

Interference Mitigation in D2D-enabled Heterogeneous Cellular Networks

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Abstract

Device-to-Device (D2D) communication is a promising technology for next generation cellular networks. The D2D communication is being considered for the LTE Advanced standards in 3GPP Release 12, as Proximity Services (ProSe) continue to be part of current 5G or beyond cellular networks to support diverse applications. To fulfil the QoS requirements and to overcome the challenges of beyond 5G (B5G) cellular networks, D2D communication plays an important role. However, to maximize the performance gain of D2D communication, there are many open challenges that need to be addressed. One of the main factors that influence the performance of D2D communication in cellular heterogeneous networks (HetNets) is interference management. Transmission mode selection, resource allocation, power control and small cell deployment strategies are key factors that contribute to interference for D2D communication in cellular HetNets. In this thesis, an empirical investigation of the key factors influencing interference for D2D communication in cellular HetNets is described and its results are reported. In the investigation, the key performance-limiting factors are identified and measured by simulation as well as analytically.

A new mode selection technique for improving D2D performance in HetNets is reported. The effect of various key performance-limiting factors, including DUEs positions and Signal-to-interference plus noise ratio (SINR) are analysed. Transmission mode is selected based on D2D user equipment (DUE), cellular user equipment (CUE) and evolved Node-B (eNB) locations and their mutual distances. The proposed mode

selection scheme provides better outage probability and sum rate for D2D communication.

Another main contribution of this thesis is the development of a new dynamic algorithm for interference management in D2D-enabled cellular HetNets. Various parameters for defining mutual interference within the 3-tier cellular network are defined and their effects on system performance are investigated. Achieved small cell density, transmission power control and device locations help to manage interference leading to higher outage probability and system throughput.

A machine learning (ML)-based power control and resource allocation for interference management in a D2D-enabled cellular network is found to have a significant effect on achieving higher throughput and better quality of service (QoS). A deep Q-network (DQN) based deep reinforcement learning (DRL) algorithm is proposed to optimize resource allocation where D2D acts as an agent and take decision independently based on learned optimal policy from the environment. D2D-enabled cellular network design and deployment strategies are outlined and recommendations are made for various system design scenarios.

Contents

Abstract	ii
Attestation of Authorship	x
List of Publications	xi
Acknowledgements	xii
Dedication	xiii
List of Abbreviations and Acronyms	xiv
1 Introduction	1
1.1 Background and research motivation	2
1.2 Research problems	6
1.3 Research methodology for investigation	8
1.4 Contributions and the structure of this thesis	10
2 D2D Communication in Cellular Networks	13
2.1 Introduction	13
2.2 An evolutionary path in 3GPP for adopting D2D technology	14
2.3 Classification of D2D communications	15
2.3.1 D2D communication mode	17
2.4 Spectrum utilization in D2D Communications	18
2.5 Interference in wireless networks	23
2.5.1 Interference for D2D communication in 2-tier network	26
2.5.2 Interference for D2D communication in 3-tier network	27
2.6 Research process for investigation	30
2.7 Summary	33
3 Interference Mitigation for D2D Communication in Cellular Networks	34
3.1 Introduction	34
3.2 Interference in D2D-enabled cellular networks	35
3.3 Interference minimization techniques	35
3.3.1 Power control mechanism	38

3.3.2	Mode selection (MS)	40
3.3.3	Radio resource allocation	42
3.4	Machine learning algorithm for minimizing interference	50
3.5	Adopted D2D link performance estimation approach	55
3.6	Summary	56
4	Mode Selection Scheme for Interference Mitigation in D2D-enabled Cellular HetNets	57
4.1	Introduction	57
4.2	Previous works on mode selection	58
4.3	System model	59
4.3.1	Network model	59
4.3.2	SINR model for D2D mode	62
4.3.3	SINR model for macrocell mode	63
4.3.4	SINR model for small cell mode	63
4.3.5	Sum rate analysis	64
4.3.6	Problem formulation	64
4.4	Joint mode selection and power control in D2D communication	66
4.4.1	Mode selection	66
4.4.2	Power control	68
4.5	Results and discussion	70
4.6	Summary	74
5	Dynamic Algorithm for Interference Management in D2D-enabled Cellular HetNets	75
5.1	Introduction	75
5.2	Summary of related works on interference management	76
5.3	System Model	80
5.3.1	Network model	80
5.3.2	SINR model	81
5.3.3	Small cell density model	87
5.4	Performance Evaluation	92
5.4.1	Simulation environment and parameters	92
5.4.2	Results and discussion	92
5.5	Summary	97
6	Machine Learning Based Resource Allocation for Interference Management in D2D-enabled Cellular HetNets	100
6.1	Introduction	100
6.2	Previous works on ML-based resource allocation	102
6.3	System model and problem formulation	104
6.3.1	System model	104
6.3.2	Cellular and D2D communication mode	105
6.3.3	Transmission rate	107

6.3.4	Problem formulation	108
6.4	ML-based resource allocation	110
6.4.1	Machine learning approach	111
6.4.2	Deep learning approach	113
6.4.3	Reinforcement learning approach	114
6.4.4	Deep reinforcement learning approach	121
6.4.5	Computational complexity	124
6.5	Performance evaluation	125
6.5.1	Simulation environment and parameters	125
6.5.2	Results and discussion	127
6.5.3	Model validation and system implication	131
6.6	Summary	132
7	Conclusions and Future Research Directions	134
7.1	Conclusions	134
7.2	System implications and deployment	136
7.3	Future research directions	137
	Appendices	153

List of Tables

1.1	KPIs comparison among 4G, 5G & 6G mobile technologies	4
2.1	Comparative analysis of D2D communication for different modes . . .	19
2.2	Comparative analysis for Inband-Outband communication in different modes	23
2.3	Relationship between DSRM and our proposed research	32
3.1	Summary of related works for power control approach	40
3.2	Summary of literature review for resource allocation approach	49
4.1	Summary of literature review for mode selection approach	58
4.2	Parameters used in the simulation	70
5.1	Parameters used in the simulation	92
6.1	Summary of related works on ML-based resource allocation	103
6.2	Parameters used in the simulation	126

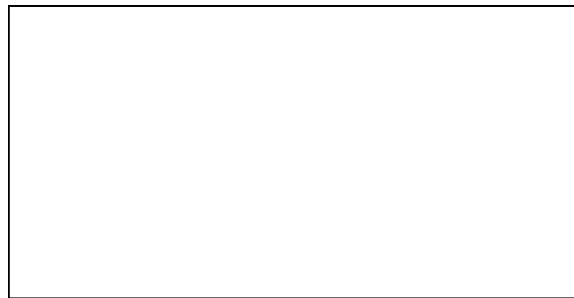
List of Figures

1.1	Interference Scenario in a 3-tiers network	6
1.2	Block diagram of the adopted methodology	8
1.3	The structure of this thesis	10
2.1	Interference scenario in a D2D-enabled tier-3 cellular network	15
2.2	a short heading for the figure	16
2.3	Various D2D Communication mode	17
2.4	Spectrum utilization in D2D Communications	20
2.5	Spectrum utilization in D2D communications	22
2.6	Adjacent channel interference in cellular network	24
2.7	Co-channel interference in cellular network	25
2.8	Interference scenario for D2D communication in 2-tier network	27
2.9	(a) Co-tier interference (b) Cross-tier interference in UL (c) Cross-tier interference in DL	28
2.10	Interference scenario for D2D communication in 3-tier network	29
2.11	Modified design science research method.	32
3.1	Performance comparison for IEI and no-IEI scenarios[32]	36
3.2	Coverage comparison for IEI and no-IEI scenarios with Tx power[32]	36
3.3	Interference Control Mechanism for D2D Communication	37
4.1	Flowchart of the proposed mode selection algorithm for D2D communications	67
4.2	SINR for different links in the D2D communications	71
4.3	Impact of distance for various nodes in D2D communications	71
4.4	Impact of distance and SINR in coverage for D2D links	72
4.5	Throughput of D2D users with increasing distances of D2D pairs	73
4.6	Throughput of D2D users with increasing number of D2D pairs	73
5.1	PPP distributions of Nodes -diamonds represent the eNB, circles represent UEs (green circles are DUEs) and asterisks represent SCeNBs in a cellular network.	88
5.2	Outage probability of D2D links with different schemes	94
5.3	Outage probability of macro links with various schemes	95
5.4	Outage probability of small cell links with various schemes	96

5.8	Transmission capacities for optimal deployment of various Schemes.	96
5.5	Outage probability of different links with various SINR threshold . . .	97
5.6	Success probability with small cell density.	98
5.7	Success probability with D2D pairs density.	98
6.1	DQN framework for D2D-enabled cellular network	111
6.2	Deep learning network model in ML	113
6.3	Agent-environment interaction in RL D2D-enabled cellular network .	117
6.4	DQN framework for D2D-enabled cellular network	122
6.5	Sum throughput of all DUEs Vs number of D2D pairs	127
6.6	Sum throughput of all CUEs Vs number of CUEs	128
6.7	Sum throughput of all DUEs Vs distance between D2D pairs	129
6.8	Sum throughput of all DUEs Vs cell radius	129
6.9	Sum throughput of all DUEs Vs transmit power of D2D pairs	130
6.10	Sum throughput of all DUEs Vs minimum QoS requirements for DUEs	131

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the qualification of any other degree or diploma of a university or other institution of higher learning.



Signature of student

List of Publications

Manuscripts relating to the D2D Interference have been published in the following academic conference/Journal proceedings:

1. Kamruzzaman, M, Sarkar, N.I, Gutierrez, J. & Ray, S.K, A study of IoT-based post-disaster management. International Conference on Information Networking (ICOIN), 2017.
2. Kamruzzaman, M, Sarkar, N.I, Gutierrez, J. & Ray, S.K., A mode selection algorithm for mitigating interference in D2D enabled next-generation heterogeneous cellular networks. International Conference on Information Networking (ICOIN), 2019.
3. Kamruzzaman M, Sarkar N.I, & Gutierrez J., A dynamic algorithm for interference management in D2D-enabled heterogeneous cellular networks: Modeling and analysis. Sensors. 2022 Jan 29;22(3):1063.

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Dedication

To my parents, siblings, kids, and lovely wife

List of Abbreviations and Acronyms

3GPP	Third generation partnership project
4G	Fourth Generation
5G	Fifth Generation
ANN	Artificial neural network
AIR	Accepted interference region
AR	Augmented reality
BS	Base station
CUEs	Cellular user equipments
CSI	Channel state information
CM	Cellular mode
CR	Cognitive radio
CBM	Concatenated bi-partite matching
D2D	Device-to-device
DUEs	D2D user equipments
DM	Dedicated mode
DDB	Distance-density based
DSRM	Design science research methodology
DL	Deep learning
DQN	Deep Q-network
DRL	Deep reinforcement learning

DNN	Deep Neural Network
D3QN	Double-dueling deep Q-network
eMBB	Enhanced mobile broadband
eNB	Evolve Node B
ESTI	European Telecommunications Standards Institute
FR	Fractional programming
FFR	Fractional frequency reuse
GCSE	Group communication system enablers
HetNets	Heterogeneous networks
IM	Interference management
ISM	Industrial, Scientific, and Medical
IoT	Internet-of-Things
IA	Interference avoidance
ILA	Interference limited area
IAPA	Interference aware power allocation
IEI	In-band emission interference
KPIs	Key performance indicators
LTE-A	Long term evolution - advanced
LoS	Line-of-sight (LoS)
MDP	Markov decision process
MS	Mode selection
mMTC	Massive machine type communications
MIMO	Multiple input multiple output
MINLP	Mixed-integer nonlinear programming
ML	Machine learning
MOS	Mean opinion score

NGN	Next generation networks
NLoS	Non-line-of-sight (NLoS)
NOMA	Non-orthogonal multiple access
NP	Non-deterministic Polynomial
NR	New radio
OPA	Optimal power allocation
PC	Power control
PPP	Poisson point process
QoS	Quality of services
RB	Resource block
RRA	Radio resource allocation
RL	Reinforcement learning
RNN	Recurrent neural network
SCA	Successive convex approximation
SUEs	Small cell user equipments
SINR	Signal-to-interference plus noise ratio
SM	Shared mode
SCeNB	Small cell evolved Node B
SOM	Self-organizing maps
SGUM	Social group utility maximization
TSF	Time sharing factor
UE	User equipment
UDNs	Ultra-dense networks
uRLLC	Ultra-reliable and low latency communication
VR	Virtual reality

Chapter 1

Introduction

Device-to-device (D2D) Communication is one of the proficient technologies for the following generation networks (NGNs), which is expected to play a vital role in the forthcoming era of wireless communication. Furthermore, D2D communication is being considered as an integral part of the fourth Generation (4G) Long Term Evolution (LTE)-Advanced standard in 3rd Generation Partnership Project (3GPP) Release 12 for proximity-based services (ProSe) and group communication system enablers (GCSE). Besides these, tens of applications and services are expected to utilize D2D communications, such as vehicular technologies, e-Health, smart grid, smart city, augmented and virtual reality, offloading cellular traffic and so on [1]. During natural disasters like earthquakes or hurricanes, an urgent communication network can be quickly set up using D2D functionality, replacing the damaged communication network and Internet infrastructure. The coverage can be enhanced by multi-hop cooperation between the devices, which can be used to communicate in case of no coverage zone, coverage holes, and emergencies. Hence, D2D links in future cellular networks are vital for traffic offloading, reducing access delays, spectral efficiency, capacity and coverage enhancements, and energy efficient communication [2].

Though in current technologies, D2D communication is possible without networks such as WiFi or Bluetooth, but those are in unlicensed spectrum bands, e.g. industrial,

scientific, and medical (ISM) bands. Although such ad-hoc communication requires significantly less control signaling, it inherits certain drawbacks, such as limited content sharing, no point-to-multipoint links, uncontrolled interference, synchronization issues, authentication, and security concerns. Moreover, the discovery process and connection setup in out-band D2D or WiFi direct/Bluetooth is complicated since it needs user manual intervention to establish the connection between the two devices [3]. Even ad-hoc mode of D2D communication in the licensed spectrum offers limited applications similar to the unlicensed counterpart. However, network-assisted D2D communication in the cellular band has many applications and services, including proximity-based commercial services, social networking, video sharing, mobile relaying, gaming, traffic offloading, capacity enhancement (frequency reuse), extended cellular coverage, and improved energy-efficient communication [2].

The ever-increasing demands of digital applications and cloud computing have created a demand for high speed and low latency in wireless technologies, a challenge for 5G and beyond cellular networks. As 3GPP LTE Release 12, where D2D is an integral part of proximity-based services for LTE-A, D2D communication can play a promising technology in satisfying the emergent requirements of 5G and Beyond 5G networks.

1.1 Background and research motivation

Throughout mobile communication systems history from 1st to 5th Generation, the mobile communications industry has achieved phenomenal progress in data communication. The data transmission speed of each Generation is increased, and to cope with this technology, it also evolves [4]. 5G and B5G can be revolutionary changes in mobile networks that will achieve the best coverage capability, energy consumption, throughput, latency, spectral efficiency, etc., compared to previous networking systems.

During the last decade, cellular networks have experienced unprecedented growth in mobile users, mobile broadband traffic, and end-user demand for faster data access using various cutting-edge applications [5]. Globally, the total number of cellular subscribers has grown up from 7.5 billion in 2017 to 8.4 billion by 2022, and by the end of 2028, it will be 9.2 billion. According to a recent Ericsson mobility report and the Cisco visual networking index [6, 7], in 2017 global mobile data traffic grew 71 percent, and more than half a billion (648 million) mobile devices and connections were added to the networks. Mobile data traffic has grown 90-fold over the past ten years. Mobile networks carried 686 petabytes per month in 2012, which was 11.6 Exabytes per month at the end of 2017 and reached 90 EB/month by the end of 2022, and this trend has continued. Global mobile data traffic is expected to increase 4-fold between 2022 and 2028, reaching 90.0 Exabyte per month to 325.0 EB/month by 2028 [7].

The number of mobile devices is drastically increasing, with a rising demand for higher data rates and faster data accessing applications in recent years. The huge growth of bandwidth-hungry applications such as video streaming and multimedia file sharing is already pushing the limits of current cellular systems. Applications such as 3D holography, artificial intelligence (AI), machine-to-machine communication, super Internet-of-Things (IoT), virtual reality (VR), e-learning and e-health, video-based applications, augmented reality (AR), ultra-broadband etc. demands more bandwidth that is simply not possible with fourth generation (4G) or even 5th Generation (5G) networks. The ever-growing demand for higher data rates and capacity requires unconventional thinking for the next generation (5G or B5G) cellular systems [8]. Capacity and data rates for wireless communication depend on spectral efficiency and bandwidth. The combined effect of an emerging hyper-connected vision and new application-specific requirements is going to trigger the next major evolution in wireless communications. B5G wireless communications envision magnitudes of increases in wireless data rates, bandwidth, coverage, and connectivity, with a massive reduction in round-trip latency

Table 1.1: KPIs comparison among 4G, 5G & 6G mobile technologies

KPI	4G	5G	6G(Possible)
Individual data rate	150 Mbps	1 Gbps	100 Gbps
DL data rate	300 Mbps	20 Gbps	> 1 Tbps
U-plane latency	60 ms	0.5 ms	0.1 ms
C-plane latency	200 ms	10 ms	< 1 ms
DL spectral efficiency	6 bps/Hz	30 bps/Hz	100bps/Hz
Operating frequency	600 MHz - 2.5 GHz	3-300 GHz	upto 1 THz

and energy consumption. According to the European Telecommunications Standards Institute (ETSI) published 5G scenarios and requirements for access technologies, the target peak rate is reported to be 10Gbps in the uplink and 20Gbps for the downlink (3GPP TR 38.913). Today's 5G network that brings mobile communications technology up to speed will be able to meet the requirements for the next few years. It is expected that 5G will reach its limits by 2030 and the chase continues. The User-centric KPIs comparison of 4G, 5G and 6G is shown in Table 1.1.

With the requirements of sub-millisecond latency and bandwidth limitations in the traditional wireless spectrum, 5G is designed with promising technologies like Heterogeneous networks, Massive MIMO, Millimeter-wave (mm) spectrum (30-300GHz), Cognitive Radio Networks, D2D communication and many more [1]. As mentioned in Ericsson's recent mobility report and Cisco VNI [6, 7], future wireless traffic explosion is unavoidable and to manage the wireless traffic explosion large numbers of small cell (SCeNBs), especially femtocells (HeNBs) deployment is inevitable. By deploying low-power small BSs, network capacity will be improved, and the coverage will be extended to coverage holes [1]. Moreover, with enhanced mobile broadband (eMBB), ultra-reliable and low latency communication (uRLLC), and massive machine type communications (mMTC), different services are surely forthcoming for 5G and beyond networks [9]. Managing such a high user density and the resulting immense data volumes is a major concern for cellular network operators [1]. To fulfil the ever-increasing data demands D2D technology is prominent not only in 5G but 6G

as well. Due to the short communication range between a D2D pair, D2D communication provides several advantages in terms of spectrum efficiency, throughput, latency, power management, coverage expansion, and capacity improvement by reusing radio resources [1]. Furthermore, D2D communication enables new services such as public safety, proximity-based services (ProSe) and group communication system enablers (GCSE), content sharing of files, videos or pictures, gaming, connectivity extension, and traffic offloading [10]. Having these benefits in 5G networks and beyond, D2D communication is a key enabler technology [10].

However, to maximize the benefits of D2D communications, there are many open challenges that need to be thoroughly addressed [11]. These challenges include mode selection, neighbour discovery, interference and radio resource management, energy consumption, coexistence of D2D with small cells, mobility management, network security, etc. Among them, interference management (IM) in a heterogeneous scenario including all tiers simultaneously is very important and complex [10].

If D2D communication technology is incorporated into a Heterogeneous Network (HetNet), cellular system architecture will be moved from tier-2 to tier-3 where tier-1 encompasses the eNBs, the SCeNBs and Femtocells will form the tier-2 and the tier-3 will be composed by D2D pairs as shown in Figure 1.1. Deploying small cells and D2D technology will not only increase the capacity and extend the coverage but also introduce interference. In HetNets, interference management for underlay spectrum sharing mode is more challenging than the two-tier cellular network as the transmit power for each base station (BS) is different. In addition, interference levels in different tiers are different due to the various access restrictions (i.e. public, private, hybrid etc.). Hence, interference management will be a real challenge in future cellular systems due to heterogeneity, dense spectrum reuse, and network densification.

To mitigate interference in D2D communication, in most cases, researchers are focused on single cell networks with single or multiple devices, e.g. focused on single or

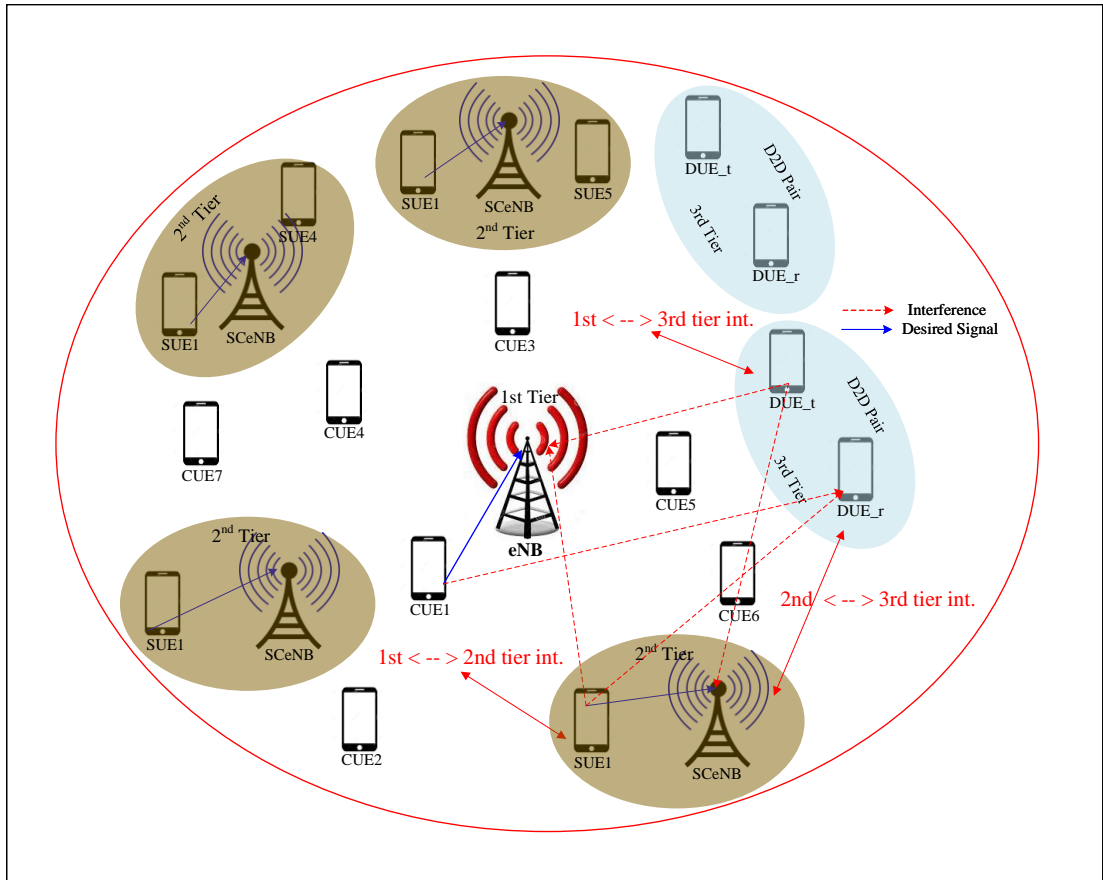


Figure 1.1: Interference Scenario in a 3-tier network

2-tier networks. But to fulfil the requirements for future wireless traffic growth, a huge number of small cells, especially femtocells will be deployed into 5G and B5G networks. There are very few ongoing research efforts to address interference management in 3-tier D2D-enabled heterogeneous cellular networks. Nonetheless, none of the authors examines the worst and at the same time, the most challenging interference case where all 3-tiers of the networks (i.e. eNB, SCeNB and D2D communication) mutually interfere.

1.2 Research problems

As mentioned in Cisco VNI [6], future wireless traffic explosion is unavoidable, and to manage the wireless traffic explosion, large numbers of small cell (SCeNBs), especially

femtocells (HeNBs) deployment is inevitable. If D2D communication technology is incorporated in such a Heterogeneous Network (HetNet), and UL cellular resources are shared by D2D pairs and small cells, CUEs will interfere with SUEs and DUEs. Similarly, DUEs will do the same with eNB, SCeNBs and other D2D pairs that share the same cellular resources.

In such a real-life scenario, where all 3-tiers of the networks (i.e. eNB, SCeNB and D2D communication) mutually interfere, improving interference is the most challenging part for D2D communication. In this thesis, the main objective is to identify the factors that affect interference and how to minimize them. To achieve this aim, the following research questions have been set:

1. What mode selection scheme can be developed to mitigate interference in D2D-enabled cellular HetNets?
2. What performance improvement can be done for D2D communication in heterogeneous cellular networks?
3. What resource allocation techniques can be developed to mitigate interference in D2D-enabled cellular HetNets?

D2D communication is a promising technology to fulfil the requirement for present and future cellular services. To unlock the full potential of D2D communication in cellular networks, interference management is the most important aspect. Mode selection, power control and resource allocation are the main tools that can be used to manage the interference in D2D-enabled cellular networks. Without having the knowledge of the above questions and their impact on D2D communication performances, interference management cannot be possible.

1.3 Research methodology for investigation

The main objective of this thesis is to identify the interference-affecting factors for D2D communication and propose suitable algorithms to minimize them. To achieve this research objective, an extensive analytical modelling approach is used as a primary tool. In addition, computer simulations are used for validating analytical models and evaluating the performance of D2D communication in D2D-enabled cellular HetNets. Figure

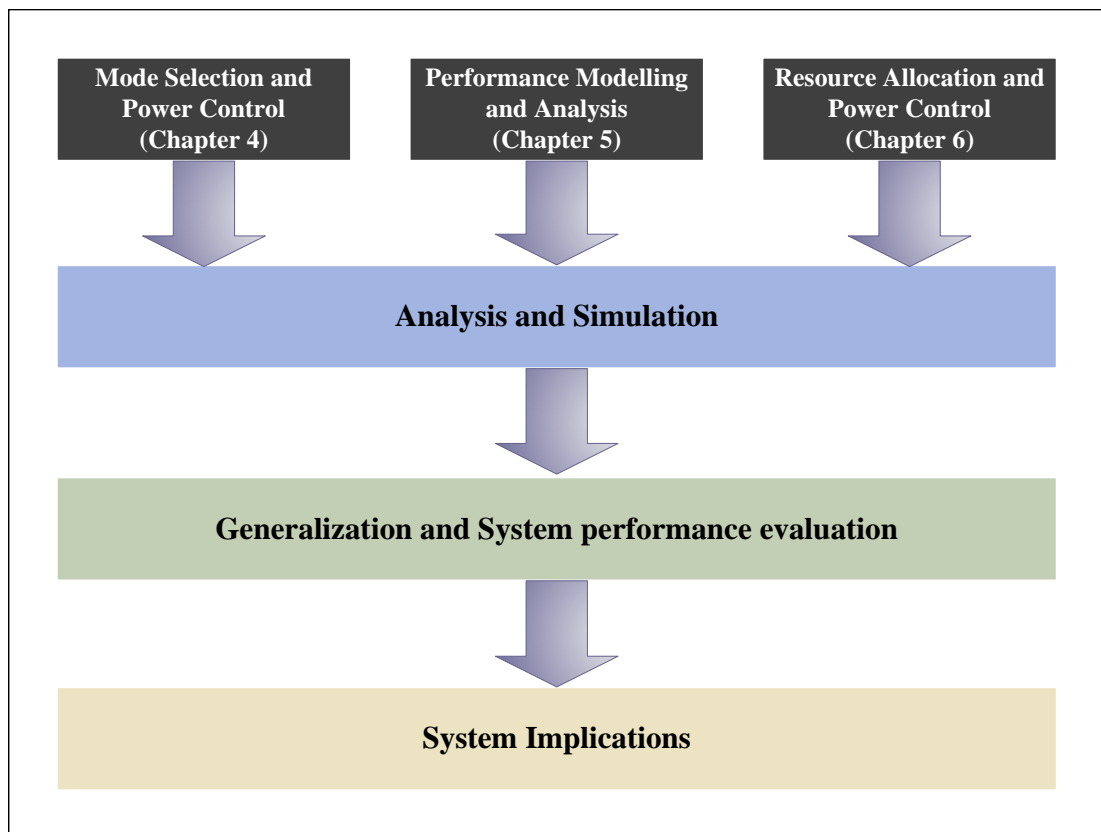


Figure 1.2: Block diagram of the adopted methodology

1.2 outlines the methodology adopted in this thesis. Both analytical and simulation-based performance estimation approaches are used to quantify (1) the factors affecting interference in D2D communication (Chapter 5), (2) joint effect of mode selection and transmit power control in system performance (Chapter 4) and (3) the combined effect of power control and resource allocation in system performance (Chapter 6).

This methodology has also been employed by many leading network researchers for propagation studies [24-28] and performance measurements for D2D communication [29-31].

Considering the requirements of this research, testing the D2D performance metrics of the proposed schemes in the real-world environment is highly expensive and not feasible. Thus, this research adopts computer simulations to test and evaluate the performance of the proposed interference mitigation schemes. Moreover, the simulation approach allows the generalisation of the findings by testing various network scenarios. To choose the computer simulation tool, various simulation tools were analysed. MATLAB is chosen as a primary tool for numerical performance analysis because it has powerful analysis capabilities, flexibility, and code reusability, making it a premier software tool for scientific researchers. Previous studies have also demonstrated MATLAB's widespread use in telecommunication research. The key features of MATLAB, such as its easy-to-learn programming capability and support for user-developed functions, motivated us to select it in our thesis. Moreover, MATLAB allows researchers to compare their proposed approaches with existing protocols on a standardized simulation platform, facilitating fair comparisons.

The thesis focuses mainly on identifying the interference-affecting factors for effective D2D communication and proposing suitable solutions to mitigate interference in a D2D-enabled cellular HetNet. In this research, we derived mathematical closed-form formulae to identify the factors influencing interference in a D2D-enabled cellular network and their impact on system performance. To verify the accuracy of the analytical model, they are compared with simulation results. The proposed MS and resource allocation schemes outperform existing ones in mitigating interference impact by yielding better system performance.

1.4 Contributions and the structure of this thesis

The overall structure of this thesis is shown in Figure 1.3. The figure presents three main sections, including the introductory part, main contributions and concluding remarks. Accurate system performance and identification of interference-affecting factors require a good understanding of different types of D2D communication and interference mitigation techniques, network modelling and performance evaluation tools. Chapters 2 and 3 provide the foundation and background material for the thesis.

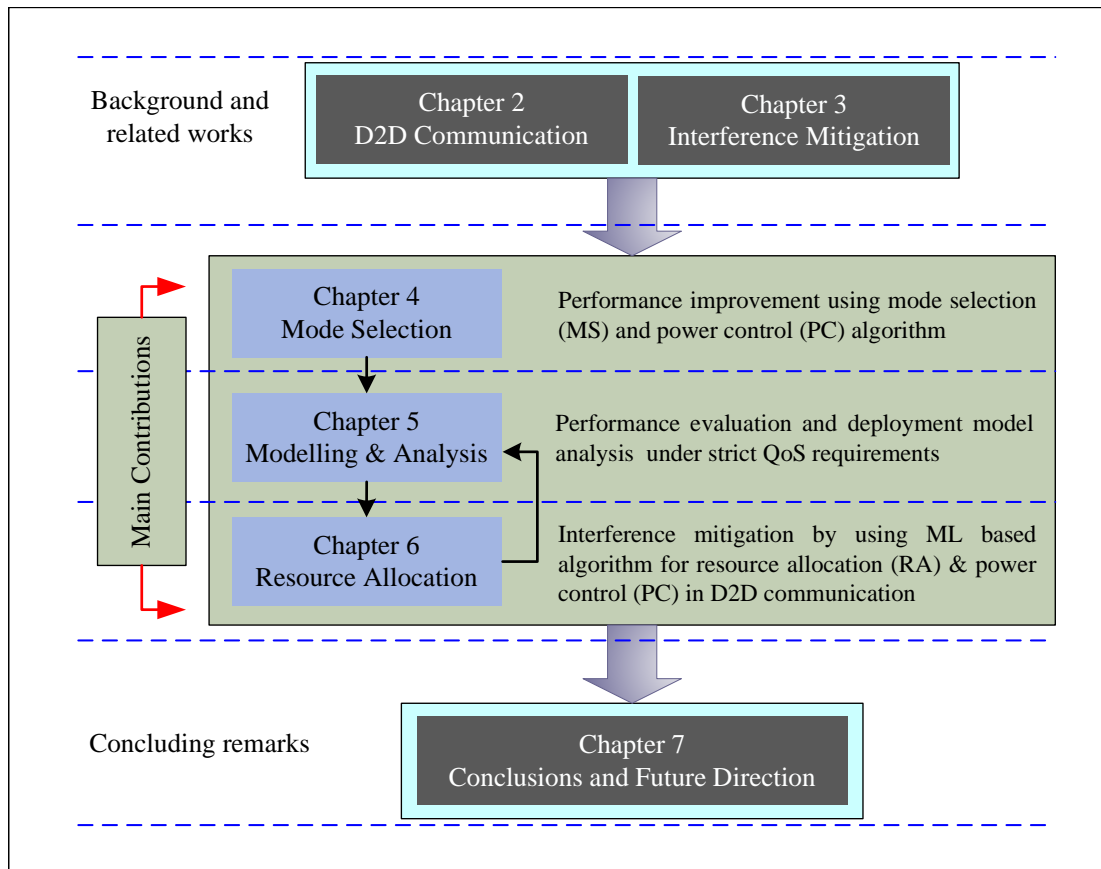


Figure 1.3: The structure of this thesis

Chapter 1 provides brief details about the research background and motivation including research problems, major contributions and research methodology for investigation. It also depicts the structure of the overall thesis.

Chapter 2 provides a detailed overview of D2D communication in cellular networks. Here we have discussed different modes of D2D communication and their spectrum utilization. Furthermore, it discussed various interferences in D2D communication both 2-tier and 3-tier cellular networks which motivated me to do intensive research on this topic.

Chapter 3 provides information about different interference and their mitigation techniques. It also contains a review of previous studies on D2D communication in cellular networks. In the review, the existing interference mitigation techniques and models are investigated. In the context of different interference scenarios, interference in tier-2 and tier-3 D2D-enabled cellular networks are summarized including existing or proposed solutions.

The original contributions of this thesis are presented in Chapters 4 to 6, which are primarily concerned with identifying the key factors that affect interference for D2D communications in cellular networks and propose appropriate schemes to mitigate them. To quantify the influence of these key performance-limiting factors, both simulation and measurement-based approaches were adopted.

Chapter 4 proposes a new mode selection scheme for improving D2D performance in heterogeneous cellular networks. The influence of different performance-impacting factors, including DUEs positions and SINR, are analysed here.

Chapter 5 analyzes new dynamic algorithms for interference management in a D2D-enabled heterogeneous cellular network. Different parameters are considered for defining mutual interference within the 3-tier cellular network and proposed Accepted Interference Region (AIR) algorithm to ensure D2D communications including ON/OFF algorithm to minimize interference.

Chapter 6 proposes AI/ML-based power control and resource allocation techniques for interference management in D2D-enabled cellular networks. It is also extensively evaluated using simulation.

Chapter 7 summarises the major findings from chapters 4 to 6 from the system planning and deployment perspective. This relates the key factors influencing interference to the design and deployment of D2D communications in a heterogeneous cellular network in a real environment. Furthermore, several potential future developments of this research are highlighted in this chapter.

Chapter 2

D2D Communication in Cellular Networks

2.1 Introduction

In Chapter 1, the motivations for interference management in a D2D-enabled cellular HetNet including main contributions and research methodology were outlined. The primary objective of this thesis is to identify the factors that affect the performance of D2D communication in cellular HetNets and provide a suitable solution to overcome these. To achieve this objective, a general understanding of D2D communication is required. This chapter aims to introduce various key concepts of D2D communication in cellular networks that are necessary to identify interference and evaluate the performances of such systems.

An evolutionary path in 3GPP for adopting D2D technology in cellular systems is highlighted in Section 2.2. Section 2.3 describes the different types of D2D communication in cellular systems. Since appropriate mode selection has a direct impact on interference and system performance, different mode selection techniques and their comparison are discussed here. Spectrum utilization and different types of interference are highlighted in Sections 2.4 respectively. Since the key focus of this thesis is to mitigate the interference in a D2D-enabled cellular network, various interference in wireless networks and their implication is discussed in Section 2.5. As our main objective is to

identify the interference affecting factors in D2D-enabled cellular networks, different interferences are pictured for such networks here. Section 2.6 outlines general research methodologies for wireless communication and adopts approaches in this thesis for D2D communication in cellular networks. Finally, this chapter is summarised in Section 2.7.

2.2 An evolutionary path in 3GPP for adopting D2D technology

Mobile communications have experienced exponential growth both in connectivity and multimedia traffic/services in recent years [7]. Recent studies have shown that to support this tremendous growth, device-to-device (D2D) communications can play an important role in 5G and beyond networks. In cellular networks until 4G, D2D communication has not been considered in 3GPP. To cope with a diverse range of applications and tremendous growth in device connectivity, an innovative technology and concept like D2D must be integrated to enable their benefits. To improve spectrum efficiency, energy efficiency, and overall throughput, D2D communication can play a significant role. The evolution of D2D communication in 3GPP is shown in Figure 2.1.

In Release 12 of the 3GPP LTE standardization, D2D communication was introduced as ProSe [12]. Direct communication allows a UE to transmit data to another UE located in proximity. Enhanced ProSe services and UE-to-network relay are introduced in Release 13 so that out-of-coverage UEs can access to eNB with another UE located in its proximity [13]. In Release 14, 3GPP further evolved D2D communication for the automotive industry referred to as LTE-based V2X services [14]. To improve throughput and latency, LTE V2X services are enhanced in Release 15 [15]. Until Release 16, D2D communications are based on an LTE network where a new radio (NR) is introduced to fulfil the requirements of a 5G mobile network. In Release 16 NR transmission is defined along with new use cases for NR V2X services such as vehicle platooning,

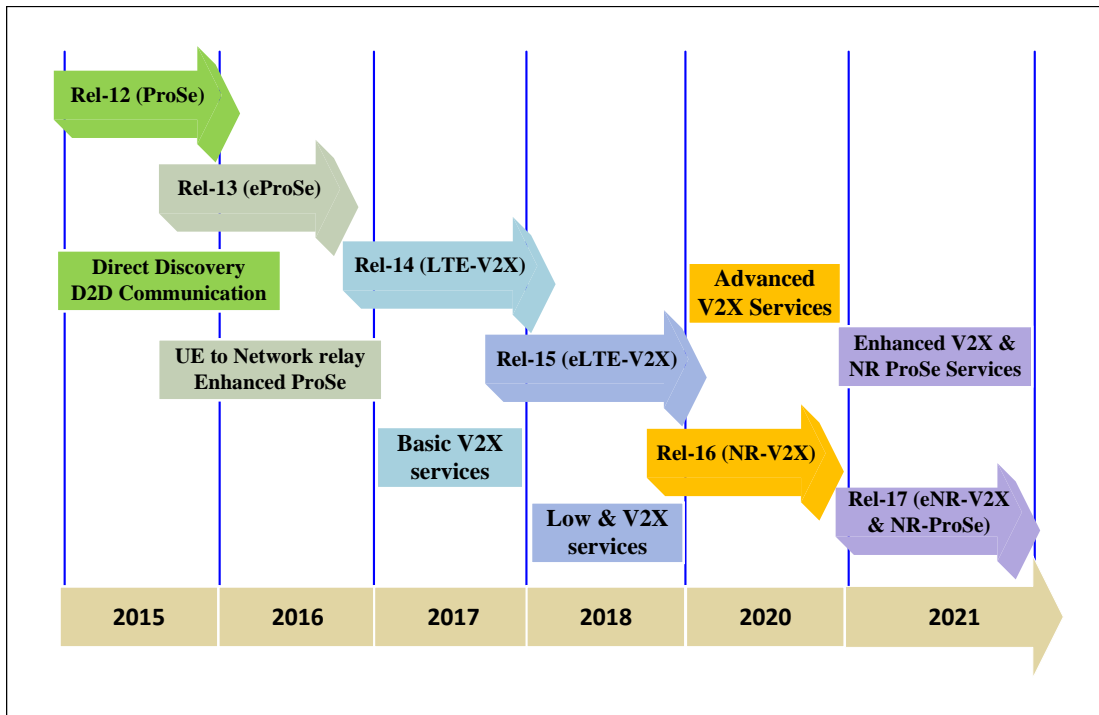


Figure 2.1: Interference scenario in a D2D-enabled tier-3 cellular network

advanced driving, exchange sensor information and remote driving [16]. Release 17 is expected to provide several key features in V2X communication such as coverage enhancements, power efficiency, reliability, and UE-to-UE relay are expected in Release 17 [17].

2.3 Classification of D2D communications

Device-to-device (D2D) communication in cellular networks is an emerging technology that enables direct communication between spatially closely located mobile UEs (User Equipment) without traversing the Base Station (BS) or core network. D2D communication can happen both cellular and unlicensed spectrum. Due to short range communication, D2D communication can provide numerous advantages like spectrum efficiency, throughput, delay, power management, coverage expansion, and capacity improvement by reusing radio resources and allowing network functionalities

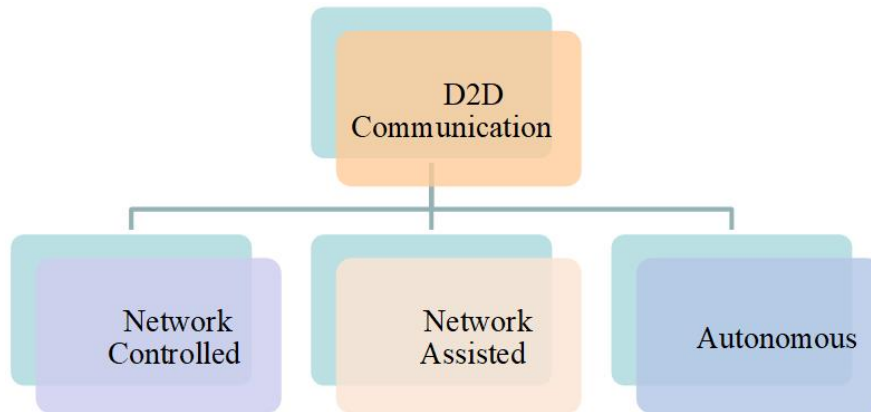


Figure 2.2: Various types of D2D Communications

to devices. Furthermore, D2D communication enables new services such as public safety services, location-based commercial proximity services, content sharing (e.g., videos and pictures), gaming, connectivity extension and traffic offloading [18]. Having these benefits, D2D communication is considered one of the key technologies in next-generation networks.

In cellular networks, D2D communication can be implemented with or without the assistance/involvement of cellular infrastructure [19]. Based on network involvement in the control of D2D communications, it can be classified into three categories: autonomous D2D, network-assisted D2D, and network-controlled D2D [20]. In autonomous D2D communication, devices in the network work in a fully distributed manner to communicate and establish links with each other. It is similar to ad hoc or peer-to-peer (P2P) networking. Thus, this mode is suitable for disaster networks or public safety services as devices can communicate without any infrastructure [21]. In the case of network assisted D2D communication, it could be partial or full control. In partial control, the infrastructure supports some network functions including link management, synchronization, and security. The devices in the network form a self-organizing network and retain control over D2D communication. The infrastructure facilitates network nodes to improve network efficiency by reducing the control signaling overhead [20].

In another case, the infrastructure has full control over D2D links including control plane functions (e.g., connection setup and maintenance), and data plane functions (e.g. radio resource management for data communication). To be more specific, the network is fully responsible for the D2D authentication process during the D2D discovery and initiation phase, it handles the D2D connection, and allocates power and radio resources. The advantage of the full control approach is that the network can easily coordinate D2D and cellular communications. Hence interference management between the CUEs and the DUEs is easier but higher signaling overhead is required to manage the D2D communication [3].

2.3.1 D2D communication mode

In D2D communication, mode selection is very important. It could be either the “D2D mode” where two D2D UEs communicate each other directly over the air, or the “cellular mode” where two D2D UEs communicate via the BS (Base station) as in traditional cellular networks [22]. However, a prominent issue in D2D communication is how to share the spectrum resources between cellular and D2D communications. Based on the spectrum resource utilization, the following communication mode shown in Figure 2.3 can be used in D2D communication.

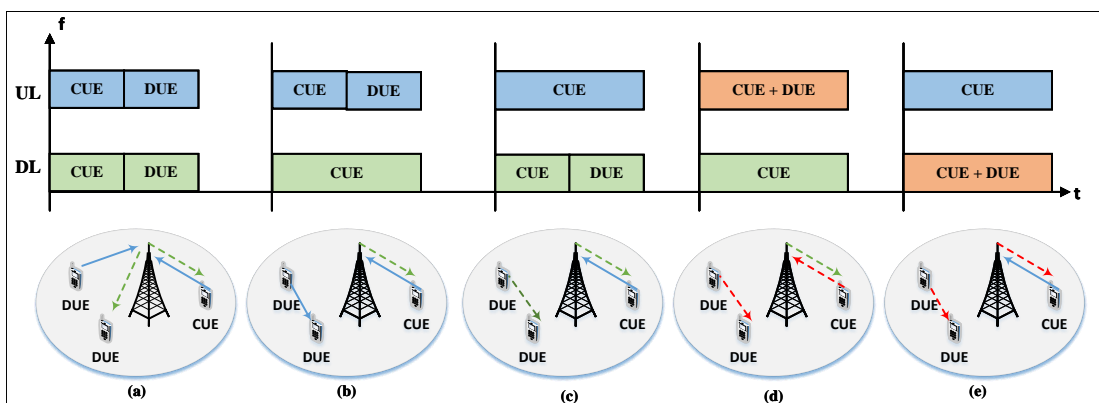


Figure 2.3: D2D communication mode: (a) CM (b) DM (UL reused) (c) DM (DL reused) (d) SM (UL reused) (e) SM (DL reused)

Cellular Mode (CM) - CM corresponds to traditional cellular communication as the DUEs exchange data through the evolved Node B (eNB) and there is no direct exchange of data between the DUEs. This mode is usually used if UEs are too far from each other or simply if D2D communication does not pay off.

Dedicated Mode (DM) - In this mode, some of the available resources are dedicated to D2D users for direct transmission. In DM, D2D transmission takes place only in one direction, either the DL or the UL. This mode of allocation is also referred to as an orthogonal mode or an overlay mode, as the transmission of the CUEs and the DUEs has assigned a non-overlapping orthogonal radio resource. The advantage of the DM is that the eNB does not need to manage interference between cellular and D2D tiers, but spectral efficiency is poor.

Shared mode (SM) - In the SM, both the DUEs and the CUEs use the same radio resources. This mode is also referred to as non-orthogonal or an underlay mode. Similar to the DM, the SM can use either the DL or the UL radio resources. From the spectral efficiency perspective, this option is better for the system, since the reuse factor is significantly higher compared to the CM or the DM. Nevertheless, the SM also has some disadvantages as strong interference could be generated between the DUEs and the CUEs. As a result, the complexity of the whole system is increased [3].

Mode selection has a significant effect on D2D communication cellular networks. Recent research into mode selection issues and challenges is outlined in Chapter 3 (Section 3.2). The performance analysis for mode selection in cellular networks is presented in Chapter 4 (Section 4.5).

2.4 Spectrum utilization in D2D Communications

A general understanding of spectrum utilization for D2D communication in cellular networks is required for efficient design and deployment of D2D-enabled cellular HetNets.

Table 2.1: Comparative analysis of D2D communication for different modes

Criteria/Types of D2D mode	CM	DM (DUEs use dedicated resources)	DM (DUEs use shared resources)	SM (DUEs use dedicated resources)	SM (DUEs use shared resources)
Spectral efficiency	Low	Medium	High	High	Very High
Cross-tier interference (Interference among CUEs and DUEs)	No	No	No	Yes	Yes
Co-tier interference (Interference among DUEs)	No	No	Yes	No	Yes
Implementation complexity	Low	Low	Medium	Medium	High

Based on the spectrum resource utilization by D2D users, D2D communication can also be categorized into in-band D2D and out-band D2D [23]. In in-band communication, cellular and D2D devices share the same spectrum band by reusing radio resources (underlay) or using dedicated resources (overlay).

In Underlay inband communication, D2D User Equipment (DUEs) compete with Cellular User Equipment (CUEs) and opportunistically access resources occupied by cellular users, resulting in improved spectral efficiency [24]. Dedicated resource blocks are assigned to the cellular users, and the D2D transmitter reuses these resource blocks for direct communication. Underlay communication enhances the performance of cellular networks by providing high spectral efficiency [25].

The advantage of this type of communication is that the infrastructure can have a high level of control over the cellular spectrum, but it will introduce interference to the cellular communication which requires an additional computation procedure for resource allocation, resulting in some overhead. Whereas in Overlay inband communication, a portion of the cellular spectrum is dedicated to D2D communication. This

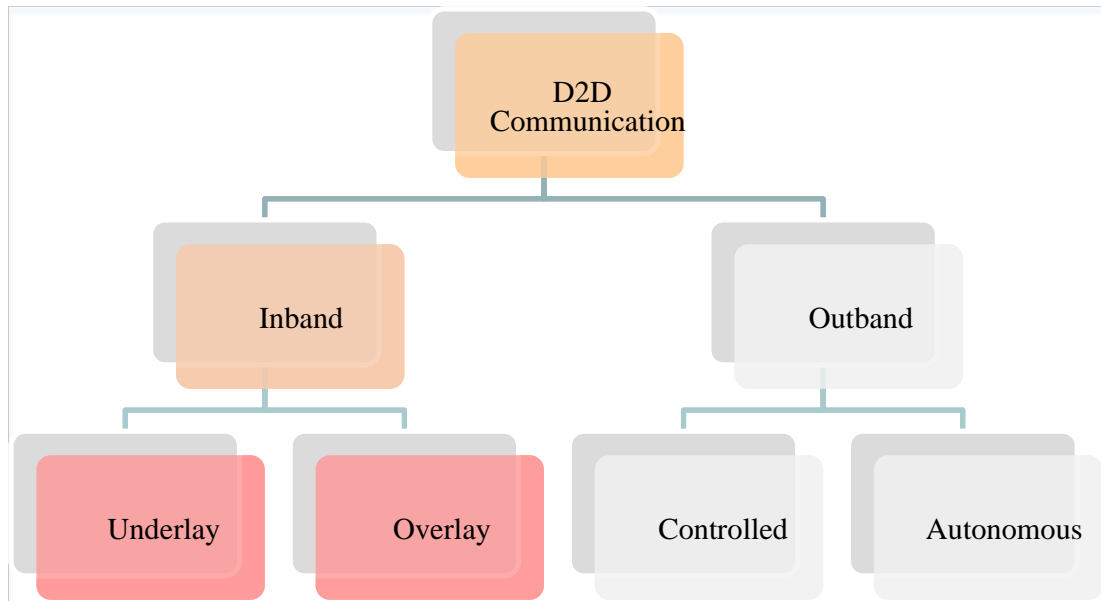


Figure 2.4: Spectrum utilization in D2D Communications

reduces the interference problem as both types of communications take place in their separate spectral bands but it reduces spectral efficiency i.e. poor resource utilization and system throughput [25].

In Outband D2D, licensed cellular spectrum is used by cellular devices for communication while D2D communication occurs through unlicensed spectrum, usually ISM bands. As cellular and D2D communications use different spectrum bands, the outbound communication eliminates interference issues in cellular links caused by D2D pairs and vice versa. However, the coordination between two different bands for achieving Out-band D2D communication has a lot of challenges. Based on the occurrence of the second interface (i.e. D2D communication interface), out-band D2D communication can be further divided into controlled and autonomous modes. In controlled mode, the cellular network fully controls the D2D communication whereas in autonomous mode, the devices control it by themselves. Nevertheless, the interference level of the unlicensed spectrum is uncontrollable, hence QoS guaranteeing in highly saturated wireless areas is a challenging task [23]. In Controlled outband communication, the

coordination between radio interfaces such as D2D, Bluetooth, ZigBee or Wi-Fi Direct is controlled by the cellular network. Spectrum resources are pre-allocated to D2D users so that they can fairly contend and utilize the ISM band resources [24]. In addition, eNB can prioritize the transmission of a particular user to meet the QoS requirements. However, this approach increases the signaling overhead especially if the network size is bigger which deteriorates the performance of the network due to long delay.

Whereas in autonomous outband communication, cellular links are controlled by eNB, and the devices communicating in D2D mode are responsible for the control of D2D communication. This approach significantly lessens the workload of cellular networks which reduces significant overhead on the cellular network. Figure 2.4 and Figure 2.5 graphically depict the difference between underlay, overlay, in-band, and out-band communications.

Both in-band and out-band communication approaches have some specific merits and demerits. The advantages of in-band D2D communications are: (i) Due to spatial diversity, spectral efficiency is remarkably high in underlay D2D; (ii) Each cellular device can use in-band D2D communication; and (iii) QoS management is easier as the BS can fully control cellular spectrum. However, the disadvantages of in-band D2D communications include (i) in case of overlay D2D, cellular resources might be wasted due to allocating dedicated spectrum; (ii) interference management between D2D and cellular transmission in underlay is very challenging; (iii) power control and interference management solutions usually resort to high complexity resource allocation methods, and (iv) simultaneous cellular and D2D transmissions are not possible.

On the other hand, the advantages of out-band D2D communications are: (i) there is no interference between cellular and D2D users; (ii) like overlay in-band D2D, dedicated cellular resources are not required, unlicensed ISM band will be used; (iii) the resource allocation is easier as scheduler does not require to take the frequency, time, and location of the users into account; and (iv) simultaneous D2D and cellular

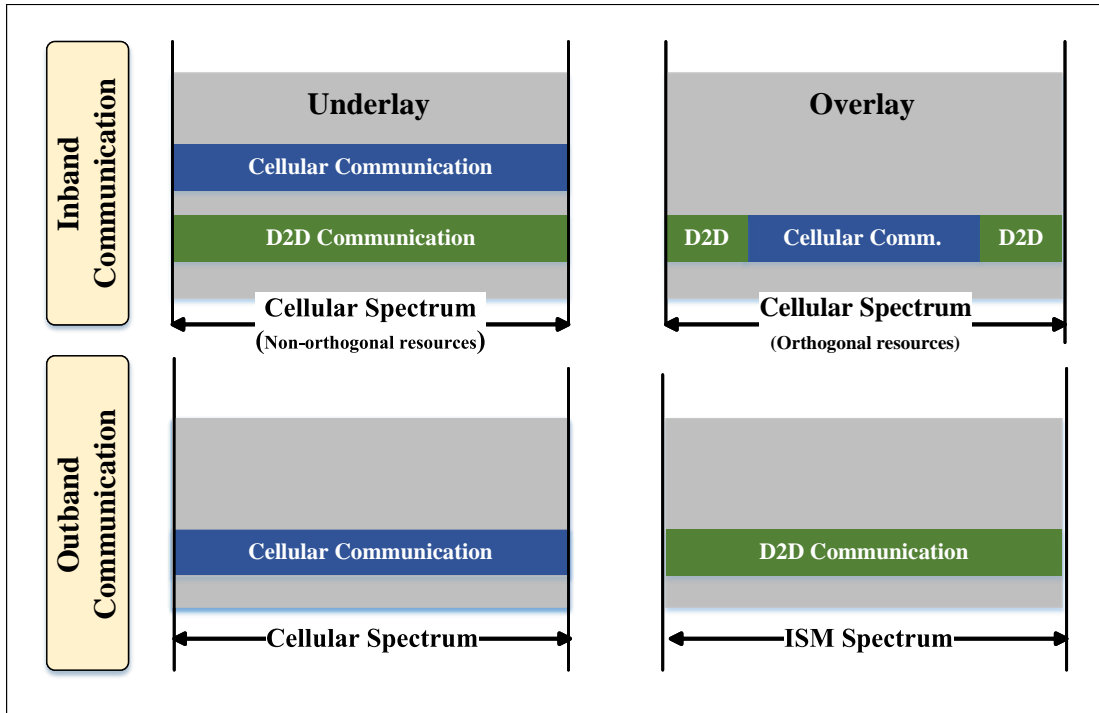


Figure 2.5: Spectrum utilization in D2D communications

communication is feasible. Nevertheless, out-band D2D has some disadvantages which are: (i) the interference in unlicensed spectrum is not in the control of the BS; (ii) only cellular devices with two radio interfaces (e.g., LTE and WiFi) can use out-band D2D communications; (iii) the efficient power management between two wireless interfaces is crucial otherwise the power consumption of the device can increase; and (iv) as protocols used by different radio interfaces are not the same, packets (at least the headers) need to be decoded and encoded (at least the headers) [23]. The state-of-art, majority of the available literature is dedicated to in-band D2D, especially D2D communications in underlying cellular networks to improve the performance of cellular networks, in terms of spectrum efficiency, energy efficiency, cellular coverage, and other performance targets.

Cellular networks operate on licensed frequency spectra and therefore it is unlikely that other transmitting devices will affect their system performance. In contrast, WLANs operate on unlicensed frequency spectra (e.g. ISM bands) and therefore other devices

Table 2.2: Comparative analysis for Inband-Outband communication in different modes

Criteria/Types of D2D Communication	Inbound		Outbound	
	Underlay	Overlay	Controlled	Autonomous
Spectrum efficiency	Very High	Medium	Low	Low
Cross-interference (Interference between D2D and cellular users)	High	No	No	No
Co-interference (Interference among D2D users)	Medium	Medium	High	High
Controlled interference environment	Yes	Yes	No	No
Simultaneous D2D and cellular transmission	No	No	Yes	Yes
Requires Inter-platform coordination	No	No	Yes	Yes
Requires devices with more than one interface	No	No	Yes	Yes
Introduces extra complexity to the scheduler	High	Medium	High	No
Energy efficiency	High	High	Low	Low

(e.g. Bluetooth devices) operating in the same ISM band can affect their system performance. Hence it is recommended that DUEs will operate at the spectra as cellular networks. The impact of interference on D2D communication performance is further discussed in Section 2.5. The effect of interference on D2D communication performance is also analysed on Chapter 5 (Section 5.4).

2.5 Interference in wireless networks

In wireless communication when desired signals are disrupted or weakened by the presence of unwanted signals, it is considered as interference. There are different causes for interference in cellular systems but the most common is channel interference which happens when the same radio frequency is shared by multiple devices at the same time.

Interference in cellular networks is one of the most common problems. In fact, it is

the major issue in cellular networks that affects performance and quality of services. Based on the spacing between desired and interfering signals, interference can be classified as intra-cell interference and inter-cell interference.

Intra-cell interference, also known as adjacent channel interference, is caused due to imperfect receiver filters which allow nearby frequencies to leak into the pass band. As shown in Figure 2.6 signal 1 and signal 2 are transmitted on adjacent frequencies f_1 and f_2 , and each one causes adjacent channel interference to the other.

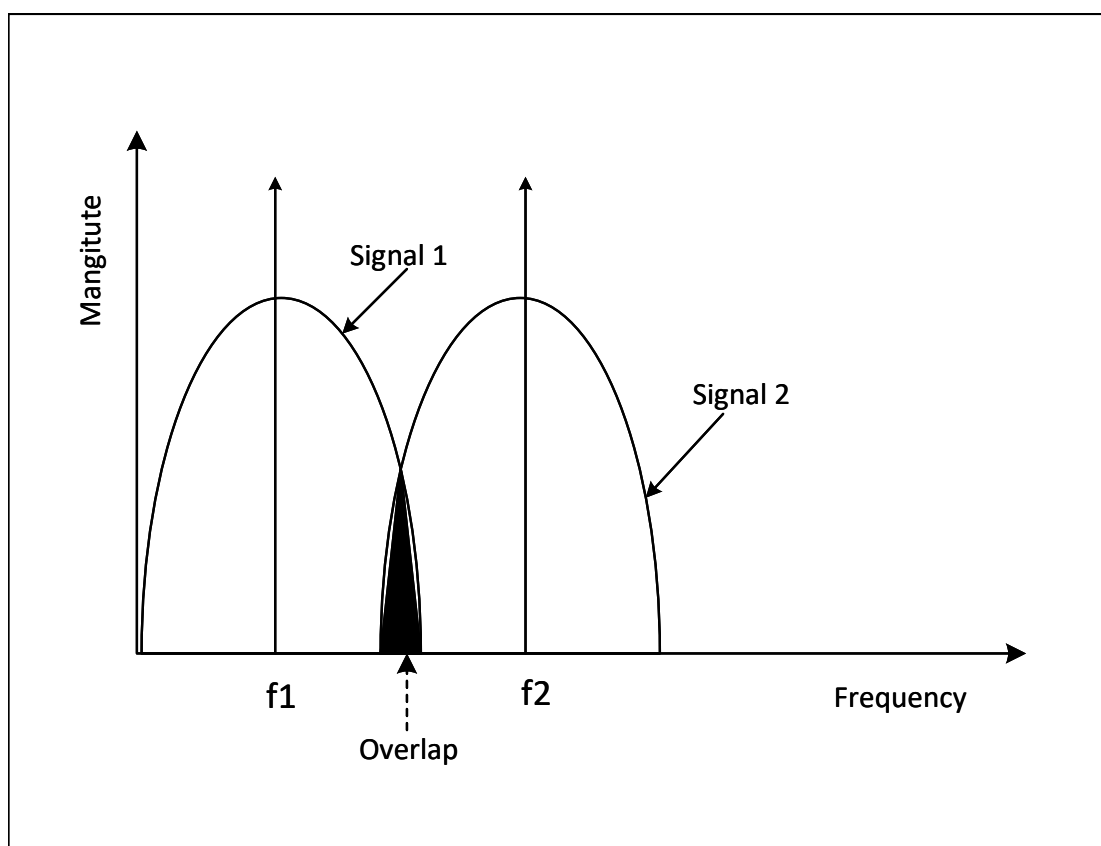


Figure 2.6: Adjacent channel interference in cellular network

On the other hand, Co-channel interference happens due to the overlapping of two or more signals transmitted on the same frequency from multiple sources. As shown in Figure 2.7 CUE1 is a received signal using f_1 frequency from two different eNB.

In heterogeneous networks, inter-cell interference is dominant where femto cells are deployed densely along with macro cells. Intercell interference is mainly categorised as

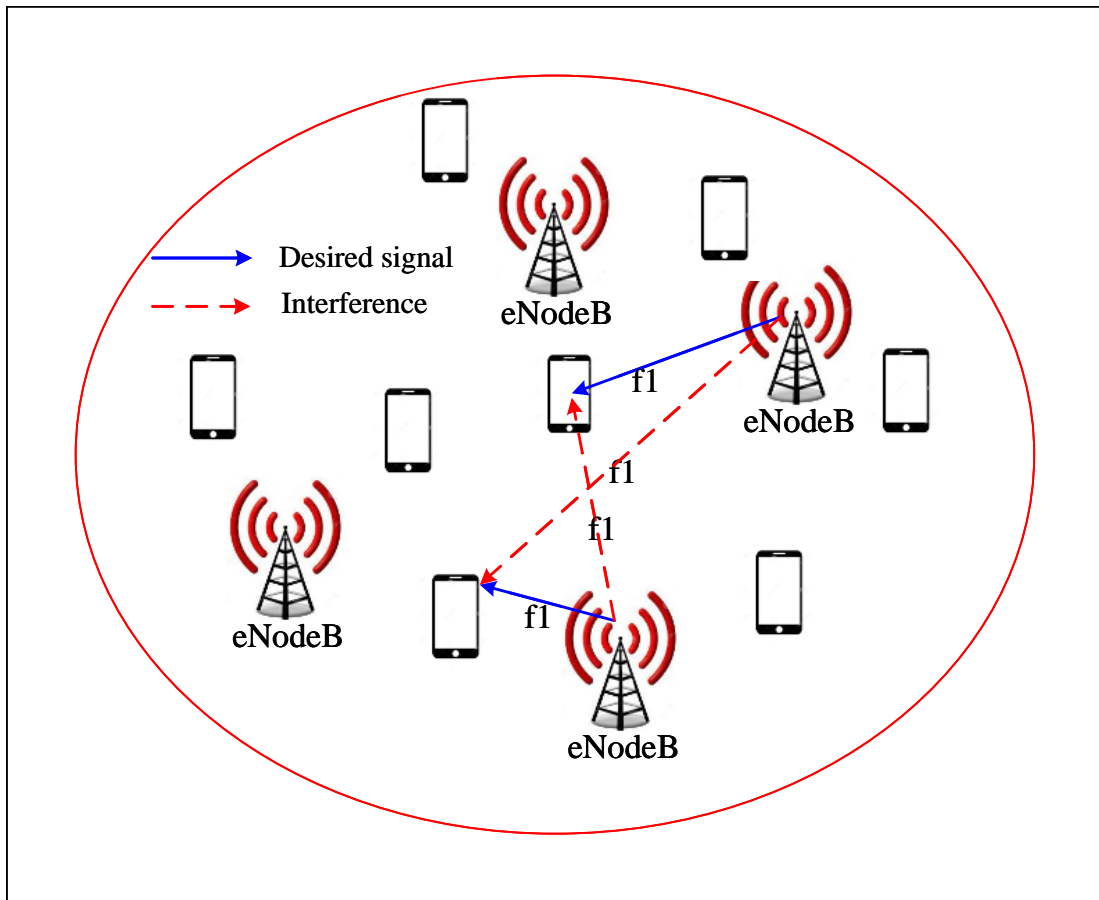


Figure 2.7: Co-channel interference in cellular network

co-tier interference where macro CUEs are interfered with by neighbouring macro eNB or femto user is interfered with by neighbouring femto base stations. This is known as interference within the same layer.

The other type of co-channel interference is cross-tier interference where macro users are interfered with by neighbouring femto base stations or femto users are interfered with by neighbouring macro base stations. It is called interference between layers.

2.5.1 Interference for D2D communication in 2-tier network

In a 2-tier network, the first tier is the conventional macrocell layer which involves the communication between the Base Station (BS/eNB) and the device as in a traditional cellular system. The other one is known as the device tier, where direct communication will happen without traditional network or eNB assistance. The device tier is an unplanned and random distribution of D2D user equipment (DUE). The new architecture has significant improvement in terms of throughput, coverage, and end-to-end latency [8]. However, it introduces several technical challenges and issues for both DUE and cellular user equipment (CUE). Among these challenges, interference management between CUEs and DUEs becomes one of the most critical issues for D2D communication in sharing mode, where the same radio resources are used for both cellular and D2D communication [26]. The network elements that are affected by interference (eNB, CUE, DUE) depend on the D2D communication mode and the way resources are used for D2D communication (UL/DL). Various types of interference that exist in D2D enable cellular networks are shown in Figure 2.8.

The interference in the new 2-tiered architecture is co-tier and cross-tier interference [5]. As shown in Figure 2.9(a) co-tier interference takes place between two devices that are operating in the same tier i.e. within D2D layers. In a D2D-enabled 2-tier communication system, interference occurs between two D2D devices, the transmitting D2D device and a receiving D2D device that are sharing the spectrum resources and that are closer to each other. In other words, co-tier interference occurs between the neighbouring D2D devices that share the same spectral resources.

Whereas cross-tier interference takes place between the devices in two different tiers i.e. between D2D and cellular layers. The source and the destination of the interference are different in the cross-tier interference, and it can be either uplink or downlink scenarios based on which frequency (UL or DL) is shared. As shown in Figure 2.9(b)

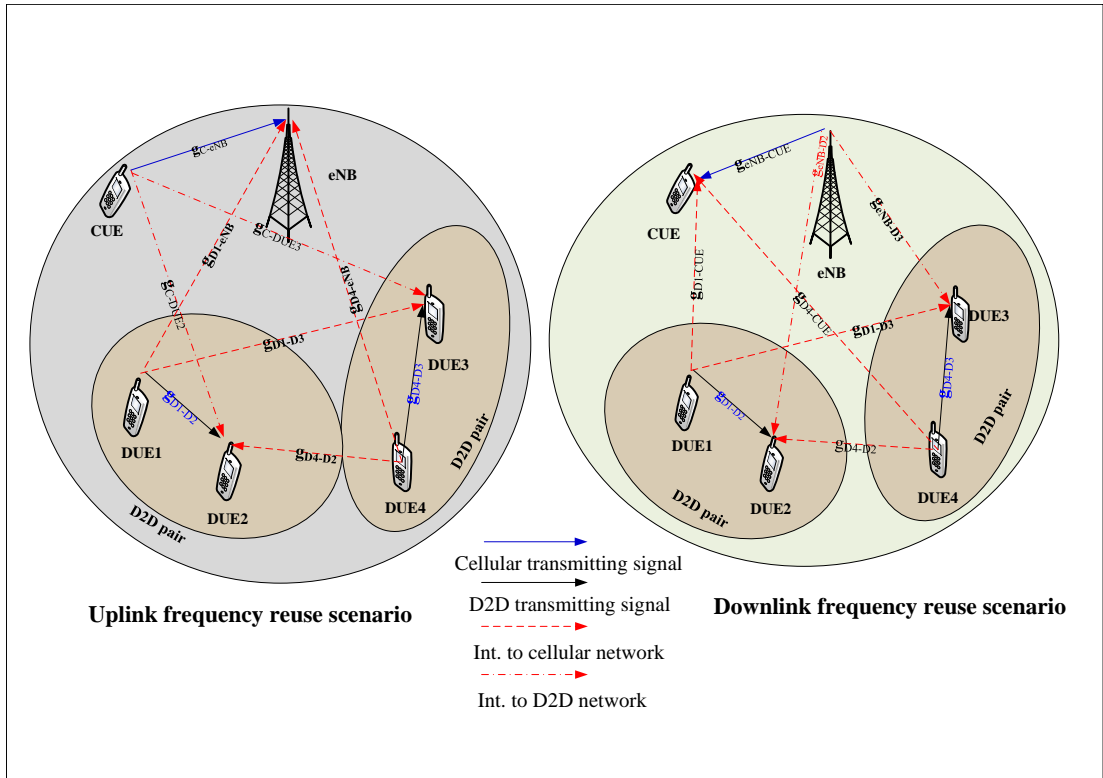


Figure 2.8: Interference scenario for D2D communication in 2-tier network

for the uplink scenario, the cellular device in the macro-tier transmits its data to eNB while the D2D device also transmits its data to the D2D receiver in the device-tier. The uplink spectrum is shared by the D2D pairs and therefore, interference occurs between the D2D and cellular layers. In Figure 2.9(c) for the downlink scenario, eNB is transmitting the data to CUEs. As the DL spectrum is shared between eNB and DUEs, interference occurs between DUEs in the D2D layer and CUEs in the macro-layer.

2.5.2 Interference for D2D communication in 3-tier network

The complexity of interference increases when the number of tiers is higher in the new architecture. As per Cisco VNI [6], future wireless traffic explosion is unavoidable and to manage the wireless traffic explosion, large numbers of small cell (SCeNBs), especially femtocells (HeNBs) deployment is inevitable. By deploying low-power

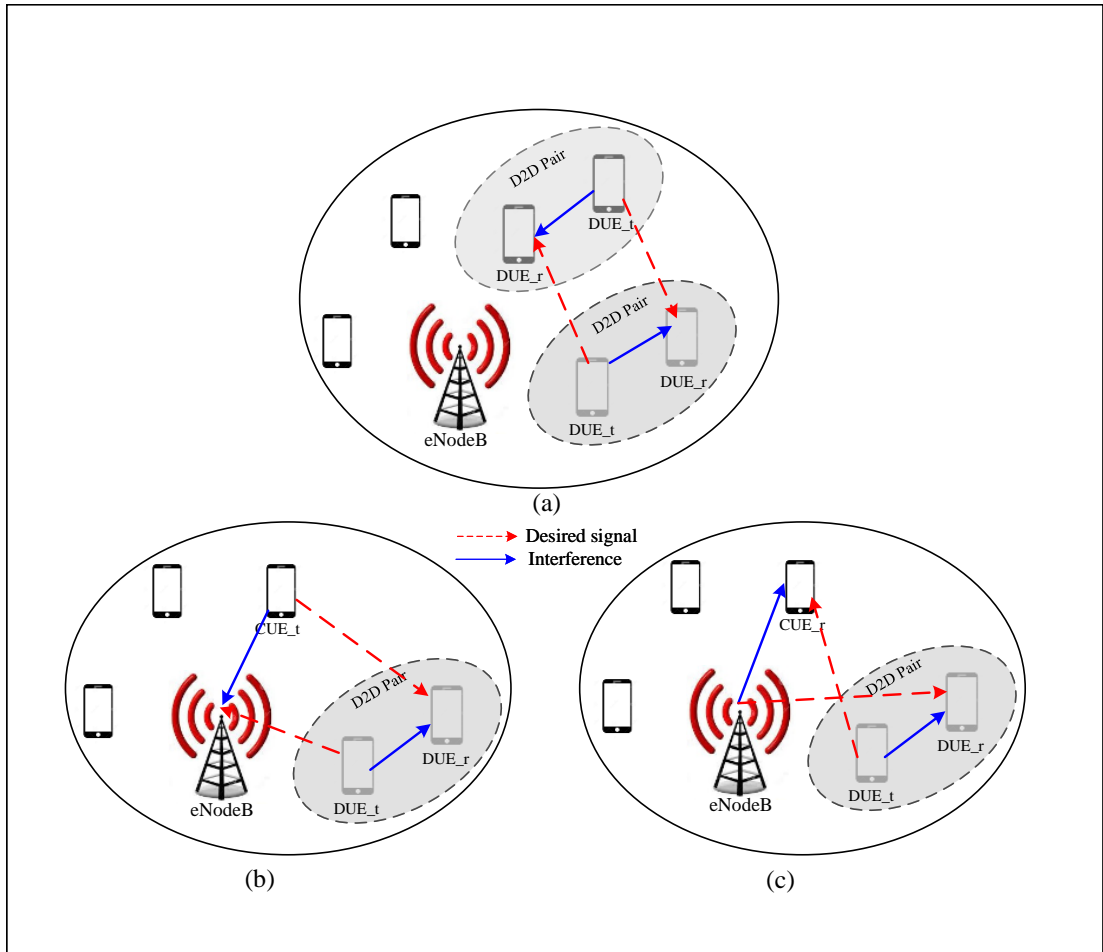


Figure 2.9: (a) Co-tier interference (b) Cross-tier interference in UL (c) Cross-tier interference in DL

small BSs, network capacity is improved and the coverage will be extended to coverage holes [27, 28]. To fulfil the growth if D2D communication is introduced in such a Heterogeneous Network (HetNet), cellular system architecture will be moved from two-tier to three-tier where the 1st-tier encompasses the eNBs, the 2nd-tier will be formed by the SCeNBs, and the 3rd-tier will be composed of D2D pairs as shown in Figure 2.10. In that situation, we can distinguish the total interference into three scenarios: 1) interference between the 1st-tier and the 2nd-tier, 2) interference between the 1st-tier and the 3rd-tier, and 3) interference between the 2-tier and 3-tier.

In cellular systems, when the same set of resources are allocated to multiple UEs in

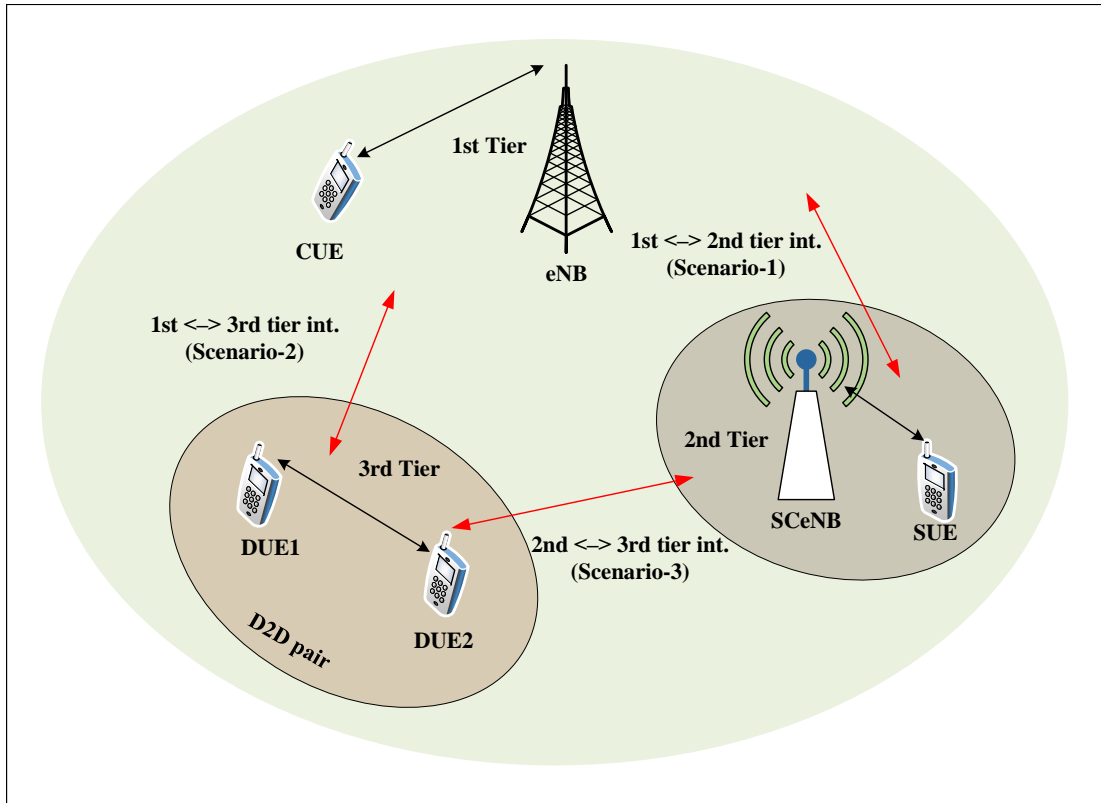


Figure 2.10: Interference scenario for D2D communication in 3-tier network

the same tier there is a possibility for interference and this type of interference is known as co-tier interference. In a D2D-enabled cellular network, co-tier interference occurs between one D2D user to another D2D user in the same tier. In this case, the interference is always generated from the D2D transmitter to the D2D receiver in a D2D pair which are assigned the same cellular resources regardless of the resource reuse direction (UL/DL) [26]. To set up a direct link between D2D users, the signal-to-interference plus noise ratio (SINR) value must be higher than a predefined threshold value otherwise communication will fail. On the other hand, in cross-tier interference one or more D2D users use the same cellular resources. Cross-tier interference can occur between a CUE and a DUE, and between a CUE and multiple DUEs. In cross-interference, the aggressor e.g. the source of interference and the victim of interference are different depending on the resource reuse direction (UL/DL) [26]. Hence based on the interferer and victim of

interference, we can divide the interference into three cases. The interference scenarios for D2D communication are illustrated in Figure 2.10.

In HetNets, interference management for underlay spectrum sharing mode is more challenging compared to the two-tier cellular network because the transmit power for each base station (eNBs) is different. In addition, interference levels in different tiers are different due to the various access restrictions (i.e. public, private, hybrid, etc.). Besides, to improve spectrum efficiency, the interference among macro-cell cellular links, small-cell cellular links, and D2D links, all need to be considered and managed efficiently. Hence, in the future cellular system, interference management will be a challenge due to heterogeneity, dense spectrum reuse, and network densification.

2.6 Research process for investigation

Wireless communication systems are a practical and applied research discipline, and researchers typically adopt three main strategies, to resolve the issues in this field. Breakthrough innovation - introducing a completely novel idea to solve the existing problem. Incremental advances - refining and enhancing current solutions to optimize performances and address specific challenges. Theoretical to practical transition - understanding the system's capabilities, limitations, and real-world implications of theoretical knowledge before standardization and widespread implementation.

In addition to strategy selection, justification, analysis, and verification are the basic components of any research methodology for a wireless communication system. The objective of system justification is to assess whether all the adopted assumptions are suitable and relevant to the given scenario. This step ensures that researchers do not make impractical or contradictory assumptions that could lead to invalid conclusions [29].

Once the system model is justified, researchers proceed to analyze the system

thoroughly using mathematical tools. This analytical phase involves examining one or more selected performance evaluation metrics. By deriving their closed-form expressions, researchers can establish the inherent mathematical relationship between these performance metrics and the system parameters in an appropriate manner. During analysis, researchers have the flexibility to convert the given scenario into a performance optimization problem. This enables them to study the attributes and complexity of the formulated performance optimization problems.

After completing the analytical investigation, researchers verify the results through numerical outcomes. Numerical results are commonly obtained by real-world data or computer-based simulation tools like MATLAB, OPNET, and NS-3. By comparing the analytical results with the numerical outcomes, researchers can validate the accuracy of the analytical findings. If the numerical results closely match the analytical predictions, it provides confidence that the assumptions and analytical approach were appropriate for the given scenario.

The main objective of this thesis is to identify the key factors influencing interference in a D2D-enabled cellular HetNet and propose a suitable solution to overcome those limitations. To achieve this, both analytical and simulation-based measurement techniques are used in our research. To find a suitable solution to our problem, we have adopted a Design Science Research Methodology (DSRM). Choosing DSRM for our thesis has two reasons. First, an artefact must solve an important problem i.e. being relevant. Second, design science research should address either an unsolved problem in a unique and innovative way or a solved problem in a more effective or efficient way [30]. According to these authors, DSRM is the best suited to address either an unsolved problem in an innovative way or a solved problem in an effective way. In [31] authors stated that research conducted under the Design Science paradigm not only proposes solutions to practical problems but can also contribute to improving theories of new ideas or concepts for a new technology that can facilitate solving a problem in a novel

way.

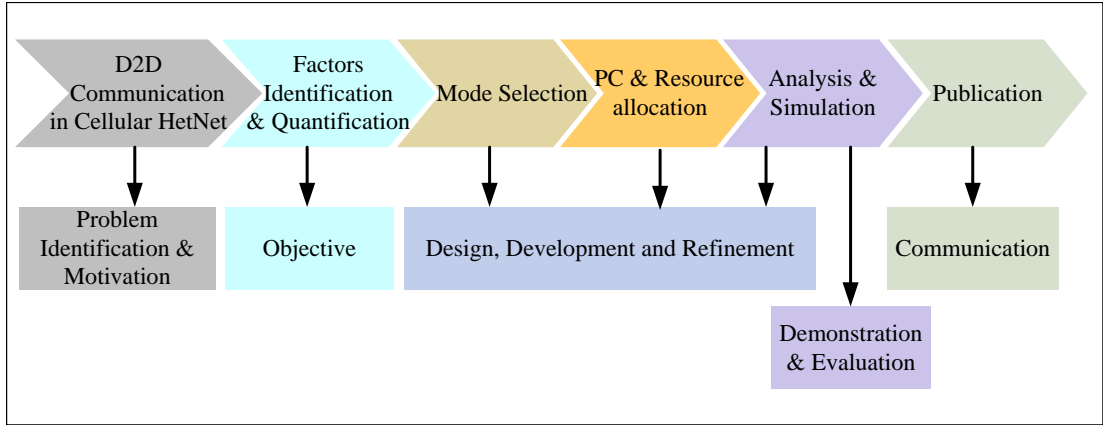


Figure 2.11: Modified design science research method.

In our modified DSRM, five main sequential activities are followed: 1) problem identification and motivation, 2) defining the expected results, 3) design and development, 4) demonstration and evaluation, and 5) communication. The proposed research activities using the modified DSRM method are shown in Figure 2.11.

Table 2.3: Relationship between DSRM and our proposed research

Activities	Proposed Research Activities
Problem Identification and Motivation	D2D is essential to fulfil the exponential data growth requirements, and to unlock the full potential of D2D communication, interference management is the most critical problem.
The objective of the Proposed Solution	Identify the key parameters that affect the performance of D2D communication in heterogeneous 5G cellular networks, and propose interference-aware mode selection and resource allocation technique for effective D2D communication in cellular HetNets.
Design and Development	Formulate and validate system models in which research contributions are embedded such as the best suitable mode of D2D communication, power control, and resource allocation to mitigate interference for D2D communication in cellular HetNets.
Demonstration and Evaluation	Execution of the analytical model into simulation tools, and validation of simulation results with existing solutions.
Communication	Communicate the problem, its solution and the utility, novelty, and effectiveness of the solution to the research community and other relevant audiences by publishing it in refereed journals and conferences.

For numerical performance analysis, MATLAB is the primary tool in this thesis. It is chosen for its powerful analysis capabilities, flexibility, and code reusability, making it a premier software tool for scientific researchers. Previous studies have also demonstrated MATLAB's widespread use in telecommunication research. The key features of MATLAB, such as its easy-to-learn programming capability and support for user-developed functions, motivated us to select it for our thesis. Moreover, MATLAB allows researchers to compare their proposed approaches with existing protocols on a standardized platform for simulations, facilitating fair comparisons.

2.7 Summary

In this chapter, the fundamentals of D2D communications were outlined. Different types of communication including comparative analysis for different D2D communication modes and spectrum utilization categories are discussed. Interference in cellular networks and its impact in 2-tier as well as 3-tier D2D-enabled cellular networks are discussed in detail in this chapter. The adopted research process and its importance are also discussed in this chapter. Research methodology in wireless communication systems involves a rigorous cycle of making assumptions, justifying, analytical investigation and validation to ensure that the proposed system is based on realistic and appropriate assumptions, leading to more reliable and practical outcomes. Interference mitigation techniques and models for D2D-enabled cellular networks are outlined in Chapter 3 including recent ongoing research works related to this issue.

Chapter 3

Interference Mitigation for D2D Communication in Cellular Networks

3.1 Introduction

The fundamentals of D2D communication were discussed in Chapter 2. It provided essential background information to understand D2D communication and its association with 2-tier and 3-tier cellular networks. The primary objective of this thesis is to identify the factors that affect interference in D2D communication and propose suitable schemes to overcome those which are essential to unlock the full potential of D2D communication in future wireless networks. A clear understanding of the related challenges in D2D communication is required to achieve this objective. At the end of this chapter, we will get a basic understanding of the issues related to D2D communication in cellular networks and the state-of-the-art researchers' ongoing work on it.

In Section 3.2 we have discussed the impact of interference in D2D-enabled cellular networks. In Section 3.3, the thesis conducts a literature review to explore various mechanisms for interference minimization in D2D-enabled cellular HetNets. It covers both conventional approaches and machine learning-based interference mitigation models in Sections 3.3 and 3.4, respectively. Section 3.5 outlines the adopted approach for D2D link performance. Finally, the chapter is summarized in Section 3.6, providing

an overview of interference management strategies in D2D-enabled cellular HetNets.

3.2 Interference in D2D-enabled cellular networks

To gain an insight into interference impact on D2D communication, it is important to have a sound understanding of how the D2D layer introduces interference into cellular networks. An overview of interference for D2D communication in cellular is given in this section. In-band emission interference (IEI) due to D2D communication in cellular network has a direct harmful impact on cellular links performance. Without managing interference in an ultra-dense D2D-enabled cellular HetNets where the number of CUEs and DUEs are very, the performance of cellular as well D2D links will be poor or impossible to continue the communication. In [32], authors evaluate the IEI impact in D2D-enabled cellular networks in terms of cellular network coverage. CUE outage probability increases rapidly not only with increasing the numbers of DUEs but also increasing the transmit powers of D2D pairs. Figure 3.1 and 3.2 show the performance comparison for IEI and no-IEI scenarios in a D2D-enabled cellular network. The impact of interference in links performance is analysed and examined details in Chapter 5.

To meet the future requirements of wireless traffic explosion, D2D is a prominent technology in the upcoming next-generation cellular network. Due to enabling D2D communications into the cellular network, the cellular architecture needs to be changed from 1-tier to two or multi-tier cellular system network [19, 8] and different tier introduces more and more complex interference scenarios.

3.3 Interference minimization techniques

D2D communication is a key enabler to fulfil the requirement and enhance performance for 5G and beyond cellular networks. D2D offers many advantages in cellular networks such as (i) energy efficiency, (ii) higher transmission rate, (ii) broader coverage,

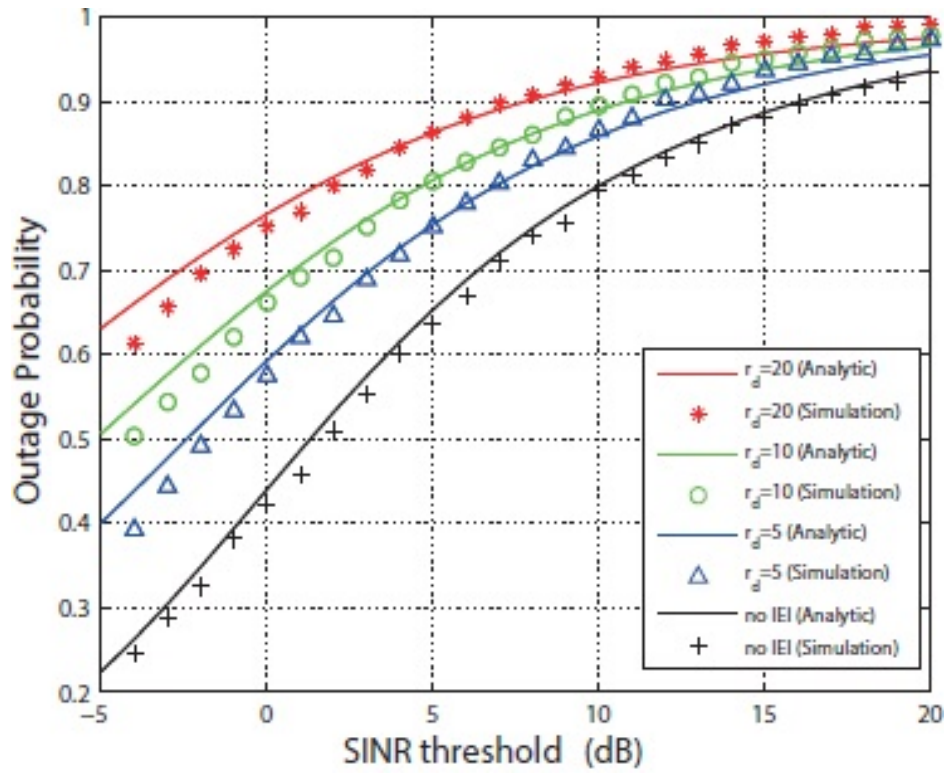


Figure 3.1: Performance comparison for IEI and no-IEI scenarios[32]

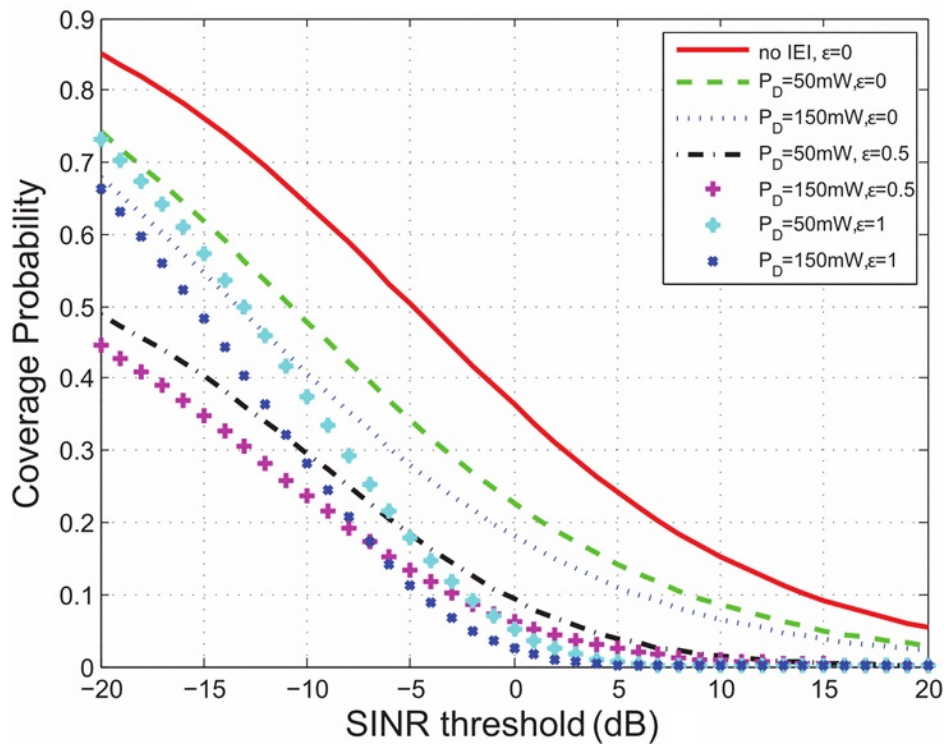


Figure 3.2: Coverage comparison for IEI and no-IEI scenarios with Tx power[32]

(iv) enhancing network capacity by offloading cellular traffic, (v) low latency and (vi) higher spectral efficiency [33]. Public safety, disaster recovery, military and gaming applications, social services etc., are the different areas where D2D communication can be used. But to unlock the full potential of D2D communication in cellular networks, we must face several challenges such as mode selection, mobility, resource allocation, interference management, network heterogeneity etc. Among them, interference management is the most critical and challenging. There are numerous ways to minimize interference in the D2D-enabled cellular network. Depending on the operational algorithm, interference management schemes can broadly be classified as centralized, distributed and semi-distributed approaches, as shown in Figure 3.3.

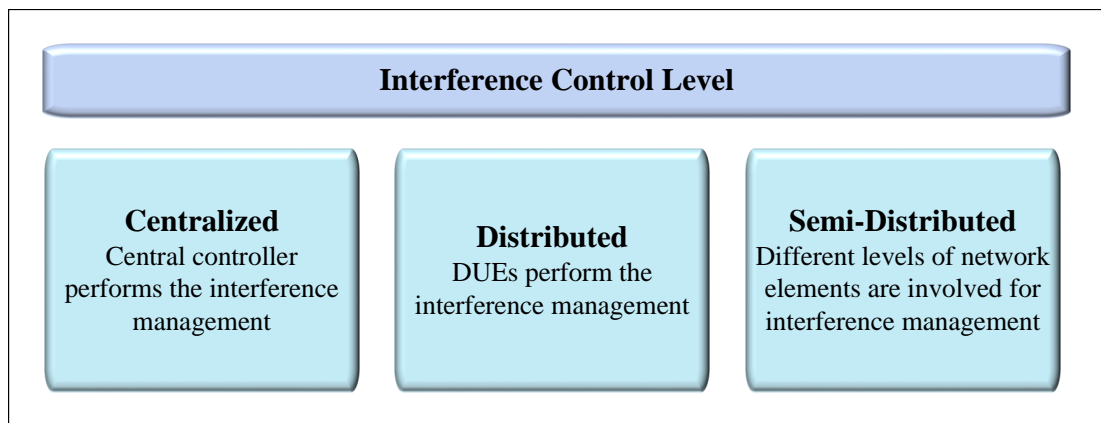


Figure 3.3: Interference Control Mechanism for D2D Communication

In the centralized control approach, eNB fully manages the interference between cellular and D2D users. This central entity collects information such as the channel state information (CSI), channel quality, device locations, interference level for each user in the network, and takes the decision on which channels to be assigned to every single user in the appropriate format and power level. The main drawback of centralized schemes is the higher amount of signaling overhead required for exchanging CSI. Moreover, the interference management complexity increases exponentially with the number of users in the network. Thus, centralized schemes are suitable for small-sized D2D

networks. However, in a distributed scheme the operation of interference management is performed autonomously by DUEs themselves and does not require any central entity. Due to limited CSI and lower overhead exchange, distributed scheme reduces the control and computational time. Centralized and distributed, both schemes have advantages and disadvantages, and hence, trade-offs can be achieved between them [26]. Such interference management schemes are known as “semi-distributed” or “hybrid”. Here, the different levels of network elements are involved to manage the interference. Such kinds of schemes could be suitable for moderately large networks.

There are various methods and models to minimize interference like mode selection, power control, resource allocation, etc. The state-of-the-art researchers proposed various schemes for interference management in D2D-enabled cellular networks with their different working principles.

3.3.1 Power control mechanism

To mitigate cross-tier interference for both UL and DL cases, co-tier interference between DUEs in a hybrid cellular network in D2D communication, power control (PC) mechanism is one of the key approaches [34, 35, 36, 37]. The higher the transmit power of D2D users, the broader coverage and better signal quality but at the same time, it causes tremendous interference to the cellular network. To compensate the interference, BS could adjust the transmitting power of the cellular network to reduce the interference from the cellular network (eNB and CUEs) to the D2D receiver. However, since the PC of the cellular network causes performance degradation of the cellular networks, it may not be the best solution to manage the cross-tier interference [26]. Different power control algorithms have been proposed for D2D communication in underlay cellular networks. The PC algorithms are designed for different objectives, such as maximizing the rate [37], minimizing total power with respect to a target rate [35], or maximizing a

utility function characterized by the trade-off between spectrum and energy efficiency [37].

In [38] authors propose a cooperative scheme to obtain joint optimal resource allocation and power control of a heterogeneous cellular network to maximize the system throughput. An interference-limited area-based power control scheme to mitigate interference followed by resource allocation is proposed in [39]. Numerical results are shown to validate that their proposed scheme performance is better in terms of coverage probability and sum rate with high D2D density and SINR scenarios. The main limitation of their works is only single-cell and single D2D pairs are considered. Similar to [39], authors propose a joint mode selection and power control scheme to solve interference issues in D2D-enabled cellular HetNets in [40]. Here ILA is adjusted dynamically by controlling power in the interference area, and the superiority of their scheme compared to existing well-known methods are shown by simulation.

In [41], authors propose an energy harvest (EH)-based D2D communication underlying cellular network. They formulated the problem in MINLP and split it into two to solve it separately. First, solve the power allocation using the Successive Convex Approximation (SCA) method. Second, develop a mechanism to allocate the resources fairly.

To increase data rate and reduce interference, an adaptive interference avoidance (IA) and mode selection (MS) framework that includes mode selection, channel gain and power allocation is proposed in [42]. Here authors employ an algorithm in two phases. First, based on D2D pairs channel gain ratio adaptively determines the D2D user mode. Second, use optimal distributed power strategy by using the Lagrangian dual decomposition method to maximize the network sum rate while minimizing interference. But in their work, they assumed that the DUEs have the knowledge of the location and channel state of the CUEs, which is not feasible in a real system. A summary of PC-based interference management related works is shown in Table 3.1

Table 3.1: Summary of related works for power control approach

Reference	Main Contribution	Method	Limitation
[41] , 2023	Maximize the minimum data volume using energy harvest based D2D communication.	Energy-harvest Successive Convex Approximation (SCA) method.	Limited to single-cell analysis.
[43], 2021	Enhance sum rate and spectral efficiency by deducing interference.	PC based on Stackelberg Game Theory.	Limited to a single cell and single user.
[40], 2020	Coverage and spectral efficiency improvement by interference management in cellular HetNets	power control within Interference Limited Area (ILA).	limited information in a performance gain.
[38] , 2019	Maximize the total system throughput.	Co-operative optimization algorithm.	Interference impact from other D2D transmitters not considered.
[39] , 2018	Mitigate interference and improve system performance.	Interference limited area (ILA) scheme.	Limited to a single cell and single user.

3.3.2 Mode selection (MS)

Both cross-tier (interference between the cellular and D2D users) and co-tier (interference among D2D users) interference can be avoided by using the proper mode selection (MS) algorithm. In the-state-of-art work, many researchers focus on MS with different criteria but simple MS can be performed based on the path loss [44], received signal strength over the D2D link [45] or the distance between the terminals [46, 47, 48]. However, these schemes do not reflect exact channel quality or interference issues.

In [49] authors propose an algorithm for mode selection and resource allocation to maximize the throughput. Here they first grouped D2D users based on their location. According to the priority, the appropriate mode is assigned to them and finally based on the signal-noise ratio resources are allocated. Though system throughput is increased in their proposed model it also increased complexity and delay. Users suffer from reduced QoS and higher interference due to resource multiplexing. Furthermore, in [50] MS has been exploited to avoid the co-tier interference between DUE and the cross-tier

interference [50] been solved using spectrum splitting. To solve the co-tier interference issue, the DUEs can measure the activity in the D2D spectrum and employ a carrier sensing threshold to determine their communication mode in a distributed manner [26]. In [51], Fan et al. worked on mode selection and resource allocation issues for D2D communications. In their proposal, they ensured the proper transmission of cellular users as well as the transmission requirements for D2D users. Initially, they proposed a mode selection scheme that guaranteed the cellular transmissions and then analysed at which conditions D2D users can reuse the same cellular resources. However, the main constraint of this proposal is they considered all CUEs and D2D pairs to be in a single cell.

In [52], a distributed joint mode selection and power control scheme is proposed in an iterative manner by using the Monte Carlo method. Based on effective interference on each RB (Resource Block), a D2D pair selects its mode and adjusts power to achieve the targeted throughput while CUE performance will be unaffected. Like [51], their proposed scheme is only validated in a single cell but different radius. By using the real-time information of local traffic channels and surrounding nodes, a distributed approach for a smart mode and power selection is proposed in [53]. Here dynamic switching is adopted between D2D transmissions when the interference is limited otherwise, continue the communication using cellular mode. To resolve the issues arising from spectrum sharing in D2D-enabled cellular network, a location-related strategy for mode selection and spectrum sharing algorithm is proposed in [54] where devices form a coalition to share the spectrum among DUEs and CUEs.

A joint mode selection and resource allocation technique in underlying cellular networks is proposed in [40]. Here D2D pairs' locations are estimated by Levenberg–Marquardt method based on received signal strength (RSS) in different eNBs, and resource block (RB) is allocated based on the highest SINR to achieve maximum throughput. An energy-efficient dynamic mode selection technique for a heterogeneous

network (HetNets) in downlink cellular resource is proposed in [55]. Here, the authors formulate an NP-hard optimization problem in terms of mode selection, power control and resource allocation. To solve the problem, Fuzzy cluster-based mode selection techniques are introduced. As higher transmission power is used for reuse mode, the system will suffer from less spectral efficiency and poor interference management. Another energy efficiency-based mode and resource allocation scheme is proposed by authors in [56]. Here for maximization of energy efficiency, the non-linear optimization problem is sub-divided into power allocation and content fetching mode selection to get an optimal solution. The main limitation of the method is the high dependency on one core network.

3.3.3 Radio resource allocation

Radio resource allocation (RRA) addresses the research issues of how to assign radio resources efficiently to a group of or all D2D pairs to optimize the performance metrics. There are several RRA techniques like Fractional Frequency Reuse (FFR), Graph Theory (GT), Game Theory, Cognitive Radio (CR) etc. Literature for a few of them is reviewed below.

Fractional frequency reuse

Fractional frequency reuse (FFR) is a cross-tier interference management technique to mitigate the mutual interference between CUEs and DUEs in the D2D-enabled cellular network. In FFR, the entire frequency spectrum is divided into sub-bands and each cell coverage area is separated based on distance from eNB. Then, each sub-band is differently assigned to each cell region. However, this technique would potentially suffer from low throughput due to inefficient use of the bandwidth resources and hence spectrum efficiency is not possible. In [57], the authors propose a frequency-sharing

mechanism that uses four resource groups to reduce cross-tier interference between CUEs and DUEs. In this scheme, each cell is split into two zones and different frequency bands are allocated to CUEs and DUEs according to their locations. A more spectral-efficient approach is proposed in [58]. The interference from CUEs to DUEs is solved by means of Interference Limited Area (ILA). Here the minimization of interference from DUEs to CUEs is accomplished by defining the coverage area around D2D pairs. If the CUE is located within an area with a specific radius from eNB, the D2D users cannot use radio resources allocated here for any CUE. Similarly, another area is defined around the receiving DUE with a certain radius. If some CUEs are within it, the D2D pair cannot reuse these resources. Nonetheless, the problem with the proposal is that interference from CUEs to DUEs in the DL is caused solely by the eNB, which transmits to the CUEs. This interference is not affected by the positions of the CUEs, but it only depends on the channel between the eNB and the receiving DUE. In [59], another FFR interference management scheme is proposed for D2D-enabled cellular networks to avoid cross-tier interference. The sub-band frequency is applied to different cell partitions like cell centre and cell edge for each sector. To reduce cross-tier interference for bandwidth sharing, a dynamic resource portioning approach in frequency and/or time can be used. In [60], they propose a dynamic FFR approach to alleviate the co-tier and cross-tier interference. Here authors introduce a scheduling approach, that jointly schedules cellular and D2D traffic. The scheduling problem is NP-hard and solved using two different low-complexity algorithms.

In [61], authors propose a radio resource allocation approach using FFR. Here authors first allocate different frequency bands between DUEs and CUEs using a fractional frequency reuse (FFR) scheme to reduce the interference. Second, minimize interference using the Hungarian weighted bipartite matching algorithm to achieve a better total system sum rate. A machine learning approach is used in [62] where deep Q learning (DQL) algorithm along with fractional frequency reuse (FFR) is proposed to

control power for D2D communication in 5G cellular network for maximizing overall sum-rate. Obtained results compared with several traditional power control algorithms and exhibits better outcome.

Graph theory models

For several recent works, an advanced mathematical tool such as graph theory has been used to mitigate the mutual interference between CUEs and DUEs for D2D communication in underlay cellular networks. In [63], graph-theory-based mode selection and resource allocation algorithms are proposed for D2D communication. Here full-duplex (FD) scheme is used for better performance and finally, authors show better performance of their proposed scheme by using numerical analysis.

Another graph theory-based scheme adopting interference-aware graph-based resource allocation is proposed in [64] to mitigate the cross-layer interference in the DL. Here radio resources are allocated to the DUEs and the CUEs in such a manner that the system sum rate is maximized. The interference relationships among the DUEs and cellular communication are formulated as an interference-aware graph. First, the interference-aware graph is constructed according to the network topology. Each vertex in the graph has three attributes; 1) the link attribute, distinguishing whether the vertex represents the DUE or the CUE, 2) the resource attribute, containing information on SNR value for individual RBs, and 3) the cluster attribute, representing assignment of RBs to individual vertexes (DUE or CUE). Second, a resource assignment algorithm is applied to allocate resource block (RB) to different cellular and D2D communication links.

To mitigate the cross-tier interference between CUEs and DUEs in the UL and increase the spectrum utilization of the system, graph colouring approach-based resource allocation is proposed in [65]. The extra functionalities are added for UEs; in which D2D transmitters use a simple interference information mechanism to detect the interference

caused by cellular transmissions to D2D communication and send this information to the eNB notifying it of the interference in their vicinity. Then the eNB uses this information to construct the network topology using a node contention graph.

In [66] authors propose a joint mode selection and resource allocation for D2D communication in cellular HetNets to maximize system throughput while keeping minimum interference and fulfilling QoS requirements. Here, initially Lagrange dual decomposition method is used for mode selection and then the low-complexity (primal) decomposition-based method is used for admission control, power control, and sub-channel allocation for DUEs and SCeNBs. Finally, simulation results are used to validate the efficiency of the proposed approaches. MS jointly with PC and/or resource allocation is another way to further reduce cross-tier interference and co-tier interference. In [67], a resource allocation scheme has been proposed using a bipartite graph strategy. The authors of [67] consider resource allocation in D2D underlay where multiple DUEs coexist with multiple CUEs to mitigate the mutual cross-layer interference between CUEs and DUEs. This algorithm groups DUEs, and each group can use the resources of only one CUE.

To model the interference between CUEs and DUEs more accurately, an interference-aware resource allocation algorithm is proposed in [68]. The authors used the matching graph theory technique to minimize the interference among them, and finally justify their analytical model with simulation results.

Game theoretic models

Game theoretic models can be used to design and analyze distributed resource allocation schemes since they can provide an insightful understanding of the complex interactions among independent rational players. There are two broad categories of a game theoretic model for D2D resource allocation: non-cooperative and cooperative, and DUEs are commonly viewed as players competing for the resources in the former type [26]. In

[69], the resource allocation issue is investigated for inter-cell interference scenarios by using a non-cooperative static Cournot game. Here, BSs are considered as players competing for resource allocation quota from D2D demand. Three scenarios are considered: (i) CUEs in both cells use UL resources, (ii) CUEs in one cell use DL resources, while the cellular users in the other cell use UL resources, and (iii) CUEs in both cells use DL resources, and the corresponding interference is modelled in each scenario.

In [70] authors developed a Stackelberg game to solve the optimization problem, in which a CUE and a DUE form a leader-follower pair to control the interference from DUE to cellular networks. In this game, the CUEs are leaders of the game and own the channel resources, and the D2D pairs are viewed as followers and charged some fee for using the radio resources. The authors further extend their work presented in [70], by taking the D2D rate in the Stackelberg game into account in [71].

The authors of [72] proposed a socially aware resource allocation approach to mitigate cross-tier and co-tier interference using cooperative game theory. The social community-aware resource allocation is formulated as a social group utility maximization problem using the social interference graph and solved using the social group utility maximization game (SGUM) [73].

In [74], they investigate large-scale networks and the problem of resource allocation by considering the cross-tier interference between the DUE and CUE. Specifically, they address the resource allocation problem for multiple D2D pairs and CUEs using coalition formation games. In [75] authors propose a non-convex mixed-integer non-linear programming (MINLP) problem which is solved in two phases. First, using game theory mode selection is performed to minimize the interference. Then, obtained optimal transmit power by using convex one and the Lagrangian dual method. Limited to CSI is the main problem of their proposed scheme.

Authors propose a joint power allocation based on Stackelberg game theory to

improve sum rate and spectral efficiency in [43]. Here Base Station (BS) is the leader, and D2D pairs are followers and maximize their own utility according to the leader's strategy. They also derived a closed-form expression for allocated power by maximising the utility functions of leaders and followers. However, their works are limited to single-cell and single D2D pairs. In [76], a centralized joint MS, PC and RA scheme for a D2D-enabled cellular network has been formulated as an optimization problem and limits the cross-tier interference from DUEs to CUEs and vice versa. Also, a cooperative game theory-based two-stage resource allocation algorithm is proposed in [38]. In their proposal weighted utilitarian and meta-bargaining game theory is used.

Cognitive Radio

Cognitive Radio (CR) is another promising technique to allocate idle radio frequencies in wireless communication. Cognitive radio (CR) based channel sensing and making interference-aware decisions can be used in D2D-enabled cellular networks for interference mitigation. In [77], an efficient cross-tier interference management scheme is proposed to avoid mutual interference from CUE to DUEs and vice-versa. In this proposal, authors considered that one DUE share the resources of only one CUE. The DUE can sense the radio spectrum by measuring the received interference level of CUE during UL transmission and passing these values to the BS. The BS then uses this information in an interference-aware resource allocation scheme. A centralized cognitive-based resource allocation algorithm between CUE and multiple DUEs is presented in [78] to mitigate cross-tier interference between CUE and DUEs. The authors first formulate the optimal resource allocation policy as an integer programming problem. As the optimal resource allocation solution is NP-hard, they propose a cognitive-based two-phase low-complexity suboptimal solution approach. First, they extend the max-min fairness algorithm proposed in [79] to perform fair resource allocation for cellular UL and DL flows. Second, a heuristic sub-channel allocation approach for the D2D pair

was conducted with rate protection for CUE. In [80], the authors investigate cognitive radio-assisted D2D communication for improved spectral efficiency, in which devices access the network with mixed overlay-underlay spectrum sharing mode without central assistance. The devices sense the spectrum to identify white spaces and a collision probability has been considered as a spectrum-sharing criterion. Performance metrics such as transmission capacity, isolation probability, and connectivity have been derived using stochastic geometry.

To realize the full potential of D2D communications, the RA should be done jointly with the MS and PC. Several works have investigated this joint problem, such as [76, 81, 82, 83, 84, 85]. They focus on the interference control and management between D2D links and cellular links such that they can efficiently reuse the radio resources whenever the interference is small. In [76], a centralized joint MS, PC and RA scheme for a D2D-enabled cellular network has been formulated as an optimization problem and limits the cross-tier interference from DUEs to CUEs and vice versa. Whereas in [81] a Markov decision process (MDP) problem is formulated to switch modes between DUEs and CUEs. To solve the MDP problem, the authors use a Q-network-based deep reinforcement learning algorithm. Simulation results are used to show effectiveness for energy efficiency and better convergence in a D2D-enabled heterogeneous network.

In [82] authors propose a DRL-based joint mode selection and resource optimization problem to maximize the system throughput. Here DRL-based online mechanism constantly refines the output generated from DNN by utilizing recent historical experiences. A resource allocation algorithm for D2D communication in cellular HetNets is proposed in [83] where sub-channel allocation and power allocation are jointly optimized to maximize the network throughput. Formulated mixed-integer non-linear programming (MINLP) problem is solved by transforming the original MINLP problem into a tractable continuous problem by using the time sharing factor (TSF) method.

Simulation results demonstrate the performance of the proposed scheme.

Table 3.2: Summary of literature review for resource allocation approach

Reference	Main Contribution	Method	Limitation
[83], 2023	Improving network performance by efficient resource allocation.	Co-operative distributed resource allocation algorithm.	Limited to co-channel interference.
[75], 2023	Improve network performance by joint MS and resource allocation.	Coalitional game-based approach.	Limited to CSI.
[68], 2023	Enhance spectral efficiency and network throughput.	Matching game theory.	Limited to cross-tier interference only.
[85], 2023	Improving spectral efficiency and user satisfaction with joint MS and RA.	Conventional approach.	Limited CSI.
[61], 2021	Mitigate interference between CUEs and DUEs using efficient resource allocation.	fractional frequency reuse (FFR) approach.	Limited network elements.
[81], 2021	Improve energy efficiency in D2D-enabled heterogeneous cellular networks	DRL-based game theory.	Dedicated resources used for D2D.
[82], 2021	Improve system performance by dealing with co-channel interference.	DRL-based online mechanism.	Cross-tier interference needs to be investigated.
[63], 2021	Improve system throughput and frequency range.	Graph-Theory-based.	Limited spectral efficiency.
[86], 2019	Enhance system total throughput while maximizing user access.	Heuristic algorithms.	Complex and higher computational time.
[87], 2019	Improved spectral efficiency and mitigate interference between DUEs.	Matching algorithm.	Higher computational complexity and limited to CSI.
[87], 2015	Improved outage probability and performance for D2D links.	Stochastic geometry bases CR approach.	Limited to strongest RSS.

To maximize energy efficiency, authors propose an RL-based framework for joint radio channels and the transmit power optimization problem in [84]. Extensive simulations were used to show that the proposed RL framework has better convergence and outperforms an existing approach. To achieve a trade-off of throughput and user satisfaction for D2D communication in underlying cellular networks, a joint mode selection and resource allocation scheme is proposed in [85]. To store offline channel state data,

an offline channel state information model based on geographic location is proposed and to evaluate the user's satisfaction Mean Opinion Score (MOS) index is used. Here optimization problem is formulated to maximize the sum rate and satisfaction of all users with resource allocation priority. Finally, simulation results show that the proposed scheme can obtain a higher user satisfaction level at the cost of slightly reduced overall throughput of the system. This work considers resource sharing between CUEs and multiple D2D pairs in an underlay communication. Here cross-tier interference is considered between multiple DUEs and a single CUE. Resource allocation-related works are summarised in Table 3.2.

3.4 Machine learning algorithm for minimizing interference

In the above literature review, various optimization problem approaches are formulated for resource management such as computation power minimization, sum-rate maximization, and latency minimization. In these conventional methods, most of the formulated optimization problems for wireless resource management are strongly non-convex and exhibit non-deterministic polynomial time hardness (NP-hard). Moreover, the time complexity of the algorithm to obtain the optimal solution gets exponentially higher with the increasing number of users in the network. Therefore with traditional optimization methods, it is difficult or impossible to optimize effectively the resource allocation problem which is modeled as a combination of an optimization problem with nonlinear constraints. Fortunately, due to the recent drastic advancement in artificial intelligence, various machine learning algorithms have been proven to be effective in solving decision-making problems under uncertainty [88].

In [11] authors minimize interference for a 3-tier network where they first derived the outage probabilities of D2D, macro cell and small cell links, and then presented the lower distance boundaries from D2D transmitter to macro base station (eNB) and

small cell receiver, and from base stations receiver to a D2D receiver. Finally, the authors proposed an optimal small cell deployment density that ensures the quality of service (QoS) requirements for both D2D and cellular communications [1]. As [11], lower distance boundaries between D2D receiver and cellular cells (both macro and small cell) are defined and based on that interference management scheme and upper boundary, small cell density is proposed in which D2D devices can only reuse the cellular resources effectively to meet QoS requirements [89]. In [90], an overlay mode of D2D communication in mm-wave 5G networks is proposed where bargaining game theory is used to improve system throughput without compromising SINR.

In recent times, reinforcement learning has been popular for solving resource allocation problems in 5G networks. In [91] authors proposed a Q-learning-based resource allocation technique for solving power allocation and spectrum problems for a single-tier D2D network. Here Q-learning is used to assign appropriate channel and power allocation for a D2D user. In [92] Kamran et.al propose a new solution for their previous resource allocation problem in a D2D multi-tier HetNets by using an ML algorithm. In their works, authors propose a distributed multi-agent learning-based spectrum allocation scheme where D2D users learn the wireless environment and select appropriate spectrum resources autonomously to maximize overall system throughput with minimum interference to the cellular users. Whereas in [93] authors propose a Q-learning-based resource allocation scheme where D2D users and small cell users select resource block (RB) in a cooperative manner to meet their QoS requirements.

In [94] the authors formulate a resource optimization problem to maximize the total throughput for a 2-tier network. Since their formulated problem is a mixed integer non-linear programming problem, they split it into 2 steps. Initially, they assign resources to the cellular users using an orthogonal technique and for D2D users, they adopted a low complexity-based ML algorithm where D2D pairs reuse different sub-carriers to further enhance the system throughput without affecting the CUEs

performance. The authors proposed a coalition game-based resource allocation for D2D communication in underlying cellular HetNets with mm-wave communication in [95]. Here the authors first formulate a resource allocation scheme for D2D pairs among both mm-wave and cellular spectrum and based on their characteristics propose a coalition game theory to maximize the overall sum rate. In [96] authors proposed a matrix channel allocation algorithm for D2D communication in an underlay cellular network to maximize the total channel capacity of the DUEs and CUEs. In [97] proposed a joint channel allocation, power control, and resource allocation scheme for D2D communication in cellular HetNets. Here the authors sub-divided the mixed-integer non-linear optimization problem to find the optimum solution for higher overall system throughput with reduced computational complexity. In [98] authors proposed ML and distributed Q-learning decision tree PC algorithms to manage interference in D2D-enabled cellular networks and achieved better throughput, and energy efficiency with lower computational complexity. In [99] the authors proposed a hybrid resource allocation scheme where deep neural network (DNN) and heuristic-based PC and resource allocation approaches are used for D2D communication in D2D-enabled underlay cellular networks for two different QoS requirements. To achieve the optimal resource allocation including wireless channel and power, in [100] a distributed resource matching scheme is proposed based on deep reinforcement learning (DRL). In the proposed algorithm, a resource allocation problem is formulated based on a random non-cooperative game with multiple players (D2D pairs) where each player is a learning agent, and its task is to learn its best strategy using locally observed information based on a Deep Q-network (DDQN) [100]. The sum throughput of CUEs/DUEs and user energy efficiency will converge to the Nash equilibrium (NE) under the mixed strategy. In [101] authors investigate the joint user association and efficient resource allocation for D2D communication in ultra-dense cellular networks using a DRL-based double-dueling deep Q-network (D3QN) algorithm and prove their proposed scheme

can achieve better sum throughput even in higher distances between D2D pairs. In [102] authors proposed a DRL-based double deep Q-network (DDQN) algorithm that enables D2D pairs to learn an optimal spectrum access strategy autonomously for maximizing the sum throughput without complete prior network information. In their works, the authors also introduce an “accessible area” concept to guarantee the communication quality of CUEs at the cell edge. To achieve faster convergence and smart power control for efficient resource allocation for D2D-enabled cellular networks, in [103] the authors proposed a Stackelberg game theory-based multi-agent DRL algorithm. In this proposal, Stackelberg game theory is used to guide the learning direction efficiently for achieving a faster optimal strategy to maximize sum throughput. In [104] the authors propose a deep learning-based algorithm for solving the resource allocation problem where a deep neural network (DNN) model is used to select an optimal policy randomly. The authors propose a multi-agent deep Q-network (DQN) based DRL algorithm to approximate the loss function for optimal policy and simulation results are used to prove the supremacy of their scheme in system throughput in [104]. Like this, to maximize the system capacity and spectral efficiency by fulfilling minimum QoS requirements in [43], authors propose a DQN-based resource allocation and power control algorithm for a 2-tier D2D-enabled cellular network. In [105], to reduce system interference and improve system throughput while obtaining a small amount of channel information authors proposed a dual DQN algorithm for resource allocation in a D2D communication wireless network.

To maximize the overall capacity with minimum global energy consumption for underlay D2D-enabled wireless network, a Federal Learning (FL)-aided DRL-based resource allocation approach proposed in [106]. In their proposed approach deep Q-network (DQN)-based DRL algorithm is used for local model training and FL-aided method is utilized for global model aggregation. Performance of the proposed schemes is validated using Simulation for 5G mm-wave and 6G THz scenarios separately. A

distributed deep deterministic policy gradient (D3PG) is proposed in [107] to maximize sum-rate and provide fairness among cellular and D2D links in an underlying cellular network with NOMA. To control transmit power and reduce interference, authors solve mixed-integer non-linear programming (MINLP) optimization problem using deep deterministic gradient policy (DDGP) and arithmetic-geometric mean approximation (AGMA) technique and finally apply D3GP for fairness to all the users. Similarly, to maximize the throughput for D2D communication in 5G and beyond NOMA wireless network, a multi-agent DRL algorithm is proposed in [108] where SNIR requirement is maintained for all the users. Obtained simulation results compared with DDPG, deep dueling and deep Q-network to validate its effectiveness. In [100] a double deep Q-network (DDQN)-based distributed resource allocation scheme is proposed to maximize system sum-rate and improve energy efficiency for D2D communication. Here authors propose an actor-learner architecture for training learning model and unlike traditional DRL agents, the actors themselves execute strategies to attain it's optimal value. A distributed deep reinforcement learning algorithm is proposed in [109] to maximize spectrum utilization in an underlay cognitive radio (CR) system where transmitting and receiving nodes exchange information like D2D communication without CSI knowledge. The performance of the proposed scheme is validated with excellent simulation results.

To improve link capacity and outage probability of D2D links, a multi-agent DRL algorithm for resource allocation is proposed for NOMA-based underlay cellular network in [110]. Obtained simulation results compared with random RA scheme where significant improvement is visible. For NOMA wireless network, a dynamic energy efficient resource allocation scheme using multi-agent DRL with deep Q-network (DQN) model is proposed in [111] for D2D communication. Proposed schemes maximize the energy efficiency while ensuring the throughput and fairness for all the users.

In [112] the authors consider multiple D2D users sharing the same cellular resource and formulate a joint channel selection and power control optimization problem. To

solve this non-convex and NP-hard problem, authors initially use fractional programming (FP) techniques. But this technique requires instantaneous CSI which is not feasible for a large and dynamic cellular network. Therefore, they propose a distributed DRL-based scheme where an agent (D2D user) interacts with the environment repeatedly to select an optimal strategy to maximize system throughput and spectrum efficiency. Finally, the authors prove how their DRL-based scheme is better compared to the FP technique even without instantaneous CSI.

3.5 Adopted D2D link performance estimation approach

The primary objective of this thesis is to identify interference factors for D2D communication and propose suitable schemes to overcome those. The performance parameters that will be affected due to interference in D2D-enabled cellular networks are throughput, latency, spectral efficiency, link outage probability and energy efficiency. This section describes methods for D2D, and cellular links performance estimation approach adopted in this thesis. Since this thesis focuses on the identification of interference affecting factors and proposes schemes to mitigate those, it is necessary to adopt a methodology that can quantify the effectiveness of such performance estimation in real systems. It would be very costly to implement realistic dense network scenarios for proposed D2D-enabled cellular HetNets to test and evaluate the network performance. Thus, this research adopts computer simulation to test and evaluate the performance of D2D and cellular links performance. Moreover, simulation methods provide a means of varying different network metrics leading to a generalisation of the research findings. For selecting the credible simulator, various simulators have been surveyed including Riverbed Modeler [113]. It is identified that Riverbed is one of the credible, widely used simulator tools for modelling WLANs [113], and MATLAB [114] is one of the leading programming languages used for developing mathematical algorithms and

analysing data. Both Riverbed and MATLAB are used to evaluate the wireless network performance. While Riverbed Modeler is used to develop, model, and simulate network scenarios for the purpose of testing and evaluating the network performance, MATLAB is used to evaluate the performance of the mathematical algorithms for wireless networks and produce the graphs based on the results produced by the MATLAB simulator. The proposed methodology is appropriate for this thesis, a view that is supported by key network researchers [115, 39, 116]. In this thesis, the performance evaluation is presented for all the proposed schemes in Chapters 4, 5 and 6.

3.6 Summary

In this chapter, a review of the literature on D2D communication for cellular networks is presented. Based on the operational algorithm, interference management schemes for D2D communications are classified into three main categories centralized, distributed, and semi-distributed. The leading network researchers and their main contributions to interference management for D2D communications are identified and discussed. Factors affecting the performance of D2D communication due to interference in a 3-tier cellular network are identified and discussed in the subsequent chapters. A mode selection (MS) algorithm for mitigating interference in a D2D-enabled cellular HetNet is discussed and analysed in Chapter 4.

Chapter 4

Mode Selection Scheme for Interference Mitigation in D2D-enabled Cellular HetNets

4.1 Introduction

Chapter 3 presented a literature review on different types of interference and their mitigation techniques for a D2D-enabled cellular network. It is noted that there are several challenges to using D2D communication effectively in a cellular network. Mode selection (MS) for interference mitigation with guaranteeing QoS is crucial among them. The key network researchers and their main contributions against various challenges for effective D2D communication in a cellular network are identified and discussed in Chapter 3. The primary objective of our thesis is to identify the interference-affecting factors for D2D communication and propose a suitable scheme to mitigate them. To achieve this objective, the state-of-the-art researchers' main contribution towards mode selection (MS) is reviewed thoroughly in Section 4.2. To fulfil the thesis requirements, an analytical model with closed-form equations and optimization problems is formulated in Section 4.3. To implement the analytical model, an innovative MS algorithm for effective D2D communication is outlined in Section 4.4. Outcomes from analytical models and simulation results are discussed in Section 4.5, and this chapter concludes with a summary of the main findings in Section 4.6.

4.2 Previous works on mode selection

The state-of-the-art researchers proposed various methods for interference management in D2D-enabled 2-tier cellular networks such as split frequency, selection of transmission mode, power control, resource allocation, cognitive radio, game theoretic, etc., and their working principles and techniques are also different. Cross-tier and co-tier interference can both be minimized by using the proper mode selection (MS) algorithm. In state-of-the-art work, many researchers focus on MS with different aspects like path loss, received signal strength over the D2D link or the physical distance among the devices. Detailed literature for mode selection is reviewed in Section 3.2.2. A summary of the MS-based interference mitigation literature review is shown in Table 4.1

Table 4.1: Summary of literature review for mode selection approach

Reference	Main Contribution	Method	Limitation
[42], 2023	Improving system throughput and SINR.	Adaptive interference avoidance and mode selection framework.	Limited to CSI.
[66], 2023	Maximizing system throughput while keeping minimum interference and fulfilling QoS requirements.	Low complexity Lagrange dual decomposition method.	Limited to Non-orthogonal multiple access (NOMA).
[56], 2021	Improved energy efficiency for D2D communication.	Lagrange dual method and a heuristic algorithm.	Depends on core network response.
[49], 2020	Improved resource allocation in a dense network.	Resource allocation based on MS and SNR.	High complexity and increased delay.
[40], 2020	Increased system throughput by MS and Resource block allocation in underlying cellular networks	Levenberg–Marquardt method.	Higher computational complexity and Overhead.
Our work	we proposed a mode selection technique with power control for a 3-tier D2D-enabled cellular HetNet to overcome the existing limitations.		

All the state-of-the-art techniques describe how to control interference in single or 2-tier cellular networks. Moreover, most of the MS or resource allocation schemes in

the above literature considered only one D2D pair, and both are in the same cell. Very few papers focus on where DUEs in a D2D pair are attached to different eNBs. But in practice, multiple CUEs may associate with different eNB and form multiple D2D pairs. Not only multi-cells but also in the future large number of small cells, especially femtocells, will be deployed into the cellular network (5G and beyond) which will create a multi-tier network. In that multi-tier network, the most prominent challenge is how to minimize interference and mode selection is one of the effective techniques.

Despite the facts, there are very few ongoing research efforts to address the MS as well as resource allocation for interference problems in tier-3 cellular networks. Future D2D-enabled cellular network will be heterogeneous and the complete distributed solutions for the mode selection as well as radio resource allocation problems in a D2D-enabled multi-tier scenario has not been studied comprehensively in the literature. Nonetheless, none of the authors examines the worst and, at the same time, the most challenging interference case, where all 3-tiers of the networks (i.e. eNB, SCeNB and D2D communication) mutually interfere. This is the main difference between the existing approach and our proposal in mode selection in a 3-tier heterogeneous network.

4.3 System model

4.3.1 Network model

For modelling a 3-tier D2D-enabled heterogeneous cellular network, we consider a macro cell (eNB) at the centre of the coverage area with radius R , which is surrounded by several small cells (SCeNBs) and D2D pairs. Small cells are randomly distributed within the macro cell (eNB) coverage area. Due to the random and unpredictable location of small cells, the spatial position of the small cells is modelled by homogeneous poisson point process PPP, and D2D pairs i.e. DUEs are also distributed in the network region according to another independent homogeneous PPP. Here DUEs, SCeNB and

evenly distributed CUEs are denoted by $j \in \{1, 2, \dots, N_D\}$, $k \in \{1, 2, \dots, N_S\}$ and $i \in \{1, 2, \dots, N_C\}$ respectively. Moreover, for modeling large-scale wireless networks and capturing the effects of network topology on network performance stochastic geometry is more suitable [117]. In a 3-tier network illustrated in Figure 1.1, each UE can communicate in any one of the following modes: (1) DUEs can communicate directly without base stations using D2D communication mode, (2) CUEs can communicate with each other through the eNB, and this is known as the macro cell or cellular communication mode, and (3) SUEs can communicate with each other through the SCeNB, and this is known as small cell communication mode. To mitigate the intra-cell interference (between UEs within the same cell) cellular resources are assigned orthogonally and each cellular UE uses separate RBs. Co-channel interference can be limited by allowing only one D2D link to share the resource of a cellular link at a time.

We assume all channel gains are independent of each other, independent of the spatial locations, symmetric, and identically distributed (i.i.d.). For simplicity of analysis, only Rayleigh fading environment is considered and channel coefficients are assumed to be exponentially distributed with unit mean. In such a D2D-enabled HetNet, the channel model is formed of large-scale path loss and small Rayleigh fading, so in general the received signal can be expressed as:

$$P_r = P_t G_{xy} D^{-\alpha} \quad (4.1)$$

Where P_t is the transmission power, α is the path loss exponent, D is the distance between the transmitter, x and the receiver, y , and G_{xy} is the channel coefficient or gain for that particular link.

With the above assumptions, the SINR, γ_y at the receiver y can be expressed as :

$$\gamma_y = \frac{\text{Received Power}}{\text{Total Interference}} = \frac{P_t G_{xy} d_{xy}^{-\alpha}}{I + N_0} \quad (4.2)$$

Where I is the total interference experienced by the receiver y and N_0 is the spectral noise density.

A receiver can decode a message successfully if and only if the SINR at the receiver is greater than the required threshold γ_{th} . If the SINR at the receiver does not meet γ_{th} , the link experiences an outage. Once we know the SINR, the maximum data rate at which information can be transmitted on the different channels can be calculated by the Shanon-Harley Theorem:

$$R = B * \log_2(1 + \gamma_y) \quad (4.3)$$

Where B is the bandwidth of the channel.

Let us consider e, s, i, j and k subscripts to denote the serving eNB, the serving SCeNB, the i_{th} CUE, the j_{th} D2D pairs and the k_{th} SUE, respectively. The subscripts t and r denote the transmitter and the receiver of the D2D pair respectively. In the context of the above-defined network where UL cellular resources are shared by D2D pairs and small cells, the mutual interference at different receivers can be expressed as:

$$I_i = \sum_{j=1}^{N_D} P_j h_{j,e} d_{j,e}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,e} d_{k,e}^{-\alpha} + N_0 \quad (4.4)$$

$$I_j = P_i h_{i,r} d_{i,r}^{-\alpha} + \sum_{j'=1, j' \neq j}^{N_D} P_{j'} h_{j',r} d_{j',r}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,r} d_{k,r}^{-\alpha} + N_0 \quad (4.5)$$

$$I_k = P_i h_{i,s} d_{i,s}^{-\alpha} + \sum_{j=1}^{N_D} P_j h_{j,s} d_{j,s}^{-\alpha} + \sum_{k'=1, k' \neq k}^{N_S} P_{k'} h_{k',s} d_{k',s}^{-\alpha} + N_0 \quad (4.6)$$

Where I_i is the combined interference received by eNB, I_j is the same for j_{th} D2D pairs receiver other than j_{th} transmitter and I_k is the same for all SUEs except k_{th} to the SCeNB.

Similarly, if downlink resources are reused by D2D pairs and small cells, the mutual interference can be expressed as :

$$I_i^{DL} = \sum_{j=1}^{N_D} P_j h_{j,i} d_{j,i}^{-\alpha} + P_s h_{s,i} d_{s,i}^{-\alpha} + N_0 \quad (4.7)$$

$$I_j^{DL} = P_e h_{e,r} d_{e,r}^{-\alpha} + \sum_{j'=1, j' \neq j}^{N_D} P_{j'} h_{j',r} d_{j',r}^{-\alpha} + P_s h_{s,r} d_{s,r}^{-\alpha} + N_0 \quad (4.8)$$

$$I_k^{DL} = P_e h_{e,s} d_{e,s}^{-\alpha} + \sum_{j=1}^{N_D} P_j h_{j,s} d_{j,s}^{-\alpha} + \sum_{k'=1, k' \neq k}^{N_S} P_{k'} h_{k',s} d_{k',s}^{-\alpha} + N_0 \quad (4.9)$$

Where I_i^{DL} is the combined interference received by CUE, I_j^{DL} is the same for j_{th} D2D pairs receiver other than j_{th} transmitter and I_k^{DL} is the same for all SUEs except k_{th} to the SCeNB, P_e , P_s and P_j are the transmit power for eNB, SCeNB and D2D transmitter respectively.

For D2D communication in a cellular network when uplink resources are reused, the eNB receives interference from D2D, and it is comparatively easy for eNB to coordinate interference by adjusting the transmission power of D2D. On the other hand. when D2D reuses downlink cellular resources, CUEs are getting suffered from interference from D2D users. Due to the nature of modern applications, uplink and downlink traffic are asymmetric, D2D communication will preferentially reuse the uplink resources because of its lower utilization. In addition, DUEs/CUEs transmit power is much lower compared to eNB/SCeNB, and victims of D2D interference are base stations for cellular communications. Keeping this in mind, rest of our analysis we will consider the uplink resource reuse case only.

4.3.2 SINR model for D2D mode

Since communications may take place in any of the earlier mentioned 3 cases, according to equation (2) the SINR at the j_{th} D2D receiver is given by:

$$\gamma_j^D = \frac{P_j h_{t,r} d_{t,r}^{-\alpha}}{I_j} = \frac{P_j h_{t,r} d_{t,r}^{-\alpha}}{P_i h_{i,r} d_{i,r}^{-\alpha} + \sum_{j'=1, j' \neq j}^{N_D} P_{j'} h_{j',r} d_{j',r}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,r} d_{k,r}^{-\alpha} + N_0} \quad (4.10)$$

4.3.3 SINR model for macrocell mode

Similar to D2D communication mode, in the case of macro cellular communications mode where UE is served by eNB, the SINR at the receiver i can be expressed as:

$$\gamma_i^M = \frac{P_i h_{i,e} d_{i,e}^{-\alpha}}{I_i} \quad (4.11)$$

4.3.4 SINR model for small cell mode

For small-cell mode communications, UE is served by small-cell SCeNB, and the link between SUE and SCeNB will be interfered with by other SCeNBs, D2D pairs and macro eNB. Therefore, the SINR at the small cell receiver can be written as

$$\gamma_k^S = (P_k h_{k,s} d_{k,k}^{-\alpha}) / I_k \quad (4.12)$$

According to the above expressions, it is easily visible that SINR depends on the density of small cells and D2D pairs, the distances between the receiver and transmitter of those links, and transmission powers. Increasing DUE receiver distances from CUEs or SUEs will decrease the cross-tier interference leading to an increase in the success of the probability for D2D links.

4.3.5 Sum rate analysis

The achievable data rate is directly affected by the signal-to-interference-plus-noise ratio (SINR). Therefore, according to the Shannon capacity formula, the achievable data rate i_{th} CUE, J_{th} D2D pairs and k_{th} SUE links can be expressed as:

$$R_i = B \log_2(1 + \gamma_i^M). \quad (4.13)$$

$$R_j = B \log_2(1 + \gamma_j^D). \quad (4.14)$$

$$R_k = B \log_2(1 + \gamma_k^S). \quad (4.15)$$

Therefore, the achievable overall data rate for all cellular users and D2D pairs can be obtained by

$$R_{total} = \sum_{i=1}^C R_i + \sum_{j=1}^D R_j + \sum_{k=1}^S R_k \quad (4.16)$$

4.3.6 Problem formulation

In a D2D-enabled cellular HetNet, when the same cellular channel is reused by multiple SUEs and DUEs, it will introduce mutual interference. So, our goal is here to maximize the overall data rate of the system under maximum transmit power and minimum SINR constraints. Therefore, the objective function and constraints for mode selection, and power control issues among cellular users, small cell users and D2D users can be formulated mathematically as follows:

$$\mathcal{P}1 : \max R_{\text{overall}} = \max \left[\sum_{i=1}^C R_i + \sum_{j=1}^D R_j + \sum_{k=1}^S R_k \right] \quad (4.17)$$

s.t.

$$C1 : \gamma_i^M \geq \gamma_{th}^M, \quad \gamma_j^D \geq \gamma_{th}^D, \quad \gamma_k^S \geq \gamma_{th}^S \quad (4.17a)$$

$$C2 : 0 \leq P_i^C \leq P_{\max}^C, \quad \forall i \in C \quad (4.17b)$$

$$C3 : 0 \leq P_j^D \leq P_{\max}^D, \quad \forall j \in D \quad (4.17c)$$

$$C4 : 0 \leq P_k^S \leq P_{\max}^S, \quad \forall k \in S \quad (4.17d)$$

$$C5 : \sum_{i \in C} \psi_{i,j} \leq 1, \quad \psi_{i,j} \in \{0, 1\}, \quad \forall j \in D \quad (4.17e)$$

$$C6 : \sum_{i \in C} \psi_{i,k} \leq 1, \quad \psi_{i,k} \in \{0, 1\}, \quad \forall k \in S \quad (4.17f)$$

Where γ_{th}^C , γ_{th}^D and γ_{th}^S are the minimum SINR requirements for the CUE, D2D pairs and SUE communication links respectively. ψ_i , $\psi_{i,j}$ and $\psi_{i,k}$ are mode selection indicators for macro cell, D2D and small cell communication respectively. However, constraints (4.17e and 4.17f) ensure that DUEs or SUEs can reuse at most one existing CUE resource. Finally, 4.17b, 4.17c, and 4.17d constraints make sure that the transmit power of CUEs, DUEs and SUEs will be within the maximum limit.

If D2D user reuses the spectrum resource of i_{th} CUE then, $\psi_{i,j} = 1$; otherwise $\psi_{i,j} = 0$. That is,

$$\psi_{i,j} = \begin{cases} 1, & \text{if DUEs share the channel with } i_{th} \text{ CUE,} \\ 0, & \text{otherwise.} \end{cases}$$

Similarly,

$$\psi_{i,k} = \begin{cases} 1, & \text{if SUEs share the channel with } i_{th} \text{ CUE,} \\ 0, & \text{otherwise.} \end{cases}$$

4.4 Joint mode selection and power control in D2D communication

Problem (4.17) is a Mixed-Integer Nonlinear Program (MINLP) problem that is NP-hard and cannot figure out the optimal solution immediately [34]. Consequently, the problem is divided into two. First, the selection of the appropriate communication mode, and second is the optimal transmit power for achieving maximum overall data rate into the system.

4.4.1 Mode selection

For effective D2D communication in a heterogeneous cellular network considering the impact of interference from all 3-tiers simultaneously, our techniques will work on two phases. Firstly, based on the proposed model, select the optimal mode of transmission for minimizing interference. In the analytical model, we will first develop a mode selection mechanism as shown in Figure 4.1 and finally construct an optimal transmit power model to quantify the performance gain for all links in D2D-enabled multi-tier cellular networks. In Figure 4.1, based on certain KPI's threshold like RB occupancy status, SINR, spectrum utilization, latency or type of services either cellular or D2D communication will be given higher priority. In our thesis/simulation, we have analysed it by giving higher priority on D2D communication.

In a multi-tier network, co-tier and cross-tier both interference exist. Therefore, designing the optimal network geometry model is an important issue in overcoming the interference problem in dense HetNets. For the design and analysis of cellular networks,

deterministic and stochastic geometry approaches are used. Deterministic methods are suitable only for topology with fixed cell sizes but not for heterogeneous networks. On the other hand, stochastic geometry is a promising approach to predict probabilistic parameters of randomly designed HetNets such as SINR (signal-to-interference-plus-noise ratio), transmission power, throughput, coverage probability and load distribution [118].

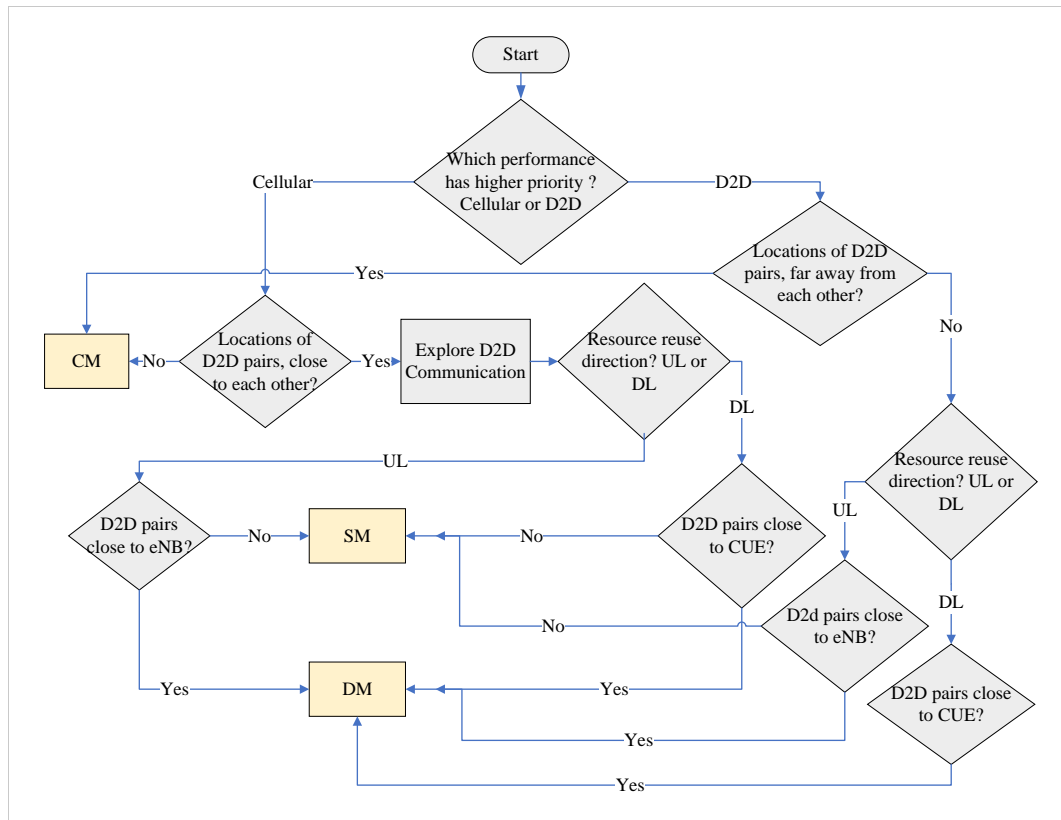


Figure 4.1: Flowchart of the proposed mode selection algorithm for D2D communications

In our proposal, we have used the stochastic geometry model to select the appropriate mode of transmission for D2D pairs. Different properties of a heterogeneous network like device location, the position of macro and small cells, the mobility of the user etc., are considered as a random (stochastic) process of specified probability distribution [119]. To determine the spatial distribution of BS and users, we have considered the

Poisson Point Process (PPP).

In our proposed algorithm, if cellular resources are available and D2D pairs are close enough to each other, D2D users can use dedicated mode. But in case of unavailable dedicated radio resources, D2D users can reuse the cellular resources if they meet the following criteria:

- SINR threshold: In a D2D-enabled cellular HetNet, due to mutual interference D2D receivers will get the interference from other D2D transmitters, SUEs and CUEs. As a result, receiver SINR as well as the system sum rate will be degraded. Therefore, at the receiver end interference has to be at an acceptable level so that it can decode the message i.e. potential SNIR has to be higher than a threshold value.
- Distance threshold: Due to the limitation of DUE's transmit power, D2D communication can be established only if the distance between the D2D transmitter and receiver is less than a threshold.

If both the above conditions are met, D2D pairs will communicate with each other using shared mode otherwise conventional cellular mode will be used.

4.4.2 Power control

In our model network, users are distributed using PPP. Based on CSI, initially all the users' locations and distances are measured. If the distances between potential D2D pairs are higher, they need to transmit higher power to meet the SINR requirements, and hence increase the interference. In that case, conventional cellular user mode is preferable otherwise explore the D2D communication mode. To improve the D2D link reliability, distances between them and transmit power are measured, and adjust the transmit power to be keep it at a minimum so that QoS requirements are met. To combat

Algorithm 1: Mode selection and power control for D2D communication

```
1 Initialization: Randomly generate the number of CUEs, DUEs, SUEs and
   determine their locations using CSI
2 Initialization: Estimate distances between the users, between users and Base
   stations (eNB and SCeNB) i.e.  $(d_e, d_s, d_d)$ 
3 Output: Mode selection and power control for D2D communication
4 if Distances between users are too large
5 then
6 |   Use cellular mode
7 else
8 |   Explore for D2D communication
9 |   Estimate distances between the users, between users and Bast stations (eNB
   and SCeNB) i.e.  $d_{i,e}, d_{j,e}, d_{k,e}, d_{j,r}, d_{j,i}, d_{j,k}$ .
10 | if Distance between DUEs and eNB/ScNB is large enough
11 |   then
12 |     Use D2D reuse mode
13 |   else
14 |     Estimate  $\gamma_j^D, \gamma_j^M, \gamma_j^S$ 
15 |     Estimate  $d_{i,e}, d_{j,e}, d_{k,e}, d_{j,r}, d_{j,i}, d_{j,k}$ 
16 |     Update distances and SINR,  $\gamma$ 
17 |   end
18 |   if Distance between DUEs and CUEs/SUEs is large enough
19 |     then
20 |       Use D2D user mode
21 |     else
22 |       Calculate  $P_j(max) = \min P_i^{max}, P_j^{max}, P_k^{max}$ 
23 |       Update distances and  $P_j(max)$ 
24 |     end
25 |     Repeat steps
26 end
```

mutual interference in a D2D-enabled cellular network, our proposed model not only measured D2D pairs transmit power but also other network elements like eNB/SCeNB, CUE and SUE power are measured along with distances and adjust automatically to

meet SINR requirements and maximize system throughput.

4.5 Results and discussion

To get numerical results, we have used a MATLAB-based simulation tool with the initial parameters as shown in Table 4.2 for the D2D-enabled cellular HetNets. In our simulation setup, we consider a single eNB with a 500m cell radius located at the centre of D2D-enabled HetNets where CUEs are randomly distributed. DUEs and SUEs are realized according to two independent PPPs with densities of λ_d and λ_s respectively. The number of CUEs is selected in such a way that the saturation condition is always satisfied. Our analytical model is only valid under the assumption that each eNB has at least one user to serve in the uplink. Here simulated throughput for D2D communication against the number of D2D pairs and their distances is compared with the same as of scheme [66]. Both cases goal is to achieve maximum sum-rate with minimum SINR threshold. Like [66], Our formulated optimization problem is also Mixed-Integer Non-linear Program (NP) – hard and optimal solution cannot be obtained immediately.

Table 4.2: Parameters used in the simulation

Simulation Parameter	Value
Intensity of SCeNBs, λ_s	10^{-5}
Intensity of DUES, λ_d	10^{-3}
CUE Transmission power, P_i	23 (dBm)
Transmission power of DUEs, P_j	20 (dBm)
Transmission power of SUEs, P_k	20 (dBm)
Path loss exponent, α	3 and 4
Required SINR threshold, γ_{th}	-2.6 dB
Noise power, N_0	-118 dBm
Cellular UE numbers, N_C	150
D2D pairs numbers, N_D	50
Small cell UE numbers, N_S	250
Channel Bandwidth, B	180KHz

Figure 4.2 represents the relation of CDFs (Cumulative Distribution Functions) with

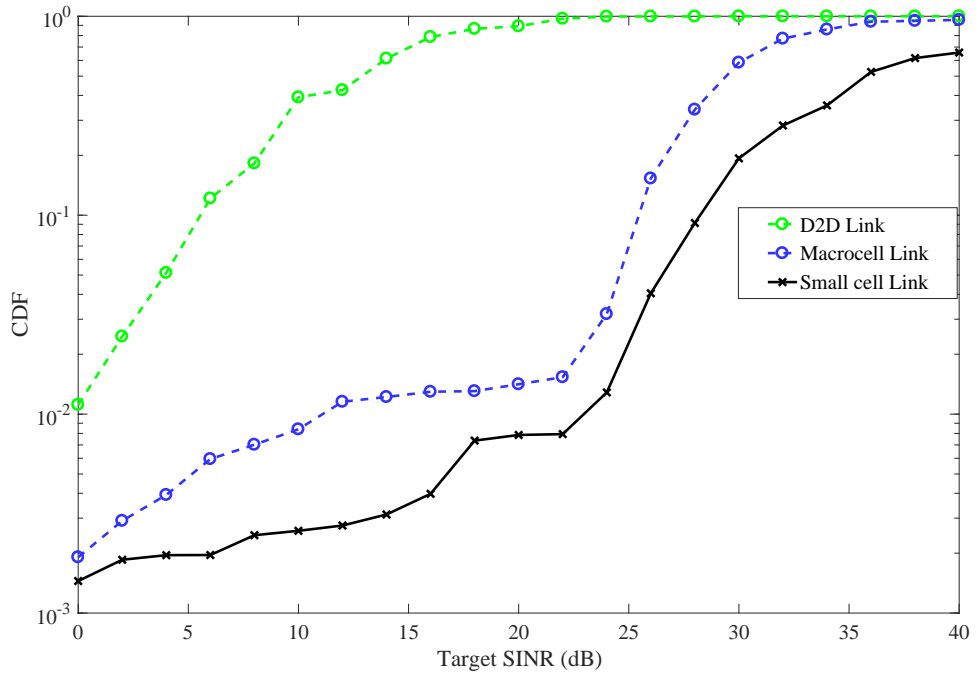


Figure 4.2: SINR for different links in the D2D communications

SINR for different links. Here it can be seen that the outage probability of D2D link sharply falls by increasing the target SINR after a certain level whereas macro and small cell links are more sustainable. This represents that D2D links are vulnerable compared

to

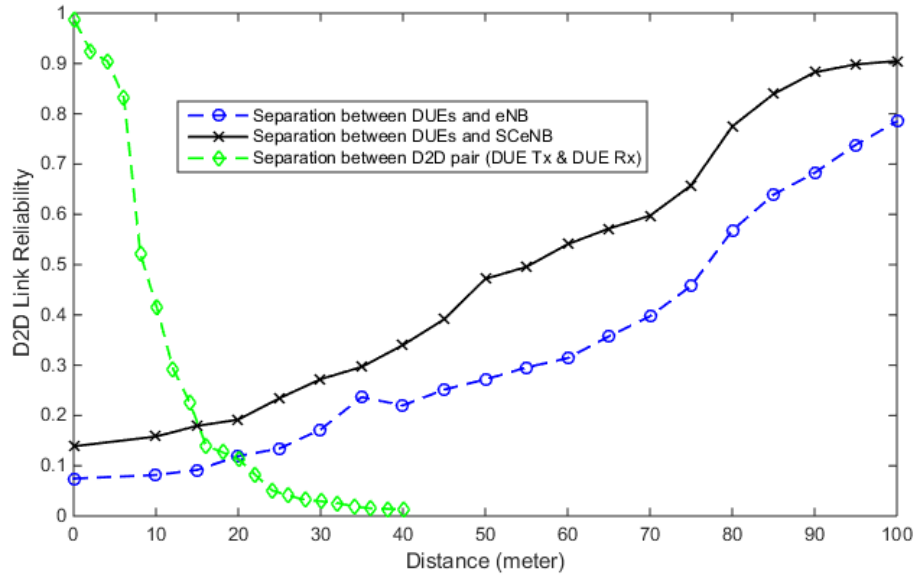


Figure 4.3: Impact of distance for various nodes in D2D communications

Figure 4.3 shows that D2D link reliability increases while the distance between

D2D pairs and eNB (macro and small cell base station) increases whereas D2D link reliability decreases when D2D pairs are moving away.

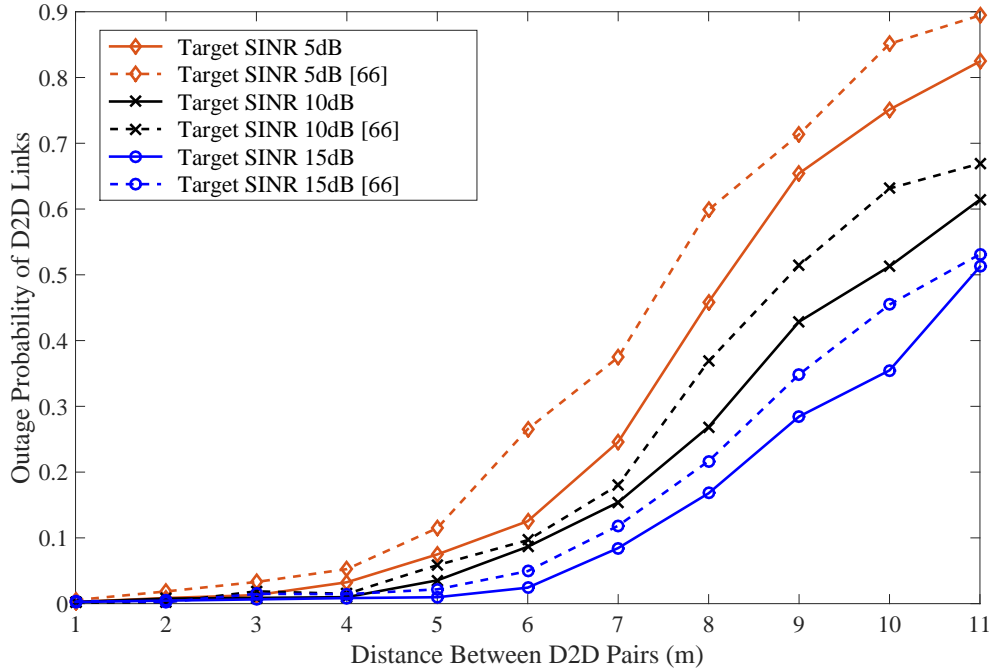


Figure 4.4: Impact of distance and SINR in coverage for D2D links

Figure 4.4 shows the relationship of D2D link outage probability with distances of D2D pairs at different SINRs. It's clear from the results that D2D link outage probability increases with increasing D2D pair distances, and it becomes worse at higher required SINR. Figure 4.5 shows the throughput of D2D users with increasing the distances of D2D pairs. It can be seen that throughput decreases with increasing D2D pair distances, and it falls sharply after a certain value as link reliability becomes vulnerable. Throughput is directly proportional to SINR and in [66] QoS is maintained only for cellular users while in our analysis we have maintained QoS for all 3 links. In addition, eNB has robust sensitivity compared to UE and Tx power of D2D pairs cannot be increased after a certain limit to maintain minimum QoS requirement. Hence, with increasing distance between D2D pairs after 70m our proposed scheme throughput

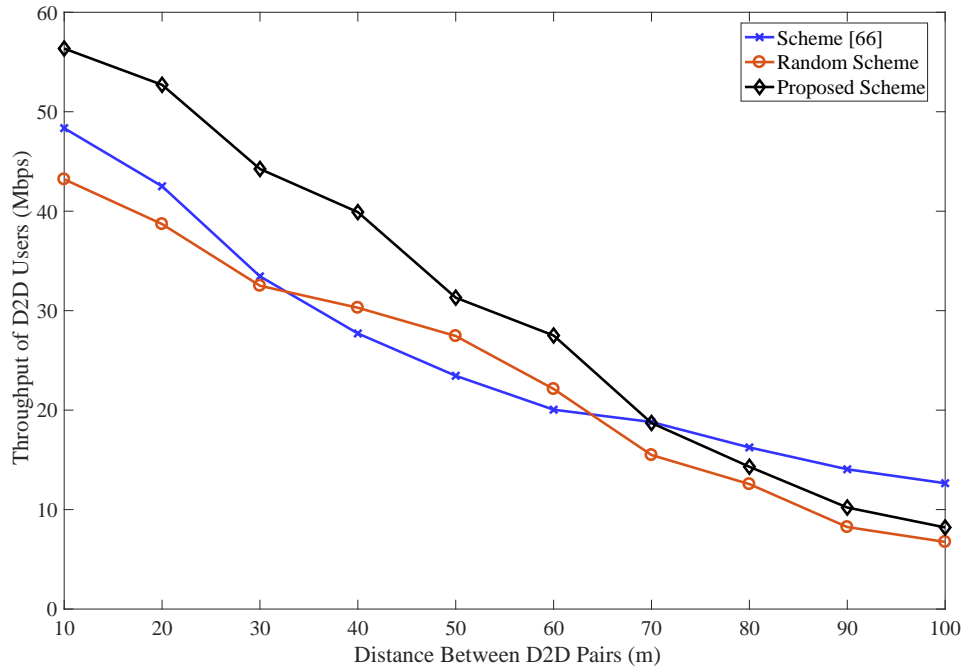


Figure 4.5: Throughput of D2D users with increasing distances of D2D pairs

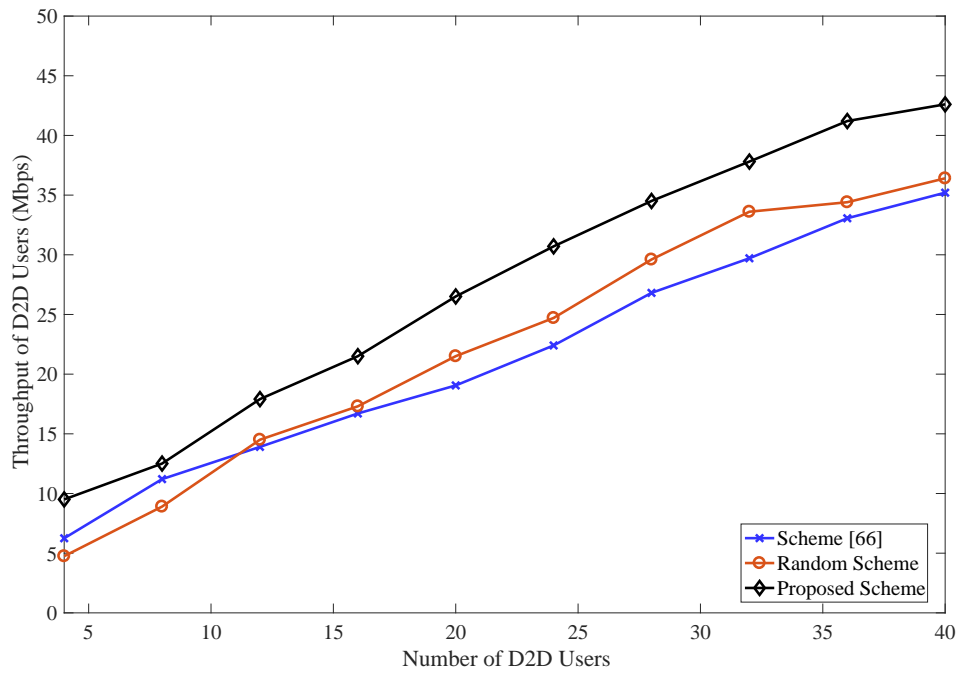


Figure 4.6: Throughput of D2D users with increasing number of D2D pairs

dropped below compared to [66]. Overall, our proposed scheme still outperforms the existing schemes as obtained from the results. Figure 4.6 shows the relationship of D2D users throughput with the active number of D2D users. As shown in the obtained

results, throughput increases with increasing active D2D users for all schemes and our proposed scheme performs better.

4.6 Summary

In this Chapter, a new mode selection algorithm for D2D-enabled heterogeneous cellular networks is proposed. These results are basic outcomes of our analytical model that links the theoretical analysis of D2D communication in a 3-tier cellular network. Results obtained have shown that the outage probability of D2D links sharply increased while participating DUEs were moving farther from each other, and reciprocal while D2D pairs were moving away from the cellular base station. Simulation results also show that the proposed scheme performs better compared to existing schemes. In Chapter 5, performance analysis and small cell deployment model using a dynamic algorithm for interference management in D2D-enabled cellular HetNets are discussed.

Chapter 5

Dynamic Algorithm for Interference Management in D2D-enabled Cellular HetNets

5.1 Introduction

In Chapter 4, mode selection techniques for mitigating interference in D2D communication for cellular heterogeneous networks were discussed. The main objective of this thesis is to identify the interference affecting factors for D2D communication in cellular HetNets and propose suitable solutions for them. To obtain these objectives, in this chapter we have analysed the different performance parameters and their impact on performance for D2D communication. In Section 5.2, the thesis conducts a literature review to explore dynamic algorithms for interference management in D2D-enabled cellular HetNets. It develops an analytical and performance evaluation model in Sections 5.3 and 5.4 respectively. Section 5.4 discusses simulation parameters and simulation results. This Chapter is summarized in Section 5.5.

In this chapter, we identify various key factors that affect performance for D2D communication in an underlay heterogeneous cellular network where uplink (UL) resources are shared among D2D pairs and small cells. The main contribution and strength of this chapter is the emphasis on the fact that a dynamic algorithm is required to manage interference management in D2D-enabled heterogeneous cellular networks.

we analysed the outage probabilities of D2D, macrocell and small cell links, SINR and small cell density for system performance evaluation. Our proposed dynamic algorithm called Acceptance Interference Region (AIR) is suitable to achieve a strict guaranteed QoS for all links in D2D-enabled heterogeneous cellular networks. We also proposed an efficient ON/OFF algorithm and optimal density for small cells to achieve maximum transmission capacity in the network.

5.2 Summary of related works on interference management

In a D2D-enabled heterogeneous cellular network, to manage interference the state-of-the-art researchers proposed different methods and their working principles and techniques were different also. Based on interference behavior all of them can be categorized as interference avoidance, interference cancellation and interference reduction.

In interference avoidance techniques, DUEs are not allowed to use the cellular resources up to a certain area of coverage which is defined by a predefined signal-to-interference-noise ratio (SINR) and the interference-limited area is normally derived with a specific transmission power level at the UEs [120], [121], or based on the distance as well as channel quality of the UEs [115], [122]. In [9], to make a robust cellular link and to reduce interference between the cellular and D2D layers, an interference-aware power allocation (IAPA) solution is proposed to improve spectral efficiency, throughput and outage probability of cellular links. In [11] authors first derived the outage probabilities of D2D, macro cell and small cell links, and then presented the lower distance boundaries from the D2D transmitter to the macro base station (eNB) and small cell receiver, and from base stations receiver to a D2D receiver. Finally, an optimal small cell deployment density that ensures the quality of service (QoS) requirements for both D2D and cellular communications is proposed. In [39], authors proposed an interference-limited area (ILA) based D2D management scheme where

an appropriate power control algorithm is used for mitigating interference. In their work, multiple DUEs but a single macro cell are considered, and DUEs can only initiate their communication outside the restricted area. Like [11], lower distance boundaries between D2D receiver and cellular cells (both macro and small cell) are defined, and based on that interference management scheme and upper boundary, small cell density is proposed in which D2D devices can only reuse the cellular resources effectively to meet QoS requirements [89].

Whereas in interference cancellation techniques- multiple antenna systems, beam-forming or pre-coding are used. The major advantage of these approaches is to manage or eliminate the interference without reducing the transmission power. Hence transmission rate is improved but at the cost of additional computation power and communication overheads. In [123] authors modelled a hybrid cellular with multi-antennas and D2D communication networks with stochastic geometry theory where base stations as well as user equipment (UEs) are deployed as poisson point process (PPP) with a specific density. Here the authors used degrees of freedom for base station transmission and proposed beam forming and interference cancellation strategies to improve the system's achievable rate. Interference alignment techniques are used to mitigate interference between CUEs and DUEs in a MIMO-based cellular network and finally propose a mode selection technique based on degrees of freedom for potential D2D users with a linear coding structure in [124]. In [90] an overlay mode of D2D communication in mm-wave 5G networks is proposed where alternate offer bargaining game theory is used to improve system throughput without compromising SINR.

But in the interference coordination approach, CUEs and DUEs transmit power as well as channel assignment are optimized to maximize the objectives. However, it often requires centralized computation at the eNB. In addition, to reduce the system complexity, D2D pairs can reuse the radio resources from only one CUE regardless of other available CUEs with better channel conditions. In [116] both line-of- Sight (LoS)

and non-line-of-Sight (NLoS) transmissions are considered in a practical path loss model and the authors proposed mode selection techniques based on the maximum received signal strength for each UE to control D2D-to-cellular interference. To minimize the impact of interference in D2D-enabled cellular networks, in [125] the authors propose a distributed algorithm using matching theory to allocate the appropriate resources. The researchers first modelled the spatial distributions of UEs and BSs in HetNets using a homogeneous poisson point process (PPP), and finally proposed a resource allocation algorithm where the QoS of D2D communications is guaranteed. Similar to [39], to minimize the interference in D2D-enabled HetNets cellular networks, a joint power control and mode selection scheme is proposed where power control is used to adjust the interference-limited area dynamically and mode selection is used to maximize the spectral efficiency [40]. In addition, to improve performance and mitigate in-band emission interference (IEI) for cellular links in D2D-enabled cellular networks, Albasry et al. [126] propose a distance-density based (DDB) frequency resources grouping strategy and optimal power allocation (OPA) algorithm. DDB strategy is used to give the higher priority on the QoS for D2D links whereas OPA is used when the number of D2D links is more important. Albasry et al. use stochastic geometry and an analytical approach for their modelling in 2-tier networks.

In [127] Hassan et al. propose a weighted bipartite matching algorithm to minimize the interference in a 2-tier D2D-enabled cellular network and later on use local search techniques to improve further their outcomes. Finally, Hassan et al. compare their proposed algorithms with a two-phase auction-based fair and interference-aware resource allocation algorithm to show the improvement of their algorithms. Huynh et al. in [128] propose an interference management algorithm to maximize the performance of D2D communication without compromising the QoS requirements for cellular link in both UL and DL by optimizing admission control, power control and resource allocation. The main disadvantage of their work is resource sharing with multiple D2D pairs is not

considered and their analysis is limited to a tier-2 network.

In [129] Chen et al. proposed two different resource-sharing strategies for co-tier and cross-tier interference separately along with their respective power control mechanisms. To optimize the problem, convex optimization and 0-1 assignment problem techniques are used for power control and resource allocation respectively. But in [130] a concatenated bi-partite matching (CBM) method is proposed to mitigate interference by appropriate sub-band assignment (SA) and resource allocation (RA). In their proposal, user equipment (UE) density, e-node-B (eNB) density, and switching frequency of small cells are adaptively determined, and the effect of UL power control is managed by full and truncated channel inversion methods. Initially, CBM is developed on single matching which is eventually generalized to multiple cells for SA and RA DUEs. By using Monte Carlo method, an iterative scheme is proposed where mode selection and power control are used jointly.

In [52], an iterative scheme is proposed where mode selection and power control are used jointly. The interference on each RB (Resource Block) is measured, and based on this D2D pair selects its mode and adjusts the transmission power for affecting CUEs to achieve the targeted throughput. Like [51], this proposed scheme is only validated using a single cell with a different radius. The state-of-the-art proposed another smart mode and power selection-based distribution approach in [53] where real-time information of local traffic channel and surrounding nodes information are used. Here dynamic switching is adopted to control interference otherwise continue the communication using cellular mode. Moreover, to resolve the issues arising from spectrum sharing in D2D-enabled cellular networks, a location-related strategy for mode selection and a spectrum sharing algorithm is proposed in [54] where devices form a coalition to share the spectrum among DUEs and CUEs.

Most of the state-of-the-art techniques described above focus on interference management in single or 2-tier cellular networks. Moreover, for interference management

most of the researchers consider only one D2D pair and the effects of macro and multiple small cells are neglected, and very few papers focus on where DUEs in D2D pairs are attached to a different eNBs or one in eNB and another in a small cell. In 5G and beyond, ultra-dense networks (UDNs) will be deployed, and in practice, multiple CUEs may associate with different cellular layers, and an additional D2D layer will create the most prominent challenge in minimizing interference. Despite the prominent usage of D2D communications, there are very few ongoing researchers who are working to address the MS as well as resource allocation for mutual interference problems in 3-tier cellular networks. Nonetheless, none of the authors reviewed the worst and, at the same time, the most challenging interference case, where all 3 tiers of the networks (i.e. eNB, SCeNB and D2D communication) mutually interfere [10]. This is the main difference between the existing approaches and our proposal for managing interference in a 3-tier heterogeneous cellular network.

5.3 System Model

5.3.1 Network model

In our analysis we have considered a 3-tier D2D-enabled cellular HetNet model which is mentioned in Section 4.1 and illustrated in Figure 1.1. In that situation a receiver can decode a message successfully if and only if the SINR at the receiver is greater than a specific threshold γ_{th} . If the SINR at the receiver does not meet γ_{th} , the link experiences an outage. So the outage probability of the x,y link can be expressed as:

$$P_{out} = P_r\{\gamma_y \leq \gamma_{th}\} \quad (5.1)$$

Let us consider e, s, i, j and k subscripts to denote the serving eNB, the serving SCeNB, the i_{th} CUE, the j_{th} D2D pairs and the k_{th} SUE, respectively. The subscripts t

and r denote the transmitter and the receiver of the D2D pair respectively. In the context of the above-defined network where UL cellular resources are shared by D2D pairs and small cells, the mutual interference at different receivers can be expressed as:

$$I_i = \sum_{j=1}^{N_D} P_j h_{j,e} d_{j,e}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,e} d_{k,e}^{-\alpha} + N_0$$

$$I_j = P_i h_{i,r} d_{i,r}^{-\alpha} + \sum_{j'=1, j' \neq j}^{N_D} P_{j'} h_{j',r} d_{j',r}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,r} d_{k,r}^{-\alpha} + N_0$$

$$I_k = P_i h_{i,s} d_{i,s}^{-\alpha} + \sum_{j=1}^{N_D} P_j h_{j,s} d_{j,s}^{-\alpha} + \sum_{k'=1, k' \neq k}^{N_S} P_{k'} h_{k',s} d_{k',s}^{-\alpha} + N_0$$

Where I_i is the combined interference received by eNB, I_j is the same for j_{th} D2D pairs receiver other than j_{th} transmitter and I_k is the same for all SUEs except k_{th} to the SCeNB. Here the impact analysis of various factors on interference in a D2D-enable cellular network is limited to performance matrices of small cell and D2D pair densities, SINR and distances.

5.3.2 SINR model

Since communications may take place in any of the earlier mentioned 3 cases, according to equation (4.2) the SINR at the j_{th} D2D receiver is given by:

$$\gamma_j^D = \frac{P_j h_{t,r} d_{t,r}^{-\alpha}}{I_j} = \frac{P_j h_{t,r} d_{t,r}^{-\alpha}}{P_i h_{i,r} d_{i,r}^{-\alpha} + \sum_{j'=1, j' \neq j}^{N_D} P_{j'} h_{j',r} d_{j',r}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,r} d_{k,r}^{-\alpha} + N_0} \quad (5.2)$$

So according to Eq. (4.4), the outage probability of the j_{th} D2D link can be given as

$$P_{out,j}^D = P_r \{ \gamma_j^D < \gamma_{th} \} = 1 - P_r \{ \gamma_j^D \geq \gamma_{th} \} \quad (5.3)$$

where γ_{th} is the required SINR threshold at the receiver for effective D2D communication.

$$P_{outj}^D = 1 - P_r \left\{ \frac{P_j h_{t,r} d_{t,r}^{-\alpha}}{P_i h_{i,r} d_{i,r}^{-\alpha} + \sum_{j'=1, j' \neq j}^{N_D} P_{j'} h_{j',r} d_{j',r}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,e} d_{k,e}^{-\alpha} + N_0} \geq \gamma_{th} \right\}$$

$$= 1 - P_r \left\{ h_{t,r} \geq \frac{\gamma_{th} d_{t,r}^{\alpha}}{P_j} \left(P_i h_{i,r} d_{i,r}^{-\alpha} + \sum_{j'=1, j' \neq j}^{N_D} P_{j'} h_{j',r} d_{j',r}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,r} d_{k,r}^{-\alpha} + N_0 \right) \right\}$$

Since the channel coefficient is exponentially distributed (Poisson point distribution), the expectation of interference from the above equation can be expressed as follows

$$P_{outj}^D = 1 - \mathbb{E} \left[\exp \left(-\frac{\gamma_{th} d_{t,r}^{\alpha}}{P_j} \left(P_i h_{i,r} d_{i,r}^{-\alpha} + \sum_{j'=1, j' \neq j}^{N_D} P_{j'} h_{j',r} d_{j',r}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,r} d_{k,r}^{-\alpha} + N_0 \right) \right) \right] \quad (5.4)$$

Here channel quality follows Rayleigh fading assumption which is an exponentially distributed random variable with unit mean. Assume $z = \frac{\gamma_{th} d_{t,r}^{\alpha}}{P_j}$ and $\mathcal{L}_{I_d}(z)$ and $\mathcal{L}_{I_s}(z)$ are the Laplace transformation of random variables I_d and I_s evaluated at z , respectively. Interference due to same cellular resource reuses by other D2D pairs and small cell links I_d and I_s are defined as $I_d = \sum_{j'=1, j' \neq j}^{N_D} P_{j'} h_{j',r} d_{j',r}^{-\alpha}$ and $I_s = \sum_{k=1}^{N_S} P_k h_{k,r} d_{k,r}^{-\alpha}$ respectively. So Eq. (5.4) can be written as

$$P_{out,j}^D = 1 - \exp(-z N_0) \mathcal{L}_{I_d}(z) \mathcal{L}_{I_s}(z)$$

$$\begin{aligned}
&= 1 - \exp\left(\frac{-N_0\gamma_{th}d_{t,r}^\alpha}{P_j}\right) \left(\frac{P_{j,r}d_{i,r}^\alpha}{P_i\gamma_{th}d_{t,r}^\alpha + P_jd_{i,r}^\alpha}\right) \mathcal{L}I_d\left(\frac{\gamma_{th}d_{t,r}^\alpha}{P_j}\right) \mathcal{L}I_s\left(\frac{\gamma_{th}d_{t,r}^\alpha}{P_j}\right) \\
&= 1 - \exp\left(\frac{-N_0\gamma_{th}d_{t,r}^\alpha}{P_j}\right) \left(\frac{P_jd_{i,r}^\alpha}{P_i\gamma_{th}d_{t,r}^\alpha + P_jd_{i,r}^\alpha}\right) \exp\left(\frac{-\kappa P_{j'}^m \gamma_{th}^m d_{t,r}^2 \lambda_d}{P_j^m}\right) \\
&\quad \exp\left(\frac{-\kappa P_k^m \gamma_{th}^m d_{t,r}^2 \lambda_s}{P_j^m}\right) \\
&= 1 - \exp\left(\frac{-N_0\gamma_{th}d_{t,r}^\alpha}{P_j}\right) \left(\frac{P_jd_{i,r}^\alpha}{P_i\gamma_{th}d_{t,r}^\alpha + P_jd_{i,r}^\alpha}\right) \exp\left(\frac{-\kappa\gamma_{th}^m d_{t,r}^2 (P_{j'}^m \lambda_d + P_k^m \lambda_s)}{P_j^m}\right) \\
&= 1 - \delta_D \exp(-\beta_D(P_{j'}^m \lambda_d + P_k^m \lambda_s)) \tag{5.5}
\end{aligned}$$

Where $E(\cdot)$ is expectation function, $\delta_D = \exp\left(\frac{-N_0\gamma_{th}d_{t,r}^\alpha}{P_j}\right) \left(\frac{P_jd_{i,r}^\alpha}{P_i\gamma_{th}d_{t,r}^\alpha + P_jd_{i,r}^\alpha}\right)$, $\kappa = \pi m \Gamma(m) \Gamma(1-m)$, $\beta_D = \kappa \gamma_{th}^m d_{t,r}^2 / P_j^m$, λ_d is density of DUEs for D2D pairs, λ_s is density of small cells and the proof of the above equation can be referred to Appendix A in [131].

From the above expression, it's clearly visible that the outage probability of D2D links depends on various factors such as path loss coefficient, required SINR, distances between UEs, transmission powers, small cell and D2D pairs density. Outage probability increases with increasing required SINR but decreases while the distance between SUEs and the D2D receiver is increased.

Similarly, in the case of macro cellular communications mode where UE is served

by eNB, the SINR at the receiver i can be expressed as:

$$\gamma_i^M = \frac{P_i h_{i,e} d_{i,e}^{-\alpha}}{I_i}$$

Hence the outage probability of the macro cell link can be written as

$$P_{out,i}^M = P_r\{\gamma_i^M < \gamma_{th}\} = 1 - P_r\{\gamma_i^M \geq \gamma_{th}\} \quad (5.6)$$

Where γ_{th} is the required SINR for i_{th} CUE for effective cellular communication, after substituting the SINR values the outage probability of the macro cellular link will be as follows

$$\begin{aligned} P_{out,i}^M &= 1 - P_r \left\{ \frac{P_i h_{i,e} d_{i,e}^{-\alpha}}{\sum_{j=1}^{N_D} P_j h_{j,e} d_{j,e}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,e} d_{k,e}^{-\alpha} + N_0} \geq \gamma_{th} \right\} \\ &= 1 - P_r \left\{ h_{i,e} \geq \frac{\gamma_{th} d_{i,e}^\alpha}{P_i} \left(\sum_{j=1}^{N_D} P_j h_{j,e} d_{j,e}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,e} d_{k,e}^{-\alpha} + N_0 \right) \right\} \\ &= 1 - \mathbb{E} \left[\exp \left(-\frac{\gamma_{th} d_{i,e}^\alpha}{P_i} \left(\sum_{j=1}^{N_D} P_j h_{j,e} d_{j,e}^{-\alpha} + \sum_{k=1}^{N_S} P_k h_{k,e} d_{k,e}^{-\alpha} + N_0 \right) \right) \right] \\ &= 1 - \exp \left(-\frac{N_0 \gamma_{th} d_{i,e}^\alpha}{P_i} \right) \mathcal{L}_{I_d} \left(\frac{\gamma_{th} d_{i,e}^\alpha}{P_i} \right) \mathcal{L}_{I_s} \left(\frac{\gamma_{th} d_{i,e}^\alpha}{P_i} \right) \\ &= 1 - \exp \left(-\frac{N_0 \gamma_{th} d_{i,e}^\alpha}{P_i} \right) \exp \left(-\frac{\kappa \gamma_{th}^m d_{i,e}^{2\alpha} (P_j^m \lambda_d + P_k^m \lambda_s)}{P_i^m} \right) \\ &= 1 - \delta_M \exp(-\beta_M (P_j^m \lambda_d + P_k^m \lambda_s)) \end{aligned} \quad (5.7)$$

Where $\delta_M = \exp\left(-\frac{N_0 \gamma_{th}^m d_{i,e}^\alpha}{P_i}\right)$, $\kappa = \pi m \Gamma(m) \Gamma(1-m)$ and $\beta_M = \frac{\kappa \gamma_{th}^m d_{i,e}^{2\alpha}}{P_i^m}$. Hence the

outage probability decreases with increasing distances between SUEs, and UEs as well as UEs and D2D transmitters.

For small cell mode communications, UE is served by small cell SCeNB, and the link between SUE and SCeNB will be interfered with by other SCeNBs, D2D pairs and macro eNB. Therefore, the SINR at the small cell receiver can be written as

$$\gamma_k^S = (P_k h_{k,s} d_{k,k}^{-\alpha}) / I_k \quad (5.8)$$

and the outage probability of the small cell link can be expressed as

$$P_{out,k}^S = P_r \{ \gamma_i^S < \gamma_{th} \} = 1 - P_r \{ \gamma_i^S \geq \gamma_{th} \} \quad (5.9)$$

So, after substituting all the values the outage probability of the small cell cellular link can be derived as

$$\begin{aligned} P_{out,k}^S &= 1 - P_r \left\{ \frac{P_k h_{k,s} d_{k,s}^{-\alpha}}{P_i h_{i,s} d_{i,s}^{-\alpha} + \sum_{j=1}^{N_D} P_j h_{j,s} d_{j,s}^{-\alpha} + \sum_{k'=1, k' \neq k}^{N_S} P_{k'} h_{k',s} d_{k',s}^{-\alpha} + N_0} \geq \gamma_{th} \right\} \\ &= 1 - P_r \left\{ h_{k,s} \geq \frac{\gamma_{th} d_{k,s}^{-\alpha}}{P_k} \left(P_i h_{i,s} d_{i,s}^{-\alpha} + \sum_{j=1}^{N_D} P_j h_{j,s} d_{j,s}^{-\alpha} + \sum_{k'=1, k' \neq k}^{N_S} P_{k'} h_{k',s} d_{k',s}^{-\alpha} + N_0 \right) \right\} \\ &= 1 - \mathbf{E} \left[\exp \left(- \frac{\gamma_{th} d_{k,s}^{-\alpha}}{P_k} \left(P_i h_{i,s} d_{i,s}^{-\alpha} + \sum_{j=1}^{N_D} P_j h_{j,s} d_{j,s}^{-\alpha} + \sum_{k'=1, k' \neq k}^{N_S} P_{k'} h_{k',s} d_{k',s}^{-\alpha} + N_0 \right) \right) \right] \\ &= 1 - \exp \left(- \frac{N_0 \gamma_{th} d_{k,s}^{-\alpha}}{P_k} \right) \left(\frac{P_k d_{k,e}^{-\alpha}}{P_i \gamma_{th} d_{k,s}^{-\alpha} + P_k d_{k,e}^{-\alpha}} \right) \mathcal{L}_{I_d} \left(\frac{\gamma_{th} d_{k,s}^{-\alpha}}{P_k} \right) \mathcal{L}_{I_{s'}} \left(\frac{\gamma_{th} d_{k,s}^{-\alpha}}{P_k} \right) \end{aligned}$$

$$\begin{aligned}
&= 1 - \left(\frac{P_k d_{k,e}^\alpha}{P_i \gamma_{th} d_{k,s}^\alpha + P_k d_{k,e}^\alpha} \right) \exp\left(-\frac{N_0 \gamma_{th} d_{k,s}^\alpha}{P_k}\right) \exp\left(-\frac{\kappa \gamma_{th}^m d_{k,s}^2 (P_j^m \lambda_d + P_{k'}^m \lambda_s)}{P_k^m}\right) \\
&= 1 - \delta_S \exp(-\beta_S (P_j^m \lambda_d + P_{k'}^m \lambda_s)) \tag{5.10}
\end{aligned}$$

Where $\delta_S = \left(\frac{P_k d_{k,e}^\alpha}{P_i \gamma_{th} d_{k,s}^\alpha + P_k d_{k,e}^\alpha} \right) \exp\left(-\frac{N_0 \gamma_{th} d_{k,s}^\alpha}{P_k}\right)$, $\kappa = \pi m \Gamma(m) \Gamma(1 - m)$ and $\beta_S = \frac{\kappa \gamma_{th}^m d_{k,s}^2}{P_k^m}$, and $I_{s'}$ is interference from all SCeNBs except respective small cell links.

According to the above expressions of outage probabilities, it is easily visible that the intensity of interference (i.e probabilities of success) depends on the density of small cells and D2D pairs, the distances between the receiver and transmitter of that links, required SINR threshold and transmission powers. Increasing DUE receiver distances from CUEs or SUEs will increase the success of the probability for D2D links. Similarly increasing distances between D2D transmitter and CUEs or SUEs will decrease the outage probability of SCeNB links.

Based on the previous expressions we propose Algorithm 2 called Acceptable Interference Regions (AIR) where links QoS for various communications modes will be guaranteed by limiting the coexistence of different UEs under a D2D link constraints as follows:

$$d_{ij}^D \geq d_{ij}^{D \min} \tag{5.11a}$$

$$d_{je}^M \geq d_{je}^{M \min} \tag{5.11b}$$

$$d_{js}^S \geq d_{ij}^{S \min} \tag{5.11c}$$

Algorithm 2: The proposed AIR dynamic algorithm

```
1 initialization: Cellular resources are not used by another D2D pair
2 Arbitrary generate the numbers of UEs and determine their locations
3 Release the cellular resources if used by D2D pairs and small cells
4 Randomly select cellular resources  $C_{ij}$  for reuse
5 eNB calculates the distances  $d_{ij}, d_{je}, d_{js}$  and  $d_{min}^*$ 
6 Compare distance with their corresponding thresholds
7 while if  $d_{ij} \geq d_{min}^D$  do
8   | D2D pairs reuse  $C_{ij}$  resource
9   | if  $d_{js} \geq d_{min}^S$  then
10  |   | SCeNB reuses cellular resource  $C_{ij}$ 
11  | else
12  |   | Explore for another D2D pair
13  |   | Use macro cellular mode
```

Where d^{min} is the lower boundary which must be satisfied to maintain the QoS for various links and it can be measured as shown in Appendix A. For any communications, UEs will fulfil the minimum distance requirement to guarantee the link QoS.

5.3.3 Small cell density model

Here both small cells and DUEs are considered to be distributed based on separate Poisson Point Processes (PPP).

Previous analysis indicates that mutual interference is heavily dependent on small cell and D2D pair densities. Small cell density, γ_s beyond a certain threshold causes excessive interference for D2D communications resulting in no solution for the AIR feasible set, and one or more links will fail to satisfy QoS requirements. Contrarily, lower values of γ_s yield a higher feasible DUEs. Nevertheless, lower γ_s may result in a smaller overall transmission rate for small cell UEs. In general, the transmission rate of

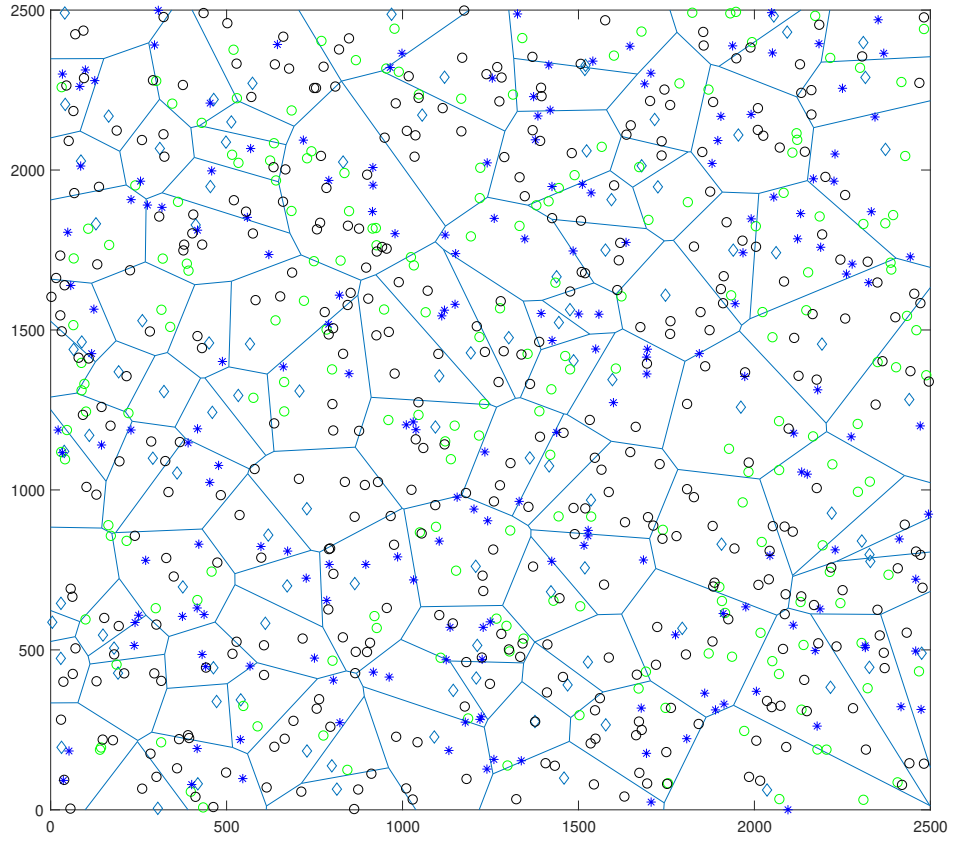


Figure 5.1: PPP distributions of Nodes -diamonds represent the eNB, circles represent UEs (green circles are DUEs) and asterisks represent SCeNBs in a cellular network.

small cell UE is defined as the number of successful transmissions per unit area [132].

So the transmission capacity of small cells can be expressed as

$$\mathcal{T}_c = \lambda_s(1 - P_{out}^S) = \lambda_s \delta_S \exp(-\beta_S(P_j^m \lambda_d + P_{k'}^m \lambda_s)) \quad (5.12)$$

And optimum problem for the above scenario can be formulated as:

$$Max \mathcal{T}_c = \lambda_s \delta_S \exp(-\beta_S(P_j^m \lambda_d + P_{k'}^m \lambda_s)) \quad (5.13)$$

An optimum value for small cell density, γ_s can be obtained by maximizing the above equation (5.13) for small cells with or without satisfying the QoS requirements for

the various links. So, the optimum solution for the above equation without considering QoS constraints is as follows:

$$\tilde{\lambda}_s = \frac{1}{P_{kt}^m \beta_S} = \frac{P_k^m}{P_{kt}^m \gamma_{th} d_{k,s}^2} \quad (5.14)$$

Therefore, under fixed transmission power conditions, a higher number of SCeNB can be added to the network for sharing cellular resources by reducing either the distance between SCeNB and SUE or the required SINR threshold. The proof of the solution for this optimal problem is shown in Appendix A.

Similarly, for D2D pair density, we can get

$$\tilde{\lambda}_d = \frac{1}{P_{jt}^m \beta_D} = \frac{P_j^m}{P_{jt}^m \gamma_{th} d_{t,r}^2} \quad (5.15)$$

From the previous analysis of outage probabilities for DUEs, CUEs and SUEs, it is very hard to avoid the monotonically increasing nature of success probabilities with increasing small cell density, λ_s , or D2D pairs density, λ_d or both. But increasing λ_s or λ_d introduces additional interference. Hence to obtain an optimum value for small cell density, λ_s by fulfilling QoS requirements for all communications mode Eq (5.1) must satisfy the following constraints.

$$P_{out}^D \leq \tau \quad (5.16a)$$

$$P_{out}^M \leq \tau \quad (5.16b)$$

$$P_{out}^S \leq \tau \quad (5.16c)$$

Where τ is the maximum allowable outage probabilities for any links. As controlling no. of small cells is easier compared to DUEs, according to the above constraints in Eq.

(5.16), the density of small cells has to satisfy the following:

$$\lambda_s \leq \min\{f(\tau), g(\tau), h(\tau)\} \quad (5.17)$$

Where

$$f(\tau) = \operatorname{argmax}_{\lambda_s > 0} \{P_{out,j}^D \leq \tau\}$$

$$g(\tau) = \operatorname{argmax}_{\lambda_s > 0} \{P_{out,i}^M \leq \tau\}$$

$$h(\tau) = \operatorname{argmax}_{\lambda_s > 0} \{P_{out,k}^S \leq \tau\}$$

Hence by considering QoS constraints in (5.16a) - (5.16c), we can obtain the solution for small cell density, λ_s for various communications mode as follows:

$$\begin{aligned} \lambda_s^S &\leq \frac{1}{\beta_S P_{kt}^m} \ln \frac{\delta_S}{1-\tau} - \rho_{jkt}^m \lambda_d \\ \lambda_s^M &\leq \frac{1}{\beta_M P_k^m} \ln \frac{\delta_M}{1-\tau} - \rho_{jkt}^m \lambda_d \\ \lambda_s^D &\leq \frac{1}{\beta_D P_k^m} \ln \frac{\delta_D}{1-\tau} - \rho_{jkt}^m \lambda_d \end{aligned}$$

The proof for this solution is shown in Appendix A. Here λ_s^S , λ_s^M , λ_s^D are the small cell density for small cell, macro cell and D2D mode communications, and ρ is the ratio

of transmission powers. Hence the arguments of Eq. (5.17) are as follows:

$$\begin{aligned}
 f(\tau) &= \frac{1}{\beta_S P_{k'}^m} \ln\left(\frac{\delta_S}{1-\tau}\right) - \rho_{j'k'}^m \lambda_d \\
 g(\tau) &= \frac{1}{\beta_M P_k^m} \ln\left(\frac{\delta_M}{1-\tau}\right) - \rho_{jk}^m \lambda_d \\
 h(\tau) &= \frac{1}{\beta_D P_k^m} \ln\left(\frac{\delta_D}{1-\tau}\right) - \rho_{jk}^m \lambda_d
 \end{aligned}$$

Therefore, the outage probability constraints of the optimal problem in Eq. (5.17) can be represented by the constraints of small cell density as follows:

$$\begin{aligned}
 \lambda_s \leq \min\{ & \left\{ \frac{1}{\beta_S P_{k'}^m} \ln\left(\frac{\delta_S}{1-\tau}\right) - \rho_{j'k'}^m \lambda_d \right\}, \left\{ \frac{1}{\beta_M P_k^m} \ln\left(\frac{\delta_M}{1-\tau}\right) \right. \\
 & \left. - \rho_{jk}^m \lambda_d \right\}, \left\{ \frac{1}{\beta_D P_k^m} \ln\left(\frac{\delta_D}{1-\tau}\right) - \rho_{jk}^m \lambda_d \right\} \} = \lambda_s^{Max}
 \end{aligned}$$

Where λ_s^{Max} is the maximum allowable small cell density to guarantee the links' QoS. Hence to maximize the transmission capacity of small cells, a transmission ON-OFF algorithm for small cells is proposed.

Algorithm 3: ON-OFF algorithm for Interference minimization

- 1 Initialize small cell density λ_s
 - 2 Randomly select an SCeNB and calculate the distance d_{j_s}
 - 3 Calculate the maximum allowable small cell density λ_s^{Max}
 - 4 Compare the ratio of λ_s^{Max} and λ_s
 - 5 **if** $\frac{\lambda_s^{Max}}{\lambda_s} < 1$ **then**
 - 6 | Turn OFF the small cells
 - 7 **else**
 - 8 | Turn ON
 - 9 **end**
-

5.4 Performance Evaluation

5.4.1 Simulation environment and parameters

The system model is validated using MATLAB-based simulation. Table 5.1 lists the parameters used in the simulation for the D2D-enabled cellular HetNets. In our simulation setup, we consider a single eNB with a 500m cell radius located at the centre of D2D-enabled HetNets where CUEs are randomly distributed. DUEs and SUEs are realized according to two independent PPPs with densities of λ_d and λ_s respectively. The number of CUEs is selected in such a way that the saturation condition is always satisfied. Our analytical model is only valid under the assumption that each eNB has at least one user to serve in the uplink. We evaluate the coverage probability of the proposed scheme with an average of 10,000 independent realizations.

Table 5.1: Parameters used in the simulation

Simulation Parameter	Value
Intensity of SCeNBs, λ_s	10^{-5}
Intensity of DUES, λ_d	10^{-3}
CUE Transmission power, P_i	23 (dBm)
Transmission power of DUEs, P_j	20 (dBm)
Transmission power of SUEs, P_k	20 (dBm)
Path loss exponent, α	3 and 4
Required SINR threshold, γ_{th}	-2.6 dB
Noise power, N_0	-118 dBm
Cellular UE numbers, N_C	150
D2D pairs numbers, N_D	50
Small cell UE numbers, N_S	250
Maximum allowable outage ie. QoS, τ	0.1,0.01 and 0.001
Channel Bandwidth, B	180KHz

5.4.2 Results and discussion

The proposed model is based on the distance-based mode selection strategy without power control. As DUEs are distributed based on the PPP function, higher distances

between the D2D receiver and transmitter are more likely to have occurred which eventually increases the transmission power and associated interference. Hence the proposed scheme with an added power control mechanism can be part of our future work.

Due to the limited related published work in the field, the proposed AIR algorithm and the resulting scheme are validated by comparing with the traditional neighbour-based scheme and the work presented in [11]. Initially, Cumulative Distribution Functions (CDFs) of outage probabilities of all three communications modes are evaluated and compared with the above-mentioned baseline schemes. The reason for comparing our results with [12] is both cases 3-tier HetNet is considered, and interference is controlled to ensure link availability by managing small cell deployment. In addition, like us in [12] distances between different links are calculated to control small cell density. But in our case, a dynamic algorithm called AIR (Acceptance Interference Region) is proposed that control interference produced by small cells and hence improve the D2D links availability.

In Figure 5.2, we plot CDF versus outage probability of the D2D link. We observe that the outage probability of the D2D link is improved up to 55% using the proposed scheme than the neighbour-based scheme. However, the improvement is marginal (up to 3%) than the scheme proposed in [11] where the interference is considered for single SCeNB and D2D pairs. It is also clearly visible that the outage probability decreases with the decrease of τ (QoS requirements for D2D links) and more than 88% D2D links can meet the QoS requirements in this scenario.

In Figures 5.3 and 5.4, macro and small cell outage probabilities are compared with the same baseline. Similar to the D2D link outage case, outage probability improvement is noticeable in our proposed scheme. However, the improvements are not as prominent as those in D2D links and the reason behind this is that D2D transmitters are chosen based on the AIR scheme which is designed for minimizing the D2D interference. In

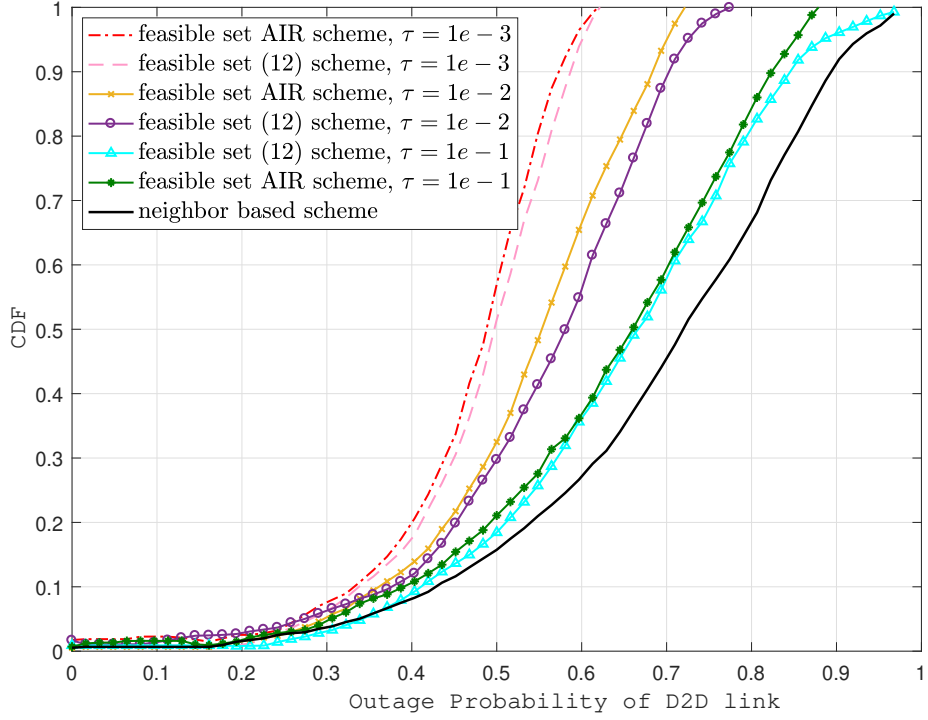


Figure 5.2: Outage probability of D2D links with different schemes

addition, due to smaller path loss, the channel quality of D2D links is much better compared with the macro and small cell links. Despite all the factors, here we can see at CDF = 0.7 the outage probability of the feasible set AIR scheme is much better when compared to the neighbor-based scheme (35% in eNB and 69% in SCeNB links) and considerably better when compared to the [11] scheme (6% in eNB and 8% in SCeNB links).

From Figure 5.5 we observe that the outage probability increases with an increase in SINR threshold requirements, and at lower SINR threshold values, the cellular coverage is nearly perfect i.e. cellular outage is almost zero. By controlling interferences, we can minimize the required threshold for decoding the message and hence improve the performance in terms of links availability. Figures 5.6 and 5.7 also reveal the impact of densities of D2D pairs and small cells on the availability of the link. In both cases, outage probability increases with increasing D2D pairs and small cell densities.

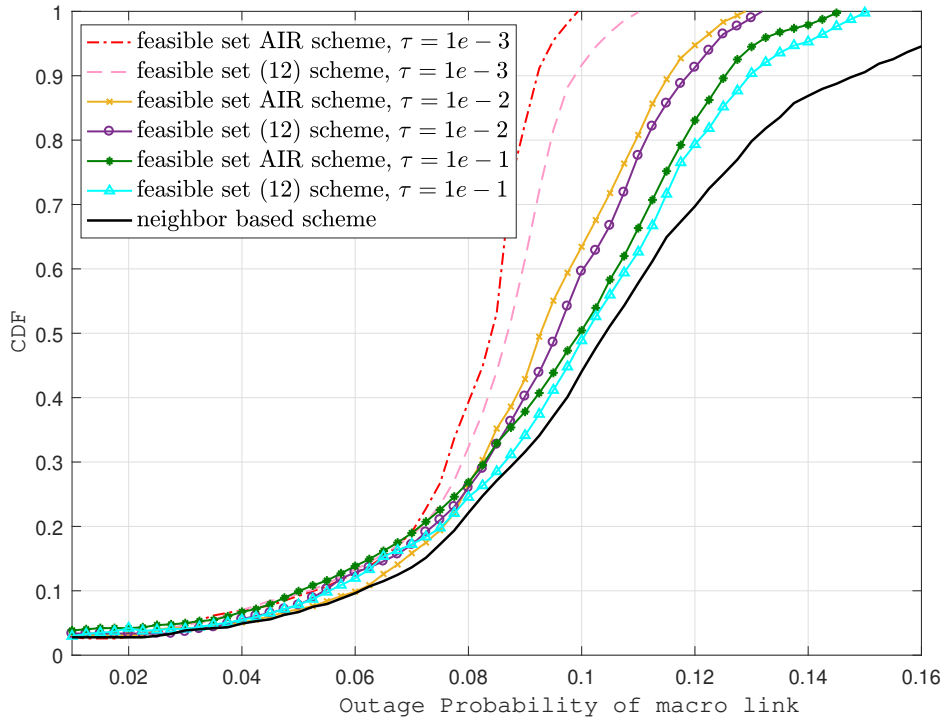


Figure 5.3: Outage probability of macro links with various schemes

In Figure 5.8, transmission capacity (bits/s/Hz) increases with path loss coefficient, α due to an increase in the fading of interference. By looking at Figure 5.8, we observe that for $\alpha = 4$ almost a similar transmission capacity is achieved with AIR scheme at $4.1e-05$ of optimal small cell density compared to $5.31e-05$ for the same in the scheme presented in [11]. For $\alpha = 3$, an equivalent transmission capacity is achieved for optimal small cell density of $3.7e-05$ and $4.23e-5$ in AIR and the [11] scheme, respectively.

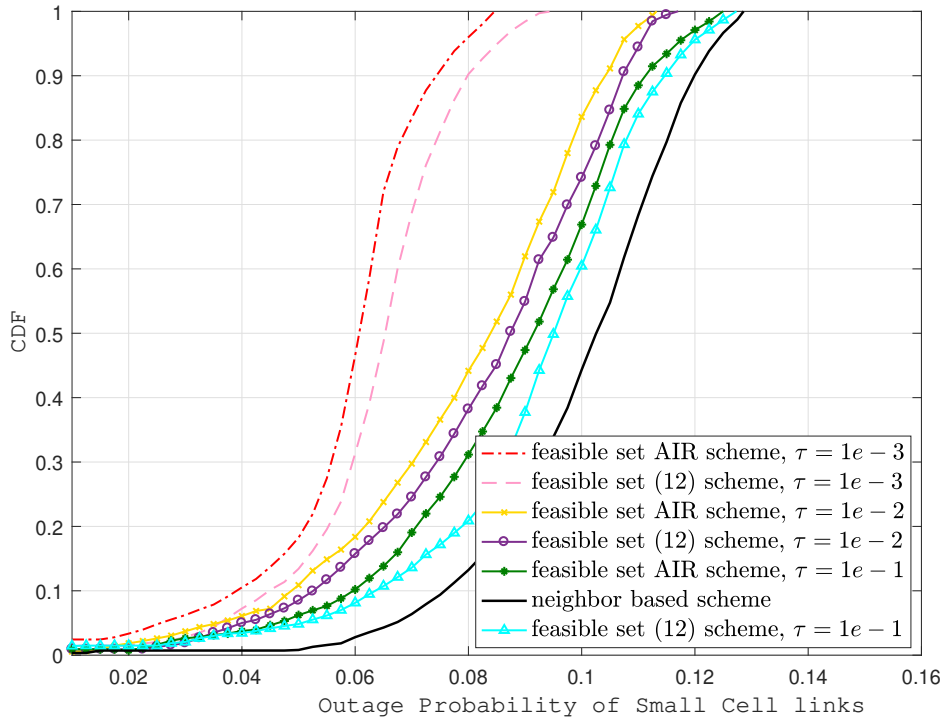


Figure 5.4: Outage probability of small cell links with various schemes

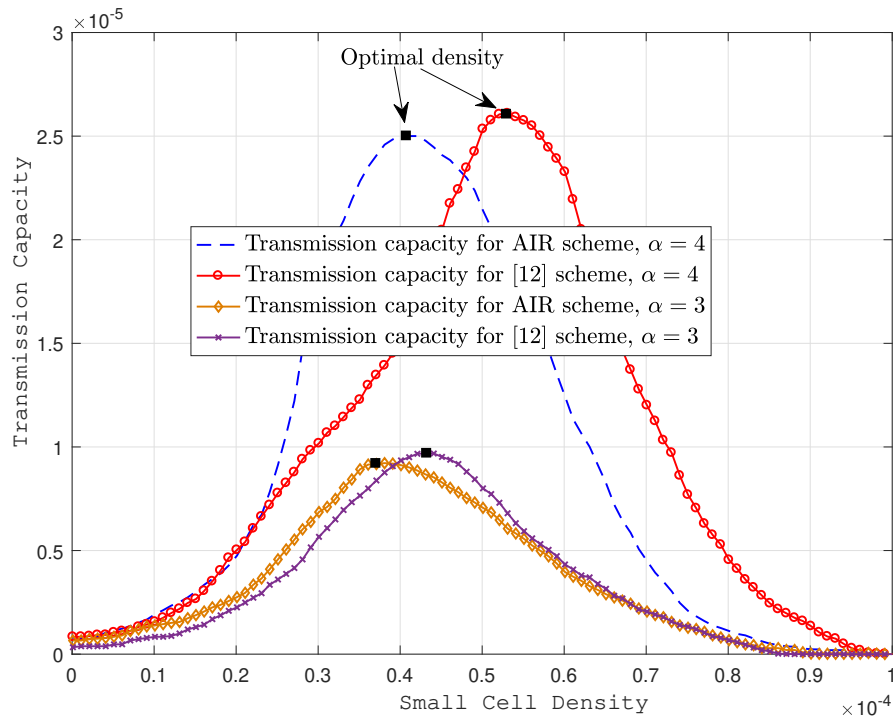


Figure 5.8: Transmission capacities for optimal deployment of various Schemes.

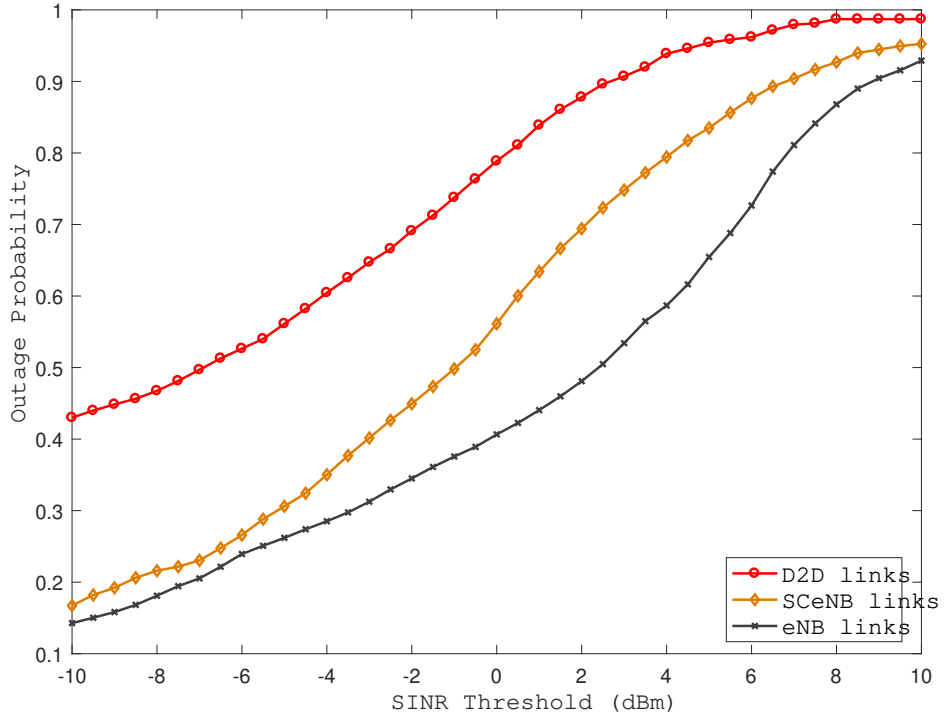


Figure 5.5: Outage probability of different links with various SINR threshold

5.5 Summary

In this Chapter, mathematical models for network, SNIR, and small cell density are developed for system performance modelling and analysis. First, the outage probabilities of D2D, macrocell, and small cell links are derived. Second, a dynamic algorithm called acceptance interference region (AIR) is proposed to achieve a strict guaranteed QoS to all links in D2D-enabled HetNets. Finally, the analytical models are validated using a MATLAB-based simulation. Results obtained have shown that the proposed AIR scheme achieved an improved outage probability of 35% and 49% in eNB and SCeNB links, respectively than the traditional neighbor-based methods. We also proposed an efficient ON/OFF algorithm to achieve a better transmission capacity in the network than the existing methods. We found that the transmission capacity is maximized

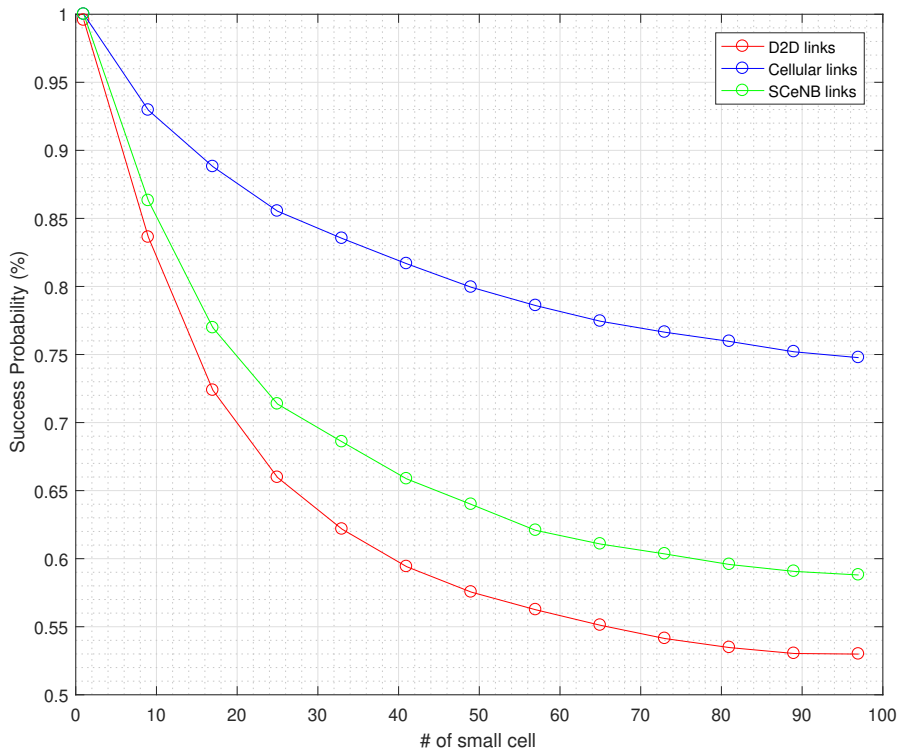


Figure 5.6: Success probability with small cell density.

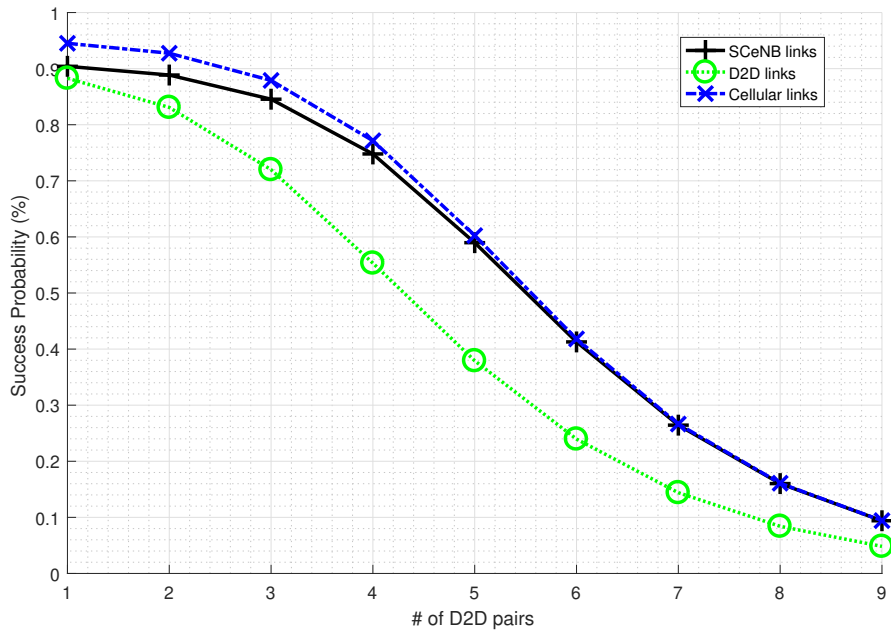


Figure 5.7: Success probability with D2D pairs density.

at lower small cell densities. Developing a test-bed measurement system for further validating the system's performance is suggested as future research work.

In Chapter 6, a machine learning-based resource allocation technique is developed to mitigate the interference for D2D communication in cellular HetNets.

Chapter 6

Machine Learning Based Resource Allocation for Interference Management in D2D-enabled Cellular HetNets

6.1 Introduction

In Chapter 5, the performance analysis model of a dynamic algorithm for D2D communication in cellular HetNets was discussed. This Chapter discusses the proposed deep Q-network-based deep reinforcement learning (DRL) algorithm for joint power control and resource allocation to mitigate interference in D2D-enabled cellular HetNets. Section 6.2 reviews the literature on interference management using both conventional and machine learning approaches in D2D-enabled heterogeneous cellular networks. Section 6.3 presents the system model, including the communication mode & transmission rate model, and problem formation. The proposed ML-based resource allocation model is discussed in Section 6.4 including RL and DRL-based algorithms. The analytical model and resource allocation algorithms are presented in this section. The system performance is evaluated in Section 6.5. The simulation results are also discussed in this section. A summary in Section 6.6 concludes the chapter.

Device-to-device (D2D) (D2D) communications are envisioned as a critical technology to support ubiquitous mobile communications in the future. However due to the

spectrum sharing among DUEs, between cellular users and DUEs, and high mobility of DUEs cause severe interference in the networks, which seriously constrains the performance improvement of D2D communications. Therefore, out of all the issues mentioned for the D2D-enabled cellular networks, interference management is the most important issue.

In any wireless communication, the resultant signal of a receiver device is always formed out of a desired signal along with undesired interference. To cancel this interference, an interference model is created and the estimated model of interference is subtracted from the resultant signal to derive only the desired signal. However, by using proper resource allocation interference can be reduced as well as avoided. In addition to interference mitigation, resource allocation also helps to improve the data rate, throughput and system sum rate of the wireless communication systems.

Different optimization problem approaches are formulated for resource management such as computation power minimization, sum-rate maximization, and latency minimization. In conventional methods, most of the formulated optimization problems for wireless resource management are strongly non-convex and exhibit non-deterministic polynomial time hardness (NP-hard). Moreover, the time complexity of the algorithm to obtain the optimal solution gets exponentially higher with the increasing number of users in the network. Therefore, with traditional optimization methods, it is difficult or impossible to optimize effectively the resource allocation problem which is modeled as a combination of an optimization problem with nonlinear constraints. Fortunately, deep reinforcement learning (DRL) has been proven to be effective in solving decision-making problems under uncertainty [88].

In this Chapter, to maximize throughputs for all users a joint resource allocation (resource block assignment, mode selection and transmit power control) problem in a D2D-enabled HetNets with a guaranteed minimum QoS requirement is formulated. To solve this NP-hard problem, a DQN-based deep reinforcement learning (DRL) algorithm

is proposed to optimize resource allocation for D2D communication. Obtained results show that higher system throughput is achieved with guaranteed quality of services (QoS) for all active users on the network.

6.2 Previous works on ML-based resource allocation

In a D2D-enabled heterogeneous cellular network, to manage interference the state-of-the-art researchers propose different methods, and their working principles as well as techniques are also different. Based on interference behavior all of them can be categorized as interference avoidance, interference cancellation and interference reduction. A rigorous literature review for resource allocation using a machine learning algorithm was presented in Section 3.3. A summary of the literature review on ML/DRL-based resource allocation is shown in Table 6.1.

As discussed, most of the state-of-the-art papers are focused on interference management in single or 2-tier cellular networks. Moreover, for interference management most of the researchers consider only one D2D pair and the effects of macro and multiple small cells are neglected. In 5G and beyond, ultra-dense networks (UDNs) will be deployed, and in practice, multiple CUEs will be associated with different cellular layers, and added D2D layers will create the most prominent challenge on minimizing interference [1]. Despite the prominent usage of D2D communications, there are very few works that address the MS as well as resource allocation for mutual interference problems in 3-tier cellular networks. Nonetheless, none of the authors considered the worst and at the same time, the most challenging interference scenario, where all 3 tiers of the networks (i.e. eNB, SCeNB and D2D communication) are mutually interfered including the effect of multiple SCeNBs and D2D pairs [1]. This is one of the main differences between the existing approaches and our proposal for managing interference in a 3-tier heterogeneous cellular network.

Table 6.1: Summary of related works on ML-based resource allocation

Reference	Main Contribution	Method	Limitation
[84], 2023	Energy efficient way to enhance convergence time and network performance.	RL-based algorithm.	Limited to a single cell and few D2D pairs.
[83], 2023	Improving network performance by efficient resource allocation.	Co-operative distributed RA algorithm.	Limited to co-channel interference.
[92], 2022	RL-based resource allocation scheme for multi-tier cellular HetNets.	RL-based approach	Not suitable for large network; high computational time.
[104], 2022	Deep learning framework for resource allocation in multi-channel cellular systems.	Deep neural network (DNN) approach	Depends on CSI availability
[99], 2022	Resource allocation using Deep neural network (DNN) in underlay cellular networks	DNN and heuristic approaches	QoS constraints are violated.
[43], 2021	Joint resource allocation and power control to maximize system performance.	DRL based ML algorithm	Limited scenarios considered.
[100], 2021	Double Deep Q-Network (DDQN) based resource allocation to maximize sum rate and energy efficiency.	DDQN approach	Focus on one-time slot only.
[101], 2021	Joint user association and resource allocation investigation for a D2D-enabled ultra-dense cellular networks.	Double-dueling-deep Q-network	Central controller in the network considered as an agent.
[102], 2021	DRL-based spectrum access scheme for D2D communication in underlay networks.	DDQN approach	Limited scenarios for resource re-usages.
[103], 2021	DRL-based Stackelberg game algorithm for power control & resource allocation.	Stackelberg game theory multi-agent DRL	Limited to uplink resources and centralised control.
[94], 2020	RNN-based resource allocation scheme in underlying cellular networks.	Recurrent neural network approach	DUEs already paired and limited to CSI availability.
Our work	We formulate a DQN-based joint resource allocation (resource block assignment, mode selection, and transmit power control) for D2D-enabled HetNets to overcome the limitations of the existing proposals.		

Table 6.1 reveals that DQN-based joint resource allocation (resource block assignment, mode selection and transmit power control) has not been explored yet. In this Chapter, we formulate a DQN-based joint resource allocation in a D2D-enabled HetNets cellular network with a guaranteed minimum QoS requirement for all users among all 3-tiers and maximize the throughput of the overall network.

6.3 System model and problem formulation

6.3.1 System model

In our analysis we have considered a 3-tier D2D-enabled cellular HetNet model which illustrated in Section 4.1 and Figure 1.1. In such a wireless network, a receiver can decode a message successfully if and only if the SINR at the receiver is greater than a specific threshold γ_{th} . If the SINR at the receiver does not meet γ_{th} , the link experiences an outage. So the outage probability of the x,y link can be expressed as:

$$P_{out} = P_r\{\gamma_y \leq \gamma_{th}\}$$

Let us consider e, s, i, j and k subscripts to denote the serving eNB, the serving SCeNB, the i_{th} CUE, the j_{th} D2D pairs and the k_{th} SUE, respectively. The subscripts t and r denote the transmitter and the receiver of the D2D pair respectively. In the context of the above-defined network where UL cellular resources are shared by D2D pairs and small cells, the mutual interference at different receivers can be expressed as:

$$I_i = \sum_{j=1}^{N_D} \zeta_{j,f} P_j h_{j,e} d_{j,e}^{-\alpha} + \sum_{k=1}^{N_S} \zeta_{k,f} P_k h_{k,e} d_{k,e}^{-\alpha} + N_0 \quad (6.1)$$

$$I_j = P_i h_{i,r} d_{i,r}^{-\alpha} + \sum_{j'=1, j' \neq j}^{N_D} \zeta_{j',f} P_{j'} h_{j',r} d_{j',r}^{-\alpha} + \sum_{k=1}^{N_S} \zeta_{k,f} P_k h_{k,r} d_{k,r}^{-\alpha} + N_0 \quad (6.2)$$

$$I_k = P_i h_{i,s} d_{i,s}^{-\alpha} + \sum_{j=1}^{N_D} \zeta_{j,f} P_j h_{j,s} d_{j,s}^{-\alpha} + \sum_{k'=1, k' \neq k}^{N_S} \zeta_{k',f} P_{k'} h_{k',s} d_{k',s}^{-\alpha} + N_0 \quad (6.3)$$

Where I_i is the combined interference received by eNB, I_j is the same for j_{th} D2D pairs receiver other than j_{th} transmitter and I_k is the same for all SUEs except k_{th} to the SCeNB. Binary variable $\psi_j^f \in \{0, 1\}$ indicates whether D2D users share the sub-channel f with cellular users. If D2D user reuses the spectrum resource of i_{th} CUE then, $\psi_j^f = 1$; otherwise $\psi_j^f = 0$. That is,

$$\psi_j^f = \begin{cases} 1, & \text{if sub-channel } f \text{ is shared } i_{th} \text{ CUE,} \\ 0, & \text{otherwise.} \end{cases}$$

Similarly,

$$\psi_k^f = \begin{cases} 1, & \text{if sub-channel } f \text{ is shared } i_{th} \text{ CUE,} \\ 0, & \text{otherwise.} \end{cases}$$

Where $\psi_k^f \in \{0, 1\}$ indicates whether small cell users share the sub-channel f with cellular users or not. Here the impact analysis of various factors on interference in a D2D-enable cellular network are limited to performance matrices of small cell and D2D pairs density, SINR and distances.

6.3.2 Cellular and D2D communication mode

Since communications may take place in any of the earlier mentioned 3 cases, according to Eq.4.2 and Eq.4.3 the uplink Signal to Interference Plus Noise Ratio (SINR) for the j_{th} D2D receiver and outage probability of the j_{th} D2D link are given by Eq.6.4 and Eq.6.5 respectively [1]:

$$\gamma_j^D = \frac{P_j h_{t,r} d_{t,r}^{-\alpha}}{I_j} = \frac{P_j h_{t,r} d_{t,r}^{-\alpha}}{P_i h_{i,r} d_{i,r}^{-\alpha} + \sum_{j'=1, j' \neq j}^{N_D} \zeta_{j',f} P_{j'} h_{j',r} d_{j',r}^{-\alpha} + \sum_{k=1}^{N_S} \zeta_{k,f} P_k h_{k,r} d_{k,r}^{-\alpha} + N_0} \quad (6.4)$$

$$P_{out,j}^D = 1 - \delta_D \exp(-\beta_D (P_j^m \lambda_d + P_k^m \lambda_s)) \quad (6.5)$$

Where γ_{th} is the required SINR threshold at the receiver for effective D2D communication, $P_{out,j}^D$ the outage probability of the j th D2D link, $\delta_D = \exp\left(\frac{-N_0 \gamma_{th} d_{t,r}^\alpha}{P_j}\right) \left(\frac{P_j d_{i,r}^\alpha}{P_i \gamma_{th} d_{t,r}^\alpha + P_j d_{i,r}^\alpha}\right)$, $\kappa = \pi m \Gamma(m) \Gamma(1-m)$, $\beta_D = \kappa \gamma_{th}^m d_{t,r}^2 / P_j^m$, λ_d is density of DUEs for D2D pairs, λ_s is density of small cells and the proof of the above equation can be referred to Appendix A in [131].

From the above expression, it's clearly visible that the outage probability of D2D links depends on various factors such as path loss coefficient, required SINR, distances between UEs, transmission powers, small cell and D2D pairs density. Outage probability increases with increasing required SINR but decreases while the distance between SUEs and the D2D receiver is increased.

Similarly, in the case of macro cellular communications mode where UE is served by eNB, the SINR at the receiver i can be expressed as [1]:

$$\gamma_i^M = \frac{P_i h_{i,e} d_{i,e}^{-\alpha}}{I_i} = \frac{P_i h_{i,e} d_{i,e}^{-\alpha}}{P_i h_{i,r} d_{i,r}^{-\alpha} + \sum_{j'=1, j' \neq j}^{N_D} \zeta_{j',f} P_{j'} h_{j',r} d_{j',r}^{-\alpha} + \sum_{k=1}^{N_S} \zeta_{k,f} P_k h_{k,r} d_{k,r}^{-\alpha} + N_0} \quad (6.6)$$

The outage probability of the macro cell link can be written as:

$$P_{out,i}^M = 1 - \delta_M \exp(-\beta_M (P_j^m \lambda_d + P_k^m \lambda_s)) \quad (6.7)$$

Where γ_{th} is the required SINR for i th CUE for effective cellular communication, $\delta_M = \exp\left(-\frac{N_0 \gamma_{th}^m d_{i,e}^\alpha}{P_i}\right)$, $\kappa = \pi m \Gamma(m) \Gamma(1-m)$ and $\beta_M = \frac{\kappa \gamma_{th}^m d_{i,e}^2}{P_i^m}$. Hence the outage

probability decreases with increasing distances between SUEs, and UEs as well as UEs and D2D transmitters.

For small cell mode communications, UE is served by small cell SCeNB, and the link between SUE and SCeNB will be interfered with by other SCeNBs, D2D pairs and macro eNB. Therefore, the SINR at the small cell receiver can be written as

$$\gamma_k^S = \frac{(P_k h_{k,s} d_{k,k}^{-\alpha})}{I_k} = \frac{(P_k h_{k,s} d_{k,k}^{-\alpha})}{P_i h_{i,s} d_{i,s}^{-\alpha} + \sum_{j=1}^{N_D} \zeta_{j,f} P_j h_{j,s} d_{j,s}^{-\alpha} + \sum_{k'=1, k' \neq k}^{N_S} \zeta_{k',f} P_{k'} h_{k',s} d_{k',s}^{-\alpha} + N_0} \quad (6.8)$$

and the outage probability of the small cell link can be expressed as

$$P_{out,k}^S = 1 - \delta_S \exp(-\beta_S (P_j^m \lambda_d + P_{k'}^m \lambda_s)) \quad (6.9)$$

Where $\delta_S = \left(\frac{P_k d_{k,e}^{-\alpha}}{P_i \gamma_{th} d_{k,s}^{-\alpha} + P_k d_{k,e}^{-\alpha}} \right) \exp\left(-\frac{N_0 \gamma_{th} d_{k,s}^{-\alpha}}{P_k}\right)$, $\kappa = \pi m \Gamma(m) \Gamma(1-m)$ and $\beta_S = \frac{\kappa \gamma_{th}^m d_{k,s}^2}{P_k^m}$, and $I_{s'}$ is interference from all SCeNBs except respective small cell links.

According to the above expressions of outage probabilities, it is easily visible that the intensity of interference (i.e probabilities of success) depends on the density of small cells and D2D pairs, the distances between the receiver and transmitter of that links, required SINR threshold and transmission powers. Increasing DUE receiver distances from CUEs or SUEs will increase the success of the probability for D2D links. Similarly increasing distances between D2D transmitter and CUEs or SUEs will decrease the outage probability of SCeNB links [1].

6.3.3 Transmission rate

The achievable data rate is directly affected by the signal-to-interference-plus-noise ratio (SINR). Therefore, according to the Shannon capacity formula, the achievable data

rate i_{th} CUE, J_{th} D2D pairs and k_{th} SUE link over the subcarrier, f can be expressed as:

$$R_i = B \log_2(1 + \gamma_i^M). \quad (6.10)$$

$$R_j = B \log_2(1 + \gamma_j^D). \quad (6.11)$$

$$R_k = B \log_2(1 + \gamma_k^S). \quad (6.12)$$

Therefore, the total throughput of the entire network will be as follows

$$R_{total} = \sum_{i=1}^C R_i + \sum_{j=1}^D R_j + \sum_{k=1}^S R_k \quad (6.13)$$

6.3.4 Problem formulation

In such a D2D-enabled HetNet, multiple DUEs and SUEs may cause mutual interference while reusing the same cellular resources. Therefore, our goal is to maximize the overall system throughput under maximum transmit power and minimum QoS requirements of all users. Therefore, the objective function and constraints for mode selection, resource allocation and power control of resource management issues among cellular users, small cell users and D2D users can be formulated mathematically as follows:

$$\mathcal{P}1: \max_{\psi_j^f, \psi_k^f, \psi_j^D, P_i^C, P_j^D, P_k^S} R = \sum_{i \in C} \left[B \log_2(1 + \gamma_i^M) + \sum_{j \in D} \psi_j^f B \log_2(1 + \gamma_j^D) + \sum_{k \in S} \psi_k^f B \log_2(1 + \gamma_k^S) \right] \quad (6.14)$$

s.t.

$$C1: \gamma_i^M \geq \gamma_{i,th}^M, \quad \forall i \in C \quad (6.14a)$$

$$C2: \gamma_j^D \geq \gamma_{j,th}^D, \quad \forall j \in D \quad (6.14b)$$

$$C3: \gamma_k^S \geq \gamma_{k,th}^S, \quad \forall k \in S \quad (6.14c)$$

$$C4: 0 \leq P_i^C \leq P_{\max}^C, \quad \forall i \in C \quad (6.14d)$$

$$C5: 0 \leq P_j^D \leq P_{\max}^D, \quad \forall j \in D \quad (6.14e)$$

$$C6: 0 \leq P_k^S \leq P_{\max}^S, \quad \forall k \in S \quad (6.14f)$$

$$C7: \sum_{i \in C} \psi_j^f \leq 1, \quad \psi_j^f \in \{0, 1\}, \quad \forall j \in D \quad (6.14g)$$

$$C8: \sum_{i \in C} \psi_k^f \leq 1, \quad \psi_k^f \in \{0, 1\}, \quad \forall k \in S \quad (6.14h)$$

Where $\gamma_{i,th}^C$, $\gamma_{j,th}^D$ and $\gamma_{k,th}^S$ are the minimum SINR requirements for the CUE, D2D pair and SUE communication links respectively. ψ_i^f , ψ_j^f and ψ_k^f are mode selection indicators cellular user, D2D pairs and small cell communication respectively. $\psi_j^f = \psi_k^f = 1$ when D2D pairs or SUE user reuse the i_{th} CUE resources, otherwise $\psi_j^f = \psi_k^f = 0$. Constraints 6.14a, 6.14b, and 6.14c represent QoS requirements of CUEs, DUEs and SUEs respectively. However, constraints (6.14g and 6.14h ensure that DUES or SUES can reuse at most one existing CUE's resource. Finally, 6.14d, 6.14e, and 6.14f constraints make sure that the transmit power of CUEs, DUEs and SUEs will be within the maximum limit.

6.4 ML-based resource allocation

Wireless resource allocation techniques can be classified as traditional and learning-based algorithms. Figure 6.1 represents the various wireless resource allocation optimization strategies. The above-formulated problem $\mathcal{P}1$ is obviously an integer nonlinear programming problem, which is Non-deterministic Polynomial (NP)-hard and difficult to optimize with polynomial time complexity [133]. To address such joint optimization problems by using conventional methods, the original problem is divided into multiple sub-problems, and they are solved individually. However, these methods usually require accurate environmental information, such as channel state information (CSI), which is not feasible in dynamic wireless networks. In our analysis, we have considered a 3-tier D2D-enabled cellular HetNet which is dynamic and complex in nature. The complexity to obtain optimal solution for such a problem gets exponentially higher with increasing the users into the network. So, it is very difficult or impossible to solve such an optimization problem with conventional method, especially when we are considering 3-tiers dynamic wireless network with large number of users. Thanks to ML techniques for its recent advancement to provide near optimal solution for this type of problems with lower computational complexity. To solve the above problem $\mathcal{P}1$, we propose a machine learning algorithm based on deep reinforcement learning (DRL) algorithms which is a combination of reinforcement learning (RL) and deep learning (DL).

In DRL, sequential decision-making is addressed by minimizing a reward function by interacting with the unknown environment in each layer of application. Combining DNN with Q-learning also known as DQN improves the learning performance and learning speed significantly [134]. The most recent advantage of DRL can achieve the near-optimal solution of a sophisticated network optimization problem by solving non-convex and complex problems like joint user association, computation, transmission

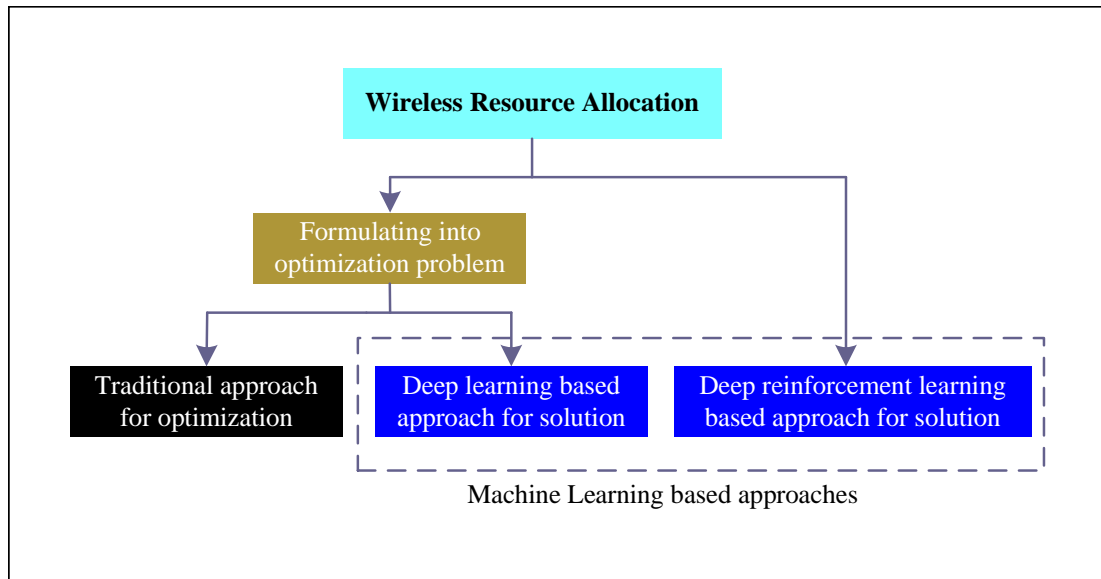


Figure 6.1: DQN framework for D2D-enabled cellular network

power control, and resource allocation without knowing the complete and accurate network information. Interacting with the environment, a DRL Agent can obtain the best policy locally with minimum or without information exchange among each other which significantly reduces communication overheads. This algorithm doesn't require many datasets for training itself [135], hence DRL is suitable for the dynamic environment characteristics in 5G and B5G networks where the number of users is very large and the network is highly complex.

6.4.1 Machine learning approach

Machine learning and DL techniques are important techniques that promise an automatic resource allocation and decision-making process [136] and overcome the limitations of existing/traditional resource allocation methods. Machine Learning is an application of Artificial Intelligence that allows the devices to learn, implement, and improve results automatically without being explicitly programmed [137]. There are two phases in an ML approach: a) the training phase where the system model is trained up or

learned through the training data and b) the decision phase in which an estimated output is generated for each new input based on the trained model [138]. Depending on how the learning is achieved, Machine Learning algorithms are simply classified as Supervised, Unsupervised and Reinforcement learning [139]. Supervised learning consists of labelled examples or training samples while unsupervised learning has neither classified nor training samples. Whereas a reinforcement learning method interacts with its environment, learns from the previous actions, produces actions, finds out the errors and finally gets rewards. In other words, it is a trial-and-error method that produces an efficient outcome.

Supervised Learning is based on a dataset with values accompanied by their respective labels. Usually, a dataset is split into a training and a test set, where the first one is used for model training and the former term refers to the prediction of a target numerical values, given a set of features/attributes, also called as predictor, through the trained estimation function. Regression, Support Vector Machines (SVM), Decision Trees (DT), Neural Networks (NN), K-Nearest Neighbor (K-NN) are the most common supervised learning techniques.

Unlike supervised learning, an Unsupervised Learning model itself tries to identify the common characteristics of the dataset [140]. The aim of unsupervised learning algorithms is to discover patterns, structures or information from unlabeled input sequences without external help. K-means clustering, the Gaussian mixture models (GMMs) and Self Organizing Maps (SOM) are the most important techniques in unsupervised learning [138, 136].

Finally, Reinforcement Learning uses a learning entity, often called an agent which acts as a representative of the system to collaborate with the environment. The agent returns feedback to the model as rewards or penalties by which it creates a policy to set up its own learning scheme and decides which action to choose in a certain situation. Maximizing the rewards over time is the main aim of an RL algorithm [141]. In RL, the

agent is not told what actions to be performed (unlike other ML techniques). Instead, the agent is expected to discover optimal strategies by experimenting with actions that will provide the most rewards. The RL system consists of four main elements: a policy, a reward signal, a value function, and an environment model.

6.4.2 Deep learning approach

Deep learning (DL) also known as deep network is a part of machine learning where several layers of a neural network are used to mimic the behavior of the human brain. Artificial neural network (ANN), recurrent neural network (RNN), long short-term memory (LSTM), convolutional neural network (CNN), deep neural network (DNN) etc. are the different existing DL algorithms.

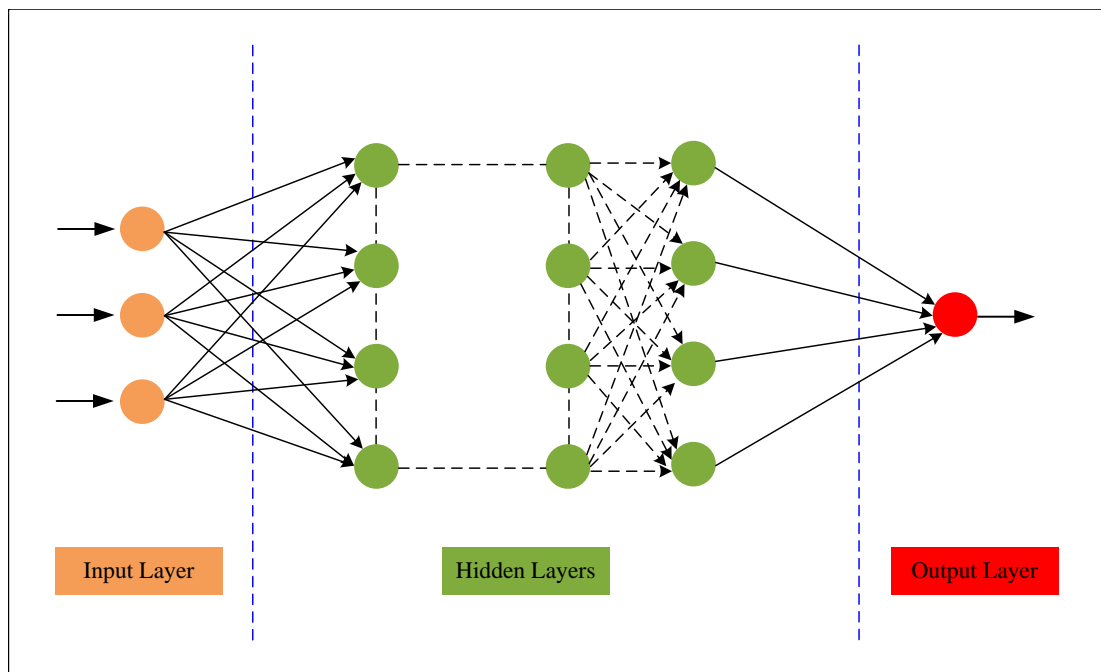


Figure 6.2: Deep learning network model in ML

A fully connected deep network model is illustrated in Figure 6.2 which comprises an input layer, hidden layers, and an output layer. Each layer is made up of several neurons. The number of neuron cells in each layer and the number of hidden layers

are varied based on different applications. One of the common and most widely used algorithms in the field of deep learning is DNN which is a collection of computational functions and an activation matrix that significantly improves the computational efficiency and provides better accuracy [142]. The output of each neuron can be input for other neurons, and each neuron activates its output when the input meets certain conditions [143]. In this way, the output of each layer is determined by the multiplication of input, weights, and the addition of a bias.

In resource allocation for a wireless communication system, DL-based resource allocation schemes have multiple benefits such as the capability to achieve near-optimal performance without solving the complicated optimization problem explicitly [144, 145], more flexibility compared to conventional approaches as the same DNNs can be used by simply changing the loss function [146], and lower computational time as DNNs perform only simple matrix operations [144, 146]. To solve our formulated optimization problem, we propose a DQN-based DL algorithm.

6.4.3 Reinforcement learning approach

Reinforcement learning (RL) is an adaptable machine learning algorithm that learns the optimal decision-making policy in a dynamic environment with the absence of a training dataset [147] by using a trial-and-error process. Thus, it automatically adapts to the new environment. In RL, the decision maker is called an agent.

In wireless communication systems under dynamic and unknown network conditions, Markov Decision Processes (MDP) are widely used as optimization tools. In an RL framework, MDP provides a mathematical model in the decision-making process which is used to interact between the agent and the environment for optimal strategies. In this process, in a particular state, 's' at a time, 't' an optimal action, 'a' for that state is selected by the agent. By executing an action, the agent receives some reward based

on the outcome of the action in that state and the process randomly moves into a new state, s' based on state transition probability.

Figure 6.3 is a basic RL framework that consists of an agent, environment, action, state, reward and other basic elements for a D2D-enabled cellular network. The different components of the learning algorithm are described as follows:

AGENT: All the transmitters in D2D pairs that are responsible for resource allocation are the agents. For each communication link, an agent learns and makes decisions by interacting with the environment. In MDP, Agent, j determines the appropriate communication modes and optimum resource blocks (RB) from a list of available resources under different network states.

STATE: To determine the states for a particular timeslot, t , a learning Agent relies on the environmental conditions. The state observed by the Agent, ' j ' can be given as:

$$s_j = (A_{RB}, A_{CSI}, A_{QoS}) \in S \quad (6.15)$$

Where A_{CSI} shows the observed channel information, A_{RB} denotes all RBs occupy status among users, and A_{QoS} indicates the requirements of QoS (e.g., the latency, the minimum data rate, and the reliability requirements etc.) for all users.

ACTION: In a D2D-enabled HetNet, the Agent has three modes and a certain number of resource blocks available for communication. The Agent will take the action according to the current state s_j , after making a decision in terms of mode selection, transmit power control and the appropriate RB allocation. So, the action of an Agent a_j can be defined as :

$$a_j = (A_{MS}, A_{PC}, A_{RB}) \in A. \quad (6.16)$$

The Agent will take the action $a_j \in A$ according to the current state s_j , after making a decision in terms of the mode selection, A_{MS} transmit power control, A_{PC} and the RB assignment A_{RB} .

TRANSITION PROBABILITY:

Transition probability describes the changes in the environmental status during the interactions with the agent. For example, in a time slot, t and state, s the Agent executes an action, a and gains a reward, r . The probability that the Agent moves to the next state, s' at time, $t+1$ is defined by the transition probability, $P(s'|s, a)$ i.e the transition probability $P(s'|s, a)$, is the probability when the Agent takes the action $a \in A$ from the state $s \in S$ and move into a new state $s' \in S$ [148]. Therefore,

$$P(s'|s, a) = \begin{cases} 1, & s' = state(a), \\ 0, & otherwise. \end{cases} \quad (6.17)$$

REWARD:

The reward function in RL is designed based on the formulated problem's objective. Each agent makes a joint decision of mode selection, power control and resource allocation to maximize the system sum rate. Therefore, the reward of the Agent, 'j' can be defined as:

$$R_j(s, a) = \begin{cases} R_j^D, & \text{if conditions C2, C5 and C7 are met,} \\ -1, & \text{otherwise.} \end{cases}$$

POLICY: The decision-making rule of the Agent is defined by the Policy π . The strategy of the Agent taking an action, a in a state s is represented by policy $\pi(s, a)$, where we have $a \in A$, $s \in S$, and $\sum_{a \in A} \pi(s, a) = 1, \forall s \in S$.

In the RL-based scheme for the given network, the D2D pair acts as an agent that

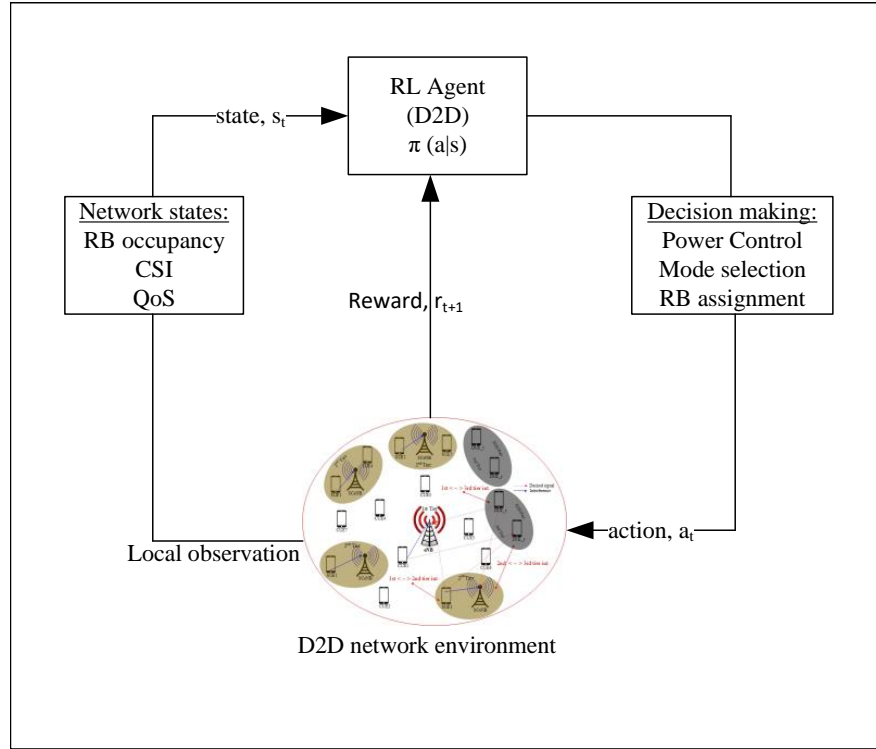


Figure 6.3: Agent-environment interaction in RL D2D-enabled cellular network

interacts with the environment, generates trajectory, and moves into a new state $s \rightarrow s'$ by executing an action a . As a result of each action, the agent will receive a reward, r from the environment. In other words, in an RL-based D2D-enabled network, each j^{th} agent follows as: i) monitors its current environment using the environment state $s \in S$; ii) selects one of the targeted valuable action $a \in A$; iii) performs an action, a and gets an instant reward, r from the environment; and iv) moves into a new state $s' \in S$. If the reward is only based on current state and action, and it's not affected by any previous state and action, then j^{th} agents satisfy the Markov property and can be defined as MDP consisting of i) discrete set of environment states S_j , ii) a discrete set of possible actions A_j and iii) the probability of state transition for environment-specific time slot, $P_r(s'|s) = P_r(s', a, s)$, where $\forall a_j \in A_j$ and $\forall s_j \in S_j$.

To determine the optimal action of a system, one of the most common algorithms used in the field of RL is Q-learning which consists of Agents, A and State, S . Figure

6.3 represents the Agent-environment interaction in an RL-based network. The main objective is to maximise the number of acquired rewards which is represented by the Q-function. The Agent explores various actions in different states and updates the Q-value given by [149, 150].

To solve the above MDPs problem smoothly, we define the state-value function

Algorithm 4: RL-based resource allocation

```

1 Input: D2D-enabled HetNets cellular network environment parameters, and
   minimum SINR requirements for D2D pairs, SUEs and CUEs;
2 Output: Power control and resource allocation using RL algorithm n
   D2D-enabled HetNets according to optimal allocation policy
    $\pi^*(s_t) = \arg \max_a Q(s_t, a_t)$ ;
3 Initialization: Initialize the storing Q-value function for the state-action pairs;
4 Initialization: For all available actions in the selected current state  $s_t$ , select the
   action  $a_t$  for maximizing the Q-value function according to the  $\epsilon - greedy$ 
   strategy to obtain  $r_t$ ;
5 for each  $s \in S$ , each  $a \in A$  do
6   for episode  $e = 1, 2, 3, \dots, E$  do
7     Initialize the current state  $s_t$  at time t in the D2D-enable HetNets
       Cellular network environment;
8     for steps  $t = 1, 2, 3, \dots, T$  do
9       The Agent (D2D pairs) takes action  $a_t$  based on  $\epsilon - greedy$  strategy
       to obtain to obtain  $r_t$ ;
10      Take action  $a_t$  and move into the next state  $s_{t+1}$  of the environment;
11      Store the experience  $(s_t, a_t, r_t, s_{t+1})$  into the memory D.
12      Update the target network by (Equation 6.20)
13      Update states and actions  $s_t \leftarrow s_{t+1}$  and  $a_t \leftarrow a_{t+1}$  until all  $Q(s_t, a_t)$ 
       converge
14     End for
15   End for
16 End for

```

$V^\pi(s)$ and the action-value function $Q^\pi(s, a)$ for $a \in A$ and $s \in S$ as follows.

$$\begin{aligned} V^\pi(s) &= \mathbb{E}^\pi \left[\sum_{t=0}^{\infty} \eta^t r(t) | s_0 = s \right] \\ &= \mathbb{E}^\pi [r(t) + \eta V(s') | s' = s] \end{aligned} \quad (6.18a)$$

$$\begin{aligned} Q^\pi(s, a) &= \mathbb{E}^\pi \left[\sum_{t=0}^{\infty} \eta^t r(t) | s_0 = s, a_0 = a \right] \\ &= \mathbb{E}^\pi [r(t) + \eta Q(s', a')] \\ &= r(s, a) + \eta \sum_{s' \in S} p(s'|s, a) \sum_{a'} \pi(a'|s') Q(s', a') \end{aligned} \quad (6.18b)$$

Where $\eta \in (0, 1)$ and $r(s, a)$ represent the discount factor and immediate reward respectively. $p(s'|s, a)$ and policy π represent transition probability and environment state, s mapping while action, a is executed respectively. Since the state and action value functions determine the sum of the agent's expected future rewards, these rewards can be obtained from each state and action on every possible strategy. Therefore, at equilibrium, there is always a maximum of state-value and action-value functions and the optimal policy π^* and Eq.6.18a & Eq.6.18b can be converted as

$$\begin{aligned} V^*(s) &= \max_{\pi} V^\pi(s) \\ &= \mathbb{E}^\pi \left[\sum_{t=0}^{\infty} \eta^t r(t)(s, a, s') | s_0 = s, \pi \right] \end{aligned} \quad (6.19a)$$

$$\begin{aligned}
Q^*(s, a) &= \max_{\pi} Q^{\pi}(s, a) \\
&= r(t) + \eta \arg \max_{a'} Q^*(s', a') \\
&= r(s, a) + \eta \sum_{s' \in S} p(s'|s, a) \max_{a'} Q^*(s', a') \tag{6.19b}
\end{aligned}$$

Thus π^* is obtained by $\pi^*(s) = \arg \max_a Q^*(s, a)$. Since transition probabilities are unavailable to the agent, we cannot derive Q^* and π^* from Eq.6.19b. But by using the Q-learning algorithm we can obtain them in an iterative manner where the RL agent continuously updates the Q-values and takes a new action to interact with the environment. Therefore, the updated Q-value functions can be expressed as

$$Q^*(s, a) \leftarrow Q(s, a) + \mu \left[(r + \eta \max_{a'} Q(s', a') - Q(s, a)) \right] \tag{6.20}$$

Where $Q^*(s, a)$ and $Q(s, a)$ are the new Q value and old Q value respectively, μ is the learning rate and the term $\max_{a'} Q(s', a')$ is the target.

As the objective of the Agent is to learn the strategy for maximising the rewards, the action is selected based on QoS i.e. SINR threshold, RB availability and data rates. The actions that meet the constraints are rewarded otherwise negatively rewarded. Under dynamic network conditions, the Agent automatically learns and adapts to the newer situation with the objectives of meeting the constraints C2, C5 and C7 and maximising the throughput. Algorithm 4 represents the resource allocation and power control in a D2D-enabled cellular network using an RL-based algorithm.

For learning state-action value functions, Q-learning is a classical algorithm in RL. For a large state and action spaces, the state of the environment is complex and dynamic. In such a situation it is not feasible for a Q-learning algorithm to use the Q-table to store all state-action values. DRL is one of the algorithms which is used to overcome

this issue.

6.4.4 Deep reinforcement learning approach

Deep reinforcement learning (DRL) is a computational approach to learning from an action and Deep Q-learning is one of the most common algorithms used in the field of DRL. DRL is the fusion of DL and RL algorithms where the Agent learns the best actions in the virtual environment to attain its goal. To overcome the issues in a large, complex and dynamic environment, DRL uses a deep Q-network (DQN) algorithm that utilizes neural network models to predict the next appropriate action. Hence, RL can further be classified as a model-based method like deep-Q-Networks and as a model-free method such as Q-Learning, State action reward state action (SARSA). The DQN algorithm uses a DNN to estimate $Q(s, a)$ instead of calculating the Q-value for each state-action pair used in the Q-learning method.

The DQN flowchart is described in Figure 6.4 where DQN uses a DNN with weight θ for an action-value function network model $Q(s, a; \theta)$ and another DNN with weight θ' for the target network model $Q(s, a; \theta')$. Here, θ and θ' are the parameters of the present and previous iterations respectively. With each iteration, the present iteration parameter θ' of the action-state function is updated. The objective of a DQN algorithm is to minimize a loss function $L(\theta)$ given by [149] as follows:

$$L(\theta) = \mathbb{E} \left[(y_t^{tar} - Q(s, a; \theta))^2 \right] \quad (6.21a)$$

Here y_t^{tar} is the target Q-value and it can be estimated by

$$y_t^{tar} = r_{t+1} + \eta \max_a Q(s', a; \theta') \quad (6.21b)$$

Where $a = \operatorname{argmax}_a Q(s', a; \theta)$ and θ' will be updated by θ after every certain

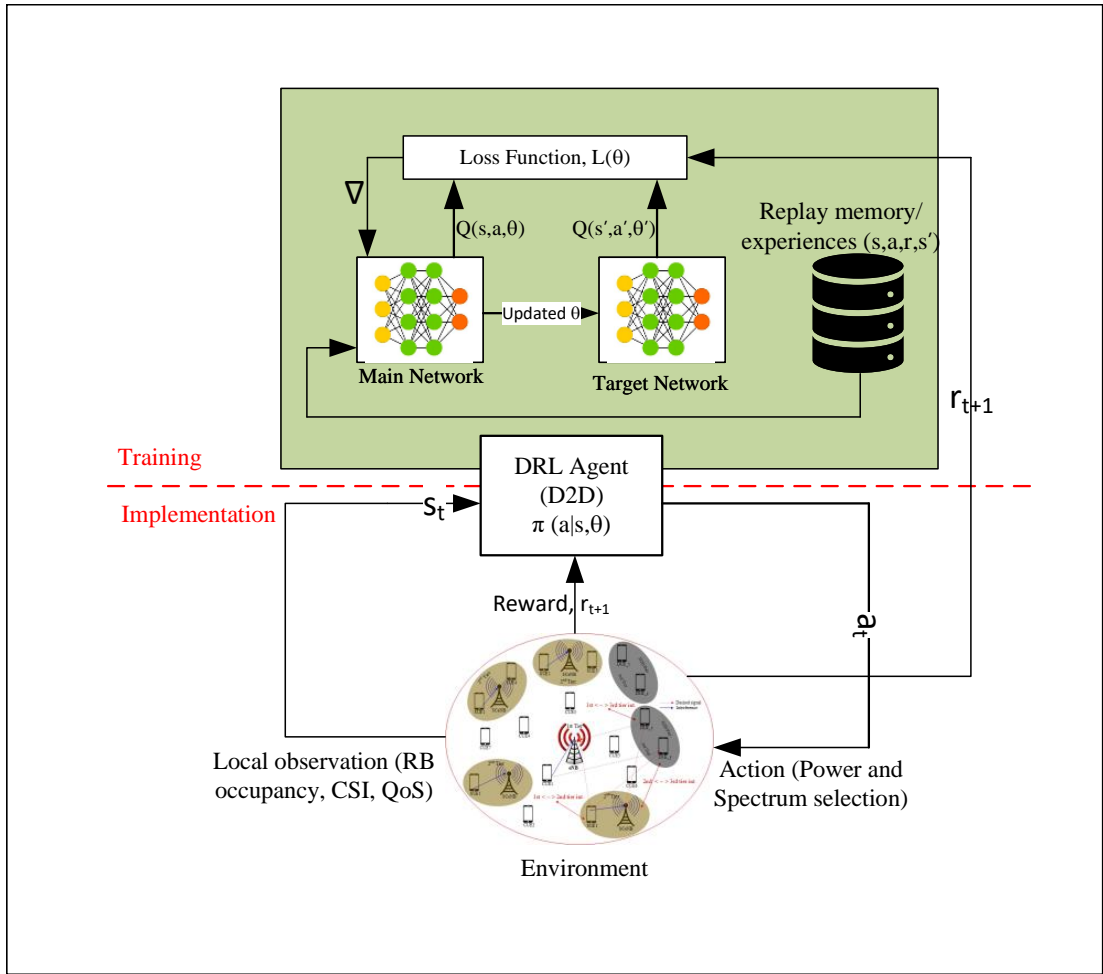


Figure 6.4: DQN framework for D2D-enabled cellular network

training steps.

To obtain the optimal value weights θ^* and corresponding Q-values, DRL adopts an interactive process like the Q-learning algorithm. In DQN, the Agent uses an ϵ -greedy strategy and interacts with the environment to receive a new experience. In each training period of DQN, by using the ϵ -greedy strategy the Agent will select the next action, a from $Q(s, a; \theta)$, then obtain the immediate reward r_t and move into the new state s_{t+1} of the next time-slot, and finally store the quadruple information (s_t, a_t, r_t, s_{t+1}) in replay memory. When network training is required, the agent reuses these sample experiences data stored in the replay memory to improve the convergence speed and stability of the

Algorithm 5: DRL-based resource allocation in D2D-enabled cellular network

```
1 Input: D2D-enabled HetNets cellular network environment parameters, and
   minimum SINR requirements for D2D pairs, SUEs and CUEs;
2 Output: DQN/RL model training and decision results in the testing phase.;
3 Output: Resource allocation and power control;
4 Initialization: Initialize the DNN parameters of the main network and target
   network randomly as  $\theta$  and  $\theta'$  respectively. Set  $\theta = \theta'$  ;
5 for ( $cue = 1; cue \leq N_C; cue ++$ ) do
6   | Resource allocation for Cellular users ie CUEs ;
7 for ( $sue = 1; sue \leq N_S; sue ++$ ) do
8   | if Check cellular resource reuse status for SCell ie SUEs then
9     | Reused for SCell
10  | else
11  | for ( $due = 1; due \leq N_D; due ++$ ) do
12  |   for episode  $e = 1, 2, 3, \dots, E$  do
13  |     Initialize the current state  $s_t$  at time t in the D2D-enabled HetNets
14  |     Cellular network environment;
15  |     for steps  $t = 1, 2, 3, \dots, T$  do
16  |       The Agent (D2D pairs) takes action  $a_t$  based on  $\epsilon - greedy$ 
17  |       strategy to obtain to obtain  $r_t$ ;
18  |       Compute the SINR using Eq.( 6.4)
19  |       Compute transmission power using Eq.( 6.5)
20  |       Take action  $a_t$  and move into the next state  $s_{t+1}$ ;
21  |       Store the experience  $(s_t, a_t, r_t, s_{t+1})$  into the memory D.
22  |       Uniformly and randomly samples H historical experience
23  |       information from the memory D.
24  |       Use gradient descent to minimize
25  |        $L(\theta) = \frac{1}{H} \sum_{e \in E} [y_t - Q(s, a; \theta)]^2$ .
26  |       Compute  $\theta$  using Eq.( 6.22) and update  $\theta$ .
27  |       Update the target network by Eq.( 6.21a).
28  |     End for
29  |   End for
30  | End for
31 End for
```

algorithm. After every iteration, the main DNN parameters θ of the network model in the action-value function are synchronized to the target network, and it's represented by

$$\theta \leftarrow \theta' + \tau \nabla L(\theta) \quad (6.22)$$

Where $\tau \in (0, 1)$ is the learning rate, ∇ is the gradient descent [150]. Algorithm 5 represents the resource allocation and power control in a D2D-enabled cellular network using a DQN-based DRL algorithm.

By repeating the above procedure until the convergence of the weights θ , the DRL agent can obtain the optimal policy. Once the convergence is achieved, it means DQN is well-trained to learn the patterns of the environment and it is capable of handling the environmental states that did not appear before. Thus, in practical implementations, to reduce overheads training will be turned off after the convergence. Hence, by using the well-trained DQN, each agent can make proper decisions to maintain high performance without further training.

6.4.5 Computational complexity

For any algorithm, complexity is defined as the amount of time taken to run it as a function of the size of the input. From algorithm 2 we can see that DNN parameters of DQN algorithm is converged into a stable state after E iterations and T time slots. The time complexity of our DNN model is determined by the number of input state-action, the number of layers in neural network and the number of neurons used in each layer. Let us consider that the deep neural network is fully connected and there are L layers in our DNN including input and out layers. In our analysis we have considered one eNB and multiples SCeNB as well as D2D pairs. Let us assume the number of neurons for s^{th} layer for small cell communication is m_s . Therefore, the computational complexity for S layers in small cells can be expressed as:

$$\mathcal{O}\left(\sum_{s=0}^{S-2}(m_{s-1}m_s + m_sm_{s+1})\right) \quad (6.22)$$

Similarly, for D2D communication in l_{th} layer, let us assume the number of neuron is n_d . The computational complexity for D2D layers is

$$\mathcal{O}\left(\sum_{d=0}^{L-1}(n_{d-1}n_d + n_dn_{d+1})\right) \quad (6.23)$$

So, the computation complexity for overall training process considering all 3-tiers simultaneously is as follows:

$$\mathcal{O}\left(m^{in}m_s^1 + ET\left(\sum_{s=0}^{S-2}(m_{s-1}m_s + m_sm_{s+1})\right) \cdot \left(\sum_{d=0}^{L-1}(n_{d-1}n_d + n_dn_{d+1})\right) + m_s^S m^{out}\right) \quad (6.24)$$

Therefore, the computational time complexity of our proposed algorithm increases in a multiplicative manner with the increasing number of D2D pairs as well as small cells which makes it suitable for a large and dynamic D2D-enabled cellular HetNet.

6.5 Performance evaluation

6.5.1 Simulation environment and parameters

Our proposed system model is validated using MATLAB-based simulation. In our proposed model, a DRL-based learning algorithm is trained by its agent i.e. DUEs instead of training eNBs/SCeNBs which help to make better coordination between network elements. In our simulation setup, we consider a single eNB with a 500m cell radius located at the centre of a D2D-enabled HetNet where CUEs are randomly

distributed. DUEs and SUEs are realized according to two independent PPPs with densities of λ_d and λ_s respectively. We assume that one RB has been reused by multiple D2D pairs and SUEs which are already occupied by one CUE. Therefore, the number of CUEs is selected equal to the number of RBs. For large-scale fading and small-scale fading, we have considered log-normal and exponential distributions respectively.

The DQN training model is based on a fully connected neural network and for quicker decision-making of each agent, we have considered a relatively small neural network with one input layer, three hidden layers and one output layer. The hidden layers have 200, 100 and 50 neurons respectively. DQN is trained with stochastic gradient descent with a batch size of 32. In addition, θ' is updated with θ in every 20 time steps. Table-6.2 represents the list of parameters used in the network as well as DRL simulations for a D2D-enabled cellular HetNet.

Table 6.2: Parameters used in the simulation

Simulation Parameter	Value
Cell Radius	500 m
Intensity of SCeNBs, λ_s	10^{-5}
Intensity of DUES, λ_d	10^{-3}
Maximum transmission power of CUEs, P_i	23 (dBm)
Maximum transmission power of DUEs, P_j	10-20 (dBm)
Maximum transmission power of SUEs, P_k	10-20 (dBm)
Path loss exponent, α	3 and 4
SINR threshold for CUE, SUE and DUE, γ_{th}	8 dB
Noise power, N_0	-118 dBm
Shadowing standard deviation	8 dB
RB Bandwidth, B	180KHz
Learning rate, τ	0.01
Discount factor, η	0.9
ϵ -greedy	0.1
Replay memory capacity, D	2000
Mini-batch size	32
Number of steps in each epoch	20

6.5.2 Results and discussion

We measure the sum throughput of all DUEs for various conditions and outputs. Figure 6.5 shows the relationship between the sum throughput of DUEs/CUEs and the number of active users in the system. With the increase in the number of users, D2D pairs i.e. DUEs also increase at the same time and that leads to an increase in the sum throughput of DUEs. But with the increases of DUEs, it also introduces more and more interference between DUEs and CUEs link which decreases the sum throughput of CUEs as seen in figure 6.6. From the output results, we can clearly see that the proposed DRL scheme is much better compared to other schemes even maximizing their performance by setting power flexibility in optimized power schemes. The proposed DRL scheme can mitigate interference efficiently and achieve a higher sum throughput of DUEs. For instance, when the number of DUEs is 50, the proposed DRL scheme achieves 10%

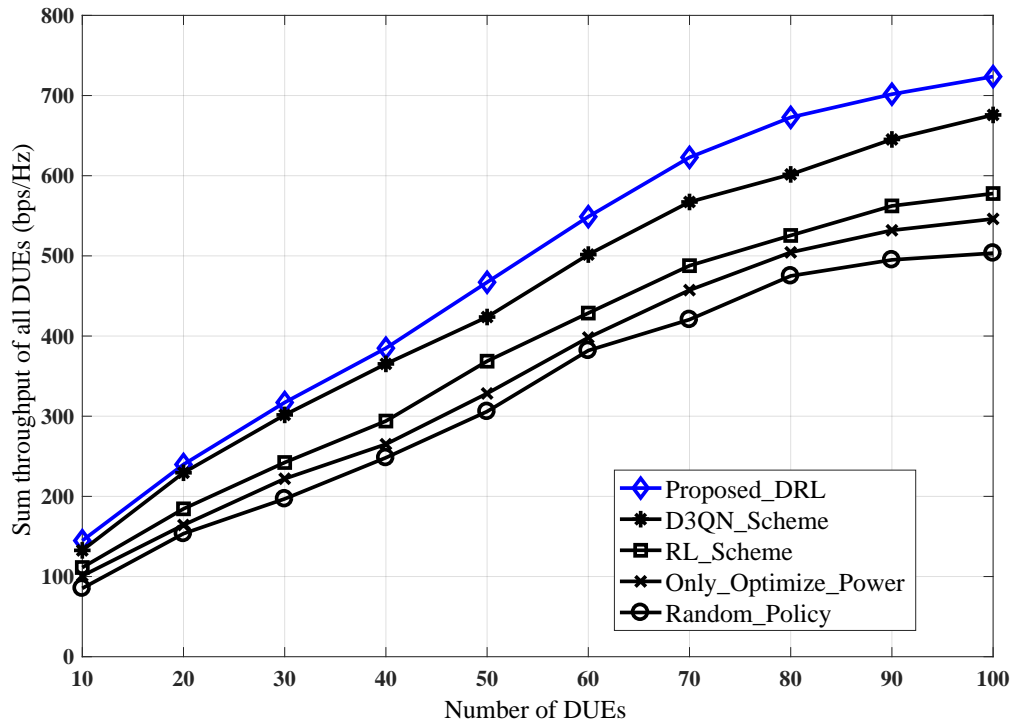


Figure 6.5: Sum throughput of all DUEs Vs number of D2D pairs

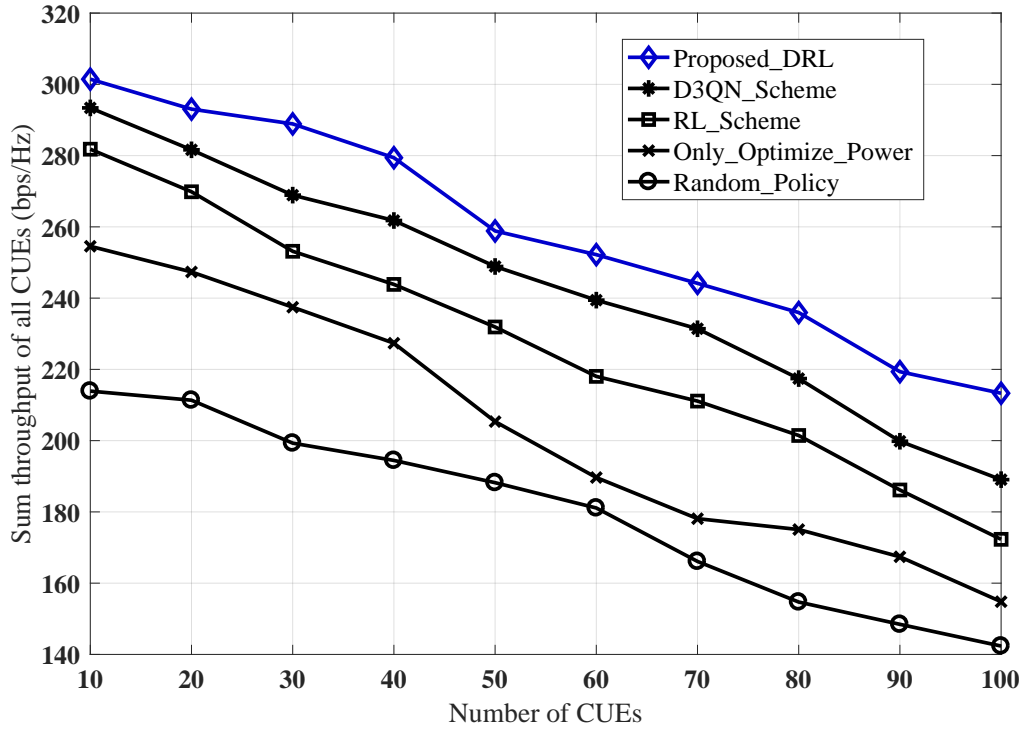


Figure 6.6: Sum throughput of all CUEs Vs number of CUEs

Figure 6.7 shows the sum throughput of DUEs as a function of the distance between D2D pairs in the system. With the increasing distance between D2D pairs, the achieved sum throughput of DUEs for all schemes gradually decreases. With increasing the distances between D2D pairs from 10m to 20m, the sum throughput of all DUEs decreases 19% and 21% in D3QN DRL and Only Power Optimize schemes respectively. Even 15% reduction in our proposed DRL indicates its capability of achieving better sum throughput at higher distances between D2D pairs compared to others. This is happening due to two major reasons. First, the average channel gain between Tx and Rx of D2D pairs decreases with increasing distances. Second, to ensure the minimum QoS requirements of D2D pairs, DUE Tx needs to increase its transmit power which increases interference between other DUEs and CUEs.

Figure 6.8 represents the influence of the cell radius of eNB/SCeNB on the sum throughput for D2D pairs. Due to the increase of cellular cell radius, the mutual interference between users, and the interference severity impact of eNBs to D2D pairs reduces. As a result with increasing the cell radius, the achieved sum throughput of

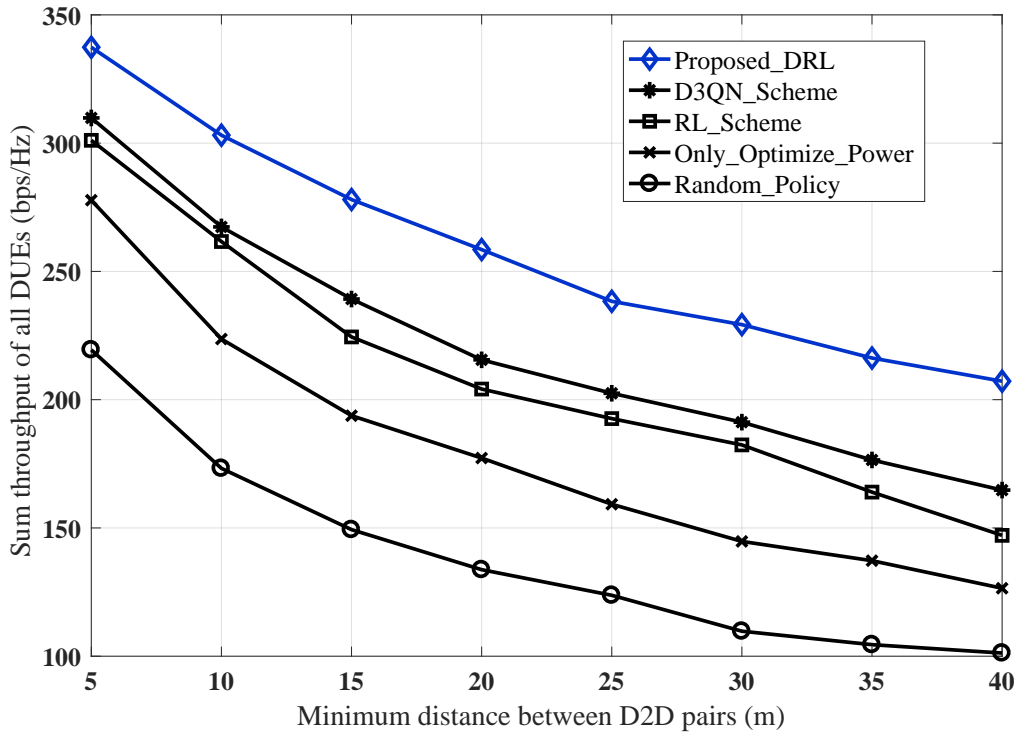


Figure 6.7: Sum throughput of all DUEs Vs distance between D2D pairs

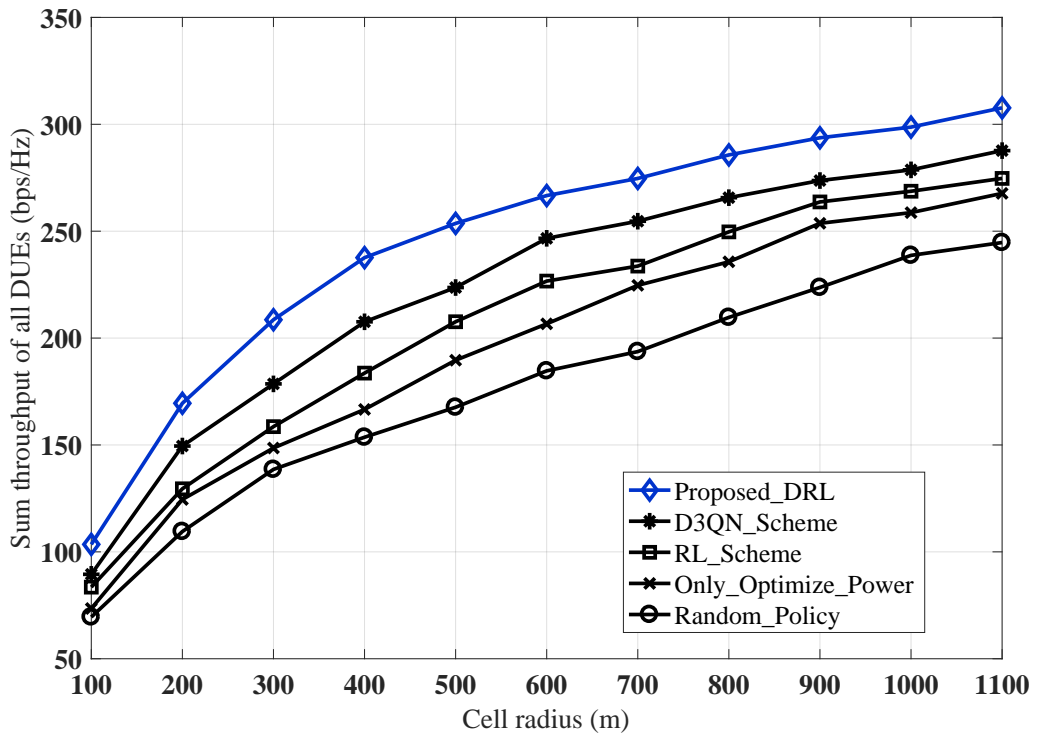


Figure 6.8: Sum throughput of all DUEs Vs cell radius

DUEs by all schemes increases gradually and our proposed DRL algorithm outperforms all the schemes which can be seen in figure 6.8. Increasing cell radius from 200m to 400m, sum throughput increases 40.2%, 38.9% and 33.8% in proposed DRL, D3QN

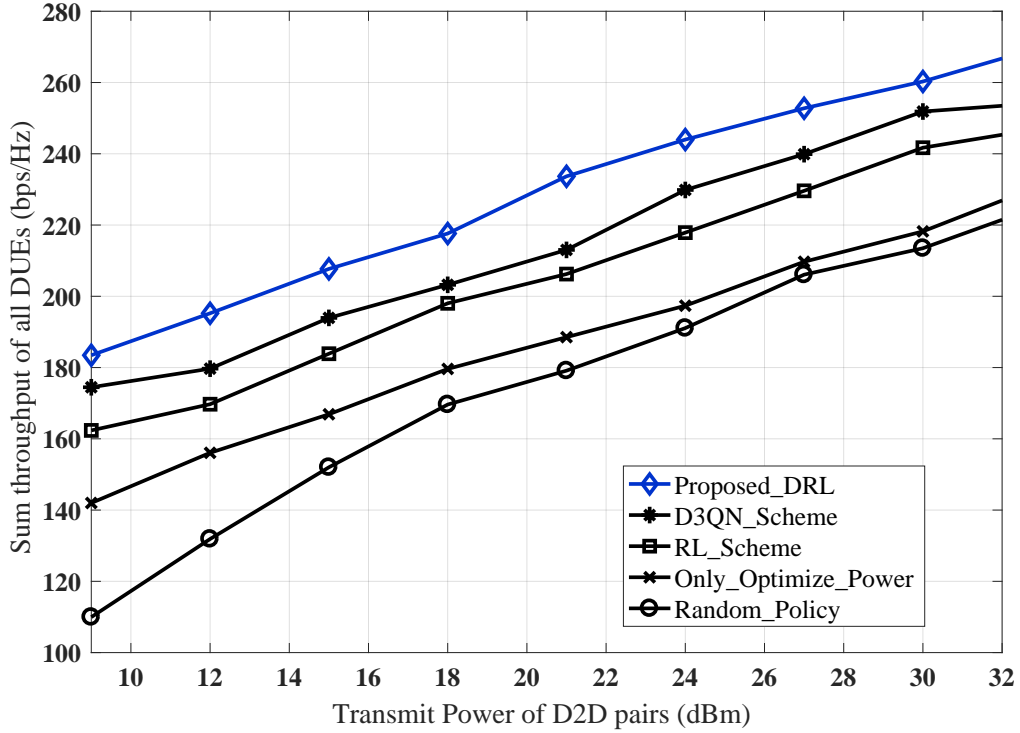


Figure 6.9: Sum throughput of all DUEs Vs transmit power of D2D pairs

Figure 6.9 shows the relation of the sum throughput of all DUEs with their Tx power. For all schemes, it can be seen that a higher maximum transmission power results in a significant improvement in the sum throughput of DUEs. Increasing D2D pairs Tx power from 10dBm to 15dBm, sum throughput improves 10.5%, 10.2% and 15.1% in our proposed DRL, D3QN DRL and Only Power Optimize schemes respectively. Only the Optimize Power scheme is showing better slop at this point as it has not reached its optimum level yet.

Figure 6.10 shows the sum throughput of all D2D pairs against the minimum QoS requirements i.e. minimum throughput requirements to establish a successful link between the users. By increasing the minimum throughput requirement from 2 bps/Hz

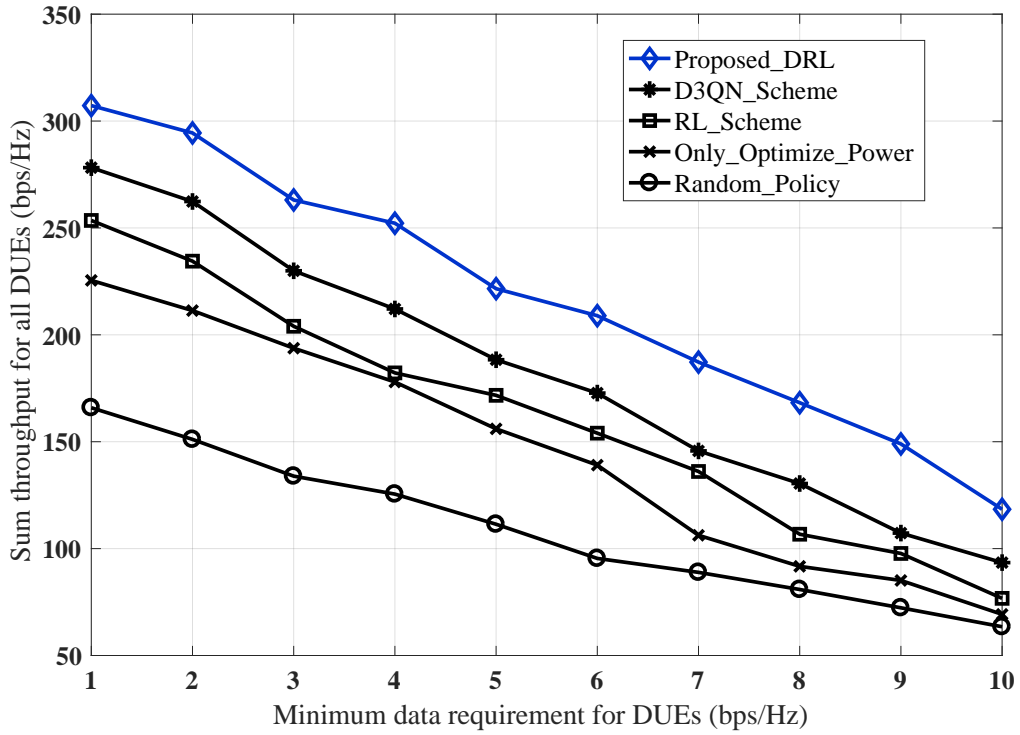


Figure 6.10: Sum throughput of all DUEs Vs minimum QoS requirements for DUEs

to 9 bps/Hz. For the proposed DRL, the sum throughput of all DUEs decreases from 300 bps/Hz to 148 bps/Hz whereas it drops to 107 bps/Hz and 85 bps/Hz for D3QN DRL and Only Optimize Power schemes, respectively. The admission constraints become tighter with increasing the QoS requirements and hence the sum throughput of DUEs is degraded if an appropriate power control, mode selection, and resource allocation approach is not applied which is clearly reflected in our simulation results.

6.5.3 Model validation and system implication

We validate our analytical models by MATLAB-based simulation. This simulation tool was selected due to its availability and credibility. In simulation, we consider large-scale path loss model, path loss component, distance, and small-scale Rayleigh fading. We validate our simulation models in the following ways. We checked simulation log files ensuring that no errors and the simulation models ran smoothly. To get a

good sample of data, the simulation was run longer to reach the steady state condition avoiding bias results. For instance, we consider 1000 different seed values to have results with a confidence level of 95%. We create a more realistic simulation scenario with -174dBm/Hz as noise power spectral density and 7dB as noise figure. In the proposed DRL model, we consider DUEs instead of training eNBs/SCeNBs which help to make better coordination between network elements. The deep reinforcement learning algorithm uses a learning rate of 0.001, a discount rate of 0.9, a greedy rate of 0.1, a training memory size of 2000MB, and a mini-batch size of 32. The DQN model is trained based on algorithms 4 and 5.

Implementing D2D technology in a cellular network is challenging due to its several known issues. First, for a small-sized network where overheads are comparatively low, a centralized approach can be used. As the network grows no matter what strategies are used, network performance degrades significantly with the increasing number of users. In a D2D-enabled cellular HetNet where interference management is a major challenge; the proposed distributed DRL method can be useful to network designers to implement the system in a large-scale network scenario. So, our DRL approach can be used to design the network with desired throughput and QoS requirements for both cellular and D2D users with appropriate mode selection and controlled interference manner.

6.6 Summary

In this Chapter, a Q-network-based deep reinforcement learning (DRL) algorithm is proposed to mitigate interference in D2D-enabled heterogeneous cellular networks (HetNets). In addition, an analytical model incorporating resource block assignment, mode selection, and transmit power control in a D2D-enabled HetNets is developed for system modelling and analysis. The proposed DRL algorithm is trained using an agent-based decision-making policy to achieve the optimal solution for computational

time, spectrum efficiency, and throughput. The system performance is validated by MATLAB-based simulation. The simulation results obtained have shown that the proposed DRL method achieved up to 10% to 53% higher sum throughput for all users on the network than the existing methods. The higher throughput is achieved because of the interference mitigation strategy of the proposed algorithm in which transmitting power is adjusted dynamically. In fact, the proposed method offers better system performance by maintaining the minimum QoS requirements for all users on the network. The findings reported in this Chapter provide some insights into the machine learning-based resource allocation approaches in achieving guaranteed throughput and QoS that can help network researchers and engineers to contribute further towards developing next-generation cellular networks. However, developing a test-bed measurement system to further validate the system's performance is suggested as future research work. Next, in Chapter 7, the conclusion and future development of this research are outlined.

Chapter 7

Conclusions and Future Research Directions

This thesis is concluded in Section 7.1, while the implications for system planning and deployment are discussed in Section 7.2. Section 7.3 outlines a number of possible extensions to this research that could help further understanding of the problem.

7.1 Conclusions

Rapid advancements in different applications, tremendous growth in connected devices and new innovations in mobile communications result in capacity crunch. To fulfil the extraordinary capacity requirements of 5G, D2D communication can play an important role. It promises significant performance gain in terms of latency, link reliability, spectral efficiency, and system capacity. This thesis has focused on identifying the key factors affecting interference in D2D communication in cellular networks and proposed efficient schemes to mitigate them. Mode selection, resource allocation, power control, link reliability, SINR, distances between D2D pairs, and cell density are the key factors that impact the system performance in a D2D-enabled cellular HetNets. While there are several factors that affect the performance of D2D communication in cellular HetNets, interference management is the most significant. In a D2D-enabled cellular HetNet, sharing the same radio resources between CUEs and DUEs (cross-tier), and sharing the same radio resources among different D2D pairs (co-tier) are the major

interference types. To evaluate the impact of these performance-limiting factors on D2D communication, both analytical and computer simulation approaches were adopted. These performance evaluation methodologies were found to be appropriate for the investigations in this thesis. This thesis has made several original contributions that are reported in Chapters 4 to 6. A summary of the contributions is outlined below.

To overcome the limitations of D2D communication in cellular HetNets, this thesis focused on developing a mode selection scheme and analysed its effectiveness in improving performance for D2D communication in a cellular network in Chapter 4. The reliability of D2D links, D2D user's throughput, the impact of the number of active D2D users and the distance between them, and transmit power are analysed. The transmission mode is selected based on D2D user equipment (DUE), cellular user equipment (CUE) and evolved Node-B (eNB) locations, their mutual distances and SINR. Based on the obtained results, this thesis concluded that the proposed mode selection scheme leads to better throughput and interference control than the existing schemes.

The outage probabilities and other performance metrics for various communication links while ensuring minimum Quality of Service (QoS) requirements in D2D-enabled heterogeneous cellular networks are analysed in Chapter 5. We have defined closed-form expressions for the outage probabilities of cellular and D2D links that depend on the density of small cell and D2D pairs, the distance between the D2D receiver and transmitter, SINR, and transmitting power. Increasing DUE receiver distances from CUEs or SUEs will increase the success of the probability for D2D links. Similarly decreasing the distances between D2D pairs gives better link reliability. Achieved small cell density, transmission power control and device locations help to manage interference leading to higher outage probability and system throughput in strict QoS requirements for all links in D2D-enabled HetNets. The proposed AIR scheme improved the outage probability of D2D links up to 55% compared to the neighbor-based scheme, and more than 88% of D2D links and almost all cellular links met the QoS requirements.

Results obtained have also shown that the proposed AIR scheme achieved an improved outage probability of 35% and 49% in eNB and SCeNB links, respectively compared to the traditional neighbour-based methods. To meet the requirements for 5G, dense small cell deployments are inevitable, and our proposed AIR scheme is capable of finding the optimal small cell density under certain QoS requirement conditions.

For effective deployment of D2D technology in cellular HetNets, interference management is very important and most challenging. Efficient resource management can play a crucial role in controlling interference in D2D-enabled cellular networks. To mitigate interference, a RL-based machine learning algorithm for effective resource allocation is proposed in Chapter 6. As the RL-based algorithm has limitations for a large network, to overcome this a DQN-based DRL algorithm is also proposed in this Chapter where D2D acts as an agent and take decision independently for resource allocation based on learned optimal policy from the environment. First, the joint effect of power control (PC) and resource allocation on system sum throughput for DUEs/CUEs are investigated using an analytical model. Second, performance for D2D communication using the proposed model is validated by simulation. Our proposed DRL method achieves up to 10% to 53% higher sum throughput for all DUEs on the network compared to existing methods against different parameters such as cell radius, minimum QoS requirements, D2D pairs distances and transmitting power.

7.2 System implications and deployment

To fulfil the extraordinary capacity requirement of 5G, the deployment of dense small cells along with D2D communication is inevitable. Employing D2D technology could offer improved energy efficiency, higher spectral efficiency, system capacity, and very low latency due to close proximity. In a D2D-enabled cellular HetNet, cross-tier interference due to sharing the same radio resources between CUEs and DUEs, and

co-tier interference for sharing the same radio resources among different D2D pairs are the major interference types. The proposed mode selection, resource allocation and power control schemes in Chapters 4 to 6 can significantly mitigate interference and maximize network performance.

To perform MS, Timeslot selection or measuring control signal is very important. Signal-to-noise interference Ratio (SINR), path loss, D2D pairs distances etc. are the important factors for selecting the appropriate mode. Measurement and control signal should be kept minimum to avoid excessive overhead signal. In Chapters 4 and 5, the proposed dynamic mode selection technique and performance analytical model will guide the system planners to choose the optimum cell density and improve system performance by ensuring QoS for all communication links.

Ultra-dense network (UDN) is inevitable for future cellular networks, and it could improve the system performance and its capacity 100-fold [33]. However, UDN introduces new challenges such as interference, degraded QoS, and high energy consumption that need to be solved and among them, interference is one the most critical. AI technique is a very promising technology that has a huge prospect for future cellular communication networks. System planners can get that benefit significantly by using the proposed DQN-based DRL algorithm for joint resource allocation and power control to mitigate interference in D2D-enabled HetNets.

7.3 Future research directions

This thesis provides a significant contribution in answering the research questions “What mode selection techniques or resource allocation algorithms can be developed for interference management in D2D communication, and how can the performance be improved in D2D-enabled cellular HetNets?” The aim of this thesis was to identify the factors that affect interference in D2D-enabled cellular HetNets and develop efficient

schemes to mitigate/minimize them. In Chapters 4 to 6, we have identified the factors that affect interference for D2D communication in cellular HetNets and proposed dynamic mode selection, machine learning-based resource allocation and power control algorithms to minimize them. However, there are some research issues that could be investigated in the future. This section outlines a number of possible extensions to this research that could help further understanding of the problem.

Overhead reduction in mode selection for D2D communication

Defining the system model, CUEs are selected in such a way that the saturation condition is always satisfied i.e. all cellular resources are occupied by CUEs. This assumption basically simplifies simulation models for performance analysis. Also in the proposed scheme, mode selection is done based on known SINR and locations of nodes (CUEs, DUEs and eNB) which will increase the signaling overheads. An in-depth study (both analytical and simulation) on the impact of higher overhead would be a useful contribution.

mm-Wave in D2D communication

In the proposed schemes, D2D communication uses cellular resources from micro-wave bands that suffer from high interference and insufficient bandwidth. Whereas mm-Wave has a very large bandwidth and provides low latency as well as high data rate, though it suffers from inefficient power consumption and propagation shortcomings [151]. Despite all the challenges, integration of D2D communication with mm-wave may become a promising solution for many issues relating to 5G and beyond, and these could be open areas for researchers in academia and industry.

DQN-based DRL model training with real-world data

Artificial intelligence (AI) and machine learning (ML) are prominent technologies that are expected to dominate future industries. The challenges and problems of 5G and B5G networks are mainly focused on interference management, energy and spectrum

efficiency, capacity, and user data rate. To solve these problems, AI/ML-based D2D communication will become one of the most critical technologies in 5G and B5G networks. It will play a significant role in reducing power consumption, delay, as well as improving spectrum utilization and data rate. A DQN ML-based resource allocation and power control scheme to mitigate interference is proposed in Chapter 6. In the simulation, the DQN-based DRL model is trained with synthesis data, but there is a scope to collect the data from the real world and train the model accordingly. By using real-world data, a completely distributed resource allocation model investigation can be another future promising research area for academia and industry.

Testbed implementation for D2D communications

As ultra-dense HetNets enables several devices to transfer data over underlay or overlay cellular networks with different attributes and protocols. In this thesis, the performances are analysed using computer-simulated network scenarios like CUE, DUE and small cell distributions, outage probability and throughput. In the future, the performance of D2D communication in cellular networks should be investigated using a testbed implementation. The real equipment may be used to verify and validate performances like outage probability, and optimal cell density for maximum throughput. Developing a test-bed measurement system as part of future research work would be a logical and valuable step to enhance the credibility and practical applicability of our findings. It could also serve as a platform for ongoing research in the field of D2D communication for future cellular networks.

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Appendix A

Proof of AIR algorithm

Appendix A.1: Proof of AIR algorithm

Let us consider a the maximum allowable outage probabilities for any link is τ . So to guarantee the QoS requirements all communications links must satisfy the following as:

$$\begin{aligned} P_{out} &\leq \tau \\ \Rightarrow 1 - \exp\left(\frac{-N_0\gamma_{th}d_{t,r}^\alpha}{P_j}\right) \left(\frac{P_j d_{i,r}^\alpha}{P_i\gamma_{th}d_{t,r}^\alpha + P_j d_{i,r}^\alpha}\right) \exp\left(\frac{-\kappa\gamma_{th}^m d_{t,r}^2 (P_{j'}^m \lambda_d + P_k^m \lambda_s)}{P_j^m}\right) &\leq \tau \\ \Rightarrow \exp\left(\frac{-N_0\gamma_{th}d_{t,r}^\alpha}{P_j}\right) \left(\frac{P_j d_{i,r}^\alpha}{P_i\gamma_{th}d_{t,r}^\alpha + P_j d_{i,r}^\alpha}\right) \exp\left(\frac{-\kappa\gamma_{th}^m d_{t,r}^2 (P_{j'}^m \lambda_d + P_k^m \lambda_s)}{P_j^m}\right) &\geq 1 - \tau \\ \Rightarrow \exp\left(\frac{-N_0\gamma_{th}d_{t,r}^\alpha}{P_j}\right) P_j d_{i,r}^\alpha \exp\left(\frac{-\kappa\gamma_{th}^m d_{t,r}^2 (P_{j'}^m \lambda_d + P_k^m \lambda_s)}{P_j^m}\right) &\geq (1 - \tau)(P_i\gamma_{th}d_{t,r}^\alpha + P_j d_{i,r}^\alpha) \\ \Rightarrow P_j d_{i,r}^\alpha \left[\exp\left(\frac{-N_0\gamma_{th}d_{t,r}^\alpha}{P_j}\right) \exp\left(\frac{-\kappa\gamma_{th}^m d_{t,r}^2 (P_{j'}^m \lambda_d + P_k^m \lambda_s)}{P_j^m}\right) - 1 + \tau \right] &\geq (1 - \tau) P_i\gamma_{th}d_{t,r}^\alpha \end{aligned}$$

$$\Rightarrow d_{i,r} \geq d_{t,r} \left[\frac{(1-\tau)P_i\gamma_{th}}{\exp\left(\frac{-N_0\gamma_{th}d_{i,r}^\alpha}{P_j}\right) \exp(-\beta_D(P_{j'}^m\lambda_d + P_k^m\lambda_s)) - 1 + \tau} * \frac{1}{P_j} \right]^{\frac{1}{\alpha}}$$

$$\Rightarrow d_{i,r}^{min} = d_{t,r} \left[\frac{(1-\tau)P_i\gamma_{th}}{\exp\left(\frac{-N_0\gamma_{th}d_{i,r}^\alpha}{P_j}\right) \exp(-\beta_D(P_{j'}^m\lambda_d + P_k^m\lambda_s)) - 1 + \tau} * \frac{1}{P_j} \right]^{\frac{1}{\alpha}}$$

Where $\beta_D = \kappa\gamma_{th}^m d_{t,r}^2 / P_j^m$, $\delta_D = \exp\left(\frac{-N_0\gamma_{th}d_{i,r}^\alpha}{P_j}\right) \left(\frac{P_j d_{i,r}^\alpha}{P_i\gamma_{th}d_{i,r}^\alpha + P_j d_{i,r}^\alpha}\right)$, $\kappa = \pi m \Gamma(m) \Gamma(1-m)$ and $m = 2/\alpha$.

Appendix A.2: Proof of small cell density and D2D pairs affecting communication link quality

The transmission capacity of small cell can be expressed as:

$$\begin{aligned} \mathcal{T}_c &= \lambda_s(1 - P_{out}^S) \\ &= \lambda_s \delta_S \exp(-\beta_S(P_j^m\lambda_d + P_{k'}^m\lambda_s)) \end{aligned}$$

As transmission capacity depends on small cell density, λ_s , so we can have

$$\begin{aligned} \frac{d\mathcal{T}_c}{d\lambda_s} &= \delta_S \exp(-\beta_S(P_j^m\lambda_d + P_{k'}^m\lambda_s)) - \lambda_s \delta_S \exp(-\beta_S(P_j^m\lambda_d + P_{k'}^m\lambda_s)) \\ &\quad \times \frac{d}{d\lambda_s} \{ \exp(-\beta_S(P_j^m\lambda_d + P_{k'}^m\lambda_s)) \} \\ &= \delta_S(1 - \beta_S P_{k'}^m \lambda_s) \exp(-\beta_S(P_j^m\lambda_d + P_{k'}^m\lambda_s)) \end{aligned}$$

As $\lambda_s \neq 0$ and here $\frac{d^2\mathcal{T}_c}{d\lambda_s^2} < 0$, so for optimal values we have

$$\begin{aligned} \frac{d\mathcal{T}_c}{d\lambda_s} &= 0 \\ \Rightarrow \delta_S(1 - \beta_S P_{k'}^m \lambda_s) \exp(-\beta_S(P_j^m \lambda_d + P_{k'}^m \lambda_s)) &= 0 \\ \Rightarrow (1 - \beta_S P_{k'}^m \lambda_s) &= 0, \quad \text{as } \exp(-\beta_S(P_j^m \lambda_d + P_{k'}^m \lambda_s)) \neq 0 \\ \Rightarrow \lambda_s &= \frac{1}{P_{k'}^m \beta_S} = \frac{P_k^m}{P_{k'}^m \kappa \gamma_{th}^S d_{k,s}^2} \end{aligned}$$

Appendix A.3: Proof of small cell density of communications mode

To guarantee link QoS for small cell links we have,

$$\begin{aligned} P_{out,k} &\leq \tau \\ \Rightarrow 1 - \delta_S \exp(-\beta_S(P_j^m \lambda_d + P_{k'}^m \lambda_s)) &\leq \tau \\ \Rightarrow \exp(-\beta_S(P_j^m \lambda_d + P_{k'}^m \lambda_s)) &\geq \frac{1 - \tau}{\delta_S} \\ \Rightarrow (P_j^m \lambda_d + P_{k'}^m \lambda_s) &\leq \frac{1}{\beta_S} \ln\left(\frac{\delta_S}{1 - \tau}\right) \\ \Rightarrow \lambda_s &\leq \frac{1}{\beta_S P_{k'}} \ln\left(\frac{\delta_S}{1 - \tau}\right) - \rho_{jk'}^m \lambda_d \end{aligned}$$

Where $\rho_{jk'}^m = P_j^m / P_{k'}^m$ is the ratio of transmission power of the participating UEs.