# Delay and Energy Efficiency Optimizations in Smart Grid Neighbourhood Area Networks

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## Statement of Originality

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# Abstract

Smart grids play a significant role in addressing climate change and growing energy demand. The role of smart grids includes reducing greenhouse gas emission reduction by providing alternative energy resources to the traditional grid. Smart grids exploit renewable energy resources into the power grid and provide effective two-way communications between smart grid domains for efficient grid control. The smart grid communication plays a pivotal role in coordinating energy generation, energy transmission, and energy distribution. Cellular technology with long term evolution (LTE)-based standards has been a preference for smart grid communication networks. However, integrating the cellular technology and the smart grid communication network puts forth a significant challenge for the LTE because LTE was initially invented for human-centric broadband purpose. Delay and energy efficiency are two critical parameters in smart grid communication networks. Some data in smart grids are real time delay-sensitive data which is crucial in ensuring stability of the grid. On the other hand, when abnormal events occur, most communication devices in smart grids are powered by local energy sources with limited power supply, therefore energy-efficient communications are required. This thesis studies energy-efficient and delay-optimization schemes in smart grid communication networks to make the grid more efficient and reliable. A joint power control and mode selection in device-to-device communications underlying cellular networks is proposed for energy management in the Future Renewable Electric Energy Delivery and Managements system. Moreover, a joint resource allocation and power control in heterogeneous cellular networks is proposed for phasor measurement units to achieve efficient grid control. Simulation results are presented to show the effectiveness of the proposed schemes.

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# List of Acronyms

**2G** Second-Generation Mobile Networks

**3GPP** Third Generation Partnership Project

**3G** Third-Generation Mobile Networks

**4G** Forth-Generation Mobile Networks

**5G** Fifth-Generation Mobile Networks

**AMC** Adaptive Modulation and Coding

**AC** Alternating Current

**Adam** Adaptive Moment Estimation

**ADP** Approximate Dynamic Programming

**AMI** Advanced Metering Infrastructure

**AWGN** Additive White Gaussian Noise

**BE** Bandwidth Efficiency

**BM** Boltzmann Machine

**BS** Base Station

**CMDP** Constrain Markov Decision Process

**CNN** Convolutional Neural Networks

**CPP** Critical Peak Pricing

**D2D** Device-to-Device

**DAU** Data Aggregator Unit

**DAU** Distribution Automation

**DBM** Deep Boltzmann Machines

**DBN** Deep Belief Networks

**DC** Direct Current

**DEC-POMDP** Decentralized Partially Observable Markov Decision Process

**DEG** Distributed Energy Generation

**DES** Distributed Energy Storage

**DGI** Digital Grid Intelligent

**DLC** Direct Load Control

**DoF** Degrees-of-Freedom

**DQN** Deep Q-learning Nerwork

**DR** Demand Response

**DRER** Distributed Renewable Energy Resource

**EE** Energy Efficiency

**EEDO** Energy Efficiency and Delay Optimization

**EH** Energy Harvesting

**FD** Full-Duplex

**FIFO** First-in-First-out

**FREEDM** Future Renewable Electric Energy Delivery and Managements

**GCRS** Graph Coloring Based Resource Sharing

**GPS** Global Positioning System

**GSM** Global System for Mobile Communication

**HAN** Home Area Networks

**HEMS** Home Energy Management System

**HetNet** Heterogeneous Cellular Network

**i.i.d** Independent and Identically Distributed

**IA** Interference Alignment

**IED** Intelligent Electronic Devices

**IEM** Intelligent Energy Management Device

**IFM** Intelligent Fault Management Device

**ILA** Interference Limited Area

**JIM** Joint Interference Management

**LAN** Local Area Network

**LEO** Low Earth Orbit

**LOS** Line-of-Sight

**LSTM** Long Short Term Memory Network

**MAC** Media Access Control

**MBS** Macro Base Station

**MDP** Markov Decision Process

**MIMO** Multiple-in-Multiple-out

**mm** milimeter

**MMDP** Multi-Agent Markov Decision Process

**mMTC** Massive Machine Type Communication

**MUE** Macrocell Users

**NAN** Neighbourhood Area Network

**NFV** Network Function Virtualization

**NLOS** Non-Line-of-Sight

**OFDMA** Orthogonal Frequency-Division Multiple Access

**ORM** Outage and Restoration Management

**PDC** Phasor Data Concentrator

**PDCC** Physical Downlink Control Channel

**PLC** Power Line Communication

**PMU** Phasor Measurement Unit

**POMDP** Partially Observable Markov Decision Process

**POSG** Partial Observable Stochastic Game

**QoE** Quality of Experience

**QoS** Quality-of-Service

**RA** Random Access

**RAN** Radio Access Network

**RBM** Restricted Boltzmann Machine

**ReLU** Rectified Linear Unit

**RI** Relaying IEM

**RL** Reinforcement Learning

**RNN** Recurrent Neural Networks

**R-R** Round-Robin

**RTP** Real-time Pricing

**SCBS** Small Cell Base Station

**SDN** Software-define Network

**SG** Stochastic Game

**SINR** Signal-to-Interference-and-Noise Ratio

**SMDP** Semi-Markov Decision Process

**SNR** Signal-to-Noise Ratio

**SRS** Sounding Reference Signal

**SST** Solid State Transformer

**SUE** Small Cell Users

**TDMA** Time-Division Multiple Access

**TIM** Topological Interference Management

**TOU** Time-of-use

**UE** User Equipment

**UHF** Ultra High Frequency

**URLCC** Ultra-reliable Low-latency communication

**VAR** Volt-Ampere Reactive

**WAN** Wide Area Network

**WiMAX** Worldwide Interoperability for Microwave Access

**WLAN** Wireless LAN

# Chapter 1

# Introduction

The growing energy demand and greenhouse gas emission problem has led to the shift from traditional power grids to smart grids. The smart grid utilizes a two-way communication between the smart grid domains to increase the reliability of the power grid. The smart grid communication plays an important role in coordinating energy generation, energy transmission and energy distribution, making it an essential part of an efficient grid control [1]. The smart grid communication can be divided into three kinds of networks which are Wide Area Networks (WANs), Neighbourhood Area Networks (NANs) and Home Area Networks (HANs). Among them, the tasks of NANs include forming communication facilities in electric distribution networks [2], which involves transmitting meter and status data to the control centre for various applications, such as demand-side management, distribution automation and outage management as well as managing local energy in the future renewable electric energy delivery and managements (FREEDM) system, an important model for electric distribution systems in smart grids [3]. Performance of the communication at distribution level is critical to ensure the stability of grids since the distribution levels are prone to faults caused by different situations, such as equipment errors and adverse weather [4], which might lead to service interruptions and power loss.

Intelligent energy management devices (IEMs) manage energy in the FREEDM system by monitoring status and collecting data of all end-devices in a local area, and providing control references to each of them. In particular, the tasks of IEMs include collecting and monitoring the status of distributed renewable energy resources (DRERs), making energy management decisions and delivering reports to the control centre for further actions. On the other hand, to make monitoring and controlling possible at DERs in distribution level, phasor measurement units (PMUs) are deployed. PMUs play a critical role to transmit real-time dynamic data on power flows to the power system control center [5]. In this context, cellular technology with Long Term Evolution (LTE)-based standard is promising for communications in NANs because

it is a widely-deployed and mature technology. Therefore, this kind of technology can provide services over a large area including to smart grid domains located in complex geographical areas [6]. However, integrating the cellular technology and the smart grid communication network is a significant challenge for LTE due to the simultaneous transmission of large volume delay-sensitive data. Specifically, when a fault occurs in a grid, for instance due to natural disasters such as floods, earthquakes or tsunamis, more information needs to be sent to the control centre, resulting in a significant increment to the size of IEM reports [7]. In this kind of situations, the grid must have resilience and self-healing capabilities to prevent power losses and blackouts, which result in stringent delay requirements to the data transmissions. On the other hand, the large volumes of simultaneous transmission of smart grid data from PMUs and other devices in NANs could cause severe radio access network (RAN) congestions, leading to excessive delay in conventional cellular networks [7]. Therefore, there is a need to improve the performance of LTE to fit the technology for smart grid NANs specifically in this kind of situations. This thesis studies the enhancements of cellular technology for smart grid NANs.

## 1.1 Problem Statement

Integrating the cellular technology and the smart grid communication network is a significant challenge for the LTE due to the simultaneous transmission of large volume and delay-sensitive smart grid data. In order to satisfy the smart grid delay requirement, specific data rate are imposed to the data transmission. Moreover, in fault conditions, the increase in message size could make the message delivery become bandwidth demanding to the cellular network with radio resources constrained [7]. Multi-hop communications can be exploited to improve the channel quality of IEM in cellular networks. However, in multi-hop communications, the link between a node and a relaying node might face the bottleneck effect due to high path loss and this will degrade the performance of relaying communications in smart grid communication scenarios. In this kind of situation, device-to-device (D2D) communications are proposed as an important way to improve the performance of relaying communications in cellular networks. In D2D communications, two cellular devices can exchange information directly by reusing cellular resources over a direct link, instead of exploiting cellular base station (BS) to receive and transmit messages. Enhancing the LTE with D2D communications might also yield improvements in energy efficiency and end-to-end delay of smart grid NANs [8].

In D2D communications, energy efficiency is one of the concerns especially when IEMs are considered. When a fault occurs, IEMs will be divided into fault zone and normal zone. IEMs in the fault zone will be isolated from the grid and powered by local energy sources with limited power supply [9]. Therefore, energy efficiency must be considered to ensure that data can be

transmitted to the control centre in this kind of situations. However, there is a trade-off between energy efficiency and delay in wireless cellular networks. Delay is also crucial in this situation since data must be delivered at control centre between 3ms to 16ms [10]. Therefore both energy efficiency and delay must be considered in D2D communications for FREEDM systems in smart grids.

Simultaneous transmissions of smart grid devices in cellular networks may lead to RAN congestions. Heterogeneous cellular networks (HetNets) are proposed as critical techniques to reduce the RAN congestion because HetNets have the ability to alleviate the RAN congestion by off-loading access attempt from a macrocell to small cells [11]. In HetNets, low-power and low-cost small cell base stations (SCBSs) are deployed to increase the data rate of small cell users (SUEs). Exploiting small cells in cellular networks can also reduce energy consumption and reduce delay of PMUs due to the shorter distance between PMUs and SCBSs.

Energy efficiency is also critical in HetNets especially when PMUs are considered. Specifically, when abnormal events occur, for example due to natural disasters such as floods, earthquakes or tsunamis, the PMUs will be isolated from the grid and powered by local energy sources, hence energy efficiency must be enhanced. Moreover, in this situation delay issues should be given high attention as the data have stringent delay requirements. Therefore, both energy efficiency and delay must be considered when exploiting HetNets for smart grid applications.

## 1.2 Contributions and Publications

Based the work presented in Chapter 4, Chapter 5 and Chapter 6, a few articles have been published, accepted or submitted. The contributions of this thesis for each chapter are explained as follows:

- An overview of smart grid neighbourhood area networks is presented in Chapter 2. In particular, we explain model and devices in smart grid distribution systems and provide background on smart grid neighbourhood area networks. In addition, we also present the communication design requirements of neighbourhood area networks. Finally, we provide information on communication technologies for smart grid neighbourhood area networks.

- In Chapter 3, we give explanation on optimization strategies and mathematical tools that are used to model the strategies. We also provide some literature of optimization strategies and tools for both D2D communications and HetNets.

- We propose a joint mode selection and power control scheme in device-to-device communications underlying cellular networks in Chapter 4. We formulate the problem as a

combinatorial problem and proposed a brute-force based algorithm to find the solution. The proposed scheme can improve energy efficiency of the network as well as satisfy the stringent delay constraints in D2D communications. The contents of this chapter are published and submitted in the following conference and journal papers:

- F. A. Asuhaimi, J. P. B. Nadas, and M. A. Imran, "Delay-Optimal Mode Selection in Device-to-Device Communications for Smart Grid," *in Proc. 2017 IEEE International Conference On Smart Grid Communications (SmartGridComm),* (Dresden), Oct. 2017.
- F. A. Asuhaimi, S. Bu, J. P. B. Nadas, and M. A. Imran, "Delay-Aware Energy-Efficient Joint Power Control and Mode Selection in Device-to-Device Communications for FREEDM Systems in Smart Grids," *IEEE Access* (accepted), Jun. 2019.

- A joint resource allocation and power control in heterogeneous cellular networks is proposed in Chapter 5. The proposed scheme can significantly reduce the delay in the network. Game-potential approach is exploited to help PMU in making decision in distributed manner. Then, to obtain the solution, the best response dynamic algorithm is adopted. The contents of this chapter is published in the following conference paper:
  - F. A. Asuhaimi, S. Bu, and M. A. Imran, "Joint Resource Allocation and Power Control in Heterogeneous Cellular Networks for Smart Grids," *in Proc. 2018 IEEE Global Telecommunications Conference (GLOBECOM 2018),* (Abu Dhabi), Dec. 2018.

- Channel access and power control heterogeneous cellular networks in smart grid communications using deep reinforcement learning is proposed in Chapter 6. The scheme aims to increase the energy efficiency and satisfy different delay requirements of PMUs. Deep reinforcement learning (DRL) approach is exploited as a mathematical tool to obtain optimal policy that can achieve the objective when the system dynamic is unknown. The contents of this chapter is submitted in the following journal paper:
  - F. A. Asuhaimi, S. Bu, P.V. Klaine, and M. A. Imran, "Channel Access and Power Control for Energy-Efficient Delay-Aware Heterogeneous Cellular Networks in Smart Grid Communications using Deep Reinforcement Learning," *IEEE Access* (accepted), Aug. 2019.

## 1.3 Thesis Organization

This thesis is organized as follows. In Chapter 2, an overview of smart grid neighbourhood area networks is provided. Explanation on optimization strategies and mathematical model in D2D communications and HetNets are given in Chapter 3. Research findings in these two areas are described in Chapters 4, 5 and 6 respectively. Finally, Chapter 7 concludes the thesis and discusses the future work.

# Chapter 2

# Overview of Smart Grid Neighbourhood Area Networks

The existing power grid has served consumers for over 100 years by directly provide electricity from large power stations to end users [12]. However, blackouts and grid failures have become critical problems, that lead to great damages and inconvenience to people's daily life [13]. Therefore, there is a need to significantly improve the efficiency and reliability of the current grid. Moreover, global warming, an increase in carbon emission and the growing world population and power demand have forced the use of renewable energies within the existing power transmission and distribution systems [14]. Smart grids have been proposed because they have the potential to improve the efficiency of the current grid as well as to solve the energy shortage problems. They can optimize the energy generation, transmission and distribution, as well as reduce peaks in the power usage, and sense and prevent blackout by integrating network and information technologies with intelligent algorithm [15].

In smart grids, bidirectional communications between smart grid domains are utilized to coordinate energy generation, transmission and distribution. Therefore, smart grid communications have become an essential part of an efficient and reliable grid control [1]. Most of meter and status data collections from smart meters and sensors, and power delivery to end users are done at the distribution level, therefore the model and devices in smart grid distribution networks is studied in this chapter. The smart grid communication network adopts a hierarchical structure to manage a massive amount of electrical devices that are communicating with the control centre. The hierarchical structure has the ability to decrease the investment cost and the network bandwidth requirement, as well as increase the scalability. The background on smart grid communication networks is discussed in this chapter. The main communications requirements of smart grid NANs, and the reasons of choosing NANs as the research interest are also explained. This chapter also studies the operations, communication design requirements and communica-

tion technology for smart grid NANs and explains why cellular technology is promising for NANs. However, since the cellular technology was initially invented for human-centric broadband purpose and not suitable for smart grid applications, the challenges and improvements in cellular technology to efficiently support smart grid NANs, specifically to cope with some of the functionalities with stringent requirements is also discussed.

## 2.1 Smart Grid Distribution Systems

In smart grids, meter and status data collections from smart meters and sensors, and power delivery to end users are done at the distribution level. Among smart grid communication networks, the tasks of NANs include forming communication facilities in electric distribution networks [2], specifically for local energy management in FREEDM systems, an important model for electric distribution systems in smart grids [3]. In the following, we give explanation about the system and some important devices in the system.

### 2.1.1 Future Renewable Electric Energy Delivery and Management (FREEDM) Systems

Currently, most of energy consumed today is generated by fossil fuel, which is non-renewable and non-environmental friendly. In a few years, this problem may lead to a future energy crisis, which is the rapidly increase of fuel prices. One way to prevent this crisis is by utilizing energy resources based on renewable energy such as solar and wind power especially in distribution networks. In FREEDM systems, distributed renewable energy resources (DRERs) which consists of distributed energy generations (DEGs) and distributed energy storages (DESs) such as solar panels, wind turbines, and electric/hydrogen fuel cell vehicles are fully utilized in large-scale (such as wind or solar farms) and wide-scale installations, where the energy management decisions are done individually and locally. Each household manages its energy usage with the assistance of small scale DEGs such as solar panels and wind turbines attached to the household. On the other hand, the local energy management is done by an IEM that is connected to large-scale centralized DEGs like wind or solar farms. The DESs consisting batteries and hydrogen storages are complements to the DREGs in order to optimize energy usage in the grid. In the FREEDM system, the intelligent energy management software analyses the pricing information and power availability. This feature allows users to sell excess power generated back to the grid.

The system model of FREEDM systems is shown in Figure 2.1. A substation of control centre is attached between the 69 kV transmission line and the 12 kV AC distribution line. Intelligent Fault Management devices (IFMs) are connected to each other using the 12 kV line. A

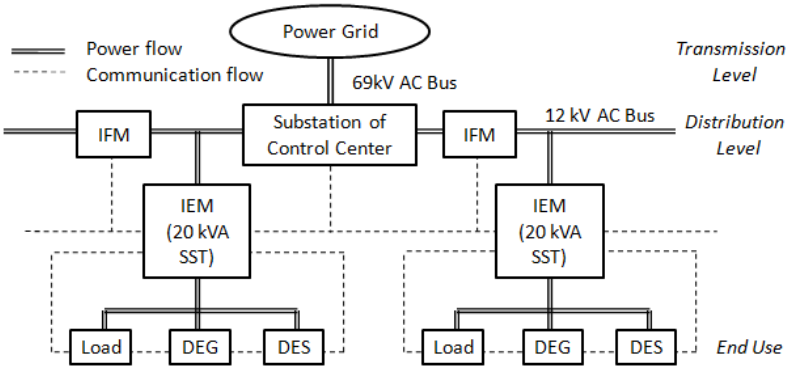


Figure 2.1: The model of FREEDM system.

solid state transformer (SST) connects an IEM to the 12 kV alternating current (AC) distribution line, the 120V AC bus and the 400V DC bus which connected to the load, DES and DEG. 1 MW of FREEDM systems could powering upwards 100 homes.

The FREEDM system interfaces with residential and industry customers. The model in Figure 2.1 also shows the future home or other distribution load's conceptualized grid interface with three key technology features. The first feature, plug-and-play that includes both a 400-V direct current (DC) bus and a conventional 120-V AC bus which contains open-standard-based communication interface that can instantly recognize any device coupled to the grid. Energy router, or IEM is the second feature which is used for recognition and management of all devices connected to the low-voltage AC and DC buses. An open-standard-based operating system for FREEDM systems, called the digital grid intelligent (DGI) is the last feature that is important to coordinate the system management with other energy routers.

### 2.1.2 Devices in Smart Grid Distribution Systems

In the following, we explain devices used for status transmission, data collection and power delivery in smart grid distribution systems.

#### Distributed Renewable Energy Resources (DRERs)

In smart grid distribution systems, DRERs consist of DEGs and DESs. DEGs based on renewable resources such as solar and wind power are very dependent to the local weather conditions and highly intermittent. Therefore, DESs are required as complements to DEGs because of their ability to cope with sudden changes in power output. Environmental-related energy generations from renewable energy sources require additional monitoring, fault detection and diagnostics in future power grids due to its stochastic characteristic [16].

### Phasor Measurement Unit (PMU)

To ensure monitoring and control are possible at electric generation domains, PMU and current sensors play a critical role to transmit real-time dynamic data to the power system control centre [5]. In power networks, a PMU is deployed at the beginning of the distribution line and it computes three-phase values of bus voltage and line current (in addition to positive, negative, or zero sequence phasors) as well to ensure the stability of the grid [17]. PMU measurements are gained by first sampling the voltage and current waveforms through the Global Positioning System (GPS) and then each sample is time stamping for the phase and amplitude variations assessment before transmitted to the local phasor data concentrator (PDC). Moreover, the sampling clocks of various PMUs are precisely synchronized, which gives advantage to advanced fault detection and location algorithm. The PDC will sort the phasor according to the GPS time stamps and forwards the data to the power system control centre for required control actions [4].

### Intelligent Fault Management (IFM)

Another important kind of device in FREEDMs systems is the IFM. The roles of IFMs include fault identification and isolation to maintain the system stability. More specifically, multiple IFMs could divide IEMs into different zones. When faults occur in a zone, IFMs will isolate the fault zone to protect other normal zones from any cascading failure due to fault current [3].

### Intelligent Energy Management (IEM)

IEMs are responsible for collecting and monitoring the status of DRERs, making energy management decisions and delivering reports to the control centre for further actions. In particular, IEMs collect data, monitor status as well as provide control commands to every end device. The control command can be a "on" or "off" or adjustable power or voltage command for the controllable load, and could be charge or discharge rate for DESD. When a fault occurs in a zone, the IEMs from a fault zone must transmit a report to trigger a response from the corresponding device as soon as possible to prevent the damage of equipments in a larger area due to the fault current. Specifically, when a fault occurs in a grid, for instance due to natural disasters such as floods, earthquakes or tsunamis, more information needs to be sent to the control centre, resulting in a significant increment to the size of IEM reports [7]. In this kind of situations, the grid must have resilience and self-healing capabilities to prevent power losses and blackouts, which result in stringent delay requirements to the data transmissions.

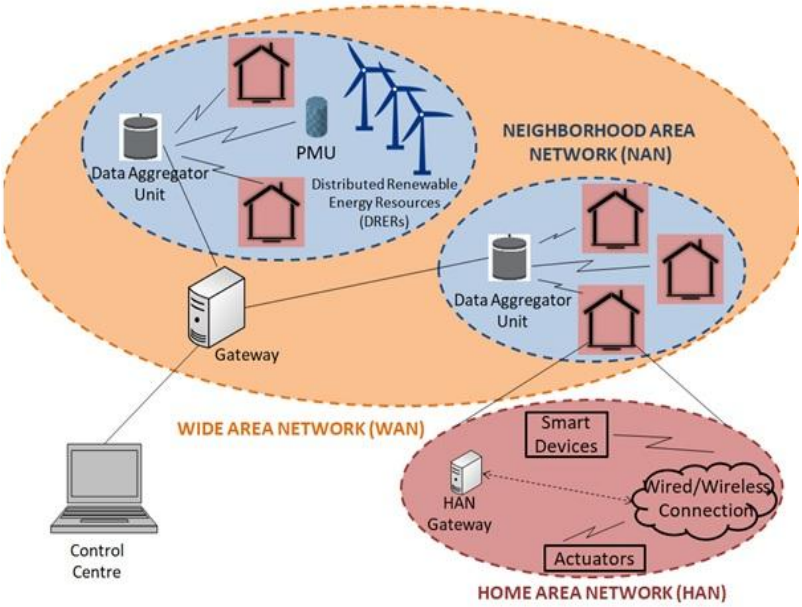


Figure 2.2: The hierarchical structure of smart grid communication network.

## 2.2 Background on Smart Grid Communication Networks

Smart grids make use of bi-directional communications between devices to enable real-time monitoring and control a large scale of the power grid. The smart grid communication networks consist of three kinds of networks: HANs, NANs, and WANs that are categorised according to its coverage area and functionality [18] as shown in Figure 2.2.

The HAN is one of the smallest subsystems in smart grids, which provides connections between the electrical appliances and smart meters. The smart meter is installed in each household for energy usage measurement and collection purposes. Beside smart meters, a HAN also comprises of sensors and actuators to measure various parameters such as light intensity and temperature, and Home Energy Management System (HEMS) that helps users in managing their power consumption based on real time pricing information. HANs cover small areas, therefore short distance with low data rate communication technologies like ZigBee and WiFi can be applied to this network.

The second kind of networks in the smart grid communication infrastructure is NANs which serves most of the communications in power distribution areas that includes multiple HANs and local access point [2]. In other words, NANs collect the meter data from smart meters and status data from sensors, to the Data Aggregator Unit (DAU) and the data is forwarded to its final destination which is the control centre. Smart grid NANs deal with a big amount of heterogeneous data and hold a large number of devices. The area covers by NANs includes small scale industry and groups of buildings, therefore it requires a medium range communication with high network capacity, such as cellular networks, Power Line Communication (PLC) and

Worldwide Interoperability for Microwave Access (WiMAX) [19].

The third kind of networks in the smart grid communication infrastructure, which is WANs offer communications between the electric utility control centre and substations. The WANs connect the NANs to the power provider to allow the exchange of information between these two domains. In particular, WANs collect different types of data from multiple distribution domains such as meter data which are collected from the meter power consumption, power status data and power capacity data from the power generation, power transmission and power distribution and then transmit all these data to the control centre [20]. A WAN covers a very large area including a full urban or suburban area, thus demanding a long range type of backhaul communication with very high data rate [14].

## 2.3 Operations and Requirements of Smart Grid Neighbourhood Area Networks

Smart grid NANs have attracted attentions from both academia and industry due to their crucial role in achieving efficient and reliable grid. In the context of communications at distribution networks, NANs play a critical role to provide connections within distribution domains. The tasks of a NAN includes collecting a large amount of various types of data from end users and distributing crucial control signals from the utility control centre to end users [21]. NANs form the most important part in the grid that can determine the efficiency of the whole grid because they are directly connected to the end users in regional areas. Moreover, a NAN can offer distribution domain with the capability to control and monitor electric power delivery to each household with respect to the user demands and electric availability.

A flexible and widely deployed communication infrastructure is required in order to achieve the vision of future smart grid, where the distribution domain is expected to be grouped into smaller, more-manageable, and potentially autonomous operating units [22]. Smart operations such as Distribution Automation (DA) and Advanced Metering Infrastructure (AMI) can be supported efficiently if a reliable communication network is available [19]. DA is a critical application in smart grids which involves system automatic functionalities that require interactions between Intelligent Electronic Devices (IEDs), such as [19, 22, 23]:

1. Distributed control and protection.

   The system deals with the introduction of time-critical communication exchanges between substations and measurement equipment installed along the distribution network such as PMUs. Fault detection and localization is a fundamental protection operation involving the use of IEDs with the abilities to exchange messages related to protection, report events

to control centres for fault diagnosis and initiate control commands.

2. Wide-area monitoring systems

   The system deals with the use of incorporated PMU information from many substation to enable fast decision-making and switching/isolation actions to avoid substantial propagation of disturbance and ensure achieving self-healing and system configuration possible.

3. Monitoring of distributed equipment

   The system involves real-time situation awareness and supervision of capacitor bank controller, fault detectors, re-closers, switches, and voltage regulators among substations [24].

### 2.3.1 Communication Design Requirements of Smart Grid NANs

The critical applications in smart grid NANs such as DA can only be enabled through a good communication design. Supporting smart grid NANs applications by exploiting a communication technology is a challenging task due to a large number of communication nodes deployed in large and complex geographical areas [13]. Moreover, the technology must be able to meet main requirements for smart grid NANs. In the following, main communication design requirements for smart grid NANs are presented.

#### Reliability

Reliability is a fundamental requirement for the communication technology in smart grids. Reliability determines the availability of data transmission links and has a significant impact on smart grids' performance. NANs should have self-healing ability to sustain the performance of the whole network in the case of abnormal conditions occurred. Moreover, the DAUs in NANs are usually deployed outdoors, therefore reliability is one of the major concerns in NANs' communication design [25]. A hybrid communication technology mixed with wired and wireless networks could be exploited to improve the reliability of smart grid NANs.

#### Scalability

In smart grids, NANs connect large numbers of devices deployed in large and complex geographical areas, therefore scalability is a critical requirement. High scalability communication technology is required to maintain the network operations when a node or a group of nodes leave or join the network [2]. Therefore, the communication technology for NANs needs to deal with the scalability.

#### Quality-of-Service (QoS)

Data exchange in smart grid NANs must be done in timely manner [20]. Status and meter data must be sent to the control centre and control commands from the control centre must be addressed and implemented within a few miliseconds to prevent outages in real-time [13]. Therefore, the communication technology should provide low latency and efficient bandwidth. In smart grids, performance degradations due to delay, outage and jitter are intolerable to ensure system stability. Data compression and congestion management schemes have been proposed to satisfy the QoS requirement in smart grids [13].

### 2.3.2 Networks System Requirements for NAN Applications

A NAN can also be defined as a network that supports information flow between WAN and a premise area networks, which enables a range of smart grid applications, including smart metering, load management, distribution automation, pricing, outage management and restoration as well as other customer-based applications [26]. Most of applications in NANs require communication technologies that can support high data rate and large coverage area. Data rate requirements and coverage areas can differ depending on the application. For instance, scheduled meter interval reading produces a typical data size of 1600 to 2400 bytes, while distribution automation application generates data in the size of 25 to 1000 bytes.

In general, the smart grid applications that require communication support can be group into two parts, which are data collection and management application, and control and operation application. The former focus on the collection of readings from sensors, meter from smart meters, and exchanging this types of data between smart grid domains for decision making purpose, while the later manages control actions in case of emergency to ensure efficient normal operation of grids [27]. In the following, a typical NAN applications and their requirement in terms of typical data sizes, typical data sampling requirements and latency requirements are discussed. All requirements are summarized in Table 2.1.

#### Meter reading

The application is used for data collection from smart meter to utility and data transfer to control centre for billing and analysis purposes. Network requirements for meter reading applications are different depending on service types, which are explained as follows

- On-demand meter reading only permits reading to be taken when needed, such as when a utility needs information to answer end users' inquiries. The typical data size is 100 bytes with latency requirement of less than 15 seconds [13].

Table 2.1: Network system requirements for NAN applications in smart grids

| Applications | Data size (bytes) | Data sampling requirement | Latency |
|---|---|---|---|
| Meter reading (on-demand) | 100 | As needed (7 am - 10 pm) | < 15 s |
| Meter reading (scheduled interval) | 1600-2400 | 4-6 times per residential meter per day | < 4 h |
| Pricing (TOU) | 100 | 1 per device per price data broadcast event 4 per year | < 1 min |
| Pricing (RTP) | 100 | 1 per device per price data broadcast event 6 per year | < 1 min |
| Pricing (CPP) | 100 | 1 per device per price data broadcast event 2 per year | < 1 min |
| Demand response (DLC) | 100 | 1 per device per broadcast request event | < 1 min |
| Distribution automation (monitoring and maintenance) | 100-1000 | 1 per device per time interval | < 5 s |
| Distribution automation (Volt/VAR control) | 150-250 | 1 per device per time interval | < 5 s |
| Distribution automation (demand response) | 150-250 | 1 per device per time interval | < 4 s |
| Distribution automation (fault detection, isolation and restoration) | 25 | 1 per device per isolation | < 5 s |
| Outage and restoration management | 25 | 1 per meter per power lost | < 20 s |

- Scheduled meter interval reading allows the collection of meter data to be taken in timely manner. For residential users, meter data are usually collected about 4 to 6 times per day, producing data with the size between 1600 to 2400 bytes with latency requirement of less than 4 hours.

**Pricing**

Pricing application comprises of the price information broadcasting to meters and devices, which usually associate with time-of-use (TOU), real-time pricing (RTP) and critical peak pricing (CPP) programs that have typical data size of 100 bytes and latency requirement of less than 1 minute [13]. In TOU programs, customers can lower their electric bills by shifting their electricity usage to off-peak hours. Different price schedules for different time periods, such as peak, shoulder and off-peak are provided for the participating customers. On the other hand, the RTP programs provide short term time-varying price information to end users. These informations are very useful to reduce electricity bills by managing the energy consumption. CPP programs are utilized during times of high peak demand, where a utility needs to reduce loads and immediately transmit CPP messages to customers for radial load reduction purpose. As a result, a higher price is charged for customers during a few hours and a discounted price for the remaining hours.

**Demand response (DR)**

The application enables communications between utility and devices at customer premises with the objective to provide load reduction during peak-demand periods. Some DR applications include direct load control (DLC) programs for central air conditioning systems, heat pumps, electric water heaters as well as RTP and TOU programs. The typical data size for this application is 100 bytes with data latency requirement less than 1 minute [13].

**Distribution automation (DAU)**

This application is used to monitor and control the distribution grid by allowing real-time operation information of grid structure, automation control, data communication and information management [13]. The requirements of DAU applications are different between utilities.

- Distribution system monitoring and maintenance involves operations such as self-diagnostics on equipment, polling equipment status at scheduled intervals as well as retrieving sensor data for equipment conditions' monitoring.

- Volt/VAR control responsible to reduce energy loss, adjust voltage in distribution circuits and balance load power factor.

- Distribution system demand response tries to decrease distribution grid voltage in order to manage load during peak periods.
- Fault detection, clearing, isolation and restoration is critical to minimize service interruptions by managing detection, isolation and restoration of grid in the case of faults.

The typical size of data for DAU applications is 25 to 1000 bytes and the latency requirement is less than 4 to 5 seconds.

**Outage and restoration management (ORM)**

The application enables outage detection by a utility immediately after power loss occurred through devices and outage detection units. The devices have the ability to report over and under voltage situations. This applications generate data in the size of 25 bytes with the latency requirement less than 20 seconds.

In FREEDM systems, IEMs collect data from end users, make energy management decision and report the decision to the control centre. When faults occur in a distribution grid, the size of IEM reports from the fault zone could increases significantly because raw end device reports (load and DRERs reports) are required to be included for identification purpose at the control centre, which may result in up to 100 times of normal data rate [7]. Therefore, there is a need for resource control schemes that can improve the data rate of IEMs to ensure reports can be delivered within the time constraint.

## 2.4 Communication Technologies for the Smart Grid NAN

Many types of communication technologies have been considered to support smart grid NAN applications, including wired and wireless technologies. In the following, some examples of wired and wireless technologies to support smart grid NANs are discussed.

### 2.4.1 Wired Technologies

Wired technologies are considered superior to wireless technologies in term of reliability, security and bandwidth as cables are easier to protect from interference and eavesdroppers. Moreover, wired technologies have lower equipment and maintenance cost compared to wireless solutions. In wired technologies, dedicated cables can be used for communication differently from the electrical power lines, resulting high capacity and low latency. Some important wired technologies used in smart grids are explained in the following.

#### Fibre Optics

Fibre optic communications transmit data through pulses of light over optical fibres and have been used by many communication applications. This technology can provide long-distance communications without intermediate relays or amplifications and also immune to electromagnetic interferences [28], making them a preference for high demand applications. The fibre optics technology could provide data rate between 155 Mbps to 40 Gbps and could cover up to 100 km communication distance. Currently, Ethernet has been widely implemented in power systems to provide real-time monitoring and control through local area networks (LANs) [29]. However, considering communication in smart grid distribution areas, which involves a massive number of power devices, fibre optics are less in flexibility and scalability to quickly adapt to topology changes [30]. Moreover, the implementation requires high installation cost to cover a large distribution area eventhough the running cost and maintenance cost could not be an issue over a period of time.

#### Power Line Communication (PLC)

Alternatively, PLC offers a cost-effective options for NAN applications, since data transmissions are enabled through the electrical power lines. The PLC was initially designed to monitor faults in distribution lines, but has gained a lot of attention now for communications in medium and low voltage network of the electrical grid [31]. The use of single medium to transmit data and electric simultaneously, as well as high availability of PLC networks making them a preference for some power applications in customer premises such as load control and demand-response [19]. In general, narrowband PLC could provide data rate between 10 and 500 Kbps, and cover from 300 m to 1 km communication distance. PLC is also a fully-controlled communication network by the grid operator. However, PLC prompts to noise, interference and attenuation because electric wires are initially designed for power delivery. Moreover, there is no standard channel model and no widely accepted channel similar to those derived for radio communications for PLC. The signal attenuation and distortion caused by the transformers, in the use cases where data signal must cross distribution transformers hinders the deployment of PLC for NANs.

### 2.4.2 Wireless Technologies

Wireless technologies are considered as a promising solution to support NAN applications due to its scalability, availability and effectiveness. In the following, we present and discuss relevant wireless technologies available for NANs.

### ZigBee

ZigBee technology with IEEE 802.15.4 standard is a possible alternative for low-cost and small-scale applications [32]. The standard defines low-rate wireless personal network's physical and medium access control layers. The IEEE 802.15.4g modification specifies a network topology in which a huge set of smart devices located in remote areas communicate with a data aggregator through peer-to-peer multi-hop technique [2], thus it can cover longer range AMI applications in NAN. This standard has the ability to support large-scale grid applications in geographically challenging deployment with low infrastructure requirements, hence reducing the running cost. However, there are some limitations that renders its impractical deployment for reliable smart grid operations, which are in terms of operation in license-free bands, security, complexity and data rate [19]. In general, the ZigBee standard can provide data rate from 20 to 250 Kbps within the range of 10 m to 1.6 km.

### Wi-Fi

Wi-Fi technologies using IEEE 802.11 standard and associated modifications that consists a mature and widely adopted wireless technology that is fitted for home applications in smart grids. This standard defines the physical and media access control (MAC) layers of wireless LAN (WLAN), where it can provide high data rate, which is between 2 Mbps up to 6.75 Gbps. However, this standard has limited coverage distance, which is from 20 m to 1 km, that limits its application for the use in power system specifically for NANs where many IEDs located in remote geographical areas [19]. For instance, IEEE 802.11n can covers roughly 70 m indoors and 250 m outdoors, therefore it is only suitable for local interconnectivity functionalities within power grid, such as meter connection to a longer network, devices interconnection within a small area [33], or intra-substation enabled communication [34].

### WiMAX

WiMAX technology with 802.16 standard [35] is also one possible solution to facilitate utilities and a massive number of power consumers in AMI systems. This technology is designed to provide large and sufficient coverage for the smart grid distribution systems. WiMAX is categorized by low latency (less than 100ms round trip time), high data rates (up to tens of Mbps), large coverage range (tens of kilometers) and advanced security protocol [36]. Moreover, the standard also has traffic management tools and QoS support for four different traffic classes, which is a critical feature in smart grid traffic differentiation. However, the installation and maintenance cost associated to WiMAX-based infrastructure may be restrictive for the development in power utility.

#### Satellite

Satellite communications could also be an alternative for NANs [37, 38]. This technology has the advantage of very large coverage areas, which can cover the power distribution grid areas. However, in satellite communications, there is a need to install large antennas which requires high installation cost, and possible geometric storm could degrade the channel quality. Moreover, high energy consumption associated to large communication distance limits the application for autonomous operating smart devices. Low earth orbit (LEO) satellite could be used for time-critical applications [39] which offers improvements in stability, security and reliability of the power and communication infrastructure. However, wide deployment of this technology requires international coordination and compliance with national regulations.

### 2.4.3 5G Networks

Recently, many researchers have focused their work on 5G networks. 5G communication networks are claimed to be more multi-functional and flexible which could support many critical issues and cater problems related to cost analysis and power applications [40]. New key concepts introduced by 5G networks addressed stringent communication requirements of smart grid applications, and among three service scenarios presented in 5G networks, the massive machine type communication (mMTC) and the ultra-reliable low-latency communication (URLLC) scenarios show a perfect match for the communication requirements of smart grid data collection and control services. The mMTC service could support massive access of machines which is up to 10 million connections/$m^2$, while the URLLC service can provide connection down to 1 milisecond with extremely high reliability, which is beneficial for applications with stringent communication requirements [27]. Additionally, in 5G networks, the concept of network slicing that enables the construction of isolated virtual entities make it possible to support different applications on the same network without any interference. Therefore, with this concept, two network slices dedicated for mMTC and URLLC can be used to support data collection and control services in smart grids while maintaining other applications and industries over the same physical network. Moreover, some other key concepts in 5G networks such as network function virtualization (NFV), software-defined network (SDN), and cloud computing could manage the smart grid big data in more efficient and flexible way as well as obtain optimal operational decision in a timely manner.

However, even though 5G networks can be considered as one of promising technologies for smart grid applications, practically, these systems have not been fully adopted due to some reasons [40]. The main concern on the 5G networks is the standardization, in which currently has not been introduced. This standardization is critical to ensure that the existing technology can be

Table 2.2: Comparison between 4G and 5G technologies

| **Features** | **4G** | **5G** |
|---|---|---|
| Deployment | 2010 | 2020 or later |
| Data | Digital Broadband packet data | Not yet defined |
| Frequency band | 2 to 8 GHz | 3 to 300 GHz |
| Speed | 100 Mbps | 10 Gbps |
| Technology | WiMax, LTE, Wi-Fi | Had to be defined |
| Multiple access | Orthogonal Frequency division | Orthogonal Frequency division |
| Core network | Internet | Internet |
| Advantages | High throughput, high data rate, high availability and maturity | High speed, high reliability, and very low latency |
| Disadvantages | More energy consumption, costly | Systems have not been fully adopted |

utilized and modified to make it compatible with 5G standard. Moreover, the research work in this area is still in an early stage that required further investigations on several challenges [27]. Most of existing work considered relatively delay-tolerant smart grid service where the communication requirement is more lenient compared to emergency services. Further study must be conducted in designing effective communication platforms based on the novel 5G concepts to enable emergency services in smart grid. Further investigation should also focus on resources competition between different applications, since 5G networks are expected to support many applications in the same network and most of current study only considered single application scenario. Security threats are also one of the main concerns in future 5G networks, therefore study on robust solution to secure smart grid data is required. Compared to 5G, cellular networks with LTE-based standard are widely deployed and also a future-looking technology which could be available for at least tens more years, therefore it is promising for smart grid applications due to its availability, scalability, flexibility, maturity and stability [19]. The comparison between 5G and 4G technologies [40] are summarized in Table 2.2.

### 2.4.4 Advantages of Cellular Technology for Smart Grid Neighbourhood Area Networks

Cellular technology with LTE-based standards has been a preference for distributed control and real-time communications in smart grid NANs. This technology can be considered as a promising technology for future smart distribution grids due it high flexibility, scalability, availability, maturity and stability even though the functionality and capabilities will continue to gradually

develop [19]. The use of licensed bands in cellular networks enable efficient interference control and also increase the security of the protected data in smart grids. Moreover, cellular technology can offer mature and ubiquitous coverage to the distributed smart grid domains located in large and complex areas due to widely deployed base stations for mobile communications [41]. In smart grids, critical automation tasks demand for high QoS requirements. Cellular networks can provide high data rate, low latency and high system reliability, therefore it can enable critical automation tasks such as in smart grids. Additionally, in cellular technology, mobile network operators offer improved business models and service level agreements adapted to energy utilities so that this technology could be promoted for smart grid using existing communication infrastructure. In short, cellular technology has the ability to assist the progress of transformation from existing current power grid to a modernized and fully automated power grid [23].

Previously, the use of general packet radio service (GPRS) technology to monitor the operational status of remote substations has been proposed in [42] and [43]. Novel access mechanisms to handle large number of metering devices in global system for mobile communication (GSM) is presented in [44]. The authors in [45] proved that second-generation mobile networks (2G) or third-generation mobile networks (3G) could be used for NAN metering and control applications after implemented medium-voltage remote applications over 2G or 3G mobile radio networks. However, it is not easy for network operators to maintain the operation of varieties of radio networks simultaneously in the long term, and higher flexibility of latest standard make the available cellular networks are preferred based on LTE standards. LTE can offer energy utilities low end-to-end latency, high throughput, high data rate and QoS differentiation in a single radio access technology. Furthermore, LTE has been proven to allow the extension of its applicability to other domains and this standard could support remote control applications over the deployment in wide geographical areas, as well as the authentication and encryption mechanism available in LTE can improve the security of smart grid data.

### 2.4.5 Challenges for the Existing Cellular Communications

Integrating cellular technology and smart grid NANs is a challenging task because LTE was not initially designed for smart grid applications. There are some of smart grid NAN functionalities that cannot be accommodated by the current cellular technology. Therefore, to support the applications at distribution smart grid domains, the following design requirements for LTE technology must be satisfied [19].

### Data Traffic Characteristics

Data generated in smart grids has different characteristics from data generated by broadband services. Most control applications in the smart grid generate data in event-driven manner while monitoring and measurement data follows a periodic traffic pattern. In smart grid NANs, most traffic is mainly uplink, but traditional cellular networks provides higher throughput in the downlink than in the uplink [46].

### QoS Differentiation

In smart grid NANs, real-time and non-real-time data have different QoS requirements. Therefore, the LTE must be enhanced to ensure the QoS of smart grid data are guaranteed. Resource allocation and traffic prioritization mechanisms are some enhancements which can be done to support different types of data delivery in LTE.

### Massive Network Access

The number of metering and mobile devices joining the communication networks is rapidly growing, therefore network access for a massive number of devices is a critical issue in LTE. Radio access method in LTE needs to support high density of devices per connection point. Efficient dynamic congestion- and overload-control schemes, and minimal signalling message exchange techniques are required to accommodate and handle devices as well as facilitate the grid operation [47].

### Congestion Control

The integration of smart grids and LTE networks will result in a very large number of devices connected to the network. Consequently, a large data volume is associated in the networks which may lead to network congestion and capacity overload [2]. Therefore, congestion avoidance techniques are required to reduce the traffic.

### Latency

The current LTE cannot enable delay-critical smart grid applications due to the fact that the current achievable end-to-end delay is still high (approximately 100 ms). Fast automatic distribution grid operations require end-to-end data delivery in tens of miliseconds, or even below 5ms as stated in the vision of fifth generation mobile networks (5G) [19]. Instant-access resource allocation, reducing transmission-time interval and D2D communications could be used as critical techniques to reduce the end-to-end delay.

#### Reliability

In smart grid, some protected-related applications are associated with high reliability which is at least 99.99%. Unreliability issues in the power grid might compromise the system stability. Reliability is usually associated with data transmission link availability. Some enhancement to the LTE such as a combination of D2D and cellular communications introduces multi-path diversity, which can increase the reliability of the network.

#### Energy efficiency

Energy efficiency is a critical issue in both cellular networks and smart grids. In cellular networks, base stations responsible for 60%-80% of the total network energy consumption and the number of base station keep growing from year to year [48]. On the other hand, some smart grid devices are battery-operated which has limited power. Moreover, the integration of cellular networks and smart grid communication networks yields a significant growth of data traffic. The increases in traffic leads to the increase of energy consumption. A combination of D2D and cellular communications technique can be used as a critical solution because D2D communications can alleviate the burden of the base station by off-loading data to direct links, which also reduce the communication distance [49], resulting reduction in power consumption.

### 2.4.6 Possible Solutions to Cellular Communications

In this subsection, we propose D2D communications underlying cellular networks and heterogeneous cellular networks to enhance the performance of LTE. We give explanations on the advantages of both technologies for the smart grid NANs.

#### Device-to-Device (D2D) Communications

Integrating the cellular technology and the smart grid communication networks is a significant challenge for LTE due to the simultaneous transmission of large volume delay-sensitive data. One critical way to enhance the performance of LTE is to exploit D2D communications. D2D communications can be categorized as Inband D2D and Outband D2D. In Inband D2D, devices are operated in cellular spectrum, while in outband D2D, devices operate in unlicensed spectrum. The Inband D2D can be further divided into underlay and overlay categories. When cellular and D2D communications share the same radio resources, the communication is categorized in underlay D2D communications while in overlay D2D, dedicated cellular resources are allocated for D2D links. Figure 2.3 illustrates the taxonomy introduced for D2D communications in cellular networks. The D2D underlay mode can improve the link quality of D2D users by reusing the resources belonging to the cellular users. High link quality is critical especially in a

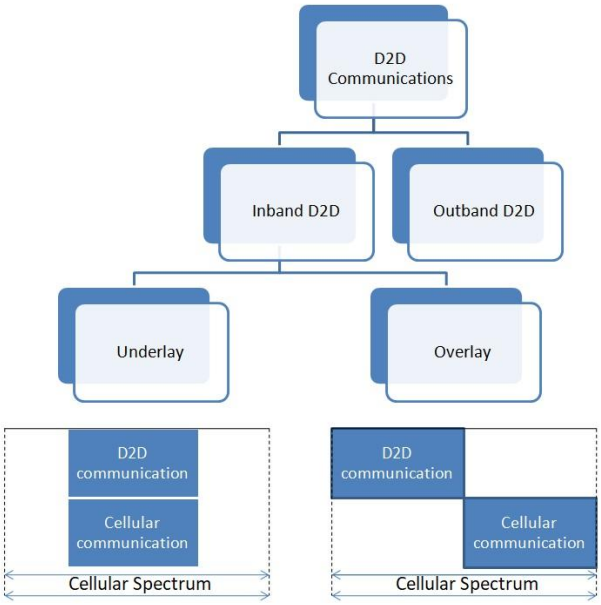


Figure 2.3: The classification of device-to-device communications.

fault condition, where the data rate over the pre-assigned sub-channel might not be able to meet the delay requirement due to the significant increment in the length of message or poor channel conditions. Therefore D2D communications underlying cellular networks are the focus of this thesis.

The introduction of D2D discovery and communication is one of the features of third Generation Partnership Project (3GPP) Release 12, in which devices can utilize cellular resources and exchange message directly without the assistant of the cellular infrastructure. D2D communications can offer a few advantages to enhance LTE performance as the enabling technology for smart grid NANs. Some of the advantages include:

- **Radio resource management.**

  In LTE, radio resources can be managed properly as it operates in licensed spectrum, resulting minimum interference and maximum overall system performance. Communications between smart grid devices can take advantage from the network in terms of cellular spectrum utilization. The nature of D2D communications allows the reuse of cellular resources while maintaining the acceptable interference levels of cellular users.

- **Throughput and Latency.**

  Direct communications between smart grid entities could give higher throughput and lower latency than communications through a cellular infrastructure (i.e., base station). Time-critical protection and control applications in distribution grid can utilize this feature as every milisecond matters. The additional latency imposed by the communication through the base station could be fatal for these applications.

- **Network offloading.**

  Base stations and other LTE network components could relieved from extensive infrastructure network load by offloading traffic onto direct D2D links [19]. The direct communication avoids traffic routing through LTE network leading to efficient and real-time load balancing.

- **Energy efficiency.**

  Direct D2D communications offer lower energy consumption due to shorter communication distance between devices compared to conventional cellular network. Moreover, energy efficient device discovery also achieved as the base station assist the discovery process through identifying potential D2D links through control messages [19].

- **Reliability.**

  When D2D communications are combined with infrastructure-based communications, reliability could be increase by means of multi-path diversity. Furthermore, shorter communication distance may lead to lower packet error rates, resulting higher reliability.

There are some work related to D2D communications for smart grid applications. Authors in [19] produced a comprehensive survey on relevant architectural and protocol enhancement, and D2D solutions for smart grid NANs. The paper also studied the capability of D2D communications in representative NAN use case in power distribution grid as well as suggested some potential research directions for future research in this field. A D2D-assisted relaying framework for the energy management in the electric distribution network to improve spectral efficiency is proposed in [7]. This paper also developed a real-time distributed data transmission scheduling scheme to solve the uncertainty of latency in data transmission. Authors in [50] proposed vehicle-assisted data delivery to offload smart grid data from cellular networks and reduce the data transfer cost. Moreover, mode selection and resource allocation schemes are also explored to maximize the total average delivery ratio, guarantee fairness among data sources, and reduce the cost for the utility. Cellular-assisted D2D communications are used in [51] to connect a large number of smart meters to the meter data management units through cluster heads to improve spectral efficiency in terms of uplink sum-rate,as well as guaranteeing a minimum throughput.

Although some work has been done in D2D communications for smart grid NANs, none of them considered delay and energy efficiency in fault condition of energy management in FREEDM system. Specifically, when a fault occurs in a grid, for instance due to natural disasters such as floods, earthquakes or tsunamis, more information needs to be sent to the control centre, resulting in a significant increment to the size of IEM reports [7]. In this kind of situations, the grid must have resilience and self-healing capabilities to prevent power losses and

blackouts, which result in stringent delay requirements to the data transmissions. Moreover, in this situation, the IEM and all loads in the fault zone are powered by local energy sources, such as small wind turbines, photovoltaic panels and local energy storage equipment [9], which have limited power supply. Our work focus on energy efficiency and delay in D2D communications underlying cellular networks for energy management in FREEDM systems.

**Heterogeneous Cellular Networks (HetNets)**

Smart grid data can be classified as machine type data (MTC) where they do not necessarily need human interaction. With the rapid growth in the number of connected devices to the cellular networks due to the integration of cellular technology and smart grid communication networks, the communication demands for high data rates, where existing cellular networks could not accommodate all devices with good data rate [11]. To enhance the performance of cellular networks in terms of accommodating massive number of devices, heterogeneous cellular networks (HetNets) are proposed. In HetNets, small cell base stations with constrained power and coverage areas can be densely deployed, overlapping with macrocells. Three typical types of small cell base station include femtocell base stations, picocell base stations, and microcell base stations. Femtocell base stations are usually deployed in home areas or small offices, while picocell base stations are usually deployed indoor to give coverage to indoor areas, such as rooms in buildings. Microcell base stations can serve a large area and deployed in places such as shopping malls, stadiums, and so forth.

HetNets can offer a few advantages to improve performance of cellular networks which can be summarized in the following:

- **Network capacity.**

  In HetNets, small cells can offload traffic from single macrocell, increasing the overall network capacity and reducing access delay [11]. Moreover, small cells can also alleviate the access congestion by offloading access attempts from macrocells to small cells, making this solution promising for smart grid NANs with many connecting devices.

- **Spectrum efficiency.**

  HetNets also offer spectrum efficiency improvement in terms of sharing resources between small cell users and macrocell users as well as between base stations as long as interference to macroccell users are within acceptable level. For instance, in intra-tier spectrum reuse scenarios, different small cells can share the same radio frequency resources, while in inter-tier spectrum reuse cases, small cells can share macrocells' radio resources when macrocells are idle or the interference to macro cell users is acceptable.

- **Energy Efficiency.**

  In HetNets, small cell users can connect to nearby small cells rather than remote macrocells, hence reducing the communication distance. The reduction in the communication distance will also decrease the transmission power used to transmit data to the base station. Moreover, since the power consumption of small cells is much lower than macrocells, offloading traffic to small cells can reduce traffic load and increase idle time of macrocells. Therefore, the overall energy consumption can be lowered.

- **Coverage area.**

  Small cells can improve the cell edge performance of macrocells and extend the service range of macrocells by deploying small cell base stations at the edge of the cell, resulting higher overall bandwidth, data rate and reduce latencies of end users [52].

Many works have considered HetNets to accommodate MTC with different objectives. Authors in [53] proposed an admission control mechanism that could either steer or reject traffic of macrocell and small cells to maximize users' quality of experience (QoE) under different traffic load scenarios (i.e., low and high). A tractable queueing model for MTC devices with random access to initiate connections for transmitting data to the eNodeB by taking into account the energy saving capability is proposed and cooperation among MTC user equipments (UEs) for relay transmission and base station selection is studied in [54]. A study on user association in HetNets with various user priorities to solve the load balancing problem due to imbalanced power and random locations among various BSs in HetNets has been conducted in [55]. Authors in [56] proposed an optimization framework for spectrum bandwidth slicing to maximize the aggregate network utility, by taking into account the of location distribution for MTCs and macrocell users, traffic statistics and differentiated QoS demands, traffic load in each cell, varying distances between BSs and devices, and inter-cell interference. A study on access mode for devices in HetNets to offload traffic from macro base stations to small base stations via D2D communications to improve the overall network capacity and mitigate the traffic congestion at macro base station has been conducted in [57].

Eventhough many works have been done in HetNets for MTC applications, none of them considered energy efficiency and delay of PMUs in smart grid. Energy efficiency is one of the critical parameters in HetNets, especially when PMUs are considered. Just like IEMs, when abnormal events occur, the PMUs will be isolated from the grid. In this situation, the PMU is powered by local energy sources, such as small wind turbine, photovoltaic panels and local energy storage equipment [9], which have limited power supply. Therefore, energy efficiency is critical in this kind of situation to ensure that status of DERs can be transmitted to the control centre successfully. However, increasing the energy efficiency might compromise delay, which

is an important performance parameter that reflects the actual user experience in the network. Delay is also important for PMUs because if the PMU data exceed the delay requirements, information loss may occur, which might lead to power loss and blackouts may occur in severe cases [58]. Therefore, it is critical to consider both parameters in HetNets.

## 2.5 Conclusions

This chapter presented an overview on smart grid NANs. Cellular technology with LTE-based standard is promising for smart grid NANs, however, the simultaneous transmission of large volume delay-sensitive data is a significant challenge in integrating cellular technology and smart grid NANs, therefore there is a need to improve the performance of the LTE. D2D communications can be exploited to increase data rate of IEM in a fault zone or experience poor channel condition, while HetNets are proposed to reduce RAN congestions when devices in smart grid NANs request access simultaneously.

# Chapter 3

# Optimization Strategies and Mathematical Tools in Device-to-Device Communications and Heterogeneous Cellular Networks

In this chapter, we give explanations on the optimization strategies that are exploited in D2D communications as well as in HetNets. Furthermore, we also provide explanations on mathematical tools which can be used to model the schemes along with recent literatures for each section.

## 3.1 Optimization Strategies in Device-to-device Communications

D2D communications offer many network enhancements by exploiting a few optimization strategies. In general, these strategies can be categorized into device discovery, mode selection, resource management, and mobility [59]. Explanation of each strategy is explained as follows:

### 3.1.1 Device Discovery

Device discovery is a critical method which enables devices to discover potential candidates in the proximity and establish a direct connection with them by sharing beacon signals among themselves to gather information such as device location/ distance, channel state and device identity. The information is important for devices to evaluate the possibility of grouping into a pair with each other. In general, device discovery in D2D communications can be classified into centralized discovery and distributed discovery.

In centralized discovery schemes, the discovery process is done with the help of centralized entity, typically the BS. The BS initiates message exchange between two devices in order to obtain the important information for device discovery. The BS could be completely or partially involved in this process. If it is completely involved, the devices only listen to the messages transmitted by the BS and transmit messages to it in order to initiate the device discovery process. On the other hand, devices send messages to each other for device discovery without obtaining prior permission from BS in partially involved discovery process. However, the communication between devices involving the BS must satisfy the level of path gains and Signal-to-Interference-and-Noise Ratio (SINR) of each device. This requirement will help the BS to determine the feasibility of communication between devices. The BS requests both devices to start the communication in the final process. In distributed discovery schemes, devices can determine the location of each other without the assistance from the BS by periodically transmit control message to the neighbouring devices.

There are some works related to device discovery in D2D communications. Authors in [60] studied neighbour discovery process that utilizes sounding reference signal (SRS) channel which is accessible by peer devices that are LTE-compliant and proposed joint neighbour detection and D2D channel estimation for listening devices using the framework of sparse channel recovery. A social-aware peer discovery framework that considers social domain information of community and centrality of mobile users to assist the communication domain peer discovery is developed in [61]. In particular, devices in the network are divided into several groups according to their centralities and different energy is allocated to each group to enhance the performance of cellular network. A study on predicting node contacts in the future based on network science is conducted in [62]. Specifically, the tradeoff between the energy consumption and system performance with power-law distributed contacts for the beacon probing and wakeup schedule is considered, in which nodes stay asleep if the probability of contact with device is low and wake up to probe for nearby devices when the probability of device discovery is high. Authors in [63] exploited the random backoff method in device discovery process, where D2D users of collision resend the beacons in next random allocated resource block. The scheme can significantly increase the average number of discovered D2D users, and also reduce both the D2D discovery delay and the collision probability. An asynchronous device discovery framework for cognitive-D2D applications, evolving timing drifts and dynamical fading channels to detect the existence of a proximity D2D device is proposed in [64]. The simulation results showed that the discovery performance is significantly improved by dynamically tracking unknown drifts and fading gains.

### 3.1.2 Mode Selection

The existence of D2D communications in conventional cellular networks enables direct transmission between devices over D2D links which can improve the overall network performance in terms of throughput and delay. In general, devices in D2D communications can select one of four transmission modes [59], which are

- **Pure cellular mode.**

  This mode is selected when there is a limited available resources and interference is high. In this mode, D2D users are not allowed to transmit data.

- **Partially cellular mode**

  This mode allows the communication between devices through the BS without co-channel spectrum sharing.

- **Dedicated mode**

  In this mode, dedicated spectrum resources are used to enable communication between devices.

- **Underlay mode**

  This mode allows the sharing of spectrum between D2D users and cellular users. D2D users can reuse the resources allocated to the cellular users.

Many works have studied mode selection problem in D2D communications. Most of them propose to use joint mode selection and resource allocation to improve network performance. In general, existing studies focus on three transmission modes, which are cellular mode, reuse mode and dedicated mode [65, 66]. Authors in [67] studied a joint D2D mode selection and interference management problem and presented degrees-of-freedom (DoF)-based mode selection and interference alignment (IA) technique for interference management. They showed improvement in the sum rate of potential D2D devices particularly in high SNR regime, low interference environment, large MIMO systems, and small-cell networks. A joint mode selection and resource allocation scheme in device-to-device communications is investigated in [68], considering dynamic channel conditions and bursty traffic arrival to minimize the average end-to-end delay under the constraint of packet dropping probability. Authors in [69] studied mode selection problems among cellular mode, direct D2D mode, and relay D2D mode with the objective to maximize overall cell throughput by considering different load scenarios (i.e., high, light). A joint mode selection and transceiver design in a network consisting of one multi-antenna base station and multiple pairs of multi-antenna user equipment's is considered in [70]. The study

aims to increase the network throughput by maximizing the sum rate through the joint optimization scheme. Finally, authors in [71] studied a physical layer perspective of mode selection that enable switching between overlay and underlay modes as well as spectrum partition scheme in which the system spectrum is orthogonally partitioned between cellular and overlay D2D communications.

### 3.1.3 Resource Management

Typically, resource management scheme is combined with mode selection scheme. Efficient resource management is crucial to mitigate interference, save energy and increase throughput. In general, two issues are related to resource management, which are interference management and power control.

#### Interference Management

The existence of D2D communications in cellular networks makes the interference issues become more complex. Therefore efficient spectrum allocation is required to maintain the level of QoS in the network. The integration of D2D communications in cellular networks has divided the cellular architecture into two-tier cellular system, consisting a macro cell tier which involves cellular communications between base station and cellular users, and a device cell tier concerning D2D communications, yielding two types of interference in the network. The types of interference can occur in this two-tier case are co-tier and cross-tier interferences. Co-tier interference occurs when the same resource clock is allocated to more than one D2D user within the same tier network, which usually occur between D2D pairs. On the other hand, cross-tier interference occurs when a resource block allocated to a cellular user is reused by one or more D2D users, where it typically occurs between cellular users and D2D users.

A variety of interference mitigation approaches exist in literature. Authors in [72] proposed a topological interference management (TIM) technique for IA, where instead of depending on channel state information to lessen the interference, the interference between devices in proximity can be aligned, thus facilitating the decoding of the intended signal,in which the network topology is represented by adjacency matrix known by all nodes in the network. Spectrum resource allocation problem in a multi-cell D2D-enabled heterogeneous cellular network aggregating multiple micro-wave bands and multiple mm-wave bands scenario is studied in [73] and a heuristic algorithm that considered network characteristics as well as taking advantage the milimeter (mm)Wave communication is proposed to effectively managed the interference and maximize the total transmission rate. Authors in [74] tried to enhance the successful transmission probability and average throughput of cellular users by proposing a guard zone based

interference mitigation scheme that force D2D users within a certain geographical area inside a cell to operate in cellular mode. A strategy that exploited the multiple-in-multiple-out (MIMO) technique in multi-user D2D scenario is adopted in [75]. Specifically, to eliminate interference, the cross-pair interference at the antenna combinations is examined and effective usage of multiple antennas based on a bucket based Degree of Freedom algorithm was introduced. Authors in [76] investigated the interference problem for devices operating in full duplex mode and adopted a graph Coloring based Resource Sharing (GCRS) scheme to solve the problem with minimum complexity.

**Power Control**

In power control scheme, devices and BS are allowed to adjust their transmission power to a certain level. Increasing the transmission power will increase the link capacity, but will also increase the interference between devices sharing the same cellular resources. Exploiting power control scheme can help devices to increase the energy efficiency. Resource allocation scheme involves strategies to allocate radio resource to different users, which is critical method to meeting the instantaneous increase in demand for resources. Joint power control and resource utilization can be exploited to improve system capacity and the overall system throughput.

Many literatures have considered the joint scheme strategy to improve the network performance. Authors in [77] adopted a game-theoretic model to address the D2D power control problem by considering both interference between D2D links and cellular links, and interference among D2D links. In this model, D2D links act as players and the combination of the positive outcome gained by that link and the negative impact on itself and other D2D links is selected as the utility function of a player. Power control problem in full-duplex (FD) scenario under reuse mode is addressed in [78], where multiple FD D2D links intend to communicate simultaneously by sharing the uplink spectrum with a cellular user. A centralized and distributed model are both proposed in this paper with different considerations but same objective, which is to improve the sum-rate of D2D links. Authors in [79] tried to maximize the frequency reuse factor in cellular networks with D2D links and dynamic power control by activating as many links as possible on a single resource assuming full power control, subject to the constraint that each active link is guaranteed a target SINR. A joint channel access and power control scheme that allows D2D links to share resources with multiple cellular users and manage interference during link establishment and maintenance is proposed in [80]. Simulation results showed that the proposed scheme enhances the coverage probability in cellular and D2D and also an increase in spectral and power efficiency. Finally, interference limited area (ILA) based D2D-management scheme along with an appropriately designed power control algorithm to mitigate the interference between a cellular users and D2D links to improve sum data rate is adopted in [81].

### 3.1.4 Mobility Management

Mobility management is an essential element in D2D communications due to dynamic nature of devices that could be moving from one location to another while communicating. This could lead to service interruption, therefore, there is a need for a mechanism that can handle communications when devices are mobile. Evaluating mobility patterns of devices and studying their impact on communication reliability is a key challenge specifically for D2D applications [59].

Typically, the literature in mobility management falls into two categories, which are location management and handoff management. The network are able to track the connection points of mobile terminals between consecutive communications when the devices roam around the network through location management scheme, while handoff management allows the network to maintain the users' connection while the devices moves from from one point to another [59]. Most of the work in D2D mobility management is related to efficient handover selection. For instance, authors in [82] proposed that D2D should be created or designed for stationary link with restricted mobility as an underlay in cellular networks, where the handoff can be executed from D2D links to the cellular link inside a cell, either when interference is high or when D2D transceivers are out of range. Two solutions to D2D handover in an underlay network is proposed in [83], where the first solution postpones handover of a pair of DUEs from the serving BS to another BS until the signal quality of the serving BS falls below a pre-defined threshold. The second solution clusters the members of a D2D group within a minimum number of cells or BSs to reduce network signaling overhead caused by the inter-BS information exchange. Finally, the impact of mobility on the relationship between Energy Efficiency (EE) and Bandwidth Efficiency (BE) in D2D communications is investigated and an EE-BE aware scheduling scheme with a dynamic relay selection strategy is proposed in [84].

## 3.2 Optimization Strategies in Heterogeneous Cellular Networks

HetNets are typically exploited to accommodate a massive number of devices. They can offer better data rate, coverage area, and energy efficiency. In this section, we give explanation on optimization method that can be used in HetNets. Generally strategies exist in HetNets that is used to meet design requirements fall into four categories which are explain below.

### 3.2.1 Resource Allocation

The next-generation cellular systems are envisioned to deploy dense HetNets, that exploit small cells to enhance the spectrum efficiency through sharing the spectrum resources with macrocells.

However, without proper spectrum resources management, interference between tiers could occur, resulting the performance of the network to degrade, therefore there is a need for efficient resource management scheme in HetNets. Resource allocation scheme is one critical method in managing the resources in HetNets, that aims at allocating radio resources efficiently and fairly to improve both spectrum efficiency (SE) and EE, as well as meeting diverse requirements [11].

There are extensive literature on resource management in HetNets. For instance, authors in [85] investigated resource allocation problem among radio radio access technologies, mobile network operators and D2D communications in network layer perspective. In particular, a social-aware virtual MAC protocol is proposed to integrate the virtualization and social-awareness features into current wireless protocols for D2D communications underlying HetNets, by extracting user social information. Resource allocation problem for D2D pairs among both mmWave and the cellular carrier band is addressed in [86] with the objective to maximize the system sum rate. A game theory point of view using coalition formation game is provided in this paper to obtain the solution. In [87], the authors considered the interweave sharing mode, where secondary users can only access the resources when it is not occupied by the primary users in non-orthogonal multiple access networks. Specifically, an optimal channel reconfiguration scheme is developed to improve the spectrum efficiency for the proposed network with limited idle spectrum resources. Finally, a scenario of multi-cell D2D-enabled heterogeneous cellular network aggregating multiple micro-wave bands and multiple mm-wave bands is considered in [73] and a heuristic algorithm is proposed to find optimal resource allocation that addressed the complicated intra- and inter-cell interferences caused by co-band cellular links and D2D links. Simulation results proved that the proposed scheme enhanced the system transmission rate and reduced the interference.

### 3.2.2 Power Control

In HetNets, the power control scheme is typically used to coordinate interference as well as increase energy efficiency. The scheme enables the regulation of transmission power of devices and base stations to certain maximum level. In general, the power control scheme is combined with the resource allocation scheme in order to satisfy QoS requirements of the network.

Many works have addressed a joint power control problem in HetNets. Authors is [88] proposed joint user association and power control in downlink HetNets for load balancing which can maximize the weighted sum of long-term rates and further reduce the energy consumption and mitigate the network interference. A two-layer iterative algorithm that alternatively optimizes the transmit power and association index is developed to obtain the solution. Authors in [89] tried to maximize the total throughput in cooperative D2D communication mechanism, which is D2D HetNets, by proposing a joint resource allocation and power control scheme.

The scheme focus on selecting a suitable idle users to work as relays for D2D link as well as allocating spectrum resource block and adjusting transmission power of each D2D user, idle user and cellular user. An investigation on a joint orthogonal frequency-division multiple access (OFDMA) scheduling, time-division multiple access (TDMA) scheduling, IA, and power control to mitigate the co-tier interference of ultra-dense small cell networks is deployed in [90]. A distributed joint interference management (JIM) algorithm is proposed to find the solutions and simulation results showed that the proposed algorithm can optimize the total throughput.

### 3.2.3 User Association

User association is a process that assign users to different base stations available in the system. A typical rule in the user association scheme is that a user can be connected to one base station at a time. A proper user association can maximize the user achievable throughput.

Some works have addressed user association problem in HetNets. Authors in [91] studied user association problem in network provider's point of view. In particular, dual-battery that is equipped at each BS to harvest, store and utilize green energy is proposed in order to reduce carbon emissions and save on-grid brown energy electricity expenses at the BSs and the user association scheme that considered green energy utilization and traffic delivery latency to maximize the profit of the network provider is designed. A joint cache partitioning, content placement, and user association problem in D2D-Enabled HetNets is investigated in [92]. Specifically, to reduce end-to-end transmission delay and alleviate transmission load on the backhaul link, efficient content fetching applications that cache popular content files at the BS of HetNets, allow users to associate with their BS and fetch required contents locally is proposed and simulation results validated the effectiveness of the proposed scheme. Authors in [93] proposed a user association scheme that can exploit the advantage of the large bandwidth of the mmWave BSs as well as fill the coverage holes is needed for mmWave HetNets with multiple tiers of the ultra high frequency (UHF) BSs and a single tier of mmWave BSs and studied coverage-rate tradeoff problem in this scenario. The authors also investigated the statistical fundamental properties of the generalized user association scheme that characterizes the general line-of-sight (LOS) and non-line-of-sight (NLOS) channel models, blockage effects and user association parameters. User association problem in HetNets with in-band interference is addressed in [94], where security-concerned issues are highlighted. A maximum secrecy capacity association is proposed to enhance the network connection and secrecy probability, as well as network secrecy throughput.

### 3.2.4 Mobility Management

In general, mobility management in HetNets can be categorized into two procedures, which are location management and handover management. In location management procedures, cell selection process is enabled in which the user is associated to a serving BS, and its location in the network is tracked when it is in idle mode, while the handover management is enabled only when the user is in active mode [95].

#### Location Management

Literatures in location management in HetNets include [96–98]. In [96], an adaptive "drop and play" deployment and mobility management of small cells in multi-tier heterogeneous networks consisting macro base stations (MBSs) and energy harvesting (EH)-SCBSs with diverse transmission powers, energy harvesting rates and traffic load distributions is proposed to enhance the total system utility, by considering not only users' data transmission requirement but also the energy consumption and traffic load trade-off from the perspective of network operators. An explicit and analytical expression bounding the Kolmogorov-Smirnov distance between the distribution of the standardized aggregate wireless interference and the normal distribution is obtained as a function of a broad range of network parameters, such as per-tier transmission power levels, per-tier BS intensity, BS locations, general fading statistics, and general bounded path-loss models in [97]. The proposed scheme has improved the outage capacity, ergodic capacity, and area spectral efficiency in the downlink of K-tier HCNs for general signal propagation models. A fault-tolerant small cells location management is proposed in [98]. The design aims to support the self-healing functionality of the forth-generation cellular technology (4G)/5G self organizing networks framework and provide continuous service to users. Each user is defined a full bit rate and a backup bit rate, where when there is a failure among the small cells, the users receive service at the backup rate, while in the case of no failure, users receive service at the full bit rate.

#### Handover Management

In HetNets, a handover occurs when an ongoing call or data session is transferred from the main base station to another base station. The process is critical in order to maintain the call as the user is moving out of the area covered by the main base station and entering the area of the other base station. There are some studies on handover management in HetNets. Authors in [99] addressed cross-tier handover problem for delay-sensitive vehicular communications in HetNets. Particularly, in this work, a scheme where the base station reserved resources in advance for the handover process is designed, then the effective capacity during the handover process is

obtained and finally the tradeoff between the effective capacity and blocking probability is analysed. A joint cell resource allocation and mobility management is considered in [100], aiming to satisfies both coverage and mobility performance requirements of users with high SINR requirements by taking into account the behaviour of expectation of handover success rate vs coverage probability. A handover decision algorithm based on a Markov Decision Process (MDP) is presented in [101], where the characteristics of mmWave channels and user's mobility information is considered. The user's mobility information is used to derived the optimal beamwidth by considering the trade-off between the directivity gain and beamforming misalignment. Optimal handover is learned through developed two-layer framework is proposed in [102]. The first layer exploited unsupervised learning for the central controller to cluster the user based on the mobility pattern and the reinforcement learning framework is used to obtain the optimal controller for each user with the same cluster in the second layer.

In this work, which focus on energy efficiency and delay optimization, a joint power control scheme is adopted. In D2D communications, a joint power control and mode selection scheme is explored, while in HetNets, a joint resource allocation and power control scheme is adopted.

## 3.3 Mathematical Tools to Model Optimization Strategies in Device-to-Device communications and Heterogeneous Cellular Networks

A lot of mathematical tools can be used to model the schemes in D2D communications and HetNets. In this thesis we focus on three main tools, which are Markov Decision Process (MDP), game theory and deep learning.

### 3.3.1 Markov Decision Process (MDP)

A MDP has been used as an optimization model to make decision under uncertain condition [103]. In particular, MDP is exploited to describe the interaction of an agent with an environment or system, which is a stochastic decision process. At every decision time, the system remains in a certain state and the agent selects an action from the available action set at that state. In return, the agent receives an immediate reward after performing the action and the system transits to a new state according to the transition probability. For example, MDP can be used to model the interaction between a wireless sensor node and their surrounding environment to achieve some goals.

The goal of MDP is to find an optimal policy, which is a mapping of a state to an action,

in order to maximize or minimize a specific objective function. A MDP could be either a finite or infinite time horizon, which is differ according to the reward an agent tries to maximized. In finite time horizon MDP, the expected total reward is maximized, while in infinite time horizon MDP, an optimal policy that tries to maximize the expected discounted total reward is obtained. Here, some solution methods for MDPs with finite and infinite are introduced.

1. Solutions for Finite Time Horizon MDP

   The system operates in a known period of time in a finite time horizon MDP. Therefore, the optimal policy that maximizes the expected total reward can be constructed at every state iteratively through solving Bellman's optimal equation [104]. Two typical approach can be employed to solve finite time horizon MDP based on the Bellman equations, which are backwards induction and forward induction.

   - Backwards induction

     The backward induction is also known as a dynamic programming approach. It can be considered as the most popular and efficient method to solve Bellman's equations. In this approach, the optimal action and the optimal value function at the known last period is first obtained and then the optimal actions for previous period from the first period can be obtained iteratively based on the Bellman optimal equations.

   - Forward induction

     Another name for the forward induction method is the value iteration approach. In this approach, the optimization problem is divided based on the future number of steps. For example, for a given optimal policy for $t-1$ time steps to go, the Q-values for $k$ steps to go are calculated. Then optimal policy are obtain based on the optimal Q-value. The process continues until the system reaches the last period.

   The complexity of both approaches depends on the time horizon of an MDP, therefore both have the same complexity. However, the application is different, where backward induction is commonly used when the last period of the state is known while if the initial state is known, forward induction can be adopted.

2. Solutions for Infinite Time Horizon MDP

   Eventhough the solution for an infinite time horizon is more complex, infinite time horizon has been used extensively because in practice, most of the operation time of systems is unknown, therefore assumed to be infinite. Many solution methods have been proposed include value iteration, policy iteration, linear programming, approximation method and online learning methods. In the following, each of them is explained briefly.

- Value iteration

  Value iteration method is the most efficient and commonly adopted to solve an infinite time horizon discounted MDP because it can converge quickly, easy to implement and very practical even when the state space of MDP is very large. This method was developed based on dynamic programming, which is similar with the forward induction method in finite time horizon MDP. However, in infinite time horizon, a stopping criteria is used to guarantee the convergence of the algorithm instead of running the algorithm for the whole time horizon [104].

- Policy iteration

  Policy iteration method aims to generate a sequence of policies, starting with an arbitrary policy. It updates the policy until the convergence has been achieved. There are two main steps in this method, which are policy evaluation and policy improvement. In the former step, the linear equations are solved to obtain the expected reward under the policy $\pi$ and in the later step, the improving decision policy for each state is selected. This method can converge faster than the value iteration method, however, each iteration takes more time because policy iteration requires solving linear equations.

- Linear programming

  In linear programming method, a static policy is obtained by solving a linear program. The optimal value can be obtain based on the optimal policy at each state by solving the linear program. Compared to value and policy iteration methods, the linear programming method is not suitable to be applied when the state space is large due to the curse of dimensionality. However, this method can be used efficiently for MDPs with constraints since the constraints can be formulate as linear equations in the linear program.

- Approximation method

  When the state space of MDP is large, approximate dynamic programming method can be adopted. In this approximation method, the value functions such as policy function and value functions are approximated with the assumption that these functions can be formulated by a suitable number of parameters. Therefore, the optimal parameters values can be seek to get the best approximation.

- Online learning

  Most of MDP solution methods are performed in an offline manner, where the transition probability function is provided. However, these methods are completely useless if the information of the function is unknown, therefore learning algorithms are pro-

posed to address this issue. In learning algorithms, the simulation-based method can be exploited to evaluate the interaction between an agent and the environment of a system. Moreover, the behaviour of the agent can be modified to achieve its goal in a given environment.

In MDP, the solution methods for discrete time MDPs can also be exploited for continuous time MDPs by adopting uniformization techniques. These related solution method are also called semi-MDPs (SMDPs).

In the following, some extensions of an MDP, which include Partially Observable MDP (POMDPs), Multi-Agent MDP (MMDPs), Decentralized Partially Observable MDP (DEC-POMDPs) and Stochastic Games (SGs) are introduced.

#### Partially Observable Markov Decision Processes (POMDPs)

Mostly classical MDPs assume that the system states are fully observable by an agent. However in some applications such as wireless sensor network, the agent cannot have a full observability due to some constraints such as hardware limitations, environment dynamics or external noise [103]. A POMDP has been proposed as a promising method to address the issue with incomplete information in MDP. An optimal policy in POMDPs is obtained by the agent through maintaining the complete history of actions and observations. However, to reduce the complexity, the agent keeps a belief state, which is the probability distribution over the states instead of storing the entire history. In the beginning, the agent forms an initial belief, selects an action and observes the environment. The agent updates a new belief state later based on the selected action and observed environment.

#### Multi-Agent Markov Decision Processes (MMDPs)

In MMDP, multiple agents can cooperate with each other to optimize a common objective. The agent maintain at certain states and selects an individual actions simultaneously at each decision time. Through some information exchange mechanism, each agent can have a full observation of the system state. An MMDP can be formulated as a classical MDP if the joint action and state of the cooperative agents is seen as a set of basic actions and states. Therefore, to solve a MMDP, the same solution method for MDPs can be applied. However, when the state space and action space grow significantly as the number of agent increase, approximate solution method ccan be applied.

**Decentralized Partially Observable Markov Decision Processes (DEC-POMDPs)**

DEC-POMDPs have the same characteristic with MMDPs, in which they involve multiple cooperative agents. However, in DEC-POMDPs, each agent can only observe the system state partially. One of the challenges in DEC-POMDPs is that each agent can only obtain local information, therefore it is not easy to solve DEC-POMDPs. Moreover, finding the joint optimal policy in DEC-POMDPs becomes complex due to lack of information about the action and state of other agents, hence each agent makes decision independently. Special features of models need to be utilized to solve DEC-POMDPs with high complexity.

**Stochastic Games (SGs)**

Different with MMDPs and DEC-POMDPs, SGs are considered in the case when agents are non-cooperative and interested only in their own payoff. In SGs, agents have full knowledge of the system, but have different objective functions. This situation often lead to conflict among agent, hence obtaining an optimal strategy knowing other agent's strategies is complex. An extension version of stochastic games is called a partial observable stochastic game (POSG), where agents only have local information. Therefore, it is difficult to solve POSGs due to incomplete information and decentralized decisions, similar to DEC-POMDPs.

Both finite and infinite time horizon MDPs have been proved to be solved by dynamic programming in complete polynomial time [103]. However, it is different for extensions of MDPs due to different complexities. In POMDPs, a history of observation must be monitored and maintained to form the belief states of agents with incomplete information. The complexity of POMDPs could be different and PSPACE-complete has the worst complexity. On the other hand, the worst case of MMDPs is P-complete. In multiple agents and partially observations MDPs such as DEC-POMDP and POSG, the complexity is significantly increased, for instance, the complexity for both finite time horizon DEC-MDPs and DEC-POMDPs considering just two independent agents is NEXP-complete.

There are some work in D2D communications and HetNets that used MDP as the mathematical model. Authors in [68] exploited a general constrain MDP (CMDP) frameworkfor the dynamic optimization of mode selection and resource allocation in D2D communications over a dynamic fading channel with and the bursty traffic model aiming to minimized delay with dropping probability constraints. The CMDP is then turned into MDP by deploying Lagrangian approach and then solved using Bellman's equation. In [105], MDP is used to model the channel allocation and slot assignment problem for real-time D2D communications underlaying cellular networks. The MDP is solved by first proposing an optimal offline algorithm which maximizes the total utility of packets meeting their deadlines by a sequential channel and slot assignment

process. Then, an online joint packet admission control, channel allocation and slot assignment algorithm is employed to deal with the complexity.

On the other hand, in HetNets, authors in [106] formulated the joint energy saving and interference coordination in HetNets problem as a finite horizon MDP, then an approximate dynamic programming (ADP) algorithm is proposed to solve the problem. The algorithm combines combines stochastic control and machine learning technique, where the cost-to-go function is estimated in the offline phase and efficient farsighted controls that guarantee the QoS is selected in the online phase. Authors in [101] applied MDP to formulate handovers management problem in mmwave HetNets which can optimize user's overall service experience. Then an action elimination method is proposed to reduce the complexity of MDP and value iteration algorithm is exploited to obtain the optimal solution.

### 3.3.2 Game Theory

A game is established by a set of players, a set of actions for each player and the payoff for each player [107]. A player forms a strategy, which is the complete plan of action and selects an action. A strategy can be a pure strategy or a mixed strategy, where in a pure strategy, an action is selected deterministically while in a mixed strategy an action is selected probabilistically according to a certain probability distribution. The payoffs of the players are determined based on the strategy. Different solution concepts are used depending on the nature of the game, however most of them tried to ensure a fair or optimal payoff of a player given the strategies of other players in the game which rely on the equilibrium concept. Another famous concept in a game is Pareto optimality or Pareto efficiency, where this strategy is applicable if it is impossible to make one player better off without necessarily making other players worse off.

In game-theoretical model, two approaches are commonly adopted, which are the non-cooperative and the cooperative game approaches. The players make decisions by taking into account only their individual payoff in a non-cooperative game, while in a cooperative game, players are grouped together and an enforceable agreement of the group is established.

#### Non-Cooperative Game

In non-cooperative game, self-interest players take decision independently. Eventhough in this concept, an enforceable agreement between players cannot be established, but it does not mean that players do not cooperate. The players could cooperate in the game with the condition it must be self-enforcing. The goal of this model is to find the equilibrium solution for networks with self-interested nodes. Nash equilibrium (NE) is commonly adopted solution concept for a non-cooperative game [107]. NE can be defined as a set of strategies for the players where no

player has any intention to change its strategy to obtain higher payoff when no player in a game changes its strategy. However, a NE might not exist in a game, and even if it exists, it may not be unique.

Another solution can be adopted in non-cooperative game is correlated equilibrium, which is a more general solution than the Nash equilibrium. Instead of selecting the marginal distribution of players' strategies, a strategy profile is selected according to the joint distribution in this concept.

A non-cooperative game could have complete or incomplete information. The information such as the payoffs and strategies of the players are accessible to all players in a complete information game, while in an incomplete information game, these information cannot be observed by other players. A Bayesian game can be exploited to model an incomplete information game. In this model, a solution named Bayesian Nash equilibrium can be obtained where each player seeks for a strategy profile that maximizes its expected payoff given its beliefs about the types and strategies of other players.

Furthermore, a game can be categorized as a static game or a dynamic game. In a static game, all players decide an action without knowing the strategy that are being selected by other players, which is also called one-shot game. The game stops after actions of all players are selected and the payoffs are obtained. On the other hand, in a dynamic game, a player selects an action in the current stage based on the information of the actions selected by other players in the previous or current stages A typical solution for dynamic game is a subgame perfect Nash equilibrium [107], where it represent the original game of every subgame's Nash equilibrium through backward induction.

A multi-stage game model is used to describe a dynamic game with incomplete information. In this model, the players take turns sequentially instead of simultaneously but all players have no knowledge about each other and follow their belief. Their beliefs are updated by adopting the Bayes' rule. A combination of the Bayesian Nash equilibrium and subgame perfect equilibrium concepts, which is a perfect Bayesian equilibrium can be adopted as the solution concept.

When the same set of players play the same stage game for a long period, the game is called repeated game. Repeated game can be classified into finite and infinite games depending on period of time the game is played. If the game is played infinitely then it is called infinite repeated games and vice versa. The most common repeated game is infinite game in which the players consider the effect of its current actions to the future actions of other player.

An extension of game theory to MDP-like environment is called Markovian game (i.e., Markovian dynamic game or Markov game). A Markovian game is a type of stochastic game that can be considered as a multiagent extension of Markov decision process [107]. However, a Markovian game is different from MDP in terms of the transition process, where in this game

the transition depends on the current state and the action profile of the players. As a result, each player could receive different reward depending on the action profile. In Markovian game, each player has a reward function and selects an action which can maximize its expected sum of discounted reward.

A game theoretic approach where an object or service is exchanged on the basis of bids done by the bidders to an auctioneer is named auction game. In Auction game, two mechanisms can be used in which an object or service is appointed to a bidder with the highest bid and pays a price equal to the amount of bid in the first mechanism which is also called first price auction. In the second mechanism, which is called second price auction, a bidder with highest bid and pays a price equal to second highest amount of bid will be given the bidding object or service.

Another mostly adopted game model is the Stackelberg game or leader-follower game. In Stackelberg game, a strategy is established by letting a player that acts as a leader takes a move first and other players who act as followers move later. The problem aims to obtain the leader's optimal strategy with the assumption that the followers react to optimize their objective functions knowing the action of the leader. One way to solve the Stackelberg game model is by using subgame perfect Nash equilibrium.

#### Cooperative Game

Different with non-cooperative game, in a cooperative game, players can establish enforceable contract. When the players in a coalition, they make a cooperation in order to maximize a common objective of a coalition, where players are able to coordinate strategies and make agreement on the division of the total payoff among them. One of cooperative games type is Nash bargaining game, in which the product of the player's gains is maximized given what a player could receive without cooperation.

In a coalition formation game, a set of players are looking for cooperative groups. In a coalition, the players agree to act as a single entity to gain a higher payoff and coalitional value [108]. The coalitional games can be formed strategically or in partition form. In the strategic form, the value of coalition depends on the members of that coalition only, while in the partition form the structure of the players effect the value of a coalition. The total payoff is divided among the players in a coalition without restriction in a transferable payoff coalitional game, while in non-transferable payoff coalitional game, the payoff division depends on the joint actions that the players of a coalition select.

Game theory has been used extensively to model the optimization strategies in D2D communications and HetNets. Authors in [109] presented a static game model to formulate resource allocation problem in multi-cell D2D communications with incomplete information. The model

is further extended to a repeated one and then a resource allocation mechanism that yield a Bayesian Nash Equilibrium is proposed. Simulation result showed improvement in the profit and sum rate of each player. A Stalkelberg game theory is used to model the resource allocation and interference management problem in D2D communications in [110], where the BS acts as a leader while D2D pairs act as followers. The BS charges the D2D pairs a fee for network satisfaction as well as a fee for reusing the cellular resources, while the D2D pairs selects an optimal transmit power and a suitable cellular resources that satisfy QoS and QoE. A distributed algorithm is then used to solve the Stackelberg game.

On the other hand, literatures in game theory approach in HetNets include [111, 112]. In the former literature, a cluster-based non-cooperative game is proposed to coordinate inter-cluster interference in order to maximize the sum rate of small cell users. The problem is solved by developing a distribute algorithm to obtain a suboptimal solution, where a Nash equilibria is proven to exist in the solution. In the later literature, the coalitional game is adopted to plan the cellular networks powered by hybrid energy sources. In particular, small cells act as players and Shapley value is used to determine the contribution of each potential small cell to the global performance of the system. Simulation results showed that the proposed coalitional planning scheme produces an efficient use of energy compared to other heuristic and optimal alternatives.

### 3.3.3 Deep Learning

The increase of number of devices due to the integration of smart grid communications and cellular technology demands for self-organized communications in a massive system [113], and deep learning is an emerging tool that can be exploited to meet the demand. Deep learning can be defined as a class of machine learning algorithm in the form of neural network that extracts features from data and make predictive guesses about new data using cascade layers of processing units. There are four main considerations that should be taken into account for the applications of deep learning [114], which are:

1. The representation of the state of the environment in numerical format, which is the input layer of the deep learning network.

2. Representation of recognition results, i.e., the output layer of the deep learning's physical meaning.

3. The reward value computation and reward function selection which can assist the updating process of the iterative weight in each neural layer.

4. The deep learning's system structure which include number of hidden layers, the structure of each layer and the connection between layers.

Many deep learning systems have similar features with reinforcement learning model [115], such as:

1. The environment is represented by some feature.
2. The environment can be changed through the action of the agent.
3. The current state and the action selected by the agent are announced by the interpreter.

Eventhough many deep learning systems are tied with reinforcement learning models, the training process for both learnings is different. The reinforcement learning model aims to train the agent to select optimal action which can give a highest reward in a given environment, while the deep learning model's goal is to train the agent through training data to create a model to classify data.

The success of applications using deep learning such us Alpha Go and face recognition on mobile phones has prove the amazing capabilities of deep learning in dealing with many real-world scenarios. Currently, an extensive attention to deep learning applications is given from researchers in computer network areas. They belief that deep learning model is a promising tools in this field as it can represent a complex network environment, obtain abstract features and achieve a better decision that can improve QoS as well as QoE of the network.

Machine learning technique has been explored extensively in wireless networks field with complicated situation [116]. The situation includes complex features in wireless networks, such as the characteristics of communication signal, path congestion situation, channel quality, etc. Moreover, the communication performance in wireless networks is affected significantly by many network control targets such as congestion control, resource allocation, queue management, etc. Machine learning has shown great improvement in the performance of wireless networks compared to traditional methods [114].

On the other hand, the evolution of technology turns the modern wireless networks to become more complicated, which therefore demands for learning system that can cater the challenges such as high computing capacity, big dataset, fast and reliable learning algorithms and more flexible input mechanism [114]. Deep learning is one of the solutions for this complicated situation. Deep learning can accept a big number of network performance parameters in wireless networks which includes link signal-to-noise ratios (SNRs), channel holding time, link access success/collision rates, routing delay, packet loss rate and bit error rate as it has the capability to facilitate the wireless network with 'human brain'. Furthermore, deep learning can also perform a deep analysis on the intrinsic patterns in wireless networks such as congestion degree, interference alignment effect and hotspot distributions [114]. Further, the pattern can be exploited for protocol controls in different protocol layers.

Deep learning can provide improvement in wireless network applications compared to traditional machine learning technique because of two advantages. Firstly, it can give higher prediction accuracy through adopting many deep neural layers to analyse the complicated features of wireless networks. Through deep learning algorithm, the in-depth patterns hidden in the input parameters can be abstracted layer by layer resulting higher prediction accuracy. Secondly, deep learning skips the pre-process input data. Unlike machine learning model that highly depends on the data pre-processing, the input of deep learning is usually feature parameters that are directly collected from the network.

The human brain's features in deep learning is the key success of the application in wireless network [114]. The features include the following:

- **Tolerance of incomplete or even erroneous input raw data.**

  The human brain can deal with incomplete information sample such as the loss of information in some part of an image. The key is the exploitation of deep neural network that can make predictive guest of the missing input using a cascade layers of processing units. This ability is very useful for wireless network application with dynamic channel conditions which is impossible to obtain all the radio links' states accurately due to the channel fading, node mobility, and control channel failure.

- **Capability of handling large amount of input information.**

  Human brain can handle multiple types of complex information simultaneously and form a good judgement. For instance, three sensor from different areas such as sound, image and smell can be used to detect a present of a dog. Similarly, deep learning has the capability to accept abundant of performance data from multiple protocol data and decide the concrete congestion location in a large network.

- **Capability of making control decisions.**

  Humans learn things and give reactions through brains. In deep learning, the learning result is used to guide the propoer network control. For instance, the DRL, which is a MDP-base deep learning model, can use the updates of system states, reward function, and policy seeking, to form an appropriate network control based on the maximum reward calculation.

Deep learning architectures are inspired by the brain architecture in the sense that brains have a deep architecture, and computers can imitate such deep architectures [117]. The architecture of deep learning can be categorized into three types, which are generative, discriminative, and hybrid deep architectures, depending on the goal of deep architecture usage. The high-order

correlation properties of the input data can be characterized for synthesis purposes using a generative deep architecture. A hybrid model is the combination of the generative and discriminative deep architectures, used to perform discrimination tasks, which are assisted by the optimized outputs obtained from the generative architecture. The state-of-the-art deep learning algorithms still attach upon multi-layer architectures [118], where a new transformation of the previously learned features is performed that is served as the input to the next level. In the following, a brief overview on the relevant deep learning models, focusing on four main models which are Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Deep Boltzmann Machines (DBM) and DRL are presented.

#### Convolutional Neural Networks (CNNs)

The Convolutional Neural Network, which is also known as CNN has a discriminative deep architecture [114], where the input is obtained from multi-channelled image. In CNN, a multiple layers of convolutions with non-linear activation functions is adopted to deal with the complex input, and to compute the output, consequently, the CNN consists of localized connections whereby each region of the input is connected to a neuron in the output. Different filters are applied to each layer and then the results of each layer are combined. A CNN learns the values of its filters based on the given task automatically during the training phase. For instance, given a raw pixels in classifying process, the CNN can learn to detect the edges from the raw pixels in the first layer. In the second layer, the edges are employed to detect simple shapes, and using this shape, higher-level features like facial shapes and so forth can be learned in the higher layers. Finally, a classifier is used to exploit these high-level features in the last layer.

Deep CNNs can successfully learn task specific features, and compared to contemporary machine learning techniques, deep CNNs achieved a better result, specifically on different computer vision task. In general, the training process in CNNs is done by employing supervised learning methods whereby a large number of input-output pairs are essential. However, to solve a new task through applying CNNs to obtain a substantially large training set is a challenge.

#### Recurrent Neural Networks (RNNs) or Long Short Term Memory Networks (LSTMs)

The Recurrent Neural Network (RNN) is classified as model with a deep generative architecture. It is very useful for sequence data modellation such as in text and speech due to its depth feature which could be as large as the length of the input data sequence. However, the usage of DNN is restricted due to the so-called 'vanishing gradient' problem. Therefore, a new optimization method that modify stochastic gradient descent to train generative RNNs has been proposed recently in [118].

**Deep Boltzmann Machines (DBM)**

The next deep architecture is the Deep Boltzmann Machines. A Boltzmann machine (BM), can be defined as a network of binary, stochastic units with an "energy" defined for the network. In a shallow BM, learning is ineffective, therefore an architecture named Restricted Boltzmann Machine (RBM) that does not allow the connections between units on the same layers, can be adopted. In the training process, the activities of its hidden units after one training RBM can be used as input for training higher-level RBM. The stacking of RBMs allows an efficient training many layers of hidden units, which is one of the most common deep learning strategies. The overall generative model of the RBM improves significantly due to the addition of each new layer. RBMs also provide a promising architecture to carry out the pre-training [114], where a stack of RBMs are considered and the learned feature activations of a single RBM is used as the input of the following layer RBMs for training process. When the pre-training is completed, a fine-tuned deep learning is constructed by deploying the back-propagation algorithm hence the RBMs are unfolded. The stack of RBMs is also called DBMs or Deep Belief Networks (DBNs).

**Deep Reinforcement Learning (DRL)**

DRL combines the reinforcement learning and deep learning, by exploiting deep neural networks method to develop an artificial agent that able to learn optimal policies directly from high-dimensional sensory inputs using end-to-end reinforcement learning. A reinforcement learning takes advantages of both supervised and unsupervised learning methods. In reinforcement learning method, rewards are produced based on the behaviour of the agent in a given environment. The agent learns to interact with the environment in this method, where the experience is build so that the long-term rewards are maximized. Q-learning is the commonly adopted reinforcement technique, where a deep Q networks is a result of reinforcement learning and deep learning combination. The Q-function of the Q-learning with deep neural network architectures is represented in deep Q network. The improvements to the deep Q networks include Double Q-learning, prioritized experience replay, dueling network architecture, and the extension to continuous action space [114].

There are some works on deep learning in D2D communications and HetNets. For example, in D2D communications, a novel deep reinforcement learning approach is applied in [119] to obtain the optimal network resource allocation action. In particular, a social trust scheme that enhances the security of MSNs with mobile edge computing, caching, and D2D. In HetNets, a deep reinforcement learning approach is used to model the user association and resource allocation problem such as in [120] aiming to maximize the long-term overall network utility while ensuring the user equipments' QoS requirements. Multi-agent reinforcement learning is con-

sidered, which increase the complexity of the model, hence to solve the problem, double deep Q-network is proposed and simulation results prove the efficiency of the proposed solution.

## 3.4 Conclusions

This chapter explained optimization strategies which can be exploited to meet design requirement of D2D communications and HetNets. Mathematical tools are used to model the strategies in mathematical form, therefore the tools that are commonly adopted to model the strategies are also presented.

# Chapter 4

# Delay-Aware Energy-Efficient Joint Power Control and Mode Selection in Device-to-Device Communications for FREEDM Systems in Smart Grids

## 4.1 Introduction

IEMs manage energy in the FREEDM system by monitoring status and collecting data of all end-devices in a local area, and providing control references to each of them [3]. In particular, the tasks of IEMs include collecting and monitoring the status of DRERs, making energy management decisions and delivering reports to the control center for further actions. In this context, cellular technology with LTE-based standard is promising for communications in the FREEDM system because it is a widely-deployed and mature technology. Hence, this kind of technology can provide services over a large area including smart grid domains located in complex geographical areas [6]. However, integrating the cellular technology and the smart grid communication network is a significant challenge for LTE due to the simultaneous transmission of large volume delay-sensitive data. Specifically, when a fault occurs in a grid, for instance due to natural disasters such as floods, earthquakes or tsunamis, more information needs to be sent to the control center, resulting in a significant increment to the size of IEM reports [7]. In this kind of situations, the grid must have resilience and self-healing capabilities to prevent power losses and blackouts, which result in stringent delay requirements to the data transmissions. One critical way to enhance the performance of LTE in this kind of situations is to exploit D2D communications. In D2D communications underlaying cellular networks, two devices which are located in a close proximity can exchange information directly by reusing cellular resources over a direct

link, instead of exploiting cellular base station to receive and transmit reports. Exploiting the D2D-assisted relaying framework which utilizes the underlay D2D communications by sharing radio spectrum between links can improve signal quality of the links, besides enabling high data rates [121].

Energy efficiency is a critical parameter in D2D communications underlying cellular networks especially when IEMs are considered. When an IEM is in the fault zone, it will be isolated from the grid to protect other normal zones from any cascading failure due to fault current. In this circumstance, the IEM and all loads in the fault zone are powered by local energy sources, such as small wind turbines, photovoltaic panels and local energy storage equipment [9], which have limited power supply. Therefore, energy efficiency is critical in these kind of situations to ensure that reports of the IEMs can be transmitted to the control center successfully. Nevertheless, researches in [122] and [123] prove that a trade-off between energy efficiency and delay exists in wireless cellular networks. Therefore, considering only energy efficiency maximization in D2D communications may not be sufficient to the network without taking delay performance into account [14], because delay is a key performance metric that reflects the users' experience. In the FREEDM system, if the delivery time of the IEM reports is after the delivery deadline, information loss could occur, where the control centre receives incomplete information resulting in the transmission of false control command.

Many works have investigated energy efficiency and delay issues in D2D communications. Jiajia *et al*. studied the energy efficiency and delay trade-off in D2D communications for mobile applications and proposed the TRADEOFF algorithm as a model to evaluate the performance of any heuristic algorithms [124]. Yulei *et al*. investigated the fundamental trade-off between energy consumption and other network factors such as available bandwidth, buffer size and service delay, then formulated a minimum energy consumption resource allocation and transmission mode selection problem in a large scale human mobility condition using a dynamic graph model [125]. Yanli *et al*. studied content delivery problem based on a flow model and proposed an optimal resource allocation method to obtain energy-efficient D2D-aided content delivery with guaranteed delay constraints for hybrid content requests [126]. In [127], Kazi *et al*. proposed a novel architecture by combining two technologies, which are cloud radio access network and D2D for mobile crowd sensing to solve the delay issue as well as capacity, energy efficiency, mobility, and cost in the networks. Luo *et al*. developed an Experience-based Irrelative State-action Abstraction (EISA) algorithm based on Q-Learning to address the energy efficiency and delay trade-off problem in energy harvesting-based D2D communication underlaying cellular network [128].

Although all previous works studied the energy efficiency and delay problems in D2D communications, all these works did not consider the special requirements in smart grid environ-

ments, specifically in FREEDM systems. In FREEDM systems, the size of reports generated by IEMs varies according to its associated zones. Moreover, reports of IEMs are delay-sensitive and must be delivered at the control center within specific delay constraints. Thus, specific data rate requirements are imposed to satisfy certain delay constraints. Therefore the D2D communication underlying cellular networks are exploited to improve the performance of smart grid communication networks by taking into account the transmission of different volume of simultaneous and delay-sensitive data due to faults, in varying channel conditions.

A joint power control and mode selection scheme is proposed as an important solution to increase energy efficiency while satisfying stringent delay constraints in D2D communications underlaying cellular networks specifically for the FREEDM system in smart grids. The mode selection scheme can be adopted to satisfy delay in the network by properly selecting the transmission mode that satisfies the QoS of IEM report, while the power control scheme is one of the critical energy efficiency maximization techniques in D2D communications which permits transmission power regulation with respect to some power constraints [129]. The proposed scheme first calculates the optimal data rate of each IEM according to its report size. Then, depending on the proposed data rate and the channel quality of each IEM, the IEM will regulate its transmission power by exploiting the power control scheme. Based on the proposed transmission power, the BS obtains the actual channel state of each IEM and then calculates data rate of each transmission mode. The transmission mode that provides the highest data rate is then selected to satisfy the delay constraints of IEM. By selecting the transmission mode with the highest data rate, the delay requirement could be satisfied even when the size of IEM report increases due to fault.

The contributions of this work can be summarized as follows:

- We study energy efficiency and delay problems in D2D communications for the FREEDM system and adopt the D2D-assisted relaying framework to increase data rate of the IEMs in the fault zone and experiencing poor channel conditions.

- We propose a joint power control and mode selection scheme to enhance energy efficiency as well as to satisfy stringent delay constraints in the networks under different report size and varying channel conditions.

- We formulate the optimization problem as a combinatorial problem and develop a ***E***nergy ***E***fficiency and ***D***elay ***O***ptimization (EEDO) algorithm based on the brute-force searching method [130] to deal with the problem and find the solutions.

The work presented in this chapter has resulted in one conference paper [131] and one journal paper.

The remainder of this chapter is organized as follows; The preliminary of FREEDM systems is explained in Section 4.2. The system model is described in Section 4.3. In Section 4.4, the joint power control and mode selection problem are formulated. Proposed solutions are derived in Section 4.5. Simulation results are presented and discussed in Section 4.6 and the chapter is concluded in Section 4.7.

## 4.2 The Preliminary of FREEDM Systems

In FREEDM systems, renewable energy resources are utilized in two ways: large-scale centralized installation by exploiting wind or solar farms in the grid, and wide-scale DRERs installation such as solar panels or small wind turbines attached to individual households, and electric or hydrogen fuel cell cars [3].

### 4.2.1 Model of FREEDM Systems

In FREEDM systems, DESs which consist of hydrogen storages or batteries, are examined as complements to DEGs. The small scale DESs and DEGs are used to help each household in managing its energy usage. In the system, energy management is done locally by the IEMs by performing real-time monitoring and data collection. In particular, IEMs collect data, monitor status as well as provide control commands to every end device. Another important kind of device in the FREEDM system is the intelligent fault management devices (IFMs). The roles of IFMs include fault identification and isolation to maintain the system stability. More specifically, multiple IFMs could divide IEMs into different zones. When faults occur in a zone, IFMs will isolate the fault zone to protect other normal zones from any cascading failure due to fault current [3].

### 4.2.2 Communication Requirements for FREEDM Systems

A hierarchical structure consisting of several layers of wired and wireless networks [7] is considered due to its merits of good scalability and low investment cost [132]. As shown in Figure 4.1, an IEM manages the load and DRERs, such as the DEG and the DES through a WLAN. A local energy management decision is done by an IEM based on the information received and a report is transmitted to the control centre in the internet architecture through the cellular network and the wired network. Connections between the BSs and the control centre are managed by wired networks through gateways in the core network. It is assumed that at the Gateway level, multipath transmission control protocol (MPTCP) is adopted to cater the issue of congestion from IEMs at cellular networks to Gateways at wired networks [133]. Moreover, it is assumed

that in the system, the number of Gateway with large buffer size is sufficient to cope with the large data volume from IEMs. Therefore, congestion at Gateway level is minimal. In this work, we focus on the performance at the IEM level to ensure that report of IEM from the fault zone can be send within limited power supply and stringent delay requirement.

The communication technology for FREEDM systems must be able to meet the delivery delay requirements of the reports. IEMs send protection data, control data and state reports to the control centre with the acceptable delay of 3ms to 16ms for the protection data, and 16ms to 100ms for other types data [10]. When faults occur in a distribution grid, the size of IEM reports from the fault zone could increases significantly because raw end device reports (load and DRERs reports) are required to be included in the fault zone IEM report for identification purpose at the control centre, which may result in up to 100 times of normal data rate [7]. Moreover, in fault scenarios, the report transmission becomes data rate demanding in order to meet the delivery delay requirement. The report must be delivered at the control centre within the specific time to trigger a response from the corresponding device as soon as possible. Otherwise, the corresponding device is inaction, which may result in the expansion of damaged area due to the fault current [10].

Multi-hop relaying communications are adopted in the system to improve the channel quality of IEMs in cellular networks. Multi-hop relaying communications have been used in wireless networks for machine type communication, specifically in situations where nodes experience high path loss due the far distance between the source node and the destination node [134]. In multi-hop relaying communications, reports of an IEM can be relayed to another IEM before reaching the control centre. Each IEM can act as a source node and also a relaying node that stores and forwards reports of other IEMs to the BS [135]. The link between an IEM and a relaying IEM (RI) is called the access link, while the link between a RI and the BS is called the backhaul link. When the access link suffers bottleneck effects, the D2D-assisted relaying framework is adopted to assist the access link.

## 4.3 System Model

The detail of the system model of D2D communications underlying the cellular networks for smart grid NANs are explained in this section. The D2D-assisted relaying framework is adopted in the OFDMA based cellular networks as shown in Figure 4.1. The nodes in a cell include a BS and $M$ IEMs, in which all nodes are transceivers over multiple sub-channels. It is assumed that the BS has full knowledge of the channel gains in the system and it assigns sub-channels using a proportional fair scheduling method to satisfy each IEM's QoS and at the same time attempts to maximize the throughput of cellular users [136].

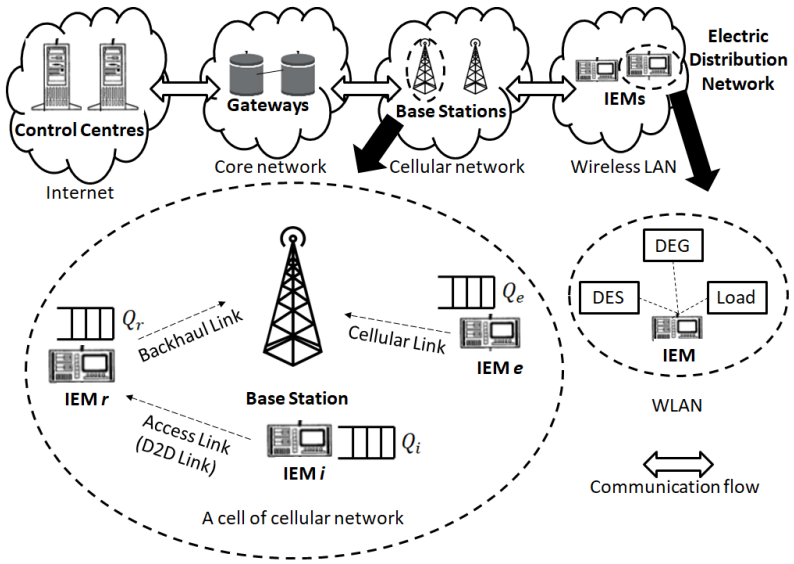


Figure 4.1: The communication structure of an electric distribution network

It is also assumed that when IEMs transmit data, the transmission power will be immediately regulated, and the queue and power state will be reported to the BS as in the existing LTE system [68]. Compared to the existing 4G LTE system, the only additional overhead signalling exists is for reporting the channel gain of access links of IEM in the fault zone or meeting poor channel conditions to the neighbouring IEMs. Furthermore, the BS selects the transmission mode to each IEM after it receives the queue state and power reports from IEM. Failure to meet the delay requirement will occur when an IEM is in a fault zone or experiences poor channel conditions. Therefore, based on transmission power reported by the IEM, the BS selects a mode for each IEM and establishes a D2D link if required. The BS informs IEMs on the uplink resources decisions over the Physical downlink Control Channel (PDCC) signal.

In general, IEMs can communicate with end devices in the WLAN and the BS and other IEMs in the cellular network using two different interfaces. The existence of D2D communication functions in the cellular network enables the IEMs located in a close proximity to reuse the sub-channel of another IEM and directly transmit reports to other IEMs over the D2D link [7]. Let $\mathcal{M} = \{1, 2, \cdots, M\}$, $\mathcal{G} = \{1, 2, \cdots, G\}$ and $\mathcal{F} = \{1, 2, \cdots, F\}$ denote the set of IEMs, RIs and reuse IEMs respectively. $\mathcal{C} = \{1, 2, \cdots, C_u\}$ denotes the set of uplink sub-channels in the system. RIs are defined as the IEMs which can be used to forward reports of other IEMs, while reuse IEMs are defined as IEMs that can be used to establish D2D links by reusing their own sub-channels for direct transmission mode and D2D-assisted relaying mode. All RIs and reuse IEMs operate in direct cellular mode. The whole uplink spectrum is divided into $C_u$ same-sized sub-channels and each device in the cell is allocated with a sub-channel. Let $C_i, C_r, C_e, \in \mathcal{C}$ de-

note the sub-channel allocated to IEM $i \in \mathcal{M}$, IEM $r \in \mathcal{G}$, and IEM $e \in \mathcal{F}$ respectively. In this work, a rural area scenario with large BS coverage and a small number of mobile users is considered. Therefore, it is assumed that the network has a sufficient number of resources and there is no shortage during operation. A similar scenario has also been considered in many research work [7, 137, 138]. Time is slotted with equal lengths in this system.

### 4.3.1 Received Signal-to-Interference-Plus-Noise Ratio of IEMs

Let $G_{ij,t}^{C_i}$ denote the channel gain of link $(i, j)$ on sub-channel $C_i$ which consists of path loss, shadowing and slow fading effect under a Rayleigh channel. The channel gains are independent and identically distributed (i.i.d) between transmissions and remain constant during a transmission phase. The received SNR of link $(i, j)$ on sub-channel $C_i$ at timeslot $t$, $\gamma_{ij,t}^{C_i}$, representing the channel quality of the link on sub-channel $C_i$, can be calculated as follows [68]:

$$\gamma_{ij,t}^{C_i} = \frac{p_{i,t}^{C_i} G_{ij,t}^{C_i}}{N_{i,t}}, \tag{4.1}$$

where $N_{i,t}$ is the noise power and $p_{i,t}^{C_i}$ is the transmission power of IEM $i$ over sub-channel $C_i$. The received SINR of IEM $i$ may not be the same as its SNR value depending on whether IEM $i$ selects the D2D mode, or the sub-channel $C_i$ is reused by other IEMs hence causing interference between the cellular link and the D2D link. Therefore, the received SINR of IEM $i$ over sub-channel $C_i$ becomes [68]

$$\text{SINR}_{i,t}^{C_i} = \frac{\gamma_{ij,t}^{C_i}}{1 + \tilde{\gamma}_{ij,t}^{C_i}}, \tag{4.2}$$

where $\tilde{\gamma}_{ij,t}^{C_i}$ is the received SNR of the interference link to sub-channel $C_i$,which could be the SNR of IEM $e$, when IEM $i$ reuses sub-channel $C_e$.

### 4.3.2 Instantaneous Data Rate of IEMs

Let $r_{ij,t}^{C_i}$ denote the instantaneous data rate of link $(i, j)$ over sub-channel $C_i$. It is assumed that the adaptive modulation and coding (AMC) scheme is adopted in the physical layer. The AMC scheme has been used extensively in several wireless standards i.e., LTE, 802.11a and 802.16e, because it has the capability of enhancing the throughput in time-varying channel conditions [139]. The AMC scheme optimizes the data rate of each IEM depending on its SINR by exploiting the best modulation and coding technique from its perspective. This allows it to create a relationship between the received SINR and the transmission rate [140].

In the AMC scheme, received SINR values are divided into $Z$ non-overlapping consecutive

regions [140]. For any region $z \in \{1, 2, \cdots, Z\}$, if the received SINR of IEM $i$ over sub-channel $C_i$ at timeslot $t$, $\text{SINR}_{i,t}^{C_i} \quad \forall \quad C_i \in C$ falls within the $z$th region $[\beta_{z-1}, \beta_z]$, where $\beta_z$ denotes the SINR threshold for state $z$ with $\beta_0 = 0$, $\beta_Z = \infty$, the corresponding instantaneous data rate of link $(i, j)$ over sub-channel $C_i$, $r_{ij,t}^{C_i}$ is a fixed value $R_z$ according to the selected modulation and coding at region $z$. $R_z$ denotes a fixed instantaneous data rate at region $z$ in the AMC scheme. The smallest region is $z = 1$ and if $\text{SINR}_{i,t}^{C_i}$ falls into this region, the corresponding data rate value is $R_1 = 0$, in which no packet is sent at this state in order to obtain low transmission error probability. Therefore, the instantaneous data rate of link $(i, j)$ over sub-channel $C_i$ at timeslot $t$ is given by [139]

$$r_{ij,t}^{C_i} = R_z. \tag{4.3}$$

Since the channel condition of links are the same as the channel condition of IEMs, the instantaneous data rate of IEM $i$ at timeslot $t$ can be formulated as follows [139]:

$$r_{i,t}^{C_i} = r_{ij,t}^{C_i} = R_{i,t}. \tag{4.4}$$

### 4.3.3 Queue Dynamics of IEMs

In FREEDM systems, the size of report of an IEM is associated with its zone. It is assumed that an IEM is in a normal zone with probability $P_n$ and the probability of IEM in the fault zone is $1 - P_n$. Each of the IEMs manages the same amount of end-devices, therefore it generates the same size of the report. Let $B_{i,t}$ denote the amount of packets generated by IEM $i$ at timeslot $t$. In the normal zone, all IEMs generate report with the size of $B_n$ packets while in the fault zone the IEMs generate report with the size of $B_f$ packets. The IEMs transmit reports to the control centre for every $T$ interval [50].

A first-in-first-out (FIFO) behaviour is adopted in the queue model. The arriving packets are placed in the queue throughout timeslot $t$ and will be transmitted at the next timeslot, $t + 1$. Packets exit the network once they reach the destination. A large buffer size is assumed and therefore no packet is dropped due to buffer overflow. Let $Q_{i,t}$ denote the queue length of IEM $i$ at timeslot $t$. The queue dynamic at IEM $i$ can be expressed as [139]

$$Q_{i,t+1} = \max\{0, Q_{i,t} - R_{i,t}\} + B_{i,t}. \tag{4.5}$$

The queue dynamic at IEM $r$ as a RI consists of the data transmitted from IEM $i$, in which the forwarded report is placed in the queue before being transmitted at the next timeslot, and can be expressed as follows

$$Q_{r,t+1} = \max\{0, Q_{r,t} - R_{r,t}\} + B_{r,t} + (Q_{i,t} - R_{i,t}). \tag{4.6}$$

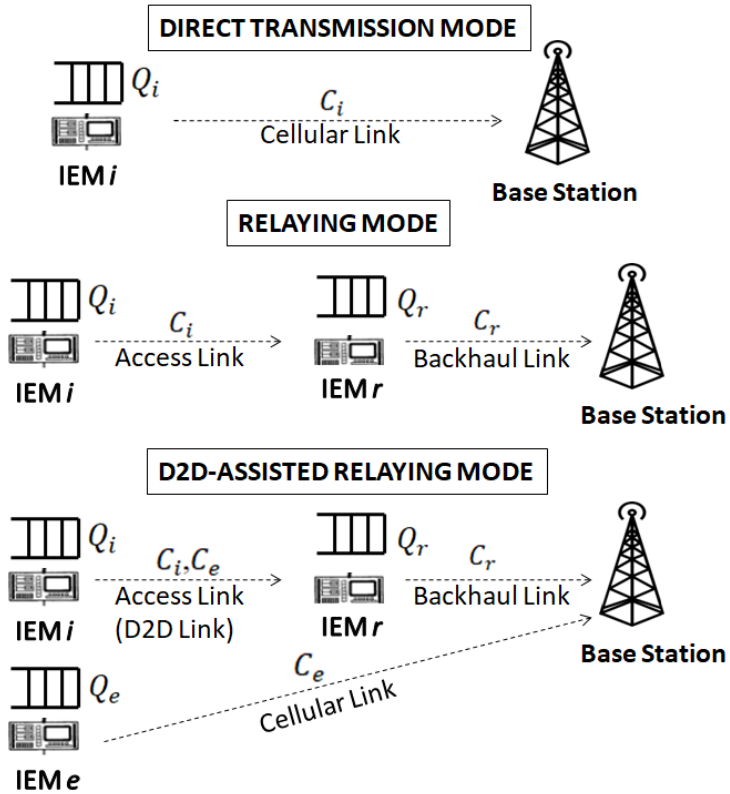


Figure 4.2: A diagram of the direct transmission mode, relaying mode and D2D-assisted relaying mode.

## 4.4 Joint Power Control and Mode Selection Problem Formulation

The system is partially centralized, where the BS determines the mode selection for each IEM based on IEMs' power and queue states. On the other hand, the transmission power of each IEM is determined by itself in a distributed manner. Therefore, the problem can be formulated as a combinatorial problem which consists of the power control and mode selection problems that maximizes energy efficiency under power and mode selection constraints. To solve the problem, calculation of the data rate, the power consumption and the end-to-end delay of each transmission mode are performed.

### 4.4.1 Delay and Power Consumption for Different Transmission Modes

As shown in Figure 4.2, a report from an IEM can be sent in one of the three transmission modes, which are the direct transmission mode, the relaying mode and the D2D-assisted relaying

mode. Mode selection and power control decisions are dependent on the data rate of each IEM, resulting in different delay and power consumption in each transmission mode.

It is assumed that all IEMs transmit data simultaneously with fixes channel gain and report length during the transmission phase. Therefore, the end-to-end delay of link $(i, j)$ over sub-channel $C_i$ can be calculated as [68]

$$D_{ij}^{C_i} = 1 + \frac{B_{i,t}}{T_i}, \tag{4.7}$$

where 1 ms represents the time interval between the time when the packets are generated and the time when the packets are placed in the queue. The throughput of IEM $i$ over sub-channel $C_i$ can be calculated as [68]

$$T_{i,t} = \min\{B_{i,t}, R_{i,t}\}. \tag{4.8}$$

On the other hand, the total power consumption of each IEM consists of the circuit power due to signalling and active circuit blocks [141], the transmission power, and the additional power depend on the transmission mode selected. The circuit power can be modelled as the total of a static term and a dynamic term, $P_c = VI_{leak} + A_s CfV^2$, where $V$, $I_{leak}$, $A_s$, $C$ and $f$ denote the transistors supply voltage, the leakage current, the fraction of gate actively switching, the circuit capacitance, and the clock frequency respectively [142]. The frequency is assumed to be dynamically scaled with the sum rate. The circuit power can be modelled as [143]

$$P_c = P_s + \xi R_{i,t}, \tag{4.9}$$

where $P_s$ denotes the static term and $\xi$ is a constant representing dynamic power consumption per unit data rate. In this work, the circuit power is calculated only when IEMs have reports to be transmitted to the control centre.

Since the main focus of this paper is to reduce delay and improve energy efficiency, the D2D underlay mode is considered in this work to improve the link quality of D2D users by reusing the resources belonging to the cellular users [144]. High link quality is critical especially in a fault condition, where the data rate over the pre-assigned sub-channel might not be able to meet the delay requirement, when an IEM is in a fault zone or experiences poor channel conditions. Considering D2D underlay mode, three transmission are available in this work. The end-to-end delay and the total power consumption for each IEM in different transmission mode can be calculated as follows.

**Direct Transmission Mode**

In the direct transmission mode, IEMs can transmit the reports directly to the BS over cellular links. Let $R_{i,t}^{DM}$ denote the data rate of IEM $i$ over sub-channel $C_i$ in the direct transmission mode at timeslot $t$, which can be formulated as [7]

$$R_{i,t}^{DM} = R_{i,t}^{C_i}. \tag{4.10}$$

The delay of IEM $i$ in direct transmission mode, which is also the delay of cellular link is given as follows

$$D_i^{DM} = D_{i0}^{C_i}, \tag{4.11}$$

in which index 0 refers to the BS. The total power consumed by IEM $i$ in the direct transmission mode at timeslot $t$ can be formulated as [145]

$$P_{i,t}^{DM} = P_c + p_{i,t}^{C_i} + \sigma(P_c + \tilde{p}_{i,t}^{C_i}), \tag{4.12}$$

where $\sigma$ denotes the interfering phase. Note that $\sigma = 0$ if sub-channel $C_i$ is not reused by any D2D link.

**Relaying Mode**

In the relaying mode, IEM $i$ relays its report to IEM $r$ through the access link. Then IEM $r$ forwards the report to the BS through the backhaul link over sub-channel $C_r$. Let $R_{i,t}^{RM}$ denote the data rate of IEM $i$ in the relaying mode, which can be formulated as follows [7]

$$R_{i,t}^{RM} = \min\{R_{i,t}^{C_i}, R_{r,t}^{C_r}\}. \tag{4.13}$$

The delay of IEM $i$ in the relaying mode when the report is transmitted through the access link and the backhaul link can be calculated as follows

$$D_i^{RM} = D_{ir}^{C_i} + D_{r0}^{C_r}. \tag{4.14}$$

The total power consumption of IEM $i$ in the relaying mode can be formulated as follows [145]

$$P_{i,t}^{RM} = P_c + p_{i,t}^{C_i} + \dot{p}_{r,t}^{C_r}, \tag{4.15}$$

where $\dot{p}_{r,t}^{C_r}$ denotes the additional power consumed by IEM $r$ to relay the report of IEM $i$, which is dependent on the queue length of IEM $r$, and can be formulated as

$$\dot{p}_{r,t}^{C_r} = \begin{cases} P_c + p_{i,t}^{C_i}, & \text{if } Q_{r,t} = 0, \\ p_{r,t}^{C_r}, & \text{otherwise.} \end{cases} \tag{4.16}$$

When IEM $r$ has no report to send, the additional power is the same power consumed by IEM $i$ at the access link. Otherwise, the additional power is the transmission power used by IEM $r$ to relay the report of IEM $i$.

**D2D-Assisted Relaying Mode**

In the D2D-assisted relaying mode, IEM $i$ transmits reports to IEM $r$ through the D2D link over sub-channel $C_e$, which is allocated for the direct transmission mode of IEM $e$ over cellular link to overcome the bottleneck effect of the access link. Then IEM $r$ relays the report to the BS through the backhaul link over sub-channel $C_r$. Let $R_{i,t}^{DRM}$ represent the data rate of IEM $i$ in the D2D-assisted relaying mode formulated as [7]

$$R_{i,t}^{DRM} = \min\{\tilde{R}_{i,t}, R_{r,t}\}, \tag{4.17}$$

where $\tilde{R}_{i,t}$ denotes the instantaneous data rate of IEM $i$ over sub-channel $C_e$ with interference from sub-channel $C_i$. This mode is enabled only when IEM $i$ and IEM $e$ are within the D2D proximity $L_{\max}$, where $L_{\max} = \left(\frac{p_{i,t}^{C_i}}{\rho_{\min}}\right)^{1/n_d}$ [146]. $\rho_{\min}$ and $n_d$ denote the receiver sensitivity and the path-loss exponent for the D2D links respectively. In the Rayleigh fading environment, various techniques could be used to relax the Rayleigh fading assumption to general fading channels [147]. As a result, the instantaneous D2D distance $L_{\max}$ only depends on the path loss exponent as formulated in [146]. Therefore, $\tilde{R}_{i,t}$ is obtained as follows

$$\tilde{R}_{i,t} = = \begin{cases} {R_{i,t}}^{C_e}, & \text{if } L_{i,e} < L_{\max}, \\ 0, & \text{otherwise,} \end{cases} \tag{4.18}$$

in which $L_{i,e}$ is the distance of IEM $i$ to IEM $e$. The delay of IEM $i$ in the D2D-assisted relaying mode when the report is transmitted by the D2D link and the backhaul link can be calculated as

$$D_i^{DRM} = D_{ir}^{C_i,C_e} + D_{r0}^{C_r}. \tag{4.19}$$

The total power consumed by IEM $i$ in the D2D-assisted relaying mode can be formulated as [145]

$$P_{i,t}^{DRM} = 2P_c + p_{i,t}^{C_i} + \tilde{p}_{e,t}^{C_e} + \dot{p}_{r,t}^{C_r}, \tag{4.20}$$

where $\tilde{p}_{e,t}^{C_e}$ denotes the transmission power of IEM $e$ at timeslot $t$ during interfering phase.

### 4.4.2 Problem Formulation

The report transmission of each IEM could be operated in one of the three modes, indicated by $\alpha_i$, $\omega_i$ and $\mu_i$. These binary indicators show whether IEM $i$ operates in the direct transmission mode, the relaying mode or the D2D-assisted relaying mode respectively. Considering the transmission mode decision, the delay of IEM $i$ during a transmission can be expressed as

$$D_i = \alpha_i D_i^{DM} + \omega_i D_i^{RM} + \mu_i D_i^{DRM} \tag{4.21}$$

Energy efficiency can be defined as information bit per unit of energy, which corresponds to the ratio of the data rate to the unit power consumption [148], which is expressed as [149]

$$\eta = \frac{\sum_{i=1}^{M} R_{i,t}}{\sum_{i=1}^{M} P_{i,t}}, \tag{4.22}$$

where $P_{i,t}$ denotes the total power consumption of IEM $i$ at timeslot $t$.

A joint power control and mode selection problem is formulated to obtain maximum $\eta_t$ under the mode selection and power constraints. The proposed solutions to the problem are $p_i$ and $a_i$, which are defined as the proposed power control and the proposed transmission mode selection of IEM $i$ respectively. Considering both proposed solution parameters, the energy efficiency can be expressed as

$$\eta(a_i, p_i) = \frac{\sum_{i=1}^{M}(\alpha_i R_{i,t}^{DM} + \omega_i R_{i,t}^{RM} + \mu_i R_{i,t}^{DRM})}{\sum_{i=1}^{M}(\alpha_i P_{i,t}^{DM} + \omega_i P_{i,t}^{RM} + \mu_i P_{i,t}^{DRM})}. \tag{4.23}$$

The joint power control and mode selection problem can be formulated as follows

$$P1 : \underset{a_i, p_i, i \in \mathcal{M}}{\text{maximize}} \quad \eta(a_i, p_i), \tag{4.24}$$

subject to

$$p_{i,t}^{C_i} \leq P^{\max}, \forall i \in \mathcal{M}, \tag{4.25a}$$

$$\overline{D} \leq D_0, \tag{4.25b}$$

$$\alpha_i + \omega_i + \mu_i = 1, \forall i \in \mathcal{M}, \tag{4.25c}$$

$$\sum_i \tau_{i,e} \leq 1, \tau_{i,e} \in \{0, 1\}, \forall e \in \mathcal{F}, \tag{4.25d}$$

$$\sum_e \tau_{i,e} \leq 1, \tau_{i,e} \in \{0, 1\}, \forall i \in \mathcal{M}, \tag{4.25e}$$

$$\sum_{i} \phi_{i,r} \leq 1, \phi_{i,r} \in \{0,1\}, \forall r \in \mathcal{G}, \tag{4.25f}$$

$$\sum_{r} \phi_{i,r} \leq 1, \phi_{i,r} \in \{0,1\}, \forall i \in \mathcal{M}, \tag{4.25g}$$

$$L_{i,e} < L_{\max}, \forall \mu_i = 1, \tag{4.25h}$$

where $\tau_{i,e}$ and $\phi_{i,r}$ denote the resource reuse indicator for IEM $i$ and IEM $e$, and relay indicator for IEM $i$ and IEM $r$ respectively. $\tau_{i,e} = 1$ when IEM $i$ reuses the resource of IEM $e$ and $\phi_{i,r} = 1$ when IEM $i$ uses IEM $r$ to relay it report, otherwise $\tau_{i,e} = 0$, $\phi_{i,r} = 0$. Constraint (4.25a) guarantees the transmission power of IEMs are within the maximum limit. Constraint (4.25b) ensures the average delay, $\overline{D} = \sum_i^M D_i/M$ under the delay constraint $D_0$ and constraint (4.25c) which ensures that only one transmission mode is selected to each IEM. Constraint (4.25d) indicates that the sub-channel of IEM $e$ can only be reused once, while constraint (4.25e) ensures that IEM $i$ can only reuse sub-channel of IEM $e$ once. Constraints (4.25f) and (4.25g) ensure that IEM $i$ can only relay its reports to one selected IEM only and IEM $r$ can only forward the report of IEM $i$ once. The last constraint (4.25h) limits the distance to establish a D2D link.

## 4.5 Proposed Solution

The problem has a mixed integer nature, which requires the P1 to decompose into two sub-problems. This is made possible because in the system, the transmission mode is selected by the BS and the power control is managed by each IEM. To solve problem $P1$, first the proposed power control under given mode selections is obtained. Then to further find the proposed mode selection,the brute-force searching method is exploited and the EEDO algorithm is proposed.

### 4.5.1 Proposed Power Control

In this subsection, it is assumed that the transmission mode selection of each IEM has been preset under condition (4.25c), $i.e.$ $a_i$ is fixed for $i$. Thus $P1$ is decomposed into a power control problem $P2$ and a mode selection problem $P3$. $P2$ is denoted as follows

$$P2: \underset{p_i, i \in \mathcal{M}}{\text{maximize}} \quad \eta(p_i), \tag{4.26}$$

subject to

$$p_{i,t}^{C_i} \leq P^{\max}, \forall i \in \mathcal{M}. \tag{4.27a}$$

Power control decisions are done based on the proposed data rate values that are dependent on the size of IEM report at each transmission phase. The proposed data rate of each IEM is obtained by calculating the minimum data rate, $R_{i,t}^{\min}$, the maximum data rate, $R_{i,t}^{\max}$, and the average data rate, $R_{i,t}^{\text{ave}}$ at timeslot $t$. Based on (4.7) and (4.8), the maximum data rate of IEM $i$ can be derived as

$$R_{i,t}^{\max} = \frac{B_{i,t}}{D^{\min}}, \tag{4.28}$$

where $D^{\min}$ denotes the minimum delay of the grid. Equation (4.28) can be used to determine $R_{i,t}^{\text{ave}}$ and $R_{i,t}^{\min}$, simply by changing the value of $D^{\min}$ to $D^{\text{ave}}$ and $D^{\max}$.

The proposed data rate of IEM $i$ at timeslot $t$, $R_{i,t}^{*}$ is computed as [130]

$$R_{i,t}^{*} = \begin{cases} R_{i,t}^{\min}, & \text{if} \quad R_{i,t}^{\text{ave}}, < R_{i,t}^{\min}, \\ R_{i,t}^{\text{ave}}, & \text{if} \quad R_{i,t}^{\min} \leq R_{i,t}^{\text{ave}} \leq R_{i,t}^{\max}, \\ R_{i,t}^{\max}, & \text{if} \quad R_{i,t}^{\text{ave}}, > R_{i,t}^{\max}. \end{cases} \tag{4.29}$$

Note that the queue length of IEM varies depending on its associated zone, which may result in varied data rate of each IEM at each transmission phase.

The proposed transmission power of IEM $i$, $p_i^{*}$, can be obtained by calculating the lowest SNR with respect to the proposed data rate $R_{i,t}^{*}$. Assuming that the perfect estimation of SNR over cellular link, based on AMC scheme, for any $R_{i,t}^{*}$ that fall in the region $\beta_z$, the $\gamma_{ij,t}^{*}$ is the minimum SNR value in region $\beta_z$, in this system, the accurate channel estimation is possible since the network operates in a slow fading environment with a static topology. The proposed transmission power of IEM $i$ is obtained based on (4.3) as follows

$$p_i^{*} = \frac{\gamma_{ij,t}^{*} N_{i,t}}{G_{ij,t}}. \tag{4.30}$$

However, in cases of $p_i^{*} > P^{\max}$, the transmission power is set to the maximum, $p_i^{*} = P^{\max}$.

### 4.5.2 Proposed Transmission Mode Selection

Based on the above $p_i^{*}$, the proposed mode selection $a_i$ for all $i \in M$ is further investigated, which is an equivalent form of $P1$ an is represented as $P3$:

$$P3 : \underset{a_i, i \in \mathcal{M}}{\text{maximize}} \quad \eta(a_i, p_i^{*}), \tag{4.31}$$

subject to

$$D_i \leq D_0, \forall i \in \mathcal{M}, \tag{4.32a}$$

$$\alpha_i + \omega_i + \mu_i = 1, \forall i \in M, \tag{4.32b}$$

$$\sum_i \tau_{i,e} \leq 1, \tau_{i,e} \in \{0,1\}, \forall e \in \mathcal{F}, \tag{4.32c}$$

$$\sum_e \tau_{i,e} \leq 1, \tau_{i,e} \in \{0,1\}, \forall i \in \mathcal{M}, \tag{4.32d}$$

$$\sum_i \phi_{i,r} \leq 1, \phi_{i,r} \in \{0,1\}, \forall r \in \mathcal{G}, \tag{4.32e}$$

$$\sum_r \phi_{i,r} \leq 1, \phi_{i,r} \in \{0,1\}, \forall i \in \mathcal{M} \tag{4.32f}$$

$$L_{i,e} < L_{\max}, \forall \mu_i = 1,. \tag{4.32g}$$

Based on $p_i^*$ reported by the IEM, the BS obtains a new $R_{i,t}^*$ that considers actual channel condition of IEM based on $\gamma_{ij,t}^*$ using (4.3), then calculates the data rate of each transmission mode and selects only the transmission mode with the highest data rate in order to satisfy the end-to-end delay of each IEM. Selecting the transmission mode with highest data rate could improve the delay when data rate differentiation occurs due to significant increment in the report size. The proposed mode selections for IEM $i$ are represented by the binary indicators $\alpha_i$, $\omega_i$ and $\mu_i$. The proposed mode selection that maximizes energy efficiency and satisfies end-to-end delay in the network can be obtained by exploiting the EEDO Algorithm. Note that the channel and report length remain constant during transmission phase, therefore the BS only performs mode selection at the timeslot in the beginning or transmission phase.

### 4.5.3 The EEDO Algorithm

The mode selection problem can be solved using the EEDO algorithm based on the brute-force searching method, which is also known as an exhaustive search method. In brute-force searching method, the proposed solutions are obtained based by enumerating of all possible actions and selecting one with the best value. The complexity of brute-force method could become an issue due to high number of actions available in the system. However, since the number of IEMs in a cell and the mode selection space is relatively low, the brute-force searching approach is a practical method for this scenario. The EEDO algorithm finds the mode selection for each IEM as described in Algorithm 1.

In this algorithm, the proposed data rate for each IEM is first obtained based on $\gamma_{ij,t}^*$ using the AMC scheme. Then, the set of RIs and reuse IEMs is obtained by performing Algorithm 2. Next, the data rate for each transmission mode is calculated and the proposed mode selection is determined. To protect the QoS of RIs and reuse IEMs, all sub-channel of IEMs can only be reused once and an IEM can act as RI once per transmission phase. Therefore, when the mode selection has been decided for an IEM, if the D2D-assisted relaying mode or the relaying mode

is selected, the resource reuse and relay counters are increased by one. If all reuse IEMs and RIs have been used, then the remaining IEMs will operate in the direct transmission mode. The computational complexity of the algorithm is $O(M^A)$ [150] in one time iteration where $A$ is the number transmission modes. The computational complexity of the algorithm is relatively low due to small number of transmission modes, hence it is possible to obtain proposed solutions in the network.

**Algorithm 1** The EEDO Algorithm

Initialize
$t = 1$
**for all** $i = \{1, 2, \cdots, M\}$ **do**
  Based on $p_i^*$, obtain $\gamma_{ij,t}^*$ by solving (3.3), then obtain $R_{i,t}^*$ from the AMC scheme
  Perform Algorithm 2
  **if** $i \in \mathcal{F}$ or $i \in \mathcal{G}$ **then**
    $a_i \leftarrow \alpha_i$
  **else**
    Initialize reuse IEM and RI counters, $f = 1, g = 1$
    **if** $g \leq G$ **then**
      **if** $f \leq F$ **then**
        Solve (3.12), (3.15), (3.19) to obtain $R_{i,t}^{DM}$, $R_{i,t}^{RM}$, $R_{i,t}^{DRM}$
      **else**
        Set $R_{i,t}^{DRM} = 0$ and solve (3.12) and (3.15) to obtain $R_{i,t}^{DM}$ and $R_{i,t}^{RM}$
      **end if**
    **else**
      Set $R_{i,t}^{DRM} = 0$ and $R_{i,t}^{RM} = 0$ and solve (3.12) to obtain $R_{i,t}^{DM}$
    **end if**
    **if** $R_{i,t}^{DM} \geq R_{i,t}^{RM} \geq R_{i,t}^{DRM}$ **then**
      $a_i \leftarrow \alpha_i$
    **else if** $R_{i,t}^{RM} > R_{i,t}^{DM} \geq R_{i,t}^{DRM}$ **then**
      $a_i \leftarrow \omega_i$
      update $Q_{g,t}$, $g = g + 1$
    **else if** $R_{i,t}^{DRM} > R_{i,t}^{RM} \geq R_{i,t}^{DM}$ **then**
      $a_i \leftarrow \mu_i$
      update $Q_{g,t}$, $\gamma_{f,t}^*$, $\gamma_{i,t}^*$, $R_{i,t}$ and $R_{f,t}$, $g = g + 1$ and $f = f + 1$
    **end if**
  **end if**
**end for**
Output: the proposed mode selection $a_i$.

### 4.5.4 Relay Selection Algorithm

In order to satisfy the delay constraints, the RIs with short report and high SNR are selected. The relay selection is dependent on the report length and the channel state of each IEM at the beginning of transmission phase. Algorithm 2 [131] is also performed based on brute-force searching method [130] to obtain a set of potential RIs, $\mathcal{G}$ which is a set of IEMs that has higher SNR than the average SNR, $\overline{\gamma}_t^*$ and smaller queue length than the average packet length $\overline{B}_t$. Additionally, based on Algorithm 2, IEMs in $\mathcal{F}$ are assigned as reuse IEMs, in which the sub-channels of the IEMs in the set can be reused for D2D-Assisted relaying mode.

**Algorithm 2** Relay Selection Algorithm

```
Initialization
Set i = 1
Calculate B̄_t = Σ_{i=1}^{M} B_{i,t}/M, and γ̄*_t = Σ_{i=1}^{M} γ*_{i,t}/M
for i ≤ M do
    if γ*_{i,t} > γ̄_t then
        if B_{i,t} < B̄_t then
            i ∈ G
        else
            i ∈ F
        end if
    end if
end for
Output: the set of G and F
```

Algorithm 2 is embedded in Algorithm 1. To see how Algorithm 1 works and how it interacts with Algorithm 2, the flow chart is provided in Figure 4.3. Firstly, Algorithm 1 finds optimal SINR for all IEM, and then performs Algorithm 2 to obtain the set of RIs and reuse IEMs. The direct transmission mode is selected for all RIs and reuse IEMs. For other IEMs, the data rate of each transmission mode is obtained and the mode with highest data rate is selected. Then the queue length of RIs, and the SINR and data rate of reuse IEMs are updated. After a transmission mode has been selected for all IEMs, the algorithm ends.

## 4.6 Simulation Results and Discussions

Computer simulations are used to evaluate energy efficiency and end-to-end delay of the proposed scheme in various conditions. System parameters are explained and simulation results are discussed in this section.

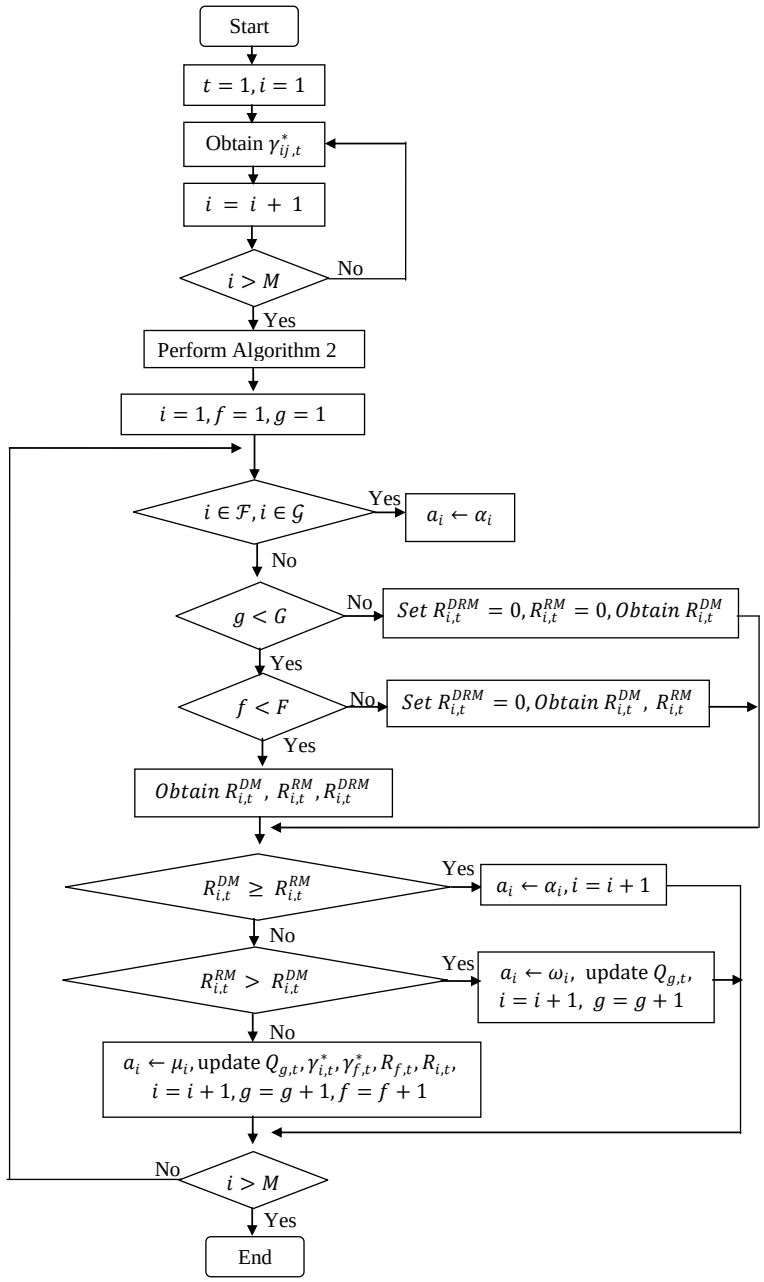


Figure 4.3: Flow Chart of EEDO Algorithm.

### 4.6.1 System Parameters

It is assumed that the coverage radius of the BS is 800m, and a total of 20 IEMs are uniformly distributed in the cell [7]. Each packet has the size of 1080 bits, and the number of packets generated in normal and fault zone are $B_n = 1$ packet and $B_f = 15$ packets respectively [7]. The timeslot length is 1ms [68] and each sub-channel has the bandwidth of 180kHz [151]. The channel model considers both the large-scale shadowing and the small-fading model as Rayleigh

Table 4.1: Simulation parameters

| Parameter | Value |
|---|---|
| BS Antenna Height | 50 [m] |
| IEM Antenna Height | 3 [m] |
| Rooftop Height | 30 [m] |
| Rood Orientation | 90 [degree] |
| Building Space | 50 [m] |
| Street Width | 12 [m] |
| Lognormal shadowing | 0 [dB] mean, 8 [dB] standard deviation |

random variable for NLOS communications. The access and backhaul links are both NLOS, and COST-231 Walfish-Ikegami path loss model with the carrier frequency of 2GHz and the additive white Gaussian noise with power density of -174 dBm/Hz [7] are employed in the simulation by assuming that $\rho_{\min} = -90$ dBm and $n_d = 4$ [146]. Other channel model parameters are given in Table I. The channel state and the number of packets can be carried by the link in a timeslot under different channel states according to AMC scheme, i.e $R_z$ with $z = \{1, 2, 3, 4, 5, 6\}$ are set to $0, 1, 2, 3, 6, 9$ respectively according the SINR thresholds for channel states given in [140], Table II. 3.6kV-120V/10kVA IEMs model is used in this research [152] which result in $V$= 120V and $I_{leak}$=1.1A. The prototype is an SST with a high-performance system controller that is used in the FREEDM system. For simplicity we set $\xi$=1. Values of $D^{\min}$, $D^{\max}$, $D^{\text{ave}}$ and $t^{\text{end}}$ are set to 0.1ms, 3.0ms, 1.5ms and 500ms respectively [6].

To validate the effectiveness of the brute-force method, the simulation on energy efficiency and average delay of the brute-force method and the Hungarian algorithm [153] under different average report lengths is conducted. The results in Figure 4.4 and Figure 4.5 show that the proposed algorithm yields higher energy efficiency and lower delay than the Hungarian algorithm, respectively. The reason for that is because the brute-force method, also known as exhaustive method, searches for all possible actions and selects the best one, therefore the results are optimal.

Considering the transmission mode in device-to-device communications underlying cellular networks for the FREEDM system, three different schemes are used for comparison, which are explained as follows

- Direct scheme: the scheme that only offers the direct transmission mode [7].
- Relay scheme: the scheme that offers direct transmission mode and relaying mode [7]. The RIs are selected using Algorithm 2.
- Proposed scheme: the scheme that offers three transmission modes namely the direct

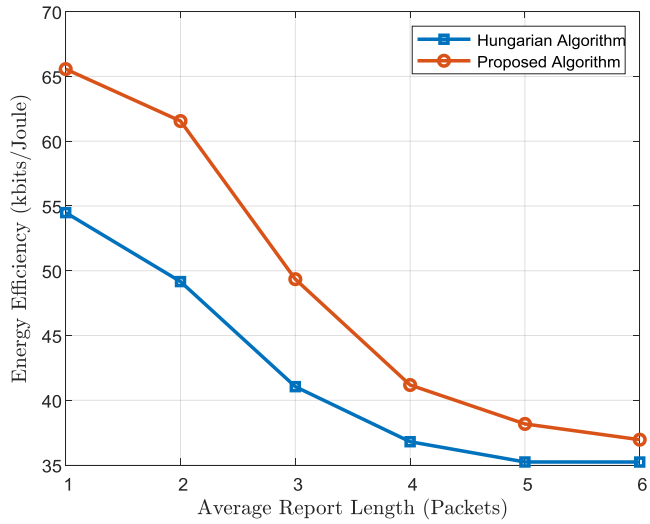


Figure 4.4: Energy efficiency comparison between the proposed algorithm and Hungarian algorithm with different average packet lengths.

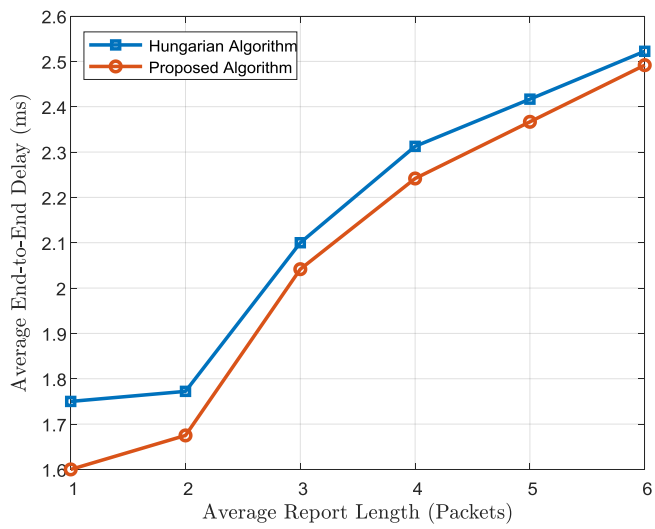


Figure 4.5: Average delay comparison among two algorithms under different average packet lengths.

transmission mode, the relaying mode and the D2D-assisted relaying mode with the power control method. The RIs are selected using Algorithm 2.

Since other existing D2D mode selection schemes [7, 50] are the revision of these modes, the comparison of these modes are believed to be sufficient to show the effectiveness of the proposed work.

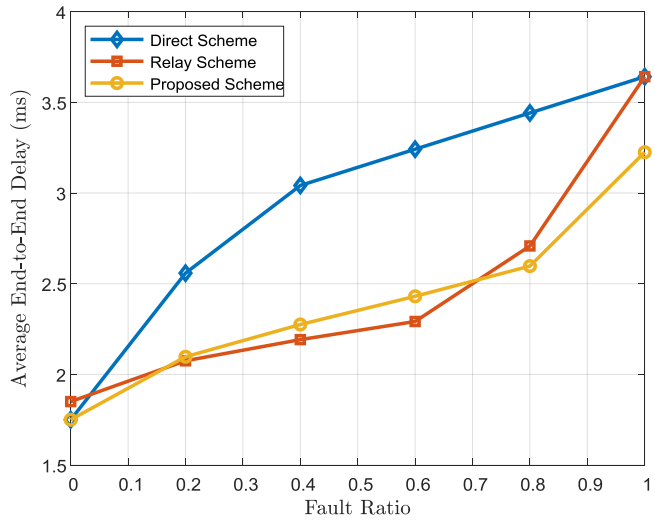


Figure 4.6: End-to-end delay comparison among three schemes under different fault ratios.

The performance of all three schemes is investigated under different fault ratios, average report lengths and average SNRs. Fault ratio is defined as the ratio of the number of IEMs in the fault zones to the total number of IEMs in a cell. A fault ratio of 0 indicates that there are no IEM in the fault zones. Considering the urban areas, the SNR of each IEM varies with an average of 20 dB [139]. The maximum transmission power for each IEM is 14 dBm [7].

### 4.6.2 The Impact of Fault Ratio

The impact of the fault ratio on the average end-to-end delay and energy efficiency of all three schemes is investigated. Figure 4.6 shows that as the fault ratio increases, the average end-to-end delay for all three schemes increases. The reason for that is because the average report length is increasing when increasing the fault ratio, hence increasing the delay. At fault ratio 0, the relay scheme has a higher delay because of the additional delay when IEMs select the relaying mode at short report length. In the proposed scheme, data rates are optimized for energy efficiency, which results in random delay improvements. Therefore when the fault ratio varies from 0.2 to 0.6, the proposed scheme has higher delays than the relay scheme and when the fault ratio varies from 0.8 to 1, the proposed scheme has lower delay than the relay scheme. Moreover, it can be seen that the average delay of the relay scheme and the direct scheme are the same at fault ratio 1 because no IEMs can be used as the relaying node at fault ratio 1.

Figure 4.7 shows that the energy efficiency of the proposed and relay schemes decrease from fault ratio 0 to 0.2, then remain constant from fault ratio 0.2 to 0.8, and decrease again from fault ratio 0.8 to 1. The reason behind this is because when the fault ratio varies from 0.2 to

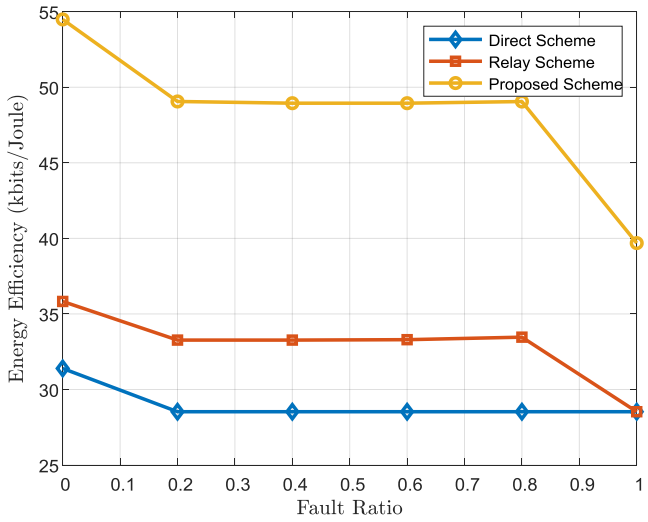


Figure 4.7: Energy efficiency comparison among three schemes under different fault ratios.

0.8, the number of RIs is the same, therefore the energy efficiency is constant, while in other values, the energy efficiency decreases as less number of IEMs can be used to support relay and D2D-assisted relaying modes due to more IEMs in the fault zone. The energy efficiency of the direct scheme decreases from fault ratio 0 to 0.2 then remain constant until fault ratio becomes 1. This is because, in the direct scheme, from fault ratio 0 to 0.2, more power is used to transmit more data due to more IEM in the fault zone, while the energy efficiency is constant because the number of IEMs meeting poor channel conditions is the same, hence yielding the same energy efficiency. The proposed scheme has the highest energy efficiency at all fault ratios because it exploits the power control scheme. Additionally, based on both figures, the results show that there is a trade-off between energy efficiency and delay in the proposed method. However, the delay is not sacrificed too much when increasing the energy efficiency. Hence, the proposed scheme is an important method to balance between energy efficiency and the average end-to-end delay no matter what the fault ratio is.

### 4.6.3 The Impact of Average Report Length

The impact of the average report length on the performance of all three schemes with fault ratio 0.5 is investigated. The largest report size of IEMs from the fault zones is 15 packets, resulting in the maximum average report length for 20 IEM with 0.5 fault ratio is 6 packets. Figure 4.8 shows that all IEMs require more time to complete the transmissions when the average report length increases, which occurs according equation (4.7). The relay scheme has higher delays than the direct scheme at average length 1 and 2 packets. This means that the scheme is not

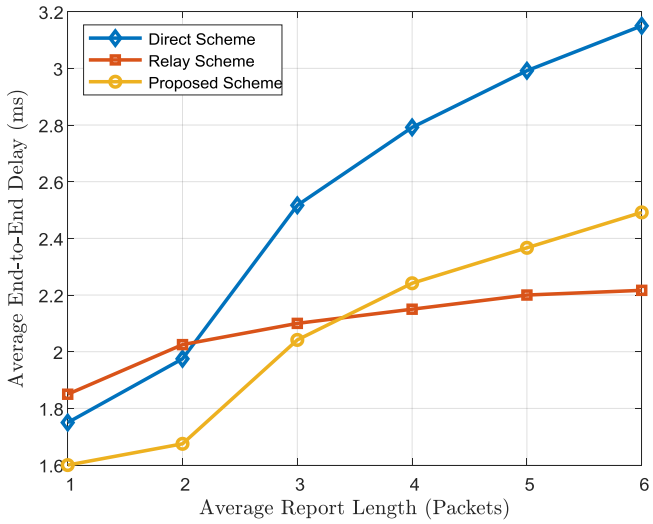


Figure 4.8: End-to-end delay comparison among three schemes with varying average report lengths.

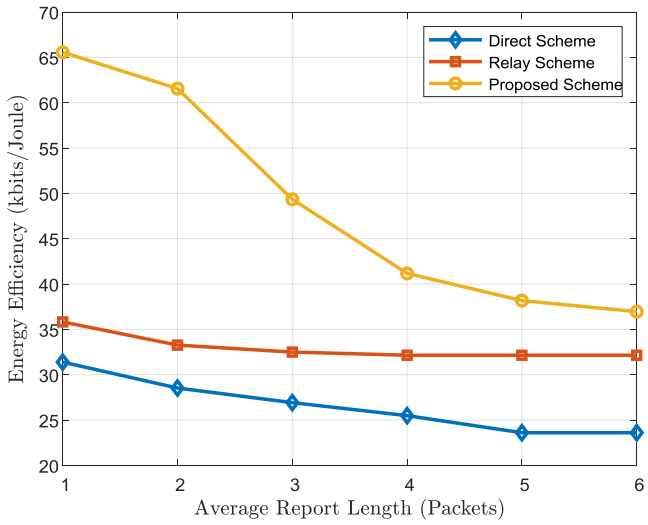


Figure 4.9: Energy efficiency comparison among three schemes with varying average report lengths.

suitable for small report lengths as selecting the relaying mode at this condition results in the excess delay due to the relaying process. Moreover, the proposed scheme has higher delays than the relay scheme when report length is more than 4 packets, because at large report lengths, optimizing data rate for energy efficiency results in the increase of delay. However the delay is still in an acceptable range, which is between 3 to 16 ms.

The energy efficiency of all three schemes for different average report lengths is shown

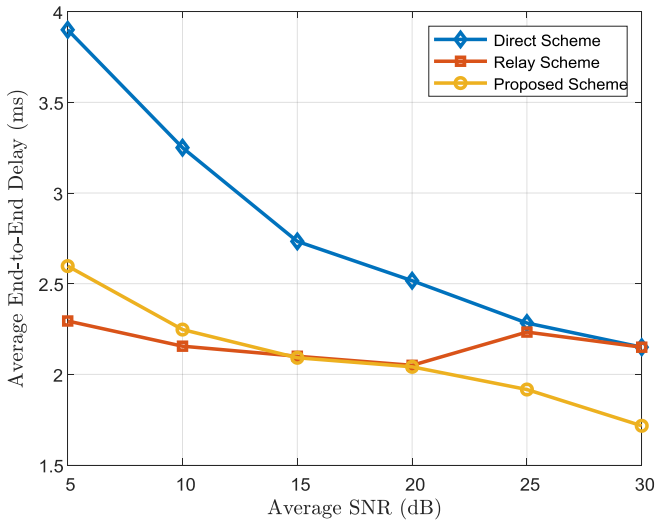


Figure 4.10: End-to-end delay comparison among three schemes under various average SNRs.

in Figure 4.9. The energy efficiency is decreasing when increasing the average report length because the increase of data size is associated with the increase of power consumption. In addition, the performance of the proposed scheme outperforms the other two schemes at all average report lengths. Based on both figures, the results show that there is a trade-off between energy efficiency and delay in the proposed method when the average report length is varied. However, the delay is still acceptable as the energy efficiency is increased.

### 4.6.4 The Impact of Average Signal-to-Noise Ratio

The impact of the average SNR on the performance of all three schemes when the average report length is 3 packets, with fault ratio 0.5 is also studied. The value of SNR represents the channel quality, where low SNR indicates that the channel is in a poor condition and vice versa. Figure 4.10 shows that the average end-to-end delay of the proposed scheme and the direct scheme decrease as the channel quality improved. The reason for that is because a high SNR enables a high data rate which leads to the decrease in the average end-to-end delay. The average end-to-end delay is defined as the summation of the total delay of all IEMs divide by the total number of IEMs, which is 20. This shows that as the number of IEMs selecting the direct transmission mode after 20 dB increases in the relay scheme, the gap between the direct scheme and the relay scheme decreases. Moreover, the delay of the proposed scheme is higher than the relay scheme when the average SNR varies from 5 dB to 15 dB because less number of IEMs can be used to support the D2D-assisted relaying mode when more IEMs are in poor channel conditions.

The energy efficiency of all three schemes increases as the average SNR increases as shown

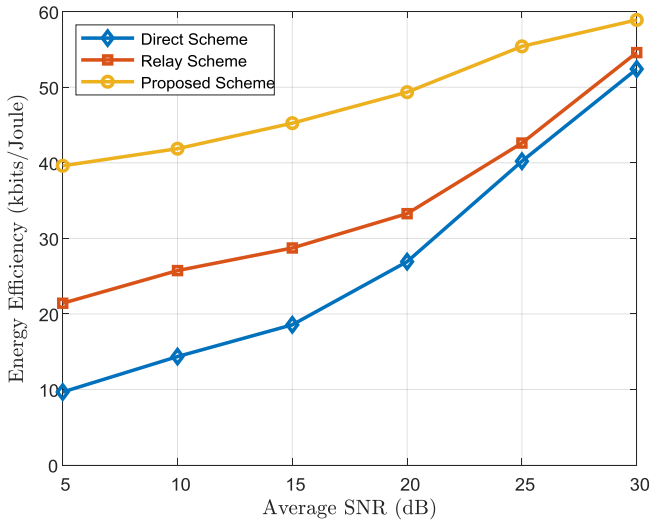


Figure 4.11: Energy efficiency comparison among three schemes under various average SNRs.

in Figure 4.11. The reason for that is because high SNR results in high data rate. Consequently, leads to less waiting time to transmit data for all schemes. Therefore it is more energy efficient. Furthermore, as the proposed scheme offers more modes and uses the power control method which optimizes the data rate, it outperforms the other two schemes at all average SNR values. Based on both figures, the results show that there is a trade-off between energy efficiency and delay in the proposed method when the average SNR varies from 5 dB to 30 dB. The trade-off is a slightly higher delay, however still outperforms the direct transmission strategy. Hence, the proposed scheme is crucial for the network in order to balance energy efficiency and average end-to-end delay regardless of the average SNR.

## 4.7 Conclusions

This chapter investigated the application of D2D communications for FREEDM systems in smart grids. D2D communications have the ability reduce power consumption and improve delay performance of smart grid applications with energy-hungry devices and real-time data. Energy efficiency and delay problems in D2D communications underlying cellular networks under different data size and time-varying channel conditions were studied. A joint power control and mode selection scheme was proposed to satisfy delay constraints and at the same time improving energy efficiency in the network. A combinatorial power control and mode selection problem was formulated and the problem was decomposed into two sub-problems. A brute-force searching method based algorithm was proposed to find proposed solutions. The performance of

the proposed scheme was evaluated under various fault ratios, average SNR and average report lengths. Simulation results showed that the proposed scheme outperforms other two schemes in terms of energy efficiency in all scenarios but has higher delay when more IEMs are in fault zone as well as during longer average report length and when SNR is low, as there is a trade-off between energy efficiency and average end-to-end delay in the proposed scheme. However, the average end-to-end delay is still acceptable when enhancing the energy efficiency. Hence, the proposed scheme is one of the important solutions to improve the performance of the network under fault and poor channel conditions. Moreover, this paper showed that simple methods such as the brute-force method can also give significant improvements in certain situation, where the search space is not too large.

# Chapter 5

# Joint Resource Allocation and Power Control in Heterogeneous Cellular Networks for Smart Grids

## 5.1 Introduction

Of the existing wireless technology, cellular technology with LTE-based standards is preferred for NANs due to its high availability and flexibility [7]. However, integrating the cellular technology and the smart grid communication network is a significant challenge for the LTE due to the large volume of simultaneous transmission delay-sensitive smart grid data. The simultaneous transmissions from smart grid devices in cellular networks may lead to RAN congestions. HetNets are proposed as critical techniques to reduce the RAN congestion because HetNets have the ability to alleviate the RAN congestion by off-loading access attempt from a macrocell to small cells [11]. In HetNets, low-power and low-cost SCBSs are deployed to increase the data rate of SUEs. Exploiting small cells in cellular networks can also improve the delay in the network by a proper communication technique design.

In smart grids, delay is one of the critical parameters that determine the performance of NANs, especially when distributed power plants based on renewable resource are considered at the distribution level. Distributed renewable energy generations are very dependent on local weather conditions which are highly intermittent. To ensure control and monitoring possible at energy generation domains, PMUs play a critical role by transmitting real-time dynamic data consisting DEGs' status to the control centre. The control centre will provide control commands to each PMU based on the status received. However, when data exceed the delay requirement, the control centre assumes that the state of a DEG remains unchanged and will not provide the desired control command. This issue may lead to power loss and blackout may occur in severe

cases.

Some previous researches had studied the delay in smart grid communication networks [154–156] but to date, no work has considered the simultaneous data transmission from PMUs. In this work, we exploit HetNets to reduce the RAN congestion by taking into account the simultaneous transmission of PMUs. In smart grid, PMU measurements are gained by first sampling the voltage and current waveforms through the Global Positioning System and then each sample is time stamped for phase and amplitude variations assessment before being sent to the local PDC. All PMUs in a microgrid are synchronized, i.e., measurements are transmitted to the PDC at the same time. This situation may cause severe access contention and may also lead to excessive delay. A joint resource allocation and power control method can be exploited to improve delay in HetNets for this scenario.

In this chapter, we study HetNets for simultaneous transmission of delay-sensitive data from PMUs. The contribution of this chapter can be summarized as follows.

- We exploit HetNets to reduce RAN congestions in smart grid NANs by considering the simultaneous transmission of PMUs.
- We formulate the joint resource allocation and power control problem as a mixed integer problem with design goals to protect the QoS of macrocell users (MUEs) and to minimize end-to-end delay of SUEs.
- We adopt a game-theoretic approach and the best response dynamics algorithm to obtain the optimal solution for each SUE in the smart grid environment.

The work presented in this chapter has resulted in one conference paper [157].

The rest of this chapter is organized as follows. The system model is described in Section 5.2. The joint resource allocation and power control problem are formulated in Section 5.3. The optimal power control is derived in Section 5.4. The game-theoretic analysis and the best response dynamics algorithm for resource optimization are explained in Section 5.5. Simulation results are presented and discussed in Section 5.6, and the chapter is concluded in Section 5.7.

## 5.2 System Model

In the HetNet shown in Figure 5.1, an OFDMA system is considered. There are one MBS and $S$ SCBSs which are connected to the MBS through wired networks in a service region. Considering the uplink transmissions, PMUs collect the status of DEGs, then transmit the data to the PDC through SCBSs and the MBS. After that, the PDC forwards the data to the control centre in the internet architecture through the gateway in the core network using the wired network.

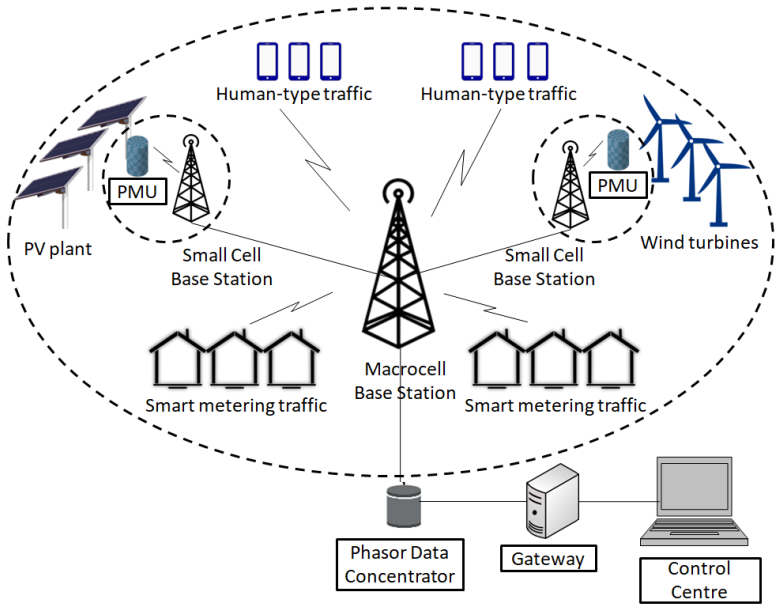


Figure 5.1: The communication architecture for the smart grid.

### 5.2.1 Heterogeneous Cellular Network Model

The MBS is located at the centre of a cell and it provides a complete coverage over the entire network, while SCBSs are hot spots which offer traffic off-loading, as well as service rate improvement within the macro-edge area. It is assumed that PMUs are located at the edge areas and always connected to SCBSs for a higher service rate. The system is operated in a timeslot manner, where in each timeslot, the spectrum resource licensed to the MBS is divided into multiple sub-channels. It is assumed that the MBS is aware of spectrum accessed by SCBSs, and SCBSs can monitor the surrounding radio channel environment and allowed to intelligently access the sub-channels.

The MBS serves $M$ MUEs by allocating a sub-channel with the same bandwidth to each MUE in each timeslot. At the same time, these $M$ sub-channels are shared with $K$ SUEs, as is the common case in real networks. Let the set of MUEs denoted by $\mathcal{M} = \{1, \cdots, M\}$, and $\mathcal{S} = \{1, \cdots, S\}$ denotes a set of SCBSs that are underlaid on the macrocell with each small cell $s \in \mathcal{S}$. The set of SUEs and the set of sub-channels are $\mathcal{K} = \{1, \cdots, K\}$ and $\mathcal{N} = \{1, \cdots, N\}$ respectively. Note that a PMU is also a SUE, therefore the SUE refers to the PMU afterwards.

Let $y^n_{mk,t} \in \{0, 1\}$ denote the sub-channel allocation profile of MUE $m$ shared with SUE $k$ at timeslot $t$. Based on the profile, the SINR at SUE $k$ over sub-channel $n$ shared with MUE $m$ is given by

$$\gamma^n_{k,t} = \frac{|h^n_{ks}| p_{k,t}}{y^n_{mk,t} |h^n_{ms}| p_{m,t} + N_0}, \tag{5.1}$$

where $|h^n_{ks}|$ represents the channel gain between SUE $k$ and SCBS $s$ over sub-channel $n$ which can be calculated as $|h^n_{ks}| = C^s \zeta_{ks}(L_{ks})^{-\alpha}$. $C^s, \zeta_{ks}, L_{ks}$ and $\alpha$ denote the path loss constant, the fast fading component with Nakagami-$m$ distribution, the distance between SUE $k$ and SCBS $s$, and the path loss exponent respectively. The transmission power of MUE $m$ over sub-channel $n$ is denoted by $p^n_m$ and the variance of the complex Gaussian thermal noise at the receiver represented by $N_0$.

The achievable data rate of SUE $k \in \mathcal{K}$ associated to SCBS $s$ over sub-channel $n$ at timeslot $t$ is given by [158]

$$R^n_{k,t} = \sum_{\forall n \in \mathcal{N}} \log_2\Big(1 + \frac{|h^n_{ks}|^2 p_{k,t}}{N_0 + I^n_{k,t}}\Big), \tag{5.2}$$

where $I^n_{k,t}$ indicates the aggregate interference encountered by SUE $k$ which can be calculated as follows [158]

$$I^n_{k,t} = \sum_{\forall m \in \mathcal{M}} y^n_{mk,t} |h^n_{ms}|^2 p_{m,t}. \tag{5.3}$$

### 5.2.2 Queue Dynamic of SUE

All SUEs generate data at the same timeslot. Let $B_{k,t}$ denote the amount of data generated by SUE $k$ at timeslot $t$ which is i.i.d over timeslots following a uniform distribution $f_B(x)$ with an average generation rate $\lambda_k$. A FIFO behaviour is adopted in the queue model and the generated data is stored in the queue first before being transmitted at the next time slot. Let $Q_{k,t}$ denote the queue length of SUE $k$ at timeslot $t$. The queue dynamic of SUE $k$ can be defined as

$$Q_{k,t+1} = \max\{0, Q_{k,t} - R^n_{k,t}\} + B_{k,t}. \tag{5.4}$$

Based on the queue length, the message delay of SUE $k$ can be calculated according to Little's law as follows [68]

$$D_{k,t} = \frac{Q_{k,t}}{T_{k,t}}, \tag{5.5}$$

where $T_{k,t}$ denotes the throughput of SUE $k$ at timeslot $t$ which can be expressed as $T_{k,t} = \min\{Q_{k,t}, R^n_{k,t}\}$.

### 5.2.3 Random Access Procedure in the Preamble Part

The procedure of random access (RA) consists of two parts which are preamble and message parts. In the preamble part, a user attempts access from the base station by transmitting a preamble in the RA window [113]. The BS will respond to the request as soon as the preamble is de-

tected by denoting the uplink resource allocation used for the transmission later in the message part. The user will construct a radio resource control connection set-up based on the assigned resource and will then transmits the message in the message part. However, the user will not receive any response from the BS if the preamble is not detected thus a new preamble needs to be transmitted in the next RA window.

When two or more users attempt access to the same BS using the same preamble at the same timeslot, a collision occurs and the BS will not detect the request [113]. It is assumed that users will retransmit preamble with equivalent retransmission probability. Let $Z_l$ denote the random number which the retransmission takes place after $l$-th collision, with uniform distribution in the range $[1, z]$. It is assumed that $z$ is fixed to 10 timeslots. The access delay of SUE $k$ can be calculated as follows [159]

$$D_k^A = D_0 + \sum_{l=1}^{R} [(Z_l + 1)T], \tag{5.6}$$

where $R, T, D_0$ denote the number of retransmission probability to successfully transmit the data, the timeslot duration of the system, and the time from the new packet arrival to the beginning of the next time slot respectively. $R$ can be approximated using a geometric distribution with transmission probability $P_{succ}$ [159], as follows.

$$P[R = r] = P_{succ}(1 - P_{succ})^r. \tag{5.7}$$

## 5.3 Joint Resource Allocation and Power Control Problem Formulation

In HetNets, SUEs share sub-channels with MUEs, therefore SCBSs need to intelligently allocate sub-channels for SUEs and SUEs need to control the transmission power in order to minimize the end-to-end delay. The design goals of the optimization problem are to protect macrocell communications and to exploit the merit of resource sharing between MUEs and SUEs. In the optimization problem, the end-to-end delay can be defined as the time instant from a packet is generated at the source node to the time instant a packet is delivered at the destination node, which includes access and message delays. Considering the RA procedure in the preamble part and the joint resource allocation and power control method in the message part, the end-to-end delay of SUE $k$ can be expressed as follows

$$D_{k,t}^{\text{end}} = D_k^A + D_{k,t}(y_{mk,t}^n, p_{k,t}^n). \tag{5.8}$$

To minimize the end-to-end delay in HetNets, sub-channel allocation and power control

schemes are jointly optimized and the problem can be formulated as follows [160]

$$P1: \min_{y^n_{mk,t}, p_{k,t}, k\in\mathcal{K}} \quad D^{\text{end}}_{k,t}(y^n_{mk,t}, p_{k,t}) \tag{5.9}$$

subject to

$$C1: \sum_{k\in\mathcal{K}} h^n_{ks} p_{k,t} y^n_{mk,t} \leq I^{th}_m, \forall m \in \mathcal{M}, \tag{5.10a}$$

$$C2: \gamma^n_{k,t} \geq \gamma^{\min}_k, p_{k,t} \leq p^{\max}_k, \forall k \in \mathcal{K}, \tag{5.10b}$$

$$C3: \sum_{m\in\mathcal{M}} y_{mk,t} \leq 1, \sum_{k\in\mathcal{K}} y_{mk,t} \leq 1, \forall m \in \mathcal{M}, \forall k \in \mathcal{K}. \tag{5.10c}$$

Let $y^n_{mk,t}$ and $p_{k,t}$ denote the optimal resource allocation and the power control for SUE $k$ at timeslot $t$ respectively. Constraint $C1$ limits the interference caused by SUE $k$ over subchannel $n$ occupied by MUE $m$ below a threshold $I^{th}_m$ to protect the QoS of MUE $m$. The next constraint indicates a minimum SINR requirement, $\gamma^{\min}_k$ and a maximum transmission power for each SUE, $p^{\max}_{k,t}$. The last constraint limits the reuse of sub-channel to one user only and each SUE can only reuse one sub-channel in a timeslot.

The formulated problem $P1$ has a mixed integers nature, which is difficult to address. Therefore, the optimal power control is obtained under a fixed resource allocation profile. Then the optimal resource allocation problem can be constructed using a game-theoretic approach. Lastly, the best response dynamic algorithm is adopted to obtain the optimal solution.

## 5.4 Optimal Power Control

It is assumed that the sub-channel allocation for each SUE has been pre-set under constraint $C3$ and fixed for all $k$ and $m$. Problem $P1$ is then converted into a power control problem, given as follows

$$P2: \min_{p_{k,t}, k\in\mathcal{K}} D^{\text{end}}_{k,t}(p_{k,t}) \tag{5.11}$$

subject to

$$C1: \sum_{k\in\mathcal{K}} h^n_{ks} p_{k,t} y^n_{mk,t} \leq I^{th}_m, \forall m \in \mathcal{M}, \tag{5.12a}$$

$$C2: \gamma^n_{k,t} \geq \gamma^{\min}_k, p_{k,t} \leq p^{\max}_k, \forall k \in \mathcal{K}. \tag{5.12b}$$

To obtain the optimal power control in $P2$, the characteristic of the feasible region under constraints $C1$ and $C2$ is investigated, with the assumption that SUE $k \in \mathcal{K}$ shares the sub-channel

occupied by MUE $m \in \mathcal{M}$. To achieve both lower and upper bounds of $p_{k,t}$, the transmission power in $C1$ is set to 0 and equation (5.1) is substituted in $C2$, given as follows [160]

$$\begin{cases} p_{k,t}^{\min} = & \frac{\gamma_{k,t}^{\min}(h_{ms}^{n} p_{m,t} + N_0)}{h_{ks}^{n}}, \\ p_{k,t}^{\text{th,max}} = & \frac{I_m^{th}}{h_{k0}^{n}}. \end{cases} \tag{5.13}$$

Here, the index 0 in $h_{k0}^{n}$ refers to the MBS. Then the restricted distance between the MUE and the SUE over the same sub-channel is investigated. The distance between MUE $m$ and SCBS $s$ associated for SUE $k$, $L_{ms,t}$ needs to satisfy the following equation [160]

$$L_{ms,t} \geq L_{ms}^{\min} = \sqrt[\alpha]{\frac{\min\{p_{k,t}^{th,\max}, p_k^{\max}\} h_{ks}^{n} - \gamma_k^{\min} N_0}{C^s \zeta_{ms} \gamma_k^{\min} p_{m,t}}}. \tag{5.14}$$

Therefore, the optimal solution to $P2$ denoted by $p_{k,t}^{\text{opt}}$, and the optimal objective function can be calculated as follows

$$\begin{cases} p_{k,t}^{\text{opt}} = \min\left\{\frac{I_m^{th}}{h_{k0}}, p_k^{\max}\right\}, \\ D_{k,t}^{\text{end}}(p_{k,t}) = D_k^A + \frac{Q_{k,t}}{\log_2\left(1 + \frac{h_{ks}^{n} p_{k,t}}{I_k^{n} N_0}\right)}. \end{cases} \tag{5.15}$$

## 5.5 Game-Theoretic Analysis and Best Response Dynamics Algorithm for Resource Optimization

The optimal resource allocation for all $k \in \mathcal{K}$ is investigated based on the obtained optimal power control, $p_{k,t}^{\text{opt}}$ which can be expressed as follows [160]

$$P3: \min_{y_{mk}^{n}, k \in \mathcal{K}} \quad D_{k,t}^{\text{end}}(y_{mk}^{n}, p_{k,t}^{\text{opt}}) \tag{5.16}$$

subject to

$$C1: \sum_{m \in \mathcal{M}} y_{mk}^{n} \leq 1, \sum_{k \in \mathcal{K}} y_{mk}^{n} \leq 1, \forall m \in \mathcal{M}, \forall k \in \mathcal{K}. \tag{5.17}$$

A game-theoretic approach is exploited in order to obtain the resource optimization. Therefore, problem $P3$ is transformed into an unconstrained game problem $P4$.

### 5.5.1 Game Formulation

In the game-theoretic approach, strategy and available strategy sets can be defined as the set of all possible resource allocation for the players, and the allowable selection set of a certain player

when the location constrained for each player has been determined, respectively.

### The Strategy Set

All SUEs in the cell are the players in the game model, $j = k, \forall k \in \mathcal{K}$. The action of $j$ is given by $\mathbf{a}_j = (y^n_{1k}, y^n_{2k}, \cdots, y^n_{Mk})^T$ where $\mathbf{a}_j \in \mathcal{A}_j = \{\mathbf{e}_1, \mathbf{e}_2, \cdots, \mathbf{e}_M\}$. The vector $\mathbf{e}_n = (e_{n1}, e_{n2}, \cdots, e_{nM})^T \in \mathbb{M}^M$ denotes the $n$-th vector of the canonical base spanning the space of real vector of dimension $M$, i.e., $e_{nn} = 1$ and $e_{nn'} = 0, \forall n' \in \frac{\mathcal{M}}{\{n\}}$. The sub-channel allocation profile for all players is denoted by $\mathbf{a} = (\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_K)$ and the space of all possible assignment is denoted by $\mathcal{A} = \mathcal{A}_1 x \mathcal{A}_2 x \cdots x \mathcal{A}_K$.

### The Available Strategy Set

$\mathcal{A}_j$ is the general strategy set for player $j, \forall j \in \mathcal{J}$, which does not consider the sub-channel allocation constrain and the location-based restriction of players. Some action strategies in $\mathcal{A}_j$ are unavailable due to these reasons when the restriction is given. Let $\mathbf{x}(\mathbf{a}_j) = x_1(\mathbf{a}_j), x_2(\mathbf{a}_j), \cdots, x_M(\mathbf{a}_j)$ denote the condition index of sub-channels, which contains the information of available sub-channels for player $j$ by taking into account the restriction $C1$ in (17), which acknowledge by $\mathcal{A}_j$. Let $x_n(\mathbf{a}_j)$ denote the set of SUEs except $j$ occupied the sub-channel $n$. The map of restrained strategy set of player $j$ based on $\mathcal{A}_j$ and $\mathbf{x}(\mathbf{a}_j)$ is given as $\bar{\mathcal{A}}_j = \mathcal{A}_j \ \{\mathbf{e}_n : x_n(\mathbf{a}_j) \bigcap \mathcal{K} \neq \emptyset \bigcup |x_n(\mathbf{a}_j)| = 1, \forall n \in \mathcal{M}\}$. The restrained action space of all players under constrain $C1$ in (4.17) denoted by $\bar{\mathcal{A}} = \bar{\mathcal{A}}_1 \mathrm{x} \bar{\mathcal{A}}_2 \mathrm{x}, \cdots, \bar{\mathcal{A}}_K$.

The available strategy set $\triangle(\bar{\mathcal{A}}_j)$ of player $j$ by means of $\bar{\mathcal{A}}_j$ with location restriction can be expressed as follows

$$\triangle(\bar{\mathcal{A}}_j) = \{\mathbf{e}_n, \forall n \in \Lambda(\bar{\mathcal{M}}\}, \tag{5.18}$$

in which $\bar{\mathcal{M}} = \{n : \mathbf{e}_n \in \bar{\mathcal{A}}_j, \forall n \in \mathcal{M}\}$ and $\Lambda(\bar{\mathcal{M}}) = n : L_{ms_j} \geq L_{ms_j,\min}, \forall n \in \bar{\mathcal{M}}\}$. The utility for unavailable strategy action is assigned to an extremely small value (0) for the decoupling of strategy set, which results in the conversion of problem $P3$ to an unconstrained optimization problem $P4$.

$$P4 : \min_{\mathbf{a} \in \mathcal{A}} \quad D^{\text{end}}_j(\mathbf{a}) = \sum_{j \in \mathcal{J}} D^{\text{end}}_j(\mathbf{a}) y_{\{\mathbf{a}_j \in \triangle(\bar{\mathcal{A}}_j)\}}, \tag{5.19}$$

where $D^{\text{end}}_j(\mathbf{a}) = D^A_j + \frac{Q_t}{\min\{Q_t, R_j(\mathbf{a})\}}$ and $R_j(\mathbf{a}) = \sum_{m \in \mathcal{M}} \log_2(1 + \gamma^n_k(p^{\text{opt}}_k)) y^n_{mk}, k \in \mathcal{K}$.

Problem $P4$ can be constructed as a potential game model [160]. The model is classified into non-cooperative game, where the players make decision independently [103]. In the potential game model, there is a potential function that characterized special behavior of payoff functions. The potential game model is extremely useful for efficient resource allocation [161].

Let $\mathcal{G}_a = \{\mathcal{J}, \{\mathcal{A}_j\}_{j \in \mathcal{J}}, \{U_j\}_{j \in \mathcal{J}}\}$ denote the utility function of the game model. Due to

the coupling among strategy sets, the expression of utility function cannot be derived, but the difference when player $j$ changes the strategy from $\mathbf{a}_j$ to $\mathbf{a}_j^{'}$ can be obtained as $\hat{U}_j(\mathbf{a}_j^{'}, \mathbf{a}) = U_j(\mathbf{a}_j^{'}, \mathbf{a}) - U_j(\mathbf{a}_j, \mathbf{a}) = \sum_{l \in \mathcal{J}}(u_l(\mathbf{a}_j^{'}) - u_l(\mathbf{a}_j))y_{l \in \bar{\mathcal{J}}(\mathbf{a}_j^{'}, \mathbf{a})}$. Locations of non-zero elements of the action vector represented by the set $\bar{\mathcal{J}}(\mathbf{a}_j^{'}, \mathbf{a}) = \{j, x_{\zeta(\mathbf{a}_j)}(\mathbf{a}_j), x_{\zeta(\mathbf{a}_j)}(\mathbf{a}_j^{'})\}$ and $\zeta(.)$

### 5.5.2 Best Response Dynamics Algorithm

**Algorithm 3** Best Response Dynamics Algorithm

1: **Initialization**
Set the time index $t = 0$ and select a sub-channel allocation profile $\mathbf{a}(0)$ randomly from $\mathcal{A}$. Obtain the optimal power ($p_k^{\text{opt}}(0)$) for $\forall k \in \mathcal{K}$ based on $\mathbf{a}(0)$ if $\mathbf{a}(0)$ satisfies the location-based restriction.

2: **Loop for** $t = 1, 2, \cdots$
Select player $j$ from $\mathcal{J}$ randomly and let $j$ update its action strategy according to the best response rule, i.e
*a*) update the condition index $\mathbf{x}(\mathbf{a}(t-1))$ and identify the available strategy set $\triangle(\bar{\mathcal{A}}_j)$, in which each element satisfies the location-based constraint.
*b*) player $j$ randomly selects an action $\mathbf{a}_j \in \mathcal{A}_j$ and gets the corresponding optimal power if $\mathbf{a}_j \in \triangle(\bar{\mathcal{A}}_j)$.
*c*) if $\hat{U}_j(\mathbf{a}_j)(\mathbf{a}(t-1)) > 0$, the sub-channel selection profile in the $t$-th iteration is updated to $\mathbf{a}(t) = (\mathbf{a}_j, \mathbf{a}(t-1))$, and $p_k^{\text{opt}}$ for $k \in \mathcal{K}$ is obtained on $\mathbf{a}(t)$ in equation (15); otherwise, let $\mathbf{a}(t) = \mathbf{a}(t-1)$ and $p_k^{\text{opt}}(t) = p_k^{\text{opt}}(t-1)$.

3: **End loop**

The best respond dynamics algorithm [160] is adopted to find a NE point of $\mathcal{G}_a$ which is the global optimal solution for problem $P1$. In the game model $\mathcal{G}_a$, at least one NE exists which minimizes the objective function of $P3$ [160]. In problem $P4$, the optimum result can be obtained by getting the difference of utilities for each player when the strategy changed. Therefore, to obtain the NE, the best response rule [160] is applied to solve $\mathcal{G}_a$ by sharing information between players of selecting the same sub-channel, as described in Algorithm 3. This rule can converged to a NE point of the game as well as finding the best NE. Therefore the optimal sub-channel allocation profile for HetNets with constraint QoS requirements can be achieved by Algorithm 3. The complexity for one iteration in Algorithm 3 is $O(|J|(M - S + 2))$ [160].

## 5.6 Simulation Results and Discussions

Computer simulations are used to evaluate the performance of the proposed scheme. System parameters are explained and simulation results are discussed in this section.

Table 5.1: Simulation parameters

| | |
|---|---|
| Macrocell radius | 400 m [158] |
| Small cell radius | 50 m [158] |
| Number of MUEs | 30 [158] |
| Number of SUEs | 15 [158] |
| Number of subchannel | 30 |
| Maximum SINR requirement of SUEs ($\gamma_k^{\min}$) | 20 dB [160] |
| Minimum interference threshold of MUEs ($I_m^{th}$) | $10^{-6}$ [160] |
| Thermal noise ($N_0$) | -174 dB [160] |
| Path loss constant ($C^s$) | $10^{-2}$ [160] |
| Path loss exponent ($\alpha$) | 4.8 [160] |
| Bandwidth of each subchannel | 180 kHz [7] |
| Maximum transmission power of SUE | 14 dBm [7] |

Each PMU has an average generation rate of 1 packet/s with the size of each packet is 102 Bytes for 50 Hz reporting state [162]. $P_{succ}$ is 0.85 [159] and the length of each timeslot is 1 ms. In this system, the number of SUEs is fixed while the number of MUEs is varied. A detailed list of simulation parameters are given in Table 5.1. These values are used in the sequel, unless otherwise specified.

Firstly, the performance of the HetNet is compared with the cellular network in terms of the number of preamble collision for various total number of simultaneous access attempts by users using the RA procedure. The cellular network refers to the network with only one serving BS in a macrocell. Figure 5.2 shows that at the same total number of attempts, the HetNet gives a significant collision reduction due to its off-load capability, consequently proves that HetNets can reduce the RAN congestion. Then, the demonstration of the algorithm to obtain the NE using parallel and sequential procedures [163] is held. Figure 5.3 illustrates that the parallel procedure converges faster than the sequential procedure. This is because in the parallel procedure, the SUEs are able to find their best-response decision simultaneously. Moreover, the result shows that the NE can be obtained using the algorithm. Next, the impact of the minimum interference thresholds of MUEs to the average end-to-end delay of SUEs for different maximum transmission power of SUEs is studied. Figure 5.4 shows that as the interference increases, the average end-to-end delay also increases. The reason for that is because when the interference increases, SUEs will try to decrease the transmission power, which will result in a lower data rate. According to Little's law, low data rate leads to high end-to-end delay.

Finally, the performance of the proposed scheme is compared with FIFO and round-robin (R-R) scheduling schemes [164] in terms of the average end-to-end delay. In the FIFO scheme, the BS allocates sub-channels based on a first-come first-served basis, while in the R-R scheduling scheme, the MBS tries to reduce collisions by scheduling users one-by-one before off-loading

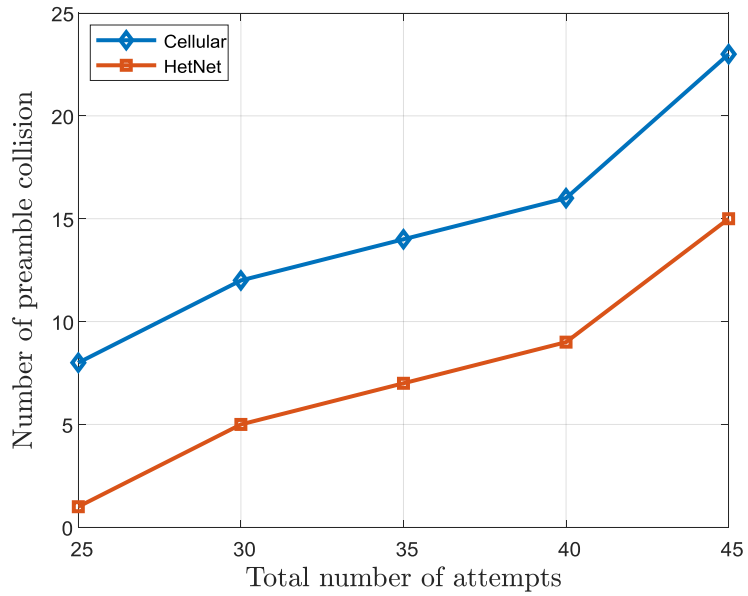


Figure 5.2: Number of preamble collision with various total number of attempts.

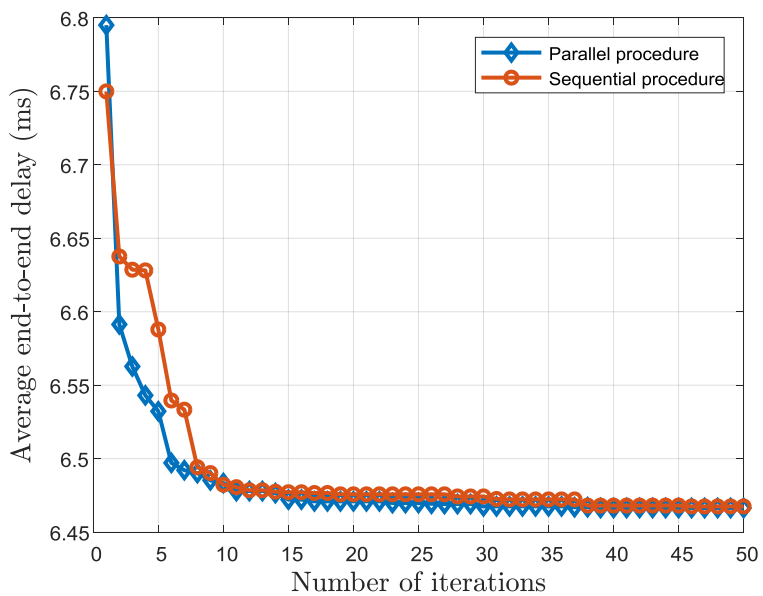


Figure 5.3: Convergence of the Nash equilibrium using the Best Response Dynamics Algorithm.

them to the corresponding SCBSs. As a result, the average end-to-end delay for both schemes are increasing when increasing the number of users in a cell. The reason for that is because in the FIFO scheme, the increase of users will increase the collisions, while in R-R scheme the increase of users will increase the number of timeslot for a complete scheduling cycle. Moreover, the R-R scheduling scheme produces highest delay when the number of users exceeds 33, making it ineffective for a large number of users with light traffic [164]. Despite the total number of users,the proposed scheme was able to outperform other two schemes as shown in Figure 5.5.

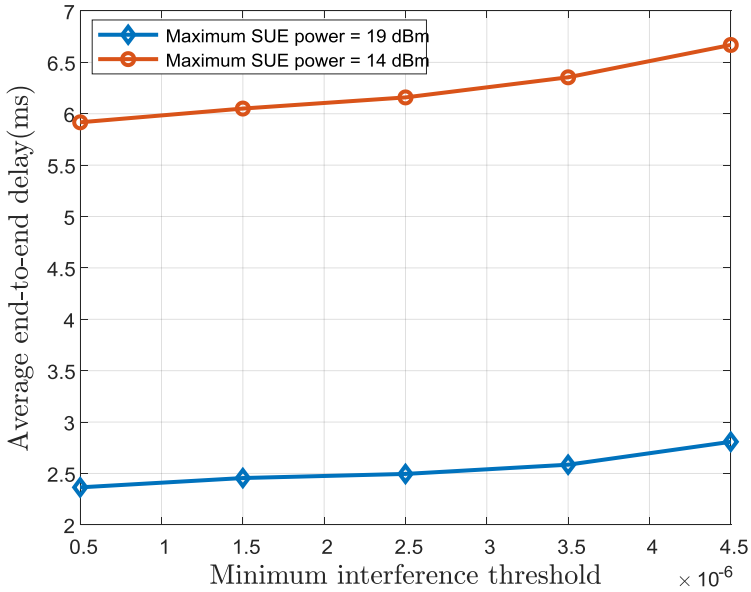


Figure 5.4: The average end-to-end delay with various minimum interference threshold.

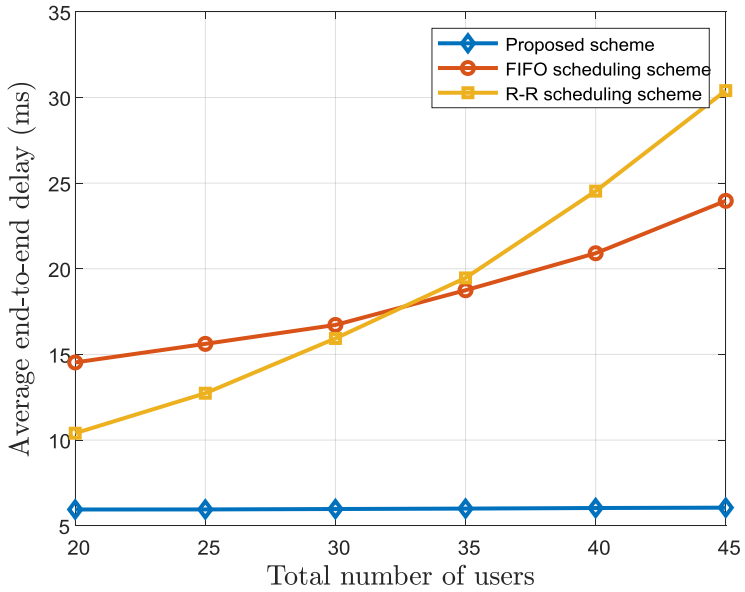


Figure 5.5: The average end-to-end delay with various total number of users.

## 5.7 Conclusions

This chapter studied HetNets for simultaneous transmissions of delay-sensitive PMU data. A joint resource allocation and power control method aere proposed to minimize the end-to-end delay in HetNets. The optimization problem was formulated as a mixed integer problem, and a game-theoretic approach and the best response algorithm were adopted to solve the problem. Simulation results showed that in the RA procedure, HetNets has lower preamble collisions as

the total number of attempts increases compared to cellular networks. Additionally,the proposed scheme has lessen the delay significantly when the total number of users increases compared to cellular and R-R scheduling schemes.

# Chapter 6

# Channel Access and Power Control for Energy-Efficient Delay-Aware HetNets in Smart Grid Communications using Deep Reinforcement Learning

In smart grid, higher penetration of distributed energy resources based on renewable energy such as solar and wind power planted at distribution level is expected in future associated with the rising of energy demand from user side [18]. The DERs are very dependent to local weather conditions and highly intermittent, which require additional monitoring [16]. In order to ensure monitoring and controlling possible at DERs at the distribution level, PMUs are deployed. PMUs play a critical role to transmit real-time dynamic data on power flows to the power system control centre [5]. PMU measurements are gained by first sampling the voltage and current waveforms through the global positioning system, then each sample is time-stamped for phase and amplitude variations assessment before it is sent to the local PDC. Moreover, all PMUs in a microgrid are synchronized, i.e., measurements are transmitted to the PDC at the same time. Of the existing wireless technology, cellular technology with LTE-based standards is a good choice for NANs due to its high availability and flexibility [7]. However, the large volumes of simultaneous transmission of smart grid data from PMUs and other devices in NANs could cause severe RAN congestions, leading to excessive delay in conventional cellular networks [7]. In dealing with this issue, HetNets are proposed as critical techniques to reduce RAN congestions. In HetNets, low-power base stations are exploited in a macrocell, which is located close to the edge of macrocell to improve the data rate of users. HetNets have the ability to alleviate RAN congestions by off-loading access attempts from macrocells to small cells [11].

Energy efficiency is one of the critical parameters in HetNets. When abnormal events occur,

for instance natural disasters such as floods, earthquakes or tsunamis, the PMUs will be isolated from the grid. In this situation, the PMU is powered by local energy sources, such as small wind turbine, photovoltaic panels and local energy storage equipment [9], which have limited power supply. Therefore, energy efficiency is critical in this kind of situation to ensure that status of DERs can be transmitted to the control centre successfully. However, increasing the energy efficiency might compromise delay, an important performance parameter that reflects the actual user experience in the network. Delay is also important for PMUs because if the PMU data exceed the delay requirements, information loss may occur, which might lead to power loss and blackouts may occur in severe cases [58]. Due to this issue, it is critical to consider both parameters in HetNets. Channel access and power control are two critical schemes in HetNets especially when energy efficiency and delay are considered. Channel access scheme can be exploited to satisfy the stringent delay requirements by allowing devices to properly select a communication channel that satisfies the QoS of their data. On the other hand, the power control scheme is one of the energy efficiency maximization schemes which permits transmission power regulation of devices with respect to some constraints. The combination of both schemes could result in better performance in HetNets.

Many studies have addressed the energy efficiency and delay problem in HetNets for cellular communications with different schemes. For example, Mohammad *et al*. proposed a joint sub-carrier and power allocation scheme in energy harvesting-enabled-power domain non-orthogonal multiple access-based HetNets and exploited optimal approach based on the monotonic optimization to solve the problem [165]. Karim *et al*. investigated cloud radio access network and ray tracing-based resource allocation problem in heterogeneous traffic LTE networks and adopted heuristic algorithms to cater the problem [166]. Lun *et al*. proposed a joint user association, clustering, and on/off strategies in dense heterogeneous networks and exploited the semidefinite programming and effective approximation approach to obtain maximum energy efficiency with satisfied QoS [167]. Cong *et al*. exploited the on-line learning approach to solve the mobility management problem in highly dynamic ultra-dense HetNets [168].

In addition to works related to energy efficiency and delay in Hetnets, the increase in number of devices due to the integration of smart grid communications and cellular technology demands for self-organized communications in heterogeneous and massive system [113], and deep learning is an emerging tool which can be exploited. Deep learning can be defined as a class of machine learning algorithm in the form of a neural network that extracts features from data and make predictive guesses about new data using a cascade of layers of processing units. DRL combines reinforcement learning and deep learning, by exploiting deep neural networks method to develop an artificial agent that is able to learn optimal policies directly from high-dimensional sensory inputs using end-to-end reinforcement learning (RL) [169]. DRL is

promising for wireless communication agents because DRL enables them to learn the system dynamics and obtain the optimal policy in random and dynamic environments without knowledge of the system [170, 171]. Moreover, DRL has the ability to deal with high-dimensional and large system states such as in HetNets [172, 173]. Based on these reasons, DRL approach is explored to train PMUs to access channel and regulate its power in order to achieve maximum energy efficiency and satisfy delay constraints in distributed manner by extracting inputs from the environment.

Although an extensive study has been conducted on energy efficient and delay in HetNets, all these works utilized conventional analytical optimization techniques and none of them tries to explore more intelligent algorithms involving deep learning. Moreover, none of these works has considered a joint channel access and power control scheme in HetNets to achieve the objectives by exploiting DRL. In this work, we exploit an intelligent channel access and power control scheme to maximize energy efficiency and satisfy delay constraints of PMU in HetNets by taking into account the simultaneous transmission and differentiated delay requirements of the PMUs using a DRL approach. By doing this, historical data can be used to train the proposed algorithm, leading it towards better decisions in the future and optimizing energy by considering the differentiated delay requirements.

The contributions of this chapter can be summarized as follows.

- We study energy efficiency and delay problems in HetNets by considering devices having different delay requirements.
- We propose channel access and power control scheme to achieve the objective for devices with high generation data in slow fading channel environment.
- We propose a DRL approach algorithm for distributed intelligent channel access and power control scheme in HetNets and analyse the distributed decision made by PMUs in a variety of different conditions.

The work presented in this chapter has resulted in one journal paper.

The rest of this chapter is organized as follows. Section 6.1 provides information on the DERs' states and delay requirements of PMUs data. Section 6.2 explains the DERs' state and delay requirements of PMUs data. The system model is described in Section 6.3. The DRL approach for intelligent channel access and power control scheme is explained in Section 6.4. Simulation results are presented and discussed in Section 6.5 and Section 6.6 concludes the chapter.

## 6.1 DERs' State and Delay Requirements of PMUs Data

Most of the energy management system applications assume that the system is in a pseudo-steady state where alternating-current circuit analysis can be carried out using the PMUs. The PMUs, usually placed at the 24.9kV distribution lines in power networks, measure voltage and current phasors of DERs, and then directly compute real power and volt-ampere reactive (VAR) flows at precise moments [174], which is crucial for grid protection and monitoring. In general, the DERs can be operated in one of three states: normal state, abnormal state, and restorative state [175].

The DER is in a normal state when some component emergency ratings and the voltage can be maintained at a safe minimum, at the same time ensuring that the service to the control centre continues. When some of these components cannot be retained, the DER needs control commands from the control centre to move back to normal states. Assume that the DER moves from normal state to other states with probability $\rho$. Let $g_{i,t}$ denote the state of DER observed by PMU $i$ at iteration $t$: normal (0), restorative (1) and abnormal (2). Depending on the $g_{i,t}$, the data from PMUs are used for different applications with different delay requirements. In normal states, the data measured by PMUs are used for controlling and monitoring applications with the delay requirement of 20 ms [162]. When abnormal events occur or the DER is in a restorative state, the data of PMUs are used for protection, in which delay delivery requirement is reduced to 8 ms [176]. If data exceed the delay requirements, information loss may occur, which might lead to power loss and blackouts may occur in severe cases.

## 6.2 System Model

The HetNet shown in Figure 5.1, is considered for a smart grid NAN, where there is one MBS and $E$ SCBSs underlaid on the macrocell and located close to the edge of the macrocell. These SCBSs are connected to the MBS through a wired network. The SCBSs offer traffic off-loading to improve the service rates. The communication devices in the macrocell include the PMUs, the smart meters and the mobile devices. All devices could attempt to access the network simultaneously. The PMUs, deployed close to the DERs, are responsible for collecting measurements related to the status of the DERs. The macrocell users (MUEs) are served by the MBS while the PMUs and the small cell users (SUEs) are served by the SCBSs for a higher service rate. The PMUs transmit the generated data to the PDC through the SCBSs and the MBS. After that, the PDC forwards the data to the control center to make decisions through the gateway in the core network.

The network is operated in a time-slot manner, where in each time slot, $U$ sub-channels with the same bandwidth are licensed to the MBS. The MBS serves $U$ MUEs by allocating one sub-

Table 6.1: SINR parameters

| | |
|---|---|
| $\lvert h_{ie}^{n}\rvert$ | channel gain between PMU $i$ and SCBS $e$ |
| $p_i$ | transmission power of PMU $i$ |
| $\sigma^2$ | variance of the complex Gaussian thermal noise at the receiver |
| $z_i$ | channel access action of PMU $i$ |

channel to each MUE. At the same time, these $U$ sub-channels are shared with the $M$ PMUs and the $J$ SUEs ($M < J \leq U$). The PMUs and the SUEs access the sub-channels intelligently in a distributed manner, and the MBS is aware of the spectrum accessed by these users. The set of the MUEs, the SCBSs, the PMUs, the SUEs and the sub-channels are denoted as $\mathcal{U} = \{1, \cdots, U\}$, $\mathcal{E} = \{1, \cdots, E\}$, $\mathcal{M} = \{1, \cdots, M\}$, $\mathcal{J} = \{1, \cdots, J\}$ and $\mathcal{N} = \{1, \cdots, N\}$ respectively.

Without any knowledge about the MUEs and the SUEs in the cell, the PMUs access the sub-channels and regulate their transmission power to maximize their own reward. Regardless of this greedy behaviour, it is important for the PMUs to adapt to the environmental changes as energy efficiency is highly dependent on environmental factors such, as MUEs' behaviour and QoS requirements [177].

### 6.2.1 Signal-to-Interference-plus-Noise Ratio and Data Rate of PMUs

The total interference plus noise measured by each PMU includes interference from MUE-MBS and SUE-SCBS over the same sub-channel, and the additive white Gaussian noise (AWGN). Let $\gamma_i$ denote the received SINR of PMU $i$ at sub-channel $n$, which can be calculated as [160]

$$\gamma_i(p_i, z_i) = \frac{\lvert h_{ie}^{n}(z_i)\rvert p_i}{\sigma^2 + \sum_{u\in\mathcal{U}} \lvert h_{ue}^{n}(z_u)\rvert p_u + \sum_{j\in\mathcal{J}} \lvert h_{je}^{n}(z_j)\rvert p_j}. \tag{6.1}$$

All symbols are explained in Table 6.1.

The channel gain over sub-channel $n$ can be calculated as $\lvert h_{ie}^{n}\rvert = C\xi_{is}(L_{is})^{-\alpha}$ [160]. $C, \xi_{is}, L_{is}$ and $\alpha$ denotes the path loss constant, the slow fading component with Nakagami-$m$ distribution, the distance between PMU $i \in \mathcal{M}$ and SCBS $e$, and the path loss exponent respectively. Nakagami-$m$ distribution is adopted as it applies to a large class of fading channels.

In order to satisfy the QoS for each PMU, different minimal SINR requirements, $\gamma_i^{\min}$, is applied to data transmissions, which is determined according to the state of DER observed by PMU $i$ at time slot $t$, $g_{i,t}$, expressed as

$$\gamma_i^{\min} = \begin{cases} \gamma_1, & \text{if } g_{i,t} = 0, \\ \gamma_2, & \text{otherwise.} \end{cases} \tag{6.2}$$

Let $r_{i,k}$ denote the data rate of PMU $i$ at timeslot $k$ which can be calculated as [158]

$$r_{i,k}(p_i, z_i) = \log_2\Big(1 + \gamma_i(p_i, z_i)\Big). \tag{6.3}$$

### 6.2.2 Queue Dynamics of PMUs

Each PMU generates data at every generation interval $K$. Let $B_{i,k}$ denote the amount of packets generated by PMU $i$ at timeslot $k$, which is periodic with the rate of $\lambda$ and same in size. A first-in-first-out (FIFO) behaviour is adopted in the queue model and the generated data is stored in the queue first before being transmitted at the next timeslot. Assuming that the size of buffer is large, no data is dropped due to buffer overflow. Let $Q_{i,k}$ denote the queue length of PMU $i$ at timeslot $k$. The queue dynamic of PMU $i$ can be defined as follows.

$$Q_{i,k+1} = \max\{0, Q_{i,k} - r_{i,k}(p_i, z_i)\} + B_{i,k}, \tag{6.4}$$

where $Q_{i,k}$ is denoted as the queue length of PMU $i$ at timeslot $k$.

### 6.2.3 Delay and energy efficiency model

The average delay of PMU $i$, $\bar{D}_i$, can be calculated based on the Little's law [68]

$$\bar{D}_i = \frac{\bar{Q}_i}{\bar{T}_i}, \tag{6.5}$$

where $\bar{Q}_i$ is the average queue length, and $\bar{T}_i$ is the average throughput, and $T_i = \min\{Q_i, r_i(p_i, z_i)\}$.

The total power consumed by PMU $i$ at iteration $t$, denoted as $P_{i,t}^{\text{Total}}$, can be calculated as

$$P_{i,t}^{\text{Total}} = P_c + p_{i,t}, \tag{6.6}$$

where $P_c$ is denoted as the circuit power due to signalling and active circuit blocks, and the transmission power $p_{i,t}$. The circuit power can be modelled as the total of a static term and a dynamic term [141], $P_c = VI_{leak} + A_s C f V^2$, where $V$, $I_{leak}$, $A_s$, $C$ and $f$ denote the transistors supply voltage, the leakage current, the fraction of gate actively switching, the circuit capacitance, and the clock frequency respectively. The frequency is assumed to be dynamically scaled with the sum rate, therefore the circuit power can be modelled as [143]

$$P_c = P_s + \beta r_{i,t}, \tag{6.7}$$

where $P_s$ denotes the static term and $\beta$ is a constant representing dynamic power consumption

per unit data rate. In this work, the circuit power is calculated when PMUs generate data until the data arrive at the control centrer.

Energy efficiency is usually defined as information bit per unit of energy, which corresponds to the ratio of the data rate to the unit power consumption, which can be calculated as [149],

$$EE_k = \frac{\sum_{i=1}^{M} r_{i,k}(p_i, z_i)}{\sum_{i=1}^{M} P_i^{\text{Total}}}. \tag{6.8}$$

## 6.3 A Proposed Deep Reinforcement Learning Approach for Channel Access and Power Control Scheme

The goal of the DRL approach is to ensure that no PMU receives SINR falls below the threshold $\gamma_i^{\min}$, for successful transmissions, $\gamma_i \geq \gamma_i^{\min}, \forall i \in \mathcal{I}$ and the interference caused by PMUs, $h_{ie}p_i(z_i)$, is not greater than an interference threshold $I_u^{\text{th}}$, $h_{ie}p_i(z_i) \leq I_u^{\text{th}}, \forall u \in \mathcal{U}$, to protect the QoS of MUEs.

Almost all RL problems can be formulated as MDP, because an MDP can describe the environment for RL, which is fully observable. Therefore, to adopt a DRL approach, first, the elements in MDP need to be defined. The goal of the MDP in a RL problem is to maximize the earned rewards [115, 172].

### 6.3.1 Markov Decision Process Elements

Let $\mathcal{S}$ and $\mathcal{A}$ denote the discrete set of environment states and the discrete set of actions respectively. The PMU $i$ senses the state $s_{i,t} \in \mathcal{S}$ and selects an action $a_{i,t} \in \mathcal{A}$ at each timeslot $t$. Based on the action taken, the environment makes a transition to a new state, $s_{i,t+1} \in \mathcal{S}$ according to probability $Pr(s_{i,t+1}|s_{i,t}, a_{i,t})$ and generates a reward, $R_{i,t}(s_{i,t}, a_{i,t})$ to the agent. In this paper, a DRL approach is proposed to obtain optimal policy for channel access and power control in HetNets. However, in order to utilize the DRL technique for the PMUs, the state space, the action space and the reward function need to be defined.

#### State Space

the environment state is defined based on local observations of the PMUs, therefore at timeslot $t$, the state $s_{i,t}$ observed by PMU $i \in \mathcal{M}$ can be expressed as follows.

$$s_{i,t} = I_{i,t}, \zeta_{i,t}, \tag{6.9}$$

where $I_{i,t} \in \{0,1\}$ indicates whether the received SINR of PMU $i$, $\gamma_{i,t}$, is above or below the minimum SINR, $\gamma_i^{\min}$, which is expressed as follows.

$$I_{i,t} = \begin{cases} 1, & \text{if } \gamma_{i,t}(p_{i,t}, z_{i,t}) \geq \gamma_i^{\min}, \\ 0, & \text{otherwise.} \end{cases} \tag{6.10}$$

On the other hand, $\zeta_{i,t}$ denotes whether the interference caused by PMU $i$ over sub-channel $n$ occupied by MUE $u$ is above or below the interference threshold, such that

$$\zeta_{i,t} = \begin{cases} 1, & \text{if } h_{ie,t}^{n}(z_{i,t})p_{i,t} \leq I_u^{\text{th}}, \forall u \in \mathcal{U} \\ 0, & \text{otherwise.} \end{cases} \tag{6.11}$$

The state space of the whole system at timeslot $t$ is expressed as $\mathcal{S}_t = \{s_{i,t}, \cdots, s_{M,t}\}$.

### Action Space

An action performed by each PMU at each timeslot considers discrete changes in the channel access, as well as the transmission power level. The action set of PMU $i$ is denoted as $\mathcal{A}_i = [\mathcal{Z}_i, \mathcal{P}_i]$, where $\mathcal{Z}_i = [Z_1, Z_2, \cdots, Z_N]$ and $\mathcal{P}_i = [P_1, P_2, \cdots, P^{\max}]$. The action set defines a discrete set of available actions that the PMU can perform at each timeslot. The action is selected to maximize the reward, by considering the minimum SINR requirement and interference to the MUE. The PMU first determines the $\gamma_i^{\min}$, then selects a set of sub-channel and transmission power that satisfies its delay as well as maximizes energy efficiency.

### Reward Function

When a distributed scheme is implemented in HetNets, one of the concerns is the reward. A higher SINR at the PMU will result in lower delay. Nevertheless, achieving a high SINR requires the PMU to transmit at a high power level, causing more power consumption as well as increasing the magnitude of interference to other MUEs. Therefore, the energy efficiency of the PMUs is selected as the reward function, expressed as [149]

$$R_{i,t}(p_{i,t}, z_{i,t}) = r_{i,t}(p_{i,t}, z_{i,t})/P_{i,t}^{\text{Total}}, \tag{6.12}$$

where $P_{i,t}^{\text{Total}}$ denotes the total power consumed by PMU $i$ at iteration $t$, which can be expressed as

$$P_{i,t}^{\text{Total}} = P_c + p_{i,t}. \tag{6.13}$$

The total power consumption of each PMU consists of the circuit power due to signalling and active circuit blocks $P_c$, and the transmission power $p_{i,t}$. The circuit power can be modelled

as the total of a static term and a dynamic term [141], $P_c = VI_{leak} + A_s CfV^2$, where $V$, $I_{leak}$, $A_s$, $C$ and $f$ denote the transistors supply voltage, the leakage current, the fraction of gate actively switching, the circuit capacitance, and the clock frequency respectively. The frequency is assumed to be dynamically scaled with the sum rate. Hence, the circuit power can be modelled as [143]

$$P_c = P_s + \beta r_{i,t}, \tag{6.14}$$

in which $P_s$ denotes the static term and $\beta$ is a constant representing dynamic power consumption per unit data rate.

The reward $R_{i,t}(s_{i,t}, a_{i,t})$ of PMU $i$ in state $s_{i,t}$ is the immediate return when action $a_{i,t}$ is executed, which is formulated as [177]

$$R_{i,t}(s_{i,t}, a_{i,t}) = \begin{cases} R_{i,t}(p_{i,t}, z_{i,t}), & \text{if } I_{i,t} = 1 \text{ and } \zeta_{i,t} = 1, \\ 0, & \text{otherwise.} \end{cases} \tag{6.15}$$

In particular, the reward is a return of selecting channel $z_{i,t}(a_{i,t})$ and power level $p_{i,t}(a_{i,t})$ in state $s_{i,t}$ that ensures the transmission delay constraints and/or achieves energy efficiency.

### 6.3.2 Q-learning for PMU

The goal of RL approach is to improve the PMU's decision-making policy, $\pi$ over time. The policy $\pi$, can be defined as a mapping from environment states to probability distribution over actions. However, learning a policy is difficult, hence, some RL approaches attempt to learn the policy indirectly [115]. This can be done by learning the optimal value function (either a state-value function or an action-value function). Depending on the function chosen, the agent will learn what is the value of being in a specific state (state-value function) or being in a specific state and taking certain action (action-value function). By learning the optimal value function, the optimal policy, $\pi^*$, can be inferred [115].

The task of the PMUs is to learn the optimal policy, $\pi^*$ that maximizes the total expected discounted reward over infinite steps, expressed as

$$V^{\pi}(s_{i,t}) = \sum_{t=1}^{T} \phi^{t-1} R_{i,t}, \tag{6.16}$$

in which $\phi$ and $T$ are the discounted factor and the time where the goal state, in which the action remains unchanged is obtained respectively. Therefore, the task becomes learning an optimal policy $\pi^*$ that can maximize $V^{\pi}$, which can be described as follows [171]

$$\pi^* = \arg\max_{\pi} V^{\pi}(s_t). \tag{6.17}$$

It is difficult to learn $\pi^*$ in (6.17), therefore Q-learning approach is adopted to solve the equation. In Q-learning, an action-value function, also known as Q function, is introduced to evaluate the expected discounted cumulative reward after execute action $a_{i,t}$ in state $s_{i,t}$. The optimal policy can be constructed by selecting the highest value in each state when an action function is learned. In Q-learning, the PMU tries to update the Q function using the update rule known as Bellman equation [177]

$$\begin{aligned} Q(s_{i,t}, a_{i,t}) =& Q(s_{i,t}, a_{i,t}) + \alpha R_{i,t}(s_{i,t}, a_{i,t}) \\ &+ \phi \max_{a_{i,t+1}} Q(s_{i,t+1}, a_{i,t+1}) - Q(s_{i,t}, a_{i,t}), \end{aligned} \tag{6.18}$$

where $\alpha$ is the learning rate and $\phi$ is the discount factor.

Equation (6.18) has been proven to converge to the optimal action-value function, which is defined as the maximum expected discounted cumulative reward by following any policy, after executing action $a_{i,t}$ in state $s_{i,t}$ [171]. In Q-learning, the number of states is finite and the action-value function is estimated separately for each state, forming a Q-table in which the rows represent the states and the columns represent the possible actions. When the Q-table converges, the PMU can select an action with the highest $Q(s_{i,t}, a_{i,t})$ value as the optimal action in state $s_{i,t}$.

However, due to the curse of dimensionality in HetNets, the Q-learning method is impractical for the problem, as it needs a value for every possible state-action pair in the Q-Table, requiring a lot of memory and time to converge [115]. Therefore, to overcome this issue, a technique, known as value function approximation, is introduced, in which the Q-Table is now represented and its values are estimated by a function. This function is learned online by the agent's interaction with the environment and it can be of any kind, such as linear or logistic regression, neural networks, or deep neural networks [115]. Based on this technique, a deep Q-learning (DQN) approach is proposed in which a DNN is utilized to approximate the action-value function, now represented as $Q(s_{i,t}, a_{i,t}; \theta)$, where $\theta$ represents the weights learned by the DNN.

### 6.3.3 Deep Reinforcement Learning Algorithm for Channel Access and Power Control Scheme

When Q-Learning is combined with a DNN, DQN is created. DQN, which is another term of DRL utilizes a DNN to derive the correlation between state-action pairs $(s_{i,t}, a_{i,t})$ then estimates its value function $Q(s_{i,t}, a_{i,t}; \theta_{i,t})$ [169]. However, when combining a DNN with Q-Learning, several problems regarding convergence and stability arise. As such in [169], the authors proposed two mechanisms to overcome these issues. First, a technique known as experience replay was added, in which the agent's experiences with the environment are stored in a memory and utilized, via a random mini-batch process to train the neural network. The second modification is

to use two separate neural networks, one which is constantly evaluated and updated according to the agent's experience, and another one, a target network, in which the weights are periodically updated. In addition to this, an online training mechanism is devised, so that based on the agent's interaction with the environment and its observations, the values of the action-value function can be learned. The training data used to train the Q-network for each PMU is generated as follows.

Given $s_{i,t}$ at iteration $t$ for PMU $i$, an action $a_{i,t}$ is randomly selected with probability $\varepsilon_{i,t}$, or selected with the largest output $Q(s_{i,t}, a_{i,t}; \theta_0)$ (following the $\epsilon$-greedy policy), where $\theta_0$ denotes the weights of the DNN at the current iteration. After taking an action $a_{i,t}$, PMU $i$ receives a reward $R_{i,t}$ and observes a new state $s_{i,t+1}$. This transition $d_{i,t} \triangleq \{s_{i,t}, a_{i,t}, R_{i,t}, s_{i,t+1}\}$, is stored in the replay memory $D$. The training of the Q-network begins when $D$ has collected a sufficient number of transitions, assume $O = 300$ transitions. Specifically, a minibatch of transitions $\{d_w | w \in \Omega_t\}$ from $D$ is randomly selected, and the Q-network can be trained by adjusting the parameter $\theta$ to minimize the loss function, expressed as follows

$$L(\theta) \triangleq \frac{1}{\Omega_t} \sum_{w \in \Omega_t} \left(Q'_{i,w} - Q(s_{i,w}, a_{i,w}; \theta)\right)^2, \tag{6.19}$$

in which $\Omega_t$ denotes the index set of the random minibatch used at the $t$-th iteration, and $Q'_{i,w}$ is a value estimated using a Bellman equation, by fixing set of weights from the previous iterations of the learning procedure.

The target of DRL can be expressed as follows

$$Q'_{i,w} = R_{i,w} + \phi \max_{a'} Q(s_{i,w+1}, a'; \theta_0), \quad \forall w \in \Omega_t, \tag{6.20}$$

where $\theta_0$ is the set of fixed weights from previous DNN iterations. In DRL, the targets are updated as the weight $\theta$ is refined, which is different form traditional supervised learning.

The algorithm of DRL training for channel access and power control is described in Algorithm 4. In the training process, a PMU achieves a goal state at $s_t$ if the action remains unchanged at the next state $s_{t+1}$. Therefore, it is not difficult to prove that the next state $s_{t+1}$ is also a goal state. Assuming that once $s_t$ achieves a goal state, it stays at the goal state until the transmission is done. Then, the policy has been converged at this rate, and the largest estimated value $Q(s, a, \theta^*)$ is obtained. After the training process, for each state, the PMU selects an action which yields the largest estimated value $Q(s, a, \theta^*)$, $p_{i,k}, z_{i,k} = \max_a Q(s, a, \theta^*)$.

In the DRL algorithm, agents learn through environment to improve their action generating policy, which therefore eliminates the need to solve optimization problem at each state, resulting low complexity process even though in large network size [178]. The computational complexity of the DRL algorithm in practical scenario is defined as $O(X^s)$ where $X$ is total number of actions and $s$ represents total number of state [179]. In terms of the trade-off between complexity and

**Algorithm 4** DRL training for channel access and power control scheme

Input: replay memory $D$ with buffer capacity $O$, training steps $T$, target network learning rate $\alpha$.
Initialize $Q(s, a; \theta_0)$ with random weights $\theta_0$
Initialize $a_{i,1}$, then obtain $s_{i,1}$
**for all** $t = 1, T$ **do**
  With probability $\varepsilon_t$, select a random action $a_{i,t}$ otherwise $a_{i,t} = \arg\max_a Q(s_{i,t}, a; \theta_0)$.
  Execute action $a_{i,t}$ and observe reward $R_{i,t}$ and obtain $s_{i,t+1}$
  Store transition $d_{i,t} \triangleq \{s_{i,t}, a_{i,t}, R_{i,t}, s_{i,t+1}\}$ in $D$.
  **if** $t \geq O$ **then**
    Sample a random minibatch of transitions $\{d_w | w \in \Omega_t\}$ from $D$, where the indexes of $\Omega_t$ are uniformly selected randomly
    Update $\theta$ by minimizing the loss function (17), in which targets $Q'_w$ are given by (18)
    Set $\theta_0 = \arg\min_\theta L(\theta)$
  **end if**
**end for**
Output: $Q(s, a, \theta)$

performance of DRL, authors in [178] proved that the trade-off exists between updating interval and convergence property, where the higher the number of interval, the better computation rate performance but with the price of higher complexity. Therefore, it is critical to select the training parameters wisely to optimize the performance of algorithm.

## 6.4 Simulation Results and Discussions

The performance of the proposed scheme is evaluated using Tensorflow, and the same environment in [160] is considered. System parameters are explained and experimental results are discussed in this section.

### 6.4.1 Simulation Parameters

There are 3 PMUs, 13 SUEs and 30 MUEs uniformly distributed in a cell with 400 m radius, located in a rural area. Each PMU generates a typical packet size of 52 Bytes with the rate of $\lambda = 60$ packets/s [13]. The length of each timeslot is 1 ms. In the simulation, each PMU selects a sub-channel from a predefined set $\mathcal{Z} = \{1, 2, \cdots, 30\}$ and the transmission power (in dBm) is selected from set $\mathcal{P} = \{14, 15, \cdots, 19\}$. Regarding the DRL parameters, each PMU is trained in the DNN to approximate its action-value function. The DRL consists of three hidden layers with 256, 256 and 512 neurons on each layer respectively. The first two hidden layers use rectified linear units (ReLUs) as the activation functions, while the last layer uses a tanh function. The weights $\theta$ are updated by adopting a recently proposed adaptive moment estimation (Adam)

Table 6.2: Simulation parameters

| | |
|---|---|
| Macrocell radius | 400 m |
| Small cell radius | 50 m |
| Number of MUEs | 30 |
| Number of SUEs | 15 |
| Number of PMU | 3 |
| Number of sub-channels | 30 |
| Minimum SINR requirement ($\gamma_1, \gamma_2$) | 15, 35 dB |
| Interference threshold of MUEs ($I_u^{\text{th}}$) | $10^-6$ |
| Noise power density ($\sigma^2$) | -174 dBm/Hz |
| Path loss constant ($C^s$) | $10^{-2}$ |
| Path loss component ($\alpha$) | 4.8 |
| Bandwidth of each sub-channel | 180 kHz |
| Transmission power of MUEs and SUEs | 19 dBm |
| Maximum transmission power of PMU | 19 dBm |
| PMU circuit power | 20 dBm |
| Number of hidden layers | 3 |
| Activation function | ReLUs |
| Size of minibatch | 256 |
| Number of iterations | $35x10^3$ |
| Weight update | Adam algorithm |
| Replay memory | 400 transitions |
| Buffer capacity | 300 transitions |

algorithm [180]. The reason for this is because it requires only first-order gradients with small memory requirement to achieve the optimum [180]. The PMUs explore new actions with the probability from 0.8 to 0.05 between iterations, in which at iteration $t$, the probability can be expressed as $\varepsilon_t = 0.8(1 - t/T)$. A detailed list of simulation parameters is given in Table 6.2.

In this paper, three different decision-making policies are used for comparison, which are explained as follows

- DRL policy: the action is selected based on Algorithm 4.
- Myopic policy: this policy selects the action with maximum expected immediate reward and ignores the impact of the current action on the future reward [181].
- Gittin policy: this policy calculates the Gittin index for each action, which is the accumulated reward per unit time and selects the action with the maximum value [182].

The Myopic policy and the Gittin policy are easy to implement but both policies require prior knowledge of the system dynamics, which is not easy to obtain beforehand [173].

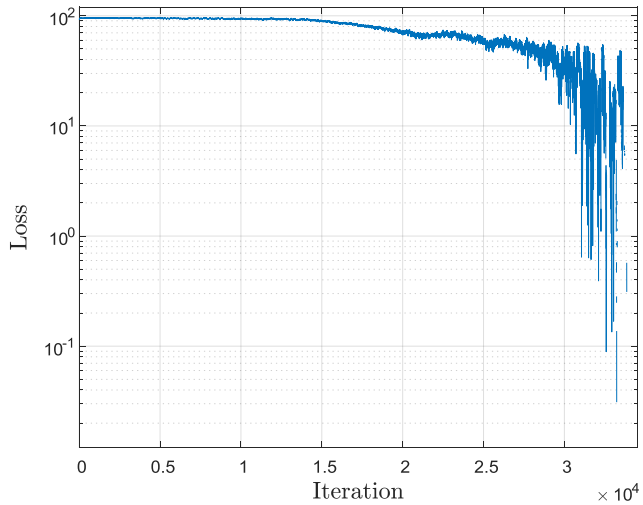


Figure 6.1: Loss of Q function with various iterations during training process.

### 6.4.2 Performance of DRL Algorithm

We conduct a simulation to evaluate performance of the proposed algorithm for $35k$ independent runs during the training process. The performance of the DRL algorithm is evaluated in terms of the loss of the Q function which is calculated as in (6.19). In general, Figure 6.1 shows that the loss Q function decreases as the number of iterations increases and becomes constant at the lowest loss function value after $34k$ training iterations. This shows that the proposed algorithm can successfully converge and the PMU can make the optimal decision given any system state.

### 6.4.3 The Impact of Number of Users

The impact of number of macrocell users on the performance of all three policies when the minimum SINR requirement of PMU is 15 dB is investigated. Figure 6.2, Figure 6.3 and Figure 6.4 compare the energy efficiency, average delay and power consumed by all three polices respectively. The results show that the Myopic policy with known system dynamics achieves the best energy efficiency but the worse average delay for all number of users. The reason for that is because the aim of the Myopic policy is to maximize the immediate reward, which is the energy efficiency. The policy consumed the lowest power, which result in lowest data rate yielding low delay and high energy efficiency. Moreover, this policy has a constant energy efficiency and average delay between 0 to 25 users and becomes worse after 30 users. The reason for that is because there are empty sub-channels that are not shared with MUEs at 0 to 25 users, therefore the policy selects the empty sub-channel, while at 30 users, all sub-channel are occu-

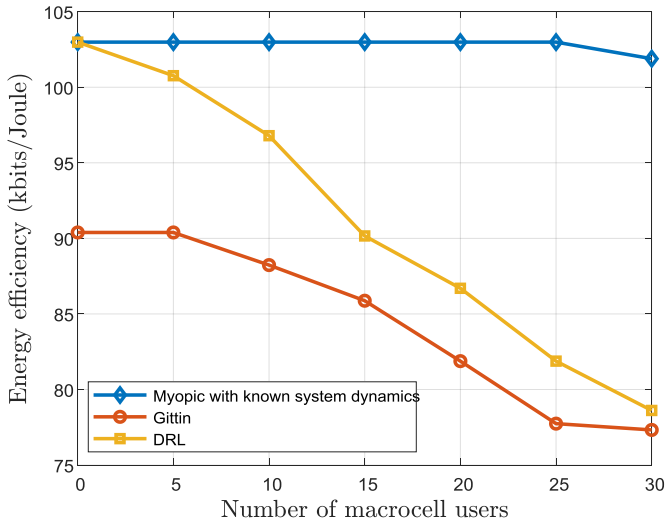


Figure 6.2: Energy efficiency comparison among three policies for various number of users.

pied by MUEs and must be shared with PMUs which increase the interference, therefore the performance decreases.

On the other hand, the energy efficiency of the DRL policy and the Gittin policy decreases as the number of users increases because there is less chance to find a good action when more sub-channels are shared with MUEs, consequently decreasing the energy efficiency. The average delay of both DRL and Gittin policies decrease from 0 to 25 users since energy efficiency is decreasing due to high power consumption, increasing the data rate. However, the delay increases at 30 user because at this number, all sub-channel are occupied, yielding the highest interference, which increases the delay when maximizing the energy efficiency. Additionally, the results show that the DRL policy can learn the system dynamics and achieve good performance as well as outperforms the Gittin policy even without knowledge of the system dynamics beforehand.

### 6.4.4 The Impact of Minimum SINR

We conduct simulations to investigate the impact of minimum SINR requirements on the performance of all three policies when all sub-channels are shared with MUEs. Figure 6.5 shows that the energy efficiency of DRL and Gittin policies are getting better as the minimum SINR requirement increases. The reason for that is because as the constraints get more stringent, there is more chance to select a good action since the actions that failed to meet the constraints have been eliminated. On the other hand, the Myopic policy with knowledge of the system dynamics

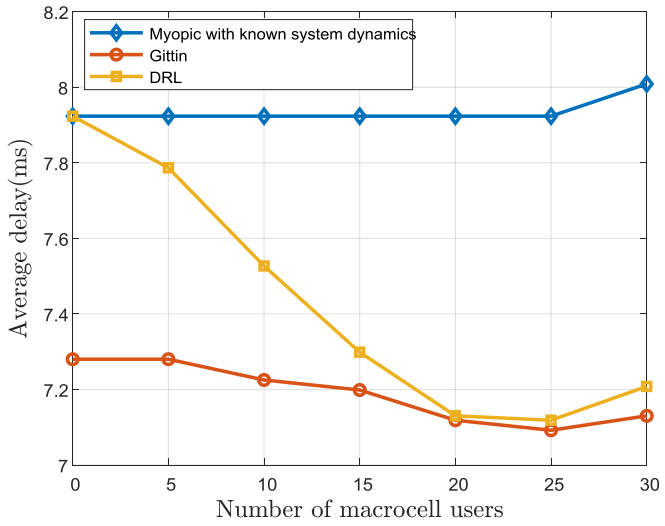


Figure 6.3: Average delay comparison among three policies for various number of users.

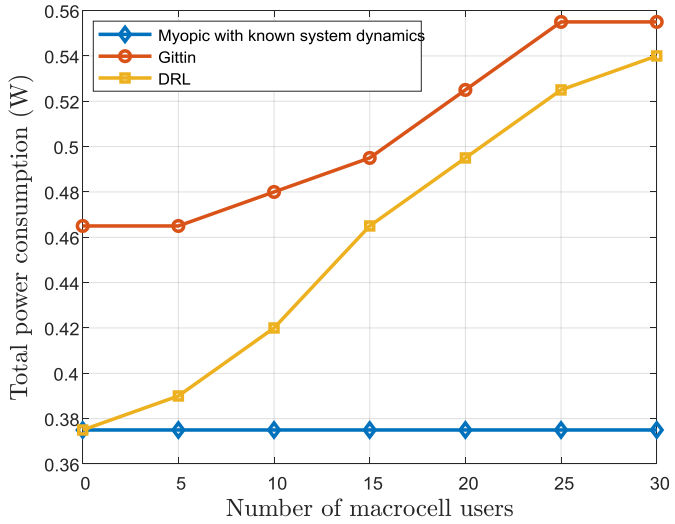


Figure 6.4: Power consumption comparison among three policies for various number of users.

has the highest and constant energy efficiency for all constraints because with this knowledge, the policy is able to obtain the best action in the very beginning. However, the average delay of this policy, as shown in Figure 6.6 is the highest and at 35 dB, and this policy fails to meet the delay constraint, which is 8 ms. The result also shows that average delay of the DRL and Gittin policies increase as the minimum SINR requirement increases since the energy efficiency

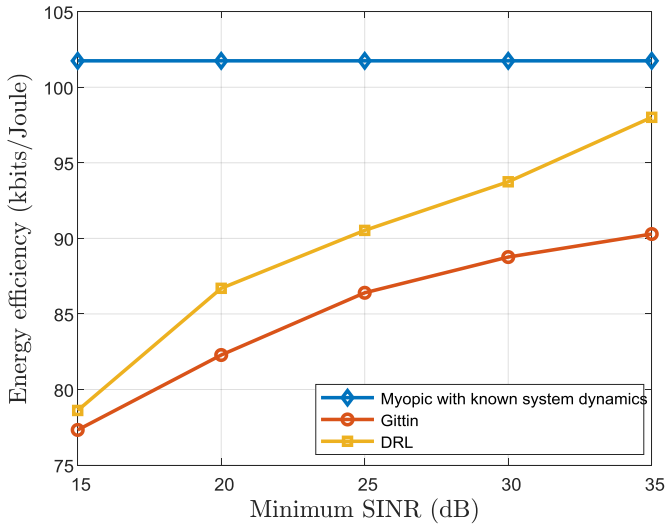


Figure 6.5: Energy efficiency comparison among two policies with varying minimum SINRs.

is maximized as the minimum SINR requirement increases. Hence, the data rate is decreases, resulting in higher delay. However, both policies are still able to meet the delay constraints in all minimum SINR requirements. Moreover, the results show that the DRL policy outperforms the Gittin policy at all minimum SINR requirements because in the DRL policy, as the constraints become more stringent, there is more chance to select a good action. Thus, the learning process becomes easier, so the PMU is able to find the optimal policy easily and quickly.

### 6.4.5 The Impact of Normal Ratio

We study the impact of normal ratio on the performance of all three policies. Normal ratio is defined as the ratio of number of PMUs in normal states to the total number of PMUs in the cell. In this work, only 3 PMUs are located in the cell, yielding the gap of $1/3$ between normal ratios. Figure 6.7 and Figure 6.8 show that energy efficiency and average delay of the DRL policy and the Gittin policy become worse as the normal ratio increases. The reason for that is because the lesser PMUs which are in abnormal or restorative states, the constraints get more lenient which is the minimum SINR requirements are lower. Therefore, there is less chance to find a good action, hence decreasing the energy efficiency. However, both policies are still able to meet the delay requirement as the normal ratio increases. On the other hand, the performance of the Myopic policy is constant even when the normal ratio increases due to the fact that the different minimum SINR requirements of PMUs do not affect the performance of the Myopic policy. Moreover, the results show that the DRL policy outperforms the Gittin policy in all

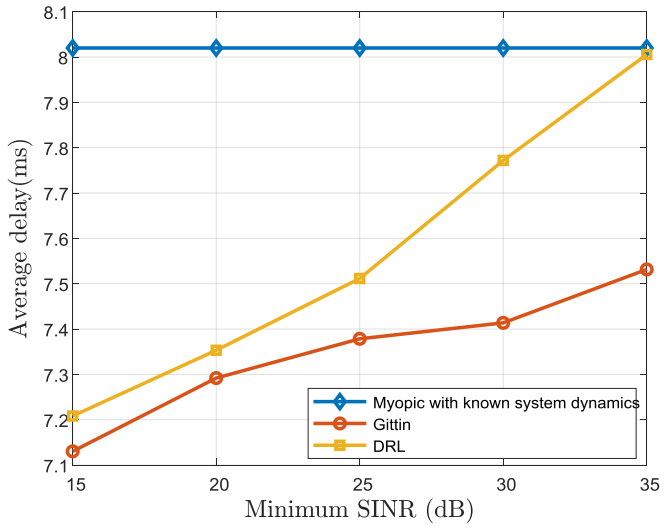


Figure 6.6: Average delay comparison among two policies with varying minimum SINRs.

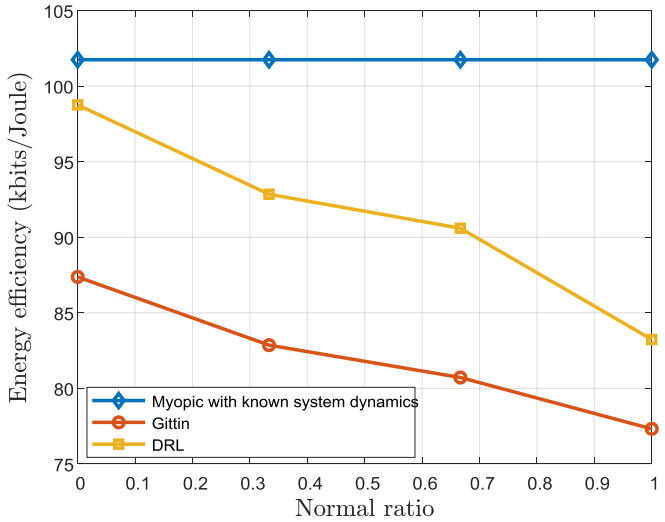


Figure 6.7: Energy efficiency comparison among three schemes with varying normal ratio.

normal ratios. This shows that the DRL policy can be applied in more complex situations where more PMUs are involved in the cell.

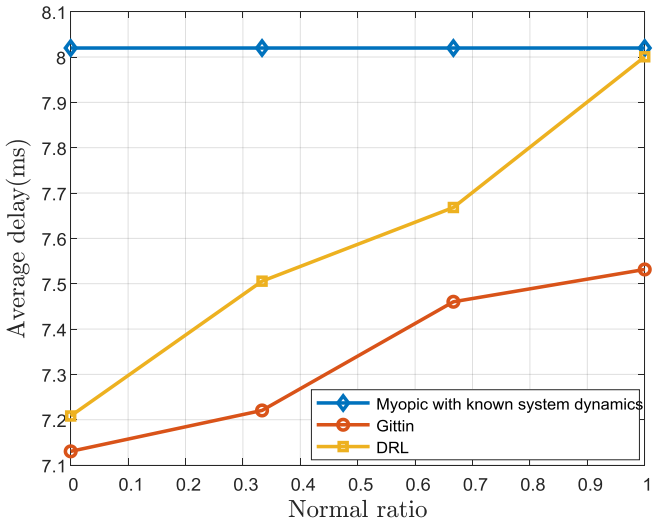


Figure 6.8: Average delay comparison among three schemes with varying normal ratios.

## 6.5 Conclusions

This chapter studied HetNets for simultaneous transmissions of smart grid NANs data, in particular the PMU data. An intelligent channel access and power control scheme were proposed to maximize energy efficiency in HetNets as well as satisfying the delay constraints. A DRL approach was exploited to obtain optimal policy that maximizes the discounted reward and enables successful data transmission with the considerations on the minimum SINR requirements of PMUs and also the interference caused by PMUs to the MUEs and other SUEs. In DRL, each PMU was trained using DQN-based intelligent channel access and power control algorithm, where the data of the environment were extracted and predictive guesses about new data were made using a cascade of layers of processing units. After the training, the PMU selects an action that maximizes the reward function. Simulation results showed that the PMUs able to learn the system dynamics and obtain optimal policy in any given state. Additionally, the DRL policy provides excellent performance in different number of users, minimum SINR requirements and normal ratios compared to the Gittin policy even without knowledge of the system dynamics beforehand.

# Chapter 7

# Conclusions and future work

In this chapter, we draw conclusions and discuss possible extensions of the work presented in Chapter 4, Chapter 5 and Chapter 6.

## 7.1 Thesis conclusions

- A comprehensive overview of smart grid neighbourhood area networks has been provided in Chapter 2. Cellular technology with LTE-based standard is promising for smart grid NANs. However, the simultaneous transmission of large volume delay-sensitive data is a significant challenge in integrating cellular technology and smart grid NANs. Therefore there is a need to improve the performance of the LTE, specifically the delay and energy efficiency. D2D communications can be exploited to increase data rate of IEM in a fault zone or IEMs experiencing poor channel condition, while HetNets are proposed to reduce RAN congestions when massive number of devices request access simultaneously.

- Explanation on optimization strategies that are commonly adopted to meet the design requirements of D2D communications and HetNets are provided in Chapter 3. The mathematical tools that can be exploited to model the method are also presented along with the recent literatures related to each section.

- Delay-aware energy-efficient joint power control and mode selection in D2D Communications for FREEDM Systems has been proposed in Chapter 4. We used a combinatorial problem to formulate the power control and mode selection problems. The optimal solution is obtained by decomposing the the problem into two sub-problems and solving the problem one by one. The brute-force based algorithm is adopted to obtain the final optimal solution.

- A joint resource allocation and power control method was proposed in Chapter 5 with the goal to minimize the end-to-end delay in HetNets. The optimization problem was formulated as a mixed integer problem, a game-theoretic approach and the best response algorithm were adopted to solve the problem. Simulation results showed that in the RA procedure, HetNets has lower preamble collisions as the total number of attempts increases compared to cellular networks. Additionally, the proposed scheme gives a significant delay improvement when the total number of users increases compared to cellular and R-R scheduling schemes.

- An intelligent channel access and power control scheme was proposed in Chapter 6 to maximize energy efficiency in HetNets as well as to satisfy the delay constraints of PMU data. A DRL approach was exploited to obtain optimal policy that maximizes the discounted reward and enables successful data transmission with the considerations on the minimum SINR requirements of PMUs and also the interference caused by PMUs to the MUEs and other SUEs. In DRL, each PMU was trained using DQN-based intelligent channel access and power control algorithm, where the data of the environment were extracted and predictive guesses about new data were made using a cascade of layers of processing units. After the training, the PMU selects an action that maximizes the reward function. Simulation results showed that the PMUs are able to learn the system dynamics and obtain optimal policy in any given state. Additionally, the DRL policy provides excellent performance despite the different number of users, minimum SINR requirements and normal ratios compared to the Gittin policy even without knowledge of the system dynamics beforehand.

## 7.2 Future work

Possible extensions of the work presented in Chapter 4 to Chapter 6 are described as follows:

- In smart grids, communication and power networks are interdependent to each other. The communication network is responsible for data and status collection from end users to the control centre, and transmitting control commands from the control centre to end users. On the other hand, operations of electric generation devices in power network are done based on received control commands. Delay in communication networks might compromise the stability in power network. Therefore, this topic can be considered in the future.

- In this study, it is assumed that perfect channel estimation is known. However, it is not easy to obtain perfect knowledge of a dynamic channel in practice. Future researches can

consider imperfect channel estimation in energy-efficient device-to-device communications and heterogeneous cellular networks.

- Furthermore, a rural area scenario with large BS coverage and a small number of mobile users is considered in this study, in which a sufficient number of resources is assumed. This work can be extended by considering the availability of radio resources in all types of communication as the number of mobile users is rapidly increasing from time to time.

- In this work also, slow-fading environment, where the channel is fixed during the transmission process is considered. However, in dynamic channel environment, the channel could be changed during the transmission process, so that fast fading environment can be studied in future work.

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