

Resource Allocation for D2D Communications Based on Matching Theory

by

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TO MY FAMILY

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Abstract

Device-to-device (D2D) communications underlying a cellular infrastructure takes advantage of the physical proximity of communicating devices and increasing resource utilisation. However, adopting D2D communications in complex scenarios poses substantial challenges for the resource allocation design. Meanwhile, matching theory has emerged as a promising framework for wireless resource allocation which can overcome some limitations of game theory and optimisation. This thesis focuses on the resource allocation optimisation for D2D communications based on matching theory.

First, resource allocation policy is designed for D2D communications underlying cellular networks. A novel spectrum allocation algorithm based on many-to-many matching is proposed to improve system sum rate. Additionally, considering the quality-of-service (QoS) requirements and priorities of different applications, a context-aware resource allocation algorithm based on many-to-one matching is proposed, which is capable of providing remarkable performance enhancement in terms of improved data rate, decreased packet error rate (PER) and reduced delay.

Second, to improve resource utilisation, joint subchannel and power allocation problem for D2D communications with non-orthogonal multiple access (NOMA) is studied. For the subchannel allocation, a novel algorithm based on the many-to-one matching is proposed for obtaining a suboptimal solution. Since the power allocation problem is non-convex, sequential convex programming is adopted to transform the original power allocation problem to a convex one. The proposed algorithm is shown to enhance the network sum rate and number of accessed users.

Third, driven by the trend of heterogeneity of cells, the resource allocation problem for NOMA-enhanced D2D communications in heterogeneous networks (HetNets) is investi-

gated. In such a scenario, the proposed resource allocation algorithm is able to closely approach the optimal solution within a limited number of iterations and achieves higher sum rate compared to traditional HetNets schemes.

Thorough theoretical analysis is conducted in the development of all proposed algorithms, and performance of proposed algorithm is evaluated via comprehensive simulations.

This thesis concludes that matching theory based resource allocation for D2D communications achieves near-optimal performance with acceptable complexity. In addition, the application of D2D communications in NOMA and HetNets can improve system performance in terms of sum rate and users connectivity.

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List of Abbreviations

4G	Forth-Generation
5G	Fifth-Generation
AWGN	Additive White Gaussian Noise
BS	Base Station
CARAD	Context-Aware Resource Allocation for D2D Communications
CDF	Cumulative Distribution Function
C-RAN	Cloud-Based Radio Access Network
DA	Deferred Acceptance
DL	Downlink
D2D	Device-to-Device
eNB	Evolved NodeB
GS	Gale-Shapley
HetNets	Heterogeneous Networks
IA	Initialization Algorithm
i.i.d.	Independent and Identically Distributed
I-JSPA	Iterative Joint Subchannel and Power Allocation Algorithm
ISM	Industrial, scientific and medical
JSAPCA	Joint Spectrum Allocation and Power Control Algorithm
LC-JSPA	Low-Complexity Joint Subchannel and Power Allocation Algorithm
LTE	Long Term Evolution

MA	Multiple Access
MCU	Macro Cell User
MIMO	Multiple-Input Multiple-Output
mmWave	millimeter Wave
NOMA	Non-Orthogonal Multiple Access
NP	non-deterministic polynomial-time
OMA	Orthogonal Multiple Access
PAA	Power Allocation Algorithm for Each D2D Group
PER	Packet Error Rate
QAM	Quadrature Amplitude Modulation
QoE	Quality of Experience
QoS	Quality of Service
RADMT	Resource Allocation for D2D Communications Using Matching Theory
RB	Resource Block
SAA	Matching-Theory Based Subchannel Assignment Algorithm
SC	Subchannel
SC-FDMA	Single Carrier Frequency Division Multiple Access
SCPAA	Sequential Convex Programming Based Power Allocation Algorithm
SCU	Small Cell User
SIC	Successive Interference Cancellation
SINR	Signal-to-Interference-Plus-Noise Ratio
SNR	Signal-to-Noise Ratio
SOEMA	Swap Operations Enabled Matching Algorithm
UE	User Equipment
UL	Uplink
UR	Underlay Receiver
UT	Underlay Transmitter

List of Notations

\mathbf{a}	Power allocation coefficient
α	α -utility function parameter
B	RB bandwidth
β	Channel constant
\mathcal{C}	Set of cellular UEs
\mathcal{D}	Set of D2D pairs
DR	D2D receiver
DT	D2D transmitter
η	Path-loss exponent
f, h, g	Channel coefficient
$\hat{f}, \hat{h}, \hat{g}$	Small scale fading
G	Channel gain
γ	SINR
γ^{thr}	SINR threshold
I^c	Interference from cellular users
I_{co}	Co-tier interference
I_{cr}	Cross-tier interference
I^{in}	Intra-group interference
I_N	Interference from superposed signal
I^{out}	Inter-group interference

L	Distance between D2D transmitter and receiver
λ	Subchannel allocation indicator
Ω	Matching function
P	D2D total transmit power
R	Data rate
\mathcal{RB}	Set of RBs
σ^2	Additive white Gaussian noise power
t	Transmit signal of D2D transmitter
τ	Fixed coefficient with unit interference of UTs bring to MCU
U	Utility function
x	Transmit signal of cellular user
z	Received signal at D2D receiver
ζ	Additive white Gaussian noise

Chapter 1

Introduction

1.1 Background

This section summarises the research motivation and research challenges in D2D communications.

1.1.1 Research Motivation

The fifth generation (5G) mobile network has evolved into a full-fledged topic around the world thus far, which is envisioned to be deployed beyond 2020. Driven by the penetration of smart devices, compelling services, and the better user interface design, the amount of overall mobile data traffic is foreseen to increase by a factor of 100: from under 3 exabytes in 2010 to over 190 exabytes by 2018 [ABC⁺14]. In addition, the number of devices is increasing at a brisk pace, which will reach the tens or hundreds of billions compared to that in the fourth generation (4G) system. The sheer volume of data and the deluge of devices provide the preliminary 5G with the impetus to address six challenges, including higher capacity, higher data rate, lower end-to-end latency, massive device connectivity, reduced cost, and consistent Quality of Experience (QoE) provisioning [MET13, Hor13], to provide a seamless user experience.

Based on the current trend, the spectrum crisis and users' desire for anywhere,

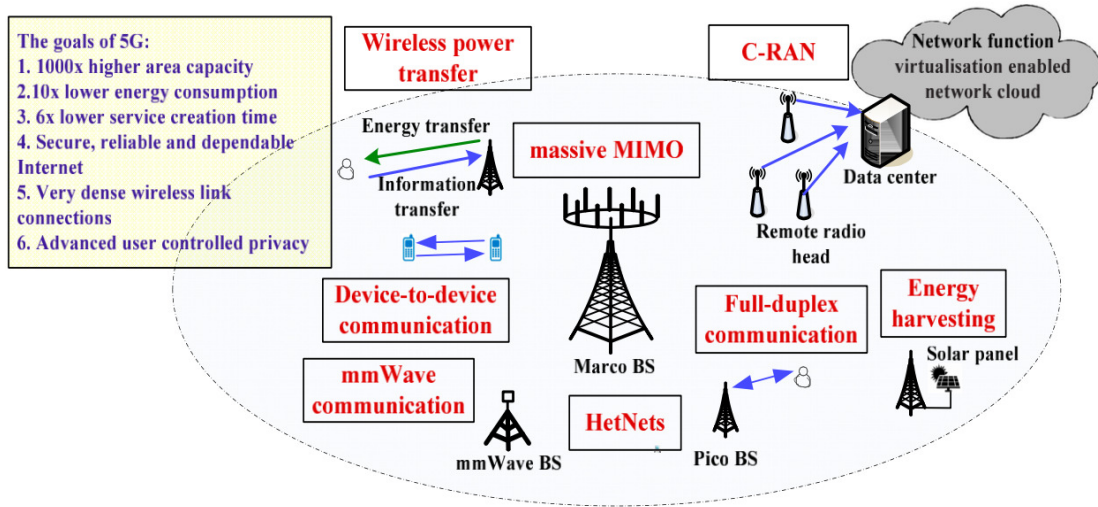


Figure 1.1: General 5G cellular network architecture [LWC⁺16].

anytime high-speed connectivity that can not be properly accommodated even by 4G, necessitate a new 5G network architecture. The primary technologies and approaches identified by E. Hossain et al. [HH15b] for 5G networks are dense heterogeneous networks (HetNets), device-to-device communication, full-duplex communication, massive multiple-input multiple-output massive (MIMO) and millimeter wave (mmWave) communications technologies, energy-aware communication and energy harvesting, cloud-based radio access network (C-RAN) and visualisation of wireless resources. Figure 1.1 illustrates the enabling technologies and expected goals for 5G networks.

D2D communications in cellular networks is defined as direct communication between two mobile users without traversing the evolved NodeB (eNB) or core network, as shown in Figure 1.2. In a traditional cellular network, all communications must go through the eNB even if both communicating parties are in range for D2D communications. This architecture suits the conventional low data rate mobile services such as voice call and text message in which users are not usually close enough to have direct communication. However, mobile users in today's cellular networks use high data rate services (e.g., video sharing, gaming, proximity-aware social networking) in which they could potentially be in range for direct communications (i.e., D2D). Hence, D2D communications in such

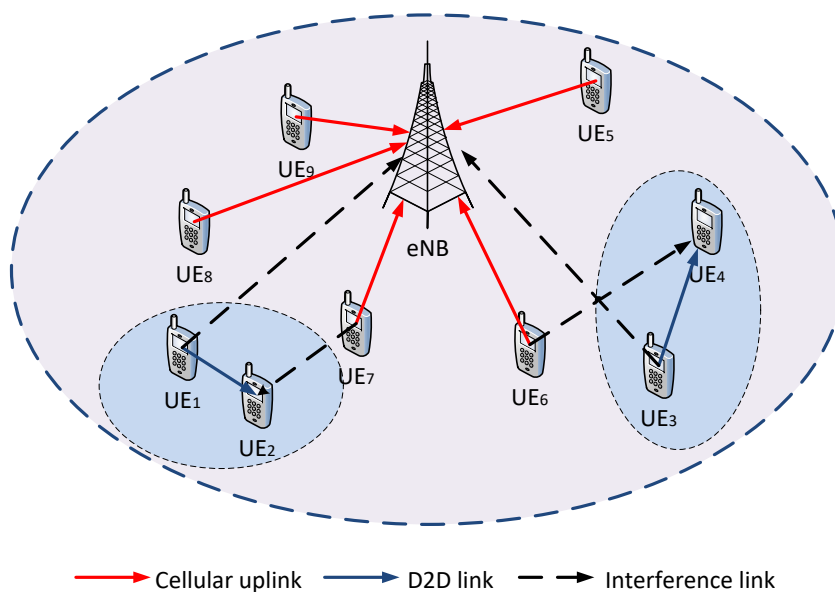


Figure 1.2: The concept of D2D communications underlaying cellular networks.

scenarios can highly increase the spectrum efficiency of the network [DRW⁺09a].

1.1.2 Research Challenge

Despite the potential gains of D2D communications, it may also cause interference to the cellular network as a result of spectrum sharing. To guarantee the quality-of-service (QoS) requirements of primary cellular users, interference constraints need to be taken into consideration, which inevitably makes the resource allocation rules complicated. Therefore, new challenges and issues arise. How to maximise system capacity while guaranteeing service quality for both cellular users and D2D users stays as a big challenge, especially when dense D2D users are supported in an underlay mode. In order to understand the problems and develop various mechanisms to support desirable D2D communications in cellular networks, this is a need to be empowered with effective analytical and simulation tools. Matching theory has recently received a great deal of attentions in wireless communications and been considered as an effective tool for this purpose. Most existing works are restricted to very limited aspects of resource allocation adopting

matching theory, which is mainly due to the sparsity of tutorials that tackle matching theory from an engineering perspective. Hence, novel resource allocation policies adopting matching theory should be investigated with respect to D2D communications.

Furthermore, inspired by the potential benefits of D2D communications, it is natural to investigate the promising application of D2D communications in some existing technologies, such as non-orthogonal multiple access (NOMA) and HetNets. Note that the co-consideration of these technologies poses additional challenges in terms of interference management since it brings additional co-channel interference to the existing network. As such, how well the application of D2D communications in NOMA and HetNets could improve the network performance, i.e., sum rate and users connectivity, still remains unknown. Investigating novel resource allocation design for intelligently managing and coordinating various types of interference is more than desired.

In this thesis, a great emphasis is given to the resource allocation design for D2D communications based on matching theory.

1.2 Research Contributions

The contributions of the thesis are summarised as follows:

- An extensive and in-depth overview of the state-of-the-art resource allocation for D2D communications and matching theory is carried out. Furthermore, the current challenges are highlighted, which sheds lights on the research directions.
- A novel resource allocation approach for D2D communications based on the many-to-many matching is proposed to improve resource utilisation. Subsequently, a novel context-aware resource allocation algorithm is proposed to address QoS requirements of different applications as well as priorities of applications in different hardware devices. Therefore, D2D users' sum rate is improved and delay and packet error rate (PER) are decreased.

- A novel NOMA enhanced D2D scheme is proposed to improve resource utilisation. With the aid of matching theory, an effective resource allocation algorithm is proposed for maximising the system sum rate. It is demonstrated that the proposed algorithm can achieve the near-optimal system sum rate, and outperform the OMA-based D2D framework.
- A novel system of D2D communications in HetNets with NOMA is proposed, and a joint spectrum allocation and power control problem is formulated with the aim of maximising the sum rate of small cell users (SCUs) and D2D users while considering fairness issues. A distributed resource allocation algorithm is proposed based on the matching theory to maximise the sum rate of SCUs and D2D users. More importantly, a novel concept of “experimentation” is introduced to the matching algorithm to further improve the performance by exploring the space of matching states.
- Thorough theoretical analysis is conducted in the development of all the proposed algorithms, which are evaluated via the comprehensive MATLAB simulations.

1.3 Author’s Publication

- Journal Papers
 1. **J. Zhao**, Y. Liu, K. K. Chai, A. Nallanathan, Y. Chen, and Z. Han. “Spectrum Allocation and Power Control for Non-Orthogonal Multiple Access in HetNets”, *IEEE Transactions on Wireless Communications*; accepted to appear.
 2. **J. Zhao**, Y. Liu, K. K. Chai, Y. Chen, and M. ElKashlan. “Joint Subchannel and Power Allocation for NOMA Enhanced D2D Communications”, *IEEE Transactions on Communications*; (minor revision).
 3. **J. Zhao**, Y. Liu, K. K. Chai, M. ElKashlan, and Y. Chen. “Matching

with Peer Effects for Context-Aware Resource Allocation in D2D Communications”, *IEEE Communications Letters*; vol. 21, no. 4, pp. 837–840, Apr. 2017.

4. **J. Zhao**, Y. Liu, K. K. Chai, Y. Chen, and M. ElKashlan. “Many-to-Many Matching with Externalities for Device-to-Device Communications”, *IEEE Wireless Communications Letters*; vol. 6, no. 1, pp. 138–141, Feb. 2017 .
5. **J. Zhao**, K. K. Chai, Y. Chen, J. Schormans, and J. Alonso-Zarate. “Joint Mode Selection and Resource Allocation for Machine-Type D2D Links”, *Transactions on Emerging Telecommunications Technologies*, DOI: 10.1002/ett.3000, Nov. 2015

- Conference Papers

1. **J. Zhao**, Y. Liu, Z. Han, K. K. Chai, Y. Chen, and A. Nallanathan. “Resource Allocation in Cache-Enabled CRAN with Non-Orthogonal Multiple Access”, in *IEEE Global Communications Conference (GLOBECOM’17)*; (under review).
2. **J. Zhao**, Y. Liu, K. K. Chai, A. Nallanathan, Y. Chen, and Z. Han. “Resource Allocation for Non-Orthogonal Multiple Access in Heterogeneous Networks”, in *Proc. IEEE International Conference on Communications (ICC’17)*, Paris, France, May 2017.
3. **J. Zhao**, Y. Liu, K. K. Chai, Y. Chen, M. ElKashlan, and J. Alonso-Zarate. “NOMA-based D2D Communications: Towards 5G”, in *Proc. IEEE Global Communications Conference (GLOBECOM’16)*, Washington, DC, USA, December 2016.
4. **J. Zhao**, K. K. Chai, Y. Chen, J. Schormans, and J. Alonso-Zarate. “Two-Level Game for Relay-Based Throughput Enhancement via D2D Communications in LTE Networks”, in *Proc. IEEE International Conference on Communications (ICC’16)*, Kuala Lumpur, Malaysia, May 2016.

5. **J. Zhao**, K. K. Chai, Y. Chen, J. Schormans, and J. Alonso-Zarate. “Joint Mode Selection and Radio Resource Allocation for D2D Communications Based on Dynamic Coalition Formation Game”, in *Proc. European Wireless (EW’15)*, Budapest, Hungary, May 2015. **(invited paper)**

1.4 Thesis organisation

Chapter 2 gives an overview of D2D communications and matching theory, and summarises the state of the art on the resource allocation for D2D communications, NOMA and HetNets, as well as the application of matching theory in wireless communications.

Chapter 3 investigates the resource allocation for D2D communications based on matching theory. It begins with the proposed many-to-many matching algorithm to improve resource utilisation. Subsequently, it presents the work about context-aware optimisation on resource allocation to improve data rates as well as decrease delay and PER. The theoretical analysis and performance evaluation are carried out for these proposed algorithms.

Chapter 4 presents the resource allocation policy in NOMA-enhanced D2D communications, where efficient joint spectrum allocation and power control algorithm is developed. The theoretical analysis and performance evaluation of the proposed algorithm provide guidelines on how well the application of NOMA could improve the performance of D2D communications.

Chapter 5 investigates the emerging paradigm of D2D communications in HetNets with NOMA, where both SBSs and D2D transmitters communicate with receivers via the NOMA protocol. A novel matching algorithm is proposed to improve sum rate while taking account of the fairness issue. The theoretical analysis and performance evaluation are conducted during the development of the proposed algorithm.

Chapter 6 generates insights into the conclusions and future work.

Chapter 2

Fundamental Concepts and State-of-the-Art

This chapter first introduces the fundamental concepts about D2D resource allocation and matching theory, and then summarises related state-of-the-art.

2.1 Fundamentals of Resource Allocation in D2D Communications

Generally, D2D communications can be classified into two categories based on the spectrum in which D2D communications occur, which are shown in the following:

- **Outband D2D:** Here, the D2D links exploit unlicensed spectrum, i.e., industrial, scientific and medical (ISM) spectrum. The motivation behind using outband D2D communications is to eliminate the interference issue between D2D and cellular links. However, outband D2D may suffer from the uncontrolled nature of unlicensed spectrum. Besides, using unlicensed spectrum requires an extra interface and usually adopts other wireless technologies such as WiFi Direct [All10] or Bluetooth [Blu01]. It should be noted that only cellular devices with two wireless interfaces (e.g., LTE and WiFi) can use outband D2D.
- **Inband D2D:** The literature under this category proposed to use the cellular spec-

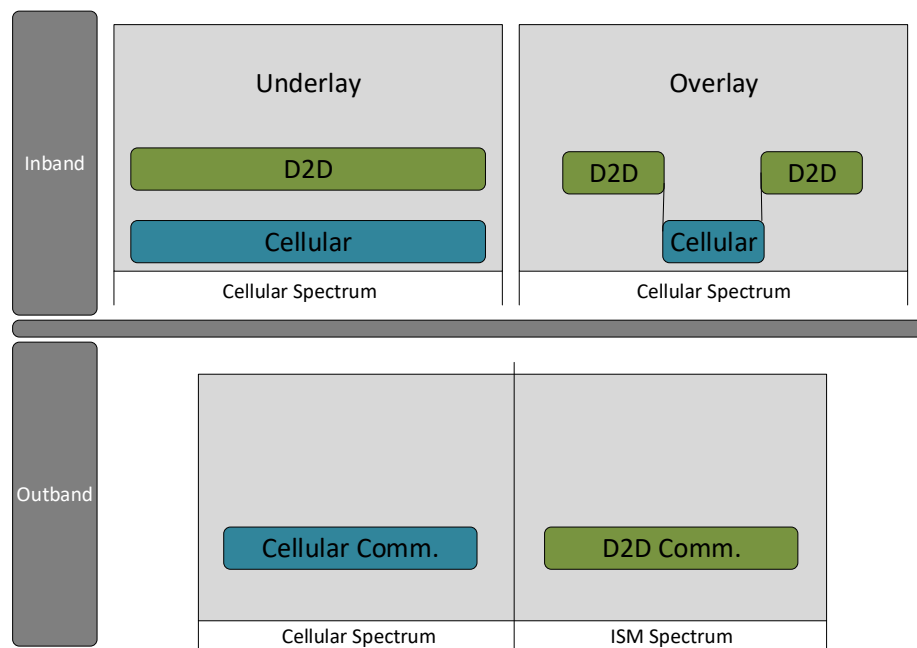


Figure 2.1: Schematic representation of overlay inband, underlay inband, and outband D2D.

trum for both D2D and cellular links. The motivation for choosing inband communication is usually the high control over cellular (i.e., licensed) spectrum. Inband communication can be further divided into underlay and overlay categories. In underlay D2D communications, cellular and D2D communications share the same radio resources. In contrast, D2D links in overlay communication are given dedicated cellular resources. Inband underlay D2D can improve the spectrum efficiency of cellular networks by reusing spectrum resources. However, it may also bring in co-channel interference between D2D and cellular links. This interference can be mitigated by introducing efficient resource allocation policies.

Figure 2.1 graphically depicts the differences among underlay inband, overlay inband, and outband communications.

To provide controllable interference as well as high spectrum efficiency, this thesis focuses on the D2D communications underlying inband cellular spectrum, which holds

the promise of three types of gains [FDM⁺12]: 1) The *proximity gain* refers to the achievement of extremely high bit rates, low delays and low power consumption thanks to the reduced transmission range bypassing the eNB; 2) The spectrum reusing between D2D and traditional cellular user equipments (UEs) could improve the spectrum efficiency, which is regarded as the *reuse gain*; and 3) The *hop gain* implies the single hop in the D2D mode instead of the two hops, i.e., uplink (UL) and downlink (DL) transmissions, in the traditional cellular mode.

Apart from the aforementioned gains, D2D communications could also bring the benefits in cellular coverage improvement, and enabling new peer-to-peer and location-based applications and services.

However, D2D communications reusing the spectrum of cellular networks poses the intra-cell interference which is no longer negligible, and subsequently the cellular communication system needs to cope with new interference situations. Some efficient interference coordination schemes have been formulated to guarantee the target performance level of the cellular communication [DRW⁺09a, YTDR09a, YTDR09b, XH10]. In order to further improve the gain brought by the intra-cell spectrum reusing, effectively pairing the cellular and D2D UEs for sharing the same resources is needed. All the aforementioned aspects mirror the inherent nature which imposes substantial challenges to the resource allocation for D2D communications. This thesis focuses attention on the resource allocation for D2D communications based on matching theory.

2.2 Fundamentals of Matching Theory

Matching theory, a Nobel-prize winning framework, is a power tool to study the formation of dynamic and mutually beneficial relations among different types of rational and selfish agents [RS92, M⁺14]. It has been widely used to develop high performance, low complexity and decentralised protocols. Recent research progresses has introduced matching theory to wireless communications to address major technical opportunities

and challenges. In particular, the advantages of matching theory for wireless resource management include:

- It is suitable for characterising interactions between heterogeneous nodes, each of which has its own type, objective, and information;
- It has the ability to define general “preferences” related to heterogeneous and complex QoS requirements for UEs in wireless network;
- The solution of matching-theory based algorithms always converges to a stable state;
- The efficient algorithmic implementations are inherently self-organising and amenable to fast implementation.

Recently, there has been significant progress in intensive research work that uses matching theory to handle resource allocation problems in wireless networks, such as in cognitive radio (CR) networks [YLZ10, BLVL13], heterogeneous cellular networks [BLH⁺14], physical layer security systems [BLH⁺13], distributed orthogonal frequency-division multiple access (OFDMA) networks [Jor11], routing, and queuing systems [LZ03, SSD07].

2.2.1 Basic Definitions

2.2.1.1 Utility function

In matching theory, utility is a measure of motivation of a player over a set of actions. To evaluate the overall satisfaction of a player in matching games, the utility function, denoted by U , is considered. It combines all the multiple related parameters to a single variable to represent the net gains [HNL09]. These parameters can be of different types. Utility functions have been widely used in wireless literature to model various radio resource management problems [LBH06, JGL05].

2.2.1.2 Preference list

The main goal of matching is to optimally match two sets of agents together, given their individual utilities. If there are two finite and disjoint sets of agents, $\mathcal{A} = \{a_1, \dots, a_n, \dots, a_N\}$ and $\mathcal{B} = \{b_1, \dots, b_m, \dots, b_M\}$, then each agent $a_n \in \mathcal{A}$ ranks the agents of the opposite set \mathcal{B} , using a preference relation \succ_{a_n} that is a complete and transitive binary relation between the set of agents of the opposite set. The notation $b_{m'} \succ_{a_n} b_m$ implies that agent a_n prefers agent $b_{m'}$ to b_m , and similarly, $a_{n'} \succ_{b_m} a_n$ implies that agent b_m prefers agent $a_{n'}$ to a_n . To put it simply, the preference of an agent over other agents can be shown by the utility value that quantifies the performance of each agent in relation with other agents.

2.2.1.3 Externalities/Peer effects

In regular matching models, the preferences of agents over each other is fixed over time. In such a model of two-sided matchings, the preference of each agent only depends on with whom the agent is being matched. It means that the agents do not care about whom the other agents are going to matching with. However, there are scenarios where it is important for an agent to know who is matched to other agents because they may share the same resources. This matching is called *matching with externalities*. For example, if a user subchannel matching is considered in a traditional D2D network, where subchannels can be accessed by multiple D2D pairs. At the beginning D2D pair A may choose subchannel C as its most preferred subchannel. However, when the network gets congested with more D2D pairs allocated to subchannel C, the interference level in this subchannel increases, and D2D pair A may change its most preferred subchannel. In other words, the preference of D2D pair A over subchannel C depends on the choices of other D2D pairs. In another example, in a college admission problem, a student may not only care about the quality of the college that he/she is going to apply for but also who else is applying for the same college.

A matching game with externalities is defined as [Gal84]:

Definition 1. A matching game with externalities is represented as a tuple $G = (\mathcal{A}, \mathcal{B}, \mathcal{U})$, where $(\mathcal{A}, \mathcal{B})$ is the set of agents and \mathcal{U} is a real valued function such that $\mathcal{U}(a_n, b_m | \Omega)$ is the utility of agent pair (a_n, b_m) when matching Ω forms.

In the matching without externalities, the actions chose by other agents do not have any effect on other agents because their utility depends only on whom the agent is matched with. Therefore, $\mathcal{U}(a_n, b_m)$ denotes the utility value of a_n when a_n and b_m are matched. Now with externalities, the amount $\mathcal{U}(a_n, b_m | \Omega)$ denotes the utility of (a_n, b_m) at Ω , where the utility of each agent depends on the underlying matching state.

2.2.2 Classifications

The simplest matching model is the marriage problem, i.e., *one-to-one* matching, which was first introduced by Gale and Shapley in [GS62]. It is an interesting and highly practical framework that discusses the matching among men and women. In the marriage problem, men have preferences over women, and women have preferences over men. The outcome of the marriage problem needs to be a set of marriages such that there are no two people of opposite sex who would both prefer each other over their current partners. In other words, the marriages need to be stable.

In addition to the classical one-to-one matching, in reality there are many practical scenarios in which the agents in one side of the matching are allowed to be matched with a number of other agents from the other side of the matching, i.e., *many-to-one* matching, such as college admission where the students are admitted to a college. Finally, if the number of the allowable matches for both sides of the matching is unrestricted, then it becomes a *many-to-many* matching problem. A general matching structure that demonstrates three types of matching configurations is shown in Figure 2.2.

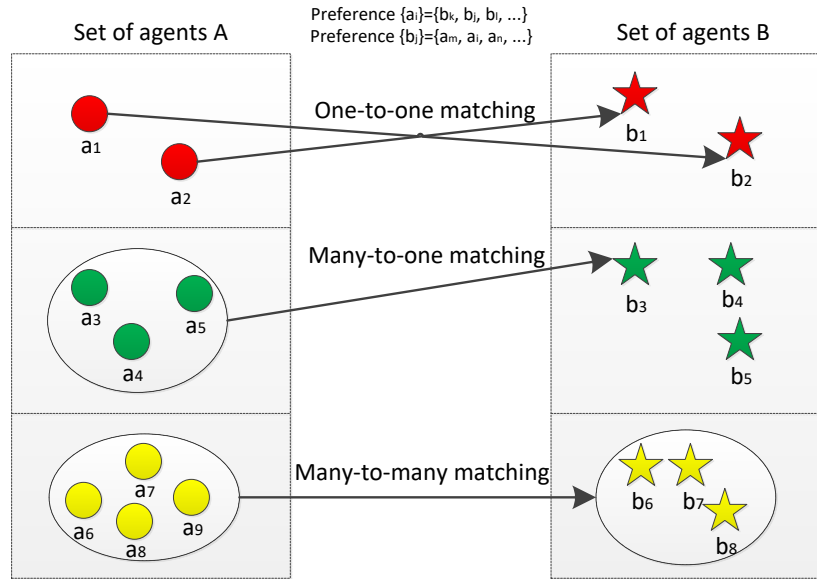


Figure 2.2: Classification of matching game.

2.2.2.1 One-to-one matching

In the classical marriage problem, there are two sets of agents, $\mathcal{M} = \{m_i\}_{i=1}^M$ and $\mathcal{W} = \{w_j\}_{j=1}^N$, which are called *men* and *women*, respectively, where each agent has ranked all members of the other set by a unique preference number. The outcome of the marriage problem is a one-to-one matching of men and women. The one-to-one matching is denoted by [RS92]

Definition 2. Given two disjoint sets \mathcal{M} and \mathcal{W} , a one-to-one matching, Ω , is defined as an allocation from $\mathcal{M} \cup \mathcal{W}$ to $\mathcal{M} \cup \mathcal{W}$ such that if $\Omega(m) \neq m$, then $\Omega(m) \in \mathcal{W}$ and if $\Omega(w) \neq w$, then $\Omega(w) \in \mathcal{M}$. The partner of w is referred to as $\Omega(w)$ if $\Omega(w) = m$.

Note that $\Omega(m) = m$ implies that man m is matched to itself, which means that it is not matched with any women. An obvious question in the matching process is that at which step the agents realise that they can not match with better partners and achieve higher utility anymore. In other words, how stable will a matching behave? The *stability* for a one-to-one matching problem is defined as the following:

Definition 3. If there is not any couple comprising one man and one woman who both

prefer each other over their current partners, all the marriages are called stable.

To implement a stable matching between two sets of agents, matching algorithms that converge to stable outcomes should be used. A well-known algorithm, which leads to a stable matching in the marriage problem, is the Deferred Acceptance (DA)/Gale-Shapely (GS) algorithm as shown in Figure 2.3. In this algorithm, players in one set make proposals to the other set, whose players, in turn, decide to accept or reject these proposals, respecting their quota. In particular, assuming the persons of gender A send proposals to persons of gender B. When the persons of gender A are proposing, each member of gender B may change between engaged and single status. When an available person of gender B received an offer, he/she will immediately accept it and become engaged to the first proposer. When an engaged person of gender B receives another offer, he/she compares the second proposer with his/her current partner and rejects the less preferred person of gender A. This iteration continues until all the persons of gender A or B are matched. In the DA/GS algorithm, players make matching decisions based on their individual preferences (e.g., available information or QoS metric). This process admits many distributed implementations which do not require the players to know each others preferences [GS62]. When the preferences are strict (no indifference), the stable matching is also Pareto optimal for the proposing players [GS62].

2.2.2.2 Many-to-one matching

There are many practical scenarios in which the agents from one side of the matching are allowed to be matched with a number of other agents from the other side of the matching, such as when students are allocated to a college. *College admission* is a good model to analyse the many-to-one matching. Let's assume that there are two finite and disjoint sets $\mathcal{C} = \{c_i\}_{i=1}^{|\mathcal{C}|}$ and $\mathcal{S} = \{s_j\}_{j=1}^{|\mathcal{S}|}$, which represent the set of colleges and students, respectively. Each student has preferences over each college, and each college has preferences over each student.

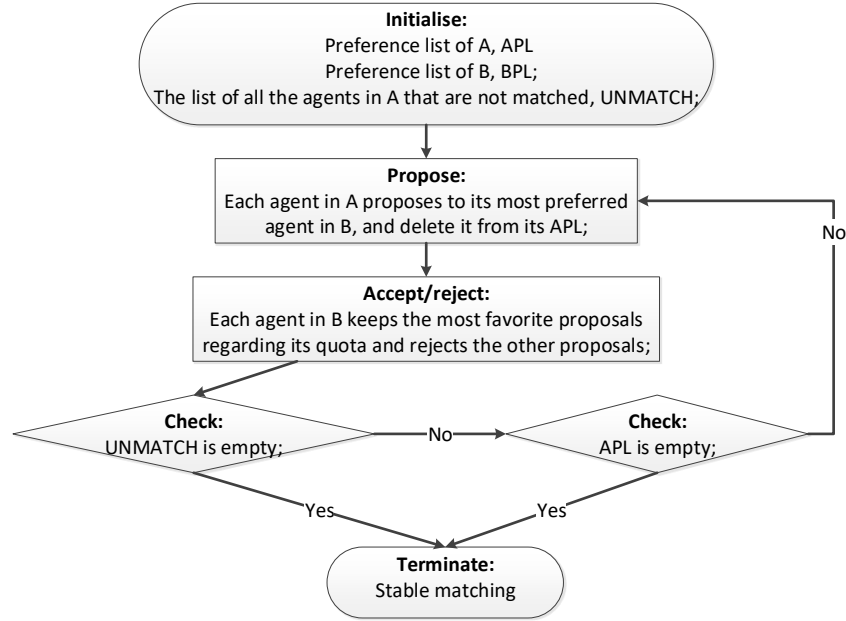


Figure 2.3: DA/GS algorithm.

The difference between the college admission and the marriage model is that associated with each college c_i there is a positive integer, $q_i \in \mathbb{N}$, called its *quota*, which indicates the maximum number of positions the college may fill. An outcome of the college admission problem is a matching of students to colleges such that each student is matched to at most one college, and each college is matched to at most its quota of students. It is notable that matching is bilateral, in the sense that a student is admitted at a given college if and only if the college admits that student. This matching is defined as the following:

Definition 4. Given two disjoint finite sets of players, $\mathcal{C} = \{c_i\}_{i=1}^{|\mathcal{C}|}$ and $\mathcal{S} = \{s_j\}_{j=1}^{|\mathcal{S}|}$, then a many-to-one matching function Ω is from the set $\mathcal{C} \cup \mathcal{S}$ into the set of all subsets of $\mathcal{C} \cup \mathcal{S}$ such that

$$1) |\Omega(s_j)| = 1, \forall s_j \in \mathcal{S}, \text{ and } \Omega(s_j) = s_j \text{ if } \Omega(s_i) \not\subset \mathcal{C};$$

$$2) |\Omega(c_i)| \leq q_i, \forall c_i \in \mathcal{C}, \text{ and } \Omega(c_i) = c_i \text{ if } \Omega(c_i) \not\subset \mathcal{S};$$

3) $\Omega(s_j) = \{c_i\}$ iff $s_j \in \Omega(c_i)$.

Condition 1) implies that each member of \mathcal{S} can be matched to at most one member of \mathcal{C} , condition 2) implies that each member of \mathcal{C} can be matched to multiple members of \mathcal{S} , and condition 3) implies that if s_j is matched with c_i , then c_i is also matched with s_j .

To formally define a stable matching, let's first define a *blocking pair*. A matching Ω can be improved upon by a pair (s_j, c_i) if s_j and c_i are not matched at Ω but would both prefer if they are matched together, i.e. if $\Omega(s_j) \neq \{c_i\}$ and if $c_i \succ_{s_j} \Omega(s_j)$ and $s_j \in Ch_{c_i}(\Omega(c_i) \cup \{s_j\})$, where Ch_{c_i} denotes c_i 's most preferred subset given a set of students. In this case, (s_j, c_i) is called a *blocking pair*. Given the definition of blocking pair, the stable matching is defined as the following.

Definition 5. A matching Ω is stable if it cannot be improved upon by any individual player or any pair (s_j, c_i) .

Since the largest coalition it considers is a (s_j, c_i) pair, this is a definition of *pair-wise stability*. It has been proved in [RS92] that, the set of stable matchings is always nonempty for matching models without externalities. For matching games with externalities, *two-sided exchange stability* should be considered, which will be discussed in details in the rest of this report.

2.2.2.3 Many-to-many matching

If the number of allowable matches for the agents in both sides of the matching is unrestricted, it is a many-to-many matching problem.

Definition 6. In the many-to-many matching model, a matching Ω is a function from the set $\mathcal{A} \cup \mathcal{B}$ into the set of all subsets of $\mathcal{A} \cup \mathcal{B}$ such that 1) $|\Omega(a_n)| \leq q_a, \forall a_n \in \mathcal{A}$, and $\Omega(a_n) = \emptyset$ if a_n is not matched to any agent in \mathcal{B} ; 2) $|\Omega(b_m)| \leq q_b, \forall b_m \in \mathcal{B}$, and $\Omega(b_m) = \emptyset$ if b_m is not matched to any agent in \mathcal{A} ; 3) $a_n \in \Omega(b_m)$ iff $b_m \in \Omega(a_n)$,

where $q_a \in \mathbb{N}$ and $q_b \in \mathbb{N}$ denote quota of agents.

In many-to-many matching models, many stability concepts can be considered depending on the number of players who can improve their utility by matching to new partners. In this work, the many-to-many matching model with externalities is considered, and therefore the two-sided exchange stability is adopted to analyse the stability property of the proposed algorithm.

Currently, the research on matching theory used in D2D communications is limited and still in its infancy. The body of work in [GZPH15, HH15a] was based on the classical deferred acceptance algorithm, where externalities among players were not taken into consideration. In [Se15], a one-to-one matching model with externalities was discussed. The authors in [PBS⁺13] formulated a many-to-one matching problem with externalities. However, the complexity for analysing the stability of both the one-to-one and many-to-one matching game with externalities is much lower than that of the many-to-many one.

2.3 State-of-the-Art

2.3.1 Device-to-Device Communications

Since the system performance can be improved by effectively pairing cellular and D2D UEs for sharing same resources, radio resource allocation is a critical issue in D2D communications underlying cellular networks. Some traditional centralised methods have been developed to tackle this issue [ZHS10, PLW⁺09, FLYW⁺13, WZZY13]. In [ZHS10], a greedy heuristic RB allocation algorithm was proposed where any cellular UE with higher channel quality could share RBs with the D2D UE that had lower channel quality. In [PLW⁺09], the authors proposed two algorithms to allocate radio resources to D2D UEs. The two algorithms were based on interference mitigation between cellular and D2D UEs using interference tracing and tolerable interference broadcasting mecha-

nisms, respectively. In [FLYW⁺13], the authors proposed a resource allocation scheme consisting of three steps, that is, access admission, optimal power control and resource allocation, to find the optimal solution of the formulated problem. In [WZZY13], a resource allocation scheme for D2D communications underlying cellular networks was proposed, where interference suppression and QoS requirements were taken into consideration.

Motivated by practical factors such as the increasing density of wireless networks and the need for communications with low latency, effectively managing resource allocation in complex environment warrants a fundamental shift from traditional centralised mechanisms toward self-organising and self-optimising approaches. Indeed, there has been a recent surge in literature that proposes new mathematical tools for implementing distributed resource allocation in D2D communications, such as the game theory [WXSH15, YXF⁺14, ZJLZ14, ZCC⁺15, ZCC⁺16]. The authors in [WXSH15] proposed a two-level combinational auction game to jointly allocate channels to D2D UEs and power to both D2D and cellular UEs to improve energy efficiency. Simulation results showed that the proposed algorithm improved the system performance in terms of lifetime and data rate. In [YXF⁺14], the authors considered resource allocation problem for D2D communications and proposed a solution based on a coalitional game among D2D UEs, which aimed at minimising the total power while guaranteeing the UEs' rate requirements. In [ZJLZ14], a distributed coalition formation algorithm was proposed to improve the overall data rate of the D2D communication system. The merge-and-split rule was used as the basic principle for the coalition formation process. In [ZCC⁺15], a joint mode selection and resource allocation algorithm is proposed for D2D communications aiming at improving overall system sum rate. In [ZCC⁺16], the spectrum and power allocation problem is investigated in D2D-enabled relay networks.

Despite the potentials by applying game theory to deal with D2D resource allocation, such approaches present some shortcomings. First, classical game-theoretic algorithms such as best response will require some form of knowledge on other players actions, thus

limiting their distributed implementation. Second, most game-theoretic solutions, such as the Nash equilibrium, investigate one-sided (or unilateral) stability notions in which equilibrium deviations are evaluated unilaterally per player. Such unilateral deviations may not be practical when investigating assignment problems between distinct sets of players. Last, but not least, the tractability of equilibria in game-theoretic methods requires having some structure in the objective functions which for practical wireless metrics may not always be satisfied. Recently, matching theory [GZPH15, HH15a, Se15, PBS⁺13] has been in the spotlight for wireless resource allocation, which can overcome some of the limitations of the game theory. The body of work in [GZPH15, HH15a] was based on the classical deferred acceptance algorithm, where externalities among players were not taken into consideration. In [Se15], a one-to-one matching model with externalities was discussed. The authors in [PBS⁺13] formulated a many-to-one matching problem with externalities. However, the complexity for analysing the stability of both the one-to-one and many-to-one matching game with externalities is much lower than that of the many-to-many one. However, the work for applying matching theory to solve resource allocation problems in D2D communications is still in its infancy. As such, this thesis presents detailed work in proposing efficient matching algorithms to provide performance enhancement in D2D communications in this report.

2.3.2 Non-Orthogonal Multiple Access

NOMA, as a promising candidate in the 5G networks for tackling the massive connectivity and high data speed challenges [DLC⁺16], has recently received a great deal of attentions. Having been included in 3GPP long term evolution (LTE) [DLC⁺16], NOMA is regarded as one of the promising candidates in future 5G networks for its potential ability to significantly improve the spectral efficiency [DWY⁺15, SBKN13]. Different from the conventional orthogonal multiple access (OMA) technique, NOMA is capable of supporting multiple users to share the same resource (e.g., time/frequency/code) with using different power level. In order to better illustrate the concept of NOMA, NOMA

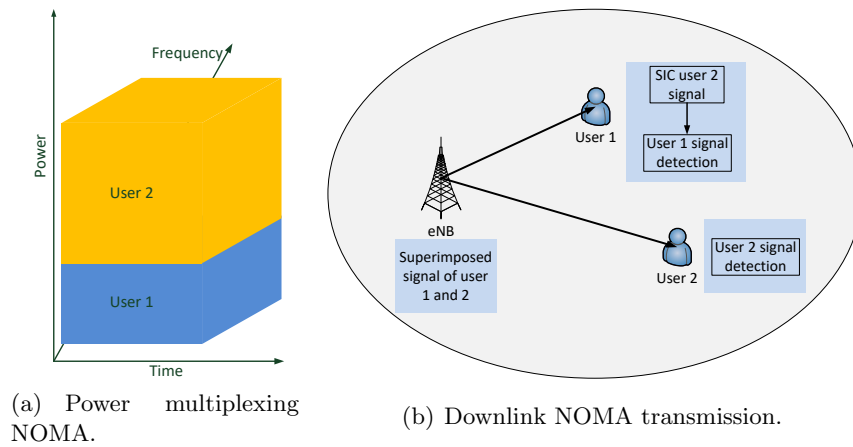


Figure 2.4: NOMA transmission.

downlink transmission with two users is taken as an example. As shown in Figure 2.4, the two users can be served by the base station (BS) at the same time/code/frequency, but with different power levels. Specifically the BS will send a superimposed mixture containing two messages for the two users, respectively. Recall that conventional power allocation strategies, such as water filling strategies, allocate more power to users with strong channel conditions. Unlike these conventional schemes, in NOMA, users with poor channel conditions get more transmission power. In particular, the message to the user with the weaker channel condition is allocated more transmission power, which ensures that this user can detect its message directly by treating the other users information as noise. On the other hand, the user with the stronger channel condition needs to first detect the message for its partner, then subtract this message from its observation and finally decode its own information. This procedure is called successive interference cancellation (SIC) (as shown in Figure 2.4). For example, a transmitter transmits contents to three receivers requiring video, audio and text messages, respectively. If the video and audio users are with good channel conditions, they can perform SIC for two or three times to remove their partners' messages completely and therefore achieve high data rates. For text users, although they will experience strong co-channel interference, this is not an issue since they need to be served only with small data rates.

Several initial technical research contributions have been made in deploying NOMA in

the power domain [DYFP14, TK15, LDEP16, Cho15]. In [DYFP14], a general downlink NOMA transmission scenario was considered in which one BS was capable of communicating with M randomly deployed users. In [TK15], the fairness issue of NOMA networks was addressed with knowing different channel state information (CSI) at the BS. Considering the energy consumption issues, a new cooperative NOMA with invoking wireless power transfer protocol was proposed in [LDEP16]. Stochastic geometry was employed to model the locations of users and evaluated the performance of networks. In terms of multiple-antenna scenarios, a two-stage beamforming approach was proposed for a multiple-input single-output (MISO) NOMA case in [Cho15], in order to minimise the system transmit power.

It is worth mentioning that due to the employment of superposition coding transmission scheme, the power allocation is an eternal problem to be investigated in NOMA, especially in multiple subchannels/subcarriers/clusters scenarios. Somewhat related power allocation and subchannel/subcarrier/cluster assignment problems have been studied in the context of NOMA [DBSL15, LYHS16, SNDS16, LEDK16]. It is worth mentioning that due to the employment of superposition coding transmission scheme, the resource allocation is an eternal problem to be investigated in NOMA, especially in multiple subchannels/subcarriers/clusters scenarios. More particularly, in [DBSL15] a many-to-many two-sided matching theory was invoked to solve resource allocation in downlink multiple subchannels NOMA scenarios, where the objective is to maximise the system sum rate. In [LYHS16], with formulating NOMA resource allocation problems under several practical constraints, the traceability of the formulated problem was analytically characterised. Moreover, a Lagrangian duality and dynamic programming combining algorithm was also proposed to solve the formulated problems. Regarding the multiple carrier NOMA resource allocation problem for the full-duplex NOMA communication scenarios, the monotonic optimisation approach was employed in [SNDS16] for investigating an optimal solution for the formulated problem. Regarding resource allocation in cluster based multiple-input MIMO NOMA scenarios, the absolute fairness

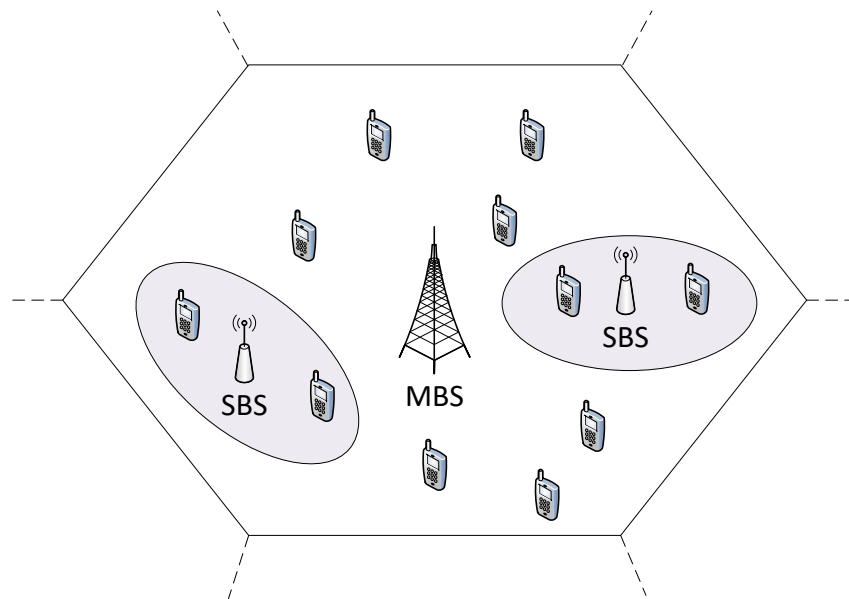


Figure 2.5: Two-tier heterogeneous networks.

issue was addressed in [LEDK16], with using the bi-section search approach for power allocation and three efficient heuristic algorithms for cluster scheduling.

2.3.3 Heterogeneous Networks

To meet the surging traffic demands for wireless services and the need for high data rates, cellular networks are trending strongly towards heterogeneity of cells with different transmit power, coverage range and cost of deployment [DGBA12, Lag97, YRC⁺13]. HetNets is capable of achieving more spectrum-efficient communications by deploying small cells, i.e., picocells and femtocells, underlaid on the macrocells, as shown in Figure 2.5. Since the spectrum sharing among multi-tier cells causes both co-tier and cross-tier interference, efficient resource allocation and interference management become the fundamental research challenges for HetNets. In [FR13], a unified static framework was employed to study the interplay of user association and resource allocation in heterogeneous cellular networks. A novel solution that jointly associated the users to the access points (APs), and allocated the femtocell access points (FAPs) to the service providers (SPs)

in an uplink OFDMA network was studied in [BLH⁺14], with the aim of maximising the total satisfaction of users. Considering the D2D-enabled multi-tier scenario, a polynomial time-complexity distributed solution approach for the heterogeneous cellular mobile communication systems was presented in [HH15a].

2.4 Summary

This chapter provides an overview of the architecture of D2D communications and matching theory. The existing research outcomes on resource allocation in D2D communications are surveyed and categorised with respect to different approaches: centralised approach, game theory-based approach and matching theory-based approach. Since the current literature on resource allocation to D2D communications based on matching theory is still in its infancy, more research on matching theory-based resource allocation design should be dedicated to develop self-organising algorithms and theoretically analyse the merits of these algorithms. To make my own contribution to fill the above gap, resource allocation for D2D communications based on matching theory is investigated in Chapter 3.

While the cutting-edge architectures and technologies such as NOMA and HetNets have been extensively solely studied in the existing literatures, their co-effects on enhancing network performance with D2D communications have not been quantified and analysed in a relatively practical scenario. Moreover, performance loss caused by the strong inter-tier interference needs to be well managed. As such, quantifying and addressing the co-effects of these highlighted technologies is also waited to be explored. In the sequel, more research endeavours should be dedicated in this field, and provide more insights on how NOMA and HetNets are capable of enhancing D2D communications underlying cellular networks. To cope with this, resource allocation for D2D communications with NOMA and HetNets are investigated in Chapter 4 and Chapter 5, respectively.

Chapter 3

Matching-Based Resource Allocation in D2D Communications

3.1 Overview

This chapter focuses on conventional D2D scheme, where each D2D transmitter communicates with one receiver in pair. As mentioned in Chapter 2, it is imperative to support spectrum efficiency and QoS in the resource allocation design, as well as address the challenging issues imposed by the inherent nature of D2D communications. The challenging issues include the co-channel interference caused by spectrum sharing between D2D and cellular users. As such, this chapter formulates resource allocation optimisation as a matching problem which considers sum rate and QoS, and also pitches in to resolve the context awareness issue in D2D communications. Specifically, in Section 3.2, the general system model in this chapter is introduced. Then, a many-to-many matching algorithm is proposed for improving resource utilisation in Section 3.3, where the SINR constraints for both D2D and cellular UEs are satisfied. Additionally, in order to meet priorities of applications in different hardware devices as well as QoS requirements of different applications, a novel context-aware matching algorithm is proposed to enhance QoS provision in Section 3.4.

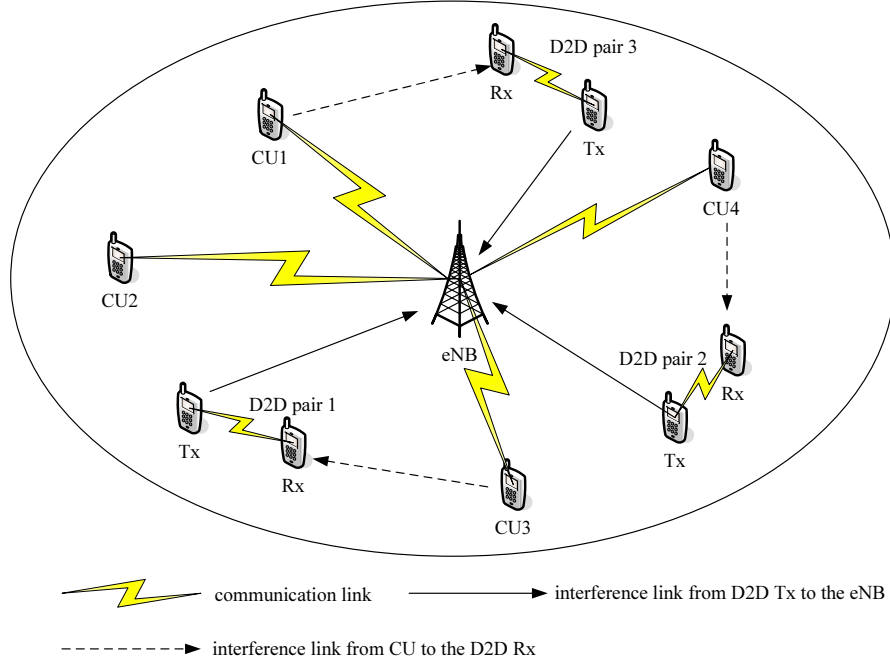


Figure 3.1: D2D communications underlaying cellular networks.

3.2 System Model

A scenario of sharing uplink resources of the cellular network is considered in this section. Both the eNB and UEs are equipped with a single omni-directional antenna. The eNB maintains the radio resource control for both cellular and D2D communications. The cellular UEs and D2D transmitters are distributed uniformly in the cell, while each D2D receiver obeys a uniform distribution inside the circle centered at the corresponding D2D transmitter, with a radius d_{max} . The set of D2D pairs is denoted by $\mathcal{D} = \{D_1, \dots, D_n, \dots, D_N\}$, and the set of D2D transmitters and receivers are denoted by $\{DT_1, \dots, DT_n, \dots, DT_N\}$ and $\{DR_1, \dots, DR_n, \dots, DR_N\}$, respectively. $\mathcal{RB} = \{RB_1, \dots, RB_m, \dots, RB_M\}$ is the set of RBs. For the sake of simplicity, the same index is used for cellular UEs with RBs, i.e., the set of cellular UEs is denoted by $\mathcal{C} = \{C_1, \dots, C_m, \dots, C_M\}$. The channel is modeled as Rayleigh fading where the channel response follows the independent complex Gaussian distribution¹. Hence, the channel gain can be expressed as $G = \beta L^{-\eta} |h|^2$, where β is the system constant, L is the dis-

¹Considering correlated coefficients in adjacent RBs is beyond of the scope of this work.

tance between signal transmitter and receiver, η is the path-loss exponent, and h is the complex Gaussian channel coefficient that obeys $h \sim \mathcal{CN}(0, 1)$. The system model is shown in Figure 3.1.

3.3 Matching with Peer Effects for Resource Allocation in D2D Communications

3.3.1 Motivation

As stated in Chapter 2, matching theory has been in the spotlight for wireless resource allocation, which can overcome some of the limitations of game theory. The body of work in [GZPH15, HH15a] was based on the classical deferred acceptance algorithm, where peer effects among players were not taken into consideration. In [Se15], a one-to-one matching model with peer effects was discussed. The authors in [PBS⁺13] formulated a many-to-one matching problem with peer effects. However, the complexity for analysing the stability of both the one-to-one and many-to-one matching game with peer effects is much lower than that of the many-to-many one. Different from the prior work, a novel resource allocation approach based on the many-to-many matching game with peer effects is proposed in this section. By doing so, the resource utilisation can be improved and the mutual interference among D2D pairs matched to the same RB can be well handled.

The main contributions of this section are summarised as follows.

1. The system sum rate maximisation problem is formulated, which takes account of the SINR constraints for both D2D and cellular UEs.
2. The formulated problem is modeled as a many-to-many matching game with peer effects, and a novel algorithm of resource allocation for D2D communications is proposed to obtain a stable matching between the D2D pairs and RBs.

3. It is proved that the proposed algorithm converges to a stable state within limited number of iterations.
4. Simulation results show that the proposed algorithm can achieve the near-optimal performance compared to the exhaustive search, which significantly outperforms a one-to-one matching algorithm.

3.3.2 Problem Formulation

It is assumed that multiple D2D pairs can share the same RB and one D2D pair can occupy multiple RBs. The element λ_{mn} is used to indicate whether a RB is allocated to a D2D pair or not. More specifically, if RB_m is allocated to D_n , $\lambda_{mn} = 1$; otherwise, $\lambda_{mn} = 0$. It is assumed that the total transmit power of each D2D transmitter is a fixed value and the power is equally divided over the occupying RBs. The power allocated to the D2D pair D_n over RB RB_m is denoted by p_m^n , satisfying $p_m^n = \frac{P_n}{\sum_{m=1}^M \lambda_{mn}}$, where P_n is the total transmit power of DT_n . Suppose that RB_m is allocated to D_n , then the received signal-to-noise-plus-interference-ratio (SINR) at DR_n on RB_m is expressed as

$$\gamma_m^n = \frac{p_m^n G_n}{Q_m G_{mn} + \sum_{m' \neq m} \alpha_{m'n} p_{m'}^n G_{m'n} + \sigma^2}, \quad (3.1)$$

where Q_m is the transmit power of C_m . G_m , G_{mn} , $G_{n'n}$ are the channel gains between DT_n and DR_n , that between C_m and DR_n , and that between $DT_{n'}$ and DR_n , respectively. σ^2 is the additive white Gaussian noise power. Similarly, the received SINR at the eNB is given by

$$\gamma_n = \frac{Q_m G_{nB}}{\sum_i \lambda_{mn} p_m^n G_{mB} + \sigma^2}, \quad (3.2)$$

where G_{mB} and G_{nB} are the channel gain between C_m and the eNB, and that between DT_n and the eNB, respectively. Based on the Shannon-Hartley theorem, the data rates of D_n on RB_m and that of C_m are $R_m^n = \lambda_{mn} B \log_2(1 + \gamma_m^n)$ and $R_m = B \log_2(1 + \gamma_n)$, respectively, where B is the bandwidth of a RB.

The objective is to maximise the system sum rate with SINR constraints for both D2D and cellular UEs, which can be expressed as

$$\max_{\lambda_{mn}} \sum_n \sum_m (R_n^n + R_m), \quad (3.3a)$$

$$s.t. \quad \lambda_{mn} \gamma_m^n \geq \lambda_{mn} \gamma_n^{min}, \quad \forall m, n, \quad (3.3b)$$

$$\gamma_m \geq \gamma_m^{min}, \quad \forall n, \quad (3.3c)$$

$$\alpha_{m,n} \in \{0, 1\}, \quad \forall m \in \{1, \dots, M\}, \forall n, \quad (3.3d)$$

$$\sum_m \alpha_{m,n} \leq q_{max}, \quad \forall n, \quad (3.3e)$$

where γ_n^{min} and γ_m^{min} are the minimum SINR targets for D_n and C_m , respectively. (3.3b) and (3.3c) restrict the SINR requirements of D2D and cellular UEs. (3.3d) shows that the value of $\lambda_{m,n}$ should be either 0 or 1. In (3.3e), it is shown that at most q_{max} D2D pairs can be allocated to each RB. This constraint is to restrict the interference on each RB, as well as reduce the implementation complexity.

Note that the formulated problem is a non-convex one due to the binary constraints as well as the existence of the interference term in the objective function [WN99]. Therefore, it may be too complex to solve this problem by utilising the conventional centralized exhaustive method, especially in a dense network. However, since problem (3.3) contains only one binary variable, it can be modeled as a matching problem. Thus to optimally solve the optimisation problem (3.3), a many-to-many matching algorithm is developed in the next section.

3.3.3 Resource Allocation for D2D Communications

3.3.3.1 Many-to-Many Matching with Peer Effects

The many-to-many matching model between D2D pairs and RBs is defined as the following:

Definition 7. *In the many-to-many matching model, a matching Ω is a function from the set $\mathcal{RB} \cup \mathcal{D}$ into the set of all subsets of $\mathcal{RB} \cup \mathcal{D}$ such that 1) $|\Omega(D_n)| \leq N, \forall D_n \in \mathcal{D}$, and $\Omega(D_n) = \emptyset$ if D_n is not matched to any RB; 2) $|\Omega(RB_m)| \leq q_{max}, \forall RB_m \in \mathcal{RB}$, and $\Omega(RB_m) = \emptyset$ if RB_m is not matched to any D2D pair; 3) $RB_m \in \Omega(D_n)$ iff $D_n \in \Omega(RB_m)$.*

The preference value for D2D pair D_n on RB_m is defined as $U_m(n) = R_m^n$. It is easy to find that $U_m(n)$ is a function of the interference from the D2D and cellular UEs occupying the same RB. Therefore, the following observation can be made:

Remark 1. *The proposed matching game has peer effects, where the preference values of D2D pairs not only depend on the RBs that they are matched with, but also on the other D2D pairs matched to the same RB.*

This type of matching is called the matching game with peer effects, where each player has a dynamic preference list over the opposite set of players. This is different from the conventional matching games in which players have fixed preference lists [GZPH15, HH15a, RS92]. In this matching model, the preference of players over the opposite set of players relies on the matching states. Therefore, a preference list over the set of matching states is adopted. For example, the preference list of the D2D pair D_n on all the possible matching states is with respect to the descending order for the value of $U_m(n, \Omega)$, where $U_m(n, \Omega)$ is the utility of the D2D pair D_n on the RB RB_m under the matching state Ω .

The preference value of RB_m on the set of D2D pairs \mathcal{S} under the matching state Ω is defined as the sum rate of both the occupying D2D pairs as well as the corresponding

cellular UE, i.e., $U_m(\mathcal{S}, \Omega) = R_m + \sum_{n \in \mathcal{S}} R_m^n$. As with the preference lists of the D2D pairs, the preference list of RB_m is ranked by RB_m 's preference values in descending order.

Motivated by the housing assignment problem in [BBLC⁺11], an extended matching algorithm is proposed for solving the many-to-many matching problem with peer effects. Different from the traditional deferred acceptance algorithm solution [RS92], the *swap operations* between any two D2D pairs to exchange their matched RBs is enabled. To better describe the interdependencies between the players' preferences, the concept of *swap matching* is first defined as follows:

$$\begin{aligned} \Omega_{nm}^{n'm'} = & \{\Omega \setminus \{(n, \Omega(n)), (n', \Omega(n'))\}\} \cup \\ & \{(n, \{\{\Omega(n) \setminus \{m\}\} \cup \{m'\})\}), (n', \{\{\Omega(n') \setminus \{m'\}\} \cup \{m\})\}), \end{aligned} \quad (3.4)$$

where $m \in \Omega(n)$, $m' \in \Omega(n')$, $m \notin \Omega(n')$, and $m' \notin \Omega(n)$. In other words, a swap matching enables D2D pair D_n and $D_{n'}$ to switch one of their matched RBs while keeping other D2D pairs and RBs' matchings unchanged. It is worth noticing that one of the D2D pairs involved in the swap can be a "hole" representing an open spot of a RB, thus allowing for a single D2D pair moving to available vacancies. Similarly, one of the RBs RB_m involved in the swap can be a "hole" if $\Omega(m) = \emptyset$. Based on the concept of *swap matching*, the *swap-blocking* pair is defined as

Definition 8. $(D_n, D_{n'})$ is a *swap-blocking* pair if and only if

- 1) $\forall x \in \{m, m', n, n'\}, U_x(\Omega_{nm}^{n'm'}) \geq U_x(\Omega)$, and
- 2) $\exists x \in \{m, m', n, n'\}$, such that $U_x(\Omega_{nm}^{n'm'}) > U_x(\Omega)$.

The swap operations are expected to take place between the *swap-blocking* pairs. That is, if two D2D pairs want to switch between two RBs, the RBs involved must "approve" the swap. Condition 1) implies that the utilities of all the involved players should not be reduced after the swap operation between the *swap-blocking* pair $(D_n, D_{n'})$. Condition 2)

indicates that at least one of the players' utilities is increased after the swap operation between the *swap-blocking* pair. This avoids looping between equivalent matchings where the utilities of all involved agents are indifferent. Note that the utilities of the “holes” and the players in the opposite set matched with the “holes” are not considered in these two conditions. Through multiple swap operations, the dynamic preferences of players which depend on the entire matching of the others, and the peer effects of matchings are well handled.

As stated in [RS92], there is no longer a guarantee that a traditional “pairwise-stability” exists when players care about more than their own matching, and, if a stable matching does exist, it can be computationally difficult to find. The authors in [BBLC⁺11] focused on the *two-sided exchange-stable matchings*, which is defined as follows:

Definition 9. *A matching Ω is two-sided exchange-stable if there does not exist a swap-blocking pair.*

The *two-sided exchange stability* is a distinct notion of stability compared to the traditional notion of stability of [RS92], but one that is relevant to the situation where agents can compare notes with each other.

3.3.3.2 Proposed Resource Allocation Algorithm

The proposed matching algorithm, i.e., resource allocation for D2D communications using matching theory (RADMT), is shown in Table 3-A. The algorithm consists of three main steps: Step 1 sets up the initial matching state; Step 2 focuses on the swap-matching process between different D2D pairs; and Step 3 outputs the final matching state. Initially, D2D pairs and RBs randomly match with each other satisfying constraints (3.3b) - (3.3e), and each D2D pair performs equal power allocation on its matched RBs. Subsequently, each D2D pair keeps searching for all the other D2D pairs and the available vacancies of RBs to check whether there is a swap-blocking pair. The swap-matching

process ends when there exists no swap-blocking pair, and the final matching is obtained.

Table 3-A: Resource Allocation for D2D Communications Using Matching Theory (RADMT)

Step 1: Initialisation

1. D2D pairs and RBs are randomly matched with each other subject to constraints (3.3b) - (3.3e).
2. Each D2D pair equally divides its transmit power on the matched RBs.

Step 2: Swap-matching process

1. For each D2D pair D_n , it searches for another D2D pair $D_{n'}$ or an open spot \mathcal{O} of RB's available vacancies to form a swap-blocking pair.
 - (a) If $(D_n, D_{n'})$ or (D_n, \mathcal{O}) forms a swap-blocking pair along with $m \in \Omega(n)$, and $m' \in \Omega(n')$,
 - i. update the current matching state to $\Omega_{nm}^{n'm'}$.
 - ii. update the number of D2D pairs matched with each RB.
 - (b) Else if there does not exist such a swap-blocking pair,
 - i. keep the current matching state.
2. Repeat **Step 2** until there is no swap-blocking pair in the current matching.

Step 3: End of the algorithm.

To evaluate the proposed algorithm, the properties in terms of effectiveness, stability, convergence, complexity and overhead are analysed in the following.

Lemma 1. *The system sum rate increases after each swap operation.*

Proof. Suppose a swap operation makes the matching state change from Ω to $\Omega_{nm}^{n'm'}$. According to RADMT, a swap operation occurs only when $U_n(\Omega_{nm}^{n'm'}) \geq U_n(\Omega)$ as well as $U_{n'}(\Omega_{nm}^{n'm'}) \geq U_{n'}(\Omega)$. Given that $U_n(\Omega(n), \Omega) = R_n(\Omega(n), \Omega) + \sum_{m \in \Omega(n)} R_m(n, \Omega)$, the following inequality holds:

$$\begin{aligned}
 \Phi_{\Omega \rightarrow \Omega_{nm}^{n'm'}} &= R_{sum}(\Omega_{nm}^{n'm'}) - R_{sum}(\Omega) \\
 &= \sum_n \left(R_n(\Omega_m^{m'n'}(mn), \Omega_{nm}^{n'm'}) + \sum_{m \in \Omega_{nm}^{n'm'}(n)} R_m(n, \Omega_{nm}^{n'm'}) \right) \\
 &\quad - \sum_n \left(R_n(\Omega(n), \Omega) + \sum_{m \in \Omega(n)} R_m(n, \Omega) \right) > 0,
 \end{aligned} \tag{3.5}$$

where $\Phi_{\Omega \rightarrow \Omega_{nm}^{n'm'}}$ is the difference of the system sum rates under the matching state $\Omega_{nm}^{n'm'}$ and that under the matching state Ω . \square

Theorem 1. *If the proposed algorithm converges to a matching Ω^* , then Ω^* is a two-sided exchange-stable matching.*

Proof. Assume that there exists a swap-blocking pair $(D_n, D_{n'})$ in the final matching Ω^* satisfying that $\forall x \in \{m, m', n, n'\}, U_x(\Omega_{nm}^{n'm'}) \geq U_x(\Omega^*)$ and $\exists x \in \{m, m', n, n'\}$, such that $U_x(\Omega_{nm}^{n'm'}) > U_x(\Omega^*)$. According to Table 3-A, the algorithm does not terminate until all the swap-blocking pairs are eliminated. To this end, Ω^* is not the final matching, which causes conflict. Therefore, it is concluded that the proposed algorithm can reach the two-sided exchange stability in the end of the algorithm. \square

Theorem 2. *The proposed algorithm converges within limited number of iterations.*

Proof. From (3.5), it is observed that the system sum rate increases after each successful swap operation. Since the system sum rate has an upper bound due to limited spectrum resources, the swap operations stop when the system sum rate is saturated. Therefore, within limited number of rounds, the matching process converges to the final state which is stable. \square

Theorem 3. *The number of communication packets between the D2D pairs and the RBs required in RADMT is upper bounded by $\mathcal{N}_{max} = \binom{N}{2} + M \times N$.*

Proof. Following the RADMT in Table I, the D2D pairs and RBs communicate with each other in the swap-matching process to find the potential *swap-blocking* pairs. The number of communication packets of the potential swap operations between any two D2D pairs is $\binom{N}{2}$. Furthermore, the D2D pairs also search for the open spots of RBs' available vacancies to form *swap-blocking* pairs, and the maximum number of communication packets for this process is $M \times N$. \square

Regarding the time scale of the proposed algorithm, the signaling packet length

required for the communication between the D2D pairs and the RBs until the algorithm converges is very short. In particular, each D2D pair is only required to send one bit to another D2D pair indicating a swap-operation offer, and then the involved D2D pairs each send a one-bit request to their occupying RBs. Finally, the RBs only need to send one bit back to the offering D2D pairs indicating either accept or reject the request. The total amount of overhead from the proposed algorithm thus can be quite small.

It can be observed that the complexity of the exhaustive searching method increases exponentially with the number of D2D pairs and RBs. In contrast, the complexity of the proposed algorithm is $\mathcal{O}(M * N)$, which is significantly lower than that of the exhaustive searching method.

Table 3-B: Simulation Parameters

Cellular radius	300 m
D2D pair radius	50 m
RB bandwidth	180 kHz
Cellular UEs' SINR threshold	4 dB
D2D UEs' SINR threshold	2 dB
Noise power	-98 dBm
D2D transmission power	24 dBm

3.3.4 Numerical Results

In this section, numerical results are provided to demonstrate the performance of the proposed algorithm. The exhaustive optimal search and one-to-one matching algorithm are also plotted as benchmarks. Specifically, the exhaustive search guarantees the global optimal result and the one-to-one matching algorithm enables the one-to-one allocation of RBs to D2D pairs. The parameter settings in the simulation are shown in Table 3-B.

Figure 3.2 plots the system sum rate versus different numbers of D2D pairs. One can observe that the sum rate increases with the number of D2D pairs. When the number of D2D pairs is large enough, the sum rate keeps increasing due to the multi-user diversity gain, but with a lower speed. It is also observed that the proposed algorithm improves

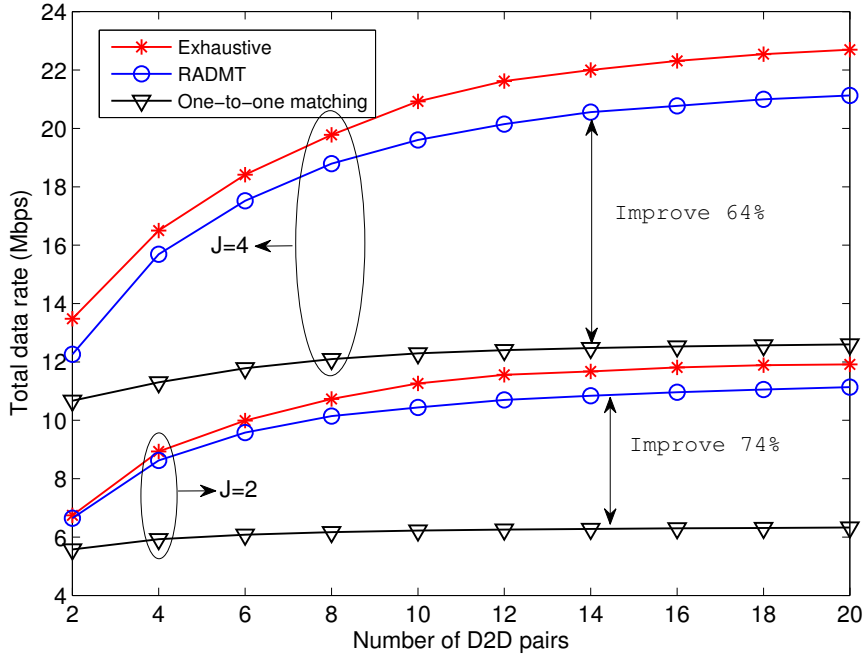


Figure 3.2: System sum rate versus different number of D2D pairs.

the sum rate by around 74% compared to the one-to-one matching algorithm in the case of number of RBs $N = 2$, and 64% in the case of $N = 4$. Meanwhile, the proposed algorithm can reach 91.3% of the exhaustive optimal result, unequivocally substantiating the plausibility of the proposed algorithm.

Figure 3.3 plots the number of accessed D2D pairs versus different numbers of D2D pairs in the network. With the increase of number of D2D pairs, the largest number of accessed D2D pairs is N in the one-to-one matching algorithm. This is because each RB can be allocated to no more than one D2D pair. The number of accessed D2D pairs of the proposed algorithm is improved by around 110% compared to that of the one-to-one matching algorithm in the case of $N = 2$, and 60% in the case of $N = 4$.

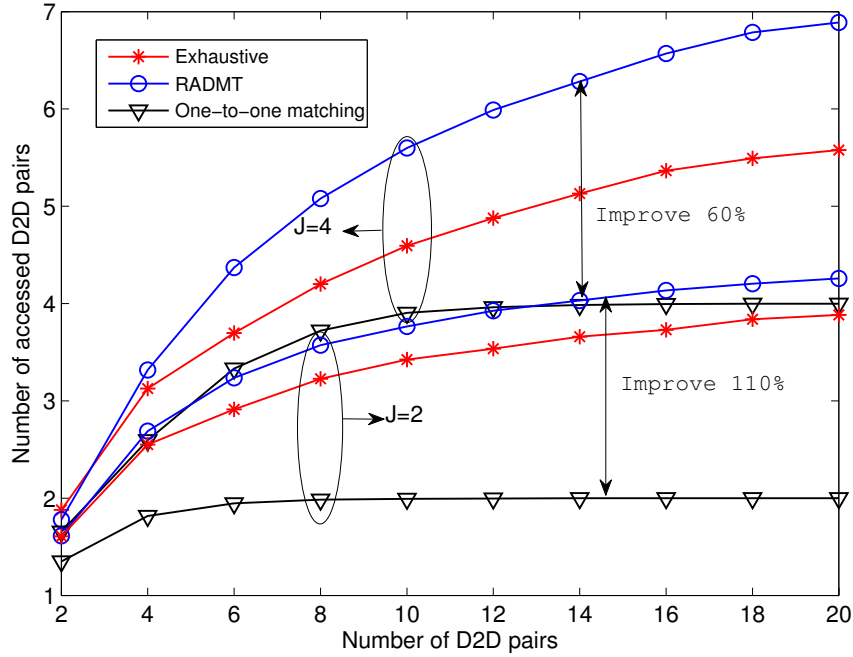


Figure 3.3: Number of accessed D2D pairs versus different number of D2D pairs.

3.4 Matching with Peer Effects for Context-Aware Resource Allocation in D2D Communications

3.4.1 Motivation

This section investigates the context-aware resource allocation for D2D communications accounting for the QoS requirements and priorities of different applications based on users' requests. A context-aware optimisation problem is formulated and the matching theory is implemented to solve the problem. A novel algorithm with peer effects is proposed, where the action of each D2D pair is affected by the decisions of its peers. This is in contrast to most existing works on matching theory for wireless networks [MHW15, Se15]. In [MHW15], peer effects were not taken into consideration because of the difficulty to analyse the stability. In [Se15], a one-to-one matching model with peer effects was discussed, for which the complexity for analysing stability is much lower than the many-to-one matching. It is analytically proved that the algorithm converges

to a two-sided exchange stability within limited number of swap operations. It is also demonstrated that the proposed algorithm significantly outperforms the context-unaware resource allocation algorithm by around 62.2%.

The main contributions of this section are summarised in the following.

1. A novel context-aware RB allocation problem is formulated for D2D communications, where different priorities of applications with respect to UEs' requests are taken into consideration.
2. To solve the formulated problem, a novel algorithm based on the many-to-one matching is proposed, which is shown to allow the D2D pairs and RBs to interact and converge to a stable matching with manageable complexity.
3. Simulation results demonstrate that the proposed algorithm outperforms the traditional Gale-Shapley (GS) algorithm, the one-to-one matching algorithm as well as the context-unaware algorithm.

3.4.2 Problem Formulation

It is assumed that multiple D2D pairs can share the same RB, while each D2D pair can use no more than one RB for transmission. The received signal-to-noise-plus-interference-ratio (SINR) at the receiver of D_n on RB_m is given by

$$\gamma_m^n = \frac{P_n G_n}{P_n G_{mn} + \sum_{m' \neq m} \alpha_{m'n} P_{m'} G_{n'n} + \sigma^2}, \quad (3.6)$$

where P_n and P_m are the transmission power of the transmitter of D_n and C_m , respectively. G_n , G_{mn} , $G_{n'n}$ are the channel gains between the transmitter and receiver of D_n , that between C_m and the receiver of D_n , and that between the transmitter of $D_{n'}$ and the receiver of D_n , respectively. σ^2 is the additive white Gaussian noise power. λ_{mn} indicates a RB is allocated to a D2D pair or not. If RB_m is allocated to D_n , $\lambda_{mn} = 1$;

otherwise, $\lambda_{mn} = 0$. Similarly, the received SINR at the eNB on RB_m is given by

$$\gamma_m = \frac{P_m G_{mB}}{\sum_n \lambda_{mn} P_n G_{nB} + \sigma^2}, \quad (3.7)$$

where G_{mB} and G_{nB} are the channel gains between C_m and the eNB, and that between the transmitter of D_n and the eNB, respectively. Based on the Shannon-Hartley theorem, the data rate of D_n on RB_m is $R_m^n = \lambda_{mn} B \log_2(1 + \gamma_m^n)$, and the data rate of C_m is $R_m = B \log_2(1 + \gamma_m)$. Here, B is the bandwidth of a RB.

The probability of packet error during the transmission between the transmitter and receiver of a D2D pair can be expressed as a function of the SINR. For uncoded quadrature amplitude modulation (QAM), this PER is given by [PBS⁺13]

$$PER_n(\gamma_m^n) = \begin{cases} a_n \exp(-b_n \gamma_m^n), & \text{if } \gamma_m^n \geq \gamma_n^{thr}; \\ 1, & \text{otherwise,} \end{cases} \quad (3.8)$$

where a_n, b_n are packet-size dependent constants and γ_n^{thr} is the minimum SINR threshold which guarantees the correct demodulation. For ease of analysis, the retransmission of the packets which are erroneously received is not taken into consideration.

The UEs' *context* in terms of priorities of their requests for different active applications is considered. On the one hand, the priorities of applications vary with respect to different UEs. On the other hand, for different active applications, the minimum QoS requirements, including data rate, PER, and delay, which guarantees the successful transmission are different. To this end, three types of UEs are considered, i.e., UE1, UE2, and UE3; and four types of applications, i.e., HD video streaming, multi-user gaming, audio streaming, and file transmission. It is assumed that the set of active applications of D2D pair D_n is $\mathcal{K}_n = \{1, \dots, K_n\}$, where the applications are ordered in descending order with respect to their priorities. For example, for UE1, the HD video streaming is with the highest priority, followed by the file transmission which is the background

application. For UE2, the audio streaming is the main application and given the highest priority to transmit, but HD video streaming is with lower priority.

Inspired by the proposed context model, where the priorities of applications with respect to D2D UEs' requests are different, D2D pair D_n is able to discriminate the traffic stream of each application. Then, D_n gives each traffic stream of the application k the k -th priority to transmit. It is assumed that the aggregated traffic of D_n is composed by packets of constant size generated using a Poisson arrival process with an average arrival rate of κ_n , where the arrival rate of each application is $\kappa_{n,k}$, and $\sum_{k=1}^{K_n} \kappa_{n,k} = \lambda_n$. It is assumed that the channel conditions are constant during the scheduling procedure, and thus the traffic at each D2D link is modeled as a priority-based M/D/1 queueing system, where the traffic requests are serviced according to the context dependent priorities. Thus, the average delay for the x -th priority stream of D2D pair D_n is given by

$$d_{m,x} = \frac{\sum_{k=1}^{K_n} \kappa_{n,k} \overline{T}_m^2}{2(1 - \sum_{k=1}^{x-1} \rho_{m,k})(1 - \sum_{k=1}^x \rho_{m,k})} + \frac{1}{R_m}, \quad (3.9)$$

where $\rho_{m,k} = \kappa_{n,k}/R_m$ is the utilization factor for the k -th stream of D2D link D_n and \overline{T}_m^2 is the second moment of service time. It can be seen from (3.9) that the knowledge of context information enables D2D links to better prioritise application requests.

To capture characteristics of different applications and their priorities, the optimisation problem is given as follows:

$$\max_{\lambda_{mn}} \sum_n U_n(m), \quad (3.10a)$$

$$s.t. \quad R_n \geq \max_{k \in \mathcal{K}_n} R_k^{thr}, \quad \forall m, \quad (3.10b)$$

$$d_{n,k} \leq d_k^{thr}, \quad \forall k, m, \quad (3.10c)$$

$$PER_n \leq \min_{k \in \mathcal{K}_n} PER_k^{thr}, \quad \forall m, \quad (3.10d)$$

$$\gamma_m \geq \gamma_m^{min}, \quad \forall m, \quad (3.10e)$$

$$\alpha_{mn} \in \{0, 1\}, \quad \forall m, n, \quad (3.10f)$$

$$\sum_n \alpha_{mn} \leq q_{max}, \quad \forall m, \quad (3.10g)$$

where $U_n(m)$ is the utility function which is defined as

$$U_n(m) = \frac{R_n(1 - PER_n)}{\sum_{k=1}^{K_n} d_{n,k}}. \quad (3.11)$$

This utility function captures the data rate and PER of D2D pair n given the achievable SINR γ_m^n on RB m . Moreover, the utility also properly accounts for the priorities of applications through the delay term $d_{n,k}$. R_k^{thr} , d_k^{thr} , and PER_k^{thr} are the minimum QoS requirements for the k -th application in terms of data rate, delay, and PER, respectively. (3.10b), (3.10c) and (3.10d) restrict these requirements. (3.10e) gives the SINR constraints of cellular UEs. (3.10f) shows that the value of λ_{mn} should be either 0 or 1. (3.10g) means at most q_{max} D2D pairs can be allocated to each RB. This constraint is to restrict the interference on each RB, as well as reduce the implementation complexity.

The formulated problem here is a 0-1 integer program, which is one of Karp's 21 NP-complete problem [Kar72]. Thus it is difficult to solve this problem via classical optimisation approaches. Moreover, for a large-scale cellular network with D2D communications, it is desirable to develop a decentralized, self-organizing approach to make resource allocation decisions based on the local context information. Therefore, the many-to-one two-sided matching is invoked for obtaining a suboptimal solution in the next subsection.

3.4.3 Context-Aware Resource Allocation for D2D Communications

The matching problem formulated here is the many-to-one two sided matching between D2D pairs and RBs. The set of D2D pairs and RBs can be regarded as two opposite groups of selfish and rational players who try to enhance their own benefits during the matching process. To proceed with proposing the resource allocation algorithm, some

notations and basic definitions are first introduced for the matching model.

Definition 10. *In the many-to-one matching model, a matching Ω is a function from the set $\mathcal{RB} \cup \mathcal{D}$ into the set of all subsets of $\mathcal{RB} \cup \mathcal{D}$ such that 1) $|\Omega(D_n)| \leq 1, \forall D_n \in \mathcal{D}$, and $\Omega(D_n) = \emptyset$ if D_n is not matched to any RB; 2) $|\Omega(RB_m)| \leq q_{max}, \forall RB_m \in \mathcal{RB}$, and $\Omega(RB_m) = \emptyset$ if RB_m is not matched to any D2D pair; 3) $D_n \in \Omega(RB_m)$ iff $RB_m = \Omega(D_n)$.*

The utility of D2D pair n occupying RB m is given in (3.11), while the utility of RB m when choosing a set \mathcal{S} of D2D pairs is the sum utility of D2D pairs $n \in \mathcal{S}$, which is expressed as

$$U_m(\mathcal{S}) = \sum_{n \in \mathcal{S}} \frac{R_n(1 - PER_n)}{\sum_{k=1}^{K_n} d_{n,k}}. \quad (3.12)$$

Given these utilities, D2D pairs and RBs can set their own preference lists with the descending order of utilities. According to (3.6) and (3.11), the utility of D2D pair n depends not only on the cellular user it is matched with, but also on the set of D2D pairs that are matched to the same RB. In other words, the preference lists of D2D pairs and RBs change as the game evolves. This kind of interdependence among D2D pairs matched to the same RB is called peer effects [BBLC⁺11]. To deal with peer effects, *swap operations* are enabled between D2D pairs to exchange their matched RBs. A *swap matching* $\Omega_n^{n'}$ is expressed as

$$\Omega_n^{n'} = \{\Omega \setminus \{(n, m), (n', m')\}\} \cup \{(n, m'), (n', m)\}, \quad (3.13)$$

where $m = \Omega(n)$, and $m' = \Omega(n')$. A swap matching enables D2D pair D_n and $D_{n'}$ to switch their matched RBs while keeping other D2D pairs and RBs' matchings unchanged. Accordingly, a *swap-blocking* pair is defined as

Definition 11. *$(D_n, D_{n'})$ is a swap-blocking pair if and only if*

$$1) \forall x \in \{m, m', n, n'\}, U_x(\Omega_n^{n'}) \geq U_x(\Omega), \text{ and}$$

$$2) \exists x \in \{m, m', n, n'\}, U_x(\Omega_n^{n'}) > U_x(\Omega).$$

Table 3-C: Context-Aware Resource Allocation for D2D Communications (CARAD)

Stage 1: GS Algorithm-Based Initialisation

- a. D2D pairs and RBs construct their preference lists.
- b. Each D2D pair proposes to its most preferred RB that has not rejected it before.
- c. Each RB keeps the most preferred q_{max} D2D pairs and rejects the others.
- d. Repeat b) and c) until each D2D pair is accepted by a RB or rejected by all its preferred RBs.

Stage 2: Swap-matching process

- a. $\forall D_n \in \mathcal{D}$, it searches for another D2D pair $D_{n'} \in \{\mathcal{D} \setminus \{D_n\}, O\}$, where O is an open spot of RB's available vacancies.
- b. If $(D_n, D_{n'})$ or (D_n, O) is a swap-blocking pair, $\Omega \leftarrow \Omega_n^{n'}$. Else, keep the current matching state.
- c. Repeat a) and b) until $\nexists(D_n, D_{n'})$ blocks the current matching.

End of the algorithm.

The above definition indicates that, if two D2D pairs want to switch their matched RBs, RBs must “approve” the swap. Condition 1) implies that the utilities of all the involved players should not be reduced after the swap operation between the *swap-blocking* pair $(D_n, D_{n'})$. Condition 2) indicates that at least one of the players' utilities is increased after the swap operation between the *swap-blocking* pair. This avoids looping between equivalent matchings where the utilities of all involved agents are indifferent.

Inspired by the work in [ZGPH14], a context-aware resource allocation algorithm is proposed for D2D communications (CARAD), where D2D pairs and RBs selfishly and rationally interact with each other to make matching decisions. The details of the algorithm is shown in Table 3-C. CARAD is composed of two main stages: Stage 1 initialises the matching state via the traditional GS algorithm. Stage 2 focuses on the swap-matching process. Particularly, in stage 1, D2D pairs and RBs first set up their own preference lists. Then, each D2D pair proposes to its most preferred RB, and each RB accepts the most preferred D2D pairs and rejects the others. Stage 1 terminates once each D2D pair is accepted by a RB or rejected by all its preferred RBs. Stage 2 enables D2D pairs to exchange their matched RBs to eliminate potential swap-blocking pairs, which ends when there is no more swap-blocking pairs.

Theorem 4. *The final matching Ω_{final} of CARAD is two-sided exchange stable. The proof is given as follows.*

Proof. As shown in Table 3-C, the swap operations occur only when the utilities of players are strictly improved. After searching for all the possible swaps, the swap-matching phase terminates and there does not exist any swap matching to further improve the utilities for players in both sides of the current matching. Hence, the final matching is two-sided exchange stable. \square

Lemma 2. *The sum utility of D2D pairs increases after each swap operation.*

Proof. Suppose a swap operation makes the matching state change from Ω to $\Omega_n^{n'}$. According to Table 3-C, a swap operation occurs only when $U_m(\Omega_n^{n'}) \geq U_m(\Omega)$ as well as $U_{m'}(\Omega_n^{n'}) \geq U_{m'}(\Omega)$. Given that $U_m(\mathcal{S}, \Omega) = \sum_{n \in \mathcal{S}} U_n(m, \Omega)$, the following inequality holds:

$$\begin{aligned} \Phi_{\Omega \rightarrow \Omega_n^{n'}} &= \sum_m \sum_n U_n(m, \Omega_n^{n'}) \\ &\quad - \sum_m \sum_n U_n(m, \Omega) \geq 0. \end{aligned} \quad (3.14)$$

Therefore, the sum utility of D2D pairs is improved after each swap-matching process in Table 3-C. \square

As shown in Table 3-C, the complexity of the proposed algorithm mainly depends on the number of iterations in the swap-matching phase. As proved in Lemma 1, the sum utility increases with the swap operations going on. However, since the number of RBs and the maximum number of D2D pairs can be allocated to each RB are both limited, the sum utility has an upper bound. The difference of the sum utilities of the final matching and the initial matching is denoted as $\Phi_{\Omega_0 \rightarrow \Omega_{final}}$, and the minimum increase of each swap operation as Δ_{min} . Thus, in the worst case, the computational complexity of the proposed algorithm is of the order $\mathcal{O}\left(\frac{\Phi_{\Omega_0 \rightarrow \Omega_{final}}}{\Delta_{min}}\right)$.

3.4.4 Numerical Results

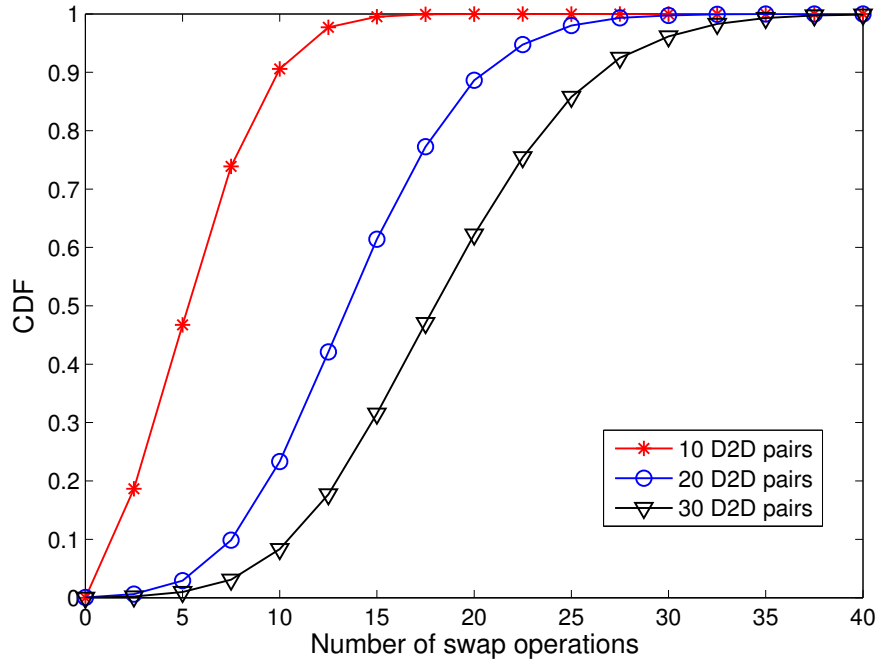
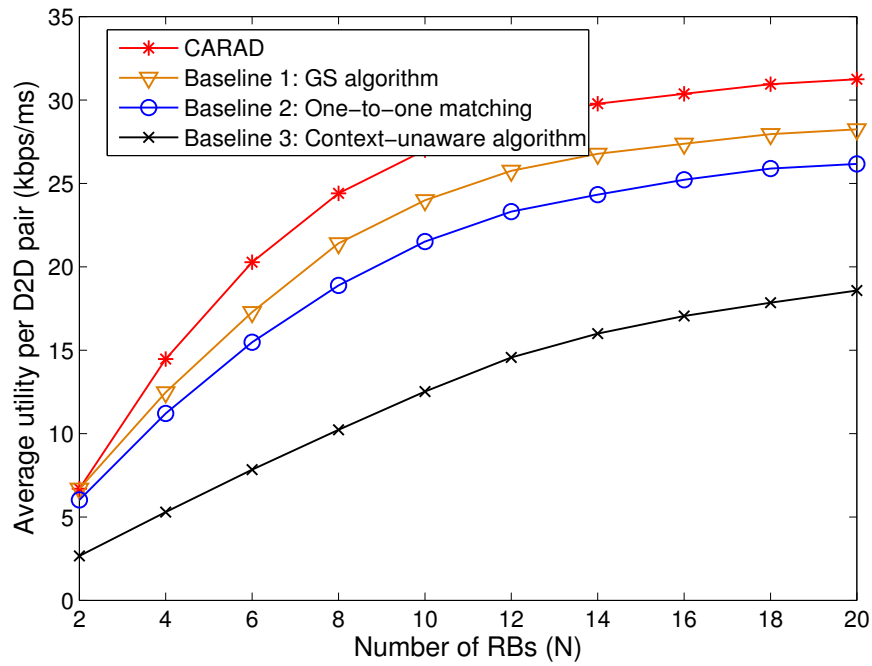
In this section, numerical results are provided to demonstrate the performance of the proposed algorithm CARAD. The traditional GS algorithm, one-to-one matching algorithm and context-unaware RB allocation algorithm are plotted as baseline 1, 2, and 3, respectively. Particularly, baseline algorithm 1 enables D2D pairs to apply for RBs, and get accepted or rejected via the GS algorithm. For baseline algorithm 2, D2D pairs and RB are matched via the one-to-one matching algorithm. For baseline algorithm 3, each D2D pair is associated with the RB that provides it with the highest SINR, without considering the context information. For the simulations, the cellular radius is set to 300 m, the bandwidth of each RB is 180 kHz, the cellular UEs' SINR threshold is 4 dB, σ^2 is -98 dBm, L is 50 m, and q_{max} is 4. The QoS parameters of popular wireless services are shown in Table 3-D [Qe12, Zam09].

Table 3-D: QoS Requirements of Multimedia Applications.

Application	Data rate (kbps)	Delay (ms)	PER
HD video streaming	1800	40	0.05
Multi-user gaming	700	30	0.01
Audio streaming	320	20	0.08
File transmission	200	3000	0.1

Figure 3.4 plots the CDF of the number of swap operations for the proposed algorithm. One can observe that the number of swap operations increases with the increased number of D2D pairs, which is due to the improved probability of the existence of swap-blocking pairs. The CDF also shows that the proposed matching algorithm converges within a reasonable number of iterations. For example, when there are 30 D2D pairs in the network, on average a maximum of 40 iterations is required to ensure the proposed algorithm to converge.

Figure 3.5 plots the average utility per D2D pair versus different numbers of RBs. It is not surprising to see that the average utility per D2D pair increases with a slow rate with larger number of RBs due to the multi-user diversity gain. The proposed algorithm

Figure 3.4: CDF of the number of swap operations, where $M = 10$.Figure 3.5: Average utility per D2D pair versus different number of RBs, where $M = 30$.

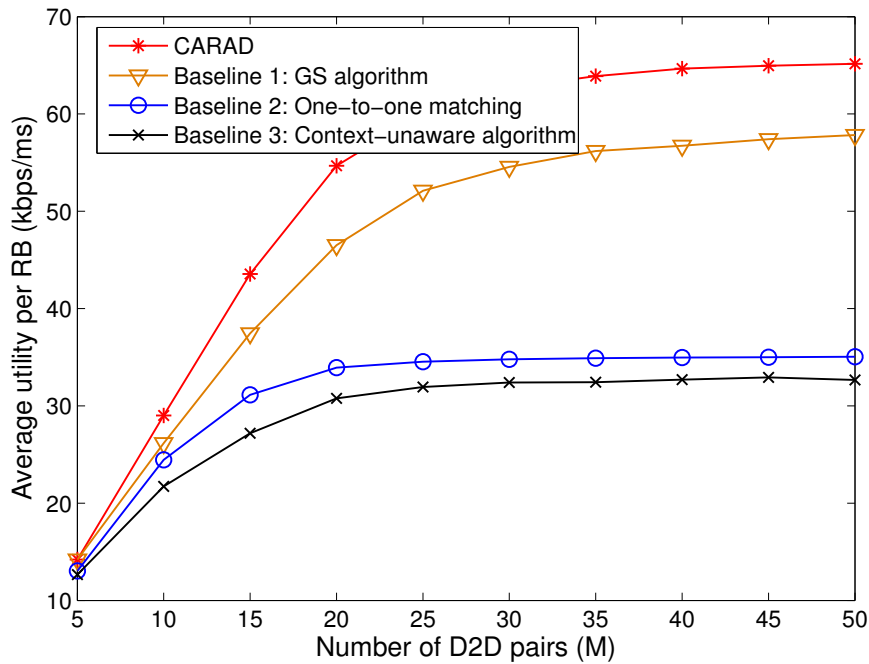


Figure 3.6: Average utility per RB versus different number of D2D pairs, where $N = 10$.

achieves a higher average utility of D2D users compared to baseline algorithm 1 since swap operations are enabled after the GS algorithm-based initialisation. For baseline algorithm 2, the average utility is restricted due to the limited number of served D2D pairs in the one-to-one matching algorithm. Baseline algorithm 3 has the lowest average utility since it does not take the context information into consideration. In particular, the proposed algorithm improves the average utility by around 11%, 20%, and 63% compared to baseline 1, 2, and 3, respectively. Recall the definition of the utility of each D2D pair, the utility enhancement indicates that the proposed algorithm can jointly provide improved data rate, decreased PER and reduced delay.

Figure 3.6 plots the average utility per RB versus different numbers of D2D pairs. Two main observations are as follows: 1) the average utility increases with the number of D2D pairs; and 2) the growth rate of the average utility is declined as the number of D2D pairs increases. This is due to the fact that the maximum number of D2D pairs that can be allocated to each RB is restricted. Moreover, the co-channel interference is

enhanced when more D2D pairs occupy the same RB, which further limits the upper bound of the average utility.

3.5 Summary

This chapter focused on resource allocation optimisation in D2D communications underlying cellular networks. More specifically, the resource allocation optimisation was formulated as a matching problem.

In Section 3.3, a novel resource allocation algorithm was proposed for D2D communications using many-to-many matching with peer effects. It was demonstrated that the proposed algorithm could converge to a two-sided exchange-stable matching within limited number of iterations. Simulation results showed that the proposed algorithm achieved the near-optimal sum rate which significantly outperformed the one-to-one matching algorithm.

Furthermore, a novel approach was presented for context-aware resource allocation in D2D communications in Section 3.4. Formulating an optimisation problem by maximising the utilities of the D2D user equipments, a novel algorithm based on the many-to-one matching game with peer effects was proposed. It has been shown that the context-aware D2D transmission is capable of providing remarkable performance enhancement in terms of improved data rate, decreased packet error rate and reduced delay, compared to that of the context-unaware approach.

Chapter 4

Spectrum Allocation and Power Control for NOMA-Enhanced D2D Communications

4.1 Overview

Inspired by the potential benefits of D2D and NOMA to improve spectrum efficiency as stated in Chapter 2, it is natural to investigate the promising application of NOMA technology in the D2D communications for further performance improvement, in term of both spectrum efficiency and massive connectivity. More specifically, a NOMA enhanced D2D communication scheme is developed in this chapter. In this new scheme, the concept of “D2D group” is proposed. Unlike the traditional concept of “D2D pair” [DRW⁺09b, CLZT16], one D2D transmitter is able to communicate with several D2D receivers via NOMA protocol. With OMA, transmitting contents to different D2D receivers requires multiple bandwidth channels; however, NOMA can serve these receivers in a single channel use. The main advantages of implementing NOMA enhanced D2D communications are the enhanced system sum rate and the increased number of accessed D2D receivers which are simultaneously served by one D2D transmitter.

4.2 Motivation

Recall that although D2D promises unprecedented increase in spectrum efficiency, it brings in interference to the cellular network [DRW⁺09b, Liu16, LWH17]. Similarly, the application of NOMA into D2D communications brings intra-“D2D group” interference among receivers in the same group as well as inter-“D2D group” interference among groups occupying the same subchannel, which makes the interference management problem more complicated. As such, whether NOMA is capable of enhancing D2D communications underlying cellular networks still remains unknown and investigating effective resource allocation strategies is more than necessary, which is one of the motivations of this work. To the best of the knowledge, there is no existing work investigating the joint subchannel and power allocation problem of NOMA enhanced D2D communications scenarios, which motivates this treatise. It is attempted to explore the potential of the NOMA enhanced D2D communications in underlay cellular networks and identify the key influence factors on system performance.

In this chapter, the setting of an uplink single-cell cellular network communications is considered, where multiple D2D groups are allowed to reuse the same subchannel occupied by a cellular user to improve the spectrum utilisation. It is recognised that the spectrum allocation can be regarded as a many-to-one matching process between the D2D groups and subchannels. Due to the co-channel interference among D2D groups occupying the same subchannel, D2D groups have peer effects with the interdependencies among each other. The spectrum allocation is formulated as a many-to-one matching problem with peer effects [GSB⁺15, DBSL15]. Appropriate power allocation among receivers in the same D2D group is also taken into consideration. Note that allocating D2D groups to orthogonal subchannels with considering power allocation generally turns out to be a combinatorial non-convex problem. Therefore, the subchannel assignment of D2D groups and the power allocation for each D2D group are decoupled.

The main contributions of the work in this chapter can be summarised as follows:

1. A novel NOMA enhanced D2D scheme that introduces the concept of “D2D group” is developed, where each D2D transmitter is enabled to communicate with multiple D2D receivers simultaneously via NOMA protocol. Based on this scheme, a mechanism that jointly performs subchannel assignment to D2D groups and power allocation in each D2D group is designed.
2. For the subchannel assignment, the fixed power allocation in each D2D group is first given, and then the subchannel assignment is formulated as a many-to-one matching problem. To maximise the system sum rate, a matching algorithm is proposed, where the peer effects among the D2D groups are taken into consideration. It is analytically proved that the proposed algorithm is capable of improving the system sum rate and converging to a stable state within limited rounds of interactions.
3. Based on the proposed subchannel assignment algorithm, the power allocation problem for each D2D group is formulated as a non-convex problem because of the existence of intra-group interference. The sequential convex programming is applied to iteratively update the power allocation vector by solving the approximate convex problem. It is proved that the proposed algorithm is convergent and the solution satisfies the Karush-Kuhn-Tucker (KKT) conditions.
4. Two approaches are proposed to jointly consider the subchannel and power allocation problems. The iterative joint subchannel and power allocation algorithm (I-JSPA) enables the power allocation under each given case of the matching between D2D groups and subchannels. Because of the high complexity of I-JSPA, a low-complexity joint subchannel and power allocation algorithm (LC-JSPA) is proposed. The result of LC-JSPA is shown to closely approach to that of the I-JSPA.
5. It is shown that the proposed joint subchannel and power allocation algorithm can achieve the near performance to the exhaustive-searching method at a low computational complexity. It is also demonstrated that the NOMA enhanced D2D

communications achieve higher system sum rate and larger number of accessed users than the OMA based D2D scheme.

4.3 System Model

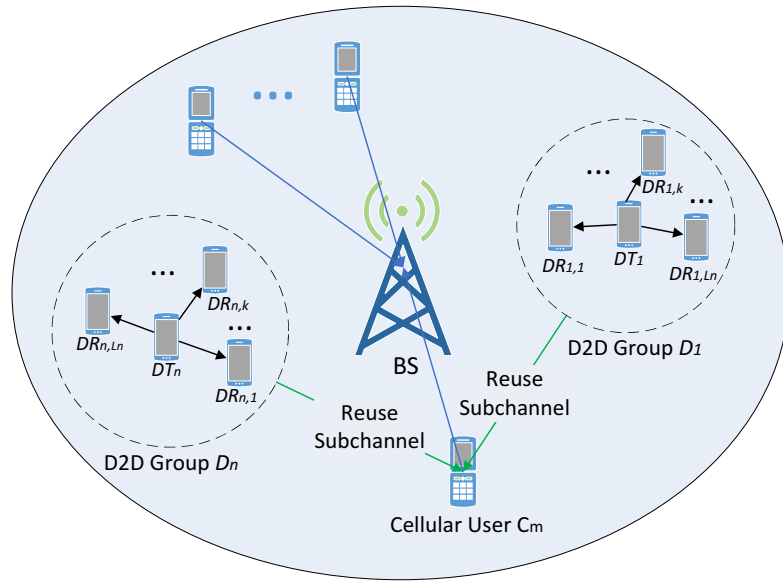
4.3.1 System Description

A single-cell uplink transmission scenario is considered, as illustrated in Figure 4.1(a). It is considered that M cellular users, i.e. $\mathcal{C} = \{C_1, \dots, C_m, \dots, C_M\}$, communicate with one BS in the traditional cellular mode. Each cellular user C_m is allocated in one subchannel $SC_m \in \mathcal{SC}$, $\mathcal{SC} = \{SC_1, \dots, SC_m, \dots, SC_M\}$ and all the subchannels are orthogonal with each other². There are N D2D groups $\mathcal{D} = \{D_1, \dots, D_n, \dots, D_N\}$ communicating underlying cellular networks. Unlike the traditional D2D-pair communications, it is assumed that the n -th D2D transmitter DT_n communicates with a group of L_n D2D receivers, i.e., $\{DR_{n,1}, \dots, DR_{n,k}, \dots, DR_{n,L_n}\}$. The D2D transmitter can send the superimposed mixture containing the required messages for the receivers in the same group by applying NOMA transmission protocol, which introduces the concept of “D2D group” (as shown in Figure 4.1(a)). Here, k is the index of the receivers in each D2D group. It is worth noticing that when $L_n = 1$, it is the special case of the conventional “D2D pair” scenario.

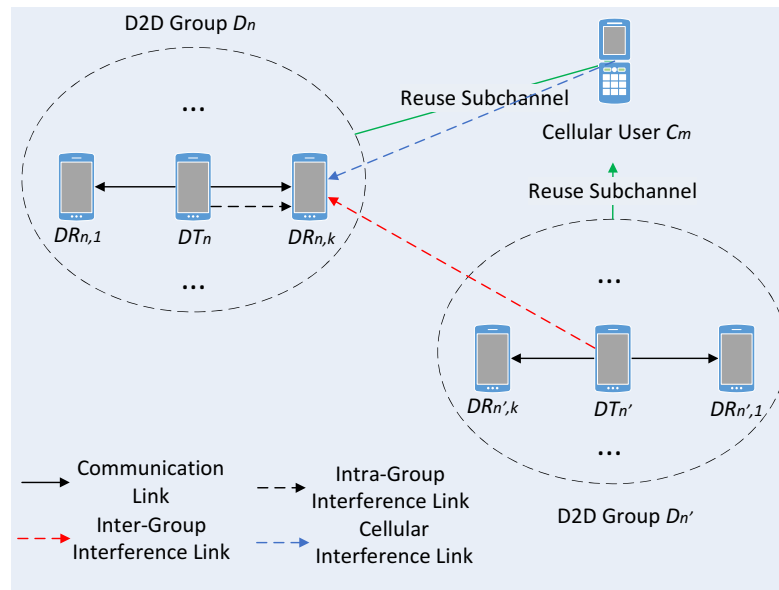
In Figure 4.1(b), the interference received at the k -th receiver of the n -th D2D group $DR_{n,k}$ is illustrated as follows:

- The intra-group interference (the black dashed line) refers to the interference of superposition signals from the D2D transmitter in the same D2D group;
- The inter-group interference (the red dashed line) indicates the interference from the D2D transmitters of other D2D groups that reuse the same subchannel;

²Considering subchannel assignment to cellular UEs is beyond the scope of this work.



(a) Cellular layout



(b) Interference illustration at $DR_{n,k}$

Figure 4.1: NOMA enhanced D2D communications scenario.

- Last, the cellular interference (the blue dashed line) represents the interference from the cellular user reusing the same subchannel.

It is assumed that the cellular users and D2D transmitters are uniformly distributed in the cell. The L_n receivers in each D2D group are uniformly distributed within a disc

with radius d_{max} , and the origin of the disc is the corresponding DT_n . All channels are assumed to undergo quasi-static Rayleigh fading, where the channel coefficients are constant for each channel.

4.3.2 Channel Model

It is assumed that each subchannel which is occupied by a cellular user can be reused by multiple D2D groups. As a consequence, the received signal at the BS corresponding to subchannel SC_m is given by

$$y_m = \sqrt{P_c}h_m x_m + \sum_n \lambda_{n,m} \sqrt{P_d}g_n t_n + \zeta_m, \quad (4.1)$$

where x_m and t_n are the transmit signals of C_m and DT_n , respectively. ζ_m is the additive white Gaussian noise (AWGN) at the BS on subchannel SC_m with variance σ^2 . The matrix $\lambda \in \mathbb{R}^{N \times M}$ with the elements $\lambda_{n,m}$ represents the subchannel allocation indicator for D2D groups, i.e., if SC_m is assigned to D_n , $\lambda_{n,m} = 1$; otherwise, $\lambda_{n,m} = 0$. P_c and P_d are the transmit power of the cellular users and D2D transmitters, respectively. In this chapter, it is assumed that all the cellular users have the same transmit power and so do all the D2D transmitters for simplicity. h_m and g_n are the channel coefficients including small-scale fading and path-loss between C_m and the BS, and that between DT_n and the BS, respectively.

Based on (4.1), the received signal-to-interference-plus-noise ratio (SINR) at the BS corresponding to C_m is

$$\gamma_m = \frac{P_c |h_m|^2}{\sum_n \lambda_{n,m} P_d |g_n|^2 + \sigma^2}, \quad (4.2)$$

where $|h_m|^2 = |\hat{h}_m|^2 (d_1^m)^{-\eta}$ and $|g_n|^2 = |\hat{g}_n|^2 (d_2^n)^{-\eta}$. Here, \hat{h}_m and \hat{g}_n are small-scale fading with $\hat{h}_m \sim \mathcal{CN}(0, 1)$ and $\hat{g}_n \sim \mathcal{CN}(0, 1)$. d_1^m is the distance from C_m to the BS, and d_2^n is the distance from DT_n to the BS. η is the path-loss exponent.

The NOMA protocol requires the super-position coding technique at the D2D transmitter side and SIC techniques at the receivers. In each D2D group, the vector $\mathbf{a}_n \in \mathbb{R}^{1 \times L_n}$ with the elements $a_{n,k}$ represents the power allocation coefficients in each D2D group. The D2D transmitter D_n sends L_n messages to the destinations based on the NOMA principle, i.e., D_n sends $\sum_{k=1}^{L_n} a_{n,k} s_{n,k}$, where $s_{n,k}$ is the message for the k -th receiver in the n -th D2D group. Therefore, the received signal at $DR_{n,k}$ is given by

$$z_{n,k} = f_{n,k} \sum_{k'=1}^{L_n} \sqrt{a_{n,k'} P_d} s_{n,k'} + \sqrt{P_c} h_{m,n,k} x_m + \sum_{n^* \neq n} \lambda_{n^*,n} \sqrt{P_d} g_{n^*,n,k} t_{n^*} + \zeta_{n,k}, \quad (4.3)$$

where $f_{n,k}$, $h_{m,n,k}$, and $g_{n^*,n,k}$ are the channel coefficients between DT_n and $DR_{n,k}$, that between C_m and $DR_{n,k}$, and that between DT_{n^*} and $DR_{n,k}$, respectively. $\zeta_{n,k}$ is the AWGN at $DR_{n,k}$ with variance σ^2 . $\lambda_{n^*,n}$ represents the presence of interference, i.e., if D2D group D_n and D_{n^*} reuse the same subchannel, $\lambda_{n^*,n} = 1$; otherwise, $\lambda_{n^*,n} = 0$.

NOMA systems exploit the power domain for multiple access, where different users are served at different power levels. The present work does not focus on the optimal SIC ordering problem, but in the design of the subchannel allocation indicator λ and power allocation coefficients \mathbf{a}_n , that maximise the network sum rate, for a given SIC ordering. More sophisticated design strategies can be developed for further enhancing the attainable performance of the networks considered, but this is beyond the scope of this treatise. For illustration, it is assumed that the SIC decoding order is as the index order of the receivers in each D2D group, i.e., the k -th receiver can decode the signals of the $\{1, \dots, (k-1)\}$ -th receivers. Specifically, the k -th receiver first successively subtracts the messages of the receivers $j < k$, and then obtain its own information by regarding the messages of the receivers $i > k$ as noise. Therefore, according to the received signal expressed in (4.3), the received SINR at the k -th receiver in the n -th D2D group to

decode its own information is given by

$$\gamma_{n,k}^k = \frac{|f_{n,k}|^2 P_d a_{n,k}}{I_{n,k}^{k,in} + I_{n,k}^{out} + I_{n,k}^c + \sigma^2}, \quad (4.4)$$

where $I_{n,k}^{k,in} = |f_{n,k}|^2 P_d \sum_{i=k+1}^{L_n} a_{n,i}$ is the intra-group interference from the superimposed signals, $I_{n,k}^{out} = \sum_{n^* \neq n} \lambda_{n^*,n} P_d |g_{n^*,n,k}|^2$ is the inter-group interference, and $I_{n,k}^c = \sum_m \lambda_{m,n} P_c |h_{m,n,k}|^2$ is the interference from the cellular user. Here, $|f_{n,k}|^2 = |\hat{f}_{n,k}|^2 (d_3^{n,k})^{-\eta}$, $|g_{n^*,n,k}|^2 = |\hat{g}_{n^*,n,k}|^2 (d_4^{n^*,n,k})^{-\eta}$, and $|h_{m,n,k}|^2 = |\hat{h}_{m,n,k}|^2 (d_5^{m,n,k})^{-\eta}$. $\hat{f}_{n,k}$, $\hat{g}_{n^*,n,k}$ and $\hat{h}_{m,n,k}$ are small-scale fading with $\hat{f}_{n,k} \sim \mathcal{CN}(0, 1)$, $\hat{g}_{n^*,n,k} \sim \mathcal{CN}(0, 1)$ and $\hat{h}_{m,n,k} \sim \mathcal{CN}(0, 1)$. $d_3^{n,k}$ is the distance from DT_n to the $DR_{n,k}$, $d_4^{n^*,n,k}$ is the distance from DT_{n^*} to $DR_{n,k}$ and $d_5^{m,n,k}$ is the distance from C_m to $DR_{n,k}$. Note that the L_n -th receiver of the n -th D2D group can decode the signals of all the other receivers in the same group, thus the SINR is expressed as

$$\gamma_{n,L_n}^{L_n} = \frac{|f_{n,L_n}|^2 P_d a_{n,L_n}}{I_{n,k}^{out} + I_{n,k}^c + \sigma^2}. \quad (4.5)$$

The k -th receiver's received SINR for the j -th receiver's required signal is given by

$$\gamma_{n,k}^j = \frac{|f_{n,k}|^2 P_d a_{n,j}}{I_{n,k}^{j,in} + I_{n,k}^{out} + I_{n,k}^c + \sigma^2}, \quad (4.6)$$

where $I_{n,k}^{j,in} = |f_{n,k}|^2 P_d \sum_{i=j+1}^{L_n} a_{n,i}$. The interference cancellation is successful if the k -th receiver's received SINR for the j -th receiver's signal is larger or equal to the received SINR of the j -th receiver for its own signal [DYFP14, SNDS16]. Therefore, the condition of the given SIC decoding order³ is expressed as

$$\frac{|f_{n,k}|^2 P_d a_{n,j}}{I_{n,k}^{j,in} + I_{n,k}^{out} + I_{n,k}^c + \sigma^2} \geq \frac{|f_{n,j}|^2 P_d a_{n,j}}{I_{n,j}^{j,in} + I_{n,j}^{out} + I_{n,j}^c + \sigma^2}. \quad (4.7)$$

³Inside a D2D group, the D2D transmitter only needs to know the channel ordering of receivers rather than the full CSIs.

The inequality in (4.7) can be simplified and rewritten in the following:

$$|f_{n,k}|^2 (I_{n,j}^{out} + I_{n,j}^c + \sigma^2) \geq |f_{n,j}|^2 (I_{n,k}^{out} + I_{n,k}^c + \sigma^2). \quad (4.8)$$

It is observed from the above inequality that the SIC order in the n -th D2D group is only related to the channel gains as well as the co-channel interference from cellular users and other D2D groups reusing the same subchannel, but not related to the power allocation coefficient \mathbf{a}_n . Therefore, the SIC order in each D2D group can be fixed after the subchannel assignment.

4.4 Problem Formulation

In this section, the constraints of cellular users' received interference from the D2D groups are first given, and then the network sum rate is introduced. Subsequently, the joint subchannel and power allocation problem for the NOMA enhanced D2D system is formulated.

4.4.1 Interference Constraints

One of the key challenges in D2D communications underlying cellular networks is the co-channel interference caused by the spectrum sharing between the D2D and traditional cellular links. To guarantee the service qualities of cellular and D2D users, the interference constraints expressed in the format of SINR are

$$\gamma_m = \frac{P_c |h_m|^2}{\sum_n \lambda_{n,m} P_d |g_n|^2 + \sigma^2} \geq \gamma_m^{thr}, \quad (4.9)$$

$$\gamma_{n,k}^k = \frac{|f_{n,k}|^2 P_d a_{n,k}}{I_{n,k}^{k,in} + I_{n,k}^{out} + I_{n,k}^c + \sigma^2} \geq \gamma_{n,k}^{thr}, \quad (4.10)$$

where γ_m^{thr} and $\gamma_{n,k}^{thr}$ are the given SINR thresholds for the m -th cellular user and the k -th receiver in the n -th D2D group, respectively.

4.4.2 Network Sum Rate

Based on the expression of SINR in (4.2) and the Shannon formula, the data rate for the m -th cellular user C_m is give by

$$R_m = \log_2 \left(1 + \frac{P_c |h_m|^2}{\sum_n \lambda_{n,m} P_d |g_n|^2 + \sigma^2} \right). \quad (4.11)$$

Similarly, the data rate for the k -th receiver in the n -th D2D group $DR_{n,k}$ is given by

$$R_{n,k} = \begin{cases} \log_2 \left(1 + \frac{|f_{n,k}|^2 P_d a_{n,k}}{I_{n,k}^{k,in} + I_{n,k}^c + \sigma^2} \right), & \text{if } k = L_n, \\ \log_2 \left(1 + \frac{|f_{n,k}|^2 P_d a_{n,k}}{I_{n,k}^{k,in} + I_{n,k}^{out} + I_{n,k}^c + \sigma^2} \right), & \text{else.} \end{cases} \quad (4.12)$$

As such, the network sum rate of all the cellular and D2D users is

$$R_{sum} = \sum_{m=1}^M \left(R_m + \sum_{n=1}^N \lambda_{n,m} \sum_{k=1}^{L_n} R_{n,k} \right). \quad (4.13)$$

4.4.3 Optimisation Problem Formulation

Now, the joint subchannel and power allocation problem for the NOMA enhanced D2D system can be formulated as the following:

$$\max_{\lambda_{n,m}, a_{n,k}} R_{sum}, \quad (4.14a)$$

$$s.t. \quad \gamma_m \geq \gamma_m^{thr}, \quad \forall m, \quad (4.14b)$$

$$|f_{n,k}|^2 (I_{n,j}^{out} + I_{n,j}^c + \sigma^2) \geq |f_{n,j}|^2 (I_{n,k}^{out} + I_{n,k}^c + \sigma^2), \\ \forall n, k, j \in \{1, \dots, k-1\}, \quad (4.14c)$$

$$\gamma_{n,k}^k \geq \gamma_{n,k}^{thr} \quad \forall n, k, \quad (4.14d)$$

$$\lambda_{n,m} \in \{0, 1\}, \quad \forall n, m, \quad (4.14e)$$

$$\sum_m \lambda_{n,m} \leq 1, \quad \forall n, \quad (4.14f)$$

$$\sum_n \lambda_{n,m} \leq q_{max}, \quad \forall m, \quad (4.14g)$$

$$a_{n,k} \geq 0, \quad \forall n, k, \quad (4.14h)$$

$$\sum_{k=1}^{L_n} a_{n,k} \leq 1, \quad \forall n. \quad (4.14i)$$

Constraint (4.14b) is imposed to restrict the interference received at the cellular links from the D2D groups. Constraint (4.14c) is to guarantee the policy for SIC decoding order. Constraint (4.14d) guarantees the minimum SINR constraints for D2D users. Constraint (4.14e) shows that the value of $\lambda_{n,m}$ should be either 0 or 1. Constraint (4.14f) guarantees that at most one subchannel can be allocated to each D2D group. Constraint (4.14g) introduces the maximum number of D2D groups q_{max} can be allocated to each subchannel, which is to reduce the implementation complexity and the interference on

each subchannel. Constraint (4.14h) is a non-negative constraint for power allocation coefficients. Constraint (4.14i) restricts the upper bound of the D2D users' transmit power.

The formulated problem here is a 0-1 integer program, besides, the objective function is non-convex. There is no systematic and computational efficient approach to solve this problem optimally. In addition, according to (4.14), the subchannel and power allocation variables are coupled. Therefore, in section 4.5 and 4.6, the formulated problem is decoupled into two sub-problems: 1) subchannel assignment of D2D groups; and 2) power allocation to the receivers in each D2D group.

4.5 Subchannel Allocation for NOMA-Enhanced D2D Groups

In this section, it is assumed that the power allocated to the transmission from the transmitter to receivers in each D2D group is a fixed value. Thus the sub-problem of subchannel assignment is

$$\max_{\lambda_{n,m}} R_{sum}, \quad (4.15a)$$

$$s.t. \quad (4.14b) - (4.14g), \quad (4.15b)$$

Note that the formulated problem is a non-convex optimisation problem due to the existence of the interference term in the objective function [WN99]. The complexity of the exhaustive method increases exponentially with the number of D2D groups and subchannels, which makes it unpractical especially in a dense network. To describe the dynamic matching between the D2D groups and subchannels, the subchannel assignment is regarded as a two-sided many-to-one matching process between the sets of D2D groups and subchannels. The D2D groups and subchannels act as two sets of players and interact with each other to maximise the sum rate. To solve this problem, the matching theory [RS92, GSB⁺15] is adopted, which provides mathematically tractable and low-complexity

solutions for the combinatorial problem of matching players in two distinct sets [Man13]. The subchannel assignment is regarded as a many-to-one matching problem and propose an efficient algorithm to solve this problem.

4.5.1 Many-to-One Matching with Peer Effects

To proceed with proposing the subchannel assignment algorithm, some notations and basic definitions are first introduced for the proposed matching model between the sets of D2D groups and subchannels.

Definition 12. *In the many-to-one matching model, a matching Ω is a function from the set $\mathcal{SC} \cup \mathcal{D}$ into the set of all subsets of $\mathcal{SC} \cup \mathcal{D}$ such that 1) $|\Omega(D_n)| = 1, \forall D_n \in \mathcal{D}$, and $\Omega(D_n) = \{D_n\}$ if $\Omega(D_n) \not\subset \mathcal{SC}$; 2) $|\Omega(SC_m)| \leq q_{max}, \forall SC_m \in \mathcal{SC}$, and $\Omega(SC_m) = \emptyset$ if SC_m is not matched to any D2D group; 3) $\Omega(D_n) = \{SC_m\}$ if and only if $D_n \in \Omega(SC_m)$.*

Based on the perfect CSI, D2D groups have preferences over individual subchannels, just as in a one-to-one matching model, and subchannels have preferences over sets of D2D groups. Note that a positive integer q_{max} called *quota* is associated with each subchannel SC_m , which indicates the maximum number of D2D groups that can be matched with each subchannel. The preference list is given by

$$\mathbf{PL} = \{\mathbf{P}(D_1), \dots, \mathbf{P}(D_N), \mathbf{P}(SC_1), \dots, \mathbf{P}(SC_M)\}, \quad (4.16)$$

where $\mathbf{P}(D_n)$ is the preference list of D_n over individual subchannels, and $\mathbf{P}(SC_m)$ is the preference list of SC_m over sets of D2D groups.

The preference lists of players are formed in descending order with respect to the preference value which is defined as the utility of each side of the players. For a D2D group D_n , the utility on a subchannel SC_m is defined as the achievable data rate of D_n

when it occupies SC_m , which is given by

$$U_n(m) = \sum_{k=1}^{L_n-1} \log_2 \left(1 + \frac{|f_{n,k}|^2 P_d a_{n,k}}{I_{n,k}^{in} + I_{n,k}^{out} + I_{n,k}^c + \sigma^2} \right) + \log_2 \left(1 + \frac{|f_{n,L_n}|^2 P_d a_{n,L_n}}{I_{n,k}^{out} + I_{n,k}^c + \sigma^2} \right). \quad (4.17)$$

From (4.17), it is not difficult to find that the utility of a D2D group depends not only on the subchannel that it is matched with, but also on the set of D2D groups that are matched to the same subchannel, due to the existence of the co-channel interference $I_{n,k}^{out}$. Therefore, the following observation holds:

Remark 2. *The proposed matching game has peer effects [BBLC⁺ 11]. That is, the D2D groups care not only where they are matched, but also which other D2D groups are matched to the same place.*

This type of matching is called the matching game with peer effects, where each player has a dynamic preference list over the opposite set of players. This is different from the conventional matching games in which players have fixed preference lists [GZPH15, HH14, RS92]. In this matching model, the preference of players over the opposite set of players replies on the matching states. To this end, it needs to define the new preference $\mathbf{P}^*(D_n)$ of D2D group D_n on the set of possible matchings rather than the $\mathbf{P}(D_n)$ which is simply the preference of D_n on the subchannels. The relationship of “prefer” for a D2D group on subchannels under different matching states is expressed as

$$(m, \Omega) \succ_n (m', \Omega') \Leftrightarrow U_n(m, \Omega) > U_n(m', \Omega'), \quad (4.18)$$

where $U_n(m, \Omega)$ is the utility of D2D group D_n when it occupies the subchannel SC_m under the matching state Ω .

The preference values of subchannel SC_m on a set of D2D groups \mathcal{S}_D is defined as the sum rate of all the D2D groups and the corresponding cellular user, which is expressed

as

$$U_m(\mathcal{S}) = \log_2(1 + \gamma_m(\mathcal{S})) + \sum_{D_n \in \mathcal{S}} \left(\sum_{k=1}^{L_n-1} \log_2(1 + \gamma_{n,k}^k) + \log_2(1 + \gamma_{n,L_n}^{L_n}) \right), \quad (4.19)$$

where $\gamma_m(\mathcal{S})$ is the SINR of the cellular user C_m when it shares the subchannel with the set of D2D groups \mathcal{S} .

Based on the utility definition of the subchannel SC_m , the “prefer” relationship of SC_m on the set of D2D groups \mathcal{S} and \mathcal{S}' is

$$(\mathcal{S}, \Omega) \succ_m (\mathcal{S}', \Omega') \Leftrightarrow U_m(\mathcal{S}, \Omega) > U_m(\mathcal{S}', \Omega'), \quad (4.20)$$

where $U_m(\mathcal{S}, \Omega)$ is the utility of SC_m on the set of D2D groups \mathcal{S} under the matching state Ω .

There is a growing literature studying many-to-one matchings with peer effects [DM97, Haf08]. However, these researches find that designing matching mechanisms is significantly more challenging when peer effects are considered. Motivated by the housing assignment problem in [BBLC⁺11], an extended matching algorithm is proposed for the many-to-one matching problem with peer effects in the following.

Like the many-to-one matching described in section 3.4, the swap operations between any two D2D groups to exchange their matched subchannels is enabled. The concept of swap matching, swap-blocking pair and two-sided exchange stability are as defined in Eq. (3.4), Definition 8 and Definition 9, respectively, in chapter 3.

4.5.2 Proposed Subchannel Assignment Algorithm (SAA) Based on Many-to-One Matching

To find a two-sided exchange-stable matching for the matching game, a matching-theory based subchannel assignment algorithm is proposed, i.e., SAA, between D2D groups and subchannels based on multiple swap operations, as shown in **Algorithm 1**. The input of the proposed algorithm includes the initial list of the number of D2D groups matched to each subchannel as well as the initial matching state. To initialise the matching state, it randomly matches each D2D group with a subchannel or an empty set. If a D2D group is matched to an empty set, it indicates that no subchannel is allocated to the D2D group in the initial state. The main process of the proposed algorithm is the swap operation between different D2D groups, where each D2D group keeps searching for all the other D2D groups to check whether there is a swap-blocking pair. Note that one of the D2D groups taking part in the swap operations can be an available vacancy of a subchannel. The swap operations continue until there are no more swap-blocking pairs, and the final matching state is the output.

Regarding the time scale of SAA, the signaling packet length required for the communication between the D2D groups and subchannels until the algorithm converges is very short. In particular, each D2D group is only required to send one bit to another D2D group indicating a swap-operation offer, and then the involved D2D groups each send a one-bit request to their occupying subchannels. Finally, the subchannels only need to send one bit back to the offering D2D groups indicating either accept or reject the request. The total amount of overhead from SAA thus can be quite small, which enables it to well perform in practical scenarios.

4.5.3 Property Analysis of SAA

To evaluate the performance of SAA, the properties in terms of effectiveness, stability, convergence and complexity are analysed in this subsection.

Algorithm 1 Matching-Theory Based Subchannel Assignment Algorithm (SAA)

1: – **Input:**

- Initial matching Ω_0 : Randomly match each D2D group with $SC \in \{SC, \emptyset\}$ satisfying the constraint that $q_m \leq q_{max}, \forall q_m \in \mathcal{Q}$;
- Initial list of the number of D2D groups matched to each subchannel $\mathcal{Q} = \{q_1, \dots, q_M\}$.

2: – **Swap Operations:**

3: **repeat**

4: **for** $\forall D_n \in \mathcal{D}$ **do**

5: **for** $\forall D_{n'} \in \{\mathcal{D} \setminus \{D_n\}, O\}$, where O is an open spot of subchannel's available vacancies, with $\Omega(n) = m$, and $\Omega(n') = m'$ **do**

6: **if** $(D_n, D_{n'})$ is a swap-blocking pair, **and** (5.11b)-(5.11f) are satisfied **then**

7: $\Omega \leftarrow \Omega^{n'}$;

8: Update \mathcal{Q} ;

9: **break**;

10: **end if**

11: **end for**

12: **end for**

13: **until** $\nexists (D_n, D_{n'})$ blocks the current matching.

14: – **Output:** Final matching Ω^* .

Theorem 5. *The final matching Ω^* of SAA is a two-sided exchange-stable matching.*

Proof. Assume that there exists a swap-blocking pair $(D_n, D_{n'})$ in the final matching Ω^* satisfying that $\forall i \in \{n, n', \Omega(D_n), \Omega(D_{n'})\}, U_i \left((\Omega^*)^{n'} \right) \geq U_i(\Omega^*)$ and $\exists i \in \{n, n', \Omega(D_n), \Omega(D_{n'})\}$, such that $U_i \left((\Omega^*)^{n'} \right) > U_i(\Omega^*)$. According to SAA, the algorithm does not terminate until all the swap-blocking pairs are eliminated. In other words, Ω^* is not the final matching, which causes conflict. Therefore, there does not exist a swap-blocking pair in the final matching, and thus it can be concluded that the proposed algorithm reaches a two-sided exchange stability in the end of the algorithm. \square

Lemma 3. *The system sum rate increases after each swap operation.*

Proof. Suppose a swap operation makes the matching state change from Ω to $\Omega_n^{n'}$. According to SAA, a swap operation occurs only when $U_m(\Omega_n^{n'}) \geq U_m(\Omega)$ as well as $U_{m'}(\Omega_n^{n'}) \geq U_{m'}(\Omega)$. Given that $U_m(\Omega(m), \Omega) = R_m(\Omega(m), \Omega) + \sum_{n \in \Omega(m)} \sum_{k=1}^{L_n} R_{n,k}(m, \Omega)$,

the following inequality holds:

$$\begin{aligned}
 \Phi_{\Omega \rightarrow \Omega_n^{n'}} &= \\
 &= U_m \left(\Omega_n^{n'}(m), \Omega_n^{n'} \right) - U_m \left(\Omega(m), \Omega \right) \\
 &= R_{sum} \left(\Omega_n^{n'} \right) - R_{sum} \left(\Omega \right) \\
 &> 0,
 \end{aligned} \tag{4.21}$$

where $\Phi_{\Omega \rightarrow \Omega_n^{n'}}$ is the difference of the system sum rates under the matching state $\Omega_n^{n'}$ and that under the matching state Ω . From (4.21), it is concluded that the system sum rate increases after each successful swap operation. \square

Theorem 6. *The proposed subchannel assignment algorithm converges within limited number of iterations.*

Proof. In the proposed matching model, the number of players is limited and the maximum number of D2D groups can be allocated to each subchannel is restricted, which indicates that the number of potential swap operations is finite. Moreover, from (4.21), it is observed that the system sum rate increases after each successful swap operation. Since the system sum rate has an upper bound due to limited spectrum resources, the swap operations stop when the system sum rate is saturated. Therefore, within limited number of rounds, the matching process converges to the final state which is stable. \square

Theorem 7. *The computational complexity of the proposed algorithm is of the order $\mathcal{O} \left(\frac{\Phi_{\Omega_0 \rightarrow \Omega^*}}{\Delta_{min}} \right)$ in the worst case.*

Proof. As shown in SAA, the complexity of the proposed algorithm mainly depends on the number of iterations in the swap-matching phase. Since it is uncertain that at which step the algorithm converges to a two-sided exchange stable matching, the number of iterations cannot be given in a closed-form expression. The number of total iterations for different numbers of D2D groups will be analysed in Figure 3, and give more detailed analysis in section VI. Here, an upper bound of the complexity is given. As proved

in (4.21), the sum rate increases with the swap operations going on. The difference of the sum rates of the final matching and the initial matching is denoted as $\Phi_{\Omega_0 \rightarrow \Omega^*}$, and the minimum increase of each swap operation as Δ_{min} . Thus, in the worst case, the computational complexity of the proposed algorithm is of the order $\mathcal{O}\left(\frac{\Phi_{\Omega_0 \rightarrow \Omega^*}}{\Delta_{min}}\right)$. \square

Theorem 8. *All local maxima of system sum rate corresponds to a two-sided exchange-stable matching.*

Proof. Assume that the sum rate achieved by matching Ω is a local maximal value. If Ω is not a stable matching, there exists a swap-blocking pair that can further improve the sum rate, as proved in **Lemma 1**. However, this is inconsistent with the assumption that Ω is local optimal. Hence, it is concluded that Ω is a two-sided exchange-stable matching. \square

However, not all two-sided exchange-stable matchings obtained from SAA can achieve the local maximum of system sum rate. The reason can be shown in a simple example. D2D group D_n does not approve the swap operation with $D_{n'}$ along with their current matched subchannels SC_m and $SC_{m'}$, due to the fact that the utility of D_n is decreased after the swap operation. However, SC_m and $SC_{m'}$ can benefit a lot from this swap operation, which causes that the optimal sum rate can not be achieved by the swap operations. Of course, it can *force* the swap operation to happen to further improve the sum rate, but this will obtain a weaker stability [DSL16].

4.6 Power Allocation for NOMA-enhanced D2D Groups

For a given subchannel assignment strategy λ , the SIC order is determined according to (4.14c), based on which the power allocation can be performed independently in each D2D group. In this section, it is assumed that the SIC order has already been given based on the subchannel assignment result λ , and thus the constraint (4.14c) does not need to be taken into consideration in the power allocation problem. To make the notation

simplified, it drops the D2D group index n , thus the power allocation problem for each D2D group can be expressed as

$$\max_{a_{n,k}} \sum_{k=1}^{L_n} R_{n,k}, \quad (4.22a)$$

$$s.t. \quad (4.14d), (4.14h), (4.14i). \quad (4.22b)$$

4.6.1 Pareto Optimal Solution

Because of the existence of the co-channel interference, the formulated problem is a non-convex problem with respect to $a_{n,k}$. Therefore, obtaining the global optimum with affordable complexity is rather difficult. Alternatively, the sequential convex programming [MW78] is applied, i.e., finding local optimum of (4.22) by solving a sequence of easier problems. In the following, a low-complexity algorithm is proposed to obtain a local-optimal solution for the optimisation problem.

The objective function in (4.22a) can be rewritten as

$$\max_{a_{n,k}} \sum_{k=1}^{L_n} R_{n,k} = \sum_{k=1}^{L_n} \left(\log_2 \left(1 + \gamma_{n,k}^k \right) \right). \quad (4.23)$$

As proved in [PE06], the following inequality exists:

$$\log_2(1 + \gamma_{n,k}^k) \geq b_k \log_2 \gamma_{n,k}^k + c_k, \quad (4.24)$$

where b_k and c_k are defined as

$$b_k = \frac{\hat{\gamma}_{n,k}^k}{1 + \hat{\gamma}_{n,k}^k}, \quad (4.25)$$

$$c_k = \log_2(1 + \hat{\gamma}_{n,k}^k) - \frac{\hat{\gamma}_{n,k}^k}{1 + \hat{\gamma}_{n,k}^k} \log_2 \hat{\gamma}_{n,k}^k, \quad (4.26)$$

respectively. The equality is satisfied when $\gamma_{n,k}^k = \hat{\gamma}_{n,k}^k$.

Based on the inequality function in (4.24), the lower bound of the objective function in (4.23) is

$$\sum_{k=1}^{L_n} R_{n,k} \geq \sum_{k=1}^{L_n} \Theta_k(a_{n,k}), \quad (4.27)$$

where $\Theta_k(a_{n,k})$ is defined as

$$\Theta_k(a_{n,k}) = b_k \log_2 \gamma_{n,k}^k + c_k. \quad (4.28)$$

Set $a_{n,k} = 2^{s_{n,k}}, \forall k \in \{1, \dots, L_n\}$, and define $\mathbf{s}_n = [s_{n,1}, \dots, s_{n,k}, \dots, s_{n,L_n}]$. A new optimisation problem from (4.22) and (4.27) can be formulated as follows:

$$\max_{\mathbf{s}_n} \sum_{k=1}^{L_n} \Theta_k(2^{s_{n,k}}), \quad (4.29a)$$

$$s.t. \quad \gamma_{n,k}^k(s_{n,k}) \geq \gamma_{n,k}^{thr}, \quad \forall k \in \{1, \dots, L_n\}, \quad (4.29b)$$

$$\sum_{k=1}^{L_n} 2^{s_{n,k}} \leq 1. \quad (4.29c)$$

Remark 3. *The new formulated problem is a concave problem, which is proved as the following:*

Proof. Rearranging $\Theta_k(2^{s_{n,k}})$, it obtains:

$$\begin{aligned} \Theta_k(2^{s_{n,k}}) = & b_k [s_{n,k} - \log_2(|f_{n,k}|^2 P_d \sum_{i=j+1}^{L_n} 2^{s_{n,i}} \\ & + I_{n,k}^{out} + I_{n,k}^c + \sigma^2)] + b_k \log_2(|f_{n,k}|^2 P_d) + c_k. \end{aligned} \quad (4.30)$$

$\Theta_k(2^{s_{n,k}})$ is a concave function of $s_{n,k}$ because of the convexity of the log-sum-exp function [BV04]. Since the objective function in (4.29a) is a summation of concave terms of \mathbf{s}_n , it can be concluded that the problem in (4.29) is a standard convex optimisation problem. \square

Since (4.29) is a standard convex optimisation problem, there exists many efficient numerical algorithms such as the interior-point method to obtain the optimal solution. It iteratively updates the power allocation vector \mathbf{a}_n by solving (4.29) to tighten the lower bound in (4.27) until convergence. The proposed power allocation algorithm (PAA) for each D2D group is shown in **Algorithm 2**. The algorithm contains two main steps. The first step is to initialise the power allocation vector $\mathbf{a}_n(0)$ to the n -th D2D group D_n . The second step is the update step. In the i -th round of the update step, set $\hat{\gamma}_{n,k}^k = \gamma_{n,k}^k(i-1)$, and subsequently derive the solution $\mathbf{s}_n(i)$ by solving the convex-optimisation problem in (4.29). This process continues until the gaps between the values of $\gamma_{n,k}^k$ in the current round and that in the previous round for all receivers in the n -th D2D group, are smaller than the convergence threshold Δ .

Algorithm 2 Power Allocation Algorithm for Each D2D Group (PAA)

- 1: – **initialisation Phase:**
 - 2: Set $i = 0$.
 - 3: initialise the power allocation vector $\mathbf{a}_n(0)$ and the maximum number of iterations I_{max} . Calculate $\gamma_{n,k}^k(0)$ based on $\mathbf{a}_n(0)$.
 - 4: Set the convergence threshold Δ .
 - 5: – **Update Phase:**
 - 6: **while** $|\gamma_{n,k}^k(i) - \gamma_{n,k}^k(i-1)| \geq \Delta, \forall k \in \{1, \dots, L_n\}$ **do**
 - 7: $i = i + 1$;
 - 8: Set $\hat{\gamma}_{n,k}^k = \gamma_{n,k}^k(i-1)$ and compute b_k and c_k according to (5.17) and (5.18).
 - 9: Solve the convex optimisation problem in (4.29) and set the result as $\mathbf{s}_n(i)$.
 - 10: Update $\mathbf{a}_n(i)$, where $a_{n,k}(i) = 2^{s_{n,k}(i)}, \forall k \in \{1, \dots, L_n\}$.
 - 11: Calculate $\gamma_{n,k}^k(i), \forall k \in \{1, \dots, L_n\}$ based on $\mathbf{a}_n(i)$.
 - 12: **end while**
 - 13: Result: $\mathbf{a}_n^* = \mathbf{a}_n(i)$.
-

4.6.2 Property Analysis of PAA

In this subsection, the analysis on the convergence and the local-optimal property of the proposed power allocation algorithm is given.

Theorem 9. *The proposed PAA for power allocation is guaranteed to converge.*

Proof. Assume that the optimal solution of the convex problem in (4.29) is $\mathbf{s}_n(i)$ after

the i -th iteration. Set $\mathbf{a}_n(i) = 2^{s_n(i)}$. Then, the following inequalities can be obtained:

$$\begin{aligned} \sum_{k=1}^{L_n} R_{n,k}(a_{n,k}(i)) &= \sum_{k=1}^{L_n} \Theta_k^{i+1}(2^{s_{n,k}(i)}) \\ &\leq \sum_{k=1}^{L_n} \Theta_k^{i+1}(2^{s_{n,k}(i+1)}) \leq \sum_{k=1}^{L_n} R_{n,k}(a_{n,k}(i+1)), \end{aligned} \quad (4.31)$$

where Θ_k^{i+1} is the expression of Θ_k during the $(i+1)$ -th iteration. The first equality holds because b_k and c_k are calculated based on $\hat{\gamma}_{n,k}^k$, thus the bound is tight; the second inequality holds because $s_{n,k}(i+1)$ is the optimal solution of (4.29) for the $(i+1)$ -th iteration; the third inequality holds because $\Theta_{n,k}^{i+1}(s_{n,k}(i+1))$ is the lower bound of $R_{n,k}(a_{n,k}(i+1))$. Therefore, from (4.31), the value of $\sum_{k=1}^{L_n} R_{n,k}$ increases after each iteration in PAA. Since the value of $\sum_{k=1}^{L_n} R_{n,k}$ is upper bounded due to limited spectrum resources, there exists an iteration after which the sum rate stops increasing. PAA then converges to a final state and outputs the final power allocation result \mathbf{a}_n^* . \square

Theorem 10. *The convergent solution of PAA is a first-order optimal solution of the problem in (4.22), which satisfies the KKT conditions.*

Proof. Denote the power allocation indicator at convergence of PAA is \mathbf{a}_n^* . Since \mathbf{a}_n^* is the optimal solution of the concave problem in (4.29), \mathbf{a}_n^* must satisfy the KKT conditions of (4.29). Actually, the problem (4.22) and (4.29) share the same constraints but have different objective functions with $\sum_{k=1}^{L_n} R_{n,k}$ and $\sum_{k=1}^{L_n} \Theta_k(2^{s_{n,k}})$, respectively. However, when PAA converges, it has $\sum_{k=1}^{L_n} R_{n,k} = \sum_{k=1}^{L_n} \Theta_k(2^{s_{n,k}})$. Therefore, \mathbf{a}_n^* also satisfies the KKT conditions of the problem in (4.22). \square

4.6.3 Proposed Joint Subchannel and Power Allocation Algorithm

Based on the two proposed algorithms, i.e., SAA and PAA, it is worth considering how to jointly consider subchannel and power allocation together. In the following, two approaches are demonstrated:

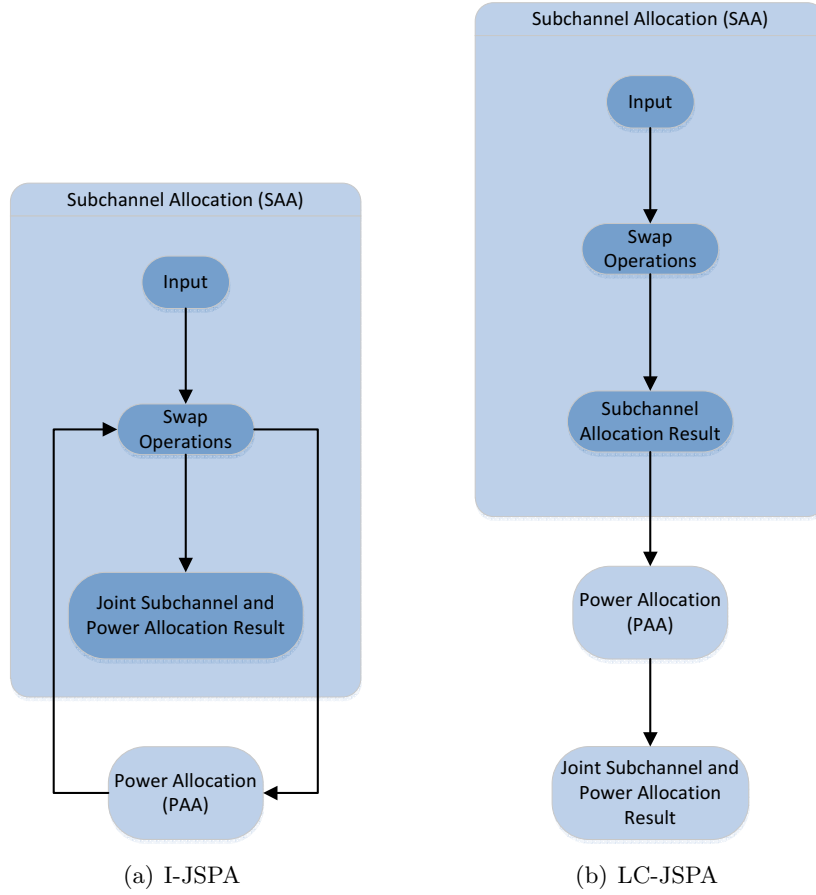


Figure 4.2: Flow charts of the two proposed joint subchannel and power allocation algorithms.

1) *Iterative Joint Subchannel and Power Allocation Algorithm (I-JSPA)*: According to the optimisation problem in (4.14), the subchannel assignment indicator λ and the power allocation coefficient \mathbf{a} jointly influence the sum data rate. Therefore, a joint subchannel and power allocation algorithm is proposed, where the power allocation, i.e., PAA, is executed iteratively after each swap operation in SAA, as shown in Figure 4.2(a). In this way, the power allocation coefficient \mathbf{a} can be updated timely after any change of the subchannel assignment indicator λ , which improves the system performance. However, the shortcoming of this approach is the high complexity, which increases exponentially with the number of swap operations.

2) *Low-Complexity Joint Subchannel and Power Allocation Algorithm (LC-JSPA)*:

Because of the high complexity of I-JSPA, an alternative low-complexity approach is proposed, which is shown in Figure 4.2(b). Without knowing the subchannel assignment result, the SIC order in each D2D group can not be decided, and thus the power allocation can not be completed. Therefore, it first solves the subchannel assignment problem via SAA based on random given initial values of the power allocation coefficients $\mathbf{a}_n, \forall n$. After the convergence of SAA, the BS can allocate power to receivers in each D2D group via PAA.

4.7 Numerical Results

In this section, the performance of the proposed joint subchannel and power allocation algorithm is investigated through simulations. For simplicity, in the following simulation results, it is assumed that all D2D groups have the same number of receivers, i.e., $L_n = K, \forall n \in \{1, \dots, N\}$. The performance of the joint subchannel and power allocation algorithm in I-JSPA and LC-JSPA is given, respectively. The performance of the exhaustive search and the one-to-one matching based algorithm are also provided as benchmarks for comparison, in order to show the effectiveness of the proposed algorithm. More particularly, the exhaustive search enables searching for all possible subchannel allocation ways while the power allocation is also performed exhaustively for each given case. Since power is a continuous variable, it is not easy to search for all possible power allocation values. Therefore, the values of $a_{n,k}, \forall k \in \{1, \dots, K\}$ are searched with an interval of ϵ , through which the approximately global optimal solution can be obtained. In the one-to-one matching algorithm, one D2D group can use no more than one subchannel, and one subchannel can only be allocated to one D2D group. The specific parameter value settings are summarised in Table 4-A unless otherwise specified.

The performance of the conventional OMA based D2D communications is also illustrated in an effort to demonstrate the potential benefits of the proposed NOMA enhanced D2D scheme. For OMA based D2D communications, the achievable data rate for the

k -th receiver in the n -th D2D group is $\frac{1}{K} \log_2 \left(1 + \frac{P_d |f_{n,k}|^2}{I_{n,k}^{out} + I_{n,k}^e + \sigma^2} \right)$, where $\frac{1}{K}$ is due to the fact that the time/frequency resource is split among the K receivers, which is as mentioned in Section II of [DLC⁺16]. The many-to-one matching, one-to-one matching and exhaustive search are also applied to the OMA based D2D scenarios, respectively, with the aim of comparing the performance of the corresponding NOMA enhanced D2D scenarios with.

Table 4-A: Simulation Parameters

Cellular radius	40 m
Maximum distance between D2D pairs	5 m
Cellular-user SINR threshold	1.8 dB
Transmit power of cellular users	23 dBm
Noise power	-98 dBm
Path-loss exponent	4
Number of subchannels	3

4.7.1 Convergence of the Proposed Algorithm

Figure 4.3 plots the cumulative distribution function (CDF) of the number of swap operations for the matching process, and thus demonstrates the convergence of the proposed subchannel assignment algorithm for different number of D2D groups in the network. The CDF shows that the proposed matching algorithm converges within a small number of iterations. For example, when there are 11 D2D groups in the network, on average a maximum of 40 iterations is required to ensure the proposed algorithm to converge. One can also observe that the number of swap operations increases with the increased number of D2D groups, which is due to the improved probability of the existence of swap-blocking pairs.

4.7.2 I-JSPA versus LC-JSPA

Figure 4.4 investigates the total sum rate versus different D2D transmit signal-to-noise-ratio (SNR). The number of D2D groups is set to $N = 6$, and the number of receivers in

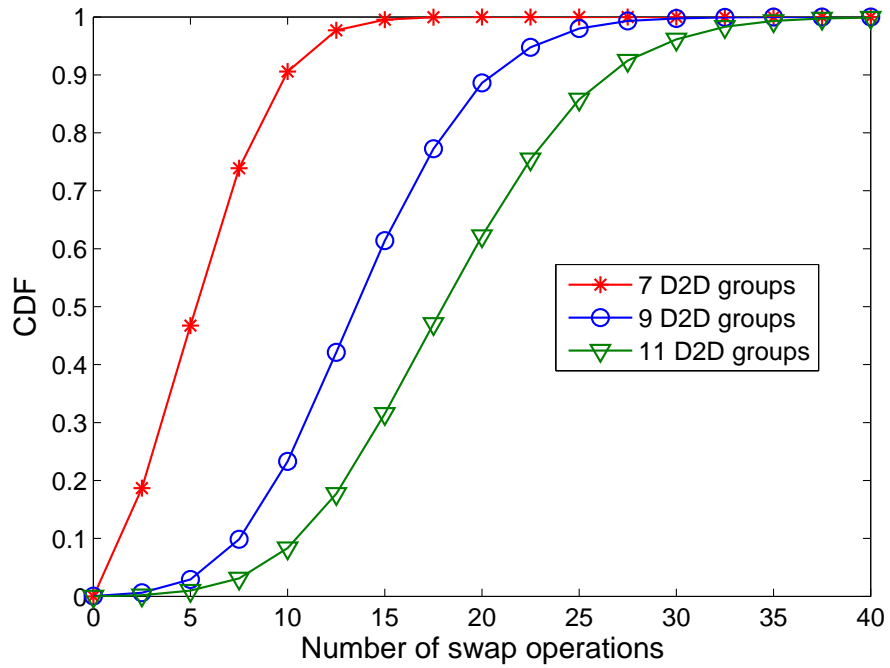


Figure 4.3: CDF of the number of swap operations, with $K = 2$.

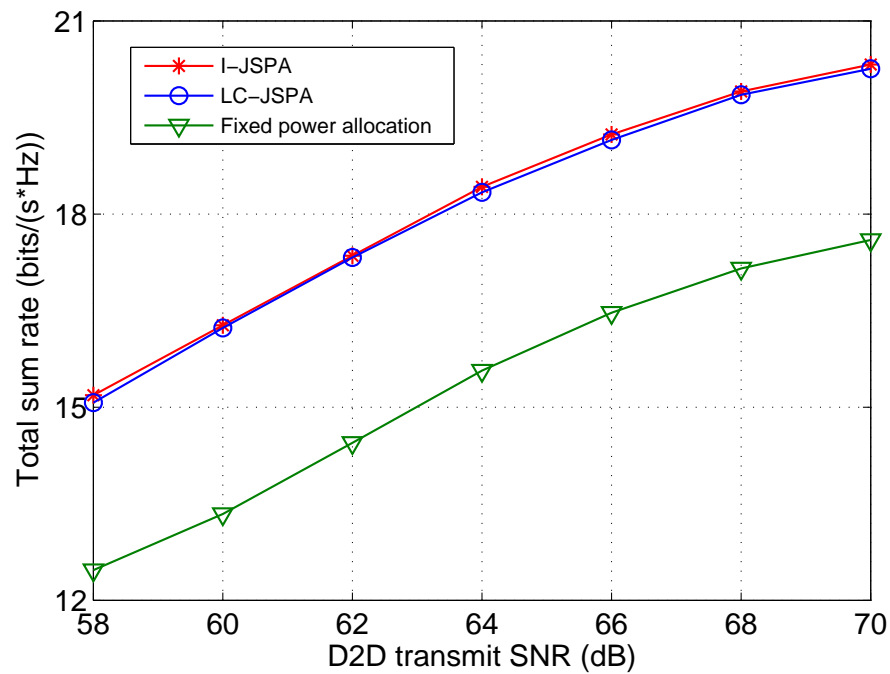


Figure 4.4: Total sum rate versus different D2D transmit SNR, with $N = 6$, $K = 2$.

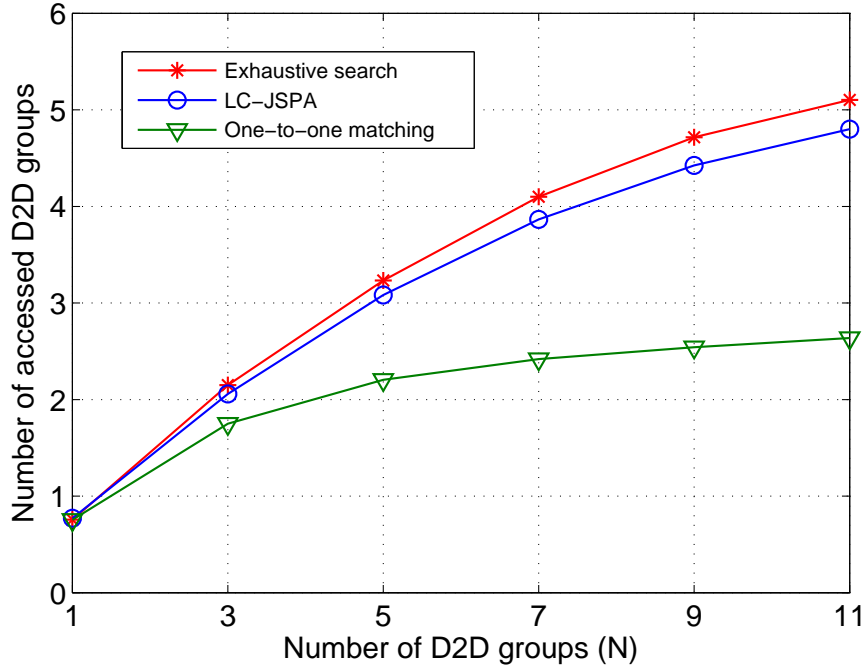


Figure 4.5: Number of accessed D2D groups versus different number of D2D groups in the network, with $K = 3$.

each D2D group is set to $K = 2$. As can be observed, the total sum rate increases with the D2D transmit SNR since the received SINR at the receivers are improved by allocating more power at the transmitters. For comparison, Figure 5.7 shows the performance of the fixed power allocation algorithm, where the power allocation coefficients are set to $a_{n,1} = 0.6, a_{n,2} = 0.4$. It can be observed that the fixed power allocation algorithm achieves substantially lower sum rate compared to the proposed algorithm. Besides, it also shows that LC-JSPA closely approaches the performance of I-JSPA. As discussed before, since the complexity of I-JSPA increases exponentially with the number of swap operations, LC-JSPA is adopted in the remaining parts of this chapter.

4.7.3 NOMA-enhanced versus OMA-based D2D Communications

Figure 4.5 shows that, the number of accessed D2D groups increases as the number of D2D groups in the network increases. This is because as N increases, the probability of D2D groups with less interference to the cellular UEs being assigned to them increases,

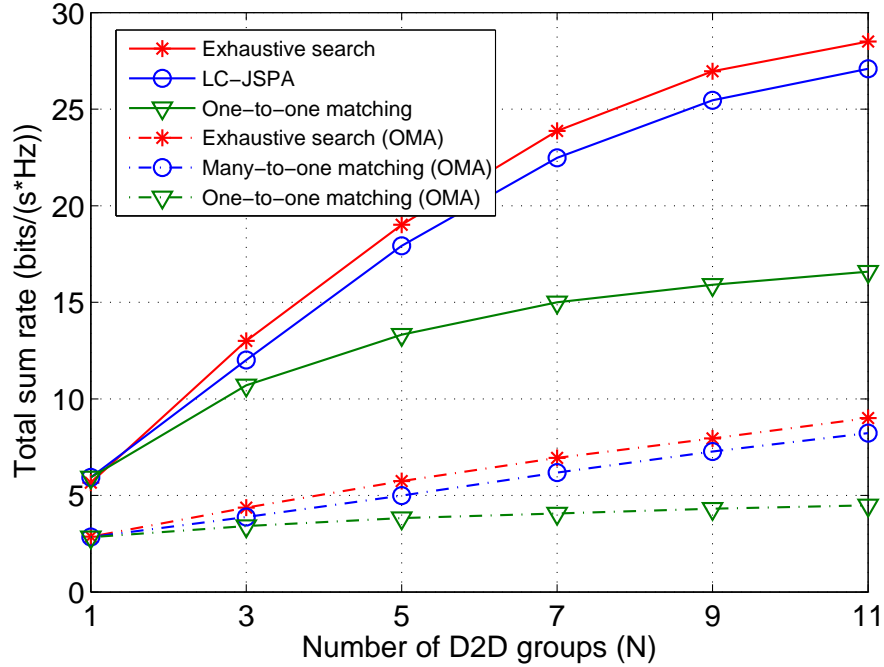


Figure 4.6: Total sum rate versus different number of D2D groups in the network, with $K = 3$.

which leads to larger number of accessed D2D groups that can meet the SINR constraints of cellular UEs. This phenomenon is similar to the effect of multi-user diversity. It is worth noting that with the increase of the number of D2D groups in the network, the increasing rate of the number of accessed D2D groups becomes smaller due to the enhanced co-channel interference. One can also observe that the number of accessed D2D groups can get saturated quickly in the one-to-one matching algorithm. This is due to the fact that each subchannel can be allocated to no more than one D2D group.

Figure 4.6 plots the total sum rate versus different number of D2D groups in the network. One can observe that the sum rate increases with the number of D2D groups, which follows the intuition that more D2D groups contribute to a higher total sum rate. It is also observed that the proposed algorithm achieves much higher sum rate compared to the one-to-one matching algorithm. Meanwhile, the proposed algorithm is capable of reaching around 93.7% of the result of the exhaustive search. Recall the complexity of the proposed algorithm, which is much lower than the exhaustive search, unequivocally

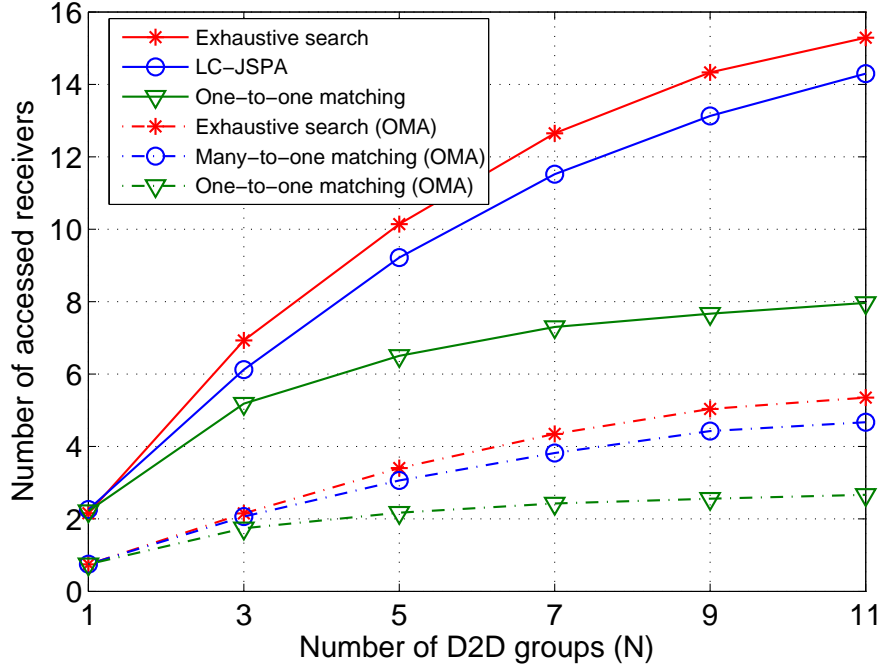


Figure 4.7: Number of accessed receivers versus different number of D2D groups in the network, with $K = 3$.

substantiates the plausibility of the proposed algorithm. Figure 5.4 also demonstrates that the NOMA enhanced D2D scheme achieves larger sum rate than the conventional OMA based D2D scheme, which demonstrates the performance gains of the prior one.

Figure 4.7 plots the number of accessed receivers versus different number of D2D groups in the network. It can be seen from the figure that the number of accessed receivers in the proposed algorithm is larger than that in the one-to-one matching algorithm. This is because more than one D2D groups are allowed to be allocated to one subchannel in the proposed algorithm, and thus the resource utilisation is improved. It is also noted that the NOMA enhanced D2D communications achieves a larger number of accessed D2D receivers than the OMA based D2D communications, which further shows the merits of applying NOMA transmission protocol in D2D communications.

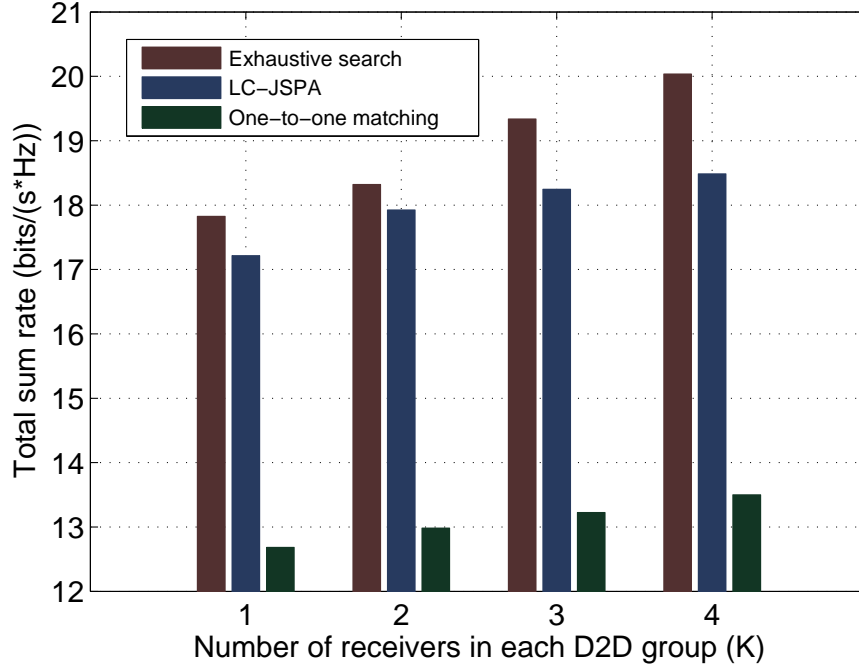


Figure 4.8: Total sum rate versus different number of receivers in each D2D group, with $N = 5$.

4.7.4 “D2D group” versus “D2D pair”

Figure 4.8 depicts the total sum rate versus different number of receivers in each D2D group. It can be seen that the sum rate increases as the number of receivers in each D2D group increases, with a small increasing rate. This is because, in this scenario, the total transmit power of each D2D transmitter is a fixed value when the number of receivers in each D2D group varies. Thus the partition of power allocated to each receiver gets smaller when the number of receivers in each D2D group gets larger. This leads to the phenomenon that the total sum rate is not increased much with the larger number of receivers in each D2D group. For the case of $K = 1$, it becomes the conventional “D2D pair” scenario. In other words, the conventional “D2D pair” scenario is the special case, and thus the proposed algorithm is also valid for the “D2D pair” scenario. Figure 4.8 demonstrates that the network sum rate of the “D2D group” scenario is improved compared to that of the “D2D pair” one.

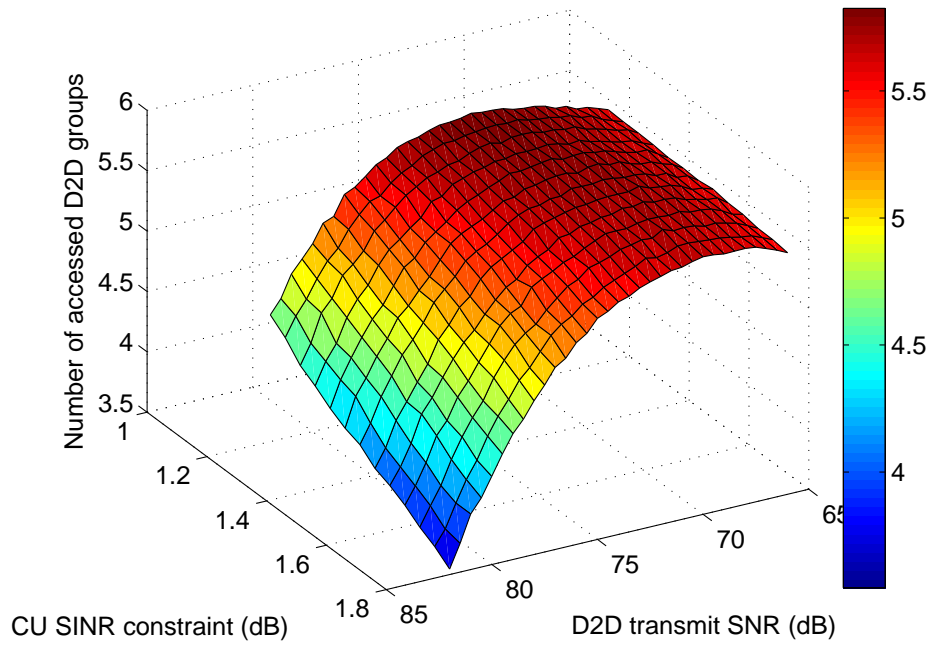
4.7.5 Impact of Interference Constraints for Cellular Users

Figure 4.9(a) shows the number of accessed D2D groups versus different D2D transmit SNR and different SINR constraints of cellular users. It can be observed that the number of accessed D2D groups decreases with higher SINR constraint of the cellular users. This is because the maximum allowed interference for the cellular users gets smaller with the higher SINR constraint, and therefore the number of acceptable D2D groups for each subchannel is decreased. Figure 4.9(a) further shows that the number of accessed D2D groups increases with the lower D2D transmit SNR. This is due to the fact that the interference caused to the cellular users and other D2D groups occupying the same subchannels gets smaller with the lower D2D transmit SNR, and thus the acceptable number of D2D groups on each subchannel is increased.

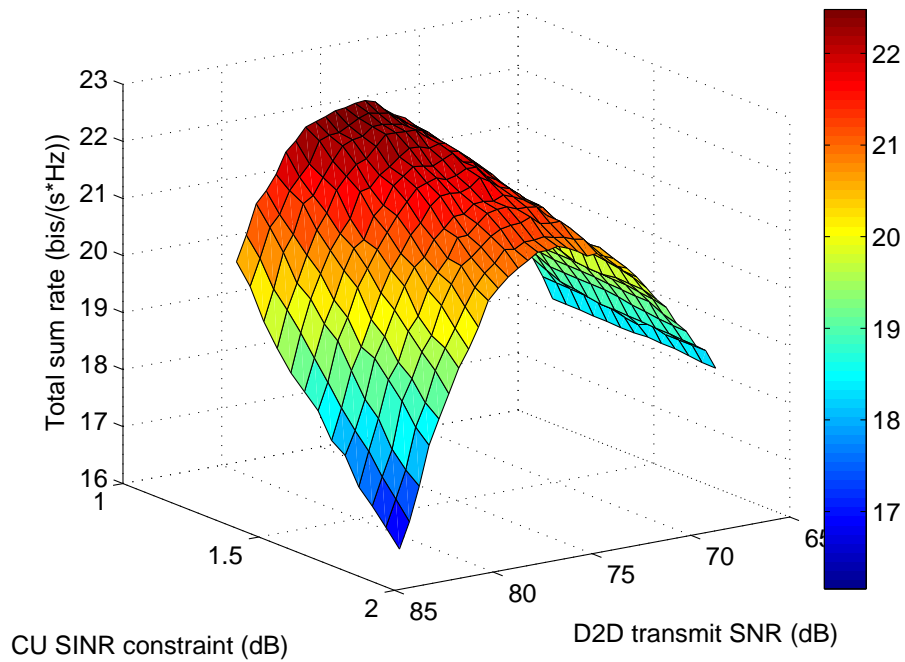
Figure 4.9(b) depicts the total sum rate versus different D2D transmit SNR and different SINR constraint of the cellular users. It can be seen that the total sum rate decreases with the higher SINR constraint of the cellular users. This can be easily understood because of the smaller number of accessed D2D groups, as shown in Figure 4.9(a). Besides, it is easy to find that, when the D2D transmit SNR is small, the total sum rate increases with the larger SNR, which is caused by the increased transmit power. When the D2D transmit SNR increases to a certain value, the total sum rate starts to decrease with the higher value of D2D transmit SNR. This is because of the smaller number of accessed D2D groups as shown in Figure 4.9(a). Figure 4.9(a) and Figure 4.9(b) illustrates how the interference constraints of cellular users influence the sum rate and number of accessed D2D groups.

4.8 Summary

In this chapter, the application of non-orthogonal multiple access (NOMA) to the device-to-device (D2D) communications has been studied. With the objective of maximising



(a) Number of accessed D2D groups versus different D2D transmit SNR and CU SINR constraint, with $N = 6, K = 2$.



(b) Total sum rate versus different D2D transmit SNR and CU SINR constraint, with $N = 6, K = 2$.

Figure 4.9: Performance analysis of the proposed algorithm.

network sum rate while satisfying the interference constraints of cellular users, a joint subchannel and power allocation problem was formulated. Since the formulated problem was a mixed-integer non-convex problem, it was decoupled into two subproblems, i.e., subchannel assignment and power allocation problems. A novel algorithm invoking many-to-one matching theory was proposed for tackling the subchannel assignment problem. Based on the subchannel assignment result, the non-convex power allocation problem for receivers in each D2D group was solved by applying the sequential convex programming, which was proved to be convergent. Simulation results showed that the proposed joint subchannel and power allocation algorithm approached close to the exhaustive-searching method. It was also shown that the proposed NOMA enhanced D2D scheme outperformed the conventional OMA based D2D scheme, in terms of both sum rate and number of accessed users.

Chapter 5

Resource Allocation for D2D Communications in HetNets with NOMA

5.1 Overview

In this chapter, a novel resource allocation design is investigated for D2D communications in HetNets with NOMA, where underlay transmitters (UTs), i.e., D2D transmitters and small cell base stations (SBSs), are capable of communicating with multiple underlay receivers (URs), i.e., D2D receivers and small cell users (SCUs), respectively, via the NOMA protocol. With the aim of maximising the sum rate of URs while taking the fairness issue into consideration, a joint problem of spectrum allocation and power control is formulated. Particularly, the spectrum allocation problem is modeled as a many-to-one matching game with peer effects. A novel algorithm where the UTs and RBs interact to decide their desired allocation is proposed. The proposed algorithm is proved to converge to a two-sided exchange-stable matching. Furthermore, the concept of ‘exploration’ is introduced into the matching game for further improving the sum rate. The power control of each UT is formulated as a non-convex problem, where the sequential convex programming is adopted to iteratively update the power allocation result by solving the approximate convex problem. The obtained solution is proved to satisfy the KKT

conditions. It is unveiled that: 1) The proposed algorithm closely approaches the optimal solution within a limited number of iterations; and 2) The ‘exploration’ action is capable of further enhancing the performance of the matching algorithm.

5.2 Motivation

Despite the fact that there are ongoing research efforts to address the resource allocation problems for D2D, HetNets and NOMA, the solutions for the resource allocation problems of D2D communications in HetNets with NOMA have not been studied in the literature. Note that NOMA and HetNets pose additional challenges in terms of interference management since it brings additional co-channel interference to the existing networks. As such, novel resource allocation design for intelligently managing and coordinating various types of interference are more than desired, which motivates us to develop this work. The joint spectrum and power allocation problem for D2D communications in HetNets with NOMA is studied, with the aim of maximising the sum rate of D2D users (DUs) and SCUs. Particularly, the downlink scenario is considered, where one macro base station (MBS) communicates with multiple macro cell users (MCUs) via the conventional OMA protocol, while each SBS communicates with two NOMA SCUs and each D2D transmitter communicates with two NOMA receivers. The small cells and DUs are referred as *underlay tier*. The SBSs and DUs are underlaid within the *macro tier* (e.g., MBS and MCUs) since both the macro tier and the underlay tier (e.g., SBSs, SCUs and DUs) use the same set of RBs.

To tackle the formulated problem, the spectrum and power allocation problems are decoupled and a joint solution where the spectrum and power allocation are executed iteratively is provided. For the spectrum allocation, multiple UTs are allowed to reuse the same RB occupied by a MCU to improve the resource utilisation. It is recognised that the spectrum allocation can be regarded as a many-to-one matching process between UTs and RBs, where the UTs and RBs act as two sets of players and interact with

each other to maximise the sum rate of underlay tier. In addition, the UTs have peer effects with the interdependencies among each other due to the co-channel interference. Therefore, matching theory [RS92, GSB⁺15] is applied to solve this problem, which provides mathematically tractable and low-complexity solutions for the combinatorial problem of matching players in two distinct sets [Man13]. Then the spectrum allocation problem is formulated as a many-to-one matching problem with peer effects and propose efficient algorithms to solve the problem. The primary contributions of this paper can be summarised as follows.

1. A new model of D2D communications in HetNets with NOMA is proposed, in which NOMA technique is invoked in underlay tier for spectrum efficiency enhancement and user access improvement. Based on the proposed model, a joint spectrum allocation and power control problem is formulated with the aim of maximising the sum rate of underlay tier while considering users' fairness issues.
2. The spectrum allocation for underlay tier is formulated as a many-to-one matching problem with peer effects. For solving the formulated problem, a swap-operation enabled matching algorithms (SOEMA-1) is first proposed to match UTs with RBs aiming at maximising the sum rate of underlay tier. For further improving the performance of SOEMA-1, the concept of "experimentation" is introduced into the matching game and propose a novel algorithm SOEMA-2, where irrational swap decisions are enabled with a small probability to explore the potential matching states.
3. To solve the non-convex power control problem of each UT, the sequential convex programming is invoked to iteratively update the power allocation vector by solving the approximate convex problem. It is proved that the proposed algorithm is convergent and the solution satisfies the KKT conditions.
4. It is demonstrated that NOMA-enhanced HetNets is capable of significantly outperforming the conventional OMA based HetNets in terms of both the sum rate

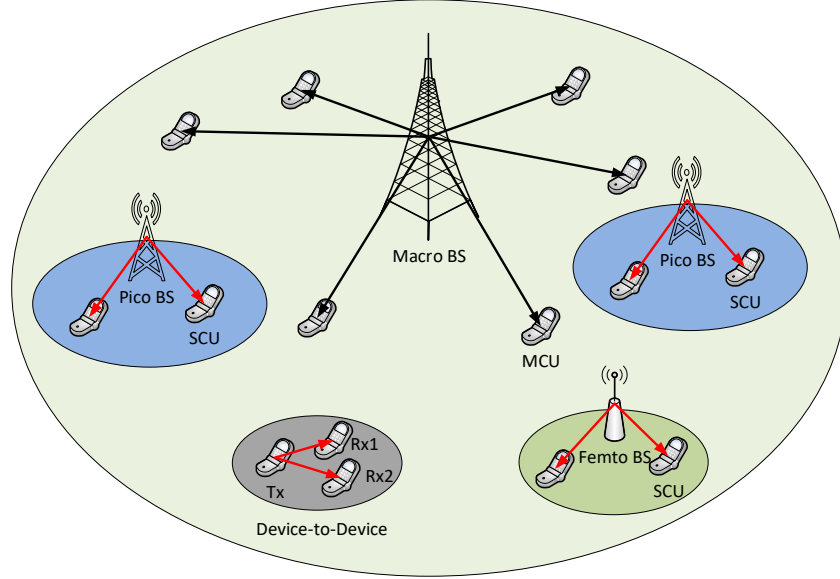


Figure 5.1: D2D communications in HetNets with NOMA.

of underlay tier and users' connectivity. Additionally, it is also presented that the performance of the matching algorithm can be further improved via the “experimentation” action.

5.3 System Model

5.3.1 System Description

Consider a downlink K -tier HetNets model, where the first tier represents a single macro cell and the other tiers represent the small cells such as pico cells and femto cells as well as D2D links. The set of UTs is represented by $\mathcal{UT} = \{1, \dots, B\}$, which is composed of both SBSs and D2D transmitters. The MBS serves a set of M MCUs, i.e., $\mathcal{MCU} = \{1, \dots, M\}$. There are M RBs, and each MCU occupies a RB. For the sake of simplicity, the RBs use the same index as the MCUs, and thus the set of RBs is represented by $\mathcal{RB} = \{1, \dots, M\}$. In this work, it is assumed that each UT b occupies no more than one RB and serves at most two URs simultaneously via the NOMA protocol. This assumption is attributed to

limit the co-channel interference and to lower the hardware complexity and processing delay⁴. The illustration of cellular layout is shown in Figure 5.1.

This work allows multiple UTs to reuse the same RB to improve the spectrum efficiency. The maximum number of UTs occupying the same RB is restricted to q_{max} . Since the spectrum sharing brings in both co-tier and cross-tier interference, efficient resource allocation is required for D2D communications in HetNets with NOMA. In this work, it is assumed that the user association is completed prior to the resource allocation.

5.3.2 Channel Model

NOMA-based transmission requires to apply the superposition coding (SC) technique at UTs and SIC⁵ technique at URs. The vector $\mathbf{a}_b = [a_{b,k}, a_{b,j}]$ represents the power allocation coefficients for URs, i.e., SCUs and D2D receivers, in each small cell/D2D group. UT b sends messages to receivers k and j on RB m , based on the NOMA principle, i.e., b sends $a_{b,k}^n x_{b,k}^n + a_{b,j}^n x_{b,j}^n$, where $x_{b,k}^n$ is the message for receiver k . The received signal at receiver k served by the b -th UT, i.e., $b \in \{1, \dots, B\}$, on the m -th RB is given by

$$\begin{aligned}
 y_{b,k}^n = & \underbrace{f_{b,k}^m \sqrt{p_b a_{b,k}} x_{b,k}^m}_{\text{desired signal}} + \underbrace{f_{b,k}^m \sqrt{p_b a_{b,j}} x_{b,j}^m}_{\text{interference from NOMA users}} + \underbrace{\zeta_{b,k}^m}_{\text{noise}} \\
 & + \underbrace{\sum_{m=1}^M \lambda_{m,b} h_{m,b,k} \sqrt{p_m} x_m}_{\text{cross-tier interference}} + \underbrace{\sum_{b^* \neq b} \lambda_{b^*,b} g_{b^*,b,k}^m \sqrt{p_{b^*}} x_{b^*}^m}_{\text{co-tier interference}}, \quad (5.1)
 \end{aligned}$$

where $x_{b,k}^m$, x_m are the symbols transmitted from the b -th UT to its serving receiver k , and from the MBS to the MCU m , respectively. $f_{b,k}^m$, $h_{m,b,k}$, and $g_{b^*,b,k}^m$ are the channel coefficients between UT b and receiver k , that between the MBS and receiver k , and that

⁴NOMA requires SIC at the receivers. A user performing SIC needs to demodulate and decode the signals transmitted to other receivers. Therefore, the hardware complexity and processing delay increases with the number of users multiplexed on the same RB.

⁵It is assumed that perfect SIC is achieved at the receivers. In practical scenarios, proceeding perfect SIC may be a non-trivial task. Therefore, this work actually provides an upper bound in terms of the attainable data rates.

between UT b^* and receiver k on RB m , respectively. p_b and p_m are the total transmit power of UT b and the transmit power from the MBS to MCU m , respectively. $\lambda_{m,b}$ represents the RB allocation indicator for UTs, i.e., if UT b occupies RB m , $\lambda_{m,b} = 1$; otherwise, $\lambda_{m,b} = 0$. $\lambda_{b^*,b}$ represents the presence of co-tier interference, i.e., if UT b and b^* reuse the same RB, $\lambda_{b^*,b} = 1$; otherwise, $\lambda_{b^*,b} = 0$. $\zeta_{b,k}^n$ is the AWGN at receiver k with variance σ^2 .

NOMA systems exploit the power domain for multiple access, where different users are served at different power levels. For illustration, assume UR j desires to decode and remove interference from the superposition signal of k via SIC. The interference cancellation is successful if UR j 's received SINR for k 's signal is larger or equal to the received SINR of k for its own signal [DYFP14, SNDS16]. Therefore, the condition of the given SIC decoding order is given by

$$\frac{|f_{b,j}^m|^2 p_b a_{b,k}^m}{I_N^{j,k} + I_{co}^j + I_{cr}^j + \sigma^2} \geq \frac{|f_{b,k}^m|^2 p_b a_{b,k}^m}{I_N^{k,k} + I_{co}^k + I_{cr}^k + \sigma^2}. \quad (5.2)$$

The inequality in (5.2) can be rewritten in the following:

$$|f_{b,j}^m|^2 (I_{co}^k + I_{cr}^k + \sigma^2) - |f_{b,k}^m|^2 (I_{co}^j + I_{cr}^j + \sigma^2) \geq 0. \quad (5.3)$$

Therefore, according to the received signal expressed in (5.1), the received SINR at UR k served by UT b on RB m to decode its own information is given by

$$\gamma_{b,k,k}^m = \frac{|f_{b,k}^m|^2 p_b a_{b,k}^m}{I_N^{k,k} + I_{co}^k + I_{cr}^k + \sigma^2}, \quad (5.4)$$

where $I_N^{k,k} = |f_{b,k}^m|^2 p_b a_{b,j}^m$ is the interference from the superposed signal to UR j , $I_{co}^k = \sum_{b^* \neq b} \lambda_{b^*,b} p_{b^*} |g_{b^*,b,k}^m|^2$ is the co-tier interference from the other UTs reusing the same RB, and $I_{cr}^k = \sum_m \lambda_{m,b} p_m |h_{m,b,k}|^2$ is the cross-tier interference from the MBS. Here, $|f_{b,k}^m|^2 = |\hat{f}_{b,k}^m|^2 (d_{b,k})^{-\eta}$, $|g_{b^*,b,k}^m|^2 = |\hat{g}_{b^*,b,k}^m|^2 (d_{b^*,b,k})^{-\eta}$, and $|h_{m,b,k}|^2 = |\hat{h}_{m,b,k}|^2 (d_{m,b,k})^{-\eta}$. $\hat{f}_{b,k}^m$,

$\hat{g}_{b^*,b,k}^m$ and $\hat{h}_{m,b,k}$ are small-scale fading with $\hat{f}_{b,k}^m \sim \mathcal{CN}(0, 1)$, $\hat{g}_{b^*,b,k}^m \sim \mathcal{CN}(0, 1)$ and $\hat{h}_{m,b,k} \sim \mathcal{CN}(0, 1)$. $d_{b,k}$ is the distance from UT b to k . $d_{b^*,b,k}$ is the distance from UT b^* to k , and $d_{m,b,k}$ is the distance from the MBS to k .

Note that UR j can decode the signal to k , thus the SINR received at j is expressed as

$$\gamma_{b,j}^m = \frac{|f_{b,j}^m|^2 p_b a_{b,j}^m}{I_{co}^j + I_{cr}^j + \sigma^2}. \quad (5.5)$$

To guarantee the service qualities of the MCUs, an interference threshold I_{thr} is given to the aggregated interference caused to the MCUs from the links in the underlay tier. The aggregated interference experienced on the MCU m is given by

$$I_m = \sum_{b=1}^B \lambda_{m,b} p_b |t_{b,m}|^2, \quad (5.6)$$

where $|t_{b,m}|^2 = |\hat{t}_{b,m}|^2 (d_{b,m})^{-\eta}$, and $\hat{t}_{b,m}$ is small-scale fading with $\hat{t}_{b,m} \sim \mathcal{CN}(0, 1)$. $d_{b,m}$ is the distance from UT b to MCU m .

5.4 Problem Formulation

In this section, the α -utility function is defined for underlay links' data rates to guarantee the fairness among the receivers served by each UT. Then the maximisation problems of underlay links' sum rate via proper spectrum and power allocation are formulated.

5.4.1 Fairness Among URs Based on α -Utility Function

Based on the SINR expressions of URs k and j in (5.4) and (5.5), the data rates of k and j served by UT b over RB m can be calculated as

$$R_{b,k}^m = \lambda_{m,b} \log_2 \left(1 + \frac{|f_{b,k}^m|^2 p_b a_{b,k}^m}{I_N^{k,k} + I_{co}^k + I_{cr}^k + \sigma^2} \right), \quad (5.7)$$

and

$$R_{b,j}^m = \lambda_{m,b} \log_2 \left(1 + \frac{|f_{b,j}^m|^2 p_b a_{b,j}^m}{I_{co}^j + I_{cr}^j + \sigma^2} \right), \quad (5.8)$$

respectively. For receivers served by the same UT, the optimal power allocation is to allocate the total transmit power to the receiver with the best channel condition [LYHS15]. To guarantee the rate fairness among URs served by the same UT, the α -proportional fairness is adopted, where the α -utility function of receiver k served by transmitter b is defined as [MW00]

$$U_\alpha (R_{b,k}^m) = \begin{cases} \ln R_{b,k}^m, & \text{if } \alpha = 1 \\ (1 - \alpha)^{-1} (R_{b,k}^m)^{1-\alpha}, & \text{if } 0 \leq \alpha < 1. \end{cases} \quad (5.9)$$

Based on the defined α -utility function, the α -fairness based sum rate of UT b is expressed as:

$$U_\alpha (R_b^m (\lambda, \mathbf{a})) = U_\alpha (R_{b,k}^m) + U_\alpha (R_{b,j}^m). \quad (5.10)$$

5.4.2 Optimisation Problem Formulation

For facilitating the presentation, $\lambda \in \mathbb{R}^{M \times B}$ and $\mathbf{a} \in \mathbb{R}^{B \times 2}$ are denoted as the collections of optimisation variables $\lambda_{m,b}$ and $a_{b,k}$, respectively. The system objective is to maximise the sum α utility of the SCUs with interference constraints for the MCUs satisfied, which

can be expressed as follows:

$$\max_{\lambda, \mathbf{a}} \sum_{b=1}^B \sum_{m=1}^M U_{\alpha}(R_b^m(\lambda, \mathbf{a})), \quad (5.11a)$$

$$s.t. \quad \sum_{b=1}^B \lambda_{m,b} p_b |t_{b,m}|^2 \leq I_m^{thr} \quad \forall m, \quad (5.11b)$$

$$|f_{b,j}^m|^2 (I_{co}^k + I_{cr}^k + \sigma^2) - |f_{b,k}^m|^2 (I_{co}^j + I_{cr}^j + \sigma^2) \geq 0, \quad (5.11c)$$

$$\lambda_{m,b} \in \{0, 1\}, \quad \forall m, b, \quad (5.11d)$$

$$\sum_m \lambda_{m,b} \leq 1, \quad \forall b, \quad (5.11e)$$

$$\sum_b \lambda_{m,b} \leq q_{max}, \quad \forall m, \quad (5.11f)$$

$$a_{b,k} \geq 0, a_{b,j} \geq 0, \quad \forall b, \quad (5.11g)$$

$$a_{b,k} + a_{b,j} \leq 1, \quad \forall b. \quad (5.11h)$$

With the constraint in (5.11b), the aggregated interference caused to the MCU m by the UTs reusing the same RB is restricted by a predefined threshold, i.e., I_m^{thr} . Constraint (5.11c) guarantees successful SIC at receiver j . Constraints (5.11d) and (5.11e) are imposed to guarantee that each UT occupies no more than one RB. Constraint (5.11f) limits the maximum number of UTs, i.e., q_{max} , reusing each RB. Constraint (5.11g) is the non-negative transmit power constraint for the UTs. Constraint (5.11h) gives the upper bound of the transmit power of the UTs.

The formulated problem is a mixed combinatorial non-convex problem due to the binary constraint for RB allocation in (5.11d) as well as the non-convex objective function. In general, there is no systematic and computational efficient approach to solve this problem optimally. As can be observed, the optimisation problem in (5.11) is coupled by the two problems of spectrum allocation and power control. To reduce the computational complexity, these two subproblems are decoupled as the following. For any fixed power

allocation, the spectrum allocation for UTs is formulated as a many-to-one matching game [GSB⁺15] where RBs and UTs interact with each other to find the optimal matching. For the given spectrum allocation result, the power allocation problem for URs is solved by applying the sequential convex programming [PE06]. Then a joint algorithm is proposed, where the spectrum allocation and power control are performed iteratively to find the joint resource allocation result.

5.5 Subchannel Allocation for D2D communications in HetNets with NOMA

In this section, the spectrum allocation problem for UTs given fixed power allocation is first considered. More particularly, for any given feasible power allocation, the original problem in (5.11) can be decomposed into the RB allocation problem for all the UTs, which can be expressed as

$$\max_{\lambda} \sum_{b=1}^B \sum_{m=1}^M U_{\alpha}(R_b^m(\lambda)), \quad (5.12a)$$

$$s.t. \quad (5.11b) - (5.11f). \quad (5.12b)$$

For obtaining the global optimal solution of (5.12), all the possible combinations of scheduling RBs to UTs need to be fully searched. Thus, even for a centralised algorithm, it is not feasible in practical systems to solve it. However, since λ is a binary variable, the RB allocation is formulated as a many-to-one matching problem [GSB⁺15].

5.5.1 Many-to-One Matching Problem Formulation

To proceed with formulating the matching problem, some important definitions are first introduced.

Definition 13. *In the many-to-one matching model, a matching Ω is a function from*

the set $\mathcal{RB} \cup \mathcal{UT}$ into the set of all subsets of $\mathcal{RB} \cup \mathcal{UT}$ such that 1) $|\Omega(b)| = 1, \forall b \in \mathcal{UT}$; 2) $|\Omega(m)| \leq q_{max}, \forall m \in \mathcal{RB}$; 3) $\Omega(b) = m$ if and only if $b \in \Omega(m)$.

For the conditions in Definition 13, condition 1) implies that each UT can only be matched with one RB; condition 2) gives the quota q_{max} of the maximum number of UTs that can be matched to each RB; and condition 3) implies that if UT b is matched with RB m , then RB m is also matched with UT b .

The utility of UT b is defined as the sum rate of all the serving receivers minus its cost for occupying RB m , which is given by

$$U_b = \sum_{k=1}^K U_\alpha (R_{b,k}^m) - \tau p_b |g_{b,m}|^2, \quad (5.13)$$

where $\tau \in \mathbb{R}^+$ is the fixed coefficient with unit interference of UT b bringing to the m -th MCU.

The utility of RB m is defined as the sum rate of the occupying underlay links, and thus the utility function of RB m can be expressed as

$$U_m = \sum_{b=1}^B \lambda_{m,b} \sum_{k=1}^K U_\alpha (R_{b,k}^m), \quad (5.14)$$

To start the matching process, both UTs and RBs need to set up the preference lists with respect to their own interests. The preference list is a descending order list formed by each side of the players according to their preference to the other side of the players. For each UT b , it forms a descending order preference list \mathcal{BLIST}_b according to its utilities over all the RBs. For example, if UT b can achieve higher data rate over RB m compared to RB m' , i.e., $U_b(m) > U_b(m')$, it has $m \succ_b m'$, which indicates that b prefers m to m' . Since each RB can be matched with up to q_{max} UTs, each RB m forms a preference list \mathcal{RBLIST}_m over all the possible sets of UTs with the descending order of its utility. That is, $U_m(\mathcal{S}) > U_m(\mathcal{S}') \Rightarrow \mathcal{S} \succ_m \mathcal{S}'$, which refers that RB m prefers the set of UTs \mathcal{S} to \mathcal{S}' .

Remark 4. *The matching game formulated above is a many-to-one matching with peer effects.*

Proof. As observed in (5.4), (5.5) and (5.13), the utility of each UT is affected by the co-tier interference from the UTs occupying the same RB. In other words, the utility of each UT depends not only on the RB it matches with, but also on which other UTs match to the same RB. Therefore, the formulated game model is a many-to-one matching with peer effects. \square

Due to the existence of peer effects in this matching model, the preference lists of players change with the matching game proceeds, which is different from conventional matching games where players have fixed preference lists [GZPH15, HH14]. There is a growing literature studying many-to-one matchings with peer effects [DM97, Haf08]. However, these research contributions have demonstrated that designing matching mechanisms is significantly more challenging when peer effects are considered. Motivated by the housing assignment problem in [BBLC⁺11], an extended matching algorithm for the many-to-one matching problem with peer effects is proposed in the following.

Remark 5. *The formulated matching game is lack of the property of substitutability.*

Proof. See Appendix A.1. \square

Due to the lack of substitutability, the traditional Gale Shapley (GS) Algorithm [RS92] does not apply to the formulated matching game any more. To better handle the interdependencies between players' preferences, the *swap operations* between any two SBSs to exchange their matched RBs is enabled. The detailed definition of swap matching, swap-blocking pair and two-sided exchange stability can be found in Eq. (3.4), Definition 8 and Definition 9, respectively, in chapter 3.

5.5.2 Proposed Spectrum Allocation Algorithm

In this subsection, an initialisation algorithm (IA) is proposed based on the GS algorithm to obtain the initial matching state [ZGPH14]. After the initialisation, it proceeds with swap operations among SBSs to further improve the performance.

1) *Initialisation Algorithm:* In the initialisation algorithm, UTs and RBs first initialise their own preference lists. The list of all the UTs that are not matched with any RB is denoted by $UNMATCH$. In the matching process, each UT proposes to its most preferred RB, then each RB accepts the most preferred UT and rejects the others. This process continues until the set $UNMATCH$ goes empty. The details of the initialisation algorithm are as shown in **Algorithm 3**.

Algorithm 3 Initialisation Algorithm (IA)

- 1: Construct the preference lists of the UTs $\mathcal{BLIST}_b, b \in \mathcal{UT}$; and the preference lists of the RBs $\mathcal{RBLIST}_m, m \in \mathcal{RB}$;
 - 2: Construct the set of the UTs that are not matched $UNMATCH$;
 - 3: **while** $UNMATCH \neq \emptyset$ **and** $\exists \mathcal{BLIST}_b \neq \emptyset$ **do**
 - 4: **for** $\forall b \in UNMATCH$ **do**
 - 5: UT b proposes to its most preferred RB that has never rejected it before;
 - 6: **end for**
 - 7: **for** $\forall m \in \mathcal{RB}$ **do**
 - 8: **if** $\sum_{b \in \mathcal{UT}} \eta_{m,b} \leq q_{max}$ **then**
 - 9: RB m keeps all the proposed UTs;
 - 10: Remove the matched UTs from $UNMATCH$;
 - 11: **else**
 - 12: RB m keeps the most preferred q_{max} UTs, and rejects the others;
 - 13: Remove the matched UTs from $UNMATCH$; and keep the rejected UTs in $UNMATCH$.
 - 14: **end if**
 - 15: Remove m from the preference lists of UTs that have sent proposals;
 - 16: **end for**
 - 17: **end while**
-

2) *Swap Operations Enabled Matching Algorithm:* After the initialisation of the matching state based on the IA, swap operations among UTs are enabled to further improve the performance of the resource allocation algorithm. The details of the proposed swap operations enabled matching algorithm (SOEMA-1) is shown in **Algo-**

rithm 4. SOEMA-1 is composed of three steps. Step 1 initialises the matching state based on the algorithm IA. Step 2 focuses on the the swap operations between the UTs. Each UT keeps searching for all the other UTs to check whether there exists a swap-blocking pair. The swap-matching process continues until there exists no swap-blocking pair, and then the algorithm goes to step 3, i.e., the end of the algorithm. Note that to prevent UT b looping in the swap operations with another UT b' , the flag $\mathcal{SR}_{b,b'}$ is set to record the time that UT b and b' swap their allocated RBs. Each UT b can at most swap with another UT b' twice.

Algorithm 4 Swap Operations Enabled Matching Algorithm (SOEMA-1)

- 1: – **step 1: Initialisation**
 - 2: Matching by the initialisation Algorithm (**IA**);
 - 3: Obtain the initial matching state: Ω_0 ;
 - 4: Initialise the number of swapping requests that UT b sends to b' , i.e., $\mathcal{SR}_{b,b'} = 0$;
 - 5: – **Step 2: Swap-matching process:**
 - 6: For each UT b , it searches for another UT b' to check whether it is a swap-blocking pair;
 - 7: **if** (b, b') forms a swap-blocking pair along with $m = \Omega(b)$, and $m' = \Omega(b')$, as well as $\mathcal{SR}_{b,b'} + \mathcal{SR}_{b',b} < 2$ **then**
 - 8: Update the current matching state to $\Omega_b^{b'}$;
 - 9: $\mathcal{SR}_{b,b'} = \mathcal{SR}_{b,b'} + 1$;
 - 10: **else**
 - 11: Keep the current matching state;
 - 12: **end if**
 - 13: **Repeat Step 2** until there is no swap-blocking pair.
 - 14: – **Step 3: End of the algorithm**
-

3) *Irrational Swap Matching Decisions:* It is observed that the final matching of the proposed algorithm SOEMA-1 is significantly affected by the initial matching state. Since the UTs can swap only between their current matchings, a better matching state that can achieve higher sum rate many not be formed directly based on the current matching state. For example, if the current matching state is $\{\{m, b\}, \{m', b'\}, \{m'', b''\}\}$ and the optimal matching⁶ is $\{\{m, b'\}, \{m', b''\}, \{m'', b\}\}$, the optimal matching can not be reached if (b, b') (or (b', b'')) is not a swap-blocking pair under the current matching state. Motivated

⁶The optimal matching here is defined as the matching that can achieve the highest sum α fairness-based data rate of SCUs.

to solve this issue, the concept of “*experimentation*” [AS02] is introduced to explore the space of matching states. Experimentation enables a player to destabilise a state involving a dominated allocation, at the cost of a temporary loss in utility. In this case, a novel experimentation enabled matching algorithm (SOEMA-2) is proposed, as shown in **Algorithm 5**. In SOEMA-2, the initialisation step is the same as that in SOEMA-1. During the swap-matching process, if a pair of UT (b, b') forms a swap-blocking pair, the swap operation between b and b' happens with probability 1. Otherwise, the swap operation between b and b' happens with the probability ϵ through experimentation. Note that $0 < \epsilon \ll 1$ is a small number that corresponds to the probability that a player makes an irrational decision. *rand* in **Algorithm 5** is a random number generator, and t_{max} is the maximum number of iterations.

Algorithm 5 Swap Operations Enabled Matching Algorithm (SOEMA-2)

- 1: – **step 1: Initialisation**
 - 2: Matching by the initialisation Algorithm (**IA**), and obtain the initial matching state: Ω_0 ;
 - 3: – **Step 2: Swap-matching with experimentation enabled:**
 - 4: **while** $t \leq t_{max}$ **do**
 - 5: For each UT b , it searches for another UT b' to check whether it is a swap-blocking pair;
 - 6: **if** (b, b') forms a swap-blocking pair along with $m = \Omega(b)$, and $m' = \Omega(b')$ **then**
 - 7: Update the current matching state to $\Omega_b^{b'}$;
 - 8: **else**
 - 9: **if** $rand < \epsilon$ **then**
 - 10: Update the current matching state to $\Omega_b^{b'}$;
 - 11: **else**
 - 12: Keep the current matching state;
 - 13: **end if**
 - 14: **end if**
 - 15: $t = t + 1$;
 - 16: **end while**
 - 17: – **Step 3: End of the algorithm**
-

5.5.3 Property Analysis

Given the proposed SOEMA-1 above, some important remarks on the properties in terms of stability, convergence, complexity and optimality are presented.

5.5.3.1 Stability

Lemma 4. *The final matching Ω^* of SOEMA-1 is a two-sided exchange-stable matching.*

Proof. See Appendix A.2. □

5.5.3.2 Convergence

The convergence of SOEMA-1 is proved here while the convergence of SOEMA-2 is usually not considered as it is constrained by the maximum number of iterations t_{max} .

Theorem 11. *SOEMA-1 converges to a two-sided exchange stable matching Ω^* within limited number of iterations.*

Proof. See Appendix A.3. □

5.5.3.3 Complexity

The complexity of SOEMA-1 is composed of two main parts, i.e., the IA and the swap-matching phases. For the IA, the complexity of setting up the preference lists of SBSs and RBs is $\mathcal{O}(BM^2)$. For the swap-matching phase, the number of iterations cannot be given in a closed form. This is because it is uncertain that at which step the algorithm converges to a two-sided exchange stable matching. This is a common problem in most heuristic algorithms. The number of total iterations for different numbers of SBSs and RBs is analysed in Figure 5.2, and more detailed analysis can be found in Section VI. Here, an upper bound of the complexity is given as follows:

Theorem 12. *The complexity of SOEMA-1 is upper bounded by $\mathcal{O}(B^2)$.*

Proof. Since it is restricted that each UT b can at most swap its allocated RB with another UT b' twice, the number of potential swap operations is upper bounded by $2 \times \binom{B}{2}$. Therefore, the complexity of SOEMA-1 is upper bounded by $\mathcal{O}(B^2)$. \square

The complexity of SOEMA-2 is restricted by the maximum number of iterations t_{max} . For traditional exhaustive searching method, the complexity increases exponentially with B and M , which is much higher than SOEMA-1 and SOEMA-2.

5.5.3.4 Optimality

It is shown below whether SOEMA-1 and SOEMA-2 can achieve an optimal matching.

Theorem 13. *All local maxima of URs' sum α fairness-based data rate corresponds to a two-sided exchange stable matching.*

Proof. Assume that the URs' sum α fairness-based data rate of matching Ω is a local maximum value. If Ω is not a stable matching, it indicates that there exists a swap-blocking pair that can further improve the sum α fairness-based data rate of URs. However, this is inconsistent with the assumption that Ω is local optimal, and hence it is concluded that Ω is two-sided exchange stable. \square

However, not all two-sided exchange stable matchings obtained from SOEMA-1 are local maxima of URs' total α fairness-based data rate. The reason can be given in a simple example: UT b does not approve a swap matching with b' along with their current matched RBs m and m' , due to the fact that its utility is not improved after the swap operation. However, m and m' can benefit a lot via this swap operation, which further improves the sum of URs' α fairness-based data rates. Of course, it can *force* the swap operation to happen, but this will obtain a weaker stability, as stated in [DSL16]. Similarly, although SOEMA-2 allows to explore the space of matching states, it still can

not guarantee the optimality of the final matching.

5.6 Power Allocation for D2D Communications in HetNets with NOMA

In this section, the power control for each UT is discussed. More particularly, for any given RB allocation result λ , the original problem in (5.11) reduces to the power allocation problem for a UT b as follows:

$$\max_{\mathbf{a}_b} U_\alpha (R_b^m(\mathbf{a}_b)), \quad (5.15a)$$

$$s.t. \quad (5.11c), (5.11g), (5.11h), \quad (5.15b)$$

where \mathbf{a}_b is the power allocation vector of UT b for its serving URs.

Because of the existence of the co-channel interference, (5.15) is a non-convex problem with respect to \mathbf{a}_b . Therefore, obtaining the global optimum is rather difficult. In this section, the sequential convex programming is adopted to solve the power allocation problem of each UT.

Based on the proof in [PE06], the following inequality for $\gamma_{b,k}^m$ holds:

$$\log_2(1 + \gamma_{b,k}^m) \geq b_k \log_2 \gamma_{b,k}^m + c_k, \quad (5.16)$$

where b_k and c_k are defined as

$$b_k = \frac{\bar{\gamma}_{b,k,k}^m}{1 + \bar{\gamma}_{b,k,k}^m}, \quad (5.17)$$

$$c_k = \log_2(1 + \bar{\gamma}_{b,k,k}^m) - \frac{\bar{\gamma}_{b,k,k}^m}{1 + \bar{\gamma}_{b,k,k}^m} \log_2 \bar{\gamma}_{b,k,k}^m, \quad (5.18)$$

respectively. The bound is tight for $\gamma_{b,k}^m = \bar{\gamma}_{b,k,k}^m$.

Consequently, the lower bound to the objective function in (5.15) is obtained as

$$U_\alpha(R_{b,k}^m) + U_\alpha(R_{b,j}^m) \geq U_\alpha(\bar{R}_{b,k}^m) + U_\alpha(\bar{R}_{b,j}^m), \quad (5.19)$$

where $\bar{R}_{b,k}^m = b_k \log_2(\gamma_{b,k}^m) + c_k$, $\bar{R}_{b,j}^m = b_j \log_2(\gamma_{b,j}^m) + c_j$.

To transform $\bar{R}_{b,k}^m$ to a concave function, set $a_{b,k} = 2^{x_{b,k}}$, $a_{b,j} = 2^{x_{b,j}}$ and define $\mathbf{x}_b = [x_{b,k}, x_{b,j}]$. Accordingly, a new optimisation problem can be obtained from (5.15) and (5.19) as follows:

$$\max_{\mathbf{x}_b} (U_\alpha(\bar{R}_{b,k}^m) + U_\alpha(\bar{R}_{b,j}^m)), \quad (5.20a)$$

$$s.t. \quad 2^{x_{b,k}} + 2^{x_{b,j}} \leq 1, \quad (5.20b)$$

Proposition 1. *The rewritten optimisation problem in (5.20) is a convex optimisation problem with respect to \mathbf{x}_b .*

Proof. See Appendix A.4. □

Since the problem in (5.20) is a convex optimisation problem, the power allocation vector \mathbf{a}_b is iteratively updated by solving (5.20) to tighten the lower bound in (5.19) until convergence. The details of the proposed power allocation algorithm is shown in **Algorithm 6**. The proposed algorithm consists of two main steps. The first step is the initialisation step, where the initial power allocation vector $\mathbf{a}_b(0)$ is set. The second step is the update step. In the i -th iteration of the second step, set $\bar{\gamma}_{b,k,k}^m = \gamma_{b,k}^m(i-1)$, and subsequently derive the solution $\mathbf{x}_b(i)$ by solving the convex optimisation problem in (5.20). This process continues until the gap between the values of $\gamma_{b,k}^m$ in the current iteration and that in the previous iteration is smaller than the threshold g_{thr} .

With the proposed subchannel allocation algorithms, i.e., IA, SOEMA-1, and SOEMA-2, and the power allocation algorithm, i.e., SCPAA, a joint spectrum allocation and power control algorithm (JSAPCA) is proposed to solve the URs' sum rate maximisation problem in (5.11), as shown in **Algorithm 7**. In the first step of initialisation, each UT

Algorithm 6 Sequential Convex Programming Based Power Allocation Algorithm (SCPAA)

-
- 1: – **Initialisation Phase:**
 - 2: Set $i = 0$.
 - 3: Initialise the power allocation vector $\mathbf{x}_b(0)$. Calculate $\gamma_{b,k}^m(0)$ based on $\mathbf{x}_b(0)$.
 - 4: Set the convergence threshold g_{thr} .
 - 5: – **Update Phase:**
 - 6: **while** $|\gamma_{b,k}^m(i) - \gamma_{b,k}^m(i-1)| \geq g_{thr}, \forall k$ **do**
 - 7: $i = i + 1$;
 - 8: Set $\hat{\gamma}_{b,k,k}^m = \gamma_{b,k}^m(i-1)$ and compute b_k and c_k according to (5.17) and (5.18);
 - 9: Solve the convex optimisation problem in (5.20) and set the result as $\mathbf{x}_b(i)$;
 - 10: Update $\mathbf{a}_b(i)$, where $a_{b,k}(i) = 2^{x_{b,k}(i)}, \forall k$;
 - 11: Calculate $\gamma_{b,k}^m(i), \forall k$ based on $\mathbf{a}_b(i)$;
 - 12: **end while**
 - 13: Result: $\mathbf{a}_b^* = \mathbf{a}_b(i)$.
-

Algorithm 7 Joint Spectrum Allocation and Power Control Algorithm (JSAPCA)

-
- 1: – **Step 1: Initialisation:**
 - 2: Randomly allocate power for URs served by each UT, where \mathbf{a} should satisfy the constraints in (5.11g) and (5.11h).
 - 3: Set $i = 0$;
 - 4: – **Step 2: Joint Spectrum Allocation and Power Control**
 - 5: **repeat**
 - 6: Update the subchannel allocation result λ according to IA, SOEMA-1 or SOEMA-2;
 - 7: Given λ , update the power allocation vector \mathbf{a} according to SCPAA.
 - 8: $i = i + 1$;
 - 9: **until** convergence **or** $i \geq i_{max}$.
 - 10: Resource allocation result: λ, \mathbf{a} .
-

randomly allocates power to URs satisfying the constraints in (5.11g) and (5.11h). In the second step, the subchannel allocation is first performed based on the current value of \mathbf{a} . Subsequently, the power allocation algorithm is executed based on the subchannel allocation result. This process is repeated for a maximum number of i_{max} iterations, where the joint solution is obtained.

Theorem 14. *The proposed algorithm JSAPCA with SOEMA-1 is guaranteed to converge.*

Proof. Each iteration of the joint algorithm JSAPCA consists of two main stages: spectrum allocation and power control. It has been proved in Theorem 11 that the sum

α -fairness based data rate of URs is improved after the swap operations in SOEMA-1. For the power allocation algorithm SCPAA, the sum α utility is guaranteed to not decrease according to the inequality in (5.19). It is assumed that $U_{\alpha\text{-total}}R_{b,k}^m(i)$ and $U_{\alpha\text{-total}}R_{b,k}^m(i')$ are the sum utilities of URs at the beginning and end of the i -th iteration. The following inequality holds:

$$U_{\alpha\text{-total}}R_{b,k}^m(i') > U_{\alpha\text{-total}}R_{b,k}^m(i). \quad (5.21)$$

Since the upper bound of the sum rate of URs exists due to the limited resources, it can be concluded that the joint algorithm JSAPCA with SOEMA-1 converges within limited number of iterations. \square

For JSAPCA with IA and SOEMA-2, the maximum number of iterations is constrained by the value of i_{max} , as shown in **Algorithm 7**.

5.7 Numerical Results

In this section, the performance of the proposed resource allocation algorithm is investigated through simulations. The adopted simulation parameters are given in Table 5-A. For convenience, it refers to the JSAPCA with IA as JSAPCA-1, the JSAPCA with SOEMA-1 as JSAPCA-2, and the JSAPCA with SOEMA-2 as JSAPCA-3. The optimal performance which is obtained by exhaustive search for both spectrum allocation and power control is given as the baseline. JSAPCA-1, JSAPCA-2, and JSAPCA-3 are compared in the proposed scheme to show differences among their performances. In addition, it also considers the performance of the traditional OMA case where each UT communicates with at most one UR in a transmission interval. In order to have a fair comparison, the resource allocation result for the OMA case is also obtained by utilising JSAPCA-1, JSAPCA-2 and JSAPCA-3, respectively. The settings of the proposed algorithms and benchmarks are summarised in Table 5-B.

Table 5-A: Parameter Values Used in Simulations

Macro cell radius	300 m
Small cell radius	30 m
Transmit power of MBS	43 dBm
Transmit power of SBSs	23 dBm
Noise power spectral density	-174 dBm/Hz
Path-loss exponent	4
Interference threshold at each MCU	-70 dBm

Table 5-B: Algorithm Settings

Algorithm	Subchannel Allocation	Power Control	Multiple Access
Optimal Solution	Exhaustive search	Exhaustive search	NOMA
JSAPCA-1	IA	SCPAA	NOMA
JSAPCA-2	SOEMA-1	SCPAA	NOMA
JSAPCA-3	SOEMA-2	SCPAA	NOMA
JSAPCA-1 (OMA)	IA	SCPAA	OMA
JSAPCA-2 (OMA)	SOEMA-1	SCPAA	OMA
JSAPCA-3 (OMA)	SOEMA-2	SCPAA	OMA

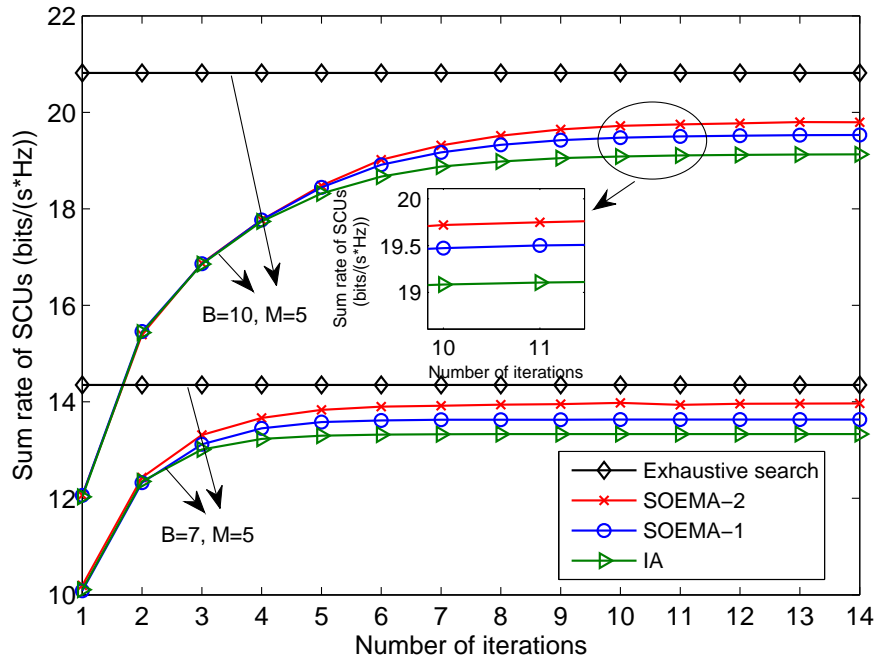


Figure 5.2: Convergence of the proposed matching algorithms with different numbers of RBs and SBSs.

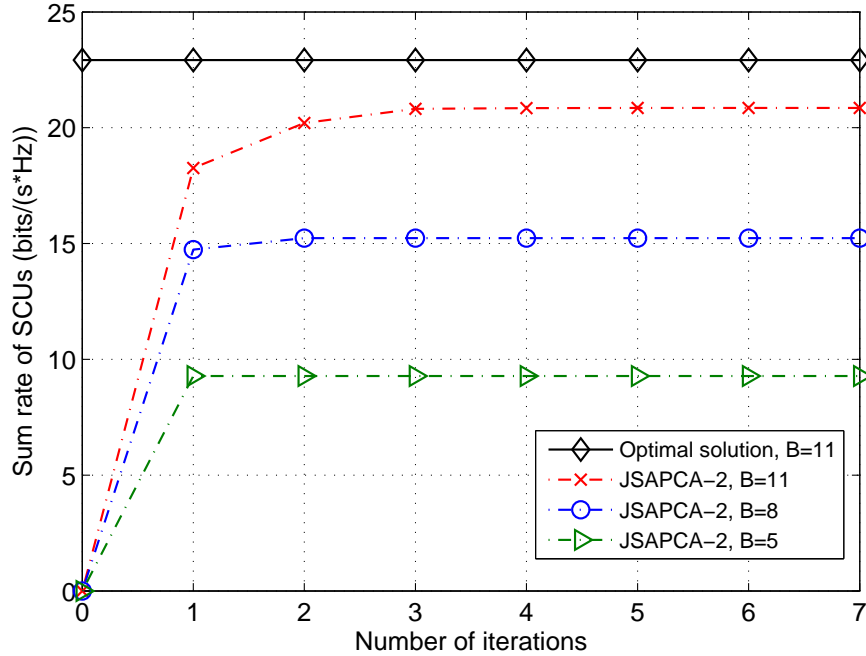


Figure 5.3: Convergence of JSAPCA-2 with different numbers of SBSs, with $M = 5$.

Figure 5.2 illustrates the convergence of the proposed algorithms, i.e., IA, SOEMA-1 and SOEMA-2, with different numbers of RBs M and UTs B . It can be seen that IA and SOEMA both converge within a small number of iterations for different values of M and B . Besides, both IA and SOEMA need more iterations to converge with a larger number of RBs and UTs. For example, when $B = 7, M = 5$, SOEMA and IA converge in less than 6 iterations on average. When $B = 10, M = 5$, SOEMA and IA converge to a stationary point at around 12 iterations. This is due to the fact that additional players participating in the matching game results in additional searching dimensions in the possible matching solutions. It is also shown in Figure 5.2 that the proposed algorithm performs very close to the exhaustive searching based spectrum allocation. In particular, for the case of $B = 10, M = 5$, SOEMA-2 gets around 93% of the sum rate of URs achieved by exhaustive search.

Figure 5.3 depicts the URs' sum rate with number of iterations in JSAPCA-2, under the case of $M = 5$. In particular, JSAPCA-2 needs more iterations to converge when the

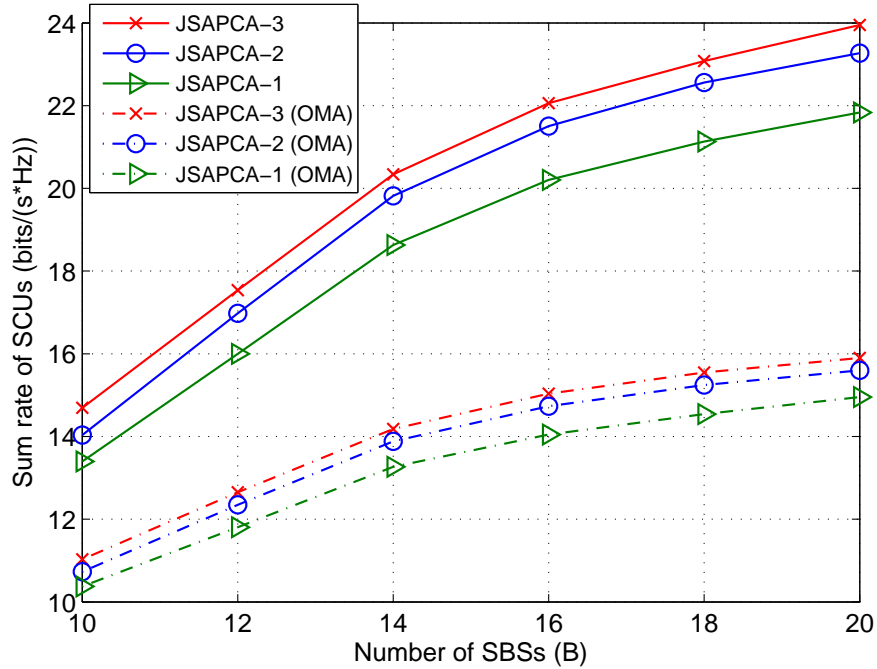


Figure 5.4: Sum rate of the SCUs with different numbers of small cells, with $M = 7$.

number of UTs B gets larger. For example, when $B = 8$, the number of iterations for convergence is 2 on average. In the case of $B = 11$, JSAPCA-2 converges to a stationary point after 4 iterations on average. This is due to the fact that more UTs need to be coordinated, which causes the higher dependency between spectrum allocation and power control. It can also be observed that, in the case of $B = 11$, JSAPCA-2 gets roughly 91% of the URs' sum rate achieved by the optimal solution.

Figure 5.4 plots the sum rate of URs versus different numbers of UTs in the network, for $M = 7$ and $q_{max} = 2$. As can be observed, the sum rate increases monotonically with the number of UTs due to the exploitation of multi-user diversity gain. Figure 5.4 also shows that JSAPCA-2 achieves a higher sum rate compared to JSAPCA-1 due to the involvement of the swap operations between the potential swap-blocking pairs. Besides, JSAPCA-3 further improves the performance of JSAPCA-2 because of the “experimentation” action to explore the space of matching states. Compared to the traditional OMA system, the NOMA-enhanced system can achieve higher sum rate since it exploits not

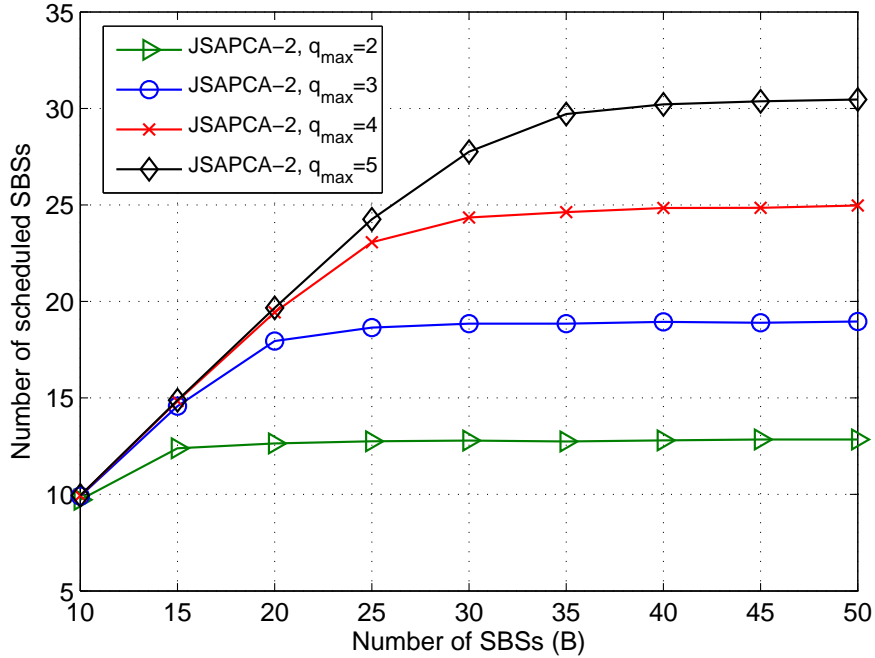


Figure 5.5: Number of scheduled SBSs with different numbers of SBSs in the network, with $M = 10$.

only the frequency domain but also the power domain for multiple access. In particular, at the point of $B = 18$, $M = 7$, JSAPCA-2 achieves roughly a 10%, 49% and 55% higher sum rate than JSAPCA-1, JSAPCA-2 (OMA), and JSAPCA-1 (OMA), respectively.

In Figure 5.5, the number of scheduled UTs versus the number of UTs is investigated, with $M = 10$ in the NOMA-enhanced system. Here, the number of scheduled UTs is defined as the average number of simultaneously scheduled UTs in a transmission interval. It is observed that the number of scheduled UTs increase monotonically with the total number of UTs. However, the increasing trend becomes slower as the total number of UTs becomes larger. This is due to the fact that the UTs causing server co-channel interference to others may not be allocated any RB for the maximisation of URs' sum rate as well as the satisfaction of interference constraints of MCUs. Besides, the proposed algorithm is capable of accommodating more UTs when the maximum number of allowed UTs on each RB gets larger, since more UTs have the opportunity to get access to the RBs.

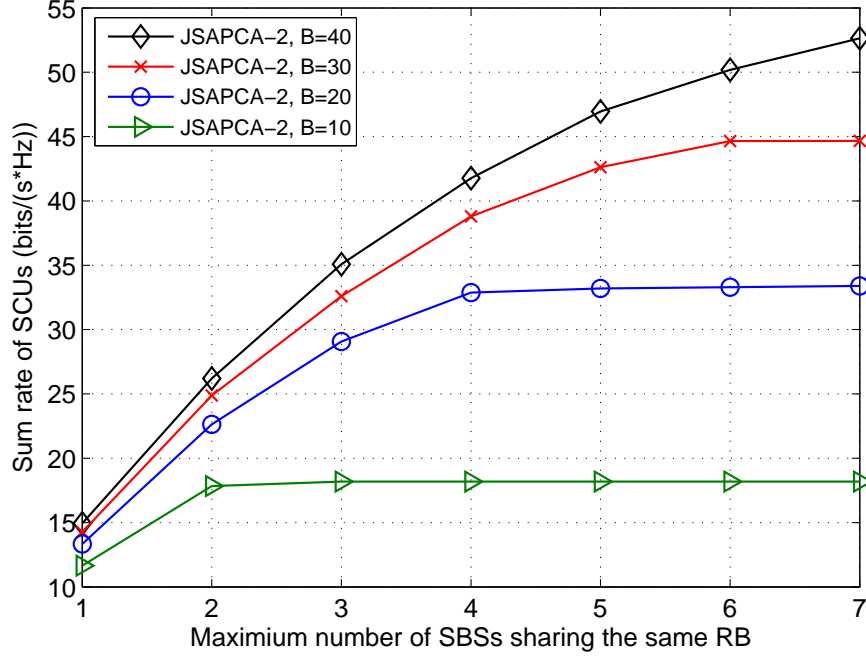


Figure 5.6: Sum rate of SCUs with different maximum numbers of SBSs allowed on each RB, with $M = 5$.

Figure 5.6 demonstrates the sum rate of URs versus different maximum numbers of UTs allowed on each RB with the RBs' number of $M = 5$. One can observe that the with a fixed value of UTs' number B , the sum rate of URs grows to a fixed value as the quota q_{max} increases since all the UTs have been matched after q_{max} reaches B/M . In particular, for the case of $B = 20$, the URs' sum rate reaches a stable value when $q_{max} > 4$. For the case of $B = 40$, the sum rate keeps increasing because $B/M > 7$. However, the growth rate gets smaller with larger value of q_{max} due to the enhanced interference on each RB.

Figure 5.7 shows the resource allocation fairness versus the total number of UTs in the network, for a fixed RB's number $M = 10$. To evaluate the fairness of the proposed algorithm, the Jain's fairness index [JCH84] is adopted, which can be calculated as $\frac{(\sum_{b=1}^B (R_{b,k}^m + R_{b,j}^m))^2}{2 \times B \sum_{b=1}^B (R_{b,k}^m + R_{b,j}^m)}$. The value of Jain's fairness index is between the range of 0 and 1. The fairest resource allocation is obtained when the value equals to 1, which indicates that all users enjoy the same data rate. One can observe that the fairness index of the

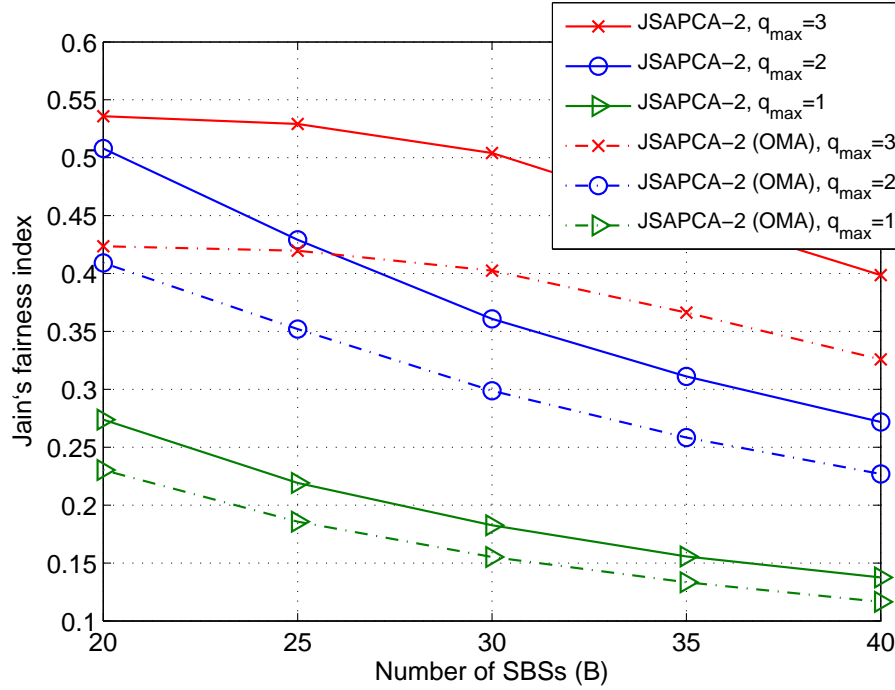


Figure 5.7: SCUs fairness index with different numbers of SBSs in the network, with $M = 10$.

proposed algorithm decreases with the number of UTs in the network. This is due to the fact that higher number of UTs contributes to more severe competition on limited spectrum resources, and hence more UTs with poor channel conditions may not be accessed to the network. This phenomenon is consistent with Figure 5.5 showing that the number of scheduled UTs increases non-linearly with the total number of UTs in the network. Besides, it is also worth noting that the proposed algorithm can achieve a higher fairness index when the maximum number of UTs allowed on each RB, i.e., q_{max} , gets larger. Actually, as q_{max} increases, the proposed algorithm is capable of multiplexing more UTs on each RB, which increases the utilisation of multiuser diversity.

5.8 Summary

In this chapter, the spectrum allocation and power control problems for D2D communications in HetNets with NOMA were jointly studied, with the aim of maximising the

sum rate of URs while considering the fairness issues. By formulating the spectrum allocation problem as a many-to-one matching game with peer effects, a low-complexity algorithm based on the swap operations was proposed to enable UTs and RBs to effectively interact with each other. In addition, the “experimentation” action was utilized to further improve the performance by exploring the space of matching states. It was proved mathematically that the matching algorithm converged to a two-sided stable state within limited number of iterations. For solving the power allocation problem, the sequential convex programming was adopted to approximate the non-convex problem to a convex one and update the power allocation result iteratively. How well the application of NOMA could improve the performance of D2D communications in HetNets was investigated, where it was shown via numerical results that NOMA-enhanced system had more potential benefits in terms of sum rate compared to conventional OMA cases.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

This thesis was dedicated to the resource allocation optimisation for D2D communications based on matching theory. Matching theory has some main advantages compared to traditional centralised solutions as well as game theory. On one hand, matching theory is a distributive solution, which can overcome some of the disadvantages of centralised solutions, such as significant overhead and high computation complexity. On the other hand, in matching theory, players make decisions locally and use preference lists rather than specific closed-form utility functions that are adopted in game theory.

A many-to-many matching algorithm was proposed to improve resource utilisation in D2D communications, which was capable of achieving the near-optimal sum rate with acceptable complexity. Subsequently, a novel approach for context-aware resource allocation in D2D communications was investigated. By formulating a utility function taking account of data rate, packet error rate and delay, a matching algorithm was proposed, which was shown to outperform the conventional context-unaware algorithm by roughly 63%.

To enhance resource utilisation, resource allocation design for NOMA-enhanced D2D communications was investigated. With the objective of maximising sum rate while

considering interference constraints, joint spectrum allocation and power control problem was studied. To reduce the computational complexity, spectrum allocation and power control were decoupled and solved using many-to-one matching and sequential convex programming, respectively. Results shown that NOMA-enhanced D2D communications could achieve promising gains in terms of network sum rate and number of accessed users compared to conventional OMA cases. Besides, the proposed algorithm was capable of reaching around 93.7% of the optimal result obtained by exhaustive search.

In order to investigate the performance of D2D communications in HetNets and co-effects of different technologies, the new paradigm of D2D communications in HetNets with NOMA was studied. Compared with the state-of-the-art schemes, the new paradigm was demonstrated to achieve roughly a 49% higher sum rate.

For all algorithms proposed in this thesis, great attention is given to accommodate the inherent nature of D2D communications and matching theory in the resource allocation design. The proposed algorithms provide useful guidelines and potential solutions for the resource allocation mechanisms in future D2D networks.

6.2 Future Work

6.2.1 Resource Allocation for Content-Centric D2D Communications

Current wireless services is experiencing a transfer from traditional *connection-centric* communications to the emerging *content-centric* communications, such as video streaming, push media, mobile applications download/updates, and mobile TV [Ind13]. A main feature of content-centric communication is that the same contents are requested by multiple users, referred to as *content diversity* [LCT⁺14] or *content reuse* [GMDC13]. Two enabling techniques to exploit such content diversity are multicasting and caching [TCZY16]. It is a very interesting topic to consider using the terminals themselves as caching helpers, which can distributed contents through D2D communications. To the

best of the knowledge, resource allocation in content-centric D2D communications is still a fairly open field, and is expected to become a rewarding research area.

6.2.2 Resource Allocation for D2D Communications with Privacy

D2D communications underlying cellular networks enables spectrum reuse between D2D users and primary cellular users, and thus increase the efficiency of spectrum sharing. While this system is anticipated to increase spectrum efficiency, primary users have raised concerns about exposing details of their operations and have questioned whether their privacy can be protected [CP16]. For example, in the United States, the Federal Communications Commission recently issued a ruling that the 3550-3700 MHz band will be opened up to new spectrum uses through advanced shared spectrum access systems [C⁺12]. Many of the incumbent systems in 3550-3700 MHz are operated by government entities, e.g., Department of Defense radars. Therefore, the information that a spectrum access system would need to assign spectrum resource, such as location, frequencies, time of use and susceptibility to interference, may be considered very sensitive by the incumbents and should be protected from exposure to a potential adversary.

To retain a critical level of privacy for primary cellular users, primary users may need to alter their operational behaviour to improve privacy and defense adversaries with sensing capabilities. One potential approach is to allow primary users to transmit dummy signals even when the spectrum is idle. Spectrum allocation strategies need to be investigated to adapt to the primary users to mitigate risks to their privacy. As such, resource allocation for D2D communications with the consideration of privacy is a promising research avenue, and more research efforts are needed for the final practical deployment.

Appendix A

Proof in Chapter 5

A.1

Proof of Remark 5: Faced with a set \mathcal{S} of SBSs, RB m can determine which subset of \mathcal{S} it would most prefer to match with. This is regarded as RB m 's choices from \mathcal{S} , and denote it by $\text{Ch}_m(\mathcal{S}) = \mathcal{S}'$. That is, for any subset \mathcal{S} of \mathcal{SBS} , the most preferred set of RB m is \mathcal{S}' satisfying: $\forall \mathcal{S}'' \subset \mathcal{S}, \mathcal{S}'' \neq \mathcal{S}' \Rightarrow \mathcal{S}' \succ_m \mathcal{S}''$. A RB m 's preferences over sets of SBSs has the property of *substitutability* if, for any set \mathcal{S} that contains SBSs b and b' , if b is in $\text{Ch}_m(\mathcal{S})$, then b is in $\text{Ch}_m(\mathcal{S} \setminus \{b'\})$.

However, in the formulated game model, due to the existence of co-tier interference, the achievable rate of RB m with SBS b may change after b' is unmatched with m , and therefore, b may not be in the preferred set any more, which is concluded that the formulated game model does not have the property of *substitutability*.

A.2

Proof of Lemma 4: Assume that there exists a swap-blocking pair (b, b') in the final matching Φ^* satisfying that $\forall s \in \{b, b', \Phi(b), \Phi(b')\}, U_s \left((\Phi^*)_{b'}^{b'} \right) \geq U_s(\Phi^*)$ and $\exists s \in \{b, b', \Phi(b), \Phi(b')\}$, such that $U_s \left((\Phi^*)_{b'}^{b'} \right) > U_s(\Phi^*)$. According to SOEMA-1, the algorithm does not terminate until all the swap-blocking pairs are eliminated. In other words, Φ^* is not the final matching, which causes conflict. Therefore, there does not exist a swap-blocking pair in the final matching, and thus it can be concluded that the proposed algorithm reaches a two-sided exchange stability in the end of the algorithm.

A.3

Proof of Theorem 11 : The convergence of SOEMA-1 depends mainly on Step 2 in **Algorithm 4**. According to Definition 2, after each swap operation between SBS b and b' along with their corresponding matched RBs m, m' , the utilities of m and m' satisfy: $U_m(\Phi_b^{b'}) \geq U_m(\Phi), U_{m'}(\Phi_b^{b'}) \geq U_{m'}(\Phi)$, in which at least one of the equalities does not stand. Since the utility of each RB is defined as the sum α fairness-based data rate of its occupying SCUs as in (5.14), the following inequality holds:

$$U_{\alpha\text{-total}} R_{b,k}^m \left(\Phi_b^{b'} \right) > U_{\alpha\text{-total}} R_{b,k}^m (\Phi), \quad (\text{A.1})$$

where $U_{\alpha\text{-total}} R_{b,k}^m = \sum_{b=1}^B \sum_{m=1}^M U_{\alpha} (R_b^m)$, which is the sum α fairness-based data rate of all the SCUs in the network. Note that the number of iterations of SOEMA-1 is limited since the number of players is limited and the system sum rate has an upper bound due to the limited spectrum resources. Therefore, there exists a swap operation after which no swap-blocking pair can further improve the sum rate of SCUs. SOEMA-1 then converges to the final matching Φ^* which is stable as proved in **Lemma 1**.

A.4

Proof of Proposition 1: $\bar{R}_{b,k}^m$ can be rearranged as the following:

$$\begin{aligned} \bar{R}_{b,k}^m = & b_k [x_{b,k} - \log_2(|f_{b,k}^m|^2 p_b 2^{x_{b,j}} + I_{co}^k + I_{cr}^k + \sigma^2)] \\ & + b_k \log_2(|f_{b,k}^m|^2 p_b) + c_k. \end{aligned} \quad (\text{A.2})$$

$\bar{R}_{b,k}^m$ is a concave function of \mathbf{x}_b because of the convexity of the log-sum-exp function [BV04]. Furthermore, as the α -fair utility function is strictly increasing and concave for any given α , their composition, $U_\alpha(\bar{R}_{b,k}^m)$ is also a concave function of \mathbf{x}_b [BV04]. Since the objective function in (5.53a) is a summation of the concave terms of \mathbf{x}_b , it is straightforward to conclude that (5.53a) is also a concave function of \mathbf{x}_b . Therefore, the optimization problem in (5.20) is a standard convex optimization problem with respect to \mathbf{x}_b .

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