Resource Management in Green Wireless Communication Networks

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

The development of wireless technologies has been stimulated by the ever increasing network capacity and the diversity of users' quality of service (QoS) requirements. It is widely anticipated that next-generation wireless networks should be capable of integrating wireless networks with various network architectures and wireless access technologies to provide diverse high-quality ubiquitous wireless accesses for users. However, the existing wireless network architecture may not be able to satisfy explosive wireless access request. Moreover, with the increasing awareness of environmental protection, significant growth of energy consumption caused by the massive traffic demand consequently raises the carbon emission footprint. The emerging of green energy technologies, e.g., solar panel and wind turbine, has provided a promising methodology to sustain operations and management of next-generation wireless networks by powering wireless network devices with eco-friendly green energy.

In this thesis, we propose a sustainable wireless network solution as the prototype of next-generation wireless networks to fulfill various QoS requirements of users with harvested energy from natural environments. The sustainable wireless solution aims at establishing multi-tier heterogeneous green wireless communication networks to integrate different wireless services and utilizing green energy supplies to sustain the network operations and management. The solution consists of three steps, 1) establishing conventional green wireless networks, 2) building multi-tier green wireless networks, and 3) allocating and balancing network resources.

In the first step, we focus on cost-effectively establishing single-tier green wireless

networks to satisfy users' basic QoS requirements by designing efficient network planning algorithm. We formulate the minimum green macro cell BS deployment problem as an optimization problem, which aims at placing the minimum number of BSs to fulfill the basic QoS requirements by harvested energy. A preference level is defined as the guidance for efficient algorithm design to solve the minimum green macro cell BSs deployment problem. After that, we propose a heuristic algorithm, called two-phase constrained green BS placement (TCGBP) algorithm, based on Voronoi diagram. The TCGBP algorithm jointly considers the rate adaptation and power allocation to solve the formulated optimization problem. The performance is verified by extensive simulations, which demonstrate that the TCGBP algorithm can achieve the optimal solution with significantly reduced time complexity.

In the second step, we aim at efficiently constructing multi-tier green heterogeneous networks to fulfill high-end QoS requirements of users by placing green small cell BSs. We formulate the green small cell BS deployment and sub-carrier allocation problem as a mixed-integer non-linear programming (MINLP) problem, which targets at deploying the minimum number of green small cell BSs as relay nodes to further improve network capacities and provide high-quality QoS wireless services with harvested energy under the cost constraint. We propose the sub-carrier and traffic over rate (STR) metric to evaluate the contribution of deployed green small cell BSs in both energy and throughput aspects. Based on the metric, two algorithms are designed, namely joint relay node placement and sub-carrier allocation with top-down/bottom-up (RNP-SA-t/b) algorithms. Extensive simulations demonstrate that the proposed algorithms provide simple yet efficient solutions and offer important guidelines on network planning and resource management in two-tier heterogeneous green wireless networks.

In the last step, we intend to allocate limited network resources to guarantee the balance of charging and discharging processes. Different from network planning based on statistical historical data, the design of resource allocation algorithm generally concerns relatively short-term resources management, and thus it is essential to accurately estimate the instantaneous energy charging and discharging rates of green wireless network devices. Specifically, we investigate the energy trading issues in green wireless networks, and try to maximize the profits of all cells by determining the optimal price and quantity in each energy trading transaction. Finally, we apply a two-stage leader-follower Stackelberg game to formulate the energy trading problem. By using back induction to obtain the optimal price and quantity of traded energy, we propose an optimal algorithm, called optimal profits energy trading (OPET) algorithm. Our analysis and simulation results demonstrate the optimality performance of OPET algorithm.

We believe that our research results in this dissertation can provide insightful guidance in the design of next-generation wireless communication networks with green energy. The algorithms developed in the dissertation offer practical and efficient solutions to build and optimize multi-tier heterogeneous green wireless communication networks.

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To my fiancée Luya

To my parents

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List of Abbreviations

LTE	Long-Term Evolution
LTE-A	Long-Term Evolution-Advanced
C-RANs	Cloud-Radio Access Networks
VANETs	Vehicular Ad-hoc Networks
WMNs	Wireless Mesh Networks
WWANs	Wireless Wide Area Networks
WLANs	Wireless Local Area Networks
WPANs	Wireless Personal Area Networks
WMANs	Wireless Metropolitan Area Networks
WBANs	Wireless Body Area Networks
QoS	Quality of Service
ICT	Information and Communication Technologies
CAGR	Compound Annual Growth Rate
BSs	Base Stations
P2P	Peer-to-Peer

D2D	Device-to-Device
M2M	Machine to Machine
FTP	File Transfer Protocol
QoE	Quality of Experience
APs	Access Points
TCGBP	Two-phase Constrained Green BS Placement
MINLP	Mixed Integer Non-Linear Programming
NP-hard	Non-deterministic Polynomial-time hard
STR	Sub-carrier and Traffic over Rate
RNP-SA-t	RNP-SA with top-down algorithm
RNP-SA-b	RNP-SA with bottom-up algorithm
OPET	Optimal Profits Energy Trading
VP	Voronoi Polygons
RNs	Relay Nodes
RNP-SA	RN Placement and Sub-carrier Allocation
LHS	Left Hand Side

Chapter 1

Introduction

It is anticipated that next-generation wireless networks will provide ubiquitous wireless services in the near future. A variety of wireless networks, e.g., long-term evolution/long-term evolution-advanced cellular networks (LTE/LTE-A) [3, 4], cloud radio access networks (C-RANs) [5, 6], vehicular ad-hoc networks (VANETs) [7, 8], wireless mesh networks (WMNs) [9, 10], wireless wide area networks (WWANs) [11, 12], wireless local area networks (WLANs) [13, 14], wireless personal area networks (WPANs) [15, 16], wireless metropolitan area networks (WMANs) [17, 18], wireless body area networks (WBANs) [19, 20], and etc., has been emerging to provide various network services for people all over the world. However, it is challenging to satisfy users' ubiquitous wireless access requirements with existing network architecture. First, the capacity of existing wireless networks may not be sufficient to support diverse network services in the future. Second, different types of wireless networks have various application scenarios, network architectures, quality of service (QoS) re-

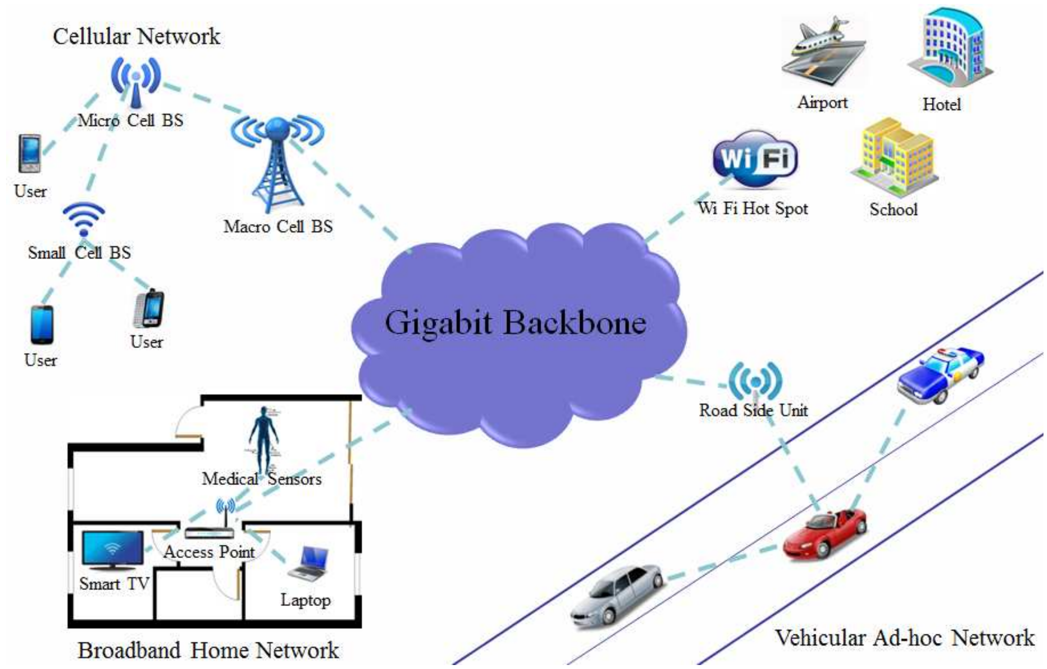


Figure 1.1: Next-Generation Wireless Networks.

quirements and underlying communication technologies, which make these networks fundamentally different from each other. Therefore, how to enhance the network capacity and let various network services co-exist has become an open issue in the design of next-generation wireless networks.

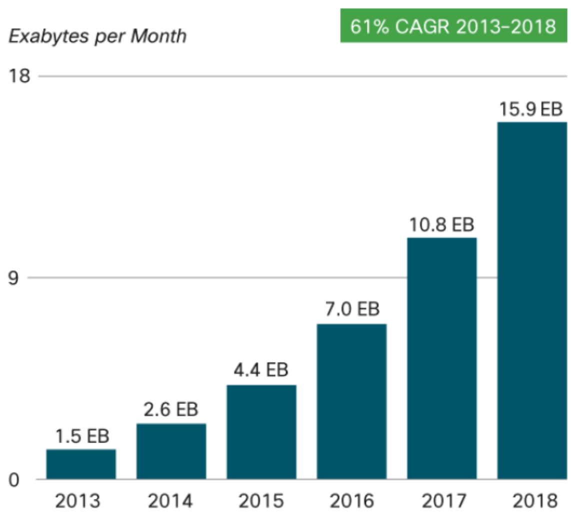
Besides network capacity and scalability issues, energy related issues have become another dimension considered in wireless networks. With the increasing concerns on environmental protection and the preservation of natural resources, energy conservation and reduction of CO_2 emissions have become consensus all over the world. The rapid development of wireless communication technologies significantly increases the energy consumption. It is reported that the power consumption of information and communication technologies (ICT) is growing over 15% every year [21, 22]. Moreover, the expanding network capacity and scalability in next-generation wireless have boosted the deployment of broadband devices. However, the higher the frequency or bandwidth, the more electricity is required. Thus, how to ensure the sustainable development of wireless communication with environmentally sound technologies has become another major concern in the design of next-generation wireless networks.

In this chapter, we first present the motivations and challenges of the research in Section 1.1. After that, a sustainable wireless network solution is proposed in Section 1.2, followed by the outline of this thesis in Section 1.3.

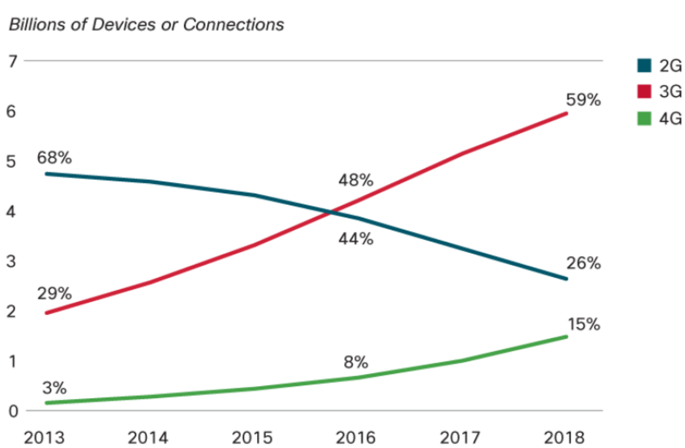
1.1 Research Motivations and challenges

1.1.1 Research Motivations

The diverse high-quality wireless service requirements have boosted the study of next-generation wireless communication networks to address both network capacity and energy consumption issues. On one hand, it is reported that the volume of the network capacity and the variety of wireless applications will dramatically increase in the near future to fulfill users' QoS requirements. According to the estimation of Cisco in Fig. 1.2(a), the global mobile data traffic is expected to reach 15.9EB in 2018, which will grow at a compound annual growth rate (CAGR) of 61 percent from 2013 to 2018; it is also anticipated in Fig. 1.2(b) that 15 percent of all global devices and connections will be 4G capable, which will co-exist with 2G- and 3G-capable devices. The



(a) Global mobile data traffic



(b) Global Mobile Devices and Connections

Figure 1.2: Prediction of global mobile trend by Cisco [1].

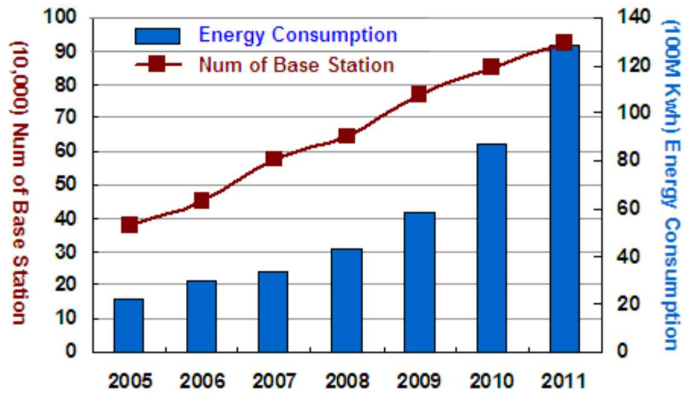


Figure 1.3: China mobiles energy consumption and wireless base station growth [2].

booming wireless services supported by various wireless networks have shown one of promising methods to provide ubiquitous high-quality wireless accesses for users, i.e., constructing multi-tier heterogeneous network architecture as next-generation wireless networks to improve network capacity and scalability, which should be capable of integrating fundamentally different wireless networks [23].

On the other hand, the energy consumption dramatically increases with the growth of deployed base stations (BSs) and traffic load. As shown in Fig. 1.3, the growth of energy consumption is much faster than the increase of BS deployment due to significant raise of each BS's traffic load. It has also been reported that devices of the network infrastructure have contributed almost 60 percent energy consumption of the whole system, even when devices are idle [24]. Therefore, in response to sustain the network operations and protect the environment, it is essential to power the network infrastructure in a sustainable way. Recent advances in green energy technologies provide an alternative energy source, e.g., energy harvested from solar,

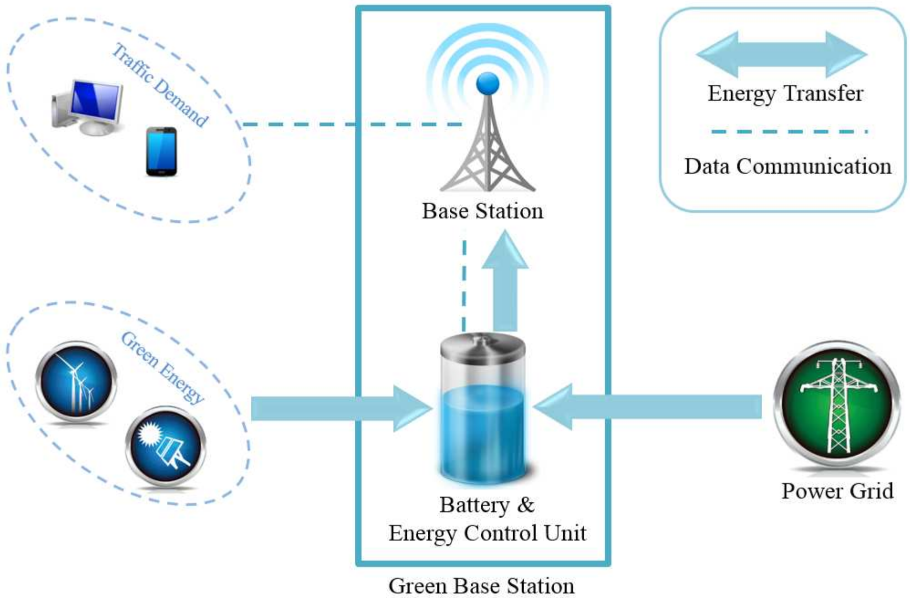


Figure 1.4: An example of green wireless BSs.

wind, and etc., to power wireless network infrastructures as shown in Fig. 1.4. With green energy technologies, research projects on communications with green energy have sprung up worldwide in recent years, such as OPERANET [25], EARTH [26], Green Touch [27] and Green Radio [28]. As green wireless network devices, i.e., network devices powered by green energy, are powered by replenishable energy, it is one of promising methods for next-generation wireless networks to sustain its network operation and management.

1.1.2 Research Challenges

Green energy provides clean and sustainable energy for network devices, and causes the minimal detrimental threats to the environment. Moreover, in some developing countries and rural areas without electrical grid, the deployment of wireless network devices with traditional energy supplies may be infeasible due to high cost and related issues to the electrical cable installation. Comparing to wireless network devices with fixed power supplies, green wireless network devices do not have to connect to the electrical grid, which makes them much cheaper and easier be installed and moved. However, it is very challenging to efficiently exploit the green energy sources for providing ubiquitous wireless services in green wireless networks. This is because, unlike stable energy supplies from the electrical grid, availability and capacity of green energy harvested from natural resources are highly dependent on the local environment and may vary with time [29]. For example, solar panels can provide relatively continuous power supply comparing with the intermittent energy supplies from wind turbines, but the charging capability of each solar energy supply also varies with the radiation levels of sunshine across a day. When the harvested energy could not sustain users' QoS requirements, the service provisioning will be interrupted and users will experience degraded QoS. Therefore, the most important fundamental design criteria and performance metric in green wireless networks have been shifted from energy efficiency to energy sustainability of the network infrastructure, i.e., the harvested energy can sustain the network operations and management.

Moreover, the relative high cost of green energy supplies is another challenging issue for green wireless networks. Generally, the cost of green energy supplies includes four parts, i.e., equipment, installation, rent of land occupation and maintenance cost. Although the green wireless network devices do not have to connect to electrical grid, the installation cost of traditional energy supplies is not expensive in most urban areas with existing electrical grid system. For the cost of equipments, the technology of green wireless network devices is not as mature as ones with electrical grid, which leads to relatively high market price. In addition, green energy supplies need additional land occupation for energy harvest, and the rent depends on the location and their power consumption, which may have very high cost in urban areas. Overall, the total cost of deploying green wireless network devices is relatively expensive than that of wireless network devices with electrical cables. Thus, how to save cost is one of the major concerns in the design of green wireless communication networks.

1.1.3 Research Issues

Based on the analysis of research challenges, we present challenging research issues in the design of green wireless communication networks as follows.

- Capacity and scalability: The booming wireless applications lead to the ever-growing density and scale of wireless networks. In addition, the widely applied ad-hoc technologies, e.g., peer-to-peer (P2P), device-to-device (D2D), machine to machine (M2M), etc., have generated a tremendous volume of information sharing and exchange. Green wireless network devices can provide wireless accesses with eco-friendly green energy supplies. However, without elaborate design, the dynamic charging capabilities of green energy may become the bottleneck of network capacity and scalability in green wireless networks. Thus, it is critical to fully utilize the harvested green energy to push up the limitation of the number of users and network scale.

- Massive traffic demands and diverse QoS requirements: The emergence of diverse wireless applications has provided ubiquitous wireless accesses, while various wireless services have different QoS requirements and evaluation criteria. For instance, interactive media such as video conference and live chat are sensitive to the latency while bulky data transfer like file transfer protocol (FTP) transmission concerns more about its link throughput. Therefore, how to satisfy the massive and diverse QoS requirements of users are essential in the design of green wireless communication networks.

- Network infrastructure: The infrastructures of traditional wireless networks are normally powered by electrical grid, and thus network device deployment in such kind of networks needs to consider the cable deployment and the coverage of users. Different from traditional wireless networks, infrastructures of green wireless networks are powered by the harvested energy from natural environment, thus there is no cable deployment issue. Instead, the dynamic charging and discharging capabilities become one of the most challenging issues in the network architecture design of green wireless networks. Therefore, it is important to re-visit the network planning in green wireless networks to satisfy the diverse QoS requirements of users with harvested energy.

- Sustainable network performance: In green wireless networks, wireless devices are powered by green energy supplies, which are highly dependent on the local weather, position and time. The residual energy of the network device will be used up when the harvested energy is not enough to support the QoS requirements of users. The ceases of green wireless devices will degrade the users' quality of experience (QoE), and may further cause network partition and affect the normal operations of green wireless networks. Thus, energy sustainability, i.e., sustaining the network performance with harvested energy, has become the most essential performance metric in the design of green wireless communication networks.

1.2 Sustainable Wireless Network Solution

In this thesis, we propose a sustainable wireless network solution as a prototype of next-generation wireless networks to address both traffic and energy issues. A sustainable wireless network consists of users and network infrastructure devices, where the infrastructure devices are powered by harvested energy from natural resources. The network infrastructure will be multi-tiered heterogeneous green wireless networks, which are composed of a variety of wireless network devices, e.g., macro cell BSs, micro cell BSs, small cell BSs, access points (APs), sensor nodes, etc., powered by green energy supplies. Based on such kind of network infrastructure, green wireless networks can allow different kinds of wireless networks to provide diverse high-quality wireless services to different or the same user(s). In addition, eco-friendly green energy can help minimize the CO_2 emissions and take care of our environment.

Our sustainable wireless network solution utilizes network planning and resource allocation to cost-effectively build multi-tier heterogeneous green wireless networks. Given a set of users and their QoS requirements, we separate the construction of sustainable wireless networks into three steps: 1) establishing single-tier green wireless networks, 2) building multi-tier green wireless networks, and 3) allocating and balancing network resources. In the first step, green macro cell BSs are deployed to establish single-tier wireless networks, which consist of users and green macro cell BSs. This step aims at cost-effectively satisfying users' basic QoS requirements by placing green macro cell BSs into networks. After that, we deploy small cell BSs to construct multi-tier green wireless networks to further improve the network throughput and the diversity of network services. These two steps are based on the charging and discharging statistics to simplify the problem. Finally, we consider to effectively allocate network resources to balance the uneven distribution of network resources. We focus on maximizing the network sustainability based on the estimation of instantaneous energy charging and discharging rates. As such, the constructed multi-tier wireless communication with green energy should be able to provide various high-quality network services to users and sustain the network by harvested energy from natural environment.

Specifically, the main contributions of this dissertation to construct and manage multi-tier heterogeneous green wireless communication networks are listed as follows.

- By exploiting the particular characteristics of green energy supplies, we present fundamental design criteria and performance metric for network planning and resource management in green wireless networks. Based on the design criteria, we propose a sustainable wireless network solution to construct multi-tier heterogeneous green wireless networks, such that diverse high-quality wireless services can be supported by eco-friendly replenishable green energy. Then, we divide our sustainable wireless network solution into three steps.

- First, we aim at cost-effectively establishing single-tier green wireless networks to satisfy users' basic QoS requirements. We formulate the constrained minimum green macro cell BSs placement problem as an optimization problem. Our objective is to select a set of candidate locations to deploy the minimal number of green macro cell BSs such that users' traffic demands can be fulfilled by the harvested energy. We design a preference level for each user to determine the relationship between the user and potential placed green macro cell BSs, which reflects the connection priority and relative data rate between the user and corresponding BSs. Based on the preference level, we propose a heuristic algorithm, namely two-phase constrained green BS placement (TCGBP) algorithm, to find an optimal green macro cell BS deployment by jointly considering power control and rate adaptation. Extensive simulation results show that TCGBP algorithm approaches the optimal solution under a variety of network settings with significantly reduced time complexity.

- Second, we focus on constructing multi-tier green wireless networks by deploying green small cell BSs. We study joint green small cell BS placement and sub-carrier allocation problem, which is formulated as a mixed-integer non-linear programming (MINLP) problem. Our objective is to minimize the number of green small cell BSs by allocating appropriate numbers of sub-carriers to each green BS, such that the network can be fully connected and the high-end QoS requirements of users can be fulfilled by the harvested energy based on the cost threshold. As formulated problem is non-deterministic polynomial-time (NP)-hard, we intend to design effective heuristic algorithms to solve the problem. A novel metric, referred to as sub-carrier and traffic over rate (STR), is introduced, which characterizes the throughput and energy demands of each user associated with a green BS. Based on the STR, two low-complexity algorithms, namely RNP-SA with top-down/bottom-up (RNP-SA-t/b) algorithms, are proposed. Extensive simulations show that both algorithms provide simple yet efficient solutions and offer important guidelines on network deployment and resource allocation in green wireless networks.

- Finally, our target is to balance the uneven distribution of network resources by conducting resource allocation based on the estimation of instantaneous energy charging and discharging rates. We consider the energy trading problem in heterogeneous green wireless networks, and formulate the problem as a Stackelberg game. Our objective is to find the optimal trading price and quantity of the green energy purchase/sale for each cell, such that all cells' profits are maximized and the energy demands in each cell are satisfied, considering the dynamic energy charging and discharging processes. By analyzing the formulated problem, we derive closed-form expressions of the optimal price and quantity for energy trading. After that, we propose an optimal algorithm, called optimal profits energy trading (OPET) algorithm, to optimize the profits of all cells by using the maximum weighted bipartite matching algorithm. Finally, we prove that the proposed OPET algorithm can achieve the optimal solution with polynomial time complexity.

1.3 Outline

The remainder of the thesis is organized as follows. Chapter 2 reviews related works in green wireless communication networks. In Chapter 3, we first formulate an optimal green BS placement problem in single-tier green wireless networks, which aims at deploying the minimal number of BSs on a set of candidate locations, subject to the constraints that QoS requirements of users can be fulfilled with the harvested energy. After that, we propose a simple yet efficient heuristic algorithm to solve the formulated problem. In Chapter 4, the joint green relay node placement and sub-carrier allocation problem in two-tier green wireless networks is investigated. Our objective is to minimize the number of green small cell BSs and allocate appropriate numbers of sub-carriers to each macro cell and small cell BS, such that the network can be fully connected and the QoS requirements of users can be fulfilled by the harvested energy along with the allocated sub-carriers based on the cost threshold. To this end, we define a novel metric to guide the algorithm design, and propose two heuristic algorithms based on the metric. In Chapter 5, the energy trading problem in heterogeneous green wireless networks is formulated as a Stackelberg game. Based on the estimation of instantaneous charging and discharging rates, closed-form expressions of the optimal price and quantity for energy trading transactions are derived. Then, an optimal algorithm is proposed to achieve the maximal profits of all cells. Finally, Chapter 6 gives concluding remarks and outlines of future work.

Chapter 2

Background and Literature

Recently, wireless communication networks powered by green energy sources have provided a promising method to sustain the network performance, which have raised great attention in both industry and academia [30–32]. Because of the dynamic charging and discharging processes of green wireless network devices, the fundamental design criteria and performance metric of green wireless networks have been shifted from energy efficiency to energy sustainability, i.e., to ensure that the harvested energy can sustain the traffic demands of network users. Therefore, it is necessary to review previous works related to both energy efficiency and energy sustainability issues. In this chapter, we first introduce related works on wireless network planning in Section 2.1. After that, we review previous works related to energy modeling and resource allocation in Section 2.2 and Section 2.3, respectively.

2.1 Network Planning

Network planning has been extensively studied in the context of different wireless networks, for example, cellular networks, IEEE 802.16 WiMAX and sensor networks [33–39]. It is usually formulated as device deployment optimization problems, aiming to maximize the network capacity [40, 41] or to minimize the cost of device deployment and/or network operation [42–44]. According to the methodologies to solve the optimization problem, these works can be further classified into two types, i.e., continuous and discrete cases. In the continuous case, it is assumed that there is no physical constraints and wireless network devices can be deployed at any location of the network region [45, 46]. Such problems can be solved by using some optimization algorithms like direct search and quasi-Newton methods [47]. However, in reality, wireless devices usually can only be placed at some candidate locations due to the physical constraints. Such problems can be formulated as the discrete cases of devices deployment problems. The discrete problems are normally modeled as a mixed integer optimization problem to find out the optimal placement of devices in a given region (or among a set of users), such that all the users in the region can be served by the deployed network devices [43, 48, 49]. In [49], a relay node placement problem was investigated with the physical constraints of sensor nodes. In [43], how to place the minimal number of APs was studied under the physical and protocol interference models; and it was found that the underlying interference models have a significant impact on the AP placement problem. In [44], the optimization of base stations' number and locations was investigated in order to minimize the energy consumption of a cellular network, considering a practical case of non-uniform user distributions.

There have been limited works on network planning in sustainable wireless networks [50], which mainly focus on how to minimize the cost and network outage, i.e., some green wireless devices do not have sufficient energy to support normal device operation or data transmission. The possibility and advantages of deploying green energy powered wireless devices are reported in [51]. It is shown that solar or wind powered APs provide a cost-effective solution in wireless local area networks (WLANs), especially for APs installed in off-grid locations. In [29, 52], the traditional AP placement problem was revisited with green power supplies. Their works focus on placing the minimal number of green energy powered APs on a set of candidate locations to ensure that the harvested energy is sustainable to serve wireless users and fulfill their QoS requirements. The minimum-cost placement of solar-powered data collection BSs was considered in [53]. BSs are placed in a wireless sensor network, such that the outage-free operation of the sensor nodes can be obtained. In [54], authors jointly considered allocating transmitting power and deploying the green APs based on the harvested energy. In their work, a closed-form power allocation scheme and an AP placement metric were proposed, and their theoretical analysis showed a dramatically improvement on overall throughput by using the proposed scheme.

2.2 Energy Modeling

The development of sensing technologies have boost the deployment of wireless networks consisting of battery-powered wireless network devices. One of the effective methods to prolong the network life is to enhance the energy efficiency by designing an accurate analytic energy model [55–58]. In [59], a model which integrates typical WSNs transmission and reception modules with realistic battery models was proposed. Based on the battery models, authors proposed two battery power-conserving schemes for two M-ary orthogonal modulations. In [60], authors designed time division multiple access medium access control protocols for healthcare applications in wireless body-area monitoring networks. They found that their proposed schemes can extend the lifetime of sensor nodes and reliability and delay-bound QoS demand for the wireless body-area monitoring networks based on the theoretical analysis and simulations.

Sustainable wireless sensor networks with solar energy supplies [61–63] is one of issues closely related to green wireless networks. In [64] and [65], authors showed that such kind of prototypes can achieve near-perpetual operation of sensor nodes. In modern wireless networks, the solar/wind powered AP is believed to be a more efficient method to save energy than energy efficient schemes in traditional AP, especially when the traditional power supply is not easy to be installed. Different from traditional energy resources, we need to consider the inherently dynamic characteristics in both energy charging and discharging processes. Therefore, it is essential to characterize the variations in the analytical model of energy conditions. In [66], authors proposed a framework to model the remaining power of sensor nodes with and without green energy, and then the expression of network lifetime was derived based on the energy model. In [67], the transmission policies for rechargeable nodes were considered to maximize the short term throughput, which refer to the amount of data transmitted in a finite time horizon. Based on the renewable energy model with discrete packets of energy arrivals, their proposed algorithm can successfully generate an optimal transmission policy, which can achieve the maximum short-term throughput and the minimum transmission completion time. In [32], the sustainable wireless sensor networks were proposed, where mobile chargers can charge multiple sensors from candidate locations. To minimize the selected number of locations, an optimization model was developed based on the energy recharging requirements of the sensors. Other works, such as [50, 68], mainly focus on the battery capacities and solar panel sizes of the BSs or APs, with an objective to mitigate the network outage by using the minimal cost of energy according to the recorded historical solar insolation traces.

2.3 Resource Allocation

It is recognized that efficient resource management [69–76] can significantly improve the resource utilization. Many studies have been conducted in various aspects of resource allocation, which include traffic scheduling and routing [77–79], optimal power management [80–82], energy efficient communication and cooperation [83–85], adaptive sleep control of mobile devices [86–88], and etc. Resource allocation [42, 89, 90] in network infrastructure with traditional energy supplies can be formulated as an optimization problem such that the network performance, e.g. network throughput and network lifetime, can be maximized with fixed yet limited energy resources, under various constraints including network connectivity, throughput, energy consumption and etc. The energy in these works was normally considered as a limited resource, thus these works generally target at maximizing the energy efficiency.

In green wireless networks, the energy is sustainable in the long term yet dynamic in the short term, which may lead to intermittent energy supply in wireless network infrastructure devices [29]. Moreover, since green wireless devices highly depend on their locations, which leads to uneven distribution of charging capabilities. Thus, in order to balance the harvested energy and traffic demands, we should concern characteristics of green wireless networks. So far, only a few works on resource management in wireless networks with green energy [91–94] focus on maximizing the network sustainability, and most existing works aim at mitigating the node outage or minimizing the cost. In [50], authors studied solar panel sizing problem of the BSs or APs based on the historical solar insolation traces, such that the network outage can be mitigated with the minimal cost. In [95], the problem of traffic scheduling for infrastructure of vehicular wireless networks was formulated into a mixed integer linear program with minimizing energy consumption as the objective. In [96], authors proposed a framework by jointly considering integrated admission control and routing under the multi-hop green wireless networks. Then, routing algorithms were proposed to improve network performance by using available energy. In [97], statistical power saving mechanism was proposed under solar-powered WLAN mesh networks. To balance the energy consumption with energy charging capability for each node, a control algorithm was developed to match the future load conditions and solar insolation for maintaining outage-free operations of the node.

Chapter 3

Green BS Deployment and Power Control in Conventional Green Wireless Networks

Green energy can provide clean and sustainable energy support for wireless network devices. However, different from wireless devices with traditional energy supplies, green-energy-powered wireless devices have dynamic charging capabilities and relatively high cost. Therefore, it is critical to consider the characteristics of green wireless network devices in the network design. In this chapter, our concern is to build conventional-architecture green wireless networks consisting of green macro cell BSs and users to fulfill basic QoS requirements of users. Considering the characteristics of green energy, we re-visit the minimum green macro cell BS deployment and power control issues in single-tier green wireless networks to improve the sustainable network performance.

The reminder of the chapter is organized as follows. In Section 3.1, we present the system model and formulation of constrained minimum green BS deployment problem. Our proposed algorithm, called two-phase constrained green BS placement (TCGBP) algorithm , is introduced in Section 3.2. Numerical results are presented in Section 3.3. Finally, we summarize the chapter in Section 3.4.

3.1 System Configuration and Problem Formulation

In this section, the system model and formulation of constrained green macro cell BS placement problem are presented. Due to relatively expensive price for macro cell BSs with green energy supplies, we aim at minimizing the cost of green macro cell BS deployment and fulfilling the QoS requirements of users with harvested energy from environment. To simplify the expression, we use (green) BSs to denote green macro cell BSs in this thesis. The introduction of the system model is presented in Subsection 3.1.1, and then we formulate the minimum green macro cell BS deployment problem as an optimization problem in Subsection 3.1.2. Finally, the QoS and energy sustainability constraints are described in Subsection 3.1.3.

3.1.1 System Model

We consider single-tier green wireless communication networks with a collection of wireless users and macro cell BSs as shown in Fig. 3.1. In the network, macro cell BSs are powered by green energy, and each wireless user connects to a green BS for wireless access. Wireless users and BSs can set different transmission power from a finite set of power levels by employing the promising adaptive modulation and coding technique. For simplicity, we assume the same transmission power is used by a BS and its users in each cell, while different BSs may select different power levels. Thus, the network may have various sizes of coverage area. The transmission links between a BS and its users are symmetrical, and BSs use orthogonal channels to communicate with each other for the sake of avoiding inter-cell interference. Due to the physical geographical constraints, green BSs can only be placed on limited locations in realistic constrained network scenarios. A set of candidate locations are provided for green macro cell BS deployment. As the charging capabilities of renewable energy supplies highly depend on the environment of geo-locations, green-energy-powered macro cell BSs placed on different candidate locations may have different charging rates. The notations used in system model are shown in Table 3.1.

We build a network communication graph $G(U \cup B, E)$ to model the network topology, where U and B are the set of users and green macro cell BSs, respectively, and E is the set of communication links between any two nodes. Let P^{-} denote the set of power levels that can be selected by green BSs and users, and D_{ub} denote the distance between user u and green BS b. As communication links are symmetric,

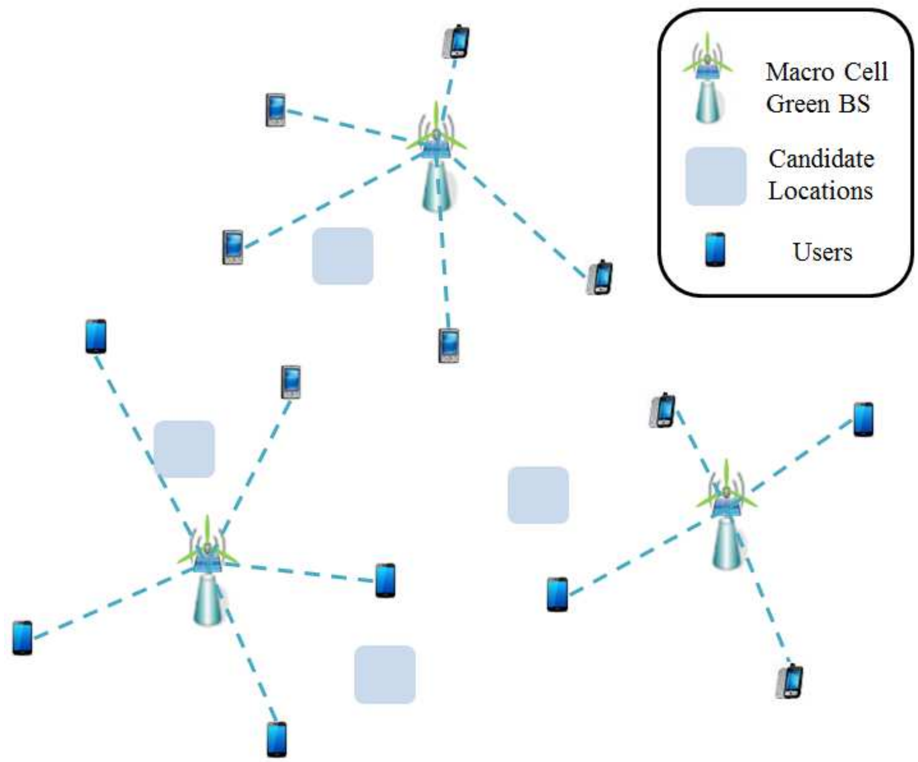


Figure 3.1: Single-tier green wireless networks with renewable power supplies.

Table 3.1: Notations for system model in Chapter 3

U	The set of users
B	The set of BSs
$G(U \cup B, E)$	The network topology with users, BSs and links
E	The set of communication links
u	User u in the set of users U
b	BS b in the set of BSs B
P^{-}	The set of power levels that can be selected
D_{ub}	The distance between a pair of nodes, u and b
(u, b)	The link consists of node u and node b
SNR_{ub}	The received signal to noise ratio of link (u, b)
α	The path loss exponent
$\aleph$	The background noise power
P_u^{-}	The adopted power of user u
c_{ub}	The achievable data rate of link (u, b)
$\mathbf{B}$	The bandwidth of the channel

(u, b) equals (b, u), we can express the received signal strength, SNR_{ub} of link (u, b), as following [98],

$$SNR_{ub} = \frac{P_u^{-} \cdot {D_{ub}}^{-\alpha}}{\aleph}, \tag{3.1}$$

where α, $\aleph$ and P_u^{-} denote the path loss exponent, the background noise power and the adopted power of user u, respectively. The achievable data rate of link (u, b), denoted by c_{ub}, is

$$c_{ub} = \mathbf{B} \log_2 (1 + SNR_{ub}), \tag{3.2}$$

where $\mathbf{B}$ is the bandwidth of the channel.

Table 3.2: Notations for problem formulation in Chapter 3

$\lvert B \rvert$	The number of BSs
$\mathcal{E}_b^+$	The consumed energy by node b during a unit time
$\mathcal{E}_b^-$	The harvested energy by node b during a unit time
β_{ub}	The achieved throughput from node u to b
${\beta'}_{ub}$	The throughput requirement of node u for link (u, b)
e_{ub}	The connection status of node u and node b
$[0, T]$	A scheduling period
t_u	A share of time T for user u to transmit data
$\mathbf{S}_b$	The set of users served by BS b
γ_u	The traffic demand of user u
P_b^+	The average energy charging rate of node b

3.1.2 Problem Formulation

Our green macro cell BS deployment problem aims at placing the minimum number of green-energy-powered BSs on a set of candidate locations, such that users' QoS requirements can be fulfilled with the harvested energy. Given a set of users and their QoS requirements, we need to find the optimal placement of BSs on a set of candidate locations, with adjustable transmission power levels at each BSs, such that the number of BSs is minimized, while energy sustainability and users' QoS constraints can be satisfied. Notations used in problem formulation are shown in Table 3.2.

The green macro cell BS placement problem can be generally formulated as:

$$\begin{aligned} Minimize \quad & |B| \\ Subject\ to: \quad & e_{ub} \in \{0,1\}, \quad && \forall u \in U, \forall b \in B \\ & \textstyle\sum_{b \in B} e_{ub} = 1, && \forall u \in U \\ & \beta_{ub} \geq \beta'_{ub}, && \forall e_{ub} = 1 \\ & \mathcal{E}_b^+ \geq \mathcal{E}_b^-, && \forall b \in B, \end{aligned} \tag{3.3}$$

where $\mathcal{E}_b^-$ and $\mathcal{E}_b^+$ denote consumed energy and harvested energy of BS b, while e_{ub}, β_{ub}, and β'_{ub} denote the connection status, throughput and traffic demand of link (u, b), respectively. When e_{ub} is equal to 1, it means the connection of link (u, b) is established. The first two conditions show that each user must be connected to only one BS [99]. The third condition indicates that the achieved throughput should be larger than the throughput of each user. The last constraint is the energy sustainability condition, which guarantees the charged energy should be able to sustain energy consumption of users.

3.1.3 QoS and Energy Sustainability Constraints

In this subsection, we further specify the energy and QoS constraints defined in Eq. (3.3). During a scheduling period $[0, T]$, each user u is allocated a share of T, t_u, for its own data transmissions. Therefore, to guarantee the fulfillment of user's traffic demands, we have the following equation,

$$\frac{c_{ub}t_u}{T} \geq \gamma_u, \forall\ u \in \mathbf{S}_b, \tag{3.4}$$

where $\mathbf{S}_b$ is the set of users served by green macro cell BS b, and γ_u is the traffic demand of user u. Substituting Eq. (3.2) into Eq. (3.4), the QoS constraint can be obtained as follows,

$$t_u \geq \frac{\gamma_u T}{\mathbf{B}\log_2\left(1 + SNR_{ub}\right)}, \forall\ u \in \mathbf{S}_b. \tag{3.5}$$

Suppose the average charging rate of BS b is P_b^+. The harvested energy during a period T, denoted as $\mathcal{E}_b^+$, is

$$\mathcal{E}_b^+ = P_b^+ T. \tag{3.6}$$

Similarly, we can obtain the energy consumption of green BS b during a period T as $\mathcal{E}_b^-$. The BS allocates time slots for users to satisfy their throughput demands, and the allocated slots should be bounded by the total time slots T,

$$T \geq \sum_{u \in \mathbf{S}_b} t_u. \tag{3.7}$$

Then, we have

$$\mathcal{E}_b^- = P_b^- T \geq \sum_{u \in \mathbf{S}_b} P_u^- t_u, \tag{3.8}$$

where $P_b^- = P_u^-$ for $u \in \mathbf{S}_b$. To ensure the energy sustainability of BSs, the harvested energy should be no less than the consumed energy for each BS in a period T. Thus, we can obtain the energy sustainability constraint as follows,

$$\sum_{u \in \mathbf{S}_b} t_u \leq \min\{\frac{P_b^+ T}{P_b^-}, T\}. \tag{3.9}$$

Notice that, t_u plays a critical role in both QoS and energy sustainability constraints defined in Eq. (3.5) and Eq. (3.9). In other words, based on the allocated time slots of each user, we can determine whether its traffic demand can be satisfied, and its BS can sustain the users' traffic demands with harvested energy or not.

3.2 Constrained Green Macro Cell BS Placement Algorithm

The formulated problem is NP-hard, because even the subproblems, such as optimal placement of BSs and optimal power control, are NP-hard in general [100]. Therefore, we design an effective heuristic algorithm to approach the optimal solution with the reduced time complexity. In this section, our heuristic algorithm, called two-phase constrained green BS placement (TCGBP) algorithm, is presented in Subsection 3.2.1, followed by time complexity analysis in Subsection 3.2.2.

3.2.1 TCGBP Algorithm

Intuitively, in order to place the minimal number of green macro cell BSs, each BS should serve as many users as possible. This may lead to strategies of placing BSs in a dense area or making BSs use a large power for data transmission. If green macro cell BSs are placed in a dense area, the burden of users' throughput requirements can be relieved. However, the harvested energy of BSs may not be sufficient to support the network devices, which may lead to outage of BSs and further cause the cease of network operations. If green macro cell BSs are deployed in a place far away from users, BSs have to use a high transmission power level to fulfill the throughput requirements of users. This may also cause the outage of BSs and the cease of network operations. Therefore, either strategy may violate the constraints in Eq. (3.5) and Eq. (3.9).

Based on the analysis of BS deployment strategies, we focus on cost-effectively designing simple yet efficient heuristic algorithms to satisfy the basic QoS requirements of users by deploying the minimal number of green BSs. We propose the TCGBP algorithm, which can be separated into two phases. In the first phase, we place one green macro cell BS in each candidate location. The whole network region is partitioned into several Voronoi Polygons (VPs), while wireless users are also divided into different clusters. Each wireless user is assigned a VP vector to determine the relationship between each user and potential BSs. Then, communication links are established between each BS and the users inside its VP region. In the second phase, cross-polygon selection of wireless users is permitted, so that green macro cell BSs can establish links with wireless users located in neighboring VP regions. Redundant BSs are deleted for the case that there is no user in their VP region. The notations used in TCGBP algorithm are shown in Table 3.3.

Initially, each candidate location is placed with a green BS, and the minimal power

Table 3.3: Notations for TCGBP algorithm in Chapter 3

VP_b	The VP region of BS b
L	The set of candidate locations
$\|L\|$	The number of candidate locations
pl_{ub}	The preference level of user u with BS b
t_{ub}	The active time of the link (u, b)
P^0	The initial transmission power of all nodes
$\|P\|$	The number of adjustable transmission power levels
$\|U\|$	The number of users

level, denoted as P^0, is assigned to all BSs and users. The VP region is determined by the relative distance between the user and deployed BSs. Let x denote an arbitrary point in the region, and D_{xb} be the distance between x and BS b. The VP region of BS b, denoted by VP_b, is defined as follows,

$$VP_b = \{x | D_{xb} \leq D_{xb'}, b' \in L, b' \neq b\}, \tag{3.10}$$

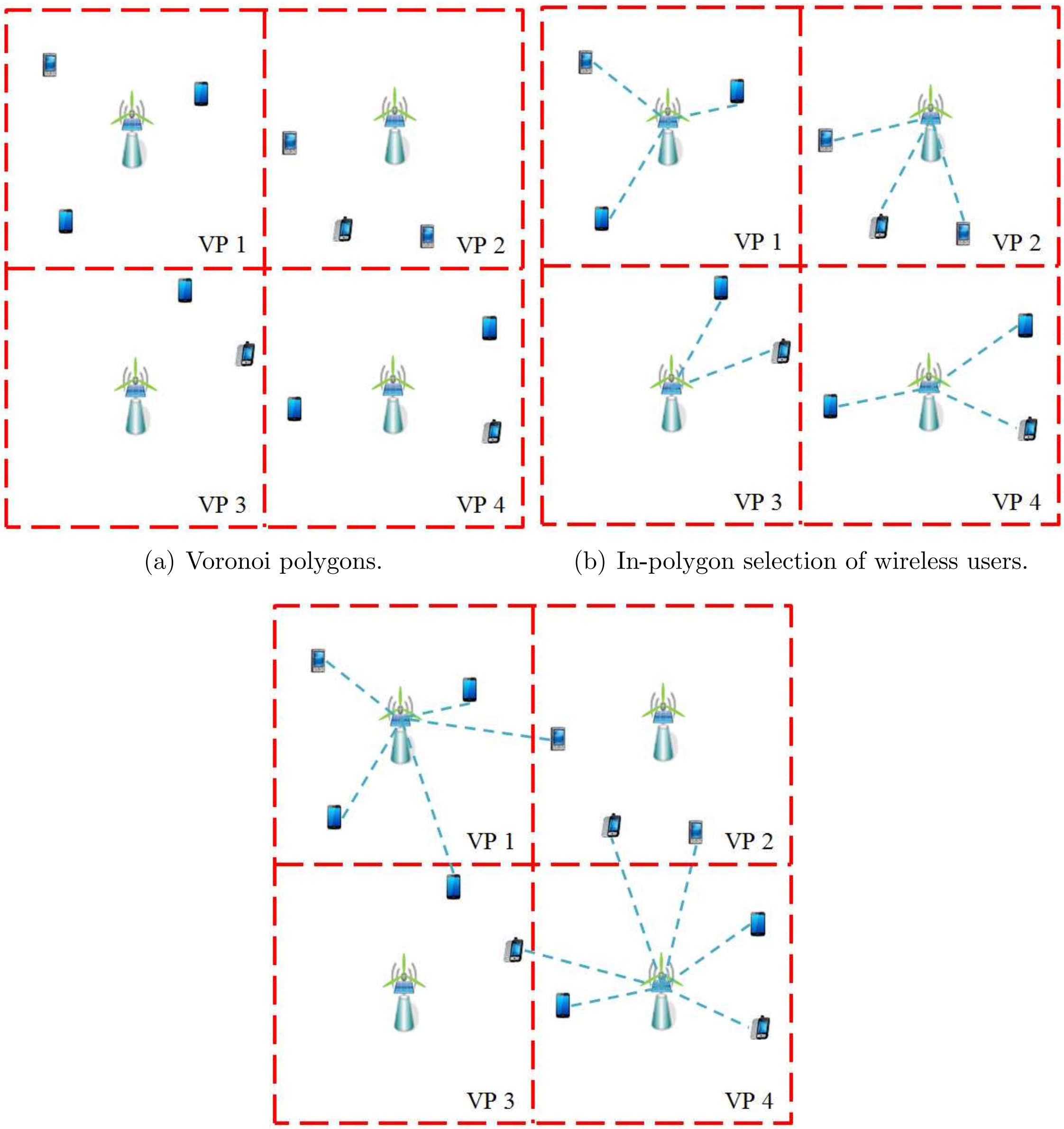
where L stands for the set of candidate locations. Based on the definition of VP region, we can divide the whole region into $|L|$ Voronoi polygons. Thus, wireless users located inside the region are also partitioned into different VP regions, where each VP region is centered by a BS. Each BS establishes links with users located in its VP region one by one. We define the preference level for BSs to determine the selection order of wireless users. Let pl_{ub} denote the preference level of user u with BS b, which can be expressed as,

$$pl_{ub} = \frac{t_{ub}}{T}. \tag{3.11}$$

In Eq. (3.11), t_{ub} is the least required active time of the link (u, b) to satisfy the QoS requirement of user u in Eq. (3.5). Each BS b sorts the connection priority of wireless users in the increasing order of $pl_{ub}, u \in VP_b$. Then, BSs connect users one by one until one of following conditions is met:

1. All wireless users in VP_b have been connected;
2. QoS and energy sustainability constraints defined in Eq. (3.5) and Eq. (3.9) cannot be held.

In the second phase, users are allowed to connect to BSs in neighboring VP regions. We start from the BS b^* with the largest number of users in its VP region, i.e., $|VP_{b^*}| \geq |VP_{b'}|, \forall b' \in B$. This is because the objective of second phase is to remove redundant BSs, and the BS with the largest number of users may have less chance to be removed. Then, we calculate the preference level of each user $u, u \notin VP_{b^*}$ with BS b^*, which is $pl_{ub^*}, u \notin VP_{b^*}$. Users outside b^*'s VP region are sorted in the increasing order of $pl_{ub^*}, u \notin VP_{b^*}$. Then, BS b^* connects users one by one until the QoS and energy sustainability constraints cannot be held. Since we consider multiple power levels, each BS can select a transmission power level $P_b^-, P_b^- \in P^-$ for communication. For each link, and the power level that can support the maximum number of users is selected by BS b^*. After that, we update the graph, and discard all the links of $(u, b^*), \forall u \notin VP_{b^*}$. Then, the TCGBP algorithm repeats the above operations in second phase until BSs cannot find more users to add. An example of TCGBP algorithm is shown in Fig. 3.2, and the algorithm description is shown in Algorithm 1.



(a) Voronoi polygons. (b) In-polygon selection of wireless users.

(c) Cross-polygon selection of wireless users.

Figure 3.2: Illustration of TCGBP.

Algorithm 1 Two-phase Constrained Green BS Placement algorithm (TCGBP)

```
B ← ∅;
P^0 ← min (P^-);
for all b ∈ L do
    for all u ∈ U do
        P_u^- ← P^0; P_b^- ← P^0;
        Determine the VP region of BS b, VP_b;
    end for
    for all u ∈ VP_b do
        Establish link (u, b);
        if QoS and energy constraints cannot be met then
            BREAK;
        end if
    end for
end for
while Any BS can connect more users do
    b* ← {b| max (|S_b|)};
    for all P_{b*}^- ∈ P^- do
        for all u ∈ U, u ∉ VP_{b*} do
            Calculate preference level pl_{ub*};
        end for
        Sort users in increasing order of pl_{ub*};
        for all Sorted u ∈ U, u ∉ VP_{b*} do
            Establish link (u, b*);
            if QoS and energy constraints cannot be met then
                BREAK;
            end if
        end for
        Record (P_{b*}^-, S_{b*});
    end for
    Assign power level {P_{b*}^-| max (|S_{b*}|)} to BS b*;
    Establish and delete links according to S_{b*};
    B ← b*;
    Delete b* from L;
end while
RETURN |B|;
```

3.2.2 Time complexity of the TCGBP

The TCGBP algorithm has time complexity of $O(|L||P||U|^2)$, where $|L|$, $|U|$ and $|P|$ are the number of candidate locations, wireless users, and adjustable power levels, respectively.

The TCGBP algorithm consists of two sequential phases: 1) establishing links inside each VP region, and 2) connecting users to BSs in other VP regions and removing redundant BSs. In the first phase, there are two sequential steps: i) it takes $O(|L||U|)$ for partitioning the whole region, ii) checking the feasibility of each VP region requires $O(|L||U|)$ time. Thus, the time complexity of the first phase is $O(|L||U|)$. In the second phase, there are three sequential steps: i) the time complexity of calculating preference level is $O(|L||P||U|)$, ii) It takes $O(|P||U|\log|U|)$ to sort the preference levels in increasing order, iii) the worst case of link connections and deletions needs $O(|L||P||U|^2)$ time, which includes power allocation and constraints verification. Thus, the time complexity of the algorithm is determined by the step with the highest order of time complexity, i.e., step 2, and is $O(|L||P||U|^2)$.

3.3 Simulation

In this section, we compare average deployed BS number of the proposed TCGBP algorithm with that of the optimal solution using the exhaustive search algorithm. Then, we evaluate the performance of the TCGBP algorithm for various system parameters, including different numbers of users, the variable traffic demands of each user, different numbers of candidate locations, and the variable charging capabilities of each BS, and etc.

3.3.1 Simulation Configurations and Performance Evaluation

We set up single-tier green wireless networks with a number of wireless users and candidate locations randomly distributed in a 1000 $m \times 1000$ m region. The transmission power of wireless users can be adjusted in three discrete levels, i.e., 10mW (10dBm), 32mW (15dBm), and 100mW (20dBm). Green macro cell BSs deployed at different candidate locations have various charging rates, which is uniformly distributed over $[20, 30]$ mW. The bandwidth is set as 40 MHz. The path loss exponent α is 4, and the background noise power $\aleph$ is -20 dBm. A time duration of $T = 1000$ time slots is used for network planning and scheduling. We repeat each simulation experiment 1000 times with different random seeds and compute the average values for performance evaluation. The simulator is generated by Java.

We first compare the performance of our proposed algorithm with the optimal solution achieved by exhaustive search as shown in Algorithm 2. In exhaustive search, we need $2^{|L|}$ for checking all $|L|$ candidate locations, $|P|^{|L|}$ for checking $|L|$ BSs with $|P|$ power levels, $|U|^{|L|}$ for checking all combinations of client-BS connections, and $|U|$ for checking the user QoS and energy sustainability constraints. The worst case time complexity of exhaustive search is $O(2^{|L|}|P|^{|L|}|U|^{|L|+1})$, which is much higher than the TCGBP algorithm.

The minimal number of BSs required to serve a given number of users is shown in

Algorithm 2 Exhaustive Search Algorithm

```
for all BS placements do
  for all combinations of BSs' power do
    for all combinations of client-BS connections do
      if Energy and traffic constraints can be met then
        Return |B|; {The minimum cost is found}
      end if
    end for
  end for
end for
```

Fig. 3.3. We have 5 candidate locations and a number of users, each of which has a 0.3 Mbps throughput requirement. We can observe that more BSs are deployed when the number of users increases, and our proposed algorithm approaches the optimal solution well. In Fig. 3.4, we have 5 BS candidate locations and 30 wireless users with varying traffic demands. The required number of BSs increases with the growth of traffic demands. By exhaustively searching all combinations, the exhaustive search algorithm can always find the optimal solutions with the minimal number of BSs, while our proposed algorithm stops when all users can be connected to a BS that satisfies both users' QoS and energy sustainability constraints. It shows that the exhaustive search algorithm slightly outperforms our proposed algorithm at the cost of significantly increasing time complexity.

We study the number of candidate locations impacting on deployed number of BSs in Fig. 3.5. 100 wireless users are deployed in single-tier green wireless networks. As shown in Fig. 3.5, for a larger number of candidate locations, it is more likely to find a feasible solution that satisfies both the users' QoS and energy sustainability requirements. The required number of BSs drops with the decreasing candidate loca-

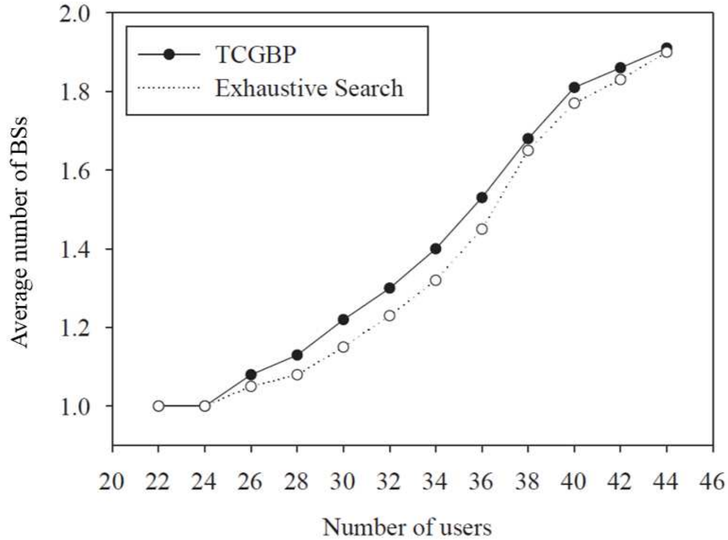


Figure 3.3: Performance comparison for different numbers of users.

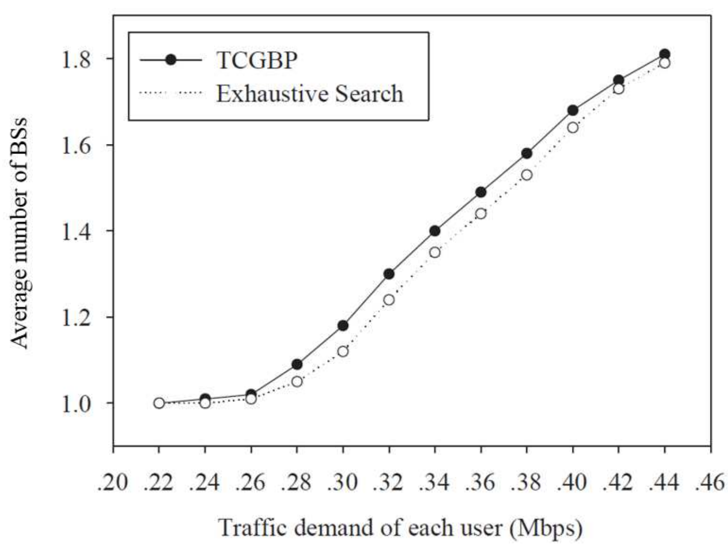


Figure 3.4: Performance comparison for different user demands.

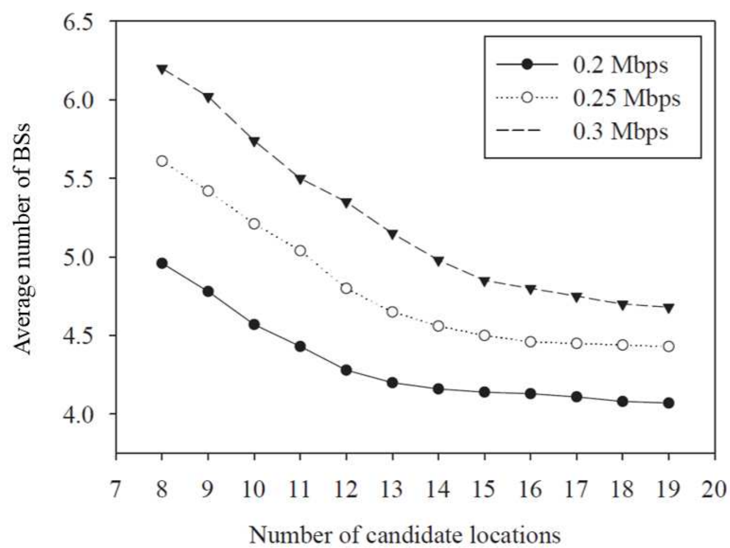


Figure 3.5: Impact of the number of candidate locations.

tion number. The impact of the charging capacities of placed BSs is shown in Fig. 3.6. The average charging rate of each BS changes from 10mW to 120mW. Similarly, with a higher average charging rate at each BS, i.e., a BS can sustain greater traffic demands of users, the number of BSs to serve all users is reduced accordingly. When the charging rate is sufficiently large, the number of BSs for a given user demand does not vary much, and BSs are required to cover the area where users are located.

3.4 Summary

In this chapter, we have investigated the network planning issue in single-tier green wireless communication networks to satisfy the basic throughput requirements of users. The main accomplishments of this chapter are summarized as follows:

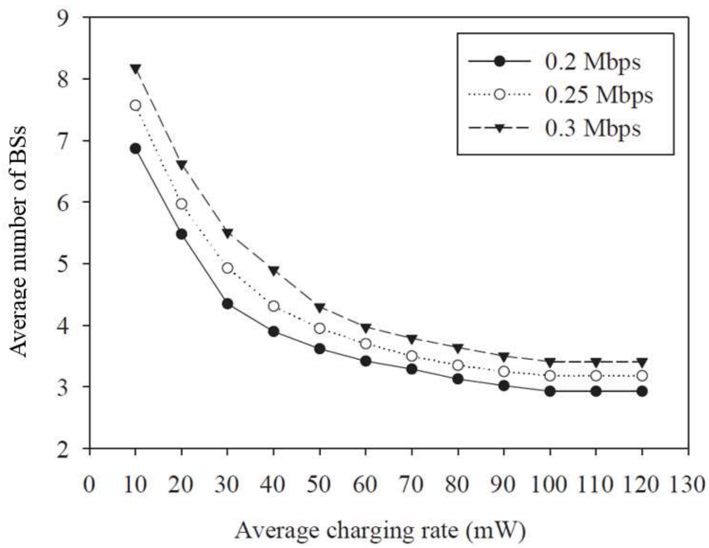


Figure 3.6: Impact of charging capabilities.

- By exploiting the particular characteristics of sustainable energy supplies, we have presented design criteria for the green macro cell BS deployment in a single-tier green wireless network. We have formulated the constrained minimum green BSs placement problem as an optimization problem, which aims at selecting a set of candidate locations to deploy the minimal number of green BSs such that users' basic traffic demands can be fulfilled by the harvested energy of the green BSs.

- We have analyzed possible strategies for the minimum green macro cell BSs problem. Based on the strategy analysis, a preference level has been assigned to each user for determining the relationship between the user and potential placed BSs. This metric is a function of distance between a user and all candidate locations of BSs, which reflects the connection priority and relative data rate between the user and corresponding green BSs.

- By jointly considering power control and network planning, a heuristic algorithm, called two-phase constrained green BS placement (TCGBP) algorithm, has been proposed to find the optimal BS deployment according to different traffic demands of users and charging capabilities of BSs. Based on Voronoi diagram and preference levels of users, the TCGBP algorithm can achieve the minimal number of green BSs by adjusting transmission power level to guarantee the satisfactory of both energy sustainability and users' QoS requirements. Extensive simulation results have shown that the proposed algorithm approaches the optimal solution under a variety of network settings with significantly reduced time complexity.

Chapter 4

Joint Green Small Cell BS and Sub-carrier Allocation in Two-tier Green Wireless Networks

After the construction of single-tier green wireless networks, the basic QoS requirements of users can be satisfied with harvested energy. However, some wireless services, such as layered video, have different levels of users' traffic demands. Therefore, it is always desirable to fulfill users' high-end throughput requirements and further improve the network sustainable performance. In this chapter, our target is to establish multi-tier green wireless communication networks to improve the network capacity with green energy. Considering high-end traffic demands of users, we envision network planning and resource allocation as two tightly related issues that have mutual impact on each other to improve the network throughput and to achieve long term energy sustainability. Specifically, we jointly address the green small cell BS deployment and sub-carrier allocation problems in two-tier wireless networks with green energy supplies, taking into account the throughput, cost and energy sustainability constraints.

The reminder of the chapter is organized as follows. The system model of a two-tiered wireless network with sustainable energy is described in Section 4.1. Based on the system model, a joint green small cell BS placement and sub-carrier allocation problem is formulated as an MINLP problem in Section 4.2. Two heuristic algorithms are proposed in Section 4.3. The performance of our algorithms is compared with that of a greedy algorithm in various network scenarios in Section 4.4, followed by the conclusions in Section 4.5.

4.1 System Model

We consider two-tiered green wireless networks, which are composed of green multiple macro cell BSs, green small cell BSs and wireless users, as shown in Fig. 4.1. The network architecture is motivated by the explosive growth of the network density and traffic intensity, which requires the deployment of extra green small cell BSs in the single-tier green network infrastructure to improve the network capacity and QoS provisioning capabilities. In single-tier green wireless networks, green macro cell BSs have been *a priori* installed in Chapter 3, while green small cell BSs can be deployed on a set of candidate locations. By employing solar panels or wind turbines, green marco cell and small cell BSs can harvest energy from the environment while wireless users use traditional power sources, e.g., battery, to power their personal devices due to the hardware and cost constraints. As green energy sources are inherently variable and dependent on the time, locations and weather, green BSs, i.e., the marco cell and small cell BSs powered by green energy supplies, distributed at different locations have various charging capabilities. Such kind of network scenario is common in real life. For example, we consider a community with several macro cell BSs powered by green energy. Each building is referred to as a user and has people work or live in it. Green small cell BSs can be installed on the roof of some buildings, which are marked as candidate locations. The traffic demand of each user and solar insolation or wind speed level of each candidate location can be obtained from the historical statistics. Since green small cell BSs help relay the traffic between users and green macro cell BSs, we use (green) BSs and (green) RNs to denote green macro cell BSs and green small cell BSs to simplify the descriptions, respectively. The notations used in system model are shown in Table 4.1.

In two-tiered green wireless networks, each RN is associated with a BS, while each user can be served by either a BS or a RN. When a user connects to a RN, the RN needs to relay the user's traffic to a BS. Therefore, a two-hop transmission is involved when a user is associated with a RN; while a direct link transmission is used when a user is connected to a BS. All nodes in the network share a set of sub-carriers, denoted as S. A sub-carrier can be re-used by users in the space domain if and only if sub-carriers occupied by users are sufficiently far away from each other, and thus cause negligible interference to each other. As users with different traffic demands

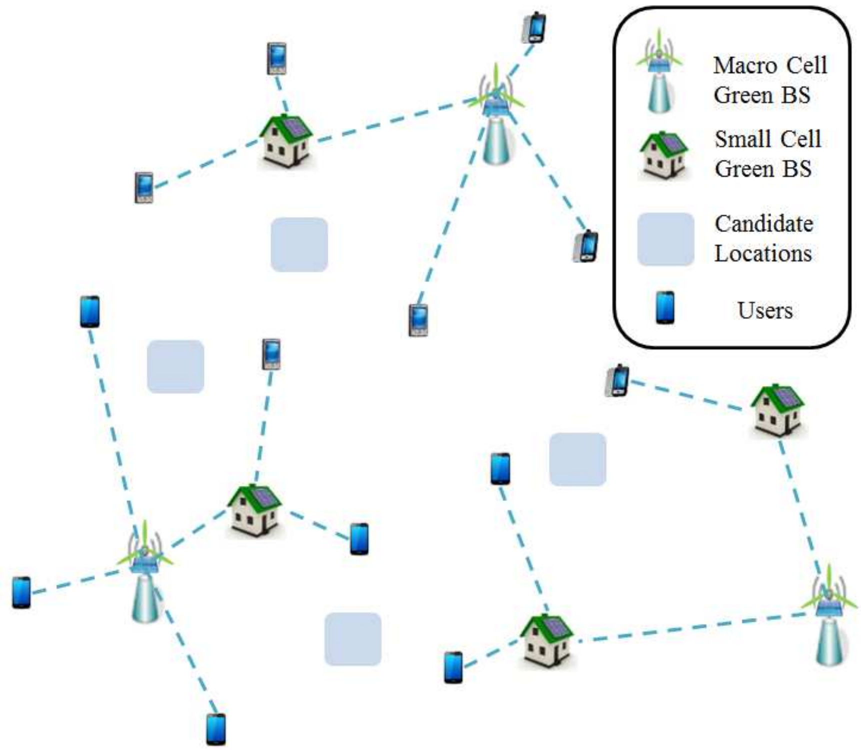


Figure 4.1: Two-tiered green wireless networks.

Table 4.1: Notations for system model in Chapter 4

S	The set of sub-carriers shared by all nodes
$G(V = U \cup R \cup B; E)$	The network topology with users, RNs, BSs and links
V	The set of all nodes
E	The set of communication links
U	The set of users
R	The set of RNs
B	The set of BSs
D_{xy}	The distance between a pair of nodes, x and y
P_x^T	The transmission power of node x
(x, y)	The link consisting of node x and node y
SNR_{xy}	The received signal to noise ratio of link (x, y)
α	The path loss exponent
$\aleph$	The background noise power
c_{xy}	The achievable data rate of link (x, y)
W	The bandwidth of each sub-carrier
S_{xy}	The set of sub-carriers allocated to link (x, y)
$\|S_{xy}\|$	The number of allocated sub-carriers to link (x, y)
s_i	The sub-carrier s_i in S
θ	The received signal strength threshold
I_y	The interference collision set of node y

are distributed over the network and various candidate locations provide different charging capacities, it is essential to appropriately select locations of green RNs and allocate a proper set of sub-carriers to green RNs based on energy charging capacities and users' traffic demands, so that the allocated bandwidth can be fully utilized by a node without energy outage.

We build a network communication graph $G(V = U \cup R \cup B; E)$ to model the topology of two-tier green wireless networks, where V is the set of all nodes, i.e., green BSs, green RNs and users, and E is the set of communication links between any two nodes. U, R and B stand for the set of users, RNs and BSs, respectively. Let D_{xy} denote the distance between a pair of nodes, x and y, and P_x^T be the transmission power of node x. The received signal to noise ratio of link (x, y), called SNR_{xy}, is

$$SNR_{xy} = \frac{P_x^T \cdot D_{xy}^{-\alpha}}{\aleph}, \tag{4.1}$$

where α is the path loss exponent, and $\aleph$ is the background noise power. Let c_{xy} denote the achievable data rate of link (x, y), then we have

$$c_{xy} = |S_{xy}| W \log_2 (1 + SNR_{xy}), \tag{4.2}$$

where W is the sub-carrier bandwidth. Let S_{xy} represent the set of sub-carriers allocated to link (x, y), and $|S_{xy}|$ be the number of allocated sub-carriers. The set of sub-carriers allocated for each link can be expressed as

$$\begin{cases} S_{xy} = \begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_m \end{pmatrix}, \forall (x,y) \in E \\ m = |S| \\ s_i \in \{0,1\}, \end{cases} \tag{4.3}$$

where $s_i = 1$ represents that sub-carrier s_i is allocated to link (x, y), and $s_i = 0$ otherwise.

We allocate sub-carriers to each green BS and RN so that users associated with the BS/RN can use the same set of sub-carriers to communicate with its BS/RN. x is in the interference range of y if the received signal strength of x from y, SNR_{yx}, exceeds a threshold θ, i.e.,

$$SNR_{yx} \geq \theta. \tag{4.4}$$

We define the interference collision set of node y as the set of nodes within the interference range of y, which is denoted by I_y. Nodes within the same interference collision set are not allowed to transmit at the same time.

4.2 Problem Formulation

Our joint relay node placement and sub-carrier allocation (RNP-SA) problem focuses on placing the minimal number of green RNs into the network and allocating an appropriate number of sub-carriers to each green BS/RN to provide full coverage, i.e., any user in the network is served by either a BS or a RN, and users' throughput requirements can be fulfilled by the harvested energy along with the allocated sub-carriers based on the cost threshold. Generally, RNs are required when the charging capacities of the BSs cannot sustain the traffic demands of users. By cooperating with green RNs, some users can achieve a higher throughput, and reduce the energy consumption at the BSs. With more allocated sub-carriers, a higher throughput can be achieved at the cost of higher energy consumption over a wider spectrum band. Due to the limited charging capabilities of green BSs/RNs, the number of allocated sub-carriers should be jointly determined by the users' traffic demands and the charging capacities of BSs/RNs. This is because, for a green BS/RN with a low energy level, allocating a large number of sub-carriers will drain out its energy quickly and cause the green BS/RN to be temporarily out of service, which degrades the utilization efficiency of the spectrum band and is not desirable. Therefore, it is important to carefully formulate a joint optimization problem to achieve satisfactory sustainable network performance.

The notations used in problem formulation are shown in Table 4.2. We study the RNP-SA problem for a given set of users (U), a set of existing BSs (B), the charging capacities of BSs, the expected charging capacities of RNs at various candidate loca-

Table 4.2: Notations for problem formulation in Chapter 4

$\|R\|$	The number of deployed RNs
$\|R'\|$	The budget of RN deployment
u	User u in the set of users U
r	RN r in the set of RNs R
b	BS b in the set of BSs B
β_{ux}	The achieved throughput from user u to node x
${\beta'}_{ux}$	The throughput requirement of node u for link (u, x)
$\mathcal{E}_x^+$	The consumed energy by node x during a unit time
$\mathcal{E}_x^-$	The harvested energy by node x during a unit time
e_{xy}	The connection status of node x and node y
t_{xy}	The active time of the link (x, y)
L	The set of candidate locations
γ_u^{up}	The uplink throughput requirement of user u
γ_u^{dn}	The downlink throughput requirement of user u
P_x^+	The average energy charging rate of node x
P_x^R	The power consumption of user x to receive and decode the signal
$T_I(x)$	The active time of the allocated sub-carriers of user x

tions, the throughput requirement of each user, the cost threshold and the available set of sub-carriers. We formulate the RNP-SA problem as an MINLP problem as follows,

$$
\begin{aligned}
\mathit{Minimize} \quad & |R| \\
\mathit{Subject\ to:} \quad & \textstyle\sum_{x \in R \cup B} e_{ux} = 1, && \forall u \in U \\
& \textstyle\sum_{b \in B} e_{rb} = 1, && \forall r \in R \\
& \beta_{ux} \geq \beta'_{ux}, && \forall e_{ux} = 1 \\
& \mathcal{E}_x^+ \geq \mathcal{E}_x^- && \forall x \in R \cup B \\
& |R| \leq |R'| \\
& e_{xy} \in \{0, 1\}, && \forall x, y \in V
\end{aligned}
\tag{4.5}
$$

The first and second constraints indicate that each user should be served by one BS or RN, and each RN should be connected to one BS. The third constraint indicates that the achieved flow throughput from node u to x, β_{ux}, should not be less than the user's throughput requirement on link (u, x), β'_{ux}. The fourth constraint ensures the energy sustainability of node x such that the harvested energy, $\mathcal{E}_x^+$, should be able to sustain traffic demands of x's users, $\mathcal{E}_x^-$. The fifth constraint guarantees that the cost of deployed RNs should not exceed the determined cost threshold. Finally, we define $e_{xy} = 1$ to represent node x to be associated with node y, and $e_{xy} = 0$ otherwise.

4.2.1 QoS and Energy Sustainability Constraints

In this subsection, we further specify the energy sustainability constraint and throughput requirement defined in Eq. (4.5). Denote t_{xy} as the active time of link (x, y) during a unit time. For all two-hop uplink transmissions, e.g., from users to BSs via RNs, the input traffic of RNs should be equal to its output traffic, which is given by

$$\sum_{u \in U} e_{ur} c_{ur} t_{ur} = \sum_{b \in B} e_{rb} c_{rb} t_{rb}, \forall r \in R. \tag{4.6}$$

Let γ_u^{up} and γ_u^{dn} be the uplink and downlink throughput requirements of user u, respectively. To meet the uplink throughput requirements of users, we have

$$\sum_{r \in R} e_{ur} c_{ur} t_{ur} + \sum_{b \in B} e_{ub} c_{ub} t_{ub} \geq \gamma_u^{up}, \forall u \in U. \tag{4.7}$$

The first item in the left hand side (LHS) of Eq. (4.7) is the achieved uplink throughput of user u if the user is connected to a RN for $e_{ur} = 1$ and $e_{ub} = 0$; The second item in the LHS is the achieved user throughput if the user is connected to a BS for $e_{ub} = 1$ and $e_{ur} = 0$.

Similarly, the input traffic of RNs should be equal to its output traffic in the downlink, and we have

$$\sum_{u \in U} e_{ru} c_{ru} t_{ru} = \sum_{b \in B} e_{br} c_{br} t_{br}, \forall r \in R. \tag{4.8}$$

To meet the downlink throughput requirements of users, we need to ensure

$$\sum_{r \in R} e_{ru} c_{ru} t_{ru} + \sum_{b \in B} e_{bu} c_{bu} t_{bu} \geq \gamma_u^{dn}, \forall u \in U. \tag{4.9}$$

Suppose the average energy charging rate of node x is P_x^+. Denote P_x^R as the power consumption of user x to receive and decode the signal. In order to satisfy the energy sustainability constraint, the charged energy should be greater than the energy required for transmitting and receiving the traffic to and from other nodes,

$$P_x^+ \geq P_x^T \sum_{(x,y)\in E} t_{xy} + P_x^R \sum_{(y,x)\in E} t_{yx}, \forall x \in R \cup B. \tag{4.10}$$

Finally, to avoid harmful interference from concurrent transmissions, users in one interference collision set should transmit data in different time slots. Let I_x denote the interference collision set of node x and $T_I(x)$ be the active time of the allocated sub-carriers of user x, we have

$$T_I(x) = \sum_{y\in I_x} \sum_{z\in V} (t_{yz}S_{yz} + t_{zy}S_{zy}) \leq 1, \forall x \in V. \tag{4.11}$$

The equation shows the summation of occupied time in each sub-carrier. It indicates that the total active time of all links associated within the same interference collision set should not exceed a unit time.

4.3 RNP-SA Algorithms

The formulated RNP-SA problem is NP-hard, because one of subproblems of RNP-SA problem, the relay node placement (RNP) problem, is a well-known NP-hard problem as proved in [101], and there is no efficient polynomial-time solution to address it now. In this chapter, we resort to efficient heuristic algorithms for the

RNP-SA problem. To this end, we first study the key parameters that affect the throughput and energy sustainability constraints. By placing a RN close to a BS, there may be little throughput gain for a user to transmit to the BS via the RN due to long distance between the RN and users, but the energy consumption of the BS can be significantly reduced as the BS only needs to communicate with the RN which is close to it. By deploying a RN in a candidate location with high traffic load but far away from the BS, there may be little energy saving as the communication distance of the BS and the RN is long, but throughput requirements of users can be fulfilled as users can communicate with a close RN at a high data rate. Thus, to efficiently deploy green RNs, we need to well balance the throughput gain and energy consumption of green BSs. By jointly considering the energy and bandwidth requirements, we design a novel link metric, referred to as the sub-carrier and traffic over rate (STR). Based on the STR metric, we propose two low-complexity heuristic algorithms, namely, RNP-SA with top-down/bottom-up (RNP-SA-t/b) algorithms.

The overview of our algorithms is introduced in subsection 4.3.1. After that, we present the design of link metric which is used for choosing relay locations and connecting users in subsection 4.3.2. The details of RNP-SA-t/b algorithms are described in subsections 4.3.3 and 4.3.4. Finally, the time complexity of the proposed RNP-SA-t/b algorithms is analyzed in subsection 4.3.5.

4.3.1 Algorithms overview

The objective of RNP-SA algorithm is to find the minimal number of green RNs to fulfill users' traffic demands under the energy sustainability and cost constraints. In order to meet the throughput requirements of users, an intuitive method is to place green RNs to the candidate locations with the heaviest traffic load. However, under this strategy, it is possible that some candidate locations far away from BSs are selected for RNs. In this case, the deployed RNs may not be able to efficiently relieve the energy demands at BSs, as BSs still need to communicate with faraway nodes. On the other side, to guarantee the energy sustainability of BSs, another intuitive method is to place RNs close to BSs. Nevertheless, under this strategy, wireless users communicating with the RN may achieve similar one-hop throughput as with BS, but need an extra hop transmission from RN to BS. This implies that wireless users may not be able to achieve a higher throughput by cooperating with RNs, and more RNs may be required to fulfill the traffic demands, which may lead to violation of cost threshold. Thus, we design a link metric, i.e., STR, which characterizes the throughput and energy demand of each user associated with a RN or BS, and thus strikes a balance between the energy consumption and users' throughput for placing RNs in the network.

Based on the proposed metric, we then propose two heuristic algorithms to deploy the minimal number of RNs with top-down and bottom-up algorithms. In the top-down algorithm, we first place RNs in all candidate locations. All links (e.g., links between users and RNs, users and BSs, and RNs and BSs) are established in an

Table 4.3: Notations for RNP-SA algorithms in Chapter 4

γ_u	The traffic demand of user u, which is the summation of γ_u^{up} and γ_u^{dn}
STR_{ux}	The Sub-carrier and Traffic over Rate of link (u, x), where $x \in B \cup R$
STR_{rb}	The Sub-carrier and Traffic over Rate of link (r, b)
(u, r, b)	(u, r) and (r, b)
STR_{urb}	$STR_{ur} + STR_{rb}$
l_i,l_j,l_k	The link l_i, l_j and l_k in the network, respectively
b_x	The BS that x is associated with including the BS itself
γ_z^I	Summation of users' traffic demand within z's interference range, $z \in L$
S_x	The sub-carriers allocated to node x
$\lvert S_x \rvert$	The number of sub-carriers allocated to node x
$\lvert S \rvert$	The number of all available sub-carriers shared by all nodes
$\lvert L \rvert$	The number of candidate locations
$\lvert U \rvert$	The number of users
$\lvert B \rvert$	The number of BSs
P^T	The transmission power of all nodes
P^R	The receiving power of all nodes

ascending order of STR until the RNs' charging capabilities cannot sustain users' traffic demands. We calculate the least number of sub-carriers required for meeting users' traffic demands and allocate them to users. Then, we delete RNs one by one based on the STR of links until any of cost, energy or throughput constraints cannot be guaranteed. In the bottom-up algorithm, we first connect each user to the closest BS and calculate the least number of required sub-carriers. We check whether the current placement is a feasible solution or not, i.e., all of the cost, energy and QoS constraints can be satisfied. If not feasible, we place one more RN on a candidate location and add users to the RN according to their STR values until constraints cannot be held. The notations used in problem formulation are shown in Table 4.3.

4.3.2 Sub-carrier and Traffic over Rate

To solve the RNP-SA problem, the foremost issue is to decide where to place the RNs and how to establish connections between users and RNs or BSs. Since our objective focuses on minimizing the number of RNs, we let each RN partake in serving as many users as possible to relief BSs' burden of energy and traffic demands. Since decoupling the energy and QoS constraints may not lead to an effective solution, we propose a metric that jointly considers energy consumption and users' throughput requirements. Let γ_u be the summation of γ_u^{up} and γ_u^{dn}. The definition of our metric is given as follows:

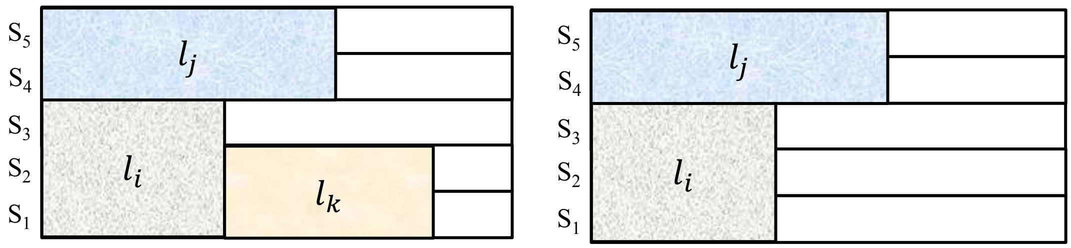
Sub-carrier and traffic over rate of link (u, x) or (r, b):

$$\begin{cases} STR_{ux} = \frac{|S_{ux}|\gamma_u}{c_{ux}}, \forall u \in U, x \in B \cup R \\ STR_{rb} = \frac{|S_{rb}| \sum_{u\in\{u|(u,r)\in E\}} \gamma_u}{c_{rb}}, \forall r \in R, b \in B. \end{cases} \tag{4.12}$$

Combining Eq. (4.12) with Eq. (4.2), we can derive STR metric as

$$\begin{cases} STR_{ux} = \frac{\gamma_u}{W \log_2(1+SNR_{ux})}, \forall u \in U, x \in B \cup R \\ STR_{rb} = \frac{\sum_{u\in\{u|(u,r)\in E\}} \gamma_u}{W \log_2(1+SNR_{rb})}, \forall r \in R, b \in B. \end{cases} \tag{4.13}$$

STR is the quotient of users' throughput requirements and achievable throughput of the link with a single subcarrier, which represents the minimal required active time for data transmission. A link with a smaller STR implies that this link consumes less energy and/or achieves a higher rate compared with other links using the same



(a) Top-down sub-carrier allocation (b) Bottom-up sub-carrier allocation

Figure 4.2: Top-down and bottom-up sub-carrier allocation.

number of sub-carriers.

4.3.3 RNP-SA with top-down algorithm

The detail of our RNP-SA-t algorithm is shown in Algorithm 3. Initially, RNs are deployed on each candidate location. We first connect each user to a RN or BS with the minimum STR, and then connect each RN to the BS with the minimum STR. Given that the total active time of all connected links, which are in the same interference collision set, should be smaller than a unit time, we calculate the least number of required sub-carriers. Then, we allocate the least used available sub-carriers to each link. An example of top-down sub-carrier allocation is shown in Fig. 4.2(a). Suppose that the total number of sub-carriers is 5, while the least number of required sub-carriers of link l_i, link l_j and link l_k are 2, 3 and 2, respectively. Based on the sub-carrier allocation sequence l_i, l_j and l_k, the least used sub-carriers are allocated first, as shown in Fig. 4.2(a). After that, we check the cost, energy and QoS constraints for each node. If the energy and/or QoS constraints can not be satisfied and the cost constraint is violated, the algorithm will return no feasible solution. If all constraints, i.e., cost, energy and QoS constraints are satisfied, we then calculate the STR of each RN, and delete a RN with the least contribution of total STR, which is defined as the difference of total STR with or without the RN. In other cases, the algorithm will stop and return the current number RNs. After deleting the RN, we connect its users to other RN or BS with the minimum STR and calculate the total value of STR of all associated links. The difference of total STR with or without the RN refers to the RN's contribution. Thus, we delete the RN with the least contribution of total STR as this node makes the least contribution in the network. The RNs are repeatedly deleted until any of cost, energy and/or QoS constraints is violated. If deleting $n+1$-th RN will violate the constraints, the algorithm returns a placement of n RNs in the last round.

4.3.4 RNP-SA with bottom-up algorithm

We design the RNP-SA-b algorithm to further reduce the time complexity compared with the RNP-SA-t algorithm. The detail of our RNP-SA-b algorithm is shown in Algorithm 4. In the bottom-up algorithm, we first generate a graph by connecting each user to the closest BS. Similar with the RNP-SA-t algorithm, we calculate the least number of required sub-carriers under the cost, energy and throughput constraints. Then, we assign unused sub-carriers to each link by bottom-up sub-carrier allocation without time domain multiplexing. Thus, bottom-up sub-carrier allocation can achieve a lower time complexity compared with the top-down sub-carrier allocation at the cost of reduced spectrum utilization. An example of the bottom-up sub-carrier

Algorithm 3 RNP-SA-t:RNP-SA with top-down algorithm

```
Place RNs on all candidate locations;
while R ≠ ∅ do
    Connect (u, r, b)or(u, b) with min(STR_urb, STR_ub), ∀u ∈ U, r ∈ R, b ∈ B;
    if P_r^+ < P_r^- ∨ P_b^+ < P_b^- then
        Connect u to the closest r or b with enough energy;
    end if
    Calculate the least required |S_x|, ∀x ∈ V;
    Conduct top-down sub-carrier allocation;
    if |R| = |R'| ∧ energy and/or QoS constraints cannot be kept then
        Return no feasible solution;
    end if
    if Cost, energy and QoS constraints can be kept then
        Save the current topology;
        for all r ∈ R do
            U* ← {u : (u, r) ∈ E};
            STR_1 ← Σ_{(u,r,b)∈E} STR_urb;
            Delete r and disconnect its links;
            for all u ∈ U* do
                Add (u, r, b)or(u, b) with min (STR_urb, STR_ub);
                STR_2 ← STR_2 + min (STR_urb, STR_ub);
            end for
            STR* ← STR_2 − STR_1;
            Load the topology;
        end for
        Delete r with min (STR*);
    else
        Return relay node number of last loop;
    end if
end while
Return 0;
```

allocation is shown in Fig. 4.2(b). Link l_k cannot be scheduled for transmission as there is no available sub-carriers at this time. After allocating sub-carriers, we check whether the current placement is feasible or not, under the cost, energy sustainability and throughput constraints. If the cost constraint is violated, we stop the program and return the number of RNs; if the energy constraint is violated, we need to place one more RN in the network on the location closest to the BS; if the throughput constraint is violated, one more RN should be placed on the location with the heaviest traffic demand. Then, we sort users by STR of user-relay links in an ascending order. The user-relay-BS link is established only when the cost constraint is not violated, while the placement of the RN can help to reduce the energy consumption of BSs and the throughput constraint of users can also be satisfied. If the energy and/or QoS constraints cannot be kept and the cost constraint is violated, the algorithm will return no feasible solution.

4.3.5 Time complexity analysis of the RNP-SA algorithms

In this subsection, we analyze the worst case time complexity of the proposed RNP-SA-t/b algorithms without cost threshold, i.e., the cost threshold is always large enough to get a feasible deployment. Assume that the number of BSs in two-tired green wireless networks is much smaller than that of RNs and candidate locations. The time complexity of RNP-SA-t/b algorithms is analyzed as follows.

The time complexity of RNP-SA-t algorithm is $O(|S||L|(|U|+|L|)^2+|U||L|^3)$. For each round, the time complexity of generating a new topology is $O(|U||L|)+$

Algorithm 4 RNP-SA-b:RNP-SA with bottom-up algorithm

```
Connect each user to the closest BS;
Calculate the least required |S_x|, ∀x ∈ V;
Conduct bottom-up sub-carrier allocation;
if Cost, energy and QoS constraints can be kept then
  Return 0;
else
  while P_x^+ < P_x^- ∨ ∑_{(x,y)∈E} |S_xy| > |S| do
    if Cost constraint cannot be kept then
      Return the number of placed RNs;
    else
      b* ← b_x;
      if P_{b*}^+ < P_{b*}^- then
        r ← z with min(D_{b*z}), ∀z ∈ L ∧ SNR_{b*z} ≤ β;
      else
        r ← z with max(γ_z^I), ∀z ∈ L ∧ SNR_{b*z} ≤ β;
      end if
      U* ← sort users by STR_ur in increasing order;
      for all u ∈ U* do
        Replace (u, b) by connecting (u, r, b);
        if P_r^+ < P_r^- ∨ P_{b*}^- is increased then
          Replace (u, r, b) by connecting (u, b);
        end if
      end for
      Calculate the least required |S_x|, ∀x ∈ V;
      Conduct bottom-up sub-carrier allocation;
      if |R| = |R'| ∧ energy and/or QoS constraints cannot be kept then
        Return no feasible solution;
      end if
      if Cost, energy and QoS constraints can be kept then
        Return the number of placed RNs;
      end if
    end if
  end while
end if
```

$O(|L||B|)$. As the number of BSs is much smaller than that of RNs and candidate locations, $O(|U||L|) + O(|L||B|)$ is the same as $O(|U||L|)$. For each node the sub-carrier allocation and checking feasibility are conducted at the same time, which needs the time complexity of $O(|S|(|U| + |L|))$. There are total $O(|U| + |L|)$ nodes to be checked, thus the time for the algorithm to do sub-carrier allocation and checking feasibility is $O(|S|(|U|+|L|)^2)$. For checking the energy constraint of each BS, it needs $O(|B|(|U| + |L|))$. The step of removing an RN needs $O(|U||L|^2)$, which consists of investigating all candidate locations and its attached users, $O(|U||L|)$, and rearranging them $O(|L|)$. Since all the steps are sequential and there are at most $|L|$ rounds, the total complexity of RNP-SA-t algorithm is

$$\begin{aligned} &O(|L|)[O(|U||L|) + O(|S|(|U| + |L|)^2) + O(|B|(|U| + |L|)) + O(|U||L|^2)] \\ &= O(|S||L|(|U| + |L|)^2 + |U||L|^3). \end{aligned}$$

The time complexity of RNP-SA-b algorithm is $O(|B||L|^2+|L||U|\log|U|+|B||U||L|)$. For each round, the time complexity is $O(|B||L|)$ to determine which candidate location to place the newly added RN. Then, it takes $O(|U|\log|U|)$ to sort users in increasing order of STR_{ur}. Adding users to the newly added RN needs $O(|U|)$, and allocating the sub-carriers for those newly connected links requires $O(|U|)$. Finally, the time complexity of checking the constraints for each BS needs $O(|B|(|U| + |L|))$. Since all the steps are sequential and there are at most $|L|$ rounds, the total complexity of RNP-SA-b algorithm is

$$O(|L|)[O(|B||L|) + O(|U| \log |U|) + O(|U|) + O(|U|) + O(|B|(|U| + |L|))]$$
$$= O(|B||L|^2 + |L||U| \log |U| + |B||U||L|).$$

Therefore, the RNP-SA-b algorithm has a lower time complexity than the RNP-SA-t algorithm.

4.4 Simulation Results

In this section, we compare the performance of the proposed RNP-SA-t/b algorithms to a traffic load oriented greedy algorithm with and without cost threshold. We first evaluate the minimal number of relay nodes that is required to fulfill the network requirement. Furthermore, when a cost threshold is set to limit the maximal number of relay nodes, we analyze the average network lifetime, which is defined as the time duration from the beginning until one of the network infrastructure nodes, either a BS or RN, drains out its energy and becomes out of service. The performance is evaluated under various network settings, e.g., diverse energy charging capabilities of candidate RNs at various locations, different traffic demands of users, variable transmission powers, and different numbers of users or BSs.

4.4.1 Simulation configurations

We set up two-tiered green wireless networks with 4 BSs, 150 wireless users and 50 candidate locations of RNs within a $200m \times 200m$ region. BSs are evenly distributed, while candidate locations and users are randomly distributed in the region. All nodes use the same transmission power, $P^T = 0.5$ W, and the reception power, $P^R = 0.05$ W, to communicate with each other. Different BSs and RNs distributed on different candidate locations have various charging capabilities, and the energy charging rates of BSs and RNs are uniformly distributed over $[0.2, 0.4]$ W and $[0.05, 0.1]$ W, respectively. The total number of sub-carriers in the network is 50, where the bandwidth of each sub-carrier is 2 MHz. The path loss exponent is 2, the background noise power $\aleph = 10^{-4}$ W, and the interference signal threshold is 1. Different users have different throughput requirements, which is randomly distributed over $[25, 55]kbps$, and the downlink traffic demand is 9 times of that in the uplink. We repeat each simulation experiment 1000 times with different random seeds and compute the average values for performance evaluation. The simulator is developed by using Java and Matlab. The parameters used in the simulation are tabulated in Table 4.4.

4.4.2 Traffic load oriented greedy algorithm

We compare the performance of the proposed algorithms with a traffic load oriented greedy algorithm as a benchmark. For the greedy algorithm, initially, we first connect each user to the closest BS. After that, the minimal number of required sub-carriers under the energy and throughput constraints is allocated to each user, which is similar

Table 4.4: Table of Parameters

region size	$200m \times 200m$
number of BSs	4
number of users	150
number of candidate locations	50
number of sub-carriers	50
maximal network lifetime	200 time slots
transmission power	$0.5W$
receiving power	$0.05W$
charging capability of BSs	$[0.2, 0.4]W$
charging capability of RNs	$[0.05, 0.1]W$
bandwidth of single sub-carrier	$2MHz$
pass loss exponent	2
background noise power	$10^{-4}W$
interference signal threshold	1
data-rate demand of users	$[25, 55]kbps$
$\gamma_u^{dn}/\gamma_u^{up}, \forall u \in U$	9

to that in the RNP-SA-b algorithm. With the greedy algorithm, a RN is always placed on the candidate location with the heaviest traffic load, i.e., the sum of the traffic load within the interference range of the RN candidate location is higher than that of any other locations. The closest users to the RN are then connected to the deployed RNs iteratively, given that the placement of the RN can help reduce the energy consumption of the BS, while the deployment cost, energy, and QoS constraints of RNs can be fulfilled. The detail of traffic load oriented greedy algorithm is shown in Algorithm 5.

Assuming that the cost threshold is large enough and the number of BSs is much smaller than the number of RNs or candidate locations, the worst case time complexity of the traffic load oriented greedy algorithm can be calculated as follows.

Algorithm 5 Traffic load oriented greedy algorithm

Connect each user to the closest BS;
Calculate the least required $|S_x|, \forall x \in V$;
Conduct bottom-up sub-carrier allocation;
while Cost, energy and QoS constraints cannot be kept **do**
  $r \leftarrow z$ with $\max(\gamma_z^I), \forall z \in L$;
  $b^* \leftarrow b$ with $\min(D_{rb}), \forall b \in B$;
  Connect (r, b^*);
  $U^* \leftarrow$ sort users by $D_{ur}, \forall u \in U$;
  for all $u \in U^*$ **do**
    Replace (u, b^*) by connecting (u, r, b^*);
    if $P_r^+ < P_r^- \vee P_{b^*}^-$ is increased **then**
      Replace (u, r, b) by connecting (u, b);
    end if
  end for
  Calculate the least required $|S_x|, \forall x \in V$;
  Conduct bottom-up sub-carrier allocation;
end while
Return the number of placed RNs;

The worst case time complexity of the traffic oriented greedy algorithm is $O(|L|^2(|L|+|U|))$. For each round, it takes $O(|L|(|L|+|U|))$ time to find out the candidate location with heaviest traffic load. The time complexity of sorting users is $O(|U|\log|U|)$, and connecting users to the newly added RN needs $O(|U|)$. Then, allocating the subcarriers for those newly connected links requires $O(|U|)$. Finally, it needs $O(|B|(|U|+|L|))$ to check the energy constraints for all the BSs. Since all these steps are sequential and there are at most $|L|$ rounds, the total complexity of the traffic oriented greedy algorithm is

$$\begin{aligned}&O(|L|)[O(|L|(|L|+|U|))+O(|U|\log|U|)+O(U)+O(U)+O(|B|(|U|+|L|))]\\&=O(|L|^2(|L|+|U|)).\end{aligned}$$

Therefore, the traffic load oriented greedy algorithm has the same worst case time complexity as the RNP-SA-b algorithm.

4.4.3 Performance evaluation

We first evaluate the minimal number of required RNs with different algorithms. The number of RNs required to fulfill throughput demands of users is plotted in Fig. 4.3. It can be seen that more RNs are required when the traffic demands of users increase. The greedy algorithm is designed to help relieve the traffic burden of the BSs, without considering the energy consumption; while our algorithms jointly consider the impact of energy sustainability and users' traffic demands, and thus achieve better performance. The impacts of variable energy charging capabilities of RNs are illustrated in Fig. 4.4. It is shown that the number of required RNs decreases with the increasing charging capabilitiy of RNs. A high capacity RN can serve more users, and thus a smaller number of RNs is required to serve a given number of users. The impacts of transmission power are shown in Fig. 4.5. Generally, when BSs use a higher transmission power to serve users, more energy is consumed at BSs and thus more RNs are required to help release the energy burden of BSs. In all cases, our proposed algorithms outperform greedy algorithm significantly. We also observe that the RNP-SA-t algorithm achieves better performance than the RNP-SA-b algorithm at the cost of a higher time complexity. This is because the RNP-SA-t algorithm uses the top-down method to iteratively remove RNs based on the network topology information, including all of the relay candidate locations; while the RNP-SA-b algorithm is only based on the current topology, thus achieves a slightly lower performance than the RNP-SA-t algorithm with the reduced time complexity.

After that, we evaluate the network lifetime performance of different algorithms under a certain cost threshold. The network lifetime of RNP-SA-t, RNP-SA-b and greedy algorithms under various cost thresholds and the number of users is shown in Fig. 4.6, Fig. 4.7 and Fig. 4.8, respectively. A longer network lifetime is achieved with a higher cost threshold or a smaller number of users for all algorithms. A higher cost threshold allows more RNs to be deployed, and more RNs can help balance the energy consumption and traffic demands of BSs, which can improve the energy sustainability of the network. Similarly, a smaller number of users implies a lower demand for both energy and bandwidth, and thus a longer network lifetime can be achieved. However,

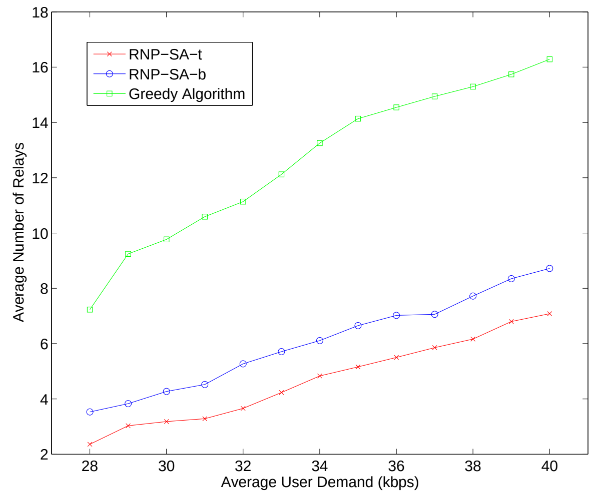


Figure 4.3: Relay number of various user demands without cost threshold.

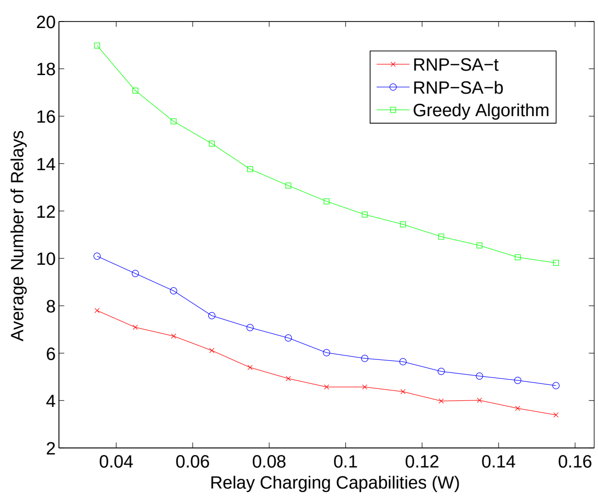


Figure 4.4: Relay number of various charging capabilities without cost threshold.

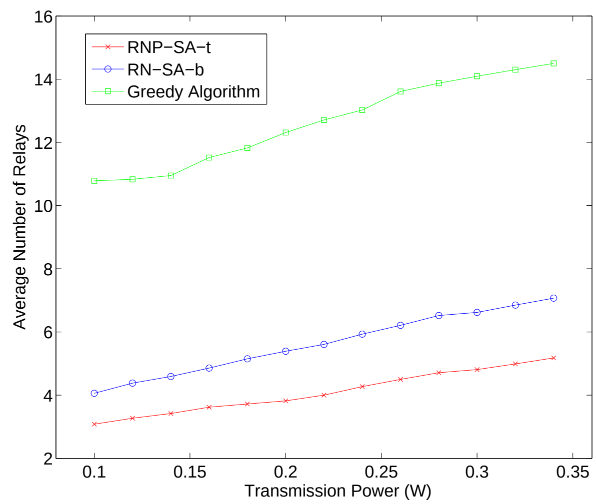


Figure 4.5: Relay number of various transmission power without cost threshold.

as the greedy algorithm only considers the throughput constraint but ignores the energy constraint, it cannot ensure high network sustainability performance. It is shown in Fig. 4.8 that the network lifetime increases slightly with the growth of cost threshold. Our proposed algorithms jointly consider the energy and throughput constraints by employing the STR metric for green small cell BS deployment. It can be seen that the increase rate of network life time of RNP-SA-t/b is much higher than that of the greedy algorithm as shown in Fig. 4.6 and Fig. 4.7.

We further study the impacts of the number of BSs on the network lifetime in Fig. 4.9. The cost threshold is set to allow the deployment of up to 5 RNs. The network lifetime improves significantly with the increasing number of BSs as shown in Fig. 4.9. Similarly, our proposed RNP-SA-t/b algorithms significantly outperform the greedy algorithm. This is because the greedy algorithm always chooses the candidate

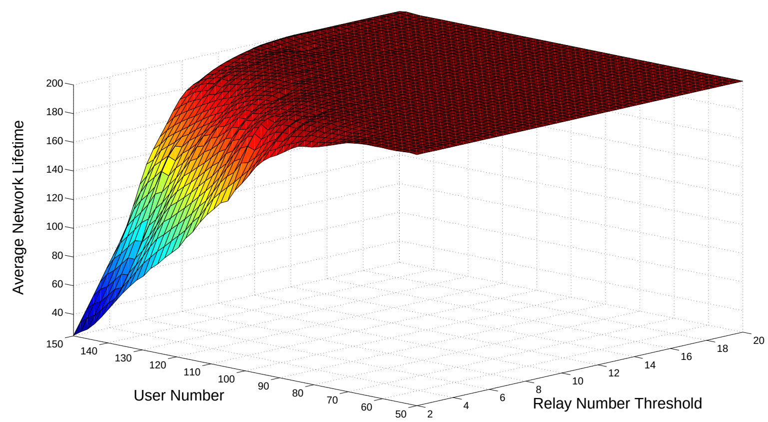


Figure 4.6: Network lifetime of RNP-SA-t algorithm with various cost thresholds and user numbers.

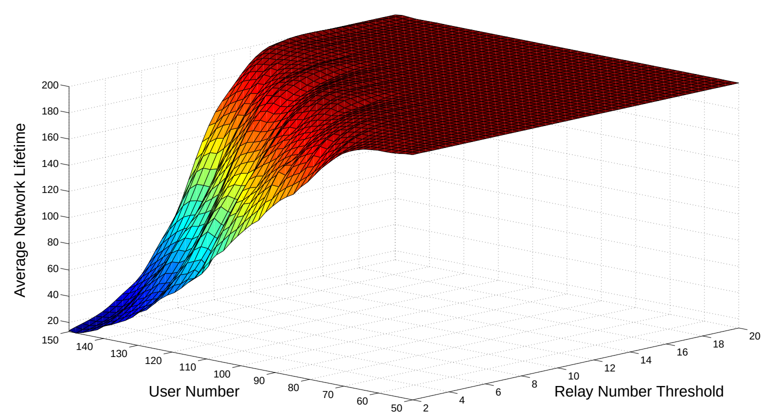


Figure 4.7: Network lifetime of RNP-SA-b algorithm with various cost thresholds and user numbers.

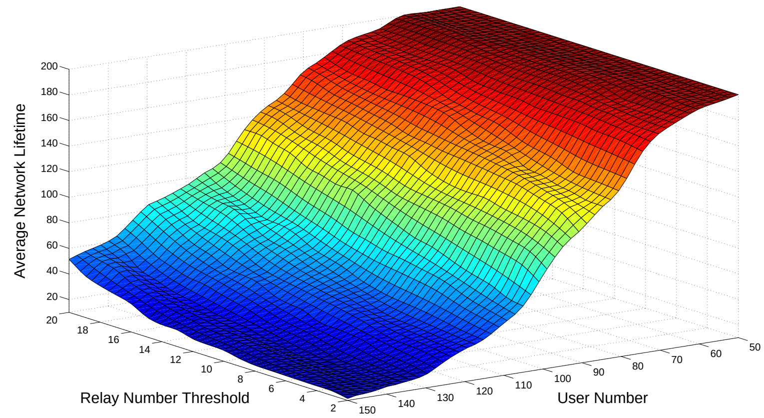


Figure 4.8: Network lifetime of greedy algorithm with various cost thresholds and user numbers.

location with the heaviest traffic load to deploy RNs. This strategy is not energy-efficient, especially when the heaviest load area is far away from the BSs.

In summary, our proposed algorithms significantly outperform the traffic oriented greedy algorithm because both the energy sustainability and users' traffic demands are considered. The RNP-SA-t algorithm performs slightly better than the RNP-SA-b algorithm at the cost of higher time complexity for building and maintaining the overall network topology.

4.5 Summary

In this chapter, we have investigated the establishment of multi-tier green wireless communication networks to fulfill high-end QoS requirements of users. We have considered a realistic two-tiered green wireless network scenario, in which green macro

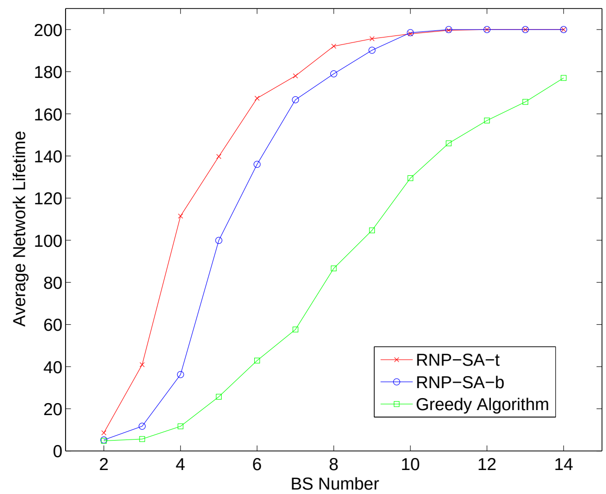


Figure 4.9: Network lifetime of various numbers of BSs.

cell BSs are deployed *a priori* while green small cell BSs can be placed at a set of candidate locations. Green macro cell and small cell BSs distributed over various locations have different charging capabilities, and can serve a limited number of users with diverse traffic demands. The main accomplishments of this chapter are summarized as follows:

- We have jointly studied the minimum green small cell BS placement and sub-carrier allocation problem, which has been formulated as a mixed-integer non-linear programming problem. our main objective is to minimize the number of deployed green small cell BSs and allocate appropriate number of sub-carriers to each green macro cell or small cell BS, such that full coverage of the network can be guaranteed and the QoS requirements of users can be fulfilled by harvested energy along with the allocated sub-carriers based on the cost threshold.

- Since the formulated MINLP problem is NP-hard, we have designed a novel metric, called sub-carrier and traffic to rate, as a guidance for heuristic algorithm design, which is the quotient of users' throughput requirements and achievable throughput of the link with a single subcarrier. The STR of a link can characterize the throughput and energy demand of each user associated with a green macro cell or small cell BS, i.e., a link with a smaller STR implies that this link consumes less energy and/or achieves a higher rate, compared with other links using the same number of sub-carriers.

- Based on the STR metric, we have proposed two low-complexity yet efficient heuristic algorithms. Our algorithms have used top-down or bottom up method to deploy the minimal number of small cell BSs until all of the cost, energy sustainability and the QoS constraints can be satisfied. In the meantime, we have calculated the number of sub-carriers that are required to fulfill the QoS requirements of users under the energy sustainability constraint. Our extensive simulation results have demonstrated that by allowing each green small cell BS to serve as many users as possible, we can significantly decrease the number of green small cell BSs that are required to fulfill the network traffic demand based on the cost threshold, compared with the greedy algorithm.

Chapter 5

A Game Theoretical Approach for Energy Trading in Heterogeneous Green Wireless Networks

Since the energy charging capabilities of green BSs are highly dependent on the dynamic local environment, different cells may have different energy charging rates. In addition, the traffic demands of various users may be different from each other, and the traffic demand of the same user may change from time to time. Therefore, it is essential to allocate limited energy resources in real time to balance the dynamic uneven distribution of energy charging and discharging capabilities. In this chapter, we investigate the resource allocation issue in heterogeneous green wireless communication networks. Specifically, we study the topic of local energy trading in heterogeneous wireless networks powered by green energy supplies to maximize the energy sustainability and benefits of all cells, considering the instantaneous charging and discharging rates.

The remainder of the chapter is organized as follows. In Section 5.1, the system model is presented, including network model, energy model, energy trading model and profit model. Based on the system model, the energy trading problem and the energy trading cooperation are described in Section 5.2. The optimal trade algorithm is proposed in Section 5.3, followed by simulation results in Section 5.4. Concluding remarks and future work are discussed in Section 5.5.

5.1 System Model

In this section, we present the system model which includes network model, energy model, energy trading model, and profit model.

5.1.1 Network Model

We consider heterogeneous green wireless networks in a community area, e.g., a residence community, where access points, femotocell BSs or small cell BSs are installed in each building to provide wireless access. These network devices are powered by green energy supplies, such as solar panels or wind turbines. To simplify the description, we use green small cell BSs to represent different kinds of wireless infrastructure devices with green energy. To make green energy usable, each green small cell BS is equipped with a battery to store the charged energy. The harvested energy can be used for powering green small cell BSs and serving the users' traffic demands in the cell. Basically, green small cell BSs may install batteries with various sizes, and their charging capabilities are also different from each other, as the charging capacity is not only determined by the number of solar panels or wind turbines installed for energy harvesting, but also dependent on the installation location and the weather. Due to different energy charging capacities and energy consumption demands in each cell, some cells may have excess energy for sale while some others may be short of energy and need to buy it from either neighboring cells or electricity grid. Usually, a community area cannot deliver the charged energy to the grid due to the limited power to pass through buses of the electricity grid, and thus they cannot sell energy back to the electrical grid. As shown in Fig. 5.1, APs and green small cell BSs can communicate with each other to negotiate the price and quantity for energy trading, and green energy will be transferred after the energy trade transaction decision is made. The notations for system model are shown in Table 5.1.

5.1.2 Energy Model

We can model the battery equipped by each green small cell BS as a G/G/1 queue, where the energy charging and discharging are random processes with arbitrary distributions. Denote the mean and variance of the inter-charging and discharging intervals as μ_a and v_a, and μ_s and v_s, respectively. Basically, energy charging process is location dependent and weather sensitive, while the energy discharging is mainly determined

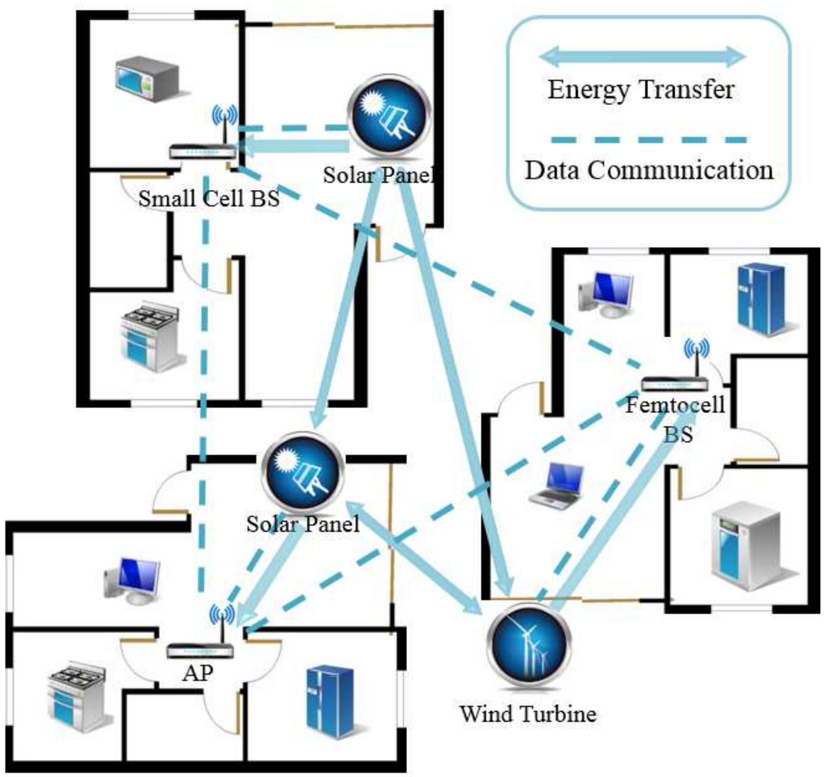


Figure 5.1: Heterogeneous green wireless networks.

Table 5.1: Notations for system model in Chapter 5

μ_a	The mean of inter-charging intervals
v_a	The variance of inter-charging intervals
μ_s	The mean of inter-discharging intervals
v_s	The variance of inter-discharging intervals
$X(t)$	A continuous process approximating the discrete buffer size
$G(t)$	A white Gaussian process with zero mean and unit variance
σ	The drift coefficient
ς	The diffusion coefficient
x_0	The initial energy buffer size
$\mathcal{D}(x_0)$	The buffer depletion time for a given x_0
$E[\mathcal{D}; x_0]$	The mean of depletion time
$\mathbb{T}$	The trading period
δ	The threshold of a cell's mean of depletion time
x_0'	The remaining or residual energy after energy trading transaction
p_{sb}	The price of the energy trading transaction between s and b
q_{sb}	The quantity of the energy trading transaction between s and b
x_0^b	The remaining or residual energy of the buyer before the transaction
x_0^s	the remaining or residual energy of the seller before the transaction
$x_0^{b'}$	The remaining or residual energy of the buyer after the transaction
$x_0^{s'}$	the remaining or residual energy of the seller after the transaction
σ_b	The drift coefficients of the buyer
σ_s	The drift coefficients of the seller
q_{MIN}	The minimum quantity of energy that the buyer has to purchase
q_{MAX}	The maximum quantity of energy that the seller can sell
$f(x)$	The utility function for energy consumption
k	A system parameter reflecting the system energy efficiency
$\Re_s(x_0^s, x_0^{s'})$	The utility gain of a seller for the energy trading transaction
$\Re_b(x_0^b, x_0^{b'})$	The utility gain of a buyer for the energy trading transaction
U_s	The profit gain a seller can earn during the energy trading transaction
U_b	The profit gain a buyer can earn during the energy trading transaction

by the energy demand of the cell. By applying diffusion approximation, we analyze the transient evolution of an energy buffer [91]. Specifically, the discrete buffer size is approximated as a continuous process $X(t)$ such that the incremental change of the buffer size over a small time interval follows normal distribution,

$$dX(t) = X(t+dt) - X(t) = \sigma dt + G(t)\sqrt{\varsigma dt}, \tag{5.1}$$

where $G(t)$ is a white Gaussian process with zero mean and unit variance, and σ and ς are drift and diffusion coefficients defined by

$$\sigma = 1/\mu_a - 1/\mu_s \tag{5.2}$$

and

$$\varsigma = v_a/\mu_a^3 + v_s/\mu_s^3, \tag{5.3}$$

respectively.

Denote $\mathcal{D}(x_0)$ as the buffer depletion time for a given initial energy buffer size x_0, i.e., the duration from $X(0) = x_0$ until the energy buffer is depleted and no longer usable for services,

$$\mathcal{D}(x_0) = inf(t \geq 0 | X(t) = 0, X(0) = x_0). \tag{5.4}$$

In other words, $\mathcal{D}$ is the first passage time of $X(t)$ from $x_0 > 0$ to 0, which satisfies

$$\begin{cases} X(0) = x_0, \\ X(t) > 0, \quad \text{for } \ \forall t, \ \ 0 < t < \mathcal{D}. \\ X(\mathcal{D}) = 0, \end{cases}$$

The conditional p.d.f. of $\mathcal{D}$ can be derived from the diffusion equation with the absorbing barrier in the origin,

$$\begin{aligned} & f_{\mathcal{D}}(t; x_0) \\ = \ & -\frac{d}{dt} Q(\frac{x_0 + \sigma t}{\sqrt{\varsigma t}}) - \exp\{\frac{-2\sigma x_0}{\varsigma}\} Q(\frac{-x_0 + \sigma t}{\sqrt{\varsigma t}}) \\ = \ & \frac{x_0}{\sqrt{2\pi\varsigma t^3}} \exp\{-\frac{(x_0 + \sigma t)^2}{2\varsigma t}\} \end{aligned} \tag{5.5}$$

Based on the p.d.f. of $\mathcal{D}$, the mean of depletion time, i.e., the time that the energy will be used up, denoted $E[\mathcal{D}; x_0]$, can be expressed as:

$$E[\mathcal{D}; x_0] = \frac{x_0}{\sigma}. \tag{5.6}$$

5.1.3 Energy Trading Model

To further improve the utilization of green energy, energy trades are allowed among different cells. Denote a time duration $\mathbb{T}$ as the trading period, during which only one energy trading transaction can be made for each cell. In a trading period, each green small cell BS needs to decide whether the remaining energy in the battery or the energy buffer is sufficient to support the minimal required energy demands of served users. To ensure this, the mean of energy depletion duration should be larger than a threshold $E[\mathcal{D}; x_0] \geq \delta$, i.e., given a certain threshold δ, each cell can determine whether it needs to buy additional energy or it can sell some of its excessively redundant energy to a neighbor. In other words, if $E[\mathcal{D}; x_0] > \delta$, the cell will perform as a seller and some of the redundant energy can be sold, while ensuring that $E[\mathcal{D}; x_0'] \geq \delta$ still holds after the energy trading transaction, where x_0' equals x_0 minus the energy for sale. If $E[\mathcal{D}; x_0] < \delta$, the cell will become a buyer that needs to buy extra energy from its neighbors, and it should have $E[\mathcal{D}; x_0'] \geq \delta$ after the energy trading transaction, where x_0' equals x_0 plus the purchased energy.

Let p_{sb} and q_{sb} denote the price and quantity of the energy trading transaction between a seller s and a buyer b, respectively. Based on the discussion above, we can conclude that the range of q_{sb} should be lager than the minimum requirement of the buyer and smaller than the maximum available energy of the seller. Therefore, the mean of depletion time of both the seller and the buyer should be no less than the required threshold δ after the energy trading transaction, which can be expressed as

$$\left.\begin{array}{l} E[\mathcal{D}; x_0^s - q_{sb}] \geq \delta \\ E[\mathcal{D}; x_0^b + q_{sb}] \geq \delta \end{array}\right\} \Rightarrow \sigma_b \delta - x_0^b \leq q_{sb} \leq x_0^s - \sigma_s \delta, \tag{5.7}$$

where σ_b and σ_s denote drift coefficients of the buyer and the seller, respectively. Let q_{MIN} and q_{MAX} denote the minimum quantity of energy that the buyer has to purchase and the maximum quantity of energy that the seller can sell, i.e., $q_{MIN} =$

$\sigma_b\delta - x_0^b$ and $q_{MAX} = x_0^s - \sigma_s\delta$, respectively. The energy trading transaction fails when $q_{MIN} > q_{MAX}$, which means either the seller or the buyer will fail to meet their energy requirements after the energy trading transaction.

Once the cell decides to be a seller or a buyer, it cannot change the character nor initialize another energy trading transaction in each trading period. For each energy trading transaction, the quantity and price will be decided by the seller and the buyer directly. As long as the energy trading transaction is made, the price and quantity of the energy are determined, no modification during this transaction is allowed. If trading negotiation between the seller and the buyer fails, no energy trading transaction will be made and no energy will be transferred between them. Our goal is to determine the optimal price and quantity to maximize the profits of both sellers and buyers, and the detail model of the profit and utility will be discussed in the following subsection.

5.1.4 Profit Model

Basically, by selling the excess energy to other cells, the seller will gain some rewards and its overall profit is the gained reward minus the cost of energy trading transaction. Similar to utility functions for bandwidth allocation, we apply a utility function $f(x)$ for energy consumption [102–104], i.e., x energy units are used for providing network services to achieve a certain utility gain. We define a utility function $f(x) = k \ln(1 + x)$ as an example, where x is the energy level required for achieving the utility and k is a system parameter reflecting the system energy efficiency. The utility curve with $k = 20$ is shown in Fig. 5.2. The obtained energy utility is a function of the consumed energy, and a higher energy consumption corresponds to a higher utility. Usually, we can achieve a high utility gain when the energy demand increases from the low level, but less utility gain after a certain threshold. The utility may saturate at some point when the energy demands are fully satisfied, and thus more available energy may not lead to a higher utility. Let x_0^s and x_0^b denote the remaining or residual energy of the seller and the buyer before the transaction, respectively. Denote $\Re_s(x_0^s, x_0^{s'}) = f(x_0^{s'}) - f(x_0^s)$ as the utility gain based on different levels of the remaining energy in the energy buffer, where x_0^s and $x_0^{s'}$ are the remaining energy levels of the seller in the energy buffer before and after energy trading transaction, respectively. For each seller who sells its residual energy after its basic requirement is satisfied, its profit U_s can be obtained according to the reward in the energy trade and the loss of utility gain due to the energy trade as follows,

$$U_s = p_{sb} q_{sb} + \Re_s(x_0^s, x_0^{s'}), \tag{5.8}$$

where $0 \leq q_{sb} \leq q_{MAX}$.

For each buyer, its profit can be derived as a function of $\Re_b(x_0^b, x_0^{b'})$, which consists of the utility gain with the purchase of the energy, $p_{sb} q_{sb}$ the total cost the buyer pays for the energy purchase, and c_t the energy delivery cost due to distant energy transfer between the seller and buyer. Thus, we have

$$U_b = \Re_b(x_0^b, x_0^{b'}) - p_{sb} q_{sb} - c_t, \tag{5.9}$$

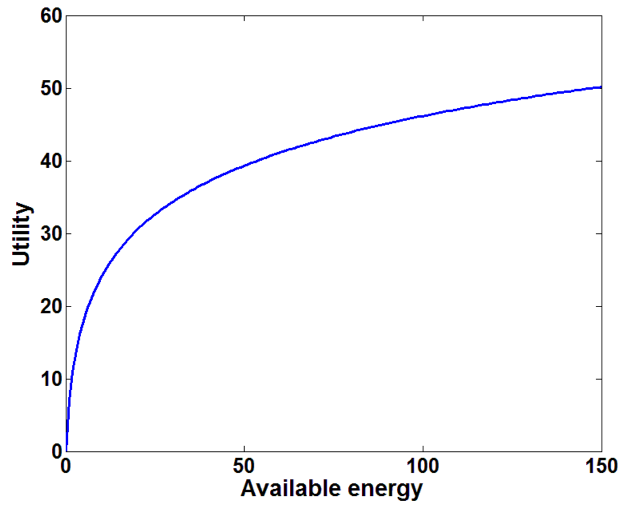


Figure 5.2: Utility function $f(x)$.

where $q_{sb} \geq q_{MIN}$.

5.2 Energy Trading Cooperation

In this section, we first formulate the energy trading problem as a Stackelberg game. By analyzing the game, we can obtain the closed-form expressions of the optimal price and quantity for each energy trading transaction.

5.2.1 Energy Trade Procedure

In the system, all cells, i.e., buyers and sellers, are rational and selfish. All sellers and buyers aim at maximizing their profits, as defined in Eq. (5.8) and Eq. (5.9). Before initiating an energy trading negotiation, each cell first decides whether it needs to buy or sell energy, based on its current energy x_0, its charging capacity and the energy demands in its cell. After all cells determine their roles, the buyer can select a seller to inquiry the price and the maximum volume of the energy that the seller can provide. The buyer includes its own residual energy level x_0^b and the minimum volume of the energy in the inquiry message. Upon receiving the inquiry from the buyer, the seller replies with its optimal price and the maximum volume of the energy it can sell. After the buyer receives the seller's reply, it first compares the selling price with the energy price from electricity grid. If the selling price is higher than that of the electricity grid and/or the minimum required energy of buyer is more than the maximum volume that seller can provide, the buyer notifies the seller that the energy trading transaction cannot be made, and the seller will close the negotiation session. Otherwise, the buyer proceeds to determine the optimal quantity and sends it to the seller. The trading procedure is a two-stage leader-follower game, which can be formulated by the Stackelberg game. In our problem, the seller acts as a leader and the buyer becomes a follower. By letting the seller decide the price based on both the seller and the buyer's profit functions, we can obtain the optimal price and quantity for both the seller and the buyer in the transaction. The procedure of energy trades is shown in Fig. 5.3. We list the notations of energy trades in Table 5.2.

5.2.2 Energy Trade Analysis

In this subsection, we analyze the formulated Stackelberg game and derive the optimal energy price and quantity for energy trading transactions. In the game, the price

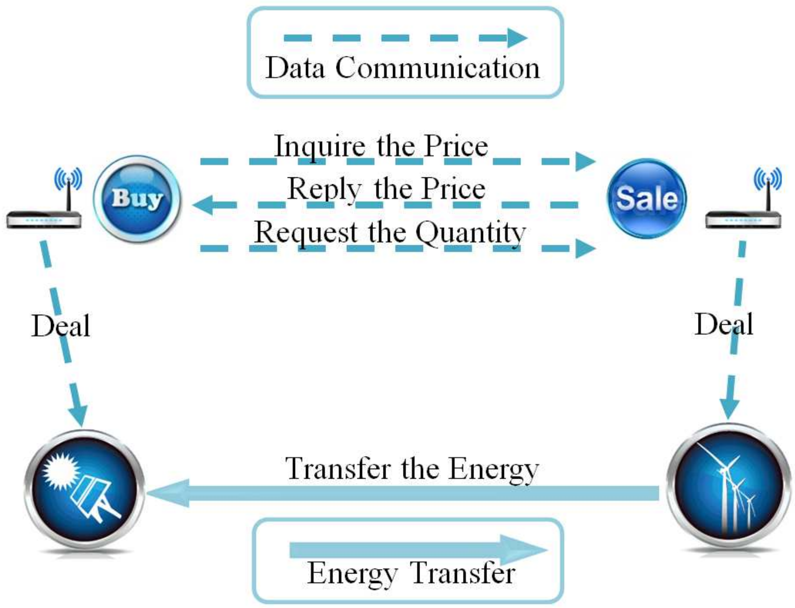


Figure 5.3: Procedure of energy trading transaction.

Table 5.2: Notations for energy trades in Chapter 5

c_t	The energy delivery cost between the seller and the buyer
p^*_{sb}	The optimal price of the energy trading transaction
q^*_{sb}	The optimal quantity of the energy trading transaction
p'_{sb}	The optimal price of the energy trading transaction when $q^*_{sb} < q_{MIN}$
q'_{sb}	The optimal quantity of the energy trading transaction when $q^*_{sb} < q_{MIN}$
p''_{sb}	The optimal price of the energy trading transaction when $q^*_{sb} > q_{MAX}$
q''_{sb}	The optimal quantity of the energy trading transaction when $q^*_{sb} > q_{MAX}$
$\mathbb{C}$	The central controller
$\mathbb{B}$	The set of buyers
$\mathbb{S}$	The set of sellers
p_g	The energy price of electricity grid
N	The set of cells

of energy from electricity grid is known to all cells. As a result, the seller should determine a price which is lower than the price of energy from electricity grid to encourage buyers to make the energy trading transaction; otherwise the buyer will buy the energy directly from the grid. Based on the profit functions defined in Eq. (5.8) and Eq. (5.9), we can use backward induction to derive the optimal price and quantity of the Stackelberg game.

Given the optimal price of energy set by the seller, the buyer aims at maximizing its profit, which is given by

$$\max_{q_{sb}} U_b(p_{sb}). \tag{5.10}$$

Solving Eq. (5.10), we can obtain the best response function of the buyer based on the given price from the seller,

$$q_{sb}^* = \frac{k - p_{sb} - x_0^b p_{sb}}{p_{sb}}. \tag{5.11}$$

Applying the best response function of the buyer into the seller's profit function, we can obtain the optimal price for the energy trading transaction provided by the seller, denoted p_{sb}^*,

$$p_{sb}^* = \frac{k(x_0^b + 1 + \Phi)}{2[2 + x_0^b x_0^s + x_0^s + (x_0^b)^2 + 3x_0^b]}, \tag{5.12}$$

where

$$\Phi = \sqrt{(1+x_0^b)(5x_0^b+4x_0^s+9)}.$$

Then, we can derive the optimal quantity q_{sb}^* according to the optimal price p_{sb}^*, which is given by

$$q_{sb}^* = \frac{(1+x_0^b)(x_0^b+2x_0^s+3-\Phi)}{x_0^b+1+\Phi}. \tag{5.13}$$

After obtaining the optimal price and quantity of the energy trade (p_{sb}^* and q_{sb}^*), we check whether the derived solution satisfies the quantity requirement of the energy trading transaction, i.e., the energy trading quantity should not be greater than the maximum energy that the seller can provide nor smaller than the minimum energy that the buyer requires to fulfill the energy demands in its cell, $q_{MIN} \leq q_{sb}^* \leq q_{MAX}$. From the analysis, we have three cases, 1) $q_{MIN} \leq q_{sb}^* \leq q_{MAX}$, 2) $q_{sb}^* < q_{MIN}$, and 3) $q_{sb}^* > q_{MAX}$. For the first case, (p_{sb}^*, q_{sb}^*) is the optimal price and quantity for the transaction. We analyze the problem according to the best response function of the buyer in Eq. (5.11). An example of the best response function of the buyer based on the given price is shown in Fig. 5.4, where $k = 20$ and $x_0^b = 100$ units of energy. We can find that the quantity monotonically decreases with the increase of the price.

Let the p_{MIN} and p_{MAX} denote the minimum and maximum price determined by the seller, which correspond to the q_{MAX} and q_{MIN} energy units that the buyer wants to purchase, respectively, based on the monotonically decreasing function as shown

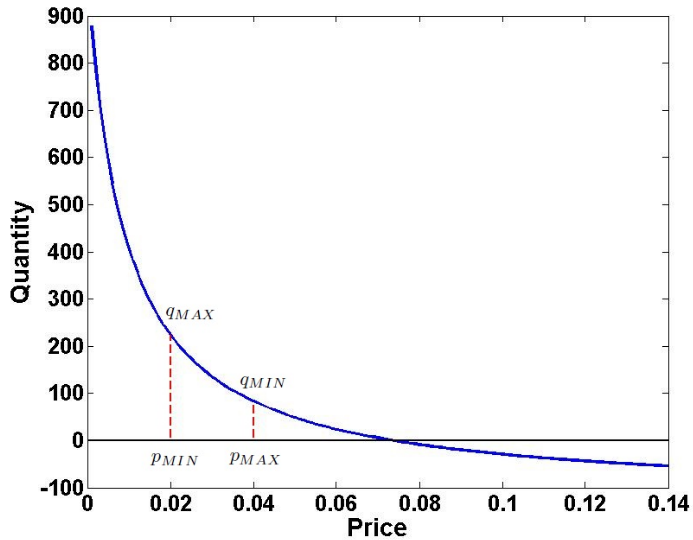


Figure 5.4: The best response function of the buyer.

in Fig. 5.2. If $q^*_{sb} < q_{MIN}$, the seller knows that if the price is higher than p_{MAX} the buyer will not accept the energy trading transaction and may purchase energy from other sellers or electrical grid. Thus, the price should be set according to the q_{sb} and the best response function in Eq. (5.11). The optimal price and quantity (p'_{sb}, q'_{sb}) under the case $q^*_{sb} < q_{MIN}$ are given by

$$\begin{cases} p'_{sb} = \frac{k}{\sigma_b \delta + 2x_0^b + 1} \\ q'_{sb} = \sigma_b \delta - x_0^b. \end{cases} \tag{5.14}$$

For the case $q^*_{sb} > q_{MAX}$, as the seller cannot sell more than q_{MAX} energy, the seller will not set the price lower than p_{MIN}. Therefore, the price should be set according to the q_{sb} and the best response function in Eq. (5.11). The optimal price and quantity

(p''_{sb}, q''_{sb}) under the case $q^*_{sb} > q_{MAX}$ can be derived as

$$\begin{cases} p''_{sb} = \frac{k}{x_0^s + x_0^b + 1 - \sigma_s \delta} \\ q''_{sb} = x_0^s - \sigma_s \delta. \end{cases} \tag{5.15}$$

5.3 Optimal Profits Energy Trading Algorithm

In this section, we present our algorithm, namely, Optimal Profits Energy Trading (OPET) algorithm, to maximize the Profits of all sellers and buyers. In our algorithm, there exists a central controller, e.g., a community center, to help allocate the energy trades between sellers and buyers. Initially, in each trading period, buyers inquiry the price and the quantity, which each seller can provide, to all the sellers with its information including the remaining energy and the minimum required energy. Then, each seller replies buyers with the optimal price and quantity based on the profit functions of both the seller and the buyer. After that, buyers send their information, including prices and quantities provided by all sellers, to the central controller. The central controller matches the optimal pairs of the seller and the buyer for energy trading transactions based on the information sent by all buyers, using the maximum weighted bipartite matching algorithm. Specifically, the central controller generates a graph, where each cell is a vertex and the profit summation of each pair of the seller and the buyer is the weight of the edge, based on the information sent by all buyers. In the graph, sellers and buyers can be divided into two groups, and thus the central controller can apply the maximum weighted bipartite matching algorithm

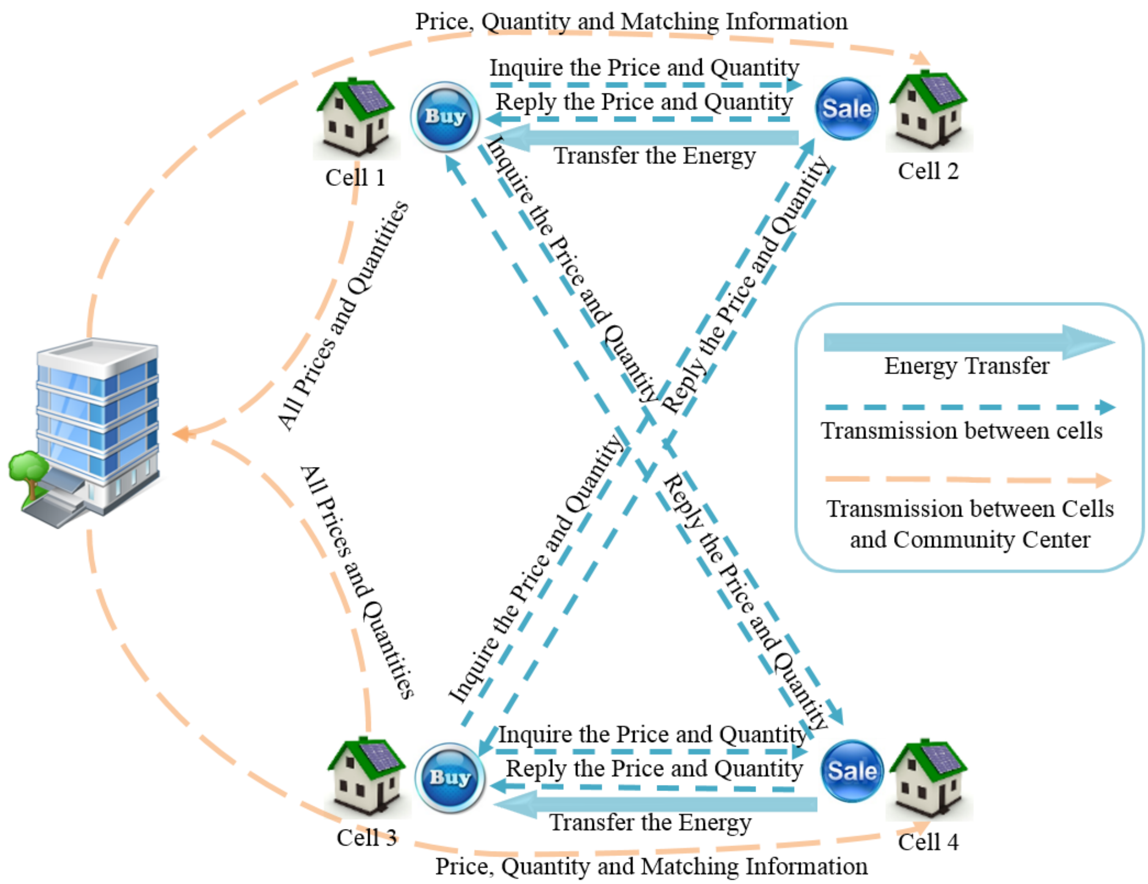


Figure 5.5: An example of green energy trades.

to get the optimal matching, which maximizes the total profits of all cells. After obtaining the matching results, the central controller sends quantity, price and the ID of the buyer to the corresponding seller. Finally, each seller sends the negotiated quantity of energy to the buyer and receives the profit from the buyer. Let $\mathbb{C}$, $\mathbb{B}$, $\mathbb{S}$ and p_g denote the central controller, the set of buyers, the set of sellers and the energy price of electricity grid, respectively. An example is shown in Fig. 5.5, and the detail of the OPET algorithm is shown in Algorithm 6.

Algorithm 6 Optimal Profits Energy Trading Algorithm

The trading session is started;
for all $b \in \mathbb{B}$ **do**
  for all $s \in \mathbb{S}$ **do**
    b sends inquiry and (q_{MIN}, x_0^b) to s;
    s replies $(p_{sb}^*, q_{sb}^*) \to b$;
    b stores (p_{sb}^*, q_{sb}^*);
  end for
  b sends $\{s \in \mathbb{S} | (p_{sb}^*, q_{sb}^*)\} \to \mathbb{C}$;
end for
$\mathbb{C}$ calculates the optimal allocation;
for all $s \in \mathbb{S}$ **do**
  $\mathbb{C}$ sends $(p_{sb}^*, q_{sb}^*, b) \to s$;
  s transfers q_{sb}^* energy to b and obtain $p_{sb}^* q_{sb}^*$;
end for
The trading session is closed;

The OPET algorithm can achieve the optimal solution with time complexity $|N|^2$, where N denotes the set of cells. For each energy trading transaction between a seller and a buyer, we can obtain the optimal price and quantity according to the analysis in Subsection 5.2.2. Based on the information sent by the buyer, the central controller obtains the optimal price and quantity of all the energy trading transactions. By applying the maximum weighted bipartite matching algorithm, it can generate the optimal matching for all cells based on the optimal price and quantity of each energy trading transaction. Thus, the OPET algorithm can achieve the optimal solution.

In the OPET algorithm, each buyer needs to inquiry all sellers and send the optimal price and quantity of each energy trade to central controller, which requires $O(N^2)$ time. The central controller solves the maximum weighted bipartite matching algorithm in $O(|\mathbb{S}||\mathbb{B}|)$ time, and sends the result to each seller, which takes $O(|\mathbb{S}|)$

time. Therefore, the total time complexity of the OPET algorithm is $O(|N|^2)$.

5.4 Simulation Results

In this section, we conduct extensive simulations to verify the performance of the proposed energy trading algorithm and investigate the impacts of important parameters on the performance. As the maximum weighted bipartite matching algorithm is used to maximize the total profits, the optimal matching will be allocated based on the energy trade of each pair of the seller and the buyer. Thus, the optimality of our algorithm depends on the performance of energy trading transaction between each pair of the seller and the buyer. We set $k = 100$ profit unit per kW·h, and $\sigma_s = \sigma_b = 0.5$. The required energy threshold δ is 32, and $c_t = 1$ profit unit per (kW·h).

The optimal quantity of energy trades according to the residual energy is shown in Fig. 5.6. We can observe that the buyer with a lower residual energy have to buy more to fulfill its energy requirement. The trading quantity increases when the seller has more energy for sale with a lower price. When the seller has insufficient redundant energy for sale to meet the energy demand of the buyer, the energy trading transaction will fail because either the seller or the buyer will violate the basic energy requirement after the energy trade. In the case that the seller has limited redundant energy but can meet the basic energy requirement of the buyer, the energy price may be relatively high and the buyer will only purchase the necessary quantity of energy to fulfill its requirement. When the redundant energy of the seller is in high volume,

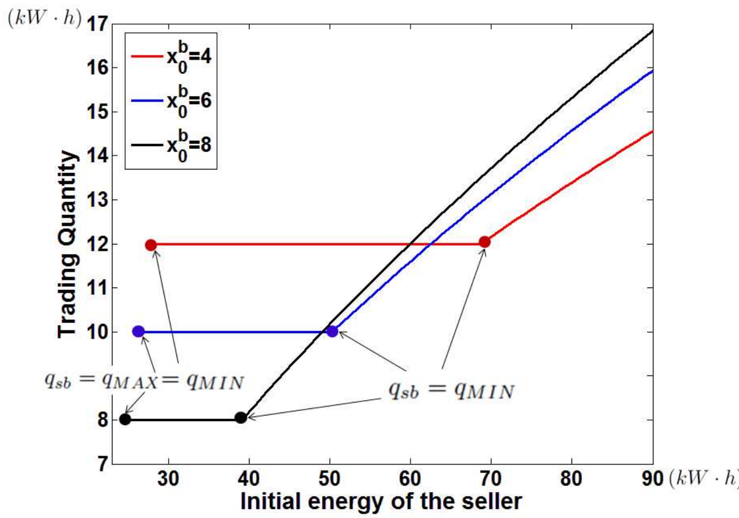


Figure 5.6: Energy of the seller vs. trading quantity.

the energy reward decreases according to the utility function. In this case, the seller will decrease the trading price, and thus will motivate the buyer to purchase more than necessary quantity as it can store the redundant energy for future use. This will result in a higher profit gain of the seller and a higher utility gain of the buyer.

The profit summation of the seller and the buyer with different levels of residual energy is shown in Fig. 5.7. We can observe that the profit summation of the seller and the buyer increases with the decrease of the buyer's residual energy. This is because the buyer is willing to pay a higher price when its energy level is low, because the buyer is able to gain more profits with the purchased energy based on the utility function. When the redundant energy cannot fulfill the requirement of either the seller or buyer, the energy trading negotiation fails and no transaction will be made. Similarly, when the seller has abundant available energy for sale, it will decrease the price, which motivates the buyer to purchase more energy.

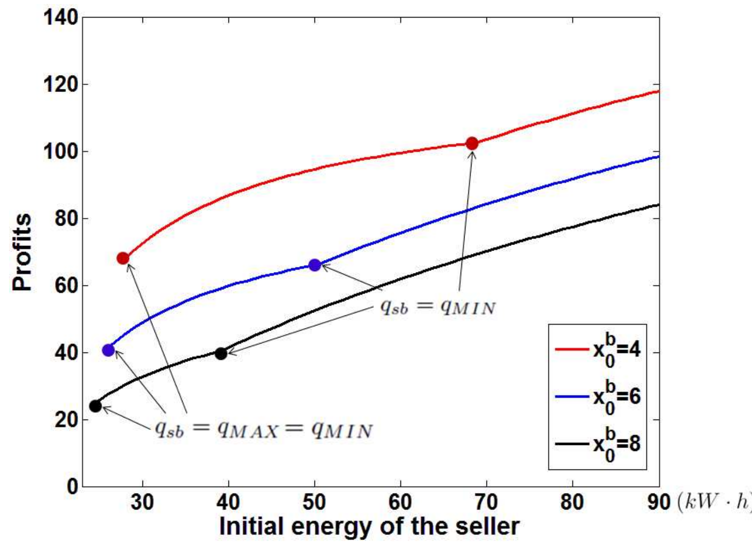


Figure 5.7: Residual energy of the seller vs. profits.

5.5 Summary

In this chapter, we have investigated the resource allocation issues in heterogeneous green wireless communication networks. Specifically, we have studied the local energy trading issue in community-area heterogeneous wireless networks powered by green energy supplies, where network infrastructure devices are installed in each building to provide wireless access. In the system, the network infrastructure devices of cells can obtain the information and send the messages from/to their green energy supplies. The main accomplishments of this chapter are summarized as follows:

- Considering the dynamic and uneven distribution of charging and discharging capabilities in heterogeneous green wireless communication networks, we have exploited the energy trading issue between network cells with different residual energy and dynamic charging/discharging capabilities. We have presented the system model and the procedure of energy trading, and defined the profit functions of both buyers and sellers based on the utility function. After that, we have formulated the local energy trading problem in heterogeneous green wireless networks. Our objective is to maximize the benefits of both buyers and sellers by improving the energy sustainability of all cells.

- To solve the formulated problem, we have separated the local energy trading problem into two subproblems, i.e., 1) the energy trading between each pair of the buyer and the seller, and 2) matching buyers and sellers into pairs to conduct energy trading transactions. The former problem is a two-stage leader-follower Stackelberg game. To solve it, we have derived the expression of the optimal price and quantity for energy trading transaction by using back induction. After that, we use the maximum weighted bipartite matching algorithm to match the energy trades between buyers and sellers to maximize the profits of all cells in the other problem.

- We have proposed an algorithm, called optimal profits energy trading algorithm, to maximize the profits of all cells by conducting energy trades between cells. We have analyzed the performance of the OPET algorithm and have discussed two special cases, i.e., i) optimal trading quantity less than the minimum required energy, and 2) optimal trading quantity more than the maximum available energy. Based on our analysis, we have proofed that the proposed OPET algorithm can obtain an optimal solution with polynomial time complexity.

Our simulation results have verified the optimality performance of the OPET algorithm.

Chapter 6

Conclusion and Future Work

The dissertation aims at cost-effectively constructing multi-tier heterogeneous green wireless networks to sustain the network operations and management. In this chapter, we first summarize this dissertation and present our major research contributions in Section 6.1. After that, we introduce our future work in Section 6.2

6.1 Major Research Contributions

We have proposed a sustainable wireless network solution as one of promising prototypes for next-generation wireless networks to address the energy and network capacity issues. In the solution, we have divided the establishment of multi-tier heterogeneous green wireless networks into three steps, i.e., 1) establishing conventional-architecture green wireless networks, 2) building multi-tier green wireless networks, and 3) allocating and balancing network resources. In this section, we present the major contributions in each step.

6.1.1 Establishment of Conventional-architecture Green Wireless Networks

The advances of green energy technologies have provided an alternative energy source to power wireless network devices with eco-friendly renewable energy. With the replenishable characteristic of green energy, it is possible to sustain the network operations and management of green wireless networks. However, the establishment of green wireless networks is challenging due to relative expensive price of green wireless network devices and dynamic charging capabilities. As such, we have re-visited the network planning issue in single-tier green wireless communication networks. Our main contributions in this step are shown as follows.

- We have analyzed the characteristics of green energy, and have presented the utmost concern, energy sustainability, in the design of green wireless networks. Considering green energy characteristics including relative expensive cost and dynamic charging capabilities, we have formulated the constrained minimum green macro cell BS placement problem. The energy and throughput constraints have been defined, which guarantee the harvested energy is sufficient to support the traffic demands of users. Subject to the energy and throughput constraints, our formulated problem targets at deploying the minimal number of green macro cell BSs on a set of selected candidate locations to provide a full coverage of the network region.

- To solve the constrained minimum green macro cell BS placement problem, we have investigated the possible strategies in previous works. We have found that the commonly used strategies for network planning in electrical-grid-powered wireless networks, i.e., place macro cell BSs in a dense area, may not be applicable for single-tier green wireless networks. This is because the harvested energy of BSs in dense area may not be sufficient to serve a large number of users. To this end, we have designed a preference level, which is a function of distance between each user and all candidate locations of BSs, to represent the connection priority and relative data rate between the user and corresponding green BSs.

- We have proposed a heuristic algorithm, namely two-phase constrained green BS placement algorithm, to provide one of simple yet efficient solutions for the constrained minimum green macro cell BS placement problem. The TCGBP algorithm jointly considers power control and green macro cell BS deployment, which can be separated into two phases. In the first phase, we have partitioned the whole network into several VPs and established connections in each VP based on the preference level of each user; In the second phase, we have built the cross-polygon connections and deleted redundant BSs. We have analyzed the time complexity of the TCGBP algorithm, and have compared it with the optimal solution. Extensive simulation results have shown that the proposed algorithm approaches the optimal solution under a variety of network settings with significantly reduced time complexity.

6.1.2 Construction of Multi-tier Green Wireless Networks

The explosion of diverse wireless applications has boosted the deployment of different types of wireless networks. By letting various wireless networks co-exist with each other, it is possible to provide ubiquitous wireless services for users with different QoS requirements at anytime and anywhere. As one of promising solution, multi-tier network architecture is promising to accommodate an enormous number of different wireless networks in next-generation wireless networks. Based on the characteristics of green energy, we have re-visited the network planning and resource allocation in the second step to construct two-tier green wireless networks. Our main contributions in this step are shown as follows.

- We have investigated the establishment of two-tier green wireless networks on the base of the generated single-tier green wireless networks in the first step. By considering both network planning and resource allocation issues, we have formulated joint green small cell BS deployment and sub-carrier allocation problem. In the problem, our objective is to place the minimum number of small cell BSs as relay nodes into networks, such that wireless services can cover the whole network region, subject to the energy sustainability, throughput and cost constraints, where the cost threshold has been defined as the budget for the equipment and installation cost of green small cell BSs.

- We have analyzed the commonly used strategies for green small cell BS deployment to solve the formulated problem: i) close to the macro cell BS to release its energy burden, and ii) close to users to improve their throughput. We have found that both strategies may lead to violating the constraints and are not applicable in green wireless networks. Therefore, to solve the formulated MINLP problem, we have designed a novel metric, namely sub-carrier and traffic to rate, to help elaborate efficient heuristic algorithms. The metric can show both throughput requirement and energy demand of each user served by a macro cell or small cell green BS.

- We have proposed top-down and bottom-up heuristic algorithms to solve the formulated RNP-SA problem based on the STR metric. The top-down algorithm deploys RNs in all candidate locations, and then deletes each RN in each round according to its STR value until any of the constraints is violated; The bottom-up algorithm places each RN with best total STR value into the network until all the constraints can be held. After that, we have calculated the time complexity of our algorithms, and have conducted extensive simulations. The results have demonstrated that our algorithms can achieve the minimal number of small cell BSs to provide full coverage, subject to energy, throughput and cost constraints with polynomial run-time complexity. We have also found that the top-down algorithm performs slightly better than the bottom-up algorithm at the cost of higher run-time complexity for building and maintaining the overall network topology.

6.1.3 Network Resources Allocation

Unlike traditional electrical grid, green energy is harvested from natural environment, which is highly dependent on the local weather, local time and position. The vagaries of the weather make the estimation of dynamic charging capabilities become a challenging task. Moreover, different cells may install different numbers of solar panels or wind turbines, and thus have different charging capacities; while the energy demand in each cells is also dynamic, and is different from each other. As a result, some cells with high energy charging capacities and low energy demands will have residual energy stored in the battery while some other cells with low energy charging capacities but high energy demands may use up the harvested energy and become out of service [51]. Therefore, to efficiently utilize green energy, it is desirable to allow energy trading among neighboring cells. We have exploited energy trading between different cells in heterogeneous green wireless networks to balance the charging and discharging capabilities. Our main contributions in this step are shown as follows.

- We have developed a framework for energy trading within a community-area heterogeneous green wireless networks. In the framework, each cell is equipped with a green energy supply and a battery for buffering energy. The mean of each cell's depletion time, i.e., the duration until the energy will be used up, has been estimated based on its residual energy and charging/discharging capabilities, which is used to determine the role of each cell in energy trading during a trading period. After that, The profit functions of both buyers and sellers are defined based on the utility function. We have formulated the local energy trading problem in heterogeneous green wireless networks, which intend to maximize the profits of all cells and sustain the network performance by ensuring the energy sustainability of each cell.

- Based on the role of each cell, the procedure for buyers and sellers to conduct energy trading transaction has been presented. It has been separated into two sub-problems: i) the energy trading between each pair of buyer and seller, and ii) matching buyers and sellers into pairs to conduct energy trading. In the first sub-problem, each pair of a buyer and a seller decides the price and quantity for the energy trading transaction. In the second sub-problem, buyers and sellers are matched as pairs to conduct energy trading, such that the profits of all cells can be maximized. We have applied a two-stage leader-follower Stackelberg game and the maximum weighted bipartite matching algorithm to solve formulated sub-problems, respectively.

- Based on the solutions for sub-problems, we have proposed an optimal profits energy trading algorithm to maximize the profits of all cells. We have obtained the optimal matching for buyers and sellers to conduct energy trading transactions, and the optimal energy trading price and quantity for each pair of the buyer and the seller to maximize total profits. After that, we have analyzed the performance and calculated the time complexity of the OPET algorithm. Our analysis have shown that our OPET algorithm can achieve the maximum total profits for all cells with polynomial run-time complexity. Moreover, we have conducted the simulations to evaluate the performance of our OPET algorithm, which have verified the optimality performance of it.

6.2 Future Work

The advances of green energy have raised a possible solution to provide sustainable energy support for wireless network devices, which is one of the promising methods to sustain network operations and management in next-generation wireless networks. Different from electrical grid, the dynamic energy harvesting has introduced another dimension, i.e., energy charging capability, to the design of green wireless networks, which also leads to many new challenging research issues under the scenario of green wireless networks [23, 30, 31]. We close this chapter by presenting our future works as research directions in this field.

6.2.1 Network Planning in Mobile Green Wireless Networks

With the emerging of diverse wireless applications, how to establish ubiquitous wireless services for mobile users has become one of hot topics. Different from traditional network infrastructure, green wireless networks have to consider not only the diverse QoS requirements of mobile users but also the charging capabilities of different green wireless devices. Moreover, the mobility of users in the network makes the estimation of energy discharging process become much more difficult, and thus it is challenging to design network planning strategies to guarantee the network sustainability. In order to predict the energy discharging process, we will investigate the characteristics of mobility models for different network scenarios [105–107], e.g., the vehicle mobility pattern in VANET is highly dynamic but predictable. Based on the mobility model and estimation of movement, we can divide the network region into several areas and analyze QoS requirements of users in each area. The green wireless device deployment algorithm can be designed in each area based on the prediction of charging capabilities of different candidate locations. Since the mobility of users varies the connections frequently, it is also critical to design topology control algorithms to modify the topology of networks according to the movement of users. Thus, green wireless device deployment and topology control should be jointly considered in the network planning of green wireless networks.

6.2.2 Cross-layer Resource Allocation in Multi-tier Heterogeneous Green Wireless Networks

Usually, the QoS requirements of users are various and varying based on capacities and usage of their terminal devices [91, 108, 109]. By constructing multi-tier heterogeneous green wireless networks, the massive and diverse QoS requirements of users could be fulfilled by the harvested eco-friendly green energy. However, the dynamic characteristics of green energy lead to a variety of charging capabilities for green network devices, which have significant impact on the allocation of network resources. Thus, efficient resource allocation methods, e.g., admission control, rate adaptation, scheduling, and etc., are required to allocate the limited network resources to provision satisfactory services for each user. To ensure the energy sustainability and satisfactory of throughput demands in multi-tier heterogeneous green wireless networks, resource allocation should be conducted in multiple network layers. Nevertheless, resource allocation algorithms in different network layers may have impacts on each others. Thus, it is of critical to design cross-layer resource allocation algorithms in multi-tier heterogeneous green wireless networks. For example, a cross-layer resource allocation scheme, including sub-carrier allocation, power control and transmission scheduling algorithms, can be applied to guarantee the network sustainability and to satisfy dynamic users' requirements with harvested energy.

6.2.3 Routing Scheme Design in green wireless networks

Routing scheme design is one of essential topics in various network scenarios [110, 111]. In wireless networks with traditional energy supplies, routing scheme design is mainly used to balance the distribution of traffic all over the whole network; in green wireless networks, design of routing scheme has to consider not only the traffic distribution but also the residual energy and charging capabilities of all relay nodes on the routing path. This is because the uneven energy consumption of users and charging capabilities of BSs may make some routers overdraw its energy buffer and may further lead to network system breaking down. Therefore, to guarantee the normal operations of green wireless communication networks, routing scheme should be carefully designed to prevent the transmission going through the node which has not sufficient remaining energy in its energy buffer. Moreover, The routing scheme should be able to determine the proper route for each transmission, such that the

QoS requirement of each transmission can be guaranteed and the remaining energy and harvested energy in energy buffer can support the transmissions.

References

[1] Cisco, “Global mobile data traffic forecast update, 2013c2018,” *Visual Networking Index*, 2014.

[2] C. L. I, “Green evolution of mobile communications,” *GreenTouch, China Mobile Research Institute*, 2012.

[3] H. Lee, S. Vahid, and K. Moessner, “A survery of radio resource management for spectrum aggregation in LTE-advanced,” *IEEE Communications Surveys & Tutorials*, vol. 16, no. 2, pp. 745–760, May 2014.

[4] N. A. Ali, A. E. M. Taha, M. Salah, and H. Hassanein, “Uplink scheduling in LTE and LTE-advanced: Tutorial, survey and evaluation framework,” *IEEE Communications Surveys & Tutorials*, vol. 16, no. 3, pp. 1239–1265, Aug. 2014.

[5] A. Checko, H. L. Christiansen, Y. Yan, L. Scolari, G. Kardaras, M. S. Berger, and L. Dittmann, “Could RAN for mobile networks - a technology overview,” *IEEE Communications Surveys & Tutorials*, Sep. 2014.

[6] M. Hadzialic, B. Dosenovic, M. Dzaferagic, and J. Musovic, "Could-RAN: Innovative radio access network architecture," in *IEEE ELMAR*, Zadar, HR, 25-27 Sep. 2013, pp. 115–120.

[7] M. J. Booysen, S. Zeadally, and G. J. V. Rooyen, "Survey of media access control protocols for vehicular ad hoc networks," *IET Communications*, vol. 5, no. 11, pp. 1619–1631, Jul. 2011.

[8] C. Sommer and F. Dressler, "Progressing toward realistic mobility models in VANET simulations," *IEEE Communications Magazine*, vol. 46, no. 11, pp. 132–137, Nov. 2008.

[9] D. Benyamina, A. Hafid, and M. Gendreau, "Wireless mesh networks design - a survey," *IEEE Communications Surveys & Tutorials*, vol. 14, no. 2, pp. 299–310, May 2012.

[10] P. H. Pathak and R. Dutta, "A survey of network design problems and joint design apapproach in wireless mesh networks," *IEEE Communications Surveys & Tutorials*, vol. 13, no. 3, pp. 396–428, Sep. 2011.

[11] S. T. Cheng, C. Y. Wang, and M. H. Tao, "Quantum communication for wireless wide-area networks," *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 7, pp. 1424–1432, 2005.

[12] C. S. Bontu, S. Periyalwar, and M. Pecen, "Wireless wide-area networks for internet of things: An air interface protocol for iot and a simultaneous access

channel for uplink iot communication," *IEEE Vehicular Technology Magazine*, vol. 9, no. 1, pp. 54–63, Mar. 2014.

[13] A. K. Salkintzis, G. Dimitriadis, D. Skyrianoglou, and N. Passas, "Seamless continuity of real-time video across umts and wlan networks: challenges and performance evaluation," *IEEE Wireless Communications*, vol. 12, no. 3, pp. 8–18, Jun. 2005.

[14] A. K. Salkintzis, C. Fors, and R. Pazhyannur, "WLAN-GPRS integration for next-generation mobile data networks," *IEEE Wireless Communications*, vol. 9, no. 5, pp. 112–124, Oct. 2002.

[15] M. J. Lee, R. Zhang, J. Zheng, and G. S. Ahn, "IEEE 802.15.5 WPAN mesh standard-low rate part: Mesmesh the wireless sensor networks," *IEEE Journal on Selected Areas in Communications*, vol. 28, no. 7, pp. 973–983, Sep. 2010.

[16] Z. Lan, C. S. Sum, J. Wang, T. Baykas, F. Kojima, H. Nakase, and H. Harada, "Relay with deflection routing for effective throughput improvement in gbps millimeter-wave wpan systems," *IEEE Journal on Selected Areas in Communications*, vol. 27, no. 8, pp. 1453–1465, Oct. 2009.

[17] H. Y. Chen, J. N. Lin, H. S. Hu, and S. J. Jou, "STBC-OFDM downlink base-base receiver for mobile WMAN," *IEEE Very Large Scale Integration Systems*, vol. 21, no. 1, pp. 43–54, Jan. 2013.

[18] B. P. Tsankov, R. A. Pachamanov, and D. A. Pachamanova, “Modified brady voice traffic model for WLAN and WMAN,” *Electronics Letters*, vol. 43, no. 23, pp. 1295–1297, Nov. 2007.

[19] M. K. Oh, J. D. Jeong, and H. Lee, “Joint modulation and coding scheme toward low-complexity WBAN system,” *IEEE Communications Letters*, vol. 15, no. 2, pp. 145–147, Feb. 2011.

[20] G. Lo, S. G. Valenzuela, and V. C. M. Leung, “Wireless body area network node localizlocal using small-scale spatial information,” *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 3, pp. 715–726, May 2013.

[21] R. Maihaniemi, “Ict getting green,” in *TELESCON*, Vienna, AT, 10-13 May 2009, pp. 1–6.

[22] S. Gosselin, F. Saliou, F. Bourgart, E. L. Rouzic, S. L. Masson, and A. Gati, “Energy consumption of ICT iinfrastructure: An operator’s viewpoint,” in *E-COC*, Amsterdam, NL, 16-20 Sep. 2012, pp. 1–3.

[23] L. C. Wang and S. Rangapillai, “A survey on green 5G cellular networks,” in *Signal Processing and Communications (SPCOM)*, Bangalore, IN, 22-25 Jul. 2012, pp. 1–5.

[24] A. Fehske, G. Fettweis, J. Malmodin, and G. Biczok, “The global footprint of mobile communications: the ecological and economic perspective,” *IEEE Communications Magazine*, vol. 49, no. 8, pp. 55–62, Aug. 2011.

[25] OPERANET. [Online]. Available: http://www.opera-net.org/default.aspx

[26] EARTH. [Online]. Available: https://www.ict-earth.eu/

[27] Green Touch. [Online]. Available: http://www.greentouch.org/

[28] GREENRADIO. [Online]. Available: http://www.mobilevce.com/green-radio

[29] L. X. Cai, H. V. Poor, Y. Liu, T. H. Luan, X. Shen, and J. W. Mark, "Dimensioning network deployment and resource management in green mesh networks," *IEEE Wireless Communications*, vol. 18, no. 5, pp. 58–65, Oct. 2011.

[30] S. Yeh, "Green 4G communications: Renewable-energy-based architectures and protocols," in *Global Mobile Congress (GMC)*, Shanghai, CN, 18-19 Oct. 2010, pp. 1–5.

[31] J. Wu, "Green wireless communications: from concept to reality," *IEEE Wireless Communications*, vol. 19, no. 4, pp. 4–5, Aug. 2012.

[32] M. Erol-Kantarci and H. T. Mouftah, "Suresense: sustainable wireless rechargeable sensor networks for the smart grid," *IEEE Wireless Communications*, vol. 19, no. 3, pp. 30–36, Jun. 2012.

[33] J. Pan, L. Cai, Y. Shi, and X. Shen, "Optimal base-station locations in two-tiered wireless sensor networks," *IEEE Transactions on Mobile Computing*, vol. 4, no. 5, pp. 458–473, Sep.-Oct. 2005.

[34] M. Soleimanipour, W. Zhuang, and G. H. Freeman, "Optimal resource management in wireless multimedia wideband CDMA systems," *IEEE Transactions on Mobile Computing*, vol. 1, no. 2, pp. 143–160, Apr.-Jun. 2002.

[35] S. Bosio, A. Capone, and M. Cesana, "Radio planning of wireless local area networks," *IEEE/ACM Transactions on Networking*, vol. 15, no. 6, pp. 1414–1427, Dec. 2007.

[36] A. Chamam and S. Pierre, "On the planning of wireless sensor networks: Energy-efficient clustering under the joint routing and coverage constraint," *IEEE Transactions on Mobile Computing*, vol. 8, no. 8, pp. 1077–1086, Aug. 2009.

[37] G. Koutitas, "Green network planning of single frequency networks," *IEEE Transactions on Broadcasting*, vol. 56, no. 4, pp. 541–550, Dec. 2010.

[38] B. Aoun, R. Boutaba, and Y. Iraqi, "Gateway placement optimization in WMN with QoS constraints," *IEEE Journal on Selected Areas in Communications (JSAC), Special Issue on Multi-hop Wireless Mesh Networks*, vol. 24, no. 11, pp. 2127–2136, 2006.

[39] B. Aoun and R. Boutaba, "Max-min fair capacity of wireless mesh networks," in *MASS*, Vancouver, CA, Oct. 2006.

[40] X. Ling and K. L. Yeung, "Joint access point placement and channel assignment for 802.11 wireless LANs," *IEEE Transactions on Wireless Communications*, vol. 5, no. 10, pp. 2705–2711, Oct. 2006.

[41] M. Unbehaun and M. Kamenetsky, "On the deployment of picocellular wireless infrastructure," *IEEE Wireless Communications*, vol. 10, no. 6, pp. 70–80, Dec. 2003.

[42] B. Lin, P. Ho, L. Xie, X. Shen, and J. Tapolcai, "Optimal relay station placement in broadband wireless access networks," *IEEE Transactions on Mobile Computing*, vol. 9, no. 2, pp. 259–269, Feb. 2010.

[43] Z. Zheng, B. Zhang, X. Jia, J. Zhang, and K. Yang, "Minimum AP placement for WLAN with rate adaptation using physical interference model," in *IEEE Globecom*, Miami, FL, USA, 6-10 Dec. 2010, pp. 1–5.

[44] P. G. Brevis, J. Gondzio, Y. Fan, H. V. Poor, J. Thompson, I. Krikidis, and P. J. Chung, "Base station location optimization for minimal energy consumption in wireless networks." in *IEEE VTC*, Budapest, HUN, 15-18 May. 2011, pp. 1–5.

[45] W. Zhang, G. Xue, and S. Misra, "Fault-tolerant relay node placement in wireless sensor networks: Problems and algorithms," in *IEEE INFOCOM*, Anchorage, AK, USA, 6-12 May. 2007, pp. 1649 – 1657.

[46] X. Han, X. Cao, E. L. Lloyd, and C. C. Shen, "Fault-tolerant relay node placement in heterogeneous wireless sensor networks," *IEEE Transactions on Mobile Computing*, vol. 9, no. 5, pp. 643–656, May. 2010.

[47] Z. Wei, G. Li, and L. Qi, "New quasi-newton methods for unconstrained optimization problems," *Applied Mathematics and Computation*, vol. 175, no. 2, pp. 1156–1188, Apr. 2006.

[48] I. K. Fu, W. H. Sheen, and F. C. Ren, "Deployment and radio resource reuse in IEEE 802.16j multi-hop relay network in manhattan-like environment," in *IEEE ICICS*, Meritus Mandarin Hotel, Singapore, 10-13 Dec. 2007, pp. 1–5.

[49] S. Misra, S. D. Hong, G. Xue, and J. Tang, "Constrained relay node placement in wireless sensor networks: Formulation and approximations," *IEEE/ACM Transactions on Networking*, vol. 18, no. 2, pp. 434–447, Apr. 2010.

[50] G. H. Badawy, A. A. Sayegh, and T. D. Todd, "Energy provisioning in solar-powered wireless mesh networks," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 8, pp. 3859–3871, Oct. 2010.

[51] A. Sayegh, T. D. Todd, and M. Smadi, "Resource allocation and cost in hybrid solar/wind powered WLAN mesh nodes," *Wireless Mesh Networks: Architectures and Protocols*, pp. 167–189, 2007.

[52] Z. Zheng, L. X. Cai, M. Dong, X. Shen, and H. V. Poor, "Constrained energy-aware ap placement with rate adaptation in WLAN mesh networks," in *IEEE GLOBECOM*, Houston, TX, USA, 5-9 Dec. 2011, pp. 1–5.

[53] S. A. Shariatmadari, A. A. Sayegh, and T. D. Todd, "Energy aware basestation placement in solar powered sensor networks," in *IEEE WCNC*, Sydney, AUS, 18-21 Apr. 2010, pp. 1–6.

[54] X. Zhang, Z. Zheng, J. Liu, X. Shen, and L. Xie, "Optimal power allocation and AP deployment in green wireless cooperative communications," in *IEEE GLOBECOM*, Anaheim, CA, USA, 3-7 Dec. 2012, pp. 4000–4005.

[55] B. Kan, L. Cai, H. Zhu, and Y. Xu, "Accurate energy model for WSN node and its optimal design," *Journal of Systems Engineering and Electronics*, vol. 19, no. 3, pp. 427–433, Jun. 2008.

[56] C. Ma and Y. Yang, "A battery-aware scheme for routing in wireless ad hoc networks," *IEEE Transactions on Vehicular Technology*, vol. 60, no. 8, pp. 3919–3932, Oct. 2011.

[57] J. Vazifehdan, R. V. Prasad, M. Jacobsson, and I. Niemegeers, "An analytical energy consumption model for packet transfer over wireless links," *IEEE Communications Letters*, vol. 16, no. 1, pp. 30–33, Jan. 2012.

[58] O. Arnold, F. Richter, G. Fettweis, and O. Blume, "Power consumption modeling of different base station types in heterogeneous cellular networks," in *Future Network & Mobile Summit*, Florence, IT, 16-18 Jun. 2010, pp. 1–8.

[59] Q. Tang, L. Yang, G. B. Giannakis, and T. Qin, "Battery power efficiency of PPM and FSK in wireless sensor networks," *IEEE Transactions on Wireless Communications*, vol. 6, no. 4, pp. 1308–1319, Apr. 2007.

[60] H. Su and X. Zhang, "Battery-dynamics driven TDMA MAC protocols for wireless body-area monitoring networks in healthcare applications," *IEEE Journal on Selected Areas in Communications*, vol. 27, no. 4, pp. 424–434, May. 2009.

[61] T. J. Kazmierski, G. V. Merrett, L. Wang, B. M. Al-Hashimi, A. S. Weddell, and I. N. Ayala-Garcia, "Modeling of wireless sensor nodes powered by tunable

energy harvesters: HDL-based approach," *IEEE Sensors Journal*, vol. 12, no. 8, pp. 2680–2689, Jun. 2012.

[62] A. S. Weddell, G. V. Merrett, T. J. Kazmierski, and B. M. Al-Hashimi, "Accurate supercapacitor modeling for energy harvesting wireless sensor nodes," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 58, no. 12, pp. 911–915, Dec. 2011.

[63] P. T. Venkata, S. N. A. U. Nambi, R. V. Prasad, and I. Niemegeers, "Bond graph modeling for energy-harvesting wireless sensor networks," *Computer*, vol. 45, no. 9, pp. 31–38, Sep. 2012.

[64] J. Taneja, J. Jeong, and D. Culler, "Design, modeling, and capacity planning for micro-solar power sensor networks," in *IPSN SPOTS*, Apr. 2008.

[65] V. Raghunathan, A. Kansal, J. Hsu, J. Friedman, and M. Srivastava, "Design considerations for solar energy harvesting wireless embedded systems," in *IPSN*. Piscataway, NJ, USA: IEEE Press, 2005, p. 64.

[66] K. Ramachandran and B. Sikdar, "A population based approach to model the lifetime and energy distribution in battery constrained wireless sensor networks," *IEEE Journal on Selected Areas in Communications*, vol. 28, no. 4, pp. 576–586, Apr. 2010.

[67] K. Tutuncuoglu and A. Yener, "Optimum transmission policies for battery limited energy harvesting nodes," *IEEE Transactions on Wireless Communications*, vol. 11, no. 3, pp. 1180–1189, Mar. 2012.

[68] M. S. Zefreh, G. H. Badawy, and T. D. Todd, “Position aware node provisioning for solar powered wireless mesh networks,” in *IEEE GLOBECOM*, Miami, FL, USA, 6-10 Dec. 2010, pp. 1–6.

[69] G. Y. Li, Z. Xu, C. Xiong, C. Yang, S. Zhang, Y. Chen, and S. Xu, “Energy-efficient wireless communications: tutorial, survey, and open issues,” *IEEE Communications Magazine*, vol. 18, no. 6, pp. 28–35, Dec. 2011.

[70] H. T. Cheng and W. Zhuang, “Qos-driven mac-layer resource allocation for wireless mesh networks with non-altruistic node cooperation and service differentiation,” *IEEE Transactions on Wireless Communications*, vol. 8, no. 12, pp. 6089–6103, Dec. 2009.

[71] G. Miao, N. Himayat, Y. G. Li, and A. Swami, “Cross-layer optimization for energy-efficient wireless communications: a survey,” *Wireless Communications and Mobile Computing*, vol. 9, no. 4, pp. 529–542, Sep. 2009.

[72] M. Veluppillai, L. Cai, J. Mark, and X. Shen, “Partner selection based on optimal power allocation in cooperative diversity systems,” *IEEE Transactions on Vehicular Technology*, vol. 57, no. 1, pp. 511–520, Jan. 2008.

[73] W. Tuttlebee, S. Fleccher, D. Lister, T. Farrell, and J. Thompson, “Saving the plannet - the rationale, realities and research of green radio,” *International Transfer Pricing Journal*, vol. 4, no. 3, Sep. 2010.

[74] C. Han, T. Harrold, S. Armour, I. Krikidis, S. Videv, P. M. Grant, H. Haas, J. S. Thompson, I. Ku, C. X. Wang, T. A. Le, M. R. Nakhai, J. Zhang, and

L. Hanzo, “Green radio: radio techniques to enable energy-efficient wireless networks,” *IEEE Communications Magazine*, vol. 49, no. 6, pp. 46 –54, Jun. 2011.

[75] P. Grant and S. Fletcher, “Mobile basestations: reducing energy,” *Engineering & Technology Magazine*, vol. 6, no. 2, Feb. 2011.

[76] H. Zhang, A. Gladisch, M. Pickavet, Z. Tao, and W. Mohr, “Energy efficiency in communications,” *IEEE Communications Magazine*, vol. 48, no. 11, pp. 48–49, Nov. 2010.

[77] L. X. Cai, L. Cai, X. Shen, and J. W. Mark, “Resource management and QoS provisioning for IPTV over mmwave-based WPANs with directional antenna,” *Mob. Netw. Appl.*, vol. 14, no. 2, pp. 210–219, 2009.

[78] A. Liu, Z. Zheng, C. Zhang, Z. Chen, and X. Shen, “Secure and energy-efficient disjoint multi-path routing for WSNs,” *IEEE Trans. on Vehicular Technology*, vol. 61, no. 7, pp. 3255–3265, 2012.

[79] Y. Liu, L. X. Cai, and X. Shen, “Spectrum-aware opportunistic routing in multi-hop cognitive radio networks,” *IEEE J. Selected Areas of Communications*, vol. 30, no. 10, pp. 1958–1969, Nov. 2012.

[80] H. T. Cheng and W. Zhuang, “QoS-driven MAC-layer resource allocation for wireless mesh networks with non-altruistic node cooperation and service differentiation,” *IEEE Transactions on Wireless Communications*, vol. 8, no. 12, pp. 6089 –6103, Dec. 2009.

[81] R. L. Cruz and A. V. Santhanam, "Optimal routing, link scheduling and power control in multi-hop wireless networks," in *IEEE INFOCOM*, vol. 1, Mar. 2003, pp. 702–711.

[82] M. Veluppillai, J. W. Mark, and X. Shen, "Performance analysis and power allocation for M-QAM cooperative diversity systems," *IEEE Transactions on Wireless Communications*, vol. 9, no. 3, pp. 1237–1247, Mar. 2010.

[83] X. Zhang, L. Xie, and X. Shen, "Energy-efficient transmission and bit allocation schemes in wireless sensor networks," *Int. J. of Sensor Networks (IJSNET)*, vol. 11, no. 4, pp. 241–249, 2012.

[84] B. Cao, Q. Zhang, J. Mark, L. Cai, and H. Poor, "Toward efficient radio spectrum utilization: user cooperation in cognitive radio networking," *IEEE Network*, vol. 26, no. 4, pp. 46–52, Jul. 2012.

[85] M. S. Alam, J. W. Mark, and X. Shen, "Relay selection and resource allocation for multi-user cooperative OFDMA networks," *IEEE Transactions on Wireless Communications*, vol. 12, no. 5, pp. 2193–2204, May. 2013.

[86] B. J. Choi and X. S. Shen, "Adaptive asynchronous sleep scheduling protocols for delay tolerant networks," *IEEE Transactions on Mobile Computing*, vol. 10, no. 9, pp. 1283–1296, Sep. 2011.

[87] Y. Dong and D. Yau, "Adaptive sleep scheduling for energy-efficient movement-predicted wireless communication," in *IEEE International Conference on Network Protocols*, Boston, MA, USA, 6-9 Nov. 2005, pp. 1–10.

[88] J. H. Jeon, H. J. Byun, and J. T. Lim, "Joint contention and sleep control for lifetime maximization in wireless sensor networks," *IEEE Communications Letters*, vol. 17, no. 2, pp. 269–272, Mar. 2013.

[89] Y. Shi, Y. T. Hou, and A. Efrat, "Algorithm design for base station placement problems in sensor networks," in *ACM QSHINE*, Waterloo, ON, CA, 7-9 Aug. 2006.

[90] H. Liang, L. X. Cai, D. Huang, X. Shen, and D. Peng, "A SMDP-based service model for inter-domain resource allocation in mobile cloud networks," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 5, pp. 2222–2232, Jun. 2012.

[91] L. X. Cai, Y. Liu, T. H. Luan, X. Shen, J. Mark, and H. V. Poor, "Sustainability analysis and resource management for wireless mesh networks with renewable energy supplies," *IEEE Journal of Selected Areas of Communications*, vol. 32, no. 2, pp. 345–355, Feb. 2014.

[92] G. Piro, M. Miozzo, G. Forte, N. Baldo, L. A. Grieco, G. Boggia, and P. Dini, "HetNets powered by renewable energy sources: Sustainable next-generation cellular networks," *IEEE Internet Computing*, vol. 17, no. 1, pp. 32 – 39, Nov. 2013.

[93] Y. Chen, S. Zhang, S. Xu, and G. Y. Li, "Fundamental trade-offs on green wireless networks," *IEEE Communications Magazine*, vol. 49, no. 6, pp. 30–37, Jun. 2011.

[94] T. D. Todd, A. A. Sayegh, M. N. Smadi, and D. Zhao, "The need for access point power saving in solar powered WLAN mesh networks," *IEEE Network*, vol. 22, no. 3, pp. 4–10, May.-Jun. 2008.

[95] A. A. Hammad, G. H. Badawy, T. D. Todd, A. A. Sayegh, and D. Zhao, "Traffic scheduling for energy sustainable vehicular infrastructure," in *IEEE GLOBECOM*, Miami, FL, USA, 6-10 Dec. 2010, pp. 1–6.

[96] L. Lin, N. B. Shroff, and R. Srikant, "Asymptotically optimal energy-aware routing for multihop wireless networks with renewable energy sources," *IEEE/ACM Transactions on Networking*, vol. 15, no. 5, pp. 1021–1034, Oct. 2007.

[97] A. Farbod and T. D. Todd, "Resource allocation and outage control for solar-powered WLAN mesh networks," *IEEE Transactions on Mobile Computing*, vol. 6, no. 8, pp. 960–970, Aug. 2007.

[98] C. Li, J. Zhang, and K. B. Letaief, "Throughput and energy efficiency analysis of small cell networks with multi-antenna base stations," *IEEE Transactions on Wireless Communications*, vol. 13, no. 5, pp. 2505 – 2517, May 2014.

[99] K. Huang and V. K. N. Lau, "Enabling wireless power transfer in cellular networks: Architecture, modeling and deployment," *IEEE Transactions on Wireless Communications*, vol. 13, no. 2, pp. 902 – 912, Jan. 2014.

[100] V. Chvatal, "A greedy heuristic for the set-covering poblem," *Math. Oper. Res.*, vol. 4, no. 3, pp. 233–235, 1979.

[101] G. Lin and G. Xue, "Steiner tree problem with minimum number of steiner points and bounded edge-length," *Inf. Process. Lett*, vol. 69, no. 2, pp. 53–57, Jan. 1999.

[102] K. H. Liu, L. Cai, and X. Shen, "Multiclass utility-based scheduling for UWB networks," *IEEE Transactions on Vehicular Technology*, vol. 57, no. 2, pp. 1178–1187, Mar. 2008.

[103] S. Shenker, "Fundamental design issues for the future internet," *IEEE Journal on Selected Areas in Communications*, vol. 13, no. 7, pp. 1176–1188, Sep. 1995.

[104] N. Lu, "Utility-based bandwidth adaptation for QoS provisioning in multimedia wireless networks," in *Diss. Ph. D. dissertation, Queen Mary University of London, London, United Kingdom,*, 2007.

[105] X. Lin, R. K. Ganti, P. J. Fleming, and J. G. Andrews, "Towards understanding the fundamentals of mobility in cellular networks," *IEEE Transactions on Wireless Communications*, vol. 12, no. 4, pp. 1686–1698, Apr. 2013.

[106] X. Wang, X. Lin, Q. Wang, and W. Luan, "Mobility increases the connectivity of wireless networks," *IEEE/ACM Transactions on Networking*, vol. 21, no. 2, pp. 440–454, Apr. 2013.

[107] Q. Dong and W. Dargie, "A survey on mobility and mobility-aware MAC protocols in wireless sensor networks," *IEEE Communications Surveys and Tutorials*, vol. 15, no. 1, pp. 88–100, Feb. 2013.

[108] A. Agarwal and A. K. Jagannatham, "Optimal adaptive modulation for QoS constrained wireless networks with renewable energy sources," *IEEE Wireless Communications Letters*, vol. 2, no. 1, pp. 78–81, Mar. 2013.

[109] H. Liang, B. Choi, W. Zhuang, and X. Shen, "Optimizing the energy delivery via V2G systems based on stochastic inventory theory," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 2230–2243, Dec. 2013.

[110] S. Sarkar, M. H. R. Khouzani, and K. Kar, "Optimal routing and scheduling in multihop wireless renewable energy networks," *IEEE Transactions on Automatic Control*, vol. 58, no. 7, pp. 1792–1798, Jun. 2013.

[111] T. Zhu, S. Xiao, Y. Ping, D. Towsley, and W. Gong, "A secure energy routing mechanism for sharing renewable energy in smart microgrid," in *IEEE Smart Grid Communications (SmartGridComm)*, Brussels, BE, 17-20 Oct. 2011, pp. 143–148.