Universidade de Aveiro Departamento de
2016 Eletrónica, Telecomunicações e Informática

Firooz Bashashi Saghezchi

Teoria de Jogos para Utilização Efetiva dos Recursos em Aplicações para 5G

Game Theory for Effective Resource Utilisation in 5G Applications

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Tese apresentada às Universidades de Minho, Aveiro e Porto para cumprimento dos requisitos necessários à obtenção do grau de Doutor em Engenharia Eletrotécnica / Telecomunicações no âmbito do programa doutoral MAP-Tele, realizada sob a orientação científica do Doutor Jonathan Rodriguez Gonzalez, Professor Associado Convidado do Departamento de Eletrónica, Telecomunicações e Informática da Universidade de Aveiro.

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referéncia SFRH/BD/79909/2011.

To my family and in memory of my father.

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Palavras-chave

5G, Teoria de Jogos, Cooperação, Seleção de Retransmissão (*Relay*), Poupança de Bateria, *Smart Grid*, Resposta de Procura, Agendamento de Eletrodomésticos.

Resumo

Esta tese tem como objetivo fornecer afirmações conclusivas em relação à utilização eficiente de recursos para redes e aplicações de 5G (5ª geração) com recurso a teoria dos jogos. Neste contexto, investigamos dois cenários principais, um relativo a comunicações móveis e um outro relativo a redes inteligentes. Uma métrica importante para o desenho das redes móveis emergentes é a eficiência energética, com particular ênfase no lado do dispositivo móvel, onde as tecnologias das baterias são ainda limitadas. Alguns trabalhos de investigação relacionados têm demonstrado que a cooperação pode ser um paradigma útil no sentido de resolver o problema do défice energético. Contudo, pretendemos ir mais além, ao definir a cooperação e os utilizadores móveis como um grupo de jogadores racionais, que podem atuar sobre estratégias e utilidades, por forma a escolher a retransmissão mais apropriada para poupança de energia. Esta interpretação presta-se à aplicação da teoria dos jogos, e recorremos assim aos jogos coalicionais para solucionar conflitos de interesse entre dispositivos cooperantes, empregando Programação Linear (*LP*) para resolver o problema da selecção da retransmissão e derivar a principal solução do jogo. Os resultados mostram que a escolha do jogo de retransmissão coalicional proposto pode potencialmente duplicar a duração da bateria, numa era em que a próxima geração de dispositivos móveis necessitará de cada vez mais energia para suportar serviços e aplicações cada vez mais sofisticados. O segundo cenário investiga a resposta da procura em aplicações *smart grid*, que está a ganhar interesse sob a égide do 5G e que é considerada uma abordagem promissora, incentivando os utilizadores a consumir electricidade de forma mais uniforme em horas de vazio. Recorremos novamente à teoria dos jogos, imaginando as interacções estratégicas entre a empresa fornecedora de energia eléctrica e os potenciais utilizadores finais como um jogo de forma extensiva. São abordados dois programas em tempo real de resposta à procura: *Day-Ahead Pricing (DAP)* e *Convex Pricing Tariffs*. A resposta dos consumidores residenciais conscientes dos preços destas tarifas, é formulada como um problema de *Mixed Integer Linear Programming (MILP)* ou *Quadratic Programming (QP)*, nos quais as soluções potenciais são o agendamento dos seus electrodomésticos inteligentes de modo a minimizar os seus gastos diários de electricidade, satisfazendo as suas necessidades diárias de energia e níveis de conforto. Os resultados demonstram que implementar o programa *DAP* pode reduzir a razão *Peak-to-Average (PAR)* até 71% e as faturas de consumo das casas inteligentes até 32%. Para além disso, a aplicação de tarifas convexas em tempo real pode melhorar ainda mais estas métricas de desempenho, alcançando uma redução de 80% do *PAR* e uma economia de mais de 50% na faturação da energia residencial.

Keywords 5G, Game Theory, Cooperation, Relay Selection, Battery Saving, Smart Grid, Demand Response, Smart Home Appliance Scheduling.

Abstract This research thesis aims to provide conclusive statements towards effective resource utilization for 5G (5$^{\text{th}}$ Generation) mobile networks and applications using game theory. In this context, we investigate two key scenarios pertaining to mobile communications and smart grids. A pivotal design driver for the upcoming era of mobile communications is energy efficiency, with particular emphasis on the mobile side where battery technology is still limited. Related works have shown that cooperation can be a useful engineering paradigm to take a step towards solving the energy deficit. However, we go beyond by envisaging cooperation and mobile users as a game of rational players, that can act on strategies and utilities in order to choose the most appropriate relay for energy saving. This interpretation lends itself to the application of game theory, and we look at coalitional games to settle conflicts of interest among cooperating user equipments, and employ Linear Programming (LP) to solve the relay selection problem and to derive the core solution of the game. The results reveal that adopting the proposed coalitional relaying game can potentially double battery lifetime, in an era where the next wave of next generation handsets will be more energy demanding supporting sophisticated services and applications. The second scenario investigates demand response in smart grid applications, which is also gaining momentum under the umbrella of 5G, which is a promising approach urging end-users to consume electricity more evenly during non-peak hours of the day. Again, we resort to game theory and picture the strategic interactions between the electric utility company and the potential end-users as an extensive form game. Two real-time demand response programmes are addressed, namely Day-Ahead Pricing (DAP) and convex pricing tariffs. The response of price-aware residential consumers to these programmes is formulated as Mixed Integer Linear Programming (MILP) or Quadratic Programming (QP) problem, which optimally schedule their smart home appliances so as to minimise their daily electricity expenses while satisfying their daily energy needs and comfort levels. The results demonstrate that implementing the DAP programme can reduce the Peak-to-Average Ratio (PAR) of demand by up to 71% and cut smart households bill by 32%. Moreover, applying real-time convex pricing tariffs can push these performance metrics even further, achieving 80% PAR reduction and more than 50% saving on the household electricity bill.

Contents

List of Abbreviations

DG	Distributed Generator	93
DOF	Degree-of-Freedom	4
DR	Demand Response	86
DSM	Demand-Side Management	7
EE	Energy Efficiency	2
EMS	Energy Management System	113
ESG	Energy Saving Gain	63
EU	European Union	89
EV	Electric Vehicle	94
FCC	Federal Communications Commission	62
FIR	Finite Impulse Response	91
LAN	Local Area Network	91
GSM	Global System for Mobile	4
GT	Grim Trigger	38
G-TFT	Generous Tit-For-Tat	38
HANET	Hybrid Ad-hoc Network	42
HEMS	Home Energy Management System	94
HSPA	High Speed Packet Access	4
IBT	Inclining Block Tariff	87
IDPS	Intrusion Detection and Prevention System	111
IETF	Internet Engineering Task Force	38
IoT	Internet of Things	2
IPM	Interior-Point Methods	35
LOS	Line-Of-Sight	68
LP	Linear Programming	10
LTE	Long Term Evolution	4
LTE-A	Long Term Evolution-Advanced	5
M2M	Machine-to-Machine	2
MAC	Medium Access Control	5
MANET	Mobile Ad-hoc Network	36
MCN	Multihop Cellular Network	42
MILP	Mixed Integer Linear Programming	34
MIMO	Multiple-Input Multiple-Output	3
mm-wave	millimetre-wave	4
MRC	Maximal Ratio Combining	41
MTC	Machine Type Communications	3

NE	Nash Equilibrium	14
NLOS	Non-Line-Of-Sight	68
NTU	Non-Transferable Utility	25
ODMA	Opportunity Driven Multiple Access	47
OpEx	Operational expenditures	43
PAN	Personal Area Network	40
PAR	Peak-to-Average Ratio	10
PDA	Proximal Decomposition Algorithm	90
PFD	Packet Forwarding Dilemma	36
PDA	Personal Digital Assistant	90
PHEV	Plug-in Hybrid Electric Vehicle	86
PHY	Physical Layer	5
PSW	Particle Swarm Optimization	92
PV	Photovoltaic	93
QoS	Quality of Service	2
QP	Quadratic Programming	85
RAN	Radio Access Network	4
RoF	Radio over Fibre	3
RS	Relay Station	42
RTP	Real-Time Pricing	85
RWP	Random Way Point	69
SC	Selective Combining	41
SCADA	Supervisory Control And Data Acquisition	86
SDN	Software-Defined Networking	5
SE	Spectral Efficiency	5
SNR	Signal-to-Noise Ratio	39
S-TFT	Suspicious Tit-For-Tat	38
TDD	Time Division Duplex	47
TDMA	Time Division Multiple Access	39
TFT	Tit-For-Tat	38
ToU	Time-of-Use	88
TU	Transferable Utility	25
UMTS	Universal Mobile Telecommunications System	40
UE	User Equipment	4
UHD	Ultra-High Definition	1
UWB	Ultra Wide Band	61

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Chapter 1

Introduction

1.1 Path Towards 5G

We are witnessing an exponential growth in the amount of traffic carried through mobile networks. According to Cisco visual networking index [1], mobile data traffic has doubled during 2010-2011; extrapolating this growth rate for the rest of the decade shows that global mobile traffic will increase by a factor of 1000 by 2020. The surge in mobile traffic is primarily driven by the proliferation of mobile devices and the accelerated adoption of data-hungry mobile smart phones. Table 1.1 provides a list of these device along with their relative data consumptions, where *feature phone* refers to a low-end mobile device that typically supports voice and text services and access to the Internet but lacks the advanced functionality of a smart phone. In addition to the increasing demand for high-end mobile devices, another important factor associated with this tremendous traffic growth is the drive towards advanced multimedia applications such as Ultra-High Definition (UHD) and 3D video, as well as augmented reality and immersive experience. Today, mobile video accounts for more than 50% of global mobile data traffic, which is anticipated to rise to two-thirds by 2018 [1].

1.1.1 Mobile Traffic

In fact, the growth rate of mobile data traffic is much higher than its voice counterpart. Global mobile voice traffic was overtaken by the global mobile data traffic in 2009, and it is forecast that Voice-over-IP (VoIP) traffic will represent only 0.4% of the mobile data traffic by 2015. In 2013, the number of mobile subscriptions reached 6.8 billion, corresponding to a

Table 1.1: Data consumptions of mobile devices [1]

Device	**Relative data usage**
Feature phone	1×
Smart phone	24×
Handheld gaming console	60×
Tablet	122×
Laptop	512×

global penetration of 96%. This ever-growing global subscriber rate, spurred on by the world population growth, will place stringent new demands on Fifth-Generation (5G) networks to cater for one billion additional new customers.

1.1.2 Machine-to-Machine Communication

Apart from 1000× mobile traffic growth, the increasing number of connected devices imposes another challenge on the future mobile network. It is envisaged that in the future connected society, everyone and everything will be inter-connected – under the umbrella of Internet of Things (IoT) – where tens to hundreds of devices will serve every person. This upcoming 5G cellular infrastructure and its support for 'Big Data' will enable cities to be smart. Data will be generated everywhere by not only people but also machines, and will be analysed in a real-time fashion to infer useful information, from people's habits and preferences to traffic monitoring on the streets and health monitoring for patients and elderly people. Mobile communications will play a pivotal role in enabling efficient and safe transportation by allowing vehicles to communicate with each other or with a roadside infrastructure to warn or even help the drivers in case of unseen hazards, paving the way towards autonomous self-driving cars. This type of Machine-to-Machine (M2M) communications may require very stringent latency (less than 1 ms) [2], which imposes further challenges on the future mobile network.

1.1.3 5G Architecture

The 1000× mobile traffic growth along with billions or even trillions of foreseen connected devices is pushing the cellular system to an ultrabroadband ubiquitous network with massive capacity and Energy Efficiency (EE) and diverse Quality of Service (QoS) support [3]. Indeed, it is envisaged that the next-generation cellular system will be the first in-

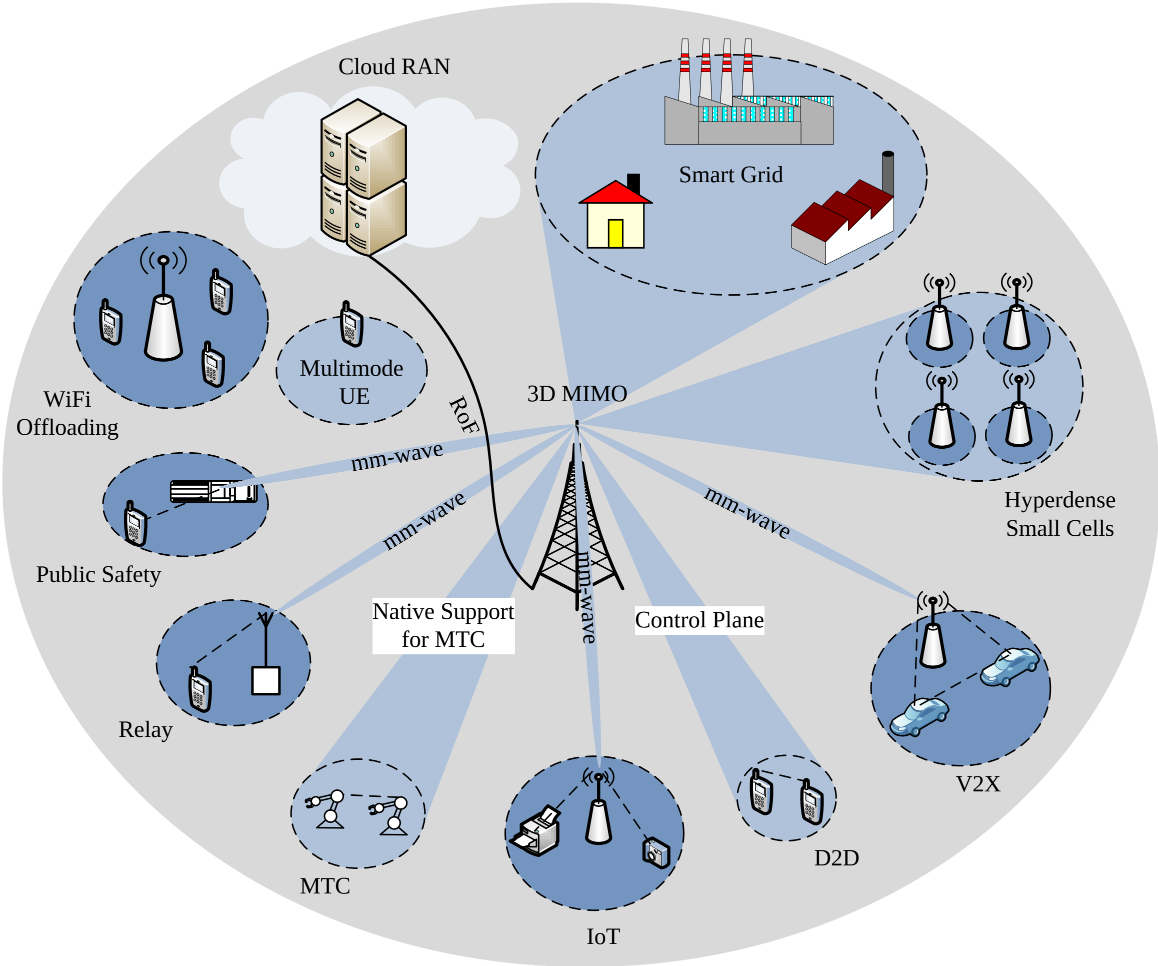

Figure 1.1: Foreseen architecture for 5G cellular systems

stance of a truly converged wired and wireless network [4], providing 'fibre-like' experience for mobile users, leveraging technologies such as Radio over Fibre (RoF). This ubiquitous, ultra-broadband, and ultra-low latency wireless infrastructure will connect the society and drive the future economy. Figure 1.1 depicts our foreseen architecture for 5G cellular systems, harnessing all the common views on the current technology trends and the emerging applications. As illustrated in this figure, 5G will be a truly converged system supporting a wide range of applications from mobile voice and multi-Giga-bit-per-second mobile Internet to Device-to-Device (D2D) [5] and Vehicle-to-X (V2X) [6] (X stands for either Vehicle, Vehicle-to-Vehicle (V2V), or Infrastructure, Vehicle-to-Infrastructure (V2I)) communications, as well as native support for Machine Type Communications (MTC) and public safety applications. Three Dimensional (3D)-Multiple-Input Multiple-Output (MIMO) will be incorporated at

Base Station (BS)s to further enhance the data rate and the capacity at the macro-cell level. System performance in terms of coverage, capacity and EE will be further enhanced in dead and hot spots using relay stations, cooperative communications, hyperdense small-cell deployments and WiFi offloading [3, 7]; directional millimetre-wave (mm-wave) links will be exploited for backhauling the relay and/or small-cell BSs [8]. D2D communications can be assisted by the macro-BS, providing the control plane. In particular, we further detail these technologies and applications that will form part of the 5G paradigm, and figure predominantly in the research scenarios:

Cloud RAN

Cloud networking [9–11] could potentially be applied to the Radio Access Network (RAN), and beyond that, to mobile User Equipment (UE)s that might form local coalitions and pool their scarce resources that could be managed either by a delegated local coordinator (selected among the UEs) or by the network operator. Cloud RAN could help not only manage the RAN resources more efficiently by sharing them among multiple operators, but also bring the applications through the cloud closer to the end-user, which might help reduce the communication latency to support delay-sensitive real-time emerging control applications, such as autonomous self-driving cars [12].

Millimetre-Wave Technology

It is envisaged that 5G will seamlessly integrate the existing RANs (e.g., Global System for Mobile (GSM), High Speed Packet Access (HSPA), Long Term Evolution (LTE) and WiFi) with the complementary new ones invented for mm-wave bands (i.e., frequencies of above 30 GHz) [11, 13, 14]. It is foreseen that mm-wave technology may revolutionise the mobile industry not only because of plenty of available spectrum at this band (readily allowing Gbps wireless pipes without need for sophisticated modulation or multiplexing scheme), but also because of diminishing antenna sizes, enabling the fabrication of array antennas with hundreds or thousands of antenna elements, even at the UE [8]. Smart antennas with beamforming and phased array capabilities will be employed to point out the antenna beam to a desired location with high precision, rotated electronically through phase shifting. The narrow pencil beams will enable the exploiting of the spatial Degree-of-Freedom (DOF), without interfering with other users. The diminishing of antenna sizes will enable Massive/3D MIMO at BSs and eventually at the UEs [15]. The mm-wave technology could also provide ultra-broadband backhaul links to carry the traffic from/to either the small BSs or the relay stations, allowing further deployment flexibility for the operators, compared to the wired (copper or fibre) backhaul link.

Small Cell Technology

Hyperdense small-cell deployment is another promising solution for 5G to meet the 1000× capacity challenge [16, 17]. Small cells have the potential to provide massive capacity and to minimise the physical distance between the BS and the UEs to achieve the required EE enhancement for 5G [18]. The traditional sub-3 GHz bands will be employed for macro-cell blanket coverage, while the higher frequency bands (e.g., cm- and mm-wave bands) will be employed for small cells to provide a spectral- and energy-efficient data plane, assisted by a control plane served by the macro-BS [19, 20]. However, this massive deployment of small cells could potentially increase the inter-cell interference level. Furthermore, the control signalling burden hampers managing these massively deployed small cells in a centralised fashion. Therefore, small cells should be smart enough to self-organise themselves and allow the network to partly or wholly delegate the resource management to themselves.

Evolution of 4G

Along with the development of new RANs and the deployment of hyperdense small cells, the existing RANs will continue to evolve to support higher Spectral Efficiency (SE) and EE. The data plane latency (round-trip time) of the Long Term Evolution-Advanced (LTE-A) [21] system is around 20 ms, which is expected to diminish to less than 1 ms in its future evolutions [22]. The SE of the existing HSPA system is 1 b/s/Hz/cell, which is expected to increase 10× by 2020 [22]. We expect energy consumption of mobile networks to decrease 10×, despite expected 100× improvement in their data rates [6]. This implies that the EE of the cellular system needs to be improved 100+× [23]. The Physical Layer (PHY) and Medium Access Control (MAC) layer techniques will be revisited for carrying short and delay-sensitive packets for MTC [24] along with incumbent data applications such as multimedia and web browsing. Software-Defined Networking (SDN) will play a key role in 5G for efficient resource utilisation in cellular systems, allowing multi-tenant networks where mobile operators will not need to own a complete set of dedicated network equipment anymore; rather, network equipment (i.e., RAN) might be shared among different operators. The existing cloud network concept mainly involves the data centres. Mobile network virtualisation will push this concept towards the backhaul and the RAN to allow sharing of backhaul links and the BSs among different operators. Last but not least, it is envisaged that 5G UEs will be multimode intelligent devices that, similar to a cognitive radio, can learn about their surrounding radio environment – e.g., the channel quality, their own and other nearby UE's remaining battery energy, the EE of different RANs, and the QoS requirement of their running application – through listening to the medium or exchanging context information with their neighbour UEs. These UEs will be smart enough to autonomously choose the right interface to connect to the network based on this context information. These smart multimode 5G UEs will accommodate dozens of antenna elements [8, 25] and help support super fast speeds up to 10 Gbps [6].

Smart Grid

The integration of Information and Communications Technology (ICT) with today's power network will transform it to an intelligent network (smart grid), connecting all stakeholder from generating units and substations to utility companies and consumers, enabling the system to operate more efficiently and more reliably [26, 27]. This opens up a wealth of opportunities for 5G, aiming to connect *everything*. M2M communications will help connect household appliances through the smart metres, smart thermostats or some other gateways to the utility companies at the electricity distribution network level [28, 29]. Two-way M2M communications could be established between the household appliances and the utility company, which will help better utilise the electricity grid infrastructure. The utility company could be able to set a more dynamic time-dependent or even demand-dependent tariff to influence the consumers' consumption habits. It might monitor the demand in real-time and based on the demand and supply conditions, could alter the short-term price to either encourage or discourage users to consume electricity. On the other hand, the smart appliances can receive the price information in or close to real-time, and based on this available pricing and users' preferences, could choose optimal intervals for their operations so as to minimise the energy cost for the user without compromising her satisfaction level [30].

1.2 Challenges

Cooperation is foreseen to be pivotal technology in 5G, as a means of promoting energy saving in handset devices. Cooperation allows the network to become both user and network centric where mobile devices also become part of the network resources, to be utilised towards improving the communication experience or effectiveness. However, it is clear that cooperation of these UEs cannot be taken for granted as they are normally owned by rational agents who seek to maximise their own utility. There might be some altruistic reasons for cooperation in some instances, for instance to save humans in occasions when their life is in danger, yet it is obvious that UEs would not always cooperate solely for altruistic reasons. Therefore, incentive mechanisms are needed to stimulate UEs to cooperate and to settle potential conflicts of interest arising from their interactions. In this context, we investigate new challenges with regards to cooperation and explore how game theory can be an effective tool towards putting in place new incentive mechanisms to promote energy efficient communications.

Under the umbrella of 5G, smart grids are seen as a potential application use-case that will allow electricity companies to manage better the production and supply of energy. Smart grids will not only be reliant on mature M2M technology as the enabler to support effective remote management, but will also require new approaches towards managing power consumption through incentive mechanisms. In today's networks, most of the electricity providers offer tariffs that are quite stable and independent from the wholesale electricity price fluctuations. Although these price-hedging mechanisms have certain benefits for a risk-averse consumer, it isolates the demand-side of the electricity market from its supply-side, preventing any demand response to real-time price variations in the spot market due to supply/demand imbalances. Therefore, there exists a need for more effective tariff designs that can help improve the economic efficiency of the electricity market. However, this might be conflicting with the consumer's satisfaction. In this regard, designing a game that can improve the market efficiency without compromising the user's convenience can be challenging. In this regard, new challenges will arise in considering new Demand-Side Management (DSM) strategies that are able to improve the economic efficiency of the electricity market, without affecting the user's QoS. In this regard, we investigate how game theory can be used to provide concrete step towards DSM in 5G smart grids.

1.3 Game Theory for 5G

Game theory has been proven as an effective technique to help improve resource utilisation is wireless networks [31–38] and smart grids [36, 39–41]. It is a fascinating mathematical tool to analyse potential conflicts of interest arising among independent rational agents[1] when they strategically interact with each other. Having classically been used as a toolkit to analyse economic and political conflicts of interest, it has recently attracted considerable amount of interest from engineers and researchers to analyse and exploit game theory to solve practical challenges in wireless communications and applications.

As an important foreseen application for 5G, cooperative communications can help improve the performance of wireless networks considerably. For instance, it could be exploited to improve the battery life of UEs. However, there is still lack of knowledge about how rational and smart 5G UEs will interact when they cooperate, how to stimulate them to cooperate and discourage them from acting selfishly. Incentive mechanisms and trust management techniques (e.g., credit or reputation scheme) are needed to ensure proper cooperation of the future generations of UEs, which are expected to be intelligent enough to act rationally, or almost rationally, with good approximation. It is also envisaged that these UEs will be able to exchange context information so as to assess the effectiveness of their cooperation in a certain scenario. Whenever the cooperation is energy efficient, they rely on cooperative communication. Otherwise, if the cooperation is not energy efficient, they execute their communications individually. Our primary objective in addressing this problem is to encourage UEs to cooperate and to discourage them acting selfishly, which lends itself to a game theory problem.

Another interesting application of game theory is DSM in the smart grid. In this context, it can be used to provide a set of solutions that help the utility companies to encourage consumers to consume electricity more evenly during the day. The daily electricity demand follows the daily work cycle of the consumers. It falls during the night when people are asleep and starts to rise in the morning when people get up and start their work. It peaks during the afternoon or evening hours, depending on the season, due to air conditioning or using cooking and entertainment appliances once people arrive home. This demand fluctuation pushes the utilities to deploy additional generation units to meet the peak demand. How-

[1] A rational agent is by definition the one that always seeks to maximise its own payoff.

ever, this additional capacity is underused during off-peak periods. This makes the grid run economically inefficient, which pushes the energy prices upwards. This is due to the fact that someone has to pay for this inefficiency, and the utilities normally pass all the costs on to the consumers. To this end, game theoretic techniques can be exploited to model strategic interaction between utility companies and the users to enhance the demand response. In fact, contrary to a load following generation, DSM solicits the demand to follow the variations in the generation side. Improving the economic efficiency, a responsive demand can benefit every user by reducing the energy prices, while ensuring the utilities about customer's satisfaction and balancing the supply and demand.

1.4 Thesis Contribution

We apply game theory along with other microeconomics tools (e.g., incentive mechanisms, market competition models, price elasticity of demand, etc.) and optimisation techniques to enhance resource utilisation in the future smart infrastructures such as mobile networks and electric power system. We particularly address the strategic interactions of rational agents in those systems and provide two contributions: (i) we apply coalitional games to encourage cooperation of UEs in a mobile network; and (ii) we exploit extensive-form games to enhance demand response in a smart electricity grid. In the former, we interpret the available relay nodes and the battery energy of the cooperative nodes as the available *resource* and match the cooperative partners in a way that maximises their total energy efficiently. In contrast, in the latter, we intrpret the power generation units as well as the power transmission and distribution systems as the available *resource* and design demand-side management programmes that can help enhance the *load factor*[2] of the power system.

To address the first problem, we go beyond the state-of-the-art and incorporate coalitional game theory to capture the strategic interactions between neibouring 5G UEs that form a coalition and cooperate to extend their battery lives. We first characterise the problem as a coalitional game and then derive its 'core' solution to settle the potential conflict(s) of interest arising between the cooperating UEs. In particular, we consider a scenario where a set of source UEs aim to communicate with a RAN, and there resides another set of nearby (idle)

[2]Load factor of a system is defined as the ratio between the average load and the peak load over a specified time period.

UEs with good channel qualities and good battery levels that are willing to cooperate as relays. We assume that a source UE can always communicate with the RAN directly (i.e., using its cellular interface); however, if it is experiencing a poor channel quality or if it is running on low battery, it can set up a cooperative short-range link with a neighbouring relay to relay its traffic back to the RAN. This cooperative link is basically a two-hop link where the first hop, from the source node to the relay, is performed over a short-range link, established exploiting the UEs' short-range interfaces (e.g., Bluetooth, WiMedia, etc.), while the second hop, from the relay to the RAN, is performed conventionally over a cellular link. We characterise the underlying relay-source matching problem as a binary Linear Programming (LP) problem that intends to maximise the (common) energy saving of the coalition subject to meeting the resource constraints of the cooperating UEs. Lastly, we provide a credit scheme based on coalitional game theory to distinguish and isolate selfish nodes from the cooperative ones. Our system level simulations in MATLAB and NS2 reveal that adopting this approach, UEs can save up to 50% in their energy consumption.

To address the second problem, we apply game theory to help enhance demand response in the electricity market. We apply non-cooperative games where every player pursues a strategy that maximises her own payoff. The payoff of the utility company is defined as the Peak-to-Average Ratio (PAR) of the aggregate demand, while the payoff of a residential customer is defined as his/her satisfaction minus his/her daily electricity cost. This allows the utility company to adopt a time-dependent tariff so as the retail price can rise when the aggregate demand is at a peak and fall when the demand goes down (in off-peak hours). This could encourage the retail customers to consume electricity during different hours as evenly as possible. We provide the game definition, as well the definition of the utility function and formulate the optimisation problems for the company and the user under both linear and quadratic generation cost functions. We validate the effectiveness of this DSM game through MATLAB simulations considering a single retail provider supplying multiple residential customers, each of them possessing a number of shiftable and non-shiftable appliances.

The results have been disseminated in 21 papers that include 8 articles in international peer-reviewed journals such as IEEE Wireless Communications; 5 book chapters in high-impact books by publishers such as John Wiley & Sons and Springer; and 8 papers in IEEE conferences that have been archived in IEEE Xplore Digital Library:

- **Journal Papers:**

J8. **Firooz B. Saghezchi**, Ayman Radwan, Jonathan Rodriguez, "Energy-aware relay selection in cooperative wireless networks: an assignment game approach," Submitted to *Elsevier Ad Hoc Networks*, pp. 1-15, 2016.

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1.5 Thesis Organisation

This PhD thesis is organised as follows:

- Chapter 2 presents a survey on game theory and its potential applications for 5G scenarios, such as cooperative communications and smart grids. In this chapter, we briefly introduce different game types such as strategic form games and the Nash Equilibrium (NE), to predict the strategic outcome of these games. As examples of strategic form games, we introduce Cournot and Bertrand games which are mainly used to analyse strategic behaviour of firms in an oligopolistic market, such as spectrum trading by cognitive radios or electricity trading in a competitive market. We also introduce the concept of Pareto-efficiency as a metric for the social wellbeing. Extensive-form games are also introduced in this chapter. These games are useful to capture situations when players move sequentially, one after another, and at each stage of game, players take actions based on their payoffs and the past moves of their opponents. We introduce a Stackelberg game, which is an extensive-form game suitable to model a number of important 5G applications such as DSM and cognitive radio. Finally, we conclude this chapter with an introduction to coalitional game theory and their solution concepts. Different from strategic-form games where players aim to maximise their own payoff, coalitional games could model scenarios where players are interested to optimise not only their individual payoffs but also their group payoff. These games could be specifically promising to capture and analyse cooperative communications scenarios for next generation cellular systems.

- Chapters 3 and 4 provide the main innovations of this thesis, covering our solutions and research findings to the two addressed research problems, i.e., cooperative communications for 5G mobile network applications and DSM in smart grids. In particular, Chapter 3 discusses the cooperation of 5G UEs to extend their battery life and enjoy network connectivity for longer periods of time without needing to frequently plug energy hungry smart phones to electrical sockets for charging. Coalitional game theory is applied to resolve arising conflict of interest between players and keep them motivated to cooperate. Inside a coalition, LP techniques are applied to solve relay selection problem, that intrinsically matches relay and source nodes in a way that maximises the coalition's payoff. Furthermore, necessary algorithms are provided to help implement necessary energy saving features at the UEs and at the RAN. Finally, the chapter concludes by validating this coalition game approach through both MATLAB and NS2 simulations results.

- Chapter 4 addresses DSM in the smart grid, adopting a game-theoretic approach. In particular, we apply a two-stage extensive form game where in the first stage, the utility company takes action choosing a certain time-dependent real-time tariff for the next hour(s) and announces the price(s) over the underlying two-way communication links, established by the smart grid. Observing the action taken by the utility company (i.e., the price signal), the consumers react by optimising the running schedules of their appliances so as to minimise their daily energy costs while meeting their satisfaction levels. We specifically study Day-Ahead Pricing (DAP) and convex pricing tariffs and attain strategic responses of a smart home for any of these pricing strategies that achieves the NE. We capture these responses as appropriate linear and convex programming problems to schedule smart home appliances for a price-aware domestic consumer. This chapter concludes by numerically validating our game-theoretic approach and the proposed household appliance scheduling algorithms through our custom-made MATLAB simulator.

- Finally, Chapter 5 concludes this PhD thesis, summarising the main results and drawing some guidelines for future work directions.

Chapter 2

Game Theory for 5G Applications

This chapter presents the essential background on game theory and its potential applications to boost the performance of 5G mobile networks and smart power grids. The chapter provides definitions of different types of games that could be employed to improve scarce resource utilisation in 5G applications along with necessary techniques to solve them. It further provides a brief introduction to mathematical optimisation, highlighting fundamental differences between a game-theoretic approach and a mathematical optimisation approach for addressing resource management problems. Game theory essentially addresses strategic interactions of independent rational agents, called players, who seek to maximise their own payoff. As the intelligence of mobile communication systems continuously increases, we expect 5G systems to host a portfolio of smart devices that can behave like rational players when they interact for instance to access the wireless medium, to relay packets, or to serve as an information backbone for smart home appliances to interact with the utility company and coordinate their operating intervals (schedules) in order to help manage household energy consumption and utilise the power grid infrastructure more efficiently. This can enable distributed management of scarce resources with practical signalling and coordination burden while ensuring a satisfactory performance.

2.1 Introduction

Game theory [31–33, 42] is essentially a mathematical tool to model and analyse potential conflict of interest arising from strategic interactions of multiple independent decision makers, any of whom seeking to maximise their own payoff. The decision makers, which are called players, are generally assumed to be rational and independent agents. The interest of players, which is generally independent from the interest of their opponents, might be in either helping or hurting their opponents: the former leads to cooperation among players, while the latter leads to competition among them. Specifically, when a player gains what her opponent loses, the game is called a zero-sum game. As a generalisation of the zero-sum game, the sum of the payoffs that players receive might be constant so if a player wants to increase her own payoff, she will need to upset at least one of her opponents.

A game is composed of at least two players. Every player, has a set of strategies and a utility function. The utility function is a function that simply maps the strategy space, $\mathcal{S}$, to the set of real numbers, $\mathbb{R}$, and serves as a measure to reflect the preference of players for their strategies. That is, players can use their utility functions to assess the usefulness of their different strategies; the more the value of a utility function for a certain strategy, the more the usefulness of that strategy for that player. In general, the utility that a player gains from playing a specific strategy might depend not only on the strategy that she chooses but also on the strategies that her opponents choose. Therefore, players may change their strategies sequentially in response to the strategic moves of their opponents. This can result in a set of dynamic decision-making interactions, which might evolve until an equilibrium strategy is reached for all players.

In 5G applications, we might use game theory to model either cooperative or competitive interactions among players. Sometimes the interest of players is to cooperate, whereas there are some other occasions, such as in zero-sum games, where their interest is to defeat their opponents. Originated by these applications, games are sometimes categorised as non-cooperative and cooperative games. Although, in the latter, players try to coordinate their actions with their opponents, both of these categories are used to capture strategic interactions of rational and independent agents. We normally model a competitive situation using strategic form games (Section 2.2) (also called non-cooperative games), while we can model a cooperative situation as either a strategic form game or a coalitional game (Section 2.5). The essential difference between a strategic form game and a coalitional game is that in the latter the players can enforce binding agreements among themselves in order to maximise their common (i.e., aggregate) payoff, while in the former the players are not allowed to enforce such binding agreements and pursue to maximise their individual payoffs. More precisely, in a strategic form game with complete information, every player completely knows the strategy sets of herself and her opponents as well her and her opponents' payoffs from any strategic outcome. We call the Cartesian product of the strategy sets of all players as the *strategy space*; any member of this set is called a game outcome or a *strategy profile*.

Our main concern in solving a strategic form game is predicting the equilibrium strategy profile that the players will finally reach. This equilibrium strategy profile is given by the NE (Section 2.2), named after John Nash who first introduced this solution reasoning method to the literature [43, 44]. NE is by definition a joint strategy in which each player's strategy is the best response to her opponent's strategy. In fact, an NE is an action profile in which none of the players could improve their payoff by a unilateral deviation while other players adhere to it [42]. As a result, when the game is at NE, the players are reluctant to change their strategies unilaterally. Note that a game might have multiple NEs. On the other hand, the equilibrium concept for a coalitional game is quite different. In fact, there are two main parts in the problem concerning the equilibrium of a coalitional game: the first part is finding a proper interaction among players in order to lead them to the most beneficial cooperation, and the second part is sharing the common achieved payoff among players in such a way that they are all satisfied and motivated to keep cooperating on instead of defecting and acting individually [33, 45]. In addressing coalitional games, each of these two parts might be tackled using a different approach: the first part is basically a resource management (or, decision making) problem, which typically leads to a network optimisation problem, and can be solved using mathematical optimisation tools (Section 2.6). The second part of the problem however concerns a fair distribution of the common payoff among players that can be tackled using solution concepts of coalitional games, such as *core* (Section 2.5.1), Shapley value (Section 2.5.2) and so forth. In the following, we will discuss these solution concepts with further details.

Interacting as independent agents while cooperating or competing for efficient resource utilisation, conflict of interest naturally arises among mobile UEs or smart home appliances. We can use game theory [33–35, 39] to analyse these conflicts of interest and predict the strategic decisions of the players (i.e., UEs or appliances and the utility company) [37, 46–52]. Specifically, as cooperative paradigm gains momentum in wireless networks, coalitional game theory has attracted considerable amount of interest among wireless engineers and researchers in recent years (see [37, 50, 50–53] and references therein). As mentioned above, solving a coalitional game means incentivising all players by distributing the common payoff that the players obtain by their cooperation in a fair way where they are all satisfied and no player or group of players has incentive to exit the cooperation. Further detail about coalitional game theory is provided later on in Section 2.5.

2.2 Strategic Form Games

A game in strategic form[1], also called normal form, has three elements [32]:

- the set of players $n \in \mathcal{N}$, which we consider to be the finite set $\{1, 2, ..., N\}$, where $N = |\mathcal{N}|$ is the cardinality of the set $\mathcal{N}$ and indicates the number of players.
- the pure-strategy set $\mathcal{S}_n$ for each player $n \in \mathcal{N}$.
- the payoff function $u_n : \mathcal{S} \to \mathbb{R}$ for each player $n \in \mathcal{N}$ that gives player n's utility for each strategy profile $s = (s_1, ..., s_N) \in \mathcal{S}$, where $\mathcal{S}$ is the cartesian product of all strategy sets; i.e., $\mathcal{S} = \mathcal{S}_1 \times \mathcal{S}_2 \times \cdots \times \mathcal{S}_n$.

We will frequently discuss varying the strategy of a single player $n \in \mathcal{N}$ while holding the strategy of her opponents fixed. To do so, we let $s_{-n} \in S_{-n}$ denote a strategy selection for all players except n and write (s'_n, s_{-n}) for the strategy profile $(s_1, ..., s_{n-1}, s'_n, s_{n+1}, ..., s_N)$. Similarly, for mixed strategies, we let $(\sigma'_n, \sigma_{-n}) = (\sigma_1, ..., \sigma_{n-1}, \sigma'_n, \sigma_{n+1}, ..., \sigma_N)$. A mixed strategy of a player is simply defined as a probability distribution over all her pure strategies [32]. In other words, a mixed strategy is a randomisation over the pure strategies. For instance, a player, i, having only two pure strategies, $S_i = \{A, B\}$, may decide to choose strategy A with probablity p and strategy B with probablity $1 - p$. In this case, her mixed strategy will be $\sigma_i = \{p, 1 - p\}$.

Definition 2.1. Pure strategy s_n is strictly dominated [32] for player n if there exists $\sigma'_n \in \Sigma_n$ such that

$$u_n(\sigma'_n, \sigma_{-n}) > u_n(s_n, s_{-n}),\ \forall s_{-n} \in S_{-n}. \tag{2.1}$$

[1] Strategic form games are also called non-cooperative games in the literature.

Figure 2.1: The Prisoner's Dilemma

		Player 2 C	**Player 2** D
Player 1	C	1,1	-1,2
Player 1	D	2,-1	0,0

The strategy s_n is weakly dominated if there exists a σ'_n such that inequality 2.1 holds with weak inequality, and the inequality is strict for at least one s_{-n}.

Nash Equilibrium

A Nash equilibrium is a strategy profile such that each player's strategy is a best response to her opponents' strategies [43, 44].

Definition 2.2. A mixed-strategy profile σ^* is a Nash equilibrium if, for all players $n \in \mathcal{N}$ [32],

$$u_n(\sigma_n^*, \sigma_{-n}^*) > u_n(s_n, \sigma_{-n}^*), \ \forall s_n \in S_n. \tag{2.2}$$

Example 2.1. As an example for strategic form games, Figure 2.1 shows the "Prisoner's Dilemma" game. This game has two players, namely Player 1 and Player 2. Thus, the set of players is $\mathcal{N}$ = {Player 1, Player 2}. Every player has two strategies, namely Cooperate and Defect, represented by s_1=C and s_2=D, respectively. For this specific game the strategy sets of the players are equal and given by $\mathcal{S}_1 = \mathcal{S}_2 =$ {C,D}. However, note that this is not the case for all games and in general players of a game might have different strategy sets. There are four possible strategic outcomes (strategy profiles) for this game; they form the strategy space of the game as follows $\mathcal{S} = \mathcal{S}_1 \times \mathcal{S}_2 =$ {(C,C), (D,C), (C,D), (D,D)}, where the times symbol depicts the Cartesian product of the two sets. In this game, strategy C is strictly dominated by strategy D, for both players. Therefore, the game has a unique NE that is (D,D). The utility functions for Player 1, u_1, and for Player 2, u_2, map these strategic outcomes to the set of real numbers as depicted in Figure 2.1.

$u_1(\text{C,C}) = 1$	$u_2(\text{C,C}) = 1$
$u_1(\text{C,D}) = -1$	$u_2(\text{C,D}) = 2$
$u_1(\text{D,C}) = 2$	$u_2(\text{D,C}) = -1$
$u_1(\text{D,D}) = 0$	$u_2(\text{D,D}) = 0$

2.3 Market Competition Models

We may model a market as one of the following three economic models: *monopoly*, *oligopoly*, or perfect competition [54]. A situation where a market is dominated by a single provider is known as a monopoly. Essentially, there is no competition in a monopolistic marker, and it is the only provider that decides which quantity to provide (q) or which price to sell (p) – it controls the output quantity to maximise its revenue. In the other extreme, we can think of (perfectly) competitive markets, where there are many providers and many consumers. Such markets naturally end up at an equilibrium point where the quantity supplied is equal to the quantity demanded. It is indeed this equilibrium that determines the prevailing price in the market. There is still a third form of market which is located between these two extremes, called oligopoly. In an oligopolistic market, there is a limited competition between few providers dominating the market. The simplest form of an oligopolistic market with only two providers is called a *duopoly*.

2.3.1 Pareto Efficiency

When a player improves her payoff without harming her opponents, the action is called a Pareto improvement move [55]. A Pareto efficient[2] outcome occurs when no player can improve her payoff without hurting her opponents' payoffs – there is no more room for Pareto improvement. We should distinguish a Pareto efficient outcome from a socially optimal outcome that occurs when the social welfare, sum of the payoffs for all players, reaches its maximum. For instance, in the Prisoner's dilemma game depicted in Figure 2.1, (C,C) and

[2] Also called Pareto optimal.

(D,D) are both Pareto optimal since none of the players has a Pareto improvement move. However, the game has only one socially optimal outcome which is (C,C). In fact, the game is called a 'dilemma' since the NE of the game is to defect while the socially optimal outcome, where both players are better off, is to cooperate.

2.3.2 Cournot Game

Cournot game [56] is an economic model of a duopoly producing a homogeneous product[3]. The strategies are quantities. Firm 1 and firm 2 simultaneously choose their respective output levels, q_i. They sell their outputs at the market clearing price $p(q)$, where $q = q_1 + q_2$. Firm i's cost of production is $c_i(q_i)$, and its payoff is $u_i(q_1, q_2) = q_i p(q) - c_i(q_i)$. Cournot game is a two-player strategic form game, and its NE is called the Cournot equilibrium.

2.3.3 Bertrand Game

In the Bertrand model [57], firms simultaneously choose prices and then must produce enough to meet the demand after the price choices become known in the market.

2.4 Extensive Form Games

In strategic from games, players have no notion about the "time." They move once and choose their strategies simultaneously. However, there exist situations where players move in a time order. Extensive form games are used to model such dynamic situations [31, 58]. They make explicit the order in which players move, and what each player knows when making each of her decisions. An example of a game in extensive form is the "Stackelberg game," elaborated in the following subsection.

Stackelberg Game

Similar to the Cournot game, Stackelberg game [59] is a model for a duopolistic competition. As in the Cournot game, there are two firms competing on the market share for a homogeneous product. The actions of the firms are choices of their output quantities, q_1 for

[3]Homogeneous products are defined by the BusinessDictionary as the goods that compete with each other in a market but which (from the consumer's viewpoint) have little or no differentiation in terms of features, benefits, or quality and are, therefore, forced to compete on price or availability.

firm 1 and q_2 for firm 2. The only difference is that we now suppose that firm 1 has the leadership power, while firm 2 is just a follower. That is, firm 1, "the Stackelberg leader," moves first and chooses its output level q_1, whereas firm 2 observes q_1 before choosing its own output level q_2.

2.5 Coalitional Games

In contrast to strategic form games where there is no communication between players, coalitional games are referred to those games that analyse conflict of interest among rational players who can communicate and make coalitions to improve their individual and group payoffs [33, 45]. For example, in wireless networks, UEs may form coalitions and pool their resources (e.g., their batteries, radio interfaces, etc.) and perform their tasks (i.e., communicating with the RAN) cooperatively whenever doing so can improve their resource utilisation efficiency (e.g., save their battery energy). In the following, we describe coalitional games along with their solution concepts.

If players of a game can enforce binding agreements to pursue group strategies and maximise their common payoff, the game is called a coalitional game. Formally, a coalitional game is defined as an ordered pair $\langle \mathcal{N}, v \rangle$ where $\mathcal{N} = \{1, \ldots, N\}$ is the set of players and $v : 2^{\mathcal{N}} \to \mathbb{R}$ is called the *characteristic function*; $\mathbb{R}$ denotes the set of real numbers and $2^{\mathcal{N}}$ denotes the power set of $\mathcal{N}$, which is defined as the set of all subsets of $\mathcal{N}$ involving the empty set and the set $\mathcal{N}$ itself. Any subset of $\mathcal{N}$ is called a 'coalition', and the set involving all players is called the 'grand' coalition. Note that $N = |\mathcal{N}|$ and $2^N = |2^{\mathcal{N}}|$, where the vertical bars denote sets' cardinalities. The characteristic function v, which is a function from the power set of $\mathcal{N}$ (i.e., $2^{\mathcal{N}}$) to the set of real numbers, assigns any coalition $\mathcal{S} \subseteq \mathcal{N}$ a real number $v(\mathcal{S})$, called the worth of coalition $\mathcal{S}$. By convention, $v(\emptyset) = 0$, where $\emptyset$ denotes the empty set. The worth of a coalition indeed indicates the maximum payoff that the players of the coalition can obtain by their full cooperation.

For any coalition $\mathcal{S}$, if $v(\mathcal{S})$ depends only on the actions of players inside $\mathcal{S}$ without being affected by the activities of the rest of players who lie outside $\mathcal{S}$ (i.e., inside $\mathcal{N} \backslash \mathcal{S}$), the function v is called the characteristic function and the game is referred to as a game in characteristic function form. Otherwise, if $v(\mathcal{S})$ depends not only on the activities of players inside $\mathcal{S}$, but also on the activities of the rest of players who lie outside $\mathcal{S}$ (i.e., inside $\mathcal{N} \backslash \mathcal{S}$), then the function v is called a *partition function* and the game is referred to as a game in partition function form. As mentioned above, the value of a coalition $\mathcal{S}$ retuned by the characteristic function or the partition function (i.e., $v(\mathcal{S})$) is called the worth of coalition $\mathcal{S}$ and indicates the maximum payoff the players in $\mathcal{S}$ can achieve by their cooperation. Putting differently, in a characteristic function game, the worth of a coalition depends only on the members of the coalition and is independent from how the rest of players outside the coalition organise themselves, while in a partition function game, the worth of a coalition depends not only on the coordination of the members of the coalition but also on how other players outside the coalition organise themselves. Thus, in a partition function game, forming a coalition might have side effects on other coalitions, referred to as externalities. We have two kinds of externalities in general: positive externality and negative externality. Positive externality means that forming a coalition increases the worth of other coalitions, while in case of negative externality, forming a coalition reduces the worth of other coalitions.

When a game involves 'monetary' or physically exchangeable units that can be freely exchanged between players, the game is called a game with Transferable Utility (TU). A game that lacks this kind of freely exchangeable unit is called a game with Non-Transferable Utility (NTU). Essentially, a game with TU is more flexible than a game with NTU and allows the common payoff to be distributed among players in an arbitrary way.

A game, $G = \langle \mathcal{N}, v \rangle$, is called a superadditive game [33] if $\forall\ \mathcal{S}, \mathcal{T} \subseteq \mathcal{N}$ and $\mathcal{S} \cap \mathcal{T} \neq \emptyset$, then

$$v(\mathcal{S} \cup \mathcal{T}) \geq v(\mathcal{S}) + v(\mathcal{T}). \tag{2.3}$$

That is, two arbitrary disjoint coalitions can always improve their position in the game by merging and forming a bigger coalition. In contrast, a game, $G = \langle \mathcal{N}, v \rangle$, is called a convex game if $\forall\ \mathcal{S}, \mathcal{T} \subseteq \mathcal{N}$, then

$$v(\mathcal{S} \cup \mathcal{T}) \geq v(\mathcal{S}) + v(\mathcal{T}) - v(\mathcal{S} \cap \mathcal{T}). \tag{2.4}$$

Equivalently, for an arbitrary player $i \in \mathcal{N}$ of the convex game $G = \langle \mathcal{N}, v \rangle$

$$v(\mathcal{S} \cup \{i\}) - v(\mathcal{S}) \leq v(\mathcal{T} \cup \{i\}) - v(\mathcal{T}),\ \forall \mathcal{S} \subseteq \mathcal{T} \subseteq \mathcal{N} \backslash \{i\}. \tag{2.5}$$

The left and right hand sides are the marginal contributions of player $i \in \mathcal{N}$ to coalitions $\mathcal{S}$ and $\mathcal{T}$, respectively. This inequality indicates that in a convex game, the marginal contribution of a player to a coalition always increases as the coalition size grows; the more the size of the coalition, the more the marginal contribution of a new player.

Convex games are indeed a subset of superadditive games; any convex game is superadditive too, but the converse may not be true [33]. It is worth mentioning that in a superadditive game, players tend to join together and form the grand coalition. This type of game where the grand coalition is trivial is referred to as the 'canonical' game. In a canonical game, the only concern is the stability of the coalition. That is, how to divide the common payoff among players such that everyone is happy and no one has incentive to leave the coalition.

Any distribution of the common payoff among players is called a payoff vector, or an allocation, vector. A payoff vector of a coalitional game is generally denoted by the vector $x = (x_1, \ldots, x_n)$ where x_i $(i = 1, \ldots, N)$ denotes the amount of assigned payoff to player $i \in \mathcal{N}$.

A payoff vector $x \in \mathbb{R}^N$ is called feasible if

$$\sum_{i \in \mathcal{N}} x_i \leq v(\mathcal{N}). \tag{2.6}$$

Furthermore, a payoff vector $x \in \mathbb{R}^N$ is called efficient or Pareto optimal if it distributes the worth of the grand coalition among players totally; i.e.,

$$\sum_{i \in \mathcal{N}} x_i = v(\mathcal{N}). \tag{2.7}$$

A payoff vector $x \in \mathbb{R}^N$ is called individually rational if it offers all players more payoffs than what they can obtain acting individually; i.e.,

$$x_i \geq v(i), \ \forall i \in \mathcal{N}. \tag{2.8}$$

Note that with an abuse of notation, we use $v(i)$ to denote $v(\{i\})$. While distributing the common payoff, $v(\mathcal{N})$, among the players, a rational player $i \in \mathcal{N}$ always compares the payoff she receives from the allocation vector, x_i, with the payoff that she can obtain by acting individually, $v(i)$. The player will prefer to cooperate if $x_i \geq v(i)$; otherwise, she will decide to leave the coalition since she can obtain more by acting individually. Hence, the first step towards ensuring the stability of a coalition is to offer each player at least a payoff that they can obtain individually – an individually rational payoff vector.

The 'excess' [33] of a coalition $\mathcal{S} \subseteq \mathcal{N}$ under an allocation vector x is defined as

$$e(\mathcal{S}, x) = v(\mathcal{S}) - \sum_{i \in \mathcal{S}} x_i. \tag{2.9}$$

That is, the excess of coalition $\mathcal{S} \subseteq \mathcal{N}$ with respect to payoff vector x is the net transferrable worth that $\mathcal{S} \subseteq \mathcal{N}$ would have left after paying x_i to each member $i \in \mathcal{N}$. Furthermore, it is worth pointing out that for a canonical game, a payoff vector is efficient if the excess of the grand coalition under this allocation vector is zero.

In contrast to individual rationality, a payoff vector x is called group rational if for any coalition $\mathcal{S} \subseteq \mathcal{N}$,

$$\sum_{i \in \mathcal{S}} x_i \geq v(\mathcal{S}). \tag{2.10}$$

Thus, a payoff vector is group rational if the excess of every coalition is either negative or equal to zero.

The 'pre-imputation' set $\mathcal{PI}(v) \subseteq \mathbb{R}^n$ is defined as the subset of $\mathbb{R}^n$ comprised of all efficient payoff vectors; i.e.,

$$\mathcal{PI}(v) = \left\{ x \in \mathbb{R}^n \mid \sum_{i \in \mathcal{N}} x_i = v(\mathcal{N}) \right\}. \tag{2.11}$$

Furthermore, the 'imputation' set $\mathcal{I}(v) \subseteq \mathbb{R}^n$ is defined as the subset of $\mathbb{R}^n$ that comprises all efficient and individually rational payoff vectors; i.e.,

$$\mathcal{I}(v) = \left\{ x \in \mathbb{R}^n \mid \sum_{i \in \mathcal{N}} x_i = v(\mathcal{N}), x_i \geq v(i),\ \forall i \in \mathcal{N} \right\}. \tag{2.12}$$

Suppose that $G = \langle \mathcal{N}, v \rangle$ is a game with TU and the set $\mathcal{P}$ is a partition of $\mathcal{N}$. We define

$$\mathcal{I}(\mathcal{P}) = \left\{ x \in \mathbb{R}^n \middle| \sum_{i \in \mathcal{C}} x_i = v(\mathcal{C}), \forall \mathcal{C} \in \mathcal{P} \text{ and } x_i \geq v(i),\ \forall i \in \mathcal{N} \right\}. \tag{2.13}$$

One can immediately notice that if $\mathcal{P} = \mathcal{N}$ (i.e., the partition consists of only one part, namely the grand coalition $\mathcal{N}$), then $\mathcal{I}(\mathcal{P})$ is nothing but the set of all imputations of the game $G = \langle \mathcal{N}, v \rangle$; cf (2.12).

An 'objection' by a player $i \in \mathcal{N}$ against another player $j \in \mathcal{N}$ and a payoff allocation x is a pair $(y, \mathcal{C})$ where y is another payoff allocation and $\mathcal{C}$ is a coalition such that

$$i \in \mathcal{C},\ j \notin \mathcal{C},\ e(\mathcal{C}, y) = 0\ \forall y >_{\mathcal{C}} x. \tag{2.14}$$

That is, the players in $\mathcal{C}$ can jointly achieve their share of y, which is strictly better for all of them, including player $i \in \mathcal{N}$, than the allocation x. A counter objection to i's objection $(y, \mathcal{C})$ against j and x is any pair $(z, \mathcal{D})$ such that

$$j \in \mathcal{D},\ i \notin \mathcal{D},\ \mathcal{C} \cap \mathcal{D} \neq \emptyset,\ e(\mathcal{D}, z) = 0,\ z \geq_{\mathcal{D}} x,\ z \geq_{\mathcal{C} \cap \mathcal{D}} y. \tag{2.15}$$

That is, in the counter objection, player j can form a coalition $\mathcal{D}$ that takes away some of i's partners in the objection (but not i himself) and makes them at least as well off as in the objection; thus, j can restore himself and the other members of $\mathcal{D}$ to payoffs at least as good as they had in x.

For any two payoff vectors x and y and any coalition $\mathcal{S}$, if x is strictly preferred to y by all members of coalition $\mathcal{S}$, x is called lexicographically larger than y. That is,

$$x >_{\mathcal{C}} y \text{ iff } x_i >_{\mathcal{C}} y_i\ \forall i \in \mathcal{S}. \tag{2.16}$$

Similarly, we can write

$$x \geq_{\mathcal{C}} y \text{ iff } x_i \geq_{\mathcal{C}} y_i\ \forall i \in \mathcal{S}. \tag{2.17}$$

A solution concept of a cooperative game is generally defined as a set of payoff vectors that all of the involved players of the game are satisfied by its proposed allocation and none of them has enough incentive to break the cooperation. Several solution concepts have been developed in the literature, namely core, Shapley value, stable set, bargaining set as well as kernel [33]. In the following, the definitions of these solution concepts are briefly provided.

2.5.1 Core Solution

The core solution is defined as the set of payoff vectors that are feasible and group rational (i.e., cannot be improved upon by any other coalition). That is [33],

$$\mathcal{C}(v) = \left\{ x \in \mathbb{R}^n \mid \sum_{i \in \mathcal{N}} x_i = v(\mathcal{N}), \sum_{i \in \mathcal{S}} x_i \geq v(\mathcal{S}) \ \forall \mathcal{S} \subset \mathcal{N} \right\}. \tag{2.18}$$

Example 2.2. Consider a game with three players $\mathcal{N} = \{1, 2, 3\}$ and the following characteristic function.

$$\begin{aligned}
&v(1) = 0.25 \\
&v(2) = 0 \\
&v(3) = -0.25 \\
&v(1,2) = 1.25 \\
&v(1,3) = 1.0 \\
&v(2,3) = 0.75 \\
&v(1,2,3) = 2.0
\end{aligned}$$

The game is super-additive because:

$$\begin{aligned}
&v(1,2) \geq v(1) + v(2) \\
&v(1,3) \geq v(1) + v(3) \\
&v(2,3) \geq v(2) + v(3) \\
&v(1,2,3) \geq v(1,2) + v(3) \\
&v(1,2,3) \geq v(1,3) + v(2) \\
&v(1,2,3) \geq v(2,3) + v(1)
\end{aligned}$$

The game is also convex since in addition to the above inequalities:

$$v(1,2,3) + v(1) \geq v(1,2) + v(1,3)$$
$$v(1,2,3) + v(2) \geq v(1,2) + v(2,3)$$
$$v(1,2,3) + v(3) \geq v(1,3) + v(2,3)$$

Furthermore, the core solution is any vector $x = (x_1, x_2, x_3)$ that satisfies the following conditions:

$$\begin{aligned}
&x_1 \geq 0.25 \\
&x_2 \geq 0 \\
&x_3 \geq -0.25 \\
&x_1 + x_2 \geq 1.25 \\
&x_1 + x_3 \geq 1.0 \\
&x_2 + x_3 \geq 0.75 \\
&x_1 + x_2 + x_3 = 2.0
\end{aligned}$$

For example, (1,1,0), (1,0.25,0.75), and (1.25,0.5,0.25) are all located in the core. It is clear in this example that the core solution is not unique; rather there can be several core solutions pertaining to a game. In fact, the core of a coalitional game can also be empty. However, the core of a convex game is always nonempty. Moreover, the core solution of a coalitional game is a (possibly empty) convex polytope in $\mathbb{R}^n$ [45]. The core solution provides all solutions including the edge points of this convex polytope. Other solution concepts exist such as the Nucleolus or the Kernel, which derive interior solutions from this polytope. Further discussion on these solution concepts is out of the scope of this chapter. The interested readers can refer to the textbooks on game theory such as [33].

2.5.2 Shapley Value

The core of a coalitional game may be empty or quite large, a situation that makes the core difficult to apply as a predictive theory. The best that we could hope for would be to derive a theory that predicts, for each game in coalitional form, a unique expected payoff allocation for the players. Shapley approached this problem axiomatically [60, 61]. That is, he asked what kind of properties we might expect such a solution concept to satisfy, and characterised the mappings ϕ that satisfy the following four axioms [33]:

1. Efficiency Axiom: $\sum_{i \in \mathcal{N}} \phi_i(v) = v(\mathcal{N})$.

2. Symmetry Axiom: If players i and j are such that $v(\mathcal{S} \cup \{i\}) = v(\mathcal{S} \cup \{j\})$ for every coalition $\mathcal{S} \subseteq \mathcal{N} \backslash \{i, j\}$, not containing players i and j, then $\phi_i(v) = \phi_j(v)$.

3. Dummy Axiom: If player i is such that $v(\mathcal{S} \cup \{i\}) = v(\mathcal{S})$ for every coalition $\mathcal{S} \subseteq \mathcal{N} \backslash i$, not containing player i, then $\phi_i(v) = 0$.

4. Additivity Axiom: If u and v are characteristic functions, then $\phi(u + v) = \phi(u) + \phi(v)$.

Shapley showed that there is a unique mapping ϕ – called the Shapley value – that satisfies these four axioms. This value is computed for every player i of the game $(\mathcal{N}, v)$ in the following manner.

$$\phi_i(v) = \sum_{\mathcal{S} \in \mathcal{N} \backslash \{i\}} \frac{|\mathcal{S}|!|\mathcal{N} - \mathcal{S} - 1|!}{|\mathcal{N}|!} [v(\mathcal{S} \cup \{i\}) - v(\mathcal{S})] \tag{2.19}$$

The Shapley value has an interpretation that takes into account the order in which the players join the grand coalition $\mathcal{N}$. When the players join the grand coalition in a random order, the payoff allotted by the Shapley value to a player $i \in \mathcal{N}$ is the expected marginal contribution of player i.

2.5.3 Stable Set

A stable set is also called a von-Neumann-Morgenstern solution. By definition, a stable set is the set of imputations $\mathcal{Z}$ that satisfies the following two stability conditions:

- *internal stability*, which means that no imputation in $\mathcal{Z}$ is dominated by any other imputation in $\mathcal{Z}$;

- *external stability*, which means that every imputation not in $\mathcal{Z}$ is dominated by some imputation in $\mathcal{Z}$.

2.5.4 Bargaining Set

The intuition behind the bargaining set solution is that the common payoff of the cooperation is distributed among players in such a way that any player would refrain from objecting to a proposed payoff allocation because of the apprehension that the objection might prompt a counter objection by another player. Formally, a barging set solution is defined as follows. Given a TU game $G = \langle \mathcal{N}, v \rangle$ and a partition $\mathcal{P}$ of $\mathcal{N}$, a bargaining set is a collection of payoff vectors $x = (x_1, \ldots, x_n)$ such that [33]:

- x belongs to the set $\mathcal{I}(\mathcal{P})$, i.e., the imputation set;
- for any coalition $\mathcal{C} \subseteq \mathcal{P}$ and for any two players $i, j \in \mathcal{C}$, there is a counter objection to any objection by i against player j and payoff vector x.

2.5.5 Kernel

Similar to the bargaining set solution, the kernel of a cooperative game is defined relative to a partition $\mathcal{P}$ of the grand coalition $\mathcal{N}$. In fact, like the bargaining set, the kernel is also a subset of $\mathcal{I}(\mathcal{P})$. The intuition behind the kernel is that if two players i and j belong to the same coalition in $\mathcal{P}$, then the highest excess that i can make in a coalition without j should be the same as the highest excess that j can make in a coalition without i. The kernel is always a nonempty subset of the bargaining set and is formally defined as follows.

The kernel of a TU game $G = \langle \mathcal{N}, v \rangle$ related to a partition $\mathcal{P}$ of $\mathcal{N}$, is composed of all payoff vectors x that [33]:

- $x \in \mathcal{I}(\mathcal{P})$; and
- for any coalition $\mathcal{C} \in \mathcal{P}$ and any two players $i, j \in \mathcal{C}$,

$$\max_{\mathcal{S} \subseteq \mathcal{N} \setminus j, i \in \mathcal{S}} e(\mathcal{S}, x) = \max_{\mathcal{T} \subseteq \mathcal{N} \setminus i, j \in \mathcal{T}} e(\mathcal{T}, x). \tag{2.20}$$

2.5.6 Nucleolus

The essential motivation behind nucleolus is that instead of applying general fairness axioms for finding a unique payoff allocation, one can provide an allocation that minimises the dissatisfaction of the players from the allocation they can receive in a given game. For a coalition $\mathcal{S}$, the measure of dissatisfaction from an allocation x is defined as the excess $e(\mathcal{S}, x)$. Hence, this solution concept is defined as follows. The nucleolus is the imputation that minimises the

- largest excess among all coalitions;
- second largest excess among all coalitions, and so on until a unique imputation is reached.

Intuitively, nucleolus makes the most unhappy coalition as little unhappy as possible, the second most unhappy coalition as little unhappy as possible, and so on. Nucleolus can be computed by solving a collection of LP problems in a sequential way. The nucleolus is in the kernel, in the bargaining set with the partition $\mathcal{P} = \mathcal{N}$ and in the core if the core is nonempty.

2.6 Mathematical Optimisation

Mathematical optimisation is referred to a set of problems that aim to minimise (or maximise) an objective function, which depends on a set of optimisation variables, subject to meeting some constraint functions defining the feasible set for the variables space [62]. Generally, the objective function and the constraints can take various forms (e.g., linear, affine, convex, etc.). Depending on the form of the objective and constraint functions as well as the feasible values that the decison variables can take, optimisation problems demonstrate themselves in several different types. For any type of optimisation problem, there exist different solution techniques and algorithms. In general, we may write an optimisation problem as follows:

$$\begin{aligned} \underset{x}{\text{minimise}} \quad & f_0(x) \\ \text{subject to:} \quad & f_i(x) \leq 0, \quad i = 1, \ldots, m \\ & h_i(x) = 0, \quad i = 1, \ldots, p \end{aligned} \tag{2.21}$$

We denote the optimal solution of this problem as $x^\star$. In the following, we briefly introduce different optimisation problems.

2.6.1 Linear Programming

LP is referred to a type of optimisation problem where both the objective function and the constraint functions are affine (loosely speaking, linear) functions [62]. A set $C \subseteq \mathbb{R}^n$ is affine if the line through any two points in C lies in C. A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is affine if $\mathbf{dom}\ f$, where $\mathbf{dom}\ f$ denotes the domain of f, is an affine set and if for all $x, y \in \mathbf{dom} f$, and $\theta \in \mathbb{R}$, we have

$$f(\theta x + (1-\theta)y) = \theta f(x) + (1-\theta) f(y). \tag{2.22}$$

If the decision variables x_i can only take binary values, indicating a kind of "*yes/no*" decision, the LP problem is called a Binary Programming problem. If they are forced to take only integer values, the resulting problem is called an Integer Programming problem. If they can take either real or integer values, the problem is called a Mixed Integer Linear Programming (MILP) problem.

In Eq. (2.21), the first line expresses the objective function, which indicates minimising the cost of performing a certain task. This is the standard form notation of an LP problem, normally written in a minimisation form; to maximise an objective function (i.e., profit), we may simply minimise its negative. The constraint inequalities basically indicate the limits on the available resources for performing the task. The region enclosed by the inequalities, the feasible region, which determines the region from where the optimal solution can be selected.

The LP problem could be solved by the well-known simplex algorithm [63]. The system of linear inequalities composing the constraints indeed defines a polytope, as the feasible region, and the simplex algorithm relies on the fact that the optimal feasible solution lies at the corner points of this polytope. The algorithm, begins at a starting vertex and moves along the edges of the polytope in the opposite direction of the gradient of the objective function until it reaches the optimum corner point. Since passing from one vertex to another is performed in the negative direction of the gradient of the objective function, the algorithm reaches the optimal solution quickly without having to check all corner points – although in worst case, it may have to check all corner points to find the optimal solution [64].

Sometimes it is convenient to show an LP problem in a matrix format.

$$\begin{aligned} \underset{x}{\text{minimise}} \quad & c^T x \\ \text{subject to:} \quad & Ax \leq b \end{aligned} \tag{2.23}$$

Here, c^T is a row vector with the same length as vector x (i.e., n); A is a matrix of size $m \times n$, and b is a column vector of length m.

We can now construct the dual of this LP problem as follows:

$$\begin{aligned} \underset{x}{\text{maximise}} \quad & b^T y \\ \text{subject to:} \quad & A^T y \geq c, \end{aligned} \tag{2.24}$$

where y is the dual variable which is a column vector of size m. We denote the optimal solution of this LP problem as $y^\star$. The interesting relationship between the primal LP problem and its dual is stated by the duality theorem [63].

Theorem 2.1. *If an optimal feasible solutions exist for the primal problem and its corresponding dual problem, then these optimal values are equal; i.e.,* $x^\star = y^\star$.

2.6.2 Convex Optimisation

Convex Optimisation [62] is referred to a set of optimisation problems where both the objective function f_0 and all constraint functions (either inequality functions f_is or the equality ones h_is) are convex functions [62]. A set $C \subseteq \mathcal{R}^n$ is convex if the line chord through any two points in C lies in C. A function $f : \mathbb{R}^n \to \mathbb{R}$ is convex if **dom** f, where **dom** f denotes the domain of f, is a convex set and if for all $x, y \in \mathbf{dom} f$, and $0 \leq \theta \leq 1$, we have

$$f(\theta x + (1-\theta)y) \leq \theta f(x) + (1-\theta) f(y). \tag{2.25}$$

Interior-Point Methods (IPM) is an efficient algorithm that can solve Convex problems in complexity of $\mathcal{O}(nm)$ [62].

2.7 Game Theory for Wireless Networks

Game theory has recently been applied to wireless networks, particularly on ad hoc and cognitive networks. Wang et al. [65] present a tutorial on the applications of game theory on cognitive radio networks. Srivastava et al. [46] survey the applications of game theory for analysing wireless ad hoc networks. These two papers provide a comprehensive list of references on the applications of game theory in wireless networks. There are also some other tutorial papers on the applications of game theory in wireless networks such as [34, 37]: Félegyházi & Hubaux [34] address the application of strategic form games, while Saad et al. [37] address the applications of coalitional games in wireless network. Félegyházi et al. [47] address the problem of whether cooperation can exist in ad hoc network without incentive mechanisms. They propose a model based on repeated games and graph theory and investigate equilibrium conditions of packet forwarding strategies in Mobile Ad-hoc Network (MANET). They conclude that it is difficult for global natural cooperation to emerge in a static network scenario since the asymmetric relationships between nodes never change and nodes have not any incentive to forward the packets of the nodes that can never reciprocate (or be punished). This motivates a study of the potential for natural cooperation in non-static scenarios considering mobility models. Mobility is likely to be a key factor in enabling natural cooperation as it allows different dependency loops to be established over time. Furthermore, Yang et al. [48] address noncooperative game analysis of selfish behaviour in wireless ad hoc networks with a focus on packet forwarding and relaying. They model two-, three- and four-player Packet Forwarding Dilemma (PFD) as a repeated game and demonstrate that natural cooperation can emerge under these conditions: (i) repeated game with uncertain ending; (ii) credible punishment for defection; and (iii) sufficiently patient players. These conditions may not hold in all networks; hence, there is always a role for extrinsic incentive mechanisms.

Packet Forwarding Dilemma

In ad hoc networks, the proper operation of the network relies on the cooperation of the nodes in forwarding packets of each other. On the other hand, packet forwarding incurs energy cost for relaying nodes. Hence, rational nodes face a dilemma called PFD [47, 48],which can be modelled as a two-player strategic form game. Suppose forwarding a packet has a cost of $C < 1$ for the forwarding node and a benefit of 1 for the packet owner. Every player has two

Figure 2.2: The 'Packet Forwarding Dilemma' Game

		Node 2 Forward	Drop
Node 1	Forward	1-C,1-C	-C,1
	Drop	1,-C	0,0

alternative strategies in response to a packet-forwarding request from her opponent: *Forward* and *Drop*. Figure 2.2 illustrates the game.

As defined before, NE is a strategic action profile that no player can increase her payoff by unilaterally deviating from it. In the PFD game represented in Figure 2.2, the only pure strategy Nash equilibrium is (Drop,Drop). Nonetheless, similar to the Prisoner's Dilemma game, there is another action profile that is more beneficial for both players, which is (Forward,Forward). Again, this is a Pareto optimal action profile. The reason that prevents players from playing this strategic action profile, although it is more socially attractive for them, is that any player fear that the opponent would be tempted to unilaterally change her strategy to further increase her payoff. In fact, this deviation of the opponent from the Pareto optimal outcome (Forwad,Forwad) leaves the cooperating player a payoff that is worse than the one he receives in the NE.

Repeated Games

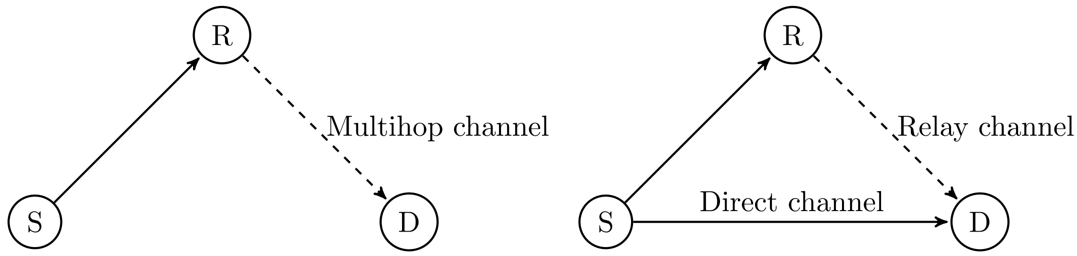
As defined before, in a strategic game, if players have to perform a single strategic move, the game is called static or a single stage game. However, if they can perform several strategic moves, the game is called a multi-stage or a repeated game. That is, in a repeated game, the players interact several times. Each of these interactions is called a stage, and any stage can be modelled as a static (single-stage) game. In repeated games, players are assured that they will encounter again in the next stages of the game. Hence, if a player deviates from a Pareto optimal action profile, the opponent can change her strategy accordingly in the following stages of the game. As a result, players have more diverse strategic choices than they have in a static game [47–49]. Next, we briefly describe some of these possible strategies [47].

- *Always Cooperate (AllC)*: a player always forwards the packet regardless of the strategy of her opponent.

- *Always Defect (AllD)*: a player always drops the packet regardless of the strategy of her opponent.
- *Tit-For-Tat (TFT)*: a player forwards the first packet and then mimics the strategy of her opponent.
- *Suspicious Tit-For-Tat (S-TFT)*: a player drops the first packet and then mimics the strategy of her opponent.
- *Anti Tit-For-Tat (A-TFT)*: a player always does the opposite of her opponent's strategy. That is, if the opponent drops (forwards) her packet, he forwards (drops) the packet of the opponent.
- *Grim Trigger (GT)*: a player forwards the packets of her opponent until the opponent forwards her packets. Once the opponent drops her packet, he drops all packets from her opponent forever.
- *Generous Tit-For-Tat (G-TFT)*: a player adopts the TFT strategy, but he is slightly generous and forgives some occasional dropping by her opponent.
- *Random*: a player forwards the packet of her opponent with probability $\frac{1}{2}$.

2.8 Cooperative Communications

The existing literature on cooperative communication can be classified into two main categories: multihop communication and cooperative relaying. The former is primarily employed in ad hoc networks to ensure connectivity in the absence of a communication infrastructure. In this form of cooperation, wireless nodes cooperate by forwarding data packets for each other. As such, two nodes that are out of their radio coverage are still able to communicate through some intermediate relay nodes (see Figure 2.3(a)). The Internet Engineering Task Force (IETF) MANET working group develops standards for IP routing protocol suitable for wireless routing application within both static and dynamic topologies. The second from of cooperative communication is cooperative relaying. In contrast to multihop communication (Figure 2.3(b)), the main motivation for this form of cooperation is not connectivity. Rather,



(a) Multihop communication (b) Cooperative relaying

Figure 2.3: Contrasting multihop communication (a) and cooperative relaying (b)

it is employed to exploit the underlying spatial diversity of the wireless channel to enhance the system performance including the link reliability, data rate, and energy efficiency.

Figure 2.3 contrasts the two above-mentioned types of cooperative communication. The main difference between these two types is that, in multihop relaying (Figure 2.3(a)), there is no direct link between the source node S and the destination node D, so the communication between theses end-nodes is to be performed through the relay node R. In contrast, in cooperative relaying (Figure 2.3(b)), there exists a direct link between the two communication parties, and the relay path serves as an alternative path to add spatial degree-of-freedom. Figure 2.4 depicts a snapshot of the Signal-to-Noise Ratio (SNR) variations of the direct path $\langle$S-D$\rangle$ and the relay path $\langle$S-R-D$\rangle$, caused by the shadowing and multipath fading impairments. As seen in the figure, there are some time instants that the received SNR drops to the acceptable threshold for reliable detection. The light-shaded regions illustrate these time intervals. As the variations of the perceived SNR from the two alternative paths $\langle$S-D$\rangle$ and $\langle$S-R-D$\rangle$ at the destination node D are statistically independent, the probability that the both links are in a deep fading is very low, illustrated by the dark shaded regions in the figure.

In a multihop cellular network, the relaying action can be performed either in the same frequency band as the cellular system or in a different frequency band. In the first approach, which is called in-band relaying, both hops from the source node to the relay node and from the relay node to the destination node are performed over the same frequency channel, but in different time slots. More precisely, they share the same frequency dimension by multiplexing over other dimensions such as time (Time Division Multiple Access (TDMA)), code (Code Division Multiple Access (CDMA)), etc. Although in-band relaying requires minimal additional complexity for the UEs, the receiver and transmitter at the relay node cannot operate simultaneously. This constrains the relay to operate in half-duplex mode, reducing the link capacity to half. On the other hand, in out-of-band relaying, the first hop (i.e. from the source node to the relay) operates at different frequency band than the second hop (i.e. from the relay to the destination), allowing "full-duplex" operation for the relay nodes. However, this scheme requires an additional frequency channel as well as good isolation between the transmit and receive signals.

Despite operating in orthogonal channels, in out-of-band relaying, the transmit signal drowns out the receive signal, due to imperfect isolation (typically, the transmit signal is 100-150 dB above the receive signal). This requires two radio interfaces at the relay node. Today, any feature phone or smart phone is equipped with a variety of radio interfaces. Therefore, a plausible solution for out-of-band relaying is to exploit prevalent Wireless Local Area Network (WLAN) or Personal Area Network (PAN) interfaces for relaying purposes. For instance, the first hop from the source to the relay can be performed over a short range link such as WiFi, Bluetooth, or WiMedia, while the second hop from the relay to the destination can be performed over a cellular link such as Universal Mobile Telecommunications System (UMTS), Worldwide Interoperability for Microwave Access (WiMAX), LTE, etc.

Notice that in Figure 2.4, communications take place in two stages. In the first stage (illustrated by the solid arrows), the source node S broadcasts the message to the destination node D and the relay node R, whereas in the second stage (illustrated by the dashed arrows), the relay node retransmits the received information to the destination node D. The relay node indeed establishes another path $\langle$S-R-D$\rangle$ in parallel to $\langle$S-D$\rangle$, providing spatial diversity.

Several relaying strategies have been introduced in the literature [66], such as Amplify-and-Forward (AF), Decode-and-Forward (DF), and Compress-and-Forward (CF). In the first strategy, the relay node R amplifies the received signal, without trying to detect it, and forwards the amplified signal to the destination node D. Despite its simplicity, AF strategy also amplifies the noise embedded in the received signal, which may deteriorate the SNR. To overcome this drawback, in the second strategy (DF) [67], the relay node R first detects the received signal then encodes and forwards it to the destination node D. Finally, in the last strategy, the relay node detects the received signal, and retransmits a quantised or a compressed version of the received message to the destination, exploiting the statistical dependencies between the message received at the relay and that received at the destination.

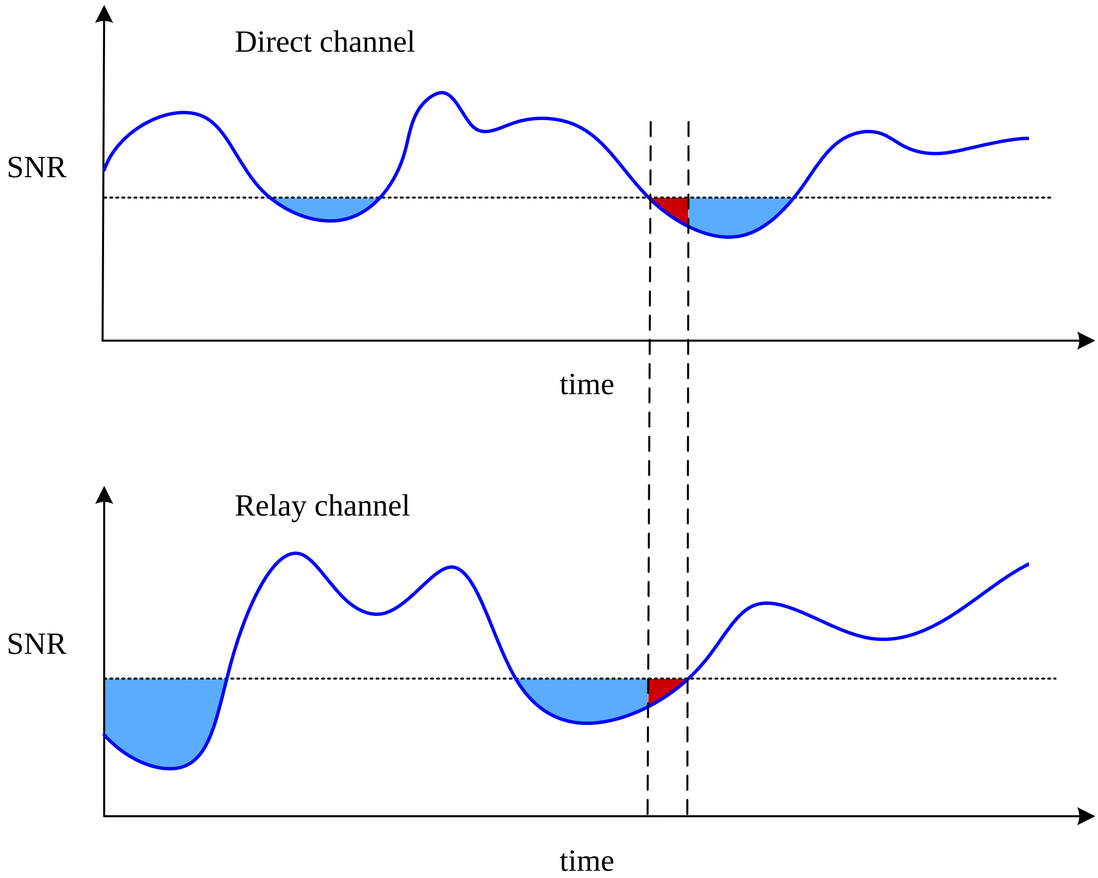


Figure 2.4: Fading of the direct and relay channels of cooperative relaying wireless channel

The performance of these strategies essentially depends on the quality of the source-relay channel. When this channel has good quality, DF strategy shows better performance than AF strategy; otherwise, AF strategy outperforms DF strategy. This is due to the fact that, when the source-relay channel quality (in terms of the received SNR) is poor, the relay fails to successfully detect the received signal. In this case, in spite of amplifying the noise, and adding the noise of the amplifier, AF strategy demonstrates better performance than DF strategy [68, 69].

At the destination node, signals from both the source and the relay paths are combined for a reliable detection. Different combining strategies are used for this purpose. For example, in the Selective Combining (SC) method, the received signal with higher SNR is chosen for detection, while the weaker signal is ignored. Alternatively, in Maximal Ratio Combining (MRC) method, both signals are considered for detection; a weighted average of the signal is consid-

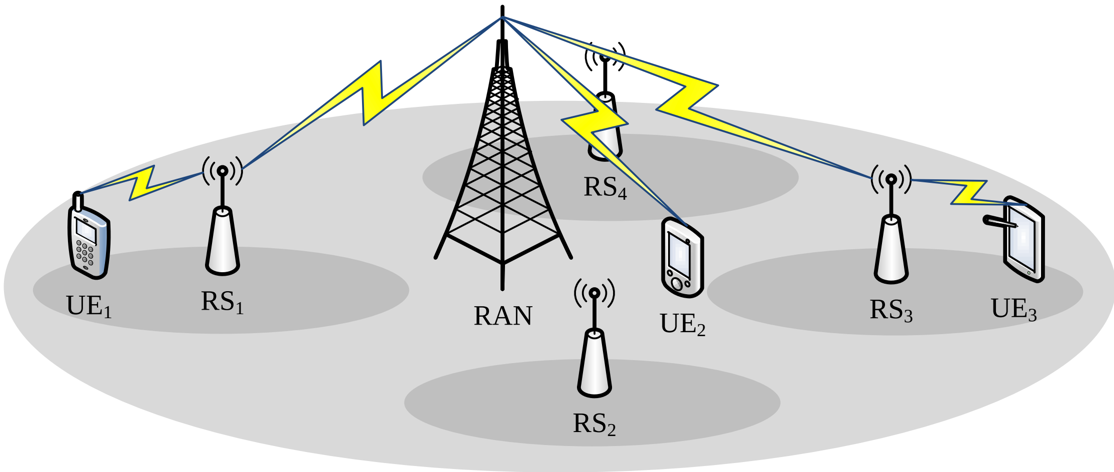


Figure 2.5: Multihop Cellular Network (MCN) with fixed Relay Stations (RS)

ered where the weight of each signal is proportional to its SNR. However, in MRC strategy, different phase shifts due to different path lengths of the direct and the relay links should be compensated before combining, to prevent any destructive addition, which requires that the phase responses of both the direct and the relay channels are available at the destination.

In a cooperative relaying setup, if there is no direct link between the source S and the destination D or if the direct signal received at the destination node D is ignored, the cooperative relaying is reduced to multihop communications. The most obvious benefit of cooperative communications is to break a long hop from the source to the destination to shorter hops. The path loss of a radio link is normally proportional to $1/r^{\alpha}$ where r is the distance between the transmitter and the receiver and α is the path loss exponent, which is normally between 2 and 4. Therefore, breaking a long link to several short links can reduce the required transmit power considerably, providing energy saving to the transmitter. Both cooperative relaying and multihop communications can be extended to more than two hops by cascading multiples of the three-node network shown in Figure 2.3. However, two-hop relaying has several desirable properties such as avoiding system complexity, reducing routing overhead and collisions, and decreasing the latency [70].

Multihop communications can also be used in cellular networks to enhance the QoS, to extend the coverage, or to improve the EE of the network. The integrated network is generally referred to as an Multihop Cellular Network (MCN) or a Hybrid Ad-hoc Network (HANET). There are two main approaches for realising MCN. In the first approach (Figure 2.5), fixed

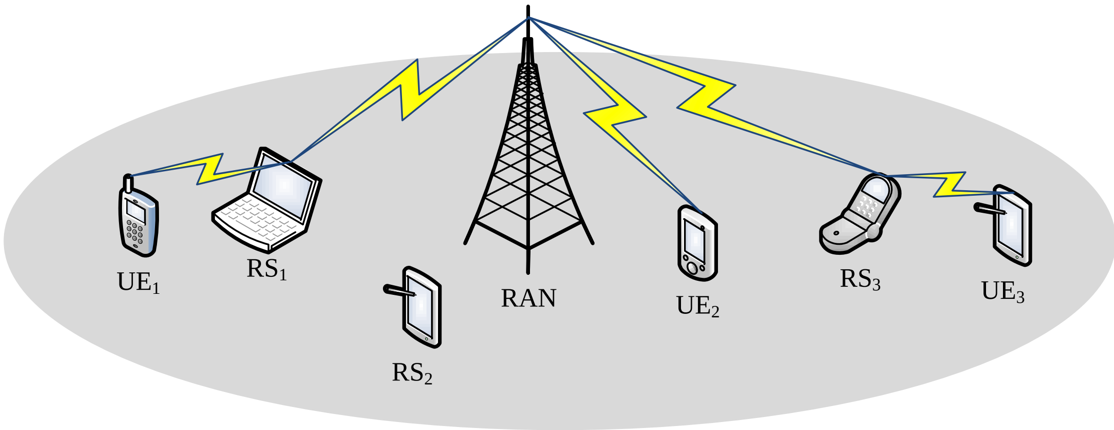


Figure 2.6: MCN with mobile RSs

Relay Station (RS) are deployed by the operator in some strategic locations – the relay stations are indeed small BSs without any cooling facility, justifying their viability in terms of both Operational expenditures (OpEx) and Capital Expenditures (CapEx). In the second approach, there is no pre-installed RSs; instead, UEs forward traffic on behalf of each other (Figure 2.6).

2.9 Cooperation Enforcement Mechanisms

Cooperation enforcement mechanisms are referred to schemes that are used to stimulate players to cooperate while mitigating the harmful threat of selfish players. These schemes can be classified into two main categories: credit-based and reputation-based schemes [71]. The former, which are also known as virtual currency based schemes [72–78], are based on remunerating cooperative nodes to ensure cooperation. Nodes get some credit as an incentive upon serving the network and use this credit to receive service from other nodes in the network. If a node runs out of credit, it will stop receiving service from other nodes. On the other hand, reputation-based schemes [79–85] use nodes' reputations to detect and isolate selfish players. Every node evaluates and maintains reputations of other nodes based on direct observation of their immediate neighbours or the exchange of reputation messages with other nodes. Behaviour of a node in response to a relaying request is monitored by other nodes. A cooperative behaviour from a node results in boosting its reputation, while a selfish behaviour leads to loosing its reputation.

Nuglets [72–77] and Sprite [78] use credit or 'micro payments' to compensate for the service that a cooperative node offers. A node receives credit for forwarding the packets of another node, and this credit is deducted from the sender (or the destination).

On the other hand, reputation-based schemes rely on neighbour monitoring to dynamically assess the trustworthiness of neighbour nodes and isolating selfish ones. Several reputation-based methods have been proposed to mitigate selfishness and stimulate cooperation in MANET such as WATCHDOG AND PATHRATER [86], CORE [80], CONFIDANT [79], OCEAN [81], SORI [82], SAFE [83] and DARWIN [84].

Finally, it is worth pointing out that there is a subtle difference between credit-based schemes and coalitional game-theoretic approaches. In the former, a player normally receives a flat credit regardless of her effort or position to the cooperation gain, while, in the later, any player receives an amount of credit proportional to her influence or contribution to the coalition payoff.

2.10 Conclusion

In this chapter, we presented the required background and definitions from game theory, microeconomics, optimisation and cooperation enforcement mechanisms. Game theory is a mathematical tool to analyse strategic interactions of rational players. As the intelligence level of mobile UEs and household appliances increases constantly, we can expect that 5G UEs and future smart home appliances will behave to a great extent like a rational player, always aiming at maximising their own payoffs. Moreover, it is envisaged that 5G will pervasively connect everyone and everything, allowing UEs to negotiate – exchanging context information and reasoning based on this information – to see if there is a mutual benefit from cooperation or not. Furthermore, it will enable smart home appliances to communicate with the utility company to enquire about the price of electricity to find the best operating interval to perform their tasks. Therefore, we find game theory as a useful tool to analyse strategic interactions of these smart devices, encourage UEs to cooperate and to predict strategic outcomes (equilibrium strategy profile) of the interactions between a set of smart home appliances and a utility company.

Chapter 3

Coalitional Games for Cooperation in 5G Mobile Networks

5G UEs are likely to be smart multimode devices supporting connectivity to multiple RANs on the move. As the density of these intelligent devices increases in typical urban environments, it becomes increasingly possible and desirable to adopt cooperative relaying strategies. In this chapter, we apply coalitional games to incentivise rational UEs to cooperate while discouraging them from acting selfishly. We further analyse how different relaying protocols and cooperation strategies among UEs can bring energy savings to the overall network. Particular strategies are to investigate how cellular working in synergy with short-range connectivity can lead to significant energy savings. Due to the proximity of cooperating devices, low energy consumption combined with high data rate can be achieved through short-range relaying. We apply coalitional game theory to model strategic interactions between UEs, allowing them to form coalitions and share their limited resources whenever profitable. We define appropriate utility functions to assess the common payoff of the coalition, and define how to distribute this common payoff among players so that all of them are satisfied. Furthermore, we address the threat of selfish players and describe how to tailor the existing credit-based schemes for our coalitional game approach to isolate selfish players from cooperative groups.

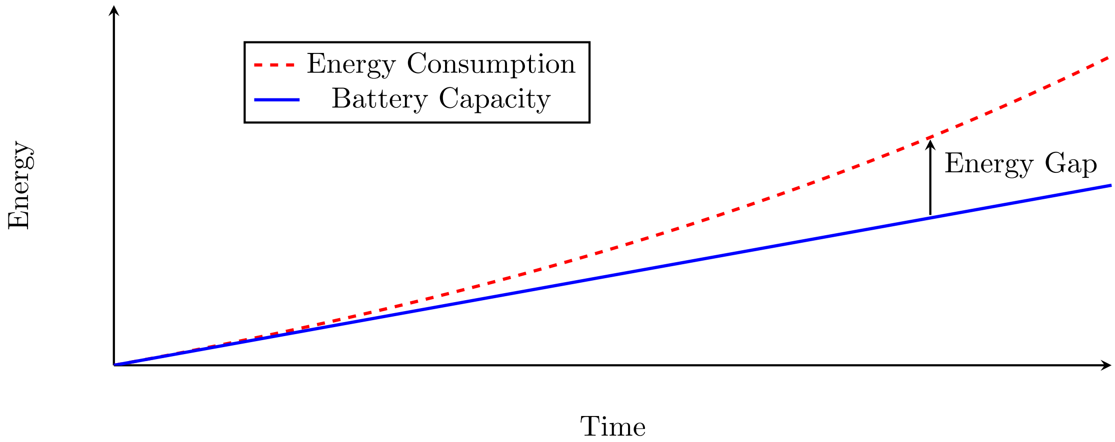


Figure 3.1: The growing 'energy gap' between battery capacity and energy consumption of User Equipments (UE)

3.1 Introduction

Battery life has indeed been identified by a TNS[1] report [87] as number one criteria of the majority of consumers purchasing a mobile phone. Reaffirming this, concern with using up battery is among the top reasons why consumers do not use advanced multimedia services (e.g., game or video) on their mobile phones more frequently. On the other hand, the evolution in battery technology is very slow comparing to the Moore's law, the average annual growth rate for the battery capacity is only 6% [88]. Thus, it is becoming a key concern that with the evolution of wireless technology, there exists a growing energy gap between actual battery capacity and the growing consumption in mobile handsets (Figure 3.1). Moreover, the current pace of technology scaling, platform improvement, and circuit design are not sufficient for bridging this gap [89]. Therefore, a clear need for energy saving strategies exists, where UEs carefully adapt their transmitter behaviour according to the dynamics of the application's requirements and the propagation conditions of the wireless channels to boost their EE, which is also important for avoiding active cooling in UEs. An issue that is of upmost concern due to power amplifier loading, leading to higher heat dissipation in handsets.

The proliferation of wireless applications and networks is driving the need for multimode UEs, which is also another factor churning up the power consumption in future emerging devices. Today, any feature phone or smart phone is equipped with a number of short-

[1]TNS is a world leader in market research, global market information and business analysis. http://www.tnsglobal.com/

range and cellular radio interfaces. Multimode UEs allow mobile users to experience higher data rates and ubiquitous connectivity. However, this comes at an expense of higher power consumption, due to multiple active interfaces.

Therefore, the power consumption dilemma introduces the need to revisit the design of the network to introduce new strategies for enhancing energy efficiency, and cooperation is a promising approach that can take a step in this direction.

The rest of this chapter is organised as follows. Section 3.2 reviews the related work. Section 3.3 describes our system model, and section 3.4 formulates our proposed coalitional relay selection game, defining the characteristic function of the game and solving it for 'core solution.' This section also introduces an energy credit function and elaborates on its application to isolate selfish players from cooperative coalitions. Section 3.5 presents algorithms for implementing our proposed relay selection game. Section 3.6 discusses the simulation results. Finally, section 3.7 concludes this chapter.

3.2 Related Work

Cooperative communication is an effective strategy to improve the efficiency of wireless networks [66]. As discussed in Section 2.8, in general, we have two forms of cooperation: multihop communications and cooperative relaying. Multihop communications have been advocated for cellular networks to improve coverage and/or QoS. The resulting network from the integration of multihop communications with cellular networks is generally referred to as MCN or HANET [77, 90, 91]. There has been considerable interest from both standardisation bodies and academia in MCNs. Opportunity Driven Multiple Access (ODMA) [92] is a multihop relaying protocol, proposed by 3rd Generation Partnership Project (3GPP) to be applied to UMTS Time Division Duplex (TDD) to: (i) increase the high data rate coverage in the network; (ii) increase the capacity of the network; and (iii) provide distributed network architecture for spot coverage and traffic hotspots. As another example, in [93], the authors integrated MANET and GSM and introduced Ad hoc GSM (A-GSM) platform, addressing practical issues contributing to the evolutionary changes of GSM in order to enable relaying of calls. Moreover, in [94], the authors overview several contributions to Working Group 4 of the Wireless World Research Forum (WWRF) and among others, present several relay-based deployment concepts such as multihop and cooperative relaying.

On the other hand, cooperative relaying has widely been investigated to improve efficiency of PHY layer, leveraging spatial diversity of the relay channels to combat the fading impairment [67–69, 95–102]. The basic idea behind this stream of works can be traced back to the groundbreaking work of Cover & El Gamal in [103] on the information theoretic characterisation of the wireless relay channel. The work builds upon a three-node (including one source node, one destination node and one relay node) channel model first introduced by Van der Meulen [104] and examines its channel capacity for the case where the channel is contaminated by an Additive White Gaussian Noise (AWGN). Spatial diversity of a relay channel can be exploited to improve the SE of the channels through distributed space-time multiplexing techniques [105, 106]. The essential advantage of cooperative relaying lies in the fact that UEs can share their antennas and form virtual MIMO channels to take advantage of the provided spatial diversity. In contrast to the transmit or receive diversity, this form of spatial diversity is generally referred to as 'cooperative diversity' [102]. Laneman et al., in [67], address different forms of cooperative relaying schemes such as AF, DF, 'selection relaying' schemes that adapt according to channel quality and 'incremental relaying' schemes that adapt based on limited feedback from destination node, examining their performance in terms of outage probabilities. Unlike this work where the authors constrain relay nodes to operate in half-duplex mode and employ TDMA scheme, Sendonaris et al. [96, 97] study the cooperation of two mobile users when both of them have data to transmit and address practical implementation issues within a CDMA system.

There are several previous research efforts on enhancing EE of multimode UEs. In [107], the authors propose a technique where Bluetooth link is exploited to wake up WLAN interface whenever there is a pending packet, avoiding unnecessary periodic wake-ups of WLAN interface. CoolSpots [108] exploits Bluetooth links not only as a wake-up channel for WLAN interfaces, but also as a data link when the application requires narrow bandwidth; WLAN interface is powered up only when the data rate reaches a certain threshold, allowing this relatively power hungry interface to spend more time in the sleep mode. A Cooperative Networking Protocol (CONET) is proposed in [109] where UEs form clusters and inside each cluster, one of cluster members is elected as the cluster head. Cluster members send their traffic to the cluster head over Bluetooth links. The cluster head then aggregates all incoming traffic from cluster members and relays the aggregate traffic to the Access Point (AP), over a WiFi link, which incurs some additional energy cost for the cluster head. To avoid the battery of the cluster head being drained all the time, the authors suggest that the role of cluster head be regularly circulated among all cluster members.

Cognitive and cooperative communications have recently been exploited to enhance EE of multimode UEs. A cognitive radio is conventionally defined as an intelligent radio that can adapt its transmitter behaviour according to the changes in the environment in which it operates to improve its efficiency in terms of resource utilisation. Traditionally, cognitive radio is used for efficient spectrum utilisation. However, recently, it has been advocated that it can also be programmed to effectively utilise other scarce resources such as the limited battery energy [110], which is a growing concern for mobile users. Lying in this stream of research, C2POWER [111] and Green-T [112] were two European research projects aiming at exploiting short-range interfaces to reduce power consumptions of multimode UEs. In [113], the authors provide quantitative analysis to study energy saving performance for different combinations of short-range and cellular technologies, namely WiMedia-WiFi, WiFi-WiMAX, and WiFi-WiFi.

In our work, we go beyond the previous works by reinterpreting the notion of cooperation as a strategic action where mobile users are players that can have potential conflicts of interest which can be solved by the application of game theory. We consider UEs partitioning themselves as coalitions. In each coalition, there can be multiple relay or multiple source UEs pooling their resources (e.g. their batteries, antennas, etc.) and communicating cooperatively. We do not intend to concentrate on performance evaluation of different cooperation techniques; instead, we aim at considering the cooperation as a strategic action and describe how potential conflicts of interest among cooperating players can be settled, using an approach based on coalitional game theory. Without loss of generality and for the purpose of exposition, we consider multihop cooperation; however, our game-theoretic approach is generic and can be applied to other cooperation techniques as well. We define the characteristic function of the game along with an appropriate utility function for assessing the profitability of the cooperation within a coalition. The technique indeed seeks to maximise the social welfare (i.e., aggregate energy saving of the UEs), while enabling their required QoS.

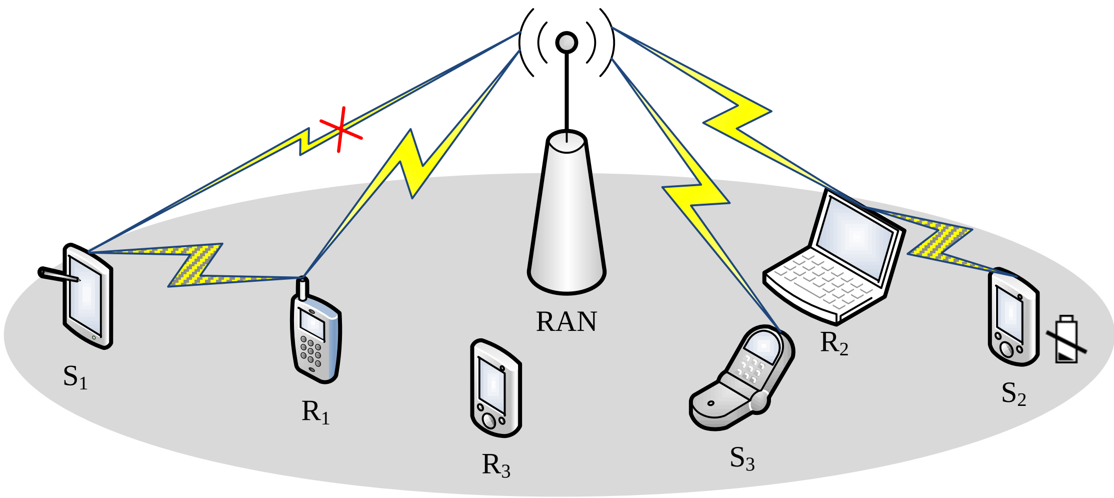


Figure 3.2: Coalitional short-range relaying, shaded links depict short-range, while the plain ones depict cellular links

3.3 System Model

Figure 3.2 illustrates our addressed scenario, where a RAN, which can represent a UMTS, LTE, WiFi, or WiMAX network, is serving multiple mobile UEs. Every UE holds two radio interfaces: one short-range (e.g., WiMedia, Bluetooth, etc.) and one cellular (e.g., LTE, WiMAX, WiFi, etc.). We assume that all UEs lie in the RAN's coverage, albeit with different channel qualities, and can send their traffic to the RAN either directly (i.e., over a conventional cellular link, or cooperatively, over a cooperative short-range relaying link, which is fundamentally a two-hop link from a source UE to the RAN. The first hop (from the source to the relay) is performed over a short-range link, while the second hop (from the relay to the RAN) is performed over a cellular link. In the scenario depicted by Figure 3.2, the shaded region shows RAN's coverage, that can be affected by path loss or shadowing phenomena. S_1 is located in a deep shadowing area, and S_2 while having good channel quality, suffers from low battery level. Therefore, they start scanning their neighbourhood with their short-range interface. As shown in the figure, S_1 discovers R_1, and S_2 discovers R_2 in their short-range coverage. After initiating a short-range session with the relays, they start relaying their traffic through them to the RAN. S_3 has a good channel quality and battery level, so it sends its traffic to the RAN over a direct link. Finally, R_3 is left unemployed, although being available as a candidate relay.

We assume that UEs can periodically sense their radio environment and can communicate with their neighbour UEs or RANs to exchange the acquired information; the frequency of sensing and context exchange generally depends on how fast the wireless medium and network topology change. Thanks to this context information, UEs become aware of their radio environment (e.g., available networks, channel qualities, nearby UEs and their available resources) and can react accordingly, akin to a cognitive radio, to reduce their power consumption. A UE may discover and join a nearby coalition, or some nearby UEs can negotiate and, when profitable, form a new coalition and adhere to a group strategy, to utilise their limited resource (e.g., battery, spectrum, etc.) more effectively. We will only consider upstream communications (from the UEs to the RAN); downstream communications can be performed over conventional single-hop links.

In a coalition, energy efficient cooperation of UEs can take place in different ways, yet energy saving performance of the coalition should outweigh the signalling and computational costs to make the coalition. A UE always needs to evaluate EE of a cooperation opportunity to choose an appropriate strategy, regarding whether to join a coalition or not or whether to communicate directly or through a relay. We use the number of bits that can be transferred spending one Joule of energy (Bits/Joule) as the EE metric of a link, which can be calculated by dividing the link's data rate by the required transmit power; i.e., $\eta_{EE} = R/P_t$ [114].

We define coalitional relay selection game as a game in which UEs form coalitions and relay each other to reduce their power consumption. There are three main challenges regarding this game. The first problem is how UEs partition themselves into coalitions. That is, whether it is better for UEs to form the grand coalition or they are better to partition themselves in mutually exclusive sets, as illustrated by Figure 3.3. To answer this question, we need to know whether the game is super-additive or not. If the game is superadditive, it is always beneficial to merge smaller coalitions and make bigger ones. Therefore, the grand coalition is trivial. However, if the game is non-superadditive, UEs need to find the best way to partition themselves in order to maximise their social welfare. The second problem regarding the coalitional relaying game is how to match relays and sources in a coalition so as to maximise the coalition's payoff-we define the payoff or the worth of a coalition as the maximum energy saving that the coalition can achieve by the cooperation of its members. Finally, the third problem regarding this game is how to incentivise relays to cooperate. As relays are normally controlled by rational players, if there is no mechanism to prevent selfish behaviour, players

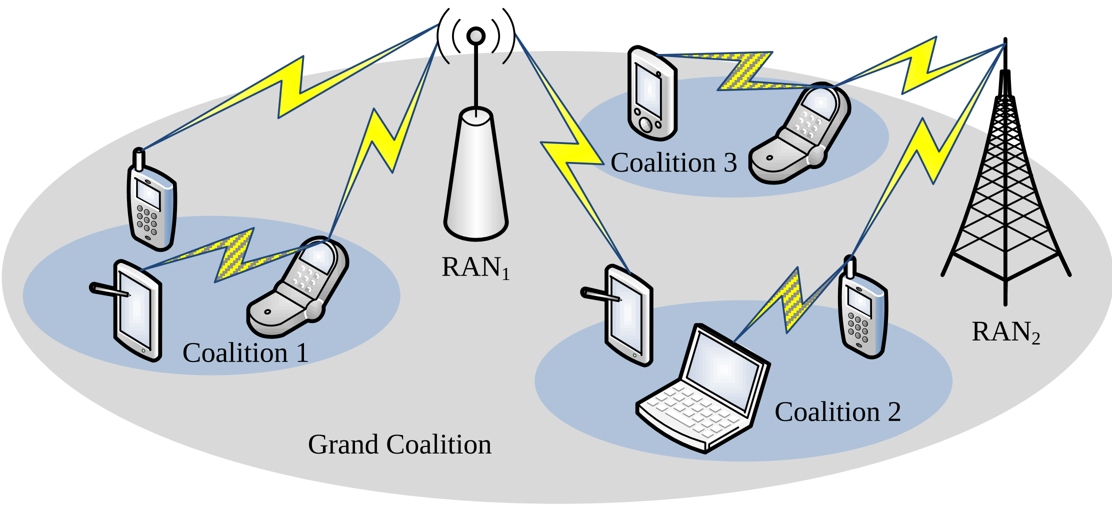


Figure 3.3: Coalition Structure Generation (CSG): partitioning UEs into coalitions

will ask others to forward their packets but refuse to forward others' packets to conserve their limited energy for their own needs. Therefore, there should be a mechanism to encourage cooperation while preventing any selfish behaviour.

As mentioned, in a non-superadditive environment, forming the grand coalition is not profitable due to the communication or computation burden associated with forming bigger coalitions. In this case, players first need to be partitioned in mutually exclusive coalitions (see Figure 3.3) in a way that their social welfare is maximised. A typical solution to this problem is to search for optimal coalition structure by performing an exhaustive search among all possible coalition structures. Nonetheless, the number of possible coalition structures, which is given by the Bell number, increases exponentially with the number of players. In fact, as stated by Proposition 1 in [115], for n players, the number of coalition structures is $O(n^n)$ and $\omega(n^{n/2})$, which means that the number of coalition structures is upper bounded by a constant factor of n^n and lower bounded by a constant factor of $n^{n/2}$. Figure 3.4 illustrates the number of possible coalition structures (i.e., the Bell number) as the number of players varies between 1 and 20 along with the associated upper and lower bounds. As apparent from the figure, exhaustive search algorithm is not computationally tractable even for moderate number of players, entailing efficient coalition structure generation algorithms. Further elaboration on designing coalition structure generation algorithms is beyond the scope of this thesis. The interested reader may refer to [115] for more discussion on the topic.

In the rest of this section, we introduce necessary parameters needed to formulate our

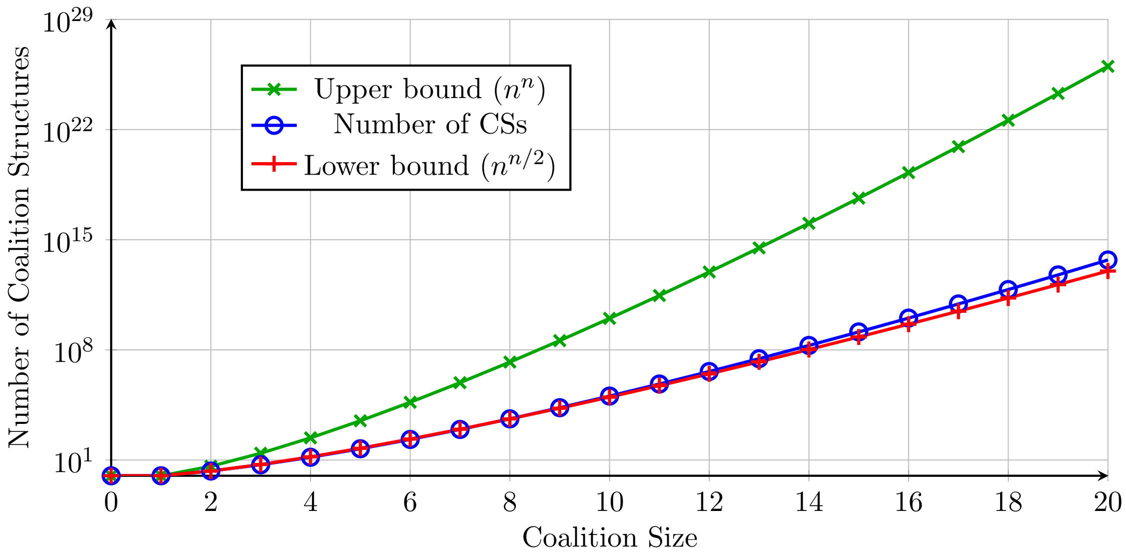


Figure 3.4: Number of possible coalition structures for different coalition sizes with its upper and lower bounds

proposed coalitional game model. Suppose that, as illustrated by Figure 3.5, we have the grand coalition $\mathcal{N}$, comprised of R relays denoted by set $\mathcal{R} = \{\mathrm{R}_1, \ldots, \mathrm{R}_R\} \subseteq \mathcal{N}$ and S source nodes denoted by set $\mathcal{S} = \{\mathrm{S}_1, \ldots, \mathrm{S}_S\} \subseteq \mathcal{N}$ where $\mathcal{R} \cup \mathcal{S} = \mathcal{N}$. A relay obviously consumes some energy for relaying a received packet. We denote the amount of energy that relay $r \in \mathcal{R}$ consumes for relaying a single bit receiving from source $s \in \mathcal{S}$, to the BS, by e_{rB}; this includes the energy consumed for receiving, processing and forwarding the received bit. We further denote the amount of energy that source $s \in \mathcal{S}$ needs to send a single bit directly to the BS by $\acute{e}_{sB}$ and the amount that it needs to send one bit to the relay $r \in \mathcal{R}$ over a short-range link by e_{sr}. These parameters are annotated on the graph model illustration in Figure 3.5. We further denote the valuation of relay $r \in \mathcal{R}$ to its own contribution, to the coalition, by c_r (in terms of energy credit) and the valuation of source $s \in \mathcal{S}$ to the cooperation of relay $r \in \mathcal{R}$, to relay one bit for it, by h_{rs}, $\forall s \in \mathcal{S}, r \in \mathcal{R}$. We interpret c_r as the amount of energy credit that relay $r \in \mathcal{R}$ expects for forwarding a single bit and h_{rs} as the amount of energy credit that source $s \in \mathcal{S}$ is willing to pay to the relay $r \in \mathcal{R}$. In our proposed model, we set $c_r = e_{rB}$ since relay $r \in \mathcal{R}$ consumes e_{rB} amount of energy totally in favour of its partner source, and it will not be satisfied unless at least its consumed energy is compensated. Generally, a source values a relay as the amount of energy saving that their cooperation can yield; the more the amount of energy saving, the more the value of the relay

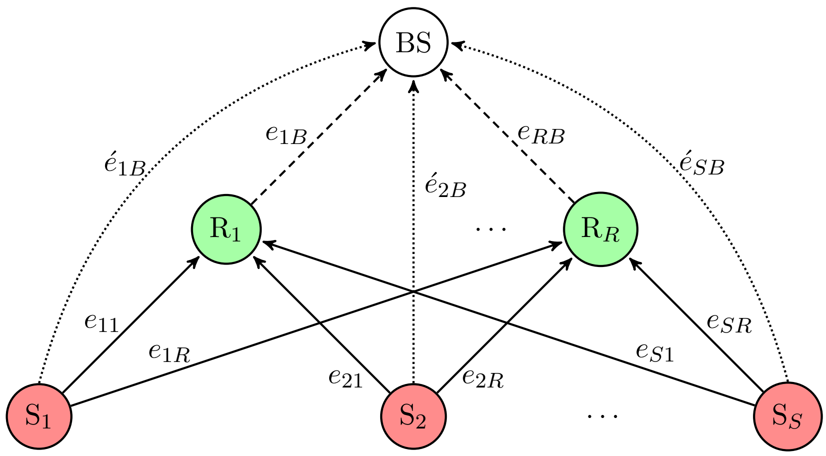


Figure 3.5: Graph model of coalitional relay selection game

for the source. Therefore, we denote the value of relay $r \in \mathcal{R}$ for source $s \in \mathcal{S}$ by h_{rs}, which we define as the difference between the energy costs of the direct link (i.e., $\acute{e}_{sB}$) and the relay link (i.e., e_{sr}); i.e.,

$$h_{rs} = \acute{e}_{sB} - e_{sr}. \tag{3.1}$$

It is worth mentioning that $h_{rs} - c_r$ yields the gross energy saving (i.e., excluding the signalling cost) of the cooperation between relay $r \in \mathcal{R}$ and source $s \in \mathcal{S}$. If $h_{rs} - c_r > 0$, then it may be favourable for both partners (i.e., relay and source) to cooperate since any arbitrary division of the achieved energy saving between them will make both of them better off. We do not however assume that this inequality holds for all combinations of sources and relays, nor in any combination at all. In fact, if this inequality fails for a pair of partner nodes, it implies that for these nodes, direct communication is more energy efficient than the cooperative communication. Therefore, they will avoid cooperation.

3.4 Coalitional Relay Selection Game

In this section, we formulate the problem as a coalitional game in characteristic function form (Section 2.5). In the following, we first define the characteristic function of the game; then, we derive its *core* solution (Section 2.5.1) and discuss how to update energy credits of the players, using this solution.

3.4.1 Characteristic Function

For an arbitrary coalition $\mathcal{T} \subseteq \mathcal{N}$, we define the characteristic function $v(\mathcal{T})$ as the maximum aggregate energy saving that the UEs lying inside $\mathcal{T}$ can achieve by their cooperation. Recall that $\mathcal{R} = \{1, \ldots, R\} \subseteq \mathcal{N}$ denotes the set of relays and $\mathcal{S} = \{1, \ldots, S\} \subseteq \mathcal{N}$ denotes the set of sources and that $\mathcal{R}$ and $\mathcal{S}$ are mutually exclusive since we assume that only idle UEs can act as relays. Furthermore, $\mathcal{R} \cup \mathcal{S} = \mathcal{N}$. To begin with, it is obvious that

$$v(\mathcal{T}) = 0 \text{ if } |\mathcal{T}| = 0 \text{ or } 1. \tag{3.2}$$

where the absolute value sign denotes the set's cardinality[2]. This makes sense since when a coalition is empty or consists of only one UE, there is no possibility for cooperation. Hence, there is no energy saving for coalition, zero value for the characteristic function. More generally, we observe that any one-sided coalition (i.e., a coalition composed of only relays or only sources) will again lead to no energy saving. Thus,

$$v(\mathcal{T}) = 0 \text{ if } \mathcal{T} \cap \mathcal{R} = \emptyset \text{ or } \mathcal{T} \cap \mathcal{S} = \emptyset. \tag{3.3}$$

In other words, only mixed coalitions of relays and sources can result in energy saving. The best a mixed coalition can do is to split up into separate cooperating pairs (i.e., relays and sources) and pool the achieved energy saving.

The simplest kind of a mixed coalition consists of two players, one of each type. To determine the characteristic function for such a coalition, we define the utility as a weighted function of the energy saving and the battery life extension that the UEs can achieve by their cooperation. We define the energy saving and the battery life extension as follows. The former is simply the amount of energy that is saved with the cooperation. The latter is the amount of battery life time extension that the UE having the minimum battery level in the coalition (i.e., either the source or the relay) attains after cooperation. Note that the utility is always non-negative because the nodes will act individually if no profit (either energy saving or battery life extension) is resulted from the cooperation.

Putting formally, the worth of a mixed coalition composed of relay $r \in \mathcal{R}$ and source $s \in \mathcal{S}$

[2]Cardinality of a set is defined as the number of elements in the set.

(i.e., when $\mathcal{T} = \{r, s\}$) is given by

$$v(\{r, s\}) = \alpha\bar{\gamma}_{rs} + (1-\alpha)\bar{\lambda}_{rs} \; \forall r \in \mathcal{R}, s \in \mathcal{S}, \tag{3.4}$$

where α is the weighting factor, which is a fraction between 0 and 1. $\bar{\gamma}_{rs}$ and $\bar{\lambda}_{rs}$ are, respectively, the normalised energy saving and the normalised battery life extension achieved from cooperation of these two nodes. Here, *normalisation* simply means that $[\bar{\gamma}_{rs}]_{R\times S}$ and $[\bar{\lambda}_{rs}]_{R\times S}$ are normalised matrices. That is,

$$\bar{\Gamma} = \frac{\Gamma}{|\gamma_{rs}|_{\max}} \tag{3.5a}$$

$$\bar{\Lambda} = \frac{\Lambda}{|\lambda_{rs}|_{\max}}. \tag{3.5b}$$

The energy saving of the cooperation is given by

$$\gamma_{rs} = \max[0, h_{rs} - c_r] \text{ if } r \in \mathcal{R} \text{ and } s \in \mathcal{S}. \tag{3.6}$$

This equation basically reflects the fact that if the direct link for source $s \in \mathcal{S}$ is more energy efficient than the relay link (i.e, $h_{rs} - c_r < 0$), the source avoids the relay path and communicates with the RAN directly, using its cellular interface. In this case, $v(r, s) = 0$. Likewise, the battery life extension achieved by the cooperation is given by

$$\lambda_{rs} = \max[0, B_{r,s} - \acute{B}_{r,s}], , \tag{3.7}$$

where $B_{r,s}$ is the minimum of the (remaining) battery levels of the source s and the relay r after performing the cooperation, while $\acute{B}_{r,s}$ is the same quantity without cooperation (i.e., if the communication were to be performed directly). Again, if cooperation leads to no battery life extension, the second argument of the maximisation operation in Eq. (3.7) will be negative. This leads to $\lambda_{rs} = 0$, which implies that it is efficient that the communication be performed over the direct link.

Now, we introduce a new matrix $U = [u_{rs}]_{R\times S}$ where $u_{rs} = v(r, s)$ – we denote $v(\{r, s\})$ as $v(r, s)$ in a slight abuse of notation – is the potential utility (i.e., worth) that can be obtained from cooperation of source s, $s = 1, \ldots, S$, and relay r, $r = 1, \ldots, R$. This matrix indeed summarises potential utility of all possible pairings of relays and sources, for the grand coalition $\mathcal{N}$. In order to compute v for a larger mixed coalition, we must optimally assign available relays to the sources, maximising coalition's worth, which is the aggregate utility of the coalition. Mathematically this can be represented as

$$v(\mathcal{T}) = \max\left[u_{r_1 s_1} + \cdots + u_{r_k s_k}\right]. \tag{3.8}$$

The maximisation is taken over all arrangements of $2k$ distinct players $r_1,\ldots,r_k$ in $\mathcal{T} \cap \mathcal{R}$ and $s_1,\ldots,s_k$ in $\mathcal{T} \cap \mathcal{S}$, where $k = \min\left[|\mathcal{T} \cap \mathcal{R}|, |\mathcal{T} \cap \mathcal{S}|\right]$. We refer to the evaluation of this maximisation problem, which is in general an *assignment problem* [116], as *relay selection problem*.

Recall that we assume that the game is superadditive, so players save more energy as the coalition size increases, encouraging them to build the biggest coalition possible, i.e., the grand coalition. Therefore, the game will result in only one coalition, the grand coalition. Thus, we need to formulate relay selection problem only for the grand coalition.

3.4.2 Relay Selection Problem

We formulate relay selection problem for the *grand* coalition, $\mathcal{N} = \mathcal{R} \cup \mathcal{S}$, as a binary LP problem (Section 2.6.1). To do so, let us consider RS binary decision variables as follows:

$$x_{rs} = \begin{cases} 1 & \text{if relay } r \in \mathcal{R} \text{ is assigned to source } s \in \mathcal{S} \\ 0 & \text{otherwise} \end{cases}$$

$\forall r = 1, \ldots, R$, $s = 1, \ldots, S$. Any x_{rs} indicates a yes/no decision in response to whether relay $r \in \mathcal{R}$ should be assigned to source $s \in \mathcal{S}$ or not. That is, the relay selection problem is essentially a binary decision making problem. We illustrate this in a graph model depicted by Figure 3.6. In this graph, $x_{rs} = 1$ means that relay r is connected to source s. Conversely, $x_{rs} = 0$ means that there is no edge between these two vertices. Relay selection problem can now be written as a binary LP problem as follows.

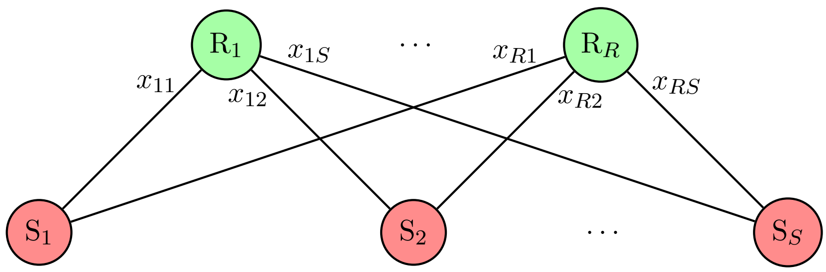


Figure 3.6: Relay selection problem as a binary decision making problem

$$
\begin{aligned}
\underset{x}{\text{maximise}} \quad & \sum_{r\in\mathcal{R}}\sum_{s\in\mathcal{S}} u_{rs}x_{rs} && \text{(3.9a)}\\
\text{subject to:} \quad & \sum_{s\in\mathcal{S}} x_{rs} \leq 1, \quad r = 1,\dots,R && \text{(3.9b)}\\
& \sum_{r\in\mathcal{R}} x_{rs} \leq 1, \quad s = 1,\dots,S && \text{(3.9c)}\\
& x_{rs} \in \{0,1\},\ \forall r\in\mathcal{R}, s\in\mathcal{S} && \text{(3.9d)}
\end{aligned}
$$

In this optimisation problem, the first set of constraint inequalities, defined by Eq. (3.9b), simply governs that any relay can be assigned to at most one source because we assume that every relay can relay only one source at any time. In other words, any relay, in the graph, is either connected to only one source or left unconnected. In contrast, the second set of constraint inequalities, defined by Eq. (3.9c), reflects the two-hop constraint. That is, any source can employ at most one relay – of course it may communicate directly without employing any relay. The optimal value of this primal LP problem (i.e., p^*) gives the maximum energy saving or equivalently the characteristic value of the grand coalition $\mathcal{N}$, composed of R relays and S sources (i.e., $v(\mathcal{N})$). That is,

$$p^* = v(\mathcal{N}), \tag{3.10}$$

The standard form of this LP problem can be written as follow:

$$
\begin{aligned}
\underset{x}{\text{maximise}} \quad & u^T x \\
\text{subject to:} \quad & Ax \preceq b \\
& x \succeq 0
\end{aligned} \tag{3.11}
$$

$$
\begin{array}{cc}
 & \overbrace{\hspace{20em}}^{R} \\
 & \overbrace{\hspace{5em}}^{S}\quad \overbrace{\hspace{5em}}^{S}\qquad\quad \overbrace{\hspace{5em}}^{S} \\
\begin{array}{c} R\left\{\begin{array}{c} \\ \\ \\ \\ \\ \end{array}\right. \\ S\left\{\begin{array}{c} \\ \\ \\ \\ \\ \end{array}\right. \end{array}
&
\left[\begin{array}{cccc:cccc:c:cccc}
1 & 1 & \ldots & 1 & 0 & 0 & \ldots & 0 & \ldots & 0 & 0 & \ldots & 0 \\
0 & 0 & \ldots & 0 & 1 & 1 & \ldots & 1 & \ldots & 0 & 0 & \ldots & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & \ldots & 0 & 0 & 0 & \ldots & 0 & \ldots & 1 & 1 & \ldots & 1 \\
\hdashline
1 & 0 & \ldots & 0 & 1 & 0 & \ldots & 0 & \ldots & 1 & 0 & \ldots & 0 \\
0 & 1 & \ldots & 0 & 0 & 1 & \ldots & 0 & \ldots & 0 & 1 & \ldots & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & & & \ddots & \\
0 & 0 & \ldots & 1 & 0 & 0 & \ldots & 1 & \ldots & 0 & 0 & \ldots & 1
\end{array}\right]
\end{array}
$$

Figure 3.7: Structure of matrix A introduced in Eq. (3.11)

where A is a sparse matrix illustrated by Figure 3.7 and b is a column vector with length $R+S$ all elements of which are equal to 1. u^T (where superscript T indicates matrix transpose) is a row vector with length RS composed of the concatenation of rows of matrix U, defined in the previous subsection. That is, $u^T = [u_1^T, \ldots, u_R^T]$, where u_r^T is the r^{th} row of the matrix U.

3.4.3 Core Solution

Relay selection game is essentially an *assignment game*, and its core solution is derived by the following theorem [116].

Theorem 3.1. *The core of coalitional relay selection game is precisely the set of solutions of the dual LP problem of the corresponding primal relay selection problem.*

Though this theorem has been originally proposed and proved by Shapley & Shubik, in [116], we summarise their proof, putting it into the wireless communications context. The dual of the primal LP problem defined by Eq. (3.11) can be written as follows.

$$
\begin{aligned}
\underset{y}{\text{minimise}} \quad & b^T y \\
\text{subject to:} \quad & A^T y \succeq u^T \\
& y \succeq 0
\end{aligned}
\tag{3.12}
$$

This dual LP problem has $R+S$ decision variables denoted by vector $y \in \mathbb{R}^{R+S}$ as follows

$$y = [w_1, \ldots, w_R, z_1, \ldots, z_S].$$

where w_r denotes the payoff allocated to relay r, $r = 1, \ldots, R$ and z_s denotes the payoff allocated to source s, $s = 1, \ldots, S$. Furthermore, this dual problem has RS constraints as follows

$$w_r + z_s \geq u_{rs} \ \forall r \in \mathcal{R} \text{ and } \forall s \in \mathcal{S}. \tag{3.13}$$

The objective function of this dual LP problem is simply the summation of the allocated payoff to all players; i.e.,

$$b^T y = \sum_{r \in \mathcal{R}} w_r + \sum_{s \in \mathcal{S}} z_s \tag{3.14}$$

According to the duality theorem [63], the duality gap for LP problems is zero, so the optimal value of the dual LP problem, d^*, meets the optimal value of the primal LP problem, p^*. Hence,

$$\sum_{r \in \mathcal{R}} w_r + \sum_{s \in \mathcal{S}} z_s = d^* = p^* = v(\mathcal{N}). \tag{3.15}$$

We interpret w_r and z_s as the amount of energy credits that relay $r \in \mathcal{R}$ and source $s \in \mathcal{S}$ receive, respectively, as an incentive to cooperate. As mentioned above, p^* is the energy saving of the grand coalition $\mathcal{N}$ and vector $y = [y_1, \ldots, y_R, y_{R+1}, \ldots, y_{R+S}]$ is the distribution of this energy saving among all players composing this coalition. Eq. (3.15) suggests that y is an efficient payoff vector. Furthermore, Eq. (3.12) entails that $y \succeq 0$, which implies that payoff vector y is individually rational since $v(n) = 0 \ \forall n = 1, \ldots, \mathcal{N}$. That is, a player $n \in \mathcal{N}$ can gain no payoff when she acts individually. Moreover, according to Eqs. (3.8) and (3.13)

$$\sum_{r \in \mathcal{T} \cap \mathcal{R}} w_r + \sum_{s \in \mathcal{T} \cap \mathcal{S}} z_s \geq v(\mathcal{T}), \ \forall \mathcal{T} \subseteq \mathcal{N}. \tag{3.16}$$

which means that the payoff vector y is group rational, i.e., cannot be improved upon by any subcoalition $\mathcal{T} \subseteq \mathcal{N}$. To recap, Eq. (3.15) indicates that an optimal solution of the dual LP problem provides a payoff vector that is efficient. The individual rationality of this payoff vector is immediate from the constrain $y \succeq 0$ of the dual LP problem in Eq. (3.12). Moreover, Eq. (3.16) indicates that this efficient and individually rational payoff vector is also group

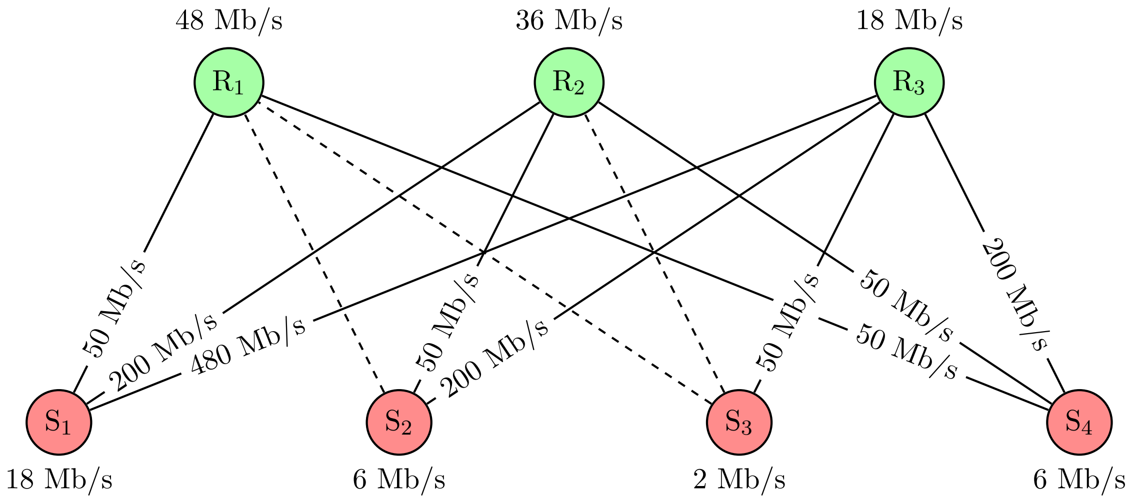


Figure 3.8: An example of relay selection problem with three relays and four sources

rational; hence, we can conclude that it is located in the core.

Example: Let us consider a scenario with three relays and four sources as illustrated by Figure 3.8. For this example, we consider WiFi (IEEE 802.11g) and WiMedia technologies for long range and short range communications, respectively. The data rates annotated around the nodes indicate their respective cellular (WiFi) data rates to RAN. The edges represent short-range (WiMedia) links; solid ones depict available short-range links, whereas the dashed ones imply that the two end nodes lie out of their short-range coverage. For example, there is no short-range connection between S_2 and R_1, while S_2 can communicate with R_3 with data rate 200 Mb/s.

For IEEE 802.11g, we assume that the transmission power is constant at 100 mW. Hence, the SNR varies with the distance between the (transmitting) UE and the (receiving) AP and with the physical characteristics of the environment, that demonstrates itself as multipath fading. The SNR variations are exploited with the Adaptive Modulation and Coding (AMC) scheme to encode bits into the transmission symbols. This results in an adaptive data rate that varies between 1 Mbps and 54 Mbps. Table 3.1 summarises the data rate of IEEE 802.11g for different distances between the transmitter and the receiver [117]. The last column of the table shows the required energy to transmit one bit of information. The energy per bit is calculated as the ratio between the transmission power, which is constant at 100mW, and the data rate.

On the other hand, for WiMedia, which is a short-range technology operating in Ultra

Table 3.1: Data rate and energy cost of IEEE 802.11g for different distances between the transmitter and the receiver

Distance (m)	**Date Rate (Mb/s)**	**Energy Cost (nJ/Bit)**
3	54	2
15	48	2
30	36	3
45	18	6
61	6	17
76	2	50
91	1	100

Wide Band (UWB) regime, the allocated frequency band is 7500 MHz unlicensed spectrum in 3.1-10.6 GHz band. In order to avoid interfering with the licensed devices operating at the same frequency band, the maximum amount of the radiation power spectral density for the unlicensed communication in this band allowed by Federal Communications Commission (FCC) is -41.3 dBm/MHz or equivalently 74.131 nW/MHz. Hence, for a UWB signal, given that the transmitted signal is spread over the whole frequency band of 7500 MHz, the maximum transmission power will be 560 μW. We assume that the transmission power of the UWB system is constant at this maximum amount, and the rate varies with the SNR variations from 53.3 Mbps up to 480 Mbps [118]. Again, the required energy to transmit one bit of information can be calculated by dividing the transmit power by the data rate.

Table 3.2 summarises valuations of the relays and sources for relaying one bit of data. The relays' valuations are just the energy cost for them to send one single bit to the RAN, which are summarised by Table 3.1. Note that these are the base (i.e., minimum) valuations, so the relays expect payoffs that are at least as large as these base valuations. In contrast, as mentioned before, the sources' valuations are figured out differently; their valuations reflect potential energy savings that relaying can bring for them as given by Eq. (3.1). Note that, in this example, we ignore the reception and the processing energy costs for the relays. However, later on, in Section 3.6, we will consider the reception costs for the relays.

Potential energy savings from all possible assignments of the relays to the sources for transmitting a single bit of data (i.e., β_{rs}) are summarised in Table 3.3, where the unique solution of the relay selection problem (i.e., the optimal assignment of the relays) is illustrated by the circled elements. As seen, the optimal solution is to assign relay 1 to source 4, relay

Table 3.2: Valuations of relays and sources for one bit relaying

Relay i	**Relay's Valuation (nJ)** c_i	**Source's Valuation (nJ)** h_{i1}	h_{i2}	h_{i3}	h_{i4}
1	2	6	0	0	17
2	3	6	17	0	17
3	6	6	17	50	17

2 to source 2 and relay 3 to source 3. Moreover, the optimal solution assigns no relay to source 1, so it has to communicate directly. The achieved energy saving from this optimal assignment is the sum of the circled numbers, which is 71 nJ, for one bit. According to Table 3.1, the required energy to communicate non-cooperatively with the RAN is 89 nJ. Hence, the achieved Energy Saving Gain (ESG) is 71/89 = 80%. The core solution, which provides a fair distribution of this 71 nJ among the UEs, is obtained by solving the dual LP problem defined by Eq. (3.12). We can inspect that the vector $y = [7, 8, 27, 0, 5, 17, 7]$, which appears as the vertical vector, w, and the horizontal vector, z, in Table 3.3, lies in the core.

Table 3.3: Coalition's energy saving and the 'core' solution (in units of nJ)

		Sources ($\mathcal{S}$) 1	2	3	4	w :
Relays ($\mathcal{R}$)	1	3	0	0	14	7
	2	2	13	0	13	8
	3	0	11	44	11	27
	z :	0	5	17	7	

3.4.4 Updating Energy Credits

The objective of the formulated relay selection problem is to maximise the aggregate payoff of the players (i.e., the UEs). This common payoff is then distributed among the UEs using the core solution of relay selection game. However, the utility – which is the amount of energy saving – is non-transferable. Only the sources save energy, while the relays are incurred some extra energy consumption. Consequently, even if the cooperation is socially desirable, relays will be reluctant to cooperate unless they are stimulated by some incentive. Although reciprocal altruism [66] can be adopted to enforce cooperation among UEs, where a relay helps others with the condition of receiving help in the future, it is highly vulnerable to potential free riding attempts from selfish nodes. Therefore, to ensure the evolution of cooperation among UEs, we need a scheme that encourages cooperative nodes while punishing the selfish ones. For this purpose, we introduce an energy credit function for each node to make a complete record of its cooperation in the network.

The energy credit function $C_r(k)$ of relay node $r \in \mathcal{R}$ at time slot k is updated as follows:

$$C_r(k) = C_r(k-1) + c_r + w_r. \tag{3.17}$$

Recall from previous section that c_r indicates the energy compensation received by relay $r \in \mathcal{R}$ and w_r indicates the amount of energy credit that is provided for this relay as an incentive to stimulate it to cooperate. It is worth mentioning that since the battery of UEs is limited, the credit that can be collected by a relay is upper bounded and cannot grow to infinity. These energy compensation c_r and the incentive w_r should be provided by the partner source. Assuming that this partner source is $s \in \mathcal{S}$, the energy credit function for it at time k is updated as follows.

$$C_s(k) = C_s(k-1) - c_r - w_r \tag{3.18}$$

Note that, in this equation, even after subtracting $c_r + w_r$ amount of energy credit from this source's account and returning it back to the relay r's credit account, the source will still be left with some amount of energy saving, z_s.

In a coalition, we can always check credit levels of the candidate sources and reject the ones that does not have enough credit. To enable UEs to start cooperation at the very beginning, one may provide an initial credit to each UE. Cooperative UEs will gain credit over time and increase their credit levels, while selfish ones will loose their initial credits and are consequently isolated from the coalition soon after.

3.5 Relay Selection Algorithms

We provide necessary algorithms to guide UEs and the RAN to play the proposed coalitional relay selection game. We start with the relay selection algorithm, which consists of two parts. The first part is performed by the UEs, and the second part is performed by the RAN.

Algorithm 3.1 Relay selection algorithm performed by a UE

START
OBTAIN the transmit power and data rate of the cellular link
FOR any UE in the coalition
    OBTAIN the transmit power and data rate of the short-range link
ENDFOR
SEND obtained information to the RAN
IF do not need relaying service
    IF do not receive any relaying command from the RAN
        GO TO START
    ELSE
        RELAY the assigned source node
        UNTIL receive a CSR_END command from the RAN
        GO TO START
    ENDIF
ELSE
    SEND CSR_REQ to the RAN
    GET ID of the assigned relay from the RAN
    ESTABLISH a Cooperative Short-Range Relaying (CSR) session with the assigned relay
    WHILE the CSR not finished AND receive no CSR_END command from the RAN
        IF have not received any command from RAN to change the relay
            KEEP the current CSR session
        ELSE
            CLOSE the current CSR session
            SEND CSR_END to RAN
            ESTABLISH a new CSR session with the new relay assigned by the RAN
        ENDIF
    ENDWHILE
    SEND CSR_END to the RAN
ENDIF
GO TO START
END

Algorithms 3.1 and 3.2 illustrate these two parts, respectively. The first algorithm consists of the procedures for a UE to collect context information such as data rates and the transmit powers of the cellular and the short-range links to send them to the RAN. It also consists of the procedures to assist the UEs to request, establish and end a CSR session. In contrast, the second part consists of procedures for the RAN to collect those context information sent by the UEs and to process and store them. It also consists of the procedures to receive and process any request for a CSR session, optimally assign available relays to the sources, obtain the core solution, and finally update the energy credits of the coalition members. Indeed, this part of the algorithm is responsible for orchestrating the cooperation by commanding

Algorithm 3.2 Relay selection algorithm performed by the RAN

START
IF receive any context information from a UE
  STORE the context information and the ID of the UE
ENDIF
IF receive CSR_END from any source
  SEND CSR_END to the relay
  OBTAIN the *core* solution of the coalitional relay selection game, defined by Eq. (3.12)
  UPDATE the energy credits of the cooperating UEs
ENDIF
IF receive CSR_REQ from any source
  SOLVE the relay selection problem, defined by Eq. (3.11)
  DETERMINE the best source-relay matching
  FOR any established matching to be dropped
    SEND CSR_END message to the source UE
  ENDFOR
  FOR any new relay-source matching
    COMMAND the relay to cooperate with the source
    COMMAND the source to establish a CSR session with the relay
    COUNT the total number of bits relayed during the CSR session
  ENDFOR
ENDIF
GO TO START
END

Algorithm 3.3 Algorithm for solving the relay selection problem

START
FOR any source node in the coalition
  CALCULATE the cellular link cost for the source, $\acute{e}_{sB}$
ENDFOR
FOR any relay in the coalition
  CALCULATE the cellular link cost for the relay, e_{rB}
  CALCULATE the cost of relaying for the relay, c_r
  FOR any source node in the coalition
    CALCULATE the cost of short-range link between the source and the relay, e_{rs}
    CALCULATE the value of the relay to the source, $h_{rs} = \acute{e}_{sB} - e_{sr}$
    CALCULATE the worth of the coalition of relay and source, defined by Eq. (3.4)
  ENDFOR
ENDFOR
DEFINE $u^T = [u_{11}, \ldots, u_{1S}, u_{21}, \ldots, u_{2S}, \ldots, u_{R1}, \ldots, u_{RS}]$
DEFINE $x = [x_{11}, \ldots, x_{1S}, x_{21}, \ldots, x_{2S}, \ldots, x_{R1}, \ldots, x_{RS}]^T$
DEFINE matrix A as illustrated by Figure 3.7
DEFINE $b = \text{ones}(R + S, 1)$
SOLVE primal LP problem defined by Eq. (3.11)
RETURN the answer, x
END

Algorithm 3.4 Algorithm to obtain the core solution

START
GET the matrices U and vectors c and b from the primal LP problem
SOLVE dual LP problem defined by Eq. (3.12)
RETURN the solution $y = [w_1, \ldots, w_R, z_1, \ldots, z_S]$
END

Algorithm 3.5 Energy credit updating algorithm

START
GET the core solution $y = [y_1, \ldots, y_R, y_{R+1}, \ldots, y_{R+S}]$
GET the total relayed traffic during the CSR session
FOR any relay node in the coalition
  GET the ID of the corresponding source node
  CALCULATE the total consumed energy by the relay during the CSR session
  ADD the calculated energy to the energy account of the relay
  REMOVE the calculated energy from the energy account of the corresponding source
  ADD the share of the relay from the saved energy to its energy account
ENDFOR
FOR any source node in the coalition
  ADD the source's share from the saved energy to its energy account
ENDFOR
END

all coalition members when and with which partner to establish a CSR session and when to terminate it. Algorithm 3.2 involves three sub-routines for solving the relay selection problem, obtaining the core solution of the game, and updating the energy credit of the players. Algorithms 3.3, 3.4 and 3.5 present these sub-routines, respectively. Algorithm 3.3 begins with calculating the cellular link costs for the relays (e_{rB}) and for the sources (e'_{sB}). As mentioned before, RAN calculates these costs by simply dividing the transmit power of the links by their corresponding data rates, collected and stored by Algorithm 3.2. Note that in a communication system, the transmit power is normally constant and the data rate changes according to the channel variations.

3.6 Performance Evaluation

For numerical validation, we perform extensive simulations both in MATLAB and NS2 environments. In the former, we try to figure out the gross ESG of a coalition, while in the latter we study the net ESG after deducting the signalling cost to form and maintain a coalition.

Table 3.4: System parameters for WiFi and WiMedia interfaces

Parameter	**WiFi**	**WiMedia**
Radiation Power	13 dBm	-52 dBm/MHz
Transmitter Power Consumption (mW)	1749	426
Receiver Power Consumption (mW)	930	356
Frequency Band (GHz)	2.40-2.4897	3.168-3.693
Carrier Frequency (GHz)	2.445	3.432
Bandwidth (MHz)	20	500
Antenna Gain (dBi)	2.2	2.2

3.6.1 MATLAB Results

Setup

For MATLAB simulations, we consider the energy saving performance of a coalition illustrated by Figure 3.2 where UEs hold a WiFi (IEEE 802.11g) interface for cellular (infrastructure-based) communications as well as a WiMedia interface for short-range communications. All system parameters are summarised in Table 3.4. For the WiFi system, the radiation power as well as the transmitter and the receiver power consumption values are according to the data sheet of the Cisco Aironet 802.11 a/b/g wireless CardBus adapter [119], and the carrier frequency and the bandwidth values are according to IEEE 802.11g standard [120, 121]. For WiMedia, the carrier frequency and the bandwidth are according to ECMA-368 standard [118], and the transmit and the receive powers are according to a sample WiMedia transceiver design proposed in [122]. According to FCC, UWB communications are allowed in the frequency band 3.1-10.6 GHz with maximum allowable radiation power spectral density of -41.3 dBm/MHz to avoid interfering with other licensed radios operating in the same frequency band. According to ECMA-368 standard, which describes the specifications for the PHY and the MAC layers of the UWB communication systems, the allocated spectrum for the UWB communications (3.1-10.6 GHz) is divided into 14 bands each of which having 500 MHz bandwidth. We assume that WiMedia system operates in the first band (3.1-3.7 GHz) and its radiation power spectral density is -52 dBm/MHz, which complies with the maximum allowed radiation power spectral density, regulated by FCC. Finally, assumed antenna gains for both WiFi and WiMedia systems are 2.2 dBi, which corresponds to a dipole antenna.

We assume Non-Line-Of-Sight (NLOS) propagation model for WiFi channels and Line-Of-Sight (LOS) propagation model for WiMedia channels. For the case of WiFi, we assume

Table 3.5: Assumed channel propagation models for WiFi and WiMedia

System	**Channel Model**
WiFi (IEEE 802.11g)	$[P_r(d)]_{dBm} = -24.8 - 50log_{10}(d) + \chi$
WiMedia	$[P_r(d)]_{dBm} = -63.8 - 17log_{10}(d)$

path loss exponent of 5, lognormal shadowing, represented by $\chi = \mathcal{N}(0, \sigma^2)$, where σ=8dBm [123]. For the case of WiMedia, we assume path loss exponent of 1.7 without any shadowing or fading defects. Table 3.5 summarises these channel models. Finally, we consider Random Way Point (RWP) [124, 125] mobility model with maximum speed of 3 m/s and pause time of 5s to take into account the nomadic mobility in an indoor scenario such as a WiFi hotspot in a coffee shop or a shopping mall for example.

In the simulations, we assume AMC scheme for both WiFi and WiMedia links. When the receiver and transmitter are close to each other, the path loss is low, so higher order modulations can be used, providing higher reliable data rates. On the other hand, when the receiver and transmitter move away from each other, the path loss increases, deteriorating the channel quality. In this case, the transmitter has to fall back to lower order modulations. In order to take into account the AMC technique in the simulations, we add the receiver and transmitter antenna gains to the transmit power (in decibels) and subtract the power loss of the channel. As a result, we come up with the received signal strength at the receiver. We compare this signal strength with the receiver sensitivity for different modulation schemes. Based on this comparison, we determine the reliable data rate of the link. Table 3.6 summarises the receiver sensitivities for both WiFi and WiMedia systems. For example, for the case of WiFi system, when the received signal strength is greater than or equal to -80 dBm, it is possible to have a reliable communication with data rate 18 Mbps. The minimum signal strength required for a reliable WiFi communication is -90 dBm, which can support reliable communication with the minimum data rate – 6 Mbps. If the signal strength drops further, an outage event will occur and no reliable communication can take place. Figure 3.9 illustrates average reliable data rates for both WiMedia and WiFi systems as the distance between the transmitter and the receiver varies between 0 and 20m. As seen from this figure, the maximum ranges of WiMedia and WiFi systems with the considered parameters and channel models are 10m and 20m, respectively. It should be pointed out that since we consider two-hop uplink communications where the first hop is performed over a WiMedia link and the second hop is performed over

Table 3.6: Receiver sensitivities for WiFi and WiMedia systems

WiFi (802.11g)		**WiMedia**	
Rate (Mbps)	**Sensitivity (dBm)**	**Rate (Mbps)**	**Sensitivity (dBm)**
6	-90	53.3	-80.8
9	-84	80	-78.9
12	-82	106.7	-77.8
18	-80	160	-75.9
24	-77	200	-74.5
36	-73	320	-72.8
48	-72	400	-71.5
54	-72	480	-70.4

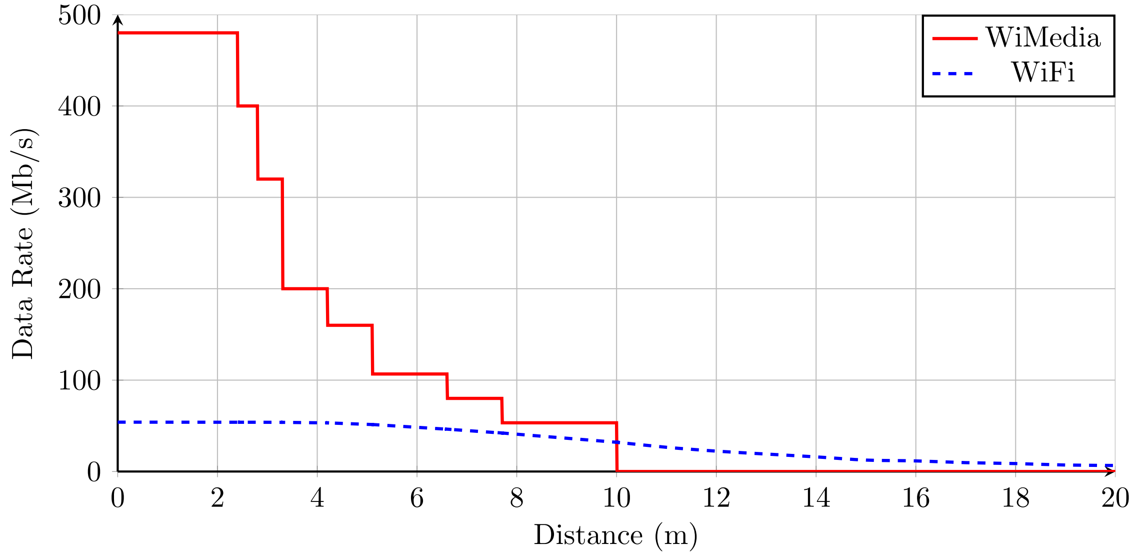


Figure 3.9: WiFi and WiMedia data rates for different distances between the transmitter and receiver

a WiFi link, the receiver of the WiFi link is an AP. Therefore, the receiver sensitivities for the WiFi system in Table 3.6 are according to the Cisco Aironet 1200 Series AP [126].

To evaluate energy saving performance, we define ESG of a coalition as the ratio of the total energy saving of the coalition to the required energy for UEs of the same coalition to act individually (i.e., communicate directly with the AP). For example, when the total energy saving of a coalition is 1J and the required energy for all member UEs to communicate without cooperation is 2J, the ESG is 0.5 or 50%.

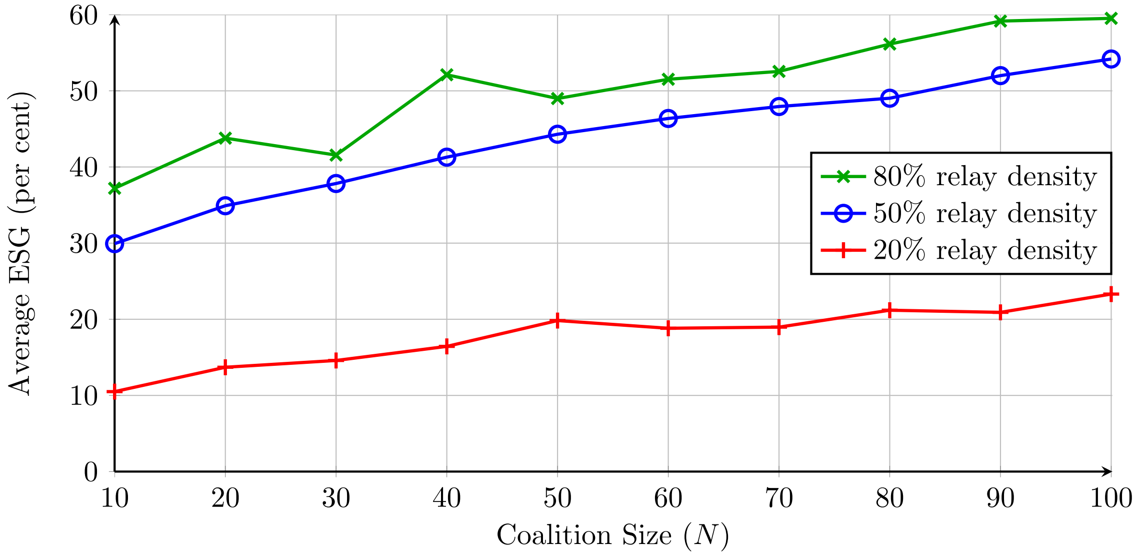


Figure 3.10: Energy Saving Gain (ESG) for different coalition sizes and relay densities

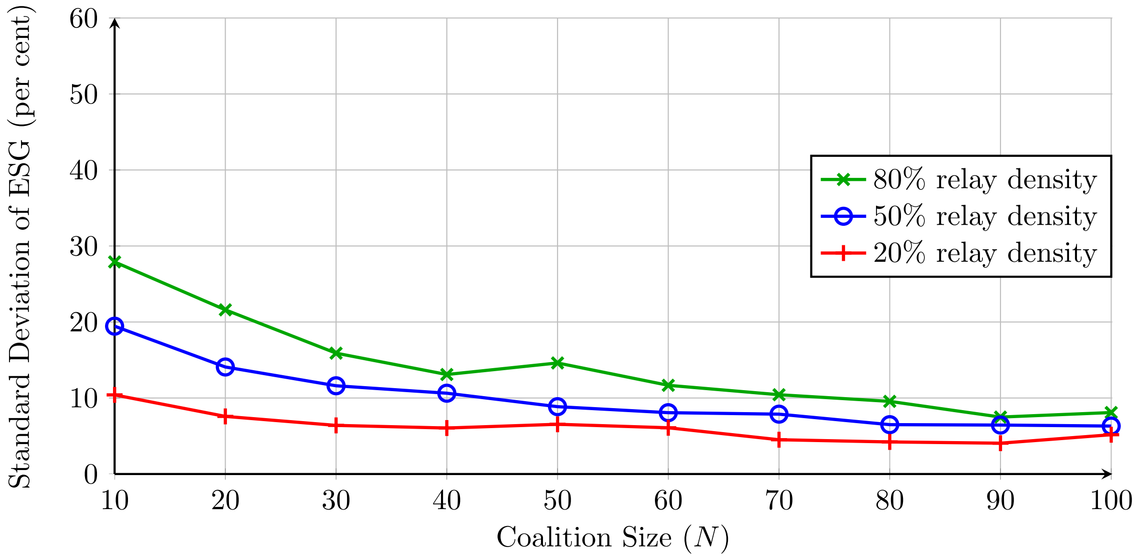


Figure 3.11: Standard deviation of ESG for different coalition sizes and relay densities

Results and Discussion

In order to evaluate the energy saving performance, we first conduct a simulation for different coalition sizes and relay densities while the weighting factor of the utility function (i.e., α) is constant at 0.5 – equal weights for the energy saving and the battery life. We vary the coalition size from 10 to 100 UEs. For each coalition size, we repeat the simulation for three different relay densities, namely 20%, 50%, and 80%. For example, when coalition size is

50 and the relay density is 20%, 10 nodes act as relays, while the rest 40 nodes act as sources. Every source node transmits with a constant rate of 10 packets per second with a packet size of 1024B (bytes). Every 10s, the roles of source and relay nodes are switched around (all relays become sources and vice versa) to give chance to every UE to act both as a source and as a relay during the simulation time. This periodic role exchange continues during the whole simulation time, which is 300s. Figures 3.10 and 3.11 illustrate average ESG and its standard deviation, respectively. Obviously, when coalition size increases, ESG increases, too, while its standard deviation shrinks. This is due to the fact that the more the number of UEs in a coalition, the more the number of opportunities for cooperation. In other words, when there are more UEs in a coalition, the chance of finding good relay-source partners increases, which increases the ESG. The decrease in standard deviation is due to the fact that the probability of finding a good partner relay increases as the coalition is populated with more UEs. The standard deviation values in Figure 3.11 in fact show the precision and reliability of the ESG values of Figure 3.10. A higher value of standard deviation shows that the ESG cannot be reliable due to its high variation from one instance to another, depending on the topology of the UEs and the wireless channel variations. Finally, as seen from Figure 3.11, when relay density increases from 20% to 50%, ESG increases significantly, yet it increases marginally when the density increases further from 50% to 80%, demonstrating a saturation trend. When the coalition size is 100 and the relay density is 80%, we achieve the maximum ESG (around 60%) with the minimum standard deviation (5%). These results can serve as a guide to choose an appropriate coalition size for a target ESG while avoiding unnecessary bigger coalition sizes to minimise the communication or computation burden.

To study the battery life extension of the UEs playing the game, we conduct another simulation with a coalition size of 50 UEs and relay density of 50% (i.e., 25 sources and 25 relays) where all UEs have equal initial battery level of 2J. The simulation runs until the first battery depletion occurs in the coalition. Figure 3.12 illustrates the battery life of the UE whose battery runs out first among the coalition members. The figure contrasts the battery life extension of this UE against a baseline scenario, where short-range WiMedia interfaces of UEs are all switched off and all communications are performed over a cellular link. As seen from this figure, cooperation is able to extend the battery life considerably. The figure presents the battery life extension for two different values of the weighting factor, namely

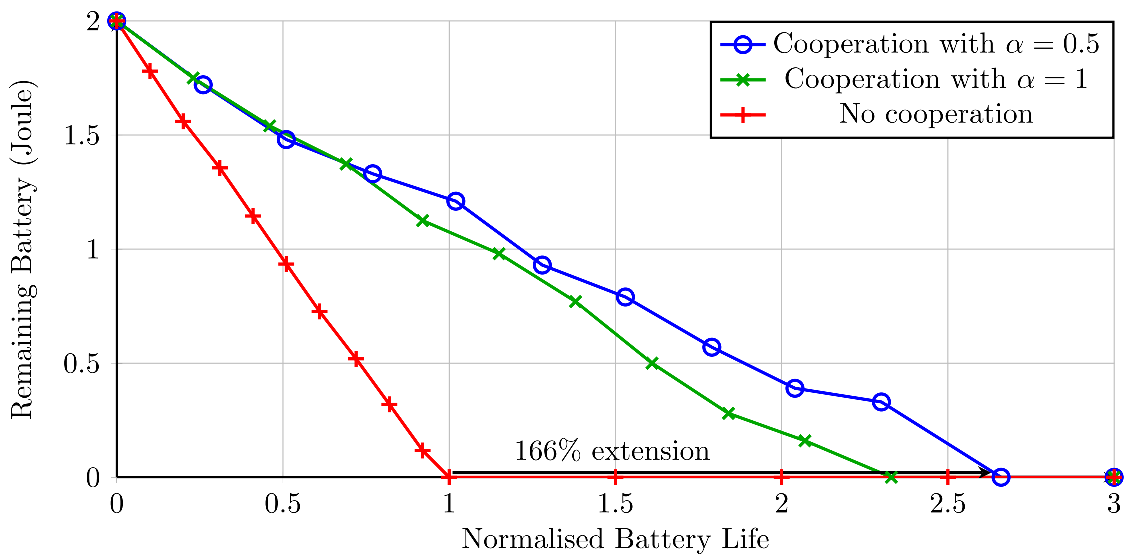


Figure 3.12: Impact of cooperative communications on battery life extension of UEs

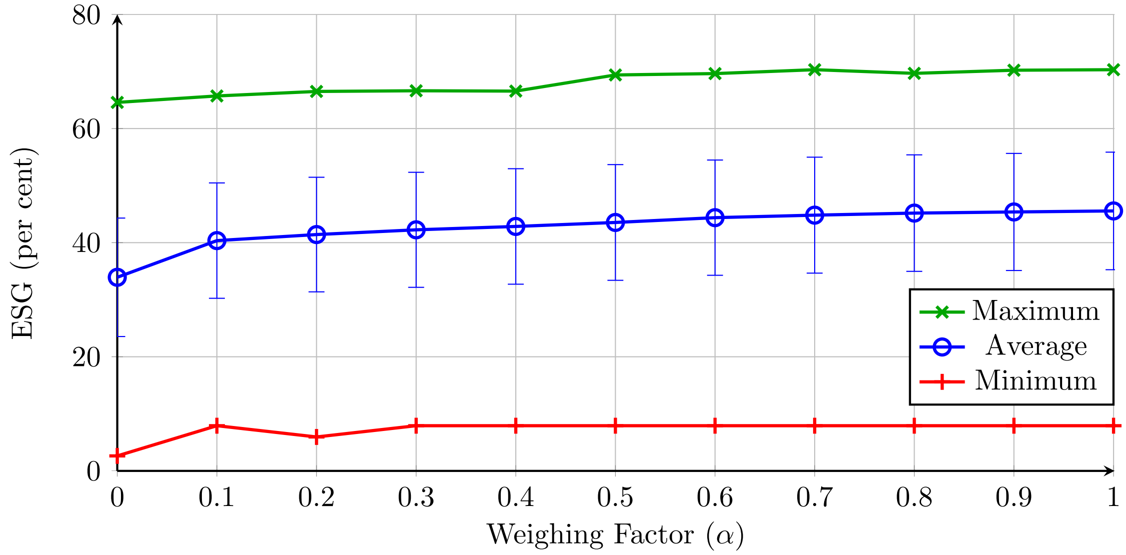


Figure 3.13: ESG for different values of utility function's weighting factor, α

$\alpha = 0.5$ and $\alpha = 1$. According to Eq. (3.4), $\alpha = 1$ only takes into account the maximisation of the energy saving of the coalition, while $\alpha = 0.5$ gives equal weights to the ESG and the battery life of the UE having the minimum battery level in the coalition. As seen from the figure, $\alpha = 1$ extends the battery life 133%, comparing to the baseline scenario, while $\alpha = 0.5$ provides 33% additional battery life extension comparing to the case of $\alpha = 1$. That is, in total, $\alpha = 0.5$ provides 166% battery life extension comparing to the baseline case. Figure 3.13 illustrates the average ESG for different values of the weighting factor α along with its maximum and minimum values. As seen from this figure, the average ESG starts from 33.9% and increases gradually until 45.6%, demonstrating 11.7% variation for the whole range variations of α (i.e., from 0 to 1), with standard deviation of around 10%. Several conclusions can be drawn from this result. First, ESG displays low sensitivity to the variations of α. Second, even the case of $\alpha = 0$ (pure battery life extension strategy) results in significant ESG (33.9%). Finally, as seen from the figure, the case of $\alpha = 0.5$ leads to 43.6% ESG. The overall conclusion that we can draw from Figures 3.12 and 3.13 is that choosing a moderate value of 0.5 for the weighting factor leads to a negligible reduction in the ESG (only 2.1%), while resulting in significant battery life extension (up to 33%), comparing to the case of $\alpha = 1$.

In order to evaluate the effectiveness of the proposed credit scheme to detect and isolate selfish players, we conduct a different simulation with a coalition size of 50 UEs and the relay density of 50% (i.e., 25 out of 50 UEs act as sources and the rest 25 act as relays); among them, 5 nodes are selfish, while the rest 45 are cooperative nodes. The simulation starts with all UEs having equal initial battery of 2J and initial credit of 0.1. Similar to the previous simulation, every source node sends 10 packets per second with packet size of 1024 bytes, but different from the previous simulation, and every 10s, the sources and the relays change their roles, giving chance to every UE to act as both a relay and a source equally likely. The simulation lasts until all UEs run out of power. Figures 3.14 and 3.15 compare average battery and credit levels of cooperative and selfish nodes, respectively. As seen from Figure 3.14, on average, battery of a cooperative node lasts about 40% more than the battery of a selfish node. As shown by Figure 3.15, all UEs start with an equal initial credit (i.e., 0.1). Cooperative nodes increase their credit level, while selfish nodes lose their initial credit soon and are isolated from the coalition accordingly. As seen from Figure 3.14, the battery level of the selfish and the cooperative nodes depletes with almost the same pace in the beginning since selfish nodes still have credit in the beginning. However, soon after, selfish nodes are left without credit. This is the time when other nodes avoid cooperating with them; consequently, their battery starts to deplete faster than the cooperative ones.

Figure 3.16 illustrates ESG for three different numbers of relay nodes as the number of source nodes increases from 1 to 30. This figure shows that, for a given number of source nodes, ESG increases as the number of relays increases. Moreover, for a constant number

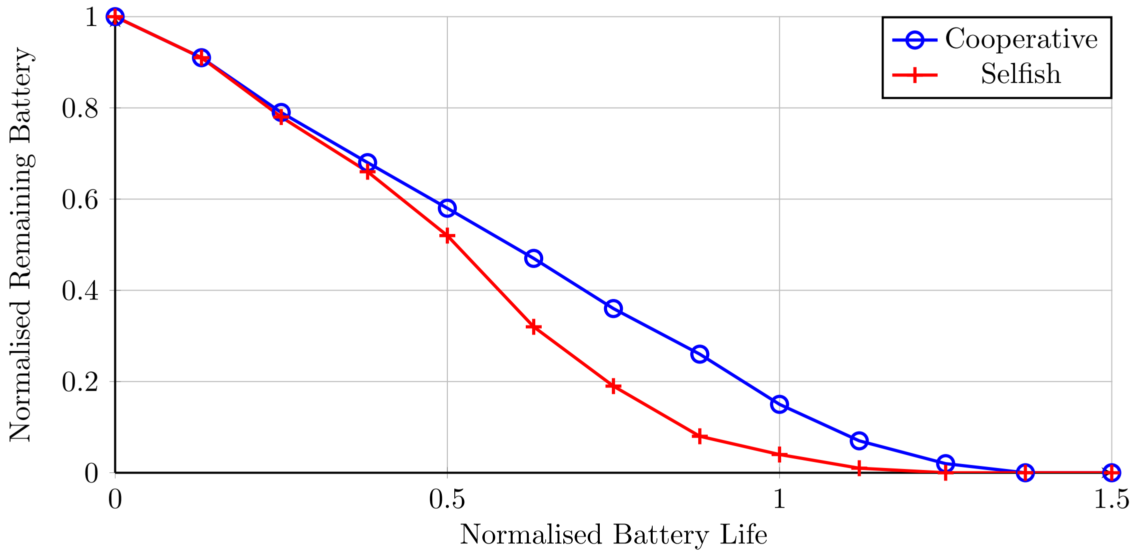


Figure 3.14: Comparing battery lives of cooperative and selfish UEs

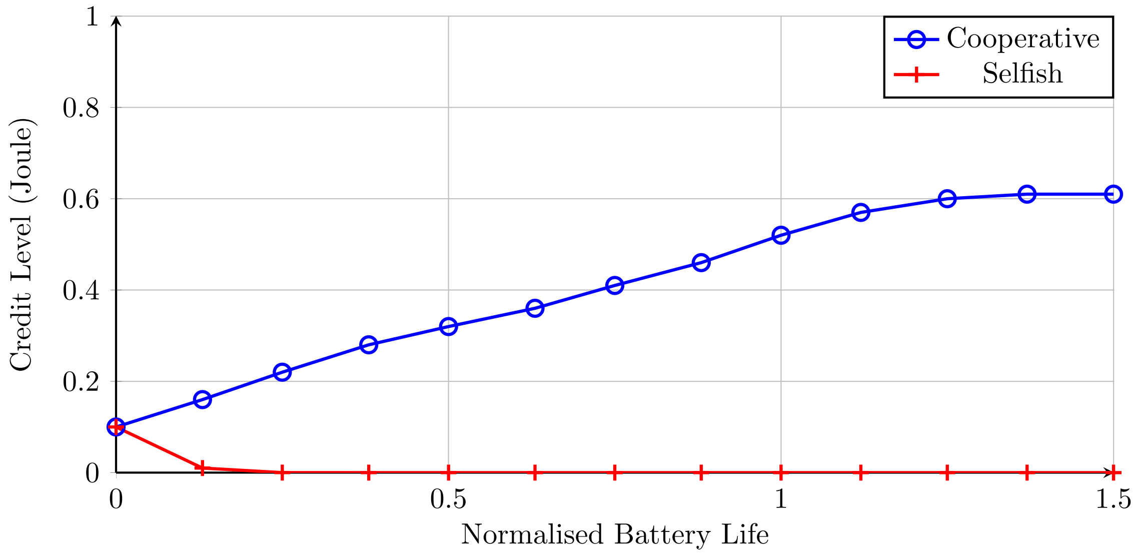


Figure 3.15: Comparing credit levels of cooperative and selfish UEs

of relay nodes, as the population of source nodes increases, ESG increases in the beginning, but it starts to saturate afterwards. In contrast, Figure 3.17 illustrates ESGs obtained by the coalition for three different numbers of source nodes when the number of relay nodes increases from 1 to 30. This figure demonstrates that the ESGs are similar for the cases with 10 and 15 source nodes, while the performance with 5 source nodes is slightly lower than the other two cases. Comparing Figures 3.16 and 3.17 reveals that for a fixed number of source nodes, ESGs increase as the number of relay nodes increases. Nevertheless, for a fixed number of

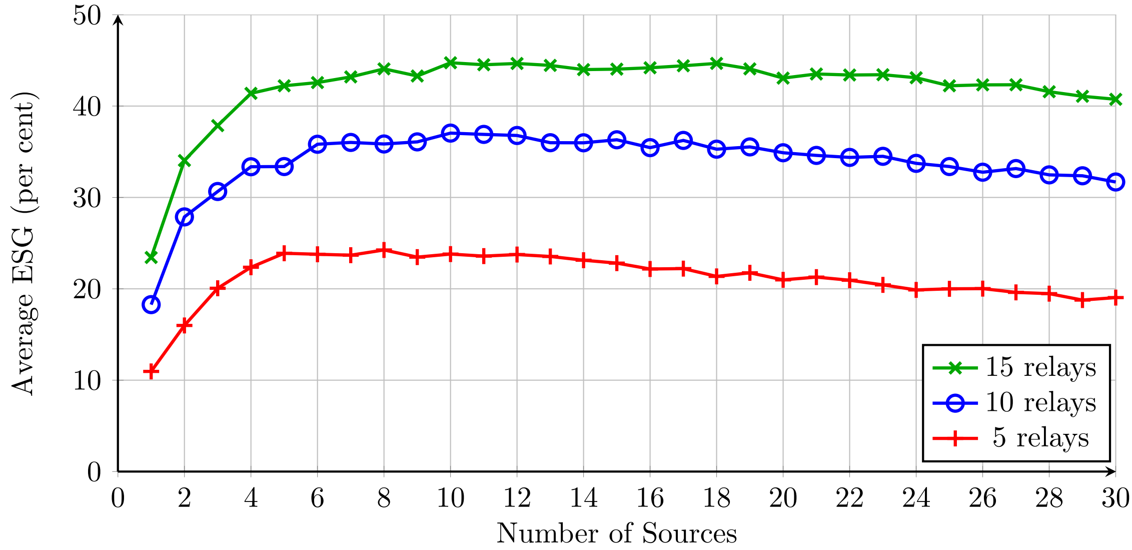


Figure 3.16: ESG of a coalition for 5, 10 and 15 relay nodes when the number of source nodes varies from 1 to 30

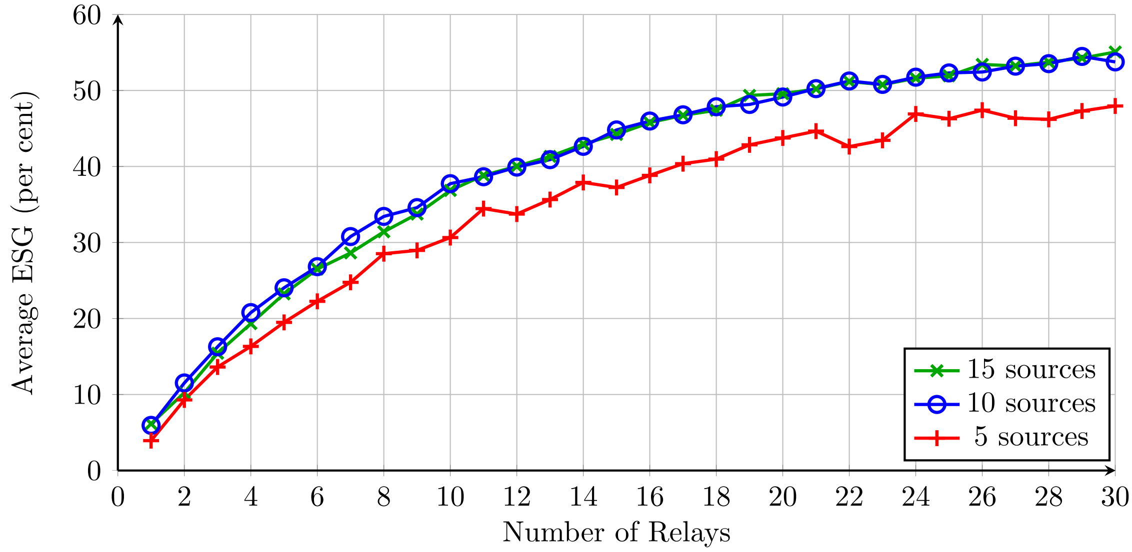


Figure 3.17: ESG of a coalition for 5, 10 and 15 source nodes when the number of relay nodes varies from 1 to 30

relay nodes, ESGs are saturated in the early stages and remain unchanged despite introducing more relays.

In order to study the effect of mobility on ESG, we vary maximum speed of RWP mobility model from 0 (i.e., static scenario) to 50 m/s (i.e., extremely dynamic). Throughout this simulation, we keep α and the pause time constant at 0.5 and 5s, respectively. Figure 3.18

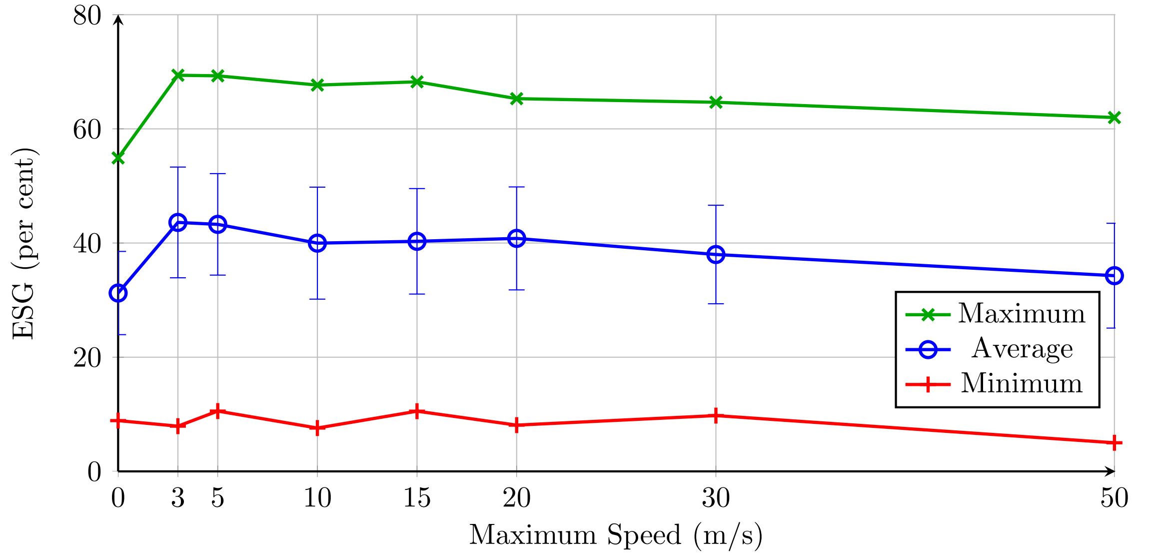


Figure 3.18: ESG for different values of the 'maximum speed' of Random Way Point (RWP) mobility model for the UEs ($\alpha = 0.5$, pause time= 5s, R=25, S=25)

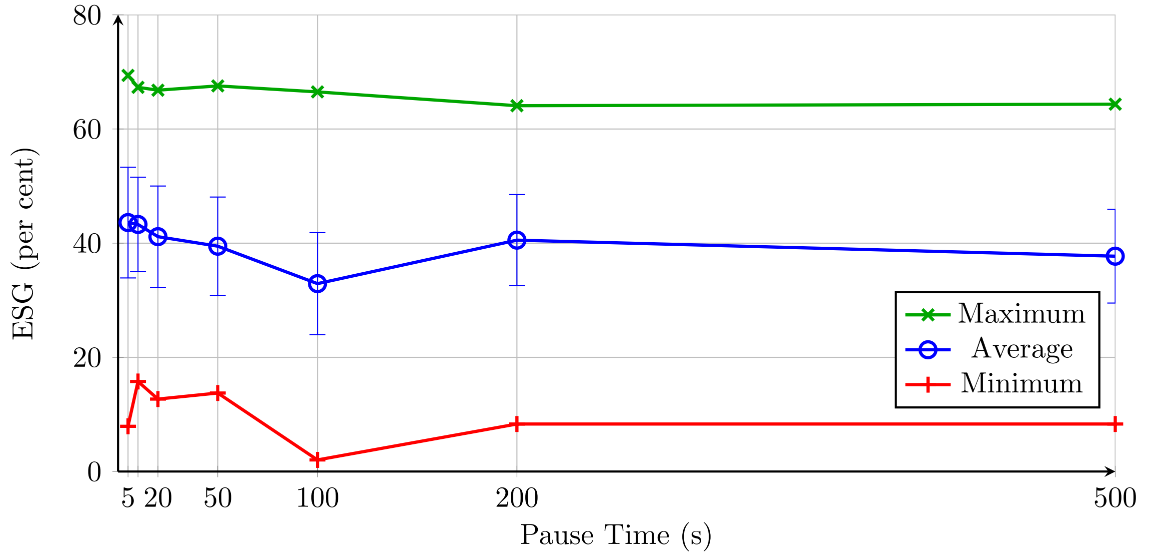


Figure 3.19: ESG for different values of the 'pause time' of RWP mobility model for the UEs ($\alpha = 0.5$, maximum speed= 3 m/s)

shows the result of this simulation. As seen from this figure, ESG starts from 31.2% (for the static case) and increases to 43.6% as the maximum speed reaches 3 m/s. Afterwards, ESG gradually decreases as the maximum speed increases and settles at 34.3% for the case of extreme mobility (i.e., when maximum speed of the nodes is 50 m/s). The standard deviation of ESG is again around 9% for this simulation. This result shows that although the potential for energy saving is higher in a mobile scenario, comparing to a static scenario, the ESG does not increase as the maximum speed exceeds 3m/s. Finally, Figure 3.19 shows the result when α and the maximum speed are constant at 0.5 and 3 m/s, respectively and the pause time varies from 5s to 500s. The ESG starts from 43.6% for the pause time of 5s and demonstrates negligible sensitivity to the variation of pause time, settling at 37.7% for the pause time of 500s. The standard deviation of ESG is around 9% for this simulation. The overall conclusion that we can draw from Figures 3.18 and 3.19 is that the ESG is almost insensitive to the variation of the pause time and the maximum speed, except for the speeds up to 3 m/s.

All in all, our simulation results demonstrate that ESG depends not only on the total number of UEs in a coalition, but also on the percentage of the relay nodes. When the coalition size increases, both the communication overhead due to context exchange (for negotiation between the UEs) and the computation time for solving the primal and the dual LP problems, defined by Eqs. (3.11) and (3.12), respectively, increases. Therefore, to keep the running time and the communication overhead of the cooperation at a practical level while ensuring a reasonable ESG, a moderate coalition size of 30 to 50 nodes is recommended. Finally, as an instance, for a coalition composing of 25 relay nodes and 25 source nodes, cooperative communication can extend average battery life of UEs to more than double while successfully detecting and isolating selfish nodes from the coalition.

3.6.2 NS-2 Results

Setup

The previous results (in MATLAB) showed the gross ESG, without considering the negotiation cost to form a coalition. To study the **net** ESG, we perform additional simulations in NS2. Our setup for these simulations is quite different from the one for the previous (MATLAB) simulations. Note that this is just an exemplary choice, and any combination of technologies could be considered. We choose this combination for the sake of their available patches in NS2. For instance, here, we consider the combination of WiFi (for short-range communications) and WiMAX (for cellular communications) interfaces. Table 3.7 shows the assumed power consumption values for each interface in each state; we consider three possible states for each interface, namely Transmission (Tx), Reception (Rx), and Idle. We consider a

Table 3.7: Power consumptions of short-range and cellular interfaces in different states

Interface	Power Consumption (mW)		
	Tx	Rx	Idle
Short Range	890	890	256
Cellular	2409	1485	660

stationary environment (without any mobility), which is an adequate model for various cases like users' using their mobile devices at coffee shops, restaurants, airports, offices, etc. We consider two rectangular cells with sizes 20 m×20 m and 60 m×60 m. The RAN is placed at the centre of the cell and the nodes are deployed randomly in the simulation area. The number of nodes varies between 2 and 20 nodes. For the traffic model, we consider Constant Bit Rate (CBR) traffic, with packet size 1024 B (bytes) and rate 3000 pps (packets per second), where every node generates traffic. Two types of traffic are considered: Traffic 1 in which the simulation time (100 s) is equally divided among the mobile nodes (as time slots); in these time slots, participating nodes transmit one by one; i.e., only one node transmits at each time slot. In contrast, in Traffic 2, node 1 transmits from slot 1 onwards; node 2 transmits from slot 2 onwards; and so on. That is, at the last time slot, all nodes are transmitting. Every 5 s a beacon is broadcast to update the nodes with the context information about the neighbour nodes as well as the short-range and cellular data rates of them. The timeout period is 15 s; that is, nodes remove entries in their neighbour list in case no beacon has been received within this period. Data rates of the short-range links vary between 6 Mbps and 54 Mbps, while that of the cellular links fluctuates between 3.8 Mbps and 56 Mbps, depending on the channel condition. Finally, in these simulations, we set the weighting factor (α) in the utility function defined by Eq. (3.4) equal to zero, to figure out the maximum ESG that can be achieved by a coalition.

Results and Discussion

Figures 3.20 to 3.24 show the net ESG obtained from our proposed coalitional game theory solution for the node selection algorithm. The gains are due to employing correlative strategy using a single intermediate relay. All the results represent average values over 10 replicas with random seeds. As for the simulation scenario, nodes are randomly deployed. There is only one BS in the centre of the cell and the UEs are deployed uniformly in a rectangular

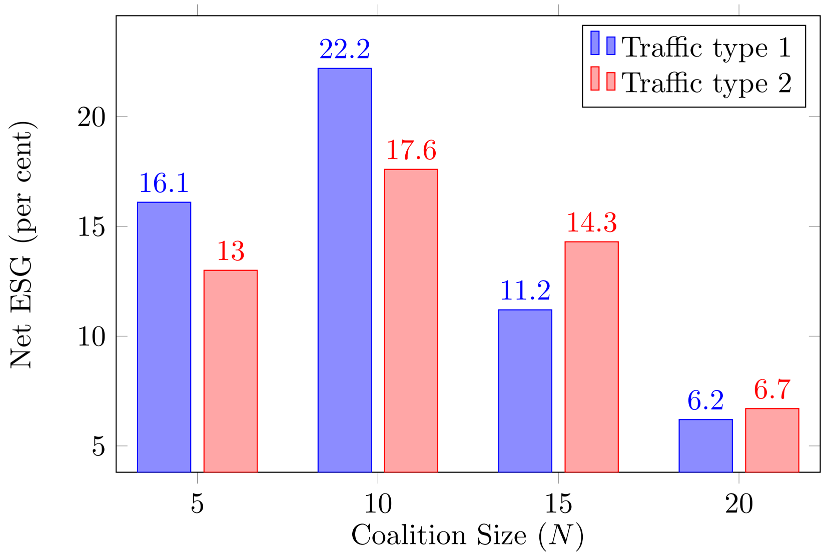


Figure 3.20: Net ESG for different coalition sizes (cell size=20 m×20 m, traffic rate=20 packet/s)

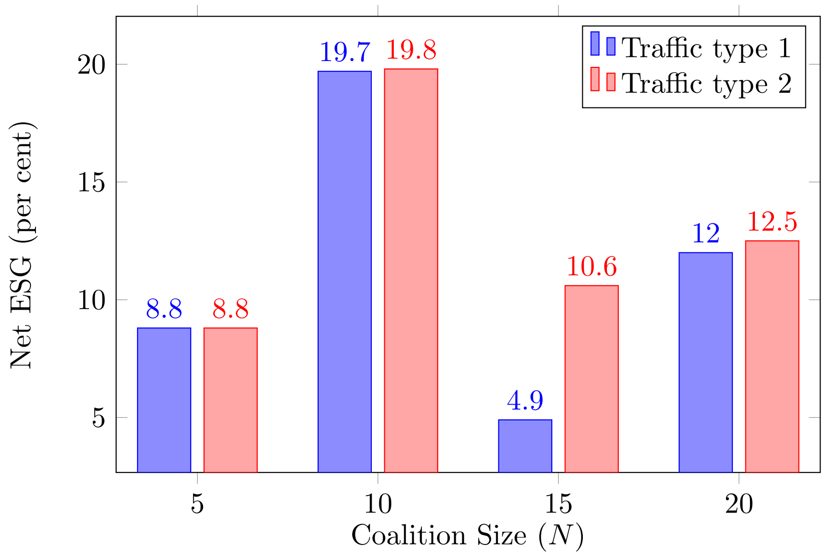


Figure 3.21: Net ESG for different coalition sizes (cell size=60 m×60 m, traffic rate=60 packet/s)

cell area. Figures 3.20 and 3.21 illustrate the simulation results for simulation areas of 20 m×20 m and 60 m×60 m, respectively. Both of these results are for CBR traffic with a rate of 20 packets per second with packet size 1024 B and 100 s traffic duration. Two types of traffics are considered: Traffic 1 in which the simulation time (100 s) equally divided among the mobile nodes (as time slots); in these time slots, participating nodes transmit one by one;

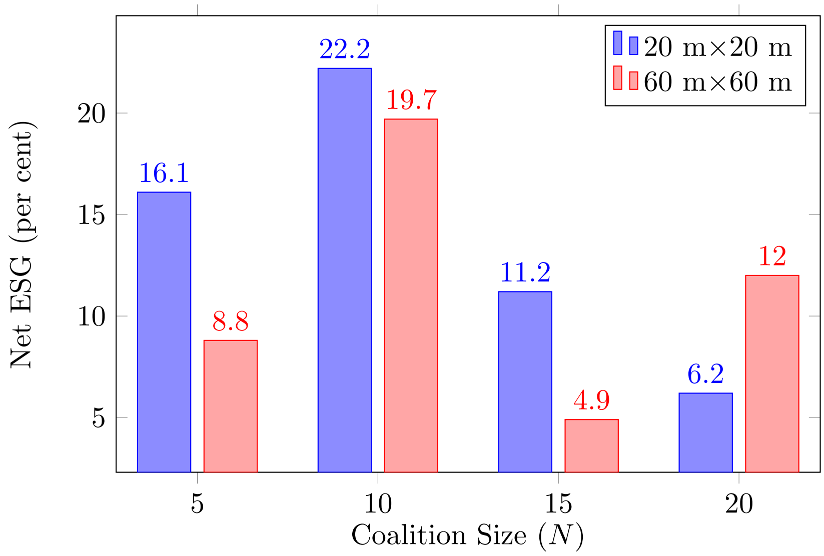


Figure 3.22: Net ESG for different coalition sizes (traffic type 1 with rate 20 packet/s)

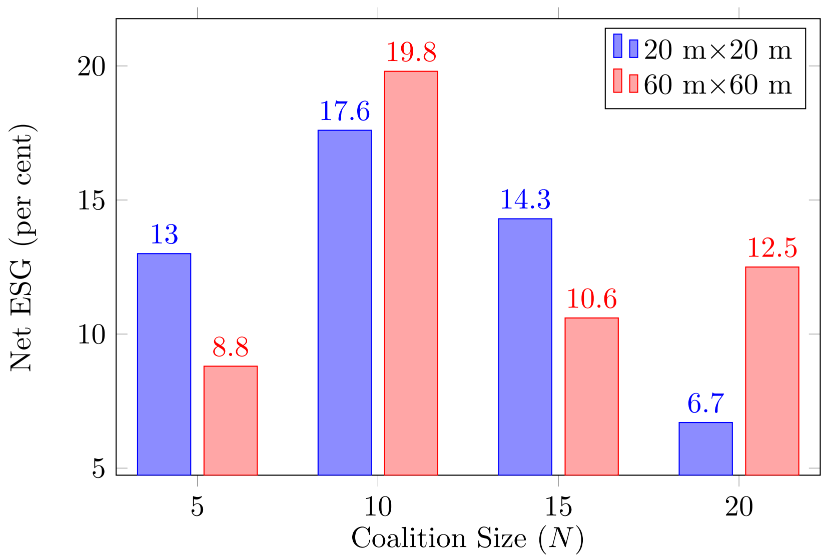


Figure 3.23: Net ESG for different coalition sizes (Traffic type 2 with rate 20 packet/s)

only one node transmits at each time slot. On the other hand, in Traffic 2, node 1 transmits from slot 1 onwards; node 2 transmits from slot 2 onwards and so on. That is, at the last time slot, all nodes are transmitting. As seen from these results, there is an optimal density of nodes for which the cooperation gain is maximum. For instance, in both of Figures 3.20 and 3.21, having 10 nodes results in maximum ESG. On the other hand, either having low density of nodes or having very high density of nodes result in poor ESGs. This is because, for the low density of nodes, the probability of finding a good relay is low, while for a dense

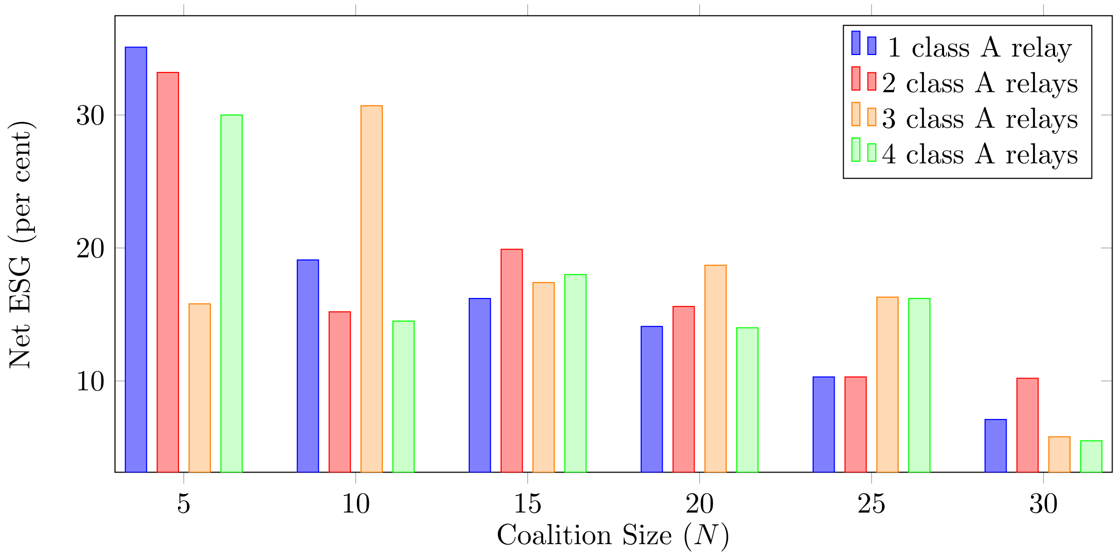


Figure 3.24: Net ESG of relay selection algorithm for 1 to 4 class A relay nodes when the coalition size varies from 5 to 30

area, the collisions from contending nodes to capture the medium essentially deteriorate the cooperation gain. Another observation from Figures 3.20 and 3.21 is that for a lower number of nodes, the ESG of Traffic 1 exceeds the gains of Traffic 2, while as the number of nodes increases, the ESG obtained from Traffic 2 outperforms that of Traffic 1.

Figures 3.22 and 3.23 illustrate simulation results for Traffics 1 and 2, respectively. Comparing these results, reveals that despite different traffic types, the trend of energy saving charts are almost similar. Figure 3.24 provides the net ESG as we increase the number of nodes in a simulation area of 60 m×60 m from 5 nodes to 30 nodes; adding five nodes at each step. We consider CBR traffic of type 1 and rate of 100 packets per second; the packet size and the flow duration are unchanged (1024 B and 100 s). The figure presents the results for varying number of *Class A relay* nodes that are defined as those UEs having good cellular channel qualities able to provide WiMAX connectivity with data rate 54 Mb/s. This figure demonstrates that: (i) ESG reaches its maximum when the coalition size is around 10 nodes; and (ii) the net ESG is more or less constant at 17% for different number of relays. Table 3.8 summarises the average ESGs for different number of Class A relays. It reveals two interesting observations. First, we obtain no additional gain by deploying more than one relay. Second, for a network with a reasonable number of nodes and with at least one Class A relay, on average, we obtain around 17% ESG.

Table 3.8: Average ESG for different number of Class A relays, each experiment is averaged over 10 replicas with random seeds.

Number of Relays	Net ESG (%)
1	17.1
2	18.9
3	17.0
4	17.0

To sum up, our main results can be enumerated as follows: (i) to keep the computation burden of the primal and the dual LP problems at a reasonable level, it is advisable to limit the coalition size by 20 to 30 nodes; (ii) For any coalition, there is an optimum density of nodes for which the ESG is maximum: having lower density of nodes leads to difficulty in finding an appropriate relay node for cooperation, while a higher density of nodes increases the interference level; (iii) as we introduce more nodes in the coalition, average ESG first increases until it reaches a saturation point, afterwards it starts decreasing; and (iv) for the considered traffic, there is no difference between obtained ESGs from having either a single Class A relay or more than one Class A relays.

3.7 Conclusion

With the trend of increased data rates and the increase in number of energy-constrained connected devices in the new era of IoT, more burdens are put on the design of the next generation of wireless networking paradigm (the 5G). One of the main challenges facing the new generation is the energy consumption of battery-operated mobile devices. With the higher required data rates and the need to ubiquitous connectivity, energy efficiency has to be addressed; otherwise, mobile users will be again chained to power outlets instead of wired networking. Addressing such issue, we proposed a relay selection problem for cooperative relaying scenario within the future heterogeneous networking paradigm. The proposed algorithm forms a coalition of source mobile devices and relays, to enhance the energy efficiency of the individual mobile devices, as well as the group combined energy consumption. The proposed algorithm is built based on a game theoretical approach, namely the *assignment game*. The proposed algorithm is split into two phases. First phase associates relays with source mobile devices, in order to optimize the energy efficiency of the whole coalition of mobile devices. The final phase determines how to distribute the obtained payoff fairly among players. We defined the characteristic function of the game and derived its *core* solution. We also introduced the utility function and the key performance indicators for evaluating the efficiency of relaying either for a pair of partners or for a coalition. Additionally, we advised a reward scheme to compensate cooperative users; hence identifying selfish users and excluding them from future cooperative coalitions. The results validate that the proposed technique can extend the battery lives of the UEs by up to 166% (2.7 times). Moreover, the gross ESG of a coalition can reach up to 50% in certain incidents. The results also show that excluding the signalling cost, on average, the proposed game can introduce 17% net energy savings, reaching up to 35%. The results also show the effect of the size of the coalition on the energy savings, as well as the optimal coalition size to avoid inefficient context and signalling costs, while keeping the running time of the relay selection algorithm at a feasible level.

Chapter 4

Extensive Form Games for Demand Response in Smart Grids

Smart grid is another envisaged scenario for 5G as a promising use case for M2M application. It essentially aims at transforming today's power grid to an intelligent grid by connecting all stakeholders from generators to utility companies and smart meters, allowing the grid to operate more efficiently and reliably. This particularly allows the utilities to implement real-time or close to real-time demand response programmes to solicit households to pursue a flat consumption pattern. In this chapter, we capture real-time strategic interactions between a utility company and the end-users as an extensive form game. We study DAP and quadratic pricing tariffs, and discuss the best strategic response of users to each of these strategies to achieve the NE. The game serves as a distributed optimisation tool to minimise load variation in the grid. That is, even if the users selfishly minimise their electricity expenses, they will automatically end up minimising the PAR of the aggregate demand, too. We study both DAP and Real-Time Pricing (RTP) tariffs, and incorporate both MILP and Quadratic Programming (QP) for scheduling smart home appliances to minimise the households' electricity costs subject to meeting their consumption preferences. The results show that the QP approach can reduce the PAR of demand significantly, whilst reducing the end user's electricity bill by up to 50%.

4.1 Introduction

Economists have long advocated that exposing consumers to the real-time price fluctuations in the wholesale electricity market can considerably enhance the market's economic efficiency [127]. To this end, RTP programmes advertise real-time prices to the end-users and monitor their instantaneous consumption. This entails the expansion of the legacy control and communications infrastructures, supporting mostly the generation and transmission systems (e.g., Supervisory Control And Data Acquisition (SCADA)), all the way down to the distribution networks and consumers' premises in order to connect the whole supply chain of the industry. To this end, Advanced Metering Infrastructure (AMI) [128] is being deployed around the globe to bridge the gap between the utility companies and the end users, establishing two-way communication links between the distribution companies and the consumers' facilities. This will permit the grid to efficiently match the supply and demand and to accommodation promising technologies such as Distributed Energy Resource (DER)s (e.g., wind, solar, etc.), distributed micro-storage devices, electric transportation, and Demand Response (DR) programmes [26, 129].

In particular, smart grid can be exploited for DR where a utility company can monitor electricity demand online and can shape user's consumption pattern through appropriate incentive mechanisms. For example, it can do so by increasing the price during peak hours when the grid is highly stressed while reducing it during off-peak hours when there is a supply surplus (e.g., over night). On the other hand, users can monitor price in electricity market in real-time and can accordingly optimise their consumption, shifting their non-urgent demand (e.g., Plug-in Hybrid Electric Vehicle (PHEV) charging) to off-peak hours. Improving the social welfare, this can benefit both the system operator and the households [127, 130–134]. It allows company: (i) to shut down inefficient and environmentally unfriendly power plants being used only during peak hours, and (ii) to avoid overdesigned transmission systems that need to operate in full capacity only few hours a day or even few hours a year. Further, it allows users to minimise their electricity expenses without decreasing their consumptions, just by wisely scheduling their shiftable appliances. Figure 4.1 illustrates an envisaged a smart grid scenario, depicting two-way power and information flows between the suppliers and the consumers, whereas Figure 4.2 depicts the supply chain of an electricity industry, highlighting its supply and demand sides.

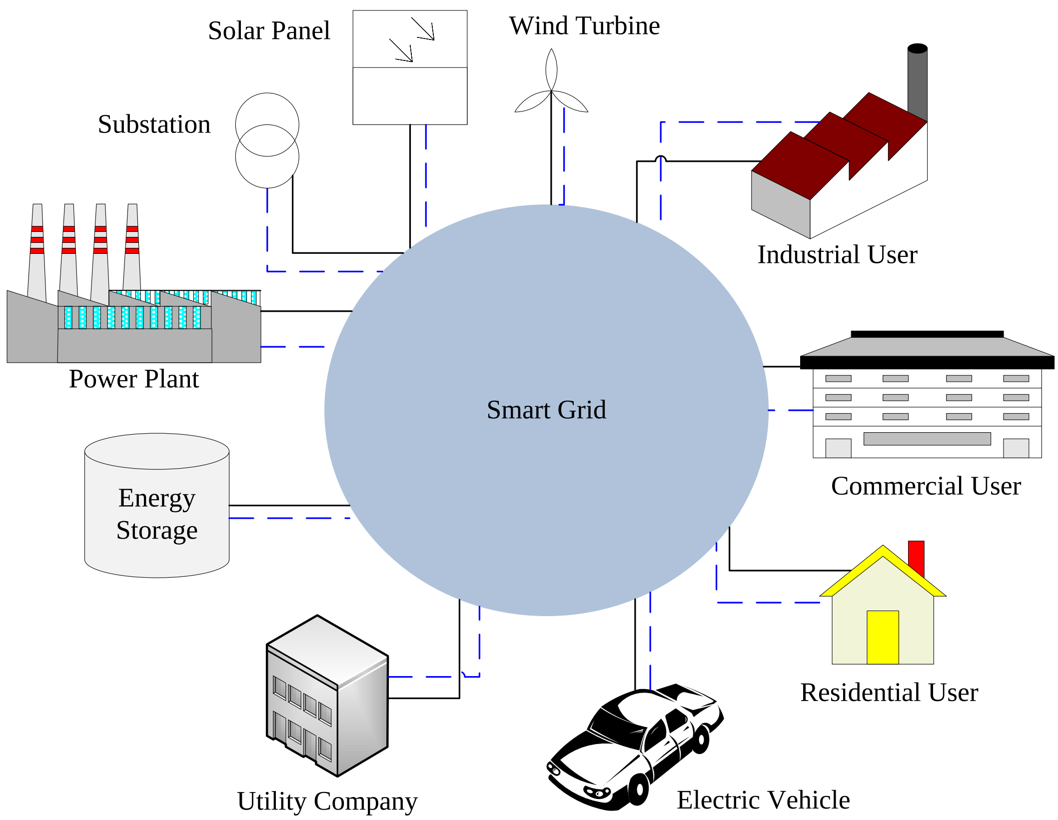


Figure 4.1: Smart power grid: the solid and dashed lines represent power and information flows, respectively

Game theory can be employed to analyse customer's behaviour in response to any change in the price of electricity in the market. In a non-cooperative game, every player adheres to a strategy that maximises its own utility, without necessarily concerning about the social welfare. A price-aware user may shift its unnecessary demand from peak hours, when the price of electricity is high, to off-peak hours, when the price becomes lower. A residential user has generally two types of appliances. The first type includes items such as lights and refrigerator that are price inelastic; i.e., no matter how much is the price of electricity, these appliances are needed to be on and cannot be interrupted. In contrast, the second type of appliances includes items such as washing machine, dishwasher, and PHEV that are price elastic; unless their task is finished before their associated deadlines, they can be shifted to other hours of the day during which the price becomes more affordable.

Adopting an effective pricing strategy by the company and an effective appliance scheduling strategy by a smart household are the main challenges for a successful DSM program.

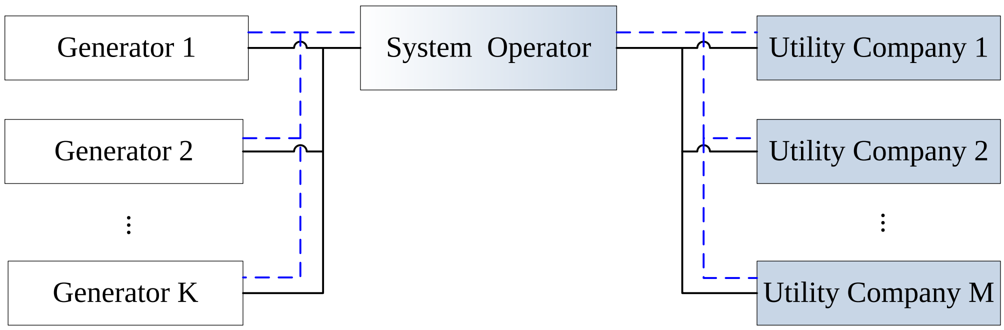


Figure 4.2: Electricity supply chain, shaded blocks depict the demand side

Inclining Block Tariff (IBT) has traditionally been practiced for many years to make electricity affordable for low-income people while charging higher rates for users who consume more to fulfil their non-basic needs such as air conditioning. Several other pricing strategies also exist for DSM programmes, including Critical-Peak Pricing (CPP), Time-of-Use (ToU) tariff, RTP, and DAP. For example, in DAP, the utility sets the price of energy for the next 24 hours and advertises it to the users. However, in RTP, the company does not determine the price in advance, rather it sets the price instantaneously based on the instantaneous demand level, and announces it with a very short notice; e.g., one hour or even few minutes in advance.

In our work, we aim at incentivising users to follow a flat consumption pattern during different hours of the day through leveraging the price of electricity to indirectly coordinate user's consumption. We study both linear and non-linear pricing tariffs to minimise the PAR and discuss optimal scheduling strategies for users to respond to each of these tariffs. Every user uses an optimisation problem to schedule its shiftable appliances to minimise her daily energy expense subject to meeting the power consumption needs of her appliances and her preferences for the operating intervals of these appliances. We validate our approach through simulations. The results show that adopting a quadratic pricing tariff by the utility and a quadratic scheduling scheme by the users is an NE (Section 2.2) that can save up to 52% in users' electricity bills, while attaining peak shaving by up to 88%.

The rest of this chapter is organised as follows. Section 4.2 reviews the related work. Section 4.3 describes our system model. Section 4.4 formulates DR as an extensive form game, while Section 4.5 details the considered pricing tariffs. Section 4.6 characterises smart home appliance scheduling as both MILP and QP problems. Section 4.7 depicts the simulation setup and discusses the results. Finally, section 4.8 concludes this chapter.

4.2 Related Work

Kirschen [135] provides a good tutorial on the potential benefits and barriers for a successful demand-side management program in a liberal electricity market, highlighting the economic characteristics of the demand (e.g., the demand-supply equilibrium and the price elasticity of the demand), describing the necessary tools for consumers to be involved in DSM (namely price prediction and consumption optimisation), and suggesting solutions to increase the price elasticity of the demand to encourage large number of small residential users to actively get involved in a DSM programme. The paper argues that increasing the short-run price elasticity of demand for electrical energy would improve the operation of these markets. It shows, however, that enhancing this elasticity is not an easy task. The tools that consumers and retailers of electrical energy need to participate more actively and effectively in electricity markets are discussed. Furthermore, it discusses the unusual economic characteristics of the demand for electrical energy and issues that must be addressed if the demand side is to participate actively in the market. It also outlines the tools and techniques that have been or should be developed to help consumers take advantage of the opportunities offered by competitive markets. A more active participation of the demand side would make electricity markets more efficient and more competitive. It would also promote a more optimal allocation of the economic resources.

In [136], the authors propose an interesting DSM technique based on utility maximisation where a user has storage battery and different types of appliances with different utilities, and the utility company employs different flat and real-time tariffs to coordinate indirectly the users' consumption to improve the system's performance in terms of load factor and generation cost and to decrease users' electricity payment.

In [137], the authors examine experiences on DR programs in the European Union (EU) and in some Member States (e.g., the UK, Italy and Spain), where there is already high penetration of Smart Meters for commercial and residential customer groups, describing initiatives, studies and policies and highlighting the factors that have facilitated or impeded advances in DR in European electricity markets. Similarly, in [138], the authors summarise the existing contributions of DR resources in the USA electricity markets.

In [139], the authors propose a DSM technique in smart grid based on a network congestion game where the price of electricity is a dynamic function of the level of congestion (i.e., the aggregate demand at the current time). The interesting property of a congestion game is that it is essentially a potential game. Hence, selfish optimisation of individual users leads to the maximisation of the social welfare. Potential games are basically the ones admitting a potential function with the property that an improvement of an individual player's payoff improves also the potential function.

In [140], the authors characterise the DR as two microeconomic market models to match the power supply and shape the demand, deriving their equilibriums in both competitive and oligopolistic markets and proposing distributed DR algorithms to achieve theses equilibriums.

Soliman & Leon-Garcia in [141] study DSM when users possess storage devices and formulate two game models when utility is excluded from or is included in the game. In the latter, they use Stackelberg game to model interaction between the users and the company and conclude that total cost and the PAR decrease when storage is present. Moreover, allowing users to sell electricity back to the grid (e.g., during peak-hours) can help them further decrease their total cost. However, it may deteriorate PAR, especially when company is absent from the game.

In [142], the authors address a DSM problem with multiple companies and multiple users, modelling it as a Stackelberg game where companies are the game leader and users are the game follower: the companies move first by setting the price, and the users react by optimally adjusting the amount of energy they purchase from each company. The authors also propose a common reserve power for the utilities to improve the grid's reliability in the presence of an attacker who aims at manipulating the price information to avoid the game settling at its equilibrium.

In [143], the authors propose a non-cooperative game model for a DSM problem with a mixture of the traditional passive users and the active users who own distributed energy generation and/or storage devices. They assume a quadratic tariff imposed by the company to charge the users and model the problem as a non-cooperative game. They solve the game to find its NE incorporating Variational Inequality (VI). They also provide a distributed algorithm based on Personal Digital Assistant (PDA) for the users to independently minimise their day-ahead cumulative monetary expenses for buying/producing their energy needs. They show that the participation of the active users in the DSM programme benefits not only themselves, but also the passive users – although the active users benefit more than the passive users do. In [144], the authors extend their previous work in [143] proposing a cooperative optimisation approach to minimise the aggregate expense of all active users. They also provide an algorithm based on Distributed Dynamic Pricing Algorithm (DDPA) to distributedly solve this cooperative optimisation problem. They demonstrate through simulation results that the non-cooperative game approach that they propose in [143] achieves the same performance that this cooperative optimisation approach can achieve in several less number of iterations.

Modelling DSM problem as an aggregate game, in [145], the authors incorporate a similar VI approach proposed in [143] to analyse the existence and the uniqueness of the NE and provide a distributed asynchronous gossip-based algorithm when there is no central unit to coordinate the users or advertise the aggregate energy consumption.

The introduced billing scheme in [39] neglects the different consumption patterns of the users and charge them solely based on their daily energy consumptions. This causes a fairness problem. The authors in [146] address this problem and propose a billing scheme that charge any user based on her not only daily energy consumption but also load flexibility and contribution to the social cost saving in the grid.

In [30], Mohsenian-Rad & Leon-Garcia formulate DSM problem as an LP problem when the real-time electricity price in the wholesale market is reflected to the retail customers using a combinational tariff composed of RTP and IBR and provide a simple and efficient Finite Impulse Response (FIR) filter for users to predict the price for the whole scheduling horizon when this information is partially revealed by the utility for only the current hour and maybe a few coming hours. They also introduce a trade-off in the objective function of the formulated LP problem, to achieve a balanced solution between minimising the electricity expenditure of the users and minimising their waiting times for the operation of their appliances.

In [39], Mohsenian-Rad et al. study a DSM problem where a single utility company serves multiple residential users interacting not only with the utility company, as in [30], but also with each other over a Local Area Network (LAN). Formulating the problem as a concave n-person non-cooperative game, they analyse the existence and the uniqueness conditions for the NE and provide an incentive-compatible iterative algorithm for the users to distributedly minimise their total energy cost, which also leads to the minimum PAR of the total load in the system. Turn-taking in a round robin fashion, which can be coordinated by the utility for example, at every iteration, the granted user partially solves the optimisation problem an provide the others with its achieved solution. The authors also analyse the convergence condition for this algorithm and show through simulation results that it converges quite fast, after around two rounds of iterations for every user.

The authors in [147] propose a heuristic optimisation algorithm for DSM based on evolutionary computation, where the algorithm admits a predesigned objective load curve and aims to bring the final load curve as close to this objective curve as possible.

In [148], similar to [30], the authors address a smart power system where several users subscribe to a single energy provider and interact with it to maximise the social welfare, i.e., the aggregate utility of all users minus the total cost imposed to the provider. They formulate the problem as a convex optimisation problem (Section 2.6.2), modelling the utility functions of the users and the cost function of the provider as a concave and a convex (parabolic) function, respectively. They propose an optimal RTP that clears the market and provide a distributed algorithm to iteratively achieve this optimal price where at each iteration, the provider re-adjusts the price and the production capacity based on the variations in the aggregate load, while each user reacts accordingly through individually re-adjusting her load such that the *marginal payoff* [1] of the user is always equal to the real-time price set by the provider.

In [41], the authors consider a similar problem formulation as in [148] and study the marker equilibrium under two different conditions: (i) when the users are price taking, i.e., they accept the price as a fixed value without considering the potential impact of their actions on the price, and (ii) when the users are price anticipating, i.e., they are aware that their actions may impact the price. They propose a strategy-proof mechanism, based on Vickrey-Clarke-Groves (VCG) mechanism, to reflect the price fluctuations in the wholesale market to the retail customers. In particular, the payment charged to each user is determined as the difference in the social welfare of the other users with and without the presence of this user. The strategy proofness property of the mechanism ensures that the users cannot do better than truthfully declaring their demands and their valuations for the energy.

In [149], Pedrasa et al. address the management of a smart home's energy services, employing Particle Swarm Optimization (PSW) algorithm [150] to determine the operation schedules

[1] Marginal payoff of a user is defined as the first derivative of her payoff/welfare function.

of a DER, e.g., Photovoltaic (PV) generation, energy storage in PHEVs, and controllable end-user loads (e.g., space heater, water heater, pool pump, etc.), to maximise the net benefit that the user derives from the energy services assigning a monetary benefit to each unit of "energy equivalent" of these services. For example, the "energy equivalent" of the space heating service is the thermal energy of the indoor air. The monetary values reflect the users' perception on the importance of their respective services. Then, the authors study the cost reduction gains of different smart home scenarios (e.g., when the weather is sunny/cloudy, or when the PHEV is (not) parked at home during day hours) under different tariff structures (e.g., ToU with feed-in rates, ToU with no feed-in compensation, and ToU with feed-in rates and peak demand charges), highlighting the scenarios where the coordination among DERs brings more value to the users.

In [151], the authors consider a DSM problem with one utility company serving multiple residential users under DAP tariff, where the price of electricity for the day is determined on the previous day. Similar to [136], they consider a marginal cost pricing, with a parabolic cost function similar to [30]. The appliances are of either uninterruptible or interruptible type. In the former, once the device is turned 'on', it has to remain 'on' until it finishes the task, whereas in the latter, the time intervals during which the device is 'on', need not be necessarily continual. Furthermore, they assume that an appliance may have different operation modes, with different power consumptions corresponding to each mode. Hence, the power consumption of an appliance can be controlled in a discrete manner from 0 to its maximum power rate. The authors model the mode and operating time mismatches of the appliances as additional (discomfort) cost, that is added to the (actual) monetary cost. They propose a greedy algorithm to find a suboptimal solution heuristically and in parallel. The proposed algorithm requires the users to communicate their load profiles to only the utility company, instead of broadcasting them to all other users, which provides a better privacy.

In [152], the authors address a DSM problem with a single retailer selling/buying electricity to/from multiple users. Some of the users have renewable Distributed Generator (DG) and can generate their daily electricity needs partly; the rest of the users are regular ones without generation capability. A user with DG can sell her excess generation back to the grid with a buyback price, which is normally lower than the retail price at the trade time. The authors propose a distributed parallel load scheduling algorithm that is run simultaneously by all users, in contrast to the sequential algorithm [153] that is run by one user after another but not by more than one user at any time. Hence, a parallel algorithm converges faster than its sequential counterpart. The proposed parallel algorithm minimises the cost of individual users, which is the sum of two terms. The first term reflects the monetary cost of consumed energy to the user, while the second term reflects her comfort loss due to the difference between her demand and her real consumption. To run the algorithm, every user requires only the price information and need to transmit their load profiles to only the utility company, without need to disclose it to other users, avoiding potential privacy issues. The authors divide the user load into three parts, namely base load, flexible load and schedulable load. Base load involves user's basic needs such as refrigerating which is considered to be fixed throughout the optimisation. Flexible load can be adjusted by the user, but the adjustment results in a satisfaction cost, e.g., adjusting the Air Conditioner (AC) temperature. The authors employ same satisfaction cost function they introduced in [40] and introduce an additional penalty term in the objective function of the formulated optimisation problem to discourage users from making big changes in consecutive iterations.

In [154], the authors develop an algorithm for Home Energy Management System (HEMS) and study its DR performance to schedule a residential user's high power-consumption appliances, e.g., water heater, space cooler, cloth dryer, and Electric Vehicle (EV). The algorithm receives as inputs: (i) the user's preferences and priorities for the operation of each appliance; (ii) the utility's demand curtailment request in terms of the demand limit level (i.e., the maximum allowable power consumption level) at the current time and the time duration that this DR event lasts. Based on these inputs, the algorithm schedules the appliances so as neither any violation from the user's comfort level nor any creation of high demand after the DR event (due to the compensation of the shed load) occurs. The authors also investigate the lowest possible demand limit level before any violation can occur when the user has different combinations of appliances or when she has different consumption habits.

In [155], the authors address a prosumer based DSM problem, where a household may be equipped with a grid tied rooftop PV system for local generation while relying on the grid for its extra demand. They propose clustering appliances with similar ToU probabilities[2] and study hourly energy cost and energy consumption of a household under different pricing and

[2]A function representing the probability of an appliance's being 'on' during different hours of a day

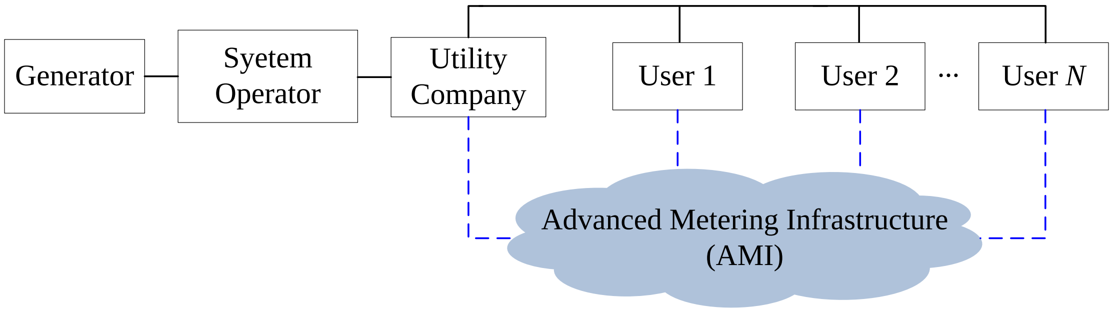


Figure 4.3: Considered DR scenario

scheduling policies.

Game theory provides a plethora of techniques that can be applied to smart grid to enable it operate more reliably and more efficiently [36]. For instance, as detailed in [36], it can be applied to better integrate micro-grids with the main power grid, by playing a coalitional energy exchange game among some nearby micro-grids, to encourage demand response using smart pricing strategies, and to ensure more efficient and more reliable multihop communications of smart elements (e.g., smart meters, EVs, etc.) with the control centre at the utility's premises. Finally, in [40], the authors propose a game-theoretic approach for designing an optimal ToU tariff.

In our work, we go beyond previous work by capturing strategic interactions between a utility operator and a residential consumer as a two-stage extensive form game (Section 2.4). We interpret different real-time demand response programmes as available strategies at retailer's disposal, who is the game leader. Then, we attain best response strategy of the consumer, as the game follower, to any of these DSM programmes that yields the NE. We characterise these responses as appropriate mathematical optimisation problems when either a DAP or a convex pricing tariff is adopted. These problems predominantly aim to schedule smart home appliances of a residential costumer so as to minimise her electricity bill while assuring her consumption preferences, without sacrificing her daily energy need.

4.3 System Model

We assume a DSM problem consisting of a utility company and multiple residential users, illustrated by Figure 4.3.

To formulate the problem, let $\mathcal{N} = \{1, ..., N\}$ denote the set of users. For each user $n \in \mathcal{N}$, let l_n^h denote the load at hour $h \in \mathcal{H} = \{1, ..., H\}$, where $H = 24$ denotes the scheduling horizon. The daily load for user n is denoted by $l_n = [l_n^1, ..., l_n^H]$. The aggregate load of all users at hour $h \in H$ can be calculated as follows.

$$L_h = \sum_{n \in \mathcal{N}} l_n^h \tag{4.1}$$

The daily peak and average load levels are calculated as

$$L_{peak} = \max_{h \in \mathcal{H}} L_h \tag{4.2}$$

and

$$L_{avg} = \frac{1}{H} \sum_{h \in \mathcal{H}} L_h, \tag{4.3}$$

respectively. The PAR is calculated as

$$PAR = \frac{L_{peak}}{L_{avg}} = \frac{H \max_{h \in \mathcal{H}} L_h}{\sum_{h \in \mathcal{H}} L_h}. \tag{4.4}$$

For each user $n \in \mathcal{N}$, let $\mathcal{A}_n$ denote the set of household appliances such as refrigerator, washing machine, PHEV and so forth. For each appliance $a \in \mathcal{A}_n$, we define an energy consumption scheduling vector

$$\mathbf{x}_{n,a} = [x_{n,a}^1, ..., x_{n,a}^H] \tag{4.5}$$

where scalar $x_{n,a}^h$ denotes the corresponding one-hour energy consumption that is scheduled for appliance $a \in \mathcal{A}_n$ of user $n \in \mathcal{N}$ at hour $h \in \mathcal{H}$. The total load of user $n \in \mathcal{N}$ at hour $h \in \mathcal{H}$ is obtained by

$$l_n^h = \sum_{a \in \mathcal{A}_n} x_{n,a}^h, \ h \in \mathcal{H}. \tag{4.6}$$

As illustrated by Figure 4.4, the scheduler embedded in a user's HEMS controls only her shiftable appliances without touching the non-shiftable ones. The task of user n's scheduler is to determine the optimal energy consumption scheduling vector $\mathbf{x}_{n,a}$ for each appliance $a \in \mathcal{A}_n$.

Next, we identify the feasible set for energy consumption scheduling vector based on user's

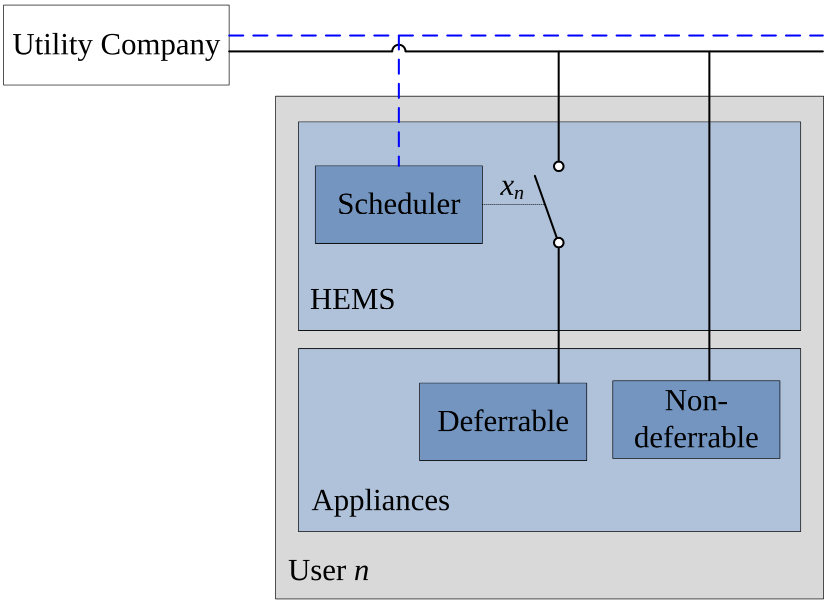


Figure 4.4: Scheduler embedded in user's Smart Meter

demand and preferences. For each user $n \in \mathcal{N}$ and each appliance $a \in \mathcal{A}_n$, we denote the predetermined total daily energy consumption as $E_{n,a}$. Note that the scheduler does not aim at changing the amount of this daily energy consumption, rather it aims at finding optimal operating time intervals for each appliance, e.g., in order to minimise the daily energy expense or the PAR of the total demand. A user needs to determine the beginning ($\alpha_{n,a} \in \mathcal{H}$) and the end ($\beta_{n,a} \in \mathcal{H}$) of a time interval that appliance $a \in \mathcal{A}$ can be scheduled. Clearly, $\alpha_{n,a} \leq \beta_{n,a}$. For example, he may select $\alpha_{n,a}$ = 6:00 p.m. and $\beta_{n,a}$ = 8:00 a.m. (in the day after) for its PHEV to have it ready before going to work. This imposes certain constraint on scheduling vector $\mathbf{x}_{n,a}$. Furthermore, we denote that

$$\sum_{h=\alpha_{n,a}}^{\beta_{n,a}} x_{n,a}^h = E_{n,a} \tag{4.7}$$

and

$$x_{n,a}^h = 0, \ \forall h \in \mathcal{H} \backslash \mathcal{H}_{n,a} \tag{4.8}$$

where $\mathcal{H}_{n,a} = \{\alpha_{n,a}, ..., \beta_{n,a}\}$. For each appliance, the time interval provided by the user needs to be larger than or equal to the time interval needed to finish its task. The daily load of the system is equal to the total energy consumed by all appliances over 24 hours. Hence, we always have the following relationship.

$$\sum_{h\in\mathcal{H}} L_h = \sum_{n\in\mathcal{N}} \sum_{a\in\mathcal{A}_n} E_{n,a}. \tag{4.9}$$

In general, some appliances may not be shiftable and may have strict energy consumption scheduling constraints. For example, a refrigerator may have to be on all the time. In that case, $\alpha_{n,a} = 1$ and $\beta_{n,a} = 24$. We define the minimum standby power level $p_{n,a}^{min}$ and the maximum power level $p_{n,a}^{max}$ for each appliance $a \in \mathcal{A}_n$ of user $n \in \mathcal{N}$. Therefore,

$$p_{a,n}^{min} \leq x_{n,a}^h \leq p_{n,a}^{max},\ \forall h \in \mathcal{H}_{n,a}. \tag{4.10}$$

We introduce energy consumption scheduling vector, $\mathbf{x}_n$, of a user, $n \in \mathcal{N}$, which is formed by stacking up the energy consumption scheduling vectors $\mathbf{x}_{n,a}$ for all appliances $a \in \mathcal{A}_n$ of the same user. We can now define the feasible set for energy consumption scheduling vector of user $n \in \mathcal{N}$ as follows.

$$\begin{aligned} \mathcal{X}_n = \{\mathbf{x}_n | \sum_{h=\alpha_{n,a}}^{\beta_{n,a}} x_{n,a}^h = E_{n,a},\ x_{n,a}^h = 0\ \forall h \in \mathcal{H} \backslash \mathcal{H}_{n,a}, \\ p_{n,a}^{min} \leq x_{n,a}^h \leq p_{n,a}^{max}\ \forall h \in \mathcal{H}_{n,a}\}. \end{aligned} \tag{4.11}$$

An energy consumption scheduling vector calculated by user n's smart meter is valid if and only if $\mathbf{x}_n \in \mathcal{X}_n$.

4.4 Demand Response Game

We define DR game as a two-stage game played by the utility company and the users. The utility moves first by choosing a pricing strategy, and then the users react by optimally scheduling their appliances. We formally define this game as follows.

- *Players*: Utility company and its registered users given by the set $\mathcal{N} \cup \{0\}$, where player 0 denotes the utility company.

- *Strategies*: Company chooses a pricing strategy that minimises the PAR and a user, $n \in \mathcal{N}$, chooses an energy consumption scheduling vector $\mathbf{x}_n$ that maximises her payoff.

- *Payoffs*: Payoff of the company is the negative of the PAR. Payoff of a user $n \in \mathcal{N}$ is the negative of her daily electricity cost, which is given by the following utility function.

$$\mathcal{U}_n(\mathbf{x}_n; \mathbf{x}_{-n}) = -\sum_{h=1}^{H} c_h(\sum_{m \in \mathcal{N}} \sum_{a \in \mathcal{A}_m} x_{m,a}^h) x_n^h \tag{4.12}$$

  Here, $\mathbf{x}_{-n} = [\mathbf{x}_1, ..., \mathbf{x}_{n-1}, \mathbf{x}_{n+1}, ..., \mathbf{x}_N]$ denotes energy consumption scheduling vectors of all users except user $n \in \mathcal{N}$, and $c_h(\cdot)$ denotes the cost of generating electricity during hour $h \in \mathcal{H}$ which might be a function of the aggregate energy consumption of all users (including user n) during the same hour.

NE of this game is a strategy profile that no player can benefit by unilaterally deviating from it. That is, the energy consumption scheduling vector $\mathbf{x}_n^*, \forall n \in \mathcal{N}$ is an NE if and only if

$$\mathcal{U}_n(\mathbf{x}_n^*; \mathbf{x}_{-n}^*) \geq \mathcal{U}_n(\mathbf{x}_n; \mathbf{x}_{-n}^*), \forall n \in \mathcal{N}. \tag{4.13}$$

As long as the cost function $c_h(\cdot)$ is a strictly convex and increasing function for each hour $h \in \mathcal{H}$, NE of DR game always exists and is unique (see Theorem 1 in [39]). This unique NE maximises social welfare (see Theorem 2 in [39]), i.e., the aggregate payoff of the company and the users.

4.5 Pricing Strategy

Figure 4.5 contrasts linear and quadratic price functions chosen by the utility company to charge consumers. The linear function, $c_h(L_h) = 0.1L_h$, charges users based on a fixed rate regardless of their consumption level at a time slot. However, the quadratic function, $c_h(L_h) = 0.1L_h^2$, charges the consumers based on a tariff that depends on the aggregate demand level at hour $h \in \mathcal{H}$: i.e., L. The more a user consumes at a specific time slot, the more is the price of energy for that user in that time slot. Furthermore, Table 4.1 summarises a three-level DAP tariff. The price is higher during evening hours, while it is lower during night hours, encouraging users to shift their loads to off-peak hours. Note that although the price is different for different hours, DAP is a linear tariff since at any time slot the marginal price is constant and independent from user's consumption level.

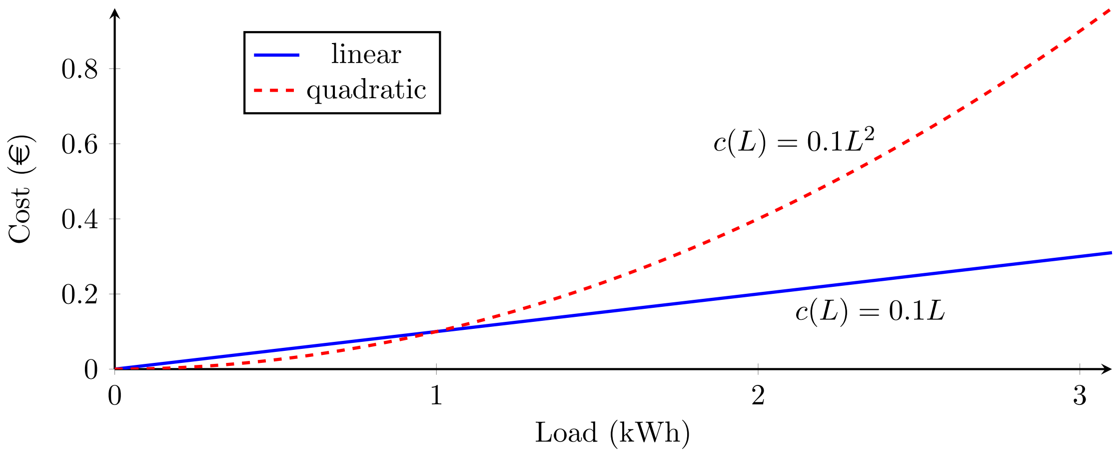


Figure 4.5: Linear and quadratic price functions

Table 4.1: Day-Ahead Pricing (DAP) tariff

Time Block	Off-Peak	Shoulder	Peak	Off-Peak
Hour	00:00-08:00	08:00-18:00	18:00-23:00	23:00-24:00
Price (Euro)	0.1	0.2	0.3	0.1

4.6 Smart Home Appliance Scheduling

4.6.1 Mixed-Integer Linear Programming

When company chooses DAP pricing strategy, NE of DR game is achieved when users adopt MILP scheduling (Section 2.6.1). To formulate this scheduling problem, we define an indicator vector $\mathbf{y}_n$ which has same dimensions as $\mathbf{x}_n$ and its element is equal to 1 when $\mathbf{x}_n \neq 0$ and is equal to 0 otherwise. For a DAP strategy given by price vector $\mathbf{f} = [f^1, ..., f^{24}]$, which indicates the price for the next 24 hours, NE of game is the solution of the following MILP problem.

$$\begin{aligned} &\min_{\mathbf{y}_n} \mathbf{f}^T(\mathbf{p}_n \circ \mathbf{y}_n) \\ s.t.: & \\ &\sum_{h=\alpha_{n,a}}^{\beta_{n,a}} p_{n,a} y_{n,a}^h = E_{n,a} \\ &y_{n,a}^h = 0 \; \forall h \in \mathcal{H} \backslash \mathcal{H}_{n,a} \\ &y_{n,a}^h \in \{0,1\} \; \forall h \in \mathcal{H}_{n,a}. \end{aligned} \tag{4.14}$$

where $\mathbf{p}_n \circ \mathbf{y}_n$ is the element-wise (Hadamard) product of the vectors $\mathbf{p}_n$ and $\mathbf{y}_n$; we have introduced a new power consumption vector $\mathbf{p}_n$ with the same size as $\mathbf{x}_n$ to factor out the power consumptions of the appliances from their binary (on/off) states. That is, $\mathbf{p}_n \circ \mathbf{y}_n = \mathbf{x}_n$, where $p_{n,a}$ denotes the power consumption of appliance $a \in \mathcal{A}_n$ of user $n \in \mathcal{N}$.

4.6.2 Quadratic Programming

Suppose that the utility company chooses a quadratic pricing strategy as follows to a consumer at hour $h \in \mathcal{H}$

$$c_h(L_h) = \alpha L_h^2, \tag{4.15}$$

where $\alpha \in \mathbb{R}$ is a real constant and L_h is the aggregate load at hour $h \in \mathcal{H}$, NE of DR game is achieved when every user adopts following QP scheduling to minimise its own energy expense, independent from other users.

$$\min_{\mathbf{x}_n \in \mathcal{X}_n} \sum_{h=1}^{h=24} \left(\sum_{a \in \mathcal{A}_n} x_{n,a}^h \right)^2 \tag{4.16}$$

Recall $\mathcal{X}_n$ is the feasible set for $\mathbf{x}_n$, defined by Eq. (4.11). Obviously, the objective function is the sum of the squares of hourly energy consumption of all appliances of user n, including both shiftable and non-shiftable ones. Note that although there is no freedom for scheduling non-shiftable appliances, they are included in the optimisation problem since their consumption affects the aggregate load level at hour $h \in \mathcal{H}$, which in turn affects the price at this hour.

4.7 Performance Evaluation

Simulation Setup

For numerical validation, we consider a scenario where a utility company serves 10 residential users. Each user has a set of shiftable appliances and a set of non-shiftable appliances. Table 4.2 and Table 4.3 present, respectively, the list of assumed non-shiftable and shiftable appliances along with their power consumption rates and the users' preferences for those appliances, including start and end times for non-shiftable and durations and deadlines for shiftable appliances. Each table has two parts, separated by a thick horizontal line. The

Table 4.2: Non-shiftable Appliances

Appliance	**Power (W)**	**Start**	**End**
Light	200	18:00	24:00
Refrigerator	30	00:00	24:00
Stove	1200	12:00 18:00	13:00 19:00
TV	200	09:00	24:00
Kettle	2000	08:30 16:00 20:00	08:35 16:05 20:05

Table 4.3: Shiftable Appliances

Appliance	**Power (W)**	**Start**	**Deadline**	**Duration (h)**
PHEV	1100	18:00	08:00	9
Space Heater	1200	00:00	24:00	2
Ventilation	250	00:00	24:00	1
Washing Machine	200	09:00	20:00	2
Tumble Dryer	2100	11:00	22:00	2

upper part includes 3 basic appliances that every user has, while the lower part includes 2 more optional appliances that a user may have. For each user, we generate a random integer between 0 and 2 to determine the number of optional non-shiftable appliances. Then, we generate another similar, but independent, random integer to determine the number of shiftable appliances for the same user.

We use *linprog* and *quadprog* MATLAB functions to solve the MILP and the QP problems formulated by Eqs. (4.14) and (4.16), respectively. During all simulations, we assume that the minimum power consumption of an appliance, $a \in \mathcal{A}$, of a user, $n \in \mathcal{N}$, is zero; i.e., $p_{n,a}^{min} = 0$. For MILP, an appliance is either *on* or *off*, without any power control mechanism. In contrast, for QP, we assume that the power consumption of a shiftable appliance can be controlled between 0 and its power consumption rate, $p_{n,a}^{max}$. For example, power consumption of PHEV charging can be controlled between 0 and 1100 W. We conduct three different experiments. In the first experiment, we do not utilise any scheduler and simply schedule shiftable appliances at most convenient time for the users (i.e., at the start times listed in Table 4.3) and assume that the utility company charges the users based on the DAP tariff defined by Table 4.1. In the second experiment, we assume that the utility charges the users based on the same tariff but the users employ MILP scheduler to run their shiftable appliances at the most appropriate

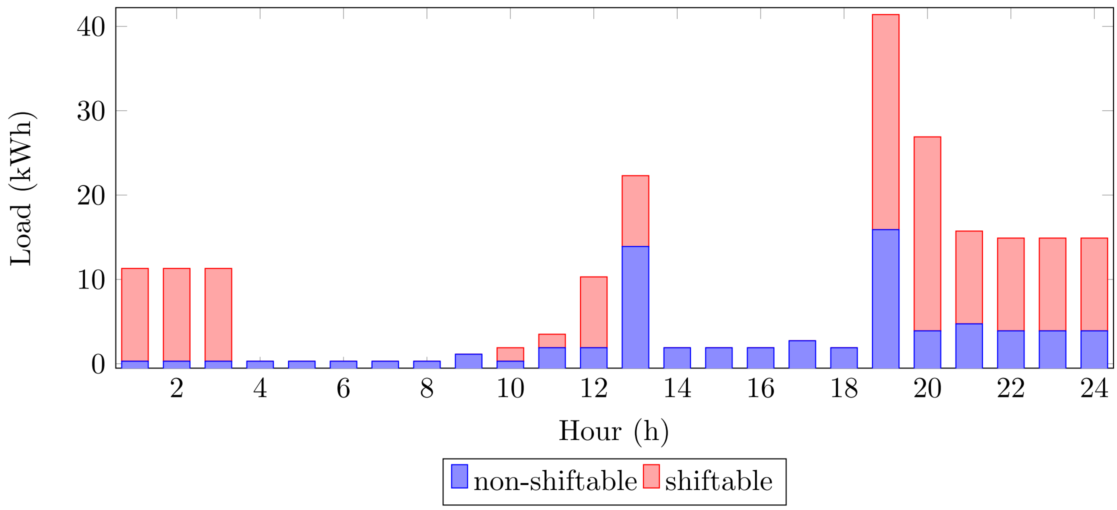


Figure 4.6: Non-shiftable and shiftable loads before scheduling

time. Finally, in the last experiment, we assume that the utility charges the users based on a quadratic tariff defined by Eq. (4.15) with $\alpha = 0.1$, and the users activate QP scheduler to control their shiftable appliances.

Results and Discussion

Figure 4.6 illustrates the hourly aggregate load resulted from the first experiment (i.e., without activating the scheduler). The figure shows both shiftable and non-shiftable loads. As seen from the figure, there are two peaks in the load, one at noon hours (1:00 p.m.) and the other at evening hours (7:00 p.m.) when the users turn their high-consumption cooking appliances on. The latter is higher than the former due to additional consumption for turning on the lights or plugging the PHEVs for charging. It is also worth mentioning that 70% of the load is of shiftable nature, mainly due to our assumption that every user possesses a PHEVs and that $PAR = 4.5$.

Figure 4.7 illustrates the hourly aggregate load resulted from the second experiment (i.e., after activating MILP scheduler). We observe that MILP avoids scheduling any shiftable load at evening hours. This is because of the fact that the price is at its maximum during these hours. We also observe that MILP schedules the shiftable load mainly at night hours (i.e., after 11:00 p.m.) when the price is at its minimum. Doing so, it reduces PAR from 4.5 to 2, which is equivalent to a PAR shaving of 71%. PAR shaving is a performance factor that we

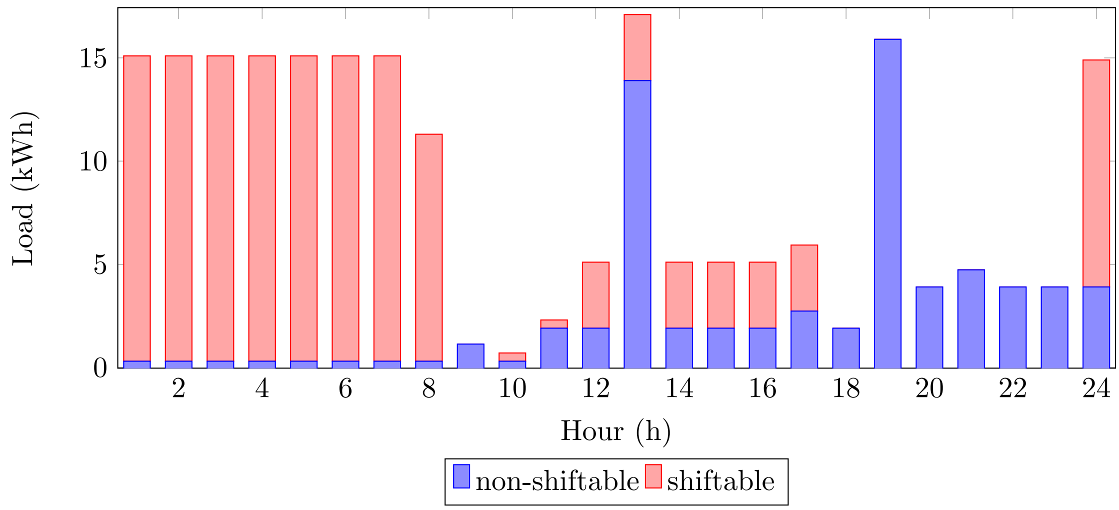


Figure 4.7: Non-shiftable and shiftable loads after Mixed Integer Linear Programming (MILP) scheduling

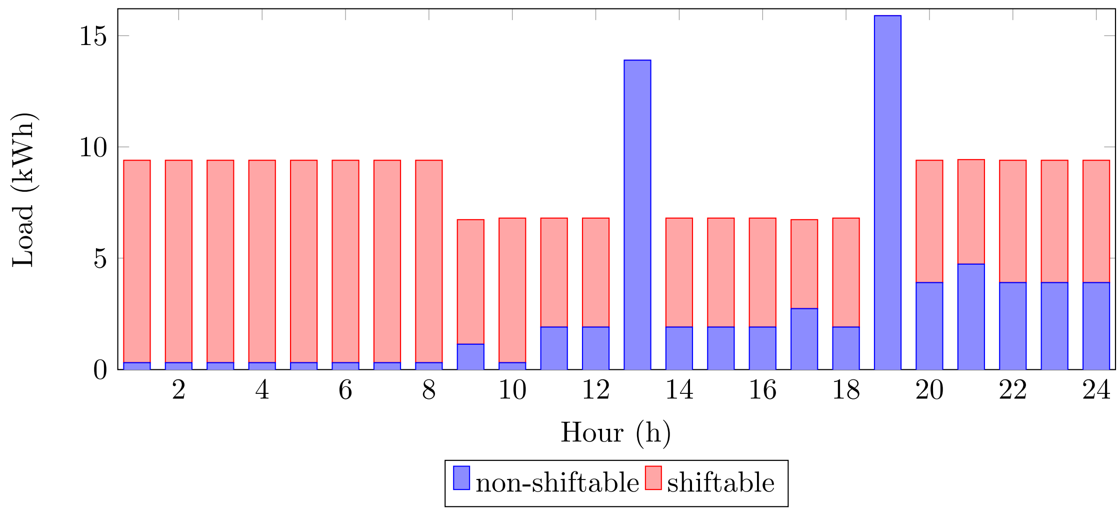


Figure 4.8: Non-shiftable and shiftable loads after Quadratic Programming (QP) scheduling

define as follows.

$$PAR\ shaving = \frac{PAR_b - PAR_a}{PAR_b - 1} \tag{4.17}$$

where PAR_a and PAR_b are PARs after and before activating the scheduler, respectively. It is worth mentioning that at 1:00 p.m., although there is already a peak of non-shiftable load, MILP still keeps scheduling shiftable load at this hour. This is due to the fact that the objective of this scheduler is to minimise the user's daily expense, which is calculated based on a linear tariff (DAP), independent from its consumption level.

Finally, Figure 4.8 illustrates the hourly aggregate load resulted from the last experiment

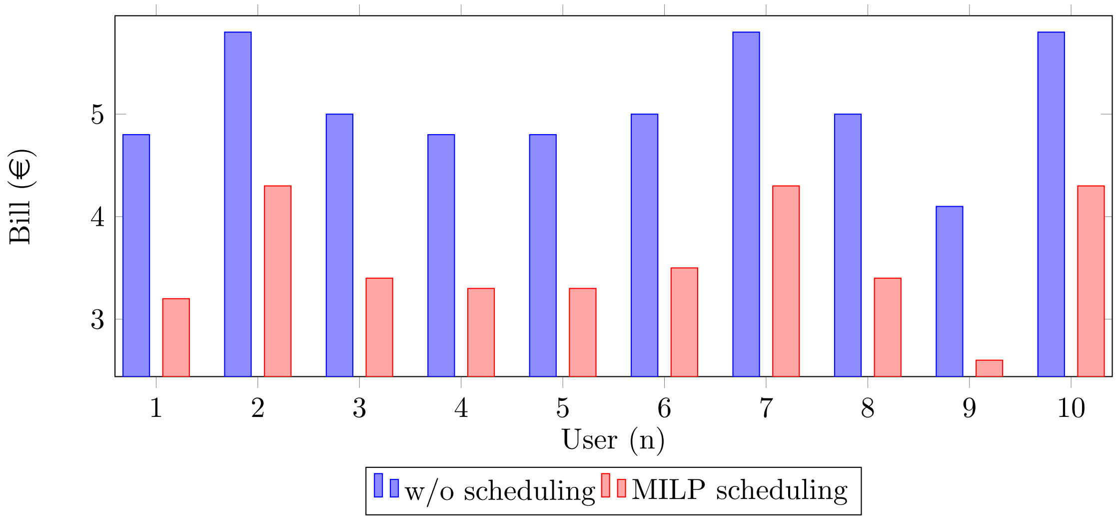


Figure 4.9: Daily bills of users before and after MILP scheduling

(i.e., after applying the QP scheduler). As expected, QP distributes the shiftable load across different hours much more evenly than the MILP does. We observe that unlike MILP, QP does not totally remove the shiftable load from the evening hours, rather it schedules it so as to fill the valleys of the non-shiftable load and to make the total load as even as possible. For the considered scenario, QP achieves a PAR of 1.7, equivalent to a PAR shaving of 80% (9% improvement comparing to the MILP). We also observe that QP avoids scheduling shiftable load at a time slot when there is already a peak of non-shiftable load (e.g., at 1:00 p.m.).

Figures 4.9 and 4.10 illustrate the impact of the game from the users' perspective. Figure 4.9 illustrates the daily bills of the users resulted from the second experiment (i.e., adopting DAP tariff and MILP scheduling). Obviously, every user pays less when they activate their schedulers. The variations in bills from one user to another are due to the fact that every user possesses a different set of optional appliances. Figure 4.10 illustrates the daily bills of the users resulted from the second experiment (i.e., adopting convex tariff and QP scheduling). Note that the bills before activating the scheduler (w/o scheduling) in Figure 4.10 are different from their counterparts in Figure 4.9. The ones in Figure 4.9 are calculated using the DAP tariff, while the ones in Figure 4.10 are calculated using the quadratic tariff. Comparing Figures 4.9 and 4.10, we further observe that: (i) for both MILP and QP schedulers, users pay less when they activate the scheduler, which implies users have incentive to participate in both of these DSM programmes; (ii) users save more in their bills when quadratic tariff is used than they do when the DAP tariff is applied.

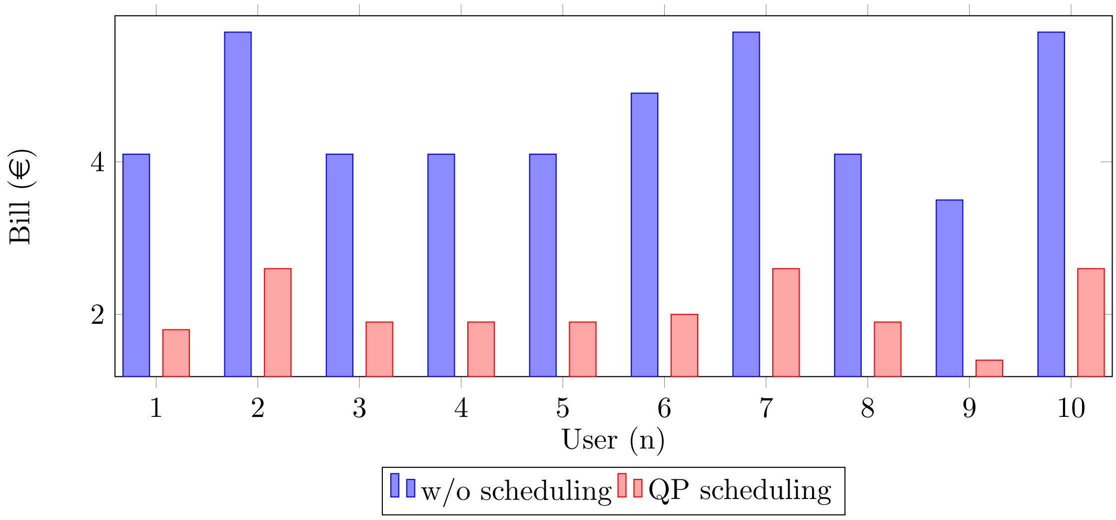


Figure 4.10: Daily bills of users before and after QP scheduling

4.8 Conclusion

We addressed a game-theoretic based distributed optimisation method for DSM in smart grids. The players of the game involve a utility company and its registered end-users. The utility's strategy set involves different DSM programmes that can be implemented, and its payoff is the peak shaving that each strategy can attain. Moreover, the strategy set of the users includes different optimisation tools that they can adopt to schedule their shiftable appliances, and their payoff is the amount of expense reduction that they can obtain in their electricity bills by adopting any of these scheduling algorithms. We specifically studied two different strategies, namely MILP and QP, and numerically evaluated the payoff that each one can provide to the players. The MILP strategy is the best response for the consumers to adopt if a DAP tariff is pursued by the utility company; and likewise, the QP strategy is optimal if the utility company adopts a quadratic (or any other convex) pricing tariff. In fact, the results show that for a DAP-MILP combination, the PAR can be shaved by up to 71% and the consumers can save by up to 32% in their electricity bills. However, if the company adopts a quadratic pricing tariff, and the users were to respond by QP scheduling, the payoffs of all players will rise, indicating a pareto-efficient strategic improvement. In particular, this pareto-optimal strategy can achieve up to 80% PAR shaving for the grid operator and up to 50% saving in the users' energy bills.

Chapter 5

Summary and Future Work

5G is expected to be deployed around 2020, providing pervasive connectivity with 'fibre-like' experience for mobile users. Apart from the expected 10 Gbps peak data rate, the major challenge for 5G is the massive number of connected machines and the 1000$\times$ growth in mobile traffic. This ultra-broadband and green cellular system will be the driving engine for the future connected society where everyone and everything will be connected at anytime and anywhere. Being in research and prototype stage, standardisation is the next milestone to achieve 5G, which will be followed by the development phase for two to three years. The last phase is network deployment and marketing, which may take another couple of years, foreseeing a potential commercial deployment by around 2020. Smart grid is a promising application for these next generation mobile networks, under the umbrella of IoT that intends to provide two-way MTCs between smart home appliances and utility companies, exploiting this smart power grid infrastructure. A utility company can monitor aggregate instantaneous load and set hourly price for the coming hour(s) and advertise this to the users. Moreover, users can monitor price fluctuations in the market and incorporate an appropriate scheduling algorithm – embedded in their HEMS – to promote saving in their electricity bills, by deferring their shiftable appliances (e.g., PHEV charging) to off-peak hours without interrupting their non-shiftable appliances (e.g., light, stove, etc.). Game theory is a fascinating tool to incentivise rational players to cooperate or to distributedly optimise smart systems where the decision is not taken centrally by one decision making entity, rather there are several independent decision makers affecting the system. As the intelligence level of mobile UEs and home appliances is constantly increasing, we expect that in the near future these devices and equipments will be smart enough to resemble rational agents seeking to maximise their own payoffs. In this thesis, we applied game theory as an optimisation tool and incentive mechanism to effectively utilise scarce resources in these 5G networks and applications. In particular, we focused on two fundamental problems, namely encouraging cooperation in mobile networks and enhancing demand response in smart grids.

In the first problem, covered in Chapter 3, we addressed cooperation strategies as a means to encourage mobile UEs to extend their battery lives. In fact, this is a legitimate concern for the future mobile networks as the energy required to keep wireless devices connected to the network dissipates quickly, while the battery technology is not mature enough to anticipate existing and future demands. In fact, without new approaches for energy saving, future mobile users will relentlessly be searching for power outlets rather than the network access, and becoming once again bound to a single location. To avoid this problem and to help wireless devices become more environmentally friendly, we addressed strategies to reduce power consumption of multimode UEs to help enable mobile users to experience a true mobile Internet. We discussed context-aware power saving strategies, based on game theory. These strategies allow the cognitive engine to make the right decision towards initiating cooperation based on the foreseen trade off between cooperation cost and potential energy saving. Simulation results validate that UEs can reduce their power consumption by up to 50% by adopting this approach. We also emphasised methods to enforce cooperative behaviour among mobile devices, isolating selfish players from cooperative coalitions to prevent any free riding attempt.

In the second problem, covered in Chapter 4, we applied game theory to enhance demand response to cope with supply (price) fluctuations and to encourage end-users to consume electricity more evenly throughout the day. We characterised smart home appliance scheduling as a mathematical optimisation problem that intends to minimise daily electricity bills of consumers subject to meeting all their consumption requirements and convenience preferences. We leveraged on the price of electricity to allow utility companies to indirectly coordinate users' consumptions to minimise PAR of the aggregate demand in order to improve the utilisation factor of the grid. We specifically incorporated extensive form game to capture the time sequence of interactions between a utility company and its subscribed users for specific DSM programmes. The utility is the game leader. It moves first by choosing the price of electricity for the next hour(s). In contrast, the users are the game followers. They react by scheduling their consumptions so as to minimise their individual energy bills, without compromising their daily consumptions. These interactions essentially enhance the demand response and help the electricity market to better utilise the (capital-intensive) power grid assets such as generating units, transmission systems, substations and distribution systems.

In the following, we sum up the main findings of our study and highlight some research directions for future work.

5.1 Concluding Remarks

Game theory can be effectively applied to resolve the conflict of interest arsing from the cooperation of UEs that belong to different independent users. It can help encourage cooperation in centralised or distributed fashion. In heterogeneous networks, multimode UEs allow mobile users to experience ubiquitous connectivity and better QoS. However, holding multiple active interfaces increases the power burden of UEs considerably. One of the biggest impediments of future mobile systems is the need to limit the energy consumption of UEs so as to prolong their operational time. Towards this end, we proposed a new promising approach based on coalitional game theory and cooperative communications. The approach allows neighbouring UEs to form coalitions and pool their resources (transceivers, antennas, battery energy, etc.) to reduce their overall consumption and extend their battery lives. Our simulation results indicate that by adopting this approach, mobile phones can reduce their power consumption by 50% under certain scenarios. However, this is reliant on energy features that already exist in the standard being enabled, and context-aware architectures that are implemented; yet many vendors until now have ignored these energy features in their products. Recall that the 50% energy saving gain for UEs is the gross saving without considering signalling cost or the overhead. Our experiments in NS2, for a scenario where UEs lie under the coverage footprint of a WiMAX BS and use their WiFi interfaces for relaying, show that the net energy saving is around 17%, reaching up to 35%, now taking into account the signalling. This moderate gain is mainly associated with the high power consumption of the WiFi interface; we expect that this gain can substantially increase provided that appropriate low-power short-range technologies (e.g., WiMedia) are exploited for the relaying purposes.

Pricing strategy and game-theoretic optimisation techniques can be exploited to optimise the demand response in smart grids, where the end-users are connected to the utility company through a two-way digital communications infrastructure. This complementary information network can carry the pricing information or other control signals from the utility's control centre to the consumers' premises, and the metering or demand biding information in the reverse path from the smart metres to the control centre. Apart from other benefits such as automatic and remote meter reading, this can allow a utility company to implement more sophisticated real-time DSM programmes. For instance, it can set the price of electricity for the next hour(s) and communicate this to the users. Receiving this information, users can independently react by optimising their energy consumption, contributing to the global optimisation of the system load. In fact, providing a scalable and distributive optimisation solution is the main advantage of applying game-theoretic techniques to the demand management issues. Particularly, we captured strategic interactions between a utility company and its end-consumers as an extensive-form game, where the company moves first by adopting a pricing tariff to encourage users to consume electricity more evenly during a day, whereas the users react by adopting appropriate scheduling algorithms to determine the best operating intervals for their shiftable appliances, minimising their electricity bills, while meeting their daily energy need and their comfort levels. We simulated a scenario with a number of users where each user had a set of shiftable and non-shiftable appliances. We studied two promising pricing tariffs, namely DAP and quadratic pricing. We characterised the appliance scheduling as an MILP problem when a DAP tariff is applied, and as a QP problem when a quadratic pricing tariff is opted. We developed and tested these two approaches on a custom-made system level simulator. A crucial problem with DAP is that when demand is highly elastic, it may cause considerable rebound effect, shifting peak demand to off-peak hours, creating new peaks. To solve this problem, utility companies can adopt a quadratic pricing tariff (e.g., $p(L) = 0.1L^2$), or any other convex pricing function. This kind of demand-dependent tariff can benefit all stakeholders by essentially aligning individual interests of the users (minimum bill) with the utility's interest (minimum PAR). Hence, even if the users act selfishly to minimise their bills, they will automatically minimise the PAR of demand, too. Simulation results reveal that this quadratic pricing tariff complemented by the QP scheduling on the user side, can help users save up to 50% in their electricity bills – without reducing their consumption quantities – just by appropriately scheduling their shiftable appliances. Moreover, this can help the utility to decrease the PAR of the total system load by up to 70%.

5.2 Future Work

While the results of this thesis support significant efficiency improvements gained from applying game theory to 5G networking and smart grids, they also provide a basis for several interesting research directions for future work:

Machine Learning

Machine Learning techniques can be incorporated to enable smart home appliances or smart UEs to learn from the context they operate and perceive how to interact and which action to choose in any particular circumstance so as to maximise their individual or group payoff.

Mechanism Design

Despite being attractive from the social welfare point of view, the players of a game might still be reluctant to reveal their private information. Therefore, appropriate strategy-proof or incentive-compatible mechanisms should be designed to encourage rational electricity consumers to reveal their consumption information or to stimulate rational UEs to reveal their available resources truthfully.

Cyber-Security Games

Tailoring game theory techniques to ensure security in wireless networks and smart grids is another interesting research path. This can be approached treating the problem as a zero-sum game played between Intrusion Detection and Prevention System (IDPS) and an attacker, as game players, who want to maximise their own payoffs. The payoff of the IDPS can be interpreted as the level of security that it attains for the system, while the payoff of the attacker being the negative of this value.

Coalition Structure Generation

Designing fast and efficient Coalition Structure Generation (CSG) algorithms in a non-superadditive context for optimal partitioning of UEs that maximises social welfare is another important issue. For this purpose, algorithmic game theory techniques [156] can be applied to bring computationally fast and efficient algorithms for distributed coalition formation and relay selection in future mobile networks.

Cooperation and Energy Efficiency

Energy efficiency performances of different cooperation techniques (e.g., antenna pooling, cooperative transmit/receive diversity, etc.) need to be evaluated. This is of crucial importance, because UEs need to figure out the payoff of adopting a certain strategy to help them decide whether they should opt for that strategy or not.

Context-Aware Coalition Formation

Designing network protocols for efficient exchange of context information among UEs and RANs, and for forming and joining coalitions is another fundamental issue.

Distributed Generation and Micro-Storage

Current research on demand response games can be expanded considering distributed micro storage devices for users [143], enabling them to store energy when there is an excess of supply, and to consume it or even sell it back to the grid when there is a supply deficit. The users may also harvest energy from renewable sources such as wind or solar energy, run a micro Combined Heat and Power (CHP) unit, or even use their EVs as a mobile storage unit for electricity to more actively participate in demand response programmes (i.e., Vehicle-to-Grid (V2G)) [157–159]. In this regard, it is essential to capture the intermittent nature of renewable sources [160] through appropriate mathematical models (e.g., stochastic game model) and to develop charging/discharging strategies for distributed storage units or for EVs, so as to assure the grid stability.

M2M Communications for Smart Grid

Designing efficient M2M communication protocols for smart grid applications supporting short and infrequent data packets generated by smart home appliances, smart meters, smart thermostats, or smart home Energy Management System (EMS) deserves further investigation is another important research direction.

Binary QP Algorithm

Finally, inventing efficient algorithms for solving binary QP scheduling [161, 162] that switches the appliances either 'on' or 'off' without any power control deserves further investigation.

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