence lower net reward\textsuperscript{17}. Although the dynamic programming-based online algorithm results in SBS activation decision similar to that of the offline algorithm, the offline algorithm yields a better throughput performance, a lower power consumption, and hence higher net reward.

In Scenario II, we consider another random realization of energy arrival where energy harvesting rate in the 4 considered time slots are $E_H$, $E_H$, $2E_H$, and $E_H$, respectively. To understand the effect of time-variation of channel fading, all sub-channels of consideration are assumed to have same fading condition in one time slot and the channel fading is assumed to take values 0.8220, 1.4635, 2.8, and 1.2683, respectively in the 4 time slots under consideration. To understand the effect of channel fading variation, all of the UEs are assumed to be active during all time slots under consideration. The results are presented in Table 5.2. The offline algorithm and the dynamic programming-based online algorithm turn the SBS off in the first time slot when the channel fading is in the worst condition. Other observations are similar to those of Scenario I.

**Variation with $E_H$**

Figs. 5.3-5.5 show variation in net reward, average throughput, and average power consumption with variation in $E_H$, respectively. Net rewards generated by the proposed algorithms are much higher than those by the baseline schemes (Fig. 5.3) since average throughputs are higher (Fig. 5.4) and power consumptions are lower (Fig. 5.5). Specifically, note that

\textsuperscript{17}Total power consumption is numerically lower in greedy algorithm than that in other proposed algorithms. However, since the penalty per unit power consumption at the SBS is higher by the factor $\beta$, the incurred penalty becomes comparable or higher.
5.5. Performance Evaluation Results

Figure 5.3: Variation in net reward with $E_H$.

Figure 5.4: Variation in average throughput with $E_H$. 
5.5. Performance Evaluation Results

power consumption at the MBS is much lower than that in *Always Off Scheme* and power consumption at the SBS is much lower than that in *Always On Scheme*. Although the total power consumption is numerically smallest for *Always On Scheme*, the incurred penalty is higher since penalty per unit power consumption at the SBS is higher by factor $\beta$. For lower values of $E_H$, performance of the *Heuristic Scheme* is better than those of the *Always On Scheme* and the *Always Off Scheme* since the SBS activation decision is taken considering the amount of energy arrived. As expected, performance of the offline algorithm is the best, which is followed by the dynamic programming-based online algorithm and then the greedy online algorithm. The reason behind such result can be understood from the results of some specific scenarios presented in Tables 5.1 and 5.2. Although power consumption at the MBS for offline and dynamic programming-based online algorithms are higher, greedy online algorithm incurs a higher penalty for power consumption. This is because power consumption at the SBS is higher and penalty per unit power consumption is higher at the SBS by the factor $\beta$. The differences among performances of the proposed algorithms in terms of power consumption and hence the net reward are observed to be small when $E_H$ is very low or very high. This is because, when harvested energy is very small, the SBS is mostly deactivated, hence resulting in maximum power consumption in the MBS. When the harvested energy is very high, the SBS is mostly activated with minimum power consumption in the MBS as well as the SBS. Since the SBS is never activated in *Always Off Scheme*, its performance does not vary with $E_H$.

**Variation with $I_{\text{max}}$**

In Figs. 5.3-5.5, we compare performance of the proposed offline algorithm for different values of $I_{\text{max}}$. When interference tolerance of MUEs ($I_{\text{max}}$) is lowered, throughput of HUEs decreases (Fig. 5.4) since transmit power of the SBS is lowered due to interference constraint $C_6$. However, non-renewable power consumption at the MBS decreases and that at the SBS increases (Fig. 5.5). It is because SBS is activated more often when $I_{\text{max}}$ is lowered. This
5.5. Performance Evaluation Results

Figure 5.5: Variation in power consumption with $E_H$.

highlights the impact of interference-aware resource allocation on SBS activation decision. The net reward of serving HUEs also decreases slightly with lower $I_{\text{max}}$ (Fig. 5.3), mainly due to lowered throughput performance.

**Variation with $\beta$**

Figs. 5.6-5.7 show performance variation of the proposed algorithms in comparison to the baseline schemes, with varying $\beta$, for $E_H = 3$ Jps. When $\beta$ is very low, penalty of power consumption in the SBS is comparable to that in the MBS. Since power consumption in the SBS is always smaller than that in the MBS, the proposed algorithms maximize throughput of HUEs by always turning the SBS on, resulting in performance similar to that of *Always On Scheme*. Hence, power consumption at the SBS to serve HUEs is maximum and that at the MBS is zero (Fig. 5.7). As $\beta$ increases, power consumption at the SBS decreases and that at the MBS increases. Average throughput of HUEs decrease to a minimum point when $\beta = 2.5$ because at this point power consumption is reduced at the SBS but the MBS is not serving HUEs. After this point, throughput performance of the proposed algorithms gradually increase and become prominently higher than that of *Always On Scheme* (Fig. 5.6).
5.5. Performance Evaluation Results

Figure 5.6: Variation in average throughput with $\beta$.

When $\beta$ is higher than 10, power consumption at the SBS reduces to zero and that at the MBS stabilizes to a maximum value indicating that, for these values of $\beta$, the SBS is activated to consume harvested energy only. However, in the Heuristic Scheme, power consumption at the SBS does not become zero since SBS is activated whenever the arrived energy is higher than $E_H$, regardless of $\beta$. The Always Off Scheme results in the lowest average throughput of HUEs and maximum power consumption at the MBS.

Variation with hotspot size

In Figs. 5.6, 5.7, we compare the performance of the proposed offline algorithm for different hotspot size. When radius of the hotspot is increased, power allocated to SBS should increase to overcome the propagation loss. Therefore, for lower values of $\beta$, power consumption at the SBS is higher (Fig. 5.7). However, due to interference constraint $C_6$, the increase in transmit power cannot fully overcome the propagation loss and hence throughput of HUEs decreases (Fig. 5.6). Therefore, for larger values of $\beta$, the SBS is deactivated more often and HUEs are
5.5. Performance Evaluation Results

Figure 5.7: Variation in power consumption with $\beta$.

Served by the MBS which causes increase in MBS power consumption and decrease in SBS power consumption (Fig. 5.7). This also highlights the impact of interference-aware resource allocation decision on SBS activation decision.

**Variation with $r_{th}$**

Figs. 5.8-5.9 show performance variation of the proposed algorithms in comparison to the baseline schemes, with varying $r_{th}$, for $E_H = 3$ Jps. Since increasing $r_{th}$ implies an increase in throughput reward, with increasing $r_{th}$, the average throughput of HUEs increase (Fig. 5.8) at the cost of higher power consumption at the MBS (Fig. 5.9). This increase is rapid when $r_{th}$ increases from 0.015/Kbps up to 0.025/Kbps, after which the values come to saturation. The Always Off Scheme exhibits a lower throughput performance and a higher power consumption at the MBS in comparison to other algorithms until $r_{th}$ is less than 0.015/Kbps after which the throughput performance and power consumption at the MBS
5.5. Performance Evaluation Results

Figure 5.8: Variation in average throughput with $r_{th}$.

Figure 5.9: Variation in power consumption with $r_{th}$. 
5.5. Performance Evaluation Results

Increases rapidly and becomes comparable to that of the proposed algorithms. At the saturation point, in the proposed algorithms, power consumption at the SBS becomes zero and that at the MBS becomes comparable to that of the Always Off Scheme, indicating that, from this point onward, SBSs are mostly deactivated. However, in the Heuristic Scheme, since the SBS is activated whenever harvested energy is higher than $E_H$, power consumption at SBS also increases with increasing $r_{th}$, as in the Always On Scheme. Given that $r_g$ is set to $0.1$/Watt, it should be noted that gain of the proposed algorithms is prominent when $r_{th}$ is much smaller than $r_g$. For the Always On Scheme, with increasing $r_{th}$, the rate of increase of throughput performance is much lower since SBS transmit power cannot increase significantly due to the interference constraint $C_6$.

5.5.3 Summary of Observations

The effects of arrival of harvested energy, channel conditions as well as number of active MUEs on performance of the proposed algorithms highlight the importance of joint consideration of energy-aware and interference-aware resource allocation in a multi-tier network with energy harvesting base stations. The performance variation with $I_{max}$ and hotspot size also highlight the impact of interference-aware resource allocation decision on SBS activation decision. Since it uses causal as well as non-causal information, the offline algorithm results in a higher achievable throughput of HUEs with minimum power consumption penalty hence generating the highest net reward. Because it only utilizes statistical information instead of non-causal information, the dynamic programming-based online algorithm exhibits an inferior throughput performance and a higher power consumption in comparison to the offline algorithm. However, differences in performances among the three proposed algorithms diminish when the amount of energy harvested is very small or very high. The proposed algorithms are most effective when penalty of power consumption at the SBS is higher than that at the MBS. For lower values of $\beta$, the proposed algorithms try to maximize achievable throughput of HUEs by always associating them to the SBS and the performance becomes
similar to that of the *Always On Scheme*. Similarly, the proposed algorithms are most effective when reward per unit achievable throughput $r_{th}$ is much lower than penalty per unit power consumption $r_g$. For higher values, the proposed algorithms try to maximize achievable throughput of HUEs at the cost of very high power consumption at the MBS and the performance becomes similar to that of the *Always Off Scheme*. Although the *Heuristic Scheme* is inferior to the proposed algorithms, it is superior to the *Always On Scheme* and the *Always Off Scheme* since the SBS activation decision takes the energy arrival information into account.
Chapter 6

Summary, Conclusions, and Future Work

6.1 Summary and Conclusions

In this thesis, we addressed different challenges of uplink and downlink resource allocation in heterogeneous and cooperative communication networks with energy harvesting constraints. As wireless energy harvesting is envisioned as promising technique for elongating battery life of small network devices such as sensor nodes, in Chapters 2-4 we studied resource allocation for uplink and downlink communication with wireless energy harvesting. To address the challenges introduced in uplink as well as downlink resource allocation of wireless energy harvesting networks, we considered uplink WPC in Chapters 2-3 and downlink SWIPT in Chapter 4. In uplink WPC, uplink information transmission is highly dependent on downlink energy harvesting phase and hence we developed algorithms to perform joint uplink and downlink resource allocation considering relay-based and user-based cooperation to mitigate the “doubly near-far” problem. On the other hand, in downlink SWIPT, information transmission rate and energy harvesting rate are two contradicting requirements. Hence, in Chapter 4 we developed resource allocation algorithms to optimize rate-energy trade-off while addressing the interference management challenge in HetNets with SWIPT. While wireless energy harvesting is suitable in small nodes of the network, renewable energy harvesting is a promising technique for reducing the power cost of bigger network nodes such as base stations. Since maximizing the throughput performance at the cost of minimum
non-renewable energy consumption is a challenging requirement of such energy harvesting networks, in Chapter 5 we designed base station activation and resource allocation algorithm to optimize the trade-off between throughput performance and power cost while considering the energy harvesting and interference constraints in HetNets with renewable energy harvesting base stations. In the following, we present the concluding remarks on the contributions made in this thesis.

In Chapter 2, we proposed two scenarios for uplink WPC networks with relay-based cooperation. In Scenario I, far-UEs harvest energy from RF transmission of the access point as well as the relay node; and in Scenario II, far-UEs harvest from relay node transmission only and near-UEs harvest from the transmission of the access point only. We proposed different resource allocation methods to maximize uplink sum-throughput, considering limited transmission time and energy available at the relay node. From simulation results, we observed that, most of the available resources (time/energy) have to be dedicated for wireless charging process. Addition of relay node resulted in a higher throughput of far-UEs and sum-throughput as well as fairness. Simulation results also revealed that the performance of Scenario II is significantly better with optimal resource allocation when compared to the iterative resource allocation and that Scenarios I and II have similar performances with iterative resource allocation. Therefore, the resource allocation methods for Scenario II can be recommended for uplink WPC networks with relay-based cooperation.

In Chapter 3, we investigated resource allocation problem in uplink WPC networks with user-based cooperation. We assumed that all UEs harvest energy from downlink transmission of the access point in energy harvesting phase. In uplink information transmission phase, the UEs were designed to cooperate among each other to enhance their throughput performance. Since uplink sum-throughput performance relies on the harvested energy, channel allocation, and relay selection, we proposed a novel resource allocation scheme to jointly optimize downlink and uplink power allocation along with uplink subcarrier and relay selection. From simulation results, we demonstrated the efficacy of our proposed resource allocation
scheme in comparison to two benchmark schemes in terms of throughput and system energy efficiency.

In Chapter \footnote{4} we investigated resource allocation problem for SWIPT in small cells underlaying a macrocell in a two-tier HetNet. By using scalarization technique of multi-objective programming, we jointly optimized achievable throughput as well as energy harvesting rates of small cell users. We proposed different resource allocation frameworks for time-switching as well as power-splitting approaches of SWIPT. In the time-switching approach, macrocell users were designed to have flexible interference tolerance levels, to provide a degree of freedom for small cell base stations to adjust their transmit powers in energy harvesting and information decoding process. Scenarios with and without co-tier interference were investigated in the time-switching approach to explore the effect of interference. Numerical results demonstrated the trade-off between achievable throughput and energy harvesting rate of small cell users, and highlighted the improvement in achieved energy harvesting rates due to the flexibility in interference tolerance levels of macrocell users in the time-switching approach, when compared with the power-splitting approach. Also, the results showed significant improvement in energy harvesting rate of small cell users in the presence of co-tier interference at the cost of degraded throughput performance.

In Chapter \footnote{5} we investigated energy-aware and interference-aware resource allocation jointly with dynamic activation of energy harvesting base stations in a two-tier HetNet taking into account the varying channel condition, user activity, and arrival of harvested energy. While ensuring QoS provisioning to hotspot users as well as macrocell users, we optimized the trade-off between throughput performance of the hotspot users and the associated power cost, by maximizing the net reward over a number of time slots. For that, positive reward was associated with achievable throughput of the hotspot users and negative reward with the corresponding power consumption at the small cell or macrocell base station. We solved the problem in offline and online mode assuming the presence and absence of non-causal information, respectively. For the online solution, we proposed a dynamic programming-
6.2 Future Research Directions

In this section, we propose some possible research directions that can be followed from this thesis.

- Since both renewable energy harvesting and wireless energy harvesting are emerging and promising concepts for the future wireless networks, considering the co-existence of these two paradigms will be important. Co-existence of renewable and wireless energy harvesting would open following research directions from our accomplished works:

  - In the context of uplink WPC networks with relay-based and user-based cooperation, relay node and access points can be designed to harvest energy from the nature and the UEs to harvest energy from the wireless signal. In that case, resource allocation problem would have additional causality constraint on availability of energy at the access points and relay nodes, which would further complicate the analysis of the resource allocation problem.

  - In Chapter 4, we have considered SWIPT in HetNets, while we have considered renewable energy harvesting in HetNets in Chapter 5. In the future work, considering renewable energy harvesting in the base stations and SWIPT to the UEs of small cells would be interesting. In that case, the interference management challenges that arise in SWIPT in HetNets and energy management challenges
that arise in renewable energy harvesting base stations would merge into a single resource allocation problem, hence increasing the complexity of the problem.

- In our research works, we assume to have perfect knowledge of the channel state information. However, the channel state information may not be perfect due to estimation errors and uncertainties. Therefore, robust resource allocation \cite{116} can be a possible future extension of the works accomplished in this thesis.

- In Chapters 4 and 5, we assume to have information about some network parameters (such as channel state, user activity, and arrival of harvested energy) ahead of time in some scenarios. To acquire such network information ahead of time, application of machine learning algorithms in communication networks is gaining much research attention recently \cite{117}. One possible future extension of our work could be joint consideration of machine learning algorithm and resource allocation algorithm in such scenarios.

- In the context of uplink WPC network with relay-based cooperation, we consider optimal time allocation but do not consider relay and subcarrier selection. In the future work, joint optimization of downlink energy harvesting time, uplink information transmission time, relay and subcarrier selection, along with downlink and uplink power allocation can be considered. With increased number of optimization variables, the resource allocation will be difficult to solve and hence finding a computationally efficient solution approach will be important.

- In the context of SWIPT in HetNets, we have proposed the resource allocation algorithms for different scenarios assuming each cell has one channel available to serve one user at a time. One possible future research direction could be considering a multi-user and multi-channel scenario in a cell. In that case, optimization of subcarrier allocation will be essential along with downlink power and power-splitting/time-switching variables.
6.2. Future Research Directions

- In the context of both downlink SWIPT and uplink WPC, we have considered a constant energy harvesting efficiency of the energy harvester, irrespective of the received power. However, energy harvesting efficiency of energy harvesting circuits highly depends on received power [14]. Hence, dependency of energy harvesting efficiency on received power can be considered in the future extension of the work.

- In the context of uplink WPC as well as downlink SWIPT, our works do not consider directive transmission of narrower energy beam. Directive beamforming can significantly increase energy harvesting efficiency [118] and should be considered for future extensions of the works accomplished in the thesis. However, beamforming vectors are additional optimization variables, thus increasing complexity of the resource allocation problem.

- In the context of base station activation and resource allocation in energy harvesting HetNets, we divide the users as hotspot users and macrocell users based on geographical location and simplify the user association scheme. For future extension, we can investigate joint optimization of user association [119] along with resource allocation and base station activation. In that case, user association variables would be additional binary integer variables, thus increasing the complexity of resource allocation problem.
Bibliography


Appendices
Appendix A

Proof of Convexity

It can be proven that $R^{(sc-II)}_{i(n)}$ (given in (2.12)) is a concave function of $t(d)$ and $t_i(n)$ by using perspective operation [80]. To prove the convexity of $\tilde{R}^{(sc-II)}_{j(f)}$ (given in (2.36)) in $t_j(f)$, $E_{(rd)}$, and $E_{j(ru)}$, let us define a function $f(E_{(rd)}, E_{j(ru)})$ as

$$f(E_{(rd)}, E_{j(ru)}) = \left(1 + \frac{\delta \alpha_j \beta E_{(rd)} E_{j(ru)}}{\alpha_j E_{(rd)} + 2 \beta E_{j(ru)}}\right).$$

The Hessian of $f(E_{(rd)}, E_{j(ru)})$ is given by

$$\nabla^2 f(E_{(rd)}, E_{j(ru)}) =
$$

$$\frac{4 \delta \alpha_j^2 \beta^2}{(E_{(rd)} \alpha_j + 2 \beta E_{j(ru)})^3}
\begin{bmatrix}
-E_{j(ru)} & E_{j(ru)} E_{(rd)} \\
E_{j(ru)} E_{(rd)} & -E_{(rd)}^2
\end{bmatrix}.$$ 

The eigenvalues of the Hessian $\nabla^2 f(E_{(rd)}, E_{j(ru)})$ are given as

$$\lambda_1 = 0, \lambda_2 = -\frac{4 \delta \alpha_j^2 \beta^2}{(E_{(rd)} \alpha_j + 2 \beta E_{j(ru)})^3} \left(E_{(rd)}^2 + E_{j(ru)}^2\right).$$

Since $\lambda_1, \lambda_2 \leq 0$, the Hessian matrix $\nabla^2 f(E_{(rd)}, E_{j(ru)})$ is a negative semidefinite matrix and therefore, $f(E_{(rd)}, E_{j(ru)})$ is a concave function. Since $\log(.)$ is an increasing concave function, $\log_2 \left(1 + \frac{\delta \alpha_j \beta E_{(rd)} E_{j(ru)}}{\alpha_j E_{(rd)} + 2 \beta E_{j(ru)}}\right)$ is also a concave function. Then, $\tilde{R}^{(sc-II)}_{j(f)}$ is also a concave function of $t_j(f)$, $E_{(rd)}$, and $E_{j(ru)}$ by perspective operation. Hence, $\sum_{i=1}^N R^{(sc-II)}_{i(n)} + \sum_{j=1}^K \tilde{R}^{(sc-II)}_{j(f)}$ is sum of concave functions and hence is a concave function. This completes the proof.
Appendix B

Proof of Lemma 5

From (2.46) and (2.47), we have

\[ \ln(1 + x) - \frac{x}{1 + x} = \frac{\sum_{i=1}^{N} \nu_i}{1 + x}. \] (B.1)

By letting \( \tilde{x} = 1 + x \) and \( A = \sum_{i=1}^{N} \nu_i \) and simplifying (B.1), we obtain

\[ \frac{A - 1}{\tilde{x}} e^{\left(\frac{A-1}{\tilde{x}}\right)} = (A - 1) e^{-1} \implies we^w = e^{-1} (A - 1), \quad \text{where} \ w = \frac{A - 1}{\tilde{x}}. \] (B.2)

Using (B.2) and the definition of Lambert-W function [81], we get

\[ w = W \left( e^{-1} (A - 1) \right) \] (B.3)

where \( W(.) \) is the Lambert-W function [81]. Therefore, using \( w = \frac{A - 1}{\tilde{x}} \), \( \tilde{x} = 1 + x \), and \( A = \sum_{i=1}^{N} \nu_i \) in (B.3), we obtain \( x^* = \frac{\sum_{i=1}^{N} \nu_i - 1}{W(e^{-1} (\sum_{i=1}^{N} \nu_i - 1))} - 1 \). The expression for \( y^* \) can be obtained in similar way by letting \( \tilde{y} = 1 + y \) and \( B = 2\mu^* T \ln(2) \) and simplifying (2.48) after which we obtain

\[ \left( -\frac{1}{\tilde{y}} \right) e^{\left(\frac{1}{\tilde{y}}\right)} = -e^{-(B+1)} \implies we^w = -e^{-(B+1)}, \quad \text{where} \ w = -\frac{1}{\tilde{y}}. \]

Now, to prove the expression for \( z^* \) in (2.52), let us use (2.49) and (2.50) to obtain

\[ 2\delta \beta z^2 = \sum_{j=1}^{K} \alpha_j \delta (1 - z)^2 \implies z^2 \left( \sum_{j=1}^{K} \alpha_j - 2\beta \right) - 2 \sum_{j=1}^{K} \alpha_j z + \sum_{j=1}^{K} \alpha_j = 0. \] (B.4)
Appendix B. Proof of Lemma 5

Equation (B.4) is a quadratic equation and therefore the solution is given by

\[
z = \frac{2 \sum_{j=1}^{K} \alpha_j \pm \sqrt{8 \sum_{j=1}^{K} \alpha_j \beta}}{2 \left( \sum_{j=1}^{K} \alpha_j - 2 \beta \right)}.
\]

Considering that \( z = z_j = \frac{b_j}{a_j + b_j} \), \( \forall j \), we know that the solution should satisfy \( z < 1 \). The solution that satisfies the condition is: \( z^* = \frac{2 \sum_{j=1}^{K} \alpha_j - \sqrt{8 \sum_{j=1}^{K} \alpha_j \beta}}{2 \sum_{j=1}^{K} \alpha_j - 4 \beta} \), which can be easily verified considering different cases such as \( 2 \beta > \sum_{j=1}^{K} \alpha_j \), \( 2 \beta < \sum_{j=1}^{K} \alpha_j \), and \( 2 \beta = \sum_{j=1}^{K} \alpha_j \). This completes the proof.
Appendix C

Proof of Proposition 2

Using definition of $a_j$, $b_j$ in (2.44), and $z$ in (2.45), we get

$$E^*_j(r_u) = \left(\frac{1 - z}{z}\right) \frac{\alpha_j E^*_j(r_d)}{2\beta}. \quad (C.1)$$

Now, using (C.1), to simplify the relation of energy variables in (2.53), we obtain

$$E^*_j(r_d) = \frac{2\beta z^* E_{max}}{2\beta z^* + (1 - z^*) \sum_{j=1}^{K} \alpha_j}. \quad (C.2)$$

We obtain (2.54) from (C.1) and (C.2). Again, using definitions of $a_j$, $b_j$ in (2.44), and $y$ in (2.45), we obtain

$$t^*_j(f) = \frac{\delta}{y \left( \frac{1}{\alpha_j E^*_j(r_d)} + \frac{1}{2\beta E^*_j(r_u)} \right)}. \quad (C.3)$$

Then, we obtain the expression for $t^*_j(f)$ in (2.55) from (2.54) and (C.3). Using definition of $x$ in (2.45) to simplify relation of DEH and UIT times in (2.53), we obtain: $t^*_d = \frac{T - \sum_{j=1}^{K} E_j(t^*_j(f))}{1 + \sum_{i=1}^{N} \nu_i}$ and $t_i(n)$ is obtained by using definition of $x$ in (2.45). This completes the proof.
Appendix D

Simplification of KKT Conditions

Since the problem in (4.8) is a convex optimization problem, KKT conditions should be satisfied. Differentiating (4.9) with respect to $\alpha_E$ and using the KKT stationarity condition, we obtain

$$\frac{\partial \mathcal{L}(\tilde{P}_I, \tilde{P}_E, \alpha_I, \alpha_E, \lambda, \gamma)}{\partial \alpha_E} = 0 \Rightarrow \lambda^t = \sum_{s=1}^{S} \frac{\eta w_{s,E} \chi_{m,s}^t}{NE_{(tar)}}, \forall t. \quad (D.1)$$

Since the right hand side of (D.1) is strictly positive, the dual variable $\lambda^t > 0$ must be satisfied for all $t$. Then, to satisfy the KKT slackness condition, the constraint $(C_2)$ corresponding to the dual variables $\lambda$ must be satisfied with strict equality, i.e. $\alpha_I^t + \alpha_E^t = 1, \forall t$ which leads to (4.11). By differentiating (4.9) with respect to $\tilde{P}_{s,I}^t$ and then using the KKT stationarity condition, we obtain

$$-\gamma^t h_{s,m}^t = 0$$

which can be simplified to obtain (4.12).