RESOURCE ALLOCATION FOR ENERGY EFFICIENT DEVICE-TO-DEVICE COMMUNICATIONS

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List of Abbreviations

1G	—	First Generation mobile network
2G	—	Second Generation mobile network
3D	—	Third Dimension
3G	—	Third Generation mobile network
3GPP	—	Third Generation Partnership Project
4G	—	Fourth Generation mobile network
5G	—	Fifth Generation mobile network
AMPS	—	Advanced Mobile Phone System
AWGN	—	Additive White Gaussian Noise
BnB	—	Branch-and-Bound
BS	—	Base Station
CA	—	Carrier Aggregation
CM	—	Cellular Mode
CNR	—	Channel to Noise Ratio
CoMP	—	Coordinated Multipoint
CUE	—	Cellular User Equipment
CCCP	—	Concave-Convex Procedure
CDMA	—	Code Division Multiple Access
D2D	—	Device-to-Device
DC	—	Difference of two convex function
DCA	—	DC Algorithm
DM	—	Dedicated Mode
DRx	—	D2D Receiver
DTx	—	D2D Transmitter
DUE	—	D2D User Equipment
EE	—	Energy Efficiency
EH	—	Energy Harvesting

eICIC	—	Enhanced Inter Cell Interference Cancellation
EPA	—	Equal Power Allocation
FDD	—	Frequency Division Duplex
FDMA	—	Frequency Division Multiple Access
FFR	—	Fractional Frequency Reuse
FTPA	—	Fractional Transmit Power Allocation
GPRS	—	General Packet Radio Service
Hetnets	—	Heterogeneous Networks
HSDPA	—	High Speed Downlink Packet Access
HSPA	—	High Speed Packet Access
HSUPA	—	High Speed Uplink Packet Access
IA	—	Interference Alignment
IoT	—	Internet of Things
IPM	—	Interior Point Method
ISM	—	Industrial, Scientific and Medical
LAA	—	License Assisted Access
LDD	—	Lagrange Dual Decomposition
LTE	—	Long Term Evolution
LTE-A	—	Long Term Evolution - Advanced
M2M	—	Machine to Machine
MIMO	—	Multiple-Input Multiple-Output
MISO	—	Multiple-Input Single-Output
MINLP	—	Mixed Integer Nonlinear Programming
MOOP	—	Multi-Objective Optimization Problem
MTC	—	Machine-Type Communication
NGMN	—	Next Generation Mobile Networks
NOMA	—	Non-Orthogonal Multiple Access
NMT	—	Nordic Mobile Telephone
OFDMA	—	Orthogonal Frequency Division Multiple Access
OMA	—	Orthogonal Multiple Access
PLMN	—	Public Land Mobile Network
ProSe	—	Proximity Services
QoS	—	Quality of Service
RB	—	Resource Block
RE	—	Resource Efficiency

RM	—	Reuse Mode
RRM	—	Radio Resource Management
SCMA	—	Sparse Code Multiple Access
SE	—	Spectrum Efficiency
SINR	—	Signal to Interference plus Noise Ratio
SMS	—	Short Messaging Services
SOOP	—	Single Objective Optimization Problem
TDD	—	Time Division Duplex
TDMA	—	Time Division Multiple Access
UE	—	User Equipment
VUE	—	Vehicular User Equipments

List of Variables

α	—	Path loss exponent
β	—	Tradeoff parameter
ϵ	—	Tolerance
γ_{cUL}	—	Received SINR at BS for uplink resource sharing
γ_{dUL}	—	Received SINR at DRx for uplink resource sharing
γ_{cDL}	—	Received SINR at CUE for downlink resource sharing
γ_{dDL}	—	Received SINR at DRx for downlink resource sharing
$\omega_{k,n}$	—	RB assignment indicator
τ_p	—	Power utilization
τ_w	—	Bandwidth utilization
ε	—	Reciprocal of drain efficiency of power amplifier
c_0	—	Path loss coefficient
C	—	Number of resource blocks allocated to CUEs
d	—	D2D pair distance
d_0	—	Reference distance
d_{ij}	—	Distance of i-j link
d_{max}	—	Maximum D2D pair distance
G_r	—	Receiver gain
G_t	—	Transmitter gain
$\mathbf{H}$	—	Channel gain matrix
$H_{i,j}$	—	Channel gain between transmitter i and receiver j
$H_{c,B}$	—	Channel gain between CUE and BS
$H_{d,d}$	—	Channel gain between DTx and DRx
K	—	Number of cellular users
L	—	Number of D2D pairs
M	—	Number of resource blocks available to D2D pairs
N_0	—	Noise power spectral density

N	—	Total number of resource blocks
P	—	Total power consumptions
P_c	—	Transmit power of CUE
P_c^{max}	—	Maximum transmit power of CUE
P_{cirUE}	—	UE circuit power
P_{cirBS}	—	BS circuit power
P_d	—	Transmit power of DUE
P_d^{max}	—	Maximum transmit power of DUE
$p_{k,n}$	—	Transmit power of the k-th CUE on the n-th RB
$P_{r,ij}$	—	Received power of i-j link
P_{tot}	—	Overall power budget
P_{tc}	—	Overall power consumption for CUE
P_{td}	—	Overall power consumption for D2D pair
R	—	Cell radius
R_c	—	Achievable rate of CUE
R_c^{min}	—	Minimum rate of CUE
R_d	—	Achievable rate of DUE
R_d^{min}	—	Minimum rate of DUE
R_{sum}	—	System sum rate
W_s	—	Resource block bandwidth
W	—	Occupied bandwidth
W_c	—	Bandwidth allocated to CUE
W_d	—	Bandwidth allocated to DUE
W_{tot}	—	Spectrum bandwidth

List of Mathematical Notations

$\log_x(.)$	—	Logarithmic function to base x
$\ln(.)$	—	Natural logarithm
$\min$	—	Argument of the minimum
$\max$	—	Argument of the maximum
$\sum$	—	Summation symbol
$\mathcal{O}(.)$	—	Complexity order

Abstract

Device-to-Device (D2D) communication is one of the technologies for next generation communication system. Unlike traditional cellular network, D2D allows proximity users to communicate directly with each other without routing the data through a base station. The main aim of this study is to improve the overall energy efficiency (EE) of D2D communications overlaying cellular system. To reduce the complexity of joint EE optimization, we decompose the main EE problem into two subproblems; resource efficiency (RE) optimization in the first stage and EE optimization for D2D pairs in the second stage. Firstly, we propose an alternative two-stage RE-EE scheme for a single cellular user equipment (CUE) and a D2D pair utilizing uplink spectrum. Later, we extend this work for multiple CUEs and D2D pairs by considering the downlink orthogonal frequency division multiple access (OFDMA). By exploiting a range of optimization tools including the Bisection method, interior point algorithm, fractional programming, Dinkelbach approach, Lagrange dual decomposition, difference of convex functions, and concave-convex procedure, the original non-convex problems are solved and we present iterative two-stage RE-EE solutions. Simulation results demonstrate that the proposed two-stage scheme for uplink scenario outperforms the cellular mode and dedicated mode of communications and the performance is close to the global optimal solution. The results also show that the proposed schemes for downlink resource sharing provide improved system EE performance with significant gain on EE for D2D users compared to a two-stage EE-EE solution, which is obtained numerically. Furthermore, the RE and EE optimization for non-orthogonal multiple access (NOMA) are considered to study the effect of users' access to the whole spectrum. The results indicate that the proposed RE scheme for NOMA with D2D communications achieves higher system EE compared to the OFDMA based schemes.

Declaration

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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Dedication

To My Family

Chapter 1

Introduction

1.1 Future Wireless Networks

The demand on wireless data traffic has been increasing significantly since the introduction of smart phones. The growth of cellular subscribers in the developed and developing countries also contributes to this demand. According to [1], the global mobile data traffic grew 63% in 2016 as it reached 7.2 exabytes per month at the end of 2016, up from 4.4 exabytes per month at the end of 2015. The amount will increase sevenfold between 2016 and 2021, reaching 49.0 exabytes per month by 2021. Furthermore, it is forecasted that in 2021, 78% of mobile data traffic will be video and there will be 11.6 billion mobile devices, which surpasses the global projected population at that time.

Currently, the fourth generation (4G) wireless communication, LTE Advanced (LTE-A) is being deployed. LTE-A improves the capacity and coverage by implementing technologies such as Carrier Aggregation (CA), Coordinated multipoint (CoMP), Advanced multiple-input multiple-output (MIMO), Relays, heterogeneous networks (HetNets), and Enhanced Inter Cell Interference Cancellation (eICIC) [2]. The performance targets that LTE-A aims to achieve are peak data rate of 1 GBps in the downlink and 500 Mbps in the uplink, mobility up to 350 km/h and less than 50 ms latency [3]. However, these performance targets would not be able to cater the tremendous growth of future mobile data network.

A lot of research have been done to find new alternatives and potential solutions for future wireless network. Research groups such as METIS [4] have been investigating new technologies for the next fifth generation (5G) cellular network.

In order to enhance the performance of wireless network beyond 4G system, several technologies have been proposed such as massive MIMO, mmWave communication full duplex communication [5] and non-orthogonal multiple access (NOMA) [6]. Another technology for increasing the achievable rate in cellular communications is Device-to-Device (D2D) communication [7] where devices can directly exchange data without having to route it through a central infrastructure communication. Future wireless network is expected to be heterogeneous and involve technologies such as Internet of Things (IoT) and machine to machine (M2M) communications. Next generation network also focuses on providing greener communication system.

1.2 Motivation

The tremendous growth of information and communication technology as well as cellular network market has contributed to world's energy consumption. The major energy consumption for wireless network came from base station (BS) which accounts for around 57% of total power consumption in a typical cellular network [8, 9]. Mobile switching and core transmission of the network are also the main contributors to the network power consumption. Energy consumption has become an important problem and this has led network operators, regulatory bodies such as ITU and 3GPP and research projects such as EARTH [10] and GreenTouch [11] to consider energy aspect of wireless communication networks. In addition, one of the requirements for 5G system is the need to improve the energy efficiency (EE) of communication networks [12].

System performances in terms of coverage and spectral efficiency have always been the focus of the network designer [13]. Coverage performance can be obtained by studying the distribution of signal to interference plus noise ratio (SINR) of users while spectral efficiency (SE) is a measure of how many bits of information can be transferred to served users for a given wireless bandwidth. Recently, another metric that has gained much attention is the EE of the network. EE is a measure of the number of delivered bits per consuming energy [14], or "bits-per-Joule" [15]. From the network operators' point of view, reducing energy costs can directly reduce their operation expenditures while other parties are also interested in reducing the carbon footprint contributed by wireless communications. Designers of future wireless technologies must also consider energy aspect of the design. In addition, a conventional system will occupy as much as bandwidth as possible to maximize the EE. As a result, it reduces the efficient use of bandwidth. On the other hand, the system requires as much power as possible to optimize the SE. This shows that optimizing EE and SE are important aspects which may lead to a conflict. Therefore, the tradeoff between EE and SE has been studied in [16–19]. In addition, a new metric called resource efficiency (RE) is proposed in [20], which is capable of exploiting the tradeoff between EE and SE by balancing consumption power and occupied bandwidth.

D2D communication, which is one of the future technologies, enables devices to communicate directly with each other, without routing the data paths through a central infrastructure such as BS or access point. Bluetooth and WiFi are two examples of traditional D2D communications as devices in the close range can operate in ad-hoc manner for file transferring and information sharing. Both Bluetooth and WiFi are operating in unlicensed industrial, scientific and medical (ISM) band. However, D2D communications in cellular network depend on licensed frequency and share the spectrum with other cellular users. A potential application of D2D is proximity-based services such as social applications, advertisements, and local exchange of information. Another important application is for public safety support, where devices would still be able to engage in communication even in case of damage to the network infrastructure. The introduction of D2D communications poses many new challenges and risks to the traditional cellular architecture and users. There are many studies have been conducted to tackle the challenges of D2D communications particularly to reduce the interference in the network. Majority of works on D2D focus on radio resource management aspects of D2D communications such as resource allocation, power control, interference management and mode selection.

Currently, the EE aspect of D2D communications has attracted a lot of attention. Although the transmission power of mobile devices is much lower compared to the BS, the small improvement in the energy aspect of D2D communications has a significant contribution towards the overall energy consumption. Furthermore, as the number of mobile devices and connections are forecasted to reach 11.5 billion, of which 40% are smartphones [1], it is vital to improve the EE of the devices since they have direct impact on the networks. In addition, D2D communications are also considered as supplements to cellular communications. Therefore, it is most likely that cellular and D2D communications will coexist.

However, few works have studied the EE-SE tradeoff of D2D communications underlaying or overlaying cellular system. These factors have become the main motivations to further investigate the EE and EE-SE tradeoff for D2D communications overlaying cellular system.

1.3 Contributions

In this thesis, several energy efficient schemes for D2D communications have been investigated. The main contributions of this thesis are summarized as follows.

1. Proposed a low complexity, two-stage scheme to maximize the system EE of D2D communication overlaying cellular system using uplink resources. In the first stage, resource efficiency (RE) problem for a cellular user equipment (CUE) is formulated and solved using the Bisection method. In the next stage, Dinkelbach and interior point method (IPM) are exploited to solve the EE optimization problem for a D2D pair.

2. Extended the proposed framework for multiple CUEs and D2D pairs in downlink resource sharing scenario. RE optimization problem is formulated as a mixed integer nonlinear problem (MINLP). We proposed a resource allocation algorithm, Full RE scheme which is based on Dinkelbach and Lagrange Dual Decomposition (LDD) methods to solve this problem.

3. Proposed a lower complexity (LC) RE scheme compared to the Full RE scheme to solve the RE optimization problem. This scheme consists of two steps; resource block (RB) allocation and power allocation. In the first step, equal power allocation is utilized while an optimal solution based on Dinkelbach and LDD approaches are employed to obtain the optimal power allocation in the second step.

4. Proposed an efficient algorithm based on Dinkelbach method and concave-convex procedure (CCCP) to maximize the EE of D2D communications in non-orthogonal resource sharing mode, where each remaining RB is allowed to be reused by multiple D2D pairs. Simulation results show that the scheme provides better EE as compared to the orthogonal resource sharing mode.

5. Provided two-stage RE-EE solutions to maximize the system EE for downlink resource sharing. Simulation results showed that the system EE achieve

by a two-stage LC RE-EE scheme is slightly higher than an upper bounds of EE-EE scheme which is solved using an optimal numerical solution. In addition, the LC RE-EE scheme performs close to the Full RE-EE scheme, while having lower complexity. Furthermore, the proposed schemes can enhance the EE of D2D pairs.

6. Studied the RE optimization problem for downlink non-orthogonal multiple access (NOMA) system, where a two-step scheme is proposed. The first step in this approach is to perform RB allocation to maximize the RE of the BS. A proper power allocation based on DC programming technique is devised in the second step to maximize the EE of the NOMA system. Simulation results show that the proposed RE for NOMA scheme with D2D operating in non-orthogonal mode achieves higher EE compared to the orthogonal multiple access (OMA) based schemes.

1.4 Thesis Organization

The rest of this thesis is organized as follows:

Chapter 2 provides the background on wireless communications. It includes the current LTE-Advanced technologies and future 5G wireless networks. The need for energy efficient communications as well as EE and SE metrics are explained in this chapter. Overview of D2D communication, its standardization, and communication scenarios are also briefly presented. Existing literatures that contribute to the radio resource management aspect of D2D are briefly reviewed.

Chapter 3 focuses on EE optimization for uplink D2D communication where a D2D pair shares the uplink resources of a CUE. In this chapter, we propose a new framework to investigate the system EE in two stages. In the first stage, RE optimization problem is formulated for the CUE and the EE maximization problem for the D2D pair is set up in the second stage.

In Chapter 4, the proposed two-stage EE optimization framework is extended for the case of multiple CUEs and D2D pairs in downlink OFDMA system. A full RE and lower complexity RE schemes are proposed. We also propose to maximize the EE for D2D pairs using non-orthogonal sharing mode, where each unallocated RB is reused by all D2D pairs.

In chapter 5, non-orthogonal multiple access (NOMA) system is studied. The

RE optimization for power domain NOMA system with the coexistence of D2D communications is evaluated in this chapter.

Chapter 6 concludes the thesis and discusses the potential future plan of this research.

1.5 List of Publications

P1. Fakrulradzi Idris, Jie Tang and Daniel. K.C So, Resource Efficiency Optimization for Energy-Efficient Device-to-Device Communications, *IEEE Transactions on Wireless Communications*. (submitted).

P2. Fakrulradzi Idris, Jie Tang and Daniel. K.C So, Resource Efficiency Optimization for NOMA with Device-to-Device Communications, *IEEE Wireless Communication Letters*. (under preparation).

P3. Fakrulradzi Idris, Jie Tang and Daniel. K.C So, Resource and Energy Efficient Device to Device Communications in Downlink Cellular System, in *IEEE Wireless Communications and Networking Conference (WCNC)*, 2018.

P4. Fakrulradzi Idris, Jie Tang and Daniel. K.C So, Energy Efficient Device to Device Communication by Resource Efficiency Optimization, in *IEEE Vehicular Technology Conference (VTC Spring)*, 2017.

P5. Fakrulradzi Idris and Daniel. K.C So, Energy Efficiency Maximization for Device-to-Device (D2D) Communication, in EEE PGR Conference, The University of Manchester, UK, 2016.

Chapter 2

Background Theory

2.1 Introduction

This chapter starts with a brief overview of the evolution of cellular network from the first generation to the current generation. A brief overview of LTE-Advanced, LTE-Advanced Pro and future 5G wireless network requirements and promising technologies are presented. The importance of energy efficient communication, EE and SE metrics are reviewed in Section 2.3. The background of D2D communications is presented in Section 2.4 which includes the advantages of D2D, standardization, and classification. To get the insight of basic D2D communications, a simple D2D simulation is provided and the overview of radio resource management aspects of D2D is briefly discussed. Finally, the system EE of D2D communications that is used in this work is defined in Section 2.5.

2.2 Wireless Communication Systems

The first generation (1G) of wireless cellular network started in early 80s with a variety of mobile radio standards such as Advanced Mobile Phone System (AMPS) in the United States and Nordic Mobile Telephone (NMT) in Europe. The primary focus of this technology is to provide voice communications over wireless channel [21]. In this analogue system, Frequency Division Multiple Access (FDMA) scheme was used. However, 1G system suffered from inefficient use of frequency spectrum.

In 1990s, the second generation (2G) network, based on digital transmission technique was introduced to provide additional enhancements from previous generation such as higher capacity, supporting more users and security improvements. The most popular technologies for 2G are GSM and IS-95. GSM uses the combination of FDMA and Time Division Multiple Access (TDMA) to allocate specific communication slots for users. Short Messaging Services (SMS) was also first introduced in GSM network. Compared to GSM, IS-95 uses Code Division Multiple Access (CDMA) to provide access to the users. CDMA increases network capacity by allowing users to occupy all channels at the same time but each user is assigned a unique code. Later, GSM network was improved further with the introduction of General Packet Radio Service (GPRS) and Enhanced Data rates for GSM Evolution (EDGE) to enhance its mobile data network capabilities.

IMT-2000 [22] is the third generation (3G) mobile system which was started around the year 2000 with the introduction of CDMA2000 and WCDMA technologies. 3G wireless systems provide higher transmission rates which are at a minimum speed of 2 Mbps for stationary users and 384 kbps in a moving vehicle. To further extend and improve the performance of existing 3G networks, a family of High Speed Packet Access (HSPA) was introduced, beginning with High Speed Downlink Packet Access (HSDPA), High Speed Uplink Packet Access (HSUPA) and HSPA-Plus. The specifications for HSUPA are included in 3GPP Release 6 while HSPA-Plus was first defined in the technical standard 3GPP Release 7.

In 2008, ITU-R issued International Mobile Telecommunications Advanced (IMT-Advanced) as the fourth generation (4G) wireless network [23]. To meet the increasing demand for high-data-rate mobile network, the Third Generation Partnership Project (3GPP) has started working on Long Term Evolution (LTE) systems during the Release 8 of the standards [24]. In LTE, new physical layer specifications consisting of an Orthogonal Frequency Division Multiple Access (OFDMA) based downlink and Single Carrier Frequency Division Multiple Access (SC-FDMA) based uplink are defined [25]. The LTE specifications provide downlink peak rates of 300Mbps and uplink peak rates of 75 Mbps. The LTE also supports scalable carrier bandwidths, from 1.4 MHz to 20 MHz and supports both Frequency Division Duplexing (FDD) and Time-Division duplexing (TDD) [2]. However, LTE system still does not fully comply with ITU 4G requirements and is considered as 3.9G technology [26].

Currently, the first accepted 4G system [27], LTE Advanced (LTE-A) has been widely deployed. IMT-Advanced is known as the formal definition of the 4G wireless network [26]. LTE-A complies with the IMT-Advanced requirements for 4G standards by providing peak data rate of 1Gbps in the downlink. Several key features of IMT-Advanced established in [3, 23] are:

1. Peak data rates of 100 Mbps for high mobility and 1 Gbps for low mobility (1 Gbps for downlink and 500 Mbps for uplink).
2. Downlink peak spectrum efficiency of 30 bps/Hz and uplink peak spectrum efficiency of 15 bps/Hz.
3. Latency round trip time is less than 5 ms.
4. Support mobility for various mobile speeds up to 350 km/h.
5. Capability of interworking with other radio access systems.

Although the LTE-A technical specification was introduced in 3GPP Release 10, it actually evolved from the initial Release 8 of LTE and with additional changes introduced in LTE through Release 9. The current release for LTE-A is Release 12 [28, 29].

In 2015, LTE-A Pro (LTE-A Pro) was approved by the 3GPP to denote the next stage in the development towards 5G, following LTE-A. LTE-A Pro will be used for specifications defined under 3GPP's Release 13 and Release 14. Some main features for LTE-A Pro include Machine-Type Communications (MTC) enhancements, License Assisted Access (LAA), Narrowband IoT, Full-Dimension (FD) MIMO and dual connectivity [30].

The 5G cellular wireless networks are conceived to overcome the challenges of present cellular networks. 5G wireless networks could provide higher data rates, lower end-to-end latency and reduce energy consumption and cost [31]. The following are essential requirements that have been identified for 5G [12, 31–35].

1. Data rate: Data rate remains the most important metric for wireless communications. The next generation wireless network need to support diverse types of applications that have different data rate requirements. Application such as high definition video streaming requires very high data rate while public safety application requires lower data rate. It is widely agreed that, the 5G system should achieve peak data rate in the range of tens of Gbps or more than 10 times of current 4G system and also 1000 times higher in terms of system capacity.

2. Latency: Real time application such as online two-way gaming has stringent delay requirement. The 5G system should be able to provide up to 1 ms end-to-end latency for applications that require extremely low latency.

3. Cost and energy consumption: The next generation network should provide a significant cost benefit in terms of operating expenditure (OPEX) and capital expenditure (CAPEX) for delivering services to the subscriber. There is also a growing concern about energy consumption per bit, which is the EE of the network.

To satisfy the important requirements for 5G wireless networks, several promising technologies have been proposed such as network densification, Massive MIMO, mmWave communications, full-duplex communications, D2D communications [12, 31–34, 36] and non-orthogonal multiple access (NOMA) [37]. The 5G cellular system will be heterogeneous networks consisting of macro cells, small cells, relays and remote radio heads (RRHs). In future, the deployment of heterogeneous cells will be significantly denser compared to current systems. High capacity and high spectral efficiency can be achieved in ultra-dense network via densely deployed wireless network equipments. Typical scenarios of ultra-dense network include office, dense residential areas, university campus, open-air gathering, stadium, and apartment.

MIMO systems consist of multiple antennas at the transmitter and receiver. By increasing the number of antennas, a significant performance improvement can be obtained. In Massive MIMO systems, the number of antennas at the base station can range to hundreds or even thousands. Massive MIMO system can offer significant enhancement in SE and EE [32]. One way to increase the throughput will be through bandwidth expansion, in which the use of new frequency spectrum is required. Huge amounts of new spectrum are likely to be found in higher frequency bands in the mmWave range of $30 - 300$ GHz [31]. There are on-going efforts to study the use of millimeter wave frequencies for next generation wireless networks. Generally, it is not possible to use the same channel for simultaneous transmission of uplink and downlink signal due to the strong self-interference. However, with the advance in RF technologies, it is possible to build in-band full duplex radios. Full duplex technology allows simultaneous transmission and reception on the same frequency and time resources [12] [36], with the potential to provide higher data rate and reduce latency. In addition, the use of direct D2D communications in future cellular system can enhance the performance in terms of SE, throughput, network offloading, fairness, coverage extension, latency and power saving [12]. Lastly, NOMA allows multiple users to be multiplexed into transmission power domain by exploiting the channel gain differences. As a promising multiple access scheme for future radio access, NOMA offers several advantages over orthogonal multiple access (OMA) such as improve spectral efficiency, support massive connectivity, and provide low transmission latency [38].

2.3 Energy Efficient Communications

The exponential growth of wireless data traffic has urged network operators to expand their network infrastructure in order to provide more coverage and higher network capacity to end users. However, operators have to invest more not only for the deployment cost but also for the operating cost, which includes the energy bill to run the network. In addition, the rapid increase of energy consumption in wireless networks contributs to the increase of greenhouse gas emission.

Realizing the effect of greenhouse to the environment, many parties have taken immediate actions to reduce greenhouse gas emission and energy consumption particularly in wireless communications. Government bodies, regulatory bodies, equipment manufacturers, network operators as well as research groups are working together to reduce carbon footprint contributed by wireless network operation. To maintain sustainable development and protect the environment, 3GPP, for example, initiated a study on Energy Saving Management (EMS) in LTE networks [39]. EMS is responsible for optimizing the resource utilization of the whole or parts of the network to actual needs for power saving purposes. Network energy consumption reduction will enable network operators to save their operating cost. Research consortium such as GreenTouch [11] was launched with the goal to improve the EE in communication networks by a factor of 1000 compared to the year 2010. The Green Meter Research [40] study demonstrated that in 2020, it is possible to reduce the end-to-end net energy consumption in the networks by up to 98% compared to 2010, in which significant improvements come from the components of mobile access networks. Huawei's Green Pipe [41] is an example on how operator can contribute to environment protection, cost reduction and energy savings.

International research projects dedicated to energy efficient wireless communications are being carried out and their solutions and visions can be found in [15, 16]. Several strategies to achieve energy efficient wireless networks such as in the area of radio resource management, network deployment aspects and transmission schemes are introduced in [15]. These areas could significantly reduce the energy consumption of the entire network. In [16], the authors presented a framework for green radio research which consists of four fundamental tradeoff: deployment efficiency versus EE, SE versus EE, bandwidth versus power, and delay versus power. The concept of energy-efficient communications is introduced [14]. Some existing fundamental works, advanced techniques and potential future research for energy efficient wireless communications are also presented. In [8], a survey of methods to improve the power efficiency of cellular networks is presented. The author discussed some research issues and challenges, as well as suggested some emerging technologies to enable an energy efficient cellular network.

Recently, Next Generation Mobile Networks (NGMN) published the 5G white paper [12] to express the operators' views on future wireless network. Based on Technology Gap Analysis Table in the white paper, the 5G system aims to reduce energy consumption of the whole network by a factor of 2. Since 5G system has to support the traffic increase in the order of 1000x, a 2000x EE increase is expected. In this aspect, EE is defined as the number of bits that can be transmitted per Joule of energy, where the energy is computed over the whole network, including legacy cellular technologies, radio access, core networks, and data centers [12].

2.3.1 Energy Efficiency, Spectral Efficiency and Resource Efficiency Metrics

In the literature, there are several definitions for EE metric [42] based on different perspectives such as ratio between efficient output energy to total input energy, performance per unit energy consumption, energy consumption ratio, and area EE [8, 43]. However, the most popular metric is bits per joule, which is defined as the ratio of system throughput over the energy consumption [15, 44–46]. EE with the unit of bits per joule which is equivalent to bits per second per watt can be expressed as

$$EE = \frac{R}{P} \tag{2.1}$$

where R is the achievable rate and P is the total power, consists of transmit power and circuit power consumptions. For long range applications, such as when the distance between a BS and a user is large, transmit power dominates the total power consumption while circuit power dominates the total energy consumption for short range applications [15, 44]. R is the achievable rate and is determined by Shannon's capacity formula [47–49] as follows

$$R = W_{tot} log_2 \left(1 + SINR\right) \tag{2.2}$$

where W_{tot} is the system bandwidth and $SINR$ stands for signal to interference plus noise ratio at the receiver terminal.

SE is another performance criterion for wireless network and is defined as the system throughput per unit bandwidth. Both EE and SE are two important system performance indicators. The tradeoff between SE and EE has been analyzed in [16]. For a communication system based on the Additive White Gaussian Noise (AWGN) channel and following Shannon's capacity formula, SE and EE can be expressed as [16]

$$\eta_{SE} = \frac{R}{W_{tot}} = log_2 \left(1 + \frac{P_r}{W_{tot} N_0}\right) \tag{2.3}$$

and

$$\eta_{EE} = \frac{R}{P} = \frac{W_{tot}}{P} log_2 \left(1 + \frac{P_r}{W_{tot} N_0}\right) \tag{2.4}$$

respectively. P_r is the received power and N_0 stands for the power spectral density of AWGN. Therefore, the EE-SE relation can be expressed as

$$\eta_{EE} = \frac{\eta_{SE}}{\left(2^{\eta_{SE}} - 1\right) N_0}. \tag{2.5}$$

On the one hand, from the above equation, η_{EE} converges to a constant when η_{SE} approaches zero. On the other hand, η_{EE} approaches zero when η_{SE} moves to infinity. However, this SE-EE relationship does not hold under practical systems because other factors such as circuit power, transmission distance, and resource management algorithms have significant impact on the tradeoff [16].

In conventional EE optimization, the bandwidth will be fully utilized in order to maximize EE. Had SE be used for optimization, the solution will use less bandwidth, allowing UEs to communicate but at the expense of higher energy consumption. Recently, a new metric called resource efficiency (RE) has been proposed which is capable of optimizing both EE and SE simultaneously by balancing the power consumption and occupied bandwidth [20]. RE can be expressed as

$$\eta_{RE} = \eta_{EE} + \bar{\beta}\eta_{SE} \tag{2.6}$$

where $\beta = \beta\,(W_{tot}/P_{tot})$. P_{tot} is the overall power budget. In (2.6), RE is a combination of EE and SE, (W_{tot}/P_{tot}) acts as unit normalizer for SE and EE and β is the weighted factor to control the balance of EE and SE. When $\beta = 0$, RE optimize EE while SE is optimized when $\beta = \infty$. Therefore, the RE metric is capable of exploiting the tradeoff between EE and SE and adapt its optimization based on the available resources.

2.4 Wireless Channel Models

Wireless communication operates through the air interface. In wireless communication, radio propagation refers to the behavior of radio waves when they are propagated from transmitter to receiver. Propagation environment in wireless communication is very dynamic and unpredictable compared to that in wired communication because of the characteristics of wireless channel. The signal transmitted over wireless channels are affected by three basic propagation mechanisms: reflection, diffraction, and scattering [50–52]. Reflection occurs when electromagnetic waves hit obstructions with very large dimensions compared to the wavelength, such as the Earth's surface and building. It causes the transmitted signal to be reflected to different direction, rather than towards the receiver. Diffraction happens when the radio signals can still propagate by bending around obstacles such as edges of buildings and walls. The secondary waves generated by diffraction propagate into shadowed region and can reach the receiver, which is not in the line of sight of the transmitter. Lastly, scattering forces the radio wave to spread out when impinge upon objects which are small compared to the propagation wavelength. Foliage, street sign and lamp posts are some examples of obstacles that can induce scattering. Furthermore, there is a special phenomenon in a wireless channel which is called fading. Fading refers to the variation of the signal amplitude over time and frequency, which can be classified into large scale fading and small scale fading [48, 50]. In the next section, a brief description of the wireless channel models for these two types of fading are described.

2.4.1 Large-Scale Fading

Large-scale fading occurs over large distances between the transmitter and the receiver. Large scale fading is characterized by path loss and shadowing.

Path loss describes the power attenuation of the signal as a function of the propagation distance. The further the signal travels, the more attenuation it experiences. The simplest model for signal propagation is the free-space path loss model which is used to predict received signal strength in the line-of-sight (LOS) environment where there is no obstacle between the receiver and the transmitter [51]. The received signal power at a distance d from the transmitter is expressed by the Friis equation [47, 50], given as

$$P_r\left(d\right) = \frac{P_t G_t G_r \lambda^2}{\left(4\pi d\right)^2} \tag{2.7}$$

where P_t represents the transmit power, G_t and G_r are the transmitter and receiver gains, respectively, and λ is the wavelength. By assuming $G_t = G_r = 1$, the free-space path loss, PL is derived as

$$PL\left(d\right)\left[dB\right] = 10\log_{10}\left(\frac{P_t}{P_r}\right) = 20\log_{10}\left(\frac{4\pi d}{\lambda}\right). \tag{2.8}$$

A simplified and more generalized form of the path loss model can be obtained by modifying the free-space path loss with the path loss exponent n that varies with the environments [47, 50], which is given as

$$PL\left(d\right)\left[dB\right] = PL\left(d_0\right) + 10n\log_{10}\left(\frac{d}{d_0}\right) \tag{2.9}$$

where d_0 is a reference distance which is typically assumed to be $1-10$ m indoors and $10-100$ m outdoors [47]. The path loss exponent can vary from 2 to around 6 depending on the propagation environment. For example, $n = 2$ corresponds to the free space [51].

Equation (2.9) implies that the average signal strength at a specific transmitter and receiver separation is always the same irrespective of the differences in the environment. However, a signal will typically experience random variation due to blockage from objects in the signal path, changes in reflecting surfaces and existence of scattering objects [47]. Therefore, additional model is required to include the effect of the random variation about the path loss. This random attenuation is called shadowing effect, which is commonly modeled using log-normal distribution. The effect of shadowing to the path loss can be expressed as

$$PL\left(d\right)\left[dB\right] = PL\left(d_0\right) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \tag{2.10}$$

where X_σ denotes a Gaussian random variable with a zero mean and a standard deviation of σ.

2.4.2 Small-Scale Fading

Small-scale fading refers to rapid fluctuations of signal levels due to the constructive and destructive interference of multiple signal paths over short period of time or short distance [50, 51]. Many factors can influence small-scale fading such as multipath propagation, speed of the mobile, speed of surrounding objects, and the transmission bandwidth of the signal [51].

Multipath fading occurs when signal arrives at the receiver through different paths, as a result of the propagation mechanisms. This creates several copies of the transmitted signal as each path can arrive with different gains, phases and delays. The baseband impulse response of a multipath channel with S number of equally spaced multipath components can be modeled as [51]

$$h\left(t,\tau\right) = \sum_{i=0}^{S-1} a_i\left(t,\tau\right)\exp\left[j\left(2\pi f_c\tau_i\left(t\right) + \phi_i\left(t,\tau\right)\right)\right]\delta\left(\tau - \tau_i\left(t\right)\right) \tag{2.11}$$

where $a_i\left(t,\tau\right)$, $\tau_i\left(t\right)$ and $\left(2\pi f_c\tau_i\left(t\right) + \phi_i\left(t,\tau\right)\right)$ are the real amplitudes, excess delays and phase shifts respectively. There are two time-related variables in (2.11), as t is time variation due to motion and τ is time variation due to multipath delay.

The received signal frequency is shifted due to relative motion of transmitter and receiver causing what is called the Doppler shift. This shift can influence small-scale fading and it depends on the velocity and direction of motion of a mobile terminal. The Doppler shift f_d can be expressed as

$$f_d = \frac{v}{\lambda}\cos\psi \tag{2.12}$$

where v is the speed of movement, λ is the wavelength and ψ is the angle between

Table 2.1 – Power delay profile

Tap	Relative delay (ns)	Average power (dB)
1	0	0
2	200	-0.9
3	800	-4.9
4	1200	-8.0
5	2300	-7.8
6	3700	-23.9

the direction of motion and the wave's arrival path.

The small scale fading can be classified into flat fading and frequency selective fading, based on the delay spread caused by multiple paths of the signal arrived at the receiver at different times. It can also be classified into fast and slow fading depending on the Doppler spread which results from the relative motion between the transmitter and receiver [50, 51]. In flat fading, the transmitted signal bandwidth is much smaller than the coherence bandwidth of the channel. The coherence bandwidth is the range of frequencies over which the channel has a constant gain and linear phase response. On the other hand, frequency selective fading occurs when the transmitted signal bandwidth is larger than the coherence bandwidth. In this case, the received signal is distorted because of multiple waveforms and channel induces intersymbol interference (ISI) to the signal.

In a fast fading channel, the coherence time is smaller than the symbol period and as a result, the channel impulse response quickly varies within the symbol period. The coherence time is the time duration that the channel impulse response remains fairly constant. In contrast, the transmitted signal undergoes slow fading if the channel impulse response changes much slower than the signal. In other words, coherence time is greater than the symbol period. Therefore, it can be assumed that the channel is static, which does not change over the duration of one or more symbols.

In this thesis, the ITU Pedestrian-B wireless channel model is used where the average power and the relative delays of the multipath are listed in Table 2.1 [53].

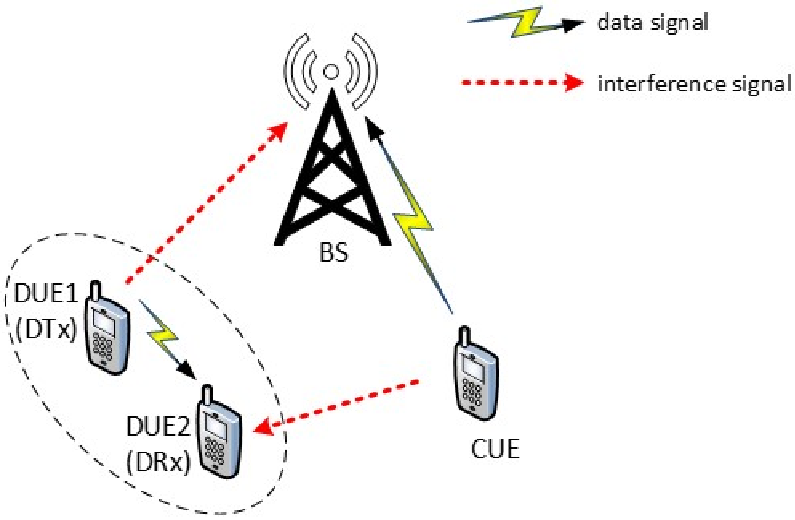

Figure 2.1 – D2D communication with uplink channel reuse.

2.5 Device-to-Device Communications

2.5.1 Overview of D2D Communications

Device-to-Device (D2D) communications are one of the potential technologies for future 5G wireless networks [54–56]. D2D communication, as shown in Figure 2.1 and Figure 2.2 allows D2D user equipments (DUEs) which are located in close proximity to communicate directly with each other without going through a BS, but reuse radio resources within the cellular network. The figures show that one cellular user equipment (CUE) is communicating with the BS using uplink or downlink resources, while one D2D pair (DUE1 and DUE2) can communicate directly in overlay or underlay mode. DUE1 is the D2D transmitter (DTx) while DUE2 is the D2D receiver (DRx). The cellular infrastructure however may assist with some tasks such as peer discovery and synchronization [57]. By sharing the radio resources and avoiding data routing through the BS, D2D communication can improve the SE and offload some traffics from the cellular network [58].

D2D communication has received a lot of attentions from research community, telecommunication companies as well as standardization bodies. Since it is considered as one of the potential candidates for next generation networks, extensive research is going on to ensure this technology can fulfill the requirements set by industries and standardization bodies. Furthermore, apart from giving advantages to service provider by lowering the total OPEX, D2D should be able

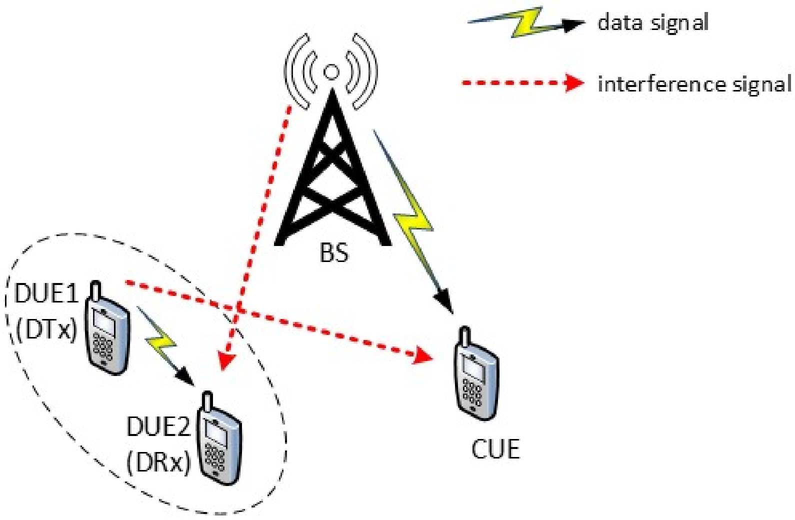

Figure 2.2 – D2D communication with downlink channel reuse.

to provide end users the best performance in terms of Quality of Service (QoS). The D2D communication will be able to provide a number of services to end users, such as public safety communication in case of infrastructure damage as well as proximity awareness. The D2D communication can achieve four types of gains [59] as follows:

- Proximity gain: the close range communication using a D2D link enables high bit rates, low delays, and low power-consumption.
- Hop gain: D2D transmission uses only a single link (one hop) rather than using uplink and downlink (two hops) resource when communicating via base station.
- Reuse gain: D2D and cellular link can simultaneously share the same radio resources.
- Pairing gain: more flexible communication as user equipment (UE) can communicate with the BS in cellular mode or communicate directly in D2D mode.

Other than providing new services, improving the SE, traffic offloading and aforementioned important gains, D2D communication also has the potential to improve the energy consumption of the network [58].

D2D communication underlaying cellular network will allow the network to benefit from the potential advantages. However, D2D communication will introduce two main challenges namely the interference to the CUE and the need to guarantee the minimum QoS requirements [60]. When a D2D pair uses the same radio resources for communication as the CUE, intra-cell interference may degrade the network performance and may not satisfy the QoS requirements of both cellular and D2D users. Mode selection, power control, resource allocation, mobility management and security are some other challenges and research issues in D2D communication underlaying LTE-A networks.

2.5.2 Standardizations and Communication Scenarios

D2D communication has been included by the 3GPP in LTE Release 12 [29]. A study item for Proximity Services (ProSe) has been specified in [61]. The objective of this study item is to examine the feasibility of D2D communications for use cases such as social and public safety applications. ProSe consists of two main components which are D2D discovery and D2D communication of devices in close physical proximity. D2D discovery allows a ProSe-enabled mobile device to use the LTE radio interface to discover the presence of other ProSe-enable devices in its vicinity and to be discoverable, as a part of social networking application. D2D communication enables mobile devices to communicate with each other in direct mode, without routing the traffic through the operator network but with some controls from operator such as in terms of radio resource allocation and security of the connections. The architectural enhancements to support ProSe are studied in [62]. In this document, a number of different possible communication scenarios are provided as shown in Table 2.2 and illustrated in Figure 2.3.

Furthermore, another study related to radio aspect of D2D communication has been performed in [63]. Since D2D communication has different characteristics compared to traditional cellular communication, the main goal of this study is to define an evaluation methodology and channel models for different D2D scenarios. The study also aimed to identify physical layer options and enhancements to incorporate proximity discovery and direct communication. Comparison with existing device to device discovery mechanisms such as WiFi Direct and Bluetooth and also possible impacts on existing operator services are also within the scope of the study.

The enhancements for D2D communication to support more advanced ProSe for public safety and consumer use case are described in LTE Release 13 [64].

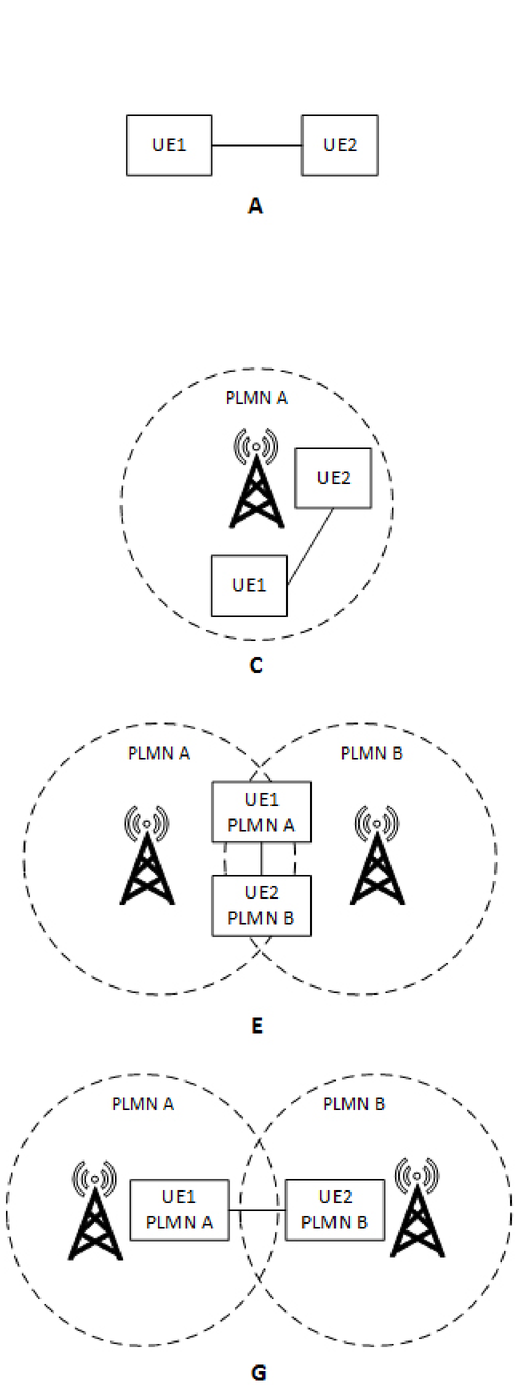

Figure 2.3 – Direct communication scenarios [62].

Table 2.2 – D2D communication scenarios [62].

Scenario	In/Out coverage		Serving PLMN/cell
	UE1	UE2	
A	Out	Out	No serving PLMN/cell
B	In	Out	No serving PLMN/cell for UE-2
C	In	In	Same PLMN, same cell
D	In	In	Same PLMN, different cell
E	In	In	Different PLMN, different cell (both UEs are in both cells' coverage)
F	In	In	Different PLMN, different cell (UE-1 in both cell's coverage and UE-2 is in serving cell's coverage)
G	In	In	Different PLMN, different cell (both UEs are in their own serving cell's coverage)

This includes the support for D2D in the presence of multiple carriers, public land mobile network (PLMN) and coverage extension by allowing a UE to operate as a relay for another UE [65]. It should be noted that scenario C is considered in this thesis.

2.5.3 Classification of D2D Communication

D2D can be classified as inband or outband depending on whether the communications occurs in licensed cellular spectrum or unlicensed spectrum [66–69]. Inband communication can be further divided into underlay and overlay while the outband communication can be categorized into controlled and autonomous.

Majority of works focus on underlaying inband D2D because it can enhance the spectral efficiency, since cellular and D2D user share the same radio resources. However, interference becomes the most important issue in this type of communication. To avoid the interference issue, overlay inband is proposed in which some portions of cellular resources are allocated specifically for D2D communications. As a result, this approach reduces the amount of available resources for cellular communications.

Controlled outband D2D communication can be managed by the cellular network while autonomous outband D2D can operate on its own. The advantage of outband D2D is that there is no interference issue between D2D and cellular communications. Outband D2D communication can provide simultaneous D2D and cellular transmission. However, interference in unlicensed spectrum is not in the control of BS and additional radio interface might be required.

2.5.4 Interference Scenarios

Two basic interference scenarios could occur when D2D communications share the spectrum with other CUEs. For public safety applications, DUEs have access to dedicated spectrum. However, for commercial or social applications, DUEs have to share the spectrum with existing cellular devices. There are two types of resource sharing direction for D2D communication, namely uplink and downlink.

When downlink resources are being reused by DUEs, CUEs will receive interference from D2D transmitters, and the BS may cause strong interference to the D2D receivers. For applications that require high data rates, downlink direction can become more congested compared to the uplink [70].

On the other hand, when uplink resources are reused by the DUEs in the cell, the BS becomes a victim and receives interference from the D2D transmitters. Similarly, the D2D receivers will receive interference signal from the nearby CUEs. Uplink resources are more favorable because they are usually less utilized compared to downlink resources. By reusing uplink resources, interference can be minimized as the interference can be better handled by the BS [58].

2.5.5 Overview of Radio Resource Management for D2D Communications

Radio resource management (RRM) in D2D communications consists of mode selection, power control, resource allocation and interference management [57] [71] [72]. Mode selection is the process to select the best mode for DUEs. There are three communication modes for the D2D pair that can be considered [73–75]:

1. Non-Orthogonal Sharing / Reuse Mode (RM): Both D2D and cellular users reuse the same downlink or uplink resources, causing interference to each other.

2. Orthogonal Sharing / Dedicated Mode (DM): D2D communication allocated some portion of the resources and the remaining resources are left to the cellular user. There is no interference between cellular and D2D user.

3. Cellular Mode (CM): The DUEs communicate with each other through the BS, similar like a traditional cellular system.

To bring more freedoms for potential DUEs, the optimal D2D mode switching problem is investigated in [76]. The optimal SE problems for the three D2D transmission modes are formulated. The aim is to maximize the system SE while considering the QoS requirements and power constraints for both D2D pairs and cellular users. The Bisection algorithm is used to solve optimization problem in the DM and CM while concave-convex procedure (CCCP) is adopted to solve the more complicated optimization problem in reuse mode.

Power control is one of the key RRM techniques to reduce intra-cell and inter-cell interference [72]. It is the most straightforward approach used for reducing interference from D2D to cellular network [68]. As new intra-cell and inter-cell interference scenarios are created by D2D communications, the existing power control may not be suitable if this proximity communication is introduced in an LTE network. Power control in D2D falls into two categories namely centralized and distributed [77, 78]. The performance of several power control schemes for D2D communication are studied in [72].

Resource allocation schemes for D2D communication generally can be categorized into centralized scheme [79] [80] and distributed scheme [59] [81]. In centralized scheme, BS fully controls the resource allocation for both traditional cellular and D2D links. Therefore, the BS needs to know the channel state information (CSI) of all involved links and has to deal with control overhead and computational requirement. On the other hand, in the distributed scheme, the resource allocation for the D2D communication is performed by UEs of each D2D link. Although the computational overhead in distributed scheme is reduced, its performance is usually worse than the centralized scheme [82]. As a result, semi-distributed resource allocation schemes have been proposed in [82,83]. Two types of resource allocation schemes which are cell level and user level for D2D underlaying LTE-A are proposed in [84]. The purpose of the first scheme is to reduce interference between DUEs and CUEs. On the other hand, the second scheme schedules the resources between DUEs and CUEs in an energy efficient manner.

Since D2D communications underlaying cellular networks introduce new interference scenario, managing this interference is important to realize its advantages. When DUEs share downlink cellular resources, the interference sources consist of interference from the BS in the same cell, interference from other co-channel D2D in the same cell, and interference from BSs and co-channel DUEs from other cells. In contrast, when the DUEs share the uplink cellular resources, the interference sources consist of interference from all co-channel CUEs in the same cell and other cells, and interference from all co-channel DUEs reside in the same cell and other cells. The radio resource managements mentioned above can also be considered as research aspects to effectively manage the interference in D2D communications underlaying cellular networks [85]. Some other techniques to mitigate interference are by using Fractional Frequency Reuse (FFR) [86], interference alignment (IA) [87] and interference coordination mechanism [88].

2.5.6 D2D Simulation Scenario

For a scenario where D2D communication is underlaying cellular system, the intra-cell interference due to uplink or downlink resource sharing need to be taken into account [55]. As mentioned in [89], uplink resource reuse has better performance on D2D rate compared to the downlink resource reuse provided that the interference from the DTx to the BS is reduced. Therefore, the effect of the co-channel interference is investigated in this section.

As illustrated in Figure 2.1, the D2D pair operates in underlay communication in which the three UEs share the uplink radio resources at the same time. The resource sharing causes co-channel interference in the cell.

The CUE is free to be anywhere inside the cell coverage area according to a uniform distribution. The distance between DTx to the BS is fixed, while DRx is uniformly distributed inside a region of radius d from the DTx. In that figure, CUE communication is through the BS while DUE1 and DUE2 are communicating directly in D2D mode. The distance between DTx and DRx is fixed to 25 m. The CUE and DTx are distributed within a range, R of 500 m from the BS.

The transmit power for BS and all UEs are set to be 46 dBm and 24 dBm respectively. All channel gains between two nodes are modelled as Rayleigh fading channels, thus the channel responses follow the independent identical complex Gaussian distribution. The free-space propagation path loss model $p = p_0 \left(\frac{d}{d_0}\right)^{-n}$ is used, where p and p_0 represent signal power measured at d and d_0 away from the transmitter. The path loss exponent is set to 4. Accordingly, the received power of each link can be expressed as

$$p_{r,ij} = p_i h_{ij}^2 = p_i d_{ij}^{-n} h_0^2 \tag{2.13}$$

where $p_{r,ij}$ and d_{ij} are the received power and the distance of the $i - j$ link respectively. p_i represents the transmit power of device i and h_0 is the complex

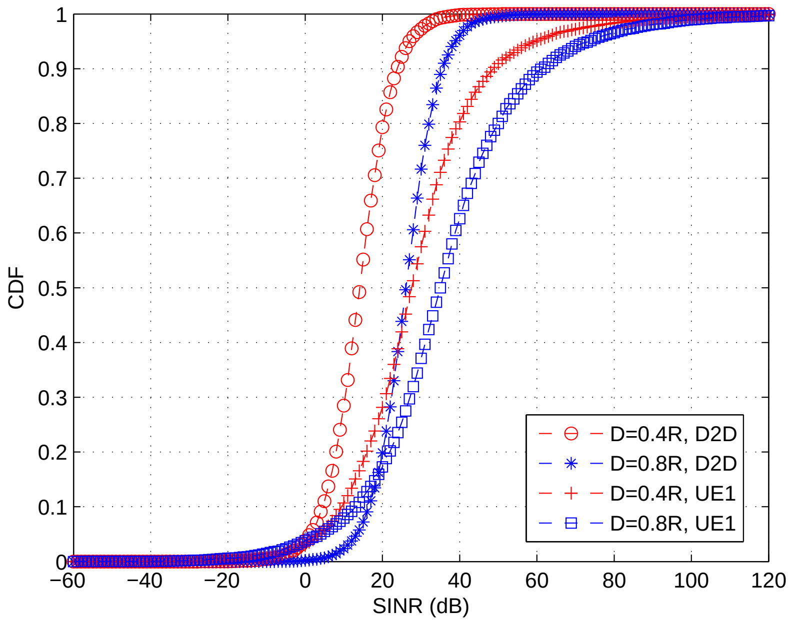

Figure 2.4 – Downlink SINR distribution.

Gaussian channel coefficient that follows the distribution $\mathcal{CN}(0,1)$. For simplicity, the received power at $d_0 = 1$ equals the transmit power. The SINR of user j is given as

$$\gamma_j = \frac{p_i h_0^2 d_{ij}^{-n}}{p_{int,j} + N_0} \tag{2.14}$$

where $p_{int,j}$ denotes the interference signal power received by user j and N_0 accounts for the noise power at the receiver. The thermal noise density N_0 is -174 dBm/Hz. The simulation results are averaged over 10000 channel realizations. The locations of users are updated for each iteration.

Figure 2.4 and 2.5 show the SINR distribution of D2D communication in the downlink and uplink, respectively. When DUEs share cellular downlink resources, D2D SINR is better if the pair is located farther away from BS [89]. D2D SINR is lower than CUE SINR due to significant interference from the BS. The interference from BS to the DRx is higher compared to the interference from DTx to the CUE because BS transmit power is larger than a DUE. As a result, SINR for CUE is better than D2D.

When D2D shares uplink resources, it is clear that the D2D SINR is better than the BS SINR [89]. The short distance between the D2D pair is likely to make

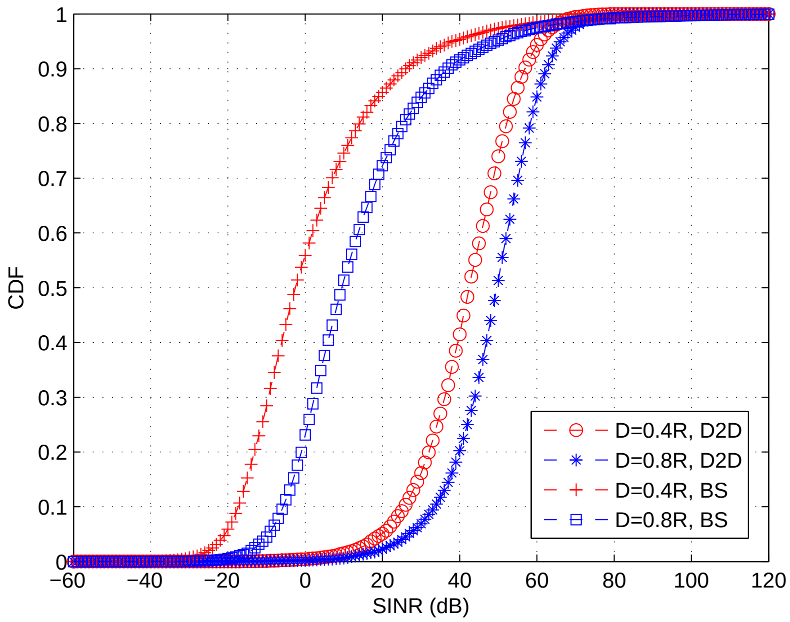

Figure 2.5 – Uplink SINR distribution.

D2D receive power larger than BS receive power. However, BS SINR increases when D2D pair is farther away from BS because the transmission power of DTx could also contribute to the interference.

2.5.7 Energy Efficiency for D2D Communication

Other than radio resource management aspects, EE is another important topic for D2D communication underlaying cellular network [90]. In this section, the EE formulation is introduced and the overall EE of a cellular system coexists with D2D communication is defined.

The scenario of D2D communication as in Figure 2.1 is referred. During the uplink period of the cellular network, the CUE transmits data to the BS, while the DTx transmits data to the DRx. The DRx suffers interference due to the transmission from the CUE. At the same time, the BS receives interference from the DTx. The received SINR at the BS is calculated as

$$\gamma_{cUL} = \frac{P_c H_{cB}}{P_d H_{dB} + W N_0}. \tag{2.15}$$

The received SINR at the DRx for uplink resource sharing is

$$\gamma_{dUL} = \frac{P_d H_{dd}}{P_c H_{cd} + W N_0} \tag{2.16}$$

where P_c and P_d are the transmit power of CUE and DTx respectively. H_{cB} represents the channel gain between the CUE and the BS whereas H_{dB} is the channel gain between DTx and the BS. H_{dd} denotes the channel gain between the D2D pair while H_{cd} is the channel gain between CUE and DRx. N_0 accounts for the thermal noise power at the receiver. Thus, the achievable rates of the CUE and DUE corresponding to γ_{cUL} and γ_{dUL} are given by

$$r_{cUL} = W log_2 \left(1 + \gamma_{cUL}\right) \tag{2.17}$$

$$r_{dUL} = W log_2 \left(1 + \gamma_{dUL}\right) \tag{2.18}$$

respectively. The total system rate can be expressed as

$$R_{sumUL} = r_{cUL} + r_{dUL}. \tag{2.19}$$

Therefore, the system EE for uplink scenario is defined as

$$\eta_{EE-UL} = \frac{R_{sumUL}}{(\varepsilon P_c + P_{cirUE}) + (\varepsilon P_d + P_{cirUE})} \tag{2.20}$$

where ε is the reciprocal of drain efficiency of power amplifier, P_{cirUE} is the circuit power consumption of the UE.

However, when D2D communications sharing the downlink resources as shown in Figure 2.2, the received SINR at the CUE can be expressed as

$$\gamma_{cDL} = \frac{P_{BS} H_{Bc}}{P_d H_{dc} + W N_0}$$

while the received SINR at the DRx for downlink resource sharing can be calculated as

$$\gamma_{dDL} = \frac{P_d H_{dd}}{P_{BS} H_{Bd} + W N_0} \tag{2.21}$$

where P_{BS} is the transmit power of the BS. H_{Bc} represents the channel gain between the BS and the CUE whereas H_{dc} is the channel gain between DTx and CUE. H_{Bd} is the channel gain between BS and DRx. Therefore, the achievable rates of the BS and DUE corresponding to γ_{cDL} and γ_{dDL} are given by

$$r_{cDL} = W log_2 \left(1 + \gamma_{cDL}\right) \tag{2.22}$$

$$r_{dDL} = W log_2 \left(1 + \gamma_{dDL}\right) \tag{2.23}$$

respectively. Similarly, the total system rate can be expressed as

$$R_{sumDL} = r_{cDL} + r_{dDL} \tag{2.24}$$

Finally, the system EE for downlink scenario is defined as

$$\eta_{EE-DL} = \frac{R_{sumDL}}{(\varepsilon P_{BS} + P_{cirBS}) + (\varepsilon P_d + P_{cirUE})} \tag{2.25}$$

where P_{cirBS} is the circuit power consumption of the BS.

We note that there are previous works that define total system EE differently such as in [91–94]. Note that the system EE defined in (2.20) and (2.25) are for reuse mode. In dedicated mode or when D2D communications operating underlaying cellular system, the interference from the BS, CUE and DTx can be removed and only the allocated bandwidth are used to obtain the corresponding achievable rates.

2.6 Summary

In this chapter, relevant background on wireless communication systems is presented. A brief history of wireless communication systems, their evolution and requirements towards 4G system are summarized. Next, the future 5G wireless network's essential requirements and potential technologies are briefly explained. The needs of energy efficient communication, EE metric and its relation with SE metric are also presented. The overview of D2D communication and important aspects of D2D which include standardization, classification and some scenarios are discussed. Finally, basic simulation for D2D communication and its EE formulation in single cell scenario are presented.

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Chapter 3

Energy Efficiency of D2D Overlaying Uplink Cellular System

3.1 Introduction

This chapter focuses on a new framework for optimizing the EE of D2D communication. It starts with a review of existing works on EE optimization for D2D communication using uplink cellular resources in Section 3.2. Section 3.3 describes the system model and the problem formulation. To solve the overall EE of the system, the problem is divided into two sub problems: the resource efficiency (RE) problem for the CUE and the EE problem for the DUE. The proposed RE optimization for the CUEs is described and solved in Section 3.4. Section 3.5 describes the EE optimization for the DUE and two different methods to solve it. Section 3.6 provides the simulation results of the proposed two-stage scheme. Note that part of this work is published in P4.

3.2 Related Works

Energy efficient D2D communication for a single CUE and one D2D pair have been investigated in [91, 95–97]. In particular, energy efficient power allocation

schemes for D2D communications are analyzed in [91] for three different uplink resource sharing modes which are reuse mode (RM), dedicated mode (DM) and cellular mode (CM). In RM, resources are reused by cellular and D2D users while in DM, exclusive resources are assigned for cellular and D2D users. Users in RM could cause interferences to each other but there is no interference in DM since resources occupied by CUE are orthogonal to those allocated to DUEs. In addition, resource utilization in RM is higher compared to DM. Lastly, in CM mode, DUEs communicate with each other via BS same like the traditional cellular system. The objective of that work is to maximize the network EE subject to the maximum transmission power constraint and the problems for the three modes are formulated while taking into account the maximum transmission power of users. However, the QoS requirement of the cellular and D2D users are not constrained. Simulation results showed that if DUEs communicate with each other directly, it could provide more energy efficient communications.

Energy efficient D2D mode switching for the three D2D transmission modes is studied in [95]. Compared to [91], this work also consider the minimum rate requirement for all users as one of the constraints. Dinkelbach method and IPM are used to solve the DM and CM modes. In RM, CCCP is used together with the Dinkelbach method to obtain the optimal power allocation. It is shown by simulation that the RM is preferred to achieve the highest EE. Slightly different from [91,95], the primary aim of [96] is to maximize the EE of DUEs while meeting the throughput requirements and maximum transmit power constraints of both the CUE and the DUEs. In that work, three different regions for the D2D's circuit power consumption are defined, namely low consumption, high consumption and medium consumption regions. For each region, the optimal power control is derived and a distributed algorithm for implementing the optimal power control is proposed. In [97], the authors investigated the energy efficient D2D communications where both CUE and DUE have outage probablity constraints. An efficient power allocation scheme based on Dinkelbach and Lagrange Dual Decomposition (LDD) methods is proposed to maximize the average EE of D2D communications.

To maximize each UE's EE subject to its specific QoS and maximum transmission power constraints, a distributed interference-aware energy-efficient resource allocation algorithm is proposed in [92]. The authors consider multiple CUEs and multiple D2D pairs sharing the uplink resources. As compared to [91,95–97], power amplifier efficiency is also taken into account in the EE optimization problem. The distributed resource allocation problem is modeled as a non-cooperative game, where each UE is self-interested and wants to maximize its own EE. The non-convex EE maximization problem is transformed into a convex optimization problem by exploiting the properties of nonlinear fractional programming. The proposed EE scheme performs better compared to spectral efficient and random power allocation algorithms.

In [93], energy-efficient resource allocation and power control algorithm to maximize the total system EE for D2D underlaying cellular networks is proposed. A grouping scheme is designed by taking into account the interference limitations and EE gain due to resource sharing. Then, for each group, a distributed iterative power control algorithm can be used to maximize the total EE of UEs. In [98], an EE optimization based network selection and power allocation scheme is proposed. The initial problem is formulated as non-convex optimization problem where three types of constraints are considered, namely minimum data rate requirement, minimum received power and maximum hardware dependent radiated power. Again, the nonlinear fractional programming and LDD are also used to solve the problem. The work in [99] investigated joint mode selection and power control to maximize the system EE of D2D communication underlaying cellular network while guaranteeing the QoS of both cellular and D2D users. The optimal solution to the problem is obtained using the fractional programming and the branch-and-bound (BnB) method. Low-complexity heuristic algorithms are also proposed for three different load scenarios.

To maximize the EE of D2D communications, a joint resource allocation and power control scheme has been studied in [100]. Based on the properties of fractional programming, the original nonconvex optimization problem in fractional form is transformed into an equivalent optimization problem in subtractive form and solved using an iterative approach. In each iteration, part of the constraints are removed by adopting the penalty function approach and a resource allocation and power allocation scheme is designed to maximize the EE.

The work in [101] studied the resource allocation problem for maximizing the minimum weighted EE of D2D links while guaranteeing the QoS of cellular links. To simplify the problem, the optimal power allocation of the cellular links is derived to transform the original problem into the joint subchannel and power allocation problem for D2D links. A dual-based algorithm which employs Bisection method and two relaxation-based algorithms; BnB and relaxation-based rounding (RBR) algorithms are proposed. The low-complexity RBR algorithm that utilizes gradient-based method can achieve excellent performance which is close to the optimal BnB algorithm.

In [102], the authors focused on joint channel allocation and power control for D2D pairs underlaid cellular network. The aim of that work is to maximize the EE of D2D links while guaranteeing the minimum throughput of CUEs, where the EE maximization problem is divided into two subproblems to obtain a suboptimal solution.The energy-efficient power control for DUEs underlaying cellular networks is studied in [103]. By considering only a single CUE, resource blocks (RBs) are reused by multiple D2D pairs to maximize the individual EE and attain the max-min fairness.

The power control problems for D2D communications underlaying cellular networks, considering the total EE and individual EE of D2D pairs are studied in [104], where multiple D2D pairs are allowed to reuse the RB allocated to one CUE. It was shown that both types of EE increase with the increase of RB but decrease with the increase of D2D pair number. With regards to user-priority-based mobile health applications, the EE maximization of all D2D users is studied in [105]. Lastly in [106], a joint power control and priority-based resource allocation approach is proposed for enhancing the EE of D2D links.

In summary, the majority of works on EE optimization for D2D communications focused on the uplink resource sharing because uplink spectrum is usually underutilized [107,108]. Moreover, CUEs have lower transmit power than the BS and can be far from the DUEs; thus causing less interference. These works also highlighted the performance gain in term of EE that D2D communication offers over conventional cellular communication. D2D communications are proven to be important for 5G networks in which one of the aims is to increase the EE.

3.3 System Model and Problem Formulation

3.3.1 System Model

To implement the new framework, a scenario as shown in Fig. 3.1 is considered, where one D2D pair is using uplink resources of one CUE. To avoid the co-channel interference in the cell if underlay mode is used, the D2D pair operates in an overlay communication [109]. In this case, separate spectrum will be used by the cellular and D2D users. Since D2D communication is proposed as a supplement to existing cellular users, priority is given to the cellular user to communicate

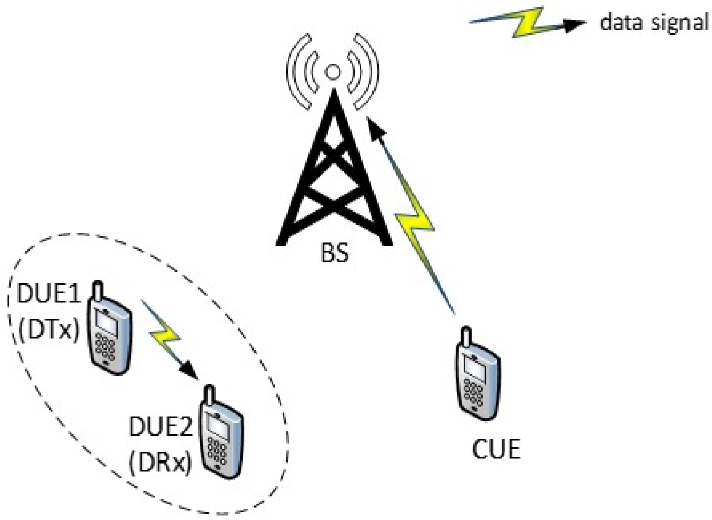

Figure 3.1 – D2D communication as an overlay to a cellular system.

with the BS and use the uplink resources. The remaining bandwidth will be allocated to the DUEs.

The achievable rates of the CUE, R_c and the D2D pair, R_d can be calculated as

$$R_c = W_c log_2 \left(1 + \frac{P_c H_{cB}}{W_c N_0}\right) \tag{3.1}$$

$$R_d = W_d log_2 \left(1 + \frac{P_d H_{dd}}{W_d N_0}\right) \tag{3.2}$$

where P_c represents the transmit power of the CUE, W_c denotes the allocated spectrum resources for CUE. P_d denotes the transmit power of the D2D transmitter (DTx) and the allocated spectrum resources for D2D is given by W_d. N_0 is the noise power spectral density, while H_{cB} and H_{dd} are the channel gains of the link between CUE and BS and D2D link respectively.

The overall power consumptions for the CUE and D2D links consist of transmit power and circuit power which can be expressed as

$$P_{tc} = \varepsilon P_c + P_{cirUE} \tag{3.3}$$

$$P_{td} = \varepsilon P_d + P_{cirUE} \tag{3.4}$$

where ε is the inverse of drain efficiency of power amplifier and P_{cirUE} is the circuit power of CUE and DUE. In the same way, the overall power budget of user can be modeled as

$$P_{tot} = \varepsilon P_{max} + P_{cirUE} \tag{3.5}$$

where P_{max} represents the maximum transmit power of user for uplink transmission.

3.3.2 Problem Formulation

In this chapter, we aim to maximize the system EE of D2D communication overlaying cellular system. In order to reduce the complexity of join EE optimization for CUE and DUEs, we develop a scheme to solve the main EE optimization problem in two stages. In the first stage, RE optimization problem for the CUE is considered and then EE optimization for the D2D pair is solved in the second stage. Both optimization problems require two types of constraints. The first constraint is to maintain the QoS for all links which are given as

$$R_c \geq R_c^{min} \tag{3.6}$$

$$R_d \geq R_d^{min} \tag{3.7}$$

where R_c^{min} and R_d^{min} denote the minimum rates for the CUE and the D2D pair, respectively. The second constraint ensures that the transmission power of individual links are limited as follows

$$P_c \leq P_c^{max} \tag{3.8}$$

$$P_d \leq P_d^{max} \tag{3.9}$$

where $P_c^{max}$and P_d^{max} are the maximum transmission power of the CUE and the D2D pair, respectively.

The first problem aims to maximize the RE for the CUE. RE which is introduced in [20], is defined as

$$RE = \frac{R_c}{P_{tc}}\left(1 + \beta\frac{\tau_p}{\tau_w}\right). \tag{3.10}$$

The tradeoff parameter, β is used to control the balance of EE and SE. Power utilization and bandwidth utilization are denoted by τ_p and τ_w respectively and are given by

$$\tau_p = \frac{P_{tc}}{P_{tot}} \tag{3.11}$$

$$\tau_w = \frac{W}{W_{tot}} \tag{3.12}$$

where W is the occupied bandwidth and W_{tot} is the total spectrum bandwidth of the system.

Therefore, the RE optimization for CUE can be formulated as

$$\max_{W_c, P_c} RE_C = \frac{R_c}{\varepsilon P_c + P_{cirUE}} \left(1 + \beta \frac{\tau_p}{\tau_w}\right) \tag{3.13}$$

$$s.t. \quad (3.6)\,, W_c \leq W_{tot}, (3.8)\,.$$

The second problem maximizes the EE of the D2D link which can be expressed as

$$\max_{P_d} EE_D = \frac{R_d}{\varepsilon P_d + P_{cirUE}} \tag{3.14}$$

$$s.t. \quad (3.7)\,, (3.9)\,.$$

3.4 Proposed Resource Efficiency Optimization for CUE

RE is introduced to optimize both EE and SE simultaneously. Generally, the CUE has the priority to transmit signals without being interfered by other users. In this first stage, RE maximization for the CUE is performed to obtain the optimal transmission power and bandwidth allocation.

The optimization problem (3.13) is difficult to be solved directly due to the non-convex fractional structure of the objective function. In order to solve this problem, we investigate the relationship of RE with respect to the optimization variables, P_c and W_c by plotting the objective function in (3.13) using parameters provided in Table 3.1.

Figure 3.2 shows the 3D plot of the RE objective function within the range of the bandwidth and power constraints. Based on the figure, for $\beta = 0$ the maximum value of RE is achieved when all bandwidth are allocated to the CUE.

Table 3.1 – Plotting parameters.

Parameters	Value
Spectrum resources for CUE (W_c)	$0 - 1.25$ MHz
Transmit power of CUE (P_c^{max})	$0 - 250$ mW
Minimum rate of CUE (R_c^{min})	1 Mbps
Tradeoff parameter(β)	0, 10

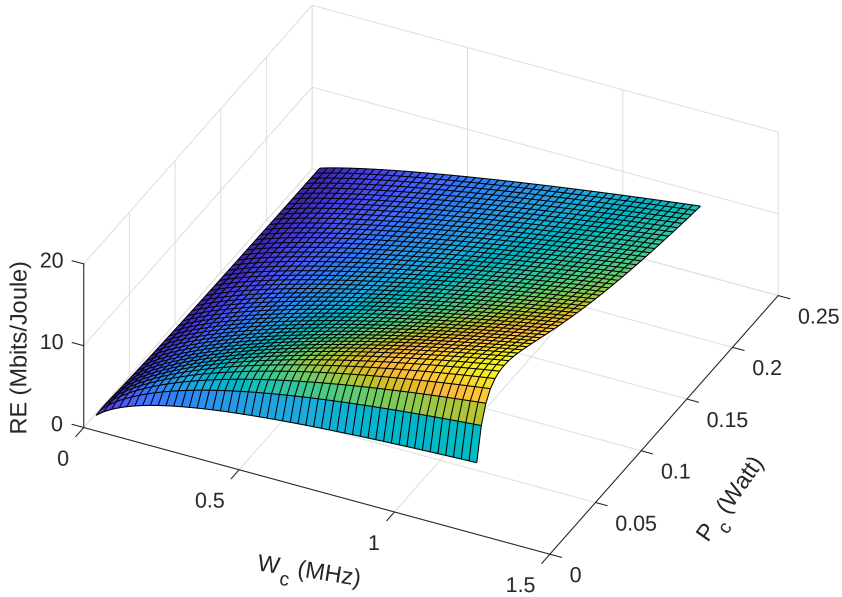

Figure 3.2 – RE plot for $\beta = 0$.

For a given value of bandwidth, the RE is quasiconcave in transmit power as shown in Figure 3.3. Furthermore, based on Figure 3.4 the gradient of RE vanishes when the optimal point is obtained.

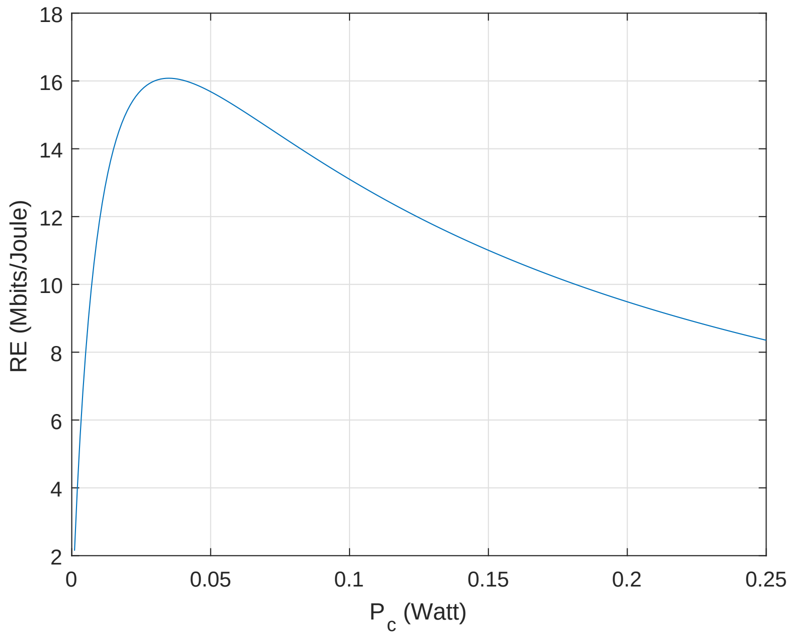

Figure 3.3 – Plot of RE versus transmit power P_c ($\beta = 0$, $W_c = 1.25\ MHz$).

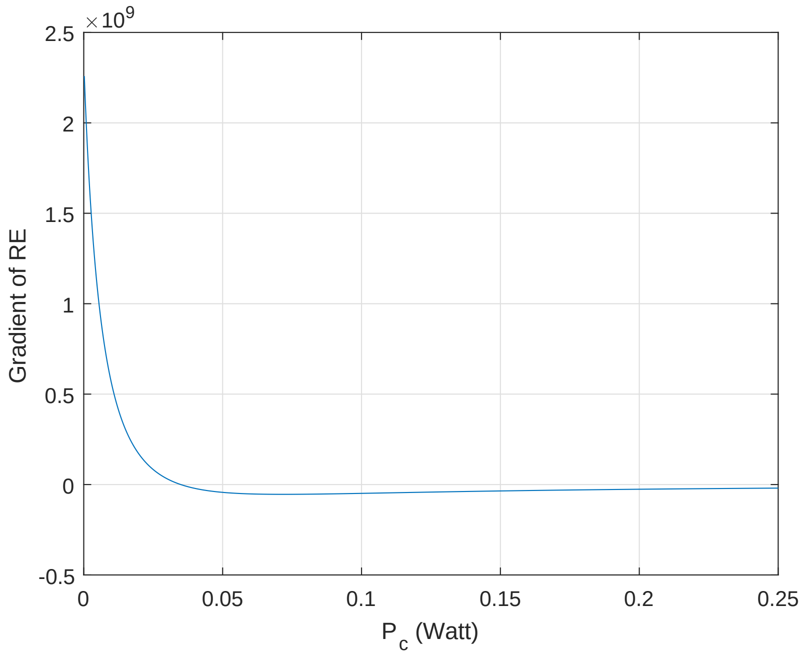

Figure 3.4 – Gradient of RE for $\beta = 0$.

When $\beta = 0$, problem 3.13 simply become an EE problem which requires the most of the bandwidth. For a larger value of β such as $\beta = 10$, the maximum value of RE is achieved while requiring a lower value of bandwidth as shown in Figure 3.5

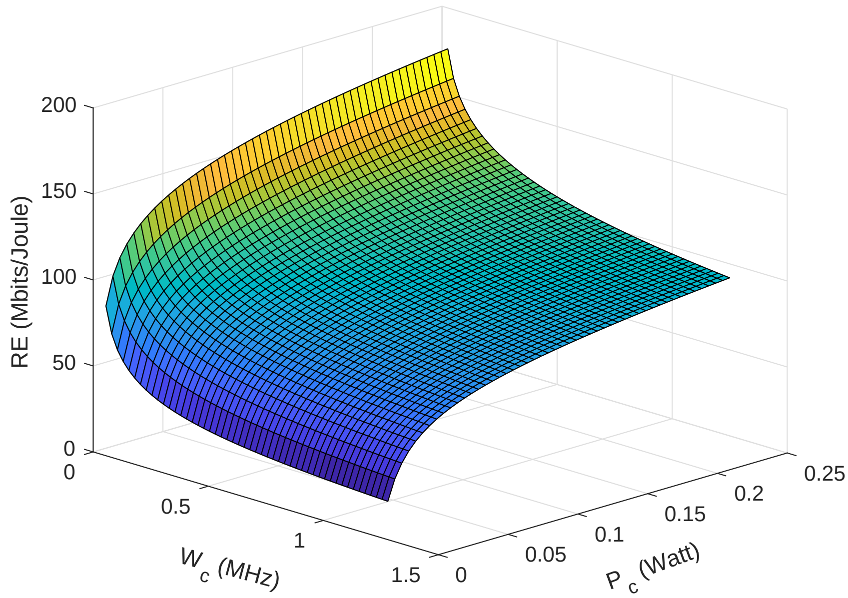

Figure 3.5 – RE plot for $\beta = 10$.

The plot of RE and its gradient with respect to transmit power P_c for $\beta = 10$ are shown in Figure 3.6 and Figure 3.7 respectively.

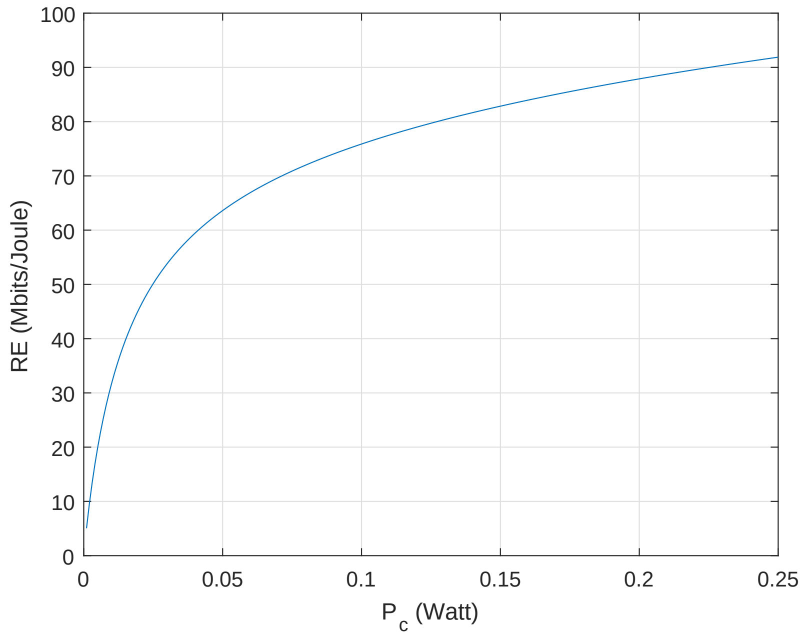

Figure 3.6 – Plot of RE versus transmit power P_c ($\beta = 10,\ W_c = 120\,kHz$).

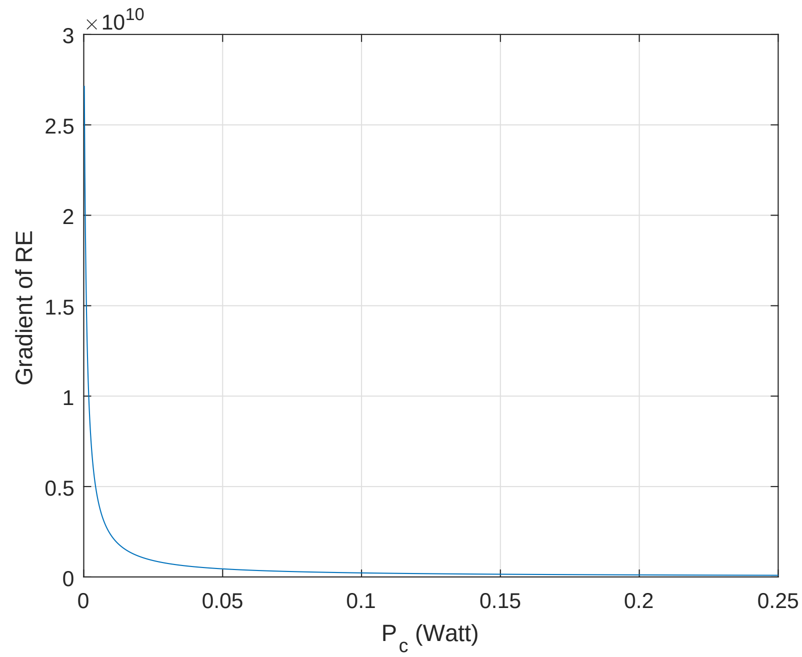

Figure 3.7 – Gradient of RE for $\beta = 10$.

By using the third dimension (3D) and single dimension plots of the RE function, we can verify that RE is quasiconcave in the transmit power for a given

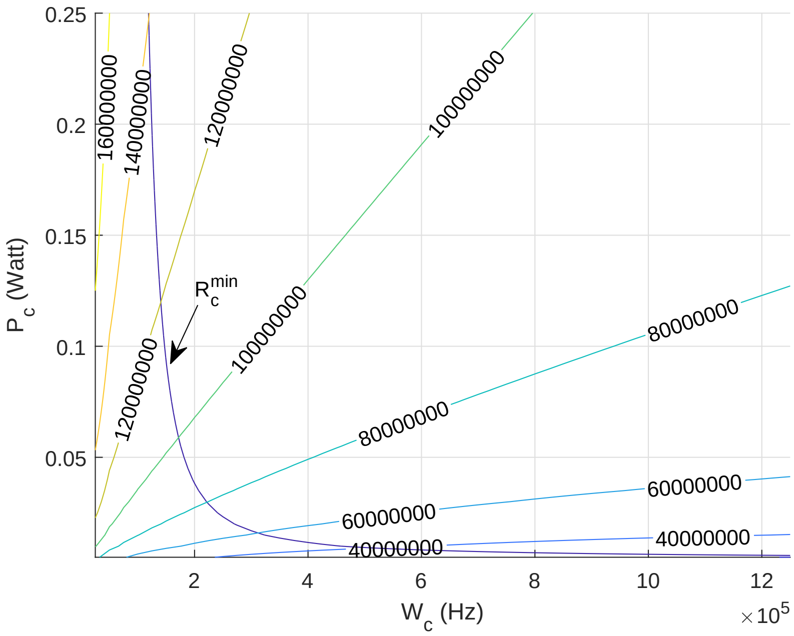

Figure 3.8 – Contour plot of RE and the minimum rate constraint line ($\beta =$ 10).

value of β and W_c. Therefore, we devise a solution to the problem by keeping one of the two optimization variables as constant and optimize the other. As a result, the Bisection method can be used to obtain the optimal power allocation for the RE problem. It is important to note that when $\beta > 0$, less amount of bandwidth will be allocated to the CUE in order to obtain the maximum value of RE. However, it does not guarantee that the minimum rate requirement for CUE can be achieved as shown in Fig 3.8. Hence, the optimal bandwidth is the one that can satisfy the minimum rate requirement.

To solve the RE problem with respect to transmit power using the Bisection method, the gradient equation of RE is required. For a given value of bandwidth, the gradient of RE can be derived as

$$\frac{dRE\left(P_c\right)}{d\left(P_c\right)} = \frac{(A/B) - C}{\left(\varepsilon P_c + P_{cirUE}\right)^2 \ln\left(2\right)} \tag{3.15}$$

where

$$
\begin{aligned}
A &= H_{cB}\left(\varepsilon P_c + P_{cirUE}\right)\left(\left(P_{cirUE} + \varepsilon P_c^{max}\right) W_c + \beta\left(\varepsilon P_c + P_{cirUE}\right) W_{tot}\right), \\
B &= \left(P_{cir} + \varepsilon P_c^{max}\right)\left(H_{cB} P_c + N_0 W_c\right), \qquad (3.16) \\
C &= \varepsilon W_c \ln\left(1 + \frac{H_{cB} P_c}{N_0 W_c}\right). \qquad (3.17)
\end{aligned}
$$

Algorithm 3.1 shows the resource allocation scheme to solve the RE optimization problem.

Algorithm 3.1 RE optimization algorithm for CUE

```
Initialization : z_a, z_b, ϵ > 0, k = 1, W_c = W_step
while W_c ≠ W_tot do
    while |z_a − z_b| ≥ ϵ do
        z = 1/2 (z_a + z_b)
        α_1 ← Solve (3.15) using P_c = z_a
        α_2 ← Solve (3.15) using P_c = z
        if α_1 α_2 < 0 then
            z_b = z
        else
            z_a = z
        end if
    end while
    W_c ← W_c + W_step
    k ← k + 1
end while
```

In each k iteration, the value of RE is calculated and saved. The maximum value of RE which satisfies the rate constraint is selected and the corresponding W_c^* and P_c^* can be obtained. In Algorithm 3.1, the transmission power constraint is considered in the interval $[z_a,\ z_b]$. The complexity of Bisection method is given as $\mathcal{O}(\log_2 n)$ where $n = \frac{z_b - z_a}{\epsilon}$. To solve the overall RE problem, the number of iteration required is K times, where $K = (W_{tot}/W_{step})$. Therefore, the complexity of RE optimization is $\mathcal{O}(K \log_2 n)$.

3.5 Energy Efficiency Optimization for D2D Pair

In this section, two different methods are proposed to solve the EE optimization for the D2D pair.

3.5.1 Dinkelbach and Lagrange Dual Decomposition

In the second stage, the D2D pair can use all remaining bandwidth to maximize its own EE. Therefore, the EE problem for D2D link becomes simpler as we only need to solve the optimal power allocation.

Dinkelbach method [110, 111] is a popular approach to solve nonlinear fractional programming problem. It is an application of the Newton method [112] to solve convex nonlinear fractional programming models by solving a sequence of nonlinear programming models successively [113]. The nonlinear fractional problem for D2D in (3.14) can be transformed into a subtractive form, which is concave as follows

$$\max_{P_d} \quad \eta_{EE} = R_d - q\left(\varepsilon P_d + P_{cirUE}\right) \qquad (3.18)$$
$$\text{s.t} \quad (3.7), (3.9).$$

where q is the value of EE.

Based on the nonlinear fractional programming theory [110], the maximum EE $q^* = \frac{R_d}{\varepsilon P_d^* + P_{cirUE}}$ is achieved if and only if $\max_{P_d} \quad R_d - q^*\left(\varepsilon P_d + P_{cirUE}\right) = R_d - q^*\left(\varepsilon P_d^* + P_{cirUE}\right) = 0$. This indicates that an equivalent optimization problem exists with an objective function in the subtractive form. The transformed problem (3.18) is a convex optimization problem which can be solved using Lagrange Dual Decomposition (LDD) method. The Lagrange dual function can be written as

$$\begin{aligned} L\left(P_d, \delta, \theta\right) &= R_d - q\left(\varepsilon P_d + P_{cirUE}\right) + \delta\left(R_d - R_d^{min}\right) \\ &\quad + \theta\left(P_d^{max} - P_d\right) \end{aligned} \qquad (3.19)$$

where δ and θ are the Lagrange multipliers that account for constraint (3.7) and (3.9), respectively. Therefore, the dual problem is formulated as

$$\min_{\delta,\theta} \max_{P_d} L\left(P_d, \delta, \theta\right) \qquad (3.20)$$
$$s.t. \quad \delta \geq 0, \theta \geq 0.$$

For the given values of q, δ and θ, the transmission power for D2D user can be computed by taking the derivative of (3.19) with respect to P_d which is given as

$$
\begin{aligned}
\frac{dL}{dP_d} &= \frac{H_{dd}}{N_0 \ln(2)\left(1+\frac{P_d H_{dd}}{W_d N_0}\right)} + \frac{\delta H_{dd}}{N_0 \ln(2)\left(1+\frac{P_d H_{dd}}{W_d N_0}\right)} \\
&\quad -\varepsilon q - \theta
\end{aligned} \tag{3.21}
$$

and then setting to zero.

The transmission power can be derived as

$$
P_d = \left[\frac{W_d\left(1+\delta\right)}{\ln(2)\left(\varepsilon q+\theta\right)} - \frac{W_d N_0}{H_{dd}}\right]^+ \tag{3.22}
$$

where $[x]^+ = \max\{0, x\}$. In addition, the Lagrange multiplier δ and θ can be updated by subgradient method using the following equations

$$
\delta\left(n+1\right) = \left[\delta\left(n\right) - s_1^n\left(R_d - R_d^{min}\right)\right]^+ \tag{3.23}
$$

$$
\theta\left(n+1\right) = \left[\theta\left(n\right) - s_2^n\left(P_d^{max} - P_d\right)\right]^+ \tag{3.24}
$$

where n is the iteration index, s_1^n and s_2^n are positive step sizes. The energy efficient algorithm for problem (3.18) is presented in Table 3.2

Algorithm 3.2 EE optimization algorithm for DUE using Dinkelbach and subgradient methods.

```
Initialization : ϵ > 0, i = 0, q(i) = 0, δ = 0.001, θ = 0.01, I_max
while |F(q)| ≥ ϵ or i ≤ I_max do
    Repeat
    Find P_d using (3.22)
    Update δ and θ using (3.23) and (3.24) respectively
    Until δ and θ are converged
    Update q(i + 1) = R_d / (εP_d + P_cir)
    Update F(q)
    i = i + 1
end while
```

3.5.2 Dinkelbach and Interior Point Method

Specifically, the EE problem in subtractive form becomes a convex optimization problem due to the concavity of the transformed objective function and the constraints are convex [95]. Therefore, the Dinkelbach method [110] together with interior point method (IPM) can also be used to obtain the optimal solution to the problem. The alternative energy efficient algorithm for problem (3.18) is presented in Algorithm 3.3

Algorithm 3.3 EE optimization algorithm for DUE using Dinkelbach and IPM.

Initialization : $\epsilon > 0,\ i = 0,\ q(i) = 0,\ \eta_{EE}(i),\ I_{max}$
while $\eta_{EE}(i) \geq \epsilon\ or\ i \leq I_{max}$ **do**
    Solve problem (3.18) by IPM to get P_d and η_{EE}
    Update $q(i+1) = \frac{R_d}{\varepsilon P_d + P_{cir}}$
    $i = i + 1$
end while

3.6 Simulation Results

In this section, we evaluate the performance of the proposed two stage RE-EE scheme. In the simulation, both CUE and DTx are uniformly distributed in a cell. DRx is randomly located with a distance of d from DTx. The channel gain between transmitter i and receiver j is calculated as $h_{i,j} = c_0 \varsigma_{i,j} \kappa_{i,j} d_{i,j}^{-\alpha}$, where c_0 is the pathloss coefficient, $\varsigma_{i,j}$ is the shadowing, $\kappa_{i,j}$ is the squared magnitude of the Rayleigh fading, $d_{i,j}$ is the distance between transmitter and receiver, and α is the path loss exponent. The channel model parameters include path loss coefficient of -20 dB, unit mean for the Rayleigh fading process, a path loss exponent of 4, and a standard deviation of 8 dB for the log-normal shadowing. Table 3.2 summarizes the main simulation parameters.

Table 3.2 – Simulation parameters

Parameters	Value
Spectrum bandwidth (W_{tot})	1.25 MHz
Cell radius (R)	500 m
D2D pair distance (d)	$20, 40, ..., 120$ m
Maximum transmit power of CUE (P_c^{max})	250 mW, 500 mW
Maximum transmit power of D2D (P_d^{max})	250 mW
Minimum rate of CUE and D2D (R_c^{min}, R_d^{min})	$[0, 5]$ Mbps
Circuit power(P_{cirUE})	100 mW
Noise power spectral density (N_0)	-174 dBm/Hz

3.6.1 RE for CUE

The impact of the weighted parameter β to EE and SE is depicted in Fig. 3.9. It shows that the EE is decreasing with β, whereas SE is increasing with β. At certain points, the value of RE's weighted factor could provide the tradeoff between RE and EE for the CUE in the system. The cross point between EE and SE occurs when $\beta = 2.25$. Fig. 3.10 compares the plot of the proposed RE-EE scheme with the global optimal solution derived using Matlab's Global Optimization Toolbox. From the figure, it can be seen that the proposed scheme allocates the bandwidth and power effectively and is similar to the global optimal solution. More importantly, this shows the relationship of RE optimization to power and bandwidth, whereby when $\beta = 0$, the optimization is focused on EE and the bandwidth is fully utilized while the power is minimized. On the other hand, when β is high, the focus is on SE and the results are reversed.

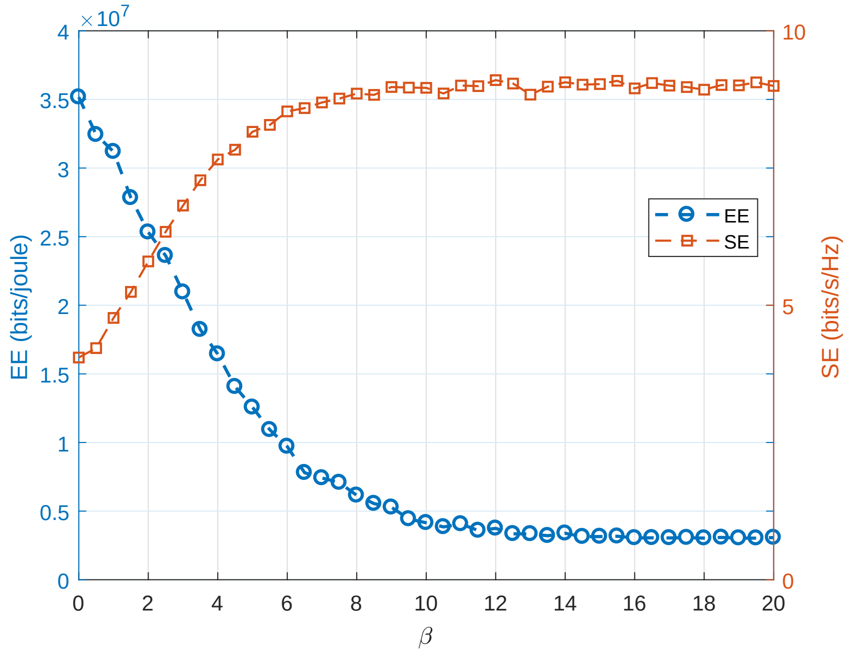

Figure 3.9 – Impact of weighted parameter to EE and SE.

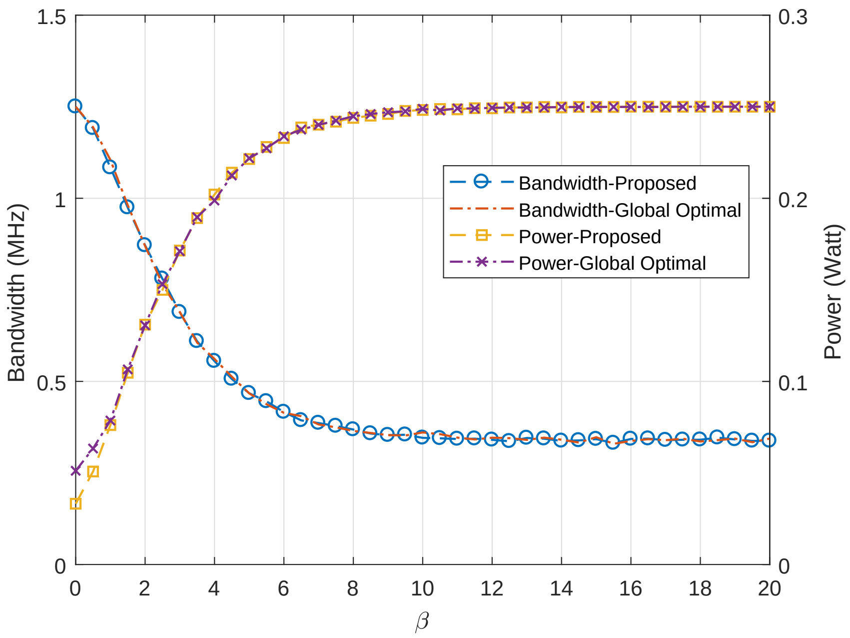

Figure 3.10 – Bandwidth and power allocation.

The ratio of optimal transmit power and P_c^{max} versus the weighted coefficient β is shown in Figure 3.11. This result indicates that to achieve maximum SE for higher values of P_c^{max}, a higher value of β needs to be chosen. However, it should be noted that lower EE is achieved when β is higher.

3.6.2 EE for D2D Pair

Figure 3.12 shows the comparison of average EE of D2D communication for three different methods. Matlab's MultiStart solver is used to obtain the global optimal solution from various start points. The average transmit power of DTx is presented in Figure 3.13. The findings show that the combination of Dinkelbach with LDD or IPM methods can solve the EE optimization problem for D2D communication and achieve similar results as the global optimal solution.

3.6.3 System EE

Fig. 3.14 shows the individual EE for CUE and D2D pair versus the D2D separation. The close proximity between D2D pair enables D2D communication to achieve higher EE than CUE. It is apparent from the figure that the EE of D2D

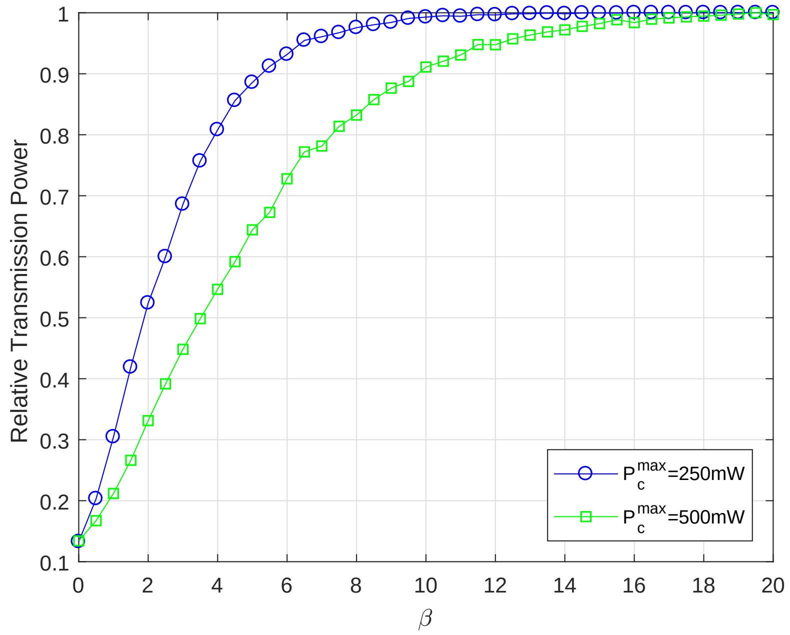

Figure 3.11 – Optimal transmit power for different values of β.

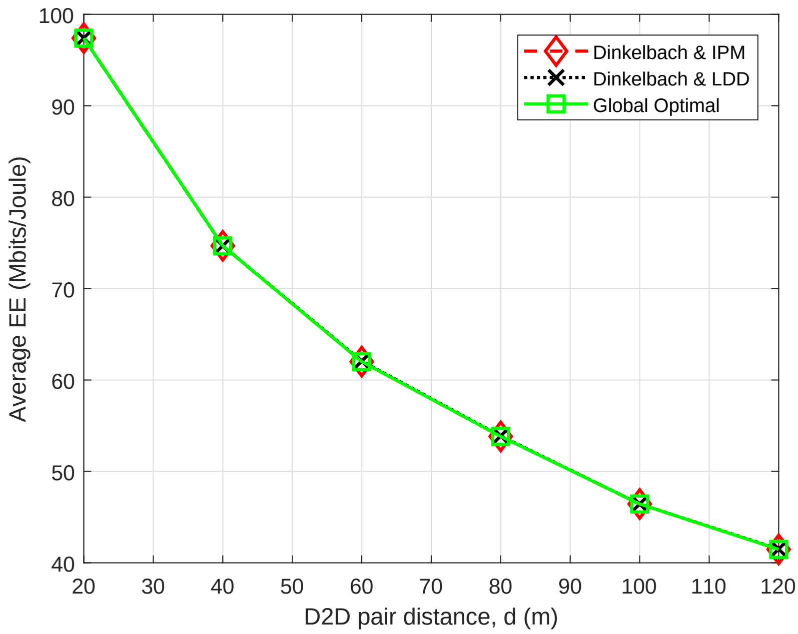

Figure 3.12 – EE versus D2D radius ($R_d^{min} = 1$ Mbps, $W_d = 625$kHz).

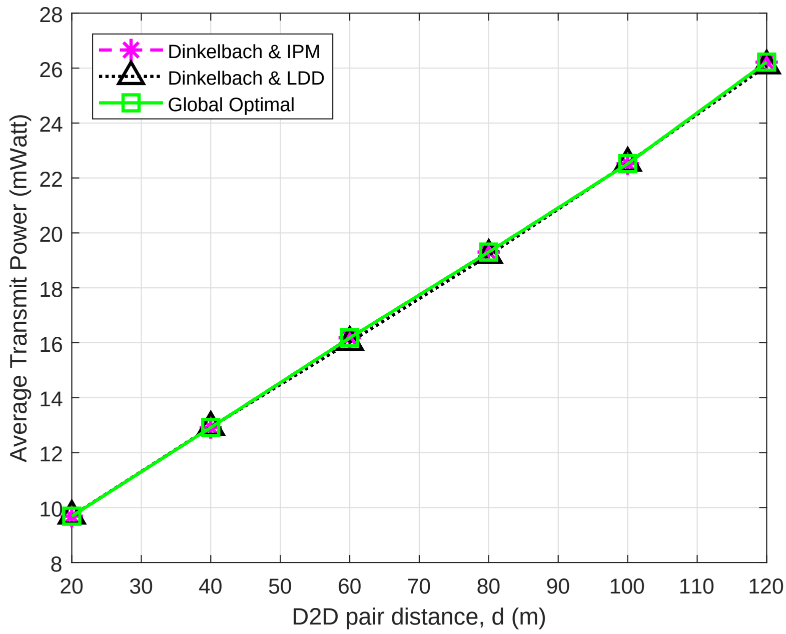

Figure 3.13 – Transmit power versus D2D radius (R_d^{min} = 1 Mbps, W_d = 625kHz).

pair is very much higher than the EE of the CUE. The result indicates that significant EE improvement can be achieved by establishing D2D communication. However, as the distance between D2D pair increases, more transmission power is required to overcome the deteriorating channel condition. As a result, the EE for D2D pair decreases. It can also be observed that the EE does not change for the CUE as the D2D users are communicating in an overlay manner which cause no interference to the CUE.

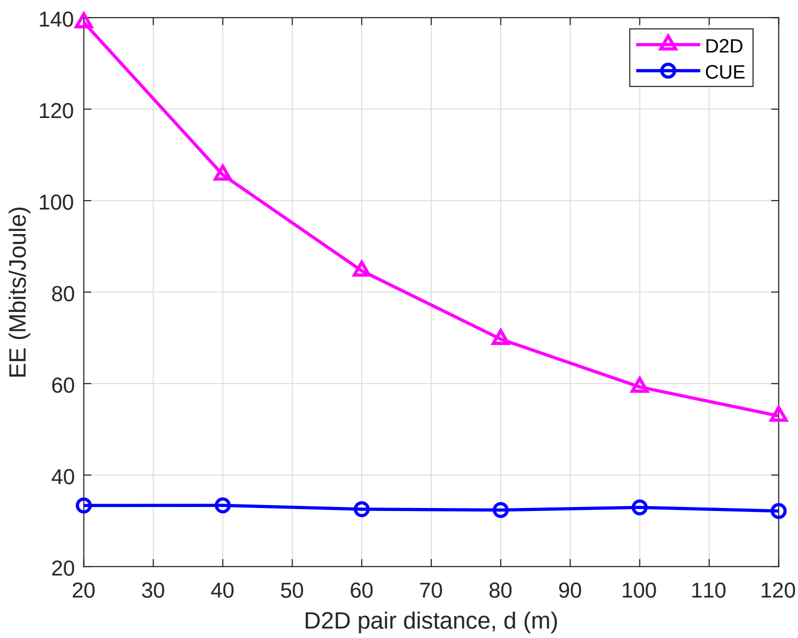

Figure 3.14 – EE versus D2D pair distance.

Fig. 3.15 compares the total EE performance of the proposed scheme with the high complexity global optimal solution. In addition, it is also compared to the dedicated mode (DM) with the bandwidth and power for the CUE and D2D pair being optimized simultaneously, and the cellular mode (CM) where all users are routed through the BS. The EE optimization problems for DM, and CM are described in [95]and solved using Matlab's numerical solution. From the figure, the performance of the proposed scheme is close to the global optimal solution but with much lower complexity due to the two stage optimization. Moreover, the proposed method is better than the DM and CM. Therefore, the proposed scheme can provide an energy efficient solution for the D2D enabled cellular system.

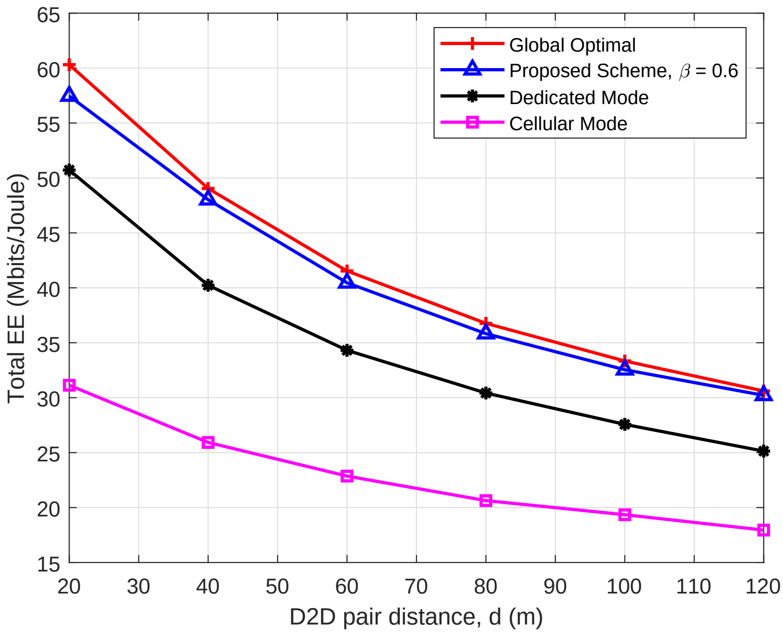

Figure 3.15 – Total EE versus D2D pair distance.

3.7 Summary

In this chapter, D2D communication overlaying cellular system and sharing the uplink resources is presented. Several works related to EE optimization for D2D communication are summarized. A two-stage framework is proposed to maximize the system EE while guaranteeing the minimum rate requirements and power constraints for all users. In the first stage, the RE problem for the CUE is formulated and solved by applying an iterative algorithm with Bisection method. Using a weighted parameter to control the available resources for CUE, the D2D pair can use the remaining bandwidth to maximize its EE. To solve the EE problem in the second stage, Dinkelbach with LDD or IPM can be adopted to obtain the optimal power allocation for the D2D pair. Simulation results showed that the proposed scheme offers higher overall EE as compared to cellular and dedicated mode of transmission. In addition, the proposed scheme performs close to the global optimal solution but with lower complexity.

Chapter 4

Energy Efficient D2D in Downlink Cellular System

4.1 Introduction

In this chapter, the RE optimization for the BS in downlink scenario and EE optimization for D2D pairs are proposed. Several works related to D2D communications sharing downlink cellular system which aim to maximize the EE are presented in Section 4.2. The system model for D2D communications overlaying cellular system with multiple CUEs and D2D pairs is provided in Section 4.3. Furthermore, a full RE and lower complexity RE schemes are presented in Section 4.4 and the EE optimization for the D2D pairs is solved in Section 4.5. Finally, simulation results which validate the effectiveness of the proposed schemes are provided in Section 4.6. The work presented in this chapter forms most of P1.

4.2 Related Works

The EE optimization for D2D in downlink scenario has rarely been discussed mainly due to the overwhelming interference from the BS in the underlay mode. During the downlink period, the CUE receives data from the BS and interference from DTx sharing the same RB. The DRx suffers serious interference due to large transmit power of the BS, which make it difficult to guarantee the quality of D2D services [114]. In [115], an interference alignment (IA)-based EE optimization for D2D MIMO downlink underlay network is proposed to maximize the EE with the constraints on maximum transmit power and data rate requirements. Both original EE problems for D2D link and cellular link are computationally difficult to be solved. Therefore, the IA technique is used to mitigate interferences so that the computational complexity can be reduced. In that work, the EE problems for D2D link and cellular link are treated independently and an IA-based energy-efficient scheme is also proposed to further improve the EE of both D2D and cellular links.

In [116], optimization problem that maximizes the EE of the D2D communications, while guaranteeing the constraints on the minimum data rate for D2D and cellular users as well as the maximum transmit power of D2D transmitters is formulated. Two different assumptions are considered; full and average CSI of the intercell interferers available at the D2D transmitters. The difference of two convex functions (DC) programming approach is used to solve the first case while iteration search based on the subgradient method is used to obtain the power allocation for the latter case. However, the BS power consumption is ignored in this work.

The authors of [117] considered the problem of resource allocation for cognitive radio systems in which a primary and a secondary link share the available spectrum by underlay or overlay communications. In both approaches, the coexistence of a multiple-input single-output (MISO) primary link with a MIMO secondary link is studied and the problems are formulated as the maximization of the secondary link's EE.

A self-organized cross-layer optimization scheme for enhancing the EE of the D2D communications, which includes RB and power allocation, is studied in [118]. A heterogeneous cellular network is considered in that work and the joint RB and power allocation is modeled as a non-cooperative game. Moreover, a joint power control and matching algorithm is outlined in [119] for D2D underlaying cellular networks. However, the focus of that work is to maximize the total EE of all D2D links as in [116], not the system EE, and D2D pairs communicate using underlay mode. In addition, the authors assume that the downlink RBs of each CUE can be shared by at most one D2D link. Therefore, the spectrum may not be efficiently utilized.

In [120], the authors addressed the downlink resource allocation problem for D2D communication with wireless power transfer (WPT) technique in a cellular network. To maximize the weighted EE of all D2D pairs, a game theoretic approach is used and a distributed learning algorithm is proposed. The authors in [121] have studied the resource allocation problem in simultaneous wireless information and power transfer (SWIPT)-based D2D underlay networks. The joint power control and partner selection problem is formulated as a two-dimensional energy-efficient stable matching scheme and the solution is obtained using the Gale-Shapley (GS) algorithm. Besides, the work in [122] aims to maximize the average EE of all D2D links. A joint energy harvesting (EH) time slot allocation, power and RB allocation iterative algorithm which based on the Dinkelbach and Lagrangian constrained optimization is proposed.

Heterogeneous statistical QoS constraints are considered in [123], where CUEs support delay tolerant services with different delay constraints while DUE groups need to guarantee the outage probability within a certain range. A hierarchical game-based power allocation algorithm is proposed which consists of power allocations for CUEs and D2D user groups. By exploiting LDD and Newton iteration method, the power allocation for the CUEs is derived in order to maximize the payoff-cost utility function of the BS. In addition, fractional programming and convex optimization techniques are employed to obtain the power allocation of the group to maximize the EE of each D2D user group subject to the outage probability constraint.

The resource allocation problems for EH aided D2D communication network are studied in [124, 125]. In both literatures, a DTx harvests energy from a cellular BS and utilizes the harvested energy to transmit its information signal to a DRx and overlay mode is considered where cellular transceivers and a D2D pair exploit orthogonal resources. Furthermore, battery capacity constraint is imposed in [125]. By exploiting fractional programming theory with additional relaxation approach, the non-convex problems are transformed into convex optimization problems and iterative algorithms are designed to maximize the system EE. Although the energy consumption at the BS is taken into account in the EE formulation, the achievable rate of the CUEs is ignored in these works.

It is worth mentioning that, most works investigating the EE of D2D communications in downlink are limited to maximizing the EE of the D2D pairs or separate EE of cellular links and D2D links. The main contribution of this chapter is therefore to maximize the system EE while considering the total achievable rate and the overall system energy consumption. In addition, resource efficiency (RE) approach that provides the EE-SE tradeoff for the cellular links is also studied in this work.

4.3 System Model

In this work, a multiuser OFDMA downlink system with one BS located at the center of the cell is considered. There are K cellular UEs (CUEs), and L D2D pairs. Each D2D pair consists of two D2D UEs (DUEs). The UEs and BS are equipped with a single omni-directional antenna. The system bandwidth is W_{tot} with a total of N RBs; hence the bandwidth for each RB is $W_s = W_{tot}/N$. The CUEs communicate via BS while the DUEs communicate directly to each other in pair. The DUEs can operate in an orthogonal or non-orthogonal resource sharing mode and utilize the remaining RBs not being assigned to the CUEs. We denote C as the number of RBs allocated to the CUEs and M as the number of RBs designated to DUEs. The relationship between C, M and N is given as $C + M \leq N$. The value of C and M are not fixed and will be determined in the RE optimization stage.

Fig. 4.1 shows the scenario of D2D communications overlaying cellular network, where four CUEs take up orthogonal downlink resources and two D2D pairs (DUE1 and DUE2, DUE3 and DUE4) sharing the same resource not allocated to the CUEs. A DUE can switch between transmitting and receiving modes in the cellular downlink band using a time division duplexing (TDD). During the downlink period of the cellular system, the BS transmits data to the CUEs without exerting any interference to the DUEs. However, D2D pairs are exposed to the interference from each other.

4.3.1 Cellular Users

Let $\mathcal{K} = \{1, 2, ..., K\}$ and $\mathcal{N} = \{1, 2, ..., N\}$ denote the sets of all CUEs and all RBs, respectively. The transmit power and the channel gain of the kth CUE on the nth RB are represented as $p_{k,n}$ and $h_{k,n}$, respectively. The achievable rate of the kth CUE on the nth RB is formulated as

$$r_{k,n} = W_s \log_2 (1 + p_{k,n}\Gamma_{k,n}) \tag{4.1}$$

where $\Gamma_{k,n} = \frac{h_{k,n}}{W_s N_0}$ denotes the channel to noise ratio (CNR). The channel gain from the BS to CUE k over RB n is modeled as $h_{k,n} = \varsigma_k g_{k,n} d_k^{-\alpha}$, where ς_k denotes the shadowing, $g_{k,n}$ accounts the effect of fading, d_k is the distance between BS and the kth CUE, and α is the path loss exponent. The achievable rate for the kth CUE is represented as R_k and the sum rate can be calculated as

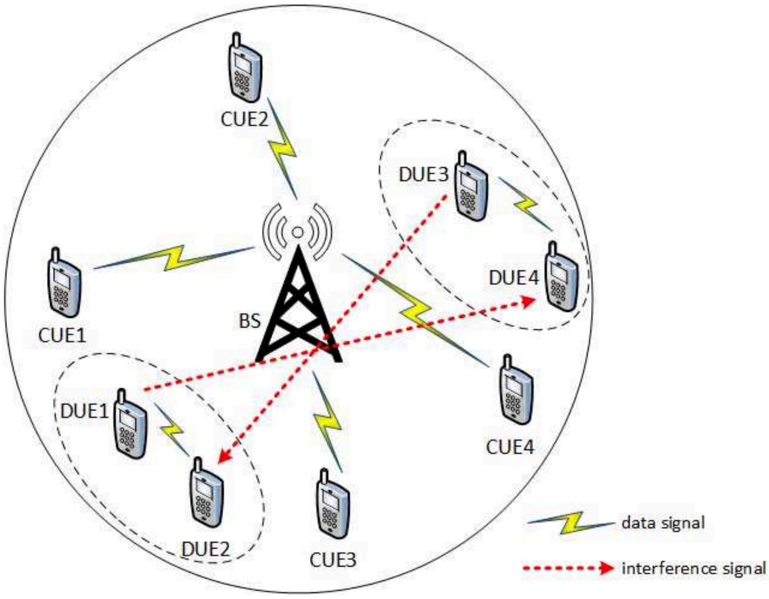

Figure 4.1 – System model of D2D communications overlaying downlink cellular system.

$$R_c = \sum_{k=1}^{K} R_k = \sum_{k=1}^{K} \sum_{n=1}^{N} \omega_{k,n} r_{k,n} \tag{4.2}$$

where $\omega_{k,n}$ denotes the RB allocation indicator for the CUEs, which equals to 1 if RB n is allocated to the kth user and 0 otherwise. The overall transmit power for the kth user, P_k and the total transmit power, P_T are given by

$$P_k = \sum_{n=1}^{N} \omega_{k,n} p_{k,n}, \quad P_T = \sum_{k=1}^{K} P_k. \tag{4.3}$$

The overall power consumption model at the BS is given as

$$P = \varepsilon P_T + P_{cirBS} \tag{4.4}$$

where ε is the inverse of drain efficiency of power amplifier and P_{cirBS} denotes the BS circuit power. The overall power budget at the base station is modeled as

$$P_{tot} = \varepsilon P_{max} + P_{cirBS} \tag{4.5}$$

where P_{max} is the maximum transmission power of the BS.

4.3.2 D2D Users in Non-Orthogonal Mode

A D2D pair consists of a DTx and a DRx. In non-orthogonal resource sharing mode, each available RB will be reused by multiple D2D pairs which results in co-tier interference. However, higher SE can be achieved by proper interference management [66]. In addition, by optimizing each DTx transmit power, the overwhelming interference can be controlled to improve the EE for D2D communications. Let $\mathcal{L} = \{1, 2, ..., L\}$ and $\mathcal{M} = \{1, 2, ..., M\}$ denote the sets of all D2D pairs and all RBs designated to the D2D pairs, respectively. The transmit power of the lth D2D pair on the mth RB is represented as $p_{l,m}$. The signal to interference plus noise ratio (SINR) of D2D pair l on RB m is given as

$$\Gamma_{l,m} = \frac{p_{l,m} h_{l,m}}{\sum_{l'=1, l' \neq l}^{L} p_{l',m} h_{l'l,m} + W_s N_0}. \tag{4.6}$$

The channel gain between the lth D2D pair over the mth RB is modeled as $h_{l,m} = \varsigma_l g_{l,m} d_l^{-\alpha}$, where ς_l is the shadowing, $g_{l,m}$ is the squared magnitude of the fading, and d_l is the distance between D2D pair. Similarly, the channel gain from the DTx l' to DRx l on RB m is represented as $h_{l'l,m}$.

Therefore, the achievable rate of the lth D2D pair on the mth RB is formulated as

$$r_{l,m} = W_s \log_2 (1 + \Gamma_{l,m}). \tag{4.7}$$

The aggregate rate for the lth D2D pair is represented as R_l and the sum rate for D2D communications is calculated as

$$R_d = \sum_{l=1}^{L} R_l = \sum_{l=1}^{L} \sum_{m=1}^{M} r_{l,m}. \tag{4.8}$$

The total transmit power of all D2D pairs, P_D is given by

$$P_D = \sum_{l=1}^{L} \sum_{m=1}^{M} p_{l,m}. \tag{4.9}$$

Finally, the overall power consumption model for D2D communications is given as

$$P_{DT} = \varepsilon P_D + L P_{cirUE} \tag{4.10}$$

where P_{cirUE} represents the circuit power for each DTx.

4.3.3 D2D Users in Orthogonal Mode

For comparison, the case of D2D communications in orthogonal resource sharing mode is also considered, where each remaining RB will be allocated to only one D2D pair. In this mode, no interference exists amongst D2D pairs. The transmit power of the lth D2D pair on the mth RB in orthogonal mode is represented as $\bar{p}_{l,m}$.

The achievable rate of the lth D2D pair on the mth RB is formulated as

$$\bar{r}_{l,m} = W_s \log_2 \left(1 + \frac{\bar{p}_{l,m} h_{l,m}}{W_s N_0}\right). \tag{4.11}$$

The aggregate rate for the lth D2D pair is represented as $\bar{R}_l$, and the overall rate for the D2D communications is given by

$$\bar{R}_d = \sum_{l=1}^{L} \bar{R}_l = \sum_{l=1}^{L} \sum_{m=1}^{M} \omega_{l,m} \bar{r}_{l,m} \tag{4.12}$$

where $\omega_{l,m}$ denotes the RB allocation indicator for D2D pairs. The total transmit power of all D2D pairs in orthogonal mode can be expressed as

$$\bar{P}_D = \sum_{l=1}^{L} \sum_{m=1}^{M} \omega_{l,m} \bar{p}_{l,m}. \tag{4.13}$$

4.4 Resource Efficiency Optimization for Downlink OFDMA System

4.4.1 RE Problem Formulation

The first subproblem in the two-stage optimization scheme aims to maximize the RE for the BS. Based on the work in [20], RE is defined as

$$RE = \frac{R_c}{P}\left(1 + \beta\frac{\tau_p}{\tau_w}\right) \tag{4.14}$$

where τ_p and τ_w represent power utilization and bandwidth utilization, respectively and are given by

$$\tau_p = \frac{P}{P_{tot}}, \quad \tau_w = \frac{W}{W_{tot}} \tag{4.15}$$

where W is the occupied bandwidth while β is the tradeoff parameter which controls the balance between EE and SE. From (4.14), we can deduce that when $\beta = 0$, the problem is optimizing the EE. However, when β is larger, it optimizes SE.

In the first stage, the RE optimization problem for downlink cellular transmission can be formulated as

$$\eta_{RE} = \max_{\omega_{k,n},p_{k,n}} \frac{R_c}{P}\left(1 + \beta\frac{\tau_p}{\tau_w}\right) \tag{4.16a}$$

$$\text{s.t} \quad \sum_{n=1}^{N} \omega_{k,n} r_{k,n} \geq R^c_{min} \tag{4.16b}$$

$$\sum_{k=1}^{K}\sum_{n=1}^{N} \omega_{k,n} p_{k,n} \leq P_{max} \tag{4.16c}$$

$$\sum_{k=1}^{K} \omega_{k,n} \leq 1, \ \forall n \in \mathcal{N} \tag{4.16d}$$

$$\omega_{k,n} \in \{0, 1\} \tag{4.16e}$$

$$p_{k,n} \geq 0, \ \forall k \in \mathcal{K}, \ \forall n \in \mathcal{N} \tag{4.16f}$$

$$\sum_{k=1}^{K}\sum_{n=1}^{N} \omega_{k,n} \leq N \tag{4.16g}$$

where R^c_{min} denotes the minimum rate requirement for each CUE. Constraint (4.16b) guarantees the quality of service (QoS) requirement of every CUE while

(4.16c) indicates the upper limit on the maximum transmit power. Constraint (4.16d) and (4.16e) ensure that RB n is allocated to at most one CUE at a particular time. Constraint (4.16g) is implemented to ensure that the number of RBs utilized for RE optimization does not exceed the total number of RBs.

4.4.2 Full Resource Efficiency Optimization Scheme (Full RE)

In the first stage, the joint RB and power allocation for RE optimization are performed to guarantee the quality of service (QoS) of the cellular links. The idea is to save as much RBs as possible during the RE optimization stage, so that the remaining RBs can be allocated to the D2D pairs. This allows D2D pairs to communicate in an overlaying manner where the strong interference from the BS can be avoided. Problem (23) is a mixed integer non-linear programming (MINLP) problem and hard to be solved directly. To solve this problem, the RB allocation integer variables $\omega_{k,n} \in \{0,1\}$ is first relaxed into continuous variables [126], $\tilde{\omega}_{k,n} \in [0,1]$ which reflects the time sharing strategy [127, 128] before transforming the original problem into a subtractive form.

By relaxing the RB allocation indicators, problem (23) can be written as

$$\eta_{RE} = \max_{\tilde{\omega}_{k,n}, p_{k,n}} \frac{R_c}{P}\left(1+\beta\frac{\tau_p}{\tau_w}\right) \tag{4.17a}$$

$$\text{s.t } (4.16b) \text{ - } (4.16d),\ (4.16f) \tag{4.17b}$$

$$\tilde{\omega}_{k,n} \in [0,1]\,. \tag{4.17c}$$

RE optimization is a non-convex problem due to the fractional form of the objective function and cannot be solved directly. However, (4.17a) can be transformed into an equivalent problem in subtractive form based on non-linear fractional programming technique [110]. We define the maximum RE of the BS as

$$\begin{aligned} q_c^* = \max_{\{\tilde{\omega}, p\}} \eta_{RE}\left(\tilde{\omega}, p\right) &= \frac{R_c\left(1+\beta\frac{\tau_p}{\tau_w}\right)}{\varepsilon P_T + P_{cirBS}} \\ &= \frac{U\left(\tilde{\omega}^*, p^*\right)}{D\left(\tilde{\omega}^*, p^*\right)} \end{aligned} \tag{4.18}$$

where $\tilde{\omega}^*$ and p^* are the optimal RB and power allocation strategies, respectively.

Theorem 1 *q_c^* can be achieved if and only if*

$$\begin{aligned}&\max_{\{\tilde{\omega},p\}} U(\tilde{\omega},p) - q_c^* D(\tilde{\omega},p)\\&= U(\tilde{\omega}^*,p^*) - q_c^* D(\tilde{\omega}^*,p^*) = 0\end{aligned} \tag{4.19}$$

Proof. Please refer to [110] for a proof of *Theorem 1.*

Theorem 1 indicates that for the considered RE optimization problem with an objective function in the fractional form, there exists an equivalent optimization problem with an objective function in the subtractive form. Therefore, the focus is given to the equivalent transformed objective function of original problem (4.17a) which can be rewritten as

$$\begin{aligned}F_c(q_c) =& R_c\left(1+\beta\frac{\tau_p}{\tau_w}\right) - q_c P\\ =& \sum_{k=1}^{K}\sum_{n=1}^{N}\tilde{\omega}_{k,n} r_{k,n}\left(1+\beta\frac{\tau_p}{\tau_w}\right)\\ &- q_c\left(\varepsilon\sum_{k=1}^{K}\sum_{n=1}^{N}\tilde{\omega}_{k,n} p_{k,n} + P_{cirBS}\right).\end{aligned}$$

$$\text{s.t } (4.16b) \text{ - } (4.16d),\ (4.16f),\ \tilde{\omega}_{k,n} \in [0,1]. \tag{4.20}$$

It should be noted that $F_c(q_c)$ monotonically decreases when q_c increases. Therefore, the optimal RE q_c^* is obtained by finding the root of $F_c(q_c)$, which can be implemented using the Dinkelbach method [110] or the bisection method [112]. From (4.20), when $q_c \to -\infty$, $F_c(q_c) > 0$; on the other hand, when $q_c \to \infty$, $F_c(q_c) < 0$. Therefore, $F_c(q_c) > 0$, when $q_c \leq 0$ because the first and second terms of (4.20) are positive. Hence, $F_c(q_c) = 0$ occurs at $q_c > 0$. As a result, (4.20) is solved for $q_c > 0$.

In the next step, we employ LDD method similar as in [129, 130] for solving (4.20). The Lagrangian function of (4.20) is given by

$$\begin{aligned}\mathcal{L}_{RE}\left(\tilde{\omega}_{k,n}, p_{k,n}, \boldsymbol{\lambda}, \mu\right) = &\sum_{k=1}^{K}\sum_{n=1}^{N}\tilde{\omega}_{k,n}r_{k,n}\left(1+\beta\frac{\tau_p}{\tau_w}\right)\\ &- q_c\left(\varepsilon\sum_{k=1}^{K}\sum_{n=1}^{N}\tilde{\omega}_{k,n}p_{k,n}+P_{cirBS}\right)\\ &-\sum_{k=1}^{K}\lambda_k\left(R_{min}^{c}-\sum_{n=1}^{N}\tilde{\omega}_{k,n}r_{k,n}\right)\\ &-\mu\left(\sum_{k=1}^{K}\sum_{n=1}^{N}\tilde{\omega}_{k,n}p_{k,n}-P_{max}\right)\end{aligned} \tag{4.21}$$

where $\boldsymbol{\lambda}$ and μ are the Lagrange multipliers for constraints (4.16b) and (4.16c), respectively. The corresponding dual problem can be expressed as

$$\min_{\boldsymbol{\lambda},\mu\geq 0}\ \max_{\tilde{\omega}_{k,n},p_{k,n}}\ \mathcal{L}_{RE}\left(\tilde{\omega}_{k,n}, p_{k,n}, \boldsymbol{\lambda}, \mu\right). \tag{4.22}$$

By taking the first-order derivation of (4.21) w.r.t $p_{k,n}$, we get

$$\frac{d\mathcal{L}_{RE}}{dp_{k,n}} = \frac{\tilde{\omega}_{k,n}W_c\left[\left(1+\beta\frac{\tau_p}{\tau_w}\right)+\lambda_k\right]\times\Gamma_{k,n}}{\left(1+\Gamma_{k,n}p_{k,n}\right)\ln\left(2\right)} - \left(\mu+\varepsilon q_c\right). \tag{4.23}$$

The power for user k on RB n can be computed by setting (4.23) to zero, yielding

$$p_{k,n} = \left[\frac{W_s\left(\left(1+\beta\frac{\tau_p}{\tau_w}\right)+\lambda\right)}{\left(\mu+\varepsilon q_c\right)\ln\left(2\right)} - \frac{1}{\Gamma_{k,n}}\right]^{+} \tag{4.24}$$

where $[x]^{+} = \max\{0, x\}$. Similarly, the first-order derivative of (4.21) with respect to $\tilde{\omega}_{k,n}$ is

$$\begin{aligned}\frac{d\mathcal{L}_{RE}}{d\tilde{\omega}_{k,n}} &= W_s\log_2\left(1+p_{k,n}\Gamma_{k,n}\right)\left[\left(1+\beta\frac{\tau_p}{\tau_w}\right)+\lambda\right]\\ &\quad - p_{k,n}\left(\varepsilon q_c+\mu\right)\\ &= Q_{k,n}.\end{aligned} \tag{4.25}$$

Since only a single user is allowed to transmit on each RB, the RB assignment index $\tilde{\omega}_{k,n}$ can be determined as

$$\tilde{\omega}_{k,n} = \begin{cases} 1, & k = \max_{1 \le k \le K} Q_{k,n} \\ 0, & otherwise. \end{cases} \tag{4.26}$$

In order to update the dual variable $\boldsymbol{\lambda}$ and μ, the subgradient method [131] can be used to solve (4.22). The subgradient updating equations are given as

$$\lambda_k\left(i+1\right) = \left[\lambda\left(i\right) - \zeta_{\lambda}^{i}\left(\sum_{n=1}^{N} \tilde{\omega}_{k,n} r_{k,n} - R_{min}^{c}\right)\right]^{+} \tag{4.27}$$

$$\mu\left(i+1\right) = \left[\mu\left(i\right) - \gamma_{\mu}^{i}\left(P_{max} - \sum_{k=1}^{K}\sum_{n=1}^{N} \tilde{\omega}_{k,n} p_{k,n}\right)\right]^{+} \tag{4.28}$$

where i is the iteration index, ζ_{λ}^{i} and γ_{μ}^{i} are positive step sizes. There are several step size selections such as diminishing step size and constant step size and if sufficiently small step size is chosen, the distance between the current solution to the optimal solution decreases [132]. Here, the step size of $\frac{1}{\sqrt{i}}$ is used [133]. The channel gain from the BS to all CUEs across different RBs can be represented as a matrix $\mathbf{H}$, which consists of K rows and N columns. For a given $\mathbf{H}$, the resource allocation algorithm for the Full RE scheme is presented in Algorithm 4.1.

Algorithm 4.1 Full RE Optimization

Require: $\beta, K, N, \mathbf{H}, z = 0, T = K - 1$

```
A ← vector of the best channel gain for K users
B ← the remaining channel gain matrix sorted in descending order
H1 = [diag(A), B]
while T ≠ N do
    T = T + 1
    H2 = H1(1 : K, 1 : T)
    Apply Algorithm 4.2 to find ω̃_{k,n} and p_{k,n}
    z = z + 1
    Calculate RE(z) according to (4.14)
end while
Obtain S = arg max_z RE(z)
C = S + (K − 1)
return (RE, C)
```

Compared to D2D communication, CUEs have the priority to access the available resources. Therefore, the first step to solve the RE problem is to allocate

Algorithm 4.2 RB and power allocation

Require: $\epsilon,\ t = 0,\ q_c(t) = 0,\ T_{max}$

while $(|F_c(q_c)| > \epsilon)\ ||\ (t < T_{max})$ **do**
  Initialize $i = 0,\ \lambda_k(i),\ \mu(i),\ I_{max}$
  while $((|\ \lambda_k(i+1) -\ \lambda_k(i)| > \epsilon)$ or
    $(|\ \mu(i+1) -\ \mu(i)| > \epsilon))$ and $(i \leq I_{max})$ **do**
    for $n = 1 : N$ **do**
      for $k = 1 : K$ **do**
        Find $p_{k,n}$ and $Q_{k,n}$ using (4.24) and (4.25)
      end for
      Obtain $\tilde{\omega}_{k,n}$ using (4.26)
    end for
    Update λ_k and μ using (4.27) and (4.28) respectively
    $i = i + 1$
  end while
  Update $q_c(t+1) = \frac{R_c(1+\beta\frac{\tau_p}{\tau_w})}{\varepsilon P_T + P_{cirBS}}$
  Update $F_c(q_c)$
  $t = t + 1$
end while
return $(\tilde{\omega}_{k,n},\ p_{k,n})$

one RB to each CUE with their respective best RB to ensure all CUEs have at least one RB to send their data. The remaining RBs are sorted by the channel gain in descending order. Then, the power allocation for each CUE on each RB is performed. To solve the overall RE optimization formulated in (4.16), lines 4 to 10 of Algorithm 4.1 is repeated until the overall RBs has been considered and the values of RE are stored. The corresponding RB and power allocation to achieve the maximum value of RE for the BS can be obtained and subsequently, the number of RBs utilized in the RE optimization stage C is determined. The remaining RBs, M, will be reused by each D2D pairs in the second stage of optimization.

4.4.3 Lower Complexity RE Optimization Scheme (LC RE)

The complexity of Algorithm 4.1 to solve problem (4.16) is potentially high due to the iterations to solve joint RB and power allocation for different number of RB sets. In order to reduce this complexity, an alternative approach is proposed to solve the RE problem suboptimally with lower complexity by separating the RB and power allocation into two separate steps.

Resource Block Allocation

The first step in this approach is to perform RB allocation to maximize the RE of the BS. Equal power allocation (EPA) is used in this step to equally distribute the maximum transmission power to all RBs. Similar to the initially steps of the Full RE solution, the best RB is first allocated to each CUE, and the remaining RBs are sorted in descending order of the channel gain. These remaining RBs are also allocated to the respective CUEs with the best channel gain. The RB allocation step is presented in Algorithm 4.3.

Algorithm 4.3 RB allocation

Require: $\beta,\ K,\ N,\ \mathbf{H},\ z = 0,\ T = K - 1$

```
A ← vector of the best channel gain for K users
B ← the remaining channel gain matrix sorted in descending order
H1 = [diag(A), B]
while T ≠ N do
    T = T + 1
    H2 = H1(1 : K, 1 : T)
    Obtain ω_{k,n} by assigning the RBs to users with best element in H2
    z = z + 1
    Using EPA, calculate RE(z) according to (4.14)
end while
Obtain S = arg max_z RE(z)
C = S + (K − 1)
return (ω_{k,n}, C)
```

Optimal Power Allocation

Once the RB allocation and selection is completed, the number of optimization variables of the original RE problem is reduced to a single one. Specifically, since $\tilde{\boldsymbol{\omega}}$ is solved in the first step, the remaining problem is to solve the power allocation for CUEs, $\mathbf{p}$. In addition, since the number of CUE RBs, C, is already obtained, power allocation is only needed for the C RBs, which make the complexity even lower. Since RE is to balance between EE and bandwidth usage, which is already used in the RB allocation step, the power allocation here therefore do not need to optimize RE but to directly maximizes EE. For a given RB assignment, the

EE maximization problem for the BS is formulated as

$$\eta_{EEC} = \max_{\mathbf{p}} \frac{\sum_{k=1}^{K} \sum_{n\epsilon\Omega_k} W_s \log_2 (1 + p_{k,n}\Gamma_{k,n})}{\varepsilon \sum_{k=1}^{K} \sum_{n\epsilon\Omega_k} p_{k,n} + P_{cirBS}} \tag{4.29a}$$

$$\text{s.t} \quad \sum_{n\epsilon\Omega_k} W_s \log_2 (1 + p_{k,n}\Gamma_{k,n}) \geq R^c_{min},\ \forall k \in \mathcal{K} \tag{4.29b}$$

$$\sum_{k=1}^{K} \sum_{n\epsilon\Omega_k} p_{k,n} \leq P_{max} \tag{4.29c}$$

$$p_{k,n} \geq 0,\ \forall k \in \mathcal{K},\ \forall n \in \mathcal{N} \tag{4.29d}$$

where Ω_k is the set of RBs for CUE k. Problem (4.29) is in fractional form and thus it can also be converted to a subtractive form as

$$\begin{aligned} \eta_{EEC}(\varphi) = & \max_{p_{k,n}} \sum_{k=1}^{K} \sum_{n\epsilon\Omega_k} W_s \log_2 (1 + p_{k,n}\Gamma_{k,n}) \\ & - \varphi \left(\varepsilon \sum_{k=1}^{K} \sum_{n\epsilon\Omega_k} p_{k,n} + P_{cirBS} \right) \\ & \text{s.t } (4.29b) \text{ - } (4.29d). \end{aligned} \tag{4.30}$$

Lemma 1 *Problem* (4.30) *is a convex optimization problem.*

Proof. The objective function in (4.30) can be divided into two parts which are the total rate, $R = \sum_{k=1}^{K} \sum_{n\epsilon\Omega_k} W_s \log_2 (1 + p_{k,n}\Gamma_{k,n})$ and the overall power consumption, $P = \left(\varepsilon \sum_{k=1}^{K} \sum_{n\epsilon\Omega_k} p_{k,n} + P_{cirBS}\right)$. For a given RB assignment, the equations can be expanded as

$$\begin{aligned} R = & \sum_{k=1}^{K} \sum_{n=1}^{C} \omega_{k,n} r_{k,n} \\ = & \sum_{k=1}^{K} \sum_{n=1}^{C} \omega_{k,n} W_s \log_2 (1 + p_{k,n}\Gamma_{k,n}), \end{aligned} \tag{4.31}$$

$$P = \left(\varepsilon \sum_{k=1}^{K} \sum_{n=1}^{C} \omega_{k,n} p_{k,n} + P_{cirBS} \right). \tag{4.32}$$

First, by assuming $\omega_{k,n} = 1$, we proof that $r_{k,n}$ is concave with respect to $p_{k,n}$.

The first order derivation of $r_{k,n}$ is given as

$$\frac{\delta r_{k,n}}{\delta p_{k,n}} = \frac{W_s \Gamma_{k,n}}{(1 + p_{k,n}\Gamma_{k,n}) \ln(2)}. \tag{4.33}$$

From (4.33) , we can verify that $\frac{W_s \Gamma_{k,n}}{\left(1+p_{k,n}\Gamma_{k,n}\right)\ln(2)}$ is strictly monotonically decreasing with $p_{k,n}$ and therefore the second order derivative, $\frac{\delta^2 r_{k,n}}{\delta^2 p_{k,n}} < 0$ or the Hessian is negative definite. Since R is the linear combination of $r_{k,n}$, thus, R is also concave in $p_{k,n}$.

Secondly, (4.32) is an affine function with respect to $p_{k,n}$. Finally, we note that the rate constraint in (4.29b) has the same structure as R and the power constraint in (4.29c) is linear. Therefore, problem (4.30) is a convex optimization problem because the objective function is concave and the constraints are concave and affine.

As a convex optimization problem, Dinkelbach and LDD methods can be used to solve problem (4.30) . The Lagrangian for (4.30) is given as

$$\begin{aligned}
\mathcal{L}_{EEC}\left(p_{k,n}, \boldsymbol{v}, \delta\right) &= \sum_{k=1}^{K} \sum_{n\epsilon\Omega_k} W_s \log_2\left(1 + p_{k,n}\Gamma_{k,n}\right) \\
&-\varphi\left(\varepsilon \sum_{k=1}^{K} \sum_{n\epsilon\Omega_k} p_{k,n} + P_{cirBS}\right) \\
&-\sum_{k=1}^{K} v_k \left(R^c_{min} - \sum_{n\epsilon\Omega_k} W_s \log_2\left(1 + p_{k,n}\Gamma_{k,n}\right)\right) \\
&-\delta\left(\sum_{k=1}^{K} \sum_{n\epsilon\Omega_k} p_{k,n} - P_{max}\right).
\end{aligned} \tag{4.34}$$

By taking the first-order derivation of (4.34) w.r.t $p_{k,n}$ and setting the result to zero, the power for user k on RB n can be computed as

$$p_{k,n} = \left[\frac{W_s\left(1 + v_k\right)}{\left(\delta + \varepsilon\varphi\right)\ln(2)} - \frac{1}{\Gamma_{k,n}}\right]^+. \tag{4.35}$$

Similarly, the Lagrange multiplier can be updated using the following equations

$$v_k\left(i+1\right)=\left[\nu\left(i\right)-\zeta_{\nu}^{i}\left(R_k-R_{min}^{c}\right)\right]^{+} \tag{4.36}$$

$$\delta\left(i+1\right)=\left[\delta\left(i\right)-\gamma_{\delta}^{i}\left(P_{max}-\sum_{k=1}^{K}\sum_{n\epsilon\Omega_k}p_{k,n}\right)\right]^{+} \tag{4.37}$$

where $R_k=\sum_{n\epsilon\Omega_k}W_s\log_2\left(1+p_{k,n}\Gamma_{k,n}\right)$. The optimal power allocation algorithm is depicted in Algorithm 4.4. For each Dinkelbach iteration, the value of φ is updated using the following equation

$$\varphi\left(t+1\right)=\frac{\sum_{k=1}^{K}\sum_{n\epsilon\Omega_k}W_s\log_2\left(1+p_{k,n}\Gamma_{k,n}\right)}{\varepsilon\sum_{k=1}^{K}\sum_{n\epsilon\Omega_k}p_{k,n}+P_{cirBS}} \tag{4.38}$$

Algorithm 4.4 Energy efficient power allocation

Require: $\epsilon,\ t=0,\ \alpha(t)=0,\ T_{max}$
while $(|\eta_{EEC}(\alpha)|>\epsilon)\ ||\ (t<T_{max})$ **do**
  Set $i=0,\ \nu_k(i),\ \delta(i),\ I_{max}$
  while $((|\ \nu_k(i+1)-\ \nu_k(i)|>\epsilon)$ *or*
    $(|\ \delta(i+1)-\ \delta(i)|>\epsilon))$ *and* $(i\leq I_{max})$ **do**
    for $n=1:C$ **do**
      for $k=1:K$ **do**
        Find $p_{k,n}$ using (4.35)
      end for
    end for
    Update ν_k and δ using (4.36) and (4.37)
    $i=i+1$
  end while
  Update φ according to (4.38)
  Update $\eta_{EEC}(\varphi)$
  $t=t+1$
end while
return (φ)

4.5 Energy Efficiency Optimization for D2D Pairs in Non-Orthogonal Mode (EENO)

In the second stage, EE optimization for D2D pairs takes place once the RE optimization stage is completed. The DUEs will utilize the remaining M RBs to maximize their EE. Here, D2D communications are implementing non-orthogonal resource sharing mode where each RB is shared by multiple D2D pairs. Therefore, the problem of EE optimization for D2D communications is simplified to solving the power allocation for D2D pairs. The optimal power allocation is required in order to mitigate the co-tier interference.

In this section, we propose an EE optimization scheme for D2D pairs using non-orthogonal resource sharing mode (EENO). This scheme will be compared with EE optimization scheme for D2D pair in orthogonal mode (EEO).

4.5.1 EE Problem Formulation

In this work, we focus on D2D communications in non-orthogonal mode. Therefore, the EE optimization problem for D2D communications in the second stage can be expressed as

$$\eta_{EE} = \max_{p_{l,m}} \frac{R_d}{\varepsilon P_D + LP_{cirUE}} \tag{4.39a}$$

$$\text{s.t} \quad \sum_{m=1}^{M} r_{l,m} \geq R_{min}^d \tag{4.39b}$$

$$\sum_{m=1}^{M} p_{l,m} \leq P_{max}^d, \ \forall l \in \mathcal{L} \tag{4.39c}$$

$$p_{l,m} \geq 0, \ \forall l \in \mathcal{L}, \ \forall m \in \mathcal{M} \tag{4.39d}$$

where R_{min}^d and P_{max}^d represent the minimum rate requirement and the maximum transmission power for each D2D pair respectively. There is no number of RB constraint for D2D pairs because all remaining RBs will be fully utilized to maximize the EE.

4.5.2 Proposed Solution

Problem (4.39) is also a fractional programming problem and hence can be converted into subtractive form as

$$\max_{\boldsymbol{p} \in \mathcal{P}} \quad F_d\left(q_d, \boldsymbol{p}\right) = R_d - q_d\left(\varepsilon P_D + LP_{cirUE}\right) \tag{4.40}$$

$$s.t \quad (4.39b) \ - \ (4.39d)$$

where $\mathcal{P}$ is the set consisting of feasible power allocation strategies. The transmission power for lth DTx on each RB is given as $\varrho_l = [\rho_{l,1}, \rho_{l,2}, ..., \rho_{l,M}]$. Therefore, the vector of all power allocation strategies is denoted as $\boldsymbol{p} = [\varrho_1, \varrho_2, ..., \varrho_L]$.

The objective function in (4.40) is still non-convex function due to the interference term in the denominator of R_d and it is difficult to find the global solution. However, we can further transform the problem to a DC programming problem [134] by formulating the objective function as

$$f(\boldsymbol{p}) = f_{cave1}(\boldsymbol{p}) - f_{cave2}(\boldsymbol{p}) \tag{4.41}$$

where

$$\begin{aligned} f_{cave1}(\boldsymbol{p}) = & \sum_{l=1}^{L}\sum_{m=1}^{M} W_s \log_2 \left(p_{l,m}h_{l,m} + \sum_{l'=1,l'\neq l}^{L} p_{l',m}h_{l',m} \right. \\ & \left. + W_sN_0 \right) - q_d \left(\varepsilon \sum_{l=1}^{L}\sum_{m=1}^{M} p_{l,m} + LP_{cirUE} \right) \end{aligned} \tag{4.42}$$

and

$$f_{cave2}(\boldsymbol{p}) = \sum_{l=1}^{L}\sum_{m=1}^{M} W_s \log_2 \left(\sum_{l'=1,l'\neq l}^{L} p_{l',m}h_{l',m} + W_sN_0 \right) \tag{4.43}$$

The constraint (4.39b) can be rearranged as linear form. Therefore, problem (4.40) can be converted as maximizing a DC objective function under a convex constraint set and given as

$$\max_{\boldsymbol{p}\in\mathcal{P}} \quad \{f_{cave1}(\boldsymbol{p}) - f_{cave2}(\boldsymbol{p})\}. \tag{4.44}$$

A DC programming problem can be solved using DC algorithm (DCA). Since $f_{cave2}(\boldsymbol{p})$ in (4.44) is differentiable, CCCP can be utilized [95] to solve the problem. The basic idea of CCCP is to iteratively linearize the convex part of the DC objective function, $-f_{cave2}(\boldsymbol{p})$ [135]. As in [95], the following iterative updating procedure is used in CCCP algorithm

$$\boldsymbol{p}^{(i+1)} = \arg\max_{\boldsymbol{p}\in\mathcal{P}} \left\{ f_{cave1}(\boldsymbol{p}) - \triangledown f_{cave2}\left(\boldsymbol{p}^{(i)}\right) * \boldsymbol{p}^T \right\} \tag{4.45}$$

where $\triangledown f_{cave2}\left(\boldsymbol{p}^{(i)}\right) \triangleq \left[\triangledown_1^{(i)}, \triangledown_2^{(i)}, ..., \triangledown_{LM}^{(i)}\right]$ represents the gradient of $f_{cave2}(\boldsymbol{p})$

at $\boldsymbol{p}^{(i)}$ and $\boldsymbol{p}^{T}$ denotes the transpose of $\boldsymbol{p}$. Note that the first part in (4.45), $f_{cave1}(\boldsymbol{p})$, is concave, and the second part, $-\bigtriangledown f_{cave2}\left(\boldsymbol{p}^{(i)}\right) * \boldsymbol{p}^{T}$, is linear. As a result, (4.45) is a convex optimization problem and can be solved efficiently using interior point algorithm. Algorithm 4.5 [136] presents the energy-efficient resource allocation algorithm for D2D communications.

Algorithm 4.5 EE Optimization for D2D pairs

Require: $\epsilon,\ t = 0,\ q_d(t) = 0,\ T_{max}$

while $(|F_d(q_d)| > \epsilon)\ ||\ (t < T_{max})$ **do**
    Initialize $i = 0,\ \forall \boldsymbol{p} \in \mathcal{P}$
    while $(|\boldsymbol{p}^{(i+1)} - \boldsymbol{p}^{(i)}| > \epsilon)$ **do**
        Update the power allocation using (4.45)
        $i = i + 1$
    end while
    Update $q_d(t+1) = \frac{R_d}{\varepsilon P_D + L P_{cirUE}}$
    Update $F_d(q_d)$
    $t = t + 1$
end while
return $(\boldsymbol{p}, q_d)$

4.6 Simulation Results

In this section, the performance of the proposed two-stage EE optimization schemes are evaluated. In the first stage, two different algorithms are proposed: the Full RE and the LC RE schemes. For each RE scheme, EE is maximized for all D2D pairs in the second stage. In this section, the results for each stage are presented separately. In the end, the performance of the proposed schemes are compared with other benchmark schemes.

In the simulation, CUEs and DTx locations are uniformly distributed in a cell with radius of 500 m. The DRx are uniformly distributed within a maximum distance of d_{max} from the DTx. The downlink frequency-selective fading channel is generated with the ITU Pedestrian-B model [53]. The channel model parameter for DUE links include unit mean for the Rayleigh fading. For all links, a path loss exponent of 4, and a standard deviation of 8dB for the log-normal shadowing are used. The drain efficiency of the power amplifier is set to 38%. Other simulation parameters are summarized in Table 4.1.

Table 4.1 – Simulation parameters

Parameters	Value
Number of cellular users (K)	4
Number of D2D pairs (L)	$2, 4$
Number of resource blocks (N)	25
Resource block bandwidth (W_s)	200 kHz
Maximum D2D pair distance (d_{max})	$20, 40, ..., 120$ m
Rate requirement for each CUE (R^c_{min})	0.5 Mbps
Rate requirement for each D2D pair (R^d_{min})	1 Mbps
Maximum transmit power of BS (P_{max})	10 W
BS circuit power (P_{cirBS})	5 W
Maximum transmit power of D2D link (P^d_{max})	250 mW
DTx circuit power (P_{cirUE})	100 mW
Noise power spectral density (N_0)	-174 dBm/Hz

Table 4.2 – Number of RBs assigned to CUEs

β	$0-10$	15	$16-17$	18	$19-20$	30
C	25	24	23	22	21	15

β	$22-23$	$24-25$	26	$27-29$	30	40
C	19	18	17	16	15	13

4.6.1 RE Optimization for BS

Fig. 4.2 shows the impact of the tradeoff parameter, β to EE and SE. As shown in the original RE paper [20], the EE decreases with increasing β while the SE increases with increasing β. Varying this β in RE provides the tradeoff between EE and SE for the BS. If larger β is used, CUEs are operating at high SE region which is not energy efficient. On the other hand if lower β is used, the solution focuses on maximizing EE for CUEs but uses more bandwidth, leaving insufficient spectrum for D2D pairs. Table 4.2 shows the average number of RBs assigned to the CUEs, which is also obtained from Algorithm 4.1 based on various β. It shows that when β is low, all 25 RBs are used by the CUEs to achieve the highest EE, while less RBs is used when β is higher. Since CUEs have higher priority and DUEs are considered as supplement to cellular system, β is set as 23 to enhance the EE of the BS, which result in an average of 19 RBs allocated to the CUEs.

The EE-SE plots for the proposed LC RE implementation is shown in Fig. 4.3. The relations of EE and SE with respect to β are similar to Fig. 4.2. However,

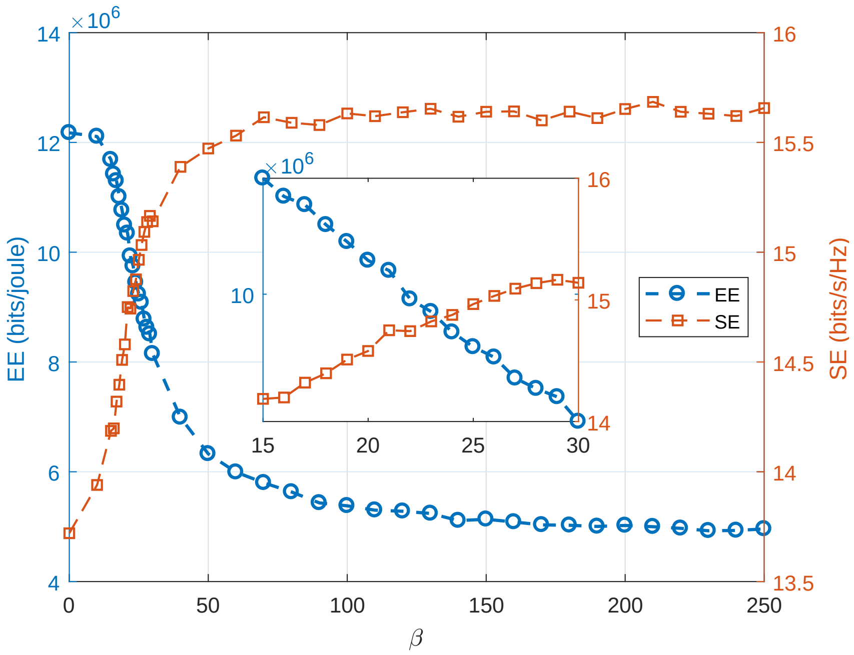

Figure 4.2 – Impact of weighted parameter β to EE and SE using Full RE scheme.

the tradeoff point of EE-SE occurs at different value of β . It is important to note that for $\beta = 6$, this lower complexity scheme allocates similar average number of RBs (19 RBs) to CUEs as in Full RE method.

4.6.2 EE Optimization for D2D Pairs

The EE results between non-orthogonal and orthogonal resource sharing mode with different number of D2D pairs and RBs are shown in Fig. 4.4. It is also compared with optimal solution in which problem (4.34) is solved using an optimal numerical tool. Due to the high complexity for the optimal solution, only the $L = 2$, $M = 8$ case is simulated. In addition, the orthogonal mode forms a MINLP problem which is also difficult to be solved directly. Therefore, a continuous relaxation version of this problem is also solved using Matlab's optimal numerical solution and presented as comparison. The figure shows that the EE for DUEs obtained using the proposed algorithm is close to the optimal solution. Considering the case of $L = 2$ with M increases from 4 to 8, the EE increases with the number of available RBs for the same number of D2D pairs. It can also be seen that the EE achieved using non-orthogonal resource sharing is higher than that

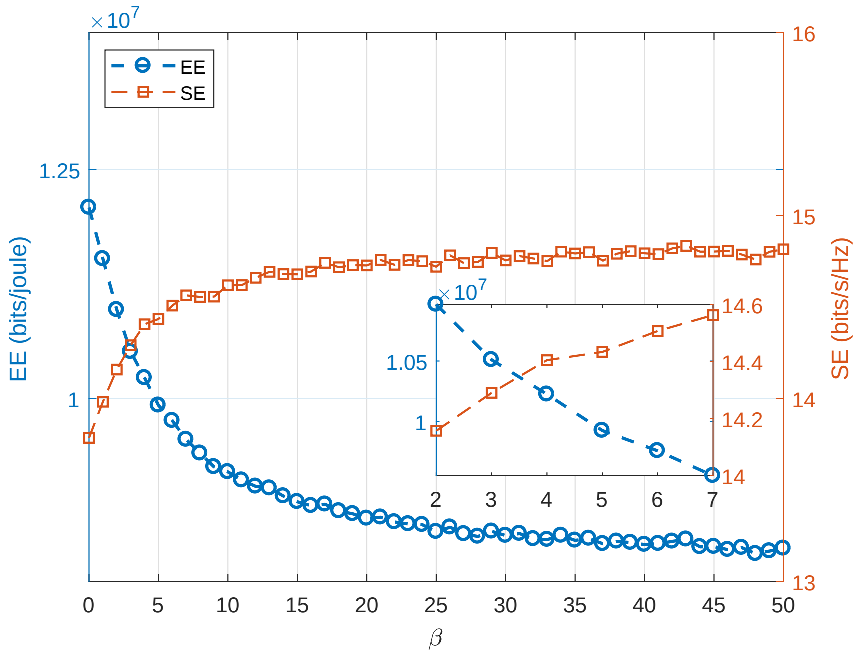

Figure 4.3 – EE-SE for LC RE approach.

of the orthogonal mode for the same number of D2D pairs and RBs. This shows that even with interference between D2D pairs, the proposed scheme can allocate the power effectively to maximize the EE. Next, we evaluate the performance when both the number of D2D pairs and number of RBs are doubled (i.e., $L = 2$, $M = 4$ to $L = 4$, $M = 8$). Although the ratio between L and M is the same, the EE is improved when these parameters are doubled due to more flexibility in the allocation. In particular, the performance gain in non-orthogonal case is much more significant than the orthogonal case as the flexibility is even higher. This further strengthens the support for operating in non-orthogonal mode. Furthermore, the EE obtained by the non-orthogonal case of $L = 4$, $M = 8$ is lower than that of $L = 2$, $M = 8$. This is because when more D2D pairs are sharing the same RB, larger co-tier interference is generated and thus the EE is reduced.

Fig. 4.5 presents the EE of D2D communications operating in non-orthogonal mode with different transmission power constraints. As expected, the shorter the distance between a D2D pair, the larger the EE becomes. In addition, EE peaks at a relatively low power level, and reduces to a certain power level when more power is allowed. This shows that D2D communications using the proposed non-orthogonal mode could achieve high EE without the need of utilizing higher transmission power.

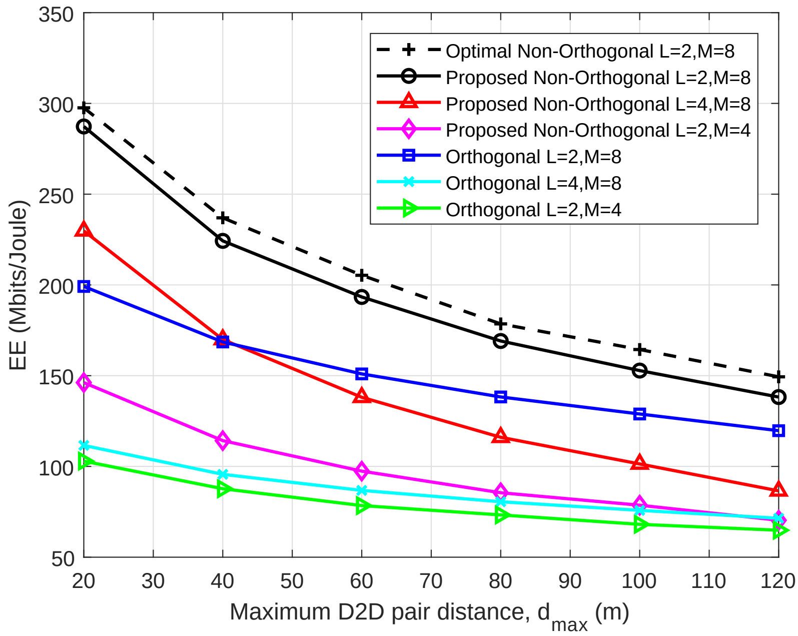

Figure 4.4 – DUEs EE versus maximum D2D pair distance.

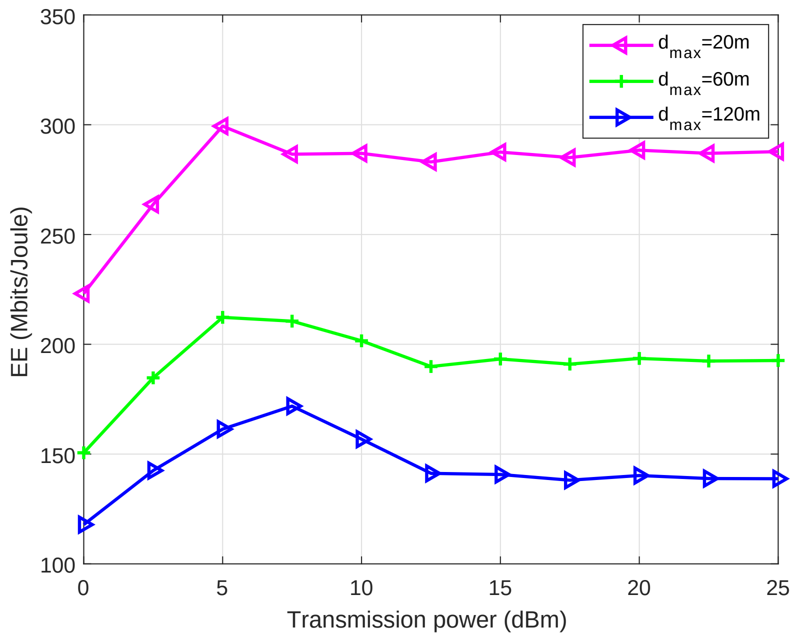

Figure 4.5 – EE of D2D communications with different transmission power constraint, P_{max}^{d} $(L = 2,\ M = 8)$.

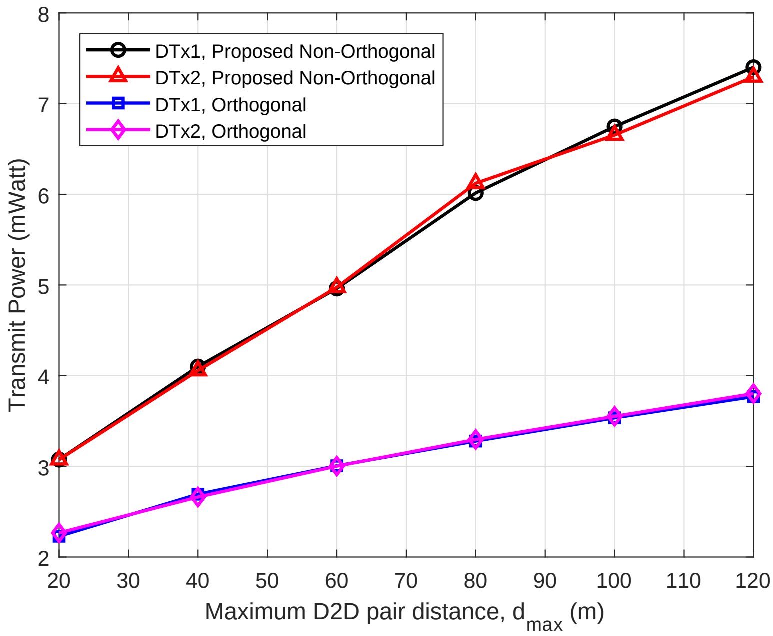

Figure 4.6 – D2D pairs transmission power ($L = 2,\ M = 8$).

The results on transmission power and rate for 2 D2D pairs with 8 RBs are depicted in Fig. 4.6 and Fig. 4.7 respectively. It can be seen that the transmission power of DUEs operating in non-orthogonal mode is always higher than that of orthogonal mode. For both modes, the transmit power increases as the distance between D2D pair increases. This is because higher transmission power is required when the separation between D2D pair is larger to overcame path loss. The gap between transmission power of non-orthogonal and orthogonal mode increases with respect to d_{max}. This is because when the separation between DTx and DRx is larger, cross-tier interference becomes more significant. Therefore, additional transmission power is required in non-orthogonal mode to satisfy the same QoS requirement with respect to the orthogonal mode. On the other hand, due to the reuse of RBs, non-orthogonal mode enables the D2D pairs to obtain higher rates as depicted in Fig. 4.7.

4.6.3 System EE

Next, the performance of the proposed schemes are compared with other benchmark schemes. For all benchmark schemes, RB and power allocation are solved for a given fixed number of RBs. Specifically, 19 RBs are allocated to the CUEs

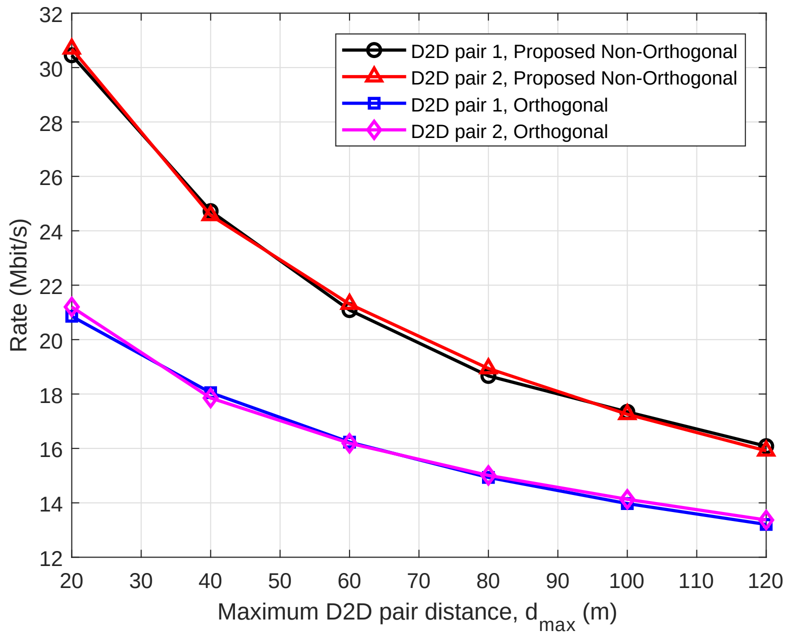

Figure 4.7 – Achievable rates for the D2D pairs ($L = 2,\ M = 8$).

based on the results from Table 4.2 and the remaining 6 RBs are designated to the D2D pairs. Two-stage energy efficient solutions such as energy efficient non-orthogonal (EE-EENO) mode, energy efficient orthogonal (EE-EEO) mode, and the solution for sum rate maximization problem (Sum Rate) are selected for comparison. The first stage of EE-EENO and EE-EEO schemes aim to maximize the EE of the BS while EE for D2D pairs is maximized in the second stage, where D2D users communicate in non-orthogonal mode for the former scheme while orthogonal mode is used in the latter. Similarly, each of our proposed scheme has two different variations depending on the D2D mode of communication and designated as Full RE-EENO, Full RE-EEO, LC RE-EENO and LC RE-EEO. It must be noted that for the benchmark schemes, numerical optimization tool is used and thus those results are effectively upper bounds; while the proposed schemes are iterative algorithms, providing actual achievable results.

Fig. 4.8 shows the overall EE of the system. It can be seen that all EE based schemes achieve much larger EE compared to the Sum Rate solution. This is because in order to maximize the sum rate, both BS and DTx use the maximum transmission power and thus achieve poor EE. It can also be observed that the LC RE-EENO scheme achieves a slightly higher overall EE than the EE-EENO, even though the latter is an upper bound. Although the EE-EENO scheme

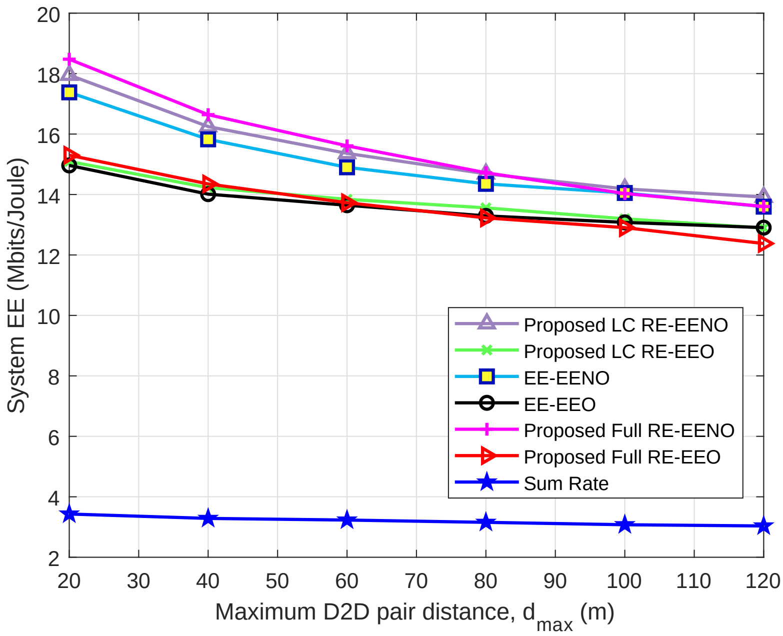

Figure 4.8 – System EE versus maximum D2D pair distance ($L = 2$).

has the lowest power consumption, the LC RE-EENO and RE-EENO schemes achieve higher sum rate by utilizing the RE optimization approach. Furthermore, the joint RB and power allocation in the Full RE scheme achieves marginally higher total EE than the LC RE-EENO. However this is only true in lower D2D distance. In larger D2D distance, the Full RE-EENO drops slightly below LC RE-EENO, which will be further explained in the next figure. The results indicate the advantage of the proposed RE-based schemes where the number of RBs utilized in both stages are dynamic. Similar to the above results, all non-orthogonal based schemes outperform their corresponding schemes in orthogonal mode.

Finally, we evaluate the EE performance of the cellular downlink and the D2D links separately by the proposed Full RE-EENO, LC RE-EENO and the EE-EENO schemes which are depicted in Fig. 4.9. The figure shows that the EE of BS in LC RE-EENO scheme is marginally lower than that of EE-EENO scheme, but the EE improvement for the DUEs is higher. It can be seen that although the Full RE-EENO scheme achieves the lowest EE for the BS compared to other schemes, the EE improvement for the DUEs is significantly higher. This also explains the result in Fig. 4.8 on large D2D distance, where the Full RE solution aims to provide more RBs to the D2D pairs for better EE, but in turn suffers on the EE of the BS. Even though the RE-based schemes achieve higher

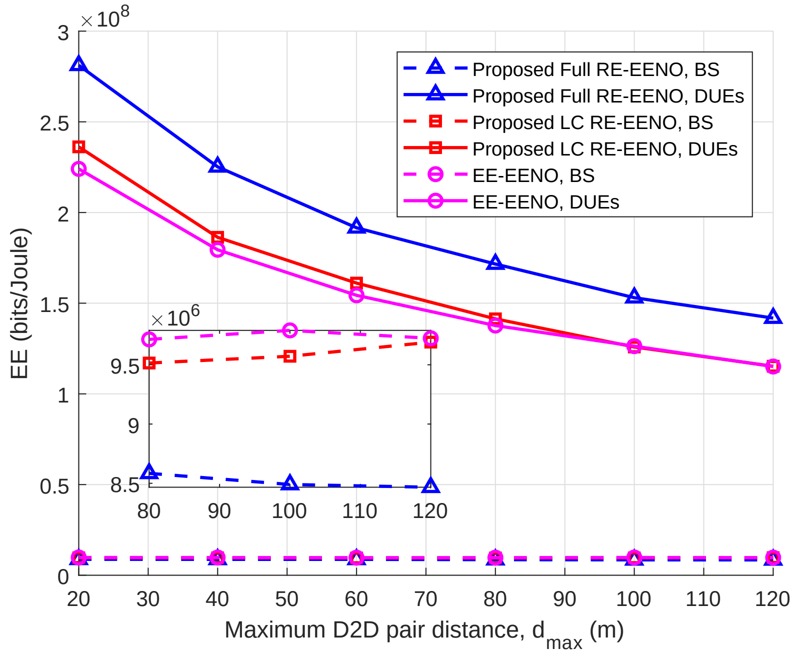

Figure 4.9 – EE comparison.

EE for DUEs, the total EE of these schemes as shown in Fig 4.8 are quite similar. This means that the total EE is dominated by the high power consumption in the BS and as such the overall gain is diminished. An important finding is that the proposed RE-based schemes can enhance the EE performance of D2D pairs, which is more critical as it is battery limited. It must also be noted that the EE of BS is slightly reduced, which is inline with the concept of RE that slightly reducing the EE performance can result large bandwidth saving for other systems (in this case the D2D pairs) to utilize. The results indicate that the use of RE optimization in the first stage can provide a balance between EE and SE performance, which allows additional degree of freedom to network operators in using cellular resources more efficiently. Therefore, the proposed schemes can provide a flexible energy efficient solution for the D2D enabled OFDMA cellular system.

4.7 Summary

In this chapter, existing works on D2D communications utilizing downlink cellular resources are reviewed. A two-stage optimization problem to maximize the system EE of D2D communications overlaying cellular system is formulated. In the first stage, a joint RB and power allocation algorithm is proposed based on fractional programming approach and LDD to maximize the RE of the BS. The RE optimization stage enables some RBs to be left unoccupied which are then used by the DUEs. To further reduce the complexity, a lower complexity RE implementation is also proposed in the first stage. In the second stage, EE optimization for D2D pairs in non-orthogonal mode is solved using a range of optimization tools including fractional programming, Dinkelbach method, and CCCP algorithm. Lastly, simulation results showing the EE improvement of the proposed schemes are presented. Simulation results showed that the overall EE achieve by the LC RE-EENO scheme is slightly higher than the upper bounds of EE-EENO and close to the Full RE-EENO schemes, while having lower complexity compared to the Full RE-EENO. Furthermore, the proposed Full RE-EENO and LC RE-EENO schemes can enhance the EE of D2D communications at the expense of slight degradation on the EE of the BS.

Chapter 5

Resource Efficiency Optimization for NOMA System with D2D

5.1 Introduction

In this chapter, an overview of non-orthogonal multiple access (NOMA) is described in Section 5.2. Section 5.3 discusses some related works on EE and EE-SE tradeoff for NOMA as well as the coexistence of NOMA and D2D communications. The scenario of D2D communications overlaying a NOMA system is presented in Section 5.4. The proposed two-stage scheme to maximize the system EE of the NOMA-D2D scenario is provided. Specifically, Section 5.5 describes the first stage of the proposed scheme, which is the RE optimization for NOMA while the EE optimization for D2D pairs in the second stage is provided in Section 5.6. Lastly, simulation results which validate the performance improvement of the NOMA-D2D system are presented in Section 5.7.

5.2 Overview of Non-Orthogonal Multiple Access

Multiple access techniques can be fundamentally categorized as orthogonal multiple access (OMA) and NOMA. In OMA, each user can utilize orthogonal communication resources such as time slot, frequency band or code to avoid interference. Example of OMA schemes are FDMA, TDMA, CDMA and OFDMA. On the other hand, NOMA allows multiple users to use non-orthogonal resources at the same time.

In general, there are two types of NOMA schemes namely code-domain and

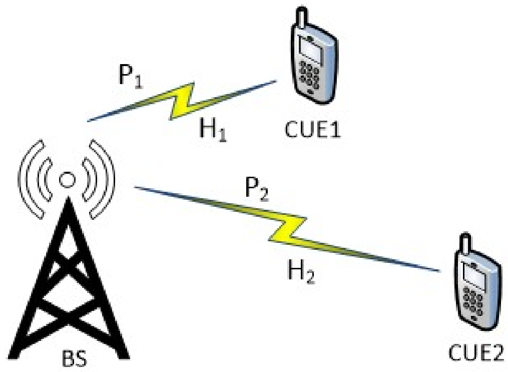

Figure 5.1 – Downlink NOMA for 2 users.

power-domain. In code-domain NOMA such as sparse code multiple access (SCMA), different users are assigned different codes and multiplexed over the same resources. This work focuses on power-domain NOMA in which different users are allocated different power level according to their channel condition to obtain higher system performance. To explain the basic principle of NOMA, a system consists of one BS and two CUEs is considered as shown in Fig. 5.1. CUE1 and CUE2 represent users near and far away from the serving BS, respectively. This means that CUE1 is the strong user as it has better channel conditions than the weaker user, CUE2. Their transmit powers are P_1 and P_2, and channel gains are H_1 and H_2.

In this scenario, the BS employs superposition coding (SC) [137] to lay over the signal designated to both CUEs. In other words, multiple users' information signals are superimposed at the transmitter side with different allocated power coefficient. The challenge for the BS is to decide how to allocate the power among users. In downlink NOMA, the weak user is allocated higher transmission power than the strong user. Moreover, all UEs receive the same signal that contains the information for all users. At the receiver side, successive interference cancellation (SIC) is employed for decoding the signal to recover the intended information for the UEs [138]. The user with the highest transmission power (CUE2) treats the signal of other user (CUE1) as noise and thus can recover its data immediately from the received signal. However, CUE1 needs to perform SIC by detecting the signal that is stronger that its own desired signal. Then the signal is subtracted from the received signal to obtain its own data. The SIC process for the 2 users scenario is shown in Fig. 5.2.

For two CUEs multiplexed over one RB with bandwidth of W_s, the achievable

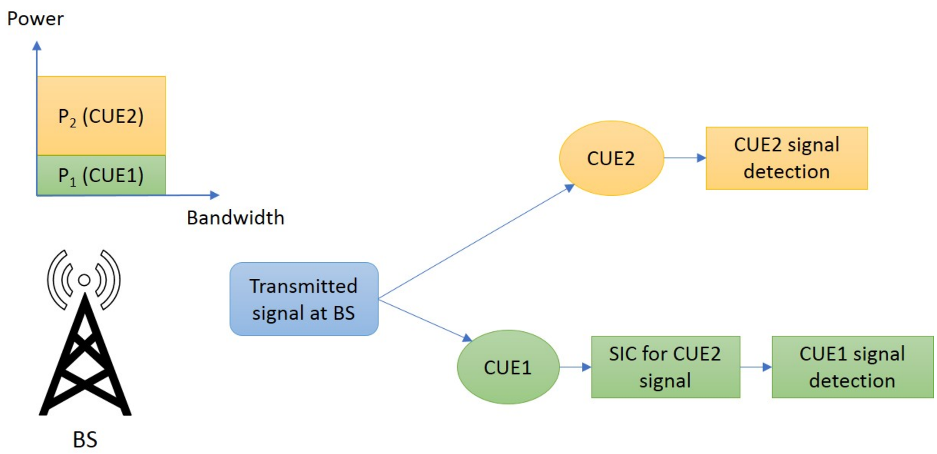

Figure 5.2 – SIC for 2 users.

rate for the strong and weak NOMA user is respectively given as

$$R_1 = W_s \log_2 \left(1 + \frac{P_1 H_1}{W_s N_0}\right) \tag{5.1}$$

$$R_2 = W_s \log_2 \left(1 + \frac{P_2 H_2}{P_1 H_2 + W_s N_0}\right). \tag{5.2}$$

On the other hand, the rate achieved by two users in OMA case can be written as

$$R_1 = \varsigma W_s \log_2 \left(1 + \frac{P_1 H_1}{\varsigma W_s N_0}\right) \tag{5.3}$$

$$R_2 = (1 - \varsigma)\, W_s \log_2 \left(1 + \frac{P_2 H_2}{(1 - \varsigma)\, W_s N_0}\right). \tag{5.4}$$

where $\varsigma \in [0, 1]$ is the factor of bandwidth allocation (bandwidth splitting factor) among the two users.

To compare the performance of NOMA and OMA, we assume $H_1 = 100$, $H_2 = 1$, $W_s = 1$ Hz, $P_1 + P_2 = 1$ and $N_0 = 1$. In NOMA [138], when the power is assigned as $P_1 = \frac{1}{5}P$ and $P_2 = \frac{4}{5}P$, the achievable rates are calculated according to (5.1) and (5.2) as $R_1 = 4.39$ bps/Hz and $R_2 = 0.74$ bps/Hz respectively. On the other hand, in OMA, when equal bandwidth and equal power are allocated to CUE1 and CUE2 $\left(\varsigma = 0.5,\ P_1 = P_2 = \frac{1}{2}P\right)$, the user rates are calculated according to (5.3) and (5.4) as $R_1 = 3.33$ bps/Hz and $R_2 = 0.50$ bps/Hz respectively. From this example, it is observed that NOMA scheme outperforms OMA in term of sum rate. In addition, it can be seen from (5.1) and (5.2) that power allocation for each CUE greatly affects the user rate performance.

5.3 Related Works

Recently, there has been growing interest in EE of NOMA system as it becomes an important performance measure of wireless communication systems. The resource allocation problem that maximizes the EE in NOMA systems has also been considered in [139–141]. In [139], EE optimization is studied in a fading MIMO-NOMA system with a limited number of two users. Whereas in [141], the authors developed the optimal power allocation for maximizing the EE with QoS constraints but only for the users on one channel. The joint power allocation and channel assignment for maximizing the EE is considered in [140], in which a solution is obtained using DC programming approach. However, each subchannel is only allocated with two users, which limits the application of NOMA.

EE-SE tradeoff is an important study for energy efficient system design as it provides a balance between EE and SE in resource allocation. A few literatures have studied the EE-SE tradeoff for NOMA system such as in [142, 143]. In [142], a multi-objective optimization problem (MOOP) to investigate the tradeoff between EE and SE with fairness is considered.α-fairness unity function is adopted to measure the fairness level among users. The original problem is transformed into a single-objective optimization problem (SOOP) by using the weighted sum method. The work in [143] studied the EE and SE tradeoff problem in hybrid multi-carrier non-orthogonal multiple access (MC-NOMA) system. To tackle the challenging non-convex problem, a weighted Tchebycheff method is used to convert the problem into a SOOP, and algorithm based on LDD and sequential convex programming is proposed to solve it. However, both works did not consider the existence of D2D communications in the system.

With regard to NOMA-D2D system, the work in [144] is one of the earliest literatures which investigated the coexistence of NOMA and D2D communications. In that work, the authors proposed a new mechanism that jointly coordinates beamforming based multiuser MIMO (MU-MIMO), NOMA, and D2D communications in a downlink cellular network. An optimization problem aiming to maximize the total system throughput performance is formulated and a suboptimal approach is developed to solve the problem.

To investigate the promising application of NOMA in the D2D communications, a NOMA-based D2D communications framework is proposed in [145]. In the framework, a D2D group concept which utilizes NOMA transmission within D2D communications is introduced. In a particular D2D group, one DTx is allowed to communicate with multiple DTx simultaneously while multiple D2D groups can reuse the same subchannel. An algorithm is proposed based on matching theory to allocate proper subchannels for the D2D groups in order to maximize the sum rate. Simulation results showed that the proposed algorithm achieved the near-optimal performance compared to the exhaustive-search method and outperformed the conventional OMA-based framework. However, that work did not consider NOMA-based cellular links.

In [146], the power control and channel assignment problem in D2D communications underlaying a NOMA cellular system is studied. The objective is to maximize the sum rate of D2D pairs while guaranteeing the minimum rate requirements of NOMA CUEs. First, the authors derive the optimal conditions for power control of the CUEs. Then, a dual-based iterative algorithm is proposed to solve the resource allocation problem. Nevertheless, one subchannel is only allocated to at most one D2D pair. As a result, the SE can not be further improved. The work in [147] investigated the potential of integrating NOMA with D2D communication. Two types of D2D-NOMA integration are specified; forward-D2D NOMA and reverse-D2D NOMA. The former involves NOMA transmission from one DTx to a cluster of DRxs while the latter allows NOMA transmission from a cluster of DTxs to a single DRx. Similar with conventional D2D communications, D2D-NOMA communications can share the uplink or downlink resources of CUEs.

In [148], NOMA technique is adopted to schedule a set of CUEs on the spectrum resource while D2D pairs reuse these spectrum resources in an orthogonal manner. Compared to [145], both CUEs and D2D pairs form a cluster and these users are scheduled over a subchannel. However, only two NOMA-based CUEs are allowed to use the same subchannel. Furthermore, [149] studied the impact of the integration of D2D communications with a downlink NOMA system where only a cluster of two CUEs and a D2D pair is considered. Mobile association and power allocation in D2D-enabled HetNets with NOMA protocol is investigated in [150]. In that work, two NOMA users can connect to any BS using direct mode or relay mode. In the direct mode, BSs broadcast the superimposed signals to the users. In the relay mode, BSs first broadcast the superimposed signals, and then the near user acts as a relay to forward the message to the far user. All the aforementioned NOMA-D2D coexistence did not consider the EE of the system.

Joint power control and time allocation problem of a D2D communication underlaying NOMA-based cellular network with energy harvesting is studied in [151]. Both CUEs and DTx harvest energy from a hybrid access point in the downlink and transmit information in the uplink. An iterative algorithm is proposed to maximize the EE of the D2D pair while guaranteeing the QoS of CUEs. Moreover, NOMA technique for D2D communications is applied in [152] to maximize the system EE. A downlink resource allocation scenario where CUEs share the RBs with D2D clusters in a single cell network is studied. Specifically, the DTx communicates with a set of DRxs on one RB simultaneously by applying NOMA technology. Suboptimal solution is proposed to solve the joint RB, D2D transmission power and allocation coefficient for the NOMA system.

In all these above related works, the EE-SE tradeoff for NOMA system with overlaying D2D communication has not been investigated, which becomes the motivation of this research.

5.4 System Model

In this work, we consider a downlink transmisson scenario where a BS simultaneously serves K single antenna CUEs where $k \in \{1, 2, ..., K\}$. The BS transmits the signals to the CUEs through n RBs where $n \in \{1, 2, ..., N\}$. The total bandwidth of the system, W_{tot} is equally divided into N RBs where the bandwidth of each RB is $W_s = W_{tot}/N$. The BS knows the instantaneous channel state information (CSI) of all users. As illustrated in Fig. 5.3, the distances between the CUEs to the BS is defined as $d_1 < d_2 < d_3 < d_K$. This means that CUE1 is located nearest to the BS, followed by CUE2 and CUE3. CUE4 is located farthest from the BS, which is near to the cell edge. Therefore, CUE1 has the best channel conditions, followed by CUE2, CUE3 and CUE4. In other words, CUE1 is the strongest NOMA user which will be allocated the least power while CUE4 is the weakest NOMA user and will be allocated the highest transmission power. Meanwhile, L D2D pairs, each including one transmitter and one receiver coexist in the system, by sharing the resources in overlay manner as presented in the subsection 4.3.2.

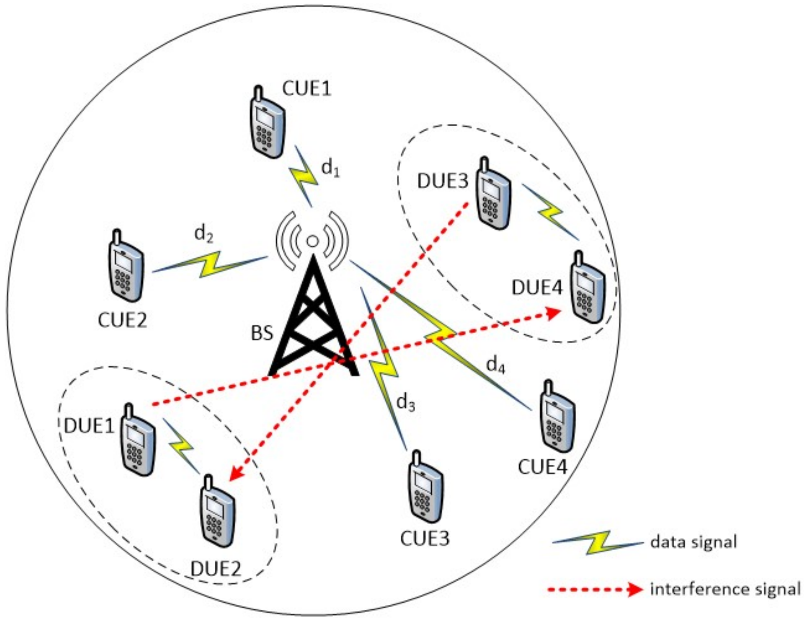

Figure 5.3 – Downlink NOMA-D2D system ($K = 4,\ L = 2$).

Let the transmit power and the channel gain of the kth CUE on the nth RB are represented as $p_{k,n}$ and $h_{k,n}$, respectively. According to the principle of NOMA, one channel can be assigned to multiple users and SIC is used to decode their signals [153]. As assumed in [150], we have $h_{1,n} \geq h_{2,n} \geq h_{3,n} \geq h_{K,n}$. The optimal order for decoding is in the order of the increasing channel gain to noise ratio (CNR), eg., $(h_{k,n}/W_s N_0)$ [138, 140, 153]. Based on this order, any user can successfully decode the signals of the other users with smaller CNR values. This means that, the interference from the weaker users can be cancelled and removed by the user who has better channel condition [140]. Therefore, the NOMA protocol allocates higher power to the users with lower CNRs [138, 154], leading to $p_{1,n} \leq p_{2,n} \leq p_{3,n} \leq p_{K,n}$.

For the kth users multiplexed over nth RB, the achievable sum rate is expressed as

$$R_c = W_s \sum_{k=1}^{K} \sum_{n=1}^{N} \log_2 (1 + p_{k,n} \Gamma_{k,n}) \tag{5.5}$$

where the received SINR of CUE1 and CUE2 are given respectively by

$$\Gamma_{1,n} = \frac{p_{1,n} h_{1,n}}{W_s N_0}, \quad \Gamma_{2,n} = \frac{p_{2,n} h_{2,n}}{p_{1,n} h_{2,n} + W_s N_0}, \tag{5.6}$$

and that of the CUE3 is given by

$$\Gamma_{3,n} = \frac{p_{3,n} h_{3,n}}{(p_{1,n} + p_{2,n}) h_{3,n} + W_s N_0}. \tag{5.7}$$

Finally, the SINR of the weakest user, Kth CUE is expressed as

$$\Gamma_{K,n} = \frac{p_{K,n} h_{K,n}}{(\sum_{k=1}^{K-1} p_{k,n}) h_{K,n} + W_s N_0}. \tag{5.8}$$

According to the SINR expression in (5.6) – (5.8), the transmit power allocation to one user affects the achievable sum rate as well as the EE of the system. The overall transmit power for the kth user, P_k and the total transmit power, P_T are given by

$$P_k = \sum_{n=1}^{N} p_{k,n}, \quad P_T = \sum_{k=1}^{K} P_k. \tag{5.9}$$

It should be noted that the overall power consumption model and the overall power budget at the BS as well as power utilization and bandwidth utilization are modeled similarly as in Chapter 3. Identically, the RE for NOMA system can be formulated as

$$RE_{NOMA} = \frac{R_c}{P} \left(1 + \beta \frac{\tau_p}{\tau_w}\right). \tag{5.10}$$

where $P = \varepsilon P_T + P_{cirBS}$.

5.5 RE Optimization for NOMA

In this section, the RE for NOMA (RE NOMA) scheme is proposed. The RE optimization problem for the NOMA system can be formulated as

$$\eta_{RE-NOMA} = \max_{p_{k,n}} \frac{R_c}{P} \left(1 + \beta \frac{\tau_p}{\tau_w}\right) \tag{5.11a}$$

$$\text{s.t} \quad \sum_{n=1}^{N} r_{k,n} \geq R_{min}^{c} \tag{5.11b}$$

$$\sum_{k=1}^{K} \sum_{n=1}^{N} p_{k,n} \leq P_{max} \tag{5.11c}$$

$$p_{k,n} \geq 0, \ \forall k \in \mathcal{K}, \ \forall n \in \mathcal{N} \tag{5.11d}$$

$$S \leq N \tag{5.11e}$$

where S denotes the number of used RBs. Constraint (5.11e) ensures that the number of RBs utilized for the RE optimization does not exceed the total number of RBs. Clearly, there is no RB allocation indicator constraint in the RE for NOMA problem because each RB will be used by all CUEs. Similar to [155], we assume each user has the same minimum rate requirement as in (5.11b).

Problem (5.11) is a non-convex problem due to the fractional of the objective function which makes it difficult to obtain the optimal solution. In order to solve this problem, an approach is proposed to solve the RE problem for NOMA suboptimally in two steps including RB allocation and power allocation.

Resource Block Allocation

The first step in this approach is to perform RB allocation to maximize the RE of the BS. Fractional Transmit Power Allocation (FTPA) is used in this step to allocate initial transmission power to all CUEs in each RB. FTPA is widely adopted in NOMA system because of its low computational complexity [138, 140, 156]. In the FTPA scheme, the transmit power of kth CUE on the nth RB, $p_{k,n}$ is allocated according to the channel gains of all the multiplexed users on RB n, which is given as [140, 154]

$$p_{k,n} = p_n \frac{(h_{k,n}/W_s N_0)^{-\alpha_{FTPA}}}{\sum_{i=1}^{K} (h_{i,n}/W_s N_0)^{-\alpha_{FTPA}}} \tag{5.12}$$

where p_n is the assigned total transmission power for nth RB which is assumed to be equal and α_{FTPA} $(0 \leq \alpha_{FTPA} \leq 1)$ is the decay factor. $\alpha_{FTPA} = 0$ represents equal power allocation. For larger α_{FTPA}, the transmit power allocated to the user with largest CNR becomes lower, and more power is allocated to the user with the lowest CNR, in order to achieve the user-fairness and the optimal decoding.

The use of FTPA allows power allocation to each CUE that shares an RB and therefore, the value of the RE objective function can be calculated. In each iteration, the value of RE is saved and finally, the corresponding number of RBs required to maximize the RE of the BS, Q can be obtained. The RB allocation step is presented in Algorithm 5.1.

Power Allocation

Once the RB allocation step is completed, the remaining problem is to find the actual power allocation for CUEs. In the second step, proper power allocation is

Algorithm 5.1 RB allocation

Require: $\beta,\ K,\ N,\ \mathbf{H},\ z=0,\ T=0$

while $T \neq N$ **do**
  $T = T + 1$
  $\mathbf{H1} = \mathbf{H}(1:K, 1:T)$
  $z = z + 1$
  Using (5.12), calculate $RE(z)$ according to (5.10)
end while
Obtain $Q = \arg\max_z RE(z)$ **return** $(Q,\ RE)$

only needed for the Q RBs. Since RE maximization is already used in the RB allocation step, the power allocation here aims to maximize the EE. For a given RB allocation, the EE maximization problem for the BS is formulated as

$$\eta_{EEC-NOMA} = \max_{\mathbf{p}} \frac{W_s \sum_{k=1}^{K} \sum_{n \epsilon Q} \log\left(1 + p_{k,n}\Gamma_{k,n}\right)}{\varepsilon \sum_{k=1}^{K} \sum_{n \epsilon Q} p_{k,n} + P_{cirBS}} \tag{5.13a}$$

$$\text{s.t} \quad \sum_{n \epsilon Q} W_s \log_2\left(1 + p_{k,n}\Gamma_{k,n}\right) \geq R_{min}^{c},\ \forall k \in \mathcal{K} \tag{5.13b}$$

$$\sum_{k=1}^{K} \sum_{n \epsilon Q} p_{k,n} \leq P_{max} \tag{5.13c}$$

$$p_{k,n} \geq 0,\ \forall k \in \mathcal{K},\ \forall n \in \mathcal{N} \tag{5.13d}$$

Problem (5.13) is in fractional form which can be transformed into a subtractive form as follows

$$\max_{\boldsymbol{p} \in \mathcal{P}} \quad F_n\left(q_n, \boldsymbol{p}\right) = W_s \sum_{k=1}^{K} \sum_{n \epsilon Q} \log\left(1 + p_{k,n}\Gamma_{k,n}\right) - q_n \left(\varepsilon \sum_{k=1}^{K} \sum_{n \epsilon Q} p_{k,n} + P_{cirBS}\right) \tag{5.14}$$

$$s.t \quad (5.13b) \ - \ (5.13d)$$

where $\mathcal{P}$ is the set consisting of feasible power allocation strategies and q_n is the value of EE for NOMA. The transmission power for kth CUE on each RB is given as $\varrho_k = [\rho_{k,1}, \rho_{k,2}, ..., \rho_{k,Q}]$. Therefore, the vector of all power allocation strategies is denoted as $\boldsymbol{p} = [\varrho_1, \varrho_2, ..., \varrho_K]^T$.

The objective function in (5.14) is still non-convex and can be further converted to a DC programming problem [157] by formulating the objective function as

$$v(\boldsymbol{p}) = f(\boldsymbol{p}) - g(\boldsymbol{p}) \tag{5.15}$$

where

$$\begin{aligned} f(\boldsymbol{p}) = W_s & \left[\sum_{n=1}^{Q} \log_2 (p_{1,n} h_{1,n} + W_s N_0) + \sum_{n \epsilon 1}^{Q} \log_2 ((p_{1,n} + p_{2,n}) h_{2,n} + W_s N_0) \right] \\ & + W_s \sum_{n=1}^{Q} \log_2 ((p_{1,n} + p_{2,n} + p_{3,n}) h_{3,n} + W_s N_0) \\ & + W_s \sum_{n=1}^{Q} \log_2 \left((\sum_{k=1}^{K} p_{k,n}) h_{K,n} + W_s N_0 \right) \\ & - q_n \left(\varepsilon \sum_{k=1}^{K} \sum_{n \epsilon Q} p_{k,n} + P_{cirBS} \right) \end{aligned}$$

and

$$\begin{aligned} g(\boldsymbol{p}) = & W_s \sum_{n=1}^{Q} \log_2 (W_s N_0) + W_s \sum_{n=1}^{Q} \log_2 (p_{1,n} h_{2,n} + W_s N_0) \\ & + W_s \sum_{n=1}^{Q} \log_2 ((p_{1,n} + p_{2,n}) h_{3,n} + W_s N_0) \\ & + W_s \sum_{n=1}^{Q} \log_2 \left((\sum_{k=1}^{K-1} p_{k,n}) h_{K,n} + W_s N_0 \right). \end{aligned}$$

Therefore, problem (5.14) can be recast as

$$\begin{aligned} & \max_{\boldsymbol{p} \in \mathcal{P}} \quad \{ f(\boldsymbol{p}) - g(\boldsymbol{p}) \}. \\ & s.t \quad (5.13b) \; - \; (5.13d) \end{aligned} \tag{5.16}$$

The function $g(\boldsymbol{p})$ in (5.16) can be approximated by its first order Taylor expansion at $p^{(i)}$ i.e., $g\left(\boldsymbol{p}^{(i)}\right) + \nabla g\left(\boldsymbol{p}^{(i)}\right)^T \left(\boldsymbol{p} - \boldsymbol{p}^{(i)}\right)$in each iteration, where $\nabla g\left(\boldsymbol{p}^{(i)}\right)^T$

denotes the gradient of $g\left(\boldsymbol{p}\right)$at the point $\boldsymbol{p}^{(i)}$which is given by

$$\nabla g\left(\boldsymbol{p}\right)\begin{cases}\sum_{n=1}^{Q}\frac{h_{2,n}W_s}{\ln 2(W_sN_0+(p_{1,n})h_{2,n})}+\sum_{n=1}^{Q}\frac{h_{3,n}W_s}{\ln 2(W_sN_0+(p_{1,n}+p_{2,n})h_{3,n})}+ & \\ \sum_{n=1}^{Q}\frac{h_{K,n}W_s}{\ln 2\left(W_sN_0+(\sum_{k=1}^{K-1}p_{k,n})h_{K,n}\right)}, & :\mathrm{CUE1} \\ \sum_{n=1}^{Q}\frac{h_{3,n}W_s}{\ln 2(W_sN_0+(p_{1,n}+p_{2,n})h_{3,n})}+ & \\ \sum_{n=1}^{Q}\frac{h_{K,n}W_s}{\ln 2\left(W_sN_0+(\sum_{k=1}^{K-1}p_{k,n})h_{K,n}\right)}, & :\mathrm{CUE2} \\ \sum_{n=1}^{Q}\frac{h_{K,n}W_s}{\ln 2\left(W_sN_0+(\sum_{k=1}^{K-1}p_{k,n})h_{K,n}\right)}, & :\mathrm{CUE3} \\ 0. & :\mathrm{CUE}K\end{cases}$$

Finally, the approximated problem is expressed as

$$\max_{\boldsymbol{p}\in\mathcal{P}} \quad v\left(\boldsymbol{p}\right)=f\left(\boldsymbol{p}\right)-g\left(\boldsymbol{p}^{(i)}\right)-\nabla g\left(\boldsymbol{p}^{(i)}\right)^{T}\left(\boldsymbol{p}-\boldsymbol{p}^{(i)}\right). \tag{5.17}$$
$$s.t \quad (5.13b) \ - \ (5.13d)$$

It can be seen from (5.17) that both $f\left(\boldsymbol{p}\right)$ and the remaining terms are concave functions. Algorithm 5.2 presents the energy efficient power allocation algorithm for the NOMA system.

Algorithm 5.2 Energy efficient power allocation for NOMA users

Require: $\epsilon,\ t=0,\ q_n(t)=0,\ T_{max}$
while $(|F_n(q_n)|>\epsilon)\ ||\ (t<T_{max})$ **do**
  Initialize $i=0,\ \forall\boldsymbol{p}\in\mathcal{P}$
  while $((|V(\boldsymbol{p}^{(i+1)})-V(\boldsymbol{p}^{(i)})|>\epsilon)$ **do**
    Solve problem (5.17) using IPM
    $i=i+1$
  end while
  Update $q_n(t+1)=\frac{R_c}{\varepsilon P+P_{cirBS}}$
  Update $F_n(q_n)$
  $t=t+1$
end while
return $(\boldsymbol{p},q_n)$

5.6 Energy Efficiency Optimization for D2D Pairs in Non-Orthogonal Mode (EENO)

The EE optimization for D2D is performed once the RE NOMA stage is completed. In this second stage, D2D communications are employing non-orthogonal resource sharing mode where each RB is used by multiple D2D pairs. The DUEs will utilize all remaining M RBs to maximize their EE. Therefore, only the power allocation problem for D2D pairs need to be solved. In this section, we only focusing on the EE optimization scheme for D2D pairs using non-orthogonal resource sharing mode (EENO) because it provides better EE performance than the D2D pair in orthogonal mode (EEO). As in Section 4.5, the EE optimization problem for D2D communications is expressed as

$$\eta_{EE} = \max_{p_{l,m}} \frac{R_d}{\varepsilon P_D + LP_{cirUE}} \tag{5.18a}$$

$$\text{s.t} \quad \sum_{m=1}^{M} r_{l,m} \geq R_{min}^d \tag{5.18b}$$

$$\sum_{m=1}^{M} p_{l,m} \leq P_{max}^d, \ \forall l \in \mathcal{L} \tag{5.18c}$$

$$p_{l,m} \geq 0, \ \forall l \in \mathcal{L}, \ \forall m \in \mathcal{M} \tag{5.18d}$$

where R_{min}^d and P_{max}^d represent the minimum rate requirement and the maximum transmission power for each D2D pair respectively. Algorithm 4.5 is used to solve this problem.

5.7 Simulation Results

In the proposed RE NOMA-EENO scheme, the first stage (RE NOMA) is implemented in two steps using Algorithm 5.1 and 5.2. However, the results for RE NOMA presented in this section are obtained by solving problem (5.13) in the second step using an optimal numerical solution. Regardless of this, the EE optimization for the D2D pairs in the second stage is performed similar as in Section 4.5. Simulation parameters used in this chapter are summarized in Table 5.1.

Fig. 5.4 shows the relationship between the tradeoff parameter, β with the EE

Table 5.1 – Simulation parameters

Parameters	Value
Cell radius (R)	500 m
Number of cellular users (K)	4
Number of D2D pairs (L)	$2, 4$
Number of resource blocks (N)	25
Resource block bandwidth (W_s)	200 kHz
Maximum D2D pair distance (d_{max})	$20, 40, ..., 120$ m
Rate requirement for each CUE (R^c_{min})	0.5 Mbps
Rate requirement for each D2D pair (R^d_{min})	1 Mbps
Maximum transmit power of BS (P_{max})	10 W
BS circuit power (P_{cirBS})	5 W
Maximum transmit power of D2D link (P^d_{max})	250 mW
DTx circuit power (P_{cirUE})	100 mW
Drain efficiency of power amplifier	0.38
Noise power spectral density (N_0)	-174 dBm/Hz
Shadowing	8 dB
Decay factor (α_{FTPA})	0.4

and SE performance of the NOMA system. Similar with the case of OFDMA, the EE performance decreases with β whereas the SE increases with β. It can be seen that the proposed RE NOMA approach achieves better EE and SE performance at low and high value of β, respectively compared with the Full RE scheme in Fig. 4.2 and LC RE scheme in Fig. 4.3.

It should be noted that the value of β for RE NOMA to achieve the same number of RB as the RE for OFDMA (19 RBs) is 2. Therefore, by fixing the $\beta = 2$ for the proposed RE NOMA in the first stage and utilizing the same EE maximization scheme for D2D pairs for the second stage, the result as shown in Figure 5.5 is obtained. The benchmark OFDMA results are obtained from Figure 4.8 in Chapter 4. By multiplexing 4 CUEs on the same RB, the proposed RE NOMA-EENO scheme improves the overall EE of the BS. As a result, the proposed RE NOMA-EENO scheme achieves the highest system EE compared to other schemes.

Figure 5.6 shows the detailed EE comparison of the proposed RE NOMA-EENO scheme with the proposed LC RE-EENO and EE-EENO schemes. The proposed RE NOMA-EENO scheme achieves the highest EE for both the BS and D2D pairs. In average, the proposed RE NOMA scheme allocates slightly more RB to the D2D pairs which leads to the EE improvement.

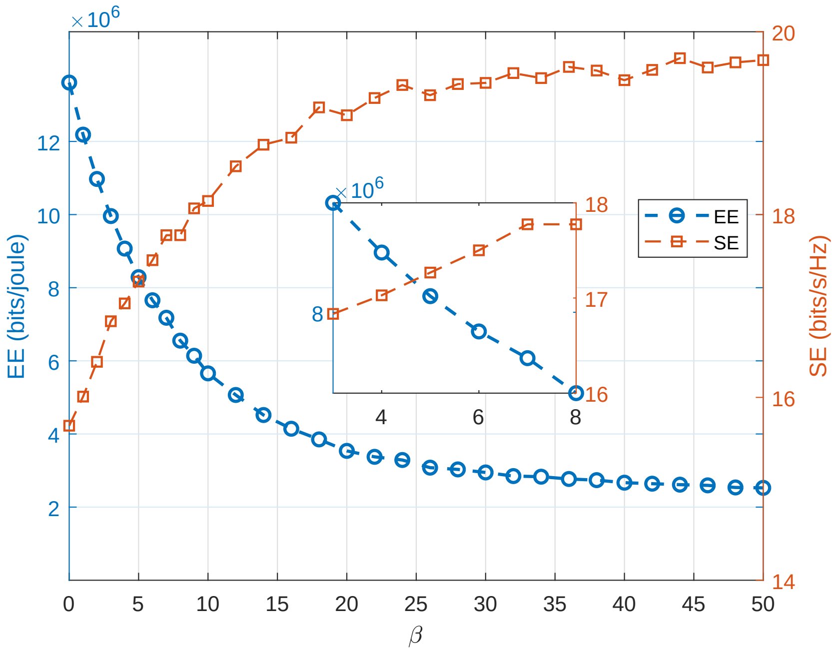

Figure 5.4 – EE-SE for NOMA

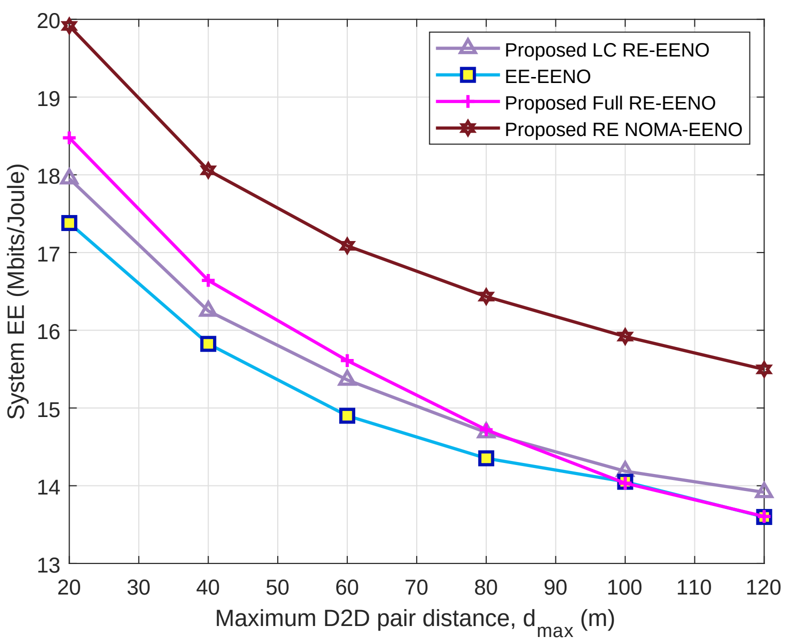

Figure 5.5 – System EE versus maximum D2D pair distance ($L = 2$).

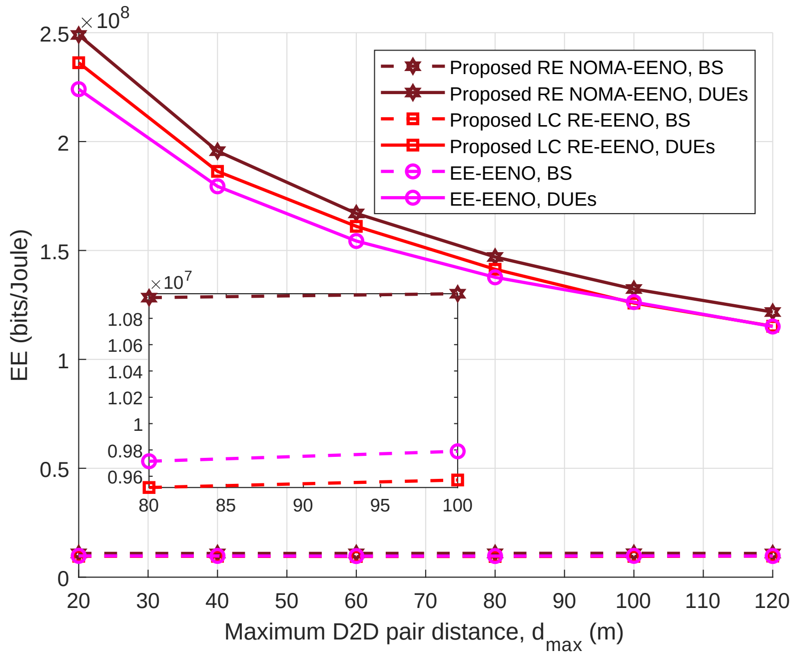

Figure 5.6 – EE comparison ($\beta = 2$).

The first tradeoff investigated in this chapter is the EE-SE tradeoff of the NOMA system. However, the value of tradeoff parameter β also affects the system EE. Figure 5.7 shows the impact of tradeoff parameter to the system EE. When larger value of β is chosen, lesser RBs are allocated to the cellular links. This means that more RB can be assigned to the D2D pairs to maximize their EE. Although the EE of CUEs is reduced, a significant EE improvement can be achieved by the D2D users. As a result, the system EE is increased.

A detailed EE comparison of the proposed RE NOMA-EENO with $\beta = 5$ is depicted in Figure 5.8. In terms of BS's EE, the proposed scheme recorded a reduction of EE compared to the case of $\beta = 2$. However, there is a significant EE improvement for the DUEs which contributes to the enhancement of the system EE.

5.8 Summary

In this chapter, an overview of NOMA is presented. Previous studies which investigated the EE and EE-SE for NOMA as well as the coexistence of NOMA with D2D communications are discussed. RE optimization problem for a NOMA system is formulated and a two-step scheme is proposed to solve the problem.

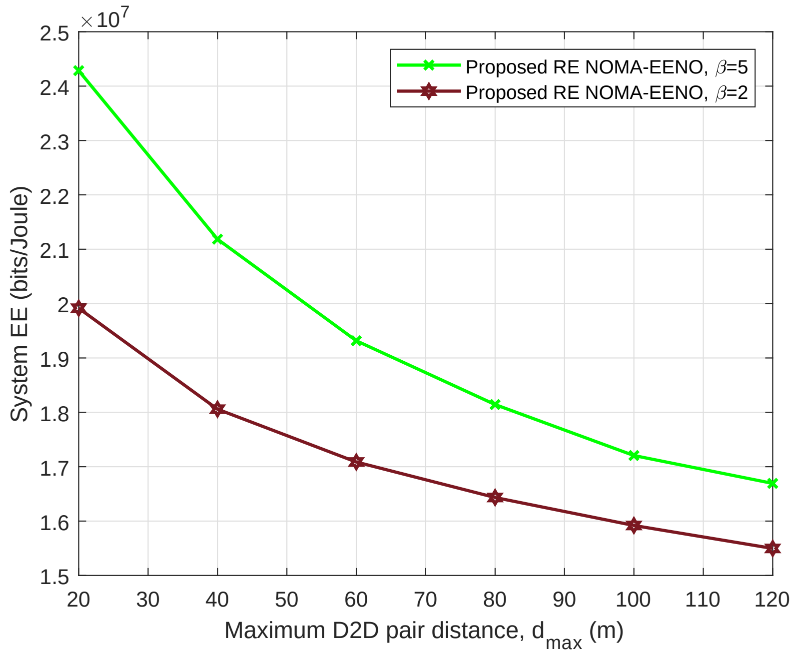

Figure 5.7 – The effect of β on system EE.

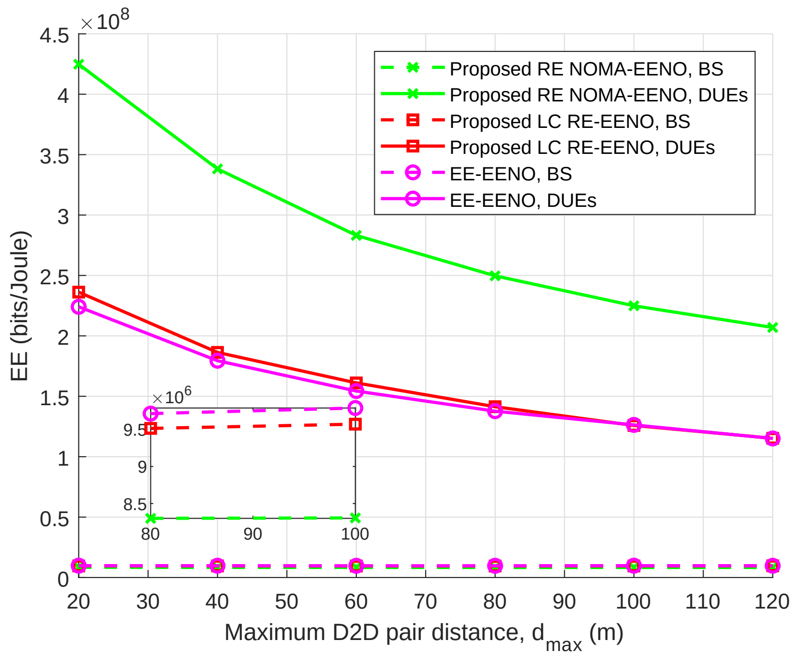

Figure 5.8 – EE comparison ($\beta = 5$).

Using the RE optimization for NOMA, some RBs are left unoccupied and can be used by D2D pairs to maximize the system EE. Moreover, non-orthogonal resource sharing mode is utilized by the D2D pair. Simulation results indicated that the use of RE optimization can provide a balance between EE and SE for the NOMA system. In addition, using the NOMA protocol for the downlink communication between the BS and CUEs can improve the EE of the BS as well as the overall EE of the NOMA-D2D system.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

This thesis studied the EE improvement of D2D communications overlaying cellular system. The main aim of this work is to enhance the overall EE of the system, where D2D pairs either sharing the uplink or downlink cellular resources. By dividing the main EE problem into two sub problems and implemented in two stages, efficient algorithms can be used to solve the complex problem effectively.

In Chapter 2, some background information on wireless communications including LTE-Advanced and 5G technologies are presented. It is clear that EE has becoming one of the important aspects of future wireless communication systems. Overview of D2D communications, advantages of D2D, its challenges, standardization, classification and related scenarios are discussed. In addition, some radio resource management of D2D communication and basic D2D simulation scenario are provided. An overview of radio resource management for D2D communications is described. Moreover, basic simulation on the performance D2D communication is also presented. Due to its proximity communication, D2D has the potential to improve the overall EE and throughput of the system. However, some aspects of communications such as the distance from D2D users to the BS or other cellular users, transmission power, and interference issue must be considered if D2D communication to take place underlaying or overlaying cellular network. Lastly, the EE formulation for a cellular system coexisting with D2D communication is defined.

In Chapter 3, a two-stage optimization framework is proposed to maximize the overall EE of D2D communication sharing the uplink cellular resources. In the first stage, RE optimization for a CUE is performed to obtain the optimal power and bandwidth allocations. The RE optimization problem for the CUE is non-convex due to the fractional structure of the objective function. However, for a given value of bandwidth, the RE is quasiconcave with respect to the transmit power of the CUE. An iterative algorithm based on the Bisection method is proposed to solve the RE problem. By selecting the value of tradeoff parameter, some bandwidth will be left unoccupied by the CUE. This remaining bandwidth will be used by a D2D pair in the second stage to maximize its EE. By converting the original EE problem into subtractive form, the optimal transmit power for the D2D pair is obtained using Dinkelbach and interior point method. Numerical results show that the proposed RE algorithm in the first stage of the optimization achieves similar performance to a global optimization solution while the optimal EE for the D2D pair is obtained in the second stage. Moreover, the simulations confirm that the proposed two-stage scheme performs close to the global optimal solution and provides better overall EE performance compared to the cellular mode and dedicated mode of communications.

The proposed two-stage optimization scheme is extended in Chapter 4 to study the EE optimization of D2D communications overlaying downlink OFDMA system. In this chapter, we consider multiple number of CUEs and D2D pairs where each CUE will be allocated orthogonal RBs while D2D pairs will reuse unallocated RBs between each other. To solve the complex EE problem of the system, it is divided into two subproblems: RE optimization for BS and EE optimization for D2D users. We provide the solution to the main EE problem using a two-stage optimization scheme. In the first stage, a joint RB and power allocation algorithm is proposed based on fractional programming approach and Lagrange dual decomposition to maximize the RE of the BS. The RE optimization stage enables some RBs to be left unoccupied which are then used by the DUEs. To further reduce the complexity, a lower complexity RE implementation is also proposed in the first stage. In the second stage of optimization, D2D pairs are allowed to reuse all remaining RBs to enhance their EE performance. By exploiting a range of optimization tools including fractional programming, Dinkelbach method, and CCCP algorithm, the power allocation for D2D pairs are solved. Simulation results showed that the system EE achieved by the LC RE-EENO scheme is slightly higher than the upper bounds of EE-EENO and close to the

Full RE-EENO schemes, while having lower complexity compared to the Full RE-EENO. Furthermore, the proposed Full RE-EENO and LC RE-EENO schemes can enhance the EE of D2D communications at the expense of slight degradation on the EE of the BS.

Finally, the performance of a NOMA-D2D system is examined in Chapter 5, in which D2D communications coexist with NOMA system and utilize the RBs in overlay manner. A two-step algorithm is proposed to study the EE-SE tradeoff of the NOMA system in the first stage. Motivated by the previous lower complexity LC RE scheme, the first step aims to maximize the RE of the NOMA system by utilizing FTPA scheme. The number of RBs allocated to the CUEs is determined in this step. Using FTPA, the power allocation for CUEs is suboptimal. Therefore, proper power allocation is performed in the second step. To obtain optimal power allocation, DC programming method can be adopted to allocate power for each CUE within each RB. The power allocation scheme in this step is designed to maximize the EE of the NOMA system. In the second stage, the EE optimization for D2D pairs is proceeded and implemented similarly as in Chapter 4. Simulation results show that the proposed RE NOMA approach achieves higher EE and SE performance compared to the RE for OFDMA schemes. In addition, the use of NOMA scheme allows the proposed RE NOMA-EENO to outperformed other schemes in term of the system EE.

6.2 Future Work

This thesis studied the resource allocation problem for maximizing the system EE of D2D communications overlaying conventional CUEs and NOMA users. There are several features and applications of D2D communications that are not considered in this work. Several potential future research as extensions to this work are elaborated as below.

Cross cell and multi cell D2D communications

The EE aspect of D2D communication with frequency reuse network has not been investigated in the existing works. Furthermore, an interesting D2D communication scenario is cross cell communication where both DTx and DRx located in different coverage area of a BS. This means that both potential D2D pair are located at cell edge. For this type of scenario, the EE for cell edge users has not been investigated well and the power transmitted by cell edge users will be higher due to larger distance from the BS. Since UE rely on battery, the battery level should be taken into account and energy usage should be optimized. One of important challenges is to manage interference in cross-cell D2D communication. Therefore, radio resource managements such as mode selection, power control and resource allocation need to be jointly considered with EE aspect of this particular network scenario.

D2D in heterogeneous and ultra-dense networks

Both small cell and D2D communications have the potential to offload traffic from the cellular network. Therefore, further work can be done to study the coexistence between D2D and small cell and their cooperation to improve the EE in the network. The performance of EE D2D communication underlay small cell network while taking into account the backhaul energy consumption can be investigated. Furthermore, ultra-dense networks is one of the emerging technologies for future wireless systems. In this type of network, CUEs and D2D users will be within the coverage of multiple small cells. Thus mitigating interference and improving the EE become complex task and required further investigation.

D2D communications with energy harvesting

Energy Harvesting (EH) for D2D communications is worth to be investigated because UEs have limited battery capacity. Therefore, UEs can be equipped with EH module and harvest energy from other sources and help in D2D communications.

NOMA-D2D scenarios

The works that considered the coexistence of NOMA and D2D communications are still limited. D2D users can implement NOMA protocol where a DTx transmits to several DTxs in group. To enhance the system EE, D2D users can communicate in underlay mode and share the resources of other NOMA users. However, the current works have not considered the capability of resource constrained D2D users which have to perform power domain multiplexing at the DTx and SIC at the DRx. Furthermore, cooperative NOMA-D2D scenario can be investigated. In addition, it is also interesting to study the resource allocation problem when code domain NOMA, such as SCMA is applied into D2D communications.

D2D-based vehicular communications One of important applications for D2D communications is related to public safety. Recently, the use of D2D in vehicular communications network has gained new interest from researchers. Vehicle-to-vehicle (V2V) communications requires low latency and reliable data transmission. One advantage of D2D-based V2V communication is that channel congestion and collision used in 802.11p based V2V communication can be avoided. D2D-based V2V communication can ensure the connectivity between vehicular user equipments (VUEs), where VUEs can communicate directly using the radio resources of CUEs. Therefore, radio resource management schemes need to be developed to control the interference and improving the SE and EE of the system. In addition, further investigation on the application of D2D communications with vehicular communications can be explored.

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