Stochastic optimizations of mobile energy management

Yang, Zhang

2015

Yang, Z. (2015). Stochastic optimizations of mobile energy management. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/65265>

<https://doi.org/10.32657/10356/65265>

NANYANG TECHNOLOGICAL UNIVERSITY

Stochastic Optimizations of Mobile Energy Management

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A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of Doctor of Philosophy

Jan, 2015

Abstract

With the growing computing power of mobile devices and increasingly sophisticated applications, mobile computing and wireless communication are nowadays pervasive. However, since mobile devices have limited energy storage and sporadic energy supply, energy management remains a critical issue in mobile networks. To address the problem, a few approaches have been introduced to develop intelligent and optimal energy management for mobile networks. Firstly, wireless energy charging can be employed to replenish batteries of mobile devices. The mobile devices can harvest or receive energy to charge its battery without being physically connected to any power source. Alternatively, to control the energy consumption and resource usage, a mobile device can offload energy-intensive jobs to other devices, e.g., cloudlets. This thesis aims to address some of the important issues of energy management in mobile networks with wireless energy charging and job offloading.

Three major contributions are presented in this thesis. Firstly, with the wireless energy transfer and harvesting technologies (e.g., radio frequency, or namely RF energy), mobile devices are fully untethered as energy supply is more ubiquitous. The mobile devices can receive energy from wireless chargers which can be static or mobile. We introduce the use of a mobile energy gateway that can receive energy from a fixed charging facility, move, and transfer the energy to other mobile users. The mobile energy gateway aims to maximize the utility by taking energy charging/transferring actions optimally. We formulate an optimal energy charging/transferring problem as a Markov decision process (MDP). The MDP model is then solved to obtain an optimal energy management policy for the mobile energy gateway. Furthermore, we prove that the optimal energy management policy has a threshold structure. We conduct an extensive performance evaluation of the MDP-based energy management scheme. The proposed MDP-based scheme outperforms several conventional baseline schemes in terms of expected overall utility.

Secondly, we develop an optimal energy charging scheme for the mobile device, considering the states of location, energy storage, as well as stochastic traffic generation which determines energy demand. In this case, energy management takes data flows in the form of traffics (i.e., job processing and data transmission) into consideration. We formulate the

energy charging problem as an MDP to obtain the mobile device's optimal policy. The objective is to maximize the expected utility. Additionally, we prove that the optimal policy of the proposed MDP has a threshold structure. The numerical results show the optimality of the proposed MDP-based wireless energy charging scheme compared with baseline schemes under various scenarios and parameter setting.

With a different approach, the emergence of mobile cloud computing enables mobile devices to offload applications to nearby mobile resource-rich devices (i.e., cloudlets) to reduce energy consumption and improve performance. However, because of mobility and limited cloudlet capacity, the connections between a mobile device and cloudlets can be intermittent. Thus, offloading actions taken by the mobile device may fail. We therefore develop an optimal offloading algorithm for the mobile device in the intermittently connected cloudlet system, considering the local load on the mobile device and availability of cloudlets. We examine mobility patterns of the mobile device and admission control of cloudlets, and then derive the probability of successful offloading actions analytically. We formulate and solve an MDP model to obtain an optimal policy for the mobile device with the objective to minimize the computation and offloading costs in terms of energy and resource consumption. We prove that the optimal policy has a threshold structure. Subsequently, we also introduce a fast algorithm for an energy-constrained mobile device to make offloading decisions.

In summary, this thesis investigates a few important energy management problems in mobile networks. Wireless energy charging is employed to replenish the battery storage of mobile devices. Moreover, mobile cloud computing is used for the mobile device to offload jobs to control the energy and resource consumptions. MDP-based schemes are employed as efficient energy managing approaches to obtain the optimal policies in the networks. The obtained optimal policies are shown to outperform baseline schemes.

Acknowledgments

Upon the completion of this thesis, I would like to express the greatest gratitude to my supervisor Prof. Dusit Niyato, for offering me the opportunity to research and pursue my doctorate degree in Nanyang Technological University. Without his guidance and advices, my work on optimizations and mobile energy management topics would not have started. Prof. Dusit Niyato is among the most insightful and vigorous researchers I have ever seen, who always “stays hungry” in learning, creating and contributing to the academic community. From him, I still have too much to learn on becoming a real qualified researcher for now, and for the rest of my career whatever it will be. I would like to thank my co-supervisor Prof. Ping Wang, who has help me a lot in the progress of completing my research during these years as a PhD student. She is a strict and serious researcher, who has pointed out hidden problems and flaws in my research papers for countless times, which I have always failed to discover.

I would also like to thank Prof. Dong In Kim from Sungkyunkwan University, Korea, for offering me an opportunity to visit and collaborate to complete a research paper as a part of this thesis. I had a very pleasant stay in Korea. As paraphrased from his words, it is always good to go out to meet different people.

I would like to express my very sincere thankfulness to my wife Zhou Yi, who also spent four struggling years as a PhD student in the same university with me. Comparing with our peers and friends at our own age, we have not been living a fantastic and fruitful life for the past years since our marriage. There were even times that we feel frustrated and lost. She never blamed me for the choices I made. The words always come to my mind that *charity suffereth long, and is kind*. Together we will make it through. We also would like to thank our family for the everlasting support and prompt help whenever we are in need.

Besides that, I wish to thank all the current and previous members of our research group for all the collaborations and discussions both in research and daily life. I would like to thank all the staffs and students of Parallel and Distributed Computing Centre (PDCC), the place where this thesis has been done, and most time of my four years has been spent.

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Chapter 1

Introduction

In this chapter, we present an overview of mobile energy management through optimal decision making of mobile devices, particularly, in wireless energy charging and mobile cloudlet systems. The research objectives and contributions are presented.

1.1 Background of Research

1.1.1 Energy Management in Mobile Networks

Mobile computing has seen tremendous growth. Computing power and network traffic in mobile networks increased significantly in recent years. Energy management becomes important to improve the energy utilization efficiency of mobile networks while enhancing users' satisfaction from running applications.

Unlike in wired networks, energy management in mobile networks faces more challenges. Mobile devices, e.g., mobile nodes, smart phones and wireless sensors, are generally powered only by batteries with limited capacity, or even battery-less. Moreover, as the mobile devices are frequently on the move, there is no constant energy supply for the devices to replenish their energy storage directly, or continuously power the devices directly. Several approaches are available for the efficient energy management in mobile networks as follows:

- *Improving hardware/software designs of network components:* Energy can be efficiently managed by improving hardware/software designs of mobile network components. For example, mobile devices can be designed to adjust their operation modes dynamically, such that they can reduce power output at idle time. Furthermore, with

the help of wireless energy transfer techniques, mobile devices equipped with energy harvesting facilities can utilize ambient and dedicated wireless energy sources to obtain energy.

- *Heterogeneous network deploying:* For a macro cellular mobile network, base stations (BSs) are generally fixed and have large coverage areas. The long transmission range may cause high communication overhead in terms of high energy consumption and low data rates. By contrast, small cells such as micro and pico cells can be promising solutions to improve the network energy management. Firstly, small cell base stations (BSs) have much smaller coverage areas. Less energy is required for shorter range communication. Secondly, small cell BSs may cooperatively help macro cell BSs to support local mobile users, so that the load of macro cell BSs will be reduced. Moreover, small cell BSs can be designed to be mobile which can move and extend the effective coverage of the network.
- *Energy-efficient mobile network resource management:* Energy efficiency can be improved by resource management of mobile networks. For example, relaying can be an effective solution for radio resource allocation/re-allocation. Data could be relayed by mobile relay nodes, aiming to reduce energy consumption and satisfy quality of service (QoS) requirements. Moreover, considering an area covered by small cell BSs, the BSs may share their resources for the mobile devices to offload part of their jobs. Thus, network resources are efficiently utilized, with low energy consumption, high transmission rates and small latency.

This thesis studies the efficient management issues in mobile networks based on the aforementioned approaches. Firstly, with the development of wireless energy charging techniques, components in mobile networks are able to obtain energy from external sources for perpetual operations, with wireless charging interfaces equipped. In the mobile networks with such wireless energy charging capability, the strategies of mobile devices to charge and utilize energy are examined. We analyze an optimal decision of mobile devices to employ accessible external resources (e.g., BSs) in small cell based networks to minimize energy

and resource consumption. Additionally, the randomness in the environment and mobile networks are taken into account, for example, the number of available wireless chargers and the energy level of the mobile device.

1.1.2 Wireless Energy Charging

Wireless energy charging is employed to power mobile devices in wireless systems without wired connections. Wireless energy charging techniques can be classified into near-field and far-field charging. Near-field energy charging includes inductive coupling and magnetic resonance coupling. However, near-field charging techniques require the energy charging and receiving devices to be close to each other. Otherwise, the coupling coefficient, which is affected by the distance between the energy transmitter and receiver, attenuates in the order of the reciprocal of the cube of distance [1]. Furthermore, inductive coupling and magnetic resonance coupling require the energy transmitter and receiver to align in a proper position, reducing the flexibility of wireless charging capability.

Radio frequency (RF) energy charging, as a far-field wireless energy charging technique, has attracted attentions recently. In mobile networks with RF energy charging, a mobile device can harvest energy from RF sources. After receiving energy, the mobile device may use the energy to process jobs or transmit data. As an extreme case, even battery-less mobile devices can be adopted, e.g., wireless sensors, which are powered by RF energy charging only. Thus, RF energy charging extends the applications of mobile networks.

1.1.2.1 Introduction to RF Energy Charging System Architectures

Three major components can be included in typical wireless systems with RF energy charging: energy sources, energy gateways and energy users.

An energy source has a constant power supply, e.g., from a power outlet, which enables the energy source to charge any energy consumers and users. In practical systems, energy sources can be access points or dedicated energy sources, e.g., Powercast devices [2]. Energy users consume the energy charged from energy sources. Since RF signal transmissions have limited ranges, in some scenarios, RF energy cannot be transferred to energy users directly. Energy gateways are designed as mobile devices which have energy storage

facilities, such as batteries. With the help of energy gateways, energy can be first transferred to the energy gateway when the energy gateway moves close to the energy source. Then the energy gateway transfers the energy to users when the energy gateway moves and contacts the users.

1.1.3 Mobile Cloud Computing and Mobile Cloudlet Systems

Although recently mobile devices are becoming much more powerful, they are still constrained by the limited energy storage and computational capability. Data processing that is not optimally managed on the mobile device easily leads to battery drain. From the energy management perspective, mobile devices may opt to send their jobs to other possible resource-rich devices for execution to reduce the local resource usage.

1.1.3.1 Mobile Cloud Systems

Cloud computing becomes a well-recognized technique to deal with the constraints of computational capacity and energy limitations of portable devices, e.g., smart mobile phones. Cloud computing provides a whole set of solutions including infrastructures, platforms and software applications, which can be utilized by cloud users as pay-as-you-go or reserved services at low costs. In particular, for a mobile device, data processing jobs that consume a large amount of computational resources and energy could be offloaded to the cloud to avoid resource and energy drains at the mobile device.

However, general cloud computing services, e.g., Amazon AWS [3], are not specifically tailored for mobile networks. The cloud services generally aim to provide services for regular non-mobile applications to extend their computational capacities, such as web services and storage systems. Such services are normally requested by complex service protocols and software. Therefore, only by requesting for such cloud services, tremendous resource usage and energy consumption may be incurred to the local mobile devices. Moreover, simply applying regular cloud computing in mobile networks may cause other overhead due to the long physical/topological distance between mobile devices and cloud providers at the far end of the Internet. Such an issue may cause problems such as bandwidth limitation, high latency and low QoS. Therefore, the concept of mobile cloud computing (MCC) has

been introduced as a series of customized cloud solutions for low-cost and small-overhead mobile applications, aiming for providing more “energy efficient” [4] cloud services.

1.1.3.2 Mobile Cloudlet

The concept of cloudlet gives rise to localized cloud-like services provided to local mobile devices. A cloudlet is a local resource-rich computing unit which can process cloud service requests from nearby mobile devices [5, 6]. For example, cloudlets can be base stations, wireless access points and local servers/clusters equipped with wireless transceivers. With the close physical proximity (e.g., one or a few hops away), a cloudlet overcomes the limitations of general cloud services by providing high bandwidth and low latency cloud-like services to local mobile devices as cloud service users.

With cloudlets deployed in the network, data processing jobs generated on or processed by a mobile device can have different execution options: (1) when there is no accessible cloudlet, a mobile device processes the jobs utilizing its own resources and energy, and (2) when there is at least one cloudlet in the adjacent area, the mobile device may access the cloudlet services.

For saving resource usage and energy consumption, it is possible for resource-limited mobile devices to offload their compute- and data-intensive jobs to the cloudlets. The offloaded jobs are in the forms of data and codes. With such cloudlet services, mobile devices can enhance the performance and expand their features when processing jobs, e.g., video rendering and decoding. However, before offloading a job, the mobile device must balance between saving cost of energy consumption and incurring communication overhead by job offloading. Therefore, optimized offloading policies are necessary to utilize the limited resources and energy efficiently.

1.2 Research Objective and Focus

In this thesis, we analyze mobile networks with wireless charging and job offloading, specifically for a mobile device. In terms of energy transfer, the mobile device is able to receive and transfer wireless energy. The mobile device may process data (i.e., jobs) locally or offload data to cloudlets to save energy. The actions of charging and offloading data that the

mobile device chooses to take will affect the system operations, as well as the overall utility of the mobile device. Thus, modeling and analyzing such mobile networks can assist the designs of intelligent mobile devices. MDP is a suitable approach to model and optimize the systems with state evolution and decision-making.

1.2.1 Research Objective

This thesis mainly presents the optimization models for mobile devices to utilize energy and resources efficiently. Specifically, three typical wireless system scenarios are studied.

- Firstly, a mobile device receives and transfers wireless energy. Such a mobile device is defined to be a mobile energy gateway, which serves as an independent energy carrier. Since the purchases and sales of energy cause negative utility (i.e., payment) and positive utility (i.e., profit), respectively, we aim to maximize the overall utility of the energy gateway.
- Secondly, we optimize the utility of a mobile device, given that it is aware of its traffic state, i.e., the current job to be processed by the mobile device. In this case, optimal decisions lead the mobile device to charge RF energy efficiently to avoid battery drain when there is energy demand for processing data.
- Besides RF energy charging to sustain the operation of a mobile device, a mobile device may offload local jobs to nearby cloudlets to reduce local energy consumption and resource usage. The offloading decisions are optimized in terms of minimized overall local execution/offloading cost.

Furthermore, by analyzing the structures of the decision-making policies, we aim to identify and prove that threshold-type structures exist in the policies. With the existence of threshold structures, the calculations or approximations of mobile devices' decision-making policies could be improved, which is practical for designing online optimization schemes.

1.2.2 Research Focus

Regarding to the aforementioned research objectives, in the following, three main issues are focused.

1.2.2.1 Mobile Energy Gateway - A Study on Optimal Wireless Energy Carrying

In RF-based wireless charging, an RF signal is used as a carrier to transfer energy from an energy source, e.g., a wireless charger, to an energy consumer, e.g., an energy user. The RF-based wireless charging can support mobile networks, which are composed of energy-constrained mobile devices. This will help to improve not only energy efficiency, but also performance of the networks. The efficiency of RF-based wireless charging depends largely on the distance between the charger and the energy users. Traditionally, wireless charging is deployed for systems only with fixed chargers and energy users. However, in many situations (e.g., sensor networks), wireless charging can be used for a mobile energy gateway that moves and reaches other devices [7]. Such a mobile energy gateway improves energy replenishment processes for various mobile and wireless networks, especially when the devices cannot or rarely visit the fixed wireless charging facilities. However, there are a few issues when the mobile energy gateway is deployed, e.g., optimal deployment, path planning, and energy management.

Figure 1.1: RF Energy gateway in a mobile system.

We consider a mobile network with a mobile energy gateway, as shown in Fig. 1.1. Unlike most of the existing works which assume that the mobility of the energy gateway can be controlled, and its path can be optimized, we consider the energy gateway with non-controllable mobility. For example, the energy gateway may be attached to other vehicles (e.g., a bicycle or trolley) or carried by human. The energy gateway works as a self-interested carrier (i.e., an agent) of energy between energy sources (i.e., chargers) and

users. The energy gateway is equipped with RF charging capability, as well as an energy storage, e.g., a battery. The fixed chargers and energy users are geographically distributed at different locations in the network. The energy gateway moves among the locations randomly. When the energy gateway encounters chargers, as shown by the left part of Fig. 1.1, the energy gateway can be charged. By contrast, when the energy gateway moves to the energy user, as shown by the right part of Fig. 1.1, energy could be transferred to the energy users. The energy gateway pays for the energy received from the chargers and receives payments from energy users when the energy is transferred. Therefore, the energy gateway aims to maximize the profit from strategically charging and transferring energy at different locations.

To address the problem of energy charging/transferring actions of the energy gateway, we propose an action decision scheme based on a Markov decision process (MDP). By employing the MDP-based scheme, the energy gateway decides whether to pay and receive energy from each fixed charger or not. By contrast, when the energy gateway meets with energy users (i.e., the users are in the energy transfer range of the energy gateway), the energy gateway decides whether to transfer energy to the users or not. The energy charging/transferring decision, which is referred to as a policy, is made based on the states of the energy gateway. The states are defined as the location, energy level of the battery, the energy users in the neighborhood, and the current prices of energy at the fixed chargers. Further details on this issue are provided in Chapter 3.

1.2.2.2 Traffic-aware Optimal Wireless Energy Charging Policy

In mobile networks, particularly, a mobile ad hoc network, energy supply is a crucial issue for mobile devices (i.e., mobile nodes in this scenario) to meet quality of service (QoS) requirements of data transmission. A mobile node, e.g., a smart phone, relies on energy storage (i.e., a battery), and needs to be charged frequently. However, the mobile node can move among different locations, and hence the energy charging process becomes intermittent and non-persistent. With the help of wireless energy harvesting and transfer techniques, the mobile node has opportunities to charge and replenish the energy storage on the move, as long as wireless energy sources exist at some certain locations.

Figure 1.2: RF energy charging with traffic generating and processing.

As shown in Fig. 1.2, in the energy charging process, when the mobile node is at the location with an energy source (e.g., a wireless charger), the mobile node can send a request for wireless energy charging. The wireless charger collects a certain price from the mobile node for transferring energy. This price can vary at different locations. For example, the wireless chargers using renewable energy may charge lower price to the node than that using power from electrical grid. The traffic loads on the mobile node are time-varying, which can be mobile applications to be executed on the mobile node, communication overhead, as well as data to be transmitted to other network users, as shown in Fig. 1.2. The mobile node not only aims to retain sufficient energy to support the generated traffic by wireless energy charging, but also has to minimize the cost paid to the wireless chargers.

To address the aforementioned challenges, we propose an MDP-based scheme for optimally deciding the mobile node's charging policy in a system with wireless chargers. In the system model under consideration, the mobile node moves among different locations, generating different traffic loads. Some locations may have wireless chargers. The payment paid by the mobile node forms the immediate cost of the mobile node when an energy charging decision is made. The mobile node employs the MDP-based scheme to make every decision based on the system states of the current location, the traffic load, and the units of energy remained as the energy state. The details on this issue will be presented in Chapter 4.

1.2.2.3 Optimal Offloading in Mobile Cloudlet Systems with Intermittent Connectivity

A cloudlet is a special mobile cloud device, which can provide cloud-like services to nearby mobile devices via Wi-Fi and cellular device-to-device (D2D) connections. Mobile devices (namely mobile cloudlet users in the scenario) and cloudlets can form a small scale cloudlet-based system. In such a cloudlet system, as shown in Fig. 1.3, a mobile cloudlet user has opportunities to access and offload jobs to nearby cloudlets to improve the performance and reduce local execution cost in terms of resource usage and energy consumption.

Figure 1.3: Offloading in a cloudlet system.

However, there are some important challenges in offloading in mobile cloud environments. Firstly, offloading may not always achieve the lowest cost. For example, possible high communication overhead may lead to substantial energy consumption. Therefore, a mobile cloudlet user has to make a decision whether to execute a job locally on the mobile device or offload it to nearby mobile cloudlets. Thus, a dynamic decision making algorithm is necessary. Secondly, random unavailability of wireless connections in mobile cloud environments can cause extra cost. The cloudlet users and cloudlets may move and change their locations and become disconnected from each other. This will cause offloading failures. Moreover, admission control policies adopted by the cloudlets may also cause rejections of offloading requests from mobile cloudlet users. This intermittent wireless connection has to be taken into account.

We aim to address the above challenges. We propose an MDP-based offloading algorithm for the mobile cloudlet users in a cloudlet system. The mobile cloudlet user has an application to be executed. As the application is divided into code sections (denoted as phases), during the execution, the user can dynamically decide to execute application phases locally on the mobile device or offload to nearby cloudlets. We formulate and solve the MDP model to obtain an optimal policy to minimize computation and communication costs of the mobile cloudlet user. The MDP model incorporates the random mobility of each mobile cloudlet user as well as a priority-based cloudlet admission control policy to analyze the intermittent connections between the mobile cloudlet user and cloudlets. We compare the MDP based algorithm with conventional static baseline offloading schemes with fixed offloading decisions. The details are provided in Chapter 5.

1.2.3 Connections among Research Issues and Organization of the Chapters

Mobile computing has seen great development as a promising technology applied to many areas. With wireless energy charging and mobile device job offloading as energy management approaches, mobile networks, which were constrained by the limited energy supply, can be improved. The applications of mobile networks have been potentially extended. Thus, to obtain and analyze policies for optimal wireless energy management becomes necessary, which will be addressed in this thesis.

For the first issue in Chapter 3, we propose a mobile device named as energy gateway, which receives energy from chargers, carries and transfers the energy to energy users, as in Fig. 1.1. In this case, the deployment of energy charging facilities and the method for energy dissemination in mobile networks are realized. Only energy flows are considered in the first issue. After that, stochastic traffic (i.e., jobs to be processed and data to be transmitted) on a mobile device is considered in Chapter 4. In this issue, data flows are also included in deriving energy charging policies for mobile devices, as illustrated in Fig. 1.2. Then, Chapter 5 specifically examines the energy management from the perspective of data flow managing to minimize energy and resource consumption. In this issue, job processing of a mobile device is examined. We apply cloudlets in the mobile network under consideration

Figure 1.4: Connections among research issues.

for any given mobile device to offload, as in Fig. 1.3, so that the performance of the mobile device is optimized in terms of minimized cost of energy and resource consumption. The connections among the three issues are shown in Fig. 1.4. For all the issues discussed in this thesis, we find optimal energy charging/data offloading policies of mobile devices, and examine the structures of the solved policies. Threshold structures are identified and proven in the solved optimal policies.

The rest of this thesis is organized as follows:

- Chapter 2: Related literature and theoretical background on the issues discussed in our research are presented in this chapter.
- Chapter 3: The concept of a self-interested mobile energy gateway is proposed, which is a mobile device with wireless charging interfaces, carrying energy from energy chargers to end users of energy. The mobile network with a mobile energy gateway is modeled and studied in this chapter.
- Chapter 4: In this chapter, we model and study a mobile device which processes traffics when operating. The mobile device is equipped with wireless energy charging facilities.
- Chapter 5: In this chapter, we discuss the optimal policy to reduce local job processing energy consumption by choosing to executing generated jobs locally in a mobile

device itself, or offloading jobs to cloudlets.

- Chapter 6: The contributions of this thesis is summarized. Furthermore, future research directions are discussed in this chapter.

1.3 Summary of Contributions

Chapter 3: The main contributions of this chapter are as follows:

- We propose the concept of a self-interested energy gateway, which is equipped with RF charging capability. The energy gateway acts as an energy carrier to assist the chargers to extend the energy transmission range to remote users.
- We design an MDP-based scheme for the energy gateway to obtain the energy management policy. The optimal performance is achieved in terms of maximized utility of the energy gateway.
- We study the structure of the optimal energy charging/transferring policy. In particular, we prove that the optimal policy obtained from the MDP-based scheme has a threshold structure with respect to the system states.
- We present extensive performance evaluation of the MDP-based scheme. We demonstrate that the MDP-based scheme outperforms several baseline schemes for energy management. This is due to the fact that the MDP-based scheme takes both the current and the future system states into account.

Chapter 4: The main contributions of this chapter are as follows:

- We propose an MDP-based scheme for a mobile device (namely mobile node) equipped with a wireless charging facility to obtain an optimal charging policy, taking a set of system states into consideration. The optimality is achieved by means of maximizing the mobile node's expected utility.
- We study the structure of the optimal charging policy obtained from the proposed MDP scheme. We prove that the optimal policy is a threshold policy in the energy

state and location state. That is, the mobile node's charging action is monotonic in terms of the two states.

- We perform extensive performance evaluation to analyze the behavior of the optimal charging policy of the mobile node. We demonstrate that although a myopic greedy scheme has the similar threshold structure, the MDP scheme still outperforms due to that the myopic scheme does not take the system state into account.

Chapter 5: The main contributions of this chapter are as follows:

- We propose the MDP-based model for a mobile cloudlet user in an intermittently connected cloudlet system to obtain an optimal offloading policy. The policy determines offloading/local execution actions based on the state of the mobile cloudlet user to achieve the minimum cost.
- We model a mobile cloudlet user distribution in an intermittent cloudlet system as a Poisson point process (PPP). We then obtain success probabilities of offloading with limited knowledge of network parameters. These probabilities are used in the MDP model to obtain an optimal offloading policy.
- We prove that the optimal solution of the MDP is a threshold policy. We introduce an algorithm with bounded errors for the mobile cloudlet user to make offloading/local execution actions based on the threshold policy.

Chapter 2

Literature Review

This chapter summarizes the literature on the topics of energy management. Firstly, we present the existing works on energy management issues in mobile networks. Then the techniques of wireless energy transfer are reviewed. Afterward, the works on Markov decision process (MDP) as an optimization technique in mobile network energy management are reviewed.

2.1 Energy Management in Wireless Systems

Energy efficiency in wireless systems, such as cellular networks and opportunistic ad hoc networks, has been vastly concerned by the community [8, 9]. A few conceptual frameworks have been proposed to address the issues of energy efficiency in wireless systems [10, 11, 12], employing techniques such as transmitter architecture updating and cooperative relaying. In a network with perpetual energy supplies, energy management aims to restrict the wasted energy (e.g., in the form of heat emission) to achieve the “greenness” of the network. On the other hand, in an energy-constrained wireless system, energy-efficient designs contribute to the objective performances subject to limited energy. The trade-offs between energy management and system performance metrics are discussed in [13].

2.1.1 Base Station Energy Management

In cellular networks, base stations (BSs) consume over 50% of energy [14, 15], and the power amplifier component in a BS consumes up to 80% of the energy consumed by the BS [15]. As a result, BS energy management plays an important role of wireless system en-

ergy management. The critical approach to manage BS energy and improve the BS energy efficiency is to update the protocol, hardware and architecture designs of the BS.

Sleep mode approaches could be adopted into the signal transmission protocols of BSs to improve the energy efficiency in terms of decreased BS energy consumption. IEEE 802.16e [16] saves energy by allowing the BS to switch off the power supply for transceivers when there is no data to transmit or receive. The work in [17] proposes a protocol where a downlink discontinuous transmission can be conducted to temporarily switch off inactive BS hardware when the load is low. Two sleep modes are discussed in [17]: A micro-sleep mode turns off the BS power supply only for milliseconds, and a deep-sleep mode switches off the BS hardware for an extended time period.

The protocols switching off BS energy deal with the fluctuations of data load with respect to time. However, data loads may also vary in space, i.e., the data load at different BSs may be different, depending on the local users and wireless environments. The standard 3GPP TS 32.521 [18] proposes the concept of self-organizing network (SON). The SON concept allows BSs to rationally adjust their energy supply to reconfigure the size of cells to improve the system energy efficiency. The reconfiguration of BS energy supply is based on the number of current local network users. Reversely, by dynamically controlling the energy level, a BS can restrict the amount of accessing users.

There are two implementations of cell reconfiguration to achieve different objectives. Firstly, by lowering down or switching off a BS with heavy load, the cell size of the BS zooms in or becomes zero. Therefore, a part of the load will be handed off to the neighbouring BS cells [19, 20]. Similarly, by increasing the energy supply level at low load occasions, the size of a cell increases to accept more load. However, in another implementation of cell reconfiguration, BSs with low load can be switched off dynamically, handing the residual load to the adjacent BSs. Numerical results examining such a cooperative BS energy management scheme [21, 22] show that energy saving by switching off “inactive” BSs in terms of load can be remarkable, i.e., more than 20%. Cell reconfigurations by controlling energy supply of BSs require the cooperation of BSs in the network as a premise [19]. In [23, 24, 25], BSs cooperate and change their own information of the energy level to lower or switch off energy supply in turns.

2.1.2 Energy Management with Heterogeneous Network Techniques

Fine-grained cell deployments in existing macrocell BS networks [26] may increase energy and data efficiency of wireless networks. With small-scaled cells, e.g., microcells, picocells and femtocells, the energy and data transferring distance shortens. As a result, energy consumptions decrease.

Given a series of system performance metrics, the authors in [27] study full load network conditions with different numbers of micro BSs deployed in a system along with macro BSs. It is shown in [27] that the deployment of micro BSs increases the performance metrics. Simulations in [28] shows that, up to 60% of energy consumption will be reduced by deploying picocells covering only 20% of network users.

However, deploying small-scaled cells may not always reduce energy consumption. Extra energy could be incurred by the increased number of micro-/pico-/femtocell BSs, as well as communication overhead among those deployed BSs. [29] proposes a scheme to turn off the inactive femtocell BSs, which saves 37.5% of energy consumption in average. As the demand of wireless services is expected to grow in the future, the network paradigm may evolve from the centralized macro BS patterns to the patterns only with self-organizing and lower-power small-cell BSs, i.e., small-cell networks (SCNs) [30]. Considering the mobility and high density features, the substantial potential and challenges in energy efficiency of SCNs are yet to be investigated [30].

2.1.3 Energy Management in Relay Networks

In the networks with BS energy reconfigurations as well as small-scaled cellular networks, cooperative relay transmission may exist to extend the coverage of different types of BSs. Relay nodes/BSs may also be deployed dedicatedly.

As discussed in [31, 32, 33, 34], energy efficiency can be achieved with cooperative relaying, since the path loss caused by long distant transmission is reduced by adopting multiple shorter transmissions [32]. According to [33], a two-hop relaying communication saves energy consumption comparing with direct transmission. [31] shows that, for the transmitter (i.e., source) supported by battery-stored energy, single- or multi-hop relay

transmission leads to slower battery drain. Energy consumption per call in CDMA networks [34] can be reduced with multi-hop relaying.

With regard to mobility patterns, a relay can be either fixed or mobile. The deployment of fixed relays does not require complicated deploying and routing algorithms. Instead of installing macrocell BSs for relaying, the deployment of fixed relay nodes is much cheaper since the recent relay facilities, unlike conventional BSs, do not require major backhaul infrastructure updating [35, 36]. It is shown in [36] that, to keep the same signal-to-noise ratio (SNR) level in some particular system scenario, the transmission power consumption is reduced by the factor of 5, as the number of deployed BSs in the system increases by 1.5 times. On the other hand, mobile relays can be adopted. Mobile relays are more flexible than fixed relays, and can extend the coverage of the network. A critical issue with mobile relays is that mobile relays may probably have non-persistent energy supply, e.g., battery drain. Therefore, cooperative relaying may harm the energy efficiency [37] given the energy management is not strategically performed. A game-theoretic approach is applied in [37] to encourage idle network users to work as relay nodes. It is shown that an optimal cooperation scheme is achievable in terms of energy efficiency. As a result, with well-designed energy management schemes, non-BS relay nodes can still improve the energy efficiency.

In a wireless network with relays, there are two important issues, including the spatial distributions and the policy of the relays. The spatial distribution issue involves optimal placement of relays to achieve energy efficiency objectives. A finite-state Markov approach is applied in [38, 39] to perform the relay selections. The policy issue of a relay indicates the operation strategies of the relay. That is, the relay node may decide whether to operate or not, based on various system states to avoid too much energy consumption [40, 41].

2.1.4 Data Offloading to Manage Energy Consumption

The existing works on reducing energy and resource consumptions in mobile networks with data offloading techniques are reviewed in the following.

2.1.4.1 The Definition of Mobile Cloudlet

Mobile cloud computing is referred to as a cloud system which enables mobile devices (e.g., smartphones and tablets) to migrate their data storage and data processing to cloud

providers. To fully exploit the potential of cloud computing, the concept of a cloudlet [5, 6] is proposed to employ various local resource-rich devices (e.g., a mobile base station) as cloud servers, instead of business cloud providers (e.g., Amazon) at the far end of the Internet.

A comprehensive survey of mobile cloud and its applications has been presented in [42]. The work in [5] introduces an architecture of a cloudlet system to seamlessly handle mobile users' computation requests. Furthermore, a general architecture for ad hoc mobile users to form an autonomous mobile cloud system is proposed in [43], where some mobile users may act as cloudlets to provide cloud services to others when they have redundant resources. The works [44, 45, 46] implement prototypes of program code partitioning and offloading algorithms on the existing architectures. Additionally, [47] compares several popular existing mobile cloud system models and implementations.

2.1.4.2 Execution, Partitioning, and Offloading of Data

As stated in [48], the modern resource-rich, energy-efficient mobile devices and high bandwidth wireless connections enable mobile users to offload jobs to the cloudlet as a practical paradigm. The authors in [49] point out that offloading part of mobile game codes can reduce energy consumption from mobile users' perspective, such that the playing time of the mobile game can be extended. The work presented in [50] shows that offloading can benefit mobile users by reducing energy consumption when the jobs to be executed require large amounts of computation resource and time (i.e., many instructions). However, [50] also shows that offloading is not always beneficial to mobile users in terms of energy saving, especially when the offloading process involves intensive communications. The offloading decisions of applications and parts of applications should be balanced optimally.

2.2 Wireless Energy Transfer

Wireless energy transfer techniques include wireless energy charging and harvesting, which have been increasingly applied to several areas, including wireless sensor networks (WSNs) [51], wireless body networks [52] and cognitive radio systems [53]. The designs and implementations of various wireless energy transfer systems will be surveyed in this section.

2.2.1 Near-field Energy Transfer

Mobile nodes carrying inductive coupling [54, 55] devices are able to be charged by the energy from chargers within tens of centimeters. Magnetic resonance coupling [56] technique can transmit power within several meters. Electric power is transferred between coils and magnetic resonators in inductive coupling and magnetic resonance coupling, respectively.

Resonance coupling can achieve 5% ~ 52% charging efficiency [57]. An interface standard for inductive energy charging named Qi [58] can regulate at least 5W energy input in its design, which requires the energy source to be within 4cm, which confines its applications. By employing a novel wireless charging technique Witricity [59], 0.5W of input energy can be supplied for the distance up to 0.2m.

However, the aforementioned energy transfer techniques require the coils and resonators to be aligned with a short distance, which limits the applications of those techniques in wireless energy transfer scenarios where mobile devices need to be charged from distance away.

2.2.2 Far-field Radio Frequency Energy Transfer

Energy charging can be performed to wireless devices in the far-field area, which is defined as the area with distance $R \geq 2D^2/\lambda$ [60], where λ is the wavelength and D is the aperture of the transmission antenna. As the result, far-field energy transfer includes energy replenishments for wireless devices at various locations ranging from several meters [52, 61, 62], a few kilometers [63] and to the near-earth orbit [64].

Recently, radio frequency (RF) energy harvesting has attracted attentions as a promising technique to sustain the operation of wireless devices in which their wired charging or battery replacement are too costly or practically infeasible. For example, body area wireless devices for human/animal health monitoring [52, 62], sensors inside civil infrastructures [65], and monitoring devices in airframes [66] can benefit from the RF energy harvesting techniques. Moreover, periodical battery replacement of wireless sensors is known as prohibitively costly [67]. Numerous applications and research works related to RF energy harvesting are reviewed in [68] and [69].

2.2.2.1 RF Energy Propagation Model

In an RF energy charging system, energy is carried by radio signals. Thus, the propagation model of RF energy charging is based on the transmission of radio waves. The propagation of RF energy in a free space can be calculated by the Friis formula [70, 68]

$$E_R = \zeta_{RF/DC} G_t G_r \left(\frac{\lambda}{4\pi r} \right)^2 E_T, \quad (2.1)$$

where E_T and E_R are the transmitted energy and the received energy, respectively. $\zeta_{RF/DC}$ is the RF-to-DC energy conversion efficiency [51]. G_t and G_r are the transmitting antenna gain and the receiving antenna gain, respectively. λ is the wavelength of RF energy transfer signal. r is the distance between the transmitter and the receiver. From (2.1), the amount of energy received by any energy user is inversely proportional to the square of the distance to the energy gateway, given fixed amount of transmitted energy E_T .

The Friis' transmission formula requires that the distance r between the transmitter and the receiver holds for the inequality $r > R_f$, where R_f is defined as the Fraunhofer distance satisfying the following conditions:

$$R_f = \frac{2D_a^2}{\lambda}, \quad R_f \gg \lambda, \quad \text{and} \quad R_f \gg D_a, \quad (2.2)$$

where D_a is the largest dimension of the receiver's antenna. For the receivers in the near-field of the transmitter, i.e., $0 \leq R_n \leq R_f$, where R_n is the n^{th} receiver's distance to the transmitter, the Friis' formula is not applicable.

For multipath RF signals propagation, a receiver may receive energy from other reflected RF signals other than the line-of-sight (LOS) signal. For example, for a two-ray ground reflection propagation model, the received RF energy can be calculated from

$$E_R = \zeta_{RF/DC} \frac{G_t G_r h_t^2 h_r^2}{r^4} E_T, \quad (2.3)$$

where h_t and h_r are respectively the antenna heights of the transmitter and receiver.

Furthermore, for more practical system, various RF propagation models [71], e.g., the Rayleigh model [72], could also be applied.

2.2.2.2 RF Energy Sources Classification

In the existing designs, RF energy may be harvested from two main types of sources, i.e., ambient sources and dedicated sources.

A dedicated RF source is designed and placed purposely to provide energy to energy users in the system. For example, in [73] and [74], mobile chargers are deployed to power wireless sensors. The Powercaster transmitters [2], which operate with the transmit power of 1W/3W, and the Powerharvester receivers [2], which harvest $-6\text{dBm}/-11\text{dBm}$, are also developed as commercialized devices to utilize RF energy. For a dedicated transmitter, the frequency usage and designed output power are regulated, e.g., by FCC regulations [75] on low-power non-licensed transmitters (namely, “part 15” transmitters).

On the other hand, in some scenarios, ambient RF sources may provide wireless energy. For example, TV towers [51, 76], GSM cellular base stations [77, 78, 79, 80], and WiFi access points [81, 82] could be important sources to charge wireless energy users. The problem with ambient RF sources is that the power density could be small that ambient RF energy is more likely to be harvested in urban areas, such as a metropolitan city [51, 83]. Moreover, high gain antennas should be used.

2.2.2.3 Efficiency and Implementation Issues on Applying RF Energy Transfer

Practically, the efficiency of RF energy can support mobile networks, as discussed in existing studies. Far-field RF energy transfer can achieve over 50% energy efficiency [84], depending on distance and frequency. The experiments in [51] and [85] show that with particular antenna and circuit designs, the RF harvested power is able to support sensor applications.

The work presented in [86] has implemented an experimental mobile device with directional antennas. The device can satisfy the 4.2mW minimum input power requirement to charge the equipped lithium battery within the range of 1m from a 15W power source. Based on experiments, wireless sensors can be charged with 20mW energy via VHF/UHF channels [51], and up to $0.011\mu\text{W}$ via 2.4GHz ISM band from access points as chargers located less than 10 meters [87]. The authors of [88] show that a mobile phone emitting 0.5W can charge the device at the distance of 1m and 10m with the power $40\text{mW}/\text{m}^2$

Table 2.1: RF energy charging: experimental data [88].

Energy source	Source power	Distance	Charging amount
AM radio station	$50kW$	$5000m$	$159\mu W/m^2$
Mobile base station	$100W$	$100m$	$800\mu W/m^2$
Mobile phone	$0.5W$	$1m$	$40mW/m^2$
	$0.5W$	$5m$	$1.6mW/m^2$
	$0.5W$	$10m$	$400\mu W/m^2$

and $400\mu W/m^2$, respectively. As required by FCC [75], 4W is the limitation of a “part 15” transmitter. According to [89], 15m is the longest possible transmission distance if a $5.5\mu W$ ($-26dBm$) energy transmission rate is required. Other general experimental data of RF energy harvesting from different wireless energy sources at different distances are shown in Table 2.1. RF energy harvesting to support cognitive radio systems is discussed in [53].

With multiple-antennas at the transmitter side, beamforming [90] can be adopted to maximize the received signal, and thus improve the efficiency of EF energy transfer [91, 92, 93, 94]. An adaptive energy receiving scheme with beamforming is proposed in [92]. The optimal channel estimation duration before energy transfer, as well as the optimal energy beamformer are derived to maximize the received energy. [93] applies an iterative algorithm similar to the Dinkelbach method [95] for joint optimization of both energy transfer duration and power.

The work presented in [96] had overlaid an RF energy transfer function to the existing cellular uplink network architecture, enabling the network users to harvest wireless energy. A harvest-then-transmit protocol for wireless energy transfer is designed in [91]. Simultaneous wireless information and power transfer is addressed in [90], which allows the existing wireless network architecture to support RF energy transferring without much modification.

2.2.2.4 Prototypes and Applications of RF Energy Transfer

RF energy harvesting in mobile networks has been studied and implemented in existing literature.

In wireless sensor networks, [51] develops a prototype of the wireless sensor network with RF energy harvesting capability. The sensors harvest ambient RF energy from far-field TV broadcast (6.6km) signals. The authors of [85] have also implemented and studied the similar RF energy harvesting sensor networks. Since RF energy transfer technique transmits energy using radioactive, it is suitable to be adopted to current architectures of mobile networks, e.g., wireless sensor network [51]. [85, 97, 98, 99, 100, 101, 102, 103] also propose various prototypes of RF energy charging in WSNs.

RFID systems supported by RF energy transfer [104] are also intensively studied. Power harvesters are designed in [105, 106, 107], and particular energy transfer components including rectifier and rectifier [108, 109, 110, 111, 112], and RF-to-DC converter [113, 114] are discussed and implemented in existing literature.

For each RF energy user, there are two modes of utilizing the energy harvested from the RF energy charger: harvest-store-use and harvest-use modes. Energy users with harvest-store-use mode are generally equipped with energy storage devices such as battery, such as [115, 116, 117, 118, 119] (sensors) and [120] (cognitive radio), energy will be stored for future usage. In the harvest-store-use mode, the battery level state is critical to observe to make optimal charging policies [119]. For the harvest-use mode, the harvested energy is employed immediately by the energy user. Therefore, the energy users are designed in a battery-free manner, e.g., [77, 78, 79, 80, 81, 82]. In the harvest-use mode, since there is no energy accumulated, the energy user has to be aware of the energy density and energy harvester designs to improve energy harvesting efficiency.

2.3 Energy Management: An RF Energy Charging User Perspective

2.3.1 Combined Data Transfer and Energy Charging

RF signals transmitted to a receiver can be employed as energy or decoded as data, depending on the circuit to process the received RF signals. To this end, various receiver architectures and circuits [90, 121, 122, 123, 124] are designed. The RF signal received will be handled in different manners by different receiver architectures [68]: Separated receivers, time switching and power splitting:

- Given the receiver with multiple antennas, the RF signal can be independently received and processed into power and data. However, the architecture of separated receivers requires multiple sets of antennas and circuits, which may not agree with the design constraints of small devices, such as wireless body sensors.
- In a time switching architecture, in a time slot, the received RF signal is processed as either energy signal or data signal. In this case, energy and data transmission works in a half-duplex mode.
- Power splitting architecture could be applied by the receiver with a single antenna. The RF signal is split into two arbitrary parts with weaker signal strength, which are decoded respectively as energy and data.

2.3.1.1 Time Switching Energy Receiver

A time-switching energy receiver design is proposed in [90], where the information receiver and energy receiver respectively have constraints on the maximum received power limit (either fixed or flexible). The work [122] extends [90] that the received power can be arbitrarily split with respect to time into different ratios of data and energy.

Two fine-grained time-switching policies are proposed in [125] for a MISO interference channel with K energy users. For a time division mode switching (TDMS) scheme, each transmission time slot is divided into two sub-time-slots. All the receivers perform energy harvesting action in the first sub-time-slot, and information decoding in the subsequent sub-time-slot. On the other hand, in a time division multiple access (TDMA) scheme, a time slot is divided into K sub-time-slots. In each of K sub-time-slots, only one out of K users performs energy harvesting, which the rest perform information decoding. Both the TDMS and TDMA schemes in [125] are solvable as convex problems.

In [126], a fading channel with time-varying co-channel interference is taken into consideration when making optimal time switching decisions, aiming to minimize the outage probability. That is, the energy user decides whether to perform information decoding or energy harvesting, depending on the channel information. Both stochastic and known channel state information cases are discussed in [126]. A threshold structure can be found in

the optimal decision of the energy user that the RF signal should be taken as energy signal whenever the channel gain is lower than a certain level. Based on the existence of threshold of information decoding and energy harvesting, authors in [127] discuss an energy receiver working at the time-switching mode receives energy from a random beamforming multi-antenna transmitter. It is proved theoretically and by simulation that the optimal trade-off between received information rate and energy can be achieved when the transmit power is sufficiently large.

2.3.1.2 Power Splitting Energy Receiver

The work in [128] examines a power-splitting scheme of received RF signal, and found that a threshold structure exists in the optimal policy with respect to the channel gain. That is, when the channel gain is above a certain level, the received RF signal is split with a fixed ratio, where a portion of signal is delivered to the energy receiver of the user. However, when the channel gain is low, all portion of the received signal is allocated to the information receiver. The reason to the existence of such a threshold is that signals from “good” channels benefit both information and energy receiving. Similarly, [122] has proposed an *on-off* power-splitting scheme, where *on* mode enables power-splitting while *off* mode allocates the received RF signal only to the energy receiver. The authors in [122] concludes that the on-off power-splitting scheme is optimal in the practical cases that receiver circuit power consumption is not negligible.

Adaptive power-splitting is discussed in [129]. The receiver starts every transmission block with a training phase, following with a data transmission phase for the rest of the transmission block. It is shown in [129] that the receiver should use most of the power in the training phase only for channel estimation. Energy and data transmissions should be done in the rest phase other than the training phase. The adaptive power-splitting scheme in [129] is shown to outperform the non-adaptive design in terms of the ergodic capacity performance.

An optimal power-splitting scheme to maximize the spectrum efficiency of information transmission (i.e., bit/Hz) is proposed in [130]. The problem is solved as a convex optimization which requires all the possible ratio of power-splitting to be searched. Two iterative

algorithms are also applied as sub-optimal solving techniques in [130]. Similarly, power efficiency of information transmission (i.e., bit/J) is considered in [131]. The optimal problem in [131] is not identified as a convex optimization. Simulation indicates that, iterative algorithm with one dimensional search converges to the optimal solution.

2.3.2 Multi-hop Wireless Energy Transfer

In a multi-hop wireless system, relay nodes may be necessary to relay RF signals. The RF signal relaying gives rise to energy consumption of the relay node itself. The critical issue from the perspective of the relay node is the policy to charge from the received RF signal or relay the data carried by the RF signal.

Two types of relay strategies from the perspective of the relay user exist, including amplify-and-forward (AF) and decode-and-forward (DF). The work [132] addresses the fact that AF may cause high peak power level of transferred energy, which is not suitable to charge device with input energy constraints, e.g., [90]. Moreover, AF may require additional source of energy to amplify the signal received, which is not practical for energy-constrained relays, e.g., wireless sensors.

2.3.2.1 Single Relay for Wireless Energy Transfer

A critical objective for a relay node in a wireless energy charging system is to balance between energy charging and signal relaying. Similar to the single-hop scenarios, the decisions are also made in a time-switching or power-splitting mode. For both AF and DF relay strategies, [133] proposes time-switching protocols to make relay decisions, based on the residual energy as well as the channel quality. Relay protocols operate in both time-switching and power-splitting modes are proposed in [134]. Analytical expressions are derived for ergodic capacity and outage probability given the perfect channel state information known at the destination. The work presented in [135] considers the case that two nodes exchange information via an energy harvesting relay, which employs the received signal to charge and then relays the data. The upperbound and lowerbound of the ergodic capacity and outage probability are derived with tight closed forms. Compared with a non-cooperative relaying scheme, the protocol in [135] is reliable and does not require additional resources to achieve higher transmission rate.

2.3.2.2 Multiple Relay and Relay Selection

In [136], a critical issue of relay selection is addressed for SWIPT that the preferable relay for data transmission may not coincide with the strongest energy harvesting channel, due to that the channels fade independently. Therefore, a balance exists between information transmission and energy charging. Two relay selection schemes are proposed in [136] including time sharing and threshold-checking schemes to achieve Pareto efficiencies of the trade-off between energy transfer and ergodic capacity, as well as the trade-off between energy transfer and outage probability.

The works in [137] and [138] consider relay selection for SWIPT in generalized large-scaled RF energy harvesting systems with multiple pairs of sources and destinations. The cooperative protocol employing relays is shown to significantly improve the trade-off between outage probability and energy harvesting transfer. Similar to [139, 140, 141] which considers different network topologies, [137] applies stochastic geometry to analyze the RF energy relay system. The relays are assumed to randomly distributed following a Poisson point process (PPP). Given the spatial distributions of relays, [137] adopts a random selection policy based on a sectorized selection area with central angle at the direction of each receiver as the relay selection policy. The authors in [138] argue that the conventional max-min relay selection potentially loses diversity gains, since the source-relay channels and the relay-destination channels are heterogeneous and with different importance levels, which are treated equally in max-min criterion.

2.3.3 Mobility and Intermittent Connections in Mobile Networks

In a wireless energy transfer system with mobile nodes, near-far phenomenon and intermittent connections exist, which affect the performance of energy and data transfer.

A doubly near-far phenomenon has been studied in [142]. That is, for a receiver located distance away from the energy and data transmitter, both energy/data signal receiving and uplink data transmission (e.g., data offloading) are affected. As a result, for a fixed transmitter, the coverage of signal is limited and the mobile users that the transmitter can efficiently serve are constrained. Beamforming of energy can be employed to amplify and

control the amount of energy received by different receivers (i.e., mobile users) by adjusting the beamformer [91]. Moreover, mobile transmitters and energy/data relays [143, 144] may also be adopted to move and cover more numbers of energy/data users.

Regarding to mobile cloud systems, most of the existing studies only considers the cases with persistent connectivity (i.e., the connection between any mobile user and cloud is guaranteed) [5, 6]. However, as stated in [145], intermittent connectivity issues may exist due to mobility, heterogeneous network environment and smart devices' connection policies. According to [145], a non-persistent connection is a key feature distinguishing mobile cloud with conventional cloud systems. Only the control signals in mobile cloud systems have persistent connections, while regular mobile cloud requests are made via "on-demand" intermittent connections. The existence of intermittent connections may fail the offloading request from the user, which forces the user to execute or re-transmit the job again.

Intermittent connectivity issues caused by the mobility feature of mobile nodes are studied in [6], [146] and [147]. A cloudlet may reject users' offloading requests, e.g., due to limited resources. Specifically, [146] and [147] jointly consider the cloud provider's revenue with mobile users' QoS requirements, i.e., admission control and resource allocation, respectively. The work [147] models the admission and resource allocation as a semi-Markov decision process. The work presented in [146] solves the optimization analytically by employing a queuing-based approach. An admission control mechanism with the objective to maximize the system throughput has been introduced in [6]. The authors in [148] study the offloading problem in a mobile cloud system with such intermittent connections. The offloading points of applications are set considering the vulnerability of connection, but only the ideal case is discussed that the present and future intermittent connectivity patterns are known. The work presented in [137] models the spatial distribution of relay nodes in the system as a Poisson point process (PPP). Two different mobility patterns of mobile RF energy source are examined in [143], i.e., center-to-center mobility (CM) and around edges moving (EM) patterns. The simulation assessment concludes that the CM pattern has better performance in small-sized networks with high density of sensors. Meanwhile, the

EM pattern is more suitable for lower sensor density scenarios, which is typical in networks of large size.

2.4 Optimization Approaches in Energy Management

2.4.1 Optimal Energy Management in Mobile Networks

With the nature of energy scarcity in mobile networks, literature has studied the energy management to efficiently manage the mobile network to achieve the optimal energy utilization.

2.4.1.1 Optimal Energy Storage Management

A few works studied the energy management problem of mobile networks.

The work presented in [117] considers a wireless sensor with finite battery capacity and wireless charging facility. A certain number of packets need to be transmitted by the sensor. The total transmission time is minimized by using cumulative curves method. Supported by wireless charging, the objective is to maximize the transmission throughput in [149]. In [150], a sensor processes self-generated data with energy charged from wireless channels. Several power management policies including the Markov decision process (MDP) model minimizing the mean delay are examined, which has shown that a greedy energy management policy is proved to be optimal with both maximized throughput and minimized delay. In [151], throughput optimization over a finite horizon is also discussed, with time varying energy charging channel between the sensor and energy sources. A relay node with energy harvesting function in [115] applies a greedy policy that a relay action is taken whenever the residual energy in the relay is sufficient to transmit information. An optimal policy of switching between energy harvesting and relay is also proposed in [115] with *a priori* complete knowledge of channel coefficients and energy transfer parameters of the whole transmission period.

Since the wireless energy supply can be intermittent, users may be far away from RF sources and cannot receive RF energy from the wireless charger [152, 153]. To overcome the transmission range limitation, in the literature, a dedicated energy transmitter (e.g.,

chargers and relays) is proposed to extend the area with RF energy supplies. For example, to charge RFID tags with RF energy, the authors of [154] propose the optimal placement of stationary RFID readers which also supply RF energy. The objective is to minimize number of readers given QoS requirement requirements. The authors of [73] and [155] use mobile chargers to travel to different locations and charge multiple sensors. The authors of [73] propose an optimal path of mobile chargers which is based on the shortest Hamiltonian cycle of the locations to visit. The authors of [74] extend the scheme in [73] by considering priorities of different sensors. An integer linear programming (ILP) optimization model is applied to maximize the power received by the prioritized sensors. [156] considers to opportunistically use available spectrum to transfer wireless energy to sensor nodes. The performance of a sensor with an integration of opportunistic spectrum access and wireless energy transfer is analyzed. The power control scheme for the wireless charging unit is proposed with the objective to minimize energy consumption.

2.4.1.2 Optimal Data Offloading

Optimal offloading decisions could be made either in a static manner or a dynamic manner to reduce the cost of energy consumption in mobile networks.

The authors in [49] employ a cost graph approach to quantify an immediate cost of each code section. Then the offloading scheme for each code section is decided statically in an off-line manner, relying solely on the code section states. [44] proposes a static and dynamic partitioning and offloading schemes. The scheme executes a graph cutting algorithm to categorize code sections into different offloading decision set.

The work presented in [46] claims that mobile users may work in different external environments and with changing workloads, such that static partitioning of jobs between mobile devices and cloud may not achieve optimal results with such externalities. As a result, a linear programming model for dynamically partitioning of an application is proposed. [45], [157] and [158] provide a grand view of the whole optimization process of a mobile user's offloading decisions. [158] optimizes a mobile user's energy cost with Lyapunov optimization. Similar to [46], a linear optimization approach is adopted in [45] and

[157] to find the optimal offloading decisions in various applications, such as face recognition and smartphone games. Furthermore, [45] and [157] develop automatic partitioning of applications with minimal programmer's involvement. As a result, this makes fine-grained code section offloading possible. Based on [45] and [157], ThinkAir [159], on the other hand, considers the scalability of a mobile cloud, i.e., the ability to handle multiple mobile users instead of one user at the cloud side.

2.4.2 Optimizations Using Markov Decision Process

Markov decision process (MDP) [160, 161, 162] is a popular model to be applied in solving stochastic optimization problems in decision making in energy management.

2.4.2.1 Markov Decision Process: Formal Definition

Markov decision process (MDP) [160, 161] is an optimization framework to model stochastic decision making processes under uncertainties. In an MDP, the system works over finite or infinite time periods. In each time period, namely a decision period, the system has a certain state $\mathcal{S}$, based on which the decision maker (e.g., a mobile device) makes a decision to take an action $\mathcal{A}$ from the set of all the possible actions. By taking the action, an immediate reward or utility is received by the decision maker. Additionally, after an action is taken, the system state $\mathcal{S}$ will transit to the next state $\mathcal{S}'$. There could be multiple possible state transitions with different probabilities, which are called transition probabilities. For example, when an RF energy gateway decides to charge, the state of stored energy level may remain the same or increase, depending on the probability of successful charging from RF energy chargers.

A typical MDP is defined by a tuple $\langle \mathcal{S}, \mathcal{A}, \mathbf{P}, U, T \rangle$.

- $\mathcal{S}$ is the set of all the system states. The states in an MDP should be finite.
- $\mathcal{A}$ is the finite set of all actions that a decision maker can take.
- $\mathbf{P}$ is the matrix for transition probabilities of all the system states.
- U is the immediate utility function.

- T is the set of all the decision period.

The goal of solving an MDP-based optimization problem is to find an optimal policy π^* . Generally, a policy is defined as a strategy indicating an action that the decision maker will take given the current system state. Classical methods to solve MDPs are value iteration [163], linear programming (LP) [164, 165], learning [166, 167] and approximation methods [168, 166, 169].

2.4.2.2 MDP Optimization in Wireless Sensor Networks

In [170], a sensor in wireless sensor networks (WSNs) can recharge from microwave energy sources with directional antenna. However, each energy charging process has a delay, which relies on the residual energy in the sensor, i.e., sensors with lower energy may take more time. The sensor employs an MDP model to analyze and decides the charging policies to minimize the charging delay, given the current residual energy level.

The authors of [171] introduce a body sensor network that a special device (e.g., a cell phone) is placed as an access point to collect the data from body sensors. The MDP is formulated for the sensors which have different transmission modes. These modes are the actions associated with different energy consumption levels and data rates. RF Energy is harvested from ambient sources. Energy in [171] is harvested objectively as a two state process, that the sensor cannot make a decision on energy charging.

In [62], wireless rechargeable biosensors implanted inside human/animal body for data sampling are applied. Since the data transmission and energy charging actions increase the sensor temperature, which is harmful to human/animal. An MDP model is applied to both obtain the maximum average sampled data and constrain the temperature below a certain level. Likewise, [119] addresses the case where a mobile node in WSNs carries and transmits data with a hard delay requirement. With limited energy stored and harvested, the mobile node employs a constrained MDP (CMDP) based model to decide whether to transmit the data or stay idle to achieve the delay requirement.

The ambient energy harvesting quality from the environment is included in the system states of an MDP model in [118]. A wireless sensor may encounter two ambient energy

harvesting mode: GOOD and BAD modes. Besides, the sensor collects a set of critical environment event data with different importance. The MDP model aims for a balance policy of an adapting transmission probability that optimally manages the sensor battery to avoid neither battery drainage or overflow. [118] also discovered that, when the MDP model is applied, the overall performance of the MDP-based transmission policy largely depends on the average power that a fully-charged battery can supply over a BAD harvesting period.

Wireless sensors in [172] apply MDP-based model to decide different data compression error levels in transmission as the actions. A sensor can harvest ambient RF energy, but with various qualities. The MDP-based model balances between the data compression error (where a low-error data compression consumes large amount of energy) and energy budget in the sensor.

In [173], a mobile user equipped with both data storage (i.e., data queues) and energy storage (e.g., batteries) is studied. In the proposed MDP model, energy charging is a possible action to be taken by the mobile user. To achieve the maximized throughput with QoS requirements, the authors of [173] study a scheme based on CMDP for a mobile user to balance between energy charging and different qualities of data transmissions. An MDP model is developed in [150] to optimize the mean delay of data transmission of a sensor node. [174] addresses data transmissions of a sensor node in WSNs could be prevented due to unmanaged energy and data buffer in various energy harvesting and channel states, which are assumed to be directly acquired by the node. An MDP model is applied to optimally decide whether to transmit or to sense the energy allocation.

In [175], both MDP and partially observable Markov decision process (POMDP) models are proposed for rechargeable nodes in WSNs designed for event monitoring. Collected events, such as the energy storage situation, the occurred events, and the node's history of activation, are included as the states of the MDP/POMDP model. If the collected information is complete, the optimization is modeled as MDP. Otherwise, POMDP is applied when only partial information can be collected.

2.4.2.3 MDP Optimization in Cognitive Radio Networks

An energy-constrained medium access control (MAC) protocol is studied in [120]. Since the sensing and access actions of a secondary user consumes energy, the secondary user

may not always sense the spectrum given the limited battery energy as the energy constraint. A POMDP-based model that only considers the primary user's traffic in the state space is proposed to maximize the throughput. No energy will be obtained to replenish the secondary user's battery in [120].

MDP-based models are employed in cognitive radio networks for energy management. [176] formulates an MDP model to determine an action of sensing/being idle for an RF energy powered secondary user. Energy is randomly harvested by the secondary user, which is not considered as a system state. [177] also studies the similar topic of channel selection in a time-varying wireless system. The energy level of the sensor and the channel information are taken into account of the MDP model. However, in [176] and [177], the reward to the secondary user (or sensor) does not include the harvested energy. Moreover, energy harvesting is not treated as an action subjectively performed by the secondary user (or sensor). [178] formulates and solves the POMDP to obtain an optimal mode selection of a sensor node. The sensor operates in a half duplex manner, choosing the mode either to harvest energy or transmit data. Both action decisions must be balanced to achieve an optimal performance.

2.4.3 Summary

To the best of our knowledge, the works in the literature do not consider the following several aspects:

- The works in the literature related to RF energy harvesting in mobile networks did not consider from the perspective of a mobile energy transmitter (i.e., a mobile energy gateway), which is designed to carry energy from sources to energy users, aiming at maximizing the profit in terms of utility or monetary reward.
- The works in the literature did not study a general mobile node facilitated with wireless energy charging functions. A full-functional mobile node differs from a sensor or a mesh node in several aspects. Firstly, the mobile node handles various types of traffic load, which may generate different levels of satisfaction to a user and consume different amount of energy. Secondly, the mobile node may move among different

locations, and wireless charging becomes intermittent. Thirdly, wireless charging can incur different cost to the mobile node. Therefore, there is a need to develop a novel optimization problem considering these issues and study the structure of the optimal energy charging policy.

- The works in the literature related to intermittent connections of cloudlets did not develop the optimal offloading algorithm of the mobile user to reduce the cost of energy. Moreover, intermittent connectivity issues caused by the mobility of mobile nodes and the impacts to the energy cost management are not studied.

The aforementioned issues will be focused in this thesis.

Chapter 3

Mobile Energy Gateway - A Study on Optimal Wireless Energy Carrying

Radio frequency (RF) energy is one of the wireless energy harvesting and transfer techniques that supports far-field wireless charging services. The other techniques are inductive coupling and magnetic resonance coupling, which are near-field charging techniques. RF energy charging devices can be deployed to send energy in mobile networks, supporting energy-constrained mobile devices to operate perpetually. Due to the fading property of RF signals, RF energy charging is only effective within a limited range. Considering the mobility feature of mobile networks, mobile devices with energy storage facilities may work as energy carriers, namely mobile energy gateways. An energy gateway can charge from RF energy chargers (i.e., energy sources), store the charged energy, and move to other locations to transfer energy to other devices which are not covered by RF energy chargers.

We consider a network with fixed RF energy chargers geographically distributed. There are also mobile energy users in the network who are not always covered by the energy chargers. Mobile energy gateways moves to different locations to charge, carry and transfer energy, are deployed in the network. Each energy gateway operates as a self-interested carrier. When the energy gateway takes an action to charge at the RF energy charger side, a payment has to be made to the charger (i.e., the price of energy charging). In the same manner, energy users have to pay the energy gateway for the energy carried and transferred. We propose a Markov decision process (MDP)-based scheme to address the energy charging/transferring actions of the energy gateway at different system states. The energy gateway aims to optimize the charging/transferring action policy to maximize the profit.

Table 3.1: Notation descriptions.

Notation	Definition
$\mathcal{S}$ $(\mathcal{L}, \mathcal{E}, \mathcal{N}, \mathcal{P})$	Composite state of the mobile node, including location state, energy state, end user number state, state of market prices of energy charging
$\mathbb{L}, \mathbb{G}, \mathbb{N}, \mathbb{P}$	State sets of location state, energy state, end user number state, and energy price state
$\mathcal{A}$	$\mathcal{A} \in \{0, 1, 2\}$, The action of being idle, charging, and transferring energy taken by the energy gateway
$\mathbf{W}(\mathcal{S}, \mathcal{S}' \mathcal{A})$	Overall transition matrix of the composite state $\mathcal{S}$, given the action $\mathcal{A}$ is taken
γ	Discount factor in the Bellman equation
$H(\cdot), U(\cdot)$	Overall utility function, expected optimal utility function in the Bellman equation
E_B	The amount of energy transferred from charger side to the energy gateway
E_S, e_n^R	Energy send by the energy gateway, energy received by the n^{th} end user covered by the energy gateway
$R(N, E_S)$	Total amount of payments paid by N end users to the energy gateway, given the energy sent to be E_S
$F(\mathcal{E})$	The holding cost of energy
$\mathcal{E}_{THRESHOLD}^{1-0}$	Threshold energy state, where the action $\mathcal{A} = 1$ is taken when energy state $\mathcal{E} \leq \mathcal{E}_{THRESHOLD}^{1-0}$, and $\mathcal{A} = 0$ otherwise

The rest of this chapter is organized as follows. In Section 3.1, we describe the mobile network with energy sources (i.e., fixed chargers), an energy gateway to carry and transfer energy to users. The RF energy propagation model is presented, and a payment scheme of users is described. Section 3.2 formulates a Markov decision process (MDP) to maximize the energy gateway's expected utility. The solution method and the existence of threshold policies of the MDP are presented in Section 3.3. Numerical results are provided in Section 3.4. Finally, Section 3.5 concludes the chapter.

For convenience, some major mathematical notations in this chapter are listed in Table 3.1.

3.1 System Model

We consider the mobile network with fixed wireless chargers (i.e., energy suppliers), an energy gateway (i.e., an energy messenger), and users (i.e., energy consumers), as shown in Figure 3.1. There are multiple fixed chargers at different locations in the network. The

Figure 3.1: System description.

energy gateway moves among locations, visiting chargers and users. The energy gateway is equipped with a battery and energy transfer interfaces. When the energy gateway is at a charger, a certain amount of energy can be transferred to the battery of the energy gateway. Then, a certain price has to be paid by the energy gateway to the charger. The energy price of different chargers can be different and time-varying. We assume that the energy gateway visits only one charger at a time, and thus it receives energy only from the corresponding charger. By contrast, when the energy gateway is at the users, a certain amount of energy may be transferred to the nearby users. The energy transfer to the users is performed in a broadcast manner (i.e., multiple users can receive energy simultaneously), which is a typical nature of RF energy transfer. The users are assumed to be geographically distributed following a Poisson spatial distribution [179]. The user receives RF energy from the energy gateway, and pays a retail energy price to the energy gateway. We assume that, once an energy user requests energy transfer from the energy gateway, it accepts all the energy transferred, e.g., the energy user could be a battery-less device which employs the received energy immediately. Note that the amount of energy transferred from the charger to the energy gateway can be different and usually higher than that transferred from the energy gateway to the users.

Based on the above system model, we aim to design an energy management scheme for the energy gateway. The scheme assists the energy gateway to decide whether to receive energy from the charger and whether to transfer energy to the users or not. The decision is

based on the system states, which are defined based on location, energy prices at chargers, and the number of users which are able to receive energy from the energy gateway. To make the model tractable, we assume that the decision making by the energy gateway is time-slotted, and each time slot is called a decision period. Only one decision is made in one decision period.

Note that the energy pricing (i.e., from chargers to the energy gateway and from the energy gateway to users) is beyond the scope of the chapter. We assume that the set of prices are predetermined. Finding optimal prices is a separate issue that could be studied in the future work.

3.1.1 RF Energy Propagation Model and User Payment

The energy gateway transfers energy to users by RF energy transfer technique. With the energy successfully received, the user makes payment to the energy gateway (e.g., in the form of real money transaction or fictitious token). Due to path loss, an amount of energy received by different users may vary. We assume that if the received energy does not exceed the demand of a user, the payment of the user will be based on the actual energy received.

We assume that the energy transferring time is fixed and less than a time slot, depending on the property of the energy gateway. Signals will be sent to the end users by the energy gateway to start and terminate the energy transfer. As a result, the durations of all the end users receiving energy are identical. As introduced in Section 2.2.2.1, the amount of energy (i.e., in Joule) received by user n during the energy transfer duration can be expressed using the Friis' formula [68], as follows:

$$e_n^R = \zeta_{RF/DC} G_t G_{r,n} \left(\frac{\lambda}{4\pi R_n} \right)^2 E_S, \quad (3.1)$$

where $\zeta_{RF/DC}$ is the RF-to-DC energy conversion efficiency [51]. G_t and $G_{r,n}$ are the energy transmitting antenna gain of the energy gateway and the receiving antenna gain of the user n , respectively. λ is the wavelength of energy transfer signal. R_n is the distance from the energy gateway to the user n . For simplicity of notation, we let $\zeta_{RF/DC} G_t G_{r,n} \left(\frac{\lambda}{4\pi} \right)^2 = g$ where g is a constant. From (3.1), the amount of energy received by any user is inversely

proportional to the square of the distance to the energy gateway, given fixed amount of transmitted energy E_S .

By Section 2.2.2.1, the Friis' transmission formula only applies when the distance R_n between the user n and the energy gateway satisfies $R_n > R_f$, where R_f is the Fraunhofer distance satisfying:

$$R_f = \frac{2D_a^2}{\lambda}, \quad R_f \gg \lambda, \quad \text{and} \quad R_f \gg D_a, \quad (3.2)$$

where D_a is the largest dimension of the user's antenna. For the users in the near-field of the energy gateway, i.e., $0 \leq R_n \leq R_f$, the distance is short such that we assume that the energy can be transferred without loss. Let the maximum energy demand of user n be e_n^D , the distance

$$R_n^D = \sqrt{g \frac{E_S}{e_n^D}}, \quad (3.3)$$

is a boundary distance. The demand of the user will not be satisfied for $R_n > R_n^D$, and the demand will be fully met otherwise.

We consider that the energy transfer is performed in a spherical spatial area (e.g., a circle area in 2-dimension space). The area is centered at the energy gateway with radius R , where R is the longest distance that the user can receive any energy. The area is divided into the following subareas:

- When user n has the distance $0 \leq R_n < \max\{R_f, R_n^D\}$, the demand of the user will be fully met.
- For $\max\{R_f, R_n^D\} \leq R_n \leq R$, the amount of energy e_n^R will be received by the user, with demand not fully being satisfied.
- For $R_n > R$, the user cannot receive any energy. The user is defined to be in the energy outage zone of the energy gateway.

The distance R is treated as a cut-off distance. All the users located at the energy outage zone will not be considered as valid users for the energy gateway.

After receiving the energy with amount e_n^R , the user n will inform the mobile energy gateway this information with the payment of energy price. We assume that the user always

reports truthful information. As we assume, the users are geographically distributed following a Poisson spatial distribution. The probability density function (pdf) of the distance l between the user n (out of maximum N users) and the energy gateway (i.e., an origin) is expressed as follows [179]:

$$f(n, l|N) = \frac{3}{R} \frac{B(n + \frac{2}{3}, N - n + 1)}{B(N - n + 1, n)} \beta\left(\frac{l^3}{R^3}; n + \frac{2}{3}, N - n + 1\right), \quad (3.4)$$

where $B(a, b) = \Gamma(a)\Gamma(b)/\Gamma(a + b)$, and $\Gamma(\cdot)$ is the Gamma function. $\beta(x; y, z) = \frac{x^{y-1}(1-x)^{z-1}}{B(y, z)}$ is the Beta density function [179].

The expected payment $\Phi(n, E_S)$ made by user n to the energy gateway is obtained as follows:

$$\Phi(n, E_S) = \int_0^{R^\circ} f(n, l|N) r(e_n^D) dl + \int_{R^\circ}^R f(n, l|N) r(g \frac{E_S}{l^2}) dl, \quad (3.5)$$

where $R^\circ = \min\{R, \max\{R_f, R_n^D\}\}$. The first term in (3.5) indicates the total payment of the users, whose demands are all fully satisfied. The second term in (3.5) indicates the total payment of users whose demands are partly satisfied, calculated from (3.1), due to path loss and RF-to-DC energy conversion efficiency. The functions $r(e_n^D)$ and $r(g \frac{E_S}{l^2})$ indicate the energy price of the amount of received energy to be e_n^D and $e_n^R = g \frac{E_S}{l^2}$, respectively.

The total average payment received by the energy gateway is obtained from

$$R(N, E_S) = \sum_{n=1}^N \Phi(n, E_S). \quad (3.6)$$

3.1.2 Uniform Payment for Energy Transfer

With large enough energy E_S transferred by the energy gateway, the demands of all the users are satisfied, i.e., $e_n^R \geq e_n^D \forall n \in \{1, 2, \dots, N\}$. This is the case when $R^\circ = R$, $\forall n \in \{1, 2, \dots, N\}$. The payment from user n to the energy gateway becomes

$$\Phi(n, E_S) = r(e_n^D), \quad (3.7)$$

since $\int_0^R f(n, l|N) dl = 1$. Thus, the total average payment from all the users to the energy gateway is

$$R(N, E_S) = \sum_{n=1}^N \Phi(n, E_S) = \sum_{n=1}^N r(e_n^D), \quad (3.8)$$

which can be simplified as $R(N, E_S) = Nr(e^D)$ for the case that all the users have the same energy demand denoted by e^D .

3.2 Optimization Problem Formulation

We formulate an MDP model to obtain the optimal energy management policy for the energy gateway. The MDP model consists of the system states, transition matrices among the states, the actions and corresponding reward of the energy gateway.

3.2.1 State Space and Action Space

The state space of the mobile energy gateway is defined as follows:

$$\mathbb{S} = \left\{ \mathcal{S} = (\mathcal{L}, \mathcal{E}, \mathcal{N}, \mathcal{P}) \mid \mathcal{L} \in \mathbb{L}, \mathcal{E} \in \mathbb{G}, \mathcal{N} \in \mathbb{N}, \mathcal{P} \in \mathbb{P} \right\}, \quad (3.9)$$

where $\mathcal{S}$ is a composite state consisting of all the system state variables $\mathcal{L}$, $\mathcal{E}$, $\mathcal{N}$, and $\mathcal{P}$.

- There are totally L locations. The location state is denoted by $\mathcal{L} \in \mathbb{L} = \{1, 2, \dots, L\}$, where $\mathbb{L}$ is the set of all locations that the energy gateway can visit.
- Energy state $\mathcal{E} \in \mathbb{G} = \{0, 1, \dots, E\}$ is the current amount of energy in the energy gateway's battery. The capacity of the battery is E units of energy.
- User state $\mathcal{N} \in \{0, 1, \dots, N\}$ denotes the number of users that the energy gateway can transfer energy to at the current location. We assume that the maximum number of users that the mobile energy gateway can transfer energy to is finite and denoted by N .
- Price state $\mathcal{P}$ is a composite state for the energy prices at all the chargers. $\mathcal{P}$ is denoted by $\mathcal{P} = (\mathcal{P}_1, \mathcal{P}_2, \dots, \mathcal{P}_M)$, where $\mathcal{P}_i, i = 1, 2, \dots, M$, is the energy price at location i with a charger. M is the total number of locations with chargers. We assume that the price state $\mathcal{P}_i$ of each charger takes a value from a finite discrete set of energy price, i.e., $\mathcal{P}_i \in \mathbb{P}_\cup = \{\rho_1, \rho_2, \dots, \rho_K\}$, where $\mathbb{P}_\cup$ is the set of all the K possible prices. This assumption is widely adopted in the literature [180].

The action of the energy gateway is denoted by $\mathcal{A} \in \mathbb{A} = \{0, 1, 2\}$, where $\mathbb{A}$ is the action space. The action $\mathcal{A} = 1$ indicates that the energy gateway requests for charging from the charger at the current location. The action $\mathcal{A} = 2$ indicates that the energy gateway transfers energy to the users. The action $\mathcal{A} = 0$ indicates that the energy gateway is idle (i.e., doing nothing).

3.2.2 Transition Matrices of System States

The current state $\mathcal{S} = (\mathcal{L}, \mathcal{E}, \mathcal{N}, \mathcal{P})$ transits to the next state $\mathcal{S}' = (\mathcal{L}', \mathcal{E}', \mathcal{N}', \mathcal{P}')$. In the following, we derive the probability matrices for the state transition.

3.2.2.1 Price State Transitions

The price state transition matrix for the charger at location i is expressed as follows:

$$\mathbf{P}_i = \begin{bmatrix} \psi_{1,1}^{p_i} & \cdots & \psi_{1,K}^{p_i} \\ \vdots & \ddots & \vdots \\ \psi_{K,1}^{p_i} & \cdots & \psi_{K,K}^{p_i} \end{bmatrix}, \quad (3.10)$$

where $\psi_{k,k'}^{p_i}$ indicates the probability that state $\mathcal{P}_i$ changes from $\mathcal{P}_i = k$ to $\mathcal{P}_i = k'$, where $k, k' \in \mathbb{P}_\cup$. Thus, the transition matrix for the composite price state $\mathcal{P}$ is obtained from

$$\mathbf{W}_P = \mathbf{P}_1 \otimes \mathbf{P}_2 \otimes \cdots \otimes \mathbf{P}_M, \quad (3.11)$$

where $\otimes$ is the Kronecker product. We denote the element in $\mathbf{W}_P$ with row k and column k' to be $\psi_{k,k'}^P$, which is the transition probability of the composite price state $\mathcal{P}$.

3.2.2.2 Location State Transitions

We divide the set of locations $\mathbb{L}$ into three subsets, i.e., $\mathbb{L}_B$, $\mathbb{L}_S$ and $\mathbb{L}_{NC}$ based on the attributes of the locations, where $\mathbb{L} = \mathbb{L}_B \cup \mathbb{L}_S \cup \mathbb{L}_{NC}$. The subset $\mathbb{L}_B$ includes all the locations with chargers. $\mathbb{L}_S$ includes all the locations where there are users but no chargers. $\mathbb{L}_{NC}$ is the subset where the energy gateway has contact to neither chargers nor users. We simply assume $\mathbb{L}_B \cap \mathbb{L}_S = \emptyset$, $\mathbb{L}_B \cap \mathbb{L}_{NC} = \emptyset$, and $\mathbb{L}_S \cap \mathbb{L}_{NC} = \emptyset$. We denote the total number of locations in the subset $\mathbb{L}_B$ to be L_B (i.e., $L_B = |\mathbb{L}_B|$). Likewise, $L_S = |\mathbb{L}_S|$ and $L_{NC} = |\mathbb{L}_{NC}|$. Clearly, $L = L_B + L_S + L_{NC}$.

The transition of the location state $\mathcal{L}$ of the energy gateway can be expressed by the following transition matrix:

$$\mathbf{W}_L = \begin{bmatrix} \mathbf{L}_{NC,NC} & \mathbf{L}_{NC,B} & \mathbf{L}_{NC,S} \\ \mathbf{L}_{B,NC} & \mathbf{L}_{B,B} & \mathbf{L}_{B,S} \\ \mathbf{L}_{S,NC} & \mathbf{L}_{S,B} & \mathbf{L}_{S,S} \end{bmatrix}, \quad (3.12)$$

the elements of which denote the transition matrices among the three subsets. $\mathbf{L}_{k,k'}$ contains the transition probabilities when the current location is in subset k , and the next location

is in subset k' . For example, $\mathbf{L}_{S,B}$ means the current location of the energy gateway is in subset $\mathbb{L}_S$, and the next location is in subset $\mathbb{L}_B$. Each element $\psi_{m,m'}^l$ in $\mathbf{L}_{k,k'}$ denotes the transition probability from a current location m in subset k , to the next location m' in subset k' .

3.2.2.3 Energy State Transitions

Next, we derive the energy state transition matrix of the energy gateway. Energy state transitions can be divided into three cases:

- Firstly, the energy state may increase. This occurs when the energy gateway receives E_B units of energy from a charger. Recall that E is the capacity of the energy gateway's battery. The transition matrix for this case is given as follows:

$$\mathbf{E}^+(\mathcal{E}, \mathcal{E}' | \mathcal{L}) = \begin{bmatrix} 1 - \eta_{\mathcal{L}} & \mathbf{0}_{(E_B-1) \times 1} & \eta_{\mathcal{L}} & & \\ & \ddots & & \ddots & \\ & & 1 - \eta_{\mathcal{L}} & \mathbf{0}_{(E_B-1) \times 1} & \eta_{\mathcal{L}} \\ & & & \ddots & \vdots \\ & & & & 1 - \eta_{\mathcal{L}} & 0 & \eta_{\mathcal{L}} \\ & & & & & 1 - \eta_{\mathcal{L}} & \eta_{\mathcal{L}} \\ & & & & & & 1 \end{bmatrix}_{(E+1) \times (E+1)}, \quad (3.13)$$

where each row of the matrix denotes the current energy state $\mathcal{E}$, and each column denotes the energy state of the next decision period $\mathcal{E}'$. $\eta_{\mathcal{L}}$ is the efficiency of energy charging at location $\mathcal{L}$, i.e., the probability of successful charging. $\mathbf{0}_{(E_B-1) \times 1}$ is a row vector, which is composed of $E_B - 1$ zeros.

- Secondly, the energy state may decrease. This can happen when the energy gateway transfers E_S units of energy to users. In this case, the energy state may decrease by E_S , except that when there is less than E_S units of energy in the battery, we assume the energy gateway still transfers energy, so that the energy state decreases to $\mathcal{E}' = 0$.

The transition matrix is as follows:

$$\mathbf{E}^-(\mathcal{E}, \mathcal{E}'|\mathcal{L}) = \begin{bmatrix} 1 & & & & & \\ 1 & 0 & & & & \\ 1 & 0 & 0 & & & \\ \vdots & & & \ddots & & \\ 1 & \mathbf{0}_{(E_S-1) \times 1} & & 0 & & \\ & \ddots & & & \ddots & \\ & & 1 & \mathbf{0}_{(E_S-1) \times 1} & & 0 \end{bmatrix}_{(E+1) \times (E+1)} \quad (3.14)$$

$\mathbf{0}_{(E_S-1) \times 1}$ is a row vector, which is composed of $E_S - 1$ zeros.

- The energy state can remain the same. For example, when the energy gateway does not receive or transfer any energy. In this case, we have the transition matrix $\mathbf{E}^0 = \mathbf{I}_{E+1}$, where $\mathbf{I}_{E+1}$ is an $(E + 1) \times (E + 1)$ identity matrix.

The changing of energy state depends on the current location, as well as the action of the energy gateway. Let $\mathbf{W}_{L,E}((\mathcal{L}, \mathcal{E}), (\mathcal{L}', \mathcal{E}')|\mathcal{A})$ denote the transition matrix from the current composite state $(\mathcal{L}, \mathcal{E})$ to the next state $(\mathcal{L}', \mathcal{E}')$. When action $\mathcal{A} = 0$ is taken, the corresponding transition matrix is expressed as follows:

$$\mathbf{W}_{L,E}((\mathcal{L}, \mathcal{E}), (\mathcal{L}', \mathcal{E}')|\mathcal{A} = 0) = \mathbf{W}_L \otimes \mathbf{E}^0, \quad (3.15)$$

where $\mathbf{E}^0$ indicates that the energy state $\mathcal{E}$ remains the same (i.e., $\mathcal{E} = \mathcal{E}'$) regardless of the location state of the energy gateway.

When action $\mathcal{A} = 1$ is taken, i.e., the energy gateway requests for energy charging, the corresponding transition matrix is expressed as follows:

$$\mathbf{W}_{L,E}((\mathcal{L}, \mathcal{E}), (\mathcal{L}', \mathcal{E}')|\mathcal{A} = 1) = \begin{bmatrix} \mathbf{L}_{NC,NC} \otimes \mathbf{E}^0 & \mathbf{L}_{NC,B} \otimes \mathbf{E}^0 & \mathbf{L}_{NC,S} \otimes \mathbf{E}^0 \\ \mathbf{L}_{B,NC} \otimes \mathbf{E}^+ & \mathbf{L}_{B,B} \otimes \mathbf{E}^+ & \mathbf{L}_{B,S} \otimes \mathbf{E}^+ \\ \mathbf{L}_{S,NC} \otimes \mathbf{E}^0 & \mathbf{L}_{S,B} \otimes \mathbf{E}^0 & \mathbf{L}_{S,S} \otimes \mathbf{E}^0 \end{bmatrix}. \quad (3.16)$$

The matrix on the right hand side of (3.16) has the dimension of $(E + 1)L \times (E + 1)L$. As shown in Fig. 3.2, in this case, when the energy gateway is not at any charger (i.e., the current location state $\mathcal{L}$ belongs to subset $\mathbb{L}_S$ or $\mathbb{L}_{NC}$) the energy gateway cannot receive any energy. Consequently, $\mathbf{E}^0$ is applied to the row corresponding to the location states $\mathcal{L} \in \mathbb{L}_S$ and $\mathcal{L} \in \mathbb{L}_{NC}$. Otherwise, the energy gateway will receive energy, and the matrix $\mathbf{E}^+$ is applied for the location state $\mathcal{L} \in \mathbb{L}_B$.

Figure 3.2: Energy charging action: (a) with a charger, and (b) without any charger at the current location.

When the action $\mathcal{A} = 2$ is taken, the energy gateway transfers energy to users. The corresponding transition matrix is expressed as follows:

$$\mathbf{W}_{L,E}((\mathcal{L}, \mathcal{E}), (\mathcal{L}', \mathcal{E}') | \mathcal{A} = 2) = \mathbf{W}_L \otimes \mathbf{E}^-. \quad (3.17)$$

In this case, the energy state of the battery decreases. Note that the energy transferring action can be taken at all the locations. For the locations without energy users (i.e., $\mathcal{L} \in \mathbb{L}_{NC} \cup \mathbb{L}_B$), the energy gateway can still transfer energy, although no users will pay for and receive the transferred energy so that the transferred energy could be wasted, as shown in Fig. 3.3.

Figure 3.3: Energy transferring action: (a) with users, and (b) without any user at the current location.

3.2.2.4 User State Transitions

Here, the user state is the number of users that the energy gateway can transfer energy to. The transitions of the user state depend on the location of the energy gateway. For the energy gateway moving from the current location $\mathcal{L}$ to the next location $\mathcal{L}'$, the transition of the user state from $\mathcal{N}$ to $\mathcal{N}'$ has the following three cases:

- The energy gateway moves to the location with users (i.e., $\mathcal{L}' \in \mathbb{L}_S$). Thus, there will be some users that can receive energy from the energy gateway, and the user state is $\mathcal{N} \in \mathbb{N} = \{0, 1, \dots, N\}$.
- However, when the energy gateway moves to the location with a charger (i.e., $\mathcal{L}' \in \mathbb{L}_B$), there will be no users receiving energy from the energy gateway (e.g., the users may receive energy directly from the charger). Consequently, the user state of the energy gateway is $\mathcal{N} \equiv 0$.
- When the energy gateway moves to the location with neither chargers nor users (i.e., $\mathcal{L}' \in \mathbb{L}_{NC}$), similar to the previous case, the user state is $\mathcal{N} \equiv 0$.

For ease of presentation, we define the following matrices:

$$\mathbf{W}_{L,E}|\mathcal{L}' \in \mathbb{L}_B \cup \mathbb{L}_{NC} = \mathbf{W}_{L,E}((\mathcal{L}, \mathcal{E}), (\mathcal{L}', \mathcal{E}')|\mathcal{A}) \times \left(\begin{bmatrix} \mathbf{I}_{(L_{NC}+L_B) \times (L_{NC}+L_B)} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}_{L \times L} \otimes \mathbf{I}_{(E+1) \times (E+1)} \right), \quad (3.18)$$

$$\mathbf{W}_{L,E}|\mathcal{L}' \in \mathbb{L}_S = \mathbf{W}_{L,E}((\mathcal{L}, \mathcal{E}), (\mathcal{L}', \mathcal{E}')|\mathcal{A}) \times \left(\begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{L_S \times L_S} \end{bmatrix}_{L \times L} \otimes \mathbf{I}_{(E+1) \times (E+1)} \right), \quad (3.19)$$

where the matrix $\mathbf{I}_{Y \times Y}$ is a $Y \times Y$ identity matrix. $\mathbf{W}_{L,E}|\mathcal{L}' \in \mathbb{L}_S$ is a matrix with $[L(E+1)] \times [L(E+1)]$ dimensions, which has the physical meaning that it represents the part of transitions in matrix $\mathbf{W}_{L,E}((\mathcal{L}, \mathcal{E}), (\mathcal{L}', \mathcal{E}')|\mathcal{A})$ where the next location $\mathcal{L}'$ of the energy gateway is in subset $\mathbb{L}_S$ (i.e., with users), and masks the rest with zeros. Similarly, $\mathbf{W}_{L,E}|\mathcal{L}' \in \mathbb{L}_B \cup \mathbb{L}_{NC}$ represents the part of transitions in $\mathbf{W}_{L,E}((\mathcal{L}, \mathcal{E}), (\mathcal{L}', \mathcal{E}')|\mathcal{A})$ where $\mathcal{L}'$ belongs to subset $\mathbb{L}_B$ (i.e., with a charger) and subset $\mathbb{L}_{NC}$.

For $\mathcal{L}' \in \mathbb{L}_B \cup \mathbb{L}_{NC}$, we have $\mathcal{N} \equiv 0$. By contrast, for $\mathcal{L}' \in \mathbb{L}_S$, $\psi_{k,k'}^u$ denotes the probability that the user state changes from k to k' . The transition matrix of user state $\mathcal{N}$

considering states $\mathcal{L}$ and $\mathcal{E}$ is derived as follows:

$$\mathbf{W}_{L,E,N}|\mathcal{L}' \in \mathbb{L}_S = \begin{bmatrix} \psi_{0,0}^u & \cdots & \psi_{0,N}^u \\ \vdots & \ddots & \vdots \\ \psi_{N,0}^u & \cdots & \psi_{N,N}^u \end{bmatrix} \otimes \mathbf{W}_{L,E}|\mathcal{L}' \in \mathbb{L}_S, \quad (3.20)$$

where $\psi_{i,j}^u$ is the transition probability of an event that the user state changes from $i \in \mathbb{N}$ (for the current state) to $j \in \mathbb{N}$ (for the next decision period). Given the case that users are distributed spatially in Poisson distribution with the spatial density α , and the maximum number of users is finite and known (i.e., $N < +\infty$), $\psi_{i,j}^u$ is in the form of a truncated Poisson process defined as follows:

$$\psi_{i,j}^u = \begin{cases} e^{-\pi R^2 \alpha} \frac{(\pi R^2 \alpha)^j}{j!}, & \forall i \in \{1, \dots, N\}, \forall j \in \{1, \dots, N-1\}, \\ \sum_{k=N}^{+\infty} e^{-\pi R^2 \alpha} \frac{(\pi R^2 \alpha)^k}{k!}, & \forall i \in \{1, \dots, N\}, j = N, \end{cases} \quad (3.21)$$

Note that other spatial distributions and user state transition processes can be applied without affecting the optimization model. $\mathbf{W}_{L,E,N}|\mathcal{L}' \in \mathbb{L}_S$ is the transition matrix of $(\mathcal{L}, \mathcal{E}, \mathcal{N})$ when the next location $\mathcal{L}'$ is in subset $\mathbb{L}_S$. Similarly, $\mathbf{W}_{L,E,N}|\mathcal{L}' \in \mathbb{L}_B \cup \mathbb{L}_{NC}$ is the transition matrix of $(\mathcal{L}, \mathcal{E}, \mathcal{N})$ when the next location $\mathcal{L}'$ is in subset $\mathbb{L}_{NC}$ or $\mathbb{L}_B$, expressed as follows:

$$\mathbf{W}_{L,E,N}|\mathcal{L}' \in \mathbb{L}_B \cup \mathbb{L}_{NC} = \begin{bmatrix} \mathbf{1}_{(N+1) \times 1} & \mathbf{0}_{(N+1) \times N} \end{bmatrix} \otimes \mathbf{W}_{L,E}|\mathcal{L}' \in \mathbb{L}_B \cup \mathbb{L}_{NC}, \quad (3.22)$$

where $\mathbf{1}_{(N+1) \times 1}$ is a $(N+1) \times 1$ matrix of ones.

Then, the transition matrix of the current composite state $(\mathcal{L}, \mathcal{E}, \mathcal{N})$ to the next composite state $(\mathcal{L}', \mathcal{E}', \mathcal{N}')$ is given as follows:

$$\mathbf{W}_{L,E,N}((\mathcal{L}, \mathcal{E}, \mathcal{N}), (\mathcal{L}', \mathcal{E}', \mathcal{N}')|\mathcal{A}) = \mathbf{W}_{L,E,N}|\mathcal{L}' \in \mathbb{L}_S + \mathbf{W}_{L,E,N}|\mathcal{L}' \in \mathbb{L}_B \cup \mathbb{L}_{NC}. \quad (3.23)$$

3.2.2.5 Overall Transition Matrix

The transition matrix of the entire state space is denoted by $\mathbf{W}(\mathcal{S}, \mathcal{S}'|\mathcal{A})$, where the current composite state is $\mathcal{S} = (\mathcal{L}, \mathcal{E}, \mathcal{N}, \mathcal{P})$, and the next composite state is $\mathcal{S}' = (\mathcal{L}', \mathcal{E}', \mathcal{N}', \mathcal{P}')$, given action $\mathcal{A}$ which is taken by the energy gateway, as follows:

$$\mathbf{W}(\mathcal{S}, \mathcal{S}'|\mathcal{A}) = \mathbf{W}_{L,E,N}((\mathcal{L}, \mathcal{E}, \mathcal{N}), (\mathcal{L}', \mathcal{E}', \mathcal{N}')|\mathcal{A}) \otimes \mathbf{W}_P(\mathcal{P}, \mathcal{P}'). \quad (3.24)$$

3.3 Solving the MDP Optimization Model

In this section, we first define an immediate utility function of the energy gateway. Then, we present the MDP model. Next, we define the threshold structure of the optimal policy obtained from the MDP model.

3.3.1 Immediate Utility Function

An immediate utility function $u(\mathcal{S}, \mathcal{A})$ is defined as the reward of the energy gateway in the current decision period, given the composite state $\mathcal{S} = (\mathcal{L}, \mathcal{E}, \mathcal{N}, \mathcal{P})$. Without loss of generality, we adopt the following function of $u(\mathcal{S}, \mathcal{A})$, which has different forms given different locations $\mathcal{L}$ and actions $\mathcal{A}$ of the energy gateway, i.e.,

$$u(\mathcal{S}|\mathcal{A}) = \begin{cases} u_B(\mathcal{S}), & \mathcal{L} \in \mathbb{L}_B \text{ and } \mathcal{A} = 1, \\ u_S(\mathcal{S}), & \mathcal{L} \in \mathbb{L}_S \text{ and } \mathcal{A} = 2, \\ u_0(\mathcal{S}), & \text{otherwise,} \end{cases} \quad (3.25)$$

where $u_B(\mathcal{S})$ denotes the reward, which is obtained when the energy gateway is at the location with a charger (i.e., $\mathcal{L} \in \mathbb{L}_B$), and the charging action $\mathcal{A} = 1$ is taken. $u_S(\mathcal{S})$ denotes the reward when the energy gateway is at the location with users, and the action energy transfer $\mathcal{A} = 2$ is taken. $u_0(\mathcal{S})$ is the reward of the energy gateway being idle. $u_B(\mathcal{S})$, $u_S(\mathcal{S})$ and $u_0(\mathcal{S})$ are defined as follows:

$$u_B(\mathcal{S}) = -E_B \mathcal{P}(\mathcal{L}) - F(\mathcal{E}), \quad (3.26)$$

where E_B is the amount of energy transferred from the charger to the energy gateway, $\mathcal{P}(\mathcal{L}) \in \{\mathcal{P}_1, \mathcal{P}_2, \dots, \mathcal{P}_M\}$ is the current price state at the location $\mathcal{L}$, and $F(\mathcal{E})$ is the holding cost of the current energy state. This cost, for example, could be due to the compensation to the self-discharging effect [181, 182].

$$u_S(\mathcal{S}) = R(\mathcal{N}, E_S) - F(\mathcal{E}), \quad (3.27)$$

where E_S denotes the amount of energy transmitted at the energy gateway to the users. $R(\mathcal{N}, E_S)$ is the function indicating the payment from all $\mathcal{N}$ users at the current location. This function is defined as in (3.6) and (3.8).

$$u_0(\mathcal{S}) = -F(\mathcal{E}), \quad (3.28)$$

where only the holding cost of energy is applied.

Note that the immediate utility function $u_0(\mathcal{S})$ is used for the following cases. Firstly, the energy gateway takes the idle action $\mathcal{A} = 0$ regardless of the current location. Secondly, the charging action $\mathcal{A} = 1$ is taken when the current location has no charger (i.e., $\mathcal{L} \notin \mathbb{L}_B$). Thirdly, the energy transferring action is taken when the energy gateway is not at the location with users (i.e., $\mathcal{L} \notin \mathbb{L}_S$).

3.3.2 Solving the MDP Optimization Model

The objective of the MDP model is to obtain an optimal energy management policy for the energy gateway. A policy $\phi(\mathcal{A}|\mathcal{S})$ is defined as a mapping of state $\mathcal{S}$ to action $\mathcal{A}$ to be taken by the energy gateway. The optimal policy, denoted by $\phi^*(\mathcal{A}|\mathcal{S})$, aims to maximize the overall utility of the energy gateway.

The following Bellman equation [183] is applied to obtain the optimal policy, i.e.,

$$U(\mathcal{S}) = \max_{\phi(\mathcal{A}|\mathcal{S})} H(\mathcal{S}|\mathcal{A}) \quad (3.29)$$

$$\phi^*(\mathcal{A}|\mathcal{S}) = \arg \max_{\phi(\mathcal{A}|\mathcal{S})} H(\mathcal{S}|\mathcal{A}) \quad (3.30)$$

$$H(\mathcal{S}|\mathcal{A}) = u(\mathcal{S}|\mathcal{A}) + \gamma \sum_{\mathcal{S}' \in \mathbb{S}} W(\mathcal{S}, \mathcal{S}'|\mathcal{A}) U(\mathcal{S}') \quad (3.31)$$

where $\mathcal{S} = (\mathcal{L}, \mathcal{E}, \mathcal{N}, \mathcal{P})$ is the current state. The Bellman equation can be numerically solved by the value iteration algorithm [163]. $H(\cdot)$ denotes the overall utility of the energy gateway, including the immediate utility of the current state as well as that of all the possible future states. $U(\mathcal{S})$ is the achieved optimal overall utility. $\phi^*(\mathcal{A}|\mathcal{S})$ is the optimal policy. $\gamma \in [0, 1)$ is a discount factor of possible future states. $u(\mathcal{S}|\mathcal{A})$ and $\sum_{\mathcal{S}' \in \mathbb{S}} W(\mathcal{S}, \mathcal{S}'|\mathcal{A}) U(\mathcal{S}')$ are the current immediate utility and the expected future utility of the energy gateway, respectively. $W(\mathcal{S}, \mathcal{S}'|\mathcal{A})$ is the transition probability from the current state $\mathcal{S}$ to the next state $\mathcal{S}'$, which can be obtained from the transition matrix as given in (3.24). The complexity of solving the Bellman equation by the value iteration algorithm is $\mathcal{O}(|\mathbb{A}| \cdot |\mathbb{S}|^2)$ [184], where $|\mathbb{A}|$ is the number of actions, and $|\mathbb{S}|$ is the total number of states.

3.3.3 Threshold Structure of MDP Solutions

Next, we introduce the concept of a threshold policy, and prove the existence of the threshold policy in the optimal energy management policy obtained from solving the proposed MDP model.

3.3.3.1 The Concept of Threshold Policy

The optimal policy $\phi^*(\mathcal{A}|\mathcal{S})$ of the MDP model is defined to be a threshold policy, if the following condition holds:

$$\phi^*(\mathcal{A}|\Theta, \mathcal{S}_{-\Theta}) = \begin{cases} \mathcal{A}_1, & \text{for } \min \Theta \leq \Theta < \Theta_{thr,1}, \\ \mathcal{A}_i, & \text{for } \Theta_{thr,i-1} \leq \Theta < \Theta_{thr,i} \quad \forall i \in \{2, 3, \dots, |\mathbb{A}| - 1\}, \\ \mathcal{A}_{|\mathbb{A}|}, & \text{for } \Theta_{|\mathbb{A}|-1} \leq \Theta \leq \max \Theta, \end{cases} \quad (3.32)$$

where Θ is a state or composite state variable. $\mathcal{S}_{-\Theta}$ denotes the composite state of other states except Θ . $\phi^*(\mathcal{A}|\Theta, \mathcal{S}_{-\Theta})$ is the optimal action solved by the Bellman equation in (3.29)-(3.31) given the current state $\mathcal{S} = (\Theta, \mathcal{S}_{-\Theta})$. $\Theta_{thr,i}$ is called the i^{th} threshold of the state Θ . In other words, the action $\mathcal{A}$ is monotonic as the state Θ increases.

To prove that the optimal policy $\phi^*(\mathcal{A}|\mathcal{S})$ in (3.30) is a threshold policy, the concept of supermodularity/submodularity [185] is applied.

Definition 3.1 For $x \in \mathbb{X} \subseteq \mathbb{R}$, $y \in \mathbb{Y} \subseteq \mathbb{R}$, a function $f(x, y) \in \mathbb{R}$ is supermodular in (x, y) if $f(x_1, y_1) - f(x_1, y_2) \geq f(x_2, y_1) - f(x_2, y_2)$, $\forall x_1, x_2 \in \mathbb{X}, \forall y_1, y_2 \in \mathbb{Y}, x_1 > x_2, y_1 > y_2$. Similarly, $f(x, y)$ is submodular in (x, y) if $f(x_1, y_1) - f(x_1, y_2) \leq f(x_2, y_1) - f(x_2, y_2)$, $\forall x_1, x_2 \in \mathbb{X}, \forall y_1, y_2 \in \mathbb{Y}, x_1 > x_2, y_1 > y_2$.

The supermodularity/submodularity property of $f(x, y)$ is a sufficient condition of the non-decreasing/non-increasing monotonicity of $y = \arg \max_y f(x, y)$ [183, 185]. Specifically, in the proposed MDP model and Bellman equation given in (3.29)-(3.31), for a given state $\theta \in \{\mathcal{E}, \mathcal{L}, \mathcal{W}\}$, the fact that $H(\mathcal{S}|\mathcal{A})$ is supermodular/submodular in $(\theta, \mathcal{A})$ indicates that $\phi^*(\mathcal{A}|\theta)$ is non-decreasing/non-increasing in $\theta \in \{\mathcal{E}, \mathcal{L}, \mathcal{W}\}$. In particular, when θ increases, the optimal action only changes from 0 to 1 for the supermodularity case (or 1 to 0 for the submodularity case). Then from the definition in (3.32), the threshold policy holds.

3.3.3.2 Threshold Policy

Firstly, when the energy gateway is at the location with a charger, the threshold policy exists with respect to the energy state $\mathcal{E}$.

We first remove the action of energy transfer $\mathcal{A} = 2$ (i.e., the energy gateway never transfers energy when it is at the location with a charger). The proof is direct that $\mathcal{A} = 2$ is always dominated by the idle action $\mathcal{A} = 0$ in this case since the following condition holds:

$$H(\mathcal{S}|\mathcal{A} = 0) \geq H(\mathcal{S}|\mathcal{A} = 2), \quad \forall \mathcal{S} \in \mathbb{S}. \quad (3.33)$$

Thus, we have the following theorem when the energy gateway is at the location with a charger.

Theorem 3.1 *Given any user state $\mathcal{N}$, price state $\mathcal{P}$, and the location state $\mathcal{L} \in \mathbb{L}_B$, the optimal action policy of the energy gateway is a threshold policy in the energy state $\mathcal{E}$, if the holding cost $F(\mathcal{E})$ is a linear function in $\mathcal{E}$. The action of the energy gateway is $\mathcal{A} = 1$ if $\mathcal{E} \leq \mathcal{E}_{THRESHOLD}^{1-0}$, and $\mathcal{A} = 0$ otherwise.*

The threshold policy is binary that only the action $\mathcal{A} \in \{0, 1\}$ will be taken. The intuition is that when the energy gateway has less energy in its battery, it is more likely to receive energy from the charger. By the definition of submodularity as in Definition 3.1, Theorem 3.1 can be proven as in Section 3.6.1.

Similarly, when the energy gateway is at the location with users, the charging action $\mathcal{A} = 1$ is eliminated. We have the following theorem for the threshold policy with respect to the energy state $\mathcal{E}$.

Theorem 3.2 *Given any user state $\mathcal{N}$, price state $\mathcal{P}$, and the location state $\mathcal{L} \in \mathbb{L}_S$, the optimal action policy of the energy gateway is a threshold policy in the energy state $\mathcal{E}$, given that the holding cost $F(\mathcal{E})$ is a linear function in $\mathcal{E}$. The action of the energy gateway is $\mathcal{A} = 0$ when $\mathcal{E} \leq \mathcal{E}_{THRESHOLD}^{0-2}$, and $\mathcal{A} = 2$ otherwise.*

Again, the intuition is that when the energy gateway has more energy in its battery, it is more likely to transfer energy to the users. The proof of Theorem 3.2 is similar to that of Theorem 3.1, and therefore we omit it for brevity.

Finally, for the energy gateway at the location without any charger or users (i.e., the location state is in the subset $\mathbb{L}_{NC}$), the idle action $\mathcal{A} = 0$ is always taken, and a threshold policy with respect to the energy state $\mathcal{E}$ exists trivially. Therefore, the existence of threshold policy with respect to the energy state $\mathcal{E}$ in the optimal policy is completely proven.

In the similar spirit, when the energy gateway is at the location with a charger, a threshold policy with respect to the energy price of a particular charger $\mathcal{P}_i$, $\forall i \in \{1, 2, \dots, M\}$ exists as stated in the following theorem.

Theorem 3.3 *Given any user state $\mathcal{N}$, price state $\mathcal{P}_{-i} = (\mathcal{P}_1, \dots, \mathcal{P}_{i-1}, \mathcal{P}_{i+1}, \dots, \mathcal{P}_M)$ (except the i^{th} price component), and the location state $\mathcal{L} \in \mathbb{L}_B$, the optimal action policy of the energy gateway is a threshold policy in the i^{th} price state component $\mathcal{P}_i$.*

The intuition is that if the energy price is higher, the energy gateway is less likely to receive energy from the charger since it incurs smaller reward.

When the energy gateway is at the location with users, we have the following theorem for a threshold policy with respect to the user state $\mathcal{N}$.

Theorem 3.4 *Given any price state $\mathcal{P}$, energy state $\mathcal{E}$, and the location state $\mathcal{L} \in \mathbb{L}_S$, the optimal action policy of an energy gateway is a threshold policy in the user state $\mathcal{N}$.*

The intuition is that when there are more number of users that can receive energy from the energy gateway, the energy gateway is likely to take the action to transfer energy due to higher reward. The proofs of Theorems 3.3 and 3.4 are similar to that of Theorem 3.1, and therefore we omit it for brevity.

3.4 Numerical Results

3.4.1 System Settings

3.4.1.1 System Parameters

Unless otherwise stated, we use the following parameter setting to evaluate and compare the performance of different schemes.

- There are three locations in the network: Location $\mathcal{L} = 1$ has neither charger nor user, i.e., $\mathcal{L} = 1$ is in the subset $\mathbb{L}_{NC}$. Location $\mathcal{L} = 2$ belongs to $\mathbb{L}_B$ where the charger exists. At location $\mathcal{L} = 3$, the energy gateway can transfer energy to users, i.e., $\mathcal{L} = 3 \in \mathbb{L}_S$. The transition matrix of location state $\mathcal{L}$ is

$$\mathbf{W}_L = \begin{bmatrix} 0.02 & 0.29 & 0.69 \\ 0.02 & 0.29 & 0.69 \\ 0.02 & 0.29 & 0.69 \end{bmatrix}, \quad (3.34)$$

which indicates that the energy gateway has the probability of 0.29 to be with the charger, and the probability of 0.69 to be with users.

- The battery of the energy gateway has the capacity of 5 units of energy, i.e., $E = 5$.
- The charger provides the energy charging service at three different prices, denoted by $\mathbb{P} = \{0.1, 1.0, 5.0\}$. The price state changes among the three prices uniformly, i.e., $\mathbf{W}_P = \mathbf{P}_1 = [\frac{1}{3}]_{3 \times 3}$, as in (3.11).

- The spatial density of users is $\alpha = 0.005$ per unit of area. The energy transferring range is set as $R = 10\text{m}$.
- The energy gateway receives one unit of energy from the charger, and transfers one unit of energy to users, i.e., $E_B = E_S = 1$. The probability of successfully receiving energy from the charger is 0.85.
- For the immediate utility function given in (3.25), we assume that the cost of holding energy is negligible, i.e., $H(\mathcal{E}) \equiv 0$. The utility function of charging is expressed as $u_B(\mathcal{S}) = -E_B \mathcal{P}$. For transferring energy to users, we consider the case where the energy demands of all users are met, as in (3.8). We set the uniform payment as follows: $r(e_d) \equiv 1.0$. Therefore, in (3.25), $u_S(\mathcal{S}) = R(\mathcal{N}, E_S) = 1.0\mathcal{N}$, where 1.0 indicates the payment from a user to the energy gateway.
- The discount factor in the Bellman equation is $\gamma = 0.95$.

3.4.1.2 Baseline Schemes and Evaluation Criteria

We compare the proposed MDP-based scheme with four baseline energy management schemes. These schemes are as follows:

- (i) A greedy scheme (GRDY): The energy gateway always takes the action to maximize the immediate utility function (i.e., a myopic strategy).
- (ii) A location-aware scheme (LOCA): The energy gateway always takes charging ($\mathcal{A} = 1$), transferring ($\mathcal{A} = 2$), and idle ($\mathcal{A} = 0$) actions at the locations with a charger (i.e., subset $\mathbb{L}_B$), with users (subset $\mathbb{L}_S$), and with neither charger nor users (subset $\mathbb{L}_{NC}$), respectively.
- (iii) A random scheme (RND): The action taken by the energy gateway is randomly selected from $\mathbb{A} = \{0, 1, 2\}$, with the probability of $\frac{1}{3}$ for each action.
- (iv) A location-aware random scheme (LRND): The energy gateway takes actions $\mathcal{A} = 0$ and $\mathcal{A} = 1$ when it is at the location in subset $\mathbb{L}_B$. It takes actions $\mathcal{A} = 0$ and $\mathcal{A} = 2$ when it is at the location in subset $\mathbb{L}_S$. Finally, it takes action $\mathcal{A} \equiv 0$ at the location in subset $\mathbb{L}_{NC}$.

We assume that the energy gateway is initialized at any state $S \in \mathbb{S}$ with the probability $p_{ent} = 1/|\mathbb{S}|$. By adopting different energy management schemes, we evaluate the expected utility of the energy gateway, energy charging (or transferring) rate, average energy level, and successful energy transferring rate. Here, the successful energy transferring rate is the probability of the states at which the energy gateway receives and stores enough energy to be transferred.

3.4.1.3 Threshold Policy

Figure 3.4 shows that an optimal energy management policy obtained from the proposed MDP-based scheme is a threshold policy. In particular, the threshold policy with respect to the price state $\mathcal{P}$ is shown in Figures 3.4(a) to (d). Figures 3.4(a) and (c) show the policies for the location state $\mathcal{L} = 1$, i.e., the energy gateway is at the location with a charger. In this case, the action taken by the energy gateway changes from $\mathcal{A} = 1$ (i.e., charging) to $\mathcal{A} = 0$ (i.e., idle) as the price state $\mathcal{P}$ increases. For example, in Figure 3.4(a), at the energy state $\mathcal{E} = 2$, the action $\mathcal{A} = 1$ is taken when $\mathcal{P} = 1$ as well as $\mathcal{P} = 2$, and $\mathcal{A}$ changes to 0 when $\mathcal{P}$ increases to 3. However, when the energy gateway is at the location with users, i.e., $\mathcal{L} = 2$, as shown in Figures 3.4(b) and (d), no threshold policy exists with respect to $\mathcal{P}$ since the energy gateway cannot request and receive energy from the charger. Consequently, the actions are not affected by the price state $\mathcal{P}$.

From Figures 3.4(d) and (f), when the energy gateway is at the location with users, i.e., $\mathcal{L} = 2$, the threshold policy exists with respect to $\mathcal{N}$. As $\mathcal{N}$ increases, the action of the energy gateway changes from $\mathcal{A} = 0$ to $\mathcal{A} = 2$ (i.e., an energy transferring action). This is due to the fact that the energy gateway gains higher utility by transferring energy when more users can receive energy. By contrast, as depicted in Figures 3.4(c) and (e) where the location state is fixed as $\mathcal{L} = 1$ (i.e., at the location with a charger), there is no threshold policy with respect to $\mathcal{N}$ since the number of users does not affect the charging decision of the energy gateway.

The energy state $\mathcal{E}$ affects the action of the energy gateway when it is at the location with either the charger or user, as shown in Figures 3.4(a), (b), (e) and (f). When the energy gateway is at the location $\mathcal{L} = 1$ where the charger exists, as shown in Figures 3.4(a) and

Figure 3.4: Threshold in actions for different (a) price state $\mathcal{P}$ and energy state $\mathcal{E}$ (when $\mathcal{L} = 1$ and $\mathcal{N} = 2$), (b) price state $\mathcal{P}$ and energy state $\mathcal{E}$ (when $\mathcal{L} = 2$ and $\mathcal{N} = 2$), (c) price state $\mathcal{P}$ and user state $\mathcal{N}$ (when $\mathcal{L} = 1$ and $\mathcal{E} = 2$), (d) price state $\mathcal{P}$ and user state $\mathcal{N}$ (when $\mathcal{L} = 2$ and $\mathcal{E} = 2$), (e) user state $\mathcal{N}$ and energy state $\mathcal{E}$ (when $\mathcal{L} = 1$ and $\mathcal{P} = 1$), and (f) user state $\mathcal{N}$ and energy state $\mathcal{E}$ (when $\mathcal{L} = 2$ and $\mathcal{P} = 1$).

(e), the action changes from $\mathcal{A} = 1$ to $\mathcal{A} = 0$ as $\mathcal{E}$ increases. This is because the energy gateway tends to request and receive energy when its battery (energy) level is low (e.g., $\mathcal{E} \leq 3$ in Figure 3.4(e)). The energy gateway stops charging when its energy level is high enough (e.g., $\mathcal{E} > 3$ in Figure 3.4(e)) to avoid the cost from charging. By contrast, when the energy gateway is at the location with users (i.e., $\mathcal{L} = 2$), the energy transferring action $\mathcal{A} = 2$ is preferred as $\mathcal{E}$ becomes larger (e.g., $\mathcal{E} \geq 2$ in Figure 3.4(b)). Specifically, the energy gateway is more likely to transfer energy to the users when it has sufficient energy in its battery.

3.4.2 Maximum Energy Capacity of Mobile Energy Gateway: Impacts to Optimality

We evaluate different performance measures and compare the proposed MDP-based scheme with the other baseline schemes. The results are shown in Figures 3.5 and 3.6, when the maximum capacity E of the energy gateway's battery changes from 0 to 9.

Figure 3.5: Impacts of maximum energy capacity E to (a) expected utility, (b) energy charging rate, and (c) energy transferring rate.

Figure 3.5(a) shows the expected utilities of the energy gateway by adopting different energy management schemes. The proposed MDP-based scheme achieves optimal performance in terms of utility, compared with all the baseline schemes. From Fig. 3.5(a), although the computational complexity of solving the MDP-based scheme is $\mathcal{O}(|\mathcal{A}| \cdot |\mathcal{S}|^2)$, which is larger than $\mathcal{O}(1)$ of the baseline schemes, the expected utility obtained increases significantly compared with other baseline schemes. As the maximum capacity E of the en-

energy gateway's battery increases, the utilities obtained from the MDP-based and baselines schemes increase. This is because that, when E becomes large, the energy gateway can store more energy to be transferred to users, and thus gain more utility.

Figures 3.5(b) and (c) show the energy charging ($\mathcal{A} = 1$) rate from the chargers and energy transferring ($\mathcal{A} = 2$) rate to users, respectively. Both Figures 3.5(b) and (c) highlight that the energy charging and transferring rates first increase, and then become stable at a certain level as the maximum capacity E increases. In this case, when E is relatively small, the increased capacity E allows the energy gateway to receive and store more energy (i.e., taking action $\mathcal{A} = 1$). Thus, the energy gateway has more opportunity to transfer energy (i.e., $\mathcal{A} = 2$) to the users. Consequently, both the energy charging/transferring rates increase. However, as E continues to increase, the cost (i.e., negative utility) of charging $u_B(\mathcal{S})$ prevents the energy gateway from charging, and thus curtails the energy transfer. Therefore, both the curves of energy charging/transferring rates plateau as E is large enough, i.e., when $E \geq 4$ in Figures 3.5(b) and (c).

Observed from the curves of GRDY in Figures 3.5(a) and (b), the greedy scheme is not practical, even though it yields acceptable utility as shown in Figure 3.5(a). As the system operates, the energy gateway tends not to charge from the chargers, since the value of $u_B(\mathcal{S})$ (as in (3.26)) is always not more than 0. Therefore, the energy charging/transferring rates are both zero. The energy gateway will only exhaust the energy stored in its battery by transferring to the users, and never recharge again.

In Figure 3.6(a), the proposed MDP-based scheme has the higher average energy level for the energy gateway (i.e., more amount of energy stored in its battery) than that of the location-aware scheme. However, as shown in Figure 3.6(b), the location-aware scheme has the highest successful energy transferring rate. Thus, Figures 3.6(a) and (b) indicate that, although outperformed by the proposed MDP-based scheme in terms of expected utility as shown in Figure 3.5(a), the location-aware scheme can have higher efficiency in utilizing the energy stored in the battery. In particular, the location-aware scheme achieves higher successful energy transferring rate with lower energy state of the energy gateway, compared to the other schemes.

Figure 3.6: Impacts of maximum energy capacity E to (a) average energy level, and (b) Successful energy transferring rate.

Figure 3.6 can assist to design the hardware infrastructure of the energy gateway adopting the proposed MDP-based scheme. As shown in Figure 3.6(a), the average energy level stops increasing when $E > 5$. Moreover, simply increasing the maximum capacity E does not stimulate the energy gateway to charge, as shown by the results when $E > 4$ in Figures 3.5(b) and (c). In this case, the battery is not efficiently utilized when $E > 5$. As a result, although larger energy capacity leads to higher expected utility (as in Figure 3.5(a)), such a benefit diminishes after reaching a certain value (e.g., $E = 5$) to balance between the utility and the design and implementation cost of the energy gateway.

3.4.3 Impacts of User Spatial Density

Figure 3.7 shows and compares the performance when the spatial distribution density α of users increases from 1.0×10^{-3} to 1.0×10^{-2} .

As the user density increases, the users at location $\mathcal{L} = 3$ (i.e., in subset $\mathbb{L}_S$) becomes denser. The energy gateway can reach and supply energy to more users. In particular, the maximum number of users N increases, and the user state $\mathcal{N}$ tends to be larger. Consequently, the energy transferring action is preferred since it generates more reward from more users. Subsequently, to have sufficient energy in the battery, the energy gateway has to take the charging action more frequently. The increases of the expected utility, energy charging and transferring rates, and successful energy transferring rate of the proposed MDP-based

Figure 3.7: Impacts of spatial density α of users to (a) expected utility, (b) energy charging rate, and (c) energy transferring rate.

scheme are shown in Figures 3.7(a), (b) and (c), respectively. The similar explanations to those in Section 3.4.2 apply.

3.4.4 Impacts of Energy Gateway Location and Energy Price

Next, we evaluate the impacts of the location states of the energy gateway, as well as the energy price of the charger on the performance and energy management policy. We will show that the performance of the MDP-based scheme is more stable comparing with the baseline schemes.

Figure 3.8: Impacts of location transmission matrix to (a) expected utility, (b) energy charging rate, and (c) energy transferring rate.

Apart from the default setting of the transition matrix of the location state $\mathcal{L}$ given in Section 3.4.2, we examine three different mobility patterns of the energy gateway. They

are based on three different location state transition matrices $\mathbf{W}_{L1}$, $\mathbf{W}_{L2}$ and $\mathbf{W}_{L3}$, with all the row vectors to be $[0.7, 0.15, 0.15]$, $[0.15, 0.7, 0.15]$ and $[0.15, 0.15, 0.7]$, respectively. Thus, $\mathbf{W}_{L1}$, $\mathbf{W}_{L2}$ and $\mathbf{W}_{L3}$ represent the cases that the energy gateway most frequently visits the locations in “no contact” subset ($\mathbb{L}_{NC}$), with a charger ($\mathbb{L}_B$) and with users ($\mathbb{L}_S$), respectively.

From Figure 3.8, the two location-aware baseline schemes (i.e., LOCA and LRND) and the random scheme (i.e., RND) are sensitively affected by the mobility variations. For example, as shown in Figure 3.8(a), when the energy gateway visits the location with the charger frequently (i.e., $\mathbf{W}_{L2}$ is applied), the utility of the location-aware scheme plunges sharply. This is because that the energy gateway loses much utility by taking the charging action ($\mathcal{A} = 1$) frequently, as shown in Figure 3.8(b). Similarly, the location-aware and location-aware random schemes require the energy gateway to increase the energy transferring ($\mathcal{A} = 2$) rate when $\mathbf{W}_{L3}$ is applied, as shown in Figure 3.8(c). This is due to the high probability that the energy gateway can transfer energy to users. We can conclude from the above results that with the proposed MDP-based scheme which incorporates the location as a state when making management (i.e., charging/transferring) decisions, the energy gateway will have more stable performance in terms of utility even with dramatically different mobility patterns.

Figure 3.9: Impacts of price state transition matrix to (a) expected utility, (b) energy charging rate, and (c) energy transferring rate.

Similarly, we examine different price variations of the chargers. For any charger i , the price state transition matrix $\mathbf{P}_i$ has all the row vectors to be $[0.7, 0.15, 0.15]$, $[0.15, 0.7, 0.15]$

and $[0.15, 0.15, 0.7]$, which, respectively, represent the cases that the charger has 70% of applying the prices of 0.1, 1.0 and 5.0 to the energy gateway, respectively (i.e., the energy gateway will experience low, medium, and high prices more frequently).

The performance measures of the MDP-based and baseline schemes in these three cases are depicted in Figure 3.9. When the charger is likely to apply a high price, the utilities obtained from LOCA, RND and LRND schemes fall because those schemes may not avoid charging when energy price is high, as shown in Figure 3.9(a). The proposed MDP-based scheme maintains utility at a high level by reducing the energy charging ($\mathcal{A} = 1$) rate when the price is high, as shown in Figure 3.9(b). However, the reduced charging rate from the proposed the MDP-based scheme causes a lower energy supply (i.e., lower average energy level of the battery).

3.5 Summary

This chapter has proposed a mobile energy gateway which carries RF energy from chargers, and transfers energy to end energy users. A Markov decision process (MDP) based model has been proposed for the energy gateway to achieve the optimal energy management policy, i.e., deciding whether the action of energy charge or transfer should be taken. The mobile energy gateway is a self-interested component. By adopting the MDP-based optimal policy, the energy gateway maximizes the overall utility. We have proven that the obtained optimal energy management policy has a threshold-type structure, which can be further used for efficient algorithm design to obtain the optimal policy given the system parameters alter. In the end, numerical results have been presented to show that the proposed MDP-based scheme outperforms other baseline schemes.

3.6 Appendix

3.6.1 Proof of Threshold Policy in the Energy State $\mathcal{E}$

Proof To prove the threshold policy, we examine the submodularity property of the overall utility function $H(\mathcal{S}|\mathcal{A})$ with respect to the energy state $\mathcal{E}$, i.e.,

$$[H(\mathcal{E}+1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=1) - H(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=1)] - [H(\mathcal{E}+1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=0) - H(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=0)] \leq 0. \quad (3.35)$$

With the definition of the overall utility function $H(\mathcal{S}|\mathcal{A})$ given in (3.31), we have the following derivations:

$$\begin{aligned} & H(\mathcal{E}+1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=1) - H(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=1) \\ = & u(\mathcal{E}+1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=1) - u(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=1) \\ & + \gamma \eta_{\mathcal{L}} \Psi_{coef} [U(\mathcal{L}', \mathcal{E}+1 + E_B, \mathcal{N}', \mathcal{P}') - U(\mathcal{L}', \mathcal{E} + E_B, \mathcal{N}', \mathcal{P}')] \\ & + \gamma(1 - \eta_{\mathcal{L}}) \Psi_{coef} [U(\mathcal{L}', \mathcal{E}+1, \mathcal{N}', \mathcal{P}') - U(\mathcal{L}', \mathcal{E}, \mathcal{N}', \mathcal{P}')], \end{aligned} \quad (3.36)$$

and

$$\begin{aligned} & H(\mathcal{E}+1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=0) - H(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=0) \\ = & u(\mathcal{E}+1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=0) - u(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=0) \\ & + \gamma \Psi_{coef} [U(\mathcal{L}', \mathcal{E}+1, \mathcal{N}', \mathcal{P}') - U(\mathcal{L}', \mathcal{E}, \mathcal{N}', \mathcal{P}')], \end{aligned} \quad (3.37)$$

where

$$\Psi_{coef} = \sum_{\mathcal{L}' \in \mathbb{L}_B \cup \mathbb{L}_{NC}} \psi_{\mathcal{L}, \mathcal{L}'}^l \sum_{\mathcal{P}' \in \mathbb{P}} \psi_{\mathcal{P}, \mathcal{P}'}^p I_{\mathcal{N}'=0} + \sum_{\mathcal{L}' \in \mathbb{L}_S} \psi_{\mathcal{L}, \mathcal{L}'}^l \sum_{\mathcal{P}' \in \mathbb{P}} \psi_{\mathcal{P}, \mathcal{P}'}^p \sum_{\mathcal{N}' \in \mathbb{N}} \psi_{\mathcal{N}, \mathcal{N}'}^u. \quad (3.38)$$

The coefficient Ψ_{coef} includes the transition probabilities from the current state $\mathcal{S}$ to the next state $\mathcal{S}'$. The first term of (3.38) represents the transition probability of the case that the location $\mathcal{L}'$ is in the subset $\mathbb{L}_B$ or $\mathbb{L}_{NC}$, such that $\mathcal{N}' \equiv 0$. The indicator function $I_{\mathcal{N}'=0}$ in (3.38) is defined as follows:

$$I_{\mathcal{N}'=0} = \begin{cases} 1, & \text{for } \mathcal{N}' = 0, \\ 0, & \text{otherwise.} \end{cases} \quad (3.39)$$

The second term of (3.38) represents the case that the location $\mathcal{L}'$ is in the subset $\mathbb{L}_S$ with users. $\Psi_{coef} \geq 0$ holds by definition.

From (3.36) and (3.37), the following inequality holds:

$$\begin{aligned} & [H(\mathcal{E}+1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=1) - H(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=1)] \\ & - [H(\mathcal{E}+1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=0) - H(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}=0)] \\ = & \gamma \eta_{\mathcal{L}} \Psi_{coef} \{ [U(\mathcal{L}', \mathcal{E}+1 + E_B, \mathcal{N}', \mathcal{P}') - U(\mathcal{L}', \mathcal{E} + E_B, \mathcal{N}', \mathcal{P}')] \\ & - [U(\mathcal{L}', \mathcal{E}+1, \mathcal{N}', \mathcal{P}') - U(\mathcal{L}', \mathcal{E}, \mathcal{N}', \mathcal{P}')] \} \\ \leq & 0. \end{aligned} \quad (3.40)$$

It holds because $\eta_{\mathcal{L}} \geq 0$, $\Psi_{coef} \geq 0$ and Lemma 3.1 in Section 3.6.2 holds. Consequently, the submodularity of $H(\mathcal{S}|\mathcal{A})$ is proven as in (3.40). According to Definition 3.1, the 1-to-0 threshold policy with respect to the energy state $\mathcal{E}$ exist.

□

3.6.2 Proof of Concavity of the Overall Utility Function $U(\mathcal{S})$

We prove the discrete concavity of the optimal overall utility function $U(\mathcal{S})$ given in (3.29) with respect to $\mathcal{E}$, given that $\mathcal{L} \in \mathbb{L}_B$, i.e., the energy gateway is at the location with a charger.

Lemma 3.1 *For any positive integer E_B , i.e., $E_B \in \mathbb{N}^+$, the optimal utility function holds for*

$$[U(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}) - U(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}})] - [U(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}) - U(\mathcal{E}, \mathcal{S}_{-\mathcal{E}})] \leq 0, \quad (3.41)$$

given the discrete concavity of the immediate utility function $u(\mathcal{S}|\mathcal{A})$ with respect to $\mathcal{E}$, which is defined as follows:

$$u(\mathcal{E} + 2, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}) - u(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}) \leq u(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}) - u(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A}), \quad (3.42)$$

regardless of $\mathcal{S}_{-\mathcal{E}}$ and $\mathcal{A}$.

Proof To solve the Bellman equation in (3.29)-(3.31), the value iteration algorithm [163] is applied to obtain the optimal overall utility $U(\mathcal{S})$. We denote the k^{th} iteration of $U(\mathcal{S})$ and $H(\mathcal{S}|\mathcal{A})$ to be $U_k(\mathcal{S})$ and $H_k(\mathcal{S}|\mathcal{A})$.

Let

$$U_k(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}) = H_k(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_3), \quad (3.43)$$

$$U_k(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}}) = H_k(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_2), \quad (3.44)$$

$$U_k(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}) = H_k(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_1), \quad (3.45)$$

$$U_k(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}) = H_k(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_0). \quad (3.46)$$

By optimality, either of the following two inequalities holds:

$$\begin{aligned}
& \leq \underbrace{[U_k(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}) - U_k(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}})] - [U_k(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}) - U_k(\mathcal{E}, \mathcal{S}_{-\mathcal{E}})]}_{\text{Term A}} \\
& \quad - \underbrace{[H_k(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_3) - H_k(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_3)]}_{\text{Term B}} \\
& \quad - [H_k(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_0) - H_k(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_0)],
\end{aligned} \tag{3.47}$$

or

$$\begin{aligned}
& \geq [U_k(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}) - U_k(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}})] - [U_k(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}) - U_k(\mathcal{E}, \mathcal{S}_{-\mathcal{E}})] \\
& \quad - [H_k(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_2) - H_k(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_2)] \\
& \quad - [H_k(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_1) - H_k(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_1)].
\end{aligned} \tag{3.48}$$

Induction is employed to prove the discrete concavity of $U(\mathcal{S})$ with respect to $\mathcal{E}$, given the discrete concavity of the immediate utility function $u(\mathcal{S}|A)$ in $\mathcal{E}$, as follows:

Case I: When (3.47) holds. For Term A:

$$\begin{aligned}
& H_k(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_3) - H_k(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_3) \\
= & I_{a_3=1} \left\{ u(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = 1) - u(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = 1) \right. \\
& + \gamma \eta_{\mathcal{L}} \Psi_{coef} \cdot [U_{k-1}(\mathcal{E} + 1 + 2E_B, \mathcal{S}'_{-\mathcal{E}}) - U_{k-1}(\mathcal{E} + 2E_B, \mathcal{S}'_{-\mathcal{E}})] \\
& \left. + \gamma(1 - \eta_{\mathcal{L}}) \Psi_{coef} \cdot [U_{k-1}(\mathcal{E} + 1 + E_B, \mathcal{S}'_{-\mathcal{E}}) - U_{k-1}(\mathcal{E} + E_B, \mathcal{S}'_{-\mathcal{E}})] \right\} \\
& + I_{a_3=0} \left\{ C(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = 0) - C(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = 0) \right. \\
& \left. + \gamma \Psi_{coef} \cdot [U_{k-1}(\mathcal{E} + 1 + E_B, \mathcal{S}'_{-\mathcal{E}}) - U_{k-1}(\mathcal{E} + E_B, \mathcal{S}'_{-\mathcal{E}})] \right\}.
\end{aligned} \tag{3.49}$$

Term B:

$$\begin{aligned}
& H_k(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_0) - H_k(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_0) \\
= & I_{a_0=1} \left\{ u(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = 1) - u(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = 1) \right. \\
& + \gamma \eta_{\mathcal{L}} \Psi_{coef} \cdot [U_{k-1}(\mathcal{E} + 1 + E_B, \mathcal{S}'_{-\mathcal{E}}) - U_{k-1}(\mathcal{E} + E_B, \mathcal{S}'_{-\mathcal{E}})] \\
& \left. + \gamma(1 - \eta_{\mathcal{L}}) \Psi_{coef} \cdot [U_{k-1}(\mathcal{E} + 1, \mathcal{S}'_{-\mathcal{E}}) - U_{k-1}(\mathcal{E}, \mathcal{S}'_{-\mathcal{E}})] \right\} \\
& + I_{a_0=0} \left\{ C(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = 0) - C(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = 0) \right. \\
& \left. + \gamma \Psi_{coef} \cdot [U_{k-1}(\mathcal{E} + 1, \mathcal{S}'_{-\mathcal{E}}) - U_{k-1}(\mathcal{E}, \mathcal{S}'_{-\mathcal{E}})] \right\}
\end{aligned} \tag{3.50}$$

Initial step: For the initial step $k = 0$, we let $U_0(\mathcal{S}) \equiv 0, \forall \mathcal{S} \in \mathbb{S}$. The discrete concavity of $U(\mathcal{S})$ holds since

$$\begin{aligned}
& H_1(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_3) - H_1(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_3) \\
= & u(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}) - u(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}}) \\
\leq & u(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}) - u(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}) \\
= & H_1(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_0) - H_1(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}|\mathcal{A} = a_0),
\end{aligned} \tag{3.51}$$

That is, $\Delta^2 U_1^{E_B} \leq 0$.

Inductive step: For the $(k - 1)^{\text{th}}$ step, suppose that $\Delta^2 U_{k-1}^{E_B} \leq 0$ holds, the following inequalities hold:

$$\begin{aligned}
& H_k(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}} | \mathcal{A} = a_3) - H_k(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}} | \mathcal{A} = a_3), \\
\leq & u(\mathcal{E} + 1 + E_B, \mathcal{S}_{-\mathcal{E}}) - u(\mathcal{E} + E_B, \mathcal{S}_{-\mathcal{E}}) \\
& + \gamma \Psi_{coef} \cdot [U_{k-1}(\mathcal{E} + 1 + E_B, \mathcal{S}'_{-\mathcal{E}}) - U_{k-1}(\mathcal{E} + E_B, \mathcal{S}'_{-\mathcal{E}})], \\
\leq & u(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}}) - u(\mathcal{E}, \mathcal{S}_{-\mathcal{E}}) \\
& + \gamma \Psi_{coef} \cdot [U_{k-1}(\mathcal{E} + 1 + E_B, \mathcal{S}'_{-\mathcal{E}}) - U_{k-1}(\mathcal{E} + E_B, \mathcal{S}'_{-\mathcal{E}})], \\
\leq & H_k(\mathcal{E} + 1, \mathcal{S}_{-\mathcal{E}} | \mathcal{A} = a_0) - H_k(\mathcal{E}, \mathcal{S}_{-\mathcal{E}} | \mathcal{A} = a_0).
\end{aligned} \tag{3.52}$$

As a result, $\Delta^2 U_k^{E_B} \leq 0$ holds, the k^{th} step is proven that $U_k(\mathcal{S})$ holds for the discrete concavity. Based on the uniqueness and convergence of the value iteration algorithm [186], the optimal overall utility function $U(\mathcal{S})$ holds for Lemma 3.1 in Case I.

Case II: (3.48) may hold when the cost of holding energy is ignored, i.e., $H(\mathcal{E}) \equiv 0$. Similar to Case I, the inequality $\Delta^2 U_{k-1}^{E_B} \geq 0$ can be proven using induction. We use contradiction to prove that the strict inequality relation does not hold in $\Delta^2 U_{k-1}^{E_B} \geq 0$. Specifically, only $\Delta^2 U_{k-1}^{E_B} = 0$ holds in this case.

Given that $\Delta^2 U_{k-1}^{E_B} > 0$ holds, $H(\mathcal{E}, \mathcal{S}_{-\mathcal{E}})$ is submodular with respect to $\mathcal{E}$ when $\mathcal{L} \in \mathbb{L}_B$. That is, the action $\mathcal{A}$ only changes from 0 to 1 when $\mathcal{E}$ increases, given other states fixed and $\mathcal{L} \in \mathbb{L}_B$. By definition, when $\mathcal{E} = E$, it is clear that $H(\mathcal{E} = E, \mathcal{S}_{-\mathcal{E}} | \mathcal{A} = 0) > H(\mathcal{E} = E, \mathcal{S}_{-\mathcal{E}} | \mathcal{A} = 1)$. Then $\mathcal{A} = 0$ will be taken when $\mathcal{E} = E$. Consequently, $\forall E \in \mathbb{G}$, $\mathcal{A} \equiv 0$ due to the submodularity with respect to $\mathcal{E}$, which contradicts the assumption $\Delta^2 U_{k-1}^{E_B} > 0$. Therefore, only $\Delta^2 U_{k-1}^{E_B} = 0$ holds, which also belongs to Case I where $\Delta^2 U_{k-1}^{E_B} \leq 0$ holds.

□

Chapter 4

Traffic-aware Optimal Wireless Energy Charging Policy

With the development of mobile devices, such as hand-held smart phones, many complex jobs can be processed on the mobile devices. However, due to the mobility feature and limited size, a mobile device is energy-constrained when processing jobs. We discuss a mobile network with RF energy charging techniques.

A mobile device named mobile node in the network moves among different locations. Only some of those locations contain RF energy chargers. Different jobs could be generated in the mobile node, causing different levels of traffic loads. The mobile node may request energy when the current location contains an RF energy charger, and process the traffic load when the stored energy is enough. An RF energy charger will charge a certain fee (i.e., price) to the mobile node for the energy charged. Different chargers have different RF energy prices.

To efficiently utilize the battery energy and charge from RF energy chargers, the mobile node aims to minimize the cost, which considers the payment paid to RF energy sources for energy charging, as well as the penalty incurred when the energy stored in the battery is not enough for job processing. As a result, the mobile node only charges whenever necessary. For instance, when the energy price is low, or when the mobile node needs to process jobs with high traffic, it is intuitive that the node is more likely to charge RF energy. To this end, a Markov decision process (MDP) based scheme is proposed for the mobile node to optimally decide its RF energy charging policy based on the current location, traffic load, and the units of energy remained as the energy state.

The works in the current literature did not study a general mobile node facilitated with wireless energy charging functions. A full-functional mobile node differs from a sensor or a mesh node in several aspects. Firstly, the mobile node handles various types of traffic load, which may generate different levels of satisfaction to a user and consume different amount of energy. Secondly, the mobile node may move among different locations, and wireless charging becomes intermittent. Thirdly, wireless charging can incur different cost to the mobile node. Therefore, there is a need to develop a novel optimization problem considering these issues and study the structure of the optimal energy charging policy.

The rest of this chapter is organized as follows. Section 4.1 describes a mobile network with energy sources. In Section 4.2, an MDP model is formulated with the solution to maximize a mobile node's expected utility, considering the location, energy and traffic generation states of the mobile node. Performance metrics are defined to measure the mobile network with energy sources. Section 4.3 proves the existence of threshold policies of the energy state and location states. Numerical results are provided in Section 4.4. Finally, Section 4.5 concludes the chapter.

Some important mathematical notations in this chapter are listed in Table 4.1 for convenience.

4.1 System Model

In this section, we first describe the system model of a mobile node with wireless energy charging. The assumptions of the system are also stated.

4.1.1 General System Model

We consider a mobile node equipped with an energy storage (e.g., a battery) and wireless energy charging facility. The mobile node moves among different locations, as shown in Fig. 4.1(a). The mobile node works as follows (Fig. 4.1(b)). The mobile application running on the mobile node generates traffic load (e.g., voice or video). This traffic load can refer to the data that will be transmitted by the mobile node to a base station or relay node via a single-hop or multi-hop communications, respectively. The data transmission requires certain units of energy from the energy storage of the mobile node. Different traffic load can

Table 4.1: Notation descriptions.

Notation	Definition
$\mathcal{S} = (\mathcal{E}, \mathcal{L}, \mathcal{W})$	Composite state of the mobile node, including energy state, location state, and the traffic state
$\mathbb{G}, \mathbb{L}, \mathbb{W}$	State sets of energy state, location state, and traffic state
$\mathcal{A}$	$\mathcal{A} \in \{0, 1\}$, The action of being idle and charging of the mobile node
$\mathbf{E}(\mathcal{A}), \mathbf{L}, \mathbf{W}$	Transition matrices for energy states, location states and traffic states
$\mathbf{P}$	Overall transition matrix of the composite state $\mathcal{S}$, i.e., $\mathbf{P} = [P(\mathcal{S}, \mathcal{S}' \mathcal{A})]$
γ	Discount factor in the Bellman equation
$H(\cdot), V(\cdot)$	Overall utility function, expected optimal utility function in the Bellman equation
$F(\mathcal{E}, \mathcal{L}, \mathcal{W} \mathcal{A})$	Immediate utility utility function of the mobile node
$F_E(\mathcal{E}), F_L(\mathcal{L} \mathcal{A}), F_W(\mathcal{E}, \mathcal{W} \mathcal{A})$	Utilities by storing energy, purchasing energy from the charger at location $\mathcal{L}$, and the utility of processing a traffic load
$\beta(\mathcal{L})$	Price of charging energy at the location $\mathcal{L}$
b, B	Number of energy units received, the maximum number of units could be requested by the mobile node
A	The maximum of the energy that can be consumed by the current traffic

(a)

(b)

Figure 4.1: System model: (a) mobility and energy charging of a mobile node, and (b) the state of the mobile node.

be generated by the application at different state, and we refer to this state as the traffic state. Depending on this traffic state, the mobile node consumes certain units of energy to transmit the generated traffic. With the wireless charging facility installed, the mobile node can charge energy from accessible energy sources (i.e., wireless chargers). To receive energy, the mobile node must make a payment to the wireless charger for the requested energy. We assume that the charging price of different wireless chargers at different locations can be different.

Given above system model for the mobile node with wireless energy charging capability, we design an energy charging scheme for the mobile node to decide whether to perform energy charging or not. The energy charging scheme is based on an optimization formulation of a Markov decision process (MDP). The optimal energy charging policy is obtained from solving the MDP. We consider a time slot based operation for the mobile node. Here the time slot is a logical time reference for the mobile node to transmit data and receive the energy. The decision of the mobile node is to charge wireless energy (i.e., make a request to a wireless charger and buy wireless energy) or not. This decision is made at the beginning of the time slot based on the current state. The state is a composite state defined as the location, energy state of the energy storage, and the traffic state.

4.1.2 Definitions and Assumptions

To develop the optimal energy charging scheme for a mobile node, we first introduce the following settings and assumptions.

4.1.2.1 Node's Mobility

The mobile node can move among different locations. The location variable is denoted as $\mathcal{L} \in \mathbb{L} = \{1, 2, \dots, L\}$, where $\mathbb{L}$ is a set of all locations and L is the maximum number of locations. In every location $\mathcal{L}$, there is a particular price $\beta(\mathcal{L}) \geq 0$ for energy charging. Several factors may affect the price $\beta(\mathcal{L})$, and the price depends on the properties of the current location that the mobile node is in. For example, the path loss exponent of each base station may vary, multi-antenna technique might be deployed to enhance the energy charging efficiency (e.g., location 4 in Fig. 4.1(a)), some cells may not be covered by any

base station (location 2 in Fig. 4.1(a)), also the power of each base station may affect its charging price. The mobile node will pay this price to the wireless charger if the mobile node decides to buy wireless energy. Without loss of generality, we assume that the set of locations is sorted according to their price, i.e., $\beta(\mathcal{L}_1) \leq \beta(\mathcal{L}_2) \iff \mathcal{L}_1 < \mathcal{L}_2$. Note that if a location does not have a charger, the price will be $\beta(\mathcal{L}) = \infty$, therefore the mobile node will rationally not take the action to buy wireless energy.

4.1.2.2 Energy Storage

$\mathbb{G} = \{0, 1, \dots, E\}$ denotes the set of possible energy units (i.e., energy level) of the energy storage of the mobile node, where E is the maximum capacity. The mobile node only utilizes the stored energy units to transmit. The energy level can increase from charging and decrease when the mobile node transmits the generated traffic.

4.1.2.3 Wireless Energy Charging

When a mobile node is at the location with a charger, the mobile node can send a request to buy wireless energy from the charger. We assume that the node's wireless charging facility can receive the maximum energy of B units, where $B \leq E$, in one time slot. However, only b units are successfully charged with the probability σ_b , where $b \in \{0, 1, \dots, B, W\}$. σ_b depends on the property of energy charging interface of the mobile user, e.g., the RF to DC energy conversion efficiency. To generalize the system model, here we also consider an extreme case of energy charging when the mobile node is directly connected to a power source in the current time slot, denoted as W . This special case occurs with the probability σ_W . When connected to the power source directly, the mobile node is able to process any traffic $\mathcal{W}$ without consuming energy storage, i.e., the energy storage in the mobile node is always full, regardless of the the energy level in the last time slot. Practically, this case can happen when the mobile node is wired to a high power source, or at a wireless high powered charger. For example, when the charger is an implementation of the 120W medium-power specification of Qi [58].

4.1.2.4 Traffic load

In each time slot, the mobile node may generate different traffic. The traffic state is denoted as $\mathcal{W} \in \mathbb{W} = \{0, 1, \dots, A\}$, where $A < E$ is assumed. Without loss of generality, at the traffic state $\mathcal{W}$, the mobile node will consume $\mathcal{W}$ units of energy in one time slot. One of examples of the traffic load is voice communication, which can be modeled as an on-off source. In this case, the traffic state is defined as $\mathcal{W} \in \mathbb{W} = \{0, 1\}$. The traffic state is $\mathcal{W} = 0$ for an off period. That is, the mobile node does not consume energy. Similarly, the traffic state is $\mathcal{W} = 1$ for an on period, where the mobile node consumes one unit of energy to transmit a voice packet.

4.2 Optimization Problem Formation

In this section, we formulate the energy charging problem of a mobile node as a Markov decision process (MDP) by defining the state and action spaces, and deriving the transition probability matrix. Then, we define the utility function and present the MDP optimization formulation and its solving method. The performance metrics of the mobile node for evaluating the MDP scheme are defined afterward.

4.2.1 State Space and Action Space

The state space of the mobile node is defined as follows:

$$\mathbb{S} = \{(\mathcal{E}, \mathcal{L}, \mathcal{W}) | \mathcal{E} \in \mathbb{G}, \mathcal{L} \in \mathbb{L}, \mathcal{W} \in \mathbb{W}\} \quad (4.1)$$

where $\mathcal{S} \in \mathbb{S}$ is a composite state variable. $\mathcal{E}$, $\mathcal{L}$ and $\mathcal{W}$ are the energy state (i.e., current energy level of the energy storage), the location state and the traffic state of the mobile node, respectively.

The action space of the mobile node is defined as $\mathbb{A} = \{0, 1\}$, where the action $\mathcal{A} = 1$ indicates that the mobile node requests to buy wireless energy from a charger. The action $\mathcal{A} = 0$ indicates that the mobile node does not request for energy charging.

Figure 4.2: Transition diagram of location state $\mathcal{L} \in \mathbb{L} = \{1, 2\}$.

4.2.2 Transition Probability Matrix

4.2.2.1 Location State and Mobility

Figure 4.2 shows an example of the state transition diagram of the mobile node when its location states belong to the set $\mathbb{L} = \{1, 2\}$, where the mobile node moves between two locations. The mobile node moves based on its own mobility pattern only, regardless of the mobile node's energy state $\mathcal{E}$ and traffic state $\mathcal{W}$. We denote $\mu_{\mathcal{L}, \mathcal{L}'}$ as the probability that the mobile node is at location $\mathcal{L}$ in the current time slot and moves to location $\mathcal{L}'$ in the next time slot.

The movement pattern of the mobile node can be arbitrary in the model. Generally, the node could have two mobility patterns: correlated and uncorrelated mobility patterns. In the correlated mobility pattern case, the location in the next time slot $\mathcal{L}'$ depends on the current location $\mathcal{L}$ of the mobile node. For example, the mobile node will only move to the adjacent locations with a high probability, such as Brownian motion. Therefore, the transition probability $\mu_{\mathcal{L}, \mathcal{L}'}$ is a function of both $\mathcal{L}$ and $\mathcal{L}'$, denoted as $\mu_{\mathcal{L}, \mathcal{L}'} = P^L(\mathcal{L}, \mathcal{L}')$. With the uncorrelated mobility pattern, the mobile node will choose the next location $\mathcal{L}'$ regardless of the current location $\mathcal{L}$, i.e., i.i.d. location distribution. In this case, $\mu_{\mathcal{L}, \mathcal{L}'}$ is only a function of $\mathcal{L}'$, i.e., $\mu_{\mathcal{L}, \mathcal{L}'} = P^L(\mathcal{L}')$. The location transition matrix is expressed as follows:

$$\mathbf{L} = \begin{bmatrix} \mu_{0,0} & \cdots & \mu_{0,L} \\ \vdots & \ddots & \vdots \\ \mu_{L,0} & \cdots & \mu_{L,L} \end{bmatrix} \quad (4.2)$$

4.2.2.2 Traffic State Transition

Figures 4.3(a) and (b) show an example of the state transition diagram of the traffic state $\mathcal{W} \in \mathbb{W}$. Each traffic state indicates a mode that the mobile node is operating at, or a job

being executed at the mobile node. The traffic state of the mobile node changes from time to time, as different traffic will be incurred in different time slots.

Figure 4.3: (a) Transition diagram of traffic and energy states when $\mathcal{A} = 0$ (i.e., not charge), and (b) for the action $\mathcal{A} = 1$ (i.e., charge).

The transition probability matrix of traffic state is expressed as follows:

$$\mathbf{W} = \begin{bmatrix} \omega_{0,0} & \cdots & \omega_{0,A} \\ \vdots & \ddots & \vdots \\ \omega_{A,0} & \cdots & \omega_{A,A} \end{bmatrix} \quad (4.3)$$

where the notation $\omega_{\mathcal{W},\mathcal{W}'}$ means the probability that the traffic state transits from $\mathcal{W}$ to $\mathcal{W}'$.

To facilitate the derivation in later Section 4.2.2.3, we denote $\mathbf{W}_i$ as follows:

$$\mathbf{W}_i = \begin{bmatrix} \vdots & & \vdots \\ 0 & \cdots & 0 \\ \omega_{i,0} & \cdots & \omega_{i,A} \\ 0 & \cdots & 0 \\ \vdots & & \vdots \end{bmatrix}. \quad (4.4)$$

Basically, $\mathbf{W}_i$ has all zero elements, except in row i whose elements are the same as those in $\mathbf{W}$, which indicates the situation that the current traffic is i .

4.2.2.3 Energy State Transition

The transitions of the energy states depend on the current location, traffic state, as well as the action taken. Figure 4.3(a) shows the transitions of energy state when action $\mathcal{A} = 0$.

In this case, the energy state only decreases depending on the traffic state. For example, for the traffic state $\mathcal{W} = 1$, one unit of energy is consumed. As a result, the energy state transits from $\mathcal{E}$ to $\mathcal{E} - 1$. Figure 4.3(b) is for the action $\mathcal{A} = 1$ when the mobile node is at a location $\mathcal{L}$ with a wireless energy charger. Energy units are utilized by the mobile node to transmit. Therefore, the amount of energy consumed is the traffic state $\mathcal{W}$. The energy charging and transmission processes can be performed at the same time, i.e., in a full-duplexing manner. Without loss of generality, we assume the charged energy can be immediately used for transmission in the current time slot. Practically, the mobile node can repeatedly try to transmit until the end of the current time slot. In this case, the mobile node can at most consume the stored energy units plus the charged energy units during the current time slot. For the convenience of explanation, the charging and transmission process can be equivalently expressed as a two-step sub-transitions, e.g., as shown in Fig. 4.3(b), where the energy state transits from $\mathcal{E}$ to $\mathcal{E} + b - A$ if b units of energy are charged with the probability σ_b and A energy units are consumed to transmit the traffic $\mathcal{W} = A$.

We define the matrix as follows:

$$\mathbf{E}^{\mathcal{W}} = [\sigma_{\mathcal{W}} \mathbf{J}_{(A+1, A+1)}, \dots, \sigma_{\mathcal{W}} \mathbf{J}_{(A+1, A+1)}]^{\top} \times [0, \dots, 0, 1] \quad (4.5)$$

where $\mathbf{J}_{(A+1, A+1)}$ is a matrix of ones with the size of $(A+1) \times (A+1)$. $\mathbf{E}^{\mathcal{W}}$ is the transition matrix for the case that the mobile node is directly connected to a power source in a time slot.

For $\mathcal{A} = 0$, there is no charge. $\mathbf{E}(\mathcal{A} = 0)$ is the energy transition matrix. $\mathbf{E}(\mathcal{A} = 0)$ is expressed as follows:

$$\mathbf{E}(\mathcal{A} = 0) = \left[\begin{array}{cccc} \sum_{i=0}^A \mathbf{W}_i & & & \\ \sum_{i=1}^A \mathbf{W}_i & \mathbf{W}_0 & & \\ \vdots & \ddots & \ddots & \\ \mathbf{W}_A & \cdots & \mathbf{W}_1 & \mathbf{W}_0 \\ & \ddots & \ddots & \ddots & \ddots \\ & & \mathbf{W}_A & \cdots & \mathbf{W}_1 & \mathbf{W}_0 \end{array} \right] \quad (4.6)$$

In the energy transition matrix, the element (i, j) indicates the probability that the energy state transits from i to j . For example, the element $\mathbf{W}_A$ at $(A, 0)$ in the matrix (4.6) indicates

that the energy level falls from A to 0, when the mobile node has a traffic A , i.e., A units of energy will be consumed by handling the traffic.

Similarly, $\tilde{\mathbf{E}}^{(b)}(\mathcal{A} = 1)$ is the transition matrix of action $\mathcal{A} = 1$ (i.e., an energy charging action) if b units of energy are successfully charged. We first omit the case of $b = W$. For $b = 0$, we have

$$\tilde{\mathbf{E}}^{(0)}(\mathcal{A} = 1) = \mathbf{E}(\mathcal{A} = 0). \quad (4.7)$$

For the case of $b \in \{1, \dots, A-1\}$ units of energy charging, we have

$$\tilde{\mathbf{E}}^{(b)}(\mathcal{A} = 1) = \begin{bmatrix} \sum_{i=b}^A \mathbf{W}_i & \mathbf{W}_{b-1} & \cdots & \mathbf{W}_0 & & \\ \sum_{i=b+1}^A \mathbf{W}_i & \mathbf{W}_b & \cdots & \mathbf{W}_1 & \mathbf{W}_0 & \\ \vdots & & & & & \ddots \\ \mathbf{W}_A & \mathbf{W}_{A-1} & \cdots & \mathbf{W}_1 & \mathbf{W}_0 & \\ & \ddots & \ddots & & \ddots & \ddots \\ & & \mathbf{W}_A & \mathbf{W}_{A-1} & \cdots & \mathbf{W}_1 & \mathbf{W}_0 \\ & & \vdots & \vdots & & \vdots & \vdots \\ & & \mathbf{W}_A & \mathbf{W}_{A-1} & \cdots & \mathbf{W}_1 & \mathbf{W}_0 \end{bmatrix}. \quad (4.8)$$

In the first part of the matrix (i.e., from row 1 to row $A-b-1$), there is the case that the amount of charging energy is not sufficient to support all cases of energy consumption. Therefore, the probability that the energy storage is empty is the summation of the probabilities of all such cases. However, for the case of $b \in \{A, \dots, E\}$ (i.e., the amount of charging energy is sufficient to support all cases of energy consumption), the transition matrix becomes

$$\tilde{\mathbf{E}}^{(b)}(\mathcal{A} = 1) = \begin{bmatrix} \mathbf{0}^{(b-A)} & \mathbf{W}_A & \cdots & \mathbf{W}_1 & \mathbf{W}_0 & \\ & & \ddots & & \ddots & \\ & & & \mathbf{W}_A & \cdots & \mathbf{W}_1 & \mathbf{W}_0 \\ & & & \vdots & & \vdots & \vdots \\ & & & \mathbf{W}_A & \cdots & \mathbf{W}_1 & \mathbf{W}_0 \end{bmatrix} \quad (4.9)$$

where $\mathbf{0}^{(b-A)} = [0, \dots, 0]$ (i.e., a zero row vector with $b-A$ zero elements). Then the overall energy state transition matrix for action $\mathcal{A} = 1$ with $b = W$ can be expressed as follows:

$$\mathbf{E}(\mathcal{A} = 1) = \sum_{k=0}^B \sigma_k \tilde{\mathbf{E}}^{(k)}(\mathcal{A} = 1) + \sigma_W \mathbf{E}^W. \quad (4.10)$$

The overall state transition matrix of the mobile node is as follows:

$$\mathbf{P} = [P(\mathcal{S}, \mathcal{S}' | \mathcal{A})] = \mathbf{E}(\mathcal{A}) \otimes \mathbf{L} \quad (4.11)$$

where $\otimes$ is the Kronecker product. With the overall state transition matrix $\mathbf{P}$ derived, the probability of all the possible transitions of the mobile node is obtained to fulfill the MDP.

4.2.3 Immediate Utility Function

Given that the mobile node transits amongst different states, and different actions are taken accordingly, for the current state, an immediate utility is incurred to the mobile node, denoted as the immediate utility function $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$, which only consider the current state while ignoring all the past and future states.

The proposed MDP model does not require the immediate utility function to have a particular form. We assume that $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ is comprised of three components, denoted as $F_E(\mathcal{E})$, $F_L(\mathcal{L}|\mathcal{A})$, and $F_W(\mathcal{E}, \mathcal{W}|\mathcal{A})$. $F_E(\mathcal{E})$ is for the energy storage, $F_L(\mathcal{L}|\mathcal{A})$ is for location-price, and $F_W(\mathcal{E}, \mathcal{W}|\mathcal{A})$ is for the traffic generation. We consider the weighted sum of these components, i.e., $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A}) = c_E F_E(\mathcal{E}) + c_L F_L(\mathcal{L}|\mathcal{A}) + c_W F_W(\mathcal{E}, \mathcal{W}|\mathcal{A})$, where c_E , c_L , and c_W are weight coefficients.

$F_E(\mathcal{E})$ could be the cost of storing energy in the battery. $F_L(\mathcal{L}|\mathcal{A})$ is the cost of purchasing energy from the charger at the location $\mathcal{L}$, and it is defined as follows:

$$F_L(\mathcal{L}|\mathcal{A}) = -\mathcal{A} \cdot \beta(\mathcal{L}) \quad (4.12)$$

where $\beta(\mathcal{L})$ is the charging price paid by the mobile node to the charger, as defined in Section 4.1.2. Note that if $\mathcal{A} = 0$, then there is no energy transferred and hence the cost is zero.

Similarly, $F_W(\mathcal{E}, \mathcal{W}|\mathcal{A})$ is expressed as follows:

$$F_W(\mathcal{E}, \mathcal{W}|\mathcal{A}) = \begin{cases} \chi(\mathcal{W}), & (\mathcal{A} = 0 \text{ and } \mathcal{E} \geq \mathcal{W}) \text{ or } (\mathcal{A} = 1 \text{ and } \mathcal{E} - 1 \geq \mathcal{W}) \\ \rho(\mathcal{W}), & \text{otherwise} \end{cases} \quad (4.13)$$

where $\chi(\mathcal{W}) \geq 0$ is the utility that the mobile node is able to successfully transmit the traffic $\mathcal{W}$. That is, there is enough energy in the storage (i.e., $\mathcal{E} \geq \mathcal{W}$ when $\mathcal{A} = 0$). However, if there is not enough energy, the cost $\rho(\mathcal{W}) \leq 0$ is incurred to the mobile node if the traffic state is $\mathcal{W}$.

4.2.4 Solving the MDP Optimization Formulation

As the MDP problem formulation is fulfilled with the transition matrices, actions and immediate utility functions proposed, the MDP optimization formulation can be solved by employing the Bellman equation [163, 183], as follows:

$$V(\mathcal{S}) = \max_{\pi(\mathcal{A}|\mathcal{S})} H(\mathcal{S}|\mathcal{A}) \quad (4.14)$$

$$\phi^*(\mathcal{A}|\mathcal{S}) = \arg \max_{\pi(\mathcal{A}|\mathcal{S})} H(\mathcal{S}|\mathcal{A}) \quad (4.15)$$

$$H(\mathcal{S}|\mathcal{A}) = F(\mathcal{S}|\mathcal{A}) + \gamma \sum_{\mathcal{S}'} P(\mathcal{S}, \mathcal{S}'|\mathcal{A}) V(\mathcal{S}') \quad (4.16)$$

The solutions of (4.14)-(4.16) are obtained by value iteration algorithm [163]. A policy function $\pi(\mathcal{A}|\mathcal{S})$ in (4.14)-(4.16) is defined as the node's action $\mathcal{A}$ taken in the current state $\mathcal{S}$. The function $F(\mathcal{S}|\mathcal{A})$ is the immediate utility function given in Section 4.2.3. $H(\mathcal{S}|\mathcal{A})$ is the utility when the action $\mathcal{A}$ is taken given the state $\mathcal{S}$. Moreover, $\gamma \in (0, 1)$ is a discount factor for the value functions of all future states. The solutions include the utility $V(\mathcal{S})$ of the mobile node considering all the possible future states, given any current state $\mathcal{S}$, as well as the optimal policy denoted as $\phi^*(\mathcal{A}|\mathcal{S})$. Therefore, we obtain the optimal action for the mobile node to take given any state $\mathcal{S}$, as well as the overall utility that the node gains accordingly.

In order to facilitate the explanation later, we refer to $V(\mathcal{S})$ as the *value function* and $H(\mathcal{S}|\mathcal{A})$ as the *utility function*. Moreover, we interchangeably use the notations $V(\mathcal{S})$ and $V(\mathcal{E}, \mathcal{L}, \mathcal{W})$, $H(\mathcal{S}|\mathcal{A})$ and $H(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$, as well as $F(\mathcal{S}|\mathcal{A})$ and $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$.

4.2.5 Performance Metrics

Based on the optimal charging policy of the mobile node, we can obtain the following performance metrics.

4.2.5.1 Expected Utility

The mobile node can have any arbitrary initial state $\mathcal{S}_{init}$. We denote the probability that the node has the initial state $\mathcal{S}$ to be $p_{init}(\mathcal{S})$, $\forall \mathcal{S} \in \mathbb{S}$. We define the expected utility $\mathcal{V}$ of the node as follows:

$$\mathcal{V} = \sum_{\mathcal{S}_{init} \in \mathbb{S}} p_{init}(\mathcal{S}) \cdot V(\mathcal{S}). \quad (4.17)$$

In this case, if the charging policy adopted by the mobile node maximizes the expected utility $\mathcal{V}$, the policy will maximize the mobile node's expected utility starting from any possible initial state.

4.2.5.2 Charging Rate

We define the steady state probability of taking action $\mathcal{A} = 1$ to be the charging rate. It is calculated as follows:

$$\eta_{cr} = \sum_{\mathcal{S} \in \mathbb{S}} p_{st}(\mathcal{S}) \cdot \Lambda(\mathcal{A} = 1|\mathcal{S}) \quad (4.18)$$

where $p_{st}(\mathcal{S})$ is the steady state probability of the state $\mathcal{S}$ when the optimal charging policy is applied. The indicator function is $\Lambda(\mathcal{A} = 1|\mathcal{S}) = 1$ when action $\mathcal{A} = 1$ is taken, and $\Lambda(\mathcal{A} = 1|\mathcal{S}) = 0$ otherwise.

4.2.5.3 Insufficient Energy Probability and Average Energy Level

When the traffic generated by the mobile node requires more energy units than the current energy level, i.e., $\mathcal{W} > \mathcal{E}$, the insufficient energy situation happens. Similar to the charging rate obtained in (4.18), the definition of insufficient energy probability metric η_{ie} is as follows:

$$\eta_{ie} = \sum_{\mathcal{S} \in \mathbb{S}} p_{st}(\mathcal{S}) \cdot \Lambda(\mathcal{W} > \mathcal{E}|\mathcal{S}) \quad (4.19)$$

where $\Lambda(\mathcal{W} > \mathcal{E}|\mathcal{S}) = 1$ when $\mathcal{W} > \mathcal{E}$, i.e., the available energy in the storage is not enough to transmit the traffic generated at the state $\mathcal{W}$, and $\Lambda(\mathcal{W} > \mathcal{E}|\mathcal{S}) = 0$ otherwise.

Moreover, average energy level of the mobile node is defined as follows:

$$\mathcal{E} = \sum_{\mathcal{S} \in \mathbb{S}} p_{st}(\mathcal{S}) \cdot \mathcal{E}. \quad (4.20)$$

4.2.5.4 Throughput

For the wireless transmission of the traffic, the throughput of the mobile node is defined as follows:

$$\mathcal{T} = \sum_{\mathcal{S} \in \mathbb{S}} p_{st}(\mathcal{S}) \cdot T(\mathcal{S}|\mathcal{A}) \quad (4.21)$$

where $T(\mathcal{S}|\mathcal{A})$ is the immediate throughput at the state $\mathcal{S}$, defined as follows:

$$T(\mathcal{S}|\mathcal{A}) = \begin{cases} (1 - \epsilon(\mathcal{S})) \cdot K(\mathcal{W}), & (\mathcal{A} = 0 \text{ and } \mathcal{E} \geq \mathcal{W}) \text{ or } (\mathcal{A} = 1 \text{ and } \mathcal{E} - 1 \geq \mathcal{W}) \\ 0, & \text{otherwise} \end{cases} \quad (4.22)$$

where $\epsilon(\mathcal{S})$ is the error rate of transmission in the state $\mathcal{S}$, and $K(\mathcal{W})$ denotes the number of packets generated corresponding to the traffic state $\mathcal{W}$.

4.3 Threshold Policy

In this section, we introduce the concept of a threshold policy and show that the optimal policy obtained from the proposed MDP has the threshold policy in certain conditions.

4.3.1 The Concept of Threshold Policy

The optimal policy of an MDP model with binary actions (i.e., $\mathcal{A} \in \{\mathcal{A}_1, \mathcal{A}_2\}$) is threshold-type, defined as follows:

$$\phi^*(\mathcal{A}|\Theta, \mathcal{S}_{-\Theta}) = \begin{cases} \mathcal{A}_1, & \text{for } \Theta \geq \Theta_{thresh} \\ \mathcal{A}_2, & \text{otherwise} \end{cases} \quad (4.23)$$

where Θ is a state variable or a set of states, and $\mathcal{S}_{-\Theta}$ indicates the set of the rest of states. Θ_{thresh} denotes the threshold value of the state Θ . The function $\phi^*(\mathcal{A}|\Theta, \mathcal{S}_{-\Theta})$ is the optimal action policy solved by the MDP model and Bellman equation, as given in (4.15). In other words, whenever $\Theta \geq \Theta_{thresh}$, the action $\mathcal{A}_1$ will always be taken. Otherwise, the action $\mathcal{A}_2$ will be taken.

The concept of supermodularity/submodularity [183, 185] is employed to prove the existence of a threshold policy given as follows.

Definition 4.2 For $x \in \mathbb{X} \subseteq \mathbb{R}$, $y \in \mathbb{Y} \subseteq \mathbb{R}$, a function $f(x, y) \in \mathbb{R}$ is supermodular in (x, y) if $f(x_1, y_1) - f(x_1, y_2) \geq f(x_2, y_1) - f(x_2, y_2)$, $\forall x_1, x_2 \in \mathbb{X}, \forall y_1, y_2 \in \mathbb{Y}, x_1 > x_2, y_1 > y_2$. Similarly, $f(x, y)$ is submodular in (x, y) if $f(x_1, y_1) - f(x_1, y_2) \leq f(x_2, y_1) - f(x_2, y_2)$, $\forall x_1, x_2 \in \mathbb{X}, \forall y_1, y_2 \in \mathbb{Y}, x_1 > x_2, y_1 > y_2$.

The supermodularity/submodularity property of $f(x, y)$ is a sufficient condition of the non-decreasing/non-increasing monotonicity of $y = \arg \max_y f(x, y)$ [185]. Specifically,

in the proposed MDP model and Bellman equation given in (4.14)-(4.16), for a given state $\theta \in \{\mathcal{E}, \mathcal{L}, \mathcal{W}\}$, the fact that $H(\mathcal{S}|\mathcal{A})$ is supermodular/submodular in $(\theta, \mathcal{A})$ indicates that $\phi^*(\mathcal{A}|\mathcal{S})$ is non-decreasing/non-increasing in $\theta \in \{\mathcal{E}, \mathcal{L}, \mathcal{W}\}$. In particular, when θ increases, the optimal action only changes from 0 to 1 for the supermodularity case (or 1 to 0 for the submodularity case). Then from the definition in (4.23), the threshold policy holds.

4.3.2 Threshold Policy in Location State

In this section, we prove the existence of a threshold policy in the optimal charging policy of the mobile node with respect to location state $\mathcal{L}$.

Lemma 4.2 Uniqueness and convergence: *The value iteration algorithm to solve the Bellman equation as in (4.14)-(4.16) will always converge to a unique optimal result [186].*

Definition 4.3 0-to-1/1-to-0 threshold: *A threshold policy in state θ is defined as a 0-to-1 (or 1-to-0) if the action $\mathcal{A}(\theta_2) > \mathcal{A}(\theta_1)$ (or $\mathcal{A}(\theta_2) < \mathcal{A}(\theta_1)$), given that $\theta_2 \geq \theta_{thresh}$ and $\theta_1 < \theta_{thresh}$.*

Theorem 4.5 Threshold policy in location state: *Given any energy state $\mathcal{E}$ and traffic state $\mathcal{W}$, the optimal charging policy is a 1-to-0 (or 0-to-1) threshold policy in location state $\mathcal{L}$, if the following conditions hold:*

- (i) *Transition probability $\mu_{\mathcal{L}, \mathcal{L}'}$ is only a function of $\mathcal{L}'$;*
- (ii) *$F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ is non-increasing (or non-decreasing) with respect to location $\mathcal{L}$, given that action $\mathcal{A} = 1$ is taken;*
- (iii) *$F(\mathcal{E}, \mathcal{L}_1, \mathcal{W}|\mathcal{A}) = F(\mathcal{E}, \mathcal{L}_2, \mathcal{W}|\mathcal{A})$, $\forall \mathcal{L}_1, \mathcal{L}_2 \in \mathbb{L}$, given that action $\mathcal{A} = 0$ is taken.*

The first condition indicates that the mobile node moves to any location $\mathcal{L}'$ with a certain probability, regardless of the current location state $\mathcal{L}$. That is, all the rows in the transition matrix defined (4.2) are identical. The second condition indicates that the immediate utility function is monotonic in the charging price corresponding to the current location $\mathcal{L}$. The third condition means that the immediate function is independent to the location state $\mathcal{L}$, if

the action $\mathcal{A} = 0$ is taken. That is, when the mobile node does not take a charging action, the current location state $\mathcal{L}$ does not affect the node's immediate utility of the current decision period, i.e., $F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A} = 0) \equiv F(\mathcal{E}, \mathcal{W})$.

For the physical meaning of Theorem 4.5, let us consider the following example. Given any energy state $\mathcal{E}$ and traffic state $\mathcal{W}$, the mobile node's action monotonically decreases from 1 to 0, if $F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A} = 1)$ is non-decreasing in location state $\mathcal{L}$. The node tends not to take a charging action if the energy sources at the current location has too high price for energy charging. The proof of Theorem 4.5 is in Section 4.6.1.

4.3.3 Threshold Policy in Energy State

Next, we prove that a threshold policy exists in the optimal MDP solution with respect to energy state $\mathcal{E}$.

Theorem 4.6 Threshold policy in energy state: *Given any location state $\mathcal{L}$ and traffic state $\mathcal{W}$, an optimal solution of energy charging actions is a 0-to-1 (or 1-to-0) threshold policy in the energy state $\mathcal{E}$, except for when $\mathcal{E} = E$, if the following conditions hold:*

- (i) *The node charges one unit of energy at most, i.e., $B = 1$.*
- (ii) *$F(\mathcal{E}, \mathcal{L}_1, \mathcal{W} | \mathcal{A}) = F(\mathcal{E}, \mathcal{L}_2, \mathcal{W} | \mathcal{A})$, $\forall \mathcal{L}_1, \mathcal{L}_2 \in \mathbb{L}$, given that action $\mathcal{A} = 0$ is taken;*
- (iii) *$F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A})$ is non-decreasing (or non-increasing) and convex (or concave) with respect to $\mathcal{E}$.*

The exception $\mathcal{E} = E$ exists in Theorem 4.6 since the mobile node cannot charge in the case of full energy stored, i.e., $\mathcal{E} = E$. In this case, $\mathcal{A} = 0$ is always taken, and the 0-to-1 threshold policy does not exist.

Theorems 4.5 and 4.6 show that the properties (i.e., monotonicity and discrete convexity/concavity) of the immediate utility function directly decide the existence and type of the threshold policy. The proof of 1-to-0 threshold policy in Theorem 4.6 is in Section 4.6.2. 0-to-1 threshold policy case can be proven similarly.

4.3.4 Threshold Policy in Traffic State

We can establish a similar theorem for the threshold policy with respect to traffic state $\mathcal{W}$, as follows. However, due to space limit, we omit its proof.

Theorem 4.7 Threshold policy in traffic state: *Given any energy state $\mathcal{E}$ and location state $\mathcal{L}$, the optimal charging policy is a 1-to-0 (or 0-to-1) threshold policy in traffic state $\mathcal{W}$, if the following conditions hold:*

- (i) *Transition probability $\omega_{\mathcal{W},\mathcal{W}'}$ is only a function of $\mathcal{W}'$;*
- (ii) *The immediate utility function has the following property: $[F(\mathcal{E}, \mathcal{L}, \mathcal{W} + 1 | \mathcal{A} = 1) - F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A} = 1)] - [F(\mathcal{E}, \mathcal{L}, \mathcal{W} + 1 | \mathcal{A} = 0) - F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A} = 0)] \leq 0$ (or ≥ 0 for the 0-to-1 threshold policy).*

4.3.5 Policy Space Complexity Analysis

A threshold policy can assist the mobile node to make energy charging decisions in the following aspects:

- **Algorithm improvement:** Once the structure of an optimal charging policy is proven to have a threshold policy, the algorithms (e.g., offline search) can be developed to directly obtain the threshold value, i.e., Θ_{thresh} in (4.23), instead of solving for the optimal actions at all the states.
- **Approximation algorithm design:** As shown in (4.23), with the binary structure of the solution space of the optimal actions, we can develop simple algorithms to determine the node's actions in every state. Similarly as discussed in [187] and [188], we can approximate an imprecise threshold $\tilde{\Theta}_{thresh}$. This imprecise threshold may be acceptable because it is close to the exact optimal policy. However, obtaining the imprecise threshold does not incur large complexity as that of obtaining the exact optimal policy. In this case, we can adopt the approximation algorithm similar to that in [187] and [188].

Next, we analyze how the existence of the threshold policy can lower down the complexity of optimization problem in terms of the reduced space of possible policies. The cardinality of a set is denoted as $|\cdot|$. In the proposed MDP model, $|\mathbb{A}|$ is the total number of possible actions, $|\mathbb{L}|$ denotes the number of locations, $|\mathbb{W}|$ is the total number of traffic states, and $|\mathbb{G}|$ denotes the number of energy states.

Suppose that no threshold structure exists in the optimal policy, all the possible actions in $\mathbb{A}$ might be taken in every state $\mathcal{S} \in \mathbb{S}$. We define the number of possible policies of the optimization problem as follows:

$$NP_{non-thresh}(|\mathbb{G}|, |\mathbb{L}|, |\mathbb{W}|, |\mathbb{A}|) = |\mathbb{A}|^{|\mathbb{G}||\mathbb{L}||\mathbb{W}|}. \quad (4.24)$$

When the action space is binary (i.e., $\mathbb{A} = \{0, 1\}$), $NP_{non-thresh}(|\mathbb{G}|, |\mathbb{L}|, |\mathbb{W}|, |\mathbb{A}|) = 2^{|\mathbb{G}||\mathbb{L}||\mathbb{W}|}$.

The existence of the optimal threshold policy can reduce the number of possible actions. Once the threshold states are decided, all the actions are already fixed due to the monotonicity in action $\mathcal{A} \in \mathbb{A}$. We take the threshold policy in energy state $\mathcal{E} \in \mathbb{G}$ as an example. The number of total policies given the existence of threshold policy is:

$$NP_{thresh}(|\mathbb{G}|, |\mathbb{L}|, |\mathbb{W}|, |\mathbb{A}|) = \left(|\mathbb{A}| + \sum_{k=1}^{|\mathbb{A}|-1} \binom{|\mathbb{G}|}{k} \binom{|\mathbb{A}|}{k+1} \right)^{|\mathbb{L}||\mathbb{W}|}. \quad (4.25)$$

The term $|\mathbb{A}| + \sum_{k=1}^{|\mathbb{A}|-1} \binom{|\mathbb{G}|}{k} \binom{|\mathbb{A}|}{k+1}$ consists of two parts. $|\mathbb{A}|$ is the policy number when the actions taken in all the energy states are identical, e.g., $\mathcal{A} = A, \forall \mathcal{E} \in \mathbb{G}$, as shown in Fig. 4.4(a). $\sum_{k=1}^{|\mathbb{A}|-1} \binom{|\mathbb{G}|}{k} \binom{|\mathbb{A}|}{k+1}$ denotes the policy number when $k+1 \in \{2, 3, \dots, |\mathbb{A}|\}$ different possible actions are taken in all the energy states, as shown in Fig. 4.4(b). Based on the definition of threshold policy, the actions are monotonic with respect to the states. Given that there are $k+1$ possible actions, all the actions can be decided in all the energy states when k thresholds are determined. Therefore, the policy number $\sum_{k=1}^{|\mathbb{A}|-1} \binom{|\mathbb{G}|}{k} \binom{|\mathbb{A}|}{k+1}$ relies solely on the enumeration of all the possible actions and thresholds. As shown in Fig. 4.4(b), $\binom{|\mathbb{G}|}{k}$ indicates that k out of all the $|\mathbb{G}|$ energy states are selected to be the thresholds, while $\binom{|\mathbb{A}|}{k+1}$ denotes that $k+1$ actions

Figure 4.4: Possible thresholds: (a) when only one action $\mathcal{A} = 1$ is taken in all the states, and (b) $k + 1$ possible actions with k thresholds in all the states.

out of the action set $\mathbb{A}$ are selected to be the $k + 1$ possible actions, given every possible combination of k thresholds.

The model that we propose has a binary action states, as a result, $|\mathbb{A}| = 2$, (4.25) can be simplified as follows:

$$NP_{thresh}(|\mathbb{G}|, |\mathbb{L}|, |\mathbb{W}|, |\mathbb{A}|) = (2 + |\mathbb{G}|)^{|\mathbb{L}||\mathbb{W}|}. \quad (4.26)$$

Figure 4.5 compares the policy number functions $NP_{non-thresh}(|\mathbb{G}|, |\mathbb{L}|, |\mathbb{W}|, |\mathbb{A}|)$ and $NP_{thresh}(|\mathbb{G}|, |\mathbb{L}|, |\mathbb{W}|, |\mathbb{A}|)$ given in (4.24) and (4.25), respectively. The parameters are set to be $|\mathbb{W}| = 2$, $|\mathbb{L}| = 2$, and $|\mathbb{A}| = 2$. From Fig. 4.5, the existence of the threshold policy clearly reduces the complexity of searching for optimal actions because of the reduced size of policy space. As the number of energy state $|\mathbb{G}|$ increases from 10 to 50, the policy number function of the non-threshold policy rapidly increases to the order of 10^{59} , while the threshold policy achieves that the number of possible policies increases much slower and below the order of 10^9 .

4.4 Numerical Results

4.4.1 System Parameters and Performance Criteria

Unless otherwise stated, we use the following scenarios and parameters in the performance evaluation.

- The mobile node moves among 11 locations, i.e., $L = 11$. We consider two cases of the mobile node's location distribution: uniform and non-uniform. The mobile node

Figure 4.5: The number of possible policies of non-threshold policy and threshold policy.

moves amongst different locations uniformly when the uniform distribution case is adopted. In the non-uniform distribution case, the node moves amongst different locations with different probabilities. In this case, regardless of the current location, the mobile node moves to a location $\mathcal{L}_h \in \mathbb{L}$ with a probability of 50%, and moves to each of other 10 locations except $\mathcal{L}_h$ with a probability of 5%. Here, the location $\mathcal{L}_h$ is denoted as the highest probability location of the mobile node.

- The maximum energy storage capacity of each node is $E = 10$. After taking a charging action, the node may receive $b \in \{0, 1, \dots, B\}$ units of energy with a uniform probability. We set $B = 5$. The case that the mobile node is directly connected to a power source, i.e., $\mathbb{W}$, is not considered in the performance evaluation.
- The traffic state is $\mathcal{W} \in \mathbb{W} = \{0, 1, \dots, 5\}$ (i.e., the maximum energy consumption is $A = 5$). Uniform and non-uniform distributions of the traffic state are considered. The traffic state $\mathcal{W}$ is uniformly distributed in the uniform distribution case. In the non-uniform distribution case, we adopt a truncated Poisson distribution, where the traffic state transition probability $\omega_{\mathcal{W}, \mathcal{W}'}$ is defined as follows:

$$\omega_{\mathcal{W}, \mathcal{W}'} = \text{Pois}(\mathcal{W}' = \nu) = \begin{cases} e^{-\lambda} \frac{\lambda^\nu}{\nu!}, & \text{for } \nu \in \{0, \dots, A-1\} \\ \sum_{k=A}^{+\infty} e^{-\lambda} \frac{\lambda^k}{k!}, & \text{for } \nu = A \end{cases} \quad (4.27)$$

where λ is a traffic generating parameter of the mobile node.

- The discount factor in the Bellman equation (4.16) is $\gamma = 0.9$.

The mobile node's immediate utility function over state $\mathcal{S} = \{\mathcal{E}, \mathcal{L}, \mathcal{W}\}$ and action $\mathcal{A}$ is set to be $F_E(\mathcal{E}) \equiv 0$, and $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A}) = c_L F_L(\mathcal{L}|\mathcal{A}) + c_W F_W(\mathcal{E}, \mathcal{W}|\mathcal{A})$, where the

weight coefficients are $c_L = 0.7$ and $c_W = 0.3$. The following form of $F_W(\mathcal{E}, \mathcal{W}|\mathcal{A})$ is applied:

$$F_W(\mathcal{E}, \mathcal{W}|\mathcal{A}) = \begin{cases} \sqrt{\mathcal{W}/A}, & (\mathcal{A} = 0 \text{ and } \mathcal{E} \geq \mathcal{W}) \text{ or } (\mathcal{A} = 1 \text{ and } \mathcal{E} - 1 \geq \mathcal{W}) \\ -(\mathcal{W} - \mathcal{E})/A, & \text{otherwise} \end{cases} \quad (4.28)$$

where $\sqrt{\mathcal{W}/A}$ indicates an increasing utility of $\mathcal{W}$ with decreasing marginal utility, when the current traffic $\mathcal{W}$ is successfully processed. $-(\mathcal{W} - \mathcal{E})/A$ means that the mobile node's loss is linear to the amount of insufficient energy units, i.e., $\mathcal{W} - \mathcal{E}$, when there are not enough energy units in the storage. Furthermore, we use $F_L(\mathcal{L}|\mathcal{A}) = -\mathcal{A} \cdot \beta(\mathcal{L})$, where all the L charging prices follow a log-normal distribution, which is generally employed to model price distribution in real world markets [189].

We evaluate the proposed MDP scheme as defined in Section 4.2.5 by comparing the performance with other four baseline schemes, including an always charging scheme (namely $\mathcal{A} = 1$ scheme) where the node always takes a charging action except for when the battery is full (i.e., $\mathcal{E} = E$), an idle scheme ($\mathcal{A} = 0$ scheme) where $\mathcal{A} = 0$ is always taken except for when the battery is empty (i.e., $\mathcal{E} = 0$), a random scheme (RND) that randomly decides whether to charge or not, and a myopic scheme (MYO). By adopting the myopic scheme, the mobile node makes short-sighted greedy charging decisions only to maximize the immediate utility $F(\mathcal{S}|\mathcal{A})$ of the current state.

4.4.2 Threshold Policy

Figure 4.6 shows the optimal threshold policy of the proposed MDP scheme, given that the defined immediate utility function holds for the conditions in Theorem 4.5. In this case, we fix the location state $\mathcal{L}$. The non-uniform truncated Poisson distribution of traffic state is adopted, since we will show the threshold variation for different traffic state patterns (i.e., different values of traffic generating parameter λ) in Figs. 4.6(a) and (b). The node is mostly in the low traffic states when λ is small, and in the high traffic states when λ is large. Figure 4.6(a) shows the threshold policy when $\lambda = 0.5$, namely a low traffic generation pattern. On the contrary, Fig. 4.6(b) shows a high traffic generation pattern with $\lambda = 3.0$. For both Figs. 4.6(a) and (b), a 1-to-0 threshold policy always exists with respect to the

Figure 4.6: Threshold in location state $\mathcal{L}$ in the case of (a) low traffic generation, and (b) high traffic generation. ($\mathcal{W} = 1$ in both figures.)

location state $\mathcal{L}$. For example, as shown in Fig. 4.6(a), when $\mathcal{E} = 2$, the mobile node's action $\mathcal{A}$ changes from 1 to 0 at the location state $\mathcal{L} = 6$. This indicates that higher prices of the location state $\mathcal{L}$ discourages the mobile node from taking a charging action.

Note that the setting of the immediate function of the mobile node with respect to $\mathcal{E}$ does not meet the conditions of threshold policy Theorem 4.6. Therefore, an optimal threshold policy does not exist for the energy state $\mathcal{E}$. For example, as shown in Fig. 4.6(b), when $\mathcal{L} = 9$, the action changes from $\mathcal{A} = 0$ to $\mathcal{A} = 1$ and from $\mathcal{A} = 1$ to $\mathcal{A} = 0$ again, as the energy state $\mathcal{E}$ increases from 0 to 10. The reason for this result is that the mobile node has to weigh between the potential future utility brought by charging (i.e., $\mathcal{A} = 1$) and the price of charging. When $\mathcal{E}$ is small, the charged energy units cannot gain enough future profit to compensate the charging price. Consequently, the action $\mathcal{A} = 1$ is not taken. When $\mathcal{E}$ is large, since there is already enough energy for the mobile node, the charging action is unnecessary.

4.4.3 Impacts of Location to Optimality

We adopt the non-uniform distribution case of the location of a mobile node. As assumed in Section 4.1.2, each location $\mathcal{L}$ corresponds to a charging price $\beta(\mathcal{L}) \geq 0$, where $\beta(\mathcal{L}) > \beta(\mathcal{L}')$ for $\mathcal{L} > \mathcal{L}'$. The horizontal axes of Figs. 4.7(a) and (b) denote the highest probability location $\mathcal{L}_h$. Intuitively, when the mobile node is at the locations with high charging prices

Figure 4.7: Impacts of the distribution of location state to (a) expected utility, and (b) charging rate.

more frequently, the utility of the mobile node will decrease. As shown in Fig. 4.7(a), the expected utility of the mobile node decreases as the highest probability location $\mathcal{L}_h$ increases. Moreover, Fig. 4.7(a) shows that the proposed MDP scheme outperforms the other baseline schemes. Specifically, when action $\mathcal{A} = 1$ is always taken, the mobile node suffers from sharp utility decrease when $\mathcal{L}_h$ becomes too high, e.g., $\mathcal{L}_h = 11$, due to the higher chance of the high energy charging price. When the $\mathcal{A} = 0$ scheme is applied, the mobile node suffers from lacking of enough energy, even when the charging price is low in some locations. The myopic scheme underperforms the proposed MDP scheme since it ignores the future utility gain.

Figure 4.7(b) shows the charging rate. We observe that the charging rate is higher when the mobile node is frequently at the locations with lower prices, which is expected. Fig. 4.7(b) also shows that, the proposed MDP scheme, which makes charging decisions considering future state transitions, has a higher charging rate than that of the myopic scheme. This can be explained as follows. For the mobile node in the location with a high charging price, the myopic scheme may refuse to charge from a short-sighted perspective, because of the low immediate utility (i.e., high charging price) of the current state. However, the proposed MDP scheme considers the fact that the action $\mathcal{A} = 1$ will increase the energy storage of the node, which may potentially increase the utility at the future states. By weighing the tradeoff between current price and potential future utility, the MDP scheme

may still decide to charge to maximize the expected utility. As a result, the MDP scheme has a higher charging rate compared with that of the myopic scheme.

4.4.4 Impacts of Energy Storage Capacity

In this section, we discuss how the maximum energy storage capacity E of a mobile node can affect performance.

Figure 4.8: Impacts of energy storage capacity E to (a) expected utility, and (b) charging rate.

The distributions of location $\mathcal{L}$ and traffic state $\mathcal{W}$ of the mobile node are both set to be uniform. We vary the maximum energy storage capacity E of the mobile node. As shown in Fig. 4.8(a), when the maximum energy storage capacity increases from $E = 6$ to $E = 15$, the expected utilities of all the schemes increase. This is because the increased maximum energy storage capacity allows the mobile node to store more energy for future use, reducing the chance of insufficient energy. Fig. 4.8(a) also shows that the proposed scheme outperforms other baseline schemes in different cases of energy storage capacity E .

Figure 4.8(b) shows the charging rate of the mobile node with different maximum energy storage capacity E . For the proposed MDP scheme, the charging rate increases when the energy storage capacity E increases. This is because when the energy storage capacity is low, the chance that there is not enough energy when the traffic state is high becomes higher. By contrast, for a larger energy storage capacity E , the mobile node tends to charge

to reduce the chance of insufficient energy in the future state. Figure 4.8(b) also shows that the proposed MDP scheme has higher charging rate than that of the myopic scheme. Similar to the explanation of Fig. 4.7(b), this is because MDP scheme considers the future utility.

4.4.5 Impacts of Traffic Generation to Optimality

In this section, the impacts of the mobile node's traffic generation state to performance metrics are discussed.

Figure 4.9: Impacts of traffic generating parameter λ to (a) expected utility, and (b) charging rate.

The non-uniform distribution of the traffic state is adopted. We examine the performance for different traffic state patterns. As shown in Fig. 4.9(a), the expected utility of the mobile node is high when the traffic generating parameter λ is relatively small. This is because the chance of insufficient energy is low, due to the lower energy consumption. Non-positive utility $\rho(\mathcal{W})$ of insufficient energy in (4.13) is seldom incurred. By contrast, as λ increases, the node will be in the higher traffic state with higher probability. In this case, insufficient energy could frequently happen, causing a penalty. Consequently, the utility of the node decreases as λ increases, as shown in Fig. 4.9(a).

Note that, as shown in Fig. 4.9(a), the utility of the proposed MDP scheme at $\lambda = 0.5$ is lower than that of $\lambda = 1.0$. This is because the mobile node is at the traffic state $\mathcal{W} = 0$ with high probability of 0.6 for $\lambda = 0.5$. That means the mobile node gains no reward at the traffic state $\mathcal{W} = 0$ most of the time. As a result, the expected utility is adversely affected.

The impact of traffic state to the action of the mobile node is shown in Fig. 4.9(b). When λ is small, the energy consumption of the mobile node is small. When λ increases, the energy consumption increases. However, as λ continues to increase, the mobile node consumes more energy. At the same time, the marginal utility decreases due to the concavity of the immediate utility function with respect to the traffic state $\mathcal{W}$. Moreover, even if action $\mathcal{A} = 1$ is taken, the charged energy still may not be enough to support the high traffic states. Therefore, the utility gained by taking the charging action cannot compensate the price paid to the charger. Consequently, the charging rate decreases as λ keeps increasing, as shown in Fig. 4.9(b).

4.4.6 Insufficient Energy Probability and Average Energy Level

In this section, we will examine the probability of insufficient energy of the node. Furthermore, we examine the average level of energy storage of the node.

Figure 4.10: Insufficient energy probability under different (a) highest probability location, (b) maximum energy storage capacity, and (c) traffic generating parameter.

Figures 4.10(a), (b), and (c) show the insufficient energy probability under the node's location distribution, maximum energy storage capacity, and traffic generating parameter, respectively. In Fig. 4.10(a), as the location with the highest probability increases, the insufficient energy probability increases. This is due to the fact that the mobile node does not want to take a charging action at the location with high price. Similarly, Fig. 4.10(b) shows that, as the maximum energy storage capacity E increases, the mobile node can store

more energy. As a result, the insufficient energy probability decreases. In Fig. 4.10(c), as the traffic generating parameter λ increases, the node will consume more energy. Therefore, the insufficient energy probability increases as λ increases.

Note that the optimal policy to maximize the utility of the mobile node does not necessarily result in a minimum insufficient energy probability, as shown in Figs. 4.10(a), (b), and (c). The always charging scheme (i.e., $\mathcal{A} = 1$) leads to the lowest insufficient energy probabilities in all the scenarios. The reason is that the always charging scheme increases the energy level of the node without concerning about the charging price. However, this scheme can incur too much cost to the mobile node, lowering the overall utility.

4.5 Summary

In this chapter, we discussed the scenario that a mobile node moves to different locations and has time-varying traffic to process. RF energy chargers are deployed for the mobile node to replenish its battery energy storage. However, as the price of energy charging differs in different locations, it is not always profitable to charge. This chapter has proposed a Markov decision process (MDP) based scheme to obtain the optimal energy management policy of energy charging actions, considering system states including the current location, the battery energy storage and the traffic generation situations of the mobile node. The proposed MDP-based energy management scheme has been shown to outperform several typical baseline schemes in the numerical results.

4.6 Appendix

4.6.1 Threshold Policy in Location State $\mathcal{L}$

Proof The case that the mobile node is directly connected to a power source, i.e., W , can be canceled during the derivation of proof. As a result, to simplify the process of proof, with a slight abuse of notation, we omit the notations of W in the proof.

Suppose the highest traffic state is $\mathcal{W} = A$, and the maximum charged energy is B as in (4.8). There are four cases in the transition matrices defined in (4.6) and (4.8) with respect to the energy state $\mathcal{E}$:

- *Case 1:* For $0 \leq \mathcal{E} < A - B$, the mobile node will have insufficient energy (i.e., $\mathcal{W} > \mathcal{E} + B$) when $\mathcal{W}$ becomes too high, e.g., $\mathcal{W} = A$, even if the charging action $\mathcal{A} = 1$ is taken and the maximum units of energy B is successfully charged at the same time.
- *Case 2:* For $A - B \leq \mathcal{E} < A$, the mobile node will possibly have sufficient energy to support high traffic (e.g., at $\mathcal{W} = A$), if action $\mathcal{A} = 1$ is taken. Otherwise, if $\mathcal{A} = 0$, insufficient energy will always happen when $\mathcal{W}$ is too high, i.e., when $\mathcal{W} \in \{A - \mathcal{E}, \dots, A\}$.
- *Case 3:* For $A \leq \mathcal{E} < E - B$, the energy storage always has enough energy to support all traffic states. Additionally, after charging, the energy storage is not full.
- *Case 4:* For $E - B \leq \mathcal{E} \leq E$, the energy storage always has enough energy to support all traffic states. However, after a charging action $\mathcal{A} = 1$ is taken, the energy storage could be full.

As an example, we prove the existence of the threshold policy for *Case 3*. Similar procedures can be applied to other cases. We examine if supermodularity/submodularity holds for $H(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ with respect to location state $\mathcal{L}$, i.e.,:

$$[H(\mathcal{E}, \mathcal{L}+1, \mathcal{W}|\mathcal{A} = 1) - H(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 1)] - [H(\mathcal{E}, \mathcal{L}+1, \mathcal{W}|\mathcal{A} = 0) - H(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 0)] \quad (4.29)$$

In *Case 3*, the first term $H(\mathcal{E}, \mathcal{L} + 1, \mathcal{W}|\mathcal{A} = 1) - H(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 1)$ in (4.29) can be expanded as follows:

$$\begin{aligned} & H(\mathcal{E}, \mathcal{L} + 1, \mathcal{W}|\mathcal{A} = 1) - H(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 1) \\ &= F(\mathcal{E}, \mathcal{L} + 1, \mathcal{W}|\mathcal{A} = 1) - F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 1) \\ &\quad + \sum_{b=0}^B \sigma_b \sum_{\mathcal{L}'=0}^L (\mu_{\mathcal{L}+1, \mathcal{L}'} - \mu_{\mathcal{L}, \mathcal{L}'}) \sum_{\mathcal{W}'=0}^{\mathcal{E}+i} \omega_{\mathcal{W}, \mathcal{W}'} V(\mathcal{E} + i - \mathcal{W}, \mathcal{L}', \mathcal{W}') \\ &= F(\mathcal{E}, \mathcal{L} + 1, \mathcal{W}|\mathcal{A} = 1) - F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 1) \end{aligned} \quad (4.30)$$

since $\mu_{\mathcal{L}+1, \mathcal{L}'} = \mu_{\mathcal{L}, \mathcal{L}'}$ due to the first condition in Theorem 4.5.

Similarly, the second term of the expression in (4.29) can be expanded as follows:

$$\begin{aligned} & H(\mathcal{E}, \mathcal{L} + 1, \mathcal{W}|\mathcal{A} = 0) - H(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 0) \\ &= F(\mathcal{E}, \mathcal{L} + 1, \mathcal{W}|\mathcal{A} = 0) - F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 0) = 0. \end{aligned} \quad (4.31)$$

The derivation in (4.31) is the result of the third condition in Theorem 4.5.

As a result, we substitute (4.30) and (4.31) into (4.29) as follows:

$$\begin{aligned} & [H(\mathcal{E}, \mathcal{L} + 1, \mathcal{W}|\mathcal{A} = 1) - H(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 1)] \\ & - [H(\mathcal{E}, \mathcal{L} + 1, \mathcal{W}|\mathcal{A} = 0) - H(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 0)] \\ = & F(\mathcal{E}, \mathcal{L} + 1, \mathcal{W}|\mathcal{A} = 1) - F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 1). \end{aligned} \quad (4.32)$$

That is, when $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 1)$ is non-decreasing, $H(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ is supermodular in $\mathcal{L}$. By contrast, when $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A} = 1)$ is non-increasing, $H(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ is submodular in $\mathcal{L}$. $\square$

4.6.2 1-to-0 Threshold Policy in Energy State $\mathcal{E}$

Given the conditions in Theorem 4.6, the following lemmas hold:

Lemma 4.3 *The monotonicity of the value function $V(\mathcal{E}, \mathcal{L}, \mathcal{W})$ is consistent with the immediate utility function $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ with respect to energy state $\mathcal{E}$.*

Lemma 4.4 *The value function is convex (or concave) in energy state $\mathcal{E}$, i.e., $[V(\mathcal{E} + 2, \mathcal{L}, \mathcal{W}) - V(\mathcal{E} + 1, \mathcal{L}, \mathcal{W})] - [V(\mathcal{E} + 1, \mathcal{L}, \mathcal{W}) - V(\mathcal{E}, \mathcal{L}, \mathcal{W})] \geq 0$ (or ≤ 0), given the discrete convexity (or concavity) of the immediate utility function $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ in energy state $\mathcal{E}$.*

Lemmas 4.3 and 4.4 are proven in Section 4.6.3 and Section 4.6.4, respectively.

In the following, we prove the 1-to-0 threshold policy in $\mathcal{E}$ as an example. That is, given the non-increasing monotonicity of $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ in $\mathcal{E}$, as well as the concavity of $V(\mathcal{E}, \mathcal{L}, \mathcal{W})$ in $\mathcal{E}$, we will prove that the utility function $H(\mathcal{S}|\mathcal{A})$ is submodular in $\mathcal{E}$. The 0-to-1 threshold policy in $\mathcal{E}$ given a non-decreasing $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ and convex $V(\mathcal{E}, \mathcal{L}, \mathcal{W})$ in $\mathcal{E}$ can be proven similarly. Note that for presentation simplicity, the $\mathcal{W}$ notations in the proof is omitted.

Proof The submodularity property should be proven respectively when the energy state $\mathcal{E}$ falls in *Cases 1 to 4* as defined in Section 4.6.1. For simplicity, we prove for *Case 1* as an example, i.e., $0 \leq \mathcal{E} < A - B$ and $B = 1$ (the first condition in Theorem 4.6). The rest could be proven in a similar way.

We expand the expression of submodularity as the derivation given in (4.39), as follows:

$$\begin{aligned}
& [H(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A} = 1) - H(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A} = 1)] \\
& - [H(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A} = 0) - H(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A} = 0)] \\
\leq & [F(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A} = 1) - F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A} = 1)] \\
& - [F(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A} = 0) - F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A} = 0)] \\
& + \sigma_1 \sum_{\mathcal{L}'=0}^L \mu_{\mathcal{L}, \mathcal{L}'} \sum_{\mathcal{W}'=0}^{\mathcal{E}} \omega_{\mathcal{W}, \mathcal{W}'} \left\{ [V(\mathcal{E} + 2 - \mathcal{W}, \mathcal{L}', \mathcal{W}') - V(\mathcal{E} + 1 - \mathcal{W}, \mathcal{L}', \mathcal{W}')] \right. \\
& \quad \left. - [V(\mathcal{E} + 1 - \mathcal{W}, \mathcal{L}', \mathcal{W}') - V(\mathcal{E} - \mathcal{W}, \mathcal{L}', \mathcal{W}')] + [V(1, \mathcal{L}', \mathcal{W}') - V(0, \mathcal{L}', \mathcal{W}')] \right\} \\
\leq & 0.
\end{aligned} \tag{4.33}$$

The term $[F(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A} = 1) - F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A} = 1)] - [F(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A} = 0) - F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A} = 0)]$ in (4.33) is zero because of the second and third conditions in Theorem 4.6. (4.33) holds due to the convexity and non-increasing monotonicity properties of $V(\mathcal{E}, \mathcal{L}, \mathcal{W})$ as stated in Lemmas 4.3 and 4.4.

Submodularity of $H(\mathcal{S} | \mathcal{A})$ in $\mathcal{E}$ holds. Consequently, the threshold policy of $\mathcal{E}$ exists in the optimal policy obtained by solving the proposed MDP formulation. $\square$

4.6.3 Proof of Lemma 4.3

Proof The value iteration algorithm [163] is employed when solving the Bellman equation (4.14)-(4.16). We denote the n^{th} iteration of $V(\mathcal{S})$ and $H(\mathcal{S})$ as $V_n(\mathcal{S})$ and $H_n(\mathcal{S})$, respectively.

Let $\mathcal{A}_0$ and $\mathcal{A}_1$ be the optimal action of the mobile node at the states $\mathcal{S}_0 = \{\mathcal{E}, \mathcal{L}, \mathcal{W}\}$ and $\mathcal{S}_1 = \{\mathcal{E} + 1, \mathcal{L}, \mathcal{W}\}$, respectively. According to the definition given in (4.14), and by optimality, the following inequalities hold:

$$\begin{aligned}
V_n(\mathcal{E} + 1, \mathcal{L}, \mathcal{W}) - V_n(\mathcal{E}, \mathcal{L}, \mathcal{W}) & \geq H_n(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A}_0) - H_n(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A}_0) \\
V_n(\mathcal{E} + 1, \mathcal{L}, \mathcal{W}) - V_n(\mathcal{E}, \mathcal{L}, \mathcal{W}) & \geq H_n(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A}_1) - H_n(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A}_1)
\end{aligned} \tag{4.34}$$

where

$$\begin{aligned}
& H_n(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A}_x) - H_n(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A}_x) \\
= & F(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A}_x) - F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A}_x) + \\
& \underbrace{\gamma \left[\sum_{\mathcal{S}'_1} P(\mathcal{S}_1, \mathcal{S}'_1 | \mathcal{A}_x) V_{n-1}(\mathcal{S}'_1) - \sum_{\mathcal{S}'_2} P(\mathcal{S}_2, \mathcal{S}'_2 | \mathcal{A}_x) V_{n-1}(\mathcal{S}'_2) \right]}_{\text{Term } \Delta PV}.
\end{aligned} \tag{4.35}$$

and $\mathcal{A}_x = \mathcal{A}_0$ or $\mathcal{A}_1$.

From the transition matrices given in (4.6), (4.8) and (4.9), the state transition term ΔPV in (4.35) can be expanded to be a linear combination of the following difference of adjacent value functions:

$$V_{n-1}([e + 1 - \mathcal{W}]^+, \mathcal{L}, \mathcal{W}) - V_{n-1}([e - \mathcal{W}]^+, \mathcal{L}, \mathcal{W}), \quad \forall \mathcal{L} \in \mathbb{L}, \forall \mathcal{W} \in \mathbb{W} \quad (4.36)$$

where $[e - \mathcal{W}]^+ = \max\{e - \mathcal{W}, 0\}$. As a result, the monotonicity of $V(\mathcal{E}, \mathcal{L}, \mathcal{W})$ in $\mathcal{E}$ can be proven by induction as follows, given that the monotonicity of the immediate utility function $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ in $\mathcal{E}$ is known:

- (i) *Initial step:* For $n = 0$, we let $V_0(\mathcal{E} + 1, \mathcal{L}, \mathcal{W}) = V_0(\mathcal{E}, \mathcal{L}, \mathcal{W}) = 0$, and hence Lemma 4.3 holds
- (ii) *Inductive step:* If Lemma 4.3 holds for $n = k$, i.e., the monotonicity of $V_k(\mathcal{E}, \mathcal{L}, \mathcal{W})$ is consistent with $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ in $\mathcal{E}$, then according to the linear combination structure of (4.36), as well as the inequalities in (4.34), the monotonicity property addressed by Lemma 4.3 also holds for the case when $n = k + 1$.

Based on the uniqueness and convergence in Lemma 4.2, the consistency property of monotonicity of $V(\mathcal{E}, \mathcal{L}, \mathcal{W})$ and $V(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ with respect to $\mathcal{E}$ in Lemma 4.3 is proven. $\square$

4.6.4 Proof of Lemma 4.4

Proof Let $\mathcal{A}_0$, $\mathcal{A}_1$ and $\mathcal{A}_2$ be the optimal actions in the states $\mathcal{S}_2 = (\mathcal{E} + 2, \mathcal{L}, \mathcal{W})$, $\mathcal{S}_1 = (\mathcal{E} + 1, \mathcal{L}, \mathcal{W})$ and $\mathcal{S}_0 = (\mathcal{E}, \mathcal{L}, \mathcal{W})$, respectively. By optimality, the following inequality holds:

$$\begin{aligned} & [V_n(\mathcal{E} + 2, \mathcal{L}, \mathcal{W}) - V_n(\mathcal{E} + 1, \mathcal{L}, \mathcal{W})] \\ & - [V_n(\mathcal{E} + 1, \mathcal{L}, \mathcal{W}) - V_n(\mathcal{E}, \mathcal{L}, \mathcal{W})] \\ \leq & \underbrace{[H_n(\mathcal{E} + 2, \mathcal{L}, \mathcal{W}|\mathcal{A}_2) - H_n(\mathcal{E} + 1, \mathcal{L}, \mathcal{W}|\mathcal{A}_2)]}_{\text{Term } \Delta_1^2 H(n)} \\ & - \underbrace{[H_n(\mathcal{E} + 1, \mathcal{L}, \mathcal{W}|\mathcal{A}_0) - H_n(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A}_0)]}_{\text{Term } \Delta_0^1 H(n)}. \end{aligned} \quad (4.37)$$

We discuss the case where $\mathcal{E} + 2, \mathcal{E} + 1, \mathcal{E} \in \{0, 1, \dots, A - 2\}$, i.e., *Case 1* defined in Section 4.6.1. Note that for the special case of *Case 4*, where $\mathcal{E} + 2 = E$ so that only action

$\mathcal{A}_2 = 0$ can be taken, the following proof still holds for both $\mathcal{A}_1 = 0$ and $\mathcal{A}_1 = 1$:

$$\begin{aligned}
& \Delta_1^2 H(n) \\
= & F(\mathcal{E} + 2, \mathcal{L}, \mathcal{W} | \mathcal{A}_2) - F(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A}_2) \\
& + I_{\mathcal{A}_2} \sum_{b=0}^1 \sigma_b \sum_{\mathcal{L}'=0}^L \mu_{\mathcal{L}, \mathcal{L}'} \left\{ \sum_{\mathcal{W}'=0}^{\mathcal{E}+1+i} \omega_{\mathcal{W}, \mathcal{W}'} [V_{n-1}(\mathcal{E} + 2 + i - \mathcal{W}, \mathcal{L}', \mathcal{W}') - V_{n-1}(\mathcal{E} + 1 + i - \mathcal{W}, \mathcal{L}', \mathcal{W}')] \right\} \\
& + \sum_{\mathcal{W}'=\mathcal{E}+2+i}^A [V_{n-1}(0, \mathcal{L}', \mathcal{W}') - V_{n-1}(0, \mathcal{L}', \mathcal{W}')] \left\{ \right\} \\
& + (1 - I_{\mathcal{A}_2}) \sum_{\mathcal{L}'=0}^L \mu_{\mathcal{L}, \mathcal{L}'} \left\{ \sum_{\mathcal{W}'=0}^{\mathcal{E}+1} \omega_{\mathcal{W}, \mathcal{W}'} [V_{n-1}(\mathcal{E} + 2 - \mathcal{W}, \mathcal{L}', \mathcal{W}') - V_{n-1}(\mathcal{E} + 1 - \mathcal{W}, \mathcal{L}', \mathcal{W}')] \right\} \\
& + \sum_{\mathcal{W}'=\mathcal{E}+2}^A [V_{n-1}(0, \mathcal{L}', \mathcal{W}') - V_{n-1}(0, \mathcal{L}', \mathcal{W}')] \left\{ \right\}
\end{aligned} \tag{4.38}$$

and

$$\begin{aligned}
& \Delta_0^1 H(n) \\
= & F(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A}_0) - F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A}_0) \\
& + I_{\mathcal{A}_1} \sum_{b=0}^1 \sigma_b \sum_{\mathcal{L}'=0}^L \mu_{\mathcal{L}, \mathcal{L}'} \left\{ \sum_{\mathcal{W}'=0}^{\mathcal{E}+i} \omega_{\mathcal{W}, \mathcal{W}'} [V_{n-1}(\mathcal{E} + 1 + i - \mathcal{W}, \mathcal{L}', \mathcal{W}') - V_{n-1}(\mathcal{E} + i - \mathcal{W}, \mathcal{L}', \mathcal{W}')] \right\} \\
& + \sum_{\mathcal{W}'=\mathcal{E}+1+i}^A [V_{n-1}(0, \mathcal{L}', \mathcal{W}') - V_{n-1}(0, \mathcal{L}', \mathcal{W}')] \left\{ \right\} \\
& + (1 - I_{\mathcal{A}_1}) \sum_{\mathcal{L}'=0}^L \mu_{\mathcal{L}, \mathcal{L}'} \left\{ \sum_{\mathcal{W}'=0}^{\mathcal{E}} \omega_{\mathcal{W}, \mathcal{W}'} [V_{n-1}(\mathcal{E} + 1 - \mathcal{W}, \mathcal{L}', \mathcal{W}') - V_{n-1}(\mathcal{E} - \mathcal{W}, \mathcal{L}', \mathcal{W}')] \right\} \\
& + \sum_{\mathcal{W}'=\mathcal{E}+1}^A [V_{n-1}(0, \mathcal{L}', \mathcal{W}') - V_{n-1}(0, \mathcal{L}', \mathcal{W}')] \left\{ \right\}
\end{aligned} \tag{4.39}$$

where $I_{\mathcal{A}} = 1$ if and only if the action decision $\mathcal{A} = 1$, and otherwise $I_{\mathcal{A}} = 0$.

We use induction to prove the concavity of $V(\mathcal{E}, \mathcal{L}, \mathcal{W})$ in $\mathcal{E}$. For the initial step $n = 1$, based on Lemma 4.2, we might as well let $V_0(\mathcal{S}) \equiv 0$. It is clear that $\Delta_1^2 H(n) \leq \Delta_0^1 H(n)$ given that $F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A})$ is concave in $\mathcal{E}$.

For the inductive step $n = k - 1$, suppose the concavity and non-increasing properties (i.e., Lemma 4.3) of $V(\mathcal{E}, \mathcal{L}, \mathcal{W})$ in $\mathcal{E}$ hold, the following inequalities can be derived from (4.38) and (4.39):

$$\begin{aligned}
& \Delta_1^2 H(k) - [F(\mathcal{E} + 2, \mathcal{L}, \mathcal{W} | \mathcal{A}_2) - F(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A}_2)] \\
\leq & \sum_{\mathcal{L}'=0}^L \mu_{\mathcal{L}, \mathcal{L}'} \left\{ \sum_{\mathcal{W}'=0}^{\mathcal{E}+1} \omega_{\mathcal{W}, \mathcal{W}'} [V_{k-1}(\mathcal{E} + 2 - \mathcal{W}, \mathcal{L}', \mathcal{W}') - V_{k-1}(\mathcal{E} + 1 - \mathcal{W}, \mathcal{L}', \mathcal{W}')] \right. \\
& \left. + \sum_{\mathcal{W}'=\mathcal{E}+2}^A [V_{k-1}(0, \mathcal{L}', \mathcal{W}') - V_{k-1}(0, \mathcal{L}', \mathcal{W}')] \right\} \\
\leq & \Delta_0^1 H(k) - [F(\mathcal{E} + 1, \mathcal{L}, \mathcal{W} | \mathcal{A}_0) - F(\mathcal{E}, \mathcal{L}, \mathcal{W} | \mathcal{A}_0)].
\end{aligned} \tag{4.40}$$

Consequently, we have

$$\begin{aligned}
& [V_k(\mathcal{E} + 2, \mathcal{L}, \mathcal{W}) - V_k(\mathcal{E} + 1, \mathcal{L}, \mathcal{W})] - [V_k(\mathcal{E} + 1, \mathcal{L}, \mathcal{W}) - V_k(\mathcal{E}, \mathcal{L}, \mathcal{W})] \\
\leq & [F(\mathcal{E} + 2, \mathcal{L}, \mathcal{W}|\mathcal{A}_2) - F(\mathcal{E} + 1, \mathcal{L}, \mathcal{W}|\mathcal{A}_2)] - [F(\mathcal{E} + 1, \mathcal{L}, \mathcal{W}|\mathcal{A}_0) - F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A}_0)] \\
\leq & 0.
\end{aligned} \tag{4.41}$$

Lemma 4.4 holds when $n = k$. It is proven that the value function $V(\mathcal{E}, \mathcal{L}, \mathcal{W})$ is concave in $\mathcal{E}$ when the immediate utility function $F(\mathcal{E}, \mathcal{L}, \mathcal{W}|\mathcal{A})$ is concave in $\mathcal{E}$.

□

Chapter 5

Optimal Offloading in Mobile Cloudlet Systems with Intermittent Connectivity

The concept of cloud computing has been extended to a mobile paradigm. Cloud providers are not necessarily to be business-level providers such as Amazon. Instead, resource-rich and trusted devices connected to the Internet, e.g., a cluster or a vehicular base station, namely a cloudlet, can also provide cloud-like services to nearby mobile devices via WiFi and cellular connections. Cloudlets provide high bandwidth and low latency local cloud services to cloudlet users. In such cloudlet network, a mobile device as a cloudlet user may offload jobs to cloudlets to reduce the cost in terms of local execution energy and resource consumptions.

However, due to the mobility feature of mobile cloudlet users (i.e., mobile devices), offloading actions should be strategically taken to achieve optimized performance. Firstly, communication overhead and remote execution costs (e.g., payments to cloudlets for offloaded job executions) may exceed local execution costs. Secondly, the mobility feature gives rise to intermittent connections between the cloudlet users and cloudlets. For a given cloudlet user, the offloaded job may fail because the connection is interrupted since the user moves out of the transmission range of the cloudlet to which the job is offloaded. As a result, the abovementioned issues should be considered in minimizing the cost of any given cloudlet in terms of energy and resource consumptions. To this end, a Markov decision process (MDP) based offloading algorithm is proposed for the mobile devices (i.e., cloudlet users) in a cloudlet system. Numerical results show the optimality of the proposed MDP offloading algorithm comparing with conventional baseline schemes in terms of expected

Table 5.1: Notation descriptions.

Notation	Definition
$\mathcal{S} = (\mathcal{G}, \mathcal{Q}, \mathcal{N})$	Composite state of a mobile user, including application phase, queue state, and the number of cloudlets
$\mathcal{A}$	Offloading action of a mobile user
$\mathbf{N}, \mathbf{G}, \mathbf{Q}$	Transition matrices for the number of cloudlets, application phase, and queue states
$P^{\mathcal{S}}(\mathcal{S}, \mathcal{S}')$	Transition probability from composite state $\mathcal{S}$ to state $\mathcal{S}'$
γ	Discount factor in the Bellman equation
$H(\cdot), V(\cdot)$	Overall cost function, expected optimal cost function in the Bellman equation
$\mathbf{G}_{EP}$	Set for exit phases
λ_c, λ_u	Spatial density of cloudlets and mobile users, respectively
λ_q	Job arrival rate to the queue
R	Bidirectional communication distance between a mobile user and a cloudlet
ε	Cloudlet's probability to accept a mobile user's offloading requests.
η_a	Probability of successful offloading to a single cloudlet
$p^\eta(\mathcal{N}, \eta_a \mathcal{A})$	Probability that the current phase is successfully executed (locally or remotely)
$C(\mathcal{S}, \mathcal{A})$	Immediate cost of a mobile user taking action $\mathcal{A}$ at state $\mathcal{S}$

cost. To the best of our knowledge, there is no existing work on stochastic modeling and dynamic optimization of a fine-grained code-level offloading decision, which considers offloading failures caused by the mobility of mobile users and admission control policy of cloudlets in an intermittently connected cloudlet system.

The rest of this chapter is organized as follows. Section 5.1 describes the system model for a mobile cloudlet environment. In Section 5.2, the MDP model is formulated and solved to minimize the computation and offloading costs from a user's perspective, considering the user's local load and the availability of cloudlets in the surrounding area. Furthermore, the existence of threshold policy is proven in MDP in Section 5.2. Section 5.3 studies the mobility feature of mobile users, and derives a set of analytical expressions for mobile users to estimate the probability of successful offloading actions. The numerical results are provided in Section 5.4. Finally, Section 5.5 concludes the chapter.

For convenience, Table 5.1 lists some important mathematical notations involved in the chapter.

5.1 System Model

In this section, we describe a general model of the cloudlet system under our consideration.

5.1.1 System Description

Figure 5.1: (a) A cloudlet system with a mobile user offloading jobs, and (b) architecture for the mobile user.

In a cloudlet system, we consider a particular mobile user which can be served by multiple mobile cloudlets, as shown in Fig. 5.1(a). Figure 5.1(b) shows the architecture of the mobile user, where the mobile device of the user contains a processor, data storage components such as memory and cache, a single-server FIFO queue to store arriving jobs pending for execution, and a wireless interface.

The job being retrieved from the queue and processed is divided into a sequence of fine-grained code sections [158], defined as application phases. The code sections can be either pre-determined or decided by the mobile user dynamically (e.g., setting break points). Processing a job means executing application phases in a certain sequence. The job processing is finished when the application transits to an exit phase, which is defined as the last phase of the job to process. Fig. 5.2 shows a typical diagram of application phases of a face recognition application (similar to [45, 190]), where phases 3 and 4 are exit phases.

Conventionally, without cloud or cloudlets, the user has to execute all the application phases on the mobile device, using local execution components, i.e., processor, memory and cache. However, in the mobile cloudlet system, the user has an option to offload parts

Figure 5.2: Application phases: The code sections of a typical mobile phone program for a face recognition application. In the figure, 0.01MB, 0.1MB, or 10MB on each phase indicates the data/code size $\delta(\mathcal{G})$ involved to process the phase.

of the application (i.e., an application phase) to the cloudlets nearby, which may potentially offer higher computing power, and thus, lower execution cost. In this section, we design a dynamic algorithm for the mobile user to decide whether to offload or not. The main procedures of the decision process are as follows:

- (i) During the application execution, we assume a time interval t which is long enough for the user to finish executing any application phase locally or remotely on cloudlets. Each of such time intervals is defined as a decision period. During a period, once an application phase is successfully executed or failed, the user starts the next decision period immediately. For simplicity of notation, $t - 1$ and $t + 1$ indicate the previous and next decision periods, respectively.
- (ii) At the beginning of each decision period, the user observes the current system states, i.e., the number of jobs $\mathcal{Q}$ in the queue, the application phase $\mathcal{G}$ that the user is executing, and the number of accessible cloudlets $\mathcal{N}$.
- (iii) Based on the observed composite state $\mathcal{S} = (\mathcal{G}, \mathcal{Q}, \mathcal{N})$ of the system, the user computes the immediate costs of local execution and offloading. Based on these immediate costs of the current state $\mathcal{S}$, the user takes an action decision $\mathcal{A}(\mathcal{S})$ (or $\mathcal{A}$ for short) of either executing the application phase locally on the mobile device (denoted as $\mathcal{A} = 0$) or offloading to the cloudlets (denoted as $\mathcal{A} = 1$).

- (iv) However, an offloading action is not always successful, due to the user mobility as well as the admission control policy of the cloudlets. An offloaded application phase may fail. As a result, the user has to restore and execute the failed application phase again (either locally or remotely) in the next decision period.

Figure 5.3 shows the flow and interaction among different parts of the chapter.

Figure 5.3: Structured view of components and methodology used in the chapter.

In the system model, a Markov decision process (MDP) is employed as an optimization method, with the aim to derive a cost-effective optimal offloading algorithm from the perspective of a mobile user (i.e., OBJ-1 in Fig. 5.3). To formulate the MDP, the system is required to have a set of states and actions, describing the operating statuses and offloading decisions of the mobile user (SYS-1 in Fig. 5.3), which is discussed in Sections 5.2.1 and 5.2.2. Moreover, an immediate cost (SYS-2 in Fig. 5.3) will be incurred to the mobile user in every system state. The immediate cost function is defined in Section 5.1.3.2 and applied in Section 5.2.3. The mobility feature (MAT-1 in Fig. 5.3) of each user has to be considered in the state transitions (SYS-1) and immediate cost function (SYS-2), which is modeled using a spatial Poisson process as defined in Section 5.1.3.1 and discussed in detail in Section 5.3.

The MDP optimization is expressed as a Bellman equation, and solved using a value iteration algorithm (MAT-2 in Fig. 5.3). The MDP solving process is shown in Section 5.2.3. Furthermore, we prove in Section 5.2.4 that the optimal policy of the MDP has a threshold structure (MAT-3 in Fig. 5.3). Based on the threshold structure, we propose a fast approximation algorithm (OBJ-2 in Fig. 5.3) to efficiently achieve offloading decisions with

bounded performance. Although OBJ-2 is not optimal compared with OBJ-1, the algorithm complexity is significantly lower.

5.1.2 Definitions and Assumptions for Optimization Model

To develop the optimal offloading algorithm for the mobile user in such a cloudlet system, we formulate and solve an MDP model. The optimization model has the following definitions and assumptions.

5.1.2.1 Jobs and Application Phases

The queue is used to store incoming jobs from the user. The queue length (i.e., the number of jobs in the queue) is denoted by Q . Without loss of generality, we assume that the job arrival is a Poisson process. Other job arrival patterns could also be applied in the MDP model. Once a job is retrieved from the queue by the mobile user, the job will be divided into application phases, as shown in Fig. 5.2. Each phase is labeled as $\mathcal{G}$. For example, $\mathcal{G} = 1$ indicates the face detection phase in Fig. 5.2. In this model, a phase is an atomic unit processed by the mobile user.

An application phase $\mathcal{G}$ involves codes and data to be processed in the current decision period. The codes are generated by applications, while the data are produced by input, output, and temporary stored files. In this section, we consider the case that the codes and data are fully portable, which means that both the codes and data can be either executed locally or offloaded to the cloudlet. We denote $\delta(\mathcal{G})$ as the size of codes and data of an application phase $\mathcal{G}$ (i.e., size of $\mathcal{G}$ for short). For example, when the mobile user is at the feature extraction & classification phase, the size of the phase includes input data passed from the previous phase, a photo taken, and related codes to process the photo. The mobile user chooses either to locally execute the feature extraction and classification algorithms to process the photo or to offload the codes and data to the cloudlets to execute. Fig. 5.2 shows the data of each application phase of the face recognition application, obtained by experiments in [190].

5.1.3 Intermittent Connections in Mobile Networks

Due to the mobility of devices in mobile networks, connections between mobile devices (e.g., mobile devices, RF energy sources and cloudlets) are not always available. For example, in a mobile cloudlet system, the following situations may happen when a mobile device (i.e., a cloudlet user) offloads its jobs to cloudlets. At the moment that the cloudlet user makes an offloading decision, the cloudlet is within the accessible range. However, as illustrated in Fig. 5.4(a), before the cloudlet transmits back the results of the offloaded jobs, the cloudlet user or the cloudlet has moved to other locations, and the distance between them becomes larger than the cloudlet coverage. Consequently, the result cannot be returned and reach the user, and the offloading ends up in failure.

Figure 5.4: (a) Intermittent connection, and (b) cloudlet user's staying time and success/failure of receiving the returned execution results from the cloudlet.

As shown in Fig. 5.4(b), $\bar{T}$ is the time interval that the cloudlet user stays in the accessible range of the cloudlet. τ is the execution time of the offloaded job. For the offloading cases 1 and 2 as shown in Fig. 5.4(b), both the offloading action and the results receiving event are in the duration of $\bar{T}$. In these two cases, the cloudlet is **available** to the user, and the offloading process succeeds. However, for the case 3 as shown in Fig. 5.4(b), soon after the offloading action is taken, the user no longer stays in the coverage. Therefore, the user cannot receive the results, and the offloading process fails. Consequently, in the optimal offloading design to manage the resources and energy of mobile devices efficiently, the intermittent connection features must be taken into consideration.

5.1.3.1 Mobility and Cloudlet Availability

We assume that the geographical distributions of both cloudlets and mobile users follow an independent Homogeneous Poisson Point Process (HPPP) [179, 191].

At the beginning of a decision period, a mobile user may observe $\mathcal{N}$ nearby cloudlets. This number $\mathcal{N}$ is referred to as *number of cloudlets*, indicating the current number of cloudlets in the adjacent area that the user can offload application phases to. A cloudlet is only accessible to the mobile user if a wireless connection can be established. Let R denote the bidirectional communication distance between the cloudlet and the mobile user. The user can offload an application phase to and receive the result from the cloudlet, if the distance between them is less than or equal to R .

Based on the HPPP assumption for the geographical distribution of cloudlets, the probability that the user can access k cloudlets in the current decision period can be calculated by the probability mass function (PMF) of HPPP as follows:

$$\Pr\{K = k\} = e^{-\pi R^2 \lambda_c} \frac{(\pi R^2 \lambda_c)^k}{k!}, \quad k = 0, 1, 2, \dots \quad (5.1)$$

where λ_c is the distribution density of cloudlets in the system.

The following conditions must hold for the user to offload and obtain the result from executing an application phase.

- At the beginning of a decision period, the user has at least one cloudlet in the communication range to offload an application phase to.
- The user is able to receive the result of the application phase or the failure signal before the end of the decision period.

However, due to the mobility of the mobile user or the cloudlets, offloading actions may not be always successful even if there are accessible cloudlets close to the mobile user. The following situations may happen. At the beginning of a decision period, the user is within the bidirectional communication distance R of a cloudlet. However, before the cloudlet transmits back the result, the user moves out of the communication range of the cloudlet. Consequently, the result of the offloading request will fail to reach the user. Besides the

mobility issue, the cloudlet availability also depends on the cloudlet's admission control decision [147]. That is, the cloudlet may refuse a request from a user with a certain probability. We define a probability η_a of successfully offloading to a cloudlet and receiving the results, namely *cloudlet availability*. It is defined as follows:

$$\eta_a = \mathbb{E} \left\{ \varepsilon \cdot \frac{T - \tau}{T} \right\} \quad (5.2)$$

where ε is the probability that the cloudlet accepts the user's offloading request (i.e., $1 - \varepsilon$ is the cloudlet outage probability). T is the user's dwell time inside the communication range R of the cloudlet. τ is the execution time of the offloaded application phase on the cloudlet, plus round-trip time (RTT) of the wireless transmission. Therefore, the physical meaning of $\frac{T - \tau}{T}$ is the probability of successful offloading given that the cloudlet always accepts offloaded jobs. We derive an estimation of η_a of a mobile user in the proposed system in Section 5.3.

In practice, the execution time τ of a program without human-computer interaction is approximately $10^{-4} \sim 10^{-2}$ s [192]. The RTT of Wi-Fi networks is in the order of tens to hundreds of ms [45], and the communication range of any cloudlet device is measured in meters [148]. Therefore, it is reasonable to presume $T - \tau > 0$ in the definition of η_a .

5.1.3.2 Immediate Cost

For the current decision period, an *immediate cost* $C(\mathcal{S}, \mathcal{A})$ will be incurred to the mobile user given the current composite state $\mathcal{S} = (\mathcal{G}, \mathcal{Q}, \mathcal{N})$. Similar to [157], as the mobile user may execute jobs locally (i.e., $\mathcal{A} = 0$) or remotely (i.e., $\mathcal{A} = 1$), the immediate cost is denoted as follows:

$$C(\mathcal{S}, \mathcal{A}) = \begin{cases} C_L(\mathcal{S}), & \mathcal{A} = 0 \\ C_R(\mathcal{S}), & \mathcal{A} = 1 \end{cases} \quad (5.3)$$

where $C_L(\mathcal{S})$ is the immediate local execution cost, and $C_R(\mathcal{S})$ is the immediate offloading cost. In the following, we present general definitions of $C_L(\mathcal{S})$ and $C_R(\mathcal{S})$.

The immediate local execution cost function $C_L(\mathcal{S})$ is the overall cost incurred when the mobile user executes the application phase locally, defined as follows:

$$C_L(\mathcal{S}) = w_{L1}E_{CPU}(\mathcal{G}) + w_{L2}C_{sch}(\mathcal{G}, \mathcal{Q}) + w_{L3}D_{usr}(\mathcal{Q}) \quad (5.4)$$

where $E_{CPU}(\mathcal{G})$ denotes the processor energy consumption of the mobile user for processing the application phase $\mathcal{G}$. According to [157], $E_{CPU}(\mathcal{G}) = P_{CPU} \cdot T_{CPU}(\mathcal{G}) = P_{CPU}(\mathcal{G}) \cdot \frac{\delta(\mathcal{G})}{s_{CPU}}$, where P_{CPU} is the processor power, $T_{CPU}(\mathcal{G})$ is the execution time of $\mathcal{G}$ on the processor, and s_{CPU} is the CPU processing speed. $C_{sch}(\mathcal{G}, \mathcal{Q})$ denotes the scheduling overhead caused by the pending jobs of the mobile user for executing the phase $\mathcal{G}$ locally. The scheduling cost $C_{sch}(\mathcal{G}, \mathcal{Q})$ is positively correlated to the queue size $\mathcal{Q}$, since the pending jobs have occupied local computational resources such as memory (e.g., memory stack occupation [193]), cache and flash storage, which affects the efficiency of employing those resources for local execution of the application phase $\mathcal{G}$. $D_{usr}(\mathcal{Q})$ denotes the current delay of all the $\mathcal{Q}$ jobs which are stored in the mobile user's queue. The delay of a job is defined as the period of time from when the job is generated to when the job is successfully completed (i.e., removed from the queue). Therefore, one unit of delay per job is incurred when the job remains in the queue for the current decision period. The immediate cost of delay $D_{usr}(\mathcal{Q}) = \mathcal{Q}$ given there are $\mathcal{Q}$ jobs remained in the queue for the current decision period.

Since the functions $E_{CPU}(\mathcal{G})$, $C_{sch}(\mathcal{G}, \mathcal{Q})$ and $D_{usr}(\mathcal{Q})$ represent different types of cost with different units. Therefore, we apply w_{L1} , w_{L2} and w_{L3} as the weight factors to combine different types of costs into a universal cost function $C_L(\mathcal{S})$. This cost function quantifies the immediate cost incurred when local execution happens. The weight factors can be set based on the mobile user's preference to different types of costs in practical systems.

By contrast, the immediate offloading cost $C_R(\mathcal{S})$ is incurred when the mobile user offloads the application phase to the cloudlet. This cost is expressed as follows:

$$C_R(\mathcal{S}) = w_{R1}C_{pay}(\mathcal{G}) + w_{R2}E_{Tx}(\mathcal{G}, r_{ch}) + w_{R3}C_{pen}(\mathcal{G}, \mathcal{N}) + w_{R4}D_{usr}(\mathcal{Q}). \quad (5.5)$$

Similarly, w_{R1} to w_{R4} are the weight factors. $C_{pay}(\mathcal{G}) = C_{bw} + C_{cloud}(\mathcal{G})$ is the payment for bandwidth usage C_{bw} and cloudlet resources usage $C_{cloud}(\mathcal{G})$. Only the first cloudlet response to the cloudlet user receives the payment. $E_{Tx}(\mathcal{G}, r_{ch})$ is the energy consumption when offloading the application phase $\mathcal{G}$ via a wireless connection with the transmission rate r_{ch} . According to [194], $E_{Tx}(\mathcal{G}, r_{ch}) = P_{cir} \cdot \frac{\delta(\mathcal{G})}{r_{ch}}$, where P_{cir} is the power consumption of the transmitter circuit. $C_{pen}(\mathcal{G}, \mathcal{N})$ is the penalty cost (e.g., the dissatisfaction level of the user) if the offloaded phase $\mathcal{G}$ fails, i.e., no result returns to the mobile user. The

exact form of $C_{pen}(\mathcal{G}, \mathcal{N})$ depends on the pattern of offloading. For example, when $\mathcal{G}$ is sent to $\mathcal{N}$ cloudlets simultaneously, failure happens only when all the $\mathcal{N}$ cloudlets refuse or fail to execute the offloaded phase $\mathcal{G}$. In this case, the penalty cost can be defined as $C_{pen}(\mathcal{G}, \mathcal{N}) = (1 - \eta_a)^{\mathcal{N}} c_{pen}$, where $(1 - \eta_a)^{\mathcal{N}}$ is the probability that offloading fails, and c_{pen} is a constant. Other forms of offloading patterns and penalty functions may also apply without altering the model. When the mobile user only has a single queue, the jobs will be blocked in the queue even when the current phase is offloaded to the remote cloudlets. In this case, the job delay $D_{usr}(\mathcal{Q})$ also exists.

5.2 Optimization Formulation

In this section, we propose an MDP model to describe the optimal offloading problem of a mobile user. Firstly, we define the state and action spaces of the mobile user. State transition matrices are then derived. Afterwards, the MDP optimization problem is expressed by a Bellman equation, and solved by employing a value iteration algorithm. Additionally, threshold policies are found in the solutions of the MDP, based on which an approximation offloading decision algorithm is proposed.

5.2.1 State Space and Action Space

The state space of the mobile user in the cloudlet system is defined as follows:

$$\Theta = \left\{ \mathcal{S} = (\mathcal{G}, \mathcal{Q}, \mathcal{N}) \in \mathbb{S} \mid \mathcal{G} \in \mathbb{G}, \mathcal{Q} \in \mathbb{Q} = \{0, 1, \dots, |\mathcal{Q}|\}, \mathcal{N} \in \mathbb{N} = \{0, 1, \dots, |\mathcal{N}|\} \right\} \quad (5.6)$$

where $\mathcal{G}$ is the application phase to be executed (either locally or remotely) by the mobile user, $\mathcal{Q}$ is the queue state (i.e., the number of jobs in the queue), and $\mathcal{N}$ is the number of cloudlets. $\mathbb{G} = \{0\} \cup \{1, \dots, |G|\}$ is the set of application phases, where $\mathcal{G} = 0$ if the user is idle. $\mathbb{G}_{EP} \subseteq \mathbb{G}$ is the set of exit phases (e.g., $\mathbb{G}_{EP} = \{3, 4\}$ in Fig. 5.2), which are the final phases of the application. $|G|$, $|\mathcal{Q}|$ and $|\mathcal{N}|$ are the maximum values of states $\mathcal{G}$, $\mathcal{Q}$ and $\mathcal{N}$, respectively.

The action space is $\mathbb{A} = \{\mathcal{A} = 0, \mathcal{A} = 1\}$, denoting that a mobile user can make a decision to execute an application phase locally on a mobile device (i.e., $\mathcal{A} = 0$), or offload to the accessible cloudlet(s) (i.e., $\mathcal{A} = 1$).

5.2.2 Transition Matrices

In the following, we derive the transition matrices for the states of the mobile user.

5.2.2.1 The Number of Cloudlet Transitions

The number of cloudlets $\mathcal{N}$ of the mobile user is distributed as an HPPP, independent of the application phase $\mathcal{G}$ and the queue state $\mathcal{Q}$. The transition probability of the number of cloudlets $\mathcal{N}$ is expressed as follows:

$$\begin{aligned} \mathbf{P}^N(\mathcal{N}, \mathcal{N}') &= \Pr\{K = \mathcal{N}'\} = e^{-\pi R^2 \lambda_c} \frac{(\pi R^2 \lambda_c)^{\mathcal{N}'}}{\mathcal{N}'!}, \\ \forall \mathcal{N} \in \{0, 1, \dots, |N|\}, \forall \mathcal{N}' \in \{0, 1, \dots, |N| - 1\}. \end{aligned} \quad (5.7)$$

We assume that the maximum number of cloudlets is finite and known (i.e., $|N| < \infty$). Therefore, the probability that the mobile user has $|N|$ accessible cloudlets within the communication range R is truncated as follows:

$$\mathbf{P}^N(\mathcal{N}, |N|) = \sum_{k=|N|}^{\infty} \Pr\{K = k\} = \sum_{k=|N|}^{\infty} e^{-\pi R^2 \lambda_c} \frac{(\pi R^2 \lambda_c)^k}{k!}. \quad (5.8)$$

The transition matrix for the number of cloudlets $\mathcal{N}$ is denoted by $\mathbf{P}^N$. It is expressed as follows:

$$\mathbf{N} = \begin{bmatrix} e^{-\pi R^2 \lambda_c} \frac{(\pi R^2 \lambda_c)^1}{1!} & \dots & e^{-\pi R^2 \lambda_c} \frac{(\pi R^2 \lambda_c)^{|N|-1}}{(|N|-1)!} & \sum_{k=|N|}^{\infty} e^{-\pi R^2 \lambda_c} \frac{(\pi R^2 \lambda_c)^k}{k!} \\ \vdots & \ddots & \vdots & \vdots \\ e^{-\pi R^2 \lambda_c} \frac{(\pi R^2 \lambda_c)^1}{1!} & \dots & e^{-\pi R^2 \lambda_c} \frac{(\pi R^2 \lambda_c)^{|N|-1}}{(|N|-1)!} & \sum_{k=|N|}^{+\infty} e^{-\pi R^2 \lambda_c} \frac{(\pi R^2 \lambda_c)^k}{k!} \end{bmatrix}_{(|N|+1) \times (|N|+1)} \quad (5.9)$$

where a row in the transition matrix (5.9) of the number of cloudlets $\mathcal{N}$ indicates the current number of cloudlets $\mathcal{N}$, while a column indicates the number of cloudlets $\mathcal{N}'$ of the next decision period. Each element is a probability of state transition.

5.2.2.2 Application Phase Transitions

We first consider the application phase transitions without offloading failures. $p^G(i, j)$ is the transition probability that the application phase j will be executed in the next decision period after the current phase i , where $i, j \in \{1, \dots, |G|\}$. As in [44], we assume that there is no cyclic self-transition from phase i to i (i.e., $p_{ii} = 0$) in a mobile application. Note that typical applications suitable for offloading should have a finite loop. The finite loop can be divided into a sequence of phases without self-transition.

Figure 5.5: (a) Transitions of application phase $\mathcal{G} = 1$ and $\mathcal{G} = 2$ given action $\mathcal{A} = 1$ is taken, and (b) transitions when action $\mathcal{A} = 0$.

However, application phase transitions also depend on the action taken by the user (i.e., offloading or executing locally). If the action is to offload (i.e., $\mathcal{A} = 1$), offloading failures may happen with the probability $1 - \eta_a$. In this case, the user has to restore the failed phase. This is illustrated in Fig. 5.5(a) for phases $\mathcal{G} = 1$ and $\mathcal{G} = 2$. By contrast, if the action is to execute an application phase locally (i.e., $\mathcal{A} = 0$), the phase will deterministically transit to the next phase (i.e., without failure), as shown in Fig. 5.5(b). We define $p^\eta(\mathcal{N}, \eta_a | \mathcal{A})$ as the probability that the current application phase is successfully executed locally or remotely by taking action $\mathcal{A}$, so that the mobile user is allowed to transit to the next phase. $p^\eta(\mathcal{N}, \eta_a | \mathcal{A})$ is defined as follows:

$$p^\eta(\mathcal{N}, \eta_a | \mathcal{A}) = \begin{cases} 1 - (1 - \eta_a)^\mathcal{N}, & \mathcal{A} = 1 \\ 1, & \mathcal{A} = 0 \end{cases} \quad (5.10)$$

where the term $1 - (1 - \eta_a)^\mathcal{N}$ indicates that all the $\mathcal{N}$ cloudlets fail to return the result of the offloaded application phase to the mobile user.

Given an action $\mathcal{A}$ taken by the mobile user as well as the probability $p^\eta(\mathcal{N}, \eta_a | \mathcal{A})$ that the current phase can be successfully executed locally or remotely, the transition probability of the application phase from $\mathcal{G}$ to $\mathcal{G}'$ is then expressed as follows:

$$P^G(\mathcal{G}, \mathcal{G}' | \mathcal{A}) = \begin{cases} 1 - p^\eta(\mathcal{N}, \eta_a | \mathcal{A}), & \mathcal{G} = \mathcal{G}' \\ p^G(\mathcal{G}, \mathcal{G}') \cdot p^\eta(\mathcal{N}, \eta_a | \mathcal{A}), & \mathcal{G} \neq \mathcal{G}'. \end{cases} \quad (5.11)$$

In the following, we construct the overall transition matrix $\mathbf{G}$ for the application phase $\mathcal{G}$, given the transition probabilities derived.

Firstly, $\mathbf{G}_0$ denotes the part of the transition matrix when the mobile user is currently idle, i.e., there is no job in the queue and the current application phase $\mathcal{G} = 0$. The matrix is expressed as follows:

$$\mathbf{G}_0 = \left[\begin{array}{cccc} I_{\mathcal{Q}=0, \mathcal{Q}'=0} \cdot \mathbf{N} & I_{\mathcal{Q}=0, \mathcal{Q}' \geq 1} \cdot \mathbf{N} & 0 & \cdots & 0 \\ \mathbf{0}_{|G| \times (|G|+1)} & & & & \end{array} \right]_{(|G|+1) \times (|G|+1)}. \quad (5.12)$$

The condition function $I_{\text{conditions}}$ in (5.12) returns 1 if the conditions hold. Otherwise, the function returns 0. For example, $I_{\mathcal{Q}=1, \mathcal{Q}'=0} = 1$ when the current queue state is $\mathcal{Q} = 1$ and the next queue state is $\mathcal{Q}' = 0$. Otherwise, $I_{\mathcal{Q}=1, \mathcal{Q}'=0} = 0$. $\mathbf{G}_0$ describes the transitions of the application phase in the following conditions: (1) $I_{\mathcal{Q}=0, \mathcal{Q}'=0} \cdot \mathbf{N}$ is for the case that given the current queue state $\mathcal{Q} = 0$, which indicates the initial state of $(\mathcal{G}, \mathcal{Q}) = (0, 0)$ as shown in Fig. 5.6, the application phase $\mathcal{G}$ transits from the initial state $\mathcal{G} = 0$ to the first phase $\mathcal{G} = 1$ if new jobs arrive at the mobile user, i.e., $\mathcal{Q}' \geq 1$. One example of such a transition is shown as $(0, 0)$ to $(1, 1)$ in Fig. 5.6; (2) By contrast, $I_{\mathcal{Q}=0, \mathcal{Q}' \geq 1} \cdot \mathbf{N}$ is for the case that, given the current queue state $\mathcal{Q} = 0$, the application phase $\mathcal{G}$ remains at the initial state $\mathcal{G} = 0$ if no new job arrives at the queue, i.e., $\mathcal{Q}' = 0$. The transition is thus $(0, 0)$ to $(0, 0)$.

$\mathbf{G}_{succ}$ is the part of the transition matrix for the cases when the mobile user is at non-exit application phases (e.g., $\mathcal{G} = 2$ in Fig. 5.2), and has a successful offloading. Without loss of generality, we denote the number of exit application phases to be $|\mathbb{G}_{EP}|$, and exit phases are labeled from $\mathcal{G} = |G| + 2 - |\mathbb{G}_{EP}|$ to $\mathcal{G} = |G| + 1$. The application phase $\mathcal{G}$ transits from the current state to the next state. The transition is defined as follows:

$$\mathbf{G}_{succ} = \left[\begin{array}{cccccc} 0 & 0 & 0 & \cdots & \cdots & 0 \\ 0 & 0 & \mathcal{F}^G(1, 2) \cdot \mathbf{N} & \mathcal{F}^G(1, 3) \cdot \mathbf{N} & \cdots & \mathcal{F}^G(1, |G| + 1) \cdot \mathbf{N} \\ 0 & \mathcal{F}^G(2, 1) \cdot \mathbf{N} & 0 & \mathcal{F}^G(2, 3) \cdot \mathbf{N} & \cdots & \mathcal{F}^G(2, |G| + 1) \cdot \mathbf{N} \\ \vdots & \vdots & & \ddots & & \vdots \\ 0 & \mathcal{F}^G(k, 1) \cdot \mathbf{N} & \mathcal{F}^G(k, 2) \cdot \mathbf{N} & \cdots & \cdots & \mathcal{F}^G(k, |G| + 1) \cdot \mathbf{N} \\ \mathbf{0}_{|\mathbb{G}_{EP}| \times (|G|+1)} & & & & & \end{array} \right] \quad (5.13)$$

where the matrix of $\mathbf{G}_{succ}$ in (5.13) has the dimension of $(|G| + 1) \times (|G| + 1)$. $\mathcal{F}^G(i, j)$ is short for $p^G(i, j) \cdot p^n(\mathcal{N}, \eta_a | \mathcal{A})$, as in (5.11). The element $\mathcal{F}^G(i, j)$ in (5.11) is for the case that the application phase state $\mathcal{G}$ transits from $\mathcal{G} = i$ to $\mathcal{G} = j$. For example, as shown in Fig. 5.6, given $\mathcal{Q} = 2$, $\mathcal{F}^G(1, 2)$ indicates the transition from the composite state $(1, 2)$ to $(2, \mathcal{Q}')$, where the value $\mathcal{Q}' \in \{2, 3, \dots, Q\}$ depends on the transition of the queue state.

$\mathbf{G}_{exit}$ denotes part of transition matrix for the case when the mobile user is at exit phases (e.g., $\mathcal{G} = 4$ in Fig. 5.2), and has a successful offloading action. It is defined as follows:

$$\mathbf{G}_{exit} = \begin{bmatrix} \mathbf{0}_{(|\mathcal{G}|+1-|\mathcal{G}_{EP}|) \times (|\mathcal{G}|+1)} & p^\eta I_{\mathcal{Q}=1, \mathcal{Q}'=0} \cdot \mathbf{N} & p^\eta I_{\mathcal{Q} \geq 1, \mathcal{Q}'=\mathcal{Q}-1} \cdot \mathbf{N} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ p^\eta I_{\mathcal{Q}=1, \mathcal{Q}'=0} \cdot \mathbf{N} & p^\eta I_{\mathcal{Q} \geq 1, \mathcal{Q}'=\mathcal{Q}-1} \cdot \mathbf{N} & 0 & \cdots & 0 & 0 \end{bmatrix}_{(|\mathcal{G}|+1) \times (|\mathcal{G}|+1)}. \quad (5.14)$$

As shown in Fig. 5.6, $p^\eta I_{\mathcal{Q}=1, \mathcal{Q}'=0} \cdot \mathbf{N}$ describes the transition from $(3, 1)$ or $(4, 1)$ (i.e., with $\mathcal{G}$ to be exit phases) to the initial idle state $(0, 0)$. This happens when the last job in the queue is completed. $p^\eta I_{\mathcal{Q} \geq 1, \mathcal{Q}'=\mathcal{Q}-1} \cdot \mathbf{N}$ describes the transitions from exit phases to $\mathcal{G} = 1$ given there is still at least one job remained in or arrived at the queue, e.g., from $(3, 2)$ to $(1, 1)$, and from $(3, 2)$ to $(1, \mathcal{Q} - 1)$ as shown in Fig. 5.6.

$\mathbf{G}_{fail}$ is part of the transition matrix for the unsuccessful offloading case. The application $\mathcal{G}$ has to be processed again with probability $1 - p^\eta(\mathcal{N}, \eta_a | \mathcal{A})$, e.g., the transition from $\mathcal{G} = 1$ to $\mathcal{G} = 1$ in Fig. 5.5(a). $\mathbf{G}_{fail}$ is defined as follows:

$$\mathbf{G}_{fail} = \begin{bmatrix} 0 & & & & \\ & (1 - p^\eta(\mathcal{N}, \eta_a | \mathcal{A})) \cdot \mathbf{N} & & & \\ & & \ddots & & \\ & & & (1 - p^\eta(\mathcal{N}, \eta_a | \mathcal{A})) \cdot \mathbf{N} & \\ & & & & \ddots \end{bmatrix}_{(|\mathcal{G}|+1) \times (|\mathcal{G}|+1)}. \quad (5.15)$$

The overall transition matrix for the application phase $\mathcal{G}$ denoted as $\mathbf{P}^G = \{\mathbf{P}^G(\mathcal{G}, \mathcal{G}' | \mathcal{N}, \mathcal{A})\}$, which includes the aforementioned parts of application phase transition matrices, shown as follows:

$$\mathbf{G} = \mathbf{G}_0 + \mathbf{G}_{succ} + \mathbf{G}_{exit} + \mathbf{G}_{fail}. \quad (5.16)$$

5.2.2.3 Queue State Transition

The job arrival follows the Poisson process, with arrival rate λ_q . In every decision period, the probability of k new arriving jobs at the local queue is $\text{Po}(k) = P[N(t+1) - N(t) = k] = \frac{e^{-\lambda_q} \lambda_q^k}{k!}$ for $k = 0, 1, \dots$, where $N(t)$ is the number of jobs arrived up to time t .

Fig. 5.6 shows an example transition diagram of queue state and application phase, without showing offloading failure. In each decision period, the number of jobs in the queue can increase until the queue is full (i.e., $\mathcal{Q} = |\mathcal{Q}|$). In particular, the queue state

Figure 5.6: Transition of the composite state $(\mathcal{G}, \mathcal{Q})$.

transition probability is obtained as follows, given $\mathcal{G} \notin \mathbb{G}_{EP}$:

$$P^Q(\mathcal{Q}, \mathcal{Q}') = \begin{cases} 0, & \mathcal{Q} > \mathcal{Q}' \\ \text{Po}(\mathcal{Q}' - \mathcal{Q}), & \mathcal{Q} \leq \mathcal{Q}' \text{ and } \mathcal{Q}' < |\mathcal{Q}| \\ 1 - \sum_{k=0}^{\mathcal{Q}' - \mathcal{Q} - 1} \text{Po}(k), & \mathcal{Q} < |\mathcal{Q}| \text{ and } \mathcal{Q}' = |\mathcal{Q}| \\ 1, & \mathcal{Q} = \mathcal{Q}' = |\mathcal{Q}| \\ 0, & \text{otherwise.} \end{cases} \quad (5.17)$$

For simplicity, the conditional parameters $\mathcal{G}$ (which is $\notin \mathbb{G}_{EP}$ or $\in \mathbb{G}_{EP}$) and $\mathcal{A} = 0$ are omitted in the function of $P^Q(\mathcal{Q}, \mathcal{Q}'|\mathcal{G}, \mathcal{A})$ in (5.17) and (5.18).

Only after the current application has finished exit phases (e.g., phases $\mathcal{G} = 3$ and $\mathcal{G} = 4$ in Fig. 5.2), the queue state may decrease by one, if there is no new job arrival, e.g., $(\mathcal{G} = 4, \mathcal{Q} = 2)$ to $(\mathcal{G} = 1, \mathcal{Q} = 1)$ in Fig. 5.6. The queue size may also increase, as shown by state $(\mathcal{G} = 3, \mathcal{Q} = 2)$ in Fig. 5.6. Given the current phase is an exit phase, i.e., $\mathcal{G} \in \mathbb{G}_{EP}$, the queue state transition probability is

$$P^Q(\mathcal{Q}, \mathcal{Q}') = \begin{cases} \text{Po}(0), & \mathcal{Q}' = \mathcal{Q} - 1 \\ \text{Po}(\mathcal{Q}' - (\mathcal{Q} - 1)), & \mathcal{Q} \leq \mathcal{Q}' < \mathcal{Q} \\ 1 - \sum_{k=0}^{\mathcal{Q}' - \mathcal{Q}} \text{Po}(k), & \mathcal{Q}' = |\mathcal{Q}| \\ 0, & \text{otherwise.} \end{cases} \quad (5.18)$$

The transition matrix of a queue state $\mathcal{Q}$ is defined as follows. $\mathbf{Q}_{incr}$ denotes the part of transition matrix for the case that the queue size does not decrease, which is the expression for the case of $\mathcal{Q} \leq \mathcal{Q}' < \mathcal{Q}$ in (5.18). This case occurs when the current application phase

is not an exit phase.

$$\mathbf{Q}_{incr} = \begin{bmatrix} \text{Po}(0) \cdot \mathbf{G}_0 & \text{Po}(1) \cdot \mathbf{G}_0 & \cdots & \text{Po}(|Q| - 1) \cdot \mathbf{G}_0 & \sum_{k=|Q|}^{\infty} \text{Po}(k) \cdot \mathbf{G}_0 \\ & \mathcal{F}^Q(1, 1) & \cdots & \mathcal{F}^Q(1, |Q| - 1) & \mathcal{F}_{trunc}^Q(1) \\ & & \ddots & \ddots & \vdots \\ & & & \mathcal{F}^Q(|Q| - 1, |Q| - 1) & \mathcal{F}_{trunc}^Q(|Q| - 1) \\ & & & & \mathcal{F}_{trunc}^Q(|Q|) \end{bmatrix} \quad (5.19)$$

where the matrix $\mathbf{Q}_{incr}$ has the dimension of $(|Q| + 1) \times (|Q| + 1)$. $\mathcal{F}^Q(i, j) = \text{Po}(j - i + 1) \cdot \mathbf{G}_{exit} + \text{Po}(j - i) \cdot (\mathbf{G}_{succ} + \mathbf{G}_{fail})$. The first term $\text{Po}(j - i + 1) \cdot \mathbf{G}_{exit}$ in $\mathcal{F}^Q(i, j)$ indicates the situation that the current application phase is an exit phase, i.e., queue length firstly decreases by one and then increases by $j - i + 1$. The second term indicates the situation that the current application phase is not an exit phase, i.e., queue length does not decrease and then increases by $j - i$. Similarly, $\mathcal{F}_{trunc}^Q(i) = \mathbf{G}_{exit} \sum_{k=|Q|-i+1}^{\infty} \text{Po}(k) + (\mathbf{G}_{succ} + \mathbf{G}_{fail}) \sum_{k=|Q|-i}^{\infty} \text{Po}(k)$.

$\mathbf{Q}_{decr}$ is part of the transition matrix for the case that the queue size in the mobile user decreases by one in the next decision period, which describes the first expression for the case of $Q' = Q - 1$ in (5.18). It is defined as follows:

$$\mathbf{Q}_{decr} = \begin{bmatrix} 0 & & & & \\ \text{Po}(0) \cdot \mathbf{G}_{exit} & 0 & & & \\ & \ddots & \ddots & \ddots & \\ & & \text{Po}(0) \cdot \mathbf{G}_{exit} & 0 & \end{bmatrix}_{(|Q|+1) \times (|Q|+1)} \quad (5.20)$$

In this case, $\text{Po}(0) \cdot \mathbf{G}_{exit}$ indicates that the current application phase is an exit phase, and no new job arrives at the queue.

The overall transition matrix for a queue state is defined as follows:

$$\mathbf{Q} = \mathbf{Q}_{incr} + \mathbf{Q}_{decr}. \quad (5.21)$$

The complexity of constructing the state transition matrices (5.9), (5.16) and (5.21) is $\mathcal{O}(|S|^2)$, where $|S|$ is the total number of all the states.

5.2.3 Solving the Optimal Policy for the MDP

Given the proposed MDP, a policy for the MDP is denoted as $\Phi(\mathcal{S}, \mathcal{A})$, which is the probability of taking an action $\mathcal{A}$ at state $\mathcal{S}$. An optimal policy for the proposed MDP aims to optimize the offloading actions of the mobile user to minimize cost.

To obtain the optimal policy, the following Bellman equation [183] based on the defined state space and derived transition matrices has to be solved:

$$V(\mathcal{S}) = \min_{\Phi(\mathcal{S}, \mathcal{A})} H(\mathcal{S}, \mathcal{A}) \quad (5.22)$$

$$\phi^*(\mathcal{S}) = \arg \min_{\Phi(\mathcal{S}, \mathcal{A})} H(\mathcal{S}, \mathcal{A})$$

$$H(\mathcal{S}, \mathcal{A}) = C(\mathcal{S}, \mathcal{A}) + \gamma \sum_{\mathcal{S}' \in \mathbb{S}} P^{\mathcal{S}}(\mathcal{S}, \mathcal{S}' | \mathcal{A}) V(\mathcal{S}').$$

where $\mathcal{S} = (\mathcal{G}, \mathcal{Q}, \mathcal{N})$. $V(\mathcal{S})$ is a *value function* of the mobile user. $\phi^*(\mathcal{S})$ denotes the optimal policy (i.e., the function that returns an optimal action for the user). $H(\cdot)$ is a *cost function* of MDP. $\gamma \in (0, 1)$ is a discount factor of future states. $C(\mathcal{S}, \mathcal{A})$ is the immediate cost with respect to the state $\mathcal{S}$ of the current decision period, as defined in Section 5.1.3.2. $P^{\mathcal{S}}(\mathcal{S}, \mathcal{S}' | \mathcal{A})$ is the transition probability of the mobile user from the current state $\mathcal{S}$ to the next state $\mathcal{S}'$, which can be obtained from the transition matrices (5.9), (5.16) and (5.21). The Bellman equation can be solved numerically by employing the value iteration algorithm [163].

5.2.4 Threshold Policy in Offloading Decision Making

In this section, we introduce the concept of threshold policy and show its existence in the optimal policy obtained from the proposed MDP.

In an MDP model with binary choice of actions (i.e., $\mathcal{A} = a_1$ or a_2), a threshold policy is in the following form

$$\phi^*(\theta, \cdot) = \begin{cases} a_1, & \text{for } \theta > \theta_{thresh} \\ a_2, & \text{otherwise} \end{cases} \quad (5.23)$$

where $\phi^*(\cdot)$ is the optimal policy function. It is defined that a state θ has a threshold policy, and the threshold is θ_{thresh} . The optimal action scheme $\phi^*(\theta, \cdot)$ is defined to have a threshold type.

Once the MDP is proven to have a threshold policy and the threshold θ_{thresh} is obtained, the user only needs to determine the threshold, and compare the current state θ with the threshold θ_{thresh} . Whenever the current state $\theta > \theta_{thresh}$, the action $\mathcal{A} = a_1$ should be taken. Otherwise, the action $\mathcal{A} = a_0$ should be taken.

To prove the existence of the threshold policy, we employ the method in [185, 183], i.e., to prove the supermodularity (submodularity) [185] feature of the cost function in the Bellman equation (5.22). That is, the cost function $H(\mathcal{S}, \mathcal{A})$ has to be supermodular (or submodular) with respect to $(\mathcal{Q}, \mathcal{A})$ and $(\mathcal{N}, \mathcal{A})$, so that the states $\mathcal{Q}$ and $\mathcal{N}$ have threshold policies, and the optimal policy solved by MDP has a threshold type.

Definition 5.4 A function $f(x, y) : (x \in \mathbb{X} \subseteq \mathbb{R}) \times (y \in \mathbb{Y} \subseteq \mathbb{R}) \in \mathbb{R}$ is supermodular in (x, y) if $f(x_1, y_1) - f(x_1, y_2) \geq f(x_2, y_1) - f(x_2, y_2)$, $\forall x_1, x_2 \in \mathbb{X}, \forall y_1, y_2 \in \mathbb{Y}, x_1 > x_2, y_1 > y_2$. Similarly, $f(x, y)$ is submodular in (x, y) if $f(x_1, y_1) - f(x_1, y_2) \leq f(x_2, y_1) - f(x_2, y_2)$, $\forall y_1, y_2 \in \mathbb{Y}, x_1 > x_2, y_1 > y_2$.

Theorem 5.8 (Threshold in the Number of Cloudlets) Given any fixed queue state $\mathcal{Q}$ and application state $\mathcal{G}$, the optimal offloading decision is a threshold policy in the number of cloudlets $\mathcal{N}$, i.e.,

$$\phi_t^*(\mathcal{S}) = \begin{cases} 1, & \text{for } \mathcal{N} > \mathcal{N}_{\text{thresh}} \\ 0, & \text{otherwise} \end{cases} \quad (5.24)$$

given the immediate cost function $C(\mathcal{S}, \mathcal{A})$ is monotonic in $\mathcal{N}$. The function $\phi_t^*(\mathcal{S})$ is the optimal policy of offloading actions, and $\mathcal{N}_{\text{thresh}}$ is the threshold in the number of cloudlets $\mathcal{N}$.

The proof of Theorem 5.8 is given in Appendix 5.6.1.

Theorem 5.9 (Threshold in queue state) Given any number of cloudlets $\mathcal{N}$ and application state $\mathcal{G}$, the optimal offloading decision is a threshold policy in the queue state $\mathcal{Q}$, given any of the following conditions of immediate cost function $C(\cdot)$.

- Condition 1: Second order cross difference of the immediate cost function $C((\mathcal{G}, \mathcal{Q}, \mathcal{N}), \mathcal{A})$ in $\mathcal{G}$ and $\mathcal{Q}$ is greater than or equal to 0, i.e., $\frac{\Delta^2 C((\mathcal{G}, \mathcal{Q}, \mathcal{N}), \mathcal{A})}{\Delta \mathcal{G} \Delta \mathcal{Q}} \geq 0$, regardless of which action is taken, i.e., $\frac{\Delta^2 C((\mathcal{G}, \mathcal{Q}, \mathcal{N}), \mathcal{A})}{\Delta \mathcal{G} \Delta \mathcal{Q}}|_{\mathcal{A}_1} = \frac{\Delta^2 C((\mathcal{G}, \mathcal{Q}, \mathcal{N}), \mathcal{A})}{\Delta \mathcal{G} \Delta \mathcal{Q}}|_{\mathcal{A}_2}$, $\forall \mathcal{A}_1, \mathcal{A}_2 \in \mathbb{A}$, the cross difference is not a function of action $\mathcal{A}$.
- Condition 2: All the application phases executed by the user are with the same size, which cause the same base cost, i.e., $C((\mathcal{G}_1, \mathcal{Q}, \mathcal{N}), \mathcal{A}) = C((\mathcal{G}_2, \mathcal{Q}, \mathcal{N}), \mathcal{A})$, $\forall \mathcal{G}_1, \mathcal{G}_2 \in \mathbb{G}$, given the same $\mathcal{Q}, \mathcal{N}$ and action $\mathcal{A}$.

The proof of Theorem 5.9 is given in Appendix 5.6.2.

The threshold policy could assist a mobile user to make offloading decisions in the following aspects:

- *Simplifying device's design:* For a user device executing a simple application (i.e., sensors), the control logic of optimal offloading decision making could be preset when manufacturing. That is, the threshold values of all the possible states of the device (i.e., potential mobile cloudlet user) are calculated in advance (e.g., employing the value iteration algorithm) and implanted into the device as sole discrete values or functions. As a result, the device simply compares its current state with the preset threshold and makes an offloading decision, instead of calculating or storing the action for every state. Thus, the hardware logic design will be simplified, since the decision logic is binary.
- *Fast threshold algorithm:* For resource-limited mobile users making dynamic offloading decisions, fast decision algorithms could also be designed to make use of the advantages of threshold policy without solving the MDP model. The idea is similar to the simple threshold activation policy in [187]. In the following, we propose a fast approximation algorithm, which has the complexity of $\mathcal{O}(1)$ compared with the complexity $\mathcal{O}(|\mathbb{A}| \cdot |\mathbb{S}|^2)$ [195] of the value iteration algorithm, where $|\mathbb{A}|$ and $|\mathbb{S}|$ are the number of actions and states, respectively. The proposed fast algorithm does not yield worst decisions under any circumstances compared with the baseline offloading schemes. In other words, the fast algorithm leads to acceptable error-bounded results without complicated and time-consuming calculation process.

We propose an equal-division decision making algorithm based on the threshold policy. The idea of the equal-division algorithm is simple, as follows:

- (i) Suppose the state space $\mathbb{S}_{thresh}$ contains all the states that have a threshold type. The user divides the state space $\mathbb{S}_{thresh}$ equally into two sides, e.g., drawing a line when the $\mathbb{S}_{thresh}$ is two-dimensional, as shown in the example in Fig. 5.7. The higher dimensional state space partition is done in the same manner.

- (ii) The user takes action 0 when the current state is on one side, and takes action 1 when the state is on the other side. To decide the action to be taken on each side, the supermodularity (or submodularity) feature of the immediate cost function $C(\cdot)$ has to be known, as discussed in Appendices 5.6.1 and 5.6.2.
- (iii) For the boundary states (e.g., the states on the line in Fig. 5.7), they are divided equally in the similar manner.

For example, if only the state $\mathcal{N}$ is considered (i.e., one dimensional threshold), where $|\mathcal{N}| = 5$, the user will take action $\mathcal{A} = 0$ when $\mathcal{N} \in \{0, 1, 2\}$, and action $\mathcal{A} = 1$ when $\mathcal{N} \in \{3, 4, 5\}$.

Figure 5.7: (a) Optimal results calculated from an MDP algorithm for comparison, (b) fast equal-division algorithm, and (c) random action decision scheme

It is clear that when the equal-division algorithm is employed, the user will at most have $\frac{|\mathbb{S}|}{2}$ suboptimal decisions, compared with the optimal actions derived by the MDP algorithm, where $|\mathbb{S}|$ is the maximum number of composite states. That is, the upper bound of suboptimal decisions is $\frac{|\mathbb{S}|}{2}$ compared with the random action decision making scheme and all local/remote action schemes (introduced as baseline offloading schemes in Section 5.4.1), which have up to $|\mathbb{S}|$ suboptimal actions in the extreme cases. For example, with the parameter settings used in Section 5.4, Fig. 5.7(a) shows the optimal actions derived by the MDP algorithm, where the filled boxes in the figure indicate $\mathcal{A} = 1$ at the corresponding system

states, and $\mathcal{A} = 0$ otherwise. Compared to Fig. 5.7(a), the fast algorithm yields only 7 sub-optimal actions, indicated by the crossed boxes shown in Fig. 5.7(b). The random action decision case is shown in Fig. 5.7(c), where there are 19 suboptimal actions compared with that of the MDP optimal actions.

5.3 Mobility of Mobile Users: Cloudlet Availability Estimation

The optimization formulation in Section 5.2 requires the cloudlet availability η_a . In this section, we estimate the value of η_a based on some assumptions of mobile user's distribution and mobility.

5.3.1 Distance Priority-based Cloudlet Admission Control

The cloudlet may refuse to accept the offloading requests from the mobile users. Consequently, cloudlet admission control is an important factor which affects the cloudlet availability. The admission control policy may vary. We design a priority-based admission control policy similar to that in [147]. That is, users in the same cloudlet coverage area have different priorities according to their distances to the cloudlet when they offload simultaneously. Nevertheless, other admission control policies can also be adopted into the proposed model.

We assume that the capacity of a cloudlet is limited. Rationally, the cloudlet has to execute its own jobs first, and shares the rest of resources to serve offloading users. We define a concept named External Service Ratio (ESR) metric, which is similar to Signal to Interference plus Noise Ratio (SINR), as follows. Only active users who are in the coverage area and currently offloading to the cloudlet are considered. Let us focus on user u . Note that there could be other users u_i , $i \in \{1, 2, \dots\}$ in the coverage area of the same cloudlet. The definition of ESR is given as follows:

$$\beta_{ESR}(r) = \frac{gr^{-c}}{E_s + \sum g_i r_i^{-c}} \quad (5.25)$$

where we further assume all $g_i \equiv g$ to be the energy consumption (e.g., transmission power) by the cloudlet to process a job offloaded by any user. E_s is the reserved energy to process

the cloudlet's own jobs. r is the user u 's distance to the cloudlet. Although the exact distance of a user to the cloudlet may not be known, the cloudlet can estimate it indirectly, e.g., by measuring the user's signal strength. c is a positive constant (e.g., $c = 1$) indicating the sensitivity of r (as well as r_i) to the function $\beta_{ESR}(r)$. By adopting ESR, a user located closer to the cloudlet has relatively larger ESR and will be possibly served with higher probability. We also assume that the cloudlet has a pre-determined constant $\hat{\beta}$, only above of which the user's offloading request will be accepted by that cloudlet (i.e., $\beta_{ESR} \geq \hat{\beta}$).

In the following, we derive the probability that the cloudlet accepts an offloading request. With the help of guard zone concept [196], from the perspective of user u located at a distance r from the cloudlet, we define the corresponding virtual zone centered at the cloudlet with radius $R_g(r)$. Once an active user who also offloads appears in the virtual zone $R_g(r)$, the user u 's ESR drops below $\hat{\beta}$ (i.e., $\beta_{ESR} < \hat{\beta}$). As a result, any offloading request from the user u will be rejected. The virtual zone radius $R_g(r)$ is calculated as follows [197]:

$$R_g(r) = \left(\frac{r^{-c}}{\hat{\beta}} - \frac{E_s}{g} \right)^{-\frac{1}{c}} \quad (5.26)$$

where $\frac{E_s}{g}$ indicates the cloudlet's own jobs. When the cloudlet's own job is relatively less energy-consuming or negligible, $\frac{E_s}{g} = 0$, such that $R_g(r) = \hat{\beta}^{\frac{1}{c}} r$. Then the failure rate (i.e., ESR outage) $1 - \varepsilon(r)$ can be expressed as follows [197]:

$$1 - \varepsilon(r) = 1 - e^{-2\pi\lambda_{au}[R_g(r)]^2} \quad (5.27)$$

which yields the admission probability $\varepsilon(r) = e^{-2\pi\lambda_{au}[R_g(r)]^2}$. In the expression, λ_{au} is the density of active users. In practice, $\lambda_{au} \leq \lambda_u$ since only some of existing users will be active. We denote $\lambda_{au} = c_a \lambda_u$, where c_a is a constant. The expression of $\varepsilon(r)$ indicates that the probability that the user can be accepted by a cloudlet depends on the density of active users in the system.

5.3.2 Dwell Time and Cloudlet Availability Estimation

In this section, we determine the dwell time of a user in a cloudlet coverage, and then derive the estimated cloudlet availability.

Assuming that the users are distributed in HPPP, the probability density that the user is located at a distance r from the cloudlet in the center of the circle is derived as follows:

$$\psi(r) = \frac{2\pi\lambda_u e^{-\pi\lambda_u r^2}}{1 - e^{-\pi\lambda_u R^2}} r \quad (5.28)$$

where λ_u is mobile users' density, r is the user's distance to the cloudlet, and R is the coverage radius of the cloudlet, where $r \leq R$.

For example, we assume that the user moves straight in the cloudlet coverage. When the user moves in the centrifugal direction to leave the cloudlet coverage area (i.e., along the fastest path) with radius R , the dwell time is $T(r) = \frac{R-r}{v}$, where v is the relative velocity of the user to the cloudlet. We define this to be *the worst case path*. By contrast, when the user moves in the centripetal direction, defined as *the best case path*, the dwell time is $T(r) = \frac{R+r}{v}$.

Considering the cloudlet admission control policy and the mobility of mobile users, the cloudlet availability is obtained as follows:

- *Worst case:*

$$\begin{aligned} \eta_{a,we} &= \mathbb{E}_r \left[\varepsilon(r) \frac{T(r)-\tau}{T(r)} \right] \\ &= \int_0^{R-v\tau} \psi(r) \cdot \varepsilon(r) \cdot \frac{T(r)-\tau}{T(r)} dr \\ &= \frac{2\pi\lambda_u}{1-e^{-\pi\lambda_u R^2}} \int_0^{R-v\tau} \left(1 - \frac{v\tau}{R-r}\right) e^{\Lambda(r)} r dr \end{aligned} \quad (5.29)$$

where $\Lambda(r) = -\pi\lambda_u r^2 - 2\pi\lambda_u [R_g(r)]^2$. The upper bound $R - v\tau$ of an integral has the physical meaning that a user located at radius $R - v\tau$ to R cannot offload jobs, since the dwell time $T(r)$ of the user is less than τ . As a result, $\eta_{a,we} = 0$ when $R - v\tau < r \leq R$.

- *Best case:*

$$\eta_{a,be} = \frac{2\pi\lambda_u}{1 - e^{-\pi\lambda_u R^2}} \int_0^R \left(1 - \frac{v\tau}{R+r}\right) e^{\Lambda(r)} r dr \quad (5.30)$$

which is derived similarly to (5.29) by using best case dwell time. Note that the upper bound of integral is R instead of $R - v\tau$.

- *Average case:* A conservative way for the user to estimate the cloudlet availability is to use a weighted average of best and worst case, i.e.,

$$\eta_{a,avg} = \alpha\eta_{a,we} + (1 - \alpha)\eta_{a,be} \quad (5.31)$$

where $\alpha \in (0, 1)$ is the weight, e.g., $\alpha = \frac{1}{2}$.

5.4 Numerical Results

In this section, the numerical results of mobile user's offloading decisions in the environment with mobile cloudlets are presented and explained.

5.4.1 Parameter Setting and Performance Metrics

We use the linear structured face recognition program [45, 190] as an example to illustrate the numerical results.

Unless otherwise stated, the following scenario and parameter settings are employed in the performance evaluation. The application phases of the face recognition in our discussed system are shown in Fig. 5.2. The queue can store 6 jobs (i.e., $|Q| = 6$). The rate of generating new job of the mobile user is $\lambda_q = 0.25$ jobs per minute. For the mobility parameters of the system: The density of mobile users is $\lambda_u = 0.0001$ per m^2 . The mobile user has the velocity of $5.0m/s$. The cloudlets have the coverage radius of $R = 10$ meters. The density of cloudlets is $\lambda_c = 0.0005$ per m^2 . For the admission control parameters as discussed in Section 5.3: The density of active mobile users is $\lambda_{au} = 10\% \cdot \lambda_u$. The ESR constant is $\hat{\beta} = 0.5$ and the sensitivity constant of a cloudlet is $c = 2$. The execution time of the offloaded application phase on the cloudlet is $\tau = 0.5s$. For the value iteration algorithm, the discount factor is $\gamma = 0.8$.

Various customized forms of cost function $C(\mathcal{S})$ can be adopted in the MDP model. As an example, the immediate cost function $C(\mathcal{S})$ defined in Section 5.1.3.2 is set as follows:

- In the immediate local execution cost $C_L(\mathcal{S})$ in (5.4), we set $\frac{P_{CPU}(\mathcal{G})}{s_{CPU}} = 1.0$ for all the application phases $\mathcal{G} \in \mathbb{G}$. The scheduling overhead is set to be $C_{sch}(\mathcal{G}, \mathcal{Q}) = \frac{\mathcal{Q}}{|\mathcal{Q}|} \cdot \delta(\mathcal{G})$. The delay is set as $D(\mathcal{Q}) = \mathcal{Q}$.
- For the immediate offloading cost $C_R(\mathcal{S})$ in (5.5), $C_{pay}(\mathcal{G})$ is set to be 0, i.e., bandwidth usage and cloudlet resources are free. Without loss of generality, $\frac{P_{cir}}{r_{ch}}$ is set to be 1.0. That is, the wireless transmission rate is fixed, and the transmission energy consumption $E_{CPU}(\mathcal{G})$ is only proportional to the size of phase $\delta(\mathcal{G})$. The penalty

function is $C_{pen}(\mathcal{G}, \mathcal{N}) = (1 - \eta_a)^{\mathcal{N}} c_{pen}$, where the coefficient $c_{pen} = 2.5$ by default, and η_a is derived in Section 5.3. The delay of job is also set to be $D(\mathcal{Q}) = \mathcal{Q}$.

- All the weight factors in the immediate cost function are set to be $\frac{1}{3}$.

We evaluate the performance of the proposed MDP optimization model (Section 5.4.3) in terms of *expected cost* and *offloading rate*. We denote the probability that the mobile user starts to operate at the state $\mathcal{S}$ to be $p_{ini}(\mathcal{S})$. The expected cost $\mathcal{C}$ of the user is defined as $\mathcal{C} = \sum_{\mathcal{S} \in \mathbb{S}} p_{ini}(\mathcal{S}) \cdot V(\mathcal{S})$. The offloading rate $\mathcal{R}$ is defined as the proportion of the user's offloading decisions made at all the states, i.e., $\mathcal{R} = \frac{1}{|\mathbb{S}|} \sum_{\mathcal{S} \in \mathbb{S}} \mathcal{A}(\mathcal{S})$, where $|\mathbb{S}|$ is the number of all the states.

We compare the performances of the proposed MDP offloading algorithm with other four baseline schemes:

- *Always executing locally scheme (LOC)*: The mobile user always executes application phases locally on the mobile device, i.e., $\mathcal{A} \equiv 0$;
- *Always offloading scheme (OFF)*: The mobile user always offloads to cloudlets, i.e., $\mathcal{A} \equiv 1$ (except when $\mathcal{N} = 0$);
- *Random scheme (RND)*: The user randomly chooses local execution or offloading action in each decision period;
- *Myopic scheme (MYO)*: The mobile user makes a short-sighted decision only based on immediate costs of the current decision period. The decision is defined as follows:

$$\mathcal{A} = \begin{cases} 0, & \text{for } C_L(\mathcal{S}, \mathcal{A}) < C_R(\mathcal{S}, \mathcal{A}) \\ 1, & \text{for } C_L(\mathcal{S}, \mathcal{A}) \geq C_R(\mathcal{S}, \mathcal{A}) \end{cases} \quad (5.32)$$

which indicates that a local execution action will be taken if the immediate cost of local execution is lower than that of offloading, i.e., $C_L(\mathcal{S}, \mathcal{A}) < C_R(\mathcal{S}, \mathcal{A})$. Otherwise, the mobile user takes an offloading action.

5.4.2 Evaluation of Cloudlet Availability Model

In Section 5.1.3.1, we present the mobility model to estimate the cloudlet availability (Section 5.4.2) in an intermittently connected cloudlet system. To verify the proposed mobility model, we simulate three general cases with different user mobility patterns, as shown in Fig. 5.8(a).

In the simulation, the user is located at a random location in the cloudlet coverage area at the beginning of a decision period, following the spatial distribution of HPPP. As Fig. 5.8(a) shows, the user has different options when choosing a mobility path: centrifugal, centripetal and random direction.

At any time before the user moves out of the cloudlet coverage area, the user may start to offload a job and receive the result. We record the probability that the offloaded job is successfully executed. For each mobility pattern, 4000 sample users are tested independently, with the cloudlet coverage radius ranging from $5m$ to $70m$.

In Fig. 5.8(b), the lines are the analytical results, while the points are the simulation results of user's average cloudlet availability, with 95% confidence interval. As the results shown from Fig. 5.8(b), for both centrifugal (i.e., the worst case) and centripetal (i.e., the best case) mobility paths, the analytical results match closely with the simulation results. Therefore, the proposed estimations given in (5.29) and (5.30) are validated.

We also consider random mobility of the user. As Fig. 5.8(c) shows, compared with simulation results with 95% confidence interval, the analytical cloudlet availability obtained from (5.31) is acceptably accurate for when the user moves with random paths.

5.4.3 Impacts of Cloudlet to Optimization

In this section, we discuss how the parameters of mobile cloudlets affect the offloading decision and performance.

5.4.3.1 Number of Cloudlets - Coverage Radius and Density

We examine the impacts of cloudlets' coverage radius R and density λ_c to the offloading decision rate and cost. From Fig. 5.9(a) and Fig. 5.10(a), as R or λ_c increases, the user's offloading rate increases. This is because with a larger cloudlet radius R or higher cloudlet

Figure 5.8: Effect of mobility for (a) centrifugal, centripetal and random movement, (b) simulation results for centrifugal (worst-case) and centripetal (best-case) movements, and (c) simulation results for random direction movement.

Figure 5.9: (a) User's offloading rate to cloudlet radius R , and (b) user's expected cost to R .

Figure 5.10: (a) User's offloading rate to cloudlet density λ_c , and (b) user's expected cost to λ_c .

density λ_c , the user has an access to more cloudlets. Consequently, as shown in Fig. 5.9(b) and Fig. 5.10(b), the user's offloading cost decreases as R or λ_c increases. Furthermore, as shown in Fig. 5.9(b) and Fig. 5.10(b), with the proposed MDP offloading algorithm, the user achieves lower expected cost than those of other schemes. Note that the expected cost of always executing locally remains constant, since the user in this case is not affected by cloudlets.

5.4.3.2 Cloudlet Availability

Fig. 5.11 shows the relationship between performances and cloudlet availability η_a , under different penalty coefficient c_{pen} of offloading failure. As expected, when there is no penalty in the cost function of offloading, the user just executes the application phase again if the offloaded phase fails. If the cost of local execution is more than that of offloading, the user still wants to offload even if η_a is small. This is observed for $c_{pen} = 0$ in Fig. 5.11(a), where the offloading rate is higher than 0.3 for $\eta_a = 0.1$.

Figure 5.11: (a) User's offloading rate to cloudlet availability η_a , and (b) user's expected cost to η_a .

When the penalty in the cost function is significant, offloading is no longer an optimal action to the user. For $c_{pen} = 2.5$ and For $c_{pen} = 5.0$, the offloading rates are lower than that of $c_{pen} = 0$, as in Fig. 5.11(a), since the possibility of offloading failure is high. As η_a increases, the penalty term has less effects to the decisions. Therefore, the immediate offloading cost $C_R(\mathcal{S})$ becomes low, as shown by the sharply increasing MYO curve in

Fig. 5.11(a) when $\eta_a > 0.6$. The decreased effect of offloading failure penalty can also be observed from Fig. 5.11(b), where we compare the MDP-based offloading algorithm with parameters $c_{pen} = 0, 2.5$ and 5.0 . The higher penalty leads to higher user's expected cost. Furthermore, the cost gaps among MDP-based schemes with different penalties (solid lines in 5.11(b)) are smaller as η_a increases since the probability of offloading failure decreases. Additionally, Fig. 5.11(b) shows that, when η_a is low, the proposed MDP algorithm achieves the lower cost than those of myopic and always offloading schemes. When η_a is high (e.g., $\eta_a \geq 0.8$), the probability of successful offloading is high enough. As a result, the performances of MDP, OFF and MYO schemes become close to each other. Moreover, the costs for different values of c_{pen} tend to converge.

5.4.4 Threshold Policy

Figure 5.12: A threshold policy in queue state $\mathcal{Q}$ and number of cloudlets state $\mathcal{N}$ when $R = 15m$: (a) The application phase $\mathcal{G} = 1$, and (b) $\mathcal{G} = 3$.

The threshold policy in the optimal solution of the proposed MDP algorithm is shown in Fig. 5.12. Given the application phase $\mathcal{G} = 2$ (in Fig. 5.12(a)) or $\mathcal{G} = 3$ (Fig. 5.12(b)) fixed, the two-dimensional threshold in $(\mathcal{Q}, \mathcal{N})$ can be observed, where the horizontal axes denote the queue state $\mathcal{Q}$ and the number of cloudlets state $\mathcal{N}$, respectively, and the vertical axis denotes the action (i.e., $\mathcal{A} = 0$ and $\mathcal{A} = 1$) taken by the mobile user. Given a certain $\mathcal{N}$ (or $\mathcal{Q}$), we increase $\mathcal{Q}$ (or $\mathcal{N}$) from 0 to $|\mathcal{Q}|$ (or $|\mathcal{N}|$), the action $\mathcal{A}$ taken by the user will monotonically change from 0 (i.e., local execution) to 1 (i.e., offloading). Consequently, a

threshold policy in $(\mathcal{Q}, \mathcal{N})$ exists. For example, in Fig. 5.12(a), the state $(Q = 2, \mathcal{N} = 4)$ is a threshold in $\mathcal{N}$ such that $\mathcal{A} = 1$ when $\mathcal{N} \geq 4$, given the queue state $Q = 2$.

Figure 5.13: User's relative expected cost (MDP cost is set as 100%): (a) with different cloudlet coverage radius R , and (b) with different offloading penalty coefficients.

Fig. 5.13 shows the suboptimality of the fast equal-division algorithm (labeled FAST) proposed in Section 5.2.4 in terms of user's expected cost. The optimal results obtained from MDP algorithm is set to be 1. Fig. 5.13 shows the relative expected cost compared with the MDP algorithm. In Fig. 5.13(a), we vary the offloading penalty coefficient c_{pen} from 0 to 8. We also vary the cloudlet coverage radius R from 8 to 15 in Fig. 5.13(b).

As shown in Fig. 5.13, when $R < 9m$ or $c_{pen} \geq 3$, the always offloading scheme (i.e., OFF) has the most unacceptable results (e.g., $> 103\%$ of optimal results when $c_{pen} \geq 4$). When $R \geq 9m$ or $c_{pen} < 3$, the always executing locally scheme (i.e., LOC) yields the most unsatisfactory results. Similarly, the random scheme (i.e., RND) could result in highly unsatisfactory cost if the offloading decisions in all or most of the states are made wrongly, e.g., the random result when $R = 10$ in Fig. 5.13(a) almost yields the worst cost. In summary, as shown in Fig. 5.13, compared with the always executing locally, always offloading and random schemes, the equal-division algorithm achieves acceptable performance in terms of the expected cost.

5.5 Summary

In this chapter, we consider offloading to cloudlet as an alternative method for the energy and resource management issues of mobile devices, which differs from the aforementioned wireless energy charging techniques. A job being processed on a mobile device (i.e., cloudlet user) can be divided into a few phases to execute. For every phase, the mobile device may decide whether to offload it to the cloudlets nearby, or to execute the phase by the mobile device locally. In some cases, offloading costs less to the mobile device, and thus reduces the energy and resource consumptions of the mobile device. This chapter proposed a Markov decision process (MDP) based scheme to model and determine the optimal offloading/local execution policy of the mobile device, considering the intermittent connection issues caused by the mobility feature in mobile networks. This chapter has also proven the existence of threshold structure in the obtained optimal policy of offloading/local execution. Moreover, a fast algorithm to obtain an approximated policy is also designed. Finally, the chapter has shown in the numerical results that the analytical model of mobility and intermittent connection proposed in this chapter is relatively accurate to describe the mobile cloudlet systems. Furthermore, the MDP-based offloading scheme has shown to efficiently reduce the overall cost of mobile devices in terms of energy and resource consumptions, comparing with some typical baseline schemes.

5.6 Appendix

5.6.1 Proof of Threshold Policy in the Number of Cloudlets $\mathcal{N}$

Proof The proof of submodularity of cost function $H_t(\mathcal{S}, \mathcal{A})$ in $\mathcal{N}$ is expressed as follows, given $\mathcal{N}_1, \mathcal{N}_2 \in \mathbb{N}, \mathcal{N}_2 \geq \mathcal{N}_1$

$$\begin{aligned}
& (H_t((\mathcal{S}_{-N}, \mathcal{N}_2), 1) - H_t((\mathcal{S}_{-N}, \mathcal{N}_2), 0)) - (H_t((\mathcal{S}_{-N}, \mathcal{N}_1), 1) - H_t((\mathcal{S}_{-N}, \mathcal{N}_1), 0)) \\
= & (C_R(\mathcal{S}_{-N}, \mathcal{N}_2, 1) - C_R(\mathcal{S}_{-N}, \mathcal{N}_1, 1)) - (C_R(\mathcal{S}_{-N}, \mathcal{N}_2, 0) - C_R(\mathcal{S}_{-N}, \mathcal{N}_1, 0)) \\
& + (C_L(\mathcal{S}_{-N}, \mathcal{N}_2, 1) - C_L(\mathcal{S}_{-N}, \mathcal{N}_1, 1)) - (C_L(\mathcal{S}_{-N}, \mathcal{N}_2, 0) - C_L(\mathcal{S}_{-N}, \mathcal{N}_1, 0)) \\
& + \Delta PV(\mathcal{N}_2) + \Delta PV(\mathcal{N}_1) \\
= & C_R(\mathcal{S}_{-N}, \mathcal{N}_2, 1) - C_R(\mathcal{S}_{-N}, \mathcal{N}_1, 1) \leq 0.
\end{aligned} \tag{5.33}$$

where

$$\begin{aligned} \Delta PV(\mathcal{N}) = & \left[\sum_{\mathcal{N}' \in \mathbb{N}} \mathbf{P}^S((\mathcal{S}_{-N}, \mathcal{N}), (\mathcal{S}_{-N}, \mathcal{N}') | \mathcal{A} = 1) V_{t+1}(\mathcal{S}_{-N}, \mathcal{N}') \right. \\ & \left. - \sum_{\mathcal{N}' \in \mathbb{N}} \mathbf{P}^S((\mathcal{S}_{-N}, \mathcal{N}), (\mathcal{S}_{-N}, \mathcal{N}') | \mathcal{A} = 0) V_{t+1}(\mathcal{S}_{-N}, \mathcal{N}') \right] \end{aligned}$$

and $\mathcal{S}_{-N} = \{\mathcal{G}, \mathcal{Q}\}$ indicates the tuple of state excluding the number of cloudlets $\mathcal{N}$. The terms $\Delta PV(\mathcal{N}_2) \equiv 0$ and $\Delta PV(\mathcal{N}_1) \equiv 0$ since $\mathbf{P}^N(\mathcal{N}, \mathcal{N}')$ is irrelevant to $\mathcal{N}$ in a Poisson Point distribution. As a result, given any action $\mathcal{A}$, submodularity of $H_t(\mathcal{S}, \mathcal{A})$ holds whenever the monotonicity property of the summation of cost functions $C_{sum}(\cdot)$ holds. $\square$

5.6.2 Proof of Threshold Policy in Queue State $\mathcal{Q}$

Proof Lemma 5.5 *The second order cross difference $[V_t(\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}) - V_t(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N})] - [V_t(\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}) - V_t(\mathcal{G}, \mathcal{Q}, \mathcal{N})] \geq 0$, which is denoted as $\frac{\Delta^2 V_t}{\Delta \mathcal{G} \Delta \mathcal{Q}} \geq 0$, given any of the conditions of $C(\cdot)$ in Theorem 5.9.*

Lemma 5.5 is proven in Appendix 5.6.3.

To prove the threshold policy in $\mathcal{Q}$, the submodularity property of cost function $H_t(\mathcal{S}, \mathcal{A})$ in $(\mathcal{Q}, \mathcal{A})$ is proven by the definition given in the following. $\mathcal{N}$ is omitted from notations. $H_t(\mathcal{G}, \mathcal{Q}, \mathcal{A})$ is employed to indicate the cost function in state $(\mathcal{G}, \mathcal{Q})$ while action $\mathcal{A}$ is taken. The submodularity condition is expressed as follows:

$$\begin{aligned} & [H_t(\mathcal{G}, \mathcal{Q}_x + 1, 1) - H_t(\mathcal{G}, \mathcal{Q}_x + 1, 0)] - [H_t(\mathcal{G}, \mathcal{Q}_x, 1) - H_t(\mathcal{G}, \mathcal{Q}_x, 0)] \\ = & \underbrace{[(C_R(\mathcal{G}, \mathcal{N}) + \gamma \sum_{\mathcal{Q}'} \mathbf{P}^S((\mathcal{S}_{-Q}, \mathcal{Q}_x + 1), (\mathcal{S}_{-Q}, \mathcal{Q}') | \mathcal{A} = 1) V_{t+1}(\mathcal{S}_{-Q}, \mathcal{Q}'))]}_{(S1)} \\ & - (C_L(\mathcal{G}, \mathcal{Q}_x + 1) + \gamma \underbrace{\sum_{\mathcal{Q}'} \mathbf{P}^S((\mathcal{S}_{-Q}, \mathcal{Q}_x + 1), (\mathcal{S}_{-Q}, \mathcal{Q}') | \mathcal{A} = 0) V_{t+1}(\mathcal{S}_{-Q}, \mathcal{Q}'))}_{(S2)}) \\ & - [(C_R(\mathcal{G}, \mathcal{N}) + \gamma \underbrace{\sum_{\mathcal{Q}''} \mathbf{P}^S((\mathcal{S}_{-Q}, \mathcal{Q}_x), (\mathcal{S}_{-Q}, \mathcal{Q}'') | \mathcal{A} = 1) V_{t+1}(\mathcal{S}_{-Q}, \mathcal{Q}''))}_{(S3)} \\ & - (C_L(\mathcal{G}, \mathcal{Q}_x) + \gamma \underbrace{\sum_{\mathcal{Q}''} \mathbf{P}^S((\mathcal{S}_{-Q}, \mathcal{Q}_x), (\mathcal{S}_{-Q}, \mathcal{Q}'') | \mathcal{A} = 0) V_{t+1}(\mathcal{S}_{-Q}, \mathcal{Q}''))}_{(S4)})] \end{aligned} \tag{5.34}$$

where $\mathcal{Q}_x$ is any queue state, and $\mathcal{G} \notin \mathbb{G}_{EP}$. When $\mathcal{G} \in \mathbb{G}_{EP}$, the proof can be conducted in the same manner.

The Terms (S1) to (S4) in (5.34) are expanded as follows:

Term (S1):

$$\begin{aligned}
& \sum_{\mathcal{Q}'} \mathbf{P}^S((\mathcal{S}_{-\mathcal{Q}}, \mathcal{Q}_x + 1), (\mathcal{S}_{-\mathcal{Q}}, \mathcal{Q}') | \mathcal{A} = 1) V_{t+1}(\mathcal{S}_{-\mathcal{Q}}, \mathcal{Q}') \\
&= p^\eta(\mathcal{N}, \eta_a | \mathcal{A} = 1) \cdot \mathbf{Po}^+(\mathcal{Q} + 1)^\top \cdot \mathbf{V}_{t-1}(\mathcal{G} + 1, \mathcal{Q} + 1) \\
&\quad + (1 - p^\eta(\mathcal{N}, \eta_a | \mathcal{A} = 1)) \cdot \mathbf{Po}^+(\mathcal{Q} + 1)^\top \cdot \mathbf{V}_{t-1}(\mathcal{G}, \mathcal{Q} + 1).
\end{aligned} \tag{5.35}$$

Term (S3) can be expanded similarly to Term (S1).

Term (S2):

$$\begin{aligned}
& \sum_{\mathcal{Q}'} \mathbf{P}^S((\mathcal{S}_{-\mathcal{Q}}, \mathcal{Q}_x + 1), (\mathcal{S}_{-\mathcal{Q}}, \mathcal{Q}') | \mathcal{A} = 1) V_{t+1}(\mathcal{S}_{-\mathcal{Q}}, \mathcal{Q}') \\
&= \mathbf{Po}^+(\mathcal{Q} + 1)^\top \cdot \mathbf{V}_{t-1}(\mathcal{G} + 1, \mathcal{Q} + 1).
\end{aligned} \tag{5.36}$$

The expansion of Term (S4) is similar to that of (S2).

(5.34) becomes

$$\begin{aligned}
& [H_t(\mathcal{G}, \mathcal{Q}_x + 1, 1) - H_t(\mathcal{G}, \mathcal{Q}_x + 1, 0)] - [H_t(\mathcal{G}, \mathcal{Q}_x, 1) - H_t(\mathcal{G}, \mathcal{Q}_x, 0)] \\
&= - (C_L(\mathcal{G}, \mathcal{Q}_x + 1) - C_L(\mathcal{G}, \mathcal{Q}_x)) \\
&\quad + \gamma(1 - p^\eta(\mathcal{N}, \eta_a | \mathcal{A} = 1)) \sum_{q=\mathcal{Q}_x}^{|\mathcal{Q}|-1} \mathbf{Po}(q) [(V(\mathcal{G}, q + 1, \mathcal{N}) - V_t(\mathcal{G} + 1, q + 1, \mathcal{N})) \\
&\quad - (V_t(\mathcal{G}, q, \mathcal{N}) - V_t(\mathcal{G} + 1, q, \mathcal{N}))] \\
&= - (C_L(\mathcal{G}, \mathcal{Q}_x + 1) - C_L(\mathcal{G}, \mathcal{Q}_x)) - \gamma(1 - p^\eta(\mathcal{N}, \eta_a | \mathcal{A} = 1)) \sum_{q=\mathcal{Q}_x}^{|\mathcal{Q}|-1} \mathbf{Po}(q) \frac{\Delta^2 V_t}{\Delta \mathcal{G} \Delta \mathcal{Q}} \\
&\leq 0.
\end{aligned} \tag{5.37}$$

The submodularity feature of $H_t(\mathcal{S}, \mathcal{A})$ in terms of $\mathcal{Q}$ is thus proven. As a result, $V_t(\mathcal{S})$ has a threshold policy in $\mathcal{Q}$.

□

5.6.3 Proof of Lemma 5.5

Proof According to the definition (5.22),

$$\begin{aligned}
V_t(\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}) &= H_t((\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}), \mathcal{A}_1) \\
V_t(\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}) &= H_t((\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}), \mathcal{A}_2) \\
V_t(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}) &= H_t((\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}), \mathcal{A}_3) \\
V_t(\mathcal{G}, \mathcal{Q}, \mathcal{N}) &= H_t((\mathcal{G}, \mathcal{Q}, \mathcal{N}), \mathcal{A}_4)
\end{aligned} \tag{5.38}$$

where $\mathcal{A}_1$ to $\mathcal{A}_4$ are actions to optimize the corresponding $V_t(\cdot)$, respectively. By optimality, we have $V_t(\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}) \leq H_t((\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}), \mathcal{A}_1)$ and $V_t(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}) \leq H_t((\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}), \mathcal{A}_4)$.

In the following, $\mathbf{Po}(\mathcal{Q})$, $\mathbf{Po}^+(\mathcal{Q})$, $\mathbf{V}_t(\mathcal{G}, \mathcal{Q})$, $\Delta_{\mathbf{G}} \mathbf{V}_t(\mathcal{G}, \mathcal{Q})$, and $\Delta_{\mathbf{Q}} \mathbf{V}_t(\mathcal{G}, \mathcal{Q})$ are defined in Appendix 5.7.

We will have the following inequalities:

$$\begin{aligned}
& V_t(\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}) - V_t(\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}) \\
\geq & \underbrace{C((\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}), \mathcal{A}_1) - C((\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}), \mathcal{A}_1)}_{(\text{Term A})} \\
& + p^\eta(\mathcal{N}, \eta_a | \mathcal{A}_1) \cdot \mathbf{Po}(\mathcal{Q})^\top \cdot \Delta_{\mathbf{Q}} \mathbf{V}_{t-1}(\mathcal{G} + 2, \mathcal{Q} + 1) + (1 - p^\eta(\mathcal{N}, \eta_a | \mathcal{A}_1)) \cdot \mathbf{Po}(\mathcal{Q})^\top \cdot \Delta_{\mathbf{Q}} \mathbf{V}_{t-1}(\mathcal{G} + 1, \mathcal{Q} + 1)
\end{aligned} \tag{5.39}$$

and

$$\begin{aligned}
& V_t(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}) - V_t(\mathcal{G}, \mathcal{Q}, \mathcal{N}) \\
\leq & \underbrace{C((\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}), \mathcal{A}_4) - C((\mathcal{G}, \mathcal{Q}, \mathcal{N}), \mathcal{A}_4)}_{(\text{Term B})} \\
& + p^\eta(\mathcal{N}, \eta_a | \mathcal{A}_1) \cdot \mathbf{Po}(\mathcal{Q})^\top \cdot \Delta_{\mathbf{Q}} \mathbf{V}_{t-1}(\mathcal{G} + 1, \mathcal{Q} + 1) + (1 - p^\eta(\mathcal{N}, \eta_a | \mathcal{A}_1)) \cdot \mathbf{Po}(\mathcal{Q})^\top \cdot \Delta_{\mathbf{Q}} \mathbf{V}_{t-1}(\mathcal{G}, \mathcal{Q} + 1).
\end{aligned} \tag{5.40}$$

Lemma 5.6 Uniqueness and convergence [186]: *the Bellman equation in (5.22) will always converge to a unique optimal result.*

When *Condition 1* in Lemma 5.5 holds, we let $V_0(\mathcal{G}, \mathcal{Q}, \mathcal{N}) = 0$ for all states $\mathcal{S} = (\mathcal{G}, \mathcal{Q}, \mathcal{N})$. This will not affect the final optimal results since the convergence and uniqueness of the Bellman equation. $[V_0(\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}) - V_0(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N})] - [V_0(\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}) - V_0(\mathcal{G}, \mathcal{Q}, \mathcal{N})] \geq 0$ holds.

For $t = 1$, i.e., the first pass iteration, $[V_1(\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}) - V_1(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N})] \geq [V_1(\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}) - V_1(\mathcal{G}, \mathcal{Q}, \mathcal{N})]$, since $V_0(\cdot) = 0$ and the two properties of $C(\cdot)$ hold, as in the statement of Lemma 5.5, i.e., $\Delta \mathbf{V}_{t-1}(\mathcal{G}) = \mathbf{0}$ and $C((\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}), \mathcal{A}_1) - C((\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}), \mathcal{A}_1) \geq C((\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}), \mathcal{A}_4) - C((\mathcal{G}, \mathcal{Q}, \mathcal{N}), \mathcal{A}_4)$.

For the iteration step $t = k - 1$, $[V_{k-1}(\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}) - V_{k-1}(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N})] \geq [V_{k-1}(\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}) - V_{k-1}(\mathcal{G}, \mathcal{Q}, \mathcal{N})]$ and the properties of $C(\cdot)$ lead to that (Term A) $\geq \mathbf{Po}^\top \cdot \Delta \mathbf{V}(\mathcal{G} + 1) \geq$ (Term B) in (5.39) and (5.40). As a result, when $t = k$, $[V_k(\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}) - V_k(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N})] \geq [V_k(\mathcal{G} + 1, \mathcal{Q}, \mathcal{N}) - V_k(\mathcal{G}, \mathcal{Q}, \mathcal{N})]$.

By contrast, when *Condition 2* in Lemma 5.5 holds, we can prove using the supermodularity (submodularity) feature of $(\mathcal{G}, \mathcal{A})$ that different actions taken are only based on different $\mathcal{Q}$ and $\mathcal{N}$, and consequently $\mathcal{A}_1 = \mathcal{A}_3$ and $\mathcal{A}_2 = \mathcal{A}_4$ in (5.38). The following equations hold:

$$\begin{aligned}
& V_t(\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}) - V_t(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}) \\
= & p^\eta(\mathcal{N}, \eta_a | \mathcal{A}_1) \cdot \mathbf{Po}^+(\mathcal{Q} + 1)^\top \cdot \Delta_{\mathbf{G}} \mathbf{V}_{t-1}(\mathcal{G} + 2, \mathcal{Q} + 1) \\
& + (1 - p^\eta(\mathcal{N}, \eta_a | \mathcal{A}_1)) \cdot \mathbf{Po}^+(\mathcal{Q} + 1)^\top \cdot \Delta_{\mathbf{G}} \mathbf{V}_{t-1}(\mathcal{G} + 1, \mathcal{Q} + 1) \\
= & \mathbf{Po}^+(\mathcal{Q} + 1)^\top \cdot \Delta_{\mathbf{G}} \mathbf{V}_{t-1}(\mathcal{G} + 1, \mathcal{Q} + 1)
\end{aligned} \tag{5.41}$$

and

$$\begin{aligned}
& V_t(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}) - V_t(\mathcal{G}, \mathcal{Q}, \mathcal{N}) \\
&= p^\eta(\mathcal{N}, \eta_a | \mathcal{A}_2) \cdot \mathbf{Po}^+(\mathcal{Q})^\top \cdot \Delta_{\mathbf{G}} \mathbf{V}_{t-1}(\mathcal{G} + 2, \mathcal{Q}) \\
&\quad + (1 - p^\eta(\mathcal{N}, \eta_a | \mathcal{A}_2)) \cdot \mathbf{Po}^+(\mathcal{Q})^\top \cdot \Delta_{\mathbf{G}} \mathbf{V}_{t-1}(\mathcal{G} + 1, \mathcal{Q}) \\
&= \mathbf{Po}^+(\mathcal{Q})^\top \cdot \Delta_{\mathbf{G}} \mathbf{V}_{t-1}(\mathcal{G} + 1, \mathcal{Q}).
\end{aligned} \tag{5.42}$$

By employing induction as abovementioned, the equation $V_t(\mathcal{G} + 1, \mathcal{Q} + 1, \mathcal{N}) - V_t(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}) = V_t(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}) - V_t(\mathcal{G}, \mathcal{Q}, \mathcal{N})$ can be proven.

Consequently, Lemma 5.5 holds when the Bellman equation (5.22) converges. $\square$

5.7 Notations

$V_t(\cdot)$ and $H_t(\cdot)$ are the value function $V(\cdot)$ and the cost function $H(\cdot)$ at the t^{th} iteration when we use the value iteration algorithm to solve the Bellman equation.

Notations $\mathbf{Po}(\mathcal{Q})$, $\mathbf{Po}^+(\mathcal{Q})$, $\mathbf{V}_t(\mathcal{G}, \mathcal{Q})$, $\Delta_{\mathbf{G}} \mathbf{V}_t(\mathcal{G}, \mathcal{Q})$, and $\Delta_{\mathbf{Q}} \mathbf{V}_t(\mathcal{G}, \mathcal{Q})$ are defined as follows:

$$\begin{aligned}
\mathbf{Po}(\mathcal{Q}) &= \begin{bmatrix} \mathbf{Po}(0) \\ \mathbf{Po}(1) \\ \vdots \\ \mathbf{Po}(|\mathcal{Q}| - \mathcal{Q} - 1) \end{bmatrix}, \\
\mathbf{Po}^+(\mathcal{Q}) &= \begin{bmatrix} \mathbf{Po}(\mathcal{Q}) \\ 1 - \sum_{k=0}^{|\mathcal{Q}| - \mathcal{Q} - 1} \mathbf{Po}(k) \end{bmatrix}, \\
\mathbf{V}_t(\mathcal{G}, \mathcal{Q}) &= \begin{bmatrix} \mathbf{V}(\mathcal{G}, \mathcal{Q}) \\ \mathbf{V}(\mathcal{G}, \mathcal{Q} + 1) \\ \vdots \\ \mathbf{V}(\mathcal{G}, |\mathcal{Q}|) \end{bmatrix}, \\
\Delta_{\mathbf{G}} \mathbf{V}_t(\mathcal{G}, \mathcal{Q}) &= \begin{bmatrix} V_t(\mathcal{G}, \mathcal{Q}, \mathcal{N}) - V_t(\mathcal{G} - 1, \mathcal{Q}, \mathcal{N}) \\ V_t(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}) - V_t(\mathcal{G} - 1, \mathcal{Q} + 1, \mathcal{N}) \\ \vdots \\ V_t(\mathcal{G}, |\mathcal{Q}|, \mathcal{N}) - V_t(\mathcal{G} - 1, |\mathcal{Q}|, \mathcal{N}) \end{bmatrix},
\end{aligned}$$

and

$$\Delta_{\mathbf{Q}} \mathbf{V}_t(\mathcal{G}, \mathcal{Q}) = \begin{bmatrix} V_t(\mathcal{G}, \mathcal{Q}, \mathcal{N}) - V_t(\mathcal{G}, \mathcal{Q} - 1, \mathcal{N}) \\ V_t(\mathcal{G}, \mathcal{Q} + 1, \mathcal{N}) - V_t(\mathcal{G}, \mathcal{Q}, \mathcal{N}) \\ \vdots \\ V_t(\mathcal{G}, |\mathcal{Q}|, \mathcal{N}) - V_t(\mathcal{G}, |\mathcal{Q}| - 1, \mathcal{N}) \end{bmatrix}.$$

Chapter 6

Conclusions and Future Work

6.1 Conclusions

Energy management methods to make full use of battery as well as wireless charging have been developed for energy devices to operate efficiently in wireless systems. The main research contributions presented in this thesis can be summarized as follows:

- *Chapter 3: Mobile Energy Gateway - A Study on Optimal Wireless Energy Carrying:* This chapter has proposed the use of a mobile energy gateway to carry and transfer energy from energy chargers to energy users, which is based on wireless energy charging technique. To obtain the optimal energy management policy (i.e., to charge or transfer) of the energy gateway, we have formulated and solved a Markov decision process (MDP) model. The optimal policy determines the action to be taken given the system states sensed by the energy gateway, including location, energy level of battery, the number of energy users, and the energy price. The optimal policy aims at maximizing the overall utility of the energy gateway. Moreover, we have proven the existence of a threshold structure in the optimal policy derived by the MDP model. The numerical results have clearly shown that the proposed MDP-based scheme for energy management of the mobile energy gateway outperforms conventional baseline schemes.
- *Chapter 4: Traffic-aware Optimal Wireless Energy Charging Policy:* We have proposed a Markov decision process (MDP) based scheme for a mobile device (i.e., a mobile node) to make wireless energy charging actions from energy sources. We

have considered the mobility, energy storage, and traffic generation processes and model them as the states of the mobile node. We have obtained an optimal charging policy, in which the mobile node makes a decision to charge its energy storage or not based on these states. The objective is to maximize the node's expected overall utility. We have also proven the existence of threshold policy of the proposed MDP model. The performance evaluation has shown that the optimal policy obtained from the proposed MDP scheme outperforms typical baseline schemes.

- *Chapter 5: Optimal Offloading in Mobile Cloudlet Systems with Intermittent Connectivity:* We have proposed the Markov decision process (MDP) based dynamic offloading algorithm for a mobile cloudlet user in a mobile cloudlet system. Consider that a mobile application can be divided into multiple phases, the cloudlet user can make a decision to execute each phase locally or offload it to nearby cloudlets. Moreover, offloading failures caused by both mobile cloudlet user mobility and cloudlet admission control have been considered. The offloading decision policy is optimized to achieve the lowest cost (e.g., computation and communication costs) by solving the MDP model using the value iteration algorithm. For the proposed MDP model, we have shown the existence of a threshold policy. A fast decision algorithm has also been introduced for the mobile cloudlet user to make effective and acceptable performance. The numerical results have shown that the analytical estimations of cloudlet availability is relatively accurate for various mobility patterns. Furthermore, the proposed MDP-based dynamic offloading algorithm outperforms other baseline schemes that do not take the state of the system into account.

6.2 Future Work

In the following, we discuss some possible issues to be addressed in the future studies.

6.2.1 Optimizing Multi-hop RF Energy Charging and Cloudlet Systems

In Chapters 3-5, both RF energy and data transmission are performed on a single-hop basis. However, some wireless networks may have multi-hop transmission structures, e.g., mobile

ad hoc networks and sensor networks. As aforementioned in Section 1.1.3.2, when a job is offloaded to a cloudlet which is connected to the Internet, the job could also be offloaded to typical cloud computing services. Multi-hop offloading can be performed in such a scenario. However, there are some issues to be addressed for offloading in multi-hop network structures.

- Firstly, network uncertainty becomes more complicated as there are more random factors in the system. Several system states may not be directly obtained or sensed. For example, the channel qualities and the job offloading payments of the connections further than the second hop are not exposed directly to the local mobile device. In this case, MDP models can be extended, considering the uncertainties of state observations.
- Secondly, wireless energy depletion becomes more critical in multi-hop structured networks. As introduced in Section 2.2.2.1, due to the broadcast nature of the RF signal transmission, multi-hop RF energy charging may not be applicable given the only energy source is at the transmitter of the first hop. To deal with this issue, techniques such as directional antenna and beamforming could be applied.

6.2.2 Combined Energy and Data Transfer

In Chapter 4, for every decision period, energy charging and traffic transmission are independent. However, as surveyed in Section 2.3.1, both data and energy can be carried simultaneously by the same RF signals, depending on how the receiver decodes the signal received. In the case of a single receiver antenna, the more portion that the signal is decoded as data, the less portion that the signal can be utilized as energy. In the future research, optimizations models can be proposed to address the trade-off between data receiving and energy charging from the same signals. Moreover, optimizations methods for different receiver architectures, e.g., multiple antennas, could also be studied.

6.2.3 Alternative Mobility Models of Mobile Devices

In Chapter 4, a mobility model of mobile devices (i.e., cloudlet users) is proposed to describe the intermittent connection feature of mobile networks. In this chapter, mobile de-

vices moves in straight lines to different locations. However, mobility of mobile devices can be complex for mathematically modeling, especially for human. In some scenarios, MDP-based models are not applicable, since the mobility considered as a system state may not have the Markovian property. Therefore, extensive studies are required to address the complex mobility models.

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Appendix A

Author's Publications

Papers Published/Accepted

- (i) **Yang Zhang**, Dusit Niyato, and Ping Wang, "Offloading in Mobile Cloudlet Systems with Intermittent Connectivity," *IEEE Transactions on Mobile Computing*, accepted for publication (9 Feb 2015).
- (ii) **Yang Zhang**, Chonho Lee, Dusit Niyato, and Ping Wang, "Auction Approaches for Resource Allocation in Wireless Systems: A Survey," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 3, pp. 1020-1041, 3rd Quarter 2013.
- (iii) **Yang Zhang**, Dusit Niyato, and Ping Wang, "Auction-Based Resource Allocation in Cognitive Radio Systems," *IEEE Communications Magazine*, vol. 50, no. 11, pp. 108-120, 2012.
- (iv) **Yang Zhang**, Dusit Niyato, Ping Wang, and Lu Xiao, "Optimizing Content Relay in Publish-Subscribe Mobile Social Networks," to be presented in *Proc. IEEE WCNC 2015*, New Orleans, LA, USA, 9-12 Mar 2015.
- (v) Dusit Niyato, **Yang Zhang**, Ping Wang, and Dong In Kim, "Optimal Wireless Energy Charging Policy for a Mobile Node in Smart Grid Environment," in *Proc. IEEE SmartGridComm 2014*, Venice Italy, Nov 2014.
- (vi) **Yang Zhang**, Dusit Niyato, Ping Wang, and Chen-Khong Tham, "Dynamic Offloading Algorithm in Intermittently Connected Mobile Cloudlet Systems," in *Proc. IEEE ICC 2014*, Sydney, June 2014.
- (vii) Yifan Li, Ping Wang, Dusit Niyato, and **Yang Zhang**, "Contract-Theoretic Modeling for Content Delivery in Relay-Based Publish-Subscribe Networks," in *Proc. IEEE ICC 2014*, Sydney, June 2014.

- (viii) **Yang Zhang**, Dusit Niyato, and Ping Wang, “An Auction Mechanism for Resource Allocation in Mobile Cloud Computing Systems,” in *Proc. Intl. Conf. on Wireless Algorithms, Systems, and Applications (WASA 2013)*, Aug. 2013.

Papers under Review

- (i) **Yang Zhang**, Dusit Niyato, Ping Wang, and Dong In Kim, “Optimal Energy Management Policy of Mobile Energy Gateway,” submitted to *IEEE Transactions on Vehicular Technology* in Dec 2014, under review.
- (ii) **Yang Zhang**, Dusit Niyato, Ping Wang, and Dong In Kim, “Optimal Wireless Energy Charging Policy for a Mobile Grid,” submitted to *IEEE Transactions on Mobile Computing* in Nov 2014, under review.